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Credit Booms, Financial Fragility and Banking Crises[¶]

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Credit Booms, Financial Fragility and Banking Crises[¶]

David Fielding* and Johan Rewilak[§]

Abstract

Recent evidence indicates that surges in capital inflows and credit booms can increase the probability of a subsequent banking crisis. Using a new country-level panel database on financial fragility, we take this analysis further by exploring the interaction of surges, booms and fragility. We find that booms and fragility are both important, but booms increase the probability of a crisis only in financial systems with a relatively high level of fragility. Booms appear not to be dangerous in countries with a robust banking system.

JEL classification: E44; G01

Key words: Panel data; Financial crises; Financial fragility; Credit booms; Capital surges

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1. Introduction

One potential concern with a high rate of growth in bank lending is that it will 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 a similar concern about high rates of growth in foreign capital inflows, either because these inflows fuel excessive growth in bank lending, or because they generate asset price bubbles (Calvo, 2012). Empirical research indicates that although there is no robust linear relationship between the level of capital inflows and the onset of a crisis, atypical ‘surges’ in inflows do make a crisis significantly more likely (Caballero, 2014). Caballero also finds the effect of a surge in capital inflows to be distinct from that of a lending boom, which is consistent with the asset price mechanisms outlined by Calvo.

Using a recently published international database on financial fragility, this paper extends the existing literature in two ways. Firstly, we estimate the probability of a crisis in a given country and given year conditional not only on lending booms and surges in capital inflows, but also on measures of financial fragility. We find that on average, over all countries and years in our sample, the effect of booms (and, to some extent, surges) is robust to the inclusion of fragility measures in the model of crises. However, when we allow the effect of booms to depend on fragility, we find that booms are significant only when fragility is relatively high. Secondly, our model allows for persistence: the probability of a crisis now depends on whether there was a crisis last year, and omitting to account for this effect leads to biased estimates of the other effects in the model.

2. The Data

Our baseline model estimates the probability of a banking crisis in year t conditional on (i) the presence of credit booms and capital inflow surges in year t–1 and (ii) measures of banking system fragility in year t–1. The dependent variable in this model is a binary measure equal to one if there is a systematic banking crisis in country *i* in year *t*, and equal to zero otherwise. This variable, denoted *crisis*(*i*,*t*), is taken from Laeven and Valencia (2013). A systematic banking crisis is indicated by (i) substantial financial distress, as reflected in bank runs, excessive bank losses, or bank insolvency, and (ii) a substantial government policy intervention in response to the distress.[1]

Our credit boom and capital inflow surge variables are based on the method outlined in Reinhart and Reinhart (2009) and Caballero (2014). Using a cubic spline,[2] we fit trend values of (i) real per capita credit to the private sector and (ii) real per capita foreign direct investment inflows for each country. Data are taken from the World Bank *World Development Indicators*. The variable *credit-boom*(*i*,*t*) is set equal to one when de-trended real per capita credit to the private sector is more than one standard deviation above zero, and equal to zero otherwise; the variable *FDI-surge*(*i*,*t*) is set equal to one when de-trended real per capita FDI inflows are more than one standard deviation above zero, and equal to zero otherwise. Using broader measures of capital inflows and larger standard deviation cut-off points produces results similar to those reported below; further details are available on request.

Our fragility variables come from two alternative sources: the newly released International Database on Financial Fragility (IDFF), documented in Andrianova *et al*. (2015), and the Global Financial Development Database (GFDD), documented in Čihák *et al*. (2012). The 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 country-level variables, the IDFF reports alternative measures based on selection rules of varying

[1] 'Substantial' is defined as the presence of at least three of the following six outcomes: deposit freezes or bank holidays, bank nationalizations, restructuring costs reaching at least 3% of GDP, asset purchases reaching at least 5% of GDP, liquidity support reaching at least 5% of deposits and liabilities to non-residents, and the introduction of significant government guarantees.

[2] Previous papers use measures based on a Hodrick-Prescott Filter. The cubic spline is virtually identical to the Hodrick-Prescott Filter, but can be fitted across missing observations.

degrees of inclusiveness, and recommends that statistical analyses employing the data include results comparing different measures. The IDFF data are based on a somewhat wider range of financial institutions than are the GFDD data.

We use two alternative country-level variables from the IDFF and GFDD that are inversely related to fragility. The first of these is a z-score aggregating asset returns and equity:

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

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 analog 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 financial distress: distress can also occur when there are substantial 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 alongside *z-score*(i,t). 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).

In addition to the baseline model, we also fit a model that includes a variety of macroeconomic controls that might be associated with the probability of a banking crisis: the consumer price inflation rate, government spending as a fraction of GDP, the real level of per capita GDP (in logs), the real GDP growth rate, the Chinn-Ito index of capital account openness, an indicator of recent capital account liberalization,[3] trade openness (imports plus exports as a fraction of GDP), and the Kaufmann-Kraay-Mastruzzi index of the control of corruption, and the share of the three largest banks in total bank assets. Data sources for these variables are given in Appendix A.

3. The Model

Combining the data sources discussed in the previous section, we have an unbalanced panel of 121 countries over a 13-year period (1999-2011). The number of missing observations depends on which fragility data are used and whether the macroeconomic control variables are included in the model; in the results below, the total sample size varies between 956 and 1,346 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 panel Probit model. The fixed-effects specification of the baseline model is:

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

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

$$y(i,t) = \zeta(i) + \delta_t + \beta \cdot crisis(i,t-1) + \Sigma_j\, \varphi_j \cdot z_j(i,t-1) \tag{3}$$

[3] This variable equals one if the Chinn-Ito index has risen in the last year and equals zero otherwise.

$+ \gamma \cdot crisis(i,0) + \Sigma_j \, \theta_j \cdot \bar{z}_j(i) + \varepsilon(i,t)$

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

Panel A of Table 1 includes estimates of the β and φ parameters in equations (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 parameter on the fragility variable *z-score* is never significantly different from zero, and panels B-C of Table 1 show parameter estimates when either one or other of the fragility variables (*z-score* or *return*) is excluded from the model.[4] In no case does the exclusion of either variable make a substantial difference to any of the other parameter estimates. The results across the three different fragility measures are very similar.[5]

The insignificance of the *z-score* variable suggests that the country-level distance from insolvency is not in 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, the *return* variable is significant at the 5% level in all of the Table 1 estimates: countries with a more profitable banking sector are significantly less prone to crises. 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,

[4] 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*.

[5] However, there is some evidence that the IDFF measure of returns explains more of the variation in *crisis* than does the GFDD measure. When the least inclusive IDFF measure is added to the model using the GFDD measure, the extra variable is significant at the 5% level (p = 0.027 in the Table 1 / panel C model and p = 0.004 in the Table 2 / panel C model). When the most inclusive measure is added instead, the significance level is only slightly lower (p = 0.065 in the Table 1 / panel C model and p = 0.020 in the Table 2 / panel C model). When the GFDD measure is added to a model with an IDFF measure, the extra variable is never significant at the 10% level.

note that the standard deviation of *return* is just over 1.5 percentage points.

There is also a large and statistically significant parameter on *credit-boom*, which is consistent with the results in Caballero (2014). The estimated marginal effect implies that on average, a credit boom (which occurs in about 20% of all country-year observations) increases the probability of a crisis by about four percentage points. The parameter on *FDI-surge* is slightly smaller and significant at the 5% level when the least inclusive IDFF data are used; in other cases, *FDI-surge* is significant at the 10% level. The estimated marginal effect implies that on average, an FDI surge (which also occurs in about 20% of all observations) 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 parameter estimate on *credit-boom* is about 25% larger and the parameter estimate on *return* is about twice as large. In other words, neglecting the persistence in the crisis data will lead to substantial over-estimation of other effects.

Table 2 reports the results of adding the macroeconomic control variables to the right-hand side of equations (2-3). The addition of these variables makes no substantial difference to the estimated parameters on *return, credit-boom* or lagged *crisis*. However, the estimated size of the *FDI-surge* parameter does fall, and this parameter is no longer significantly different from zero at the 10% level.[6]

Tables 1-2 show estimates of the average effect on the probability of a banking crisis of credit booms, FDI surges and returns across all countries and years in the sample. 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 that is able to withstand any moral hazard or adverse selection effects

[6] Nevertheless, as shown in Caballero (2014), 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).

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 $returns(i,t\text{-}1)$ with $[returns(i,t\text{-}1) \times \mathrm{I}(credit\text{-}boom(i,t\text{-}1) = 1)]$ and $[returns(i,t\text{-}1) \times \mathrm{I}(credit\text{-}boom(i,t\text{-}1) = 0)]$. The table records both the estimated parameters on these variables and the difference between the parameter values, along with the t-ratio on this difference. The 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 parameter 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 Figure 1, which shows the implicit credit boom parameter (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 parameter estimates, so these results are not shown.

4. Discussion

Using recently published data on financial fragility, we show that both fragility (as captured by the poor financial performance of banks) and credit booms are important predictors 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 estimates that fit our data the best, a boom by itself (in the absence of fragility) or fragility by itself (in the absence of a boom) does not 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,[7] 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.

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

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Table 1: Dynamic Panel Probit Parameter Estimates for P(*crisis*(*i*,*t*)) = 1 (Baseline Model)

	A			*B*			*C*		
IDFF data (i): N = 1,011 †	*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-boom(*i*,*t*-1)	0.778	3.31	0.036				0.809	3.51	0.040
FDI-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-score(*i*,*t*-1)	-0.042	-1.19	-0.002						
IDFF data (ii): N = 1,346 †	*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-boom(*i*,*t*-1)	0.939	4.29	0.040	0.953	4.56	0.045	0.940	4.31	0.041
FDI-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-score(*i*,*t*-1)	0.015	0.70	0.001	0.000	0.00	0.000			
GFDD data: N = 1,210	*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-boom(*i*,*t*-1)	0.877	3.73	0.036	0.863	3.92	0.039	0.916	4.02	0.040
FDI-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-score(*i*,*t*-1)	0.046	1.39	0.002	0.024	0.82	0.001			

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

Table 2: Dynamic Panel Probit Parameter Estimates for P(*crisis*(*i*,*t*)) = 1 (Model with Extra Controls)

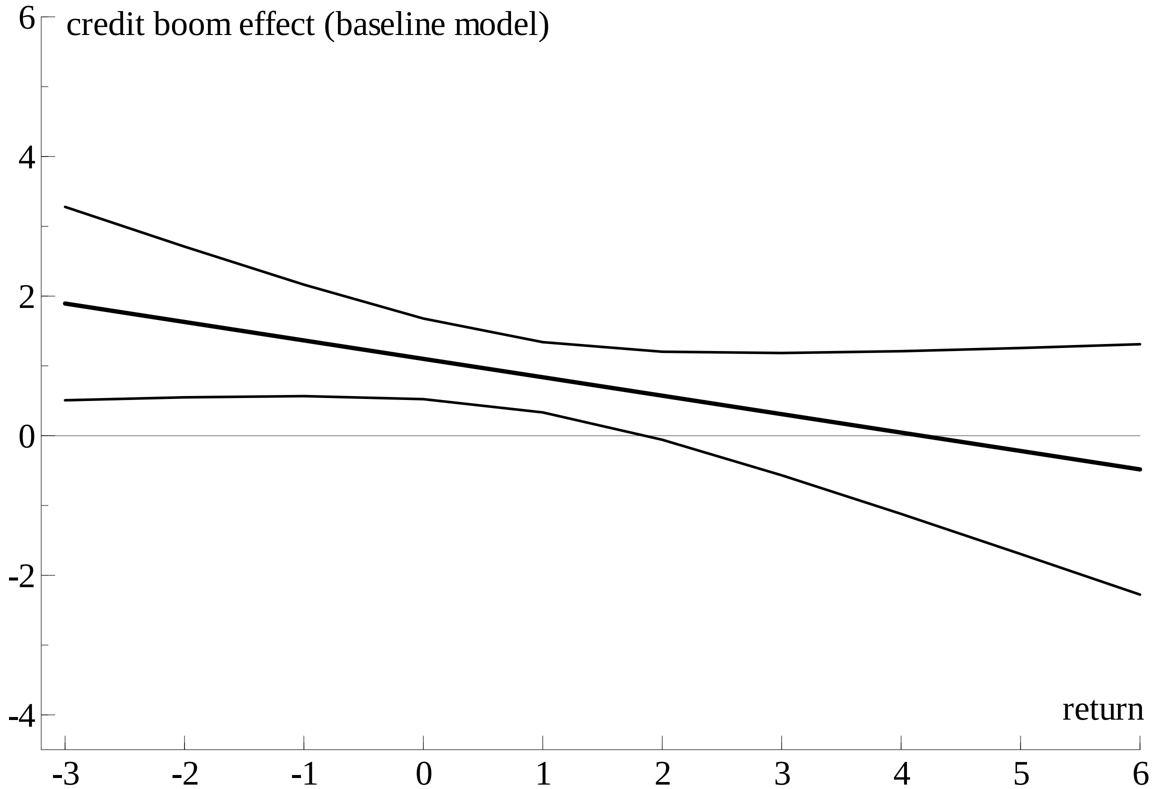
	A			*B*			*C*		
IDFF data (i): N = 956 †	*coeff.*	*t-ratio*	*m.e.*				*coeff.*	*t-ratio*	*m.e.*
crisis(*i*,*t*-1)	3.983	7.77	0.138				4.118	8.32	0.153
credit-boom(*i*,*t*-1)	0.706	2.15	0.025				0.788	2.50	0.029
FDI-surge(*i*,*t*-1)	0.408	1.25	0.014				0.431	1.36	0.016
return(*i*,*t*-1)	-0.276	-2.62	-0.010				-0.316	-3.15	-0.012
z-score(*i*,*t*-1)	-0.037	-0.75	-0.001						
IDFF data (ii): N = 1,162 †	*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-boom(*i*,*t*-1)	0.813	2.72	0.028	0.776	2.78	0.029	0.842	2.87	0.030
FDI-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-score(*i*,*t*-1)	0.024	0.69	0.001	-0.019	-0.52	-0.001			
GFDD data: N = 1,072	*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-boom(*i*,*t*-1)	0.568	1.70	0.017	0.610	2.63	0.019	0.701	2.26	0.024
FDI-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-score(*i*,*t*-1)	0.091	1.78	0.003	0.037	1.20	0.001			

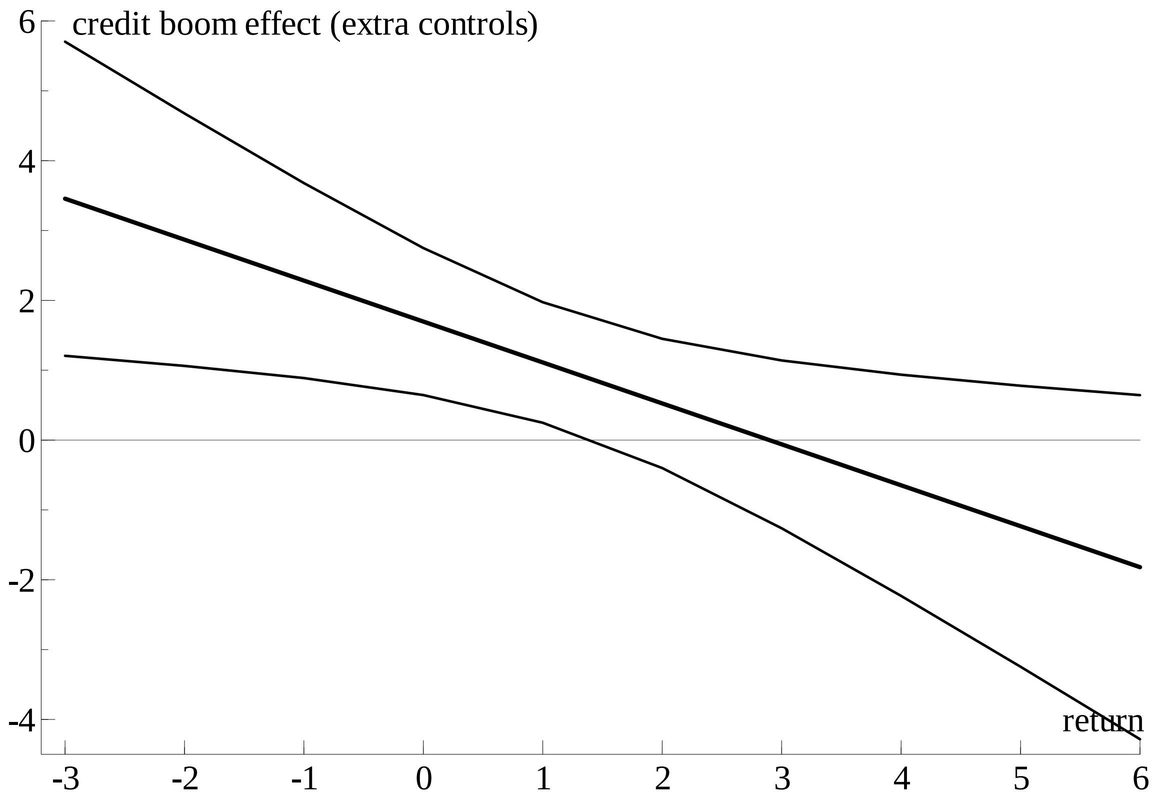
† 'IDFF data (i)' indicates estimates with the least inclusive IDFF measure of returns, and 'IDFF data (ii)' estimates with the most inclusive measure.

Table 3: Models with Interaction Terms

	Baseline Model			*Extra Controls*		
IDFF data (i) †	*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-boom(*i*,*t*-1)	1.101	3.81	0.050	1.697	3.22	0.049
FDI-surge(*i*,*t*-1)	0.682	2.51	0.031	0.729	1.87	0.021
return(*i*,*t*-1)*I(*credit-boom*(*i*,*t*-1) = 1)	-0.415	-2.97	-0.019	-0.705	-3.50	-0.021
return(*i*,*t*-1)*I(*credit-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) †	*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-boom(*i*,*t*-1)	1.186	4.41	0.049	1.136	3.06	0.036
FDI-surge(*i*,*t*-1)	0.518	2.27	0.021	0.541	1.72	0.017
return(*i*,*t*-1)*I(*credit-boom*(*i*,*t*-1) = 1)	-0.314	-2.32	-0.013	-0.538	-2.97	-0.017
return(*i*,*t*-1)*I(*credit-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-boom(*i*,*t*-1)	0.847	2.97	0.036	0.688	1.80	0.022
FDI-surge(*i*,*t*-1)	0.406	1.70	0.017	0.443	1.31	0.014
return(*i*,*t*-1)*I(*credit-boom*(*i*,*t*-1) = 1)	-0.091	-0.70	-0.004	-0.160	-0.98	-0.005
return(*i*,*t*-1)*I(*credit-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	

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


credit boom effect (baseline model)
6
4
2
0
-2
-4
return
-3
-2
-1
0
1
2
3
4
5
6


credit boom effect (extra controls)
6
4
2
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-2
-4
return
-3
-2
-1
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4
5
6

Figure 1: Credit boom effects with 95% confidence intervals for different levels of returns

Appendix A (Not for Publication)

Table A1: Sample Descriptive Statistics

	mean	*overall s.d.*	*s.d. between countries*	*s.d. within countries*
return (IDFF data (i))	1.43	1.60	1.09	1.16
return (IDFF data (ii))	1.35	1.60	1.14	1.22
return (GFDD data)	1.86	1.81	1.42	1.24
Z-score (IDFF data)	14.7	10.6	10.1	4.2
Z-score (GFDD data)	14.2	9.6	8.9	3.8

	binary variables: proportion of observations = 1
crisis	0.09
credit-boom	0.19
FDI-surge	0.20

Table A2: Countries Included in the Sample

Albania	Chad	France	Kenya	New Zealand	Spain
Algeria	Chile	Gabon	Korea	Nicaragua	Sri Lanka
Angola	China	Gambia	Kyrgyzstan	Niger	Sudan
Argentina	Colombia	Georgia	Latvia	Nigeria	Swaziland
Australia	Congo Dem. Rep.	Germany	Lesotho	Norway	Sweden
Austria	Congo Republic	Ghana	Liberia	Pakistan	Switzerland
Azerbaijan	Costa Rica	Greece	Libya	Paraguay	Tanzania
Bangladesh	Côte d'Ivoire	Guatemala	Lithuania	Peru	Thailand
Belarus	Czech Republic	Guinea	Madagascar	Philippines	Togo
Belgium	Denmark	Guinea-Bissau	Malawi	Poland	Tunisia
Benin	Djibouti	Hong Kong	Malaysia	Portugal	Turkey
Bolivia	Dominican Rep.	Hungary	Mali	Romania	Uganda
Botswana	Ecuador	India	Mauritania	Russia	Ukraine
Brazil	Egypt	Indonesia	Mauritius	Rwanda	United Kingdom
Bulgaria	El Salvador	Ireland	Mexico	São Tomé	United States
Burkina Faso	Equatorial Guinea	Israel	Morocco	Senegal	Uruguay
Burundi	Eritrea	Italy	Mozambique	Seychelles	Venezuela
Cabo Verde	Estonia	Japan	Namibia	Sierra Leone	Vietnam
Cameroon	Ethiopia	Jordan	Nepal	Singapore	Zambia
Canada	Finland	Kazakhstan	Netherlands	South Africa	Zimbabwe
C.A.R.					

Table A3: Data Definitions and Sources

Variables in Tables 1-2	*Definition*
crisis	A binary variable indicting a systematic banking crisis, as in Laeven and Valencia (2013).
return	The average annual rate of return on bank assets in a country. There are three alternative measures of this variable: *ROAA* and *ROAAR5* from Andrianova *et al*. (2015) and *GFDD.EI.09* from Čihák *et al*. (2012). The variables are trimmed at ± five percentage points from their database mean. The data are available at www2.le.ac.uk/departments/economics/research/esrc-dfid-project/financial-fragility-database-excel and http://data.worldbank.org/data-catalog/global-financial-development.
z-score	This variable is defined in equation (1) of the text. There are two alternative measures of this variable: *Z* from Andrianova *et al*. (2015) and *GFDD.SI.01* from Čihák *et al*. (2012). The variables are trimmed at ± 35 percentage points from their database mean. The data are available at the sites above.
credit-boom	For each country, this variable is constructed by fitting a cubic spline to the 1960-2012 time series for real credit to the private sector (deflated using the GDP deflator): *credit-boom* = 1 if the de-trended series is greater than one standard deviation above its mean; otherwise *credit-boom* = 0. Data are from World Bank (2015).
FDI-surge	For each country, this variable is constructed by fitting a cubic spline to the 1960-2012 time series for real inward foreign direct investment (deflated using the GDP deflator): *FDI-surge* = 1 if the de-trended series is greater than one standard deviation above its mean; otherwise *FDI-surge* = 0. Data are from World Bank (2015).

Control variables	*Source*	*Website*
annual rate of consumer price inflation	World Bank (2015)	http://data.worldbank.org/data-catalog/world-development-indicator
government spending ÷ GDP	World Bank (2015)	
log real per capita GDP	World Bank (2015)	
annual rate of real GDP growth	World Bank (2015)	
(imports + exports) ÷ GDP	World Bank (2015)	
capital account openness index	Chinn and Ito (2006)	http://web.pdx.edu/~ito/Chinn-Ito_website.htm
capital account liberalization	Chinn and Ito (2006)	
control of corruption index	Kaufman *et al*. (2009)	www.govindicators.org/
assets of three largest banks ÷ total bank assets	Čihák *et al*. (2012)	see above

Appendix References not Cited in the Main Text

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