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The Riskiness of Credit Allocation and Financial Stability—Online Appendix

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The Riskiness of Credit Allocation and Financial Stability

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Abstract

We explore empirically how the time-varying allocation of credit across firms with heterogeneous credit quality matters for financial stability outcomes. Using firm-level data for 55 countries over 1991-2016, we show that the riskiness of credit allocation, captured by Greenwood and Hanson (2013)'s ISS indicator, helps predict downside risks to GDP growth and systemic banking crises, two to three years ahead. Our analysis indicates that the riskiness of credit allocation is both a measure of corporate vulnerability and of investor sentiment. Economic forecasters wrongly predict a positive association between the riskiness of credit allocation and future growth, suggesting a flawed expectations process.

JEL Classification Numbers: E44, E47, G01, G21, G23, G28, G32

Keywords: Corporate debt; credit allocation; credit risk; financial leverage; financial vulnerability; financial crises, macro-financial stability

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Construction of the Expected Default Frequency (EDF) indicator

As Greenwood and Hanson (2013), we calculate the EDF based on the Black-Scholes-Merton (BSM) model. The firm's default risk is derived from its equity price by assuming that investors' calculation of default risk is accurate. The BSM default probability measures the theoretical probability of default one year ahead. The model may generate default probabilities that are biased, if markets are not arbitrage-free —a possibility in emerging markets with thin trading—or if the distribution of asset returns is not approximately normal.

The EDF is computed as follows. Using variable names *A* for the value of assets; *B* for the sum of short-term debt, half of long-term debt, and interest payments; μ for asset drift; and σ_A for the standard deviation of asset returns, we first compute the one-year-ahead distance to default (*DtD*) as:

$$DtD = \frac{\log(A) - \log(B) + (\mu - \frac{\sigma_A^2}{2})}{\sigma_A}$$

Following Greenwood and Hanson (2013), we use the annual stock return as the asset drift. The theoretical distribution of DtD implied by the BSM model is a normal distribution. Letting Φ denote the standard normal cumulative distribution function, the EDF is then calculated as:

$$EDF = \Phi(-DtD)$$

A and σ_A are not observable but can be computed from the following system of 2 equations, i.e. the BSM pricing formula for call options and the optimal hedge equation:

$$E = A\,\Phi(DtD + \sigma_A) - Be^{-r}$$

$$\sigma_E E = \sigma_A A\,\Phi(DtD + \sigma_A)$$

where *E* is the value of equity, *r* is the risk-free rate, and σ_E is the standard deviation of equity prices, which is computed using annualized weekly equity returns.

These two equations are solved iteratively by first fixing the standard deviation of asset returns to search over asset values, and then fixing the asset value to search over the standard deviation of asset returns, until the squared error of approximation falls below 10^{-4}.

The country-specific risk-free rate series are sourced from the IMF's International Financial Statistics and from DataStream International Limited.

Construction of the Financial Conditions Index (FCI)

The financial conditions indices (FCIs) are estimated for 1990–2016 at a quarterly frequency for 43 advanced and emerging market economies using a set of eight price-based financial indicators (depending on availability of the individual series): (1) term spread; (2) corporate spread; (3) sovereign spread; (4) interbank spread; (5) first difference in real long-term rate; (6) equity returns; (7) equity volatility; and (8) house price returns. See Appendix Table B1 for data sources.

The FCIs are estimated based on Koop and Korobilis (2014) and build on the estimation of Primiceri's (2005) time-varying parameter vector autoregression model and dynamic factor models of Doz, Giannone, and Reichlin (2011). The FCIs are estimated using Koop and Korobilis' (2014) code available at: https://sites.google.com/site/dimitriskorobilis/matlab.

This approach has two advantages. First, it can control for current macroeconomic conditions. Second, it allows for dynamic interactions between the FCIs and macroeconomic conditions, which can also evolve over time. The model takes the following form:

$$x_t = \lambda_t^y Y_t + \lambda_t^f f_t + u_t$$

$$\begin{bmatrix} Y_t \\ f_t \end{bmatrix} = B_{1,t} \begin{bmatrix} Y_{t-1} \\ f_{t-1} \end{bmatrix} + B_{2,t} \begin{bmatrix} Y_{t-1} \\ f_{t-1} \end{bmatrix} + \cdots + \varepsilon_t$$

in which x is a vector of financial variables, Y is a vector of macroeconomic variables of interest (including real GDP growth and inflation), λ^y are regression coefficients, λ^f are the factor loadings, and f is the latent factor, interpreted as the FCI.

Online Appendix Table B1 - Data Sources for the input series of the Financial Conditions Index

Variable	Description	Source
Macro-financial Variables		
Term Spread	Yield on 10-year government bond minus yield on 3-month Treasury bill	Bloomberg Finance L.P.
Interbank Spread	Interbank interest rate minus yield on 3-month Treasury bill	Bloomberg Finance L.P.
Change in Long-Term Real Interest Rate	Percentage point change in the 10-year government bond yield, adjusted for inflation	Bloomberg Finance L.P.
Corporate Spreads	Corporate yield of the country minus sovereign yield of the benchmark country; JPMorgan Corporate Emerging Markets Bond Index Broad is used for emerging market economies where available.	Bloomberg Finance L.P.; Thomson Reuters Datastream
Equity Returns (local currency)	Log difference in equity index	Bloomberg Finance L.P.
House Price Returns	Log difference of the house price index	BIS, Haver Analytics
Equity Return Volatility	Exponential weighted moving average of equity returns	Bloomberg Finance L.P.
Sovereign Spread	Yield on 10-year government bond minus the benchmark country's yield on 10-year government bond	Bloomberg Finance L.P.

Appendix Table B2 - Crisis Prediction Model - Logit with country dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ(Credit-to-GDP Ratio)	0.228***		0.142	0.0126		0.224*	-0.170		0.193**	0.0508
	(0.0828)		(0.0893)	(0.202)		(0.127)	(0.154)		(0.0838)	(0.106)
Financial Conditions Index		-2.857**	-2.595**	-6.707***			-12.00***			-4.895***
		(1.196)	(1.172)	(2.170)			(4.060)			(1.417)
ISS^{EDF}					1.438**	1.266**	5.312***			
					(0.584)	(0.641)	(1.840)			
$ISS^{Leverage}$								1.300***	1.235**	3.117***
								(0.433)	(0.578)	(1.040)
Number of Observations	443	443	443	361	361	361	361	443	443	443
Number of Countries	21	21	21	17	17	17	17	21	21	21
Number of Crisis Episodes	21	21	21	17	17	17	17	21	21	21
Pseudo R^2	0.206	0.324	0.340	0.539	0.271	0.309	0.667	0.264	0.257	0.471
Test for country effects = 0	4.876	21.53	5.484	8.494	14.25	30.59	18.29	17.54	18.67	13.15
p-value	0.181	8.18e-05	0.241	0.0751	0.00258	3.71e-06	0.00261	0.000548	0.000914	0.0220
AUROC	0.855	0.914	0.916	0.967	0.893	0.905	0.985	0.860	0.877	0.951

Source: Authors' estimates.

Note: The estimates are obtained through a logit regression with country dummy variables. Standard errors are shown in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in credit-to-GDP ratio is winsorized at 1 percent. Controls include the change in current account-to-GDP ratio and the real GDP growth rate. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix Table B3 - Crisis Prediction Model - Individual lags of ISS

	(1)	(2)
Δ(Credit-to-GDP Ratio)	-0.107	0.0412
	(0.108)	(0.0770)
Financial Conditions Index	-9.174***	-4.028***
	(3.012)	(1.095)
Lag 1 ISS^{EDF}	1.655**	
	(0.690)	
Lag 2 ISS^{EDF}	0.860**	
	(0.334)	
Lag 3 ISS^{EDF}	1.822**	
	(0.718)	
Lag 1 $ISS^{Leverage}$		0.687*
		(0.368)
Lag 2 $ISS^{Leverage}$		0.953***
		(0.360)
Lag 3 $ISS^{Leverage}$		0.890***
		(0.305)
Number of Observations	361	443
Number of Countries	17	21
Number of Crisis Episodes	17	21
Pseudo R^2	0.778	0.552

Source: Authors' estimates.

Note: The estimates are obtained through a conditional fixed effects logit regression. Standard errors are shown in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average (except for ISS) and are demeaned at the country level; the change in credit-to-GDP ratio is winsorized at 1 percent. Controls include the change in current account-to-GDP ratio and the real GDP growth rate. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix Table B4 - Crisis Prediction Model - Excluding 3-years post crisis

In line with the post-crisis bias discussed in Bussière and Fratzscher (2006), it is plausible that the riskiest firms have a more difficult access to credit in the aftermath of a financial crisis, so that the riskiness of credit allocation would mechanically decline in those years and its pre-crisis level would mechanically be above average. In order to reduce concerns about this potential source of bias, we repeat the analysis shown in Table 3 but exclude the observations during the three years following a crisis as in Gourinchas and Obstfeld (2012).[2]

	(1)	(2)
Δ(Credit-to-GDP Ratio)	-0.124	0.0470
	(0.118)	(0.0891)
Financial Conditions Index	-8.633***	-3.873***
	(2.219)	(0.960)
ISS^{EDF}	3.902***	
	(1.357)	
$ISS^{Leverage}$		2.427***
		(0.913)
Number of Observations	318	391
Number of Countries	17	21
Number of Crisis Episodes	17	21
Pseudo R^2	0.827	0.605

Source: Authors' estimates.

Note: The estimates are obtained through a conditional fixed effects logit regression. Standard errors are shown in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average (except for ISS) and are demeaned at the country level; the change in credit-to-GDP ratio is winsorized at 1 percent. Controls include the change in current account-to-GDP ratio and the real GDP growth rate. *** p<0.01, ** p<0.05, * p<0.1.

[2] Gourinchas and Obstfeld (2012) exclude the observations during the crisis year and following four years. Their sample starts in 1973, which is much earlier than ours, so we only exclude three years post crisis.

Online Appendix Table B5 - Downside Risks to Cumulative GDP Per Capita Growth

	(1)	(2)	(3)	(4)	(5)	(6)
	1 year		2 years		3 years	
	Decile 1	Decile 2	Decile 1	Decile 2	Decile 1	Decile 2
Panel A: ISS based on EDF						
Real GDP Growth	0.0951**	0.138***	-0.00517	0.122***	-0.0911	0.107
	(0.0402)	(0.0283)	(0.0541)	(0.0319)	(0.114)	(0.0720)
Δ(Credit-to-GDP Ratio)	-0.0532***	-0.0681***	-0.0551***	-0.158***	-0.163***	-0.237***
	(0.0194)	(0.0116)	(0.0202)	(0.0168)	(0.0402)	(0.0172)
Financial Conditions Index	0.342	0.00381	2.198***	1.353***	0.855	-0.0945
	(0.436)	(0.313)	(0.0812)	(0.160)	(0.849)	(0.276)
ISS^{EDF}	-0.138	-0.228***	-0.330***	-0.849***	-1.012***	-1.391***
	(0.122)	(0.0611)	(0.0975)	(0.145)	(0.313)	(0.181)
Number of Observations	586	586	586	586	586	586
Number of Countries	40	40	40	40	40	40
Panel B: ISS based on leverage						
Real GDP Growth	0.126***	0.116***	0.136**	0.0801**	0.0232	-0.00616
	(0.0319)	(0.0337)	(0.0654)	(0.0341)	(0.0654)	(0.0907)
Δ(Credit-to-GDP Ratio)	-0.0525***	-0.0640***	-0.192***	-0.155***	-0.241***	-0.253***
	(0.0101)	(0.0152)	(0.0613)	(0.0152)	(0.0508)	(0.0364)
Financial Conditions Index	0.702	0.297	0.825	0.0733	0.693	0.813
	(0.483)	(0.189)	(1.074)	(0.326)	(0.520)	(0.781)
$ISS^{Leverage}$	-0.403***	-0.386***	-0.750***	-0.802***	-1.013***	-1.033***
	(0.133)	(0.0485)	(0.240)	(0.0934)	(0.262)	(0.244)
Number of Observations	658	658	658	658	658	658
Number of Countries	42	42	42	42	42	42

Source: Authors' estimates.

Note: The estimates are obtained through quantile regressions with nonadditive fixed effects. Standard errors are in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in the credit-to-GDP ratio is winsorized at 1 percent. Controls include real GDP growth. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix Table B6a - Downside Risks to Growth Model - Additional Controls

In Appendix Table B6a and Appendix Table B6b, we show that the predictive power of both core ISS measures in the downside risks to growth and crisis models is robust to controlling for other non-credit-related earning warning indicators (EWIs).
In column (2), we control for real effective exchange rate and foreign exchange reserves, as in Gourinchas and Obstfeld (2012).[3] In columns (3) and (4), we show that the predictive power of ISS is robust to the addition of firm vulnerability indicators as controls. The first vulnerability indicator is defined as the median level of expected default frequency (in panel A) or the median level of leverage (in panel B) for each country*year. The second vulnerability indicator is the share of assets in firms with an EDF above the 75th percentile of the historical distribution (in panel A), or with leverage above the 75th percentile of the historical distribution (in panel B) for each country. Either of them provides meaningful information in predicting banking crisis.
Because of limited sample coverage, we are unable to check the robustness of our findings to the inclusion of the property price gap and the debt service ratio, two indicators recently suggested by Aldosoro, Borio, and Drehmann (2018), in a statistically meaningful way.

	(1)	(2)	(3)	(4)
Panel A: Riskiness of Credit Allocation Based on EDF				
Real GDP Growth	-0.0546	0.0153	0.0717	0.126
	(0.144)	(0.120)	(0.0930)	(0.146)
Δ(Credit-to-GDP Ratio)	-0.257***	-0.203***	-0.198***	-0.158***
	(0.0293)	(0.0303)	(0.0289)	(0.0303)
Financial Conditions Index	-0.641	0.0687	1.482***	3.075***
	(0.587)	(0.917)	(0.231)	(0.346)
ISS^{EDF}	-1.321***	-1.208***	-1.138***	-0.968***
	(0.164)	(0.237)	(0.185)	(0.161)
Real Exchange Rate		-7.334**		
		(3.278)		
Reserves-to-GDP		0.101**		
		(0.0437)		
Median EDF			-0.0801*	
			(0.0446)	
Share of Assets in High EDF firms				-0.00241
				(0.0175)
Number of Observations	586	586	586	577
Number of Countries	40	40	40	40
Panel B: Riskiness of Credit Allocation Based on Leverage				
Real GDP Growth	-0.0316	-0.0565	-0.359**	-0.109
	(0.118)	(0.102)	(0.154)	(0.0937)
Δ(Credit-to-GDP Ratio)	-0.264***	-0.368***	-0.355***	-0.225***
	(0.0459)	(0.0258)	(0.0976)	(0.0386)
Financial Conditions Index	0.209	-1.172**	-0.526*	-0.00485
	(0.758)	(0.560)	(0.299)	(0.645)
$ISS^{Leverage}$	-0.614***	-0.818***	-0.464**	-0.566***
	(0.200)	(0.187)	(0.230)	(0.214)
Real Exchange Rate		-14.22***		
		(3.147)		
Reserves-to-GDP		0.0163		
		(0.0176)		
Median Leverage			-18.86***	
			(4.287)	
Share of Assets in High Leverage Firms				-0.0252**
				(0.0102)
Number of Observations	658	658	658	651
Number of Countries	42	42	42	42

[3] We don't have long and large enough sample to test whether this mitigation effect is stronger for emerging market as suggested by Gourinchas and Obstfeld (2012).

Online Appendix Table B6b - Crisis Prediction Model - Additional Controls

Panel A: Riskiness of Credit Allocation Based on EDF	(1)	(2)	(3)	(4)
Δ(Credit-to-GDP Ratio)	-0.109	-0.329	-0.0965	-0.0844
	(0.0983)	(0.256)	(0.106)	(0.120)
Financial Conditions Index	-8.072***	-11.35**	-7.933***	-6.718***
	(2.247)	(4.680)	(2.191)	(2.100)
ISS^{EDF}	3.594***	5.893***	3.668***	3.355***
	(1.042)	(2.178)	(1.077)	(1.301)
Real Exchange Rate		62.96		
		(58.00)		
Reserves-to-GDP		-1.375***		
		(0.500)		
Median EDF			-0.674	
			(1.184)	
Share of High Vulnerability Assets				-0.132
				(0.0878)
Number of Observations	361	361	361	339
Number of Countries	17	17	17	16
Number of Crisis Episodes	17	17	17	16
Pseudo R^2	0.749	0.890	0.755	0.752
Panel B: Riskiness of Credit Allocation Based on Leverage	(1)	(2)	(3)	(4)
Δ(Credit-to-GDP Ratio)	0.0361	-0.533***	-0.0161	-0.0544
	(0.0807)	(0.128)	(0.0964)	(0.0886)
Financial Conditions Index	-3.993***	-17.73***	-6.745***	-7.469***
	(1.055)	(4.205)	(1.563)	(2.124)
$ISS^{Leverage}$	2.560***	9.275***	3.454***	3.904***
	(0.746)	(2.704)	(0.757)	(1.172)
Real Exchange Rate		16.30		
		(12.22)		
Reserves-to-GDP		-1.916**		
		(0.806)		
Median leverage			29.79***	
			(7.890)	
Share of High Vulnerability Assets				0.163***
				(0.0460)
Number of Observations	443	443	443	432
Number of Countries	21	21	21	20
Number of Crisis Episodes	21	21	21	20
Pseudo R^2	0.550	0.880	0.632	0.658

Online Appendix Table B7a. Downside Risks to Growth Model with Interaction Terms

We ask whether the usefulness of signals provided by ISS depend on the strength of the underlying credit expansion. One might expect that large credit expansions that are accompanied by a rise in the riskiness of credit allocation pose stronger downside risks to growth than those that are not. We thus add an interaction term between the size of the credit expansion and the riskiness of credit allocation to equation (5) and run:

$$\Delta y^{d}_{i,t,t+h} = \beta\Delta\left(\frac{Credit}{GDP}\right)^{mv3}_{i,t-1} + \gamma FCI^{mv3}_{i,t-1} + \delta ISS^{V,mv3}_{i,t-1}$$

$$+\theta\Delta\left(\frac{Credit}{GDP}\right)^{mv3}_{i,t-1} \times ISS^{V,mv3}_{i,t-1} + \mu Controls^{mv3}_{i,t-1} + u_{i,t} \qquad (xx)$$

Table B7a summarizes the results for the 2-year and 3-year horizons (h=2,3). Columns (1), (3) and (7) show that a rise in aggregate credit volumes combined with a high ISS level signals elevated downside risks to growth, measured by the first decile of the GDP growth distribution, two and three years ahead.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2 years		3 years		2 years		3 years	
	Decile 1	Decile 2	Decile 1	Decile 2	Decile 1	Decile 2	Decile 1	Decile 2
Δ(Credit-to-GDP Ratio)	-0.116***	-0.134***	-0.217***	-0.241***	-0.230***	-0.177***	-0.594***	-0.267***
	(0.0210)	(0.0243)	(0.0706)	(0.0353)	(0.0162)	(0.0199)	(0.0302)	(0.0421)
Financial Conditions Index	1.718***	0.655***	1.772	-0.0266	2.405***	-0.127	1.407***	0.337
	(0.126)	(0.222)	(1.095)	(0.769)	(0.250)	(0.395)	(0.498)	(0.631)
ISS^{EDF}	-0.678***	-0.618***	-0.744***	-1.295***				
	(0.132)	(0.128)	(0.121)	(0.188)				
Δ(Credit-to-GDP Ratio) x ISS^{EDF}	-0.0577**	0.00659	-0.0774**	-0.0456*				
	(0.0224)	(0.0290)	(0.0356)	(0.0269)				
$ISS^{Leverage}$					-0.486**	-0.545***	0.971***	-0.726***
					(0.194)	(0.204)	(0.300)	(0.213)
Δ(Credit-to-GDP Ratio) x $ISS^{Leverage}$					-0.286***	-0.0406	-0.0845***	-0.0403
					(0.0308)	(0.0356)	(0.0283)	(0.0346)
Number of Observations	586	586	586	586	658	658	658	658
Number of Countries	40	40	40	40	42	42	42	42

Source: Authors' estimates.
Note: The estimates are obtained through quantile regressions with nonadditive fixed effects (Powell 2016). Standard errors are in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in the credit-to-GDP ratio is winsorized at 1 percent. Real GDP growth is controlled for. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix Table B7b - Crisis Prediction Model with Interaction Terms

We ask whether the early warning properties of the riskiness of credit allocation depend on the size of the underlying credit expansion by adding interaction terms between the change in the credit-to-GDP ratio and the riskiness of credit allocation to Equation (6):

$$log\frac{P\left[Crisisstart_t = 1|X_{i,t-1}\right]}{P\left[Crisisstart_t = 0|X_{i,t-1}\right]} = \alpha_i + \beta\Delta Credit_{i,t-1}^{mv3} + \gamma FCI_{i,t-1}^{mv3}$$

$$+\delta ISS_{i,t-1}^{V,mv3} + \theta\Delta Credit_{i,t-1}^{mv3} \times ISS_{i,t-1}^{V,mv3} + \mu Controls_{i,t-1}^{mv3} + u_{i,t} \qquad (yy)$$

Columns (1) and (2) of Table B7b present the results. We do not find evidence that the predictive power of ISS for financial crises depends on the size of the credit expansion.

	(1)	(2)
Δ(Credit-to-GDP Ratio)	-0.0596	0.329
	(0.107)	(0.387)
FCI	-7.804***	-4.117***
	(2.165)	(1.115)
ISS^{EDF}	3.329***	
	(0.997)	
$ISS^{Leverage}$		2.842***
		(0.756)
Δ(Credit-to-GDP Ratio) * ISS^{EDF}	0.107	
	(0.0841)	
Δ(Credit-to-GDP Ratio) * $ISS^{Leverage}$		-0.124
		(0.155)
Number of Observations	361	443
Number of Countries	17	21
Number of Crisis Episodes	17	21
Pseudo R^2	0.753	0.556

Source: Authors' estimates.
Note: The estimates are obtained through a conditional fixed effects logit regression. Standard errors are shown in parentheses. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in credit-to-GDP ratio is winsorized at 1 percent. Controls include the change in current account-to-GDP ratio and the real GDP growth rate. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix Table B8 - Downside Risks to Growth Model - Pre-Crisis Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	1 year		2 years		3 years	
	Decile 1	Decile 2	Decile 1	Decile 2	Decile 1	Decile 2
Panel A: ISS based on EDF						
Real GDP Growth	-0.202**	-0.120**	-0.380**	-0.250**	-0.994***	-0.715**
	(0.100)	(0.0613)	(0.174)	(0.124)	(0.321)	(0.283)
Δ(Credit-to-GDP Ratio)	-0.0685***	-0.0495***	-0.0861**	-0.119***	-0.0536	-0.190***
	(0.0264)	(0.0165)	(0.0414)	(0.0446)	(0.0776)	(0.0660)
Financial Conditions Index	-0.227	0.242	0.118	0.0283	0.347	-0.488
	(0.270)	(0.314)	(0.404)	(0.476)	(0.674)	(0.673)
ISS^{EDF}	-0.421	-0.266	-1.415***	-1.122***	-1.015	-1.066
	(0.318)	(0.180)	(0.323)	(0.284)	(0.735)	(0.693)
Number of Observations	296	296	296	296	296	296
Number of Countries	34	34	34	34	34	34
Panel B: ISS based on leverage						
Real GDP Growth	-0.0103	0.0170	-0.146	-0.219	-0.399**	-0.343***
	(0.0589)	(0.0575)	(0.161)	(0.149)	(0.194)	(0.115)
Δ(Credit-to-GDP Ratio)	-0.0606***	-0.0345**	-0.136***	-0.0808**	-0.159***	-0.111***
	(0.0203)	(0.0149)	(0.0512)	(0.0365)	(0.0497)	(0.0355)
Financial Conditions Index	0.289	0.0938	-0.394	-0.262	-0.0232	0.163
	(0.354)	(0.195)	(0.633)	(0.632)	(0.411)	(0.578)
$ISS^{Leverage}$	-0.0964	-0.198**	-0.599*	-0.571**	-1.628***	-0.918**
	(0.242)	(0.0823)	(0.364)	(0.276)	(0.315)	(0.364)
Number of Observations	355	355	355	355	355	355
Number of Countries	39	39	39	39	39	39

Source: Authors' estimates.

Note: The estimates are obtained through quantile regressions with nonadditive fixed effects (Powell 2016). Standard errors are in parentheses. The sample excludes all years after 2005. Explanatory variables enter the regression as the lag of their simple three-year moving average and are demeaned at the country level; the change in the credit-to-GDP ratio is winsorized at 1 percent. Real GDP growth is controlled for. *** p<0.01, ** p<0.05, * p<0.1.

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