Contagion of bank failures through the interbank network in Argentina

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Why do banks fail?

Contract theory: capital structure

The equity buffer e_i

"Virtually all [empirical] studies find that low capital ratios raise the probability of bank failure."
Berger & Roman (2020)

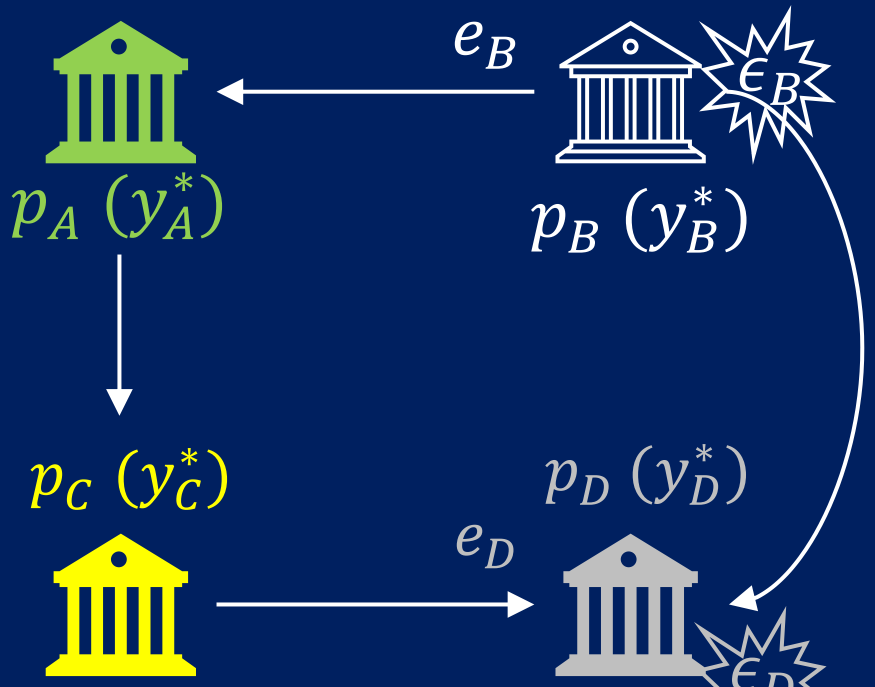
Virtually all such studies assume independent and thus isolated banks.

Network theory: Contagion in financial networks

Why do banks fail?

Network theory: Contagion in financial networks

Arrows describe cash-flow direction when the market clears



Bank C *owes* money to D

Allen & Gale (2000)

- The structure matters for the propagation of shocks.
- The more links the better

Gai & Kapadia (2010)

- Sometimes less links is better.
- Robust-yet-fragile systems

The $in\ degree_i$ of node i

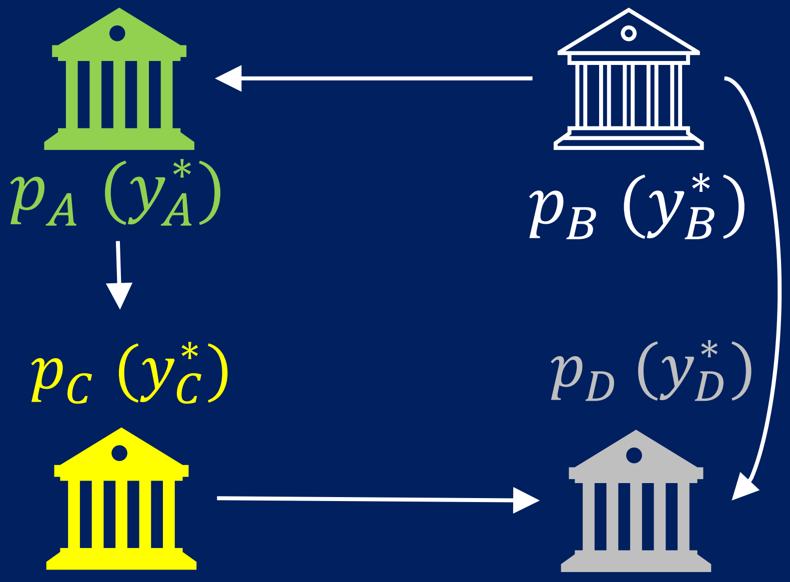
$$p_i \propto in\ degree_i$$

The spatial approach

Network data

The spatial approach

The weight matrix



Bank C *owes* money to D

$W =$

Borrower →

	Bank A	Bank B	Bank C	Bank D
Bank A	0	0	0.2	0
Bank B	0.1	0	0	0.3
Bank C	0	0	0	0.4
Bank D	0	0	0	0

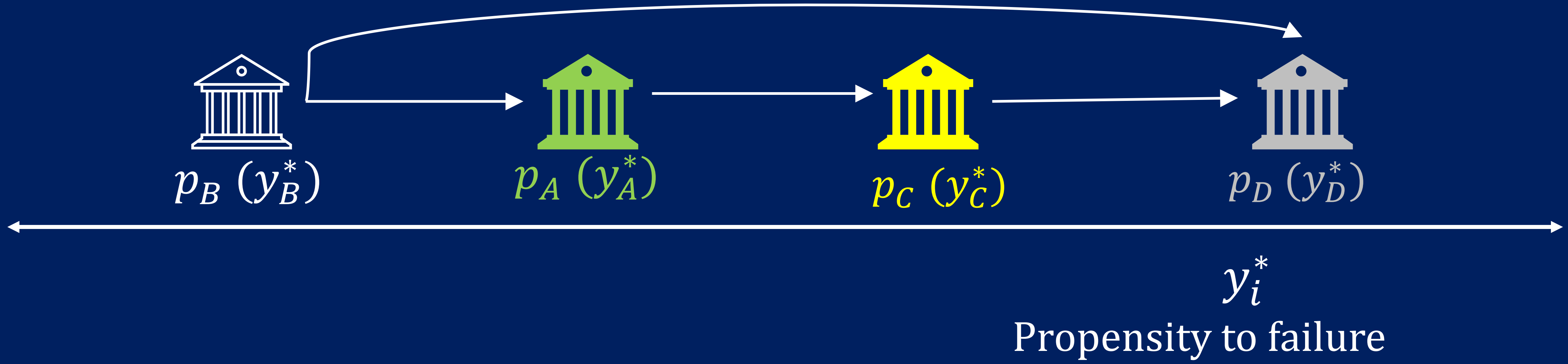
- $w_{C,D} = \frac{Loan\ \$}{Total\ loans\ D\ \$}$

- Main diagonal is 0

The spatial approach

Spatial autoregressive process (SAR)

The latent variable is spatially correlated



$$\mathbf{y}^* = \rho \mathrm{W}\, \mathbf{y}^* + \mathrm{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad \boldsymbol{\varepsilon} \sim \mathcal{N}(\mathbf{0}, \mathrm{I}_\mathrm{N})$$

- W main diagonal is 0
- The scalar $|\rho| \in (0,1) \approx$ a correlation coefficient

The spatial approach

Spatial autoregressive process (SAR)

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

$$\mathbf{y}^* = \underbrace{(I_N - \rho W)}(^{-1}) X\boldsymbol{\beta} + (I_N - \rho W)^{-1}\boldsymbol{\varepsilon}$$

$$(I_N - \rho W)^{-1} \approx I_N + \rho W + \rho^2 \underbrace{W^2}_{W^2 \equiv W \times W} + \rho^3 W^3 + \cdots.$$

- The "friends of your friends"

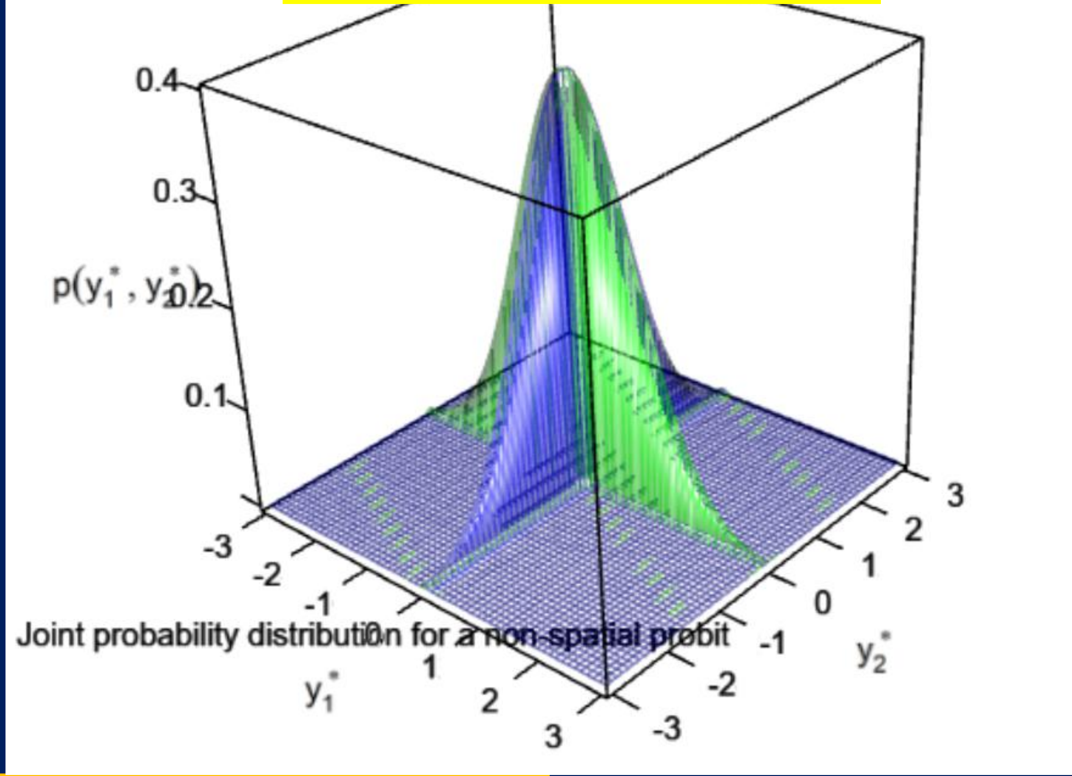
Feedback effects

Higher-order effects

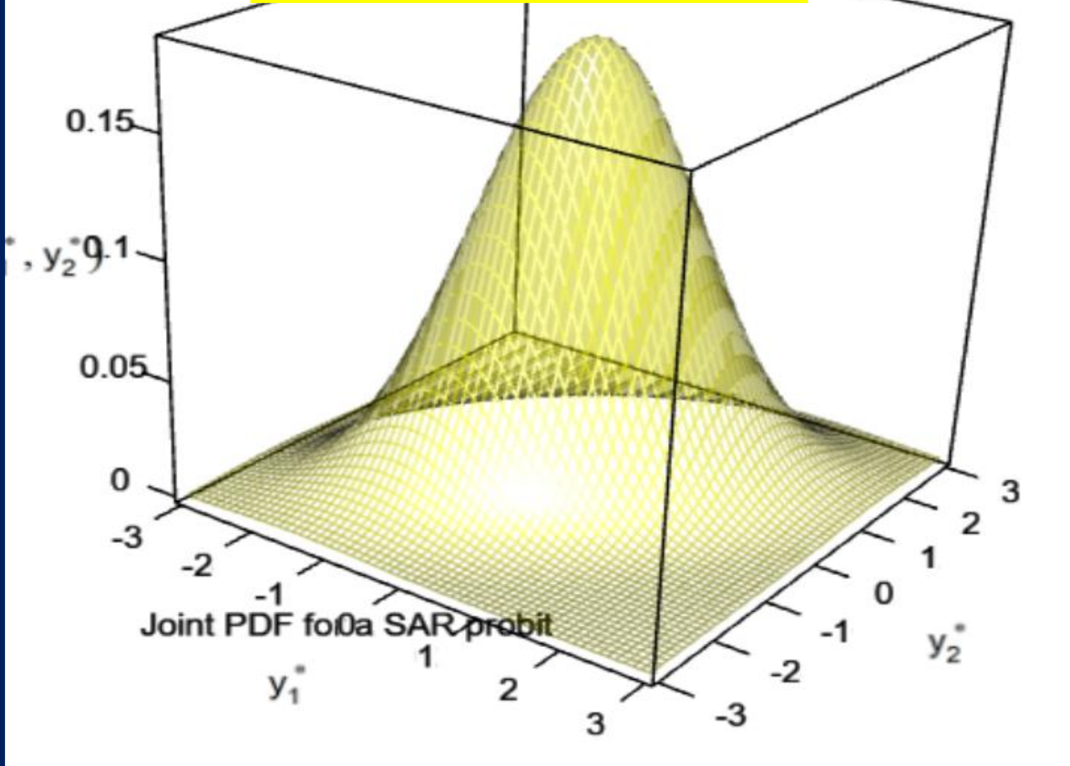
The joint probability of $\boldsymbol{y}^*$ and $\boldsymbol{y}$

The problem with $N = 2$

$\mathcal{L}$ non-spatial probit



$\mathcal{L}$ spatial probit



Numerical integration

Simulation

Analytical approximation

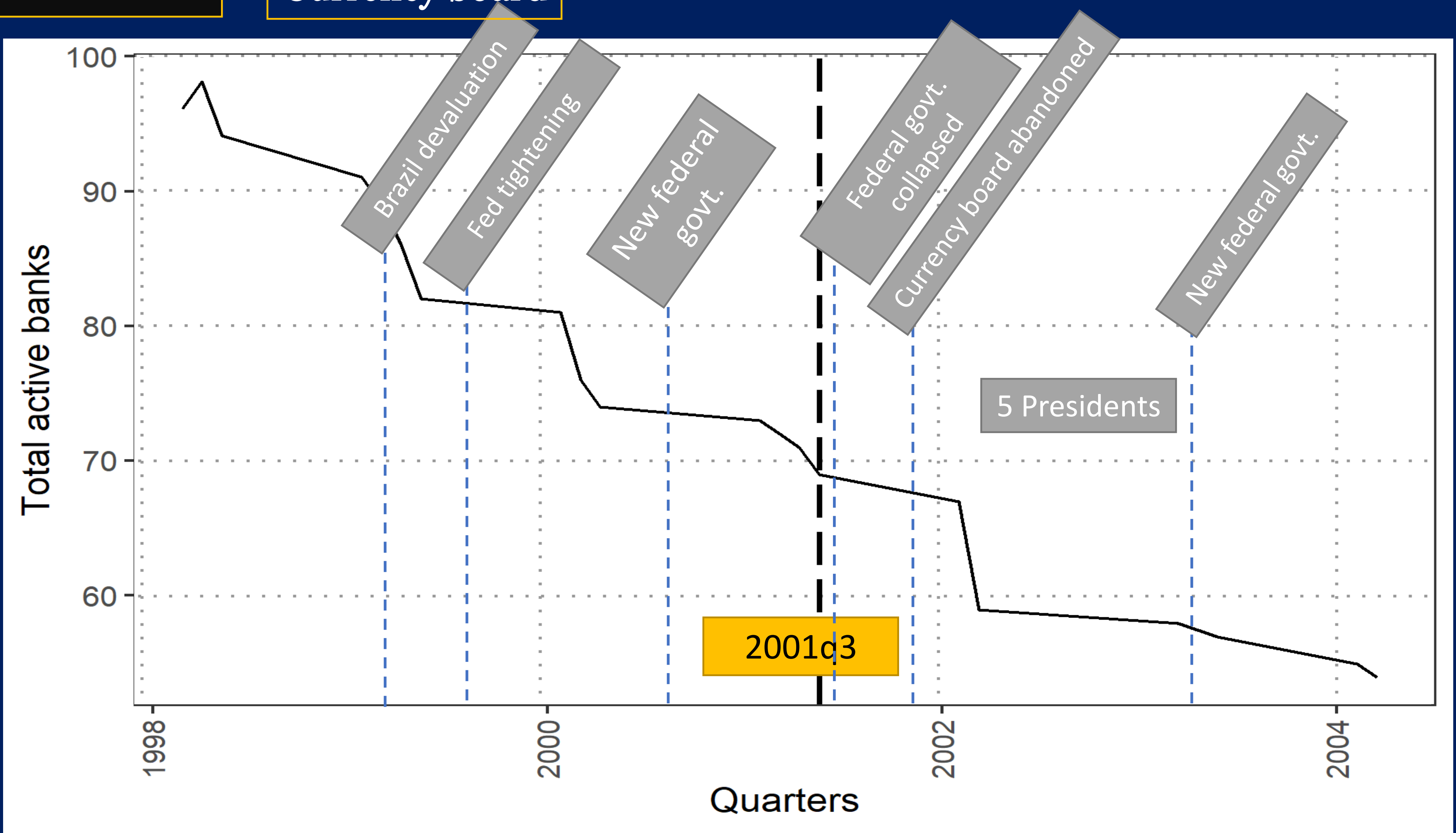
Martinetti & Geniuaux (2017), *Approximate likelihood estimation of spatial probit models*

Sample description

$$\mathbf{y}_t^* = \rho W_{t-1}\mathbf{y}_t^* + X_{t-1}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

Historical context

Currency board



Sample description

Historical context

Currency board

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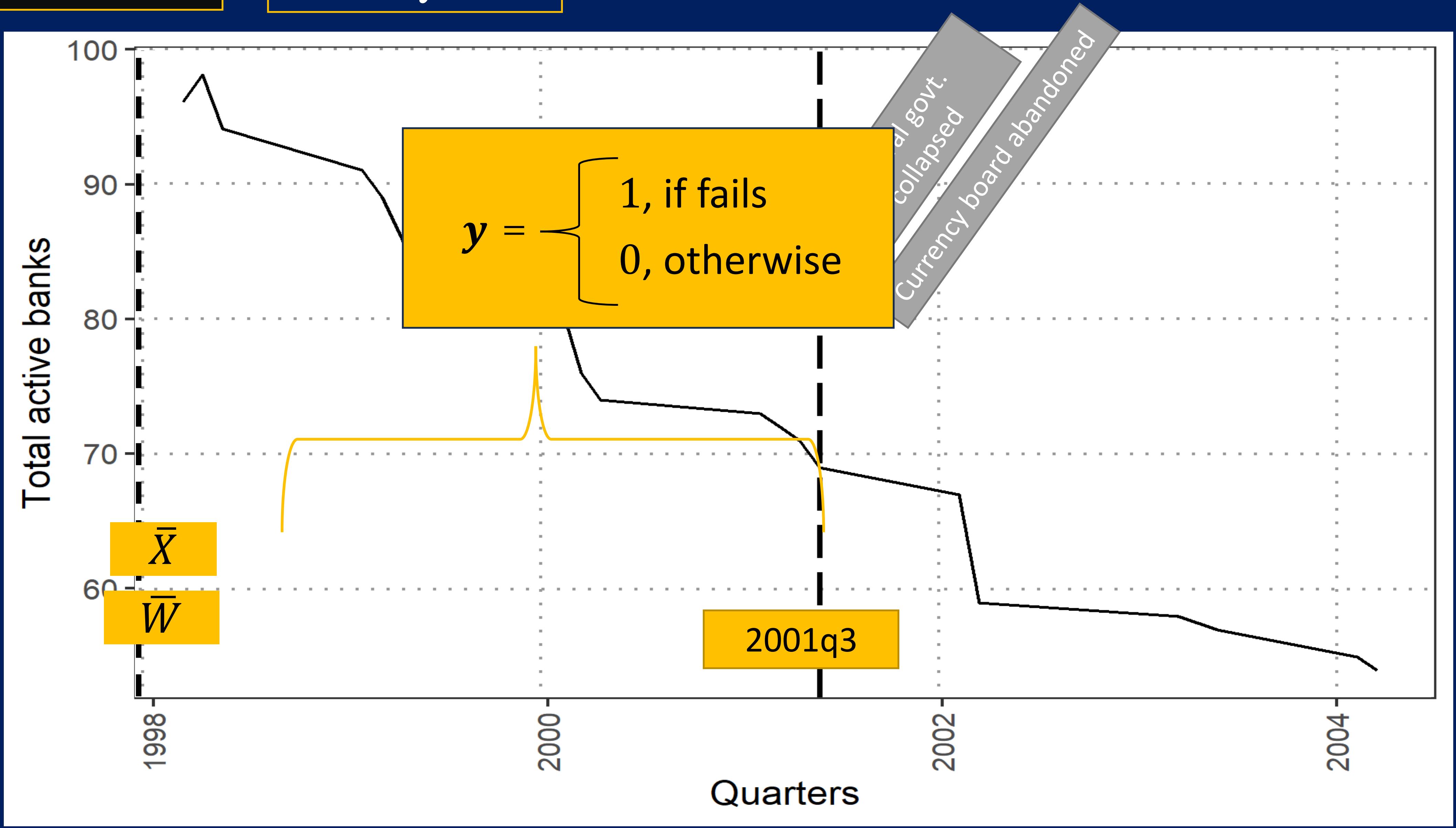


$$\boldsymbol{y} = \begin{cases} 1, \text{ if fails} \\ 0, \text{ otherwise} \end{cases}$$

$\bar{X}$

$\bar{W}$

The Network

$$\mathbf{y}_t^* = \rho W_{t-1}\mathbf{y}_t^* + X_{t-1}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

Credit registry

Central Bank *Central de Deudores*

# Links	# lender banks	# borrower banks	Avg loan size
584	61	72	1.52

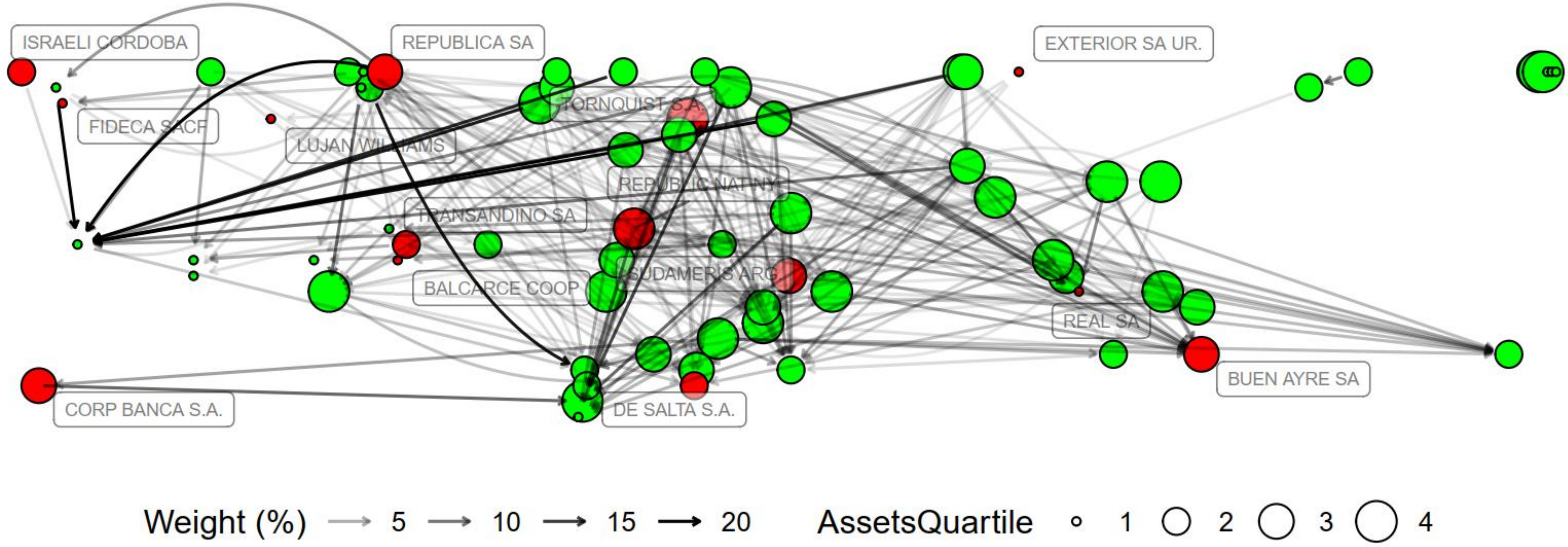
- Links are from borrower to lender.

The Network

$$y_t^* = \rho W_{t-1} y_t^* + X_{t-1}\beta + \varepsilon_t$$

# Links	# lender banks	# borrower banks	Avg loan size
584	61	72	1.52

- 70% of failing banks were directly connected before the crisis



The Network

$$\mathbf{y}_t^* = \rho W_{t-1}\mathbf{y}_t^* + X_{t-1}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

# Links	# lender banks	# borrower banks	Avg loan size
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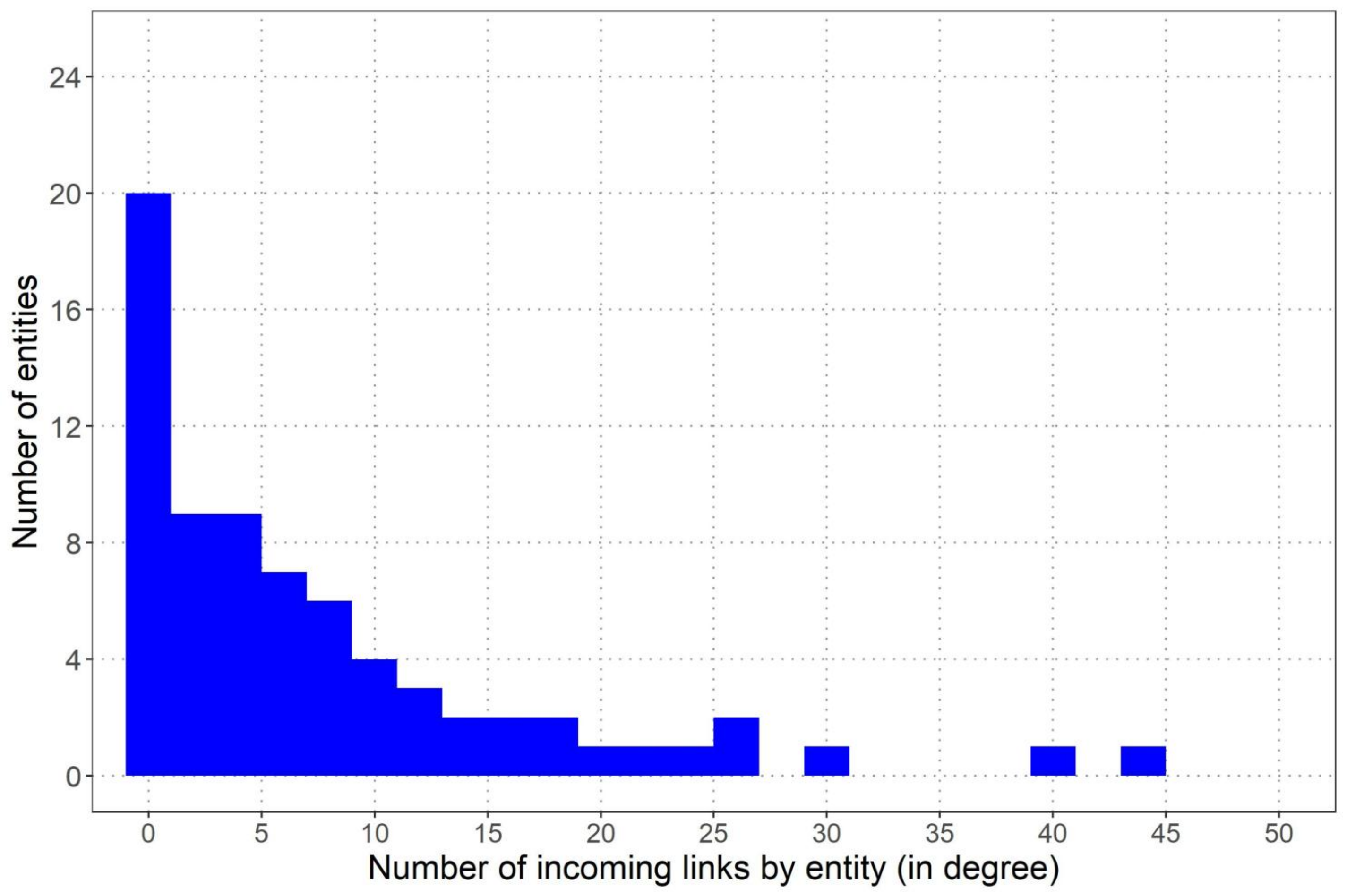
In-degree distribution (# assets)



Is there network contagion?

$$\mathbf{y}_t^* = \rho W_{t-1}\mathbf{y}_t^* + X_{t-1}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

Coefficient estimates

Cross-section

	Predicted variable:= $\mathbf{1}(failure)$	
PREDICTOR / MODEL	Probit	SAR probit
Size		
Logarithm of Assets	-0.40**	-0.47***
Asset-side risk		
Non-performing loans	0.03	-1.13
Lending rate	0.96	1.01
Lending in USD	1.68	2.83
Funding		
Equity-to-Assets (%)	-4.94**	-4.20**
Spatial		
ρ		-0.53**

Number of observations is 72; *** p<1%, ** p<5%, * p<10%,

Panel data results

The network dampens shocks

$$\mathbf{y}_t^* = -0.53\mathrm{W}_{t-1}\mathbf{y}_t^* + \mathrm{X}_{t-1}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

$\hat{\rho} = -0.53$

$$\mathbf{y}^* = \cdots (\mathrm{I}_N - \rho \mathrm{W})^{-1}\boldsymbol{\varepsilon}$$

with $\mathrm{W}\mathbf{1}_N = \mathbf{1}_N$.

$$(\mathrm{I}_N - \rho W)^{-1} \approx \mathrm{I}_N + \rho W + \rho^2 W^2 + \cdots.$$

The network multiplier

$$\frac{1}{1-\rho} = 0.65 < 1$$

- $\rho < 0 \rightarrow$ "substitution effect" of failures

Is there network contagion?

$$\mathbf{y}_t^* = -0.53\mathbf{W}_{t-1}\mathbf{y}_t^* + \mathbf{X}_{t-1}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t$$

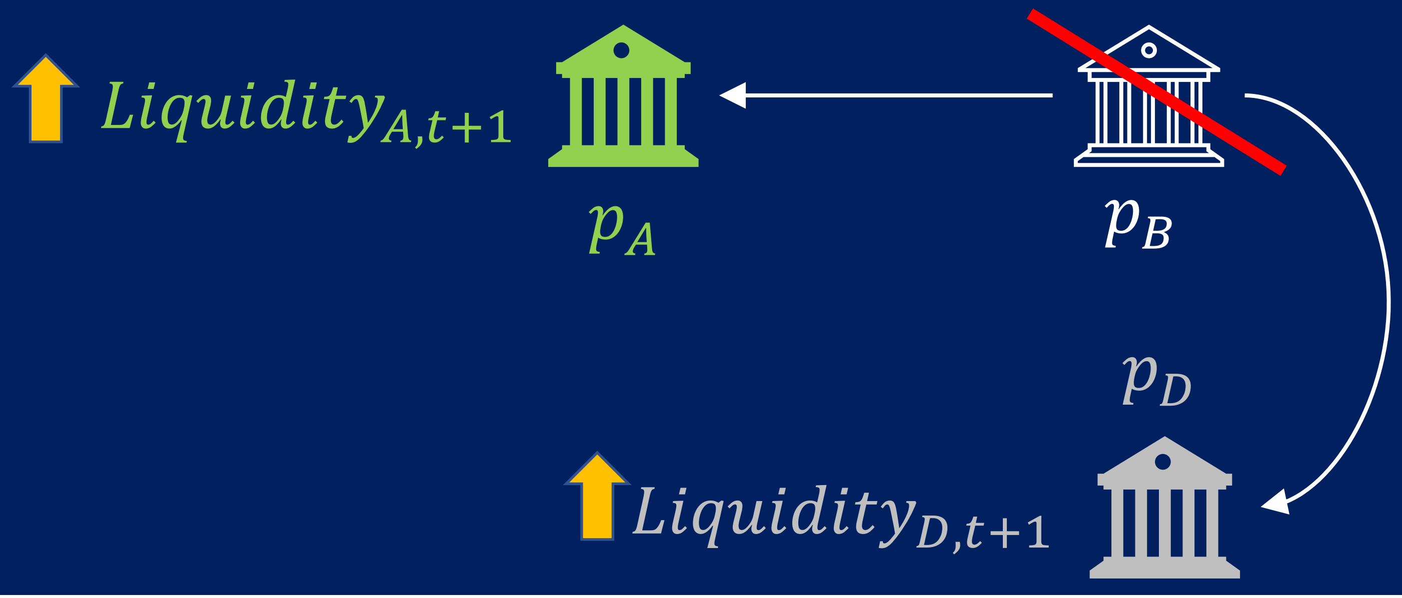
Yes. The failure of a bank *reduces* its neighbors failure probability

Why?

A bank failure increases liquidity in the system (Diamond & Rajan 2001)

The network facilities the redistribution of this extra liquidity among surviving banks

- On average surviving neighbors (lenders) increase their liquid assets by 5% and their deposits by 0.5% the quarter after a failure
- Deposit insurance



The network *protects* the banking system. But not necessarily the macroeconomy!

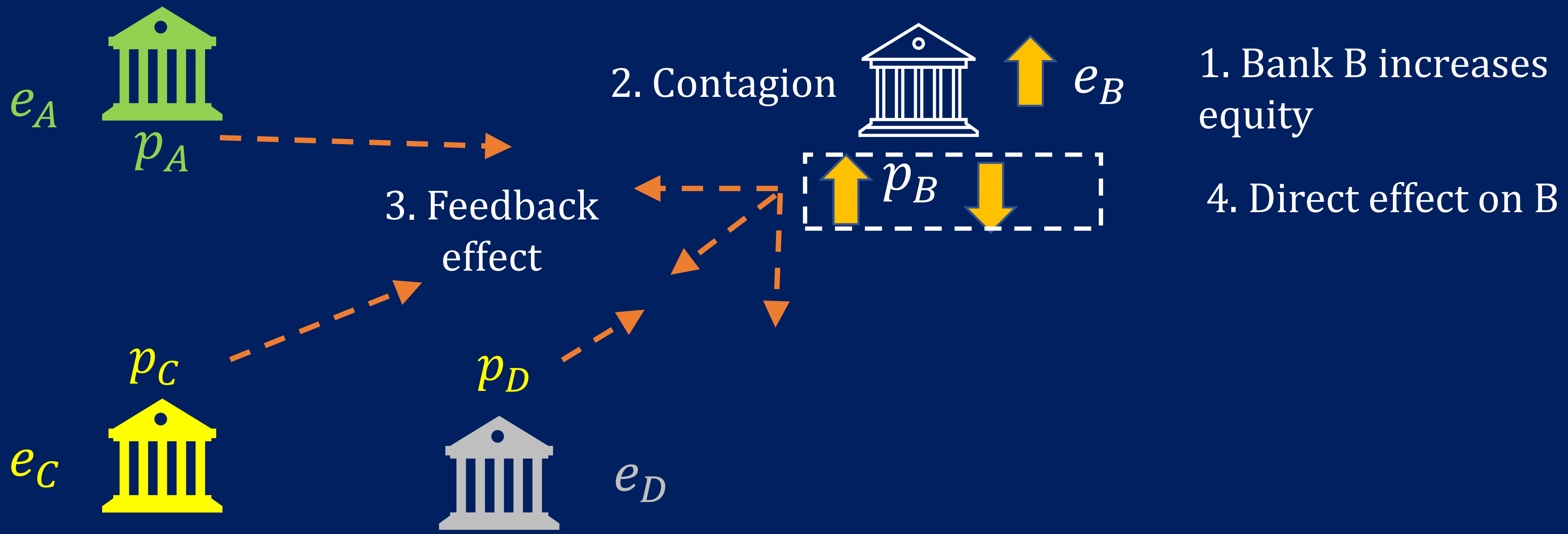
Consequences of network contagion

The direct marginal effect of equity

$$E\left[\frac{\partial p_i}{\partial x_{i,e}}\right]$$

Own spillover effect

	SAR Probit			Probit
	Direct	Indirect	Total	
Equity-to-Assets	-0.84		-0.54	-1.08



Consequences of network contagion

The indirect marginal effect of equity

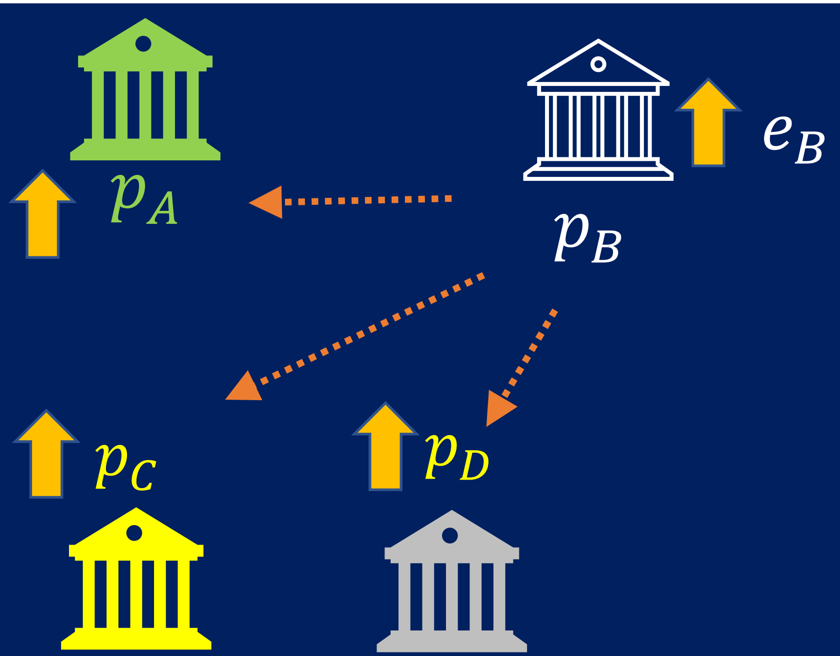
$$\boxed{E\left[\frac{\partial p_i}{\partial x_{j,e}}\right]}$$

Spillover effect

	SAR Probit			Probit
	Direct	**Indirect**	Total	
Equity-to-Assets	-0.84	0.30	-0.54	-1.08

1. Bank B increases equity

2. Other banks increase their failure probability



Equity as a public good

$\varepsilon_{IL,e} > 1$

Consequences of network contagion

The total marginal effect of equity

	SAR Probit			Probit
	Direct	Indirect	Total	
Equity-to-Assets	-0.84	0.30	-0.54	-1.08

Equity is 50% less effective when banks are interconnected

$$E\left[\frac{\partial p_i}{\partial x_{i,e}}\right] + E\left[\frac{\partial p_i}{\partial x_{j,e}}\right] = \boxed{E\left[\frac{\partial p}{\partial x_e}\right]}$$

Consequences of network contagion

The total marginal effect of lending in USD

	SAR Probit			Probit
	Direct	Indirect	Total	
Equity-to-Assets	-0.84	0.30	-0.54	-1.08
Lending in USD	0.56	-0.20	0.37	0.37

$$E\left[\frac{\partial p_i}{\partial x_{i,e}}\right] + E\left[\frac{\partial p_i}{\partial x_{j,e}}\right] = \boxed{E\left[\frac{\partial p}{\partial x_e}\right]}$$

Lending in the USD ¿is the same?

Strategic interactions: Farhi & Tirole (2012)

Conclusions & further agenda

Network

Complete and observable network of interbank linkages

The spatial approach

Captures feedback and higher-order effects

Separately identifies spillover effects

Results

70% of failing banks were directly connected

Evidence of network contagion is economically and statistically significant

Equity buffers are 50% less effective

Lender banks become more liquid after their borrowers fail

Is there network contagion?

$$\mathbf{y}^* = \rho W\,\mathbf{y}^* + X\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

Panel sample - Pool

With quarter fixed effect.

	Predicted variable:= $\mathbf{1}(failure)$			
PREDICTOR / MODEL	LPM	SAR LPM	Probit	SAR Probit
Size				
Logarithm of Assets	-0.01*	-0.01	-0.15	-0.04
Asset-side risk				
Non-performing loans	0.001	0.001	0.001	0.001
Lending rate	-0.001	-0.001	-0.02	-0.006
ROA	-0.001***	-0.001***	-0.04***	-0.02*
Funding				
Log of equity-to-Assets	-0.02**	-0.02*	-0.29**	-0.15.
Spatial				
ρ		-0.71**		-0.32***
In-degree	0.001	0.000	-0.001	0.006

Number of banks is 97. Number of observations is 938. *** p<1%, ** p<5%, * p<10%, . p<15%

The Network

$$\mathbf{y}^* = \rho W \, \mathbf{y}^* + X\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

Interbank loans

(Overnight) Interbank market

Forte (2020)

Balance sheet

Veld Lelyveld (2014)

Credit registry

Central Bank *Central de Deudores*

$W =$

	Bank A	Bank B	Bank C	TOTAL
Bank A	0	?	?	100
Bank B	?	0	?	120
Bank C	?	?	0	15
TOTAL	60	25	150	0

The Network

$$\mathbf{y}^* = \rho W\, \mathbf{y}^* + X\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

Credit registry

Central Bank *Central de Deudores*

Links weighted from the lender bank perspective

Date	Lender bank name	Lender bank ID	Debtor TFN	Debtor name	Debtor bank ID	Loans ARS$
1998m7	CREDICOOP COOP.LTDO.	191	30500000747	BANCO COMERCIAL DE TRES ARROYO	107	0.60
1998m7	BANSUD S.A.	67	30500000747	BANCO COMERCIAL DE TRES ARROYO	107	13.00
1998m7	BANKBOSTON, NATIONAL ASSOCIA…	15	30500000747	BCO DE TRES ARROYOS	107	0.20
1998m7	MORGAN GUARANTY TRUST CO OF …	165	30500001735	BANCO DE GALICIA Y BUENOS AI…	7	0.00
1998m7	RIO DE LA PLATA S.A.	72	30500001735	BANCO DE GALICIA Y BS AS	7	861.00
1998m7	NAZIONALE DEL LAVORO S.A.	265	30500001735	BANCO DE GALICIA Y BUENOS AIR…	7	20,003.50
1998m7	REAL DE ARGENTINA S.A.	167	30500001735	BANCO DE GALICIA Y BS AS	7	2,500.40
1998m7	BANK OF AMERICA S.A.	3	30500001735	BCO DE GALICIA Y BUENOS AIRES	7	4,568.70
1998m7	DE GALICIA Y BUENOS AIRES	7	30500001735	BCO GALICIA Y BS AS SOC DEP F…	7	92.00
1998m7	QUILMES S.A.	43	30500001735	BANCO DE GALICIA Y BUENOS AIRE	7	91.40
1998m7	MBA BANCO DE INVERSIONES S.A.	312	30500001735	BANCO DE GALICIA Y BUENOS AIR…	7	0.00
1998m7	B.I.CREDITANSTALT S.A.	147	30500001735	BANCO DE GALICIA Y BUENOS AIR…	7	0.00
1998m7	DO BRASIL S.A.	46	30500001735	BANCO DE GALICIA Y BUENOS AIR…	7	18.30

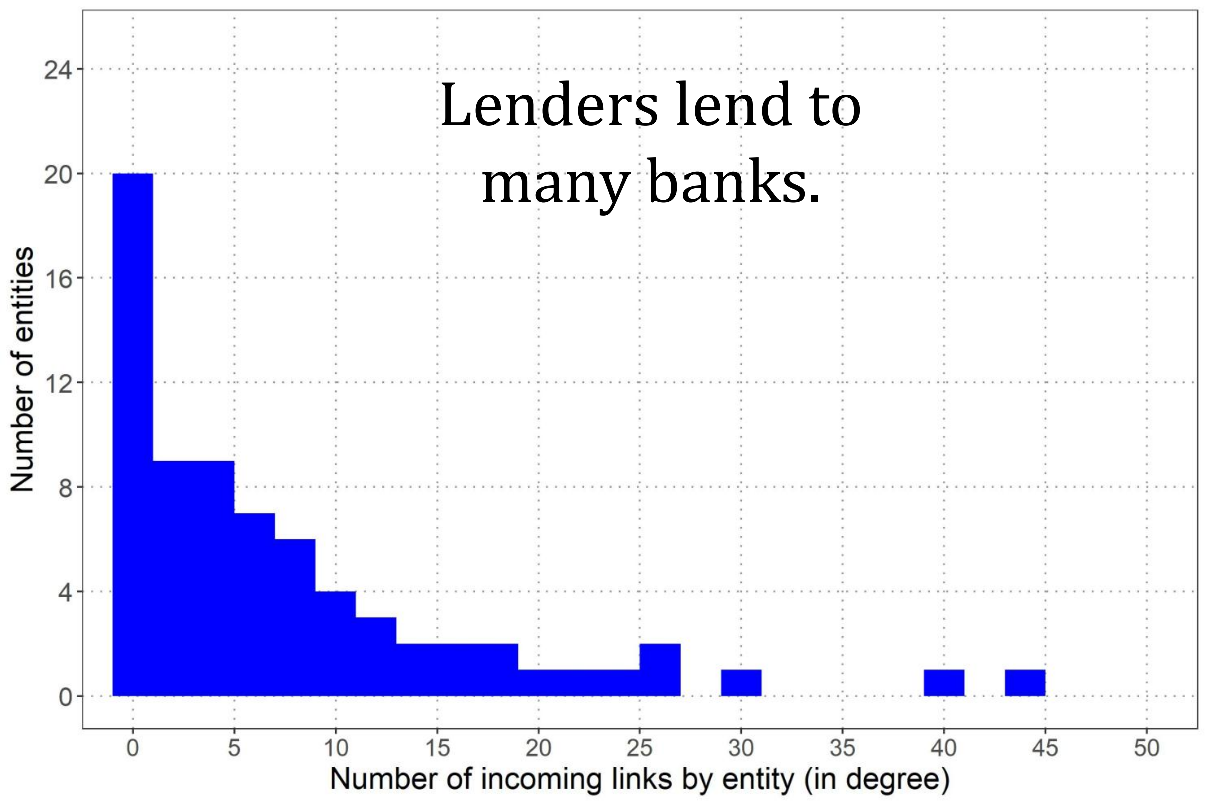
The Network

$$\mathbf{y}^* = \rho W \, \mathbf{y}^* + X\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

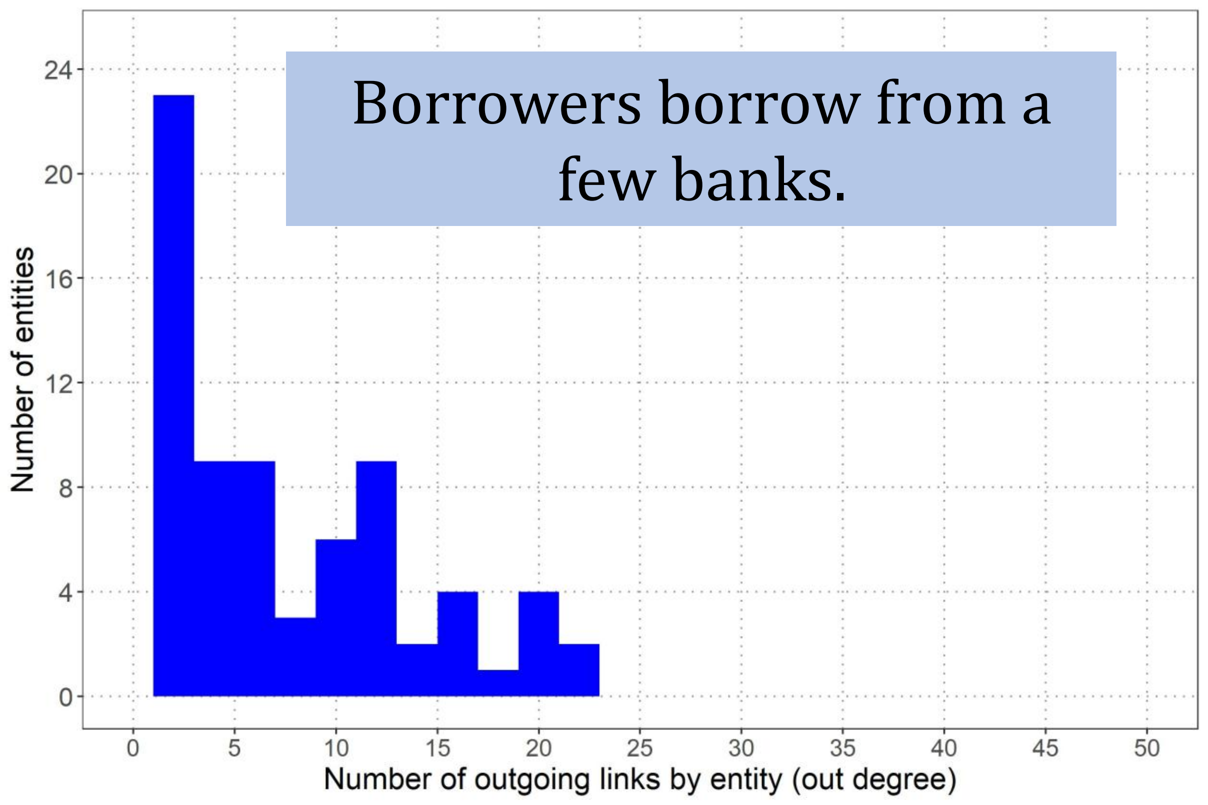
Links are from borrower to lender

# Links	# lender banks	# borrower banks	Avg loan size (% lender total loans)
584	72	61	1.52

In-degree distribution (# assets)



Out-degree distribution (# debts)



Sample description

$$\mathbf{y} = \rho W\,\mathbf{y} + X\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

Entities

- Active at 1997q4
- Local private
- Complete observations
- In the network

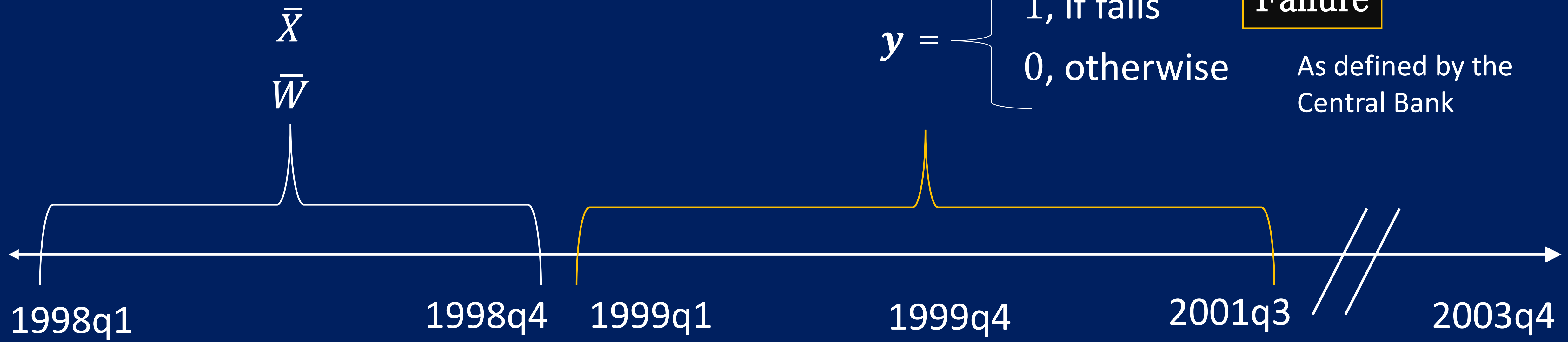
N	72
Failure rate	0.19

Time

$$y = \begin{cases} 1, \text{ if fails} \\ 0, \text{ otherwise} \end{cases}$$

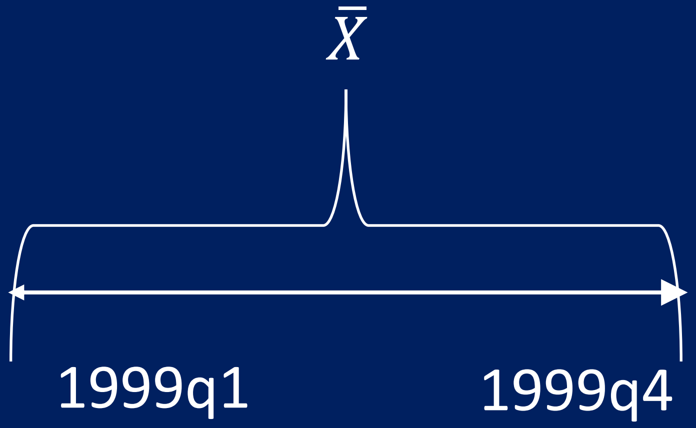
Failure

As defined by the Central Bank



Sample description

$$\mathbf{y} = \rho W\,\mathbf{y} + X\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$



- Annual predictors: within average for **1998**
- Failure between 1999q1 y 2001q3

N	72
Failure rate	0.19

Predictor	**Mean**	**Coef. of variation**
Size		
Assets in ARS \$ (mill)	1,341	1.9
Credit risk		
Non-performing assets (%)	7.66	0.71
Lending rate (%)	23.3	0.4
Lending to Public Sector (%)	4.19	1.9
Lending in USD (%)	57.8	0.4
Loans-to-Assets (%)	51.1	0.3
Funding		
Equity-to-Assets (%)	15.8	0.7
Return-on-Assets (%)	0.9	3.1
Deposit rate (%)	5.20	0.56

$$R_e = \left[\frac{\partial Pr(\boldsymbol{y}=1)}{\partial x'_e}\right] = \mathrm{diag}[\phi(\boldsymbol{\eta})]\,(I_N - \rho W)^{-1}\,\beta_e.$$

$$= \begin{bmatrix} \frac{\partial \mathbb{E}y_1}{\partial x_{1,k}} & \cdots & \frac{\partial \mathbb{E}y_1}{\partial x_{i,k}} & \cdots & \frac{\partial \mathbb{E}y_1}{\partial x_{N,k}} \\ \cdots & & & & \\ \frac{\partial \mathbb{E}y_i}{\partial x_{1,k}} & \cdots & \frac{\partial \mathbb{E}y_i}{\partial x_{i,k}} & \cdots & \frac{\partial \mathbb{E}y_i}{\partial x_{N,k}} \\ \cdots & & & & \\ \frac{\partial \mathbb{E}y_N}{\partial x_{1,k}} & \cdots & \frac{\partial \mathbb{E}y_N}{\partial x_{i,k}} & \cdots & \frac{\partial \mathbb{E}y_N}{\partial x_{N,k}} \end{bmatrix}$$