

## Network externalities across financial institutions

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# Network externalities across financial institutions

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## Abstract

We propose and estimate a financial distress model that explicitly accounts for the interactions or spill-over effects between financial institutions, through the use of a spatial continuity matrix that is build from financial network data of interbank transactions. Such setup of the financial distress model allows for the empirical validation of the importance of network externalities in determining financial distress, in addition to institution specific and macroeconomic covariates. The relevance of such specification is that it incorporates simultaneously micro-prudential factors (Basel 2) as well as macro-prudential and systemic factors (Basel 3) as determinants of financial distress. Results indicate network externalities are an important determinant of financial health of a financial institutions. The parameter that measures the effect of network externalities is both economically and statistical significant and its inclusion as a risk factor reduces the importance of the firm specific variables such as the size or degree of leverage of the financial institution. In addition we analyse the policy implications of the network factor model for capital requirements and deposit insurance pricing.

Keywords: systemic risk; network models; spatial econometrics.

JEL Classification: C21,C58,G32.

## 1 Introduction

The 2007-2008 financial crisis has shifted the focus from the assessment of the resilience of individual financial institutions towards a more systemic approach. Hence, macro-prudential supervision and regulation will play a vital role in the new financial architecture, on Banking Supervision (2010). The crisis vividly showed the complex interconnections within the financial system, in particular how problems in some institutions could easily be transmitted to other institutions independently of how far from each other they appeared to be. Although, in the last thirty years we have witnessed important efforts toward the standardization of financial regulation and supervision around the globe (Basel 1), as well

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as the implementation of techniques that made financial institutions more aware of the risk they were facing in their own portfolios (Basel 2), systemic risk was largely overlooked. Basel 2 placed a strong emphasis on how each financial institution was able to integrate their credit and market information, in a timely manner, so as to determine and quantify the level of risk of the portfolio and calibrate the required capital. In general there was a myopic focuss on the micro-prudential side of financial supervision. Financial literature also gave a strong role to the firm specific level determinants (firm size and age, financial ratios, among others) of financial distress along with a set of macroeconomic cyclical components (Ergungor and Thomson (2005); Laeven and Majnoni (2003); Uhde and Heimeshoff (2009)). To a great extent this myopic view has changed due to the financial crisis. Basel 3 strongly advocates financial regulation focused on limiting systemic risk among other issues like defining a liquidity ratio standard and controlling for excessive leverage. The magnitude of systemic risk and the consequences of accumulating such risk, mostly depends on the collective behavior of the financial institutions, their interconnections (within the system) and their connections to the rest of the economy. The mapping of such connections is fast becoming an important tool for macro-prudential supervision.

After the Great Depression, policymakers were faced with the daunting task of rethinking the way economic activity was measured. These innovations lead to the development of comprehensive set of national income accounts. Brunnermeier et al. (2011), argue that we now face a similar task, because during 2007-2008 financial crisis policymakers found themselves without the relevant information about the linkages within the financial sector as well as the linkages to the real economy.

The challenge of building this risk topography has received important methodological feedback from network and graph theory. This branch of mathematics has provided a set of definitions, tools, techniques that have been extensively applied to analyze financial networks, Newman (2010). Financial network models have been developed both at the theoretical level as well as the empirical or applied level. Theoretical models have focused on identifying how a particular topology of the financial system can channel and amplify shocks affecting a single financial institution. In other words the question has been: How does a particular structure (topological structure) of the financial system provides higher or lower systemic risk and resilliance? Various simple models (Allen and Gale (2000), Babus (2005), Glasserman and Young (2015), Haldane (2009)) have addressed the *robust-yet-frigile* property of the financial system. This property illustrates a trade-off with respect to the number of interconnections within the system, because connections serve both as shock-absorbers as well as shock-amplifiers. One of the main results and more or less a consensus that has emerged is that, when the network is not too much connected; then the higher the connectivity of the system, the higher risk-sharing and diversification. However, above a certain connectivity threshold, those connections that before served as mutual insurance against shocks, can now act as factors that aggravate an initial adverse shock to the system.

The more applied branch of the financial network literature is focused on us-

ing data on financial counterparts across and within countries to map existing networks, and in some cases analyze the robustness of financial systems using simulations (see Anand et al. (2009); Boss et al. (2003); Castrén and Kavonius (2009); Bastos and Cont (2010); Cajueiro and Tabak (2007); Degryse and Nguyen (2007); Chan-Lau (2010a,b); Espinosa-Vega and Sole (2010)). Most of these applications use either simple reaction functions based on balance sheet identities or more complex agent-base models, that interact with the observed network maps and through a series of simulations generate different types of indicators of financial stability.

Within the financial network literature there is an emerging literature that use network data and econometric techniques (Jorion and Zhang (2009); Signori and Gencay (2012); Keiler and Eder (2013)). There is a well consolidated literature in social interaction models: Manski (1993); Durlauf and Young (2001), and their respective empirical applications in education Lin (2005), and technology adoption (Case (1992), just to name a few. More recently, the links to these social interaction model and the spatial autoregressive model (SAR) in the spatial econometric literature has been well established, Lee (2007, 2004). Beyond financial networks there is an active field of research on the econometrics of network data (see de Paula (2015) for a complete survey). Econometric models related to network data for the moment have the following intentions: a) models where a particular outcome of interest are mediated by predetermined networks (a prime example of this is social interaction models); b) models for network formation and with a possibility of analysing the joint determination of both network formation and outcomes mediated by these evolving networks; or c) measurement issues related to networks and outcomes.

In this paper we introduce the interconnections between financial institutions, through the use of a spatial continuity matrix, as predictor of financial distress. The introduction of the interconnections allows us to determine the importance of network externalities after controlling for firm specific effects as well as macroeconomic factors. These network externalities will allow us to determine how fragile are the institutions to the complex interconnections that may lay hidden with in the financial system. From a methodological point of view we are interested in how a given observed network determines how fragile is a particular financial institution, that is we are interested on how the existing network configuration has an effect on an outcome variable such a fragility. We estimate the financial distress model using a panel of financial institutions from the colombian financial sector. In addition we explore how such models could potentially be used in a particular policy setting such as the definition of capital requirements or the premiums paid for deposit insurance by financial institutions. Our interest is to introduce a discussion on the use of econometric network models to quantify fragility and potentially illustrate the challenges.

Our paper is related to (Signori and Gencay (2012)) because they use, a network of trade credit relationships to proxy for counterparty risk, in an effort to understand how counterparty risk determines the credit spread on corporate bonds. Signori and Gencay (2012) propose and estimate a network autoregressive moving Average model (NARMA) to explicitly account for the supplier-

customer network across firms. Their results indicate that network effects, measured as the leverage of its main customers, are as important as the firms own leverage in its effect over the credit spread. In a recent paper Keiler and Eder (2013) using a methodological approach similar to ours, propose a spatial autoregressive model to estimate a three factor model on CDS spreads for 15 financial institutions in Germany. One of the factors captures the interrelation or distance between the financial institutions. The distance across financial institutions are approximated using a standardized correlation matrix based on the stock market information for the financial institutions.

The results indicate that network externalities are an important factor to determine financial health of an institution. Under different sets of specifications and control variables we find that the financial health of institutions that are interconnected has a positive (economically and statistically significant) feedback effect on the financial health of the institution in question. The result are in line with the macroprudential approach of basel 3 as a complementary tool to microprudential supervision advocated in basel 2. Our framework, the network factor model, provides a way to: a) links macroprudential supervision to standard microprudential factor models, and b) provides a first approach to measure financial fragility across financial institutions.

We provide a discussion on the the policy implications of the results. Although the notion and measurement of systemic risk, contagion or network externalities for that matter has always been a relevant issue for regulators and academics, there is still no concrete and well accepted methodology to incorporate the relevance of these interconnections in a concrete capital requirement formula or in terms of deposit insurance pricing. We survey the exiting literature and find some approaches to introduce interactions across financial institutions, however, there are still many unsolved issued regarding how to do so with capital requirement or deposit insurance pricing principles, and the empirical evidence with regard to the importance of interconnections.

The remainder of the paper is organized as follows. Section 2 presents the financial network information that we will use to quantify the interconnections across the institutions. In section 3 we introduce a network factor model for credit risk. Section 4 provides a brief discussion of the empirical results. Section 5 discusses the literature on capital requirements and interconnections and deposit insurance pricing. Section 6 concludes.

## 2 Financial network data and spatial continuity

One of the main challenges of building financial network models is the data requirements. The preferred data for creating such maps are the counterparty relationships between the financial institutions. Such relationships can be observed from the bilateral exposures on either side of the balance sheet or in most cases by mapping the interbank market.

### Definition

A network (graph)  $G$  consist of a non-empty set of elements  $V$  called vertices, and a list of unordered pairs of these elements called edges  $E$ . The set of vertices (nodes) of the network is called a vertex set and the list of edges is called edge list.

An edge is identified by an ordered pair of vertices. In other words, if  $i$  and  $j$  are vertices of  $G$ , then an edge of the form  $(i, j)$  is said to joint or connect  $i$  and  $j$ .

The functions  $G$  can take many forms, although the most common are as follows:

$$G : VXV \rightarrow \{0, 1\} \quad (1)$$

such that  $G(i, j) = 1$  if and only if there is an edge between  $(i, j)$ . In most cases there are no self loops such that  $G(i, i) = 0 \forall i$ . This particular form of the function  $G$  only considers the existence of a link between the edges without taking into account the possible strength of such relationships. Another possible interpretation for the function is that of a distance function between vertices  $i$  and  $j$ , Pinksey and Slade (2009), different to the binary measure (1).

$$G : VXV \rightarrow \mathbb{R} \quad (2)$$

such that  $G(i, j)$  determines the strength of the relationship between institutions  $i$  and  $j$ . In both cases the function  $G$  can be interpreted as a square (adjacency) matrix  $\mathbf{W}$ , where  $G(i, j) = w_{i,j}$ . Such adjacency matrix is row normalized by dividing each element by the sum of it entries,  $\tilde{w}_{i,j} = \sum_{j=1}^V w_{i,j}$ .

The financial network we use is build from the information of a large value payment system administered by the Central Bank of Colombia (Banco de la Republica). The vertices represent the financial institutions and the edges represent (in COP) the value of the transactions that are registered in the payment system. Element  $w_{i,j}$  corresponds to the payment from institution  $i$  to institution  $j$ . Each element was expressed as a percentage of the total value of the transaction during the time frame when the transactions are recorded.

## 3 Network factor model

Most models of financial distress derived their specification from structural credit risk literature (Merton type models). The model we propose incorporates the standard the elements of a financial distress model: a)  $y_{i,t}$  a proxy for the financial health of institution  $i$  at time  $t$ , b) a set of institution specific covariates  $\mathbf{X}_{i,t}$ , c) a set r macroeconomic covariates  $\mathbf{Z}_t$ , and d) possible some firm specific non-observable effects. The fundamental difference is the introduction of the spatial continuity matrix  $W$ . In the section 2 we have shown how we can use the information from a financial network model to build a spatial continuity matrix that quantifies the interconnections across the institutions.

$$y_{i,t} = \alpha_i + \rho W y_{i,t} + \beta \mathbf{X}_{i,t} + \gamma \mathbf{Z}_t + \varepsilon_{i,t} \quad (3)$$

where  $Wy_{i,t}$  is a standardized measure of the distance to some possible troubled institutions and  $\varepsilon_{i,t} \sim (0, \sigma^2)$ . The distance is measured using the observed interbank interactions across the institutions determined by the financial network data. Therefore  $\rho$  will indicate the relative importance of the average distress of institutions close (where the measure of closeness is established according to the level of interbank transactions) to institutions  $i$ .

From the supervisors point of view the set of determinants of financial health for a financial institution can be organized into two groups: first, the risk factor factors advocated by the microprudential aspects of Basel 2. Such as firm specific variables  $\mathbf{X}_{i,t}$  and state variables (primarily macroeconomic conditions)  $\mathbf{Z}_t$ . Second, the risk factors advocated by the macroprudential outlook of Basel 3. Mainly, the importance of the interconnections across the financial institutions.

$$\mathbf{y} = \underbrace{\rho \mathbf{W} \mathbf{y}}_{\text{Basel III}} + \underbrace{\alpha \mathbf{I} + \beta \mathbf{X} + \gamma \mathbf{Z}}_{\text{Basel II}} + \varepsilon \quad (4)$$

As mentioned previously  $\rho$  measures the importance of network externalities as a determinant of financial distress, therefore this is our parameter of interest.

From an econometric point of view the financial distress models outlined above are nothing different than spatial autoregressive models (SAR) proposed by Cliff and Ord (1973).

$$\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \alpha \mathbf{I} + \beta \mathbf{X} + \gamma \mathbf{Z} + \varepsilon \quad (5)$$

where  $\varepsilon \sim (0, \sigma^2 \mathbf{I}_n)$ . Anselin (1988); Anselin et al. (2008); Baltagi et al. (2003, 2007); Elhorst (2003); Kapoor et al. (2007); Yu et al. (2008) have extended the use of these method in a panel data setting. Estimation of these models is via maximum likelihood (where the distribution of the error is assumed to be Gaussian) or generalized method of moments (more precisely instrumental variables). As a special case of GMM is an estimation strategy based on two-stage least squares with instrumental variables. Kelejian and Prucha (1998) shows that the estimators from this method are asymptotically efficient as long as the instruments are not correlated with the dependent variable. In the first stage we estimate the average distress of those institutions that have strong ties to financial institution  $i$  (expression 3), where  $(j_{i,t}) = (\theta_1 x_{i,t}, \theta_2 W_1 x_{i,t}, \theta_3 W_1)$ . In the second stage we use the estimated instrument  $\widehat{W_1 y_{i,t}}$  to obtain the parameters of interest  $(\alpha, \rho, \beta, \gamma)$ .

$$W_1 y_{i,t} = \theta(j_{i,t}) + u_{i,t}$$

$$y_{i,t} = \alpha_i + \rho \widehat{W_1 y_{i,t}} + \beta \mathbf{X}_{i,t} + \gamma \mathbf{Z}_t + \varepsilon_{i,t}$$

## 4 Empirical results

In this paper we introduce the interconnections between financial institutions, through the use of a spatial continuity matrix, as predictor of financial distress.

The introduction of the interconnections allows us to determine the importance of network externalities after controlling for firm specific effects as well as macroeconomic factors. These network externalities will allow us to determine how fragile are the institutions to the complex interconnections that may lay hidden within the financial system. We estimate the financial distress model using a panel of financial institutions from the Colombian financial sector. We give a brief description of the financial network data. According to Leon (2013) the literature on financial networks recognizes two main data sources: financial transactions or balance sheet exposures. Financial transaction data is preferred to the latter because it is highly detailed since it contains information on the origin and destiny of the transaction, the quantity, the type of transaction, the underlying assets involved, among other things. In addition it can be available in real time if you can monitor the register of transactions. On the other hand balance sheet financial exposures relies on the quality of accounting data and is subject to the strict oversight needs of the regulator, as such it is not provided in a timely manner or the cross exposures between institutions might be difficult to identify.

The contiguity matrix that we use for our estimation was constructed from the transaction level data registered in a high value payment system that is administered by the Central Bank of Colombia. The transactions represent the average conditions for the year 2009. The network, on which the contiguity matrix  $W$  is based, is represented in figure 1. Each interconnection or  $\{i, j\}$  pair in the matrix corresponds to a payment from institution  $i$  to institution  $j$ , expressed as a percentage of the total transactions over the period of analysis for institution  $i$ .

Although in the previous section we define the dependent variable  $y_{i,t}$  as an indicator of the fragility of institution  $i$  at time  $t$ , in the empirical application we take  $y_{i,t}$  as the financial health of institution  $i$ . There are different variables a supervisor should follow to assess the financial health of an institution. In the credit risk literature the preferred indicator for credit worthiness and financial resilience of an institution is the probability of default. Practitioners (supervisors) and academic have been particularly interested in determining which set of observable variables are early warning indicators of trouble within a financial institution. Altman (1968) created one of the first methods to rank firms according to their creditworthiness. The indicator, the Z-score, provided a way to discriminate between institutions that went bankrupt versus those that did not following some stressed event. The credit risk literature provides three commonly used sources to measure creditworthiness, in particular default probabilities (Leon (2013)): Financial statements, market prices and firms own expectations. The preferred method Merton (1974) provides a measure, distance-to-default, that relates the market value of the firm, its debt (leverage) and the volatility of the value of its assets. This approximation combines financial statement data and market data. With the creation of a market for financial insurance spreads on CDS (credit default swap), contracts on the debt of firms, also provide a market based indicator of creditworthiness. Although, these measures would be the preferred tool to quantify the health of a financial institution at a given



point in time, these indicators are not available for financial institution that are not internationally active or in particular, for our data set are not available for all of the financial institutions that make up our representative sample of the Colombian Financial system. Some authors (Gorton (1990); Flannery and Sorescu (1996)) have tried to substitute the market information for the book value of the firm (in their financial statements), however they still require to make strong assumptions on the volatility of the value of the assets, which ends up driving the results. Because of the unavailability of market data on most financial institutions in Colombia (less than 25% of financial institutions have gone public) we resort to building a balance sheet based indicator on financial health.

We apply the methodology known as CAMEL (Capital, Assets, Management, Earnings and Liquidity) to build a synthetic indicator of financial health. The CAMEL measure basically is a weighted average of financial balance sheet ratios. In particular, we use the CAMEL weights that the deposit insurance institution of Colombia (FOGAFIN) uses for pricing deposit insurance.

Table 1 presents the weights and balance sheet ratio that we have used to build the dependent variable  $y_{i,t}$ , our proxy of financial health of each institution. Each of the financial ratios in table 1, is build with the monthly information (for the year 2009) reported by the financial institution supervisor (Superintendencia Financiera de Colombia).

The control variables that are included in the model characterize by expression 3, include a set of firm specific variables  $X_{i,t}$  and macroeconomic variables  $Z_t$ . The firm specific variables are:

- Leverage: for some time is has been known that highly levered financial institution are more prone to bankruptcy (Merton (1974); Crosbie and Bohn (2003)). The recent financial crisis showed that the most levered institutions were the most fragile and in grater risk of default.
- Size: larger institutions can be better equipped to handle changes in the economic environment or could simply be consider ex-ante too-big to fail. Keiler and Eder (2013) finds evidence that on average larger institutions have lower probabilities of default.
- Indicator variable that identifies whether a financial institution is domestic or foreign owned.
- Indicator variable that identifies if a domestic financial institution belongs to a financial conglomerate or group.

One of the limitations of using a CAMEL base indicator (as oppose to market based indicators like CDS spreads) for financial health is that we cannot introduce other firm specific balance sheet based control because they have a close relationship with the variables that are incorporated in the CAMEL measure.

The macroeconomic controls try to link the financial cycle to the real economy. Investment opportunities for financial institutions are highly correlated with the economic cycle (Laeven and Majnoni (2003); Uhde and Heimeshoff

(2009)). We are mainly interested in variables related to GDP (but with monthly frequency), inflation and real interest rates:

- Energy demand.
- 12 month inflation rate.
- average real interest rate.
- lagged unemployment rate.

Tables 2 and 3 present the estimation results of expression 3. The difference between the tables is that in the former we use a matrix  $\mathbf{W}$  obtained from a graph that only considers the existence of a link between the institutions (a matrix of ones and zeros before row standardization); while the later the same matrix is obtained from a graph that considers not only the existence of a transaction between institution but also the magnitude of the transaction. In other words in table 3 the spatial weights that are represented in  $\mathbf{W}$  reflect a percentage of the total value of the transaction during the time frame when the transactions are recorded. In both tables the first two columns do not take into account the network effects, only the fixed effects, the firm level variables and the macroeconomic controls. Columns three, four and five sequentially include the network effects with the firm level variables and the macroeconomic controls. Finally column six includes all of the previous variables plus the dummy variables for banking groups. All of the estimation presented include fixed effect for each financial institutions.

The first two columns in both tables represent the Basel 2 specification in expression 4, in the sense that financial health is only determined by firm specific variables and macroeconomic conditions. Both the size and leverage variables are significant and have the expected sign; larger institutions are healthier and more levered institutions have lower health scores. On the other, hand macroeconomic conditions are not individually significant (they are jointly significant as indicated by joint significance test). The most likely reason for this last result is that the sample only considers one year of data therefore the sample length is not capturing medium term variation in the economic cycle. Column 2 also includes a dummy variable control for the existence of large financial groups in the Colombian financial sector, there is however no particular change in the estimated variables after controlling for this type of capital ownership. Furthermore, we find that financial institution belonging to one of the large groups are not on average healthier than those that are not a part of a larger group.

Column three to six includes the network effects, therefore this specification is in line with the active macro-prudential outlook of Basel 3, where the interconnections between institutions are an important determinant of financial health. Network effects on financial health are significantly and robust to firm level and macroeconomic controls. The network effects indicate a positive relationship between the financial health score of a financial institution and the

average financial health score of its interconnected institutions; where the average is determined by the existence of such interconnections or the strengths of the interconnections (measures in terms of the value of transactions).

## 5 Policy implications of network externalities for financial institutions

One of the most important concerns regarding the regulatory overhaul that came after the financial crisis was the measurement of systemic risk and how to account for such risk in terms of regulatory capital. Although, how do we measure systemic risk? is still an open question there seems to be a strong consensus regarding the importance of visible or hidden interconnections between the financial institutions, as a determinant of the extent of the crisis, in terms of the number of institutions affected and the ripple effects on the real economy<sup>1</sup>. With this in mind, the most relevant question in terms of policy recommendations, that can come out of specifying and estimating a network factor model is: how do we account for the relevance of interconnections between institutions for capital requirements (credit risk portfolio models) and deposit insurance pricing<sup>2</sup>.

Most of the literature concerning default risk models augmented to account for interactions between firms, counterparty risk or contagion, follow the usual distinction in the credit risk literature of structural (Egloff et al. (2007), Neu and Kuhn (2004), Hatchett and Kuhn (2006)) or reduced form models (Giesecke and Weber (2004), Giesecke and Baeho (2011)). Our purpose is to establish an analogy between portfolio credit risk models for determining capital requirements and a similar problem for financial regulators in managing the financial health of individual institutions that make up the financial system. In standard portfolio credit risk models the purpose is to estimate economic capital and allocate these requirements to the different positions of the portfolio. In a similar vein financial regulators are interested in the possibility that the financial health of each financial institution is not only affected by its own characteristics but also by the financial health of the institutions that are very connected to the institution of interest.

The workhorse of portfolio credit risk models is the so-called Asymptotic risk factor model (Aas (2005), De Servigny and Renault (2004)). In this model changes in the creditworthiness of the positions in the portfolio are driven by a systematic and an idiosyncratic factor. As every position in the portfolio

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<sup>1</sup>The open question is in fact broader because some proposals to measure systemic risk can actually be measuring the fragility of a financial institution to shocks in other institutions rather than the effect of a particular large or very connected institution on the system as a whole.

<sup>2</sup>We are concerned with identifying the relevance of these so called network externalities, that is the introduction of the contiguity matrix in the factor model. Any inference above what we have done, such as the effects of a particular topology of the network, its effects on the contiguity matrix and the estimated coefficients is beyond the scope of the paper and is a subject of future research

becomes in relative terms less important (more and more fine-grained) idiosyncratic risk is diversified away. In this context, and more general in the Basel II framework, one can show that the portfolio wide capital charge is the sum of the individual capital charges for every position (asymptotic capital additivity). In this framework capital per dollar of exposure  $C_\tau(L)$ , at some confidence level  $\tau$ , depends primarily on the difference between unexpected losses ( $q_\tau(L)$ ) and expected losses ( $E(L)$ ) from the portfolio.<sup>3</sup>

$$C_\tau(L) = q_\tau(L) - E(L) \quad (6)$$

$$q_\tau(L) = \sum_{i=1}^N w_i s_i P(y_i < \Phi^{-1}(p_i)) \quad (7)$$

$$P(y_i < \Phi^{-1}(p_i)) = \Phi\left(\frac{\Phi^{-1}(p_i) + \sqrt{\rho_i} \Phi^{-1}(\alpha)}{\sqrt{1 - \rho_i}}\right) \quad (8)$$

$$E(L) = \sum_{i=1}^N w_i s_i p_i \quad (9)$$

where  $w_i$  is the weight of exposure  $i$ ,  $p_i$  is the probability of default,  $P(y_i < \Phi^{-1}(p_i))$  is the conditional (on the systematic factor) probability of default,  $s_i$  is the loss given default and  $\rho_i$  is the average asset correlation of position  $i$  with the other elements in the portfolio.

As we mentioned previously we make an analogy with the problem of the regulator and consider  $i$  as an institution, as a position in the portfolio of the regulator. In the context of counterparty credit risk Neu and Kunh (2004) proposes an expression for the conditional probability of default 8 that takes into account the interconnections between a network of firms. Following Neu and Kunh (2004) we formulate a conditional probability of default for a financial institution. The difference is that the conditioning variables are the factors in the network factor model 3.

From section 3  $y_{i,t}$  denotes a variable that proxies the financial health of financial institution  $i$  at time  $t$ . As in any structural credit risk model if  $y_{i,t}$  falls below a threshold then the financial institution goes into bankruptcy. Now for simplicity suppose this threshold is an unobserved institution specific factor  $\alpha_i + \Phi^{-1}(p_i)$  then from expressions 8 and 3 we have,

$$P(y_i < \Phi^{-1}(p_i)) = \Phi\left(\frac{\Phi^{-1}(p_i) + \rho \widehat{W} y_{i,t} + \beta \mathbf{X}_{i,t} + \gamma \mathbf{Z}_t}{\sigma}\right) \quad (10)$$

In order to satisfy the distributional assumptions we must impose some restrictions on the loading coefficients of the factors as well as  $\sigma$ .  $\sigma$  is usually a function of the loading coefficients of the factor. We do not derive an explicitly formulas imposing some restrictions, however Egloff et al. (2007) derives a recursive numerical method to derive such representation for a similar model that

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<sup>3</sup> $q_\tau(L)$  is also known as the CreditVar

accounts for credit contagion using a spatial contiguity matrix that is called the business matrix because its  $(i, j)$ -elements indicate the strengths of the business interdependence between counterparties in a network. With this conditional probability of default based on the network factor model we can in theory use the empirical model presented in the previous section to obtain a capital charge. This capital charge will be sensible not only to the specific characteristics of the financial institution and the macroeconomic conditions but will also incorporate the conditions of the institutions that are connected to the institution of interest. However, this capital charge is more related to the concept of fragility rather than systemic importance, Castro and Ferrari (2010). Therefore, such capital charge should probably not be levied on systemically important financial institutions (SIFI's) but rather the institutions that are at the periphery of the network.

The idea of measuring the fragility of a financial institution could actually make much more sense, not only methodologically but also from the point of view of the regulator and supervisor, in terms of deposit insurance pricing rather than a formal capital charge. The main reason is that institutions that are heavily reliant on liquidity provision from the central players in the financial network will also be the institutions that are more fragile during periods of widespread bank failure. Hence in the aftermath of their own failure the recovery value on their assets will be probably much lower than for the other institutions in the network (Acharya and Yorulmazer (2010))<sup>4</sup>. Ex-ante the actuarially fair deposit insurance premium for more fragile institutions should be larger. If this were the case the network factor model could play the role of accounting for the sensibility of interconnections in the deposit insurance premium. In particular, deposit insurance pricing at many deposit insurance institutions is a function of a proxy of the financial health of the institution such as CAMELS ratings Bloecher et al. (2003). The network factor model and our empirical results provide a risk mapping that includes network externalities, therefore for a given deposit insurance pricing scheme mapped to such CAMELS ratings it would be feasible from our result to account for interconnections across financial institutions.

## 6 Conclusions

The empirical results from the network factor model indicate the importance of network externalities, quantified through the strength of interconnections between financial institutions. The spatial econometric model provides a statistical methodology that is in line with recent efforts to include network information to explain outcomes of interest, in this case the health or creditworthiness of a financial institution. With this model we are able to confirm that the average

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<sup>4</sup>To be fair there is no strong consensus among deposit insurers that they are designed to provide coverage in the cases of widespread bank failure (systemic risk events). Some argue that the designs and mandate of deposit insurance institutions should only be focused on idiosyncratic bank failures Laeven (2004).

financial health of those institutions for whom the institutions of interest shares a sizable relationship have an important and a significant effect on the financial health of an institution of interest. Our results are based on a set of Colombian financial institutions: their balance sheet information, the transactions, and financial health indicators used for deposit insurance pricing.

With the empirical results at hand we survey the literature and discuss the impact of network factor models on the quantification of capital requirements and deposit insurance premiums. We conclude that the network factor model can be used for capital requirements, however such requirements should be levied on the most fragile institutions in the network, that is those institutions whose financial health are heavily affected by the situation of the other (connected) institutions. Therefore, our capital requirement measure is not intended for systemically important institutions (SIFI's). Following a similar argument the network factor model can also be a tool for pricing deposits insurance under the premise that the expected cost to the deposit insurance provider should not only increase in relation to individual bank failure but also in relation to joint bank failure risk.

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| Indicator   | Weight | Rank  | Rating                |
|---|--------|---|-----------------------|
| Capital:<br>Tier 1 Capital/assets<br>weighted assets by risk level+(100/9*MR) | 25%    | $< 8\%$<br>$\geq 8\% \text{ y } < 9\%$<br>$\geq 9\% \text{ y } < 10\%$<br>$\geq 10\% \text{ y } \leq 12\%$<br>$> 12\%$                      | 1<br>2<br>3<br>4<br>5 |
| MR: Market Risk<br>Quality:<br>Non-performing loans/Gross Loans               | 20%    | $> 8\%$<br>$> 6\% \text{ y } \leq 8\%$<br>$> 4\% \text{ y } \leq 6\%$<br>$> 3\% \text{ y } \leq 4\%$<br>$\leq 3\%$                          | 1<br>2<br>3<br>4<br>5 |
| Management:<br>Total Operational Expenditures /<br>Gross financial margin     | 20%    | $> 80\% \text{ o } < 0\%$<br>$\geq 70\% \text{ y } \leq 80\%$<br>$\geq 60\% \text{ y } < 70\%$<br>$\geq 50\% \text{ y } < 60\%$<br>$< 50\%$ | 1<br>2<br>3<br>4<br>5 |
| Profitability:<br>Utility / Average Assets                                    | 25%    | $< 0\%$<br>$\geq 0\% \text{ y } < 1\%$<br>$\geq 1\% \text{ y } < 2\%$<br>$\geq 2\% \text{ y } < 3\%$<br>$\geq 3\%$                          | 1<br>2<br>3<br>4<br>5 |
| Liquidity:<br>(Liquid assets - liquid liabilities) /<br>Deposits              | 10%    | $\leq -10\%$<br>$> -10\% \text{ y } \leq 4\%$<br>$> 4\% \text{ y } \leq 6\%$<br>$> 6\% \text{ y } \leq 15\%$<br>$> 15\%$                    | 1<br>2<br>3<br>4<br>5 |

Table 1: FOGAFIN Camel.

| 2SLS-IV with contiguity matrix as binary |                        |                        |                      |                        |                        |                        |
|--|------------------------|------------------------|----------------------|------------------------|------------------------|------------------------|
| VARIABLES                                | (1)                    | (2)                    | (3)                  | (4)                    | (5)                    | (6)                    |
| $\rho$                                   |                        |                        | 0.515***<br>(0.0858) | 0.332***<br>(0.128)    | 0.421***<br>(0.150)    | 0.313**<br>(0.142)     |
| size                                     | 1.101***<br>(0.208)    | 1.051***<br>(0.207)    |                      | 1.002***<br>(0.205)    | 1.026***<br>(0.207)    | 1.008***<br>(0.207)    |
| leverage                                 | -0.0836***<br>(0.0154) | -0.0772***<br>(0.0154) |                      | -0.0705***<br>(0.0156) | -0.0718***<br>(0.0158) | -0.0699***<br>(0.0157) |
| inflation                                | -0.000391<br>(0.00706) | -0.00288<br>(0.00785)  |                      |                        | -0.00167<br>(0.00699)  | -0.00374<br>(0.00780)  |
| growht                                   |                        |                        |                      |                        |                        |                        |
| energy demand                            | 0.0707<br>(0.317)      | 0.0511<br>(0.353)      |                      |                        | -0.00469<br>(0.315)    | -0.0133<br>(0.351)     |
| real interest rate                       | 0.0414<br>(0.0443)     | 0.0579<br>(0.0492)     |                      |                        | 0.0330<br>(0.0438)     | 0.0509<br>(0.0489)     |
| lagged employment                        | -0.0151<br>(0.0197)    | 0.000531<br>(0.0218)   |                      |                        | 0.0159<br>(0.0224)     | 0.0257<br>(0.0245)     |
| Conglomerates                            | N                      | Y                      | N                    | N                      | N                      | Y                      |
| Fixed Effects                            | Y                      | Y                      | Y                    | Y                      | Y                      | Y                      |
| No. observations                         | 348                    | 348                    | 348                  | 348                    | 348                    | 348                    |
| $R^2$                                    | 0.253                  | 0.252                  | 0.330                | 0.875                  | 0.876                  | 0.882                  |
| Adjusted $R^2$                           | 0.0454                 | 0.0599                 | 0.0445               | 0.863                  | 0.862                  | 0.863                  |

Standard errors in parenthesis  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 2: Estimated network factor model with weighting matrix of ones and zeros .

| 2SLS-IV with weighted contiguity matrix |                        |                        |                      |                        |                        |                        |
|---|------------------------|------------------------|----------------------|------------------------|------------------------|------------------------|
| VARIABLES                               | (1)                    | (2)                    | (3)                  | (4)                    | (5)                    | (6)                    |
| $\rho$                                  |                        |                        | 0.422***<br>(0.0858) | 0.381***<br>(0.115)    | 0.479***<br>(0.134)    | 0.330**<br>(0.130)     |
| size                                    | 1.101***<br>(0.208)    | 1.051***<br>(0.207)    |                      | 0.871***<br>(0.215)    | 0.890***<br>(0.216)    | 0.926***<br>(0.214)    |
| leverage                                | -0.0836***<br>(0.0154) | -0.0772***<br>(0.0154) |                      | -0.0574***<br>(0.0169) | -0.0579***<br>(0.0170) | -0.0618***<br>(0.0166) |
| inflation                               | -0.000391<br>(0.00706) | -0.00288<br>(0.00785)  |                      |                        | -0.00404<br>(0.00713)  | -0.00531<br>(0.00792)  |
| growht                                  |                        |                        |                      |                        |                        |                        |
| energy demand                           | 0.0707<br>(0.317)      | 0.0511<br>(0.353)      |                      |                        | 0.0499<br>(0.317)      | 0.0347<br>(0.353)      |
| real interest rate                      | 0.0414<br>(0.0443)     | 0.0579<br>(0.0492)     |                      |                        | 0.0387<br>(0.0443)     | 0.0535<br>(0.0493)     |
| lagged unemployment                     | -0.0151<br>(0.0197)    | 0.000531<br>(0.0218)   |                      |                        | 0.0274<br>(0.0230)     | 0.0313<br>(0.0250)     |
| conglomerates                           | N                      | Y                      | N                    | N                      | N                      | Y                      |
| Fixed effects                           | Y                      | Y                      | Y                    | Y                      | Y                      | Y                      |
| No. observations                        | 348                    | 348                    | 348                  | 348                    | 348                    | 348                    |
| $R^2$                                   | 0.253                  | 0.252                  | 0.317                | 0.873                  | 0.873                  | 0.879                  |
| Adjusted $R^2$                          | 0.0454                 | 0.0599                 | 0.0475               | 0.861                  | 0.859                  | 0.861                  |

Standard errors in parenthesis  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 3: Estimated network factor model with weighting matrix given by strength of transactions.

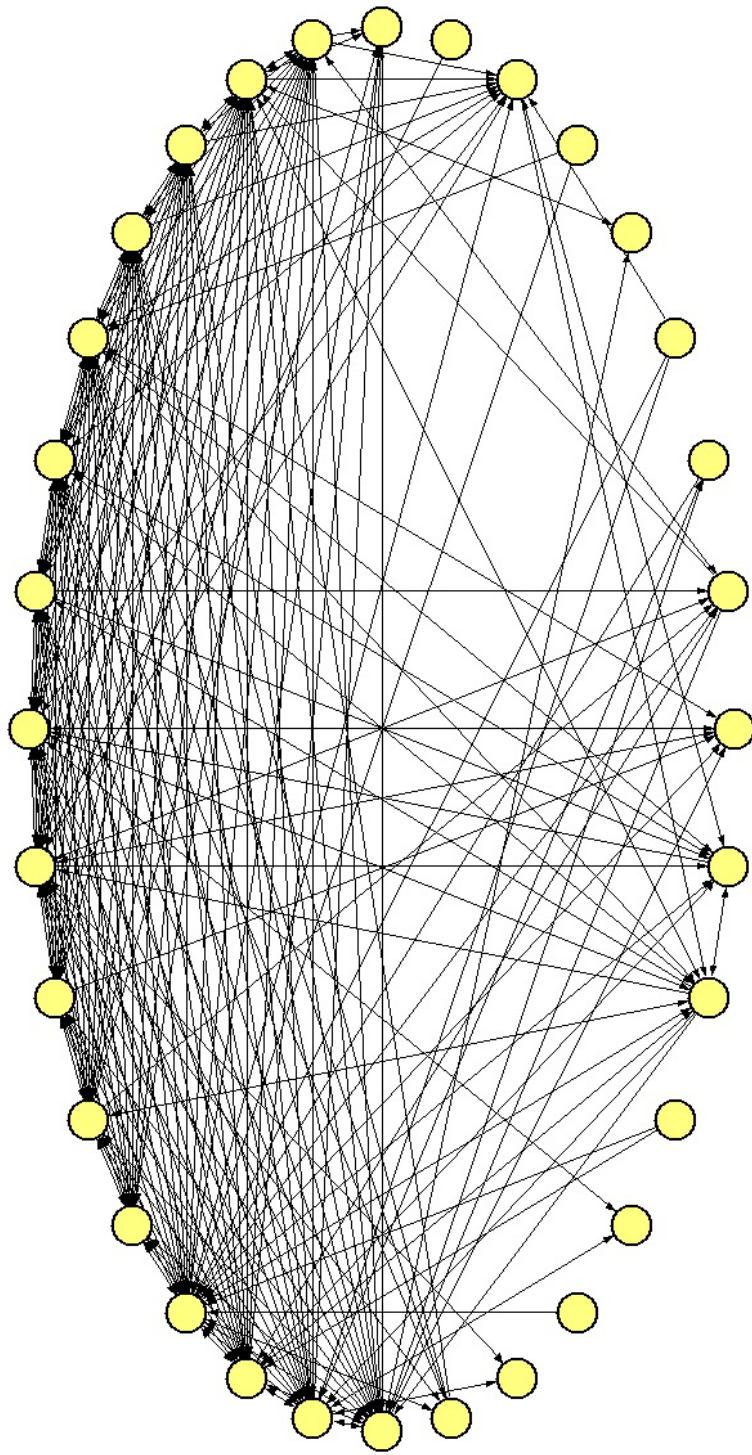


Figure 1: An example of the Colombian financial network.