

Discussion Paper

Deutsche Bundesbank
No 46/2014

Banking market structure and macroeconomic stability: are low-income countries special?

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Internet <http://www.bundesbank.de>

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ISBN 978-3-95729-112-7 (Printversion)

ISBN 978-3-95729-113-4 (Internetversion)

Non-technical summary

Research Question

The structure of banking markets in low-income countries differs from that in higher-income economies. Banking systems in low-income countries are typically smaller and less open. Consequently, access to finance is more limited. Moreover, the effects of volatility on growth and welfare are more pronounced. One reason for differences in macroeconomic stability between low- and higher-income economies could be differences in the structure of banking markets.

Contribution

In this paper, we investigate whether banking market structures affect macroeconomic volatility and whether this link differs in low-income countries. Based on micro- and macro-level data, we explore the channels through which the structure of banking markets impacts macroeconomic stability. A special focus lies on low-income countries. Using a panel-dataset that covers the period 1997-2011 and 89 countries, of which 13 are classified as “low-income” economies, we analyze the role of banking sector risk, banking sector size, and financial openness for the volatility of GDP per capita growth.

Results

The regression results reveal that bank-level risk as measured by bank-specific volatility can have an impact on macroeconomic volatility. Countries with more risky or more volatile banking systems tend to experience higher macroeconomic volatility in the longer term. Moreover, the larger a country’s banking system is in terms of the ratio of credit to GDP, the stronger are macroeconomic fluctuations in the short run. The impact of international financial integration is mixed. We find that a higher degree of cross-border asset holdings can increase GDP-volatility in low-income countries. Yet, reducing capital controls, and hence a higher degree of de jure financial openness, enhances macroeconomic stability.

Nicht-technische Zusammenfassung

Fragestellung

Die Struktur des Bankensektors ist in Entwicklungsländern anders als in Industrie- und Schwellenländern. So ist das Bankensystem in Entwicklungsländern typischerweise kleiner und weniger stark international vernetzt. Folglich ist der Zugang zu Finanzierungsquellen begrenzter. Außerdem sind die negativen Auswirkungen gesamtwirtschaftlicher Schwankungen auf Wachstum und Wohlstand ausgeprägter. Ein Grund für die Unterschiede zwischen Entwicklungsländern und fortgeschrittenen Volkswirtschaften mit Blick auf die gesamtwirtschaftliche Volatilität könnten unterschiedliche Marktstrukturen im Bankensektor sein.

Beitrag

Das vorliegende Diskussionspapier untersucht, ob die Struktur des Bankensektors eine Rolle für die gesamtwirtschaftliche Stabilität spielt und ob sich dieser Zusammenhang in Entwicklungsländern und fortgeschrittenen Volkswirtschaften unterschiedlich darstellt. Wir analysieren verschiedene Wirkungskanäle, über die sich Marktstrukturen im Bankensektor auf die gesamtwirtschaftliche Stabilität auswirken können. Der Fokus liegt dabei auf Entwicklungsländern. Anhand von mikro- und makroökonomischen Daten für den Zeitraum 1997-2011 und 89 Länder, unter denen 13 als Entwicklungsländer klassifiziert werden, untersuchen wir, welche Rolle Risiko, Größe und Offenheitsgrad des Bankensystems für die Volatilität des Pro-Kopf-Wachstums einer Volkswirtschaft spielen.

Ergebnisse

Die Regressionsergebnisse zeigen, dass bankspezifisches Risiko die gesamtwirtschaftliche Volatilität beeinflussen kann. In Ländern mit einem risikoreicheren Bankensektor ist die gesamtwirtschaftliche Volatilität langfristig tendenziell höher. Außerdem zeigt sich, dass die Größe von Bankensystemen – gemessen am Verhältnis von Kreditvolumen zu Bruttoinlandsprodukt – die Stabilität der Gesamtwirtschaft in der kurzen Frist beeinträchtigen kann. Die Auswirkungen der internationalen Finanzmarktoffenheit sind gemischt. Wir finden, dass ein höherer Bestand an grenzüberschreitenden Aktiva die gesamtwirtschaftliche Volatilität in Entwicklungsländern erhöht. Eine Verringerung von Kapitalverkehrskontrollen kann die makroökonomische Stabilität allerdings fördern.

Banking Market Structure and Macroeconomic Stability: Are Low-Income Countries Special?¹

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Abstract

Does the structure of banking markets affect macroeconomic volatility and, if yes, is this link different in low-income countries? Banking markets in low-income countries differ from those in developed market economies. Banking systems in lower-income countries are typically smaller and less open. In this paper, we explore the channels through which the structure of banking markets affects macroeconomic volatility. Our research has three main findings. First, we study the relevance of granular effects: if the degree of market concentration in the banking sector is sufficiently high, idiosyncratic volatility at the bank-level can impact aggregate volatility. We find weak evidence for a link between granular banking sector volatility and macroeconomic fluctuations. Second, a higher share of domestic credit to GDP coincides with higher volatility in the short run. Third, a higher level of cross-border asset holdings, i.e. a higher degree of de facto financial integration, increases volatility in low-income countries.

Keywords: bank market structure, financial integration, granularity, macroeconomic volatility, low-income countries

JEL-Classification: G21, E32

¹ Contact address: Franziska Bremus, German Institute for Economic Research (DIW Berlin), Mohrenstraße 58, 10117 Berlin, Germany. Phone: +49 30 89789590. E-Mail: fbremus@diw.de. Discussion Papers represent the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank or its staff. This paper is part of a research project on macroeconomic policy in low-income countries supported by the U.K.'s Department for International Development (DFID). Franziska Bremus acknowledges funding from the DFID. The paper was presented at the Conference on "Macroeconomic Challenges Facing Low-Income Countries: New Perspectives" (Washington, DC, January 30–31, 2014). The views expressed herein are those of the authors and should not be attributed to the IMF, its Executive Board, or its management, to DFID, or to the Deutsche Bundesbank. We thank two anonymous referees, César Calderón, Atilim Seymen and the conference participants for helpful comments and suggestions. Hanna Schwank provided very valuable research assistance. All remaining errors or inconsistencies are our own.

1 Motivation

Negative effects of macroeconomic volatility on growth and welfare can be particularly pronounced in low-income countries (Calderon and Yeyati 2009, Loayza et al. 2007, Pallage and Robe 2003). Shocks are more frequent and larger. Moreover, structural characteristics of low-income economies like a low degree of diversification can amplify the effect of shocks (Acemoglu and Zilibotti 1997, Koren and Tenreyro 2007, 2013). Given that real and financial cycles are closely related (Claessens et al. 2011, 2012), an additional reason for differences between high- and low-income countries in terms of macroeconomic stability could be differences in the structure of banking systems. The banking systems in low-income countries in fact differ in numerous aspects from those in higher-income economies. Banking systems in low-income countries are typically smaller and less open than those in developed economies. Access to finance is thus more limited.

In this paper, we explore the channels through which the structure of banking markets affects macroeconomic instability as measured by the volatility of GDP per capita.² We particularly focus on low-income countries. We use a linked micro-macro panel-dataset including low-, middle-, and high-income countries. Bank-level data are taken from *Bankscope*. We investigate the impact of three structural characteristics of banking systems. First, we link annual GDP-volatility to microeconomic risk at the bank-level by drawing on the concept of granularity (Gabaix 2011). Second, we evaluate how the size of the banking sector impacts macroeconomic instability. Third, we analyze the effect of the degree of financial openness on aggregate volatility.

Recent research shows how heterogeneous size distributions of firms can affect macroeconomic volatility (Gabaix 2011). If firm sizes follow a fat-tailed power law distribution so that market concentration is high, shocks to large firms (or banks) do not cancel out across a large number of firms as they would under normally distributed firm sizes. In this case, macroeconomic volatility is proportional to the product of firm-specific volatility and the Herfindahl index of concentration – “granular volatility”. The link between asset growth fluctuations at the bank-level and aggregate fluctuations gets stronger as market

² Instability refers to higher volatility here. Other reasons for macroeconomic instability are not analyzed in this paper.

concentration and/or idiosyncratic bank-level volatility increase – even when abstracting from the issue of interconnectedness between large banks. Using matched bank-firm loan data for Japan, Amiti and Weinstein (2013) find that idiosyncratic loan growth shocks at the bank-level can explain about 40 percent of the variation in aggregate credit and investment growth. Based on industry-level data, Carvalho and Gabaix (2013) show that part of the recent increase in macroeconomic volatility can be attributed to the raising importance of the financial industry.

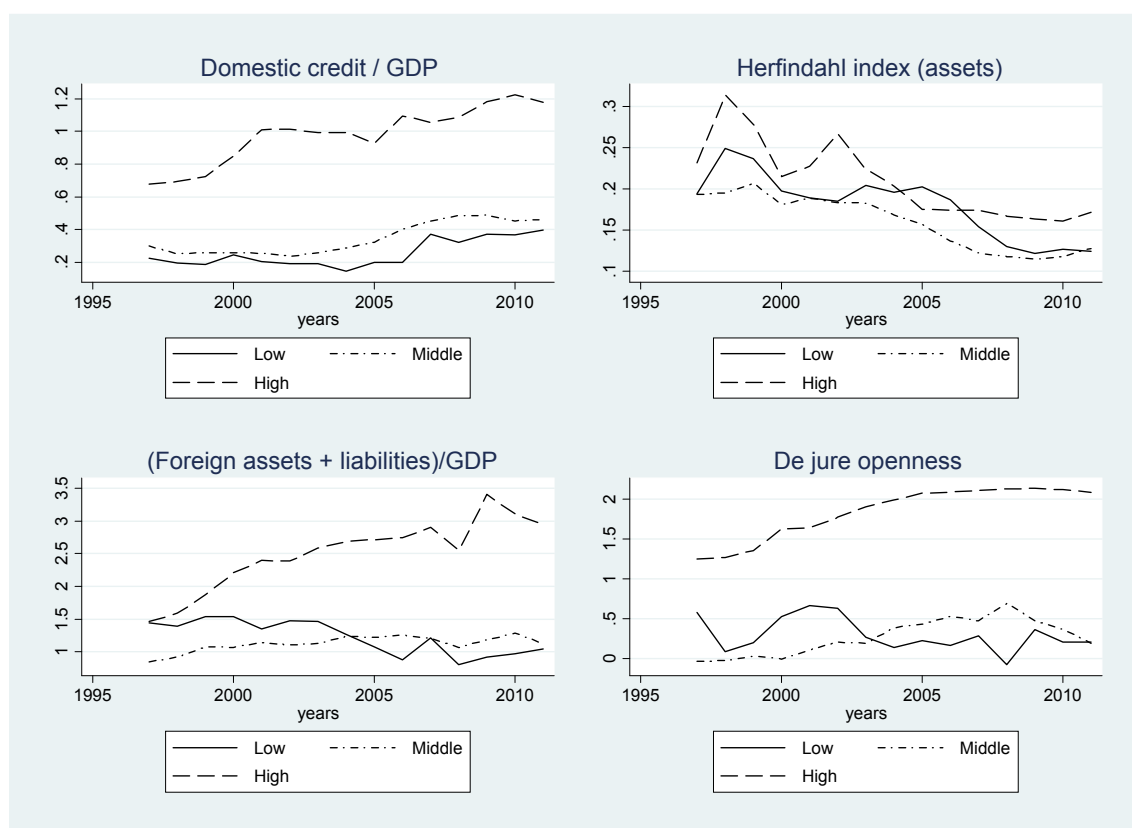
A priori, the link between bank-specific and macroeconomic fluctuations should be stronger if the banking sector is more concentrated. Even though banking market concentration is high in both low- and higher-income countries (Figure 1), our results in this paper show that it is difficult to relate macroeconomic volatility to fluctuations at the bank-level. The relation between macroeconomic volatility and “banking granular volatility” – a weighted sum of bank-specific asset growth volatility where each bank’s weight is given by its squared market share – is mostly insignificant. Yet, as opposed to the link between *volatilities* at the micro- and macroeconomic level, the relationship between bank-specific credit growth *shocks* and aggregate *growth* has been shown to be positive and significant in previous work (Amity and Weinstein 2013, Bremus et al. 2013, Buch and Neugebauer 2011).

While low-income countries do not necessarily have a more concentrated banking market structure, banking sector size as measured by domestic credit to GDP is much smaller in low- than in high-income countries (Figure 1). The expected impact of credit to GDP on macroeconomic volatility is not clear a priori: In the literature, credit to GDP is often used as a proxy for financial development. Our results show a consistently positive effect of credit to GDP on macroeconomic volatility in the short run though. This hints at the destabilizing effects of high leverage in an economy; higher credit implies larger multiplier effects and hence higher volatility for a given shock. Yet, in the long run, we find that a higher level of credit to GDP can reduce volatility.

The effect of financial openness on macroeconomic stability is a priori unclear. On the one hand, a low degree of financial openness in low-income countries (Figure 1) may shield these economies from shocks originating abroad. Moreover, capital inflows are pro-cyclical and volatile in low-income economies (Lane 2014). While low-income economies tend to borrow in good times, they face credit constraints in bad times (Gavin and Perotti 1997), meaning that they have to pay back their debt in times of unfavorable economic conditions. This can prevent countercyclical fiscal policies and exacerbate macroeconomic volatility (Kaminsky et

al. 2005). On the other hand, countries which are less open financially may experience higher macroeconomic volatility because of less international risk-sharing. Recent studies indeed find little consistent evidence on the link between output volatility and financial openness (Kose et al. 2003, 2009). This could be due to threshold effects (Kose et al. 2011): at low levels of institutional or financial development, financial integration may increase volatility on financial markets. At high levels of institutional development, financial integration would lead to stronger fluctuations.

Figure 1: Banking Market Structures



The two graphs at the top show the evolution of banking sector size and concentration by income groups. The graphs give the median values for each income group. The two graphs at the bottom show the evolution of total foreign assets and liabilities relative to GDP (median for each income group) and a de jure measure of financial openness, the Chinn-Ito index of capital controls (mean for each income group).

Table 1 illustrates institutional and regulatory differences between the financial systems in low- versus high-income countries (i.e. middle- and high-income economies). Regarding institutional development, the quality and range of available information about borrowers is much lower in low-income countries. The “depth of credit information index” from the World Bank’s *Doing Business Indicators* reflects the scope and accessibility of credit information available from public or private credit registries. It ranges from 0 to 6 with higher

values indicating a better availability of credit information. In low-income countries, this index is just half as high as in higher-income economies with an average of 2.15. The differences in the coverage of private credit registries is particularly pronounced: While, on average, 36.6 percent of the adult population are covered by private credit registries in higher-income economies, this figure is much lower (2.5 percent) in low-income countries. As a consequence, information asymmetries between banks and borrowers are more pronounced. This can translate into less efficient and more risky lending in low-income countries – both for domestic and foreign banks. In addition, deposit insurance schemes are much less common in these countries than in higher-income economies (Barth et al. 2013). This can cause financial instability due to bank runs, and, in turn, increase macroeconomic volatility.

Table 1: Indicators of Institutional Development in the Banking Sector

	Low-income countries					Higher-income countries				
	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
Depth of credit information	72	2.15	1.85	0	6	454	4.47	1.44	0	6
Public registry coverage (% of adults)	72	3.56	6.45	0	26.4	454	8.47	16.84	0	100
Private registry coverage (% of adults)	72	2.48	7.63	0	33.9	454	36.56	35.27	0	100
Deposit insurance funds relative to total bank asset	29	11.4	19.5	0	57.2	380	35.25	28.31	0	100
Percent of 10 biggest banks rated by international rating agencies	48	22.1	38.9	0	100	714	69.04	32.54	0	100
Share of foreign-owned banks	66	0.39	0.22	0.06	0.84	732	0.35	0.30	0	1
Share of total bank assets that are government-owned	66	0.15	0.19	0	0.70	750	0.16	0.20	0	0.80

These descriptive statistics are based on the baseline regression sample (Table 3, column 1). The index of the depth of credit information, as well as public and private registry coverage are available from the Doing Business Indicators by the World Bank. The remaining information is taken from Barth et al. (2013). Definitions and sources of each indicator can be found in the Appendix. Higher-income economies include middle- and high-income countries.

In terms of the effects of financial openness on macroeconomic volatility, we find differences according to the measure of financial openness used. Higher de jure openness in the sense of weaker controls on cross-border capital flows has a stabilizing effect. Higher de facto openness measured through foreign assets and liabilities relative to GDP, has a volatility-enhancing effect in low-income countries. These differences point to the importance of managing international financial integration and strengthening institutions when opening up for foreign capital.

In the following Part 2, we describe our data. Part 3 presents the regression model and the results, while Part 4 concludes.

2 Data and Measurement of Volatility

2.1 *Macroeconomic and Bank-Level Data*

The macroeconomic data used in this paper are taken from the World Development Indicators (WDI) by the World Bank. Details on the measurement and the data sources are given in the Appendix; Table 2 shows descriptive statistics for the baseline regression sample.

We start from a dataset which includes a large variety of countries, and we keep those with complete strings of observations of at least ten years for key variables, including GDP per capita growth and domestic credit relative to GDP. This sample includes 89 countries for 15 years (1997-2011). Due to the unbalanced nature of the panel, the maximum number of country-year observations is 1106 if we include control variables.

Our country sample includes 13 low-income countries. We define the group of low-income economies following the classification of the Poverty Reduction and Growth Trust (PRGT)-eligible countries from the IMF. In our sample, these are Bangladesh, Bolivia, Cote d'Ivoire, Kenya, Kyrgyz Republic, Malawi, Moldova, Mongolia, Nepal, Tanzania, Uganda, Vietnam, and Zambia. In terms of macroeconomic data, we could use a larger country sample, but the binding constraint is finding low-income countries with a sufficiently large number of banks. We keep only those countries which contribute at least two observations to the baseline regressions.

Our source for bank-level data is *Bankscope*, a commercial database provided by Bureau van Dijk which provides income statements and balance sheets for banks worldwide. In *Bankscope*, we have banking data for more than these 13 low-income countries, but the number of banks for many of the low-income countries is less than five per year.

A number of screens are imposed on the banking data in order to eliminate errors due to misreporting. We exclude the bottom 1% of the observations for total assets, and we drop observations where the loans-to-assets or the equity-to-assets ratio is larger than one. We also drop banks with negative equity, assets, or loans. This reduces the sample size by about 5%.

Table 2: Descriptive Statistics

These descriptive statistics are based on the baseline regression sample (Table 3, column 1).

Full Sample

	Obs.	Mean	Std. Dev.	Min.	Max.
<u>Macroeconomic volatility</u>					
GDP per capita growth (squared residuals)	1106	0.02	0.02	0.00	0.19
<u>Banking sector structure</u>					
Domestic credit to the private sector / GDP	1106	0.72	0.55	0.02	2.84
HHI (assets)	1106	0.24	0.18	0.01	1.00
Market capitalization of listed companies / GDP	1106	0.54	0.66	0.00	6.06
Banking granular volatility (assets)	1106	0.05	0.04	0.00	0.47
Banking granular volatility (assets, time-invariant variance)	1106	0.08	0.05	0.02	0.40
Mean banking sector risk (assets)	1106	0.02	0.03	0.00	0.33
Mean banking sector risk (assets, time-invariant variance)	1106	0.04	0.03	0.00	0.21
<u>Macroeconomic control variables</u>					
Real private consumption per capita (USD)	1106	7537.45	8132.34	184.26	32011.91
Inflation (consumer prices, annual)	1106	0.07	0.33	-0.04	10.58
(Exports + Imports) / GDP	1106	0.91	0.61	0.16	4.46
Volatility of Terms of Trade (absolute residuals)	982	0.05	0.05	0.00	0.36
M2 / GDP	1106	0.78	0.55	0.09	3.28
Volatility of M2 / GDP (absolute residuals)	1106	0.04	0.04	0.00	0.28
Government final consumption expenditure / GDP	1106	0.16	0.05	0.05	0.30
Share of government-owned banks	816	0.16	0.20	0.00	0.80
<u>Banking sector openness</u>					
(Total foreign assets + liabilities) / GDP	1106	2.83	3.83	0.38	33.34
Chinn-Ito index of capital controls	1106	1.00	1.52	-1.86	2.44

Low-income countries

	Obs.	Mean	Std. Dev.	Min.	Max.
<u>Macroeconomic volatility</u>					
GDP per capita growth (squared residuals)	130	0.02	0.02	0.00	0.11
<u>Banking sector structure</u>					
Domestic credit to the private sector / GDP	130	0.29	0.23	0.04	1.25
HHI (assets)	130	0.23	0.17	0.07	1.00
Market capitalization of listed companies / GDP	130	0.14	0.12	0.00	0.51
Banking granular volatility (assets)	130	0.05	0.04	0.00	0.33
Banking granular volatility (assets, time-invariant variance)	130	0.08	0.04	0.04	0.21
Mean banking sector risk (assets)	130	0.02	0.03	0.00	0.19
Mean banking sector risk (assets, time-invariant variance)	130	0.03	0.02	0.01	0.09
<u>Macroeconomic control variables</u>					
Real private consumption per capita (USD)	130	448.81	214.38	184.26	1108.32
Inflation (consumer prices)	130	0.09	0.07	-0.00	0.39
(Exports + Imports) / GDP	130	0.73	0.33	0.32	1.78
Volatility of Terms of Trade (absolute residuals)	128	0.06	0.06	0.00	0.27
M2 / GDP	130	0.41	0.23	0.11	1.25
Volatility of M2 / GDP (absolute residuals)	130	0.03	0.03	0.00	0.19
Government final consumption expenditure / GDP	130	0.12	0.05	0.05	0.21
Share of Government-owned banks	66	0.15	0.19	0.00	0.70
<u>Banking sector openness</u>					
(Total foreign assets + liabilities) / GDP	130	1.23	0.65	0.42	3.47
Chinn-Ito index of capital controls	130	0.27	1.45	-1.86	2.44

In order to eliminate large (absolute) growth rates that might be due to bank mergers, we winsorize growth rates at the top or bottom percentile, i.e. the growth rates are replaced with the respective percentiles. In terms of specializations of banks, we keep bank holding companies, commercial banks, cooperative banks, and savings banks.³

2.2 *Measuring Macroeconomic Volatility*

The dependent variable of interest is the volatility of GDP per capita growth. Many previous studies use the standard deviation of GDP growth rates as a measure of (aggregate) volatility, where the standard deviation is calculated over a certain window of observations of five or ten years. The disadvantage of this method is that the choice of the time window is somewhat arbitrary and, perhaps more importantly, that the dependent variable is autocorrelated by construction. This autocorrelation needs to be taken into account when estimating the determinants of volatility by, for instance, estimating a dynamic panel model. Yet, dynamic panel models are sensitive to the choice of the instruments.

For these reasons, we resort to a simple alternative measure of volatility, which has been used in recent work by Kalemli-Ozcan et al. (2010), Loutskina and Strahan (2014) or Morgan, Rime and Strahan (2004). To calculate the volatility of house prices, Loutskina and Strahan (2014) use the absolute deviation of house price growth after removing time and regional fixed effects. Applying their methodology, we regress the growth of GDP per capita on country-fixed effects and time-fixed effects

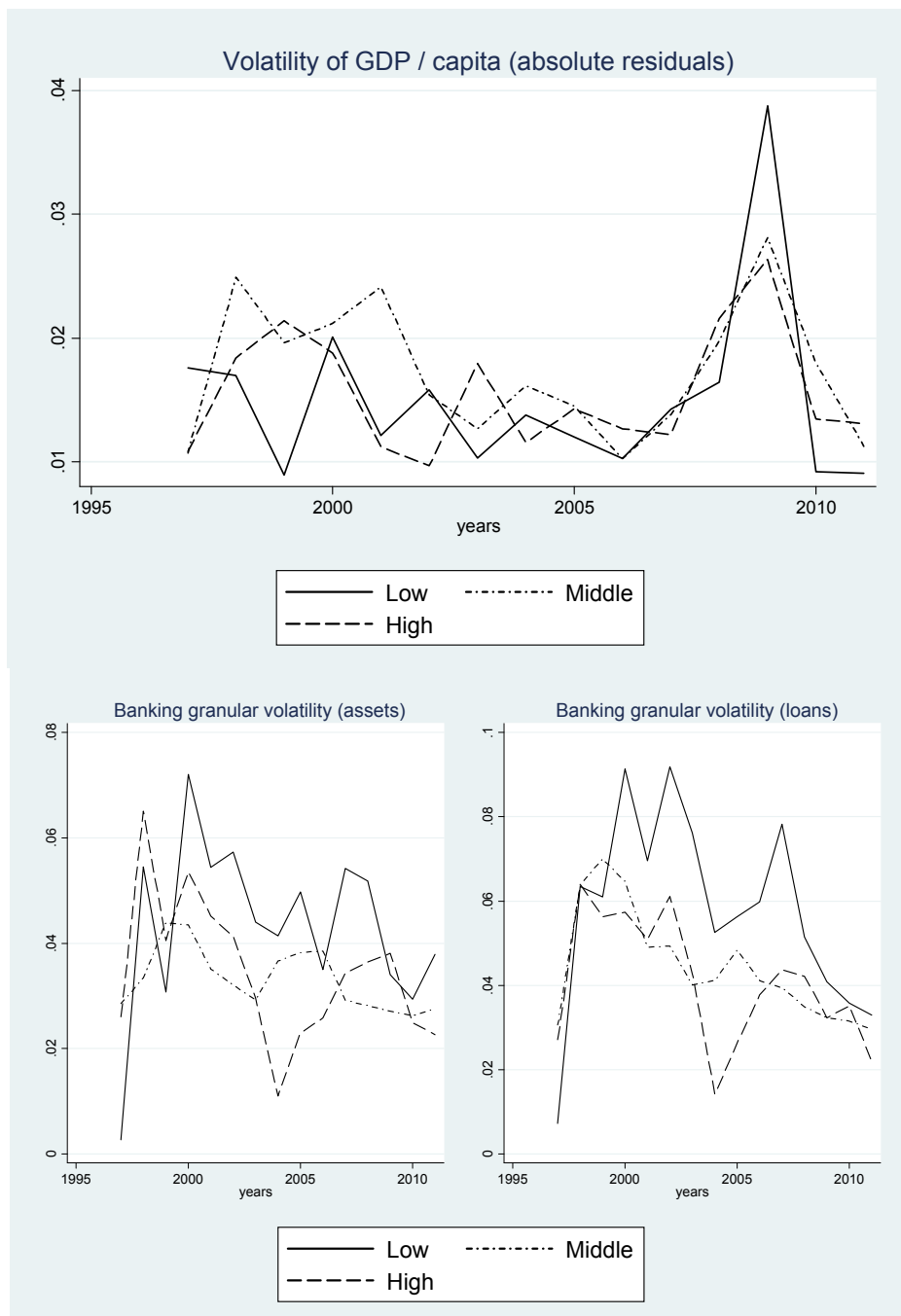
$$\ln(\text{GDP}_{c,t}) - \ln(\text{GDP}_{c,t-1}) = \Delta \ln(\text{GDP}_{c,t}) = \alpha_t + \gamma_c + \text{GDPShock}_{c,t} \quad (1)$$

where α_t and γ_c are time- and country-fixed effects, respectively. The residual of this regression informs us about how much GDP per capita growth in country c differs from the average GDP-growth rate in this year across all countries and from average growth of country c . The absolute value of this growth shock captures GDP-growth fluctuations in each country and year. The volatility of GDP growth is thus given by $\text{vol}(\text{GDP}_{c,t}) = |\text{GDPShock}_{c,t}|$. In order to prevent large outliers from affecting the results, large growth rates in the top and bottom percentile are winsorized. This measure of volatility can be interpreted as the annual

³ In low-income countries, public banks may play a different role for macroeconomic stability than in advanced economies. The Bankscope data used in our regressions include information on partially publicly-owned banks. Yet, analyzing the effects of bank-level volatility separately for private and public banks is not feasible because we do not have consistent ownership data for all banks.

equivalent to the standard deviation of GDP-growth of each country across time. Figure 2 shows that macroeconomic volatility, measured by absolute residuals, has increased across all income groups during the global financial crisis and has subsequently fallen.

Figure 2: Aggregate and Idiosyncratic Volatility



This figure plots the volatility of growth in real GDP per capita and idiosyncratic volatility in the banking sector. All graphs give the median values for different income groups. “absolute residuals” are the absolute values of residuals of a regression of GDP per capita growth rates on time and country fixed effects. Banking granular volatility is computed as described in the main body of the text, using idiosyncratic asset (loan) volatility and squared market shares of each bank. Asset (loan) volatility is computed as the squared absolute value of residuals of a regression of bank-level asset (loan) growth on a set of country-and-year-fixed effects.

2.3 Banking Granular Volatility

In addition, we need a measure of the volatility at the bank-level. Using a discrete choice model with heterogeneous banks, Bremus et al. (2013) theoretically show that bank-specific assets growth shocks can translate into fluctuations of aggregate credit in highly concentrated markets, and hence into aggregate investment and output fluctuations. To compute banking granular volatility (BGV), i.e. the weighted sum of idiosyncratic asset growth volatility at the bank-level in each country and year, we proceed in two steps. Let $X_{ic,t}$ be bank i 's assets (or loans) at time t where bank i is located in country c . In a first step, we regress the growth of bank assets on fixed effects, and we retain the residuals:

$$\ln(X_{ic,t}) - \ln(X_{ic,t-1}) = \Delta \ln(X_{ic,t}) = \alpha_{c,t} + e_{ic,t} \quad (2)$$

where $\alpha_{c,t}$ is a set of country-and-year fixed effects⁴ and $\Delta \ln(X_{ic,t})$ is the log growth rate of bank i 's assets. The residual of equation (2) is a measure for idiosyncratic shocks at the bank-level, which is purged from macroeconomic and common banking factors.

In a second step, we compute banking granular volatility following Gabaix (2011) and Carvalho and Gabaix (2013). These authors show that, if granularity holds, macroeconomic volatility is proportional to the product of firm-level volatility and market concentration:

$$\sigma_{GDP} = \left[\sum_{i=1}^N Vol_{it} \left(\frac{S_{it}}{Y_t} \right)^2 \right]^{1/2}$$

where Vol_{it} is the variance of sales at the firm-level, S_{it} represents firm i 's sales and Y_t is total output at time t . Applying this concept to the banking sector, we calculate BGV based on the squared absolute values of the resulting residual growth rate of bank assets from equation (2). This gives the variance of idiosyncratic asset growth. To check the robustness of our results, we also use loans.

We then multiply this residual volatility with the squared market share of each bank i , and we sum across all banks per country and year. Hence, we construct a weighted measure of idiosyncratic volatility at the bank-level:

$$BGV_{c,t} = \left[\sum_{i=1}^N |e_{ic,t}|^2 \cdot \left(\frac{X_{ic,t}}{X_{c,t}} \right)^2 \right]^{1/2} \quad (3)$$

⁴ This set of fixed effects includes country fixed effects, year fixed effects and the interactions between country and year fixed effects.

where $X_{i,c,t}$ denotes total assets of bank i in country c at time t , whereas $X_{c,t}$ are aggregate total bank assets in country c and year t .

Figure 2 shows that aggregate and bank-level volatility have different time patterns. Aggregate volatility has shown distinct time trends – a “Great Moderation” before the crisis, followed by a spike in volatility at the time of crisis. Bank-level volatility has, if anything, tended to decline over time. In terms of differences across countries, banking granular volatility – be it based on loans or on total assets – was higher in low-income countries than in high-income countries.

To interpret our results, it is useful to decompose banking granular volatility into different components.⁵ In order to simplify notation, we rewrite BGV as

$$BGV_{c,t} = \left(\sum_i^N s_{i,c,t}^2 \varepsilon_{i,c,t} \right)^{\frac{1}{2}}$$

where $\varepsilon_{i,c,t} = |e_{i,c,t}|^2$ is bank-specific volatility and $s_{i,c,t}^2$ is the squared market share of bank i in country c at time t . Following Di Giovanni et al. (2012), BGV can be split up in the following way:

$$BGV_{c,t} = \left(\bar{\varepsilon}_{c,t} \sum_i^N s_{i,c,t}^2 + 2 \bar{s}_{c,t} \sum_i^N s_{i,c,t} \varepsilon_{i,c,t} + \sum_i^N (s_{i,c,t} - \bar{s}_{c,t})^2 (\varepsilon_{i,c,t} - \bar{\varepsilon}_{c,t}) - \text{const} \right)^{\frac{1}{2}} \quad (4)$$

where $\sum_i^N s_{i,c,t}^2$ is the Herfindahl index in country c 's banking sector at time t and

$\sum_i^N s_{i,c,t} \varepsilon_{i,c,t}$ reflects mean risk, i.e. the weighted average risk - as measured by volatility - of country c 's banking sector. The weights for bank risk $\varepsilon_{i,c,t}$ are given by each bank's market share $s_{i,c,t}$.

$\sum_i^N (s_{i,c,t} - \bar{s}_{c,t})^2 (\varepsilon_{i,c,t} - \bar{\varepsilon}_{c,t})$ is the “curvature”, that is the interaction between the Herfindahl index of concentration and mean risk of the banking sector, where $\bar{\varepsilon}_{c,t}$ denotes the average variance of banks' asset growth in country c at time t , $\bar{s}_{c,t}$ is the average market share based on banks' assets, and *const* is a constant. A detailed derivation of this decomposition can be found in the Appendix.

The curvature term has a very intuitive interpretation: If the curvature is positive, the banks with the largest market shares, $s_{i,c,t}$, in country c 's banking sector are risky banks in the sense

⁵ We owe this point to our discussant César Calderón.

that they are more volatile than the average, $\bar{\varepsilon}_{c,t}$. If the curvature is negative, the largest banks in country c are safer than average, i.e. volatility $\varepsilon_{ic,t}$ of the most important banks is smaller than $\bar{\varepsilon}_{c,t}$.

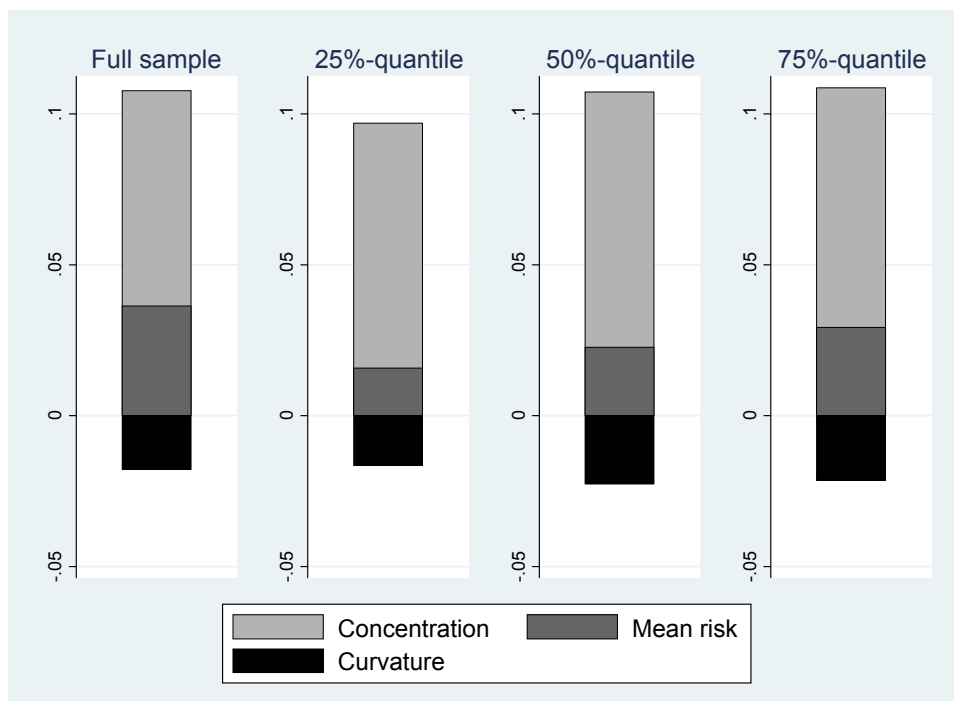
Figure 3 shows the median values for the three main components of banking granular volatility (BGV). The top panel plots the medians of concentration, mean risk, and curvature for the full sample, together with the 25-, 50-, and 75-% quantiles of BGV. In the full sample, concentration is the most important part of BGV, followed by mean risk. Curvature is negative across all quantiles. That is, BGV is mostly driven by high concentration and mean risk, while the largest banks are, on average, less volatile than the average. This reduces the size of banking granular volatility and hence the role of the banking system as a potential source of aggregate volatility.

The bottom panel of Figure 3 divides the sample by income groups. The average riskiness of the banking sector is the dominant component of banking sector volatility in low-income countries. Also, the curvature term is only slightly negative, which means that the banks with the largest market shares are relatively risky. For middle-income countries, the curvature term is well below zero, indicating that the largest banks are safer than the average and reduce banking granular volatility. Mean risk is less important but concentration is more important in middle-income countries compared to low-income economies. Patterns are similar for high-income economies.

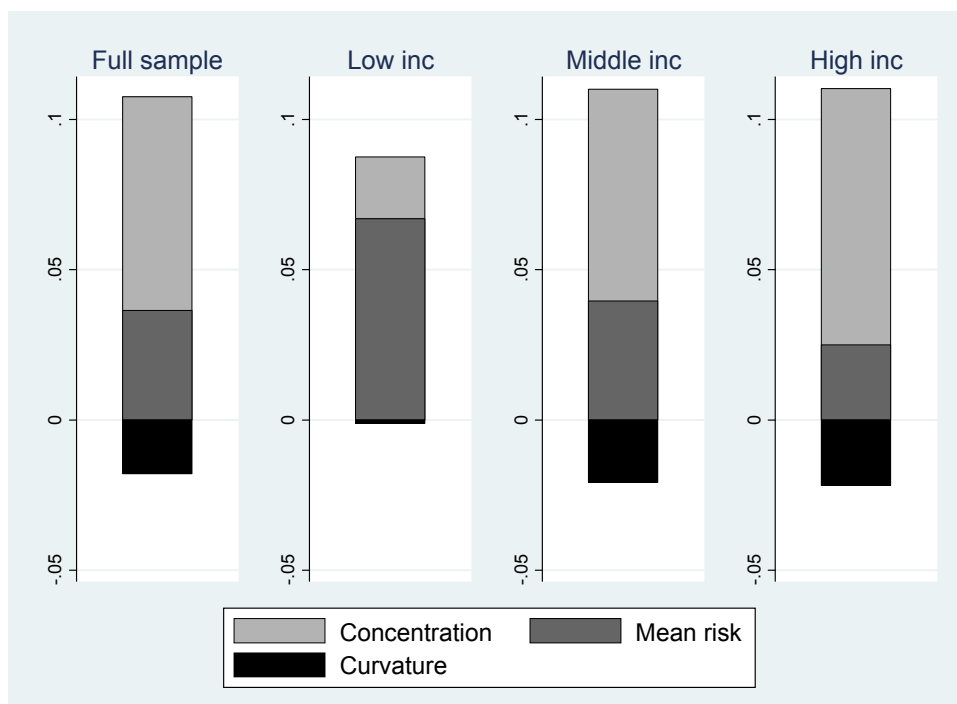
Decomposing banking granular volatility into its three main parts thus reveals that more concentrated banking systems need not be necessarily the riskier ones. If banks with the largest market shares are rather safe (less volatile than the average bank in the market), then BGV can be low even if concentration is high. However, if the big banks are the risky ones in the market, the curvature term of BGV can be positive. As a consequence, BGV is elevated due to the compounding effect of concentration and high riskiness of the largest players in the market. Given that the risk structure of banking sectors differs across countries, the decomposition of BGV illustrates that banking systems with the same degree of concentration can have different mean risk.

Figure 3: Decomposing Banking Granular Volatility (BGV)

BGV by quantile



BGV by income group



This figure shows the decomposition of BGV based on total assets as laid out in equation (4) in the text. The first panel shows the median values for concentration, mean risk and curvature for the full sample and the three quartiles. The second panel plots the median values for the full sample and for each income group. Note that the “curvature” component is negative if larger banks are less volatile than the average. This reduces overall banking sector volatility.

2.4 Banking Sector Size and Concentration

We measure the size of banking markets as the share of domestic credit to the private sector, relative to GDP. Even though credit to GDP has increased in low-income countries during the last years, it remains much lower than in advanced economies (Figure 1). Previous literature has often interpreted the share of credit to GDP as a measure for financial development (Beck et al. 2000, Levine et al. 2000). Yet, credit to GDP is also a measure for the degree of leverage in an economy.

The concentration of banking markets, i.e. the dispersion of assets across banks, is measured through the banking system's Herfindahl index (HHI). The underlying data are taken from *Bankscope*.⁶ The HHI is computed as the sum of banks' squared market shares for each country and year. We use this measure of concentration because the effects of idiosyncratic shocks on aggregate developments, i.e. granular effects, tend to be stronger in more concentrated markets.

Figure 1 reveals that banking market concentration has followed a downward trend in our sample. The Herfindahl index tends to be higher in the most developed economies, which may point to a larger role of granular effects for macroeconomic stability for this group of countries.

2.5 Financial Openness

To measure the degree of financial openness, we use a de facto and a de jure measure. Our de facto measure is taken from an updated and extended version of the external wealth dataset constructed by Lane and Milesi-Ferretti (2007), which is available for the period 1970-2011. In the international trade literature, the degree of trade openness is often measured as the sum of imports and exports relative to GDP. In line with this, we use the sum of foreign assets and foreign liabilities relative to GDP as a proxy for de facto financial integration. Note that this measure of financial integration includes not only cross-border bank lending, but also foreign direct investment (FDI) and portfolio investment. We opt for this broad measure of financial integration because data on external "other investment" or "bank loans" are available for a much smaller sample of low-income countries only.

⁶ Note that *Bankscope* does not cover all banks in a given country and year. Consequently, the Herfindahl index computed from *Bankscope* is a proxy for concentration.

Information on capital controls as a de jure measure of financial openness comes from Chinn and Ito (2006, 2008). These authors use the IMF’s Annual Report on Exchange Restrictions and Regulations to construct a measure of capital account openness. The Chinn-Ito index is based on dummy variables which codify restrictions on cross-border financial transactions. The minimum number is -1.82 (financially closed), the maximum number is 2.46 (financially open). Hence, both financial openness measures are scaled such that a higher number indicates a more open financial system.

The bottom panel of Figure 1 shows our measures of de facto and de jure financial openness. Low-income countries are generally less open than high-income countries. Financial openness in low- and middle-income countries is similar. At the beginning of the sample period, the ratio of foreign assets and liabilities to GDP was even higher in low- than in middle-income economies. This is due to the fact that the official sector in low-income countries holds high amounts of foreign reserves (Lane 2014). On the liability side, official debt dominates. This leads to a relatively high ratio of foreign assets and liabilities to GDP in low-income countries. In terms of de jure openness, low-income countries mostly have less open capital accounts than middle-income economies.

3 Empirical Model and Results

With data on macroeconomic volatility and bank market structures at hand, we are now in the position to answer our main research questions: Does the structure of banking markets affect macroeconomic volatility and, if yes, is this link different in low-income countries?

3.1 Regression Model

As a baseline setup, we regress macroeconomic volatility on banking granular volatility, on banking sector size, and on financial market integration. Hence, we estimate the following equation:

$$Vol_{c,t} = \alpha_t + \gamma_c + \beta_1 BGV_{c,t} + \beta_2 \frac{Credit}{GDP}_{c,t} + \beta_3 FI_{c,t} + \epsilon_{c,t}$$

where $Vol_{c,t}$ is GDP-volatility, α_t is a vector of year-fixed effects capturing global macroeconomic factors, γ_c are country-fixed effects, $BGV_{c,t}$ is banking granular volatility,

$\frac{Credit}{GDP}_{c,t}$ is the ratio of bank credit to GDP, and $FI_{c,t}$ includes de facto and de jure financial market integration.

Second, we use the mean risk and the Herfindahl index of concentration as individual regressors instead of BGV, so that the regression model becomes

$$Vol_{c,t} = \alpha_t + \gamma_c + \beta_1 MRisk_{c,t} + \beta_2 HHI_{c,t} + \beta_3 \frac{Credit}{GDP}_{c,t} + \beta_5 FI_{c,t} + \epsilon_{c,t}$$

where *MRisk* is mean risk computed as the weighted average of bank-level asset growth variances, the weights being each bank's market share as described in section 2.3.

Our empirical analysis proceeds in the following steps: Table 3 presents the results for our baseline regressions using the annual volatility of GDP per capita growth as the dependent variable. In Table 4, we run the regressions for different income groups separately, differentiating between low-income countries, i.e. countries classified by the IMF as Poverty Reduction and Growth Trust (PRGT)-eligible, middle-, and high-income countries. Table 5 shows similar regressions for the full country sample, but including interaction terms between the explanatory variables and a dummy variable for low-income countries which equals one if a country is PRGT-eligible. The purpose of both sets of regressions is to analyze the determinants of macroeconomic volatility while allowing for differences between low-income countries and the remaining sample. Table 6 presents results from cross-sectional regressions of the baseline specification to evaluate longer-term relationships between bank market structures and macroeconomic stability. Finally, we show selected results from robustness tests in Tables 7 and 8.

3.2 *Determinants of Macroeconomic Stability*

Banking granular volatility. Banking granular volatility does not significantly impact aggregate stability (Table 3). Presumably, this is due to the high degree of variability in the annual BGV. Concentration as measured by the Herfindahl index does not have a significant impact on annual macroeconomic fluctuations either. When taking longer-term averages, as is done in Table 6, countries with higher BGV experience higher aggregate volatility. Intuitively, higher average risk in the banking system is related to higher GDP-volatility. If the banking system is more risky, firms' access to finance from banks gets more volatile so that investment and output tend to fluctuate more. Higher banking sector concentration does not significantly affect aggregate volatility in the longer-term.

Table 3: Determinants of the Volatility of GDP per Capita

	(1)	(2)	(3)	(4)	(5)	(6)
Banking Granular Volatility (BGV)						
BGV (assets)	0.006 (0.293)		0.007 (0.318)		0.010 (0.518)	
Mean risk (assets)		-0.002 (-0.097)		-0.004 (-0.153)		-0.005 (-0.240)
HHI (assets)		-0.006 (-0.998)		-0.005 (-0.882)		-0.010 (-1.220)
Banking market structure						
Domestic credit to private sector / GDP	0.018*** (2.680)	0.018*** (2.762)	0.028*** (2.672)	0.028*** (2.680)	0.033** (2.466)	0.033** (2.499)
(Foreign assets + liabilities) / GDP	-0.000 (-0.897)	-0.000 (-0.898)	-0.000 (-0.240)	-0.000 (-0.273)	0.000 (0.214)	0.000 (0.140)
Chinn-Ito index of capital controls	-0.004*** (-3.107)	-0.004*** (-3.130)	-0.004*** (-2.914)	-0.003*** (-2.905)	-0.003* (-1.858)	-0.003* (-1.748)
Macroeconomic control variables						
Market capitalization of listed companies / GDP			-0.003 (-0.821)	-0.003 (-0.820)	-0.001 (-0.341)	-0.001 (-0.360)
Private consumption per capita			-0.000 (-0.124)	-0.000 (-0.150)	-0.000 (-0.876)	-0.000 (-0.946)
Government consumption expenditure / GDP			0.020 (0.308)	0.024 (0.376)	0.080 (1.178)	0.083 (1.276)
Inflation (consumer prices)			0.003 (1.584)	0.003 (1.609)	0.048 (1.510)	0.051 (1.560)
Money and quasi money (M2) / GDP			-0.023*** (-2.659)	-0.022** (-2.607)	-0.024* (-1.961)	-0.023* (-1.935)
Absolute residual of M2 / GDP			0.026 (1.251)	0.026 (1.242)	0.019 (0.776)	0.019 (0.756)
(Imports + Exports) / GDP			0.011 (1.297)	0.011 (1.319)	0.013 (1.111)	0.013 (1.112)
Share of government-owned banks					-0.015 (-1.615)	-0.013 (-1.541)
Observations	1,106	1,106	1,106	1,106	816	816
R ²	0.110	0.111	0.130	0.131	0.172	0.174
Number of countries	89	89	89	89	85	85

The dependent variable is macroeconomic volatility measured as the absolute value of the residual of a regression of (log) growth in real GDP per capita on time and country fixed effects. Time and country fixed effects are included in all regressions but are not reported. ***, **, * = significant at the 1%, 5%, 10% level.

Coming back to the panel-regressions, we find that the effect of BGV on GDP-volatility is weakly significant and negative in low-income countries (Table 4). When including interaction terms for low-income countries (Table 5), the effects of most explanatory variables remain the same as in the baseline setup. The direct effect of BGV remains insignificant. The interaction term itself is negative and significant, i.e. granular effects from banking are weaker and even negative in low-income countries. Contrary to intuition, higher banking sector risk reduces aggregate volatility in low-income countries. In countries where

access to finance is limited, more risky banking systems may enhance macroeconomic stability if they provide more financial services and hence access to finance. Considering mean risk and concentration as separate regressors, their effects are mostly insignificant for macroeconomic volatility in our sample of low-income countries (Tables 4 and 5).

Table 4: Determinants of GDP Volatility by Income Group

	(1)	(2)	(3)	(4)	(5)	(6)
	Low-income		Middle-income		High-income	
Banking Granular Volatility (BGV)						
BGV (assets)	-0.074*		0.038		0.006	
	(-2.045)		(0.716)		(0.356)	
Mean risk (assets)		-0.095		0.031		-0.015
		(-1.349)		(0.655)		(-0.734)
HHI (assets)		0.002		0.000		-0.010
		(0.150)		(0.022)		(-1.579)
Banking market structure						
Domestic credit to private sector / GDP	0.056*	0.061**	0.052**	0.051**	0.016*	0.016*
	(2.042)	(2.284)	(2.683)	(2.592)	(1.838)	(1.891)
(Foreign assets + liabilities) / GDP	0.012**	0.013*	-0.000	-0.000	0.000	0.000
	(2.316)	(1.896)	(-0.016)	(-0.003)	(0.145)	(0.082)
Chinn-Ito index of capital controls	-0.006	-0.006	-0.004***	-0.004**	-0.005**	-0.004**
	(-0.944)	(-0.900)	(-2.724)	(-2.704)	(-2.269)	(-2.180)
Macroeconomic control variables						
Market capitalization / GDP	-0.003	-0.003	0.001	0.001	-0.004	-0.004
	(-0.199)	(-0.189)	(0.094)	(0.098)	(-1.074)	(-1.028)
Private consumption per capita	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(1.399)	(1.105)	(-1.476)	(-1.423)	(-0.299)	(-0.357)
Government consumption expenditure / GDP	0.186***	0.189**	0.058	0.056	-0.014	-0.008
	(3.175)	(2.600)	(0.704)	(0.670)	(-0.094)	(-0.059)
Inflation (consumer prices)	-0.034	-0.036	0.003	0.003	0.019	0.022
	(-0.797)	(-0.822)	(1.430)	(1.431)	(1.161)	(1.409)
Money and quasi money (M2) / GDP	-0.084**	-0.085**	-0.020	-0.019	-0.022**	-0.020**
	(-2.631)	(-2.455)	(-1.087)	(-0.982)	(-2.693)	(-2.552)
Absolute residual of M2 / GDP	-0.022	-0.020	0.062	0.061	0.014	0.014
	(-0.587)	(-0.502)	(1.391)	(1.358)	(0.508)	(0.504)
(Imports + Exports) / GDP	0.044	0.044	0.021	0.022	-0.005	-0.006
	(1.452)	(1.421)	(1.117)	(1.148)	(-0.679)	(-0.682)
Observations	130	130	465	465	511	511
R ²	0.356	0.346	0.166	0.164	0.172	0.176
Number of countries	13	13	36	36	40	40

The dependent variable is macroeconomic volatility measured as the absolute residual of a regression of growth in log real GDP per capita on time and country fixed effects. Time and country fixed effects are included in all regressions but are not reported. ***, **, * = significant at the 1%, 5%, 10% level.

Banking sector size. Macroeconomic fluctuations are higher in countries with a high level of credit to GDP and thus a large banking sector (Tables 3 and 4). If credit to GDP was an indicator of financial development, higher credit should lead to lower macroeconomic volatility (Aghion et al. 1999, Easterly et al. 2001). The positive coefficient instead suggests a destabilizing effect of higher credit. Interestingly, it is the volume of credit, not of bank

liabilities that has a destabilizing effect. As in previous studies (Kose et al. 2003), a higher ratio of money supply (M2) relative to GDP decreases macroeconomic volatility, and this effect matters especially in low-income countries.

Our findings regarding the impact of credit to GDP are in line with the results by Loayza and Ranciere (2006) who show that the link between finance and growth varies across different time horizons. While higher credit can support growth in the long run, a larger financial sector can exacerbate the impact of shocks in the short run. Our cross-sectional regression results for data averaged across the entire sample period (Table 6) confirm this interpretation: In this long-term setup, a higher ratio of credit to GDP can reduce macroeconomic volatility.

Financial openness. De jure financial openness as measured by the Chinn-Ito index of capital controls mitigates aggregate volatility in the full sample (Table 3). Economies with weaker regulations on cross-border capital flows are thus more stable. A high de facto degree of financial openness, however, can become destabilizing. The volatility of GDP growth is higher in countries with higher foreign assets and liabilities relative to GDP, but only in the sample of low-income countries (Tables 4 and 5). High de facto openness does not significantly affect macroeconomic stability in the richer economies. The higher sensitivity in low-income countries with respect to increases in de facto financial openness may be due to the fact that institutional quality is poorer (Acemoglu et al. 2003), and financial development is lower in low-income countries (Bekaert et al. 2006, Kose et al. 2011). As a consequence, capital is used less efficiently.

Moreover, the portfolio of foreign assets and liabilities is more tilted towards debt than towards equity holdings in low-income countries (Lane 2014), which can harm aggregate stability. In the longer-term, the effects of both de jure and de facto financial openness are insignificant in the full sample (Table 6).

Economic significance. In order to gauge the economic significance of the different explanatory variables, we compute standardized beta-coefficients. We multiply the estimated coefficients with the standard deviation of the explanatory variable (Table 2) and divide by the standard deviation of the dependent variable, namely the volatility of GDP per capita growth.

Table 5: Determinants of GDP-Volatility with Interaction Terms

	(1)	(2)	(3)	(4)
Banking Granular Volatility (BGV)				
BGV (assets)	0.017 (0.728)	0.017 (0.720)		
BGV (assets) * Dummy(PRGT)	-0.090** (-2.612)	-0.084** (-2.275)		
Mean risk (assets)			0.007 (0.294)	0.007 (0.285)
Mean risk (assets) * Dummy(PRGT)			-0.094 (-1.526)	-0.094 (-1.460)
HHI (assets)			-0.007 (-1.096)	-0.007 (-1.185)
HHI (assets) * Dummy(PRGT)			0.019* (1.723)	0.010 (0.673)
Banking market structure				
Domestic credit to private sector / GDP	0.028** (2.612)	0.028** (2.612)	0.028** (2.628)	0.028*** (2.635)
Credit/GDP * Dummy(PRGT)	0.000 (0.013)	0.017 (0.515)	0.010 (0.632)	0.018 (0.558)
(Foreign assets + liabilities) / GDP	-0.000 (-0.307)	-0.000 (-0.175)	-0.000 (-0.371)	-0.000 (-0.228)
FI * Dummy(PRGT)	0.003 (0.596)	0.010* (1.742)	0.002 (0.431)	0.009 (1.396)
Chinn-Ito index	-0.004*** (-2.951)	-0.004*** (-2.879)	-0.004*** (-2.942)	-0.003*** (-2.842)
Chinn-Ito * Dummy(PRGT)	0.000 (0.015)	-0.001 (-0.215)	-0.000 (-0.054)	-0.001 (-0.146)
Macroeconomic control variables				
Market capitalization of listed companies / GDP	-0.003 (-0.833)	-0.003 (-0.801)	-0.003 (-0.843)	-0.003 (-0.785)
Market capitalization * Dummy(PRGT)		0.013 (1.119)		0.015 (1.268)
Private consumption per capita	-0.000 (-0.167)	-0.000 (-0.094)	-0.000 (-0.244)	-0.000 (-0.131)
Private consumption * Dummy(PRGT)		0.000*** (2.826)		0.000 (1.488)
Government consumption expenditure / GDP	0.026 (0.385)	0.008 (0.110)	0.030 (0.443)	0.013 (0.170)
Government consumption * Dummy(PRGT)		0.164* (1.700)		0.174 (1.596)
Inflation (consumer prices)	0.003 (1.623)	0.003 (1.542)	0.003 (1.644)	0.003 (1.563)
Inflation * Dummy(PRGT)		-0.028 (-0.990)		-0.026 (-0.853)
M2 / GDP	-0.023*** (-2.679)	-0.022** (-2.611)	-0.022** (-2.581)	-0.021** (-2.527)
M2 / GDP * Dummy(PRGT)		-0.044 (-1.114)		-0.040 (-0.901)
Absolute residual of M2 / GDP	0.026 (1.262)	0.029 (1.284)	0.026 (1.225)	0.029 (1.268)
Absolute residual of M2/GDP * Dummy(PRGT)		-0.061 (-1.297)		-0.063 (-1.330)
(Imports + Exports) / GDP	0.011 (1.326)	0.009 (1.073)	0.011 (1.362)	0.009 (1.090)
(Imports + Exports) / GDP * Dummy(PRGT)		0.035 (1.253)		0.036 (1.269)
Observations	1,106	1,106	1,106	1,106
R ²	0.134	0.139	0.133	0.139
Number of countries	89	89	89	89

The dependent variable is macroeconomic volatility measured as the absolute residual of a regression of growth in log real GDP per capita on time and country fixed effects. Time and country fixed effects are included in all regressions but are not reported. ***, **, * = significant at the 1%, 5%, 10% level.

Table 6: Cross-Sectional Baseline Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Banking Granular Volatility</i>						
BGV (assets)	0.146** (2.540)		0.145*** (2.850)		0.181*** (3.937)	
Mean risk (assets)		0.219** (2.416)		0.243*** (2.648)		0.310*** (3.592)
HHI (assets)		0.009 (1.028)		0.006 (0.662)		0.008 (0.957)
<i>Banking market structure</i>						
Domestic credit to private sector / GDP	-0.009*** (-3.619)	-0.009*** (-3.697)	-0.006 (-1.130)	-0.007 (-1.340)	0.002 (0.522)	0.001 (0.149)
(Foreign assets + liabilities) / GDP	0.000 (1.349)	0.000 (1.574)	-0.001 (-0.785)	-0.001 (-0.842)	-0.000 (-0.746)	-0.000 (-0.895)
Chinn-Ito index of capital controls	0.001 (0.904)	0.001 (0.916)	0.001 (1.086)	0.001 (1.061)	0.001 (1.072)	0.001 (1.046)
<i>Macroeconomic control variables</i>						
Market capitalization / GDP			-0.005* (-1.857)	-0.005* (-1.892)	-0.003 (-1.261)	-0.003 (-1.386)
Private consumption per capita			-0.000 (-0.006)	0.000 (0.023)	-0.000 (-1.066)	-0.000 (-1.114)
Government consumption expenditure / GDP			-0.019 (-0.514)	-0.015 (-0.403)	0.005 (0.171)	0.010 (0.367)
Inflation (consumer prices)			0.013 (0.969)	0.008 (0.570)	0.014 (1.025)	0.007 (0.508)
Money and quasi money (M2) / GDP			0.002 (0.264)	0.002 (0.280)	-0.007* (-1.802)	-0.007 (-1.653)
Absolute residual of M2 / GDP			0.092 (1.014)	0.115 (1.162)	0.113 (1.583)	0.149* (1.900)
(Imports + Exports) / GDP			0.006 (1.612)	0.007 (1.614)	0.007** (2.235)	0.007** (2.441)
Share of government-owned banks					0.009 (1.203)	0.009 (1.129)
Observations	89	89	89	89	85	85
R ²	0.142	0.144	0.237	0.244	0.315	0.334

The dependent variable is macroeconomic volatility measured as the average of year-on-year GDP-volatility across the sample period (1997-2011). ***, **, * = significant at the 1%, 5%, 10% level.

An increase in BGV by one standard deviation implies an increase of 0.01 standard deviations in macroeconomic volatility in the full sample. De jure financial openness and credit to GDP are economically much more important with standardized beta-coefficients of -0.3 and 0.8, respectively. For the sub-sample of low-income countries, the ranking is the same as in the full sample: credit to GDP matters most for macroeconomic volatility, followed by de facto financial openness. Banking granular volatility is economically much less important.

However, an increase in financial openness and credit to GDP leads to higher macroeconomic volatility in low- than in high-income countries. When estimating the model separately by income group (Table 4), credit to GDP has a higher economic significance for the low-income than for the high-income countries: The standardized beta-coefficients reveal that an increase in credit to GDP by one standard deviation increases macroeconomic volatility by 0.7 standard deviations in low-income countries. In high-income economies, a one standard deviation increase in credit to GDP raises macroeconomic volatility by 0.45 standard deviations only. Again, weaker institutions in low-income countries may explain the difference. In the cross-sectional regressions, the economic significance of BGV is as high as the economic significance of credit to GDP with a standardized beta coefficient of 0.3.

3.3 Robustness Tests

In order to test the robustness of our results, we have run several alternative regressions. First, we have used banking granular volatility and its components based on loans instead of assets as an alternative specification of banking sector volatility.⁷ The results remain broadly the same. Moreover, following Carvalho and Gabaix (2013), we have computed BGV using (time-invariant) standard deviations for each bank across the sample period instead of the time-varying squared absolute values of bank-specific shocks. This allows us to concentrate on the effects of market structure by abstracting from changes in annual bank-specific volatilities. Table 7 reveals that this alternative measure of granular effects from the banking sector does not affect the results for the full sample. In the sample of low-income countries, the negative effect of BGV turns insignificant if BGV is based on time-invariant volatility (not reported).

Second, in order to test how our results are influenced by the global financial crisis, we interact all variables of interest with a banking-crisis dummy which is available from Laeven and Valencia (2012). Again, the results remain broadly unchanged. The effect of the Herfindahl index on GDP-volatility turns negative when including an interaction with the crisis-dummy. As expected, volatility is higher in times of crisis. Hence, higher banking sector concentration increases volatility in crisis times while it stabilizes output in normal times.

⁷ The regression results are available upon request.

Table 7: Baseline Regressions with Time-Invariant Bank-Level Volatility

	(1)	(2)	(3)	(4)	(5)	(6)
Banking Granular Volatility						
BGV (assets, time-inv. var.)	0.007 (0.323)		0.008 (0.394)		0.017 (0.533)	
Mean risk (assets, time-inv. var.)		0.089 (1.655)		0.077 (1.556)		0.085 (1.174)
HHI (assets)		-0.009 (-1.309)		-0.007 (-1.188)		-0.010 (-1.375)
Banking market structure						
Domestic credit to private sector / GDP	0.018*** (2.676)	0.018*** (2.904)	0.028*** (2.674)	0.027*** (2.708)	0.033** (2.470)	0.033** (2.525)
(Foreign assets + liabilities) / GDP	-0.000 (-0.935)	-0.001 (-1.065)	-0.000 (-0.266)	-0.000 (-0.399)	0.000 (0.169)	0.000 (0.040)
Chinn-Ito index of capital controls	-0.004*** (-3.105)	-0.004*** (-3.149)	-0.004*** (-2.904)	-0.004*** (-2.921)	-0.003* (-1.858)	-0.003* (-1.861)
Macroeconomic control variables						
Market capitalization / GDP			-0.003 (-0.837)	-0.002 (-0.759)	-0.001 (-0.358)	-0.001 (-0.310)
Private consumption per capita			-0.000 (-0.132)	-0.000 (-0.173)	-0.000 (-0.842)	-0.000 (-0.963)
Government consumption expenditure / GDP			0.020 (0.316)	0.027 (0.445)	0.083 (1.229)	0.086 (1.335)
Inflation (consumer prices)			0.003 (1.598)	0.003* (1.769)	0.047 (1.494)	0.049 (1.501)
Money and quasi money (M2) / GDP			-0.023*** (-2.645)	-0.021** (-2.560)	-0.024* (-1.950)	-0.021* (-1.890)
Absolute residual of M2 / GDP			0.026 (1.274)	0.026 (1.260)	0.020 (0.811)	0.019 (0.785)
(Imports + Exports) / GDP			0.011 (1.289)	0.010 (1.225)	0.013 (1.117)	0.012 (1.031)
Share of government-owned banks					-0.014 (-1.587)	-0.012 (-1.413)
Observations	1,106	1,106	1,106	1,106	816	816
R ²	0.110	0.116	0.130	0.134	0.172	0.177
Number of countries	89	89	89	89	85	85

The dependent variable is macroeconomic volatility measured as the absolute residual of a regression of growth in log real GDP per capita on time and country fixed effects. BGV is computed based on the time-invariant variances of bank assets as described in the main body of the text. Time and country fixed effects are included in all regressions but are not reported. ***, **, * = significant at the 1%, 5%, 10% level.

Third, we interact credit to GDP and de facto financial openness with variables measuring institutional quality in order to account for possible threshold effects in the relation between financial system size (both domestic and international) and macroeconomic volatility. We measure institutional quality using different variables from the *Doing Business Indicators* and from the *World Bank Governance Indicators* and include interaction terms in the regressions for the full sample and for the sub-sample of low-income countries.

Table 8: Instrumental Variables Regressions

	(1)	(2)
<i>Banking Granular Volatility</i>		
BGV (assets)	-0.003 (-0.286)	
Mean risk (assets)		-0.003 (-0.286)
HHI (assets)		-0.006 (-1.504)
<i>Banking market structure</i>		
Domestic credit to private sector / GDP	0.010** (2.207)	0.011** (2.519)
(Foreign assets + liabilities) / GDP	-0.000 (-0.198)	-0.000 (-0.564)
Chinn-Ito index of capital controls	-0.000 (-0.225)	-0.001 (-1.104)
<i>Macroeconomic control variables</i>		
Market capitalization / GDP	-0.002 (-1.290)	-0.001 (-0.951)
Private consumption per capita	0.147*** (4.474)	0.164*** (5.364)
Government consumption expenditure / GDP	0.009 (1.532)	0.010* (1.742)
Inflation (consumer prices)	-0.000 (-0.687)	-0.000 (-0.096)
Money and quasi money (M2) / GDP	-0.009*** (-3.405)	-0.009*** (-3.624)
Absolute residual of M2 / GDP	0.046*** (4.012)	0.047*** (5.457)
(Imports + Exports) / GDP	-0.000 (-0.031)	-0.007* (-1.974)
Observations	912	912
R^2	0.045	0.051
Number of countries	85	85
p -value of Hansen j -statistic	0.583	0.351
Hansen j -statistic	21.94	34.46

The dependent variable is macroeconomic volatility measured as the absolute residual of a regression of growth in log real GDP per capita on time and country fixed effects. Time and country fixed effects are included in all regressions but are not reported. ***, **, * = significant at the 1%, 5%, 10% level.

The interactions between institutional quality indicators and credit to GDP or financial openness are mostly insignificant. Exceptions are the interactions between an indicator for government effectiveness and for the control of corruption and credit to GDP: The more effective the government or the better the control of corruption, the weaker is the volatility-enhancing effect of credit to GDP. The remaining effects are broadly unchanged if we include interaction terms between the size of the banking sector and institutional variables in the full sample.

Interestingly, the effect of BGV gets more statistically significant and positive in some of the regression models which include (insignificant) measures of institutional quality. This is due to the different sample compositions: Most of the institutional variables are available for

shorter time periods or fewer countries than in our baseline sample. Hence, depending on the sample composition, the significance of granular effects from the banking sector is more or less pronounced.

Table 8 presents results for instrumental variables regressions. Even though BGV is exogenous by construction, the other explanatory variables of interest may be endogenous. For example, domestic credit may drop due to a decline in credit demand during bad times, and financial markets may close down in periods of high macroeconomic instability.

We use the second lag of the Herfindahl index, domestic credit to GDP, and de facto and de jure financial openness as instruments for their contemporaneous counterparts. In order to increase efficiency of the instrumental variable regressions and to be able to run Sargan-Hansen tests of orthogonality conditions, we employ the methodology proposed by Lewbel (2012). This approach allows constructing heteroscedasticity-based instruments as simple functions of the regressors. Additional external instruments can be obtained from auxiliary (first-stage) regressions, where each endogenous variable is regressed on all exogenous variables. The generated instruments are then obtained by multiplying the residuals from the auxiliary regressions with the demeaned exogenous variable. Identification is achieved by having regressors that are uncorrelated with the heteroscedastic error terms (Baum and Schaffer 2012).

The results support our previous findings that a higher ratio of credit to GDP increases macroeconomic volatility. When instrumenting the regressors, the effect of de jure financial openness turns insignificant though.

4 Summary

In this paper, we study the impact of banking market structure on macroeconomic volatility with a focus on low-income countries. Compared to higher-income countries, low-income countries are characterized by higher average banking sector risk, lower degrees of international integration, and smaller overall banking systems. The degree of concentration in banking markets is similar. Our study has three main findings.

First, idiosyncratic risk at the bank-level has no strong impact on year-to-year macroeconomic volatility. Cross-sectional regressions show that a high degree of mean risk

in banking markets increases aggregate volatility. Hence, we find evidence for a positive link between bank-level and macroeconomic volatility in the longer term.

Second, a higher ratio of bank credit relative to GDP increases macroeconomic volatility, also in low-income countries. This destabilizing effect of banking sector size occurs, however, in the short run only. Our results point to possible volatility-reducing effects of credit to GDP in the long run.

Third, increased financial integration is a double-edged sword. Reducing capital controls – and thus a higher degree of de jure openness – has a stabilizing effect. High ratios of foreign assets and liabilities relative to GDP increase macroeconomic instability in low-income countries, in contrast.

In terms of policy implications, our results imply that there are different channels through which macroeconomic volatility can potentially be reduced: by limiting the excessive expansion of domestic and foreign credit in an economy, and by reducing idiosyncratic and thus bank-level volatility. We have also shown that the impact of financial openness on macroeconomic volatility depends on the openness measure chosen.

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Appendix

1 Data Definition and Sources

Income groups: The group of low-income countries follows the classification of the Poverty Reduction and Growth Trust (PRGT)-eligible countries from the IMF/WEO. The group of middle-income countries includes countries which are classified as middle-income countries by the World Bank, but without PRGT-eligible countries. High-income countries are classified according to the World Bank.

List of countries (PRGT-eligible countries are in *italics*): Argentina, Armenia, Australia, Austria, *Bangladesh*, Belgium, *Bolivia*, Botswana, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, *Cote d'Ivoire*, Croatia, Cyprus, Czech Republic, Denmark, Ecuador, Egypt, El Salvador, Estonia, Finland, France, Germany, Greece, Guatemala, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Kazakhstan, *Kenya*, Korea. Rep., *Kyrgyz Republic*, Latvia, Lebanon, Lithuania, Macedonia, *Malawi*, Malaysia, Malta, Mexico, *Mongolia*, *Moldova*, Morocco, Namibia, *Nepal*, Netherlands, New Zealand, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Swaziland, Sweden, Switzerland, *Tanzania*, Thailand, Trinidad and Tobago, Tunisia, Turkey, *Uganda*, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela, *Vietnam*, *Zambia*.

Banking granular volatility: To compute banking granular volatility as described in the text, we use bank-level data on total net loans and total assets from the *Bankscope* database for the period 1997-2011. In *Bankscope*, we keep observations with the consolidation codes C1 (consolidated and companion is not on the disc), C2 (consolidated and companion is on the disc), U1 (unconsolidated and companion is not on the disc or the bank does not publish consolidated accounts), and A1 (aggregated statements with no companion), so that double-countings are eliminated.

Bank-level volatility: Computed as the squared absolute residual of a regression of bank-level assets (loan) growth on country-year-fixed effects using the *Bankscope* dataset.

Capital controls: We use the Chinn-Ito index as a de jure measure for financial openness. This variable measures a country's degree of capital account openness and is available for the period 1970-2011 and 182 countries. It ranges from -1.82 to 2.46 with a sample mean of zero. The smaller the Chinn-Ito Index, the lower (de jure) financial openness.

Concentration: As a measure of concentration in the banking sector, we compute Herfindahl-indexes for each country and year based on net loans and assets from *Bankscope*.

Credit to GDP: Credit to the private sector in percent of GDP is taken from the World Development Indicators.

Deposit insurance funds relative to total bank asset: This information is available from Barth et al. (2013).

Depth of credit information: Scope and accessibility of credit information provided by public or private credit registries. This index ranges from 0 to 6 with higher values indicating better availability of credit information and thus facilitated lending decisions for banks. The index is available from the Doing Business Indicators by the World Bank.

GDP per capita growth: We compute growth as the log-difference in constant 2005 US-Dollars. The data on GDP per capita come from the World Development Indicators.

Government consumption expenditure / GDP: Data on general government final consumption expenditure in percent of GDP (in constant 2005 USD) is taken from the World Development Indicators.

Inflation (consumer prices, annual %): World Development Indicators.

Market capitalization of listed companies (relative to GDP): The data is taken from the World Development Indicators.

Mean banking sector risk: We compute mean risk as the weighted sum of the squared absolute value of idiosyncratic bank-level asset growth, where the weights are given by each bank's market share (see equation (4) in the main text).

M2 / GDP: Money and quasi money (M2) relative to GDP is retrieved from the World Development Indicators.

Percent of 10 biggest banks rated by international rating agencies: This information is available from Barth et al. (2013).

Private registry coverage (% of adults): Percentage of the adult population that is covered by private credit bureaus. We take this information from the Doing Business Indicators by the World Bank.

Public registry coverage (% of adults): Percentage of the adult population that is covered by public credit registries. We take this information from the Doing Business Indicators by the World Bank.

Real private consumption per capita (USD): Data on real private consumption and on total population come from the World Development Indicators.

Share of foreign-owned banks: The information is available from Barth et al. (2013).

Share of total bank assets that are government-owned: The information is available from Barth et al. (2013).

Total foreign assets and liabilities relative to GDP: We use data on total foreign assets and liabilities in US-Dollars from the updated database by Lane and Milesi-Feretti (2007) which is available for the period 1970-2011 for 178 countries. GDP-data is taken from the WDI.

Trade openness: We take exports and imports relative to GDP from the World Development Indicators.

Volatility of M2 / GDP: We compute absolute residuals from a regression of M2 / GDP on country- and time-fixed effects.

2 Decomposition of Banking Granular Volatility (BGV)

Following Di Giovanni et al. (2012), Banking Granular Volatility can be decomposed as follows:

$$BGV_{ct} = \left(\bar{\varepsilon}_{ct} \sum_i^N s_{ict}^2 + 2 \bar{s}_{ct} \sum_i^N s_{ict} \varepsilon_{ict} + \sum_i^N (s_{ict} - \bar{s}_{ct})^2 (\varepsilon_{ict} - \bar{\varepsilon}_{ct}) - \mathbf{const} \right)^{\frac{1}{2}}.$$

Writing out the expression explicitly and simplifying, it can be shown that this decomposition is equivalent to BGV as defined in equation (2) in the main text:

$$\begin{aligned} BGV_{ct}^2 &= \bar{\varepsilon}_{ct} \sum_{i=1}^N s_{ict}^2 + 2 \bar{s}_{ct} \sum_{i=1}^N s_{ict} \varepsilon_{ict} + \sum_{i=1}^N (s_{ict}^2 - 2s_{ict}\bar{s}_{ct} + \bar{s}_{ct}^2) (\varepsilon_{ict} - \bar{\varepsilon}_{ct}) \\ &= \bar{\varepsilon}_{ct} \sum_{i=1}^N s_{ict}^2 + 2 \bar{s}_{ct} \sum_{i=1}^N (s_{ict} \varepsilon_{ict}) + \sum_{i=1}^N s_{ict}^2 \varepsilon_{ict} - 2 \bar{s}_{ct} \sum_{i=1}^N (s_{ict} \varepsilon_{ict}) \\ &\quad + \bar{s}_{ct}^2 \sum_{i=1}^N \varepsilon_{ict} - \bar{\varepsilon}_{ct} \sum_{i=1}^N s_{ict}^2 + 2 \bar{s}_{ct} \bar{\varepsilon}_{ct} \sum_{i=1}^N s_{ict} - N \bar{s}_{ct}^2 \bar{\varepsilon}_{ct} \\ &= \sum_{i=1}^N s_{ict}^2 \varepsilon_{ict} + \bar{s}_{ct}^2 \sum_{i=1}^N \varepsilon_{ict} + 2 \bar{s}_{ct} \bar{\varepsilon}_{ct} \sum_{i=1}^N s_{ict} - N \bar{s}_{ct}^2 \bar{\varepsilon}_{ct} \\ &= \sum_{i=1}^N s_{ict}^2 \varepsilon_{ict} + N \bar{s}_{ct}^2 \bar{\varepsilon}_{ct} + 2 N \bar{s}_{ct}^2 \bar{\varepsilon}_{ct} - N \bar{s}_{ct}^2 \bar{\varepsilon}_{ct} \\ &= \sum_{i=1}^N s_{ict}^2 \varepsilon_{ict} + \underbrace{2 N \bar{s}_{ct}^2 \bar{\varepsilon}_{ct}}_{\mathbf{const}} \\ \Rightarrow BGV_{ct} &= \left(\bar{\varepsilon}_{ct} \sum_i^N s_{ict}^2 + 2 \bar{s}_{ct} \sum_i^N s_{ict} \varepsilon_{ict} + \sum_i^N (s_{ict} - \bar{s}_{ct})^2 (\varepsilon_{ict} - \bar{\varepsilon}_{ct}) - \mathbf{const} \right)^{\frac{1}{2}} \\ &= \left(\sum s_{ict}^2 \varepsilon_{ict} \right)^{1/2} \end{aligned}$$