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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-boom*(i,t) [*FDI-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:

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

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-score*(i,t) and their least inclusive estimates of *return*(i,t), (ii) using the IDFF estimates of *z-score*(i,t) and their most inclusive estimates of *return*(i,t), and (iii) using the GFDD estimates of *z-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:

$$P(crisis(i,t) = 1) = \Phi(y(i,t))$$
$$y(i,t) = \alpha_i + \delta_t + \beta \cdot crisis(i,t-1) + \Sigma_j \varphi_j \cdot z_j(i,t-1) + \varepsilon(i,t). \quad (2)$$

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):

$$y(i,t) = \zeta(i) + \delta_t + \beta \cdot crisis(i,t-1) + \Sigma_j \varphi_j \cdot z_j(i,t-1) + \gamma \cdot crisis(i,0) + \Sigma_j \theta_j \cdot z_j(i) + \varepsilon(i,t). \quad (3)$$

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*.

Table 2
Dynamic panel probit coefficient estimates for $P(crisis(i, t)) = 1$ (Model with extra controls).

	A			B			C		
IDFF data (i): $N = 956$[a]	*coeff.*	*t-ratio*	*m.e.*				*coeff.*	*t-ratio*	*m.e.*
$crisis(i, t-1)$	3.983	7.77	0.138				4.118	8.32	0.153
$credit\text{-}boom(i, t-1)$	0.706	2.15	0.025				0.788	2.50	0.029
$FDI\text{-}surge(i, t-1)$	0.408	1.25	0.014				0.431	1.36	0.016
$return(i, t-1)$	−0.276	−2.62	−0.010				−0.316	−3.15	−0.012
$z\text{-}score(i, t-1)$	−0.037	−0.75	−0.001						
IDFF data (ii): $N = 1162$[a]	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*
$crisis(i, t-1)$	3.989	8.97	0.139	3.916	9.52	0.145	3.980	9.21	0.141
$credit\text{-}boom(i, t-1)$	0.813	2.72	0.028	0.776	2.78	0.029	0.842	2.87	0.030
$FDI\text{-}surge(i, t-1)$	0.327	1.12	0.011	0.243	0.86	0.009	0.356	1.22	0.013
$return(i, t-1)$	−0.248	−2.59	−0.009				−0.242	−2.73	−0.009
$z\text{-}score(i, t-1)$	0.024	0.69	0.001	−0.019	−0.52	−0.001			
GFDD data: $N = 1072$	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*
$crisis(i, t-1)$	4.075	8.04	0.122	4.129	9.10	0.131	3.962	8.71	0.134
$credit\text{-}boom(i, t-1)$	0.568	1.70	0.017	0.610	2.63	0.019	0.701	2.26	0.024
$FDI\text{-}surge(i, t-1)$	0.314	0.93	0.009	0.313	0.98	0.010	0.323	1.00	0.011
$return(i, t-1)$	−0.317	−2.51	−0.010				−0.229	−2.15	−0.008
$z\text{-}score(i, t-1)$	0.091	1.78	0.003	0.037	1.20	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.

Table 3
Models with interaction terms.

	Baseline model			Extra controls		
IDFF data (i)[a]	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*
$crisis(i, t-1)$	4.247	9.30	0.193	5.269	6.54	0.153
$credit\text{-}boom(i, t-1)$	1.101	3.81	0.050	1.697	3.22	0.049
$FDI\text{-}surge(i, t-1)$	0.682	2.51	0.031	0.729	1.87	0.021
$return(i, t-1) * I(credit\text{-}boom(i, t-1) = 1)$	−0.415	−2.97	−0.019	−0.705	−3.50	−0.021
$return(i, t-1) * I(credit\text{-}boom(i, t-1) = 0)$	−0.151	−1.57	−0.007	−0.119	−0.81	−0.003
Difference in return effects	−0.264	−1.58		−0.586	−2.40	
IDFF data (ii)[a]	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*
$crisis(i, t-1)$	4.071	10.57	0.169	4.407	8.35	0.141
$credit\text{-}boom(i, t-1)$	1.186	4.41	0.049	1.136	3.06	0.036
$FDI\text{-}surge(i, t-1)$	0.518	2.27	0.021	0.541	1.72	0.017
$return(i, t-1) * I(credit\text{-}boom(i, t-1) = 1)$	−0.314	−2.32	−0.013	−0.538	−2.97	−0.017
$return(i, t-1) * I(credit\text{-}boom(i, t-1) = 0)$	−0.082	−0.98	−0.003	−0.162	−1.53	−0.005
Difference in return effects	−0.232	−1.50		−0.376	−1.90	
GFDD data	*coeff.*	*t-ratio*	*m.e.*	*coeff.*	*t-ratio*	*m.e.*
$crisis(i, t-1)$	3.880	10.46	0.164	4.146	8.28	0.131
$credit\text{-}boom(i, t-1)$	0.847	2.97	0.036	0.688	1.80	0.022
$FDI\text{-}surge(i, t-1)$	0.406	1.70	0.017	0.443	1.31	0.014
$return(i, t-1) * I(credit\text{-}boom(i, t-1) = 1)$	−0.091	−0.70	−0.004	−0.160	−0.98	−0.005
$return(i, t-1) * I(credit\text{-}boom(i, t-1) = 0)$	−0.200	−2.07	−0.008	−0.220	−1.86	−0.007
Difference in return effects	0.109	0.74		0.060	0.34	

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

substantial difference to any of the other coefficient estimates. The results across the three different fragility measures are very similar.

The insignificance of *z-score* suggests that the country-level distance from insolvency is not itself a predictor of banking crises; one interpretation of this result is that crises can be triggered long before a country gets close to insolvency. By contrast, *return* is significant at the 5% level in all of the Table 1 estimates. The marginal effect on *return* is about −0.01: in other words, a one percentage point increase in average returns on assets will reduce the probability of a crisis by about one percentage point, i.e. from 0.09 to 0.08 at the mean. In order to interpret the magnitude of this effect, note that the standard deviation of *return* is just over 1.5 percentage points.

There is also a significant coefficient on *credit-boom*. The estimated marginal effect implies that on average, a credit boom increases the probability of a crisis by about four percentage points. The coefficient on *FDI-surge* is somewhat smaller, and the corresponding marginal effect implies that on average, an FDI surge increases the probability of a crisis by about two percentage points.

Table 1 shows that there is a high level of persistence in the data. The estimated marginal effect on the lagged dependent variable ranges from 0.16 to 0.19. This implies that at the mean ($\Phi = 0.09$), the presence of a crisis in the previous year triples the probability of a crisis in the current year. If the lagged dependent variable is excluded from the model, then the resulting coefficient estimate on *credit-boom* is about 25% larger and the coefficient estimate on *return* is about twice as large. In other words, neglecting the persistence in the crisis data will lead to substantial overestimation of other effects.

Table 2 reports the results of adding some additional macroeconomic control variables to the right-hand side of Eqs. (2)–(3). The addition of these variables (listed in Appendix A) makes no substantial difference to the estimated coefficients on *return*,

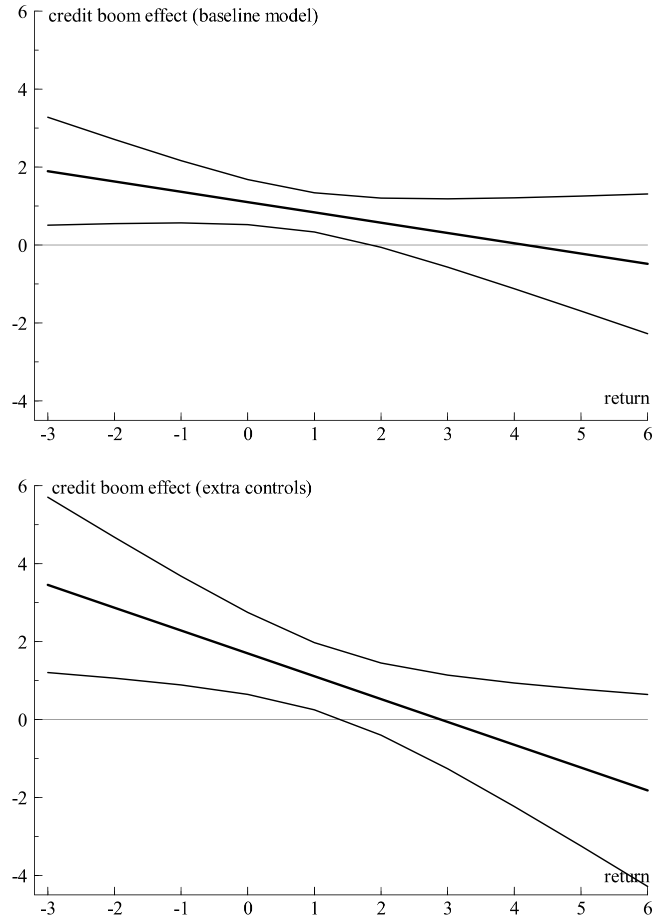

Fig. 1. Credit boom effects with 95% confidence intervals for different levels of percentage returns.

credit-boom or lagged *crisis*. However, the estimated size of the *FDI-surge* coefficient does fall, and this coefficient is no longer significantly different from zero at the 10% level.[4]

In Eqs. (2)–(3), the effects of surges, booms and fragility are assumed to be linearly separable. It is also possible that the effect of surges and booms varies according to the level of returns: a high level of returns may reflect a more robust banking system which can withstand any moral hazard or adverse selection effects attending a surge or boom. The results in Table 3 show some evidence for a significant interaction between the effect of returns and the effect of credit booms. These results are from a model that replaces $returns(i, t-1)$ with $[returns(i, t-1) \times I(credit\text{-}boom(i, t-1) = 1)]$ and $[returns(i, t-1) \times I(credit\text{-}boom(i, t-1) = 0)]$. The table records both the estimated coefficients on these variables and the difference between them. This difference is not significant in all cases, but it is significant at the 2% level in the model using the least inclusive IDFF data and the macroeconomic control variables. (This is the specification that produces the best fit according to a pseudo-R^2 statistic.) Here, the coefficient estimates imply that the effect of returns on the probability of a crisis is small and statistically insignificant in the absence of a credit boom, but large and statistically significant in the presence of a boom. To put it another way, a higher level of returns mitigates the effect of a boom. This is illustrated in Fig. 1, which shows the implicit credit boom coefficient (not the marginal effect) for different values of returns, using the model fitted with the least inclusive IDFF data. Credit booms make a crisis more likely as long as returns are below about 1.5 percentage points, but have no significant effect at higher levels of returns. Adding similar interaction terms with *FDI-surge* does not produce any significant coefficient estimates, so these results are not shown.

4. Discussion

Both financial fragility (as captured by the poor financial performance of banks) and credit booms are important determinants of the probability of a banking crisis, although their effect might be somewhat overstated in estimates that do not allow for persistence in crises. Moreover, it seems to be the combination of fragility with a boom that creates the conditions for a crisis: in the model that fits our data the best, neither booms alone nor fragility alone make a significant difference to the probability of a crisis. As a rule of thumb, if the annual average return on bank assets is greater than 1.5% then large fluctuations in liquidity should not endanger the banking system. To put this figure in context, in our sample,[5] the mean annual return for Canadian banks (excluding the atypical year of 2008) is 2.3%, compared with 0.9% for US banks and −0.5% for Greek ones. Credit booms should be less of a concern in Canada than in countries such as Greece and the United States.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.econlet.2015.09.041.

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[4] Nevertheless, as shown in Caballero (forthcoming), capital inflow surges are significant predictors of crises in models fitted to longer sample periods (but without the fragility variables for which early data are lacking).

[5] These figures relate to the most inclusive IDFF data.