Anti-contagion of bank failures through the interbank network

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Abstract

Capital regulation on banks aims to reduce the probability of bank failures. Theoretically, the effectiveness of capital buffers in doing so depends on the network structure of linkages among financial institutions. The structure of a financial network can either amplify or dampen shocks within the banking system. These linkages are typically omitted from empirical models studying bank failures. I examine the effectiveness of capital regulation in preventing bank failures using a spatial autoregressive probit model that accounts for interbank linkages and feedback effects. I study the 2001 Argentine banking crisis, for which I reconstruct the complete interbank network. I find that interbank lending helped protect the financial system by facilitating the resolution of failing banks and the following redistribution of liquidity across banks. Nevertheless, estimates from the spatial model indicate that equity buffers were approximately 10% less effective in preventing bank failures than suggested by a model that ignores interconnections among banks.

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

JEL classification: C21, E44, G01, G21.

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1 INTRODUCTION

> With regard to the stability of the financial system despite the aftermath of the Asian crisis of 1997 and the Russian crisis of 1998, the devaluation in Brazil at the beginning of the year and the potential effects associated with the arrival of the year 2000, the financial system's high degree of solvency and liquidity made it possible to preserve investor confidence. This prevented the sector from becoming an amplifier of the prevailing uncertainty and instead enabled it to contribute to mitigating it.
>
> **Dr Pedro Pou**
>
> *Governor of the Central Bank of Argentina*
>
> *Report to the Congress*, 1999

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 10% lower than previously estimated.

Theoretically, 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, it 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) or 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 facilitate both risk sharing and contagion, giving rise to a robust-yet-fragile financial system (Gai & Kapadia, 2010). By redistributing liquidity towards institutions that need it most, these networks can increase the efficiency of the banking system (Allen & Gale, 2000). During a crisis, however, this beneficial property may become detrimental if banks attempt to hoard liquidity by reducing interbank lending and delaying or withholding payments. In such circumstances, network linkages may generate feedback or cascade effects, whereby the default of one bank triggers the default of other connected institutions. Under certain conditions, these feedback effects act as an amplification mechanism and may ultimately 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. From the regulator's perspective, a bank may appear "well-capitalised" when assessed in isolation under a microprudential framework, yet be undercapitalised once the credit risk arising from its interbank linkages is taken into account. Establishing whether network contagion is present in actual financial systems is therefore important for assessing the effectiveness of capital regulation and determining whether financial linkages amplify or dampen shocks.

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 2001q4 using data from a credit registry. 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 negative spatial autocorrelation among banks, which I interpret as financial network contagion. This implies that network linkages dampened shocks and protected the banking system. I find that pre-existing network linkages facilitated the redistribution of extra liquidity generated by failing banks. At the same time, the results from the spatial model predict that bank equity is 10% less effective in averting failures compared to a non-spatial model. This is so because some increments in equity in a bank are likely to increase interbank lending, thus increasing the fragility of other banks in the system.

These findings relate 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 empirical 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

[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.

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, the study adds a new interbank network from an emerging economy 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) for 2003-2017. The network introduced here differs from Forte's because it covers a different period and is built from end-of-the-quarter data comprising all forms of interbank lending.

The Argentinian crisis under consideration has four attractive features to understand the dynamics 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. 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 funnelling (or not) liquidity

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

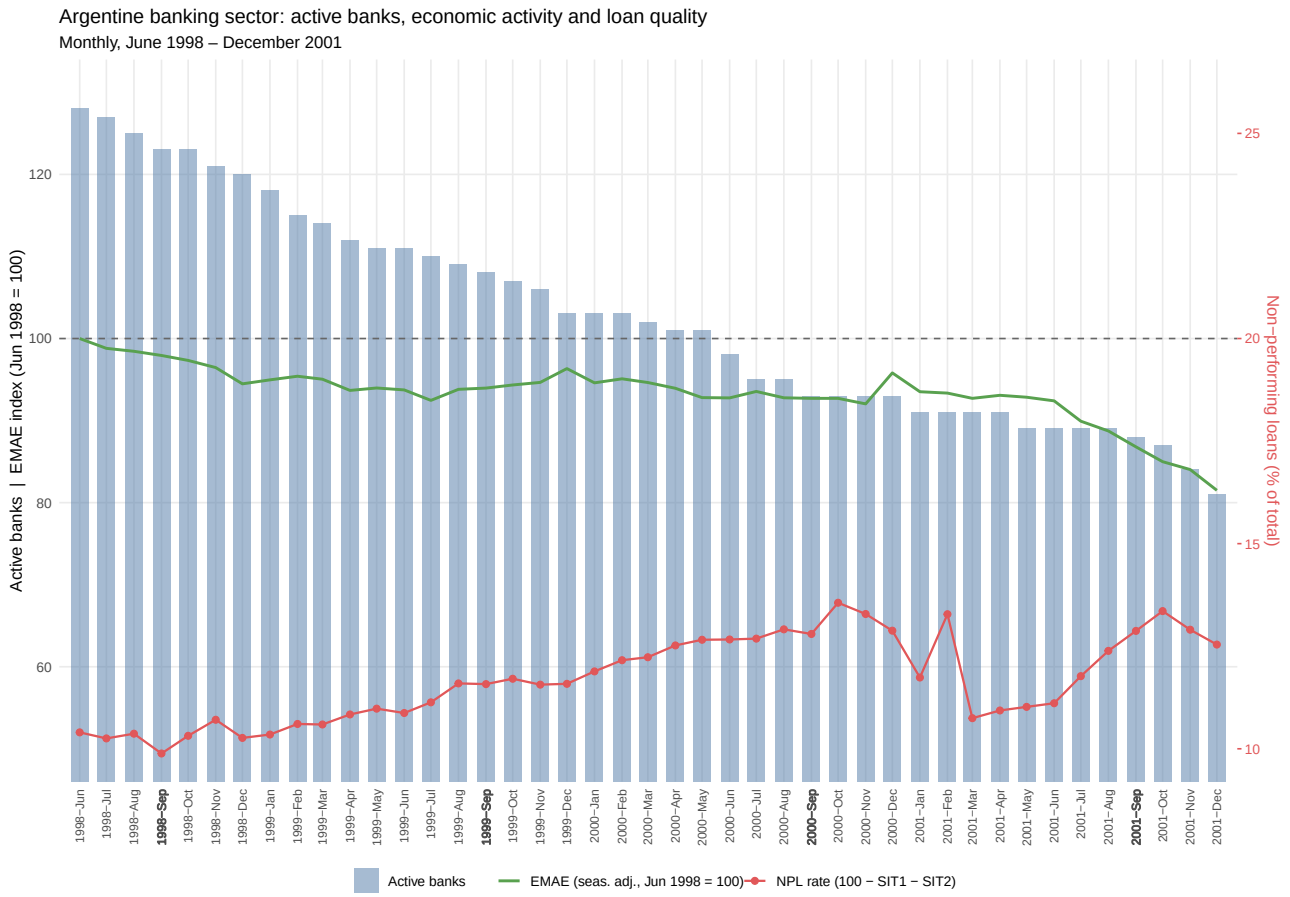


Figure 1: TIMELINE. Number of active banks, monthly bank failures, and the monthly economic activity index (EMAE) are shown on the left-hand axis. The non-performing loan in percentage is shown on the right-hand axis. The recession began in the fourth quarter of 1998.

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 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 devalu-

[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)

ation of its currency, the Real, in 1999. They estimate that by 2000 the Argentine peso was 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

[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.

subsidising exports (a fiscal devaluation for trade transactions), softening the Convertibility by 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

[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).

intrinsic to the financial system; the banking system was rather a victim of the recession (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

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

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:

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

where $E_i = A_i^{\text{IB}} + A_i^{\text{M}} - L_i^{\text{IB}} - D_i$ 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 default if

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

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,

[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.

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 at time t represented by $N \times N$ matrix W_t. At time t, each element w_{ij} for $i \neq j$ of W_t represents the loans of lender bank i to borrower bank j as share of the lender bank i to total amount of loans of bank i, thus representing the exposure of bank i to bank j. Consequently, the main diagonal of W is zero ($w_{i,i} = 0$ for $i = 1, \cdots, N$). The matrix W_t is a spatial weight matrix containing all weighted links among the N banks at time t. [11]

Let $\boldsymbol{y}_t^* = [y_{1,t}^*, \cdots, y_{N,t}^*]'$ be a vector of latent variables representing the propensity to fail for the N banks in period t, and $X_t = [\boldsymbol{x}_{1,t}', \cdots \boldsymbol{x}_{N,t}']'$ be the $N \times K$ matrix of predictors with $\boldsymbol{x}_{i,t} = [1 \;\; x_{i,t,2} \cdots x_{i,t,K}]$ representing the i^{th} row. The spatial autoregressive model (SAR) is

$$\boldsymbol{y}_t^* = \rho W \boldsymbol{y}_t^* + X_{t-1}\boldsymbol{\beta} + \alpha_t \boldsymbol{\iota}_N + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(0, I_N), \tag{2}$$

where the vector $W_{t-1}\boldsymbol{y}^*$ is the spatial lag of the latent variable capturing the mutual influence of failure propensity across banks and its associated scalar parameter ρ represents the strength

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

of spatial dependence among banks with $|\rho| \in (-1, 1)$. The scalar parameter α_t is a time fixed effect, $\boldsymbol{\iota}_N$ is a $N \times 1$ vector and the $N \times 1$ vector $\boldsymbol{\varepsilon}_t$ corresponds to the structural shock term, which, for example, contains innovations to expectations of a devaluation and the predetermined currency mismatch in the balance sheet of a bank. The errors are assumed to follow a multivariate normal distribution with mean $\mathbf{0}$ and variance matrix I_n.[12]

The SAR model captures higher-order effects of changes in any bank and their propagation through the financial system. Define the power of W_{t-1} as $W_{t-1}^q \equiv W_{t-1}^{q-1} \times W_{t-1}$, for $q = 2, 3, \ldots$. Then the term W_{t-1}^q with $q > 1$ represents indirect paths of order q between banks, such that W^2 represents an indirect connection between bank i and k through a common neighbour j.[13] This is particularly informative for systemic risk management because a lender bank that has lent to 2 borrower banks may be seen as safer than an equivalent bank that lends to only 1 bank, but if the two borrower banks are linked, the benefit of risk diversification is only apparent. The SAR is especially able to capture higher-order effects. We can see this by writing the corresponding reduced-form model from (2), including the time fixed-effect parameter in the matrix X we have

$$\boldsymbol{y}_t^* = (I_N - \rho W_{t-1})^{-1} X_{t-1}\boldsymbol{\beta} + (I_N - \rho W_{t-1})^{-1}\boldsymbol{\varepsilon}_t \tag{3}$$

where

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

The power series representation in (4) shows that the SAR captures the direct effect contained in W_{t-1} emanating from first-order neighbours, as well as *all* possible indirect effects in the powers of W_{t-1}. This contrasts sharply with models that consider only first-order links between units. The model captures higher-order effects of changes in any predictor of a bank, captured by the first term on the right-hand side of equation (3) or a shock to any bank in the last term.

The invertibility of $(I_N - \rho W_{t-1})$ depends on the eigenvalues of ρW_{t-1} see LeSage and Pace, 2009, p.88–89. I re-scale W_{t-1} to guarantee invertibility conditions; see details in Subsection 5.2.

[12] The latent variable does not have a meaningful scale, and its variance is not separately identifiable in binary outcome models.

[13] For example, in a social network these are the friends of my friends.

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

$$\Omega = \mathbb{E}[\mathbf{u}\,\mathbf{u}'] = (I_N - \rho W_{t-1})^{-1}\left[(I_N - \rho W_{t-1})^{-1}\right]' \tag{5}$$

with $\mathbf{u} = (I_N - \rho W_{t-1})^{-1}\boldsymbol{\varepsilon}_t$ and $\mathbb{E}\left[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}'\right] = I_N$. This equation forms the basis for estimation.

4.1 Estimation of the SAR probit model

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,

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

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).[14] The methods can be computationally burdensome, with the risk of producing unreliable estimates (Cheng, 2022; Elhorst et al., 2016; Calabrese & Elkink, 2014). As a result, in the empirical section I employ three different estimators: a Bayesian Markov Chain Monte Carlo (MCMC) estimator, a maximum-likelihood-based (ML) estimator and a generalised method of moments (GMM) estimator.

The Bayesian MCMC is described by LeSage and Pace (2009, Ch. 10) and implemented in the R package spatialprobit by Wilhelm and Godinho de Matos (2024). This method treats the unobserved $\boldsymbol{y}_t^*$ in the likelihood function above as parameters to estimate; once fixed and given the priors, the remaining model parameters $(\rho, \boldsymbol{\beta})$ can be resampled from the conditional posterior distribution. For the SAR probit model, the conditional posterior distribution takes the form of a multivariate truncated normal distribution. To sample from this posterior distribution, they use a Gibbs sampler with a precision matrix that follows ideas put forth by Geweke et al. (1991), which can be done using a distribution function with a known form, making computation faster.

[14] See McMillen (1992), LeSage (2000) and Elhorst et al. (2016) for three different methods.

Martinetti and Geniaux (2017) propose an ML estimator using an analytical approximation technique that relies on a univariate conditioning approximation to the MVN probabilities. The algorithm requires the factorisation 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.

Likelihood-based methods rely on the assumption of a normal distribution of the unobserved shocks. Klier and McMillen (2008) proposed a GMM estimator and implemented in R package spldv by (Sarrias & Piras, 2023). The estimator relies on population moment conditions of the form $\mathbb{E}\left[\mathbf{h}_i'\tilde{u}_i(\rho,\boldsymbol{\beta})\right] = 0$, where the scalar $\tilde{u}_i$ is the generalised residual for bank i and the vector $\mathbf{h}_i$ is the i row of linearly independent columns of the matrix $H = (X, WX, W^2X, W^3X, W^4X)$ with X the $N \times k$ matrix of predictors including the constant. Instruments are thus the predictors for each bank and the predictors of neighbour banks up to order 4 in the network. I use the two-step GMM estimator with the optimal initial weighting matrix.[15]

Given my sample size, my preferred estimator is the Bayesian MCMC. Calabrese and Elkink (2014) conduct Monte Carlo studies to assess the performance of SAR probit estimators and their results indicate that GMM-based estimators tend to have higher biases than ML estimators when the sample size is small ($N = 50$ and $\rho = 0.45$). For this reason, in the main text I present results from the Bayesian MCMC and, as a robustness check, the GMM estimator which does not require normality. As a robustness check, I present results from the ML approximation.

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

[15] See a discussion of the merits of estimators for spatial probit models in Elhorst et al. (2016, p425).

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 $x_{i;k}$ 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]

Indirect effects are relevant because they capture the externality 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

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

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, $N^{-1}\,\mathrm{tr}[R_k]$, where tr is the trace operator. The *average total effect* is the average over observations of all marginal effects given by $N^{-1}\boldsymbol{\iota}_N^T R_k \boldsymbol{\iota}_N$. 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: $N^{-1}\boldsymbol{\iota}_N^T R_k \boldsymbol{\iota}_N - N^{-1}\,\mathrm{tr}[R_k]$. 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).

A network centrality measure estimated by the model is a node's vulnerability to changes in the survival probability of its neighbours, with the $N \times 1$ vulnerability vector given by $(I_N - \rho W)^{-1}\boldsymbol{\iota}_n$. This vector corresponds to the authority-based Katz-Bonacich centrality measure.[17] As I define the matrix W in subsection (5.2), the network centrality of a bank is going to be higher for more vulnerable banks.

5 FAILURE, BANK PREDICTORS AND THE INTER-BANK NETWORK

The baseline results use a pooled sample comprising four periods. The dependent variable for bank failure equals one if a bank failed during any of the following periods: 1998Q4–1999Q3, 1999Q4–2000Q3, 2000Q4–2001Q3, or 2001Q4–2002Q3. The beginning of each period coincides with a critical event: the onset of the recession in the last quarter of 1998, as shown by the economic activity index in Figure 1; the inauguration of the new federal administration; the resignation of the Vice President; and, in the last quarter of 2001, the imposition of restrictions on withdrawals from transaction deposits and the abandonment of the currency board.

For each failing period the predictors are the average of the 4 preceding quarters, eliminating seasonality.

In the Appendix I consider alternative periodisation.

[17] See Sargent and Stachurski (2024, p. 45)

5.1 Bank failure

I consider that a bank fails when any type of license termination occurs, including those that are voluntary, a merger or acquisition or forced termination for failing to meet financial regulations. 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 grant or 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 transferred or cancelled. I also consider a bank failure 4 banks that received central bank emergency liquidity assistance. With this definition the sample contains 43 failures with 15 of them representing a liquidation of selected assets and liabilities and 16 a M&A process, see further details in Table 6.

I consider all financial entities including local for-profit banks, cooperative banks, state-owned banks, private financial companies, savings and loans institutions and branches of international banks. To account for the government support that state-owned banks may enjoy I include an indicator variable taking the value of 1 for state-owned banks.

5.2 The interbank liabilities network

I build an interbank liabilities network considering bilateral linkages among banks that are registered in the BCRA Credit Registry. The Registry reports on a quarterly frequency: the lending bank identification number, the borrower tax file number, the amont of the debt, and the credit score assigned by the lending bank to that borrower.[18] Using public tax number information, I match the tax file number that appears in the Registry to the bank license identification number, which allows establishing direct linkages among financial entities.

Each link (i, j) represents the debt of bank i to lender bank j. As such shocks can travel directly from the borrower bank 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 only indirectly through other banks in the network. The spatial weight matrix is thus asymmetric. [19]

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

[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.

The weight for a link in a given quarter is the share of the debt in the total loans of the lender bank j. Weights represent the exposure of the lender bank to the borrower bank. I do not find evidence of spatial correlation when using the interbank network of assets, that is the credit flow *from* a lender *to* a borrower bank. 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).

I build four spatial weight matrices W_t, one for each period t. Each W_t is the time average of the four preceding quarters for each period. Taking the time average of the interbank network allows handling seasonality in interbank lending and captures potential information gathering by the lender bank of the borrower that takes time to build and may be related to relationship lending. This potential information acquisition of the lender bank will be important in the case of liquidation of a borrower bank.

In the pooled estimation, the spatial weights matrix W is constructed as a block diagonal matrix $W = \text{diag}(W_1, W_2, W_3, W_4)$ see, for example, equation (7) in Grieser et al. (2022).[20]

Following Kelejian and Prucha (2010) I normalise the spatial weights matrix W by its spectral radius such that $W^\star = W/\tau$ is the normalised matrix with τ the spectral radius of W.[21] Unlike row normalisation which rescales each row of W by a different scalar, spectral-radius normalisation restricts the admissible values of ρ to $(-1, 1)$ while also preserving the interpretation of the parameter.

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, evidence by Forte (2020) using trading data from the Argentinian overnight interbank market during the period 2003-2017, finds that that the network evolves smoothly and there is a reduction

[20] The zeros outside the diagonal in this matrix impose the restriction that past bank linkages do not drive current failures (beyond current linkages) and, symmetrically, future linkages do not affect current failures.

[21] The spectral radius τ of a matrix A is defined as $\tau \equiv \max\{|\lambda_1|, |\lambda_2|, \ldots, |\lambda_n|\}$ where $\lambda_1, \ldots, \lambda_n$ are the eigenvalues of A.

in the number of active nodes and links during the crisis period of 2008. Third, the average bank has a quite robust capitalization, see Table 1), and consequently "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).[22]

Figure 2 illustrates the graphic representation of the network. Each circle represents a financial entity with a light blue colour is bank that did not fail during any period, a red circle corresponds to a bank that was liquidated by the central bank in any period while an orange colour a bank that went through a merger & acquisition process. The nodes in the plot are positioned such that banks with a higher network centrality are closer to the centrer. The network centrality measure is the model-implied vulnerability as in describe in Section 4.2. . Each of the line represents a liability with the arrows omitted for readability. For example, Scotiabank Quilmes SA is one of the bank with higher vulnerability network and appears in the centre has been borrowing from Banco Bansud SA since 2000Q2 witn a total exposure at the end of 2001Q3 of about USD 5 millions but no exposure reported by 2001Q4. On 18/04/2002 Scotiabank Quilmes SA was suspended and by August that year the Central Bank announced that all selected assets and liabilites of the failing bank were sold to Banco Bansud SA and Banco Comafi SA.

In contrast, Banco del Buen Ayre has one of the lowest vulnerability measures, was borrowing from Banco Itaú since the beginning of 1999 and was finally merged with Banco Itaú at the end of that year.

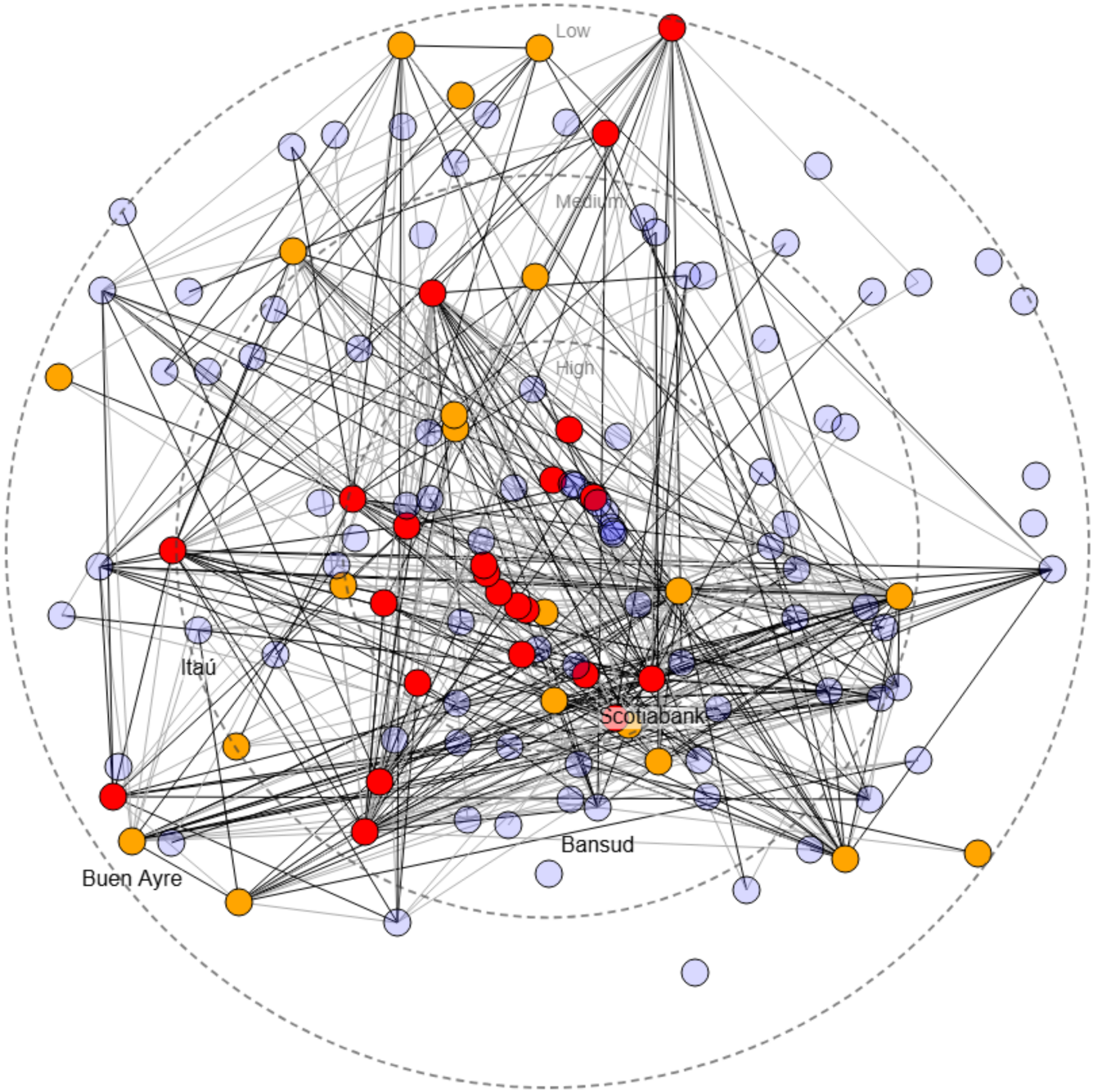
5.3 Predictors at bank level

Predictors are averages over the preceding year of each period, same horizon and time as the network.

Default risk is a combination of asset risk and leverage variables (Calomiris and Powell (2001)). I include 11 of those variables which are standard in the literature: (i)-(iii) *funding* – equity-to-assets ratio, return on assets (ROA), implicit interest rate on USD nominated liabilities, (iv) *liquidity* the ratio of Loans to Assets, (v)-(viii) *asset-side risk* – the ratios of

[22] I do not observe the duration of the interbank loans. Since the Credit Registry captures all forms of interbank lending, not only overnight loans, it is possible long-duration loans between banks generate a smooth variation over time in the structure of the network.

Figure 2: INTERBANK LIABILITIES NETWORK. Directed network with links from borrower bank to lender bank. Time average over 1998Q3 and 2001Q3. The weight on links is the ratio of the outstanding loan to the total loans of the lender bank. For readability only links involving failing banks are shown. Banks with higher network centrality, as predicted by the model, are drawn closer to the centre.



non-performing loans to total loans, the interest rate on loans, loans to the government to total loans and USD-nominated loans to total loans. (ix)-(xi) *structure* – the logarithm of nominal assets in Argentinian pesos (ARS), an indicator variable for state-owned bank and as control the logarithm of nominal Liabilities in ARS; All bank-level variables are available monthly, which are transformed to yearly frequency by taking the annual average, and, therefore, eliminating

Table 1: DESCRIPTIVE STATISTICS. All predictors measured as percentages unless otherwise noted.

Predictor	**Mean & standard deviation**	
	Failed	Non-Failed
FUNDING		
Equity-to-Assets	16.603	20.529
	(19.354)	(21.128)
ROA	−1.939	0.152
	(5.272)	(4.263)
USD financing cost	6.100	5.944
	(2.225)	(2.677)
LIQUIDITY		
Loans-to-Assets	49.747	54.498
	(16.210)	(18.499)
ASSET-SIDE RISK		
Non-performing loans	14.118	11.419
	(13.583)	(9.750)
Lending interest rate	24.703	24.712
	(11.148)	(11.427)
Govt. loans to Loans	5.929	6.926
	(10.838)	(11.865)
USD loans to Loans	63.764	59.979
	(16.844)	(21.133)
STRUCTURE		
Assets (ARS millions)	1.023	1.397
	(2.602)	(2.993)
Liabilities (ARS millions)	0.969	1.391
	(2.438)	(2.939)
State-owned bank	0.140	0.135
	(0.349)	(0.342)
Number of banks	43	89
Number of periods	4	
Number of observations	326	107

Standard errors are reported in parentheses. State-owned bank is an indicator variable that equals 1 when the bank is wholly owned by the state.

their seasonality.

Table 1 presents the summary statistics of the predictors for failed and non-failed institutions. For ease of interpretation, the predictors in ARS are presented in level, but their logarithms are used in the regressions.

Equity-to-assets ratio, return on assets, and the interest rate on USD-nominated liabilities, including deposits, capture bank funding costs. The equity-to-assets ratio 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 by investors.

The ratio of loans to assets is a broad measure of (i)liquidity of the asset side of the balance sheet because loans can become highly illiquid during a systemic crisis. In principle, a higher loans-to-assets ratio and thus a more illiquid asset side of the balance sheet makes it harder for the bank to generate extra liquidity to, for example, serve a deposit outflow and makes the bank itself more difficult to be sold during a crisis, increasing the failure probability.

Non-performing loans, the interest rate on loans, loans to the government, and USD-nominated loans reflect the riskiness of the loans portfolio. Loans are classified on a scale from 1 to 5 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, including loans with substantial risk of unrecoverability, which are considered high-default risk according to the BCRA classification guideline. The lending interest rate is measured as the implicit lending rate, computed as accrued interest income on loans during the previous 12 months divided by average loans outstanding, expressed as a nominal annual rate. This variable is a forward-looking measure of risk. The sign of this predictor may be positive or negative. While a higher lending interest rate captures loans of a higher default risk and thus a higher bank failure probability, it also provides a buffer to the bank and more liquidity during the life of the loan. The proportion of lending to the government is relevant due to the 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, particularly lending to the non-tradeable sector. In general, an increase in any of these variables signals a riskier loan portfolio, and, thus, an increase in the failure probability.

Nominal assets capture the size of the firms,[23] 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

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

banks may be supported by the government during a crisis (the 'too-big-to-fail' argument).[24] The direction of the effect of bank size on failure is, however, indeterminate *a priori*: large banks may be more efficient due to economies of scale, but they also may engage in ex-post risky businesses to exploit their too-big-to-fail franchise (Chiaramonte & Casu, 2017).

The average capitalisation (Equity-to-Assets ratio) across all banks and periods is 19.6%, with a median of 11.3%, which is well above the minimum 8% capital ratio requirement for risk-weighted assets in the Basel II regulatory framework.[25] The distribution of the share of government loans across banks is concentrated in a few banks, with a maximum exposure through loans of 58.8%. This only captures the exposure to the federal and local governments through loans, but it does not capture exposure through holding government bonds as liquid assets. Finally, more than half of the loans are denominated in USD dollars with a mean of 60.9%, which creates, on the one hand, a currency-mismatch risk if a devaluation occurs, but, on the other hand, it makes 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

In the baseline analysis, I report results based on the non-spatial probit and the SAR probit. For the SAR probit, I focus on estimates from the Bayesian MCMC estimator and linearised generalised method of moments (GMM) estimator while in the robustness section I also present estimates from the maximum-likelihodod estimator, see Subsection (4.1) for details of estimation.

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

[25] 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 system was well capitalised.

6.1 Failures during 1998-2002

The estimated coefficients for all models appear in Table (2). Predictors are measured as percentages except those that are logarithms. The average marginal effects of a unit change in the predictors on the probability of failure are shown in Table (3). For probit models, the average effect for covariate k is computed as the average over observations, i.e. $N^{-1}\partial\mathbb{E}\left\{Pr[y_i = 1|\mathbf{x}_i]\right\}/\partial x_{i,k}$.

The central hypothesis of this work is the role of the network in shaping banking failures, manifested in the empirical model as spatial autocorrelation among banks. I hence first focus on the implications of spatial autocorrelation in general. Then, I turn to a discussion of how this form of dependence affects the role of predictors, referring to both tables.

Results show a negative and statistically significant spatial autocorrelation among banks in all estimations of the SAR probit models in columns 2 and 3 of Table 2. The SAR probit estimate of $\hat{\rho} = -0.099$ yields is statistically significant at 5% and the direction of the predictors is in line with the non-spatial probit. A negative ρ indicates that in equilibrium the failure of a borrower bank *reduces* the failure probability of *its* lenders, that is, there is a positive spillover effect of neighbours' failures. This is an exercise of static comparative where one compares the initial equilibrium failure probabilities of banks with the alternative equilibrium probabilities *after* all adjustments that lead to the new equilibrium have occurred.[26]. The failure of a bank generates more liquidity than it erodes, and the interbank network then redistributes this liquidity among surviving banks. I explore this mechanism in Section 6.3. More generally, a negative ρ implies that the structure of bank linkages works as a shock absorber rather than an amplifier of idiosyncratic shocks.

The magnitude of ρ determines the size of indirect or contagion effects. From the marginal effects in Table 3, we see that the indirect effect represents around 1/10 of the total marginal effect for each predictor. For example, a 1 percentage-point increase in ROA has an average *total* effect on a given bank of reducing the failure probability by 0.827 percentage points (pp), while the indirect or spillover effect of increasing ROA is around 1/10 of the total effect, which is around 0.097pp.

A higher equity-to-assets ratio predicts a lower probability of failure, as initially quoted

[26]While the model in itself is not dynamic, it does capture dynamic decision making. A cross-section model captures the long-run equilibrium or steady-state of the dynamic forms in which decisions are taken, see LeSage and Pace (2009, Ch2, p25, p37)

Table 2: BASELINE COEFFICIENT ESTIMATES. Pooled sample with the outcome variable taking the value 1 if a bank fails between 1998q4 and 2002q3. Predictors and the interbank network are annual averages. All predictors are ratios except for the state-owned bank, which is an indicator variable, and assets and liabilities, which are the logarithms of nominal Argentine pesos.

	Probit	**SAR Probit**	
		GMM	**MCMC**
	(1)	(2)	(3)
ρ		-0.127^{***}	-0.099^{**}
		(0.047)	(0.038)
FUNDING			
Equity-to-Assets	-0.017^{**}	-0.016^{*}	-0.017^{**}
	(0.008)	(0.009)	(0.008)
ROA	-0.057^{***}	-0.050^{**}	-0.055^{***}
	(0.020)	(0.021)	(0.021)
USD financing cost	0.058	$0.057^{\dagger}$	0.057
	(0.042)	(0.037)	(0.040)
LIQUIDITY			
Loans-to-Assets	-0.014^{**}	-0.011^{*}	-0.014^{**}
	(0.006)	(0.006)	(0.006)
STRUCTURE			
Log of Assets	$0.444^{\dagger}$	$0.475^{\dagger}$	$0.404^{\dagger}$
	(0.270)	(0.307)	(0.258)
Log of Liabilities	-0.482^{*}	$-0.469^{\dagger}$	-0.442^{*}
	(0.247)	(0.296)	(0.239)
State-owned bank	$-0.523^{\dagger}$	-0.391	-0.546^{*}
	(0.323)	(0.274)	(0.325)
ASSET-SIDE RISK			
Non-performing loans	0.006	0.004	0.006
	(0.009)	(0.010)	(0.009)
Lending interest rate	0.001	0.006	0.001
	(0.010)	(0.011)	(0.010)
USD loans to Loans	0.005	0.003	0.004
	(0.005)	(0.005)	(0.005)
Govt. loans to Loans	0.003	0.002	0.004
	(0.010)	(0.007)	(0.009)

$***p < 0.01$; $**\ p < 0.05$; $*p < 0.10$; $^{\dagger}p < 0.15$.

The number of observations is 433, covering 4 periods. Time indicator variables included. Standard errors are reported in parentheses. Column (4) uses the SAR Probit MCMC estimates and reports posterior standard deviations.

Table 3: AVERAGE MARGINAL EFFECTS. Average computed over observations. Effects are in percentages. The outcome variable takes the value 1 if a bank fails between 1998q3 and 2002q3. All predictors are measured as percentages except for the state-owned bank, which is an indicator variable, and assets and liabilities, which are the logarithms of nominal Argentine pesos.

	Non-spatial probit	**SAR Probit**		
		Direct	**Indirect**	**Total**
	(2)	(3)	(4)	(5)
FUNDING				
Equity-to-Assets	−0.273**	−0.283**	0.030**	−0.254**
	(0.128)	(0.136)	(0.015)	(0.122)
ROA	−0.897***	−0.923***	0.097***	−0.827***
	(0.310)	(0.344)	(0.036)	(0.309)
USD financing cost	0.910	0.949	−0.098	0.851
	(0.652)	(0.673)	(0.068)	(0.606)
LIQUIDITY				
Loans-to-Assets	−0.218**	−0.238**	0.025**	−0.214**
	(0.092)	(0.100)	(0.010)	(0.089)
STRUCTURE				
Log of Assets	6.935†	6.778†	−0.709†	6.069†
	(4.223)	(4.373)	(0.456)	(3.920)
Log of Liabilities	−7.540*	−7.398*	0.774*	−6.624*
	(3.870)	(4.060)	(0.424)	(3.640)
State-owned bank	−6.514**	−9.138*	0.957*	−8.181*
	(3.151)	(5.471)	(0.573)	(4.902)
Asset-side risk				
Non-performing loans	0.095	0.107	−0.011	0.096
	(0.141)	(0.156)	(0.016)	(0.140)
Lending interest rate	0.023	0.019	−0.002	0.017
	(0.161)	(0.168)	(0.017)	(0.150)
Govt. loans to Loans	0.053	0.069	−0.007	0.062
	(0.149)	(0.158)	(0.016)	(0.142)
USD loans to Loans	0.074	0.072	−0.007	0.064
	(0.078)	(0.084)	(0.009)	(0.076)

$***p < 0.01$; $**p < 0.05$; $*p < 0.10$; $^{\dagger}p < 0.15$. The number of observations is 433, covering 4 periods.

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 -0.273 for the probit model in Table 3 implies that, on average, an additional 1 percentage point increment in the capital ratio reduces the failure probability by 0.273pp. The comparable average marginal effect from the SAR probit is smaller, implying a reduction in the failure probability of 0.254pp as indicated by the total effect in column 5 of Table 3. Surprisingly, the spatial model identifies a positive indirect effect of equity such that, on average, an increment in equity in a bank *increases* the failure probability of neighbouring banks, see column 4. The model predicts that an increment in equity in a bank imposes a negative spillover effect on other banks in the system. I will turn to this result in the following subsection.

The size of the effects of equity is relatively close to the marginal effect of -0.40pp estimated by Shaffer (2012) during the Savings and Loan crisis during 1985 and 1986 in the US and smaller than the value of 1.3pp reduction in failure probability estimated by Arena (2008) for Latin American countries during the Tequila crisis of 1995. Banks in Arena's sample were on average substantially less capitalised; for example, his sample of failed banks had on average an equity-to-asset ratio of 9.00 vs 16.6 in this work.[27]

More profitable banks on average are less likely to fail, with a 0.05pp reduction in failure probability with an additional 1 percentage point higher ROA, on average.

At the same time, a higher financing cost positively predicts failure, as found, for example, by Betz et al. (2014) when predicting bank distress in European banks between 2000 and 2011. The fact that a higher financing cost positively predicts failure suggests that indeed the debt market efficiently priced in weaker banks, although the statistical significance is weak. This result relates to the literature exploring the market discipline of the debt market, and in particular, demandable demand deposits impose on banks as described in theoretical models as Calomiris and Kahn (1991). Empirically, the positive sign of this predictor agrees with empirical evidence on the disciplinary effect of deposits found by Martinez Peria and Schmukler (2001) in Latin American countries.[28]

A higher (i)liquidity captured by a higher Loans-to-Assets reduces the probability of failure

[27] Indeed, the average equity ratio of failed banks here is larger than the average equity ratio of *non-failed* banks in Arena's sample.

[28] Also see Levy-Yeyati et al. (2010) which studies depositors run during Argentinian and Uruguayan crises of 2001 and 2002.

by about 0.21pp. The direction of this predictor is the opposite of that found by Shaffer (2012) for the US and Arena (2008) for Latam. This is predicted by Diamond and Rajan (2005)'s model: as a bank approaches failure, it becomes more liquid by reducing lending in an attempt to serve deposits outflows. I further explore this mechanism in subsection 6.3.

A deterioration in the loans portfolio, measured by higher non-performing loans, weakly predicts an increment in the probability of failure in both models, although neither the coefficient nor the marginal effects are statistically significant. This predictor needs to be interpreted in tandem with the lending interest rate. The ratio of non-performing loans, being the realised percentage of impairment loans during the previous years, is a backwards-looking measure of the quality of a portfolio; the loans interest rate variable, in contrast, is forward-looking. These two variables hence mix backwards and forward-looking information making it difficult to interpret them in isolation. Direct exposure to the public sector through lending positively predicts failure, although the effects are imprecisely estimated. This weak evidence likely reflects that lending to the public sector is concentrated in both the cross-sectional and the time series dimensions. Only a handful of banks have high exposure to the public sector, either state-owned or recently privatised and formerly state-owned banks. At the same time, higher exposure to the public sector materialised only in the last period of observation, since 2000, when access to international financial markets by the public sector was severely reduced.[29] In both models, exposure to exchange-rate risk, captured by the proportion of loans denominated in USD, 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 0.074, suggesting a 1 percentage point increment in the share of USD-denominated loans in the portfolio moves the probability of failure up by 0.074pp, cfr. the unconditional probability of failure across all periods is 10% (43 failures over 433 observations, see Table 1).

6.1.1 Robustness analysis

I split the 4 periods of the baseline result in two subsamples of 2 periods. The first subsample includes the first two periods of the baseline sample, which includes the beginning of the

[29] See Burdisso et al. (2001) for a description of the crowding out effect that this higher lending to the public sector since 2000 had on small and medium-sized private firms.

recession, the change of Administration, Russian default and Brazilian devaluation, but it stops short of the deposit runs of the year 2001 and the abandonment of the currency board at the end of that year. The last subsample contains the periods with failures from 2000q4 to 2001q3 and from 2001q4 to 2002q3, thus including the height of the crisis and the devaluation.

The coefficient estimates are presented in the last two columns of the Table (4). The first difference in the estimates with the baseline ones is that the spatial correlation parameter ρ becomes statistically indistinguishable from 0 towards the end of the Crisis. The predictors on the share of loans to the Government become statistically significant and positive, signalling that banks with greater exposure to the Government towards the end of the Crisis were more likely to fail during this last period. Most of the predictors lose statistical significance towards the end of the Crisis, which likely reflects the regime change implied by the asymmetric pesification for the viability of some banks. This change of regime eliminated some mechanisms that would have allowed banks to fail and free up liquidity that would have been redistributed among surviving banks. For example, during this last part of the Crisis the Central Bank could not sell some banks due to lack of interest by other participants eliminating the possibility that the liquidity in the balance sheet of these banks were transfered to other banks[30]

6.2 The effect of equity in averting failures

The estimated effect of equity in averting failures is smaller when banks are interconnected, as emerges by comparing the marginal effect of -0.273 for the probit model in Table 3 with the estimated total effect of -0.254 from the SAR probit, see the last column of Table 3.

This result follows because the indirect effect of 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 rely on each other for capitalisation. When a bank increases its equity ratio by 1 percentage point, it reduces its own failure probability by -0.283pp (direct effect in column 3). At the same time, when a bank increases its equity, it creates a *negative spillover* on other banks by increasing their failure probability by 0.03pp.

An increase in a bank's equity protects that bank, but some of that additional protection

[30]Consider the case of the three banks: Banco Bisel SA, Suqía SA and De Entre Ríos SA that had to transferred to the largest state-owned bank Banco Nación due to the lack of bids by other private banks.

Table 4: ROBUSTNESS ANALYSIS. Pooled samples with the outcome variable taking the value 1 if a bank fails in the considered period. Predictors and the interbank network are annual average before each period. All predictors are ratios except for the state-owned bank, which is an indicator variable, and assets and liabilities, which are the logarithms of nominal Argentine pesos.

	SAR Probit ML	**Failures between 1998q4 and 2000q3**	**Failures between 2000q4 and 2002q3**
	(1)	(2)	(3)
ρ	−0.057***	−0.132**	0.036
	(0.004)	(0.051)	(0.026)
FUNDING			
Equity-to-Assets	−0.018***	−0.022*	−0.018
	(0.004)	(0.012)	(0.014)
ROA	−0.057***	−0.091***	−0.060**
	(0.016)	(0.034)	(0.027)
USD financing cost	0.059*	0.108†	0.070
	(0.032)	(0.071)	(0.056)
LIQUIDITY			
Loans-to-Assets	−0.014***	−0.016*	−0.011
	(0.004)	(0.009)	(0.009)
STRUCTURE			
Log of Assets	0.439***	1.062*	−0.010
	(0.119)	(0.573)	(0.427)
Log of Liabilities	−0.483***	−1.030*	−0.120
	(0.104)	(0.528)	(0.412)
State-owned bank	−0.528†	−1.280*	−0.305
	(0.326)	(0.669)	(0.452)
ASSET-SIDE RISK			
Non-performing loans	0.005	0.011	0.007
	(0.006)	(0.015)	(0.014)
Lending interest rate	0.001	−0.023	0.015
	(0.008)	(0.016)	(0.014)
Govt. loans to Loans	0.004	−0.030	0.019†
	(0.009)	(0.021)	(0.012)
USD loans to Loans	0.004	0.003	0.010
	(0.003)	(0.008)	(0.007)
Number of failures	43	24	20
Number of banks	132	122	112
Number of periods	4	2	2

$***p < 0.01$; $**$ $p < 0.05$; $*p < 0.10$; $^{\dagger}p < 0.15$.

The number of observations is 433, covering 4 periods. Time indicator variables included. Standard errors are reported in parentheses. Column (4) uses the SAR Probit MCMC estimates and reports posterior standard deviations.

Table 5: DETERMINANTS OF INTERBANK LENDING. Dependent variable is the log of the market share in interbank lending. Monthly panel regressions between 1998-01 and 2001-06. Effects are in percentages. All predictors are percentages except for assets, which is the logarithm of nominal Argentine pesos.

	Between	**Between IV**
FUNDING		
Equity-to-Assets	0.018***	0.019***
	(0.007)	(0.007)
ROA	−0.019	−0.004
	(0.032)	(0.037)
USD financing cost	0.025	0.021
	(0.023)	(0.023)
Lending interest rate	0.008	0.009
	(0.010)	(0.010)
STRUCTURE		
Log of Assets	0.773***	0.789***
	(0.090)	(0.092)
Efficiency	0.001	0.001
	(0.001)	(0.002)
ASSET-SIDE RISK		
Non-performing loans	−0.038***	−0.039***
	(0.012)	(0.013)

$***p < 0.01$; $**p < 0.05$; $*p < 0.10$; $^{\dagger}p < 0.15$. The number of observations is 4,366 with 141 banks and a maximum of 54 periods (unbalanced panel).

builds fragility elsewhere in the system.

To shed some evidence on this negative spillover effect of equity, I study the relevance of equity in driving participation in interbank lending. If the additional equity of a bank generates higher leverage (lower equity) in other banks through higher interbank lending, it would explain this negative spillover. I use monthly panel data regression where the dependent variable is the log of the market share in interbank lending each month. The set of regressors is similar to the bank failure specification, but I also include the net financial margin relative to administrative expenses in percentage as a measure of efficiency. To diminish endogeneity issues, I use a one-month lag of all the regressors in one estimation, and an instrumental variable estimator in another estimation which uses the same one-month lag regressors, but the Equity-to-Assets ratio is instrumented with its 2-month lag. The results using the between estimator are presented in the second and third columns of Table 5.

The estimated semi-elasticity of equity to interbank lending is around 1.8% to 1.9%, implying that a marginal increment of 1 percentage point in the equity ratio increases the market share as a lender in the interbank market by about 1.8%. . Overall results suggest that the healthier a bank becomes, the more it lends to other banks: the better capitalised, the more efficient, and the lower its non-performing loans, the more it participates as a lender in the interbank market.

Any marginal increment of equity in a bank is thus ought to increase interbank lending. The network allows the redistribution of the additional equity, maximising the return on equity in the system. But at the same time it makes the system more fragile since borrowing banks can rely on their neighbours' equity instead of their own, making their balance sheets more fragile. In other terms, borrowers may fail to price in the systematic increase in risk of their coordinated action of borrowing from their well-capitalised neighbours.

This evidence relates to the literature on strategic complementarity in non-financial firm-leverage decisions as recently studied by Grieser et al. (2022). They find significant evidence that a firm's leverage decision is influenced by its competitors. Using a SAR model, they estimate a value of $\rho = 0.25$, which suggests that, on average, a firm's leverage decision depends positively on its closest competitors.

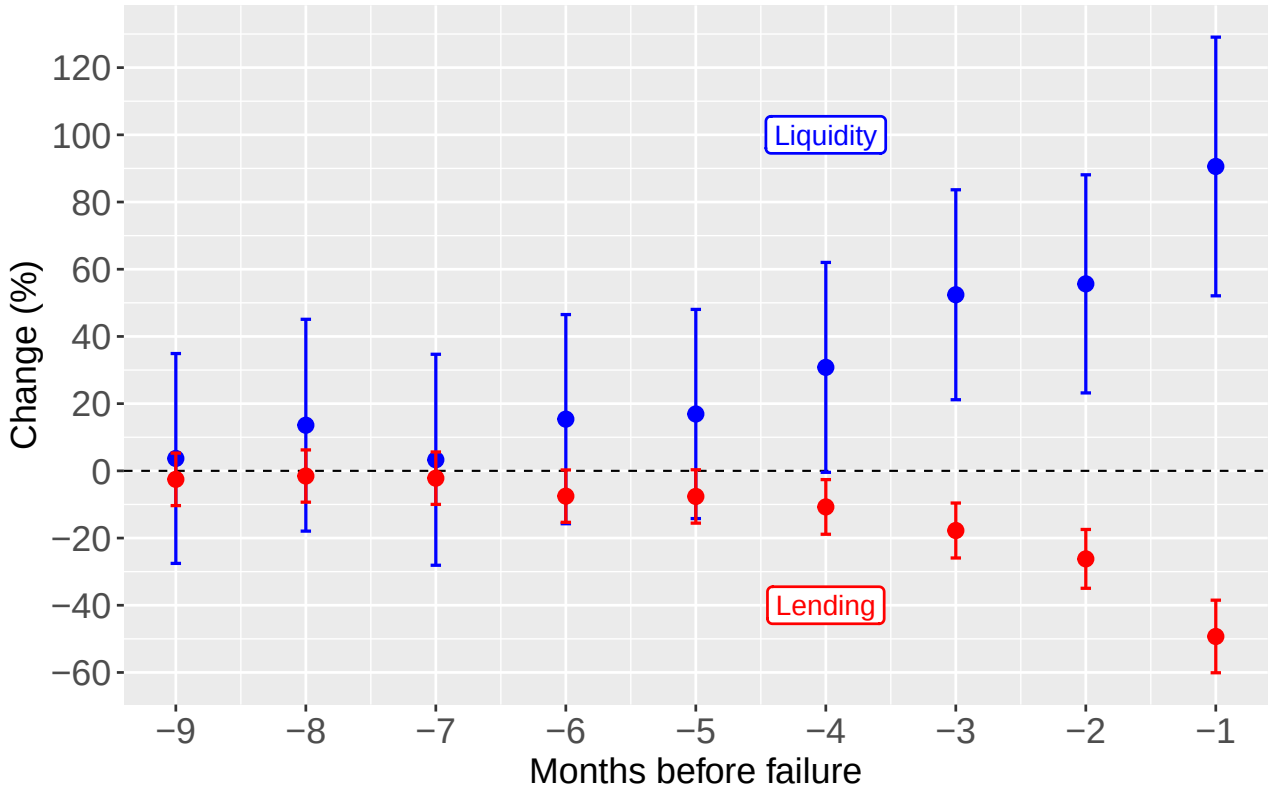
Banks with higher equity lend more in the interbank market, facilitating the share of equity across the system. Estimates of the elasticity of interbank lending to equity are greater than 1.

6.3 Bank failures free up liquidity

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.

On average failed banks are liquid. As a bank approaches failure, it produces liquidity. In the presence of an adverse shock such as non-performing loans, the bank creates liquidity by reducing lending (calling back loans). In Diamond and Rajan (2005)'s model, when the fraction of non-performing loans in a bank is too high, such that the bank becomes insolvent, depositors

Figure 3: LIQUIDITY AND LENDING BEFORE FAILURE. Liquidity is the ratio of liquid assets to deposits, and lending is the nominal value of disbursed loans. Both variables are in logarithms. The plot shows point estimates and 90% confidence intervals for the coefficients on the event-time dummies in regressions that include bank fixed effects.



run on that bank. The bank thus calls bank all loans to produce liquidity to satisfy depositors. From the perspective of a prospective buyer of a bank, after a deposit run, the liability side of the balance sheet contains fewer liquid liabilities since depositors most likely to flee have already done so. Thus, the behaviour of depositors and the bank makes the balance sheet of a failing bank insolvent but liquid.

The Figure 3 precisely shows that, on average, a bank becomes more liquid as it approaches failure by cutting down on lending. The measure of liquidity is the ratio of liquid assets (cash and marketable securities) to deposits. The higher this ratio, the more attractive the failing bank is to a potential buyer since the bank requires less immediate liquidity. Lending is the face value of disbursed loans. Hoarding liquidity prevents a run, and it makes the bank attractive for an M&A exit. In the Supplementary Material, I show that on average, banks that exited as M&A became more liquid as they approached failure than those liquidated by the central bank.

Indeed the critical assumption of Diamond and Rajan (2005) is that all bank loans to non-

banks are relationshiop lending such that only that bank has unique extraction skill that is lost if the bank fails. This implies that the value of a loan is lower when shold to another bank, "banks assets are unsolvable". There is no direct interbank lending in Diamond and Rajan (2005) but all banks linked to a common pool of liquidity. It is reasonable to think that relationshiop lending also occurrs between banks when a interbank network exists. Relathioshiop lending between banks makes the creditor of a failing bank having a unique extraction skill of the loans of the failed bank. The network mitigates this unsellable characteristic

In addition to the above mechanism, bank failures create liquidity through the Deposit Insurance Corporation. Of the 43 failures, in 7 cases the Deposit Insurance Corporation provided support in the form of cash or warrantees totalling ARS $ 323 millions between 1999Q1 and 2001Q4 importing an amount equal to 9% of all cash of the financial entities at December 2000.

The interbank lending network helps to redistribute this extra liquidity across the financial system. One sepecficing mechanis through this ocurred is through the liquidation of failing institutions. Between 1999 and 2002 there were 43 failing banks, 31 of these failures of these failures another bank bought the failing bank either entirely through a merger & acquisition or selected assets and loans through a liquidation process. In 15 of these 31 cases the buyer bank was a former lender to the failed institution, see Table 6. This suggest that previous lending gave the former lender bank an informational advantage as a buyer since as previous lender it has already obtained unique information about the failing institution.

Table 6: WHO BUYS A FAILING BANK? Failures between 1998Q4 and 2002Q3 by type of failure and buyers.

Type of failure	Frequency	Percent	Buyers with previous link
Revoked and Partial sale	14	33%	7
M&A	16	37%	8
Voluntary closure	9	21%	-
Central-bank liquidity assistance	4	9%	-
Totals	43	100	13

7 CONCLUSIONS

Financial networks can amplify shocks, configuring a cascade effect where the failure of a bank leads to the failure of linked banks; or they can increase the efficiency of the banking system by redistributing liquidity where it is more needed.

I find that the financial network protected the banking system in the Argentinian case under study. The estimated contagion effect is negative, economically and statistically significant, showing that the failure of a borrower bank *reduces* the failure probability of lender bank(s). This contagion effect protects the financial system because it *reduces* the failure probability of remaining banks. The protective feature emerges because bank failures free more liquidity than they destroy, and the interbank network then redistributes the extra liquidity among surviving banks. Preexisting interbank linkages facilitated the resolution of bank failures.

I find, notwithstanding that, as a result of contagion, the beneficial effect of bank capital in averting failures is lower than when banks are not interconnected. The spatial model predicts that when a bank raises its equity levels, it has a negative externality effect on other banks because, on average, some of this extra equity is funnelled towards interbank lending, thus building up a fragility in other parts of the system.

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.

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