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Credit booms, financial fragility and banking crises[☆]

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HIGHLIGHTS

- We model the determinants of banking crises using a new country-level panel database.
- We allow for the interaction of capital surges, credit booms and financial fragility.
- Booms increase the likelihood of crises only in relatively fragile financial systems.

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ABSTRACT

Using a new country-level panel database, we explore effect of capital inflow surges, credit booms and financial fragility on the probability of banking crises. We find that booms increase the probability of a crisis only in relatively fragile financial systems.

1. Introduction

Rapid growth in bank lending could exacerbate the moral hazard and adverse selection problems that undermine the stability of the banking system, increasing the probability of a banking crisis (Schularick and Taylor, 2012). There is similar concern about rapid growth in foreign capital inflows, which could fuel excessive growth in lending or generate asset price bubbles (Calvo, 2012). Caballero (forthcoming) finds that both capital inflow 'surges' and credit booms make a crisis significantly more likely. We extend the existing literature by fitting a model that combines the effects of booms, surges and financial fragility. The model also allows for persistence in crises.

2. Data

Our baseline model estimates the probability of a banking crisis in year t conditional on credit booms, capital inflow surges, and banking system fragility in year $t-1$. The dependent variable, $crisis(i, t)$, is taken from Laeven and Valencia (2013): it equals one if there is a banking crisis in country i in year t, and zero otherwise.[2]

Our credit boom and capital inflow surge variables are based on the method of Reinhart and Reinhart (2009) and

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2 Omitting Laeven and Valencia's 'borderline' cases makes no substantial difference to our results.

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Table 1
Dynamic panel probit coefficient estimates for $P(crisis(i,t)) = 1$ (Baseline model).

	A			*B*			*C*		
IDFF data (i): $N = 1011$[a]	*coeff.*	*t-ratio*	*m.e.*				*coeff.*	*t-ratio*	*m.e.*
$crisis(i,t-1)$	3.942	9.83	0.183				3.909	10.14	0.191
$credit\text{-}boom(i,t-1)$	0.778	3.31	0.036				0.809	3.51	0.040
$FDI\text{-}surge(i,t-1)$	0.564	2.17	0.026				0.541	2.13	0.026
$return(i,t-1)$	−0.198	−2.63	−0.009				−0.239	−3.21	−0.012
$z\text{-}score(i,t-1)$	−0.042	−1.19	−0.002						
IDFF data (ii): $N = 1346$[a]	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*
$crisis(i,t-1)$	3.941	11.01	0.169	4.169	11.82	0.195	3.912	11.16	0.170
$credit\text{-}boom(i,t-1)$	0.939	4.29	0.040	0.953	4.56	0.045	0.940	4.31	0.041
$FDI\text{-}surge(i,t-1)$	0.417	1.88	0.018	0.352	1.66	0.016	0.436	1.98	0.019
$return(i,t-1)$	−0.154	−2.13	−0.007				−0.158	−2.25	−0.007
$z\text{-}score(i,t-1)$	0.015	0.70	0.001	0.000	0.00	0.000			
GFDD data: $N = 1210$	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*
$crisis(i,t-1)$	3.872	10.27	0.161	4.159	11.35	0.189	3.823	10.66	0.166
$credit\text{-}boom(i,t-1)$	0.877	3.73	0.036	0.863	3.92	0.039	0.916	4.02	0.040
$FDI\text{-}surge(i,t-1)$	0.408	1.69	0.017	0.391	1.71	0.018	0.390	1.65	0.017
$return(i,t-1)$	−0.222	−2.38	−0.009				−0.178	−2.12	−0.008
$z\text{-}score(i,t-1)$	0.046	1.39	0.002	0.024	0.82	0.001			

[a] 'IDFF data (i)' indicates estimates with the least inclusive IDFF measure of returns, and 'IDFF data (ii)' estimates with the most inclusive measure.

Caballero (forthcoming). Using a filter, we fit trend values of (i) real per capita credit to the private sector and (ii) real per capita gross foreign direct investment inflows for each country. $Credit\text{-}boom(i,t)$ [$FDI\text{-}surge(i,t)$] equals one when de-trended credit [FDI] is over one standard deviation above zero, and equals zero otherwise. Using broader measures of capital inflows and larger standard deviation cut-off points produces results similar to those reported below.

Our fragility variables come from two alternative sources: the International Database on Financial Fragility (IDFF; Andrianova et al., 2015), and the Global Financial Development Database (GFDD; Čihák et al., 2012). These two databases include the same country-level fragility measures constructed from bank-level data, but differ in the selection rules used to determine whether an individual bank is included in the aggregate. For some variables, the IDFF reports alternative measures based on selection rules of varying degrees of inclusiveness. The IDFF data are based on a somewhat wider range of financial institutions than are the GFDD data.

We use two alternative variables that are inversely related to fragility. The first of these is a *z*-score aggregating asset returns and equity:

$$z\text{-}score\,(i,t) = \frac{return\,(i,t) + equity\,(i,t)\,/assets\,(i,t)}{\sigma\,(i)}. \qquad (1)$$

Here, $equity(i,t)$ is the total value of bank equity in country i in year t, $assets(i,t)$ is the total value of bank assets, $return(i,t)$ is a weighted average of the banks' annual return on these assets, and $\sigma(i)$ is the standard deviation of $return(i,t)$ over time. This *z*-score is a country-level analogue of the *z*-score of an individual bank (Laeven and Levine, 2009), and measures the distance of the whole banking system from insolvency under the assumption that bank profits are normally distributed.

Note that in Laeven and Valencia (2013), insolvency is a sufficient but not necessary condition for the presence of a crisis: a crisis can also occur when there are bank runs that do not lead to insolvency. Moreover, bank runs might be triggered even when the banking system is still a long way from insolvency: for example, runs might be triggered by an expectation of a government intervention that freezes bank deposits. Such expectations might be raised simply by a poorly performing banking sector, and for this reason we include $return(i,t)$ as a second inverse-fragility measure. Since the IDFF includes alternative estimates of $return(i,t)$, we fit three alternative versions of our model: (i) using the IDFF estimates of $z\text{-}score(i,t)$ and their least inclusive estimates of $return(i,t)$, (ii) using the IDFF estimates of $z\text{-}score(i,t)$ and their most inclusive estimates of $return(i,t)$, and (iii) using the GFDD estimates of $z\text{-}score(i,t)$ and $return(i,t)$.

3. The model

We have an unbalanced panel of 121 countries over 1999–2011. The number of missing observations depends on which fragility data are used, and the total sample size varies between 956 and 1346 observations. Appendix A includes the list of countries and descriptive statistics for the sample. In order to allow for the persistence of $crisis(i,t)$ we fit a dynamic Probit model. The fixed-effects specification of the baseline model is:

$$\begin{aligned} &P(crisis(i,t) = 1) = \Phi(y(i,t)) \\ &y(i,t) = \alpha_i + \delta_t + \beta \cdot crisis(i,t-1) \\ &\qquad + \Sigma_j \varphi_j \cdot z_j(i,t-1) + \varepsilon(i,t). \end{aligned} \qquad (2)$$

Here, $\Phi(.)$ is the cumulative normal density function, $z_j \in \{credit\text{-}boom, FDI\text{-}boom, return, Z\text{-}score\}$, and $\varepsilon(i,t)$ is an error term. Although there is no consistent estimator for this model, the coefficients in Eq. (2) can be estimated consistently using the following random-effects specification of the latent variable y (Wooldridge, 2005):

$$\begin{aligned} y(i,t) &= \zeta(i) + \delta_t + \beta \cdot crisis(i,t-1) + \Sigma_j \varphi_j \cdot z_j(i,t-1) \\ &\quad + \gamma \cdot crisis(i,0) + \Sigma_j \theta_j \cdot z_j(i) + \varepsilon(i,t). \end{aligned} \qquad (3)$$

Here, $\zeta(i)$ is a normally distributed random effect and $z_j(i)$ is the mean of $z_j(i,t)$ over time.

Panel A of Table 1 includes estimates of the β and φ coefficients in Eqs. (2)–(3), along with the corresponding t-ratios and marginal effects evaluated at the mean value of Φ (which is 0.09). There are three sets of estimates corresponding to the three alternative fragility measures: (i) IDFF using the least inclusive measure of returns, (ii) IDFF using the most inclusive measure of returns, and (iii) GFDD. It can be seen from panel A that the coefficient on *z-score* is never significantly different from zero, and panels B and C of Table 1 show coefficient estimates when either one or other of the fragility variables (*z-score* or *return*) is excluded from the model.[3] In no case does the exclusion of either variable make a

[3] In panel B (which shows results excluding *return*) there are only two sets of estimates, because the IDFF reports only one measure of *z-score*.