Foreign Booms, Domestic Busts: The Global Dimension of Banking Crises

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*The views expressed in this paper do not necessarily reflect the position of the Bank of England.

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- Elevated domestic credit growth is the best single predictor of the occurrence of banking crises at home [Schularick and Taylor (2012)]...

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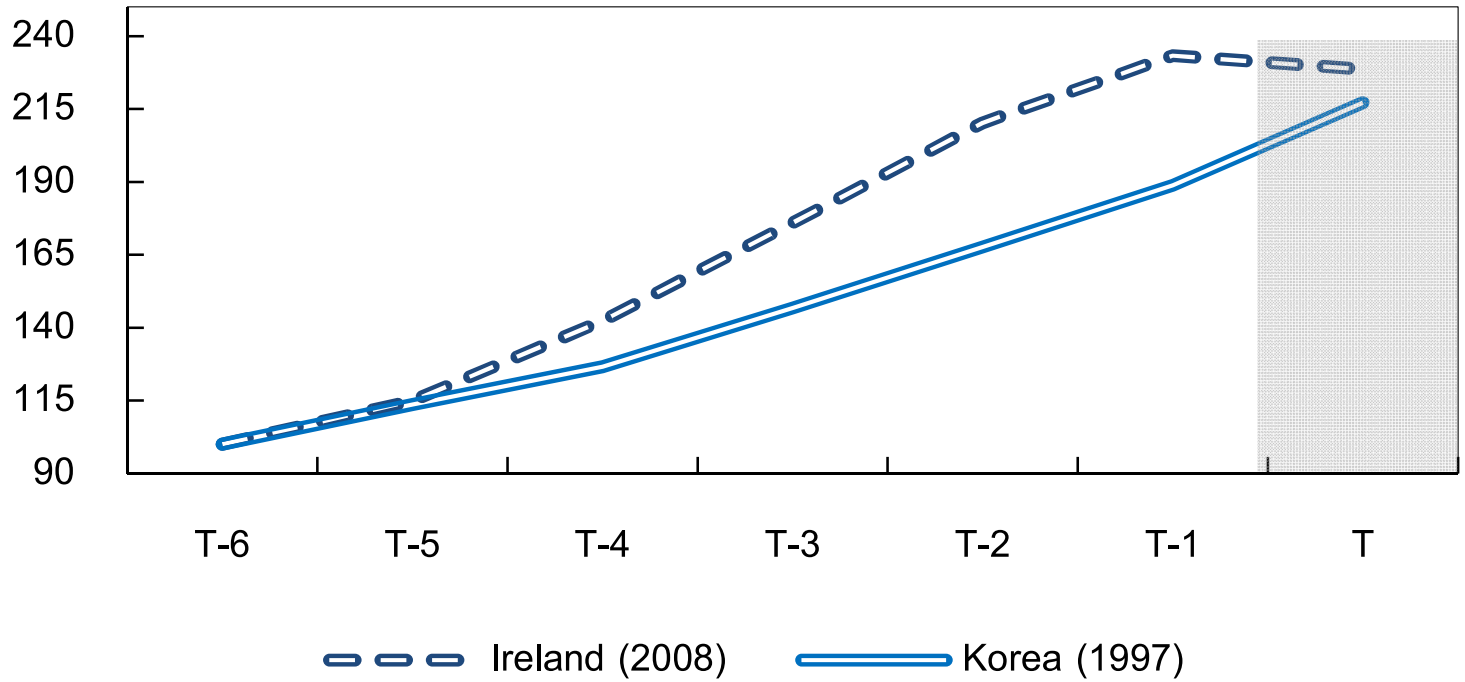

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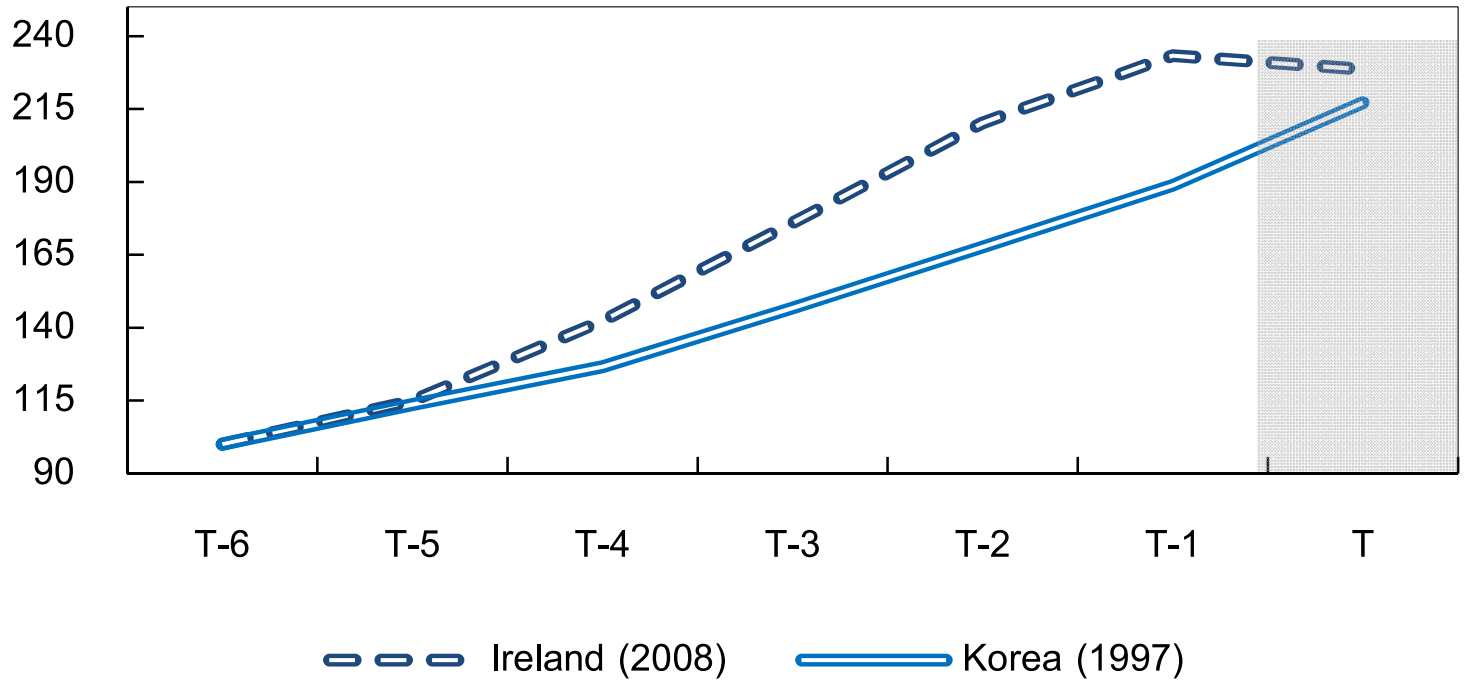
- ... but in some cases banking crises are not preceded by booming domestic credit



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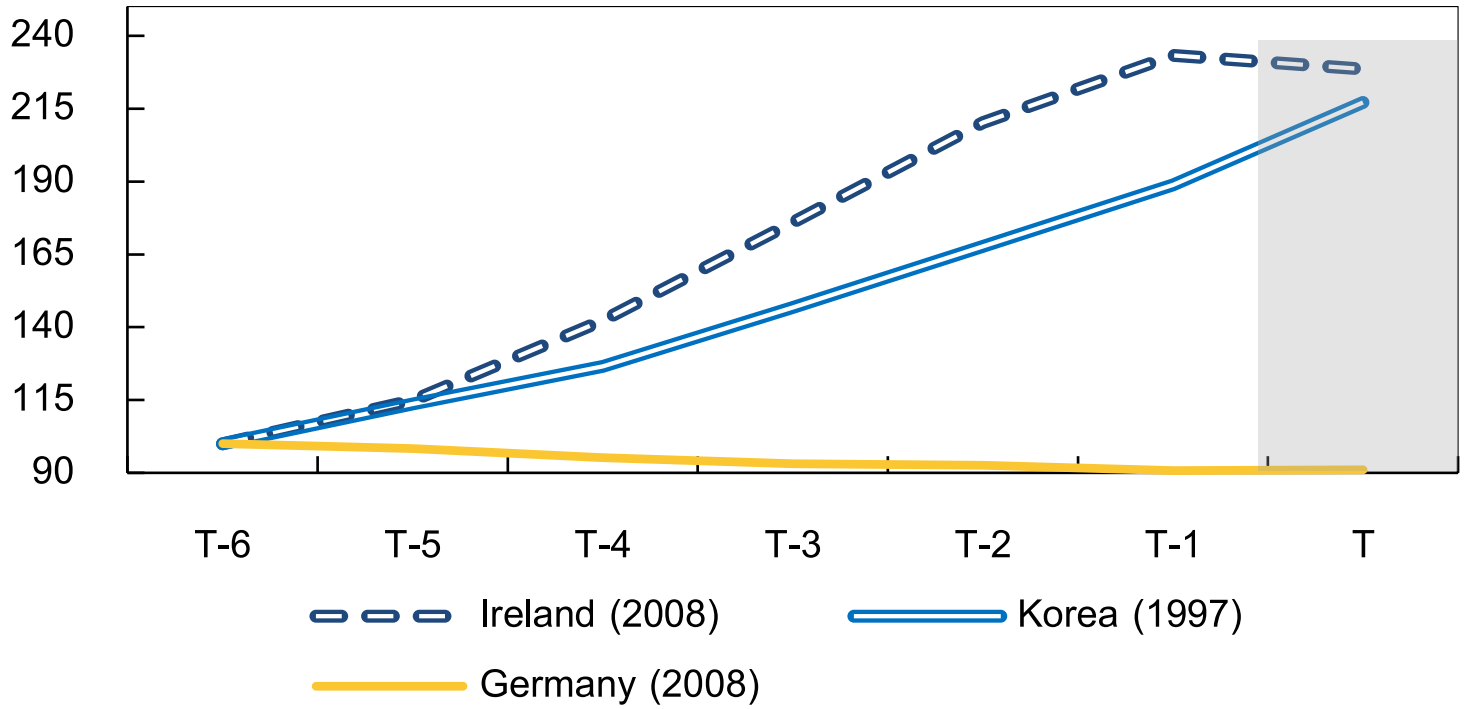

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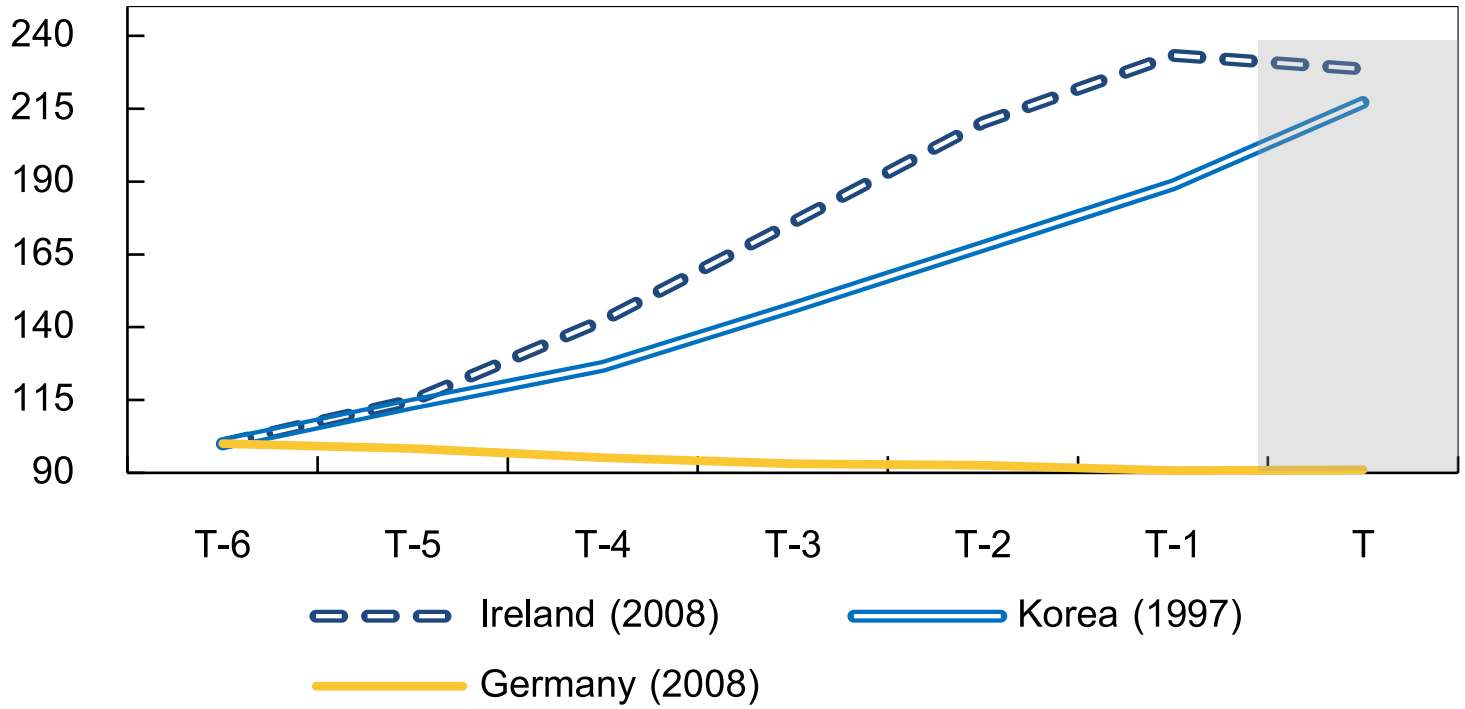
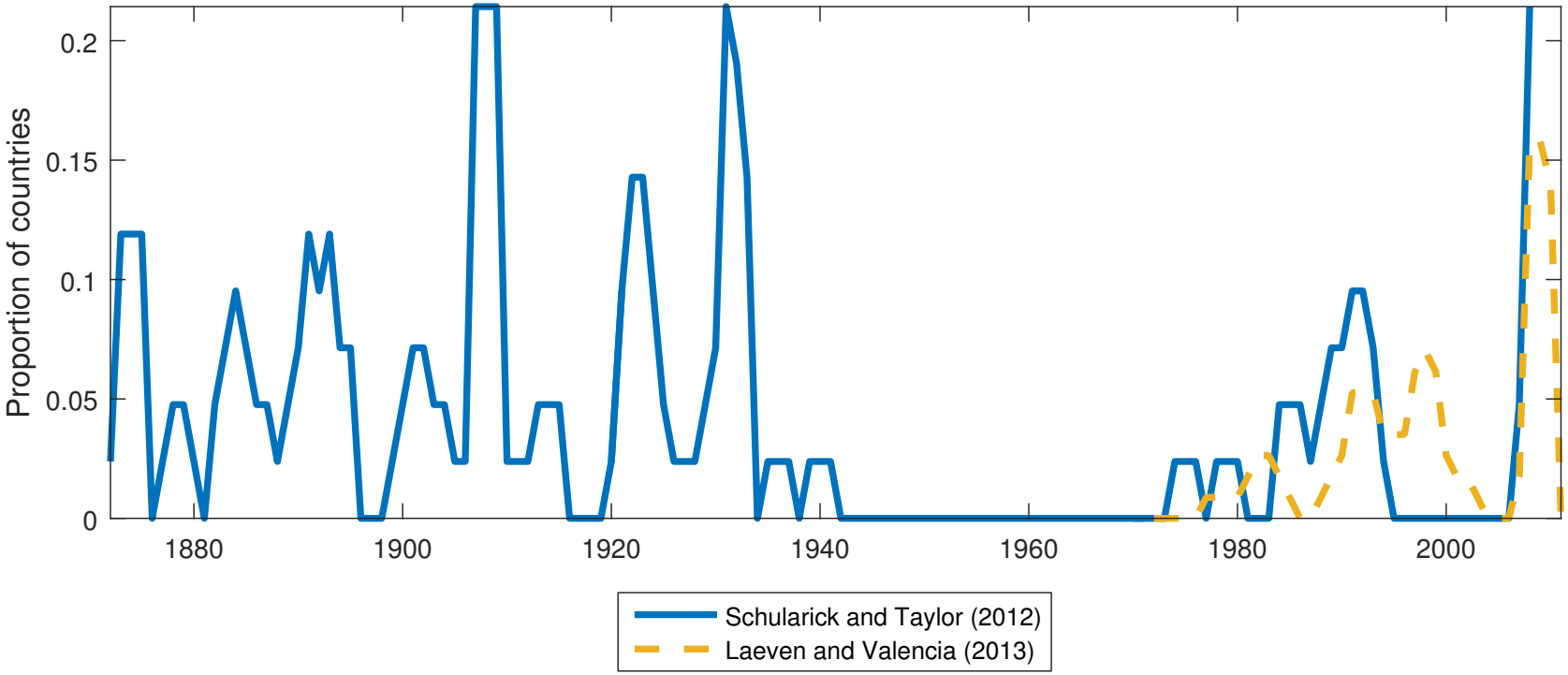


- **Question** What other factors can explain the occurrence of banking crises?

"Waves" of banking crises

- Proportion of countries with systemic banking crises



NOTE. Proportion of countries with (the start of) systemic banking crises over a long historical sample going from 1870 to 2008 using ST historical data set; and over the shorter period from 1970 to 2011 using LV data set. 3-year moving average as in Reinhart and Rogoff (2009).

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- **This paper** Departs from domestic focus and considers the role of *foreign* factors for predicting *domestic* banking crises

The global dimension of banking crises

- "Boom-less" busts
- Banking crises come in waves [Reinhart and Rogoff (2009)]
- **This paper** Departs from domestic focus and considers the role of *foreign* factors for predicting *domestic* banking crises
- Other questions
  - Does financial/trade openness matter?
  - What is the economic mechanism?

Approach & Preview of the results

- Probabilistic model of banking crises: A foreign factor improves the model's binary classification ability

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  - Benchmark: domestic model of ST
  - Foreign credit natural starting point (ST, synchronization)
  - Booming foreign credit predicts subsequent banking crises
  - The effect is as big as that of domestic credit
  - The effect is significantly larger in financially open countries (not so in those more open to trade)

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  - The effect is as big as that of domestic credit
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- Inspecting the mechanism: Evidence of a range of financial channels
  - Contagion
  - Capital flows
  - Risk sentiment

Related literature (subset)

- Properties of financial crises and their determinants
  - Reinhart and Rogoff (2009), Laeven and Valencia (2013), Reinhart and Kaminsky (1999)
- Binary classification and signal detection in context of banking crises
  - Schularick and Taylor (2012), Jorda, Schularick and Taylor (2011)
- Global factors and domestic financial stability
  - Alessi and Detken (2011), Lo Duca and Peltonen (2013)

Outline

1. **Data**
2. Empirical results
3. Inspecting the mechanism
4. Robustness

Data

- Banking crises: Dataset from Laeven and Valencia (2013)
  - Timing of banking crises for 162 countries over 1970-2011
  - Based on range of indices including bank runs, banking system losses, bank liquidations and banking policy interventions

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  - Unbalanced panel covering 38 countries over 1970-2015

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  - Unbalanced panel covering 38 countries over 1970-2015

- Baseline dataset: unbalanced panel covering 38 countries over 1970-2011
  - Also consider longer but narrower panel in Schularick and Taylor (2012)
    - 14 advanced economies over 1870-2008

Outline

1. Data and stylized facts
2. **Empirical results**
3. Inspecting the mechanism
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The global determinants of banking crises

- Specification due to Schularick and Taylor (2012)

$$p_{it} = b_{0i} + \sum_{j=1}^{L} b_{1,j} \Delta Cred_{i,t-j} + e_{it}$$

  - p_{it} dummy variable that takes value of one when crisis begins
  - Estimate both linear probability model and Logit

The global determinants of banking crises

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$$p_{it} = b_{0i} + \sum_{j=1}^{L} b_{1,j} \Delta Cred_{i,t-j} + \sum_{j=1}^{L} b_{2,j} \Delta Cred^*_{i,t-j} + e_{it}$$

  - p_{it} dummy variable that takes value of one when crisis begins
  - Estimate both linear probability model and Logit

- Introduce foreign credit ($\Delta Cred^*_i$) as additional explanatory variable

$$\Delta Cred^*_i = \frac{\sum_{j=1}^{N} w_j \Delta Cred_{jt}}{N-1} \quad \text{for} \quad j \neq i$$

  - Proxy for a common factor [Pesaran (2006)]

Elevated foreign credit growth increases the likelihood of future domestic banking crises

Specification	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	Logit	Logit
Fixed effects	None	Country	None	Country
ΔCred				
Sum of lag coeffs	0.21**	0.27**	7.37**	10.66***
	[0.031]	[0.014]	[0.029]	[0.008]
ΔCred*				
Sum of lag coeffs	1.44***	1.42***	48.76***	49.71***
	[0.004]	[0.006]	[0.002]	[0.001]
Constant	-0.06**	-0.09***	-7.23***	-21.11***
	(0.024)	(0.027)	(1.048)	(1.299)
Observations	1118	941	1118	941
R2	0.04	0.06	0.18	0.21

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The predictive ability of global variables

- Significance of variables is important but not fully informative
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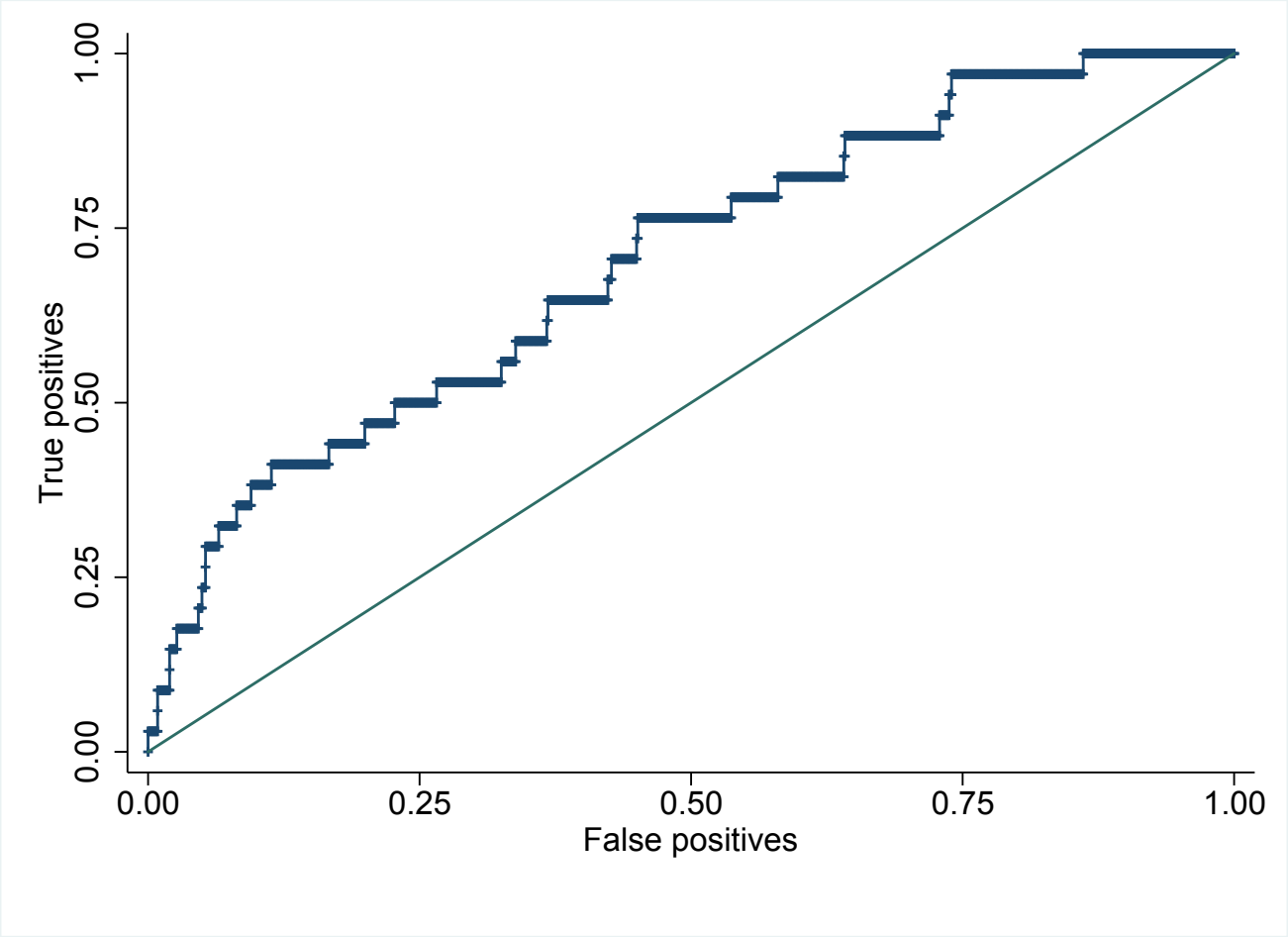
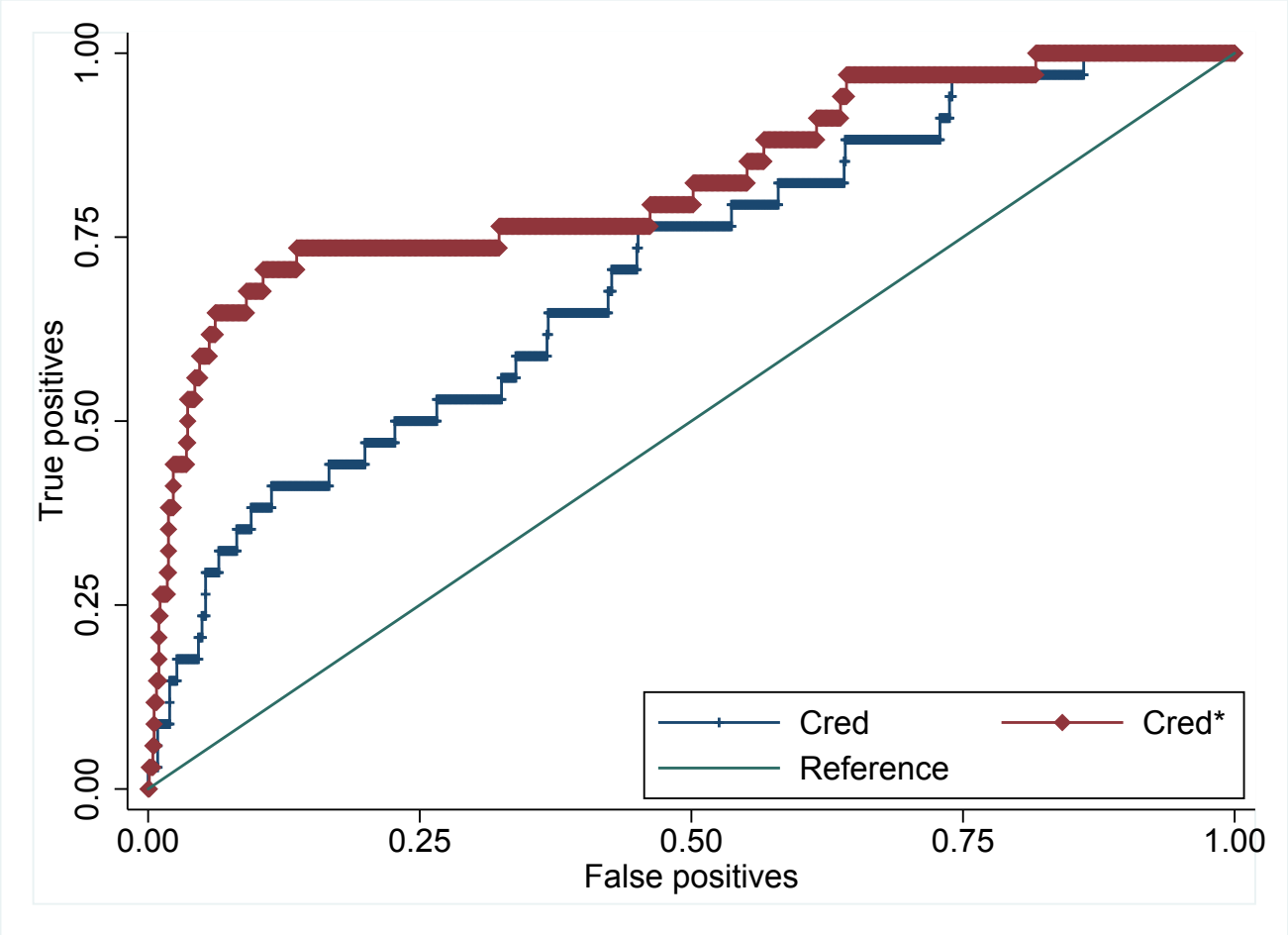
- Significance of variables is important but not fully informative
- Does the binary classification ability of model improves after including foreign credit growth?
- Use Receiving Operating Characteristic (ROC) curve
  - Predict crisis event when fitted probability goes above a pre-defined threshold
  - Plots frequency of "true positives" against "false positives" for different discrimination thresholds
  - Good models generate plots above the 45 degree line (better than random)

Binary classification ability of the model with domestic credit only



NOTE. *Cred* refers to the specification with domestic credit only and *Cred** refers to the specification with the addition of foreign credit.

Foreign credit increases ability of model to classify forthcoming crisis episodes



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The role of openness: Trade vs. Financial

- $FinOpen_{it}$: gross external liabilities over GDP [Lane and Milesi-Ferretti (2007)]

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ΔCred*				
Sum of lag coeffs	-0.16	-52.2***	1.04*	-8.45
	[0.766]	[0.010]	[0.095]	[0.818]
ΔCred* x Open				
Sum of lag coeffs	1.01***	73.36***	0.44	90.24
	[0.001]	[0.000]	[0.303]	[0.268]
Open	-0.05***	-4.85***	-0.03	-8.74
	(0.016)	(1.354)	(0.036)	(7.953)
Constant	-0.01	-17.08***	-0.07**	-17.04***
	(0.026)	(1.122)	(0.034)	(3.361)
Observations	1,115	941	1,110	936
Crises	34	34	34	34
R2	0.1	0.4	0.06	0.29

The role of openness: Trade vs. Financial

- $TradeOpen_{it}$: exports plus imports over GDP (DOTS)

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Channels of transmission

- Foreign credit is a powerful predictor for domestic crisis, but is silent about the mechanism. What are the (financial) channels of transmission?

- Could simply be that foreign credit captures crisis contagion
  - That is: $cred_{j,t-1} \Rightarrow crisis_{j,t} \Rightarrow crisis_{i,t}$

- Range of other (non mutually exclusive) channels
  1. Capital inflows [Reinhart and Reinhart (2009), Mendoza and Terrones (2014)]
  2. Risk sentiment [Bacchetta et al (2012), Bacchetta and van Wincoop (2013)]

Channels of transmission

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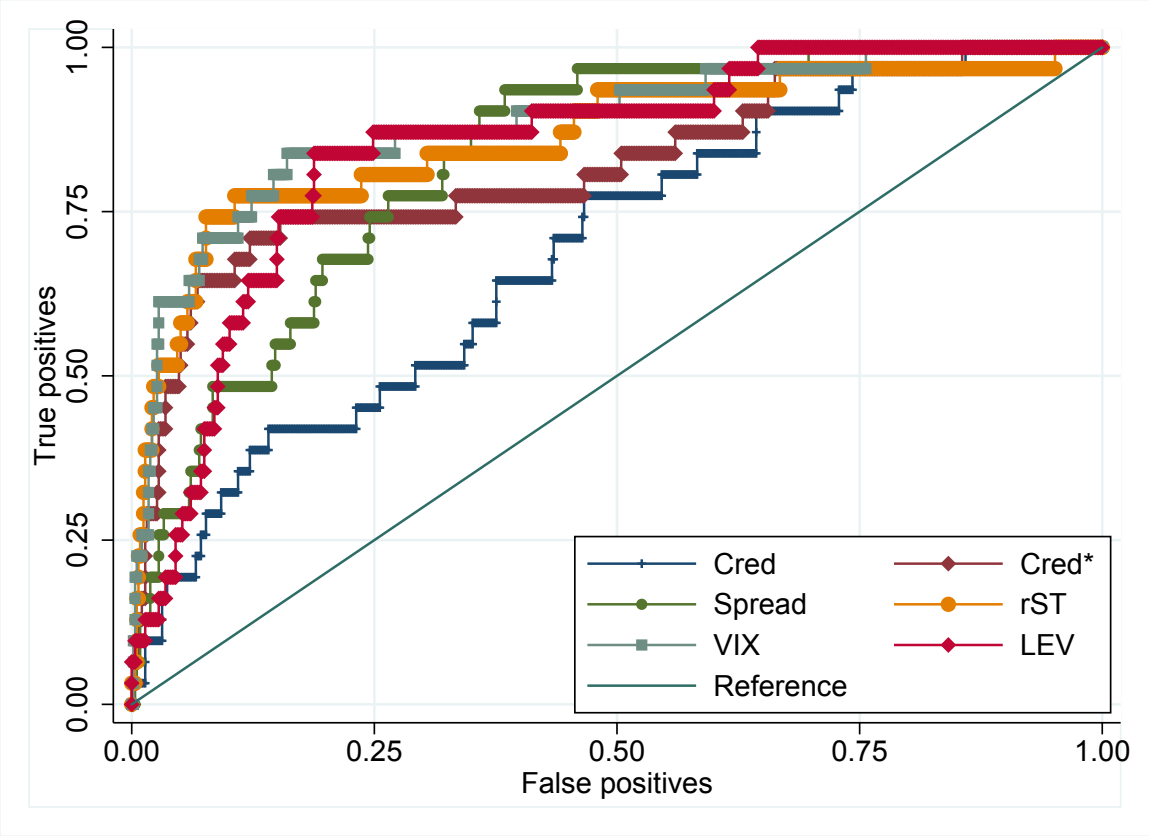
- Portfolio inflows increase probability of crises (banking inflows do not), but foreign credit remains significant
- Booming risk sentiment subsequently increases the probability of banking crises, and capture similar effects as foreign credit

ROC curves


True positives
0.00
0.25
0.50
0.75
1.00
False positives
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0.25
0.50
0.75
1.00
Cred
Spread
VIX
Reference
Cred*
rST
LEV

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Robustness checks

- Alternative dataset from Schularick and Taylor (2012)
- Sub-samples: AEs vs. EMs
- Alternative weighting schemes for foreign credit
  - Equal weights, banks' foreign positions, export-based
- Alternative lag structure
  - 3 lags

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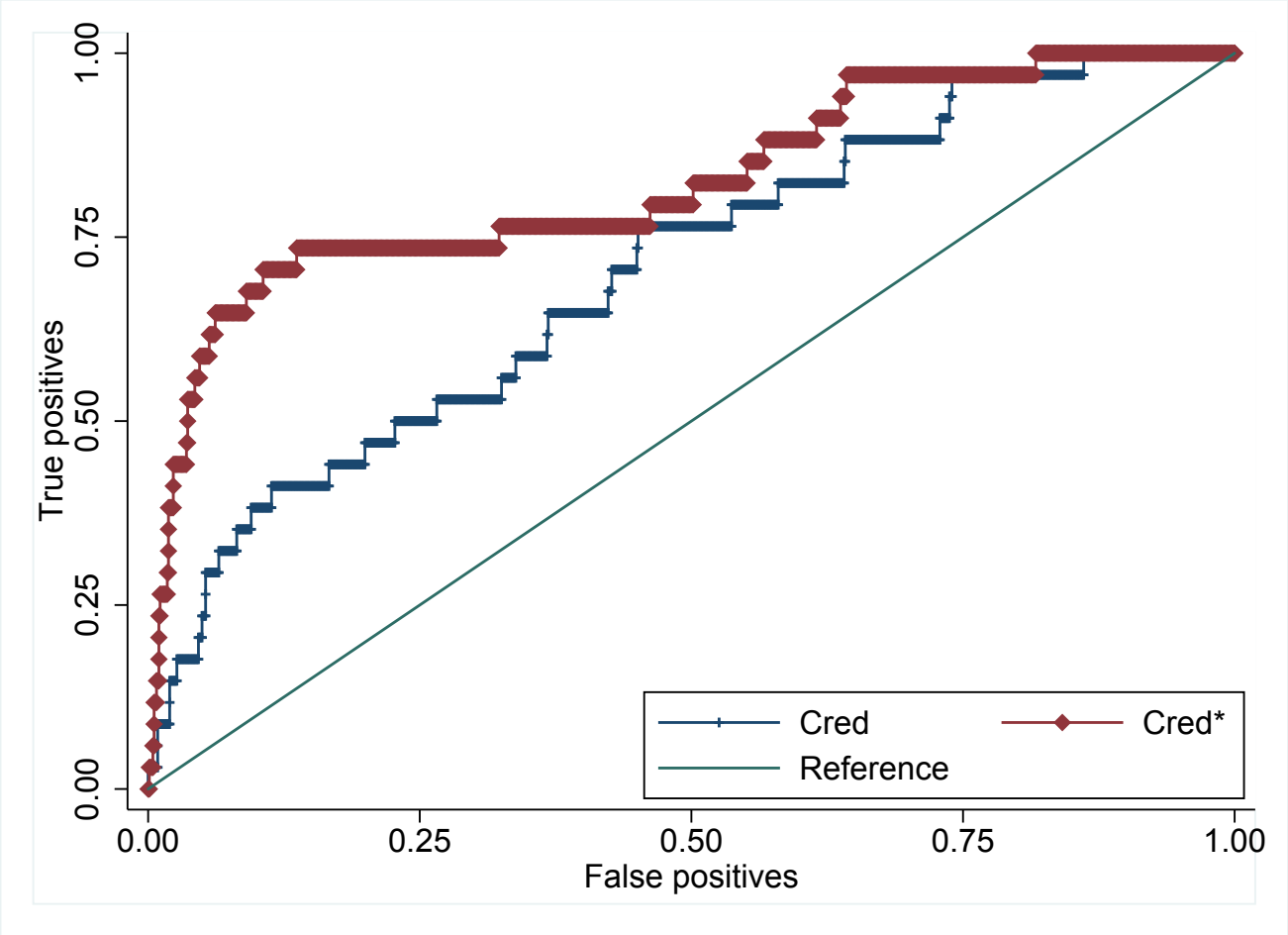
- There is suggestive evidence of a range of channels being at play
  - Contagion
  - (Portfolio) Capital flows
  - Risk sentiment transmission
- Policy implications
  - Keeping your house in order might not be enough
  - Important to monitor foreign financial conditions

Foreign credit increases ability of model to classify forthcoming crisis episodes



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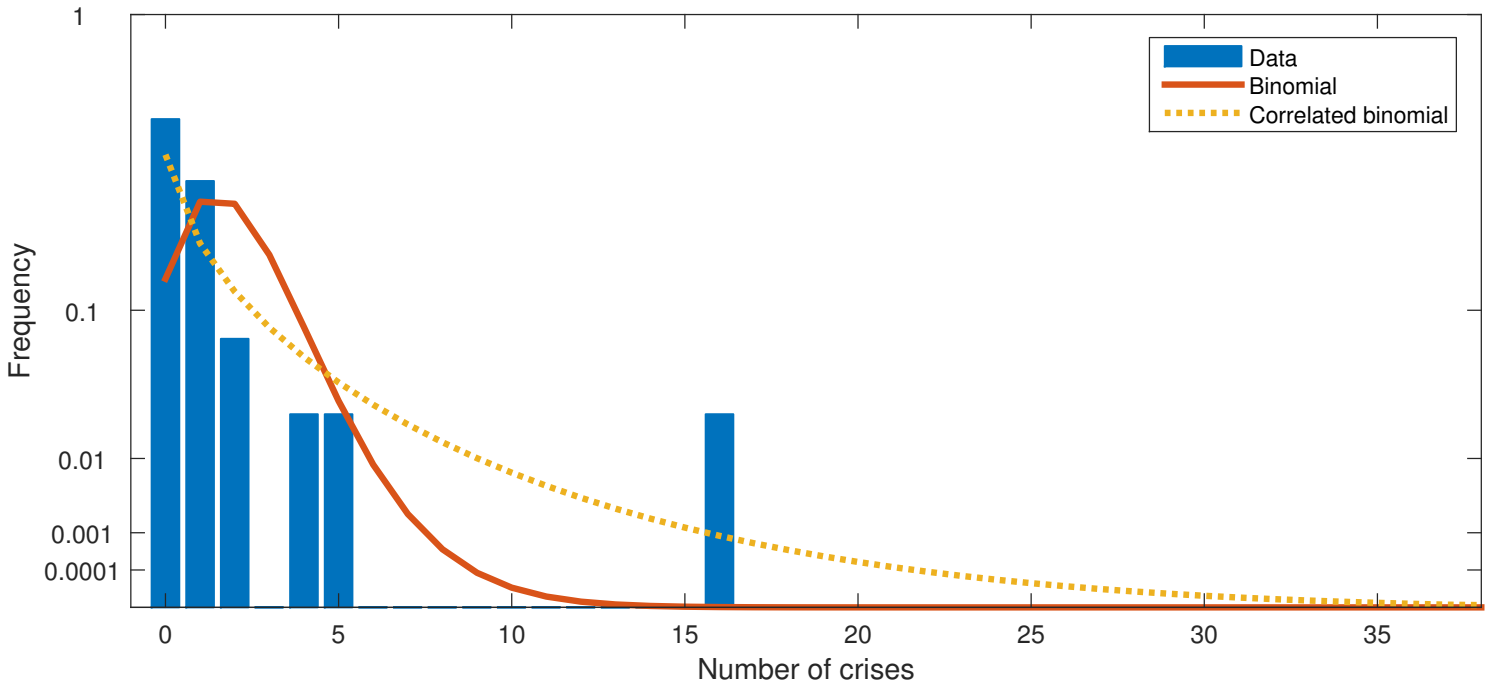
Appendix

Appendix: are banking crises synchronized across countries? A parametric approach

- If crises were independent across countries with time-invariant probability, they would follow a binomial distribution
- Heuristically, it does not seem to be the case
- Stable correlation binomial model [Witt (2014)]
  - Unconditional probability of any one country suffering a crisis is p
  - Unconditional correlation between any two pairs of trials is ρ
- Fit the model with crises data and test for $\hat{\rho} \neq 0$

Appendix: cross-country dependence of banking crises

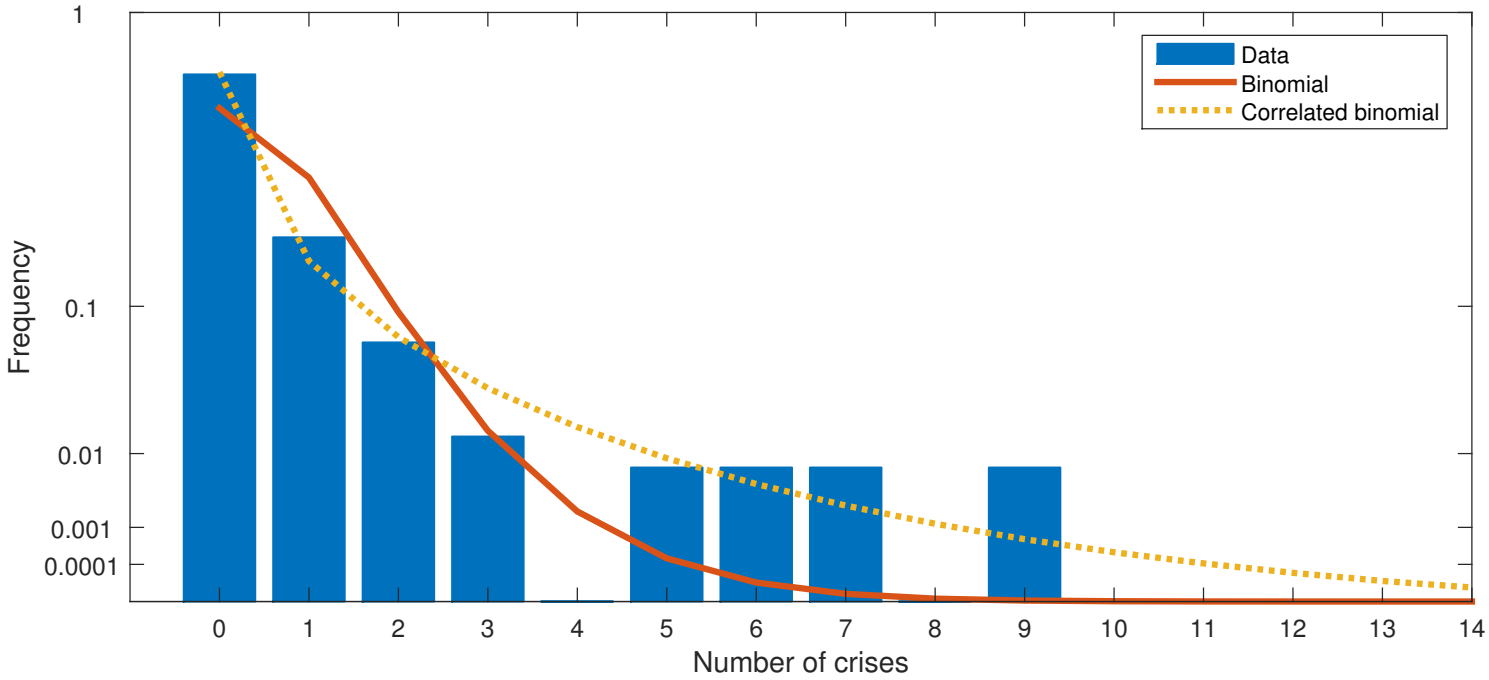
- Fat tails of correlated binomial distribution point to cross-country dependence of banking crises ($\rho = 0.08$)



NOTE. Proportion of countries experiencing (the start of) systemic banking crises in the data (bars), predicted by a standard binomial distribution (solid line), and predicted by a correlated binomial distribution (dotted line). Data from Laeven and Valencia (2013)

Appendix: cross-country dependence of banking crises

- Fat tails also in Schularick and Taylor (2012) dataset ($\rho = 0.11$)



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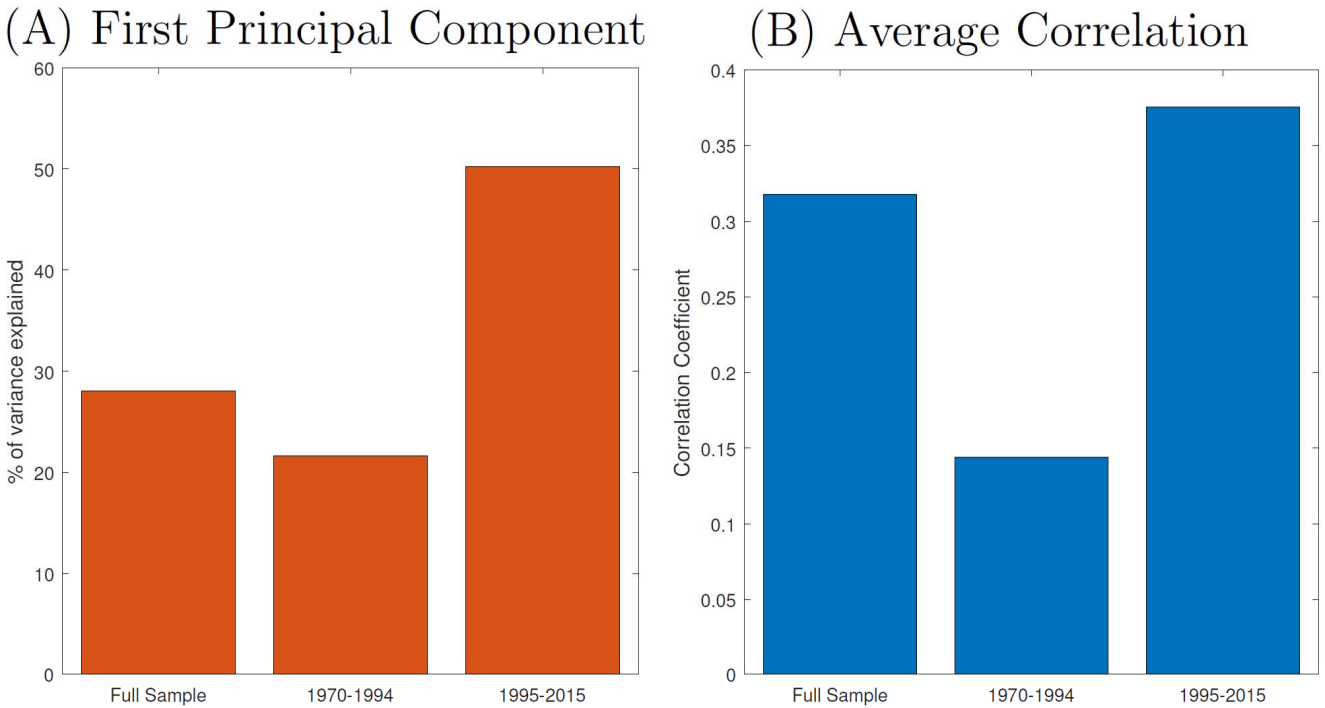
Appendix: domestic credit co-movement across countries

- *Domestic* credit growth is correlated cross countries, and increasingly so over time



NOTE. The first principal component has been estimated using a sample of 22 countries for which we have data covering the 1970–2015 period. The average correlation between country i's credit growth and (average) rest of the world credit growth has been computed using the full sample that include 38 countries.

Appendix. Potential channels (I): Contagion

- $Crisis^{*}_{it}$: PPP-weighted average of crisis occurrence in remaining countries

Specification	(1)	(2)	(3)	(4)
Estimation method	OLS	Logit	OLS	Logit
ΔCred				
Sum of lag coeffs	0.25**	10.3***	0.24**	9.08***
	[0.020]	[0.006]	[0.024]	[0.008]
ΔCred*				
Sum of lag coeffs	0.87*	30.65*	-0.49	-52.55**
	[0.054]	[0.062]	[0.362]	[0.019]
ΔCred* x FinOpen				
Sum of lag coeffs			0.92***	72.79***
			[0.002]	[0.001]
Crisis*	0.33***	5.42***	0.26***	0.25
	(0.094)	(1.839)	(0.084)	(3.425)
Constant	-0.07***	-20.38***	-0.01	-17.06***
	(0.025)	(1.242)	(0.026)	(1.522)
Observations	1,118	941	1,115	941
R2	0.08	0.23	0.11	0.4

Appendix. Potential channels (II): Capital flows

- Δ*Bank inflows*: cross-border bank lending (BIS, locational data by residence)

	Bank inflows to non-banks		Bank inflows to banks		Portfolio inflows		
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔCred							
Sum of lag coeffs	11.7***	11.61***	10.68***	10.42**	12.01**	12.22*	14.36**
	[0.000]	[0.005]	[0.002]	[0.010]	[0.031]	[0.056]	[0.016]
ΔCred*							
Sum of lag coeffs		46.09***		44.95***		45.96**	62.21***
		[0.008]		[0.008]		[0.037]	[0.005]
ΔCross-border inflows	-0.295	-0.826	1.193	0.887	36.43***	28.39***	
Sum of lag coeffs	[0.627]	[0.240]	[0.395]	[0.490]	[0.000]	[0.003]	
Constant	-17.21***	-21.87***	-17.40***	-22.16***	-20.87***	-24.82***	-23.85***
	(0.409)	(1.458)	(0.683)	(1.614)	(0.987)	(2.181)	(2.019)
Observations	795	795	795	795	622	622	622
R2	0.08	0.2	0.09	0.21	0.19	0.32	0.28

Appendix. Potential channels (II): Capital flows

- Δ*Portfolio inflows*: portfolio (equity + bond) from financial account (WEO)

	Bank inflows to non-banks		Bank inflows to banks		Portfolio inflows		
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Appendix. Potential channels (III): Risk sentiment

- Many different proxies identified in the recent literature

Specification	(1)	(2)	(3)	(5)	(6)	(7)
ΔCred	10.66***	13.23***	10.7*	9.78**	11.76**	11.11**
Sum of lag coeffs	[0.008]	[0.007]	[0.050]	[0.032]	[0.022]	[0.017]
ΔCred*	49.71***	89.37***	6.26	36.79***	12.47	25.95
Sum of lag coeffs	[0.001]	[0.001]	[0.678]	[0.006]	[0.386]	[0.168]
Spread		-5.97***				
Sum of lag coeffs		[0.000]				
r			-43.73***			
Sum of lag coeffs			[0.003]			
Slope				102.5		
Sum of lag coeffs				[0.127]		
VIX					-0.38***	
Sum of lag coeffs					[0.000]	
LEV						21.06***
Sum of lag coeffs						[0.002]
Constant	-21.11***	-12.42***	-19.03***	-22.02***	-12.49***	-23.79***
	(1.299)	(2.047)	(1.369)	(1.633)	(1.479)	(1.262)
Observations	941	941	941	941	772	606
R2	0.21	0.35	0.33	0.31	0.39	0.39

Appendix: alternative database

Specification	(1)	(2)	(3)
Estimation method	OLS	Logit	OLS
ΔCred			
Sum of lag coeffs	0.47***	11.3***	0.54***
	(0.001)	(0.001)	(0.000)
ΔCred*			
Sum of lag coeffs	-0.20	-5.85	0.77***
	(0.328)	(0.189)	(0.004)
ΔCred* * Non-mobile K			
Sum of lag coeffs			-0.15
			(0.897)
Constant	0.01	-4.31***	-0.03
	(0.724)	(0.000)	(0.263)
Observations	1,272	1,272	1,272
R2	0.03	0.08	0.06

Appendix: sub-samples

	AEs		EMs	
Specification	(1)	(2)	(3)	(4)
ΔCred				
Sum of lag coeffs	16.59**	30.34*	8.54***	12.22***
	[0.018]	[0.085]	[0.007]	[0.005]
ΔCred*				
Sum of lag coeffs	114.7***	-49.97	-37.61	-154.9***
	[0.000]	[0.226]	[0.117]	[0.000]
ΔCred* x FinOpen				
Sum of lag coeffs		145.6**		112.6
		[0.012]		[0.115]
Constant	-28.13***	-17.81***	-1.70	1.99
	(2.966)	(2.162)	(1.991)	(2.612)
Observations	690	690	251	251
R2	0.45	0.6	0.13	0.26

Appendix: alternative weighting scheme

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	Logit	OLS	Logit	OLS	Logit
Weighting method	Equal		Banking exposures		Exports	
ΔCred	0.23**	9.55**	0.33**	13.74***	0.3**	10.6***
Sum of lag coeffs	[0.036]	[0.011]	[0.027]	[0.002]	[0.012]	[0.008]
ΔCred*	1.58***	50.53***	0.68**	28.41***	0.65*	22.51**
Sum of lag coeffs	[0.002]	[0.002]	[0.042]	[0.007]	[0.070]	[0.020]
Constant	-0.11***	-21.38***	-0.06***	-21.72***	-0.06***	-20.62***
	(0.030)	(1.439)	(0.017)	(1.313)	(0.019)	(0.584)
Observations	1,118	941	913	799	1,065	915
R2	0.06	0.21	0.04	0.16	0.04	0.14

Appendix: alternative lag structure

Specification	(1)	(2)	(3)	(4)
Estimation method	OLS	Logit	OLS	Logit
ΔCred				
Sum of lag coeffs	0.14	4.75	0.12	2.78
	[0.122]	[0.151]	[0.187]	[0.300]
ΔCred*				
Sum of lag coeffs	1.07***	34.99***	-0.17	-43.18***
	[0.005]	[0.001]	[0.668]	[0.001]
ΔCred* x FinOpen			0.81***	65.47***
Sum of lag coeffs			[0.002]	[0.000]
FinOpen			-0.04***	-4.19***
			(0.012)	(1.095)
Constant	-0.06***	-20.08***	-0.01	-15.59***
	(0.020)	(0.856)	(0.019)	(0.786)
Observations	1,194	1,006	1,189	1,001
R2	0.05	0.16	0.09	0.36