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Financial asymmetries, risk sharing and growth in the EU[♦]

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Abstract

We focus on the structural and stability dimensions of financial development and build an index to benchmark EU financial systems against their potential to enhance resilient growth and international risk sharing. We have the following results. (i) Based on the transitional dynamics of the index over 2000-2019, EU financial systems are converging towards a clustered pattern; (ii) our measure of financial development is highly significant in growth regressions, suggesting that greater openness, market-based financing, and equity positions, longer debt maturities, and enhanced stability are key to stable growth; (iii) financial asymmetries have implications for the heterogeneous vulnerability to domestic output shocks: the risk sharing mechanism is more effective in financially resilient economies that benefit by the contribution of the capital market channel, while a larger fraction of the GDP shocks remains unsmoothed in less resilient economies that feature a considerable down-seizing of the saving channel in the post-global financial crisis.

Keywords: financial resilience, financial asymmetries, growth, volatility, risk sharing

JEL codes: F15 · F36 · O16 · E44 · G1

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1. Introduction

The global financial crisis of 2008-2009 and the widespread deleveraging of subsequent years have highlighted unsolved asymmetries within the EU. Peripheral economies have been more vulnerable to the capital withdrawal from global investors and have suffered a sharper drop in output, pointing to pitfalls in the financial integration process within the EU (Estrada *et al*., 2013; European Central Bank, 2016, 2018, 2020, and 2022; Cavallaro and Villani, 2021). Financial integration can act as a catalyst for per-capita output convergence by contributing to the development of domestic financial systems: it can increase access to financial services, raise the resources available to consumers and firms and enhance efficiency, promote convergence in regulation and supervision. By increasing cross-border flows, financial integration has the potential to raise the opportunities for international risk diversification and consumption smoothing. In practice, all this may depend on the *type* of financial integration: the empirical evidence shows that the expansion of the financial sector beyond a critical level has no positive effect on growth (Rousseau and Wachtel, 2011; Arcand *et al*., 2015; Cavallaro and Villani, 2022) and that pro-cyclical and volatile cross-border flows can make economies more vulnerable to global shocks (Kose *et al*., 2009; Emter *et al*., 2019).

The issue lies at the heart of the on-going debate on the resilience of financial integration within the EU, following the global financial crisis, and has sparked renewed interest on the relationship between financial structure, financial development, and growth (Beck *et al*., 2016; Kremer and Popov, 2018; Hoffmann *et al*., 2022). Based on these contributions, we uncover the asymmetries in EU financial systems and analyse the implications for long-run growth and risk diversification. Our work relates to two strands of the literature. The first focuses on the finance-growth puzzle, that is, the vanishing effect of finance found in growth regressions for economies with large financial sectors (Rousseau and Wachtel, 2011; Arcand *et al*., 2015; Cavallaro and Villani, 2022). We develop on the idea that the threshold effects to financial deepening established empirically stem from the failure to consider certain relevant dimensions of financial systems (Beck *et al*., 2014). In other words, the *type* of financial development matters for growth and the volatility of growth. The second strand of the literature analyses the patterns of consumption smoothing and international risk sharing in the EU (Sørensen *et al*., 2007; Furceri and Zdniecka, 2013; Alcidi *et al*. 2023). We build on the insight that the benefits of opening economies may depend on the features of financial integration, specifically, on the composition of cross-border flows, and uncover the implications of the uneven development of EU financial systems for vulnerability to idiosyncratic shocks and effective risk-sharing.

Against this background, in our work we introduce a novel broad-based measure of the development of financial systems, the Financial Resilience index (FR, henceforth). The FR index is designed to benchmark financial systems against their potential to channel resources into high-risk and highly innovative projects and to allow risks to be diversified within a sound institutional setting. The index is a composite measure of financial openness, market orientation, equity position vis-à-vis debt, maturity structure, and stability, as it is recognized that these dimensions are key to endurable growth and resiliency of financial systems.

We draw on the following motives emphasized in the recent literature. (i) Global diversification of asset ownership and debt financing reduces firms' dependence on domestic sources of financing, thus improving resiliency to domestic shocks (Beck *et al*., 2016); (ii) market-based financing is increasingly important in developed economies (Gambacorta *et al.* 2014): it fosters the highest levels of technology-intensive innovation (Hsu *et al*., 2014), facilitating the adoption of cleaner technologies in carbon-intensive industries and investment in green-industries (De Haas and Popov, 2019); it shelters firms against the pitfalls of domestic credit market distress, which can be particularly severe for firms which have limited reliance on foreign lending, as in the peripheral EU economies in the wake of the eurozone crisis (Hoffmann *et al*., 2022); (iii) equity and direct investment financing is less prone to runs than debt, due to the state-contingency nature of the repayment flows, and is provided for an unlimited period of time, thereby eliminating the rollover risk typically associated with debt financing (Artis and Hoffmann 2012); (iv) longer debt maturities shields firms and household against the capital flows reversals and sudden stops associated with severe crises (Beck *et al*., 2016); v) sound financial institutions and a high quality of regulation and supervision make largescale financial sectors less susceptible to the “too much finance” effect, and thus represent “enabling factors” for growth and stability of growth (Čihák *et al*., 2012; Sahay *et al*. 2015).

Based on the FR index, we benchmark EU financial systems and analyse the implications of the identified asymmetries for long-run growth and risk-sharing. The analysis is developed in the following steps. First, we employ the FR index to assess the evolution of asymmetries across EU financial systems over the period 2000-2019. We employ the nonlinear time-varying factor model of Phillips and Sul (2007, hereafter PS) and test convergence in financial resilience. Based on the estimated transition curves, we find that financial convergence occurs only for subgroups of economies, and we identify the financial convergence clusters endogenously. Second, we run panel estimations for the EU 27 economies and UK over 2000-2019, to test the effect of financial development on growth and volatility of growth. We augment a basic panel growth regression with a measure of financial development (Beck and Levine, 2004; Rousseau and Wachtel, 2011; Arcand *et al.* 2015) employing first the IMF financial development index (FD index) and then the FR index. We find that financial development measured through FD is not significant, whereas when it is measured through the FR index it has a significant and robust effect on economic growth. Analogously, we find a beneficial effect of FR in reducing the volatility of economic growth. Finally, we analyse the implications of the financial asymmetries for risk sharing over 1995-2019. Following the methodology first introduced by Asdrubali *et al*. (1996), we run panel estimations to determine the fraction of shocks to GDP which is unsmoothed for the economies belonging to the different financial clusters and identify the amount of risk that is absorbed through the various channels. We find that highly resilient economies are more protected from shocks to domestic output, and the fraction of risk smoothed out by capital markets is higher among these economies than among the less-resilient groups, where the role of credit markets is relatively higher. The heterogeneities between the groups are accentuated in the aftermath of the global financial crisis: in the highly resilient economies, the fraction of the shocks to domestic output that is unsmoothed is significantly reduced, while it increases in the less-resilient economies that experience a considerable fall in the contribution of the credit channel to consumption smoothing.

The paper is organised as follows. Section 2 outlines data and empirical methodologies employed; Section 3 the FR index; Section 4 identifies the financial clusters; Section 5 reappraises the finance-growth nexus; Section 6 deals with the patterns of consumption smoothing and international risk-sharing. Section 7 draws concluding remarks.

2. Data and methodology

We consider a panel of the 27 EU countries plus UK, throughout 2000-2019. The UK is included because it was part of the EU during the period considered. We source data from EUROSTAT, the World Development Indicators (WDI, World Bank), the Global Financial Development Database (GFDD, World Bank), the Worldwide Governance Indicators (WGI, World Bank) and the Financial Development Index Database (FDID, IMF). The list of variables, with description and source is in the Appendix, Table A.1.

Our empirical strategy is developed in four steps: i) we build the FR index; ii) we apply the system dynamic Generalized Method of Moments (SYS-GMM) to estimate the finance-growth and finance-volatility relationships; iii) we employ the PS econometric convergence test to identify clusters for our measure of financial resilience; iv) we run different types of panel regressions to determine the amount of unsmoothed consumption and the contribution of each channel to risk diversification for the economies belonging to high-, intermediate-, and low-resilience groups.

In building the FR index, we follow the analogous two-step approach employed for the IMF Financial Development Index (Sahay *et al.*, 2015; Svirydzenka, 2016). We identify a list of variables to be included, aggregate them into five sub-indices (globalization, market orientation, equity vs. debt, debt maturity, stability) corresponding to the five dimensions of the index, using the weights obtained from the principal component analysis; we then aggregate the sub-indices to obtain the FR index.

As to the dynamic SYS-GMM estimator employed in the growth regression, it has been introduced by Arellano and Bover (1995) and Blundell and Bond (1998) to overcome problems of heteroscedasticity, serial correlation, and endogeneity of the explanatory variables. It is suitable for short panels when: (i) there is persistence in the dependent variable, (ii) the independent variables are not strictly exogenous and are correlated with past and current realizations of the error, (iii) there are arbitrarily distributed fixed individual effects; (iv) there is heteroscedasticity and autocorrelation within panels (Roodman, 2009).

Briefly, consider the following dynamic panel data model:

$$Y_{it} = \alpha Y_{it-1} + \beta X_{it} + \gamma W_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

where Y_{it} is the log of real per capita GDP, Y_{it-1} is the log of initial level of per capita GDP, X_{it} is a vector of endogenous variables, W_{it} is a set of exogenous variables, μ_i is the unobserved time-invariant fixed individual effect and ε_{it} is the error term.

The first-difference transformation of (1), performed by means of the Difference GMM estimator, removes the fixed effects, but the issue of endogeneity remains because the newly obtained error term $\varepsilon_{it} - \varepsilon_{it-1}$ is correlated with the lagged dependent variable:

$$Y_{it} - Y_{it-1} = \alpha(Y_{it-1} - Y_{it-2}) + \beta(X_{it} - X_{it-1}) + \gamma(W_{it} - W_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1}) \tag{2}$$

The following assumptions are required: the error term is not serially correlated; the explanatory variables are weakly exogenous. Blundell and Bond (1998) showed that in case the explanatory variables are characterised by persistency, their lagged levels are weak instruments, and this may affect the estimation results. To overcome this issue, the implemented System GMM estimator combines into a system the regression in differences and in levels, which are distinctly instrumented. The first equation is expressed in levels, with first differences as instruments; the second equation is expressed in first-differenced form, with the levels as instruments, on the assumption of no correlation between the first differences and the individual specific effects.

As to the convergence analysis, it is based on the log-*t* test formulated by PS that allows testing convergence in panel data and modelling the transitional dynamics.[1] There are several appealing features of this methodology: (i) it lies on the concept of σ-convergence, *i.e.*, the reduction of disparities through time; (ii) it considers heterogeneity both across countries and over time, *i.e.*, with the possibility of transitional divergence; (iii) it does not require stationarity of the series; (iv) the identification of convergence clubs is endogenous, avoiding a-priori grouping of countries.

Briefly, consider the following nonlinear time-varying factor model:

$$X_{it} = \delta_{it}\mu_t \tag{3}$$

Where X_{it} is a variable of interest referred to a generic country *i*, δ_{it} is an idiosyncratic factor loading and μ_t is the latent unobservable common factor. The loading factor measures country *i* deviation from the common path, and varies along the transition process towards μ_t. In case of panel or sub-group convergence, the individual transition coefficient δ_{it} tends to a constant δ as $t \to \infty$. Taking ratios to cross-sectional averages, the unobservable common factor is dropped out, thus obtaining the relative transition coefficient, h_{it}, at each time *t*:

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N} \delta_{it}} \tag{4}$$

[1] The PS methodology is being increasingly employed to assess panel (subgroups) convergence in real per-capita incomes among groups of regions (Bartkowska and Riedl, 2012; Lyncker and Thoennessn, 2017; Cutrini, 2019) and countries (Monfort et al., 2013; Borsi and Metiu, 2015; Cavallaro and Villani, 2022), and in financial development (Apergis *et al*., 2012, Cavallaro and Villani, 2021), stock market indices (Apergis *et al*., 2014), retail banking (Rughoo and Sarantis, 2014) and asset returns (Caporale *et al*. 2015).

The parameter h_{it} traces out the transition of economy i in relation to other economies in the panel. Convergence attains if the panel (or the sub-group) cross-sectional variance decreases over time until reaching 0, i.e., if $H_t = N^{-1}\sum_{i=1}^{N}(h_{it}-1)^2 \rightarrow 0,$ as $t \rightarrow \infty$. This happens if h_{it} approaches unity as $t \rightarrow \infty$.

The PS methodology entails two main steps: first, investigating panel convergence employing the log t test; then, identifying the convergence clubs through a recursive clustering algorithm which applies the log t test to subsets of data when the null hypothesis is rejected for the full sample.

The regression-based convergence test takes the following functional form:

$$\log(H_1/H_t) - 2\log L(t) = a + b\log t + u_t, \qquad t = [rT], [rT]+1, \ldots.., T \tag{5}$$

Where $r \in (0.2, 0.3)$ is the fraction of observations removed from the sample before running the regression, to focus on the transitional dynamics of the latest period. The term 2log $L(t)$ on the left-hand side acts as a penalty function to avoid upward biased estimations of b, with $L(t) = \log t$. The estimated coefficient $\hat{b} = 2\hat{\alpha}$ measures the speed of convergence of δ_{it} , with $\hat{\alpha}$ the least squares estimation of α. The statistics employed is the one-sided t-test for $\alpha \geq 0$ with HAC (heteroscedasticity and autocorrelation consistent) standard error. The null hypothesis of convergence is $H_0: \delta_i = \delta$ and $\alpha \geq 0$, while the alternative non-convergence hypothesis is $H_1: \delta_i \neq \delta$ for some i, or $\alpha < 0$.

Convergence clubs are identified focusing on the behaviour of the idiosyncratic transitions with respect to the common component and employing recursively the log t test. Units (k) are added one by one to a core group G_k, formed by the two highest-income countries at the beginning (i.e., k = 2), if $t_{\hat{b}} > -1.65$, and the log t test is run for each additional unit (up to $k = n$) until the condition $t_{\hat{b}} > -1.65$ is rejected for the candidate club. Then, the n^{th} unit is dropped, and the procedure is repeated to identify the following groups.

As for the extent of risk-sharing in country *j*, it is measured by the β-coefficient obtained in the following regression (Attanasio and Davis, 1996; Park and Shin, 2010; and Dynarski and Gruber, 1997):

$$log\ C_{i,t+1} - log\ C_{i,t} = \alpha_t^u + \beta_t^u \left(log\ GDP_{i,t+1} - log\ GDP_{i,t}\right) + \varepsilon_{i,t} \tag{6}$$

Where $C_{i,t}$, $C_{i,t+1}$, and $GDP_{i,t}$, $GDP_{i,t+1}$ are, respectively, consumption and output of country *i* at time *t* and *t*+1, α_t^u is the undiversifiable risk and $\varepsilon_{i,t}$ the residual. If $\beta^u = 0$, the dynamics of consumption is disconnected from the dynamics of output and therefore all risk is smoothed out.

The contribution of the different channels to risk diversification can be identified decomposing the cross-sectional variance of the shocks to *GDP*, as originally shown by Asdrubali *et al*. (1996). The idea is to consider the chain equation where *GDP* is disaggregated into the various national aggregates, i.e., gross national income (*GNI*), net national income (*NNI*), national disposable income (*DI*), and total (private and government) consumption (*C*):

$$GDP_i = \frac{GDP_i}{GNI_i}\ \frac{GNI_i}{NNI_i}\ \frac{NNI_i}{DI_i}\ \frac{DI_i}{C_i}\ C_i \tag{7}$$

The risk diversification channels may be identified as follows: the capital markets channel is operating whenever, in the face of shocks to domestic output, *GDP* changes while *GNI* remains constant; the capital depreciation channel whenever *GNI* changes while *NNI* stays constant, the international fiscal transfers channel whenever *NNI* changes while *DI* remains constant and, finally, the credit market channel, when disposable income varies while consumption remains unchanged. The fraction of the output shock that is absorbed through the various channels can be calculated by running panel estimations for the following system of equations resulting from the decomposition of the total variance of equation (6):

$$\Delta log\ GDP_{i,t} - \Delta log\ GNI_{i,t} = \alpha_t^m + \beta_t^m \Delta log\ GDP_{i,t} + \varepsilon_{i,t} \tag{8}$$

$$\Delta log\ GNI_{i,t} - \Delta log\ NNI_{i,t} = \alpha_t^d + \beta_t^d \Delta log\ GDP_{i,t} + \varepsilon_{i,t} \tag{9}$$

$$\Delta log\ NNI_{i,t} - \Delta log\ DI_{i,t} = \alpha_t^g + \beta_t^g \Delta log\ GDP_{i,t} + \varepsilon_{i,t} \tag{10}$$

$$\Delta log\ DI_{i,t} - \Delta log\ C_{i,t} = \alpha_t^s + \beta_t^s \Delta log\ GDP_{i,t} + \varepsilon_{i,t} \tag{11}$$

The fraction of income smoothing achieved by holding an internationally diversified portfolio is given by the coefficient β^m in equation (8), the fraction resulting from capital depreciation by the coefficient β^d in equation (9), the fraction obtained from the international fiscal transfers by the coefficient β^g in equation (10), and the fraction resulting from the adjustment of (private and government) savings by the coefficient β^s in equation (11).

Given the objective of our analysis, we shall focus on the contribution of capital markets and credit channels: the larger the parameter β^m, the more GDP shocks are smoothed through international income flows, creating a wedge between changes in GDP and changes in net incomes from abroad; the larger β^s the more consumption smoothing accrues through saving/dissaving achieved by credit markets.

3. The FR index: benchmarking EU financial systems

The FR index is a composite measure of openness, market orientation, equity position vis-à-vis debt, maturity structure, and stability of financial systems. We employ the methodology used to build the IMF FD index. There are two levels of aggregation: at the bottom level, the selected variables are aggregated to form the five distinct sub-indices: GLOBAL (globalization), MKT vs. INST (markets vs. institutions), EQUITY vs. DEBT, DEBT MATURITY, STABILITY; at the upper level, the five sub-indices are aggregated to obtain the FR index. Figure 1 shows the composition of the FR index.

The GLOBAL sub-index measures the breadth of financial globalization in terms of cross-border-liabilities and cross-border assets holdings (as shares of GDP). Cross-border portfolio holdings can insulate consumption from idiosyncratic shocks to output thus increasing resilience. Thus, higher financial openness is beneficial for resilient growth. We consider: (i) cross-border market-based financing, corresponding to debt securities, equity and investment fund shares held by non-residents; (ii) cross-border bank-based financing, i.e., loans from foreign banks; (iii) residents' holdings of foreign securities (i.e., debt, equity, and investment fund shares); (iv) domestic banks' cross-border loans. Data are from EUROSTAT.[2]

The second dimension captured by the FR index is the market orientation of financial systems. The MKT vs. INST sub-index comprises the ratio of the market-based financing (i.e., debt securities, equity, and investment fund shares) to the bank-based financing (loans), distinctively with regards to the total economy and the cross-border share.[3] By including the cross-border component, we emphasize that the *type* of financial integration is an important feature of the development of financial systems. Series are calculated using EUROSTAT data.

We then consider the argument that equity and direct investment are more resilient sources of financing than debt and, in the case of debt, longer maturities provide a protection from short-run volatility. The EQUITY vs. DEBT sub-index measure is calculated as the ratio of equity to debt securities and loans for both the total economy and the cross-border components. The DEBT MATURITY index includes the ratio of long-term to total loans, and long-term to total debt securities,

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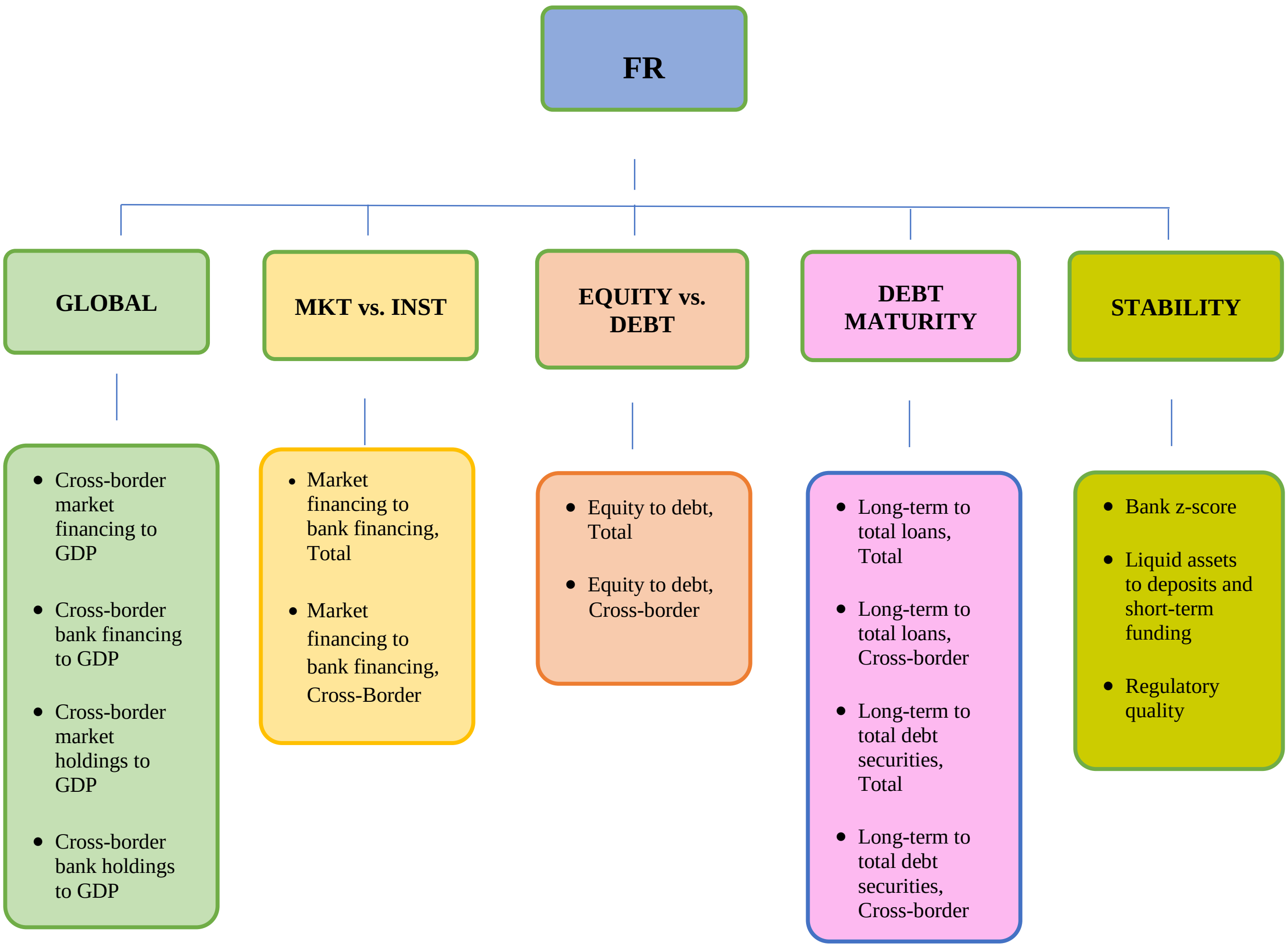
[2] The financial series are deflated by end of period inflation and their average is divided by GDP deflated by annual consumer price index (CPI), according to the formula:

$\{(0.5)*[F_t/P\_e_t + F_{t-1}/P\_e_{t-1}]\}/[GDP_t/P\_a_t]$ where F is financial stock, P_e is end-of period CPI, and P_a is average annual CPI.

[3] The MKT vs. INST cross-border share is the ratio between cross-border market-based finance as a share of total market-based finance and cross-border bank-based finance as a share of total bank-based finance.

similarly for both the total economy and the cross-border component. Series are calculated using EUROSTAT data.

Figure 1. The Financial Resilience Index

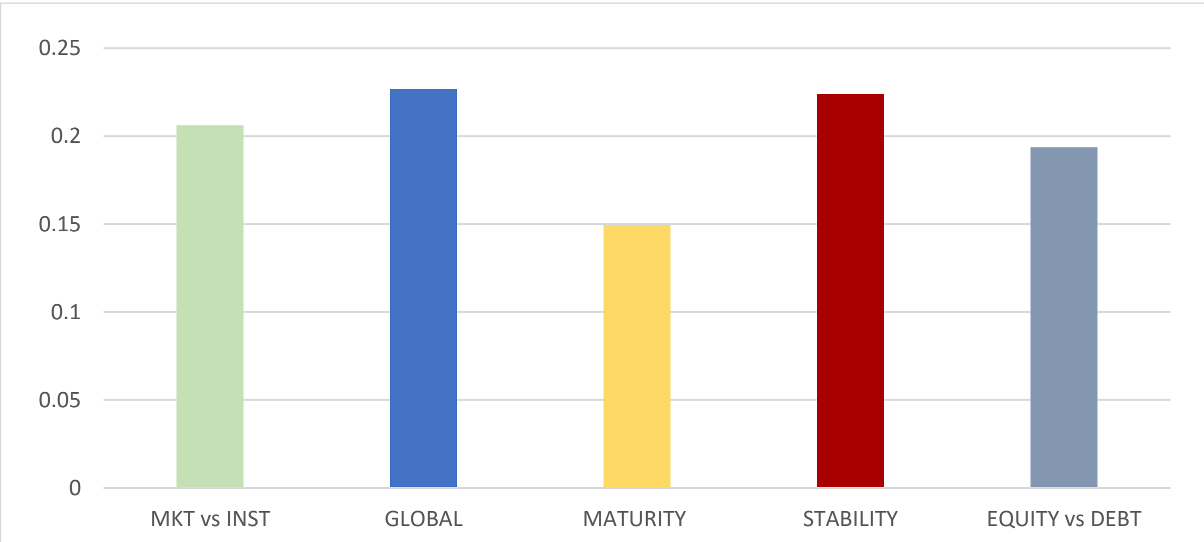


Notes: The Financial Resilience index (FR) is a broad-based measure of financial openness (GLOBAL), market-based vs. bank-based financing (MKT vs INST), equity to debt financing (EQUITY vs. DEBT), debt maturity structure (DEBT MATURITY), institutional soundness (STABILITY). Authors' calculations on EUROSTAT, Global Financial Development Database, GFDD, World Bank, Worldwide Governance Indicators, WGI, World Bank).

Finally, the stability dimension of financial environments is key in the case of large and sophisticated financial systems. With the STABILITY sub-index we consider two variables typically employed to capture the soundness of financial institutions, namely, bank z-score and liquid assets to deposits and short-term funding, as they have a clear link to the policy variables, *i.e.*, regulation and supervision (Čihák, *et al.* 2012). These indicators are sourced from the Global Financial Development Database (GFDD, World Bank). We then include regulatory quality from the World Development Indicators (WDI, World Bank), to capture the soundness of the institutional environment.

Figure 2 shows the weights of the five sub-indices, representing the amount of the variability in the panel which is explained by each component: GLOBAL, STABILITY, and MKT vs. INST have the largest weights, about 0.23, 0.22, and 0.21, respectively, followed by EQUITY vs. DEBT, around 0.19, and DEBT MATURITY, about 0.15.

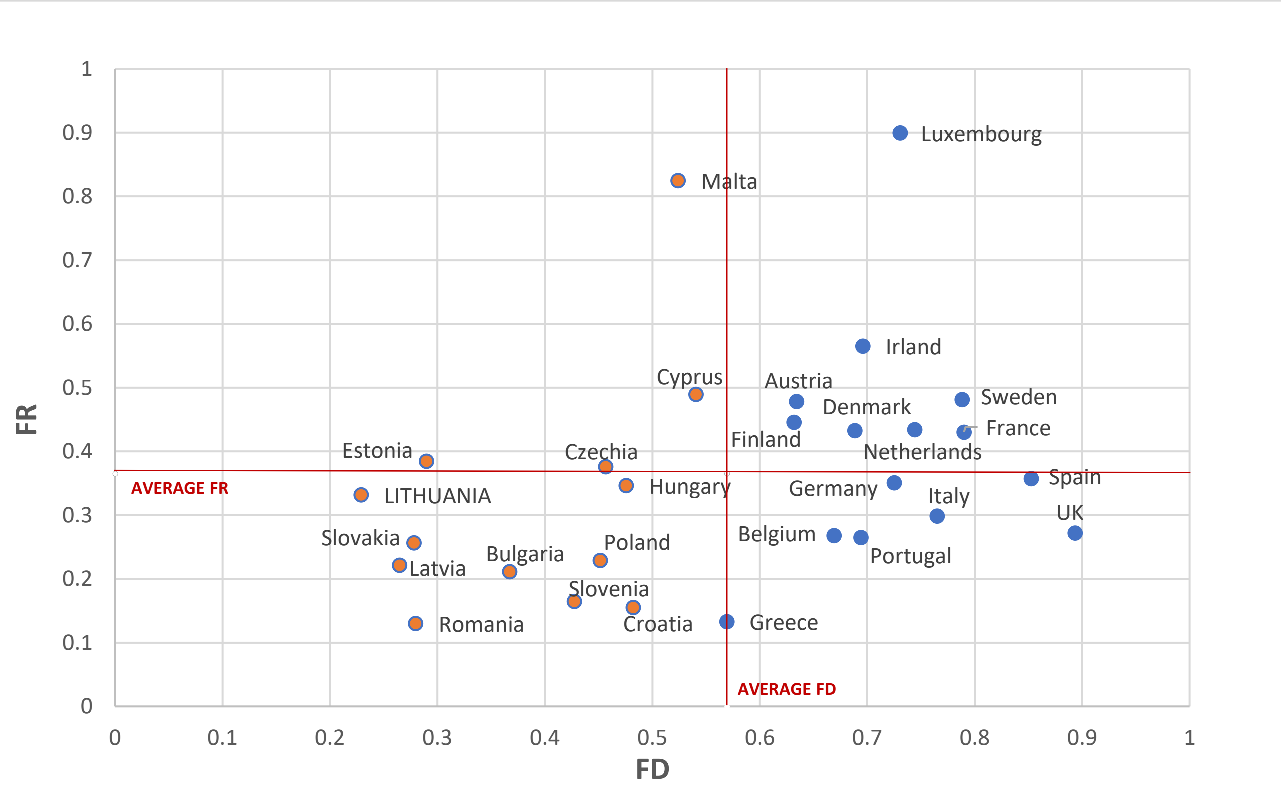
Figure 2. Principal component analysis, weights of the sub-indices



Notes: The graph plots the weights of the five sub-indices of the FR index, obtained from the PCA.

Based on the FR measure we can benchmark the European financial systems and contrast the results with those obtained employing the IMF FD index. A first glance of these differences can be picked up by considering the average FD and FR over the more recent subperiod, i.e., 2008-2019, as outlined in the graph of Figure 3. Economies which acceded to the European Union at an earlier stage are marked in blue, in orange the economies that joined after 2004, mostly the Central and Eastern European countries.

Figure 3. The FD index and the FR index, average values 2008-2019



Notes: Average values of the FD index and the FR index for the EU-28 economies, 2008-2019.

The graph highlights the clear separation between the two groups of economies in terms of FD: the old EU Member States in the right quadrants, corresponding to high FD, and the new EU Member States on the left, characterized by low FD, as highlighted in Cavallaro and Villani (2021). Geography shapes the asymmetries in financial resilience: amongst the older EU member states, Northern European economies share high levels of FR, except for Belgium, Germany, and UK, while the Southern European economies, namely, Spain, Italy, Portugal, and Greece feature below-average levels of FR, though to a different extent. FR is generally low for the Central and Eastern European economies, except for Estonia and Czechia that are quite at the panel average, while Malta and

Cyprus, two offshore centres, stand out for their very high records. Overall, the chart shows that only a subset of economies featuring high levels of FD over the period have similarly high levels of FR. In other words, fragmentation of EU financial systems worsens when we consider the structural and stability dimensions of financial development.

4. The patterns of financial convergence in the EU. Identifying convergence clubs

We are interested in analysing how EU financial systems have evolved over time in terms of the FR measure. Focusing on average levels over a 10-year period, as in Fig 3, says little about the dynamical transitions, i.e., whether differences between countries have tended to increase or decrease over time. This is a major aspect of the convergence of EU financial systems which we uncover employing the PS nonlinear factor model.

We first filter the data to remove the business cycle component with the Hodrick and Prescott (1997) smoothing filter.[4] We set the trimming parameter to 0.3, as suggested in the case of short panels (t < 50). Convergence attains if the cross-sectional variance approaches zero. Table 1 shows the results of the log-t test. The null hypothesis is rejected for the whole panel since the T-stat ($\boldsymbol{t_{\hat{b}}}$) is largely below the threshold value -1.65, as shown in the first row. We thus apply the log-t test recursively to test whether convergence attains for subgroup of economies. i.e., the relative transition curves h_{it} within each group get closer over time (see eq. 4). We employ the adjusted algorithm developed by Schnurbus, et al. (2017) and set the sieve criterion to zero to ensure that it is highly conservative. We find five convergence clubs according to descending levels of FR.[5]

[4] We run the log$t$ test employing the Stata routine developed by Du (2017).

[5] Several robustness checks were carried out because the choice of a specific data filtering procedure, clustering algorithm, trimming parameter and sieve criterion can all have an impact on the estimation results. In particular: (i) PS suggest employing the HP filter when the dataset is relatively small. As an alternative, we employed the high-pass Butterworth (1930) filter, and the estimation results were unaffected (ii) we set the trimming parameter to 0.25, which implies

Table 1. Results of log-*t* test for the Financial Resilience Index, 2000-2019

	No. of Countries	$\hat{b}$	$t_{\hat{b}}$	SE	FR index 2000 (Average)	FR index 2019 (Average)
WHOLE SAMPLE	28	-1.3824	-30.9158	0.0447	0.32	0.41
Club 1 Cyprus, Ireland, Luxembourg, Malta	4	0.0467	0.4439	0.1053	0.36	0.76
Club 2 Austria, Denmark, Estonia, Finland, France, Latvia, Netherlands, Sweden, United Kingdom	9	0.1112	1.7351	0.0641	0.36	0.44
Club 3 Belgium, Bulgaria, Czechia Germany, Hungary, Italy, Lithuania, Slovenia, Spain	9	0.0798	0.7582	0.1052	0.29	0.35
Club 4 Croatia, Poland, Portugal, Slovakia	4	0.1817	1.3677	0.1328	0.28	0.25
Club 5 Greece, Romania	2	0.5332	0.2760	1.9317	0.27	0.17

Notes: FR index is the Financial Resilience Index (authors' calculations on EUROSTAT and World Bank data). Truncation parameter: r = 0.3; critical value: c = 0.

discarding the first 5 periods instead of the first 6, and the results were only slightly affected, with Latvia belonging to club 3 instead of club 2, and Croatia diverging; (iv) we set the sieve criterion to 0.5, i.e., even further conservative, and the clustering was unaffected. All results are available upon request.

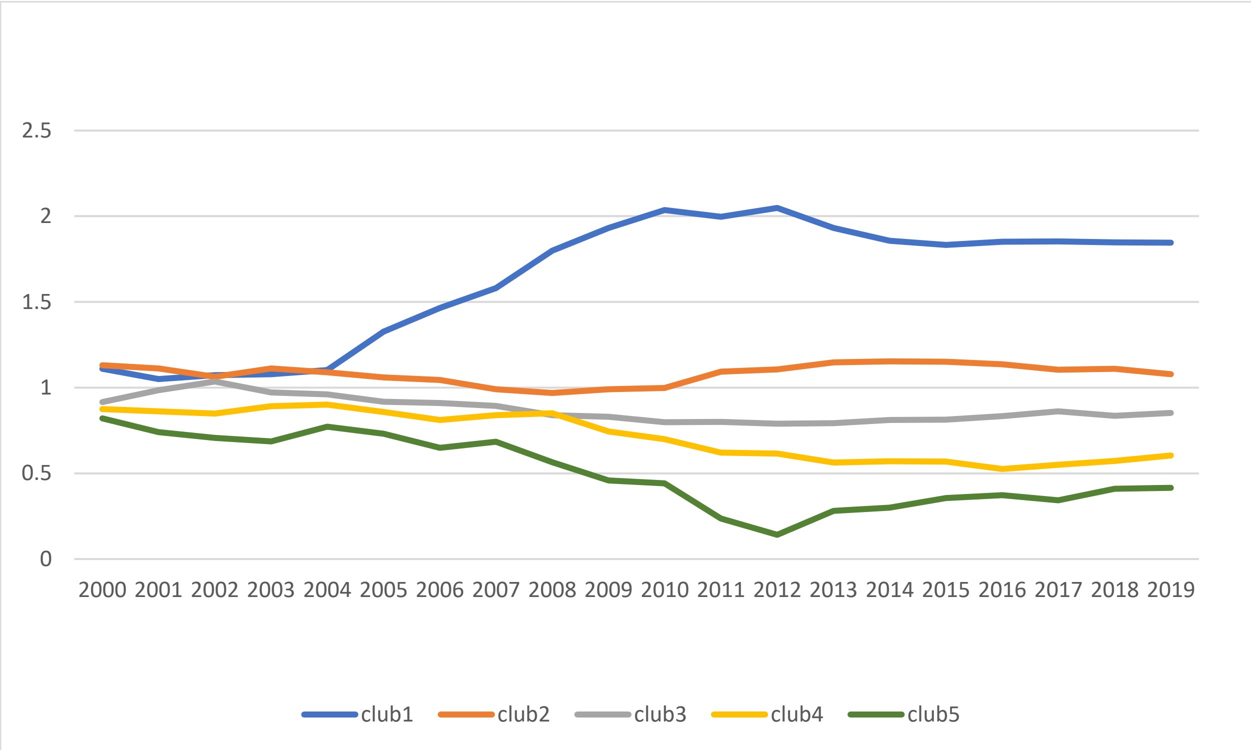
The estimated $\hat{b}$ coefficient is positive for all clubs, although close to zero for Club 1 and Club 3, indicating weak convergence. We see that the clustering is driven by geographical factors, with Northern European countries approaching the higher levels of the FR index - Club 1 and Club 2 - with a few exceptions, and the peripheral Southern and Eastern European economies converging towards the intermediate and low FR clusters. Noticeably, the countries in Club 1, i.e., Cyprus, Ireland, Malta, and Luxembourg, are offshore centres.

The time of accession to the EU is also a distinguishing feature of the identified groupings, as the economies approaching the high-resilience clusters are a sub-group of the old EU Member States, except for Estonia and Latvia. Among the remaining old EU members, Belgium and Germany gather in Club 3, together with Italy and Spain, while Portugal belongs to Club 4 and Greece to Club 5.

The evolution of financial asymmetries throughout the period can be grasped by the relative transition paths h_{it} derived from the log-t test (see equation 4). In Figure 4 we plot the $\overline{h}_{ct}$ curves tracing the (average) transition path of economies belonging to club c=1,…,5 with respect to the (average) transitions of economies in other clubs.

The graph shows that Club 1 transition curve is well above the others, though almost overlapping with Club 2 transition path, up to 2004. The transition paths of Club 3 and Club 4 remain below, but not too distant from Club 2 until 2007-08 and, since then, they depart. As for Club 5, the transition curve goes down from the start to its lowest level in 2012 and then slightly recovers. Overall, the graph in Figure 4 points to the widening of financial asymmetries across the EU in the aftermath of the global financial crisis.

Figure 4. FR index transition curves, club averages, 2000-2019



Note: The graph plots the relative transitions curves (club averages) over the period 2000-2019. Club 1: Cyprus, Ireland, Luxembourg, Malta. Club 2: Austria, Denmark, Estonia, Finland, France, Latvia, Netherlands, Sweden, United Kingdom. Club 3: Belgium, Bulgaria, Czechia, Germany, Hungary, Italy, Lithuania, Slovenia, Spain. Club 4: Croatia, Poland, Portugal, Slovakia. Club 5: Greece, Romania.

5. Reassessing the finance-growth puzzle

Recent finance-growth literature typically considers the development of a financial system in terms of size measures, namely, the ratio of bank credit or liquid liabilities to GDP for the bank sector, and the turnover ratio of market liquidity for the stock market (Beck and Levine, 2004; Rousseau and Watchel, 2011 Arcand *et al.* 2015). A common result of this literature is a bell-shape relationship between financial development and growth, highlighting the side effects from larger financial sectors. These results suggest the need to rethink the development of financial systems along dimensions that have not been considered so far in the literature. Beck *et al.* (2014) show that the threshold beyond which the impact of finance on growth is negative is pushed further out in regressions where financial controls are added to conventional size measure; Cavallaro and Villani (2022) point to the importance of controlling for the financial environments' stability features in regressions that include the post-global financial crisis period.

On these grounds, we re-examine the finance-growth relationship employing the FR index to measure the development of financial systems for our panel of 28 countries, over 2000-2019. Table 2a and Table 2b show the two-step System GMM estimation results of variants of the typical growth models employed in the empirical literature. The dependent variable is real income per capita growth, regressed on the lagged value of real income per capita, to capture persistence, and a set of controls: CPI-based inflation rate; trade openness; government final consumption expenditure; education (all variables are in logs, except for inflation, transformed in log(1+*variable*). In column 1, we measure financial development with the IMF FD index;[6] in column 2 we employ the FR Index, in column 3 we include both FD and FR, and in the last two columns we add two controls, the share of gross-capital formation over GDP and labour force. Table 2b replicates the models of Table 2a, but with the financial variables in levels, rather than in logs. We consider non-overlapping 4-year spells between 2000 and 2019 and data for all variables are cross-sectionally demeaned to account for unobserved dependence across state output which is correlated with the common shock. All available lags are used as instruments and all instruments are collapsed to avoid proliferation (Roodman, 2009). Regressions are implemented with the Windmeijer (2005) correction for robust standard errors.[7] Consistency and efficiency of the GMM estimator are tested employing the AR(2) test (Arellano-Bond for second-order autocorrelation) and the Hansen test. In the AR(2) test the null hypothesis is that the differenced error term is not second-order serially correlated. In the Hansen test the null

[6] The importance of looking at financial development as a multidimensional concept is first addressed in the preliminary work of Cihak *et al.* (2012), which provides the conceptual framework of the IMF FD index (Svirydzenka, 2016). The FD index - and its components - is employed by Sahay *et al.* (2015) in growth regressions for 128 countries throughout 1980-2010, confirming the nonlinear finance-growth relationship.

[7] The SYS-GMM estimations in Table 2a, Table 2b, and Table 3 are performed with the Stata command xtabond2.

hypothesis is the overall validity of the instruments used, in other words, the endogeneity issue is properly addressed. Our analysis also meets the general requirements for GMM estimations that the number of groups, *e.g.* countries, be greater than the number of time periods and that the number of instruments be lower than the number of groups.

Table 2a. The finance-growth relationship. System GMM regression results, 2000-2019

Variable	(1)	(2)	(3)	(4)	(5)
GDP0	-0.219*** (0.053)	-0.176*** (0.023)	-0.186** (0.084)	-0.107*** (0.033)	-0.169*** (0.026)
Inflation	0.153 (0.214)	0.207 (0.24)	0.064 (0.376)	0.066 (0.233)	0.22 (0.233)
Trade	0.083 (0.051)	0.035 (0.021)	0.023 (0.041)	0.050** (0.023)	0.041** (0.016)
GovExp	0.042 (0.095)	0.085 (0.122)	-0.001 (0.105)	-0.108 (0.064)	0.070 (0.103)
Education	0.071* (0.039)	0.109*** (0.034)	0.113** (0.050)	0.102*** (0.031)	0.062 (0.055)
FD	0.064 (0.076)		0.009 (0.108)		
FR		0.108*** (0.031)	0.124*** (0.043)	0.101*** (0.031)	0.080** (0.031)
GrossCapital				-0.29*** (0.100)	
LabourForce					0.140 (0.235)
Constant	0.000 (0.008)	-0.002 (0.006)	-0.005 (0.010)	0.001 (0.009)	-0.001 (0.006)
Obs.	140	140	140	140	140
Countries	28	28	28	28	28
Instr.	26	17	22	27	22
AR (2) test[a]	0.014	0.099	0.088	0.179	0.083
Hansen *J* test[b]	0.254	0.275	0.144	0.545	0.470

Note: The table reports the outcome values of panel regressions consisting of 4-year non-overlapping period averages, spanning from 2000 to 2019, estimated using Dynamic System GMM. All variables (see Appendix, Table A.1 for a detailed description) are cross-sectionally demeaned and all available lags are used as instruments; all sets of instruments are collapsed. The dependent variable is real per capita GDP growth regressed on the following variables in logs: initial per capita GDP (GDP0); Inflation, transformed in log(1+variable); Trade; Government Expenditure (GovExp); Education; FD; FR; Share of gross capital formation at current PPPs (GrossCapital); Labour Force Participation Rate (LabourForce). The table reports the coefficient values and, in parenthesis, the standard errors; significance at the different levels is indicated with * (p<0.10), ** (p<0.05), *** (p<0.01). [a] P-value. The null hypothesis is that there is no second-order serial correlation of errors in the first-difference regression. [b] P-value. The null hypothesis is that the employed instruments are not correlated with the residuals.

Our results show that the estimated coefficient of the FD index is positive, but not significant, in line with the vanishing effect result of the literature. FR has the expected positive sign and is statistically significant in all regressions of Table 2a and Table 2b, also when FD is included. As to the other coefficients, the results are in line with those of the literature: initial GDP has the expected negative sign and is always significant, confirming the presence of persistence; education has the expected positive coefficient and is significant, except for the models of column 6 (Table 2a) and column 1 (Table 2b), and trade has a positive coefficient, though not always significant.

Inflation, government expenditure, and labour force are not significant, while the share of gross capital formation to GDP is significant in the estimation in logs (column 4, Table 2a). The estimations with FR are robust to serial correlation and heteroschedasticity issues.

Overall, we find clear evidence that the evolution of financial systems along the dimensions captured by the FR index are key to explaining long-run growth for European economies, over the twenty years considered. We also run the SYS-GMM estimations adding a nonlinear moment restriction to obtain an estimator that is robust to deviations from “mean stationarity” (Ahn and Schmidt,1995).[8]

[8] The “mean stationarity condition” required for the validity of the SYS-GMM estimations (Blundell and Bond, 1998; Roodman, 2009) excludes correlation between deviations of y_{it} and X_{it}, respectively, from their long-run mean and the individual effect v_i.

The results, reported in Table A1 of the Appendix,[9] are qualitatively like the ones obtained from the conventional SYS-GMM, namely FR has a positive and significant impact on growth, while FD does not.

Table 2b. The finance-growth relationship (continued). System GMM regression results, 2000-2019

Variable	(1)	(2)	(3)	(4)	(5)
GDP0	-0.377***	-0.187***	-0.221**	-0.20***	-0.211***
	(0.131)	(0.052)	(0.105)	(0.051)	(0.058)
Inflation	-0.719	-0.100	-0.383	-0.181	-0.513
	(1.431)	(0.245)	(0.535)	(0.211)	(0.885)
Trade	0.156**	0.019	0.0186	0.033	0.027
	(0.072)	(0.023)	(0.049)	(0.024)	(0.026)
GovExp	0.157	0.056	-0.074	0.067	0.027
	(0.144)	(0.171)	(0.065)	(0.173)	(0.139)
Education	0.083	0.121***	0.135***	0.112**	0.093*
	(0.062)	(0.062)	(0.041)	(0.040)	(0.049)
Level_FD	0.307		0.034		
	(0.242)		(0.244)		
Level_FR		0.322***	0.310***	0.341***	0.275**
		(0.105)	(0.133)	(0.108)	(0.111)
GrossCapital				-0.070	
				(0.094)	
LabourForce					0.139
					(0.420)
Constant	-0.004	-0.001	-0.003	0.000	0.000
	(0.019)	(0.007)	(0.009)	(0.007)	(0.008)
Obs.	140	140	140	140	140
Countries	28	28	28	28	28

[9] The SYS-GMM estimations that include the Ahn and Schmidt (1995) nonlinear moment condition are implemented with the Stata command xtdpdgmm (Kripfganz, 2019).

Instr.	24	24	25	27	27
AR (2) test[a]	0.030	0.091	0.060	0.147	0.071
Hansen *J* test[b]	0.135	0.212	0.145	0.199	0.187

Note: The table reports the outcome values of panel regressions consisting of of 4-year non-overlapping growth spells (the last is a 3-year spell) spanning from 2000 to 2019, estimated using Dynamic System GMM. All variables (see Appendix, Table A.1 for a detailed description) are cross-sectionally demeaned and all available lags are used as instruments; all sets of instruments are collapsed. The dependent variable is real per capita GDP growth regressed on the following variables in logs: initial per capita GDP (GDP0); Inflation, transformed in log(1+variable); Trade; Government Expenditure (GovExp); Education; Share of gross capital formation at current PPPs (GrossCapital); Labour Force Participation Rate (LabourForce). FD and FR are in levels. The table reports the estimated coefficients and, in parenthesis, the robust (Windmeijer) standard errors; significance at the different levels is indicated with * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$). [a] P-value. The null hypothesis is that there is no second-order serial correlation of errors in the first-difference regression. [b] P-value. The null hypothesis is that the employed instruments are not correlated with the residuals.

We now turn to the effect of the development of financial systems on the volatility of output growth. According to the literature (Easterly *et al*., 2001; Silva *et al*. 2017), the expansion of the financial sector reduces the volatility of output growth but only up to a level; beyond that level, output volatility increases. This empirical evidence mirrors the nonlinearity result of the finance-growth literature. One reason for this result could be that large financial sectors determine the buildup of excessive leverage, making the economies vulnerable to balance-sheet effects after a shock; frictions in credit markets may amplify disturbances stemming from the real or the financial sector of the economy and the more firms are bank dependent, the larger the propagation of the shock through the credit channel, and the larger the swing in economic growth. Consequently, economies with well-developed capital markets are less exposed to the amplifying effect arising from agency costs (Beck *et al*, 2006).

The literature focuses on the size dimension of financial systems, i.e., the development of financial systems is captured by credit markets depth. In line with the aforesaid reasonings that explain the nonlinearities in the finance-growth volatility nexus, we expect the dimensions captured by the FR index to be key to reducing the swings in economic growth. To test this, we run SYS-GMM estimations for different specifications of the finance-volatility relationships. Table 3 shows the results. We measure growth volatility with the (spell) standard deviation of real per capita output growth; in all regressions we include the lagged dependent variable, real output growth, trade, and government expenditure, which are the controls typically considered in the literature. We first employ the IMF FD index to measure the development of financial systems, alternatively with inflation, in column 1, and with the volatility of annual inflation rates and volatility of annual terms of trade changes, in column 2, to proxy for instability arising from the monetary and real sectors, respectively, as suggested in Beck *et al*. (2006). We then replicate in columns 3 to 5 the models of columns 1 and 2, employing FR instead of FD and, finally, in the last two columns including both FD and FR.

Our estimations show that financial development measured with the FD index has the expected negative sign on the volatility of economic growth, but the estimated coefficient is not significant (column 1) unless we control for the instability from the real sector (SD_TOT) and the financial sector (SD_INFL) (column 2). In the regressions where we employ the FR index to measure the development of financial systems, raising FR reduces volatility and the effect is significant throughout all models, i.e., when FR is with inflation (column 3), real-sector volatility (column 4), both real and financial sectors volatility (column 5), and when FD is included (column 6 and column 7). We find that instability from the real side of the economy is always a significant driver of economic growth volatility, while instability from the financial sector of the economy is significant when we employ FD (column 2) but not in the regressions with FR (column 5 and column 7).

The results are robust to serial correlation and heteroskedasticity issues, as indicated by the AR(2) test and the Hansen test; we obtain qualitatively similar findings running regressions with the additional Ahn-Schmidt (1995) nonlinear moment conditions, reported in Table A3 of the Appendix.

Table 3. Finance and growth volatility. System GMM regression results, 2000-2019

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SD(t-1)	0.051	-0.06	0.195**	0.039	0.037	-0.032	-0.006
	(0.128)	(0.053)	(0.084)	(0.105)	(0.081)	(0.126)	(0.067)
GDP0	0.02	0.034**	0.024**	0.008	0.025*	0.024	0.052***
	(0.026)	(0.016)	(0.0116)	(0.012)	(0.013)	(0.019)	(0.015)
Inflation	0.288		0.395				
	(0.273)		(0.308)				
Trade	0.011	- 0.03	0.015***	0.021	0.016***	-0.03	0.0063
	(0.012)	(0.001)	(0.005)	(0.005)	(0.005)	(0.016)	(0.007)
FD	-0.026	-0.052*				-0.047	-0.049*
	(0.043)	(0.029)				(0.042)	(0.023)
FR			-0.06**	-0.054***	-0.057***	-0.054***	-0.058***
			(0.023)	(0.013)	(0.018)	(0.014)	(0.007)
SD_TOT		0.063*		0.028**	0.079**	0.321***	0.074**
		(0.036)		(0.123)	(0.035)	(0.091)	(0.029)
SD_INFL		0.013**			0.011		0.012
		(0.001)			(0.008)		(0.007)
Constant	0.001	0.001	0.001	0.001	0.001	0	0
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
Obs.	112	112	112	112	112	112	112
Countries	28	28	28	28	28	28	28
Instr.	15	25	19	19	24	24	26
AR (2) test[a]	0.185	0.472	0.133	0.628	0.460	0.816	0.482
Hansen *J* test[b]	0.720	0.778	0.803	0.714	0.553	0.673	0.783

Note: The table reports the outcome values of panel regressions consisting of 4-year non-overlapping growth volatility spells, spanning from 2000 to 2019, estimated using Dynamic System GMM. All variables (see Appendix, Table A.1 for a detailed description) are cross-sectionally demeaned and all available lags are used as instruments; all sets of instruments are collapsed. The dependent variable is per capita GDP growth volatility (SD) regressed on the following variables: lagged SD; Inflation (log(1+Inflation); Trade (logs); Government Expenditure (GovExp, logs); FD; FR, Standard Deviation of annual Terms-of-Trade changes (SD_TOT); Standard Deviation of annual Inflation rates (SD_INFL). The table reports the coefficient values and, in parenthesis, the robust (Windmeijer) standard errors; significance levels are indicated with * (p<0.10), ** (p<0.05), *** (p<0.01). [a] P-value. The null hypothesis is that there is no second-order serial correlation of errors in the first-difference regression. [b] P-value. The null hypothesis is that the employed instruments are not correlated with the residuals.

Overall, our results suggest that the development of financial system in terms of the FD measure can have a beneficial impact on the volatility of growth but only after controlling for the instability arising from the real and financial sectors, whereas the development of financial systems in terms of FR is always highly significant in reducing the volatility of growth.

6. Financial asymmetries across the EU: The effectiveness of the risk sharing mechanisms

We examine the implication of the heterogeneities across European financial systems in terms of the FR index. We expect economies approaching higher levels of the index to be more insulated from shocks to output with respect to economies converging to lower levels and to feature a relatively larger contribution of capital markets to risk diversification.

To show this, we calculate the amount of risk that is smoothed out and the contribution of the different channels, in the first place for our panel of countries, and then for three distinct groups of economies obtained from the FR index clustering: HIGH FR, pooling the very-high and high FR economies of Club 1 and Club 2, with average transition paths above the unit limit (see Figure 4); MIDDLE FR, corresponding to the intermediate FR economies of Club 3; LOW FR gathering the low and very-low FR economies in Club 4 and Club 5.[10]

We use equations (6-10) to estimate the percentage of shocks to GDP that remains unsmoothed, and the percentage absorbed through each channel in the GDP chain decomposition. We run Prais-Winsten regressions with panels corrected standard errors, heteroskedasticity and serial correlation (PCSE). As a robustness check, we run regressions with alternative estimators, namely the within estimator with country and time fixed effects (FE), the feasible generalised least square estimator

[10] We do not include Romania, due to lack of data for net disposable income.

(FGLS),[11] and the system generalized methods of moments (SYS-GMM). Following Furceri and Zdzienicka (2013), in each equation we include a dummy variable for the financial crisis periods[12] and the interacted term between the dummy and (the log of) income growth to measure the change in the slope. Data are drawn from EUROSTAT for the period 1995-2019, deflated and in per-capita terms.

The results for the whole panel of countries are in Table 4. For each regression we report the estimated percentage of unsmoothed shock to GDP (β^u) and the percentage of the shock which is absorbed through the three distinct channels, namely, capital markets (β^m), depreciation **(**β^d), international government transfers (β^g), and credit markets (β^s), along with the estimated change occurred in the financial crisis period (δ^j, $j = u, m, d, g$, and s).[13]

Overall, the different estimation methods provide qualitatively similar results. We find that more than 80% of the shocks to domestic output remains unsmoothed and that the credit market contribution to consumption smoothing (β^s) is about 20%, while there is dis-smoothing through the capital market channel ($\beta^m < 0$) and the depreciation channel **(**$\beta^d < 0$**),** and a non-significant contribution through the international transfers channel (β^g), except for the SYS-GMM regression. The unsmoothed shock increases remarkably during periods of financial crisis, with $\beta^u + \delta^u > 1$. In other words, faced with a negative shock to domestic output, the drop in saving ($\delta^s < 0$) is not offset by the increased

[11] PCSE is as an alternative to FGLS for fitting linear cross-sectional time series when disturbances are heterosckedastic across panels. Though FGLS estimates are more efficient, Beck and Katz (1995) have shown that they are typically unacceptably optimistic (anticonservative) when used with the type of data commonly analysed, i.e., 10–20 panels with 10–40 periods per panel. In this case, they suggest using PCSE that have coverage probabilities that are closer to nominal.

[12] Data on financial crises (banking, currency, and debt) are from Laeven and Valencia (2018).

[13] The focus of our analysis is on financial asymmetries, so we restrict our discussion to the capital market and credit market channels. As to depreciation, it is generally calculated as a fixed proportion of the stock of capital, and thus its contribution to risk diversification is not very informative; as to the international fiscal transfer channel, it is key for addressing fiscal policy issues at the EU level (Furceri and Zdzniecka, 2013), which is out of the scope of our analysis.

contribution of capital markets ($\delta^m > 0$) and depreciation ($\delta^d > 0$), and overall the fall in consumption is more than proportional with respect to the fall in domestic output.

Table 4. Channels of risk sharing. All countries, 1995-2019

	PCSE[(a)]	Country and Time FE[(b)]	FGLS[(c)]	GMM[(d)]
Unsmoothed (β^u)	0.821*** (0.022)	0.825*** (0.016)	0.878*** (0.017)	0.862*** (0.077)
ΔFinancial Crisis (δ^u)	0.219*** (0.025)	0.217*** (0.018)	0.148*** (0.020)	0.034 (0.070)
Capital markets (β^m)	-0.029** (0.014)	-0.040** (0.017)	-0.012 (0.009)	0.021 (0.040)
ΔFinancial Crisis (δ^m)	0.060*** (0.018)	0.075*** (0.020)	0.042*** (0.013)	-0.049 (0.126)
Depreciation (β^d)	-0.022** (0.010)	-0.019** (0.007)	-0.036*** (0.005)	-0.063* (0.032)
ΔFinancial Crisis (δ^d)	0.024** (0.010)	0.019** (0.008)	0.031*** (0.007)	0.075 (0.117)
Intern. transfers (β^g)	0.01 (0.006)	0.005 (0.005)	0.004 (0.003)	0.020* (0.011)
ΔFinancial Crisis (δ^g)	-0.00 (0.001)	-0.002 (0.005)	-0.001 (0.004)	-0.051 (0.051
Saving (β^s)	0.230*** (0.025)	0.229*** (0.023)	0.167*** (0.019)	0.148* (0.079)
ΔFinancial Crisis (δ^s)	-0.301*** (0.031)	-0.310*** (0.027)	-0.226*** (0.026)	-0.206** (0.077)

Notes: The Table reports the estimated percentage of the shock to GDP which is unsmoothed β^u and the estimated percentage which is smoothed by the different channels: capital markets β^m, depreciation β^d, international transfers β^g, and credit market β^s, along with the estimated change in the slope during periods of financial crises, δ^j, with $j = u, m, g, s$. Standard errors in parenthesis. Data for GDP and its components are from EUROSTAT, deflated and in per-capita terms; data for financial crises (banking, currency, and debt) are from Laeven and Valencia (2018). [(a)] Prais-Winsten regressions with PCSE: AR1 autocorrelation structure and panel-level heteroskedastic errors. [(b)] Fixed-effects within regression. [(c)] FGLS regressions with panels heteroskedasticity and AR1 autocorrelation structure. [(d)] SYS-GMM regressions consisting of 5-year non-overlapping spells (the last is a 4-year spell), with all available lags of income growth as instruments, collapsed instruments, and robust (Windmeijer) standard errors.

Our findings are in line with previous results of the literature, although they are not immediately comparable due to differences in the set of countries and the time-period considered: Furceri and

Zdzienicka (2013) consider a panel of 15 Euro area countries over 1979-2010, while Alcidi *et al.* (2023) a panel of 11 old EU member states, throughout 1998-2016.

Our focus is on the heterogeneity stemming from differences in the evolution of financial systems, i.e., in the type of financial integration, as suggested by Sørensen *et al.*, 2007. In Table 5 we show the PCSE estimations results for the three different groups of economies based on the FR index clustering.[14]

Table 5. Financial resilience and risk sharing. 1995-2019

	HIGH FR	**MIDDLE FR**	**LOW FR**
Unsmoothed (β^u)	0.736*** (0.044)	0.815*** (0.026)	0.921*** (0.035)
ΔFinancial Crisis (δ^u)	0.127** (0.059)	0.230*** (0.028)	0.006 (0.083)
Capital_markets (β^m)	0.078** (0.034)	-0.080*** (0.014)	-0.036** (0.017)
ΔFinancial Crisis (δ^m)	-0.084 (0.068)	0.115*** (0.016)	0.133*** (0.038)
Depreciation (β^d)	0.016 (0.024)	-0.028*** (0.010)	-0.050*** (0.018)
ΔFinancial Crisis (δ^d)	-0.059* (0.034)	0.032*** (0.011)	-0.014 (0.049)
Intern_transfers (β^g)	0.004 (0.008)	0.009 (0.007)	0.002 (0.012
ΔFinancial Crisis (δ^g)	0.006 (0.016)	-0.006 (0.009)	-0.014 (0.029)
Saving (β^s)	0.169*** (0.049)	0.288*** (0.032)	0.185*** (0.042)
ΔFinancial Crisis (δ^s)	-0.00 (0.097)	-0.373*** (0.035)	-0.073 (0.099)

Notes: The Table reports the estimated percentage of the shock to GDP which is unsmoothed β^u and the estimated percentage which is smoothed by the different channels: capital markets β^m, depreciation β^d, international transfers β^g, and credit market β^s, along with the estimated change in the slope during financial crises periods, δ^j, with $j = u, m, g, s$. Standard errors in parenthesis. Data for GDP and its components are from EUROSTAT, deflated and

[14] Results are qualitatively similar employing the fixed effect regressor. See the Appendix, Table A.4. We do not run the FGLS and the SYS GMM regressions due to the limited data sample.

in per-capita terms. Prais-Winsten regressions with PCSE: AR1 autocorrelation structure and panel-level heteroskedastic errors. HIGH FR is the group of economies in clubs 1 and 2; MIDDLE FR consists of economies belonging to club 3; LOW FR is formed by pooling economies belonging to club 4 and club 5.

We find notable differences among the three groups both in the magnitude of shock absorption and contribution of the distinct channels to risk diversification, especially during the periods of financial crisis. The coefficient β^u ranges from about 0.70 for the HIGH FR group, to approximately 0.80 for the MIDDLE FR and 0.90 for the LOW FR group; during financial crises, the increase in unsmoothed shock, captured by δ^u, is particularly large for the MIDDLE FR group.

As to the different channels of risk sharing, capital markets contribute by about 8% in the high-resilient group, whereas there is dis-smoothing in the MIDDLE FR and LOW FR groups, except during financial crises when the estimated change in the slope is significant, with δ^m approximately 12% and 13%, respectively. On the other side, the percentage of shock to domestic output absorbed through the saving channel is less than 20% for the HIGH FR and LOW FR groups, while almost 30% for the MIDDLE FR group, where the change in the slope during financial crises is strikingly large (-37%).

The relative transition paths estimated with the log*t* test (see Fig. 4) remarked increasing fragmentation in the aftermath of the global financial crisis. To gauge more insights on the implications for risk-sharing, we consider the before-crisis and after-crisis subperiods, namely 1995-2007 and 2008-2017. We run the PCSE regressions for two distinct groups, the HIGH FR and the (MID + LOW) FR, respectively, as the number of observations is reduced after splitting the period. The results are in Table 6.[15]

[15] Results are qualitatively similar employing the fixed effect regression model. See Table A.5 in the Appendix.

Table 6. Financial resilience and risk sharing. 1995-2007 and 2008-2019

	HIGH FR		**(MID + LOW) FR**	
	1995-2007	**2008-2019**	**1995-2007**	**2008-2019**
Unsmoothed (β^u)	0.906***	0.515***	0.825***	0.914***
	(0.041)	(0.087)	(0.027)	(0.048)
ΔFinancial Crisis (δ^u)	0.072	0.261***	0.218***	0.033
	(0.075)	(0.094)	(0.030)	(0.074)
Capital_markets (β^m)	0.016	0.156***	-0.088***	0.037
	(0.026)	(0.055)	(0.016)	(0.032)
ΔFinancial Crisis (δ^m)	-0.108**	-0.078	0.124***	0.021
	(0.048)	(0.074)	(0.018)	(0.047)
Depreciation (β^d)	-0.067***	0.118**	-0.031**	-0.044***
	(0.020)	(0.049)	(0.013)	(0.013)
ΔFinancial Crisis (δ^d)	-0.005	-0.13**	0.036***	-0.026
	(0.048)	(0.051)	(0.013)	(0.013)
Intern_transfers (β^g)	0.007	0.001	0.007	0.005
	(0.013)	(0.011)	(0.005)	(0.015)
ΔFinancial Crisis(δ^g)	0.00	0.010	-0.005	0.025
	(0.030)	(0.016)	(0.006)	(0.023)
Saving (β^s)	0.163**	0.183***	0.294***	0.095*
	(0.065)	(0.067)	(0.034)	(0.056)
ΔFinancial Crisis (δ^s)	0.043	-0.045	-0.377***	-0.058
	(0.117)	(0.110)	(0.038)	(0.096)

Notes: The Table reports the estimated percentage of the shock to GDP which is unsmoothed β^u and the estimated percentage which is smoothed by the different channels: capital markets β^m, depreciation β^d, international transfers β^g, and credit market β^s, along with the estimated change in the slope during financial crises periods, δ^j, with $j = u, m, g, s$. Standard errors in parenthesis. Data for GDP and its components are from EUROSTAT, deflated and in per-capita terms. Prais-Winsten regressions with PCSE: AR1 autocorrelation structure and panel-level heteroskedastic errors. HIGH FR is the group of economies in clubs 1 and club 2; (MID + LOW) FR consists of economies belonging to club 3, club 4, and club 5.

Significant differences between the two groups emerge when comparing the two sub-periods. Following the global financial crisis, unsmoothed consumption is almost halved in the HIGH FR group, going from 0.92 to 0.50, with the increased ability to absorb shocks to domestic output being achieved through a larger contribution of capital markets and credit markets, that stand at approximately 16% and 18%, respectively. In the (MID + LOW) FR group, after 2008 unsmoothed consumption increased from 0.82 to 0.91, with the contribution of capital markets becoming positive, though the estimated coefficient is not significant, and the contribution of credit markets collapsing from 29% to 9.5%. The down-seizing of the credit market channel is clear evidence of the fragility of credit markets in the less-resilient economies.

Overall, our results confirm that the features captured by the FR index are key to explaining the asymmetric vulnerability to idiosyncratic shocks in the EU: economies benchmarked as highly resilient, according to the FR index, are those featuring greater financial openness, deeper capital markets and more stable financial institutions; these economies benefit to a larger extent by the income insurance provided by holding an internationally diversified portfolio, as well as the stability of credit provision.

Concluding remarks

How should financial systems evolve to foster economic growth and enable economies to reap the benefits of financial integration? We focus on the structural and stability dimensions of financial development and build an index (FR index) to benchmark EU financial systems against their potential to enhance endurable growth and international risk diversification. The index is a composite measure of financial openness, market orientation, equity position vis-à-vis debt, maturity structure, and stability, as it is recognized that these dimensions are key to endurable growth and resiliency of financial systems. Based on our index we assess EU-wide financial asymmetries and analyse the implications for long-run growth and risk diversification. We have the following results. First, our measure of financial development is highly significant in growth regressions, highlighting that the threshold effects of finance on growth detected in the literature stem from not considering important dimensions of the development of financial systems that attain to structure and stability. Second, raising the FR index has a significant effect in reducing the volatility of economic growth in the EU. Third, the estimated transitional dynamic paths of the index over 2000-2019 indicate that EU financial systems are converging towards a clustered pattern, remarking ongoing financial fragmentation. Finally, risk diversification varies across the different financial clusters and heterogeneities become more pronounced in the aftermath of the global financial crisis: more resilient economies, in terms of the FR index, smooth out a larger fraction of the shocks to domestic output and benefit to a larger extent of the contribution of the capital market channel to risk diversification; less resilient economies experience an increase in the fraction of unsmoothed consumption due to the sharp fall in the contribution of credit markets.

Our results point to the need for further actions at national and pan European level to build resilience in the EU's financial environments. To achieve this goal, the range of financial instruments need to be increased to facilitate firms' capital raising and enhance households' opportunities of risk diversification, at the same time, regulatory and fiscal frameworks need to be shaped to limit undue risk taking by financial institutions.

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APPENDIX

Table A.1 Variables, description, and source

Variables	Description	Source
Bank Z-Score (ln)	Measure capturing the probability of default of a country's banking system. Z-score compares the buffer of a country's banking system (capitalization and returns) with the volatility of those returns. It is estimated as (ROA+(Equity/Assets))/SD(ROA); SD(ROA) is the standard deviation of ROA. ROA, equity, and assets are country-level aggregate figures Calculated from underlying bank-by-bank unconsolidated data from Bankscope.	Global Financial Development Database (GFDD), World Bank
Education	Indicator defined as the percentage of people aged 25-64 who have successfully completed at least upper secondary education. This educational attainment refers to ISCED (International Standard Classification of Education) 2011 level 3-8 for data from 2014 onwards and to ISCED 1997 level 3-6 for data up to 2013. The indicator is based on the EU Labour Force Survey. This indicator aims at measuring the share of the population that is likely to have the minimum necessary qualifications to actively participate in social and economic life. It should be noted that completion of upper secondary education can be achieved in European countries after varying lengths of study, according to different national educational systems.	Authors' calculations on Educational Attainment Level (EUROSTAT)
FD index (Financial Development Index)	Broad-based index elaborated by the IMF which measures access, depth and efficiency in financial markets and financial institutions. Built with standard practice (winsorized and normalized series), weights from PCA.	Financial Development Index Database (FDID), IMF
Gov Exp (Government Expenditure)	General government final consumption expenditure (% of GDP). General government final consumption expenditure (formerly general government consumption) includes all government current expenditures for purchases of goods and services (including compensation of employees). It also includes most expenditures on national defense and security but excludes government military expenditures that are part of government capital formation.	World Development Indicators (WDI), World Bank
Inflation	Inflation, consumer prices (annual %). Variable measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly.	World Development Indicators (WDI), World Bank
Liquid Assets to Deposits and Short-Term Funding	Ratio of the value of liquid assets (easily converted to cash) to short-term funding plus total deposits. Liquid assets include cash and due from banks, trading securities and at fair value through income, loans	Global Financial Development Database (GFDD),

	and advances to banks, reverse repos and cash collaterals. Deposits and short-term funding include total customer deposits (current, savings and term) and short-term borrowing (money market instruments, CDs and other deposits).	World Bank
Real output per capita	GDP per capita, PPP (constant 2011 international $). GDP per capita based on purchasing power parity (PPP). PPP-adjusted GDP is gross domestic product converted to international dollars using purchasing power parity rates.	World Development Indicators (WDI), World Bank
Regulatory Quality	Measure capturing perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. It gives the country's rank among all countries covered by the aggregate indicator. The percentile rank indicator assigns 0 to the lowest position and 100 to highest.	Worldwide Governance Indicators (WGI), World Bank
Trade	Trade (% of GDP). Variable obtained as the sum of exports and imports of goods and services measured as a share of gross domestic product.	World Development Indicators (WDI), World Bank
TOT	Terms of Trade. It is obtained as the ratio of the Export value index to the Import value index, multiplied by 100.	World Development Indicators (WDI),

Table A.2

Finance and growth. System GMM regression results, nonlinear estimator. 2000-2019

Variable	(1)	(2)	(3)	(4)	(5)	(6)
GDP0	-0.247***	-0.208***	-0.352***	-0.257***	-0.226***	-0.313***
	(0.078)	(0.040)	(0.091)	(0.064)	(0.037)	(0.089)
Inflation	0.633	0.163	-0.006	0.279	-0.300	-0.496
	(0.883)	(0.525)	(0.559)	(0.203)	(0.515)	(0.520)
Trade	0.102	0.040	-0.005	0.09	0.051	0.080
	(0.064)	(0.070)	(0.080)	(0.057)	(0.074)	(0.052)
Government	0.098	0.079	-0.121	0.007	0.168	0.088
	(0.113)	(0.202)	(0.132)	(0.079)	(0.174)	(0.159)
Education	0.084**	0.090***	0.156**	0.109***	0.115***	0.162***
	(0.038)	(0.090)	(0.058)	(0.023)	(0.031)	(0.030)
FD	0.108		0.126			
	(0.096)		(0.099)			
FR		0.113***	0.168***			
		(0.040)	(0.055)			
Level_FD				0.271		0.213
				(0.178)		(0.164)
Level_FR					0.332**	0.343***
					(0.132)	(0.121)
Constant	-0.010	-0.003	-0.005	-0.002	-0.006	-0.006
	(0.012)	(0.009)	(0.013)	(0.009)	(0.011)	(0.011)
Obs.	140	140	140	140	140	140
AR (2) test[a]	0.011	0.093	0.076	0.014	0.098	0.073
Sargan-Hansen test[b]	0.288	0.161	0.282	0.182	0.257	0.336

The table reports the outcome values of panel regressions consisting of 4-year non-overlapping period averages, spanning from 2000 to 2019, estimated using Dynamic System GMM with the additional nonlinear moment restriction. All variables (see Appendix, Table A.1 for a detailed description) are cross-sectionally demeaned and all available lags are used as instruments; all sets of instruments are collapsed. The dependent variable is per capita GDP growth regressed on the following variables (in logs): initial per capita GDP (GDP0); Inflation, transformed in log(1+variable); Trade; Government Expenditure (GovExp); Education. The financial variables are in logs (FD and FR), and in levels (Level_FD and Level_FR). Th are in levels. The table reports the coefficient values and, in parenthesis, the standard errors; significance at the different levels is indicated with * (p<0.10), ** (p<0.05), *** (p<0.01). [a] P-value. The null hypothesis is that there is no autocorrelation of order 2 of the first-differenced residuals. [b] P-value. The null hypothesis is that the overidentifying restrictions are valid.

Table A.3

Finance and growth volatility. System GMM regression results, nonlinear estimator. 2000-2019

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SD_GDPg (t-1)	-0.014	-0.122	-0.020	-0.081	0.142	-0.060	0.052
	(0.122)	(0.124)	(0.151)	(0.105)	(0.215)	(0.212)	(0.126)
GDP0	0.012	0.016**	0.023	-0.001	0.012	0.022*	0.040***
	(0.014)	(0.1725)	(0.014)	(0.009)	(0.017)	(0.012)	(0.014)
Inflation	0.160		0.398				
	(0.230)		(0.248)				
Trade	0.004	0.005	0.021*	0.018**	0.019**	-0.002	0.001
	(0.012)	(0.012)	(0.005)	(0.008)	(0.008)	(0.007)	(0.008)
FD	-0.032	-0.046*				-0.050*	-0.035*
	(0.027)	(0.024)				(0.028)	(0.019)
FR			-0.055**	-0.038**	-0.058**	-0.044***	-0.050**
			(0.021)	(0.018)	(0.026)	(0.015)	(0.022)
SD_TOT		0.193***		0.119*	0.119*	0.245**	0.100**
		(0.063)		(0.123)	(0.059)	(0.098)	(0.043)
SD_INFL		0.010*			0.003		0.011
		(0.005)			(0.006)		(0.006)
Constant	0.001	0.001	0.001	-0.001	-0.001	0.001	0
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Obs.	112	112	112	112	112	112	112
AR (2) test[a]	0.107	0.831	0.262	0.609	0.464	0.772	0.497
Sargan-Hansen test[b]	0.623	0.461	0.842	0.864	0.802	0.428	0.379

Note: The table reports the outcome values of panel regressions consisting of 4-year non-overlapping period averages, spanning from 2000 to 2019, estimated using Dynamic System GMM. All variables (see Appendix, Table A.1 for a detailed description) are cross-sectionally demeaned and all available lags are used as instruments; all sets of instruments are collapsed. The dependent variable is per capita GDP growth volatility (SD_GDPg) regressed on the following variables: lagged SD_GDPg (SD_GDPg (t-1)); initial income (GDP0, logs) Inflation (log(1+Inflation); Trade (logs); Government Expenditure (GovExp, logs); the financial indices FD and FR; Terms-of-trade volatility (SD_TOT); Inflation volatility (SD_INFL). The table reports the coefficient values and, in parenthesis, the standard errors; significance levels are indicated with * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$). [a] P-value. The null hypothesis is that there is no autocorrelation of order 2 of the first-differenced residuals. [b] P-value. The null hypothesis is that the overidentifying restrictions are valid.

Table A.4

Financial resilience and risk sharing. Country and Time FE model. 1995-2019

	HIGH FR	MIDDLE FR	LOW FR
Unsmoothed (β^u)	0.750***	0.813***	0.926***
	(0.038)	(0.019)	(0.044)
ΔFinancial Crisis (δ^u)	0.122**	0.234***	0.009
	(0.061)	(0.020)	(0.097)
Capital_markets (β^m)	0.083	-0.087***	-0.038**
	(0.053)	(0.011)	(0.017)
ΔFinancial Crisis (δ^m)	-0.069	0.121***	0.117**
	(0.085)	(0.012)	(0.054)
Depreciation (β^d)	0.019	-0.025***	-0.032
	(0.020)	(0.007)	(0.021)
ΔFinancial Crisis (δ^d)	-0.060*	0.028***	-0.012
	(0.032)	(0.007)	(0.046)
Intern_transfers (β^g)	0.005	0.008	0.004
	(0.012)	(0.005)	(0.014)
ΔFinancial Crisis (δ^g)	0.015	-0.005	-0.016
	(0.018)	(0.005)	(0.032)
Saving (β^s)	0.153**	0.2291***	0.140***
	(0.066)	(0.024)	(0.052)
ΔFinancial Crisis (δ^s)	-0.001	-0.377***	-0.099
	(0.105)	(0.026)	(0.114)

Notes: The Table reports the estimated percentage of the shock to GDP which is unsmoothed β^u and the estimated percentage which is smoothed out through the different channels: capital markets β^m, depreciation β^d, international transfers β^g, and credit market β^s, along with the estimated change in the slope in periods of financial crises δ^j, with $j = u, m, g, s$. Standard errors in parenthesis. Data for GDP and its components are from EUROSTAT, deflated and in per-capita terms; data for financial crises (banking, currency, and debt) are from Laeven and Valencia (2018). Fixed-effects within regression. HIGH FR is the group of economies belonging clubs 1 and 2; MIDDLE FR consists of economies belonging to club 3; LOW FR is formed by pooling economies belonging to club 4 and club 5.

Table A.5

Financial resilience and risk sharing. Country and Time FE model. 1995-2007 and 2008-2019

	HIGH FR		(MID + LOW) FR	
	1995-2007	**2008-2019**	**1995-2007**	**2008-2019**
Unsmoothed (β^u)	0.904***	0.603***	0.812***	0.922***
	(0.042)	(0.063)	(0.018)	(0.054)
ΔFinancial Crisis (δ^u)	0.110	0.192***	0.232***	0.012
	(0.080)	(0.086)	(0.019)	(0.086)
Capital_markets (β^m)	-0.005	0.186**	-0.095***	0.038
	(0.082)	(0.074)	(0.010)	(0.033)
ΔFinancial Crisis (δ^m)	-0.100	-0.102	0.131***	0.009
	(0.156)	(0.101)	(0.010)	(0.053)
Depreciation (β^d)	-0.039*	0.095**	-0.018**	-0.054***
	(0.020)	(0.037)	(0.008)	(0.015)
ΔFinancial Crisis (δ^d)	-0.003	-0.109**	0.024***	-0.039
	(0.038)	(0.050)	(0.009)	(0.024)
Intern_transfers (β^g)	0.011	0.002	0.006	0.002
	(0.015)	(0.019)	(0.005)	(0.019)
ΔFinancial Crisis(δ^g)	0.019	0.011	-0.005	0.032
	(0.029)	(0.027)	(0.005)	(0.029)
Saving (β^s)	0.150	0.114	0.295***	0.092
	(0.099)	(0.094)	(0.022)	(0.066)
ΔFinancial Crisis (δ^s)	-0.027	0.007	-0.382***	-0.013
	(0.188)	(0.128)	(0.023)	(0.104)

Notes: The Table reports the estimated percentage of the shock to GDP which is unsmoothed β^u and the estimated percentage which is smoothed out through the different channels: capital markets β^m, depreciation β^d, international transfers β^g, and credit market β^s, along with the estimated change in the slope during periods of financial crises, δ^j, with $j = u, m, g, s$. Standard errors in parenthesis. Data for GDP and its components are from EUROSTAT, deflated and in per-capita terms; data for financial crises (banking, currency, and debt) are from Laeven and Valencia (2018). Fixed-effects within regression. HIGH FR is the group of economies belonging to club 1 and club 2; (MID + LOW) FR is the group of economies belonging to club 3, club 4, and club 5.