Contagion of bank failures through the interbank network in Argentina

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Abstract

Capital regulation on banks aims to reduce the probability of failures. In theory, the effect of capital buffers in preventing failures could depend on the linkages among financial institutions. These linkages are nevertheless usually omitted in empirical models. I study the effectiveness of capital regulation in preventing failures using a spatial autoregressive probit model, which accommodates links among banks and feedback effects. I study the Argentinian banking crisis of 2001 for which I build the complete interbank network. By allowing linkages between banks, estimates from the spatial model show that capital regulation is 50% less effective than estimates of a model in which banks are not interconnected.

Keywords: Spatial Autoregressive Probit, Banking Crises, Financial Contagion, Argentina

JEL classification: C21, E44, G01, G21.

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1 Introduction

Bank failures impair capital formation by reducing aggregate liquidity in the economy (Holmström & Tirole, 1998), disproportionately diminishing credit to smaller firms (Holmstrom & Tirole, 1997) and contracting aggregate supply of credit (Bernanke & Gertler, 1995). Bank failures can also disrupt the political system by giving rise to authoritarian regimes (Doerr et al., 2022). Understanding the causes of these failures is thus of the greatest relevance for the economy and society. The regulation of banks' capital levels emerges to prevent failures and their associated costs. I show that, in the Argentinian case, the effectiveness of bank capital in averting failures is almost 50% lower than previously estimated.

Contagion is a significant driver of bank failures. I define contagion as whenever a bank's decision affects the failure probability of other banks. In perfectly competitive markets, contagion is absent since firms are too small to influence each other. In imperfectly competitive markets of non-financial firms, a negative shock to a firm improves its competitors' market share. In the banking sector, however, asymmetric information makes contagion a rational equilibrium such that when contagion is possible, bank failures could lead to a meltdown of the complete financial system and the economy (Diamond & Rajan, 2001). Contagion among banks arises from the demand side when depositors run on banks (Diamond & Dybvig, 1983). From the supply side, contagion emerges indirectly when all banks are connected to a central source of risk; for example, during fire sales, the liquidation of an asset by a bank reduces the asset price in the market for all banks (Walther, 2016; Diamond & Rajan, 2005). Another example of indirect contagion is collusive behaviour, when banks coordinate their portfolios having exposure to the same risk to exploit a too-many-to-fail government guarantee (Farhi & Tirole, 2012). Finally, network contagion is a direct mechanism of contagion when individual connections exist among banks, as in the interbank market. Network contagion implies direct linkages of interbank claims and obligations that configure a financial network structure.

Financial networks favour risk sharing and contagion, leading to a robust-yet-fragile financial system (Gai & Kapadia, 2010). The network redistributes liquidity where it is more needed, thus increasing the efficiency of the banking system (Allen & Gale, 2000). In times of crisis, however, this network's beneficial property could become detrimental when each bank tries to hoard liquidity by reducing lending to other banks and relinquishing its payments. Network contagion features a feedback (or cascade) effect such that the default of a bank could trigger the default of other linked banks. Under certain conditions, this feedback effect works as an amplifying mechanism that could potentially lead to a catastrophic collapse of the banking system (Gai & Kapadia, 2010). The presence of network contagion may reduce the effectiveness of capital regulation in averting the social costs of bank failures because, from the perspective of the regulator, a bank may be "well-capitalised" in isolation (microproduential regulation), but under-capitalised when considering the credit risk emanating from its interbank links. Strategic behaviour also emerges when unhealthy banks use the interbank network to free-ride on well-capitalised banks. Establishing whether network contagion is present in real financial systems is, thus, relevant in understanding the effectiveness of capital regulation.

I empirically study network contagion during the Argentinian banking crisis of 2001-2002 using the network of interbank loans. I reconstruct the network from 1997q3 to 2001q3 using data from a credit registry. From this, I find that 56% of failed banks were directly linked to another failed one before the Crisis. Using this network, I then predict failures during the Crisis. I depart from existing literature by borrowing from the spatial econometrics toolkit and estimating a spatial autoregressive (SAR) probit model, which allows for feedback effects. I focus on a) identifying the presence of network contagion, which is manifested in the model as spatial autocorrelation, and b) the effect of its presence on the marginal effect of the capital ratio on a bank's survival.

I find statistically significant spatial autocorrelation among banks, which I interpret as financial network contagion. The estimates from the spatial model indicate that bank equity is 50% less effective in averting failures compared to a non-spatial model that does not allow for bank linkages.

This finding relates to two strands of the financial literature. On the one hand, it connects to the empirical literature on the prediction of bank failures which is reviewed by Berger and Roman (2020). They conclude that "Virtually all (...) studies find that low capital ratios raise the probability of bank failure". At the same time, virtually all studies assume that the probability of failure for a bank is independent of other banks. This assumption effectively rules out network contagion, despite the established role of networks in amplifying failures in theoretical models. Recent progress has been made by including in the regression analysis various summary measures of banking networks, see, for example, Das et al. (2021), and Constantin et al. (2018). While this approach facilitates a better understanding of the relevance of banks' location in a network in explaining subsequent failures, all cascade effects are absent from the model.

The effect of individual-bank capital levels on survival is also informative to the literature on networks and systemic risk. This literature studies which general properties of a network reinforce contagion. The estimation of the network and its properties is centrepiece here [1] While I do not study the properties of the network per se, I use it as a predictor and show how different networks generate different strengths and directions for contagion.

From the spatial model I find that when a bank increases its capitalisation, it *increases* the probability of failures of the banks linked to it, generating a negative spillover effect. This last result speaks to the literature in industrial organisation that ties corporate finance decisions with decisions related to competition in the product market. Research in this area stresses that financial decisions are taken in tandem with competitive decisions, that is, price or quantity. Ergo a firm's leverage hinges not only on the cost of capital but also on the responses of its competitors in the marketplace, see Frésard and Phillips (2022) for a recent survey. Focusing on publicly traded firms Grieser et al. (2022) uncover significant evidence that when a firm decides its leverage, it considers the leverage of its competitors. A. F. Silva (2019) shows a causal effect between a bank's liquidity holdings and its competitors' liquidity levels. I do not specifically study bank leverage but I find that failures spread through the network and since leverage determines failures, my findings are compatible with this literature.

This work makes two contributions to our understanding of bank failures. First, the estimates on the effectiveness of bank capital in preventing failure are, to my knowledge, the first that fully account for the interlinkages among banks by using a spatial model. This is valuable for a regulator who needs to calibrate capital requirements for credit risk in a real-world financial system where banks are interconnected. Second, a new interbank network from an emerging economy is added to the literature. This network is not inferred from incomplete data but rather completely rebuilt using novel bank-level data. Forte (2020) builds a network for Argentina relying on daily transactions in the interbank money market (the "call" market)

[1]Examples of interbank network estimates are in 't Veld and van Lelyveld (2014) for the Netherlands, T. C. Silva et al. (2017) for Brazil, and Forte (2020) for Argentina.

for 2003-2017. The network introduced here differs from Forte's one because it covers a different period and it is built from end-of-the-quarter data comprising any interbank lending.

The Argentinian crisis under consideration has four attractive features to understand the dynamic of bank failures. 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 (Iori & Mantegna, 2018; Béreau et al., 2020). Second, the regulatory framework in place was the second best among developing economies in 1998.[2] Argentinian banks during this period were "well-capitalised" by Basel II standards, making it a good sample for testing the effectiveness of capital regulation. Third, 72 banks are in the network, providing a reasonable sample size. Last, the banking crisis did not originate 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). Because banks had different exposure to exchange rate risk, variations over time in the expectation of a devaluation created heterogeneous liquidity needs. This widens the scope for the network to act as a risk-sharing and contagion device by (not) funnelling liquidity where it is most needed.

2 Historical context

In this section, I argue why the Argentinian crisis is suitable to study the contagion of bank failures through the interbank network by providing a historical context to the bank failures during this period. The crisis under consideration was the third most severe one in the country's history (Reinhart & Rogoff, 2014) and it is considered the Argentinian "Great Depression" (Gerchunoff & Llach, 2007, p449). Between 1998 and 2002, the national income dropped by 20%, and, in the biggest cities, the unemployment rose to 21.5% in 2002.

Since 1989, structural economic reforms were implemented during the Menem administration, including a fiscal reform introducing a value-added tax, the removal of restrictions on international trade and capital controls, the establishment of the customs union Mercosur, privatisations of state-owned companies and pension funds, the independence of the Central Bank authorities from the Executive branch of the government, among others. The single most

[2] It was only surpassed by Singapore and tied with Hong Kong according to the World Bank (Calomiris & Powell, 2001)

important reform was the establishment of a currency board system that guaranteed a fixed exchange rate of one-to-one of the local currency, the peso, with the USD dollar. The exchange rate was fixed by the Convertibility Law enacted by Congress in 1991. The Convertibility gave a legal framework to a bimonetary economy: the banking system can issue deposits and lend in local and foreign currencies.

The currency board limited the role of the central bank as a lender of last resort because the law only allowed the Central Bank to issue pesos (ARS)[3] against US dollars (USD). A dollarised banking system without a lender of last resort can be thought of as a banking system in real terms, see Diamond and Rajan (2006). In principle, this nominal rigidity makes the financial system more vulnerable to shocks since the Central Bank has limited capacity to lend to a solvent but illiquid bank.

The hard peg provided an implicit government insurance on exchange-rate risk which resulted in the appearance of a currency mismatch on the balance sheets of governments, corporate sector, and banks: agents had liabilities in foreign currency but assets in local currency (De la Torre et al., 2003a).[4] In the case of banks, USD-nominated liabilities funded pesos-nominated loans. Moreover, a significant share of these loans was to the non-tradeable sector. This made some banks vulnerable to a devaluation: bank borrowers in the non-tradeable sector were particularly susceptible to default on their debts after a devaluation. Even in the absence of devaluation, loan default in the non-tradeable sector was more likely given the deflation that was taking place; the simple average annual inflation rate between 1999 and 2001 was -1.05%. As a consequence, the higher a bank portfolio's exposure to the non-tradeable sector, the more susceptible to loan defaults either through a realignment of the nominal exchange rate or the local price level.[5]

External shocks that the Argentinian economy received between 1999 and 2000 are remarked either as a cause or amplifier of the ensuing crisis. Calvo et al. (2003) highlight the Russian default of 1998 as a tipping point in capital flow to emerging markets, particularly to Argentina. Perry and Serven (2002) emphasize changes in real exchange rates after the Brazilian devaluation of its currency, the Real, in 1999. They estimate that by 2000 the Argentine peso was

[3]ARS stands for Argentinian Peso.

[4]As noted by De la Torre et al. (2003b) a currency mismatch may be desirable to increase the credibility of a hard peg since it raises the exit cost.

[5]Local regulation on capital requirement partially acknowledged this risk by mandating higher capital buffer for banks with a higher currency mismatch, see De la Torre et al. (2003b)

overvalued by around 55%.

Perry and Serven (2002) distinguish a period of a virtuous cycle of economic growth and structural reforms between 1990 and 1997. Indeed, GDP grew from 1995q4 to 1998q2, being 1998 the year of the end of the expansionary cycle. After the Tequila crisis of 1995, there were several improvements in financial regulation which included liquidity requirements for banks, capital requirements depending upon the currency of the loans, and deposit insurance, among others.[6] The deposit insurance established in 1995, which was mandatory and financed by all financial institutions, covered deposits of up to ARS/USD 10,000. The Guarantee Fund of Deposits (FGD), which is a private corporation, managed the insurance.[7] This resulted in Argentina being ranked second (after Singapore, tied with Hong Kong, and ahead of Chile) in terms of the quality of its regulatory environment by late 1998, according to the CAMELOT rating system developed by the World Bank (Calomiris & Powell, 2001).

Calvo et al. (2003) and Perry and Serven (2002) remark that a fixed exchange rate hides the severity of fiscal problems by misrepresenting the size of debt denominated in foreign currency. This made the political problem worse because the policymaker had a tougher time selling on the idea of correcting fiscal imbalances. Indeed, in December 1999 a new administration, led by President De La Rúa and formed by the coalition of the second and third biggest political parties in opposition to the party that enacted the 1989 reforms, took office. It initially delayed addressing the fiscal problems and demonstrated hesitation towards the exchange rate regime (Perry & Serven, 2002).

De La Rúa administration tried to address the problem of currency overvaluation indirectly by pushing for greater flexibility in labour markets. After the approval of the labour market reform, the vice president, who represented one of the parties in the coalition, resigned on October 2000. On December 2000 a bailout package with the International Monetary Fund (IMF) was negotiated. During 2001, events unfolded rapidly, with 3 ministers for the economy during the year. In April, Domingo Cavallo, former Minister for the Economy and known as the "Father of the Convertibility", took office and was granted special powers by Congress. Policies enacted to tackle the overvaluation of the currency included imposing a tax on imports while subsidising exports (a fiscal devaluation for trade transactions), softening the Convertibility by

[6]See details of these financial regulatory reforms in Appendix B on De la Torre et al. (2003b)

[7]See https://www.sedesa.com.ar/index.php/en/seguro-de-depositos-s-a-en.

announcing the eventual peg of the peso to both the dollar and the euro (with equal weights), once these two currencies reached parity, and forcing the resignation of the Governor of the Central Bank, Pedro Pou, who was viewed as a strict guardian of monetary and banking system soundness by investors. In October 2001, the government lost the legislative mid-term elections. During the last weeks of November, a third bank run took place draining deposits from the system. By December 2, a partial suspension of convertibility of deposits was decreed, publicly known as *corralito* (little fence).[8]

President De La Rúa resigned in December 2001, almost half of his tenure. Following the President's resignation, 3 Presidents appointed by Congress took office between December and January 2002. Towards the end of December 2001, the federal government defaulted on part of its foreign-currency-nominated debt during the brief presidencies of Ramón Puerta and Adolfo Rodriguez Saá. On January 2002, during Duhalde Presidency, the sought-after correction on the real exchange rate was brought about through a devaluation and by forcing a devaluation on dollar-nominated contracts, thus destructing property rights (De la Torre et al., 2003b). The Currency Board system was abandoned for a float exchange rate, the nominal exchange rate jumped from ARS1/USD1 in January 2002 to ARS3.8/USD1 in September 2002, and the annual inflation rate for 2002 was 41% (Cavallo & Runde, 2018, Ch15).

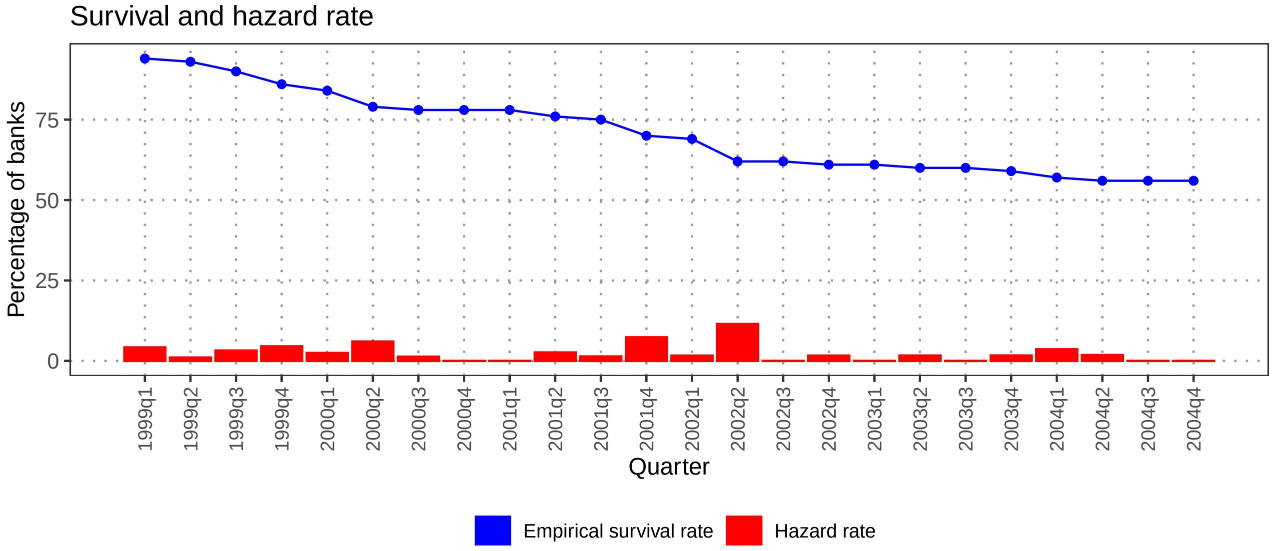
The forcible conversion of dollar-denominated financial contracts into peso-denominated ones with different conversion rates applied to bank loans and deposits, triggering losses for banks and depositors alike. This was known as asymmetric pesification. Furthermore, some courts ruled out that this decision was not legal and ordered banks to pay some depositors the face value of their deposits previous to the devaluation, producing additional losses for banks. The government issued a series of bonds to compensate banks for these losses. Asymmetric pesification created a massive redistribution of wealth between USD-nominated debtors, who were able to dilute their debts, and ARS-nominated creditors, who saw the value of their credits lowered.[9]

The corollary of this section is that the roots of the crisis were at macro level rather than intrinsic to the financial system; the banking system was rather a victim of the recession

[8]These restrictions on the convertibility of deposits changed the regime and it is thus excluded from the analysis by McCandless et al. (2003) when analysing the determinants of bank runs during 2001.

[9]For details on the asymmetric pesification, see Damill et al. (2010) and for details of events during 2001 McCandless et al. (2003).

Figure 1: Number of active banks and failures per quarter.



(De la Torre et al., 2003b). This is in contrast to the Asian financial crisis of 1997 or the Global Financial Crisis of 2007 where the financial crisis preceded the recession. Movements in the expectation of a devaluation created runs on deposits of the banks most susceptible to a devaluation (Martinez Peria & Schmukler, 2001; Calvo et al., 2003; McCandless et al., 2003), which I argue were then transmitted through the network to banks not subjected to the initial runs. The subsequent empirical section focuses only on failures before the 2002 devaluation because the devaluation together with the asymmetric pesification of 2002 introduced additional heterogeneity in bank losses.

3 Contagion in financial networks

This section introduces basic concepts of networks and makes precise the notions of contagion through financial networks by following the theoretical models of Allen and Gale (2000) and Gai and Kapadia (2010). In the former model, banks subjected to a liquidity shortfall have a strict pecking order in the liquidation of claims, which is a reasonable feature for the empirical case. The framework in Gai and Kapadia (2010)'s model is attractive because it does not limit the number of nodes in the network.

Following the definition in Goyal (2017) and de Paula (2017), a network is represented by a graph g which is a pair of sets $(\mathcal{N}_g, \mathcal{E}_g)$ where $\mathcal{N}_g = \{1, 2, \ldots, n\}$ with $n \geq 2$ is the set of nodes and $\mathcal{E}_g$ is the set of links (or edges) $\{i, j\}$ between nodes, where $i, j \in \mathcal{N}_g$. In our case, the nodes represent banks and the links their interbank claims to each other. The links $\{i, j\}$ can be weighted representing the intensity of the relationship between nodes i and j, or the distance between them given a sensible measure of distance. The links on a network can be unordered pairs of links such that $\{i, j\} = \{j, i\}$ or an ordered pair making each link unique, $\{i, j\} \neq \{j, i\}$. In the unordered case, the network is said to be *undirected* since links do not have an orientation while in the ordered case links are oriented and the network is *directed*. In a directed network, the transmission of a shock from one node to another is restricted by the direction of the links.

The set of neighbours incident with node i is $N_i(g)$. This set contains first-order neighbours of node i and if node j belongs to this set, we conclude there is a link $\{i, j\} \in \mathcal{E}_g$ and we say j is a neighbour of i. When $j \notin N_i(g)$, we can only conclude that there is not a direct link $\{i, j\}$, however, i and j may be linked indirectly through higher-order neighbours. An important feature of a node is the dimension (cardinality) of $N_i(g)$ representing the number of links the node has. This is the *degree* of node i and is denoted by $|N_i(g)|$. In a directed graph, each node has two degrees of interconnection: the number of incoming links to a node, its *in* degree, and the number of outgoing links, its *out* degree. Since there are many nodes with potentially different degrees, there exists a distribution of degrees, which is an important property determining the propagation of shocks in the network.

In the model proposed by Gai and Kapadia (2010), the interbank network is a directed graph with weighted links (edges). Each node in the network represents a bank that can borrow and/or lend to other linked banks in the market. Incoming links to a node (bank) reflect the interbank assets/exposures of a bank while outgoing links from a bank correspond to its interbank liabilities. A bank i has two assets on its balance sheet: interbank loans A_i^{IB}, which are short-term assets, and mortgage loans A_i^M, which represent long-term assets. On the liability side, there are interbank liabilities L_i^{IB} and retail deposits D_i. For simplicity, interbank loans for bank i are equally diversified along bank i borrowers, thus each link corresponds to loan of size $\frac{1}{j_i}$ where j_i denotes the number of interbank borrowers of bank i.

The liquidation of the long-term asset A_i^M is subject to a haircut loss such that the resale price is qA_i^M with $q < 1$. The lower resale price could be due to the low real value of premature liquidation of a project (Allen and Gale, 2000), lender-specific collection skills (Diamond and

Rajan, 2001) or the illiquidity of the secondary mortgage market during a fire sale (Walther, 2016).

A bank faced with a liquidity shortfall has a *liquidation pecking order*: it first liquidates interbank asset A_i^{IB} (call back interbank loans), then defaults on its interbank liabilities L_i^{IB} before resorting to the liquidation of A_i^M. This pecking order configures the free-riding problem: a bank in need of liquidity will attempt to squeeze liquidity from its peers without accounting for this action's negative spillover effect (Allen and Gale, 2000).

In this model, there is only an idiosyncratic shock in nature, which is the default of a given bank. Admittedly bank failures rarely occur in isolation but occur within a macroeconomic crisis. In the empirical case at hand, one can think of the idiosyncratic shock as the result of a change in expectations of a devaluation with the predetermined currency mismatch of a bank, see Section 2.

A bank i is solvent if

$$(1-\tau)A_i^{\mathrm{IB}} + qA_i^{\mathrm{M}} - L_i^{\mathrm{IB}} - D_i > 0,$$

where τ is the fraction of borrower banks of i that default and $q \in [0,1)$ is the resale price of the mortgage asset.[10]

The goal is to understand how the default of a linked (borrower) bank in the network, captured by τ can trigger the default of the lending bank i thus configuring a linked form of contagion. Expressing the solvency condition in terms of τ we have:

$$\tau < \frac{E_i - (1-q)A_i^{\mathrm{M}}}{A_i^{\mathrm{IB}}}, \qquad \text{for } A_i^{\mathrm{IB}} \neq 0, \tag{1}$$

where $E_i = A_i^{\mathrm{IB}} + A_i^{\mathrm{M}} - L_i^{\mathrm{IB}} - D_i$ is the bank's equity buffer, that is, its net worth. This equation makes clear that for any given shock size τ a higher equity buffer reduces the probability that bank i defaults. Thus, equity works as a firewall preventing contagion.

Now consider how the vulnerability to a default of bank i varies with the degree of interconnection with other banks. Bank i will default if the losses associated with its interbank assets A_i^{IB} are greater than its equity buffer. In particular, if borrower j defaults, then bank i will

[10] Differently from Allen and Gale (2000) who define a bank is solvent if it can meet its obligation *without* liquidating its long-term asset, this definition of solvency comprises all assets.

default if

$$\frac{E_i - (1-q)A_i^{\mathrm{M}}}{A_i^{\mathrm{IB}}} < \frac{1}{j_i},$$

recalling that interbank loan are of size $\frac{1}{j_i}$ since they are equally distributed among bank i borrowers. From this follows that the j_i represents the number of incoming links for bank i. The higher the number of incoming links, the more *vulnerable* to its interbank exposure bank i is, assuming the default probability is the same across borrowers.

The network remains static over time and is taken as given. It is the stability of the network that gives rise to the spillover effects: if the network were to react rapidly enough to changes in bank's risks, as in a friction-less model, the network of interbank linkages becomes irrelevant, no real effect is derived from it. The stability of the financial network could stem from contracts that fix links temporally, like credit lines that have a maturity. Additionally, during crises, contagion spreads very rapidly through the financial system, meaning that banks are unlikely to have time to alter their behaviour before they are affected, see in section 5.2 for other arguments applicable to the Argentinian case. For the same argument, the optimal level of equity in equation (1) is given and thus does not depend on the network. One can think as E having been chosen in a previous period based on, for instance, the bank had to have a stake on projects that finance as certification of investment, an incentive-compatible restriction as in Holmstrom and Tirole (1997).

The direction of the graph adopted by Gai and Kapadia (2010) from the borrower to lender implies that a bank's vulnerability is measured as the *in* degree: links are drawn from the borrower bank to the lender one. An alternative definition is from lender to borrower as in Allen and Gale, 2000. The direction from the borrower to the lender is more appropriate for our setting since it allows shocks to travel from borrower to lender but not the other way around.

What is the effect of a bank failure on aggregate liquidity? When general equilibrium effects are considered a bank failure may free more liquidity than it destroys, under certain circumstances. In the partial-equilibrium framework here presented a bank failure monotonically reduces aggregate liquidity. For instance, in Allen and Gale (2000), when a bank fails (becomes bankrupt in their terminology), all assets are liquidated and depositors are paid on a pro-rate basis (no first-serve first-come constraint). In principle, this destroy liquidity but as noted by Diamond and Rajan (2005), in this model there are 2 depositors, early and late consumers. When a failure occurs, the early consumer gets hit since its deposits are valued less than in absence of a failure. The late consumer, however, finds herself with liquidity at a date in which is of no value, thus she chooses to deposit this liquidity in surviving banks. This increases liquidity for remaining banks in the current period. Banks with excess liquidity will then transfer this through the interbank network. In Diamond and Rajan (2005)'s model banks are not directed linked through interbank claims but are linked indirectly through a common pool of liquidity, an interbank market in which all banks have access to and where the interest rate is determined. In this model, when an aggregate liquidity shock occurs, driving up the interest rate, aggregate liquidity may increase as banks fail. When a bank fails it liquidates late projects on its asset side paying back depositors. Equity shareholder claims, though, are reduced, shareholders take a hit on their claims. Depending on the initial conditions, a bank failure may actually lead to an increase in liquidity in the current period. Additionaly, a deposit insurance scheme, as it was in place in Argentina during this time may increase liquidity as it pays out immediately to depositors of the failing bank. As before, these payments would then be funneled back to the banking system and redistributed through the interbank network. As a result, surviving banks may end up facing higher liquidity as a result of the initial failure.

The previous discussion highlights that the effect of a bank failure on surviving banks requires an empirical inquiry. The proposed spatial model in the next section will attempt that by explicitly incorporating the interbank network. In doing so it will assess whether τ in the solvency condition (1) is a relevant driver of bank defaults after conditioning for the other determinants of solvency. Here, I define contagion as the spillover effect that the failure of a bank has on the propensity to fail of remaining banks. In other terms, the interdependence of probabilities of failures; see Forbes and Rigobon (2002) for an alternative definition of financial contagion.

4 The spatial autoregressive probit model

Consider an economy with N banks and an interbank network of loans represented as an $N \times N$ matrix W_0. In our case, the typical element $w_{i,j}$ for $i \neq j$ represents the loan ratio of bank i to bank j over the total amount of loans of bank i, that is, the share of the loan from the lender-bank perspective. All the main diagonal elements of W are zero, that is, $w_{i,i} = 0$ for

$i = 1, \cdots, N$. The matrix W is interpreted as a spatial weight matrix containing all possible weighted links among the N banks. [11] The rows of W is the normalised such that $\sum_{j=1}^{N} w_{i,j} = 1$ for all i in W.

Let $\mathbf{y}^* = [y_1^*, \cdots, y_N^*]'$ be a vector of latent variables representing the propensity to fail for the N banks, and $X = [X_1', \cdots X_N']'$ be the $N \times K$ matrix of explanatory variables with $X_i = [1 \;\; x_{i,2} \cdots x_{i,K}]$ representing the i^{th} row with individual covariates. A model that accommodates spatial dependence is the spatial autoregressive model (SAR) which is represented as

$$\mathbf{y}^* = \rho W \mathbf{y}^* + X\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \qquad \boldsymbol{\varepsilon} \sim \mathcal{N}\left(0, \sigma^2 I_N\right) \tag{2}$$

where ρ is a scalar that captures the average spatial dependence among banks and is restricted to be in the unitary interval to guarantee the stability of the system.[12] The $N \times 1$ vector $\boldsymbol{\varepsilon}$ corresponds to the structural shock term, which can be interpreted as the product of innovations to expectations of a devaluation and the predetermined currency mismatch of a bank. The shocks are assumed to be homoskedastic, following a normal distribution with variance $\sigma^2 = 1$, which is standard in the literature, guaranteeing the identification of β and ρ parameters, see de Paula (2017), Proposition 2. The normalisation of W rows is a necessary condition for the invertibility of the model, see H. Kelejian and Piras (2017, p.16).[13]

From equation (2), we observe that the vector $\mathbf{y}^*$ is determined by the right-hand regressor $W\mathbf{y}^*$, an endogenous regressor. This feature allows the failure of a bank to affect the propensity of failure of other linked banks. In the literature, the influence of a shock to a unit affecting other linked units is known as feedback or spillover effect. In our case, I interpret this effect as contagion.[14]

From (2), we obtain the following the reduced-form model

$$\mathbf{y}^* = \left(I_N - \rho W\right)^{-1} X\boldsymbol{\beta} + \mathbf{u} \tag{3}$$

where $\mathbf{u} = (I_N - \rho W)^{-1}\boldsymbol{\varepsilon}$. The invertibility of $(I_N - \rho W)$ depends on the eigenvalues of ρW,

[11] This matrix is also known as adjacency matrix or spatial distance matrix. The spatial adjective refers to the position of the banks in the interbank network and not the physical location of bank branches.

[12] This is analogous to restrictions on autoregressive coefficients in time series.

[13] A drawback of this row-normalised weight matrix is that banks that have no links, that is, banks that do not lend to other banks, have a row of zeros in W and, thus, have to be dropped from the sample.

[14] Other names are multiplier, reverberation, or endogenous effect (de Paula, 2017).

which can be complex numbers since W is an asymmetric matrix. LeSage and Pace, 2009, p.88–89, proves nevertheless that the invertibility condition only depends on the real eigenvalues. A sufficient condition for the invertibility is that ρ is restricted to be in the interval $(r^{-1}, 1)$ where r is the smallest-real eigenvalue of W.

The inverse of $(I_N - \rho W)$ can be approximated by the following infinite series

$$(I_N - \rho W)^{-1} \approx I_N + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots . \tag{4}$$

where $W^n \equiv W^{n-1} \times W$, for $n = 2, 3, \ldots$. This equation tells us that the spatial model captures the direct effect contained in W emanating from first-order neighbours, as well as *all* possible indirect effects from the W^n matrices, emanating from indirect links between units. This is in sharp contrast to models that only consider first-order links between units.

The reduced-form variance-covariance matrix is the $(N \times N)$ matrix

$$\Omega = \mathbb{E}[\mathbf{u}\,\mathbf{u}'] = (I_N - \rho W)^{-1}[(I_N - \rho W)^{-1}]' \tag{5}$$

4.1 Estimation of the SAR probit model: maximum likelihood

I describe first the estimation of the SAR probit in a maximum-likelihood framework followed by the estimation of SAR linear probability model (LPM) using the generalised method of moments (GMM) method. Calabrese and Elkink (2014) conduct Monte Carlo studies to access the performance of SAR probit estimators. Their results indicate that GMM-based estimators tend to have higher biases than ML estimators when the sample size is small ($N = 50$ and $\rho = 0.45$). [15] For this reason, I focus on the ML-based estimator for the SAR probit.

4.1.1 Estimation SAR probit

The likelihood function $\mathcal{L}(\boldsymbol{\beta}, \rho)$ of the SAR probit leads to a multivariate normal (MVN) distribution expressed as an N-dimensional integral,

$$\mathcal{L}(\boldsymbol{\beta}, \rho, W) \equiv \frac{1}{(2\pi)^{N/2}|\Omega|^{1/2}} \int_{a_1}^{b_1} \int_{a_2}^{b_2} \cdots \int_{a_N}^{b_N} \exp\left(-\frac{1}{2}\mathbf{u}'\,\Omega^{-1}\,\mathbf{u}\right)\mathbf{du} \tag{6}$$

[15] This is an active area of research. Recently, Sarrias and Piras (2022) propose a 2-step GMM estimator for SAR probit.

where the limits in the integrals are such that $(a_i, b_i) = (-\infty, v_i)$ when $y_i = 1$, and $(a_i, b_i) = (v_i, +\infty)$ when $y_i = 0$ where v_i is the i^{th} row of the $N \times 1$ vector $\boldsymbol{v} = (I_N - \rho W)^{-1} X\boldsymbol{\beta}$ and $d\mathbf{u} = du_N du_{N-1} \cdots du_1$.

There is not a unique method for the computation of the high-dimensional integral in equation (6), see McMillen (1992), LeSage (2000) and Elhorst et al. (2016). The methods can be computationally burdensome with the risk of producing unreliable estimates (Elhorst et al., 2016; Cheng, 2022). We relay on the method of Martinetti and Geniaux (2017), who propose an analytical approximation technique that relies on a univariate conditioning approximation to the probabilities from the MVN. The algorithm requires the factorization of Ω using a Cholesky decomposition. This approximation is an order of magnitude faster than solutions based on simulations methods. Furthermore, it can be readily implemented in R through the library ProbitSpatial. I employ the options which *a priori* leads to a more precise approximation to the full log-likelihood. The standard errors are based on the variance-covariance matrix instead of the precision matrix.

4.1.2 Estimation of the spatial autoregressive linear probability model

I also estimate equation (2) using the SAR LPM, that is, where the latent variable y_i^* is replaced by the observable y_i. The variance-covariance matrix of the SAR LPM is heteroskedastic, as in the case of the (non-spatial) LPM. The source of heteroskedasticity in the spatial model, however, is different so I review it. Given that $y_i \sim \mathcal{B}\text{ernoulli}(p_i)$, $\mathbb{V}\text{ar}(y_i) = p_i(1 - p_i)$. In the non-spatial model, $p_i = X_i\beta$, and heteroskedasticity emerges because the heterogeneity of covariates X_i (see Cameron and Trivedi (2005, p. 471). Following McMillen (1992), in the spatial model, $p_i = \delta_i X\beta = \tilde{X}_i\beta$ where δ_i the i^{th} row of $(I_N - \rho W)^{-1}$. Since δ_i varies across units, so does p_i, generating heteroskedasticity.

To accommodate the heteroskedasticity, I consider the generalised-spatial 2-stage least squares (GS2SLS) estimator proposed by H. H. Kelejian and Prucha (1998) and implemented in the R library sphet (Piras, 2010). Estimation is performed in 2 steps: in the first step, the model is transformed into the spatial Cochrane-Orcutt representation to estimate the residuals; then, in the second step, these residuals are used in an IV estimator procedure within the GMM framework. There are two set of moment conditions: the linear $\mathbb{E}\left(H^T\boldsymbol{\varepsilon}\right) = \mathbf{0}$ and the quadratic

$\mathbf{E}\left(\boldsymbol{\varepsilon}^T A_s \boldsymbol{\varepsilon}\right) = 0$. The linear moment condition contains the matrix of instruments H. In the SAR LPM, the only endogenous variable is $W\mathbf{y}$. Given that $\mathbb{E}[W\mathbf{y}] = W(I - \rho W)^{-1}X\beta$ from the reduced-form representation (3), an approximation to $W(I - \rho W)^{-1}X$ can be constructed from linear combinations of powers of W, specifically $H = [X, WX, W^2X]$. The quadratic moment condition contains the matrix A_s which also depends on W. The procedure then follows estimating Ω using a non-parametric design that accommodates heteroskedasticity of unknown form. See Bivand and Piras (2015) for an overview of the estimator, and H. Kelejian and Piras (2017, Ch2) for a detailed textbook treatment.

4.2 Marginal effects

The goal is to understand how the expected probability of failure for a bank i changes when the k covariate of bank j, $x_{j;k}$, does: $\partial Pr[y_i = 1|\eta_i]/\partial x_{j;k}$ where η_i is the predicted value for the propensity to fail for bank i given by the i^{th} row of $\boldsymbol{\eta} = \mathbb{E}[\boldsymbol{y}^*] = (I_N - \rho W)^{-1}X\boldsymbol{\beta}$. In a SAR probit model, the effect on the dependant variable of a change on a covariate varies across units, since units are heterogeneously located in the network. The probability of failure for each bank comes from a normal distribution with its own mean and variance. From the conditional distribution, we have $Pr[y_i = 1|\eta_i] = \Phi(\tilde{\eta}_i)$ where $\Phi(\cdot)$ is the normal cumulative distribution function, $\tilde{\eta}_i = \dfrac{\eta_i}{\omega_i}$, and ω_i is the squared of i^{th} diagonal term of the variance matrix Ω defined in equation (5) . Taking the derivative of $Pr[y_i = 1|\eta_i]$ with respect to $x_{j;k}$, we find

$$\frac{\partial Pr[y_i = 1|\eta_i]}{\partial x_{j;k}} = \frac{\partial \Phi\left(\tilde{\eta}_i\right)}{\partial x_{j;k}} = \phi(\tilde{\eta}_i)\,\frac{\partial \tilde{\eta}_i}{\partial x_{j;k}} \tag{7}$$

where $\phi(\cdot)$ is the standard normal density function.

The second term on the right-hand side of the equation (7) contains the marginal effect on the latent variable due to a change in the k^{th} covariate of observation j, which, in a spatial model, depends not only on $x_{j;k}$ but also on the expected value of other remaining $N-1$ observations. This gives rise to N^2 marginal effects depending on where in the network the change in $x_{;k}$ occurs and which bank i is affected. As such, the $N \times N$ matrix containing the marginal effects on the probability of failures is

$$R_k = \left[\frac{\partial Pr(\boldsymbol{y}=1)}{\partial \boldsymbol{x}_k^{'}}\right] = \text{diag}\left[\phi\left(\boldsymbol{\eta}\right)\right]\ \left(I_N - \rho W\right)^{-1}\beta_k. \tag{8}$$

The marginal *direct effect* on bank i due to a change in the $x_{i;k}$ is captured by the diagonal element $[R_k]_{ii}$. The direct effect includes the feedback mechanism such that the change in $x_{i;k}$ impacts the failure probability for bank i and this, in turn, affects all remaining banks' probabilities in the network thus feeding back into bank i probability of failure. The marginal *indirect effects* on bank i due to a change in $x_{j;k}$ is at entry $[R_k]_{ij}$, while the indirect marginal effect on bank j caused by a change in $x_{i;k}$ is captured by $[R_k]_{ji}$ with $j \neq i$. The indirect effects capture how a change in a covariate in bank i affects the probability of failure of another bank j. The indirect effects represent the spillover or contagion.[16] The indirect effects are relevant because they capture the externalities that a bank leverage decision imposes on its peers. This encompasses a situation in which a well-capitalised bank could fail due to its linkage (via lending) to an ill-capitalised bank in the network. This link could be through an indirect path that may be unobservable to the well-capitalised bank. Clearly, marginal effects will be the same as a non-spatial probit if $\rho = 0$.

Summary measures of the N^2 marginal effects in R_k have been proposed and I follow the definitions by LeSage and Pace (2009, p. 37). The *average direct effect* of the k^{th} covariate on the probability of failure is the average over the diagonal elements of R_k, that is, $N^{-1}\text{tr}[R_k]$, where tr is the trace operator. The *average total effect* is the average over observations of all marginal effects given by $N^{-1}\iota_N^T\ R_k\iota_N$, where ι_N is a $N \times 1$ vector of ones. This average represents the expected change in the probability of failure of bank i by a marginal change in $x_{j;k}$ where i and j are two randomly chosen banks. The total effect combines the direct and indirect effects. The *average indirect effect* can be simply computed as the difference between total and direct effects: $N^{-1}\iota_N^T\ R_k\iota_N - N^{-1}\text{tr}[R_k]$. In all cases, these averages represent the average of the *cumulative effect*, after the initial change in $x_{i;k}$ has travelled through the network and a new stationary equilibrium vector $\boldsymbol{y}$ emerges, see equation (4) and Lacombe and LeSage (2015).

[16] In the classical LPM, these off-diagonal elements are all zero due to the assumption of independence across observations.

5 Failure, bank predictors and the interbank network

5.1 Bank failure

The outcome variable is a binary indicator that takes the value of 1 if a bank fails between 1999q1 and 2001q3, and 0 otherwise. The Central Bank of the Argentine Republic (BCRA) through the Superintendency of Financial Entities (*Superintendencia de Entidades Financieras y Cambiarias*) is the sole authority that can terminate a financial entity license. I track the license history for each bank following the central bank decrees (*Comunicaciones*). These decrees specify the date and the reason that a license was cancelled. I consider that a bank fails when any type of license termination occurs, including those that are voluntary, those that are due to a merger or acquisition, or forced termination for not meeting financial regulations.

I only consider private banks. This comprises incorporated local banks, cooperative banks, private financial companies, savings and loans institutions and branches of international banks. The sample thus excludes state-owned banks similar to Dabos and Escudero (2004), restricting the network. State-owned banks may have implicit support from the government.

5.2 The interbank network

I build the network considering bilateral linkages among banks that are registered in the BCRA Credit Registry. The Registry, to which banks compulsorily submit their borrowing levels each quarter, contains information on each borrower-bank relation including the loan amount, the lending bank identification number, the borrower tax file number, and the credit score assigned by the lending bank.[17] Using public tax number information, I match the bank license identification number to the corresponding tax file number that appears in the Registry, which allows me to establish direct linkages among financial entities.

The network is built with links from a borrower bank to a lender bank: shocks can travel directly between the borrower to the lender but not the other way around. In this case, the default of the borrower could affect the lender directly; however, the default of the lender affects the borrower indirectly through other banks in the network. The spatial weight matrix is thus asymmetric.

[17] See Hertzberg et al. (2011) for details about the Credit Registry.

For each link at a given quarter in our sample, I compute the weight for a link between lending bank i and borrower bank j as the share of the loan to total loans of lender bank i. Then the spatial weight W contains on each element $w_{i,j}$ the average weight between bank i and j during the 1998q1 and 1998q4. In the cases in which the links represent a lending bank in liquidation or no loan is reported, the given weight is zero. Finally, the main diagonal is also zero (no circular links).

The estimation of the SAR probit regression does not allow for the weighting matrix to have rows with zero elements, that is, banks that are not connected to any other bank.[18] Due to this technical restriction, 16 banks are discarded: 9 of these did not report any lending to another bank during any quarter in 1999 but did borrow, 6 did not lend nor borrow, and one lent to a bank that did not borrow or lend. The resulting baseline sample contains 72 local private banks that were active in 1997q4, survived or failed on or after 1999q1, and were lenders in the interbank network.[19]

In the analysis, I treat the network as fixed and predetermined relative to the failures. There are three reasons for assuming that the network is stable. First, much of the interdependence among banks is built on relationship lending. This type of lending can take years to construct in over-the-counter deals which hinge upon mutual knowledge. Additionally, building a lending relationship is presumably less likely during a crisis when asymmetric information among banks is amplified.Anastasi et al. (2009) find evidence of relationship lending among Argentinian banks, which results in interest-rate reductions paid by borrowing banks. Second, trade data from the Argentinian overnight interbank market during the period 2003-2017 suggests that the network evolves smoothly, see Forte (2020).[20] Third, the average bank has a quite robust capitalization, see Table 1), and "very minor variations in banks default probabilities do not affect the decision of whether or not to lend to them in the interbank market" (Gai & Kapadia, 2010), even during a crisis.

Figure 2 illustrates the graphic representation of the network for all private banks. Each

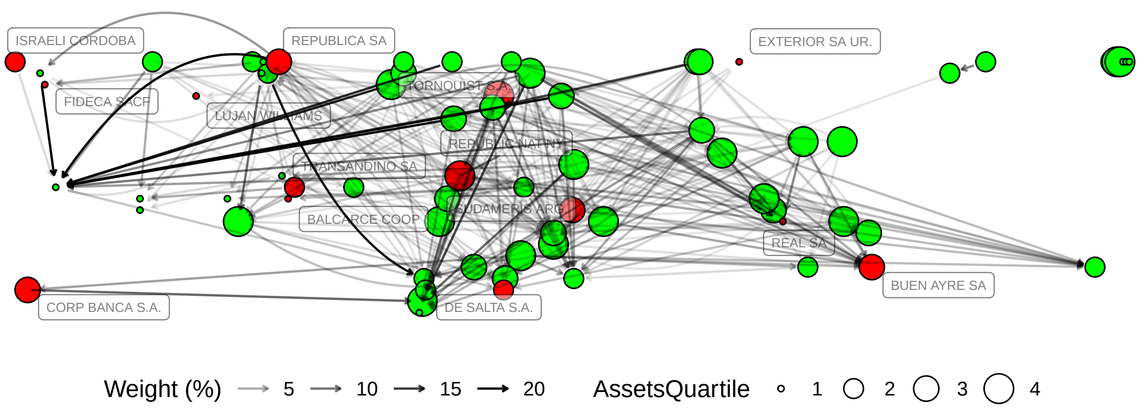
[18] In principle, if a bank has no links, there are no spatial correlations with other banks, and, therefore, no spatial contagion. Estimation for those banks should then follow a non-spatial model, which comprises a sample of only 16 banks.

[19] I also consider an indirect graph in which I do not distinguish between lender and borrower: an edge is unweighted and represents any connection between banks. By not distinguishing between lender and borrower, 10 banks are included in the sample leading to 82 observations.

[20] The author also observes a reduction in the number of active nodes and links during the 2008 crisis, implying that banks were less able to trade during this period, limiting the possibility for a bank to hedge against any shock.

circle represents a financial entity, and its size is the total assets. A green circle is a surviving bank, while a red circle corresponds to a bank that failed between 1999q1 and 2001q3. Line thickness measures the loan share over the total loans by the lender bank. The network graph uses the Kamada-Kawai layout algorithm.

Figure 2: INTERBANK NETWORK OF PRIVATE ENTITIES 1998. Directed network from borrower bank to lender bank over the year 1998. The weight on links is the ratio of the outstanding loan to the total loans of the lender bank. Links with a weight smaller than 0.001 of the lender bank assets are not drawn. The position of nodes followsthe Sugiyama layout.



While some of the failing banks are isolated, most of them are connected to other banks, and some have a strong relationship given by their weight.

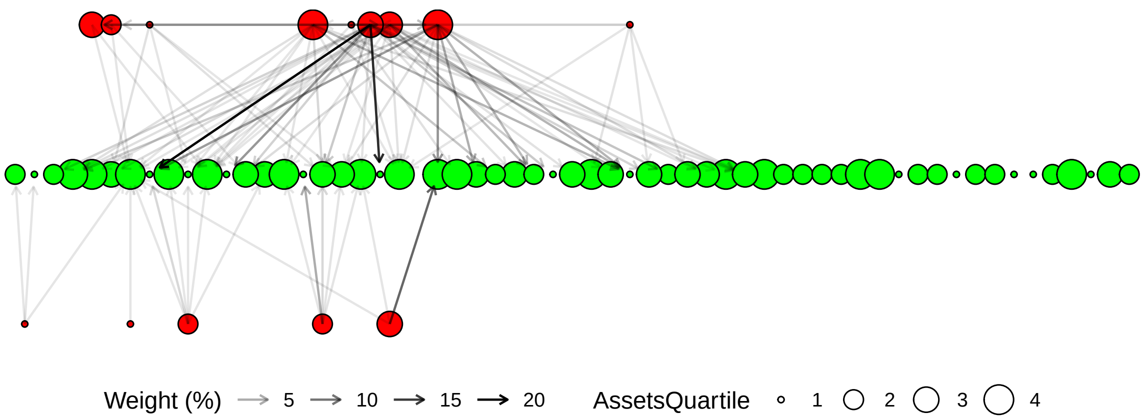
Figure 3 presents the network only with links originating in failing banks, that is, interbank loans where the borrower eventually fails. Among the 23 failing banks, 16 of them have a direct link to another failing one (approximately 70%), suggesting the presence of a contagion effect: the failure of a bank raises the probability of neighboring banks failing as well. Many failing bank were borrowing from the same non-failing bank.s are also indirect path among failing banks through a non-fail bank

5.3 Predictors at bank level

The explanatory variables are obtained from monthly data in 1998 and converted into yearly data by taking averages.[21] The network is also computed as the average of linkages between 1998q1 and 1998q4. Therefore, both bank covariates and the network are, thus, set before

[21]In 1998 the recession that led to bank runs on deposits in 2001 started.

Figure 3: INTERBANK NETWORK OF PRIVATE ENTITIES IN 1998 - ONLY LINKS FROM FAILING BANKS.



failures occur, alleviating endogeneity concerns between predictors and failure.

Default risk is a combination of asset risk and leverage variables (Calomiris and Powell (2001)). I include 10 of those variables which are standard in the literature: (i) *size* – the logarithm of nominal assets in Argentinian pesos (ARS); (ii)-(vi) *asset-side risk* – the ratios of non-performing loans to total loans, loans to the government to total loans, loans in dollars to total loans, the ratio of loans to assets, and the interest rate on loans; (vii)-(x) *funding* – equity-to-assets ratio, return on assets (ROA), interest rate on deposits, and interest rate control for funding risk. All bank-level variables are available monthly, which is transformed to yearly frequency by taking the annual average, and, therefore, eliminating their seasonality.

Nominal assets capture the size of the firms,[22] which is relevant for two reasons. First, large banks have a lower probability of ex-ante failure because they can access international debt markets even during turmoil (or at least at a lower cost than small ones), and, second, large banks may be supported by the government during a crisis (the 'too-big-to-fail' argument).[23] The direction of the effect of bank size on failure is, however, indeterminate *a priori*: large 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).

Non-performing loans, loans to the government, USD-nominated loans, and the interest rate on loans reflect the riskiness of the loans portfolio. Loans are classified on a scale from 1 to 5

[22] The inflation rate in 1998 and 1999 was, respectively 1% and -0.3%.

[23] Farhi and Tirole (2012) provide a theoretical explanation of bank coordination in risk-taking by exploiting a potential government bailout.

based on the borrower's current capacity to repay, cash flow projections, and repayment history. Non-performing loans include loans classified with a default risk of 3 or higher (substandard risk to unrecoverable loans), which are considered a high-default risk according to the BCRA classification guideline. The proportion of lending to the government is relevant due to the Argentinian federal government and some provincial governments defaulting on their debt in 2001. The share of loans denominated in US dollars implicitly captures exchange-rate risk through lending in foreign currency to the non-tradeable sector. The ratio of loans to assets is a broad measure of (i)liquidity of the balance sheet because loans can become highly illiquid during a systemic crisis. Finally, the interest rate on loans, which is the implicit interest rate on loans in the last 12 months computed as interest payments over loans, expressed as a nominal annual rate, is a forward-looking measure of risk. An increase in any of these variables signals a riskier loan portfolio, and, thus, an increase in the failure probability.

Equity-to-assets ratio, return on assets, the interest rate on deposits, and interest rates control for funding risk are proxies for bank funding costs. The equity-to-assets is the ratio of book equity, including retained earnings, to total assets. The ROA is the ratio of net earnings in the last 12 months to the average level of assets in the previous 12 months. The implicit interest rate paid on deposits is the ratio of all interest payments on all deposits during the month over the average balance on all deposits during the same month. It is expressed as an annual nominal rate. The higher the funding cost is, the greater is the perceived risk from investors. The summary statistics of the main variables are presented in Table 1.

The average capitalisation (Equity-to-Assets ratio) is 15% with a median of 12%, which is well above the minimum 8% requirement of the capital ratio requirement of risk-weighted assets in the Basel II regulatory framework.[24] The distribution of the share of government loans across banks is concentrated in a few banks with a maximum exposition through loans of 37%. This only captures the exposition to the federal and local governments through loans, but it does not capture exposition through holding government bonds as liquid assets. Finally, more than half of the loans are nominated in USD dollars with a median of 60.27%, which creates on the one hand a currency-mismatch risk if a devaluation occurs, but on the other hand, it makes

[24]See Basel II capitalisation standards in https://www.bis.org/publ/bcbs107.htm. This ratio is actually underestimated relative to the Basel standards because the latter uses a risk-weighted sum of assets in the denominator instead of nominal assets. During the worst part of the Argentinian crisis in July 2001, the capitalisation for the complete financial system using Basel norms was around 22%. Therefore, the prudential regulation in Argentina was among the best in emerging markets.

Table 1: DESCRIPTIVE STATISTICS. Ratios are presented in percentages.

Variable	Mean & standard deviation	Coef. variation
Failure	0.19 (0.40)	2.05
Size		
Assets in ARS (millions)	1,341 (2,540)	1.89
Asset-side risk		
Non-performing loans to Loans	7.66 (5.47)	0.71
Govt. loans to Loans	4.19 (8.21)	1.96
USD loans to Loans	57.88 (22.39)	0.39
Loans-to-Assets	51.18 (17.49)	0.34
Loans interest rate	23.36 (9.46)	0.41
Funding		
Equity-to-Assets ratio	15.81 (11.0)	0.70
ROA	0.92 (2.83)	3.10
Deposits interest rate	5.20 (2.90)	0.56
Number of observations	72	

the convertibility more credible since it raises the exit cost. To some extent, the credibility of the monetary regime is priced in the (implicit) loans interest rate in ARS which was 23.36% (nominal annual rate) on average during 1998 (cf. the average annual inflation rate for 1998 was 0.92%).

6 Results

I report regression results based on 4 models: probit, SAR probit, the linear probability (LPM) and SAR LPM. The preferred set of results is within the Convertibility regime, which lasted till 2001q3. As a robustness check, I consider results from a regression including failures until

2003q4, which includes the period of the partial freeze of deposits and devaluation of January 2002.

6.1 Failures during the Convertibility

The estimated coefficients for all 4 models appear in Table (2). Predictors are measured as ratios, not percentages, except for the assets variable which is the logarithm of nominal ARS. Both probits are estimated in the maximum likelihood framework, the LPM is OLS with MacKinnon-White heteroskedastic var-cov matrix and the SAR LPM is estimated by GMM, allowing for heteroskedasticity, as described in section (4.1.2). The average marginal effects for a unitary change in predictors on the probability of failure appear in Table (3). For probit models, the average effect for covariate k is computed as the average over observations, i.e. $N^{-1}\partial\mathbb{E}\left\{Pr[y_i = 1|\mathbf{x}_i]\right\}/\partial x_{i,k}$. Due to the limitations of the algorithm, the statistical significance of the marginal effects for the SAR probit is not reported. When comparing the marginal effect between a spatial and a non-spatial model I compare the average effect from the non-spatial model to the (average) total effect from the spatial model.

The central hypothesis of this work is the relevance of the network in driving banking failures due to the existence of spatial autocorrelation among banks. I hence first focus on the implications of spatial autocorrelation in general. Then, I turn to the discussion of how this form of dependence affects the interpretation of predictors referring to both tables.

Results show a negative and statistically significant spatial autocorrelation among banks in both the SAR probit and the SAR LPM, columns 3 and 5 of Table 2. The value of -0.53 for the SAR probit results in a sizeable and persistent spatial autocorrelation, emphasising the relevance of higher-order linkages in driving failures. For the SAR LPM the magnitude of the spatial dependence is around half of the SAR probit but still negative and statistically significant at 5% and the direction of the predictors is in line with the SAR probit. A negative ρ indicates that the failure of a borrower bank *reduces* the failure probability of *its* lender, that is, there is a positive spillover effect of neighbours' failures. This suggests that the failure of a bank generates more liquidity than it erodes, and the interbank network then redistributes this liquidity among surviving banks. As a result, the structure of bank linkages works as a shock absorber rather than an amplifier.

Following Diamond and Rajan (2005) model, a bank approaching failure scrambles for liquidity by recalling illiquid loans (long-term assets) from the non-financial sector. When failure materialises, the failing-bank balance sheet could be more liquid than before. It is this additional liquidity that is redistributed through the financial network: depositors from the failing bank recycle their deposits among surviving institutions.

The size of the indirect or contagion effects in Table 3, which is determined by ρ, is around 53% of the total marginal effects for each covariate. For example, a higher proportion of USD loans has an average *total* effect on a given bank of 0.37 on its failure probability. The indirect effect is 53% of the total effect, which gives -0.20 in column (4).

Finally, the SAR probit model better fits the data compared to the non-spatial probit as judged by their log-likelihood values.

The negative coefficient on the bank size (ln Assets) across subsamples and models provides some evidence that larger banks are better able to diversify their loan portfolios reducing their asset-side risk; and exploit a "too-big-to-fail" franchise. The magnitude of the marginal effect for all models is around half of the value of -0.20 estimated by Arena (2008) for banks during the Asian Financial Crisis during 1997-1999. A lower marginal effect on size is compatible with a lower value of the "too-big-to-fail" franchise. This is reasonable under the Convertibility regime since the central bank had limited capacity to issue pesos to rescue banks.

A deterioration in the loans portfolio, measured by higher non-performing loans, weakly predicts a lower probability of failure in both models. Two caveats are worth mentioning here. The interpretation of the coefficient on non-performing loans in isolation is of little value since it keeps fixed loans interest rate and loans-to-asset ratio, coefficients that also flip signs across subsamples. Second, the ratio of non-performing loans being the proportion of impairment loans during 1998 is a backwards-looking measure of the quality of a portfolio; the loans interest rate variable, in contrast, is forward-looking. These variables hence mix backwards and forward-looking information making it difficult to interpret them in isolation.

In all models, currency mismatch, captured the proportion of USD loans in the portfolio, predicts a higher probability of failure. As the expectation of a devaluation increased during the period, banks more susceptible to currency risk approached default. The marginal effect from the probit is 0.37, suggesting a 0.1 increase in the ratio of USD loans (a 10 percentage

Table 2: BASELINE COEFFICIENT ESTIMATES. The outcome variable takes the value 1 if a bank fails between 1999q1 and 2001q3. Predictors are the annual average during 1999 and the spatial matrix is the average of each link during the same year. All predictors are ratios except for assets which is the logarithm of nominal Argentine pesos.

	Probit	**SAR probit**	**LPM**	**SAR LPM**
	(2)	(3)	(4)	(5)
Size				
ln(Assets)	−0.40**	−0.47***	−0.10**	−0.09***
	(0.18)	(0.03)	(0.04)	(0.03)
Asset-side risk				
Non-performing loans	0.03	−1.13***	0.40	0.33
	(4.46)	(0.01)	(1.31)	(1.05)
Loans interest rate	0.96	1.01***	0.04	−0.06
	(3.07)	(0.09)	(1.01)	(0.81)
Govt. loans to Loans	−6.00	−1.73***	−0.61·	−0.64*
	(5.00)	(0.38)	(0.40)	(0.34)
USD loans to Loans	1.68	2.83***	0.39	0.36·
	(1.26)	(0.31)	(0.27)	(0.22)
Loans-to-Assets ratio	−0.07	−0.55***	−0.01	0.01
	(1.23)	(0.08)	(0.41)	(0.33)
Funding				
Equity-to-Assets ratio	−4.94**	−4.20***	−1.09*	−0.95**
	(2.47)	(0.60)	(0.63)	(0.49)
ROA	−6.58	−10.82***	−0.87	−1.05
	(9.15)	(2.04)	(2.02)	(1.65)
Deposits interest rate	−5.60	−1.84***	−0.77	−1.11
	(7.58)	(0.22)	(1.71)	(1.40)
Spatial				
ρ		−0.53***		−0.24**
		(0.07)		(0.10)
Log Likelihood	−28.59	−27.36		

Number of observations is 72; $***p < 0.01$; $**p < 0.05$; $*p < 0.1$; $\dot{}p < 0.15$

Table 3: AVERAGE MARGINAL EFFECTS. Average computed over observations. The outcome variable takes the value 1 if a bank fails between 1999q1 and 2001q3. All predictors are ratios except for the assets variable which is the logarithm of nominal Argentine pesos.

Predictor	**Probit**	**SAR probit**[1]			**LPM**	**SAR LPM**		
	Average (2)	Direct (3)	Indirect (4)	Total (5)	Average (6)	Direct (7)	Indirect (8)	Total (9)
Size								
ln(Assets)	−0.09**	−0.09	0.03	−0.06	−0.10**	−0.09***	0.02**	−0.07***
	(0.04)				(0.04)	(0.03)	(0.01)	(0.03)
Asset-side risk								
Non-performing loans	0.01	−0.23	0.08	−0.15	0.40	0.29	−0.06	0.24
	(0.97)				(1.31)	(1.05)	(0.21)	(0.85)
Loans interest rate	0.21	0.20	−0.07	0.13	0.04	−0.08	0.02	−0.05
	(0.67)				(1.01)	(0.83)	(0.17)	(0.67)
Govt. loans to Loans	−1.31	−0.35	0.12	−0.22	$-0.61^{\cdot}$	−0.63**	0.13*	−0.50**
	(1.08)				(0.40)	(0.36)	(0.09)	(0.28)
USD loans to Loans	0.37	0.56	−0.20	0.37	0.39	0.36*	−0.07*	0.29*
	(0.27)				(0.27)	(0.22)	(0.05)	(0.18)
Loans-to-Assets ratio	−0.02	−0.11	0.04	−0.07	−0.01	0.01	0.00	0.00
	(0.27)				(0.41)	(0.33)	(0.07)	(0.27)
Funding								
Equity-to-Assets ratio	−1.08**	−0.84	0.30	−0.54	−1.09*	−0.94**	0.18*	−0.76**
	(0.50)				(0.63)	(0.48)	(0.12)	(0.39)
ROA	−1.44	−2.16	0.76	−1.40	−0.87	−1.05	0.21	−0.84
	(1.98)				(2.02)	(1.65)	(0.35)	(1.34)
Deposits interest rate	−1.22	−0.37	0.13	−0.24	−0.77	−1.20	0.26	−0.93
	(1.64)				(1.71)	(1.44)	(0.33)	(1.14)

$***p < 0.01$; $**p < 0.05$; $*p < 0.1$; $^{\cdot}p < 0.15$

[1] Standard errors for marginal effects are not available.

points increment) moves the probability of failure up by 0.037 (the unconditional probability of failure is 0.19 as per table 1). Remarkably, the marginal effect from the probit is identical to the (total) marginal effect from the SAR probit. While the magnitude of the effect is the same in both models, their interpretations are startlingly different. In the case of the spatial model, the total effect of 0.37 is the sum of both, the direct effect of 0.56 and the indirect or contagion effect of -0.20. This means that the decision on currency mismatch is not necessarily taken in isolation by a bank (the direct effect) but it is the result of strategic interaction with other banks in the network. The non-spatial probit, however, confounds portfolio decisions taken by a bank in isolation with the strategic decisions taken by its neighbours in the network.[25] Empirical evidence of strategic portfolio decisions among banks in OECD countries is reported in A. F. Silva (2019): a bank increases its liquidity by around 22% if its neighbours in the network do.

A higher equity-to-assets ratio predicts a lower probability of failure, as initially quoted by Berger and Roman (2020). This result underpins the rationale for bank capital regulation at the individual bank level (microprudential regulation). The estimated marginal effect of -1.08 for the probit model in Table 3 is almost identical to the estimate of -1.3 by Arena (2008) for Latin American countries during the Tequila crisis of 1995. The comparable marginal effect from the SAR probit is -0.54, which is the total effect on column 5 of 3. The effect of equity in averting failures is almost halved when banks are interconnected. This result follows because the indirect effect for equity, capturing the spillover, is positive (column 4): an increase in *a* bank's capitalisation increases *other* banks' failure probability on average and conditioning on all other variables. This supports a market equilibrium in which banks free-ride on other banks' capitalisation. When a bank increases its equity, it reduces its own failure probability by -0.84 (direct effect in column 3). At the same time when a bank increases its equity creates a *negative externality* on other banks by increasing their failure probability by 0.30. Other banks may then be tempted to increase their return to shareholders by reducing their capitalisation and borrowing in the interbank market effectively free-riding on other banks' capitalisation. This is possible if equity financing is more expensive than interbank loans, which is the case during a crisis when equity issuance is prohibitively expensive. Thus bank leverage decisions are not

[25] Farhi and Tirole (2012) present a model without a network in which banks strategically choose to correlate their balance sheet to increase the chances of a government rescue.

taken in isolation.

Strategic complementarity in non-financial firm-leverage decisions are recently studied by Grieser et al. (2022). They find significant evidence that a firm leverage decision is influenced by its competitors. Using a SAR model they estimate a value of $\rho = 0.25$ which translates into a 1% increase in the leverage of the neighbours of a firm, will have an initial effect on that firm leverage of 0.25%, on average.

From the regulatory perspective, results from spatial and non-spatial models lead to markedly different policies. For example, considering the estimate for currency mismatch of 0.37 from the non-spatial model which indicates that, on average, and keeping all other predictors constant, increasing the ratio of USD loans to Loans for any given bank increases its failure probability by that amount. In the SAR probit model, the same coefficient is to be interpreted *keeping fixed the network*. This implies that one can achieve the same increment in survival by changing the topology of the network *without* altering currency mismatch. The same argument applies to the equity ratio. Increasing regulatory equity for banks may have a cost that could be offset by the adoption of a network topology that enhances the beneficial effect of higher equity.[26] Additionally, the relevance of the network in driving failures as captured by no-zer $\hat{\rho}$ implies that results cannot be easily extrapolated to other banking systems with different network structures or at different points in time. In fact, I briefly touch on this last point using the interbank network from 1997.

We note that the direction of effects from the SAR LPM agree with the SAR probit. The total marginal effect for equity of -0.76 (column 9 in table 3) is 40% bigger than the estimated from the SAR probit in column 5. The direction of the direct and indirect effects remains the same, with the indirect effect showing a negative spillover effect. Similarly, the currency mismatch variable (USD loans to Loans) shows a smaller positive total effect. In a SAR LPM the dose-response function is linear such that an additional increase in a risk factor, like currency mismatch, has the same additional increment in the failure probability regardless of the initial level of the risk factor. This is a major drawback of this model since this linearity is unlikely to hold in practice but rather one would expect that default probability increases more than proportional with the level of risk.

[26]See Begenau (2020) for a quantification of the cost of equity for banks in a general-equilibrium model.

6.2 Additional results

6.2.1 Including failures after the Convertiblity

Table 4 presents coefficient estimates when the failure window is extended till 2003q4, thus including the devaluation of January 2002 and the compulsory asymmetric pesification. The fitting of models for failures after 2001 is worse than when studying failures before the devaluation. This is expected since, as explained in Section 2, different policies implemented after the devaluation introduced heterogeneity in bank losses, in particular the effect of the asymmetric pesificiation which implies that bank's assets and liabilities were converted to pesos at different exchange rates.

6.2.2 Alternative networks

Table 5 presents results using the SAR probit based on 6 different networks. The second column reproduces baseline results in table 2, columns (3), (4) and (5) rely on a directed but unweighted baseline network; the weighted network during 1997 and the network contemporaneous to failures, between 1999q1 and 2001q3. When using the network built from the interbank exposure during 1997 results here show that while the network is still a relevant predictor of failures its effect is reversed: the positive ρ in column (3) indicates that now the network works as an amplifier of shocks. Data from the Credit Registry during the first two quarters of 1997 are incomplete, with some banks reporting no links at all. This is reflected in the sample size of 51, which limits its comparability with baseline estimates. The direction of most predictors remains the same, but the standard errors of estimates shrink. Another potential problem is the extensive lag between the network measured in 1997 and the failures between 1999 and 2001. To explore the effect of this time lag column (5) instead evaluates a network built from the average of links *during* the failure window. A negative ρ is estimated coinciding with the baseline result that the network works as a shock absorber. The magnitude of spatial autocorrelation is smaller. Using the contemporaneous network could introduce an endogeneity problem, however. The last three columns show estimates using networks from the same periods as previous ones but unweighted and undirected networks (W is now symmetric). There are two reasons for studying undirected networks. A direct graph results in an asymmetric W matrix which amounts to restricting the path a shock among banks can take. An undirect

Table 4: INCLUDING FAILURES AFTER THE CONVERTIBILITY - COEFFICIENT ESTIMATES. The outcome variable takes the value 1 if a bank fails between 1999q1 and 2003q4. Predictors are the annual average during 1999 and the spatial matrix is the average of each link during 1999. All predictors are ratios except for assets which is the logarithm of nominal Argentine pesos.

	Probit (2)	**SAR probit** (3)	**LPM** (4)	**SAR LPM** (5)
Size				
ln(Assets)	−0.08	−0.09***	−0.04	−0.01
	(0.15)	(0.03)	(0.04)	(0.04)
Asset-side risk				
Non-performing loans	6.45*	6.00***	2.09	2.32**
	(3.86)	(0.82)	(1.45)	(1.13)
Loans interest rate	−1.06	−1.79***	−0.52	−0.88
	(2.80)	(0.14)	(1.02)	(0.79)
Govt. loans to Loans	−0.83	0.26	−0.05	−0.16
	(2.72)	(0.29)	(0.51)	(0.45)
USD loans to Loans	0.69	1.08***	0.25	0.20
	(1.07)	(0.05)	(0.33)	(0.29)
Loans-to-Assets ratio	1.37	1.03***	0.45	0.37
	(1.15)	(0.10)	(0.45)	(0.36)
Funding				
Equity-to-Assets ratio	−2.53	−0.88***	−0.72	0.05
	(2.10)	(0.05)	(0.72)	(0.60)
ROA	−15.92*	−17.69***	−3.33	−3.57˙
	(9.56)	(1.32)	(2.80)	(2.35)
Deposits interest rate	−7.59	−6.57***	−1.57	−2.39˙
	(6.70)	(0.40)	(1.73)	(1.46)
Spatial				
ρ		−0.53***		−0.51***
		(0.13)		(0.14)
Log Likelihood	−37.97	−35.61		

Number of observations is 72; $***p < 0.01$; $**p < 0.05$; $*p < 0.1$; $^{\cdot}p < 0.15$

Table 5: DIFFERENT NETWORKS - SAR PROBIT ESTIMATES. Column (2) uses the baseline network, estimates from columns (3), (4) and (5) rely on: the directed but unweighted baseline network; the directed weighted network during 1997 and the directed network contemporaneous to failures, between 1999q1 and 2001q3; respectively. The last 3 columns show estimates using networks from the same periods as previous columns, but unweighted and undirected network resulting in symmetric W.

Predictor	$\bar{W}_{98}$ (2)	$\bar{W}_{98;Unw}$ (3)	$\bar{W}_{97}$ (4)	$\bar{W}_{99-01}$ (5)	$\bar{W}_{98,Unw,S}$ (6)	$\bar{W}_{97;Unw,S}$ (7)	$\bar{W}_{99-01;Unw,S}$ (8)
ln(Assets)	−0.47***	−0.44***	−0.64***	−0.48***	−0.33***	−0.37***	−0.43***
	(0.03)	(0.17)	(0.01)	(0.10)	(0.01)	(0.01)	(0.04)
Non-performing loans	−1.13***	−0.41	13.41***	−1.69***	−2.26*	5.39·	0.75
	(0.01)	(1.55)	(0.50)	(0.45)	(1.30)	(3.60)	(1.64)
Loans interest rate	1.01***	0.87	−9.56***	2.08***	0.18·	−2.13***	1.37·
	(0.09)	(1.85)	(0.23)	(0.62)	(0.11)	(0.81)	(0.92)
Govt. loans to Loans	−1.73***	−4.63	−11.00***	−4.57*	−5.04**	−9.30**	−4.63
	(0.38)	(3.97)	(0.38)	(2.64)	(2.18)	(4.66)	(3.56)
USD loans to Loans	2.83***	1.72*	4.04***	1.85*	0.66**	1.62***	1.56***
	(0.31)	(0.98)	(0.09)	(0.98)	(0.27)	(0.55)	(0.23)
Loans-to-Assets ratio	−0.55***	0.10	−2.93***	−0.50***	0.36**	−0.20	0.12
	(0.08)	(0.22)	(0.17)	(0.15)	(0.16)	(1.10)	(0.26)
Equity-to-Assets ratio	−4.20***	−5.01**	−2.50***	−6.27***	−2.59**	−5.02***	−6.43***
	(0.60)	(2.49)	(0.09)	(1.66)	(1.19)	(1.61)	(0.57)
ROA	−10.82***	−7.68***	−3.55***	−6.20·	−10.53**	−14.16·	−10.22
	(2.04)	(0.69)	(0.19)	(4.28)	(4.21)	(9.30)	(7.48)
Deposits interest rate	−1.84***	−4.79·	10.13***	−8.60***	−6.23***	−5.04	−10.03***
	(0.22)	(3.07)	(0.33)	(1.93)	(2.34)	(5.54)	(0.61)
ρ	−0.53***	−0.25**	0.49***	−0.32***	−0.41*	0.26	−0.48**
	(0.07)	(0.12)	(0.02)	(0.08)	(0.23)	(0.54)	(0.21)
logLik	−27.36	−28.38	−15.35	−30.08	−35.03	−26.66	−32.87
Num. obs.	72.00	72.00	51.00	75.00	82.00	73.00	83.00

$***p < 0.01$; $**p < 0.05$; $*p < 0.1$; $\cdot p < 0.15$

graph, in contrast, does not impose a restriction and it allows more paths for banks to be correlated. Second, it is possible that weights are measured with error since the data from the Credit Registry comes from end-of-quarter exposure, which may differ from the average exposure during the quarter. When considering unweighted networks, there is no distinction between a lender and a borrower bank. As a consequence sample size varies across the last columns. The column (6) sample contains 82 banks since the 10 banks that did not lend are now included, while 6 active banks that did not lend nor borrow remain excluded.

Focusing on the spatial autocorrelation parameter ρ, the absolute size and the statistical significance are both smaller than in baseline results. This is expected under our hypothesis of financial contagion. By allowing superfluous paths for contagions, compared to the directed network, the spatial dependence among banks is weakened. The direction of the coefficients on predictors remain,s with respect to the weighted and directed networks. The statistical significance and model fit weaken, in line with the theoretical framework described in which the risk stems from the borrower to the lender.

6.3 Limitations

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. We treat the network as fixed and use lagged values of it in the main specification, avoiding possible endogeneity of the network. Under this assumption above results do not reject the hypothesis that contagion through the network drives bank failures. In this section, I discuss two limitations of the results.

The above results ignore potential unobservable idiosyncratic factors at the bank level or common factors. These could be addressed in a panel-data sample with a fixed-effect estimator as in Vacaflores and 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 ahaving 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.

The stricto sensu legal definition of failure taken here excludes state-owned banks that, while not legally failing, were subjected to distress. Since state-owned enjoy implicit government guarantees the failure probability are implicitly different than those of private institution. A better approach is modelling the probability of bail-out for these banks which is beyond the scope of this reserach. I note that excluding these banks has the unintended consequence of trimming the network of potential indirect linkages between private banks via the excluded state-owned banks.

Finally, no inferecence is made on the marginal effects of the SAR probit.

7 Conclusions

Financial networks can increase the efficiency of the banking system by redistributing liquidity where it is more needed Allen and Gale (2000). In times of crises, however, this beneficial property of the network becomes detrimental when each bank tries to grasp liquidity by reducing lending to other banks and relinquishing on its payments. Changes in the liquidity at each bank can be transmitted through the network configuring a contagion effect.

I find that the contagion effect through the interbank network is economically and statistically significant, suggesting that the failure of a borrower bank *reduces* the failure probability of lender bank(s). This contagion effect is beneficial since it *increases* the survival probability of remaining banks. The beneficial effect could result from bank failures freeing more liquidity than destroying and then the interbank network redistributing the extra liquidity among surviving banks.

I find that, as a result of contagion, the beneficial effect of bank capital in averting failures is halved. When a bank raises its capitalisation has a negative externality effect on other banks increasing their failure probabilities. Strategic complementaries lead a bank to increase risk-taking when other linked banks increase their capitalisation. It can then transfer its higher risk in the interbank market and free-ride on well-capitalised banks. In principle, each bank does not internalise the beneficial contagion effect when choosing its optimal capitalisation. Whether this is the case is left for future research. Another possible avenue for research is identifying a particular feature of the interbank network considered here that provides this beneficial effect.

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