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Regulating Interbank Exposures against the Risk of Contagion

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Abstract:

This study is built on Eisenberg and Noe model of payment systems to show an increase in banks liabilities in interbank market results in a higher risk of cognition and could trigger systemic risk. So first at the theoretical level, it justifies the central bank intervention to regulate banks borrowing in the interbank market. Then to provide the regulator with the required tool to deal with banks exposures, it shows how setting a limit for each bank borrowing from the interbank market could be used to gauge the systemic risk against a given target for the stability of the system. To uncover the interbank bilateral exposures, it goes through several decomposition process. First, it exploits payment flow data to decompose the whole payment liabilities into interbank retail settlement exposures and the exposures arising from direct lending relationships. Taking the structure of retail exposures fixed, it makes another decomposition to separate the stochastic weight matrix from the vector of total payments made by each bank. Finally, it decomposes the total retail exposures coming from gross and net retail payment systems. Daily payment flow data of Real-Time Gross Settlement (RTGS) System for a 19-month period including about 56000 observations for each day are used to make the estimation. So, at the first step, the ACH aggregate net exposures are used to generate the bilateral exposures using the maximum entropy algorithm. Second, ARIMA modeling is used to forecast the elements of the matrix of total retail exposures. That is put together with the matrix of borrowing from interbank market to form the total liability matrix. A simulation analysis then is applied to investigate the level of borrowing that is allowed to sustain the system stability at the desired level set by the regulator.

Introduction

There are two very different reasons for banks' liquidity shortfall; First, a liquidity shortfall that could even happen for a sound institution arising from a turmoil in market liquidity that the bank depends on for funding. Second it could be because of liquidity mismanagement or the creditors run away due to their concerns over bank solvency. Carlson et al (2015) advise central banks to take different measures against these two type of institutions. They argue that generally central bank lending is the best response to the troubled sound institution, while orderly resolution (by the institution as it gets through the problem on its own or via a controlled failure) is the best response to the second ones.

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Landier and Ueda (2012) in their seminal paper acknowledge the challenges that central banks face in dealing with banks liquidity needs and designing the restructuring plan for the troubled banks. They urge central banks to take into consideration the payoffs and incentives for the various key stakeholders including government and bank managers in drafting their policies. While the government aims to reduce the probability of a bank's default by pushing banks towards restructuring plans, bank's mangers often looking for new financing mainly through borrowing from the interbank market; a policy that entails higher financing costs as well as higher systemic risk for the whole banking sector.

The work of Bowe et al (2015) sheds some light on the design of the appropriate central bank regulatory policy in this context. They claim the key factors influencing the design of the optimal central bank financial stability policy are the volume of interbank lending, the relative riskiness of financial institutions in the system, and the probability of any crisis becoming systemic. They develop a theoretical model examining the balance between the central bank short term rescue plans; acting as the lender of last resort and a more fundamental plan to force the restructuring of the troubled financial institution. These two plans are complementary and resemble the proper rescuing plan of drowning victims, while first all efforts should be directed towards restoring the breathing by CPR, the next step is to transfer the victim to hospital for more thoughtful treatments. The complexity arises from the fact that in the eyes of a troubled bank, these two plans are indeed substitutes and the bank manager may prefer to rely excessively on borrowing rather than going through a painful structural reform with all hassles. The main concern of the central banks, on the other hand, is the possibility of financial contagion brought about by excessive borrowings from interbank market by troubled bank and the negative externality of the bank behavior. That presents a rationale for the central banks call for monitoring banks borrowing in interbank market.

This paper evaluates the danger of contagion and the possibility of systemic risk triggered by excessive borrowing by banks in the Iranian banking sector. But more generally, it proposes a tool for the regulators in money market to take precautionary measures against the adverse consequences of banks behavior. This study is in line with Rochet (2009) recommendation for banking supervisors to implement a set of risk mitigation tools such as bilateral credit limits.

The tool introduced in this paper is not based on economy-wide measure of systemic risk. It uses a combination of balance sheet and payment data and among various risk dimensions it covers only systemic risk stemming from interbank exposures. A more comprehensive approach to systemic risk measurement of course takes into account banks' exposure to overheating sectors and the economic system as a whole. This allows the regulators to uncover any sign of systemic risk builds up at its early stage. That, however, requires access to a huge quality data that are not normally available to the researchers. With poor quality data, any attempt to expand the model to include more factors and channels would associate with the higher probability of arriving at more unreliable outcomes.

Using both indicators of funding structures and payment data allows us to design a forward-looking tool for higher-frequency risk monitoring and policy response. In evaluating the impact of interbank exposures on systemic risk, it follows a two-step procedure: first, it exploits the payment flow data as the ex-post realization of the interbank bilateral exposures to calculate the structural parameters of the model, then it replaces the accounting-data in the model with the more recent information on interbank large exposures and their maturity to make the most of the existing information for suggesting accurate policy recommendations.

The interbank obligations are typically not big in size compared to the bank's capital or total liquid assets. So it is unlikely in practice that the bank exposures to interbank market cause real problem and lead to insolvency. But for the sake of systemic risk evaluation, it is the inability of a bank to fulfil its commitments in interbank market that matters, because that is the one that could trigger the contagion. Here of course the definition of a threshold for risk tolerance, the amount of debts that bank could accommodate, is of great importance. Nevertheless, the simplifying assumption used in this paper that each bank's liquidity buffer is proportional to its capital is not restrictive for its real world application as we also introduce a coefficient that could be gauged for each bank considering other available related regulatory information.

This paper contributes to the systemic risk literature by proposing a new method for constructing a forward-looking interbank exposure matrix using the detail information from the interbank micro and large value payments. The payment system, as Chiu and Lai (2007) insist, is itself a combination of some payment subsystems. So the network pattern of bilateral linkages structure depends on underlying settlement relationships. Following this line of argument, we decompose the whole settlement relationships into retail settlement exposures and the exposures arising from direct lending relationships. Then a structural VAR model is used to forecast the banks position in payment system considering the pattern of network linkages under both normal and stressed scenarios and to show the results in terms of bank failures and capital losses in response to exogenous shocks. The results allow the central bank to evaluate the impact of banks borrowing on contagion using the change in domino effects due to change in bilateral exposure matrix.

This paper is structured as follows. Section 2 deals with theoretical and empirical literature on systemic risk and bilateral exposures. In section 3 a general framework for analyzing systemic risk is introduced. Section 4 presents the methodology employed in the paper. An overview of the Iranian payment system is provided in section 5 and the systemic risk inherent in the Iranian interbank netting system is quantified by way of simulation in the following section. Section 7 concludes.

Literature on Contagion in Interbank Market

There exists an extensive literature on systemic risk in interbank market (For the most recent survey on this issue see Benoit et al (2017)). The literature can be classified based on the channels through which the shocks are transmitted. The one that is close to ours, concentrates on the inter-institutional linkages through bilateral exposures in interbank market. Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000) are some early works based on this approach. They explore contagion via the interbank exposures and argue a segmented interbank market structure where each bank borrows from only one bank is more fragile than a system where the sources of funds are more diversified.

The second branch of works focuses more on the contagion stemming from linkages in asset liquidities rather than funding liquidity. Therefore, they come up with a different measure and consider a significant jump in the asset correlation as an evidence of contagion. While both argue that the architecture of the interbank market is of crucial importance for financial contagion, they are split in linkages that are considered to follow in order to study the risk propagation. Following the same line of argument, Blancher et al (2013) introduce a systemic risk monitoring tool called SysMo wherein, in its underlying methodology, they make a clear distinction between fundamentals-based and market-based models. Market-based models, however, do not capture the determinants of single bank failures and this is even more in case for systemic failures, whose determinants are to be found in common idiosyncratic risk factors and/or common macroeconomic causes. Therefore, for the purpose of this study these models are not applicable and we more focus on fundamentals-based models.

An important stream of the literature on systemic risk in payments network has focused on interbank contagion building on Eisenburg and Noe (2001) model. Since its introduction, the model has been widely used by researchers and also central banks to study default cascades in the banking systems. Recently the Bank of England has adopted this model to analysis solvency contagion in the UK financial system (Bardoscia et. al. 2017). Regulator bodies including Basel committee on banking sector supervision used the model in stress test analysis. This study is built on Eisenberg and Noe model of payment systems to show an increase in banks liabilities in interbank market results in a higher risk of cognition and could trigger systemic risk.

A key ingredient required to estimate contagion in Eisenburg & Noe model is the liability matrix that shows the bilateral exposures. It is a big challenge to uncover the interbank bilateral exposures with real world data. As information on bilateral exposures in the interbank market are often unobserved there is a branch of research that combines information-theoretic arguments with economic incentives to produce some hypothetical interbank networks. Researches in this field propose two methods for constructing the interbank linkages matrix. The first method is known as "maximum entropy" and is built on this assumption that the matrix slots are filled as evenly as possible, using the available information on each bank's total interbank lending (Upper 2011, Elsinger et al. 2013). That implies that banks diversify their exposures by spreading their lending and borrowing across all other active banks. The second is known as "minimum-density" method and is based on the economic rationale that interbank linkages are costly to add and maintain (Anand et al. 2014). The method loads the most probable links with the largest exposures consistent with the total lending and borrowing of each bank.

Despite the fact that data about interbank exposures are scarce and often of limited quality, there are still some sources of information available to exploit and construct the bilateral exposures matrix. The empirical literature on systemic risk and construction of bilateral exposures matrix from real world data could be broadly divided by whether the bilateral exposures is estimated from bank balance sheets data, payment system data or a mixture of these two sources. First, the one that is called accounting-data approach estimates the matrix of bilateral credit relationships from bank accounting information (See the pioneer work of Upper and Worm, 2002; Acharya et al. 2010, Brownlees and Engle, 2011, for more recent works). The second, could be called payment-data approach that consists of using the information from payment systems (see Humphrey, 1986; Angelini et al. 1996 and Elsinger et al. 2004). The third technique which is called mixed technique combines both of the previous techniques and data sources (Degryse and Nguyen, 2004).

Since the original work of Humphrey (1986), that appears to be the first attempt to quantify systemic risk in a payment system, the empirical literature and estimation techniques have evolved dramatically. Humphrey (1986) applied a time series technique to analyze the U.S. banking sector to study how the failure of the bank with the largest settlement obligation may generate a major disruptive system-wide effect. New applied researches use time-varying models that takes the network structures into account. Diebold and Yilmaz (2014) build and analyze static and time-varying directed and complete networks based on variance decompositions from a vector auto-regression (VAR) model. Hautsch et al. (2014) model static and time-varying tail risk spillovers between banks using a LASSO-type quantile regression to select the relevant risk drivers across banks and thus define the directed network's edges and gauge their systemic impact and changing roles in time.

A new empirical models also have recently emerged that focuses on the role of spatial dependence in the data and its implications for interdependence in financial networks. These researches apply advance techniques including threshold methods to obtain a sparse adjacency matrix that can be used for spatio-temporal analysis of shocks across banks in a spatial auto-regression model (See Bailey et al. 2015, and Craig and Saldias, 2016). Craig et al. (2016) provide empirical evidence on the relevance of systemic risk through the interbank lending channel using spatial auto-regression model. Their results show evidence of significant "spatial" dependencies reflecting unobservable factors in the cross-section of interbank market exposures.

Recent Development in Monitoring and Regulation of Systemic Risk

A joint research by IMF, BIS, and FSB in the G20 countries revealed that a variety of methods are applied to measure systemic risk. The Banco de Mexico, the Bank of England (BoE), De Nederlandsche Bank (DNB), the Deutsche Bundesbank, the Monetary Authority of Singapore (MAS), the National Bank of Belgium (NBB), the Oesterreichische Nationalbank (OeNB), and the Swiss National Bank (SNB) regularly conduct network analyses with a view to identifying institutions whose failure could have systemic implications.

While a number of countries have established quantitative methodologies that primarily serve diagnostic purposes, the reaction by central banks is limited to imposing some static measures for compliance. Two example of such static measures are presented in the following sections.

The Bank of England Framework

The Bank of England's Risk Assessment Model for Systemic Institutions (RAMSI), which is currently under development, is a novel approach toward analyzing the interaction between institution-specific and system wide vulnerabilities. The original idea to establish systemic risk assessment frameworks was pioneered by the Bank of England. The Bank's framework was deliberately designed in a flexible way so as to capture a wide variety of crisis situations. It can be applied to banking crises, which is the most common form of financial distress, as well as to financial market and financial infrastructure disruptions. The Bank of England's framework was dubbed "The Wheel of Misfortune," as the overall assessment is expressed graphically in a radar diagram with six spokes. It distinguishes between internal damage to the financial system and damage to the real economy. Four dimensions, or spokes, indicate the "internal" damage to the financial system: "capital" and "funding" together determine the financial system's capacity for intermediation, while "infrastructure" and "markets" are the key tools for harnessing that capacity through the delivery of financial services of financial services to the economy. The other two spokes of the wheel capture the direct impact on the real economy, as financial crises may lead to reductions in financial wealth and loss of access to financial services. These factors limit consumption and production potential.

The Bank of England is in the process of further developing its analytical tools. While the Wheel of Misfortune is applied in the context of crisis situations, the Bank of England is also exploring how systemic risk can be integrated in microprudential and macroprudential policy. In a discussion paper (Bank of England 2009) a proposals are made to capture systemic risk by establishing capital surcharges over and above the prevailing statutory capital requirements. The starting point of the analysis is the observation that current prudential regulation does not address two key aspects of systemic risk. First, financial firms tend to overexpose themselves to risk in the upswing of a credit cycle and to become overly risk-averse in a downswing. Second, individual banks typically fail to take account of the spillover effects of their actions on risk in the rest of the financial network.

The first aspect of systemic risk could be addressed by calibrating time-varying capital surcharges contingent upon the degree of exuberance prevailing in financial markets. By requiring banks to raise equity, the marginal cost of lending can be raised and thus provide incentives to slow balance sheet growth. In regulatory terms, this could be described as varying the risk weights that apply to different classes of lending and other exposures. Note that capital surcharges would fall in a downturn, to provide incentives for banks to maintain the supply of credit.

The second aspect of systemic risk could be addressed by imposing so-called cross-section systemic capital surcharges aimed at reducing the default probabilities of institutions whose failure would cause greater damage across the financial system and the real economy. An obvious challenge is to quantify an individual institution's contribution to systemic risk. It is the product of its Probability of Default (PD) and the system-wide spillover effects associated with distress or default. The latter is derived on the basis of an institution's size, the distribution of its exposures (using a network model), and fire sale propensities.13 After calculating an institution's systemic impact score, the Loss Given Default (LGD) for the entire financial system is determined. These system-wide losses are then allocated across financial institutions according to their systemic impact score. The final step is to calculate the additional amount of capital needed for each institution to neutralize the expected system-wide losses.

The European Central Bank Framework

The European Central Bank (ECB) has on occasion communicated about the main characteristics of the European systemic risk assessment framework. The framework, which was strongly inspired by the Bank of England's Wheel of Misfortune, was designed to provide cross-border authorities with a "common language," hence enriching the quality of the policy discussion of the systemic impact of a particular crisis situation. It also aimed to reduce the risk that under the pressure of circumstances authorities would roll out public support measures before assessing the potential impact of a particular crisis.

The framework calls on authorities to conduct separate assessments of the impact of a crisis on financial infrastructure, financial markets, financial institutions, and the real economy. The systemic impact is assessed taking into account the critical importance of the affected parts.

Payment Systems and Contagion Mechanism

Suppose there are *n* banks operating in the payment system: ℵ={1,2,3,…,N}. The matrix of interbank liabilities or exposures (a promise made by i to pay to j) $L = [L_{ij}], \forall i, j \in \aleph, L_{ij} \geq 0, L_{ii} = 0$. For i, e_i is the external assets (cash injected from sources outside of the payment system) capable of settling the other banks claims on *i*, $e_i \geq 0$. Recall that any claim is captured by *L* so here non-negativity is not restrictive indeed. So the payment system can be characterized by a pair *(L, e)* consisting of a nominal obligations matrix *L* and an external assets vector *e*. The cash infusion to each bank comes from sources outside the banking system, for instance it could be either the cash inventory at the beginning of the day or a credit line from the central bank denoted by L_0. The total interbank nominal liabilities of banks can be calculated using *L* as $Li = l$. These nominal obligations represent the promised payments by each bank due to other banks in the system.

The stylized bank i 's balance sheet including both internal and external assets and liabilities is illustrated in table 1 where c_i denotes the bank's equity capital and $a_i = \sum_{j=1} L_{ji}$ is internal assets.

Table 1: An Illustration of Banki's Balance Sheet

Assets	Representation	Liabilities	Representation
Internal External	a_i e_i	Internal External	l_i L_{i0} c_i

Let *p* be the payment vector $p=(p_1, p_2, \ldots, p_n)$ where *pi* represents the total dollar payment by bank *i* to the other banks. Also let π represent the relative liability of one bank to another in the system as a proportion of the debtor bank's total liabilities. The distribution of payments is captured by π an $n \times n$ matrix where $\pi_{ij} = L_{ij}/l_i$. Using the relative liability matrix we may also describe a payment system by a triple (π, l, e). The interchange of these two descriptions of payment system has some practical implications. Recall the information of interbank payments are normally more accessible than data on all bank's obligations. But considering the fact that payments are the realization of the interbank liabilities, we can calculate the matrix of liabilities based on the payments data. Let L^r denote the interbank payments that is the realization of promises under no-bank-default condition. Then we may claim that $L^r = \pi.diag(l)$. Now we define the clearing payment vector as follows.

Definition 1: Clearing Payment Vector

A clearing payment vector for the financial system (π,,) is a vector p∈* $[0,\ l]$ *that satisfies the following conditions:*

a. *Limited Liability- that implies for* $\forall i \in \aleph$, $p_i^* \leq \sum_j \pi_{ij}^T p_j^* + e_i$

b. *Absolute Priority- that implies for* $\forall i \in \aleph$, *a bank either honors all it's promises and pays* $p_i^* = l_i$ *or it is insolvent and pays not less than* $p_i^* = max(\sum_j \pi_{ij}^T p_j^* + e_i, 0)$.

Absolute priority is analogous to Walrus's law in consumer behavior and guarantees that the debtors utilize all their available resources to honor their obligations. Definition 2 is for the sake of technical simplification.

Definition 2: Regularity- a financial system (π,,) is regular if for $\forall i \in \aleph$, $\sum_j \pi_{ij}^T p_j^* + e_i \geq 0$

It can be argued that corresponding to every financial system (π, l, e) that is regular, there always exits a clearing payment vector that under some mild assumption the clearing payment is also unique. There are two strategies to prove existence of a clearing payment vector suggested by Eisenberg and Noe in their seminal work. That could be done through fixed point theorem or by considering the clearing payment vector as the solution of a maximization program.

For the first strategy, one can make use of lattice algebra to introduce the map of $\varphi(p; \pi, l, e)$: $[0, l] \rightarrow [0, l]$ where $\varphi(p; \pi, l, e) \equiv (\pi^T p + e) \wedge l$. Then it shows that p is the fix point of $\varphi(p)$ map. In the second strategy for the problem that is characterized by (π, l, e, f) , clearing payment vectors can be identified by solving almost any programming problem that places weight on maximizing payments by all banks in the system subject to the limited liability condition or $Max\ f(p)\ s.t. p \leq \pi^T p + e$ where f is any increasing function $f: [0, l] \rightarrow R$. Note that the constraint satisfies the limited liability constrain while maximization implies the full utilization of the available resources that in turn guaranties absolute priority condition.

The clearing payment vector is indeed a function of total liability and external assets. Theorem 1 establishes the expected relationship between the clearing payment vector and its determinants.

Theorem 1: The clearing payment vector $p^*(\pi,\ e, l)$ *is an increasing and concave function of the level of nominal liabilities* l *and external assets vector* e.

Proof: See the proof of Theorem 2 in Eisenberg and Noe (2001)

The loss of bank'i for $\forall i \in \aleph$, given the payment vector p, is equal to $V_i = \sum_j \pi_{ij}^T p_j + e_i - p_i$ where V_i takes the values less than zero. Banks can accommodate the loss if it does not go below a certain level, otherwise the bank defaults. This threshold is set based on the regulatory capital c_i,

$$[\frac{(\alpha C_i - loss_i)}{RWA} - c_{\ i}] \times 100 = \Delta c_{\ i}$$

where α is a fraction of regulatory capital that could be readily used to cover the loss and is set by the regulator. To introduce a measure for systemic risk one needs to define the process of sequential defaults. Let assume the system follows the simple *fictitious default algorithm* introduced by Eisenberg and Noe (2001). The algorithm starts with evaluation of each bank's payout, assuming that all other banks satisfy their obligations. If, under the assumption that all banks pay fully, it is, in fact, the case that all obligations are satisfied, then the algorithm is terminated. If some banks default even when all other banks pay, try to solve the system again, assuming that only these "first-order" defaults occur. If only first-order defaults occur under the new clearing vector, then the algorithm is terminated. The final exposure of banks after the termination of the algorithm would be a measure for systemic risk. As Halaj and Kok, (2013) asserts the loss due to contagious defaults on the interbank deposits is detected by comparing l and $p*$.

Corollary 1: The total loss due to systemic risk in the interbank under fictitious default algorithm is calculated by $S(l, e) = \pi^T(l, e)[l - p^*(l, e)]$.

For a given level of external assets, $S: \Re^n \to \Re^n$ is a vector-valued function of nominal liabilities. Note that $\pi: \Re^n \to \Re^{n\times n}$ is also a function of nominal liabilities. In fact for each bank $S_i = \sum_j \pi_{ji}^T(l)(l_j - p_j(l))$. So the investigation to uncover the relationship between banks' borrowing in the interbank market and systemic risk led us to the next theorem.

Theorem 2: Given the external assets constant, *the total loss due to systemic risk in the interbank under fictitious default algorithm is increasing in nominal liabilities.*

Proof: Differentiating the total loss function with respect to nominal liabilities, we get the Jacobian $D_l S(l) = D\pi^T(l)\big(l - p(l)\big) + D(l - p(l))\pi^T(l)$. Note that $\big(l - p(l)\big)$ is greater than zero for $\forall l \in \Re^n$ by definition. It also follows the definition of π that the product of vector derivative of the matrix π by $\big(l - p(l)\big)$ which is a Kroneker product indeed is zero. In the second term of the Jacobian, $D(l - p(l)) \geq 0$ since following theorem 1 $p(.)$ is an increasing and concave function in l, we may conclude that $D_l S(l) \geq 0$. ■

Theorem 1 that links the change in nominal liability and the loss due to systemic risk provides us with a justification for the central bank intervention in the interbank market to regulate excessive borrowing by troubled banks. The fact that the clearing payment vector is an increasing function of both banks nominal liabilities and external assets suggests any increase in banks' nominal liability or a reduction in external assets could trigger the systemic risk in the banking network. In this study we are not dealing with the stress test and scenario design. We are interested in doing a sensitivity analysis to find out under which circumstances the banking system may experience contagious defaults. In the next section, we exploit that payment system data to create a tool for central banks to accomplish its task in the interbank market.

Estimating Banks Bilateral Exposures Matrix

The key element in systemic risk measurement is the bilateral exposures matrix that shows the banks total liabilities. There are several sources of data to estimate the total liability matrix. In this study, we had a unique access to daily payment flow data of Real-Time Gross Settlement (RTGS) System for a 11-month period that results from the activities of 20 banks in the Iranian banking system from October 26th of 2013 to September 8th of 2014.

The total liability matrix L is decomposed into retail gross payment matrix L^R and large-value payments matrix denoted by L^L; e.g., $L = L^R + L^L$. The rationale behind this decomposition is the fact that these data are coming from the behavior of different payers with different motives. While retail data consists of C2C obligations and thus follow a relatively fixed pattern over time, large-value payments are mainly coming from payments made by banks in interbank market, so it is of a very volatile nature.

Figure 1 shows the change in value of payments over time where the black line shows the total value of all banks' daily payments. The thin lines are the actual daily data, while the thick ones are the smoothed series. A threshold is used to make a distinction between the retail and large-value payments in the system. The blue line is the value of retail payments when a 10 billion Rials is the threshold. While the orange line shows that for a threshold of 50 billion Rials. Note the main source of volatility is rest with large-value payments. That is quite understandable because the banks C2C obligations are driven from household behavior and that would not change dramatically at least in short term.

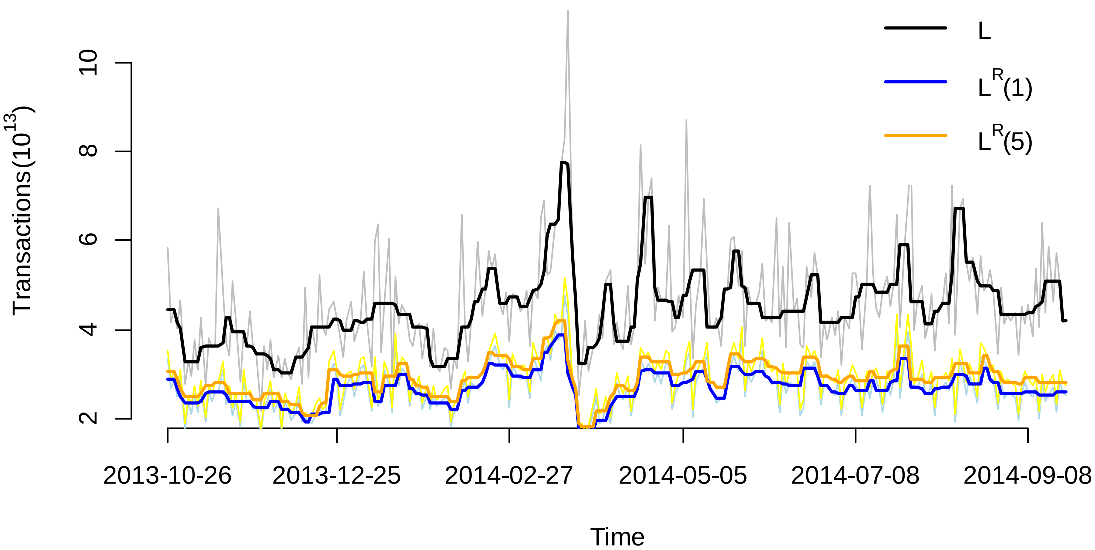

Figure 1. The size of retail and interbank markets.

As we approach the end of year in Iranian calendar which is around the 23th of March, both the level and the volatility of the total value of payments increase. For the rest of the year total value of payments follow a relatively smooth trend.

The distribution of total payments in L^L and L^R are different as expected. Figure 2 represent the distribution of two class of payments over the buckets of payment values in 50 billion Rials.

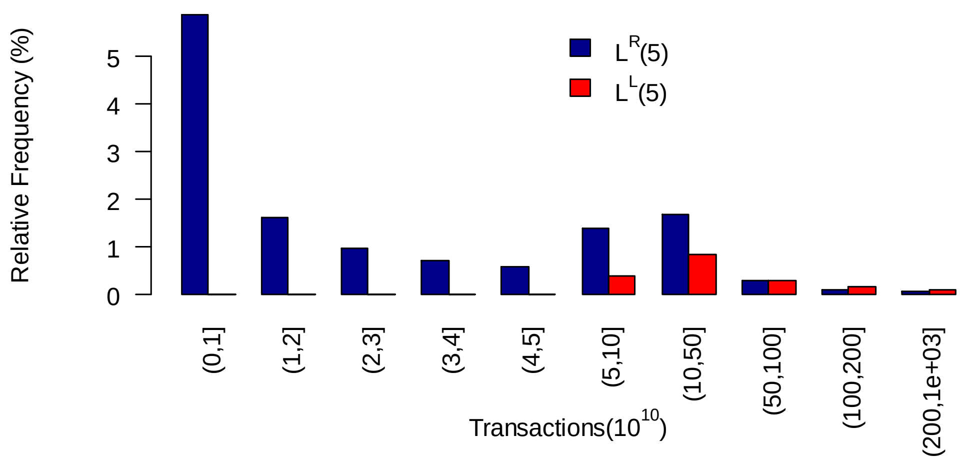

Figure 2: The relative frequency of two classes of payments

The large-value payments are presented in red with the maximum frequency around 100 to 500 billion Rials. With no floor on payments and the negligible fee that is applied in Iranian payment system, the highest percent of retail payments belongs to 0 to 10 billion bucket.

An explanation is needed regarding the retail payments over 50 billion Rials (i.e., the blue columns after [4, 5) bucket). As part of the payments are coming from auxiliary systems in payment system and, the existing information regarding these systems are only available in net values, we need to use an algorithm to extract the gross payments underlying of the net values. Let L^{Ra} denote the extracted matrix. So, in fact $L^R = L^{Ra} + L^{Rb}$where L^{Rb} is the matrix of bilateral gross retail payments.

So it makes sense to decompose the total retail exposures coming from gross and net retail payment systems. The data of retail auxiliary systems comes in a batch file that enters in the RTGS once in a day. Recall for our analysis we need this data in gross values. Here to generate the bilateral exposures using the ACH aggregate net exposures, some algorithm is needed for calculation. This study applies maximum entropy algorithm as described below.

The algorithm (also known as iterative proportional fitting procedure) is an iterative algorithm for estimating the elements of a matrix, given the sums of rows and columns. Let $B \in \mathbb{R}^k$ be a matrix with nonnegative unknown elements. Let $r: \mathbb{R}^k \longrightarrow \mathbb{R}$ be an operator which produces row marginals of a matrix. Similarly, let $c: \mathbb{R}^k \longrightarrow \mathbb{R}$ be an operator which produces column marginals. Let $v = r(R)$ and $w = c(R)$ and both are known. The goal is to estimate a matrix such as $\hat{B}$, which is consistent with given row and column sums. Let $d: (\mathbb{R} \times \mathbb{R}) \longrightarrow \mathbb{R}^k$ be an operator which divides the two inputs, element-wisely, and produces a diagonl matrix with the result on the main diagonal. For $p \geq 0$, set

$$\begin{cases} B^{(2p+1)} = d\big(v, r(B^{(p+1)})\big)B^{(2p)} \\ B^{(2p+2)} = B^{(2p+1)}d\big(w, c(B^{(p+1)}\big) \end{cases}$$

and we have $\hat{B} = \lim_{p\to\infty} B^{(p)}$.

There are two strategies to estimate the value of total retail payments matrix L^R for a projection period. First, with more than 360 observation for each element of L^R we may directly forecast the value of each element for the projection period. Second, the total retail payments matrix L^R is decomposed in a relative liabilities matrix π and a the vector of total liabilities, l. The as the elements of relative liabilities matrix are fixed at least in short term, we just focus on the vector of total liabilities l to estimate the value of total retail payments matrix L^R for a projection period using some econometric model. Here we adopt the first strategy. The forecast model is an ARIMA(p,d,q) with exogenous variables, i.e.,

$$\varphi(L)(1-L)^d Y_{ijt} = c_{ij} + \theta_{ij}X_{it-1} + \gamma_{ij}X_{jt-1} + \psi(L)\varepsilon_{ijt}\ i \neq j\ (1)$$

where Y_{ijt} is the logarithm of bilateral gross retail payment made on t and X_{it} is the value of bank'i deposits on time t in logarithm. L is the lag operator and $\varphi(L)$ and $\psi(L)$ are polynomials. The value of deposits is only available in weekly period so despite of having daily payment data, we can only have projection on a weekly base. ε_{ijt} is the error term.

Apart from zero expected value, no other specific structure is assumed regarding the error term in the regression, since "when regression models are used solely for forecasting, it is not necessary for the regression coefficients to be unbiased estimates of causal effects" (Stock & Watson (2007) p. 307). However, to test external validity of the forecasts, the forecast model is selected using a pseudo out-of-sample forecasting procedure.

The model set in the proposed psudo out-of-sample method can be constructed based on different restrictions on the parameters, i.e., p, d, and q. Furthermore, zero restriction on θ_{ij} and γ_{ij} is also a choice. For current application, a model set with $p, q \in \{0,1,2,3\}$ and $d \in \{0,1\}$ is estimated and best model is selected based on the average of RMSFE in three different pesudo out-of-sample forecast simulations.

Weekly data of deposits of those 20 banks for 42-month period, from March 27th of 2013 to Septabmer 7th of 2017. Regarding the sample of transactions explained before, a common sample of 27 weekly data points for a 6-month period, from March 27th of 2014 to September 25th of 2014.

Figure 3 shows the distribution of the mean of RMSFEs for the selected model for all 380 experiments, i.e., $i, j = 1, \dots, 20$ and $i \neq j$. For more than half of our experiments, the best model's forecast error is less than 0.4 percent. For the whole experiments, the forecast errors does not exceed 2 percent which is a great achievement and could be interpreted as a highly reliable estimation.

In other words, the results show that the degree of forecastability of bilateral exposures is relatively high. Of course, this is not surprising since the retail payments (as it is explained before) are not volatile (See figure 1).

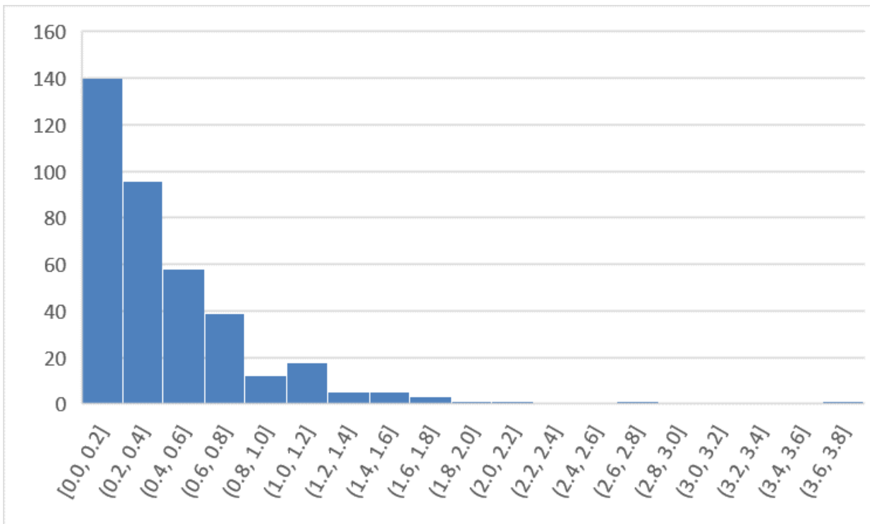

Figure 3. Frequency of the mean of RMSFEs in three pseudo out-of-sample forecasting simulations.

Borrowing Scenarios and Systemic Risk

Now, with the forecasted value for the total retail payments, the information on the banks' obligations for the period under study is needed to construct the liabilities matrix L. Then a simulation analysis is applied to investigate the level of borrowing that is allowed to sustain the system stability at the desired level set by the regulator.

Figure 4 illustrates the results of a simulation analysis under a scenarios for a certain level of available cash set as a percentage of bank deposits for one of the banks in the Iranian banking system. The

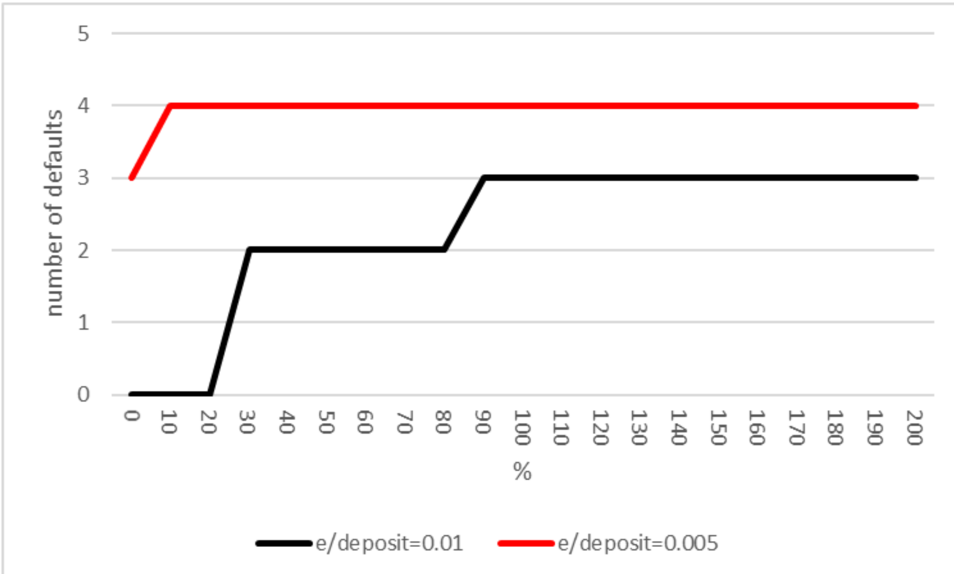

Figure 4: Simulating the behaviour of the system as a function of bilateral exposure in constant level of cash flow.

vertical axe shows the number of banks that default when the value of its nominal liabilities increases by 0 to 200 percent depicted by the horizontal axe at given level of external assets that is set at 1 and 0.5 percent of the bank's deposits in this example. Regarding the relatively higher external asset case (the black line), an increase in this bank borrowing from the interbank market up to 20 percent could be accommodated well by the system and results in no contiguous event. But when the bank's borrowing exceeds that level, it triggers systemic defaults and wipes out 2 or 3 banks from the system. For the relatively lower external asset case, 3 banks are already in default and an increase in this bank borrowing from the interbank market up to 10 percent wipes out another bank from the system.

Based on these results the central bank could be advised to set a ceiling for the bank borrowing in the interbank market. It also could inject cash if that is deemed necessary and postpone its repayment to sometime when a cash flow is realized that covers the bank's obligations.

We end the discussion by providing more information about the sensitivity of the results to the size of cash flow, i.e., e/deposit in figure 4. Assuming that the level of bilateral exposures are constant, figure 5 depicts the results of a simulation in which the ratio of cash flow to deposit increases. Low levels of external asset might wipe out up to 7 banks from the system.

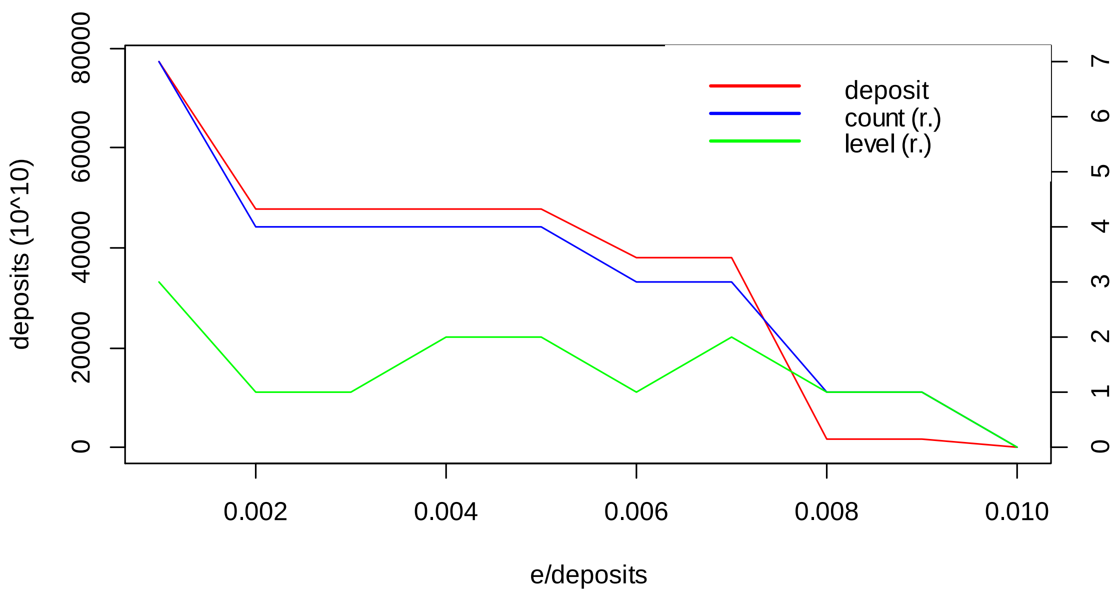

Figure 5. Simulating the behavior of the system as a function of cash flow in constant levels of bilateral exposure.

Conclusion

Most of the central banks around the globe confine their policy regarding the systemic risk to monitoring and assessment of systemic risk with some diagnostic tool. Some of them take a further step and also introduce some static measures to limit the systemic risk. This study goes beyond that and calls for the central bank's intervention in interbank market to regulate the excessive borrowing by troubled bank from this market. First, it proves that this borrowing, that resolve the banks immediate liquidity problem, may jeopardize the stability of the banking system. Therefore, central banks should step in and adopt an appropriate regulatory policy.

It is important to note that the allocation of funds in interbank market and bank lending and borrowing, as far as it does not result in a contagious defaults, enhances the efficiency of the system and therefore should be allowed and even encouraged. So the regulator is faced with the exact value for a threshold for that borrowing. This study used the data from the main and auxiliary payment systems to utilize all the available information.

We applied some simplifying assumptions regarding the relationship between payments and liabilities, the default algorithm, the money available to cover the banks' obligations, the construction of gross values from the net ones and also the forecasting of the value if banks' liabilities in the interbank market. To have a more accurate estimation of the impact of banks borrowing on systemic risk, we need more updated information and a more rigorous treatment. This task is left for future studies.

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