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Exploring network effects during bank failures in Argentina

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SUMARIO

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Resumen

La probabilidad de que un banco quiebre está inversamente relacionada con su índice de capital. Esta relación, sin embargo, puede verse afectada por los vínculos entre instituciones financieras. La evidencia empírica generalmente ignora estos vínculos. En este análisis se estudia la propagación de las quiebras bancarias utilizando un modelo espacial autorregresivo, que permite una dependencia específica entre los bancos. Considero el caso de Argentina durante la crisis bancaria de 2001; al permitir la dependencia, los resultados sugieren que la estructura de los vínculos distorsiona el efecto del capital sobre las quiebras.

Abstract

The probability that a bank fails is inversely related to its capital ratio. This relationship, nevertheless, can be affected by the linkages among financial institutions. Empirical evidence usually ignores these linkages. I study the propagation of bank failures using a spatial autoregressive model, which allows for a specific dependence among banks. I consider the case for Argentina during the 2001 banking crisis. By allowing dependence, results suggest that the structure of the linkages hampers the effect of capital on failures.

1. Introduction

A firm can fail due to firm-specific decisions, like its financial leverage making the firm more susceptible to an idiosyncratic shock; a macroeconomic shock which shrinks the whole market in which the firm operates; or contagion, a failure resulting from the transmission of an idiosyncratic shock from another firm. Contagion can be a random process or deterministic. In the banking literature, an example of a random contagion emerges in a sunspot model in which uninformed depositors run on any bank. The second form of contagion is deterministic, with the idionsycratic shock orderly transmitted based on the linkages among firms. Here we label this form of contagion as linked contagion.

I empirically explore network contagion during the Argentinian banking crisis of 2001-2002 using the network of interbank loans. I find that 70% of the failing banks were linked to another failing bank. Using a spatial autoregressive model, I find statistically significant spatial dependence among banks, which I interpret as linked contagion. Under this interpretation, the structure of the linkages among banks has real economic consequences, and in particular, it can affect the effectiveness of capital regulation.

Contagion is a distinctive feature of banks from other firms in the economy. In a standard oligopolistic model, a negative shock to a firm improves the other firm's market share. This result does not usually carry over to the banking sector, where asymmetric information makes contagion a rational equilibrium. When contagion is possible, bank failures can lead to a meltdown of the financial system and the macroeconomy (Diamond & Rajan, 2001).

Contagion of bank failures can occur in an unlinked manner with no direct link between banks, but a variable, like a market price, indirectly links them. Alternatively, contagion emerges in a linked form when a direct relationship exists between banks. Bank runs, fire sales, and correlated balance sheets correspond to the unlinked form, whereas contagion through the interbank market corresponds to the linked form.

Bank runs are a demand-side form of contagion stemming from the inability of bank creditors to distinguish an illiquid bank from an insolvent one. In such a scenario, the failure of an insolvent bank might trigger a run on the liabilities of a solvent but illiquid bank (Diamond & Dybvig, 1983). Fire-sales is another indirect mechanism for contagion: the liquidation of assets from a bank reduces asset prices in the market thus reducing the value of these assets in another bank balance sheet (Walther, 2016)[1]. Finally, contagion can be the intended result of banks coordinating to exploit a too-many-to-fail government guarantee. This is achieved by exposing to the same risks and correlating balance sheet decisions such that any failure can be potentially systemic, forcing the government to bail out all banks regardless of their behaviour (Farhi & Tirole, 2012).

Interbank loans constitute a linked channel for contagion: if an "important" bank exits from this market, it can impair the function of the whole market, in the extreme case freeze it as during the Global Financial Crisis (Gorton & Metrick, 2012). A dry interbank market reduces the ability of all banks to withstand an idiosyncratic shock: a liquidity shortfall of a bank cannot be transferred to a bank with a liquidity surplus. The functioning of the interbank market then depends upon the properties of the network, which determines the propagation of shocks (Acemoglu *et al*., 2015; Allen & Gale, 2000).

Despite the theoretical role of contagion during bank failures, empirical models do not usually allow for it. The empirical literature on the prediction of bank failures is vast and it concentrates on accounting variables. Berger & Roman (2020) in their review confirm that "Virtually all (...) studies find that low capital ratios raise the probability of bank failure". At the same time, virtually all studies rely on the assumption that every bank failure probability is independent of other bank failure probabilities, after controlling for observables. This assumption effectively rules out the above forms of contagion.

I explore linked contagion by rebuilding the interbank network from 1997q3 to 2001q4 using public credit registry data. I then use this network to predict bank failures during the 2001-2002 banking crisis with a spatial autoregressive model. This model allows for dependence between banks that occurs through the network, that is, spatial dependence. The Argentinian case has some attractive features. First, the complete network of interbank lending is available. Indeed, limited access to data on banks' mutual lending has hindered the empirical results on the network's role in the propagation of bank failures (Béreau *et al*., 2020; Iori & Mantegna, 2018). Second, the regulatory framework in place was the third-best among developing economies in 1998, only surpassed by Honk Kong and Singapore according to the World Bank (Calomiris & Powell, 2001). Second, the number of private banks I examine is 78, providing a reasonable sample size. Finally, the 2001-2002 banking crisis did not originate

[1] Diamond and Rajan (2005) is another example of unlinked contagion rooted in a general-equilibrium result. In their model, all banks share a common pool of liquidity. Due to the order in which failures occur, after a failed bank's assets are liquidated, it can destroy more liquidity that it frees. As a result, the price for liquidity, the interest rate in the economy, increases, transmitting the shock to all other banks who face now a higher financing cost.

within the financial system itself, but it was the result of a balance of payments crisis during a currency board that fixed the nominal exchange rate (Levy-Yeyati *et al*., 2010).

The banking crisis of 2001-2002 occurred after a successful period of structural reforms started in 1989, including a fiscal reform, liberalisation of international trade, financial and competition restrictions, incorporation in the MERCOSUR, privatisations of public companies and pension funds, among others. The single most important reform was the establishment of a currency board that guaranteed a fixed exchange rate of 1:1 of the local currency peso with the USD dollar. The exchange rate was fixed by the Convertibility Law enacted by Congress in 1991. The currency board limited the role of the central bank as a lender of last resort for two reasons: first, the Convertibility Law allowed issuing pesos against USD dollars and second, the government guarantee on exchange-rate risk facilitated the dollarisation of the banking system (De la Torre *et al*., 2003). A dollarised banking system without a lender of last resort can be thought as a banking system in real terms, see (Diamond & Rajan, 2006). In principle, this nominal rigidity makes the financial system more vulnerable to shocks.

After a series of external shocks since 1998 and failed programs to balance the fiscal and trade accounts, the Currency Board was abandoned and a 300% devaluation befell on January 2002. This created a massive redistribution of wealth when banks deposits and loans were converted to pesos at a lower exchange rate than the market rate, see McCandless *et al*. (2003) for an account of events during 2001. Importantly, in the leading up to the mega devaluation banks that made USD loans to the non-tradeable sector faced increments in loan defaults.

2. Methodology

2.1 Empirical model

The object of interest is the effect of a indvidiaul bank variable on its own survival probability keeping constant the contagion or spillover effect. Denoting the $(N \times 1)$ vector of individual banks probabilities by $y^* \coloneqq [y_i^* \ldots y_N^*]$ and let X be the $(N \times K)$ matrix with K variables for the N banks such that row i, $X_i \coloneqq \left[1 x_{1,i} \ldots x_{K,i}\right]_t$ contains a constant and the K covariates for bank i. This matrix contains, for example, the capital ratio of each bank.

The standard approach in the literature is to model the unobserved failure probability at the end of the sample, y_T^*, where T highlights that during the sample a period some bank failed and some did not ignoring the time of failure. The empirical model generally is represented as:

$$y_T = f(X\beta) + \varepsilon \qquad Eq\ 1$$

where y_T is a binary variable for observed bank failures during the sample period, $f(\bullet)$ is a function that links bank covariates X and the failure, which could be a linear or exponential function; X is observed at the beginning of the sampling period hence these are predictor variables; the vector β are the estimated parameters linking the observable bank features with the observed failures and the $(N \times 1)$ vector ε is uncorrelated among banks. Variations in this setup allow for multiple types of bank exits like M&A in a multinomial model (Spokeviciute *et al*., 2019) or some (non-spatial) correlation among banks, for example, allowing for a common shock.

Recognising the contagion among banks implies dropping the assumption of independence among observations and instead assuming a specific form of dependence: spatial dependence. I consider an empirical model that allows spatial dependence through the dependant variable, the survival probability, making the probability of failure of a bank depends on the probability of failures of all other banks in the system. The form of the dependence is governed by the spatial matrix W.

Let a matrix W define the lending relationships among banks. Consider a loan from bank i to bank j, then let $w_{i,j}$ be the share of the loan on bank i total Loans, that is, the share of the loan from the lender bank perspective. Then W is a spatial weight matrix containing all possible links among banks such that each element $w_{i,j}$ of W represents the share of loans from bank i to j and the diagonal of W is zero.

A model that accomodate these feautres is the spatial autoregressive model (SAR) where y is a N × 1 vector of the binary variable with 1 for surviving banks and 0 otherwise, the N × N matrix and the N × k + 1 matrix X storing all k individual bank covariates and where the first column is a constant vector. A SAR(1) model, with a lag on the dependant variable, for survival is,

$$y = \rho W y + X\beta + \varepsilon \qquad \varepsilon \sim \mathcal{N}(0, \sigma^2 I_N) \qquad \textit{Eq 2}$$

where ρ is a scalar that captures the average spatial dependence among banks, the k × 1 vector β is the relationship between individual covariates and bank survival and finally, the N × 1 vector ε corresponds to the structural error term. I assume the error term follows a Normal distribution with variance σ^2.

The model allows the failure of a bank to affect the failure outcome of other banks via the dependence on the survival variable. This model then features reverberation of shocks leading to a multiplier effect. This dependence of observations through y is coined as endogenous effects by de Paula (2017). Notice that this reverberation or multiplier effect is not present when the dependance among observations only ocurrs via individual covariates X and/or the error term ε.

The above specification does not recognise the binomial nature of the dependent variable, other than assuming that the link between the unobservable (latent) survival probability and the observable survival is linear in X. A solution to this is considering a specific link function, like a Normal CDF giving rise to a spatial probit model; in the Discussion section below I discuss this.

In the model above, the average total effect on the survival probability of a change in covariate $x_{,k}$ is the sum of: the average direct effect, capturing how the change in $x_{i,k}$ impacts on each bank i; and the average indirect effect or contagion effect which captures how the change in $x_{,k}$ in a bank affects all other banks.

The direct effect encompasses the regular channel present in non-spatial regression which is controlled by the parameter β and the reverberation or feedback effect. The feedback effects follows from the change in $x_{i,k}$ in bank i affects y_i and this in turn is transmitted through the network to all other banks y_{-i}, but now yi is affected by the change in y_{-i}. The feedback effect is governed by the strength of spatial dependence ρ and the network structure W. Thus the average direct effect summarises how a change that originates in a bank affects that bank survival either directly through β and through the feedback from other banks.

Then the average indirect effect capture how a change in $x_{j,k}$ by bank j impacts the survival probability of bank i. In this case, the change originates in a different bank. The average indirect effect admits two interpretations, as the average effect that other banks have on a bank (average total impact to an observation) and the average effect that a bank has on other banks (average total impact from an observation). Kelejian & Piras (2017), in fact, refer to the indirect effect as the emanating effect, since it shows how a change in bank i covariate spread to all other units. Numerically both interpretation are equal, see (LeSage & Pace, 2009, [p. 37) for a textbook treatment.

The distinction between direct and indirect effects is relevant for the problem at hand since, for example, it reflects the externality that a bank leverage decision has on its peers. Specifically, the survival probability of bank i depends upon its own capital structure, as well as the survival probability of all other banks, probability that in turn depends on all other banks covariates like the capital ratio. From this follows that for each bank i the marginal effect is different depending on who its neighbours are. This feature precisely encompasses a situation in which a well-capitalised bank could fail due to its relationship (via lending) to an ill-capitalised bank.

A corollary of this is that the average marginal effect on the survival probability of a change in one bank covariate, like the capital ratio, depends on the structure of the network. The structure of the network has real effects. See LeSage & Pace (2009, [p. 43) and Kelejian & Piras (2017, p.-61) for a treatment on how the average marginal effects are computed. Hence, the ability of capital ratio to avert a bank failure depends on the network's structure.

The reduced-form model is:

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \varepsilon \qquad \textit{Eq 3}$$

$$\Omega = \mathbb{E}[(I - \rho W)^{-1} \varepsilon \, [(I - \rho W)^{-1} \varepsilon]'] = \sigma^2 (I - \rho W)^{-1} \, [(I - \rho W)^{-1} \varepsilon]' \qquad \textit{Eq 4}$$

The existence of the above inverse matrix is guaranteed if the spatial weight matrix W is row-normalised such that the sum of each row is 1 (Kelejian & Piras, 2017, p. 16). I thus row-normalise the "distances" among banks.

Given the normality assumption on the error term, estimation follows by a maximum likelihood procedure. Defining ω as the N × 1 vector of eigenvalues of W, the log-likelihood function is

$$ln\, L\,(\beta, \sigma^2, \rho) = -\left(\frac{n}{2}\right) l\,n(\pi\, \sigma^2) + ln|I_n - \rho W| - \frac{e'e}{2\,\sigma^2} \qquad \textit{Eq 5}$$

$$e = y - \rho W\, y - X\beta \qquad \textit{Eq 6}$$

$$\rho \in [\min(\omega)^{-1}, \max(\omega)^{-1}] \qquad \textit{Eq 7}$$

The last equation follows from the properties of the spatial weight matrix W, in particular, the row-normalisation of W guarantees it.

This full log-likelihood depends on β, σ^2 and ρ. It turns out β and β can be concentrated out of the log-likelihood expressing them as functions of ρ. Then, the optimization of the log-likelihoood becomes a univariate optimization problem in ρ. An iterative procedure over ρ can then recover $\hat{\rho}$ and subsequently the remaining parameters, see LeSage & Pace (2009, p. 46) for details.

2.2 Data and variables

The sampling is defined by the timing of the Crisis, with 1998 being the last year before the start of the recession and 2001 the peak on bank runs on deposits. In January 2002 a massive devaluation ensued. During 2002 and 2003, many bank failures followed.

The sample contains every bank that was active in 1997q4 and failed on or after 2000q1. The bank covariates are annual averages for 1999 and the network is the average linkages between 1997q3 and 1998q4.

1) Bank failure

The Central Bank of Argentina through the Superintendency of Financial Entities is the soley authority that can terminate a financial entitie license. I track the licence history for each bank following the central bank decrees (Comunicaciones). These decrees specify the date and the reason that a licence was cancelled.

I consider that a bank fails whenever its license is terminated by the Central Bank between 2000q1 and 2003q4. I regard as failure any type of licence termination, those that are voluntary, including those that are due to a merger or acquisition; or force termination including not meeting financial regulation. A further treatment could distnigish between an M&A that is not due to an inminent failure and or a situation of bank distress as in (Chiaramonte & Casu, 2017).

I only consider local private banks, this comprises local incorporated banks, cooperative banks, private financial companies and saving & loans institutions but excludes branches of international banks and state-owned banks as in (Dabos & Escudero, 2004). The above legal definition of failure restricts the observable variable only to entities that terminate their licence. Local private banks are the most susceptible to this since they may not be able to access foreign credit lines from their parent company nor explicit (or implicit) support from the government. This restriction on the sampled entities also restricts the network such that it only contains local private banks. This potentially hinders higher-order linkages between local private banks that are through a state-owned or international bank.

2) The network

I build the linkages among banks considering interbank loans that are registered in the Central Bank Credit Registry. Each financial entity is obliged to provide borrower-level information each quarter to this credit registry which the Central Bank administers. The Registry contains information on each borrower-bank relation including the loan amount, the lending bank ID, the borrower tax file number, economic and its credit score assigned by the lending bank.[2] Each financial entity must report information on every borrower, including those borrowers that are themselves financial entities.

[2] Hertzberg *et al*. (2011) for details about the credit Registry.

Using public tax number information, I map the bank licence ID for each bank in operation during my sampling period to the corresponding tax file number that appears in the Registry. Then I can recreate direct linkages between financial entities and more importantly map the information in the Registry with the corresponding covariates for each bank.

I weigh each link from the lending-bank perspective as the share of the loan on the lender bank total Loans.

I fix the network W to the average W between 1997q3 and 1998q4. W contains on each cell the average weight of the link between bank i and j during the above period. I eliminate circular links (from and to the same entity), links with no value (loans equal to zero), and links that involve non-active banks, that is, banks that have failed and are in liquidation.

The analysis regards the network as exogenous determined, and thus fixed. For this reason, I consider the average of bank links lagged with respect to the failures which occurred since 2000q1. In other terms, this specification evaluates how past linkages predict failure.

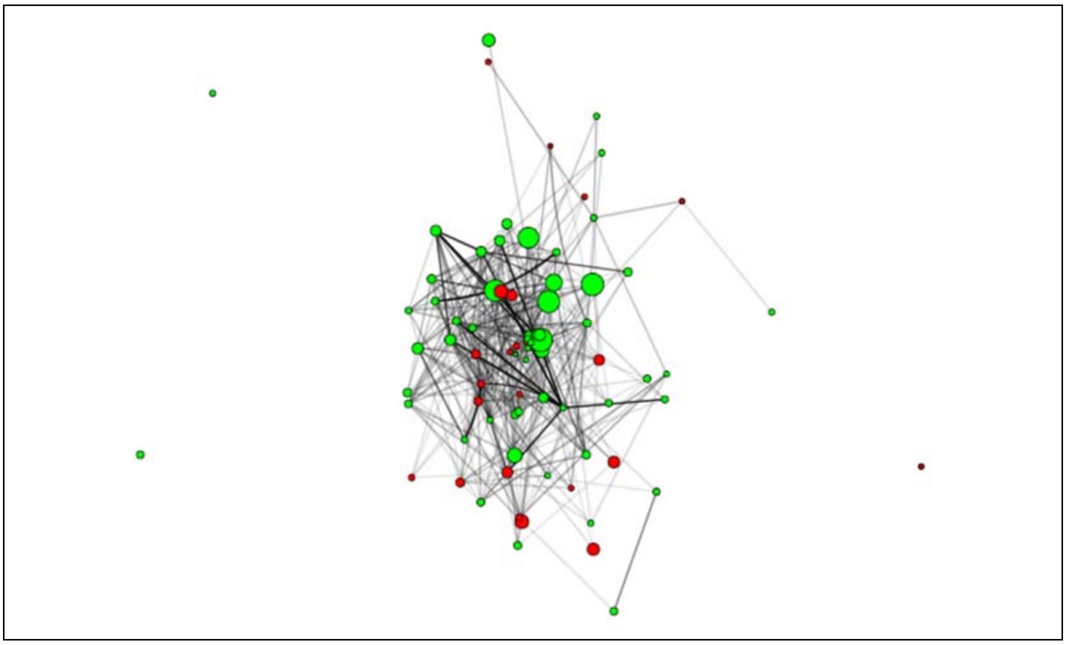
Two reasons make plausible the assumption of a stable network. First, much of the interdependence among banks is built on relationship lending, which involves over-the-counter deals and thus hinge upon mutual knowledge. Relationship lending takes time to build so it will not be quickly created. Additionally, building a lending relationhip may presumably be less likely during crisis time when asymmetric information between banks is amplified. Second, evidence using trade data from the Argentinian overnight interbank market during the period 2003-2017 by (Forte, 2020) suggest that the network evolves smoothly. He observes a reduction in the numbero of active nodes in the overnight interbank market and links during the 2008 crisis. This implies that less banks were able to trade during this Crisis (W being more sparse) reducing the possibility for a bank to hedge any shock to others. By fixing W at the beginning of the 2001 Crisis I probably overestimate the network's density during the Crisis. It is not clear what would be the effect of this on estimated effects and in particular of the network effect controlled by $\hat{\rho}$. If during the Crisis the network shrinks, distressed banks are less able to find financing, thus the shrinkage in the network causes higher bank failures. On the other hand, the shrinkage isolates healthy banks from failing ones.

The average network for all local private banks appears in Figure 1. Nodes in red corresponds to banks that failed between 2000q1 and 2003q4. While some of these failing banks are isolated, most of them are connected to other banks and have a strong relationship given by the weight.

Failing banks are connected among themselves as shown in Figure 2, which only shows the network for failing banks with connections with a weight greater than 0.01%. Among failing banks, 70% of them are directly linked: there are 23 failing banks, 16 of them are directly connected to another failing bank. This is what one would expect if there were contagion of the shocks: the failure of a bank makes it more likely that its neighbours' bank fail. Had it be the case that all failing banks were completely isolated, that is, not connected among themselves nor to the surviving banks, it would have made an explanation of contagion through the network unlikely; unless one assumes higher-order linkages.

Figure 1: Interbank network of local private entities.

Each circle represents a financial entity and its size is in direct relation to total Assets. A green circle is a bank that survives, wheres red is a failing bank. Lines represent loans among entities; the intensity of the line relates to the share the loan represents in Loans by the lender bank. Representation using the Kamada-Kawai layout algorithm.



3) Bank covariates

All bank-level variables are available and computed at monthly frequency. The regression analysis relies on the annual average for these variables, ergo eliminating seasonality.

I consider 10 variables that are standard in the literature. Assets in nominal Argentinian pesos, capture size of the firms, which is relevant for two reasons. First, bigger banks have a lower probability of ex-ante failure because they can access international debt markets even during turmoil or at a lower cost than small ones. Second, big banks may implicitly be covered by the government guarantee of 'too-big-to-fail' argument. The direction of the effect of bank size of survival is indeterminate a priori: bigger banks may be more efficient due to economics of scale but they also may engage in ex-post risky businesses to exploit their too-big-to-fail franchise (Chiaramonte & Casu, 2017). See Farhi & Tirole (2012) for a theoretical explanation of banks coordination in risk-taking exploiting a potential government bailout.

The ratio of non-performing loans to total loans, loans to the government, USD loans to total Loans, and the interest rate on loans reflect the ex-ante riskiness of the loans portfolio. An increase on any of these variables signals a riskier loans portfolio, and thus one would expect them to predict a reduction in survival probability. Non-performing loans include all loans from borrowers which the entity has classified as high default risk, following the Central Bank borrower classification guideline.

Figure 2: Network of failing banks.

The network of local private entities that failed between 2000q1 and 2003q4. Each circle represents a financial entity and its size is in direct relation to total Assets. A green circle is a bank that survives wheres red is a failing bank. Lines represent loans among entities, the intensity of the line relates to the share the loan represent in Loans by the lender bank. Representation using the Kamada-Kawai layout algorithm.

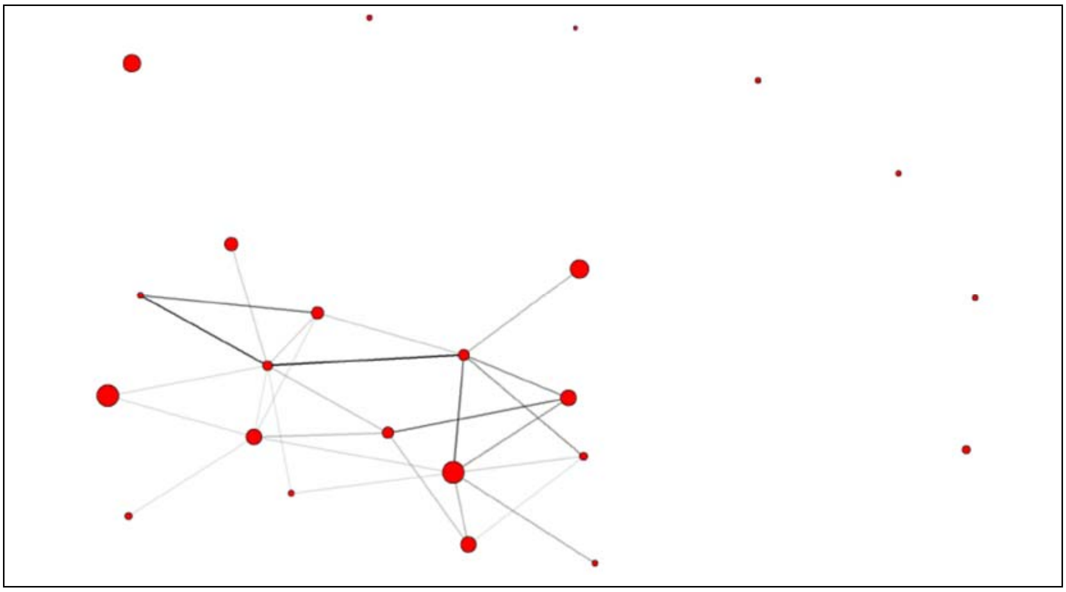
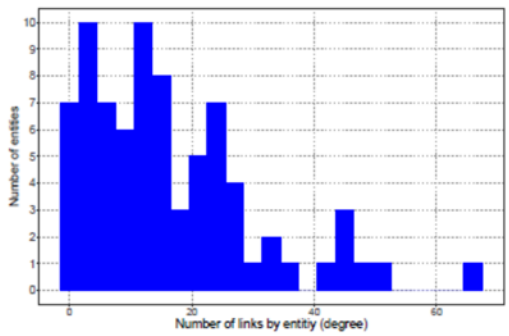
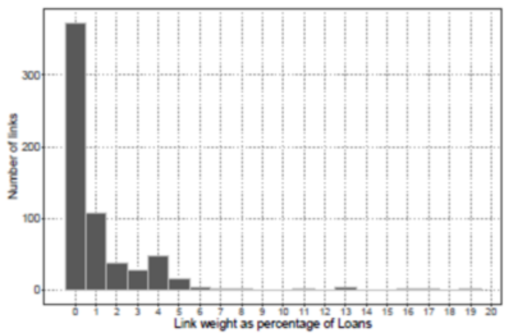


Table 1: Panel A shows the distribution of the number of links by entity, the node degree. Panel B contains the distribution of links by weight.

The height of the bar corresponds to the number of links among banks of the given weight on the horizontal axis. The weights is defined from the lending bank perspective: it is the share of the loan on Loans of the lending bank, expressed as percentage.

Panel A. Distribution of links by entity (node degree)	Panel B. Distribution of the weight of each link (edge)
	

The guideline establishes a scale to classify each borrower's risk based on: the borrower's current capacity to repay, cash flow projections and repayment history. Loans from borrowers with a default risk of 3 or higher are considered as high default risk. The proportion of lending to the government in either of three levels may be relevant in this case due to the Argentinian federal government default on its debt in December 2001. The share of USD loans implicitly captures exchange-rate risk through lending in foreign currency to borrowers in the non-tradeable sector. Finally, while non-performing loans and USD-denominated loans are contemporaneous variables of risk, the average interest rate on loans is a forward-looking measure of risk. This rate is the implicit interest rate on loans in the last 12 months computed as interest payments over loans capital, and it is expressed as a nominal annual rate.

The ratio of Loans to Assets is a broad measure of (i)liquidity of the balance sheet being loans generally illiquid and opaque assets which can become highly illiquid during a systemic crisis. As with the above variables of risk, this variable might be negatively correlated with survival (González-Hermosillo, 1999).

Capital-asset ratio, return on Assets (ROA) and deposits interest rate control for funding risk. The capital measure is the ratio of equity capital (including retained earnings) to Assets while Return on Assets is the sum of net earnings in the last 12 months to the average Assets in the previous 12 months. The implicit interest rate paid on deposits is the sum of all interest payments on all deposits during the month over the average balance on all deposits during the month. It is expressed as an annual nominal rate. A higher funding cost signals a perceived greater risk from investors

Table 2: Descriptive statistics

Variable	Mean & standard deviation	Coef. variation
Survival	0.705	0.651
Size		
Assets in ARS (millions)	1300 (2680)	2.06
Asset-side risk		
Non-performing loans	13.3 (10.6)	0.798
Loans interest rate	23.9 (10.3)	0.431
Govt. loans to Loans	4.72 (8.58)	1.82
USD loans to Loans	54.6 (24.1)	0.441
Loans-to-Assets ratio	49.8 (16.1)	0.323
Funding		
Capital-asset ratio	18.4 (13.6)	0.736
ROA	-0.337 (3.61)	-10.7
Deposits interest rate	5.49 (2.58)	0.47
Number of observations	78	

3. Results

I consider three models using cross-sectional data: linear OLS, probit and (linear) spatial autoregressive (SAR). The results appear in Table 3.

Table 3: The outcome variable is binary with value 1 if a bank survives between 2000q1 and 2003q4.

SAR is Linear spatial autoregressive. Predictors are the annual average by 1999 and the spatial matrix is the average of each relation between 1997q3 and 1998q4. Only banks alive by 1997q4 are included. All predictors are in percentage except for Assets which are in nominal Argentine pesos.

Predictor	Dependant variable: survival		
	Linear OLS	Probit	SAR
Intercept	1.343***	2.757***	1.742***
	(0.312)	(1.167)	(0.316)
Size			
Assets in ARS	0.000*	0.000	0.000***
	(0.000)	(0.000)	(0.000)
Asset-side risk			
Non-performing loans	-0.013**	-0.038**	-0.018***
	(0.007)	(0.022)	(0.006)
Loans interest rate	0.004	0.007	0.001
	(0.006)	(0.021)	(0.006)
Govt. loans to Loans	-0.005	-0.014	-0.005
	(0.006)	(0.022)	(0.006)
USD loans to Loans	-0.006***	-0.022***	-0.007***
	(0.003)	(0.009)	(0.002)
Loans-to-Assets ratio	-0.005	-0.014	-0.006***
	(0.003)	(0.012)	(0.003)
Funding			
Capital-asset ratio	0.003	0.014	0.004
	(0.004)	(0.014)	(0.004)
ROA	0.008	0.042	0.001
	(0.019)	(0.064)	(0.017)
Deposits interest rate	-0.009	-0.036	-0.006
	(0.021)	(0.069)	(0.019)
ρ			-0.314***
			(0.119)
Num.Obs.	78	78	78
R2	0.209		0.265
R2 Adj.	0.104		
AIC	102.5	97.1	99.0
BIC	128.5	120.7	127.3
Log.Lik.	-40.273	-38.571	-37.506
F	1.998		
Wald test spatial dependence (p-value)			0.008
LR test spatial dependence (p-value)			0.019

* $p < 0.15$, ** $p < 0.1$, *** $p < 0.05$

All coefficients have the same sign across models. A higher capital ratio is associated with a higher probability of survival, although surrprisingly this variable is non-significant in any specification. In contrast, non-performing loans is significant in all models, and the estimated coefficient indicates that a higher proportion of non-performing loans predicts a lower probability of survival. The ratio of loans nominated in USD dollar is associated with lower survival. A significant proportion of these loans were to the non-tradeable sector and were affected by the peso's 2002 devaluation, rendering them in non-performing loans. The share of total loans on the asset side reduces survival, as expected, since more loans on the asset side correspond to a less liquid balance sheet.

The spatial parameter ρ is negative and statistically significant at 99%, suggesting spatial dependence via the dependant variable among observations. An interpretation of this result is the existence of network effect or contagion among banks: the failure of a bank affects the survival probability of the remaining banks. The absolute value of ρ is restricted to be in the unitary interval, and the size of 0.31 determined the share of the average indirect effect of a change in a predictor variable x_r on the survival probability. In this case, the suggested value implies that on average, 1/3 of the effect of a change in variable x_r in a bank corresponds to the indirect effect, that is, 1/3 of the effect is dissipated away or spread to other banks.[3]

The average marginal effects appear in Table 4 distinguishing between the direct and indirect effect of a change in a predictor variable.

Table 4: The outcome variable is binary with value 1 if a bank survives between 2000q1 and 2003q4.

SAR is Linear spatial autoregressive. Predictors are the annual average by 1999 and the spatial matrix is the average of each relation between 1997q3 and 1998q4. Only banks alive by 1997q4 are included. All predictors are in percentage except for Assets which are in nominal Argentine pesos.

Predictor	Effects × 100		
	Direct	Indirect	Total
Size			
Assets in ARS (millions)	0.0000	0.0000	0.0000
Asset-side risk			
Non-performing loans	-1.7726	0.4266	-1.3461
Loans interest rate	0.1168	-0.0281	0.0887
Govt. loans to Loans	-0.5259	0.1266	-0.3994
USD loans to Loans	-0.7178	0.1727	-0.5451
Loans-to-Assets ratio	-0.6505	0.1565	-0.4939
Funding			
Capital-asset ratio	0.4307	-0.1036	0.3270
ROA	0.1010	-0.0243	0.0767
Deposits interest rate	-0.6354	0.1529	-0.4825

Notably, some impact estimates have opposing direct and indirect impacts, such as non-perfoming loans or capital-asset ratio. For non-performing loans, the positive value on the indirect impact suggests that, keeping all other variables fixed, on average, an increase in other banks non-performing loans increases a bank probability of survival. Framing this results in a partial-equilibrium competitive model for banks, this positive indirect effect may be explained by the positive effect on a bank that its competitors suffer loans loses and thus lose

[3] See the dual interpretation of the indirect effect as the total impact from an observation and the total impact to an observation in Section 2.1 above.

market share. Turning to the capital-asset ratio, while the direct effect is positive its indirect effect is negative. This is unexpected since it indicates that on average and conditioning on all other variables, an increase in a bank capitalisation reduces other banks survival probability. This estimated impact is nevertheless statistically non-significant as per Table 3.

4. Discussion

My main hypothesis is that the properties of the network have real consequences by amplifying or reducing the propagation of the shocks. This relies on a network that is sufficiently stable to transmit the shocks. I treat the network as fixed and use lagged value of it in the main specification, thus I do not consider a possible endogeneity of the network. Under this assumption above results do not reject the hypothesis that network effects are present during bank failures. In this section, I discuss alternative explanations, highlight shortcomings of the empirical analysis and consider possible solutions.

4.1 Demand-driven dependence

My hypothesis states that contagion stems from the supply-side: the network among banks facilitates the propagation of a shock. In the banking context, however, contagion can spur from the demand side when uninformed depositors randomly running on bank deposits. For example, under 'sunspot models' (Diamond & Dybvig, 1983; Friedman & Schwarts, 1963) bank runs are unconditional on the fundamental of a bank. Under this explanation, the above spatial correlation is the reflection of depositors randomly running on different banks simultaneously, hence driving a correlation in the data.

Nevertheless, the empirical evidence during this period for Argentina rules out an explanation of contagion based on random runs on banks. Deposit withdrawals indeed were not random but responded to bank variables. Martinez Peria & Schmukler (2001) study the influence of bank fundamentals on deposits and interest rates before, during and after the Tequila crisis using quarterly data. They find that bank fundamentals in all three periods account for about 75% of the variation in interest rates on deposits and around 2/3 of the variation in deposits after the Tequila crisis (March 1995 to March 1997). D'Amato et al. (1997) also consider the Tequila crisis using daily data on deposits. They claim that bank fundamentals are the biggest driver of variation of daily deposits accounting for 27% of the variation while contagion would represent 17% and macroeconomic variables 11%. Consider the bank runs during 2001, McCandless *et al*. (2003) study the variation in deposits with monthly data and conclude that estimates on bank fundamental variables have statistically significant power to explain deposits variation. Finally, for the same period and with daily data on deposits Levy-Yeyati *et al*. (2010) expand the information set by considering macro variables as explanatory variables highlihgitn that both, banks and macro covariates, are jointly statistically significant in explaining depositors' behaviour.

This evidence then points out that demand-side contagion among banks seems unlikely after conditioning on observable bank fundamentals during this period.

4.2 Linearity of the link function

The specification for the SAR(1) model above ignores the limited dependant variable, which invalidates inference. Assuming that the link between the latent variable probability of survival and the observable survival is given by the Normal CDF, a spatial probit model as in LeSage & Pace (2009, p. 283) or Craioveanu & Terrell (2016) could handle this. While these models accommodate the limited dependant variable, the order of failure over time may be relevant in the presence of network effect. An initial shock to an isolated small bank has different consequences than a shock to a big and highly-linked bank. This emphasises the relevance of time as a variable to consider. A spatial duration probit model could address this as in Elhorst *et al*. (2016). Their estimation algorithm relies on an efficient importance sampling which I have been unsuccessful in obtaining a non-singular Hessian.[4]

4.3 Unobservable idiosyncratic factor or common factors

The above preliminary results ignore potential unobservable idiosyncratic factors at the bank level that could be addressed in a panel-data sample with a fixed-effect estimator as in Vacaflores & LeSage (2020). A panel-data sample is highly relevant if one worries that the network is endogenous to some time-fixed bank variables, like their institutional type, e.g, all cooperative banks having tight links among them. Macroeconomic variables are also omitted from the cross-sectional sample analysed here. Indeed, one might argue that the spatial dependence parameter ρ may instead capture the diffusion of the macro shock across the cross-section observations rather than the diffusion of idiosyncratic bank shocks.

4.4 Definition of failure

The stricto sensu legal definition of failure taken here excludes state-owned banks that, while not legally failing, were subjected to distress. This exclusion not only left unexplained banks that represent almost half of the financial system but has the unintended consequence of trimming the network of potential indirect linkages between private banks via the excluded state-owned banks. A better approach is probably a redefinition of failure that encompasses distress and thus including state-owned banks in the sample.

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[4] Another approach to estimation of this model Bayesian MCMC algorithm as in LeSage & Pace (2009).

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