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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Bank-based versus market-based financing: implications for systemic risk*

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Abstract

Against the background of the great financial crisis, this paper assesses the merits of bank-based versus market-based financing by exploring the relationship between financial structure and systemic risk. A fixed effects regression model is estimated over a panel of 22 OECD countries. The results show that bank-based financing generates systemic risk while market-based debt and especially market-based stock financing reduce systemic risk. A threshold regression model estimated over the same panel suggests that banks no longer contribute to systemic risk when there is little bank-based financing. In the case of relatively market-based financial structures, the influence of banks on systemic risk is low. The findings indicate that countries can increase their resilience to systemic risk by reducing the share of bank-based financing and increasing the share of market-based financing.

Keywords: financial structure, systemic risk, bank-based financing, market-based financing.
JEL classifications: E44, G10, G21, O16.

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Declaration of interest: none.

1. Introduction

Financial structures mobilize savings, price risks, allocate capital and absorb shocks in different ways. In a bank-based financial structure, financing consists mostly of institutions that conduct financial intermediation on their balance sheet. These financial institutions bear risks and generally lend through close relationships with their clients. By contrast, a market-based financial structure primarily channels savings directly to borrowers through markets. These markets serve as a platform where equity and debt securities are priced, distributed and traded.

In light of these differences, there is a long-standing debate on the real economic merits of bank-based versus market-based financial structures. The results have changed over time. The literature published before 2008 does not favor one particular financial structure over the other. Instead, these studies find that the overall provision of financial services matters for the real economy (Demirgüç-Kunt and Levine, 2001c, Levine, 2002, Beck and Levine, 2002, Demirgüç-Kunt and Maksimovic, 2002) and that banks and markets are similarly important for economic growth (Levine and Zervos, 1998, Boyd and Smith, 1998, World Bank, 2001, Beck and Levine, 2004). However, the literature published after the great financial crisis of 2008 generally has a preference for market-based systems. This is because a financial crisis (Gambacorta et al. 2014) or a housing market crisis (Langfield and Pagano, 2016) is economically more severe in bank-based than in market-based financial structures. Banks overextend and misallocate credit in financial upturns and ration credit in financial downturns more than markets (Pagano et al. 2015).

The real economic benefits of bank-based financial structures therefore depend on the stability of the financial system. But this stability can be upset by systemic risk. Systemic risk may be defined as a disruption to the flow of financial services that is (i) caused by an impairment of all or parts of the financial system; and (ii) has the potential to have serious negative consequences for the real economy (BIS, FSB and IMF, 2009). Banks can generate systemic risk for a number of reasons. First, they are highly leveraged. When times are good – that is, when asset values are rising – leveraged institutions can extract higher returns on their equity. However, when times are bad – that is, when asset values are falling – these institutions may be required to raise capital or shrink their balance sheet in order to meet regulatory requirements.[1] In a system of leveraged banks, fire sales amplify downturns (Adrian and Shin, 2014). Also, when higher bank leverage induces stronger creditor discipline, systemic risk rises on account of contagious bank runs prompted by creditors liquidating their claims (Acharya and Thakor, 2016). Second, the large asset-liability mismatches of banks make them vulnerable to liquidity and interest rate shocks, and in the extreme to bank runs. This contributes to systemic risk. Third, banks trade with each other through many markets, intermediaries and systems. This creates long intermediation chains, adds complexity and leads banks to be highly interconnected (Craig and von Peter, 2014). Interconnectedness is a key driver of systemic importance (Drehmann and Tarashev, 2013). Due to settlement, liquidity and funding risk, this interconnectedness can propagate losses through the financial system, as losses for one bank may cause losses for another. Market-based financing, by contrast, is less leveraged, has more asset-liability matching and more direct financing from savers to investors, implying less financial system interconnectedness. These attributes make market-based financing less likely to contribute to systemic risk.

This paper studies the extent to which bank-based financial structures actually contribute more to systemic risk than market-based financial structures. The novelty of this study is not to test the impact of financial structure on economic growth; the existing empirical literature has already investigated this for business cycles with or without a financial crisis. Instead, this study seeks to explain the recent changes in the results of the empirical literature by determing the financial structure's contribution to systemic risk.

A linear regression model and a threshold regression model are estimated over a panel of 22 OECD countries. The models distinguish between bank-based financing, market-based debt financing and market-based stock financing. The results lead to four key conclusions. First, financial structure influences systemic risk. While bank-based financing generates systemic risk, market-based debt and stock financing reduce systemic risk. Second, from a systemic risk perspective market-based equity financing is preferred over market-based debt financing. Third, when the financial structure has limited

[1] The failure of the UK bank Northern Rock is an example of how sudden de-risking in credit markets can create problems at highly leveraged banks (Shin, 2009).

bank-based financing, banks do not generate systemic risk. Fourth, when the financial structure is relatively market-based, the influence of banks on systemic risk is low. The impact of financial structure on systemic risk is thus found to be non-linear. These findings have implications for public policies that impact financial structure.

The rest of this paper is organized as follows. Section 2 presents the methodology and section 3 describes the data. The empirical results are shown and discussed in section 4. Section 5 concludes.

2. Methodology

The empirical analysis is conducted in two ways. First, a linear fixed effects regression model estimates the total effect of bank-based and market-based financial structures on systemic risk. Second, a threshold model is used to determine whether the influence of financial structure on systemic risk changes according to the amount of bank-based financing and the composition of the financial structure.

The linear regression model draws on the relationship between financial structure and systemic risk:

$$SRISK_{i,t} = \alpha_0 + \alpha_1 BANK_{i,t} + \alpha_2 DEBT_{i,t} + \alpha_3 STOCK_{i,t} + \beta_1 X_{1i,t} + \beta_2 X_{2i,t} + u_i + \eta_t + \varepsilon_{i,t} \quad (1)$$

To account for the financial structure of country *"i"* at time *"t"*, three indicators are used. The first indicator, $BANK_{i,t}$, represents the degree of bank-based financing and is defined as the ratio of bank credit to GDP. The second indicator, $DEBT_{i,t}$, signals the degree of market-based debt financing (such as bonds, notes, and debentures) and is defined as the logarithm of the ratio of total non-financial debt market capitalization to GDP.[2] The third indicator, $STOCK_{i,t}$, reflects the degree of market-based stock financing and is defined as the logarithm of the ratio of stock market capitalization to GDP. Subsequently the higher $BANK_{i,t}$, the more a financial system is bank-dependent; the higher $DEBT_{i,t}$

[2] The debt indicator excludes financial debt market capitalization to avoid double-counting and biased results: banks that extend credit may finance themselves via debt securities. This is a different approach to the financial structure literature which, next to including bank credit, generally defines the debt indicator as total debt market capitalization (see e.g. Langfield and Pagano, 2015, and the robustness check in footnote 5 of Gambacorta et al. 2014). In our model, using total debt market capitalization produces spurious results for the impact of market-based debt financing on systemic risk.

and $STOCK_{i,t}$, the more a financial system is market-dependent. $BANK_{i,t}$ and $DEBT_{i,t}$ are debt financing indicators whereas $STOCK_{i,t}$ is an equity financing indicator.

The model controls for time-invariant effects that differ across countries by including country fixed effects represented by u_i. Additionally, the model controls for country-invariant effects that change over time by including year fixed effects represented by η_t. Lastly, the error term is represented by $\varepsilon_{i,t}$.

Furthermore, the model includes a control variable $X_{1i,t}$ for the size (total assets held by deposit money banks as a share of GDP) and a control variable $X_{2i,t}$ for the concentration (assets of the three largest commercial banks as a share of total commercial bank assets) of the banking sector relative to the economy. Since larger banks tend to be more interconnected with other banks, conduct more trading activities and induce moral hazard since they are more likely to receive public support, they generate more systemic risk (Afonso et al. 2014, Langfield et al. 2014 and Laeven et al. 2014).

The model maps out the impact of financial structure on systemic risk. Systemic risk comprises various dimensions – including the financial system's size, leverage, maturity mismatches and interconnectedness – and is difficult to measure. Traditional institution-level indicators such as Value-at-Risk and volatility fail to capture the interconnectedness of the financial system. One approach to measure systemic risk is to calculate ΔCoVaR, the change in the Value-at-Risk of the financial system conditional on an institution being under distress (Adrian and Brunnermeier, 2016). While ΔCoVaR accounts for the interconnectedness of financial institutions with the market, differences in volatility between institutions are not reflected in the measurement of systemic risk.

This paper uses a systemic risk indicator that also accounts for differences in volatility between individual institutions and follows the approach proposed by Acharya et al. (2012) and Brownlees and Engle (2012). It measures the nominal amount of the expected equity capital shortfall ($CS_{fin,t:t+6\ months}$) of a stock-listed financial institution *"fin"* in case of a 40% broad stock market index decline during a 6 month time period and is defined as:

$$CS_{fin,t:t+6\ months} = E_t\left[\theta A_{fin,t+6\ months} - W_{fin,t+6\ months} \mid Marketdecline_{t:t+6\ months}\right] \quad (2)$$

where A_{fin} and W_{fin} denote the book value of assets and market value of equity of a financial institution *"fin"* respectively, and θ is a prudential ratio of equity to assets. This ratio represents the fraction of assets that satisfies the minimum unweighted capital requirement.[3] Assuming the sum of assets equals the sum of equity (W) and the sum of the book value of debt (D), i.e. $A = W + D$, equation (2) can be rewritten as:

$$CS_{fin,t:t+6\,months} = E_t\left[\theta D_{fin,t+6\,months} - (1-\theta)W_{fin,t+6\,months} \mid Marketdecline_{t:t+6\,months}\right] \quad (3)$$

Assuming the book value of debt is not affected by the crisis and remains constant in the short run, equation (3) can be rewritten as:

$$CS_{fin,t:t+6\,months} = \left\{\theta\left(L_{fin,t} - 1\right) - (1-\theta)E_t\left[\frac{W_{fin,t+6\,months}}{W_{fin,t}} \mid Marketdecline_{t:t+6\,months}\right]\right\} W_{fin,t} \quad (4)$$

Where $L_{fin,t} = A_{fin,t}/W_{fin,t}$ denotes a financial institution's leverage, so that $D_{fin,t} = \left(L_{fin,t} - 1\right)W_{fin,t}$. The equity capital shortfall is thus dependent on the financial leverage of an institution and the long-run marginal expected shortfall of an institution's return in the event of a 40% broad stock market index decline.

To aggregate the data and to calculate the extent to which the financial system as a whole is undercapitalized, the sum of the nominal amount of all institutions' equity capital shortfall is divided by the sum of the nominal amount of all institutions' assets for all countries per year:

$$SRISK_{i,t} = \frac{\sum_{fin} CS_{fin,t:t+6\,months}}{\sum_{fin} A_{fin,t}} \quad (5)$$

This ensures that the results are not affected by the size of individual banks and allows countries' systemic risk values to be compared with each other. Furthermore, following Acharya et al. (2012), negative $SRISK_{i,t}$ values (equaling negative equity capital shortfalls) are set at zero since these values do not add to systemic risk.

[3] This is in line with the non-risk based leverage ratio introduced under Basel III.

For this study, the capital requirement for European financial institutions is set at 5.5% and for American financial institutions at 8%. As explained by Engle et al. (2015), these are comparable requirements due to differences in accounting principles between the institutions from which the data is obtained: European institutions follow the International Financial Reporting Standards (IFRS); American institutions follow the Generally Accepted Accounting Principles (GAAP). If the capital requirement for European institutions were set higher than 5.5%, these institutions would have to raise relatively more capital than American firms; therefore favoring the latter.

As a robustness check, the effects of bank-based and market-based financing are also tested on the dependent variable $CISS_{i,t}$, a composite indicator of systemic stress in the financial system (Holló et al. 2012). In contrast to $SRISK_{i,t}$, the calculation of $CISS_{i,t}$ is not economically modelled, but takes a more structural approach based on portfolio theory. It aggregates market-specific subindices created from 15 individual financial stress measures. These subindices are highly relevant for systemic risk and involve money, equity, bond and foreign exchange markets, as well as the sector of bank and non-bank intermediaries. $CISS_{i,t}$ is only weakly correlated with $SRISK_{i,t}$ (53%).

To find out whether the amount of bank-based financing (bank credit to GDP) and the financial structure (bank credit to stock market and non-financial debt market capitalization) change the impact of financial structure on systemic risk, a threshold model is constructed following Hansen (1999). To establish a threshold (λ) around bank-based financing and the financial structure, model (6) and (7) detect a break between financial structure and systemic risk:

$$SRISK_{i,t} = \begin{cases} \alpha_{01} + \alpha_{11}BANK_{i,t} + \alpha_{21}DEBT_{i,t} + \alpha_{31}STOCK_{i,t} + \alpha_{41}X_{1i,t} + \alpha_{51}X_{2i,t} + u_i + \eta_t + \varepsilon_{i,t} & BANK_{i,t} > \lambda \\ \alpha_{02} + \alpha_{12}BANK_{i,t} + \alpha_{22}DEBT_{i,t} + \alpha_{32}STOCK_{i,t} + \alpha_{42}X_{1i,t} + \alpha_{52}X_{2i,t} + u_i + \eta_t + \varepsilon_{i,t}, & BANK_{i,t} \leq \lambda \end{cases} \quad (6)$$

$$SRISK_{i,t} = \begin{cases} \alpha_{01} + \alpha_{11}BANK_{i,t} + \alpha_{21}DEBT_{i,t} + \alpha_{31}STOCK_{i,t} + \alpha_{41}X_{1i,t} + \alpha_{51}X_{2i,t} + u_i + \eta_t + \varepsilon_{i,t}, & FINSTR_{i,t} > \lambda \\ \alpha_{02} + \alpha_{12}BANK_{i,t} + \alpha_{22}DEBT_{i,t} + \alpha_{32}STOCK_{i,t} + \alpha_{42}X_{1i,t} + \alpha_{52}X_{2i,t} + u_i + \eta_t + \varepsilon_{i,t}, & FINSTR_{i,t} \leq \lambda \end{cases} \quad (7)$$

where $FINSTR_{i,t}$ represents the financial structure and equals bank credit to stock market and non-financial debt market capitalization.

The slopes of α_{01}, α_{11}, α_{21}, α_{31}, α_{41}, α_{51} and α_{02}, α_{12}, α_{22}, α_{32}, α_{42}, α_{52} are estimated separately to show the effect below and above the estimated thresholds. The threshold level is found by estimating model (6) and (7) for a range of different threshold values of $BANK_{i,t}$ and $FINSTR_{i,t}$. The threshold value in the regression with the smallest sum of squared residuals is chosen.

Hansen's (1999) F-test is used to test the significance of the threshold values λ for all indicator variables.[4] The following five constraints are tested:

$$H_0 : \begin{cases} \alpha_{11} = \alpha_{12} \\ \alpha_{21} = \alpha_{22} \\ \alpha_{31} = \alpha_{32} \\ \alpha_{41} = \alpha_{42} \\ \alpha_{51} = \alpha_{52} \end{cases} \tag{8}$$

where under null hypothesis H_0 the threshold value λ is not identified. To compare the fit of the two models (a model where λ is identified and one where it is not) the likelihood ratio test of H_0 is based on:

$$F_1 = (S_0 - S_1(\hat{\lambda}))/\hat{\sigma}^2 \tag{9}$$

where S_0 and $S_1(\hat{\lambda})$ denote the sum of squared errors under the null hypothesis of no threshold and the alternative hypothesis of a threshold respectively.[5] The null hypothesis (8) is rejected if the p-value is smaller than 0.05.

3. Descriptive data

The analysis relies on four different data sources. Data for the systemic risk variable $SRISK_{i,t}$ is provided by New York University (NYU) Stern's Volatility Laboratory.[6] Data for the alternative systemic risk variable $CISS_{i,t}$ are taken from European Central Bank (ECB) Statistical Data Warehouse. Data for non-financial debt market capitalization, $DEBT_{i,t}$ is obtained from the debt securities statistics of the BIS. Data for all other independent variables (the ratio of bank credit to GDP, stock market

[4] The estimation and significance test of the threshold are conducted on data containing no missing values by interpolating the data as a function of time and do not incorporate fixed effects. However, the estimation of (6) and (7) include country and time fixed effects and an interpolation of the data is not applied.

[5] Hansen's (1996) bootstrap procedure is used, since p-values constructed from a bootstrap are asymptotically valid. This procedure is repeated 5000 times. The percentage of draws for which the simulated F_1 value exceeds the actual value is calculated and the resulting value is the bootstrap estimate of the asymptotic p-value.

[6] This group of financial institutions can be found on NYU Stern's Volatility Laboratory's website - https://vlab.stern.nyu.edu/welcome/risk.

capitalization to GDP, the size and the concentration of a country's banking sector) are obtained from the World Bank's Global Financial Development Database.[7] Since the $SRISK_{i,t}$ values start in 2000, the panel covers the timespan from 2000 to 2015, with yearly observations for all variables. To distinguish between different financial structures, the panel focuses on the following 22 OECD countries for which $SRISK_{i,t}$ data is available: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Turkey, the United Kingdom and the United States.

Table 1 gives a summary of the statistics and Table 2 provides a correlation matrix. Importantly, there is sufficient time variation in all three indicator variables so that all coefficients can be identified.

Table 1: Descriptive statistics

Variables	**Unit of measurement**	**Obs**	**Mean**	**Std dev**	**Min**	**Max**
Dependent variable						
Systemic risk	% of assets	352	1.8	1.6	0.0	5.6
Financial structure						
Bank credit	% of GDP	350	95.2	38.3	12.5	212.9
Non-fin debt market	% of GDP	327	11.6	9.1	0.0	56.4
Stock market	% of GDP	337	72.7	40.3	13.8	250.0
Control variable						
Bank assets	% of GDP	344	113.9	40.9	32.6	225.8
Concentration banks	% of assets	348	67.9	20.3	21.4	100.0

This table presents the descriptive statistics of all variables in the linear and threshold regression models. The first variable represents the dependent variable systemic risk and reports the descriptive statistics for a country's systemic risk per unit of financial asset. The second, third and fourth variable are the financial structure indicator variables and report the descriptive statistics for: bank credit as a percentage of GDP, non-financial debt market capitalization as a percentage of GDP and stock market capitalization as a percentage of GDP. The last two variables are the control variables and report the descriptive statistics for: the total assets held by deposit money banks as a share of GDP and the total assets of the three largest commercial banks as a share of total commercial bank assets.

Table 2: Correlation matrix

Variables	Bank credit	Debt market	Stock market	Bank size	Concentration banks
Bank credit	1.000				
Non-fin debt market	0.051	1.000			
Stock market	0.038	0.477	1.000		
Bank assets	0.233	-0.224	-0.418	1.000	
Concentration banks	0.242	-0.160	-0.337	-0.034	1.000

This table presents the correlation matrix for all independent variables in the linear and threshold regression models. The variables are: bank credit as a percentage of GDP, non-financial debt market capitalization as a percentage of GDP, stock market capitalization as a percentage of GDP, the total assets held by deposit money banks as a share of GDP and the total assets of the three largest commercial banks as a share of total commercial bank assets.

[7] Data on the ratio of bank credit to GDP for Canada is obtained from the credit statistics of the BIS since the World Bank's Global Financial Development Database provides no bank credit data for Canada after 2008.

To illustrate the difference in financial structures and systemic risk between countries and their evolution over time, Figure 1 presents time-plots for the ratio of bank credit to GDP, the ratio of stock market capitalization to GDP, the ratio of non-financial debt market capitalization to GDP, and the ratio of bank credit to stock market and non-financial debt market capitalization. The time-plots for the European average are based on the 16 European countries in the sample.[8] The shaded time-plots for the European bound present the minimum and maximum observations of the European countries with relatively large financial structures.[9]

Figure 1.1 shows that bank credit to GDP is highest for the United Kingdom and the European maximum bound (Spain). It is lowest for Turkey and the United States. The European average is in the upper half. Figure 1.2 demonstrates that non-financial debt market capitalization to GDP is highest in the United States and lower in Europe and Turkey. During the crisis, non-financial debt financing increased substantially in all countries. This signals the relevance of market-based debt financing in times financial distress. Figure 1.3 shows that stock market capitalization to GDP is particularly low in Turkey, and to a lesser extent also in Europe.[10] Stock market capitalization to GDP is highest in the United States. Figure 1.4 indicates that the United States and Canada have relatively market-based financial structures, while Europe has a relatively bank-based structure. The highest European bound represents Germany before the crisis, and Italy during and after the crisis.

Figure 2 presents a time-plot of systemic risk as a percentage of financial institutions' total assets. While systemic risk decreased after the financial crisis of 2008 in the United States, Australia, Canada, and to a lesser extent the United Kingdom, it remained broadly constant for several years in Europe and initially even increased in Japan.

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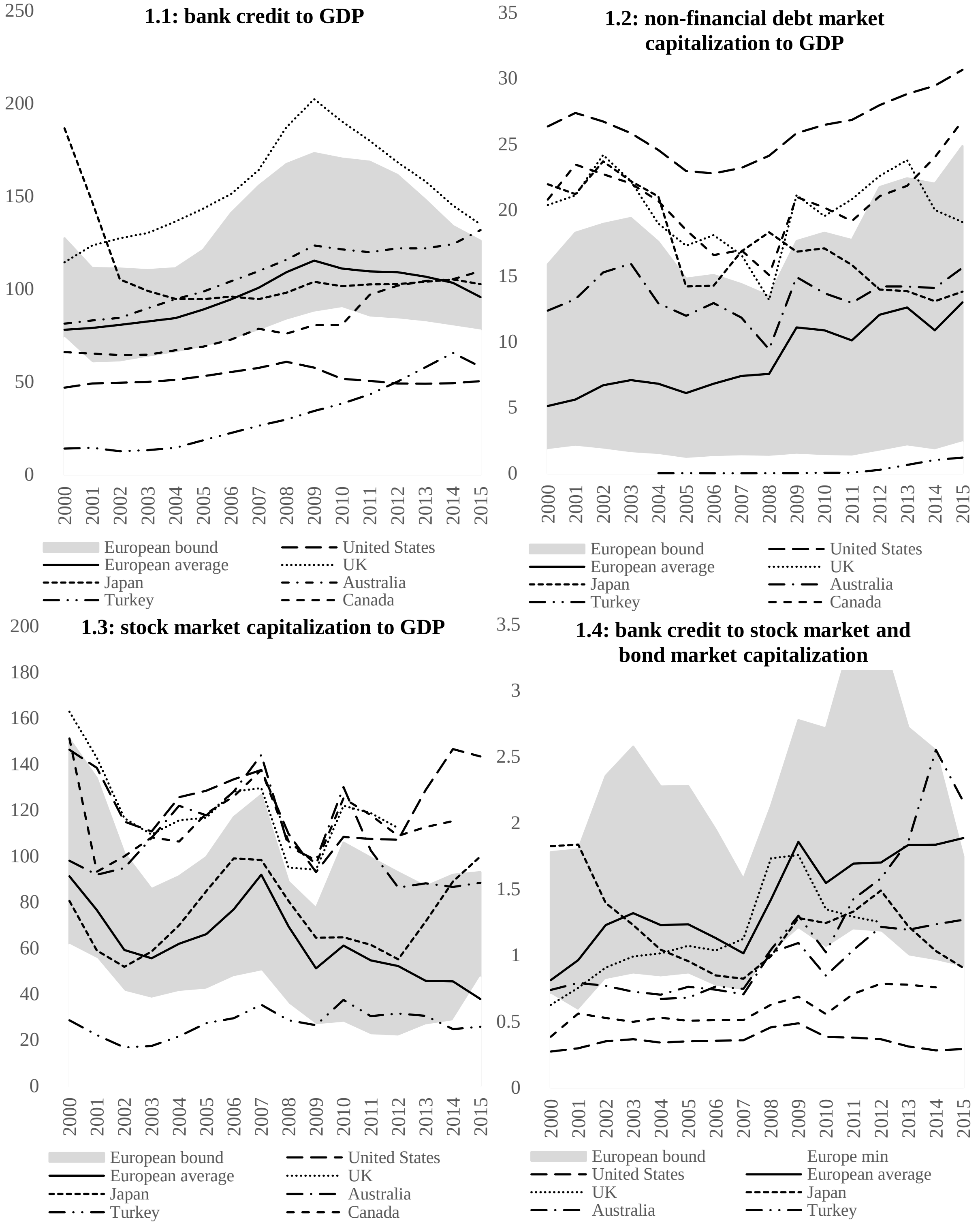
[8] These countries are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain and Sweden. The United Kingdom is treated separately.

[9] All European countries with financial structures larger than 5% of the total European financial structure in the samples are included. These countries are: France, Germany, Italy, Netherlands, Spain and Sweden.

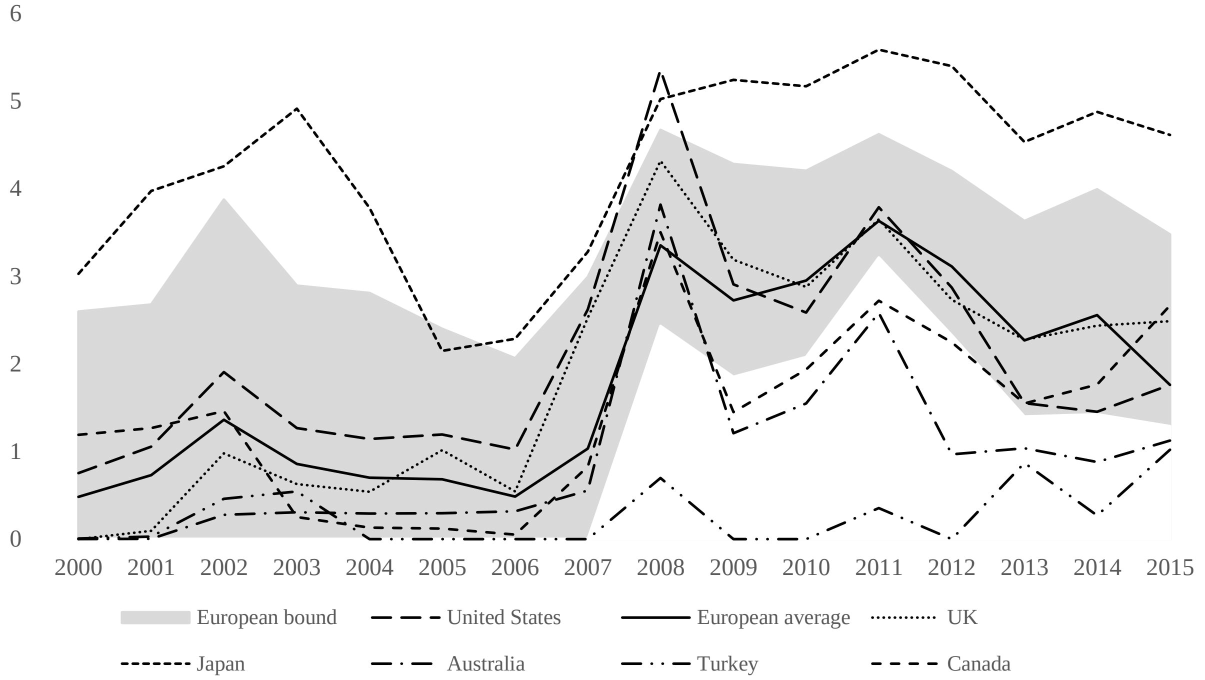
[10] The European average also includes European countries with relatively small financial structures and is therefore lower than the European bound.

Figure 1: Financial structure



This figure shows time-plots for the ratio of bank credit to GDP, the ratio of stock market capitalization to GDP, the ratio of non-financial debt market capitalization to GDP, and the ratio of bank credit to stock market and non-financial debt market capitalization. The time-plots for the European average are based on the following 16 countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain and Sweden. The United Kingdom. The shaded area presents the minimum and maximum observations of the European countries with financial structures larger than 5% of the total European financial structure (France, Germany, Netherlands, Spain and Sweden).

Figure 2: Systemic risk



This figure shows a time-plot of a country's systemic risk as a percentage of financial institutions' total assets. The time-plot for the European average are based on the following 16 countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain and Sweden. The United Kingdom. The shaded area presents the minimum and maximum observations of the European countries with financial structures larger than 5% of the total European financial structure (France, Germany, Italy, Netherlands, Spain and Sweden).

4. Results

This section presents the results of the fixed effects panel regression model (1) and the structural break model (6) and (7).

4.1 Fixed effects regression model

Table 3 presents the estimations for model (1) and reports the outcomes of serial correlation and multicollinearity tests. The model includes HAC standard errors since all regressions test positive for serial correlation. The severity of multicollinearity is measured via the variance inflation factor (VIF). The highest VIF reports the highest factor of all financial structure indicators (which is bank credit to GDP in all regressions). The highest VIF equals 6.51 when the control variables are excluded and 3.52 once time fixed effects are excluded. Therefore, multicollinearity does not create major issues for the results.[11]

[11] Additionally, Table 2 shows no strong correlations.

Table 3: Fixed effects panel regression model

Regressors	I	II	III
Bank credit	0.0139***	0.0190**	0.0138***
	(0.0045)	(0.0068)	(0.0046)
Non-fin debt market cap (log)	-0.0014***	-0.0017***	-0.0013***
	(0.0003)	(0.0004)	(0.0005)
Stock market cap (log)	-0.0120**	-0.0116**	-0.0124**
	(0.0047)	(0.0047)	(0.0056)
Banking sector size		-0.0055	
		(0.0084)	
Banking sector concentration			-0.0025
			(0.0077)
Constant	-0.0127***	-0.0124***	-0.0109
	(0.0039)	(0.0043)	(0.0064)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
R-sqr (within) [1]	0.735	0.736	0.732
N	308	302	304
Serial correlation test [2]	0.0060	0.0075	0.0090
Mean VIF [3]	1.98	2.70	2.78
Highest VIF [4]	6.51	7.97	8.74

This table presents the estimations for model (1). The dependent variable is systemic risk per unit of asset. HAC standard errors are given in parentheses. The regression controls for time and country fixed effects in all columns. Column 1 shows the effect of financial structure on systemic risk excluding the control variables, column 2 controls for banking sector size (the total assets held by deposit money banks as a share of GDP) and column 3 control for the banking sector concentration (the total assets of the three largest commercial banks as a share of total commercial bank assets). Significance levels: * p<0.1, ** p<0.05, *** p<0.01. [1] Regressing systemic risk on lagged regressors changes the R-squared and coefficients little. [2] Reports p-values from the Wooldridge test for the null hypothesis of no first-order serial correlation. [3] Reports the mean variance inflation factor of all variables (including control variables) to quantify the severity of multicollinearity. [4] Reports the highest variance inflation factor of all independent variables (excluding control variables) to quantify the severity of multicollinearity.

The results provide strong evidence for the influence of financial structure on systemic risk, indicating that banking activity generates systemic risk and market activity reduces systemic risk. Specifically, bank-based financing increases systemic risk at the 1% significance level, market-based debt financing decreases systemic risk at the 1% level and market-based stock financing decreases systemic risk at the 5% level. These results differ from Langfield and Pagano (2016), who find no significant effects of financial structure on systemic risk outside crisis dummies. Furthermore, as expected from the perspective of systemic risk, equity financing is to be preferred over market-based debt financing since market-based stock financing reduces systemic risk to a much larger extent than market-based debt financing.[12] Nonetheless, the debate on bank-based versus market-based financing is found to be relevant, since bank and market-based debt financing have opposite signs.

Including the size and concentration of the banking sector as control variables hardly changes the significance of bank credit.[13] The influence of bank-based financing on systemic risk is therefore robust to the size and concentration of the banking sector. Furthermore, including the size or the concentration of the banking sector as an interaction with bank credit does not give significant results. This suggests that the impact of bank-based financing on systemic risk is not dependent on the size or concentration of the banking sector.

As a robustness check, the effects of the financial structure's indicators are also tested on an alternative indicator for systemic risk, the dependent variable $CISS_{i,t}$. Similar to Table 3, the results show that bank-based financing generates systemic risk and that market-based financing does not influence systemic risk (see Appendix 1).[14]

4.2 Structural break model

The evident contribution of bank activity to systemic risk raises the question whether this effect is linear. Is the influence larger or more significant when the financial structure is relatively bank-based or once bank-based financing exceeds certain levels? When financing is dominated by banks, borrowers will be dependent on bank lending (Greenspan, 1999) and markets will have less room to develop and function as 'spare tires' in the financial intermediation process when, for whatever reason, bank lending is constrained. In more market-based financial structures, markets can better substitute for lost bank credit during a financial crisis, as was the case in the United States in 2007-2011(Adrian et al. 2012). By implication, systemic risk may be expected to be higher in less diversified financial structures.

[12] This beneficial impact of equity financing comes on top of its contribution to promoting innovation (Claessens, 2016)
[13] The p-value of bank credit's significance level increases from 0.7% to 1.1%. The effects of the bank sector size and concentration remain insignificant when country fixed effects are excluded.
[14] The composite indicator of systemic stress has been developed for a limited set of European countries in the sample. The robustness check is therefore based on 15 countries only: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Poland, Portugal, Spain, Sweden and the United Kingdom.

Similarly, the larger the banking system, the greater its impact on GDP and the more interconnected, cross-border and complex its activities are likely to be. This also contributes to systemic risk.[15]

In this light, Table 4 and 5 show the results for the structural break model (6) and (7) and include HAC standard errors. The null hypothesis of no threshold effect is rejected using Hansen's (1999) F-test. Subsequently, the null hypothesis (8) is rejected using Hansen's (1996) bootstrap procedure with a P-value lower than 5% for all threshold regressions. A break in the data is thereby detected.

For model (6), the slopes and constants are estimated separately for bank credit to GDP above and below/equal to its threshold value. The results indicate that below/equal to 54% of GDP, the effect of bank credit on systemic risk is no longer statistically significant. Above 54%, the effect of bank credit on systemic risk turns positive and statistically significant at the 1% level. Table 4 therefore provides evidence that the positive effect of banks on systemic risk is negligible when there is little bank-based financing.

Financing via debt securities has a negligible effect on systemic risk above and below the threshold value. Stock market financing on the other hand, has a negative effect on systemic risk when bank credit to GDP is above 54%, at the 5% significance level. This effect is not present when bank credit to GDP is below/equal 54% of bank credit to GDP. This suggests that, from a systemic risk perspective, the potential contribution of stock markets as an alternative source of financing is larger in financial structures with large banking systems.

For model (7), the slopes and constants are estimated separately for $FINSTR_{i,t}$ above and below/equal to its threshold value. The results show that bank credit has a much larger effect on systemic risk when the size of bank financing is more than two-and-one half times the size of non-bank financing. This is significant at the 1% level. Below this threshold, the effect of bank credit on systemic risk is much smaller and only weakly significant. Diversity of financing in the financial sector is thus beneficial in terms of systemic risk.

[15] The Financial Stability Board (FSB) identifies systemically important banks using an indicator-based measurement approach calibrated on the size, interconnectedness, substitutability, cross-border activity and complexity of banks (BCBS, 2013).

Table 4: Structural break model

Regressors	I	II	III
Threshold (λ) [1]	0.5365	0.5365	0.5365
$\boldsymbol{BANK_{i,t} > \lambda}$			
α_{11} - Bank credit	0.0139***	0.0135*	0.0137***
	(0.0045)	(0.071)	(0.046)
α_{21} – Non-fin debt market cap (log)	-0.0012	-0.0012	-0.0012
	(0.0007)	(0.0007)	(0.0007)
α_{31} - Stock market cap (log)	-0.0123**	-0.0118**	-0.0128**
	(0.0044)	(0.0044)	(0.0046)
α_{41} – Banking sector size		0.0010	
		(0.0091)	
α_{51} – Banking sector concentration			-0.0056
			(0.0079)
α_{01} - constant	-0.0125***	-0.0134***	-0.0088
	(0.0042)	(0.0045)	(0.0072)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
$\boldsymbol{BANK_{i,t} \leq \lambda}$			
α_{12} - Bank credit	-0.0259**	0.0066	-0.0188***
	(0.0056)	(0.0230)	(0.0028)
α_{22} – Non-fin debt market cap (log)	-0.0000	-0.0013	0.0005
	(0.0010)	(0.0010)	(0.0015)
α_{32} - Stock market cap (log)	-0.0080	-0.0033	-0.0103
	(0.0043)	(0.0041)	(0.0112)
α_{42} – Banking sector size		-0.0268	
		(0.0154)	
α_{52} – Banking sector concentration			0.0023
			(0.0139)
α_{02} - constant	-0.0080	0.0170*	0.0042
	(0.0085)	(0.0063)	(0.0070)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Bootstrap P-value [2]	< 0.05	< 0.05	< 0.05
N<λ	37	37	34
N>λ	271	265	270

This table presents the estimations for model (6). The dependent variable is systemic risk per unit of asset. HAC standard errors are given in parentheses. The regression controls for time and country fixed effects in all columns. Column 1 shows the effect of financial structure on systemic risk excluding the control variables, column 2 controls for banking sector size (the total assets held by deposit money banks as a share of GDP) and column 3 control for the banking sector concentration (the total assets of the three largest commercial banks as a share of total commercial bank assets). Significance levels: * p<0.1, ** p<0.05, *** p<0.01. [1] The threshold is bank credit as a percentage of GDP presented in decimals. [2]Reports P-value from Hansen’s (1996) bootstrap procedure for the null hypothesis of (7) with a bootstrap sample of 5000.

Table 5: Structural break model

Regressors	**I**	**II**	**III**
Threshold (λ) [1]	2.5743	2.5743	2.5743
$\boldsymbol{FINSTR_{i,t} > \lambda}$			
α_{11} - Bank credit	0.0352***	0.0540***	0.0798***
	(0.0087)	(0.0051)	(0.0174)
α_{21} – Non-fin debt market cap (log)	-0.0021***	-0.0040***	-0.0247***
	(0.0004)	(0.0008)	(0.0041)
α_{31} - Stock market cap (log)	-0.0344***	-0.0595***	-0.0015*
	(0.0044)	(0.0131)	(0.0006)
α_{41} – Banking sector size		0.0685**	
		(0.0266)	
α_{51} – Banking sector concentration			-0.1233**
			(0.0476)
α_{01} - constant	-0.0843***	-0.0635***	-0.0192
	(0.0147)	(0.0130)	(0.0201)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
$\boldsymbol{FINSTR_{i,t} \leq \lambda}$			
α_{12} - Bank credit	0.0079	0.0173**	0.0076
	(0.0047)	(0.0067)	(0.0049)
α_{22} – Non-fin debt market cap (log)	-0.0009**	-0.0014**	-0.0009
	(0.0004)	(0.0006)	(0.0006)
α_{32} - Stock market cap (log)	-0.0053	-0.0044	-0.0057
	(0.0054)	(0.0052)	(0.0058)
α_{42} – Banking sector size		-0.0103	
		(0.0096)	
α_{52} – Banking sector concentration			-0.0055
			(0.0088)
α_{02} - constant	-0.0047	-0.0033	-0.0009
	(0.0050)	(0.0059)	(0.0082)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Bootstrap P-value [2]	< 0.05	< 0.05	< 0.05
N<λ	276	270	272
N>λ	32	32	32

This table presents the estimations for model (7). The dependent variable is systemic risk per unit of asset. HAC standard errors are given in parentheses. The regression controls for time and country fixed effects in all columns. Column 1 shows the effect of financial structure on systemic risk excluding the control variables, column 2 controls for banking sector size (the total assets held by deposit money banks as a share of GDP) and column 3 control for the banking sector concentration (the total assets of the three largest commercial banks as a share of total commercial bank assets). Significance levels: * p<0.1, ** p<0.05, *** p<0.01. [1] The threshold is bank credit as a percentage of GDP presented in decimals. [2]Reports P-value from Hansen's (1996) bootstrap procedure for the null hypothesis of (7) with a bootstrap sample of 5000.

Furthermore, market-based debt financing strongly and significantly reduces systemic risk in relatively bank-based financial structures. The effect remains negative in the case of relatively market-based financial structures, albeit its significance declines slightly. Similarly, equity financing strongly and significantly reduces systemic risk when the financial structure is bank dominated. The downward impact of stock market activity on systemic risk becomes small and insignificant in market-based financial structures.

The results confirm that Europe is too bank-based in terms of systemic risk, as suggested by Langfield and Pagano (2016), since for all European countries, bank credit to GDP is above the first threshold of 54% during the last years of the data. In line with these results, as illustrated in Figure 1.1, the financial structure of the United States is close to this optimum. Other countries can reduce systemic risk by decreasing the financial structure's reliance on bank-based financing.

5. Conclusion

Financial structure matters. In contrast to markets, banks contribute to systemic risk due their more leveraged nature, larger asset-liability mismatches and greater interconnectedness. The systemicness of banks is clearly evident in data on financial structures since the turn of the century. However, banks are found not to generate systemic risk when bank-based financing is limited. Moreover, in relatively market-based financial structures, the influence of banks on systemic risk is low. Diversity within the financial sector is thus important. Markets can provide 'spare tire' insurance against problems within the banking sector turning into economy-wide distress. The less banks are dominant, the easier banks' financial intermediation process can be substituted for by markets.

The recent empirical literature on the effects of financial structure on economic growth shows that market-based financial structures outperform bank-based financial structures once the data covers the financial crisis of 2008. The contribution of bank-based financial structures to systemic risk explains this economic underperformance in times of financial instability. While market-based financing generally helps reduce systemic risk, market-based equity financing contributes most to financial sector resilience.

The findings indicate that the financial structure of the United States is close to optimal in terms of systemic risk. Other countries can increase their resilience to systemic risk by reducing the share of bank-based financing and increasing that of market-based debt and especially market-based stock financing. The design of financial sector and fiscal policies can take this into account. The introduction of the European capital markets union is a case in point. However, financial structures are path dependent and changes require time. Moreover, adjustments in regulatory requirements change the inherent contribution of different financial structures to systemic risk. In particular, the tightened regulatory framework for banks, including higher capital requirements and bail-in rules, may make banks more resilient and systemically less relevant. Further research should determine to what extent these requirements lower the contribution of bank-based financing to systemic risk.

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Appendix 1

Table A: Fixed effects panel regression model

Regressors	I	II	III
Bank credit	0.3583***	0.4937*	0.3440***
	(0.0936)	(0.2675)	(0.0965)
Non-fin debt market cap (log)	-0.0010	-0.0024	-0.0094
	(0.0145)	(0.0151)	(0.0274)
Stock market cap (log)	-0.1428	-0.1469	-0.1352
	(0.1106)	(0.1113)	(0.1184)
Banking sector size		-0.1446	
		(0.2419)	
Banking sector concentration			-0.0037
			(0.1490)
Constant	-0.3274**	-0.3047**	-0.3373*
	(0.1125)	(0.1073)	(0.1590)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
R-sqr (within)	0.682	0.684	0.670
N	208	208	205
Serial correlation test [1]	0.0001	0.0001	0.0001
Mean VIF [2,4]	2.26	2.97	3.41
Highest VIF [3,4]	7.37	8.48	9.30

This table presents the estimations for the robustness check as described in the last paragraph of section 4.1. The dependent variable is the composite indicator of systemic stress. HAC standard errors are given in parentheses. The regression controls for time and country fixed effects in all columns. Column 1 shows the effect of financial structure on systemic risk excluding the control variables, column 2 controls for banking sector size (the total assets held by deposit money banks as a share of GDP) and column 3 control for the banking sector concentration (the total assets of the three largest commercial banks as a share of total commercial bank assets). Significance levels: * p<0.1, ** p<0.05, *** p<0.01. [1] Reports p-values from the Wooldridge test for the null hypothesis of no first-order serial correlation. [2] Reports the mean variance inflation factor of all variables (including control variables) to quantify the severity of multicollinearity. [3] Reports the highest variance inflation factor of all independent variables (excluding control variables) to quantify the severity of multicollinearity. [4] Without time fixed effects, the mean VIF equals 3.21 and the highest VIF equals 4.06.

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