Global Banking Stability, Financial Development, and Growth:

Broad-Based Evidence from FinTech Credit Flows

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Abstract

The study examines the impact of Fintech credit flows on global banking stability, broad-based financial development, and growth. Fintech and big tech credit flows are favorable to global banking stability, with a predicted increase (decrease) in bank Z-score (non-performing loans). Commercial banking systems present a predicted decrease in after-tax profitability. Increased Fintech and big tech credit flows present a predicted decrease in one year-ahead GDP growth. Global financial development presents marginal growth and the broad-based development of financial institutions and markets. FinTech and big tech credit flows decrease the financial institutions' access and financial market efficiency. Economies with the highest fintech credit flows present a predicted increase in financial instability of commercial banks. The development of financial markets and institutions is sensitive to fintech and big tech credit flows. The findings offer global and thorough evidence on the multifactorial impacts (opportunities and threats) of fintech and big tech credit flows on banking stability, broad-based financial development, and global growth.

Keywords: Fintech and big tech credit, global financial development, growth, commercial banks, and financial stability.

JEL codes: G21, E44.

1. Introduction

Rapid developments in digital technology are changing the financial and economic environments[2]. The financial industry is facing both new opportunities and challenges because of financial technology, or fintech, for regulators, financial institutions, and customers alike. From enhancing the efficiency and competitiveness of their financial systems to expanding access to financial services for marginalized groups, fintech presents governments with numerous opportunities. Nevertheless, it may also pose possible hazards to investors and consumers as well as, more generally, to the integrity and stability of the financial system. The current study examines the impact of FinTech on the stability and growth of global banks. Distinguished from extant literature, the study comprehensively examines the impact of FinTech and Big Tech credit flows on the broad-based development of financial markets and institutions over the past decades[3].

Employing a global data set of commercial banking systems of 134 countries, the overall findings present the following main findings. Fintech and big tech credit flows are beneficial to global banking stability. The study presents heterogeneous effects of Fintech and Big Tech credit flows on the broad-based financial development. Bank stability is strengthened with a predicted

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[2] See, https://www.worldbank.org/en/topic/fintech

[3] The study makes use of Credit flows by fintech and big tech companies to GDP (%) [GFDD.DM.16] to examine the impacts of FinTech and Big Tech credit on the multidimensional financial development, bank stability and growth.

increase in Bank Z-score and bank performance (Bank return on assets after taxes), and a predicted decrease in bank non-performing loans. However, countries with the highest development of FinTech and Big Tech credit flows present a marginal increase in bank non-performing loans and decreased bank profitability. A unit change in FinTech and Big Tech credit flows is associated with a predicted decrease in the gross domestic product (GDP growth, annual %).

Diving into multidimensional financial development globally, Fintech and Big Tech credit flows heterogeneously affect the development of markets and institutions. Overall, Fintech and Big Tech credit flows marginally benefit the broad-based and overall development of both financial markets and institutions (FD). A unit increase in FinTech and Big Tech credit flows is associated with a predicted increase in the financial institutions depth (FID), efficiency (FIE), financial markets depth (FMD), and accessibility (FMA). On the other hand, Fintech and Big Tech credit flows induce a predicted decrease in the overall development of financial institutions (FI), financial markets (FM), and financial institutions accessibility (FIA), and financial markets efficiency (FME). The study documents heterogeneous impacts of Fintech and big tech credit flows on the multidimensional development of financial markets and institutions.

For economies with the highest developed FinTech and Big Tech credit flows, FinTech and Big Tech credit flows are more favorable to the broad-based development of both financial institutions and markets. With a marginal predicted decrease in financial institutions' accessibility (FIA), the study presents persistent favorable outcomes of FinTech and Big Tech credit flows to global bank stability of economies worldwide. Controlling for a comprehensive set of bank-related characteristics, the unfavorable impact of FinTech and Big Tech credit flows on growth is swallowed. The findings offer insights into the potential contributions of Fintech and Big Tech credits for inclusive growth through heightened banking stability and broad-based financial development outcomes.

Our global evidence contributes to several related literature niches. Globally, Fintech and Big Tech credit flows are important determinants of bank stability. The findings complement prior literature on the effects of FinTech and Big Credit flows on bank stability for China and international banking systems (Daud et al., 2022; Sikalao-Lekobane, 2024). Prior studies show that FinTech development negatively affects Chinese banking systems (Li et al., 2023; Wang et al., 2021; Zhao et al., 2022). Our findings complement prior literature by showing that the negative effects on bank performance remain for economies with the highest FinTech and Big Tech credit flows. On the other hand, continuous FinTech and Big Tech credit flows enhance the one-year-ahead financial performance of global banking systems. Although there may be disruptive effects on financial profitability, the development of FinTech and Big Tech credit flows is favorable to the financial stability of banking systems, with a persistent decrease in bank non-performing loans. Economies with the highest FinTech and Big Tech credit flows strengthen the depth of financial institutions and markets.

The study empirically contributes to the favorable outcomes of FinTech and Big Tech credit developments for the future of banks, as reviewed by recent literature (Murinde et al., 2022; Stulz, 2019; Thakor, 2020). Evident from broad-based financial development, the findings empirically support the notion of Stulz (2019) that Big Tech credit flows could pose a far greater threat to existing banking systems, such as consumer finance and loans to small businesses. Our findings show that FinTech and Big Tech credit flows decrease financial institutions' accessibility. The findings may imply that FinTech and Big Tech credit flows are becoming popular, in which commercial banking systems experience a decreased comparative advantage. The decreased comparative advantage could be derived from immediate access to information about credit-seeking parties. Employing broad-based financial development measures, the study also adds to related literature on the contribution of FinTech and Big Tech credit flows as an important explanatory determinant of the impact of financial inclusion on bank stability (Ahamed & Mallick, 2019; Danisman & Tarazi, 2020; Wang & Luo, 2022).

Our global evidence shows the adverse effects of FinTech and Big Tech credit flows on global growth. Although the effects of FinTech and Big Tech credit flows on bank stability and broad-based financial development are potentially favorable, economies present a predicted decrease in annual GDP growth. Through the role of FinTech and Big Tech credit flows, the findings complement established literature on the finance-growth nexuses (Arestis et al., 2015; Arestis & Demetriades, 2012; Benhabib & Spiegel, 2000; Breitenlechner et al., 2015; De Gregorio & Guidotti, 1995; Herwartz & Walle, 2014; Kendall, 2012; Shen & Lee, 2006; Sikalao-Lekobane, 2024; Yilmazkuday, 2011). The current study employs a total of nine broad-based measures to examine the impact of FinTech and Big Tech credit flows on multidimensional financial development. With the predicted decrease in GDP growth and the heterogeneous effects on broad-based financial development, the study offers critical insights into future studies.

The remaining parts are structured as follows. Section 2 presents a literature review and develops related hypotheses. Section 3 presents empirical findings and discussion. Section 4 concludes the main findings with policy implications and future direction. The study reports detailed elaborations of variables used, sample distribution, and definitions in the Appendix.

2. Literature review

Our study is related to several strands of literature. The first strand of literature explores the link between credit growth, financial innovations, and the banking system to provide theoretical and empirical insights that shed light on how credit flows from FinTech and Big Tech impact financial stability. Given the active academic debate and policy concern around financial innovations after the Global Financial Crisis, the extant literature on its relationship with financial stability still provides mixed views on whether credit flows from these innovations pose a threat or an opportunity to the banking sectors (Murinde et al., 2022; Daud et al., 2022; Feyen et al., 2021; Henderson and Pearson, 2011; Nguyen & Dang, 2022). On the one hand, there is supporting evidence that FinTech and Big Tech innovations that provide a complementary service to those provided by existing financial institutions, such as credit, could enhance banking stability, to the extent that greater decentralization and diversification of financial services caused by heightened competition from these companies may increase market transparency, which improves credit assessment and allocation, thus increasing banking system's resilience (FSB, 2019a). Scholars with a contrary view, on the other hand, have demonstrated that financial innovation and its "market-based" credit system with reduced asymmetric information may contribute to aggressive risk-taking, reduction in lending standards, and thus fragility in the banking system (Rajan, 2006; Dell'Ariccia et al., 2008; Gennaioli et al., 2012). Such contrast in this strand of literature is explained through the *innovation-growth* and the *innovation-fragility* hypotheses on the influences of financial innovation on the banking and overall financial system (Beck, Chen, Lin, & Song, 2016).

The second strand of literature is closely related to our focus on how FinTech and Big Tech lending impact the growth of the global economy. The seemingly ambiguous relationship between FinTech and Big Tech credit and banking stability raises this empirical question of its influence on the real sectors. The traditional *innovation-growth* view posits that credit flows from financial innovations help broaden access to the economies' credit channel (Hikida & Perry, 2020), facilitate risk sharing (Allen and Gale, 1991; 1994), complete the market (Fuster, Plosser, Schnabl, & Vickery, 2019), ultimately improve allocative efficiency (Houston et al., 2010) and thus fund growth opportunities in the real sectors. However, emerging literature with an *innovation-fragility* view has identified financial innovations and their contribution to unprecedented credit expansion as one of the most robust crisis predictors (Jorda et al., 2013), which suggests that FinTech and Big Tech credit flows may potentially hurt economic growth (Palmié et al., 2020).

The last strand of literature explores how FinTech and Big Tech penetration affect financial development. Despite having emerging attention in finance literature, the impact of FinTech and Big Tech credit on financial development is still understudied with limited empirical evidence (Joseph et al., 2023). Olga et al. (2023) have identified that FinTech has a significant relationship to financial developments, to the extent that it is positively correlated to indexes of financial market depth (FMD) and efficiency (FMI), as well as financial institutions depth (FID); though, empirical evidence on causality was not demonstrated in the study. Joseph et al. (2023) have contributed significant findings that a higher level of FinTech penetration drives and improves financial development, as measured by broad money, private credit, and bank deposits. Our study contributed to this strand literature by investigating both the continuous and treatment effects of FinTech and Big Tech lending on a multidimensional measure of financial development (FD) with the sub-proxies for financial institutions (FI) and markets (FM), accounting for all the perspectives of access, depth, and efficiency for each of the sub-FD indexes (FIA, FID, FIE, and FMA, FMD, FME). Motivated by related literature, the study examines the following hypotheses:

H1: Fintech and big tech credit flows benefit global banking stability.

H1A: Given the innovative credit flows, commercial banking systems present a decrease in financial profitability.

H2: Fintech and big tech credit flows are favorable to broad-based financial development (FD). There are heterogeneous impacts on sub-FD indicators.

H2A: Alternative credit flows could mitigate financial institutions' access and market efficiency.

Finance-growth nexuses are established in extant literature with favorable outcomes of financial innovation. However, digitalization could threaten growth in the short-term horizon due to its transitional risk to the wider economy and adaptation of institutions and markets.

H3: Fintech and big tech credit flows could impose adverse effects on GDP growth.

H3A: The adverse effects of FinTech and big tech credit on growth could be swallowed, controlling for bank-related characteristics.

3. Data and methodology

3.1. Data sources

The study extracts data from multiple sources. We first extract data on financial stability and bank-related variables, including data on our main variable of interest – FinTech and Big Tech credit flows, from the Global Financial Development Database (GFDD, 2023)[4]. Data on macroeconomic factors are extracted from the World Bank, while data on the overall financial development (FD), institutions (FI), markets (FM), and sub-proxies are extracted from the International Monetary Fund. After matching from our data sources, our strongly balanced sample data we used for the study includes 134 economies from 1996 to 2019, with a total of 2814 country-year observations.

3.2. Variables and models

3.2.1. Baseline regression models

To overcome potential endogeneity issues caused by omitted variables and reverse causality[5]. This study employs the two-step system GMM model proposed by Holtz-Eakin et al. (1988) to

[4] Global Financial Development. https://www.worldbank.org/en/publication/gfdr/data/global-financial-development-database

[5] This is in-line with evidence from previous literature showing that capital inflows are highly affected by local financial development (Desbordes and Wei, 2017; Nguyen and Lee, 2021). For example, financial development facilitates credit flows from FinTech and Big Tech companies, while these flows contribute to further development of the financial market.

investigate the impacts of FinTech and Big Tech credit flows on global GDP growth (GDPG, %, annual), banking stability (BS), and broad-based financial development (FD). Our study proposes the following baseline regression models:

$$GDPG_{i,t} = \beta_0 + \beta_1 GDPG_{i,t-1} + \beta_2 CF\_FINTECH_{i,t-1} + \sum \beta_k Macro\_Controls_{k,i,t-1} + \varepsilon_{i,t} \quad (1)$$

$$BS_{i,t} = \beta_0 + \beta_1 BS_{i,t-1} + \beta_2 CF\_FINTECH_{i,t-1} + \sum \beta_k Macro\_Controls_{k,i,t-1} + \varepsilon_{i,t} \quad (2)$$

$$FD_{i,t} = \beta_0 + \beta_1 FD_{i,t-1} + \beta_2 CF\_FINTECH_{i,t-1} + \sum \beta_k Macro\_Controls_{k,i,t-1} + \varepsilon_{i,t} \quad (3)$$

To quantify the impacts of credit flows from FinTech and Big Tech companies on the stability global banking system (BS), we employ Bank Z-score as the main proxy for financial stability and further conduct robustness check using Bank non-performing loans to total gross loan (%) and Bank return on assets (%, after tax) as alternative proxies for this dependent variable[6]. The Bank Z-score captures the distance from insolvency for each of our 134 banking systems around the world. It compares the buffer of a country's banking system with its return volatility. According to GFDD, the Z-score is computed as follows:

$$ZSCORE = \frac{\left(ROA + (EQUITY/ASSET)\right)}{\sigma(ROA)}$$

[6] This is consistent with most bank stability literature. See Beck et al. (2013); Fang et al. (2014); Houston et al. (2010); Turk Ariss (2010).

$\sigma(ROA)$ is the standard deviation of return on assets (ROA), which is estimated for a country-year with no less than five bank-level observations. ROA, equity, and assets are the aggregated bank-level measures for each of our sample countries each year. These measures are estimated using the underlying bank-by-bank unconsolidated data extracted from Bank Scope and Orbis.

The study further examines the impacts of FinTech and Big Tech credit flows on financial development, using a broad-based index offered by Svirydzenka (2016) for the overall development (FD) that aggregates both financial institutions (FI) and markets (FM) and accounts for all the perspectives of access, depth, and efficiency for each of the sub-FD indexes (FIA, FID, FIE, and FMA, FMD, and FME).

The characters of i and t in our regressions indicate country i and year t. $CF\_FINTECH$ is our main independent variable of interest, proxying the credit flows by fintech and big tech companies to GDP (%). Motivated by modern literature, we include a vector of explanatory macroeconomic variables controlled for income (US$), broad money (% of GDP), unemployment (% of total labor force), labor force (% of total population ages 15-64), industry (% of GDP), trade (TRADE), research and development expenditure (% of GDP), inflation rate (%, annual), and foreign direct investment net inflow (% of GDP). In the spirit of dynamic panel data regressions, all the independent variables are lagged by one year.

3.2.2. Regression models with treatment

After quantifying the impacts of continuous credit flows from FinTech and Big Tech companies, we use a treatment dummy instead of $CF\_FINTECH$ as our main independent variable in the previous models to stimulate the consequences and response of the treated global banking system, growth, and financial development to FinTech and Big Tech penetration. $FINTECH\_DUMMY$ is a treatment dummy set equal to one for banking systems belonging to the top quartile of the Fintech and Big Tech credit flows to GDP. Our two-step system GMM models with treatment are designed as follows:

$$GDPG_{i,t} = \beta_0 + \beta_1 GDPG_{i,t-1} + \beta_2 FINTECH\_DUMMY_{i,t-1} + \sum \beta_k Macro\_Controls_{k,i,t-1} + \varepsilon_{i,t} \quad (5)$$

$$BS_{i,t} = \beta_0 + \beta_1 BS_{i,t-1} + \beta_2 FINTECH\_DUMMY_{i,t-1} + \sum \beta_k Macro\_Controls_{k,i,t-1} + \varepsilon_{i,t} \quad (6)$$

$$FD_{i,t} = \beta_0 + \beta_1 FD_{i,t-1} + \beta_2 FINTECH\_DUMMY_{i,t-1} + \sum \beta_k Macro\_Controls_{k,i,t-1} + \varepsilon_{i,t} \quad (7)$$

3.2.3. Controlling for the characteristics of global banking systems

We further follow existing literature to include a vector of bank-related variables controlled for bank credit, capital, deposit, liquidity, concentration, crisis, and cost to income in the previous regression models:

$$GDPG_{i,t} = \beta_0 + \beta_1 GDPG_{i,t-1} + \beta_2 CF\_FINTECH_{i,t-1} + \sum \beta_k Macro\_Bank\_Controls_{k,i,t-1} + \varepsilon_{i,t}$$

(8)

$$BS_{i,t} = \beta_0 + \beta_1 BS_{i,t-1} + \beta_2 CF\_FINTECH_{i,t-1} + \sum \beta_k Macro\_Bank\_Controls_{k,i,t-1} + \varepsilon_{i,t} \quad (9)$$

$$FD_{i,t} = \beta_0 + \beta_1 FD_{i,t-1} + \beta_2 CF\_FINTECH_{i,t-1} + \sum \beta_k Macro\_Bank\_Controls_{k,i,t-1} + \varepsilon_{i,t} \quad (10)$$

The Arellano-Bond estimator is used in the study to construct a linear dynamic panel-data model in which unobserved panel-level effects are linked with dependent variable lags (Arellano & Bond, 1991; Windmeijer, 2005). This estimator is intended for datasets with many panels and few periods, and it demands that there be no correlations in the idiosyncratic errors.

4. Empirical findings

[Table 1 Inserted Here]

Table 1 reports the descriptive statistics of the variables used for the study. Our global panel data includes approximately 2814 country-year observations for the period 1996-2019. The average logarithm (mean) value of the bank Z-score of global banking systems is 2.712, ranging from -0.394 (minimum) to 4.214 (maximum), with a standard deviation of 0.565. The logarithm average (mean) value of the bank fintech and big tech credit flows to GDP is 0.010, ranging from 0 (minimum) to 1.68 (maximum), with a standard deviation of 0. The study provides a list of 134 sample economies in the appendix

[Table 2 Inserted Here]

Table 2 reports on the estimations of both continuous and treatment effects of FinTech and Big Tech credit flows on the global banking system and growth. The findings show that FinTech and Big Tech lending are beneficial to global banking stability. Regarding the continuous effects (Columns 1-3), a unit increase in FinTech and Big Tech credit flows is associated with a predicted increase in bank Z-score and bank performance by 0.1212 and 0.1079, and a predicted decrease of -0.1498 in bank non-performing loans. The treatment effects (Columns 4-6) support our finding with consistency, showing that countries with active FinTech and Big Tech credit flows obtain a predicted increase in financial stability of their banking sectors. Statistically speaking, bank Z-score and bank performance are predicted to respectively increase by 0.0508 and 0.0213-unit change, and bank non-performing loans is predicted to decrease by 0.0161-unit change. Both specifications of FinTech and Big Tech lending reveal a negative relationship with economic growth, contributing to *innovation-fragility* literature with robust empirical results. The findings are strongly robust and significant at the 1% level for all the tested models.

[Table 3 Inserted Here]

Table 3 reports the regressions of FinTech and Big Tech credit flows on the broad-based financial development indexes, with Panel A showing the direct effects and Panel B revealing treatment effects. With multidimensional measures of financial development, the results show that, on the one hand, a unit increase in FinTech and Big Tech credit flows is associated with predicted increases in financial institutions depth (FID), efficiency (FIE), financial markets depth (FMD), and accessibility (FMA). On the other hand, Fintech and Big Tech credit flows induce a predicted decrease in the overall development of financial institutions (FI), financial markets (FM), and financial institutions accessibility (FIA), and financial markets efficiency (FME). The effects are statistically significant at 1% for most of the tested models. Overall, the findings complement previous literature on the potential opportunities and threats offered by FinTech and Big Tech credit, to the extent of enhancing intermediation efficiency and broadening credit access, while heightening market competition and thus leading to possible substitution away from traditional financial services. Consistent results on the treatment effects validate our proposed hypothesis of the heterogeneous effects on financial development, such that the presence of FinTech and Big Tech improves banking efficiency and credit accessibility on the market, while potentially hurting overall development of financial institutions and the market due to its inherent risks and volatility.

[Table 4 Inserted Here]

We extend our empirical analyses with an additional set of variables controlling characteristics of the banking system in Table 4. The significant results on global growth and banking system are consistent with our previous models; though, most of the tested models are statistically insignificant at 5% level. However, we found that the result on bank non-performing loans is robust and amplified, showing that a unit increase in FinTech and Big Tech credit flows is predicted to decrease bank non-performing loans by 0.4273 units. The treatment effects on bank Z-score are also strongly robust, which suggests favorable impacts of FinTech and Big Tech credit on global banking systems. Regarding the results on financial development, most of the tested models for the continuous and treatment effects of FinTech and Big Tech credit flows are strongly significant at 1%, with meaningful economic implications for future studies

5. Conclusion

The study empirically examines the ups and downsides of FinTech and Big Tech credit flows to global banking stability, financial development, and growth. On the bright side, Fintech credit flows benefit global banking stability and broad-based financial development. Commercial banking systems present a predicted increase in Z-score and non-performing loans. The evolution of FinTech and Big Tech credit flows induces decreased bank profitability, financial institutions' access, and financial markets' efficiency. Fintech and big tech credit flows induce a predicted decrease in GDP growth. Even though there are favorable outcomes of global digitization, FinTech and Big Tech credit flows impose uneven effects on the broad-based development of financial institutions and markets. Evolutionary fintech credit flows could unfavorably affect the financial profitability of commercial banks and the short-term growth prospects of the global economy. The study offers comprehensive evidence on the opportunities and risks for how Fintech and big tech credit flows could affect the financial stability of banking systems, broad-based development, and global growth. Future studies are needed to delve further into how economies may benefit from FinTech credit flows with minimized risks associated with growth prospects.

Table 1: Descriptive Statistics

Variable	N	Min	Mean	Max	SD	Median
Bank Z Score	2278	-.394	2.712	4.214	.565	2.766
Bank NPL	1861	.01	1.728	4.06	.788	1.602
Bank ROA	2184	-6.587	0.798	3.137	.502	.82
GDP growth	2792	-50.339	4.009	88.958	4.927	3.968
FD	2814	0	0.316	1	.243	.229
FI	2814	0	0.385	1	.23	.318
FM	2814	0	0.235	.989	.272	.09
FID	2814	0	0.253	1	.267	.139
FIA	2814	0	0.308	1	.278	.232
FIE	2814	0	0.557	.843	.127	.571
FMD	2814	0	0.229	.998	.283	.087
FMA	2814	0	0.221	1	.269	.041
FME	2814	0	0.246	1	.349	.038
FinTech credits	2814	0	0.010	1.684	.082	0
Income	2786	4.65	8.233	11.548	1.605	8.2
Broad money	2375	1.815	3.771	6.355	.703	3.765
Unemployment	2814	.095	1.955	3.684	.649	1.928
Labor force	2814	3.657	4.204	4.505	.165	4.238
Industry	2731	1.445	3.315	4.474	.355	3.289
Trade	2685	2.554	4.260	6.083	.483	4.258
R&D	2814	0	0.321	1.815	.437	.094
Inflation	2647	-3.356	1.752	8.477	1.015	1.761
FDI net	2722	-4.902	1.334	4.648	.808	1.318
Bank credit	2638	2.27	4.484	7.959	.513	4.503
Bank capital	1785	.912	2.322	3.453	.344	2.334
Bank concentration	2281	2.842	4.190	4.615	.305	4.225
Bank crisis	2546	0	0.060	1	.237	0
Bank deposit	2619	1.106	3.561	5.527	.768	3.635
Bank liquidity	2226	1.864	3.451	5.061	.497	3.464
Bank cost to income	2238	2.757	4.026	5.472	.245	4.054

Table 2: The impact of FinTech and Big Tech credit flows on global banking stability and growth

VARIABLES	(1) Bank Z Score	(2) Bank NPL	(3) Bank ROA	(4) Bank Z Score	(5) Bank NPL	(6) Bank ROA	(7) GDP growth	(8) GDP growth	(9) GDP growth	(10) GDP growth
Bank Z Score$_{t-1}$	0.1688***			0.1748***						
	(0.0072)			(0.0094)						
FinTech credits$_{t-1}$	**0.1212*** **	**-0.1498*** **	**0.1079*** **				**-5.125*** **		**-2.8713*** **	
	(0.0113)	(0.0437)	(0.0363)				(0.3394)		(0.8994)	
Income$_{t-1}$	-0.0123***	0.0497***	-0.1617***	-0.0091**	0.0423***	-0.1596***			-7.3428***	-7.4041***
	(0.0038)	(0.0074)	(0.0078)	(0.0039)	(0.0093)	(0.0081)			(0.1914)	(0.1954)
Broad money$_{t-1}$	0.1232***	0.1206***	-0.2165***	0.1171***	0.0851***	-0.2444***			13.8045***	14.0232***
	(0.0073)	(0.0199)	(0.0232)	(0.0075)	(0.0237)	(0.0205)			(0.3581)	(0.4655)
Unemployment$_{t-1}$	0.0342***	-0.1007***	0.0370***	0.0310***	-0.1033***	0.0154*			1.8106***	1.8022***
	(0.0041)	(0.0134)	(0.0130)	(0.0044)	(0.0104)	(0.0090)			(0.3664)	(0.3537)
Labor force$_{t-1}$	-0.2052***	0.1116	-0.2016	-0.2163***	0.0716	0.5427***			-0.7882	0.5899
	(0.0480)	(0.2374)	(0.2611)	(0.0395)	(0.1760)	(0.1499)			(2.5890)	(3.2965)
Industry$_{t-1}$	0.0345***	-0.0918***	0.3997***	0.0301***	-0.1097*	0.4240***			-4.6509***	-5.0258***
	(0.0074)	(0.0273)	(0.0236)	(0.0056)	(0.0560)	(0.0194)			(0.3105)	(0.3487)
Trade$_{t-1}$	0.0467***	-0.1453***	0.3526***	0.0534***	-0.1192***	0.3801***			-3.9692***	-3.9588***
	(0.0063)	(0.0220)	(0.0244)	(0.0071)	(0.0267)	(0.0230)			(0.3756)	(0.4050)
R&D$_{t-1}$	0.0040	0.0111**	0.0380***	0.0070***	0.0099	0.0457***			-0.3958***	-0.4321
	(0.0034)	(0.0051)	(0.0094)	(0.0019)	(0.0073)	(0.0104)			(0.1304)	(0.3869)
Inflation$_{t-1}$	0.0031***	0.0077**	-0.0037	0.0033***	0.0064**	-0.0045*			0.7902***	0.7481***
	(0.0009)	(0.0037)	(0.0026)	(0.0008)	(0.0025)	(0.0027)			(0.0205)	(0.0283)
FDI net$_{t-1}$	-0.0079***	0.0354***	-0.0917***	-0.0089***	0.0336***	-0.0983***			0.0051	-0.0069
	(0.0009)	(0.0020)	(0.0030)	(0.0011)	(0.0027)	(0.0030)			(0.0454)	(0.0390)
Bank NPL$_{t-1}$		0.6981***			0.7005***					
		(0.0087)			(0.0080)					
Bank ROA$_{t-1}$			0.0153***			0.0130***				
			(0.0023)			(0.0018)				
FinTech dummy$_{t-1}$				**0.0508*** **	**0.0213*** **	**-0.0161*** **		**-3.376*** **		**-0.8710*** **
				(0.0023)	(0.0053)	(0.0058)		(0.0490)		(0.1627)
GFP growth$_{t-1}$							0.0587***	0.0360***	-0.1223***	-0.1239***
							(0.0004)	(0.0006)	(0.0014)	(0.0014)
Constant	2.3941***	0.1827	1.0875	2.4190***	0.5028	-2.0955***	3.8207***	4.1437***	42.1718***	37.6014***
	(0.2267)	(1.0352)	(1.1250)	(0.1858)	(0.7936)	(0.6786)	(0.0179)	(0.0248)	(10.2145)	(14.0521)
Observations	1,337	1,055	1,262	1,337	1,055	1,262	2,130	2,130	1,486	1,486
Number of countries	107	96	106	107	96	106	134	134	114	114

The table reports Arellano-Bond linear dynamic panel-data estimations using lags of the dependent variables as covariates. The estimations are implemented by computing the two-step estimators. The independent variables are lagged by one year. The Arellano-Bond estimator is used in the study to construct a linear dynamic panel-data model in which unobserved panel-level effects are linked with dependent variable lags. This estimator is intended for datasets with a large number of groups and few intervals, and it demands that there be no correlations in the idiosyncratic errors. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3: Broad-based financial development
Panel A: Continuous Fintech and Big Tech Credit Flows

VARIABLES	(1) FD	(2) FI	(3) FM	(4) FID	(5) FIA	(6) FIE	(7) FMD	(8) FMA	(9) FME
FD_{t-1}	0.5684***								
	(0.0062)								
FinTech $credits_{t-1}$	**0.0017***	**-0.0023**	**-0.0165*****	**0.0191*****	**-0.0199*****	**0.0707*****	**0.0074*****	**0.0059*****	**-0.0324*****
	(0.0010)	(0.0016)	(0.0001)	(0.0010)	(0.0005)	(0.0133)	(0.0003)	(0.0005)	(0.0072)
$Income_{t-1}$	0.0171***	0.0227***	0.0013***	0.0225***	0.0269***	0.0104***	0.0266***	-0.0045***	-0.0221***
	(0.0006)	(0.0011)	(0.0000)	(0.0003)	(0.0002)	(0.0011)	(0.0002)	(0.0001)	(0.0009)
Broad $money_{t-1}$	0.0031***	0.0094***	-0.0149***	0.0064***	0.0100***	0.0141***	0.0081***	-0.0170***	-0.0131***
	(0.0009)	(0.0013)	(0.0001)	(0.0007)	(0.0006)	(0.0020)	(0.0004)	(0.0003)	(0.0036)
$Unemployment_{t-1}$	0.0041***	0.0007	0.0064***	0.0019***	-0.0028***	0.0059***	0.0119***	0.0058***	0.0010
	(0.0007)	(0.0011)	(0.0001)	(0.0003)	(0.0002)	(0.0021)	(0.0001)	(0.0003)	(0.0013)
Labor $force_{t-1}$	0.0357***	0.0784***	-0.0300***	0.1076***	0.0130***	0.0733***	0.0007	-0.0817***	0.0575***
	(0.0062)	(0.0055)	(0.0005)	(0.0031)	(0.0017)	(0.0141)	(0.0018)	(0.0025)	(0.0164)
$Industry_{t-1}$	-0.0048***	0.0003	0.0006*	0.0060***	0.0122***	0.0037**	-0.0317***	0.0069***	0.0295***
	(0.0013)	(0.0019)	(0.0003)	(0.0008)	(0.0014)	(0.0018)	(0.0006)	(0.0009)	(0.0065)
$Trade_{t-1}$	0.0146***	0.0021	0.0279***	-0.0017***	0.0019***	0.0247***	0.0405***	0.0301***	0.0133***
	(0.0011)	(0.0020)	(0.0001)	(0.0005)	(0.0003)	(0.0028)	(0.0002)	(0.0004)	(0.0024)
$R\&D_{t-1}$	0.0039***	0.0046***	0.0032***	0.0109***	-0.0004***	0.0044***	0.0095***	0.0174***	-0.0234***
	(0.0003)	(0.0006)	(0.0000)	(0.0002)	(0.0001)	(0.0017)	(0.0001)	(0.0001)	(0.0010)
$Inflation_{t-1}$	-0.0011***	0.0006***	-0.0020***	-0.0019***	0.0000	0.0030***	-0.0029***	0.0006***	-0.0039***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0003)
FDI net_{t-1}	0.0010***	-0.0019***	0.0042***	-0.0015***	0.0053***	-0.0079***	-0.0001***	-0.0014***	0.0206***
	(0.0002)	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0008)	(0.0000)	(0.0001)	(0.0005)
FI_{t-1}		0.7138***							
		(0.0099)							
FM_{t-1}			0.5602***						
			(0.0001)						
FID_{t-1}				0.6471***					
				(0.0025)					
FIA_{t-1}					0.7545***				
					(0.0010)				
FIE_{t-1}						0.3545***			
						(0.0053)			
FMD_{t-1}							0.3872***		
							(0.0004)		

FMA_{t-1}								0.4951***	
								(0.0003)	
FME_{t-1}									0.3810***
									(0.0014)
Constant	-0.2275***	-0.4492***	0.1284***	-0.5853***	-0.2834***	-0.2043***	-0.2162***	0.3742***	-0.0738
	(0.0227)	(0.0238)	(0.0027)	(0.0152)	(0.0062)	(0.0505)	(0.0075)	(0.0126)	(0.0775)
Observations	1,486	1,486	1,486	1,486	1,486	1,486	1,486	1,486	1,486
Number of countries	114	114	114	114	114	114	114	114	114

The table reports Arellano-Bond linear dynamic panel-data estimations using lags of the dependent variables as covariates. The estimations are implemented by computing the two-step estimators. The independent variables are lagged by one year. The Arellano-Bond estimator is used in the study to construct a linear dynamic panel-data model in which unobserved panel-level effects are linked with dependent variable lags. This estimator is intended for datasets with a large number of groups and few intervals, and it demands that there be no correlations in the idiosyncratic errors. Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Broad-based financial development
Panel B: A dummy variable of Fintech and Big Tech Credit Flows

VARIABLES	(1) FD	(2) FI	(3) FM	(4) FID	(5) FIA	(6) FIE	(7) FMD	(8) FMA	(9) FME
FD_{t-1}	0.5685***								
	(0.0067)								
FinTech $dummy_{t-1}$	**0.0037*** **		**0.0041*** **	**0.0103*** **	**-0.0061*** **	**0.0202*** **	**0.0086*** **	**0.0084*** **	**-0.0044*** **
	(0.0005)		(0.0000)	(0.0003)	(0.0002)	(0.0025)	(0.0001)	(0.0001)	(0.0008)
$Income_{t-1}$	0.0169***	0.0218***	0.0006***	0.0222***	0.0271***	0.0077***	0.0261***	-0.0052***	-0.0217***
	(0.0007)	(0.0011)	(0.0000)	(0.0003)	(0.0002)	(0.0012)	(0.0001)	(0.0001)	(0.0011)
Broad $money_{t-1}$	0.0046***	0.0121***	-0.0169***	0.0063***	0.0110***	0.0107***	0.0071***	-0.0181***	-0.0191***
	(0.0008)	(0.0018)	(0.0002)	(0.0005)	(0.0003)	(0.0026)	(0.0005)	(0.0003)	(0.0031)
$Unemployment_{t-1}$	0.0050***	0.0032**	0.0070***	0.0022***	-0.0035***	0.0070***	0.0125***	0.0064***	-0.0004
	(0.0007)	(0.0015)	(0.0000)	(0.0004)	(0.0003)	(0.0021)	(0.0002)	(0.0004)	(0.0011)
Labor $force_{t-1}$	0.0263***	0.0741***	-0.0380***	0.1029***	0.0180***	0.0610***	-0.0037	-0.0852***	0.0386**
	(0.0052)	(0.0063)	(0.0007)	(0.0028)	(0.0023)	(0.0163)	(0.0029)	(0.0038)	(0.0153)
$Industry_{t-1}$	-0.0030***	0.0069***	0.0025***	0.0058***	0.0131***	0.0036	-0.0298***	0.0081***	0.0234***
	(0.0011)	(0.0012)	(0.0002)	(0.0012)	(0.0008)	(0.0026)	(0.0004)	(0.0012)	(0.0043)
$Trade_{t-1}$	0.0170***	0.0004	0.0291***	-0.0012**	0.0014***	0.0255***	0.0415***	0.0330***	0.0130***
	(0.0009)	(0.0011)	(0.0001)	(0.0006)	(0.0004)	(0.0026)	(0.0002)	(0.0003)	(0.0030)
$R\&D_{t-1}$	0.0037***	0.0053***	0.0031***	0.0104***	-0.0004***	0.0042*	0.0090***	0.0166***	-0.0218***
	(0.0003)	(0.0006)	(0.0000)	(0.0002)	(0.0001)	(0.0022)	(0.0001)	(0.0002)	(0.0013)
$Inflation_{t-1}$	-0.0009***	0.0006***	-0.0020***	-0.0018***	-0.0001**	0.0033***	-0.0028***	0.0006***	-0.0040***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0003)	(0.0000)	(0.0000)	(0.0003)
FDI net_{t-1}	0.0012***	-0.0018***	0.0045***	-0.0013***	0.0053***	-0.0072***	-0.0000	-0.0014***	0.0217***
	(0.0002)	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0009)	(0.0000)	(0.0001)	(0.0004)
FI_{t-1}		0.6921***							
		(0.0120)							
FinTech $dummy_{t-2}$		**0.0083*** **							
		(0.0009)							
FM_{t-1}			0.5627***						
			(0.0001)						
FID_{t-1}				0.6284***					
				(0.0023)					
FIA_{t-1}					0.7532***				
					(0.0008)				
FIE_{t-1}						0.3620***			
						(0.0060)			
FMD_{t-1}							0.3870***		

							(0.0004)		
FMA_{t-1}								0.4929***	
								(0.0008)	
FME_{t-1}									0.3799***
									(0.0011)
Constant	-0.2132***	-0.4478***	0.1616***	-0.5638***	-0.3086***	-0.1291**	-0.1969***	0.3790***	0.0411
	(0.0190)	(0.0222)	(0.0044)	(0.0144)	(0.0099)	(0.0554)	(0.0113)	(0.0204)	(0.0680)
Observations	1,486	1,394	1,486	1,486	1,486	1,486	1,486	1,486	1,486
Number of countries	114	113	114	114	114	114	114	114	114

The table reports Arellano-Bond linear dynamic panel-data estimations using lags of the dependent variables as covariates. The estimations are implemented by computing the two-step estimators. The independent variables are lagged by one year. The Arellano-Bond estimator is used in the study to construct a linear dynamic panel-data model in which unobserved panel-level effects are linked with dependent variable lags. This estimator is intended for datasets with a large number of groups and few intervals, and it demands that there be no correlations in the idiosyncratic errors. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4: Controlling for the characteristics of global banking systems.
Panel A: Global banking stability and Growth

VARIABLES	(1) Bank Z Score	(2) Bank NPL	(3) Bank ROA	(4) Bank Z Score	(5) Bank NPL	(6) Bank ROA	(7) GDP growth	(8) GDP growth	(9) GDP growth	(10) GDP growth
Bank Z Score$_{t-1}$	0.0350			0.0231						
	(0.0219)			(0.0180)						
FinTech credits$_{t-1}$	**-0.0021**	**-0.4273*****	**-0.0773**				**-0.2113**		**0.2630**	
	(0.0407)	(0.1204)	(0.1032)				(0.5052)		(0.8136)	
Bank credit$_{t-1}$	-0.0085	0.6898***	-0.1984***	-0.0371***	0.7353***	-0.1547***	-8.1511***	-8.3638***	-5.2246***	-6.0250***
	(0.0148)	(0.0221)	(0.0468)	(0.0130)	(0.0289)	(0.0495)	(0.2534)	(0.2598)	(0.6941)	(0.7014)
Bank capital$_{t-1}$	-0.0044	0.2490***	-0.1993***	-0.0126	0.2391***	-0.1530***	-0.5899**	-0.2675	0.7972**	0.7723*
	(0.0102)	(0.0174)	(0.0225)	(0.0130)	(0.0155)	(0.0404)	(0.2560)	(0.2763)	(0.3570)	(0.4349)
Bank concentration$_{t-1}$	0.1053***	-0.0334**	-0.0490**	0.0937***	-0.0378**	-0.0821***	0.3659***	0.2110*	0.7456***	0.4870
	(0.0079)	(0.0141)	(0.0207)	(0.0077)	(0.0169)	(0.0186)	(0.1028)	(0.1173)	(0.2872)	(0.3304)
Bank crisis$_{t-1}$	-0.0702***	0.1065***	-0.0848***	-0.0647***	0.1031***	-0.0502**	-2.2965***	-2.2756***	-2.4984***	-2.5721***
	(0.0070)	(0.0186)	(0.0320)	(0.0114)	(0.0175)	(0.0251)	(0.1626)	(0.1857)	(0.2241)	(0.3701)
Bank deposit$_{t-1}$	0.0063	0.1138**	-0.1876*	0.0265**	0.0743*	-0.1245	-0.7446***	-0.5642***	0.1004	0.1846
	(0.0091)	(0.0487)	(0.1086)	(0.0117)	(0.0379)	(0.1104)	(0.1012)	(0.1576)	(0.5300)	(0.4287)
Bank liquidity$_{t-1}$	0.0525***	-0.1031***	0.1065***	0.0468***	-0.0981***	0.0754***	1.9535***	2.0618***	1.2709***	1.0740***
	(0.0076)	(0.0126)	(0.0177)	(0.0069)	(0.0141)	(0.0202)	(0.2203)	(0.0868)	(0.3238)	(0.3334)
Bank cost to income$_{t-1}$	0.0028	-0.1152***	-0.4339***	0.0076	-0.1280***	-0.4097***	-0.1783	-0.2353	-0.1391	-0.2545
	(0.0147)	(0.0241)	(0.0453)	(0.0125)	(0.0208)	(0.0413)	(0.1221)	(0.1438)	(0.2527)	(0.2258)
Income$_{t-1}$	0.0166	-0.1371***	-0.0448***	0.0104	-0.1607***	-0.0814***			-4.1069***	-4.1695***
	(0.0115)	(0.0197)	(0.0170)	(0.0108)	(0.0249)	(0.0199)			(0.2854)	(0.3383)
Broad money$_{t-1}$	0.0811***	0.2278***	-0.3854***	0.0231	0.2506***	-0.4854***			5.7433***	5.6327***
	(0.0190)	(0.0670)	(0.1164)	(0.0167)	(0.0511)	(0.1264)			(0.6543)	(0.9299)
Unemployment$_{t-1}$	0.0646***	-0.1927***	0.0789***	0.0772***	-0.1965***	0.1301***			4.3435***	4.3426***
	(0.0101)	(0.0173)	(0.0277)	(0.0111)	(0.0351)	(0.0331)			(0.3728)	(0.3158)
Labor force$_{t-1}$	0.1024	0.1179	-0.3804	0.0379	-0.0064	-0.6098*			-8.5202***	-11.148***
	(0.1268)	(0.3221)	(0.4073)	(0.1432)	(0.3330)	(0.3531)			(2.2028)	(2.1714)
Industry$_{t-1}$	-0.0343***	0.1765**	0.7482***	-0.0375	0.2915***	0.9801***			-0.1370	-0.5976
	(0.0131)	(0.0881)	(0.1012)	(0.0268)	(0.0674)	(0.1340)			(0.9297)	(0.8281)
Trade$_{t-1}$	0.0590***	-0.1898***	0.4556***	0.0676***	-0.1989***	0.4612***			-0.2161	-0.3476
	(0.0081)	(0.0320)	(0.0470)	(0.0120)	(0.0390)	(0.0712)			(0.4912)	(0.4934)
R&D$_{t-1}$	0.0227***	-0.0084	0.0651***	0.0269***	-0.0189*	0.0995***			-0.1552	-0.3551
	(0.0051)	(0.0118)	(0.0143)	(0.0048)	(0.0097)	(0.0190)			(0.2277)	(0.4132)
Inflation$_{t-1}$	-0.0018	0.0190***	-0.0263***	0.0017	0.0143***	-0.0318***			0.0530	0.0788*
	(0.0018)	(0.0033)	(0.0055)	(0.0019)	(0.0026)	(0.0057)			(0.0470)	(0.0434)

FDI net$_{t-1}$	-0.0001	0.0008	-0.1168***	-0.0009	0.0009	-0.1046***			0.2961***	0.3179***
	(0.0024)	(0.0041)	(0.0057)	(0.0025)	(0.0047)	(0.0072)			(0.0697)	(0.0567)
Bank NPL$_{t-1}$		0.7151***			0.6949***					
		(0.0162)			(0.0149)					
Bank ROA$_{t-1}$			-0.0933***			-0.0893***				
			(0.0115)			(0.0133)				
FinTech dummy$_{t-1}$				**0.0404*****	**-0.0145***	**-0.0255****		**-0.1085**		**-0.2931**
				(0.0041)	(0.0076)	(0.0117)		(0.1284)		(0.1888)
GFP growth$_{t-1}$							0.1098***	0.1040***	0.0436***	0.0277*
							(0.0064)	(0.0061)	(0.0145)	(0.0161)
Constant	0.8886	-2.4605*	3.7192*	1.5648**	-2.0989	4.0479***	37.7949***	37.9527***	58.5635***	78.7078***
	(0.6320)	(1.2557)	(1.9194)	(0.6927)	(1.4734)	(1.5266)	(2.0535)	(1.7418)	(12.0218)	(10.5997)
Observations	866	853	816	866	853	816	1,167	1,167	877	877
Number of countries	90	91	89	90	91	89	108	108	91	91

The table reports Arellano-Bond linear dynamic panel-data estimations using lags of the dependent variables as covariates. The estimations are implemented by computing the two-step estimators. The independent variables are lagged by one year. The Arellano-Bond estimator is used in the study to construct a linear dynamic panel-data model in which unobserved panel-level effects are linked with dependent variable lags. This estimator is intended for datasets with a large number of groups and few intervals, and it demands that there be no correlations in the idiosyncratic errors. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4: Controlling for the characteristics of global banking systems
Panel B: Continuous FinTech and Big Tech Credit Glows

VARIABLES	(1) **FD**	(2) **FI**	(3) **FM**	(4) **FID**	(5) **FIA**	(6) **FIE**	(7) **FMD**	(8) **FMA**	(9) **FME**
FD_{t-1}	0.5064***								
	(0.0120)								
FinTech $credits_{t-1}$	**0.0057****	**0.0068**	**-0.0044*****	**-0.0016***	**-0.0193*****	**0.0773*****	**-0.0363*****	**0.0017**	**0.0320*****
	(0.0026)	(0.0051)	(0.0010)	(0.0008)	(0.0016)	(0.0272)	(0.0013)	(0.0014)	(0.0053)
Bank $credit_{t-1}$	-0.0097***	-0.0257***	0.0003	-0.0129***	0.0070***	-0.0797***	0.0278***	0.0113***	0.0251***
	(0.0020)	(0.0027)	(0.0007)	(0.0011)	(0.0017)	(0.0036)	(0.0016)	(0.0011)	(0.0080)
Bank $capital_{t-1}$	0.0005	0.0082***	0.0002	-0.0041***	-0.0037***	0.0217***	-0.0157***	0.0081***	-0.0137***
	(0.0014)	(0.0016)	(0.0008)	(0.0011)	(0.0014)	(0.0021)	(0.0009)	(0.0009)	(0.0022)
Bank $concentration_{t-1}$	-0.0110***	0.0031*	-0.0120***	0.0043***	0.0053***	-0.0212***	-0.0069***	0.0148***	-0.0298***
	(0.0018)	(0.0016)	(0.0006)	(0.0010)	(0.0015)	(0.0047)	(0.0012)	(0.0004)	(0.0069)
Bank $crisis_{t-1}$	0.0041***	-0.0074***	0.0144***	0.0050***	-0.0096***	-0.0263***	0.0205***	-0.0018***	0.0350***
	(0.0009)	(0.0010)	(0.0006)	(0.0006)	(0.0008)	(0.0031)	(0.0007)	(0.0004)	(0.0019)
Bank $deposit_{t-1}$	-0.0057*	-0.0097**	-0.0017*	-0.0001	0.0212***	-0.0477***	-0.0042**	0.0018**	0.0092
	(0.0029)	(0.0046)	(0.0010)	(0.0016)	(0.0032)	(0.0058)	(0.0018)	(0.0008)	(0.0114)
Bank $liquidity_{t-1}$	0.0002	-0.0055***	0.0098***	0.0051***	-0.0065***	-0.0089***	-0.0095***	0.0077***	0.0423***
	(0.0010)	(0.0010)	(0.0003)	(0.0006)	(0.0005)	(0.0029)	(0.0004)	(0.0004)	(0.0021)
Bank cost to $income_{t-1}$	0.0025**	0.0064***	0.0009***	-0.0015	0.0103***	0.0007	-0.0055***	-0.0059***	0.0030
	(0.0010)	(0.0023)	(0.0003)	(0.0012)	(0.0010)	(0.0063)	(0.0012)	(0.0006)	(0.0032)
$Income_{t-1}$	0.0220***	0.0339***	0.0044***	0.0309***	0.0408***	0.0027	0.0254***	-0.0083***	-0.0071***
	(0.0015)	(0.0019)	(0.0003)	(0.0007)	(0.0015)	(0.0034)	(0.0006)	(0.0003)	(0.0016)
Broad $money_{t-1}$	0.0088***	0.0299***	-0.0127***	0.0083***	0.0072*	0.0550***	0.0052	-0.0092***	-0.0170
	(0.0029)	(0.0058)	(0.0011)	(0.0020)	(0.0038)	(0.0060)	(0.0033)	(0.0008)	(0.0114)
$Unemployment_{t-1}$	0.0025*	0.0005	0.0053***	0.0021**	0.0010	-0.0151***	0.0060***	0.0048***	-0.0140***
	(0.0013)	(0.0020)	(0.0005)	(0.0009)	(0.0010)	(0.0036)	(0.0010)	(0.0008)	(0.0029)
Labor $force_{t-1}$	0.0022	0.0669***	-0.0959***	0.0167**	0.0359***	0.2143***	-0.2295***	-0.1027***	-0.0540**
	(0.0098)	(0.0114)	(0.0052)	(0.0070)	(0.0041)	(0.0298)	(0.0152)	(0.0077)	(0.0266)
$Industry_{t-1}$	0.0134***	0.0144***	0.0274***	-0.0001	0.0279***	0.0188*	-0.0035	0.0254***	0.0650***
	(0.0038)	(0.0038)	(0.0027)	(0.0018)	(0.0030)	(0.0097)	(0.0031)	(0.0030)	(0.0075)
$Trade_{t-1}$	0.0238***	0.0094***	0.0321***	-0.0083***	0.0027	0.0235***	0.0350***	0.0387***	0.0236***
	(0.0012)	(0.0021)	(0.0005)	(0.0019)	(0.0019)	(0.0043)	(0.0008)	(0.0016)	(0.0037)
$R\&D_{t-1}$	0.0046***	0.0051***	0.0038***	0.0123***	-0.0004	0.0137**	0.0096***	0.0241***	-0.0231***
	(0.0005)	(0.0006)	(0.0002)	(0.0005)	(0.0005)	(0.0054)	(0.0002)	(0.0004)	(0.0013)
$Inflation_{t-1}$	-0.0003	0.0013***	-0.0027***	-0.0011***	0.0002	0.0059***	-0.0016***	-0.0021***	-0.0048***
	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0005)

FDI net$_{t-1}$	0.0023***	-0.0019***	0.0055***	-0.0026***	0.0081***	-0.0075***	0.0017***	-0.0055***	0.0243***
	(0.0002)	(0.0005)	(0.0001)	(0.0002)	(0.0003)	(0.0011)	(0.0002)	(0.0002)	(0.0012)
FI$_{t-1}$		0.5614***							
		(0.0169)							
FM$_{t-1}$			0.4699***						
			(0.0016)						
FID$_{t-1}$				0.5481***					
				(0.0084)					
FIA$_{t-1}$					0.6582***				
					(0.0049)				
FIE$_{t-1}$						0.2490***			
						(0.0234)			
FMD$_{t-1}$							0.3887***		
							(0.0026)		
FMA$_{t-1}$								0.5049***	
								(0.0022)	
FME$_{t-1}$									0.2871***
									(0.0031)
Constant	-0.1242**	-0.4768***	0.3137***	-0.1686***	-0.6581***	-0.2457**	0.7289***	0.2515***	0.0697
	(0.0492)	(0.0440)	(0.0267)	(0.0300)	(0.0288)	(0.1204)	(0.0687)	(0.0287)	(0.1068)
Observations	877	877	877	877	877	877	877	877	877
Number of countries	91	91	91	91	91	91	91	91	91

The table reports Arellano-Bond linear dynamic panel-data estimations using lags of the dependent variables as covariates. The estimations are implemented by computing the two-step estimators. The independent variables are lagged by one year. The Arellano-Bond estimator is used in the study to construct a linear dynamic panel-data model in which unobserved panel-level effects are linked with dependent variable lags. This estimator is intended for datasets with a large number of groups and few intervals, and it demands that there be no correlations in the idiosyncratic errors. Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Controlling for the characteristics of global banking systems
Panel C: A dummy variable of FinTech and Big Tech Credit Flows

VARIABLES	(1) FD	(2) FI	(3) FM	(4) FID	(5) FIA	(6) FIE	(7) FMD	(8) FMA	(9) FME
FD_{t-1}	0.4729***								
	(0.0164)								
FinTech $dummy_{t-1}$	**0.0084*****		**0.0101*****	**0.0087*****	**-0.0023****	**0.0247*****	**0.0121*****	**0.0007**	**0.0117*****
	(0.0009)		(0.0002)	(0.0006)	(0.0009)	(0.0026)	(0.0003)	(0.0004)	(0.0016)
Bank $credit_{t-1}$	-0.0126***	-0.0261***	0.0018**	-0.0115***	0.0083***	-0.0742***	0.0315***	0.0115***	0.0129**
	(0.0016)	(0.0029)	(0.0009)	(0.0012)	(0.0018)	(0.0040)	(0.0021)	(0.0011)	(0.0059)
Bank $capital_{t-1}$	-0.0011	0.0065***	-0.0019**	-0.0063***	-0.0031***	0.0207***	-0.0174***	0.0095***	-0.0158***
	(0.0014)	(0.0015)	(0.0007)	(0.0009)	(0.0008)	(0.0024)	(0.0015)	(0.0009)	(0.0034)
Bank $concentration_{t-1}$	-0.0099***	0.0011	-0.0116***	0.0048***	0.0038***	-0.0218***	-0.0055***	0.0162***	-0.0419***
	(0.0016)	(0.0017)	(0.0010)	(0.0010)	(0.0009)	(0.0038)	(0.0020)	(0.0006)	(0.0038)
Bank $crisis_{t-1}$	0.0049***	-0.0096***	0.0152***	0.0047***	-0.0097***	-0.0246***	0.0223***	-0.0020***	0.0403***
	(0.0009)	(0.0011)	(0.0006)	(0.0002)	(0.0010)	(0.0025)	(0.0007)	(0.0004)	(0.0036)
Bank $deposit_{t-1}$	-0.0065***	-0.0154***	-0.0039***	0.0015	0.0177***	-0.0478***	-0.0069**	0.0017	0.0035
	(0.0023)	(0.0048)	(0.0009)	(0.0011)	(0.0030)	(0.0043)	(0.0028)	(0.0016)	(0.0161)
Bank $liquidity_{t-1}$	0.0023**	-0.0057***	0.0118***	0.0050***	-0.0054***	-0.0060**	-0.0060***	0.0084***	0.0453***
	(0.0010)	(0.0010)	(0.0003)	(0.0007)	(0.0007)	(0.0026)	(0.0003)	(0.0004)	(0.0018)
Bank cost to $income_{t-1}$	0.0034***	0.0062***	0.0010***	-0.0001	0.0107***	-0.0005	-0.0048***	-0.0065***	0.0003
	(0.0011)	(0.0023)	(0.0003)	(0.0011)	(0.0006)	(0.0048)	(0.0014)	(0.0005)	(0.0047)
$Income_{t-1}$	0.0228***	0.0379***	0.0040***	0.0314***	0.0416***	0.0035	0.0254***	-0.0085***	-0.0106***
	(0.0015)	(0.0018)	(0.0004)	(0.0006)	(0.0016)	(0.0033)	(0.0006)	(0.0002)	(0.0019)
Broad $money_{t-1}$	0.0077**	0.0390***	-0.0141***	0.0058***	0.0118***	0.0457***	0.0016	-0.0087***	-0.0140
	(0.0033)	(0.0062)	(0.0011)	(0.0020)	(0.0029)	(0.0067)	(0.0035)	(0.0018)	(0.0175)
$Unemployment_{t-1}$	0.0024***	0.0052***	0.0064***	0.0033***	0.0008	-0.0105***	0.0079***	0.0059***	-0.0159***
	(0.0008)	(0.0017)	(0.0007)	(0.0010)	(0.0010)	(0.0033)	(0.0012)	(0.0010)	(0.0037)
Labor $force_{t-1}$	-0.0131	0.0622***	-0.0942***	0.0290***	0.0413***	0.1521***	-0.2234***	-0.1041***	-0.0483*
	(0.0107)	(0.0108)	(0.0058)	(0.0070)	(0.0045)	(0.0312)	(0.0164)	(0.0036)	(0.0250)
$Industry_{t-1}$	0.0127***	0.0167***	0.0310***	0.0024	0.0277***	0.0141	0.0020	0.0272***	0.0673***
	(0.0035)	(0.0038)	(0.0021)	(0.0027)	(0.0030)	(0.0091)	(0.0032)	(0.0026)	(0.0088)
$Trade_{t-1}$	0.0250***	0.0093***	0.0357***	-0.0050***	0.0025	0.0224***	0.0398***	0.0409***	0.0190***
	(0.0016)	(0.0021)	(0.0009)	(0.0019)	(0.0019)	(0.0050)	(0.0012)	(0.0010)	(0.0036)
$R\&D_{t-1}$	0.0043***	0.0054***	0.0033***	0.0115***	-0.0005	0.0100**	0.0082***	0.0237***	-0.0245***
	(0.0006)	(0.0006)	(0.0001)	(0.0004)	(0.0004)	(0.0049)	(0.0005)	(0.0004)	(0.0018)
$Inflation_{t-1}$	-0.0001	0.0015***	-0.0029***	-0.0013***	0.0004*	0.0056***	-0.0019***	-0.0024***	-0.0046***
	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0007)	(0.0003)	(0.0001)	(0.0005)
FDI net_{t-1}	0.0023***	-0.0019***	0.0052***	-0.0024***	0.0079***	-0.0072***	0.0018***	-0.0058***	0.0252***
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0011)	(0.0003)	(0.0002)	(0.0011)
FI_{t-1}		0.5244***							
		(0.0183)							
FinTech $dummy_{t-2}$		**0.0088*****							

		(0.0010)							
FM_{t-1}			0.4731***						
			(0.0010)						
FID_{t-1}				0.5173***					
				(0.0049)					
FIA_{t-1}					0.6555***				
					(0.0055)				
FIE_{t-1}						0.2700***			
						(0.0173)			
FMD_{t-1}							0.3797***		
							(0.0020)		
FMA_{t-1}								0.5001***	
								(0.0010)	
FME_{t-1}									0.2929***
									(0.0022)
Constant	-0.0458	-0.4936***	0.2855***	-0.2445***	-0.6957***	0.0204	0.6519***	0.2384***	0.2111
	(0.0495)	(0.0481)	(0.0258)	(0.0369)	(0.0312)	(0.1150)	(0.0593)	(0.0159)	(0.1655)
Observations	877	833	877	877	877	877	877	877	877
Number of countries	91	91	91	91	91	91	91	91	91

The table reports Arellano-Bond linear dynamic panel-data estimations using lags of the dependent variables as covariates. The estimations are implemented by computing the two-step estimators. The independent variables are lagged by one year. The Arellano-Bond estimator is used in the study to construct a linear dynamic panel-data model in which unobserved panel-level effects are linked with dependent variable lags. This estimator is intended for datasets with a large number of groups and few intervals, and it demands that there be no correlations in the idiosyncratic errors. Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix 1: List of sample countries [1996-2019]

	Country Name	Freq.	Percent	Cum.
1	Albania	21	0.75	0.75
2	Algeria	21	0.75	1.49
3	Angola	21	0.75	2.24
4	Argentina	21	0.75	2.99
5	Armenia	21	0.75	3.73
6	Australia	21	0.75	4.48
7	Austria	21	0.75	5.22
8	Azerbaijan	21	0.75	5.97
9	Bangladesh	21	0.75	6.72
10	Belarus	21	0.75	7.46
11	Belgium	21	0.75	8.21
12	Benin	21	0.75	8.96
13	Bolivia	21	0.75	9.7
14	Bosnia and Herzegovina	21	0.75	10.45
15	Botswana	21	0.75	11.19
16	Brazil	21	0.75	11.94
17	Bulgaria	21	0.75	12.69
18	Burkina Faso	21	0.75	13.43
19	Burundi	21	0.75	14.18
20	Cambodia	21	0.75	14.93
21	Cameroon	21	0.75	15.67
22	Canada	21	0.75	16.42
23	Central African Republic	21	0.75	17.16
24	Chad	21	0.75	17.91
25	Chile	21	0.75	18.66
26	China	21	0.75	19.4
27	Colombia	21	0.75	20.15
28	Congo, Rep.	21	0.75	20.9
29	Costa Rica	21	0.75	21.64
30	Croatia	21	0.75	22.39
31	Czechia	21	0.75	23.13
32	Denmark	21	0.75	23.88
33	Dominican Republic	21	0.75	24.63
34	Ecuador	21	0.75	25.37
35	Egypt, Arab Rep.	21	0.75	26.12
36	El Salvador	21	0.75	26.87
37	Eritrea	21	0.75	27.61
38	Ethiopia	21	0.75	28.36
39	Finland	21	0.75	29.1
40	France	21	0.75	29.85
41	Gabon	21	0.75	30.6
42	Gambia, The	21	0.75	31.34

43	Georgia	21	0.75	32.09
44	Germany	21	0.75	32.84
45	Ghana	21	0.75	33.58
46	Greece	21	0.75	34.33
47	Guatemala	21	0.75	35.07
48	Guinea	21	0.75	35.82
49	Guinea-Bissau	21	0.75	36.57
50	Haiti	21	0.75	37.31
51	Honduras	21	0.75	38.06
52	Hungary	21	0.75	38.81
53	India	21	0.75	39.55
54	Indonesia	21	0.75	40.3
55	Iran, Islamic Rep.	21	0.75	41.04
56	Ireland	21	0.75	41.79
57	Israel	21	0.75	42.54
58	Italy	21	0.75	43.28
59	Jamaica	21	0.75	44.03
60	Japan	21	0.75	44.78
61	Jordan	21	0.75	45.52
62	Kazakhstan	21	0.75	46.27
63	Kenya	21	0.75	47.01
64	Korea, Rep.	21	0.75	47.76
65	Kuwait	21	0.75	48.51
66	Kyrgyz Republic	21	0.75	49.25
67	Lao PDR	21	0.75	50
68	Latvia	21	0.75	50.75
69	Lebanon	21	0.75	51.49
70	Lesotho	21	0.75	52.24
71	Liberia	21	0.75	52.99
72	Libya	21	0.75	53.73
73	Lithuania	21	0.75	54.48
74	Madagascar	21	0.75	55.22
75	Malawi	21	0.75	55.97
76	Malaysia	21	0.75	56.72
77	Mali	21	0.75	57.46
78	Mauritania	21	0.75	58.21
79	Mexico	21	0.75	58.96
80	Moldova	21	0.75	59.7
81	Mongolia	21	0.75	60.45
82	Morocco	21	0.75	61.19
83	Mozambique	21	0.75	61.94
84	Myanmar	21	0.75	62.69
85	Namibia	21	0.75	63.43
86	Nepal	21	0.75	64.18

87	Netherlands	21	0.75	64.93
88	New Zealand	21	0.75	65.67
89	Nicaragua	21	0.75	66.42
90	Niger	21	0.75	67.16
91	Nigeria	21	0.75	67.91
92	North Macedonia	21	0.75	68.66
93	Norway	21	0.75	69.4
94	Oman	21	0.75	70.15
95	Pakistan	21	0.75	70.9
96	Panama	21	0.75	71.64
97	Papua New Guinea	21	0.75	72.39
98	Paraguay	21	0.75	73.13
99	Peru	21	0.75	73.88
100	Philippines	21	0.75	74.63
101	Poland	21	0.75	75.37
102	Portugal	21	0.75	76.12
103	Qatar	21	0.75	76.87
104	Russian Federation	21	0.75	77.61
105	Rwanda	21	0.75	78.36
106	Saudi Arabia	21	0.75	79.1
107	Senegal	21	0.75	79.85
108	Sierra Leone	21	0.75	80.6
109	Singapore	21	0.75	81.34
110	Slovak Republic	21	0.75	82.09
111	Slovenia	21	0.75	82.84
112	South Africa	21	0.75	83.58
113	Spain	21	0.75	84.33
114	Sri Lanka	21	0.75	85.07
115	Sudan	21	0.75	85.82
116	Sweden	21	0.75	86.57
117	Switzerland	21	0.75	87.31
118	Tajikistan	21	0.75	88.06
119	Tanzania	21	0.75	88.81
120	Thailand	21	0.75	89.55
121	Togo	21	0.75	90.3
122	Tunisia	21	0.75	91.04
123	Turkmenistan	21	0.75	91.79
124	Uganda	21	0.75	92.54
125	Ukraine	21	0.75	93.28
126	United Arab Emirates	21	0.75	94.03
127	United Kingdom	21	0.75	94.78
128	United States	21	0.75	95.52
129	Uruguay	21	0.75	96.27
130	Uzbekistan	21	0.75	97.01

131	Venezuela, RB	21	0.75	97.76
132	Vietnam	21	0.75	98.51
133	Yemen, Rep.	21	0.75	99.25
134	Zambia	21	0.75	100
	Total	2,814	100	

Appendix A2: Definitions of variables used.

Variable	Definition
Bank Z Score	The logarithm value of one plus Bank Z Score [GFDD.SI.01]
Bank NPL	The logarithm value of one plus Bank non-performing loans to gross loans (%) [GFDD.SI.02]
Bank ROA	The logarithm value of one plus Bank return on assets (%, after tax) [GFDD.EI.05]
GDP growth	GDP growth (annual %) [NY.GDP.MKTP.KD.ZG]
FD	FD: Financial development index
FI	FI: Financial institutions
FM	FM: Financial markets
FID	FID: Financial institutions depth
FIA	FIA: Financial institutions access
FIE	FIE: Financial institutions efficiency
FMD	FMD: Financial markets depth
FMA	FMA: Financial markets access
FME	FME: Financial markets efficiency
FinTech credits	The logarithm value of one plus Credit flows by fintech and big tech companies to GDP (%) [GFDD.DM.16]
Income	The logarithm value of one plus GDP per capita (current US$) [NY.GDP.PCAP.CD]
Broad money	The logarithm value of one plus Broad money (% of GDP) [FM.LBL.BMNY.GD.ZS]
Unemployment	The logarithm value of one plus Unemployment, total (% of total labor force) (modeled ILO estimate) [SL.UEM.TOTL]
Labor force	The logarithm value of one plus Labor force participation rate, total (% of total population ages 15-64)
Industry	The logarithm value of one plus Industry (including construction), value added (% of GDP) [NV.IND.TOTL.ZS]
Trade	The logarithm value of one plus Trade (% of GDP) [NE.TRD.GNFS.ZS]
R&D	The logarithm value of one plus Research and development expenditure (% of GDP) [GB.XPD.RSDV.GD.ZS]
Inflation	The logarithm value of one plus Inflation, GDP deflator (annual %) [NY.GDP.DEFL.KD.ZG]
FDI net	The logarithm value of one plus Foreign direct investment, net inflows (% of GDP) [BX.KLT.DINV.WD.GD.ZS]
Bank credit	The logarithm value of one plus Bank credit to bank deposits (%) [GFDD.SI.04]
Bank capital	The logarithm value of one plus Bank capital to total assets (%) [GFDD.SI.03]
Bank concentration	The logarithm value of one plus Bank concentration (%) [GFDD.OI.01]
Bank crisis	The logarithm value of one plus Banking crisis dummy (1=banking crisis, 0=none) [GFDD.OI.19]
Bank deposit	The logarithm value of one plus Bank deposits to GDP (%) [GFDD.OI.02]
Bank liquidity	The logarithm value of one plus Liquid assets to deposits and short-term funding (%) [GFDD.SI.06]
Bank cost to income	The logarithm value of one plus Bank cost to income ratio (%) [GFDD.EI.07]

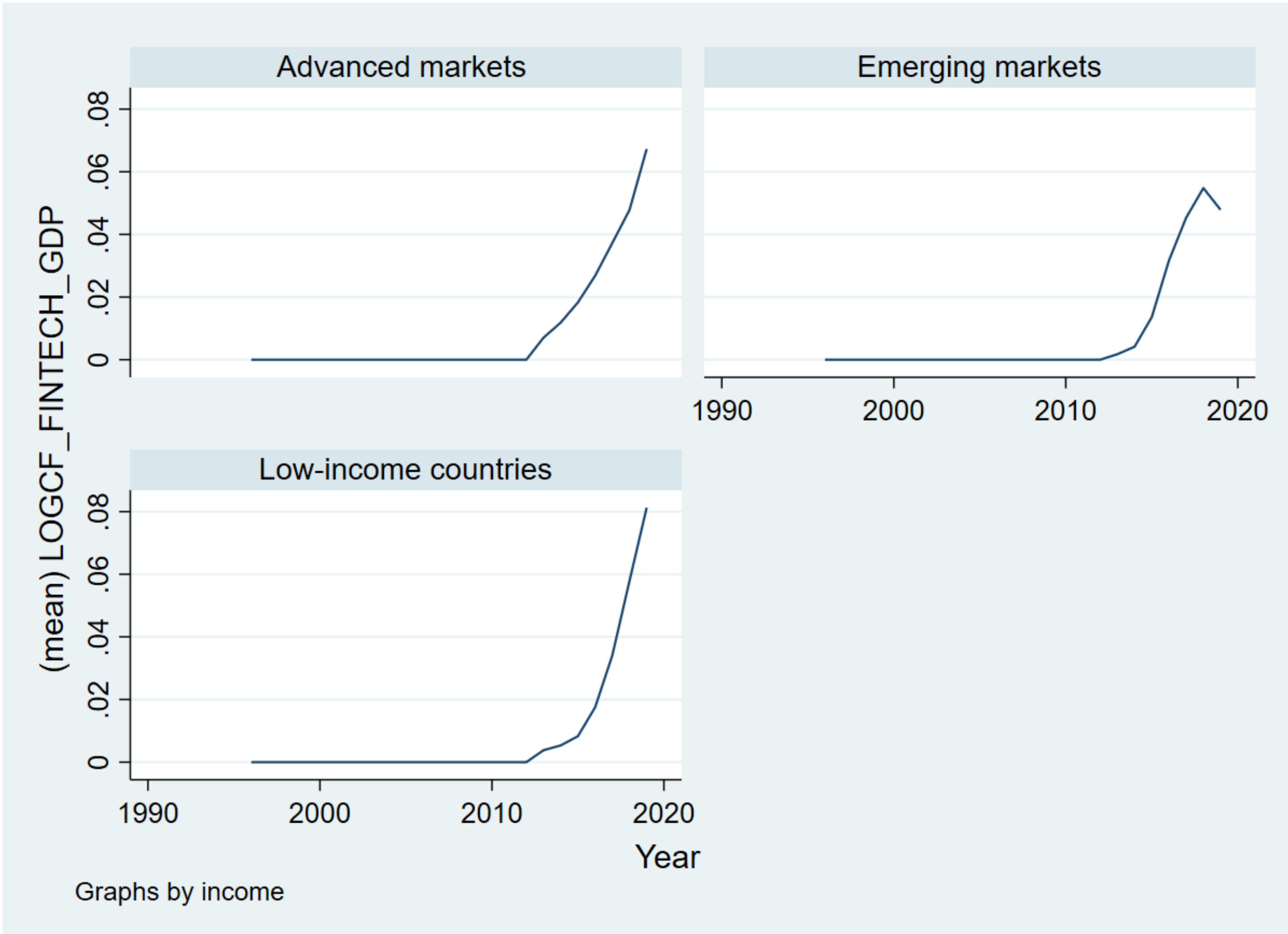

Figure 1: Credit flows by fintech and big tech companies to GDP (%) by income group [GFDD.DM.16].
Source: Authors' work.

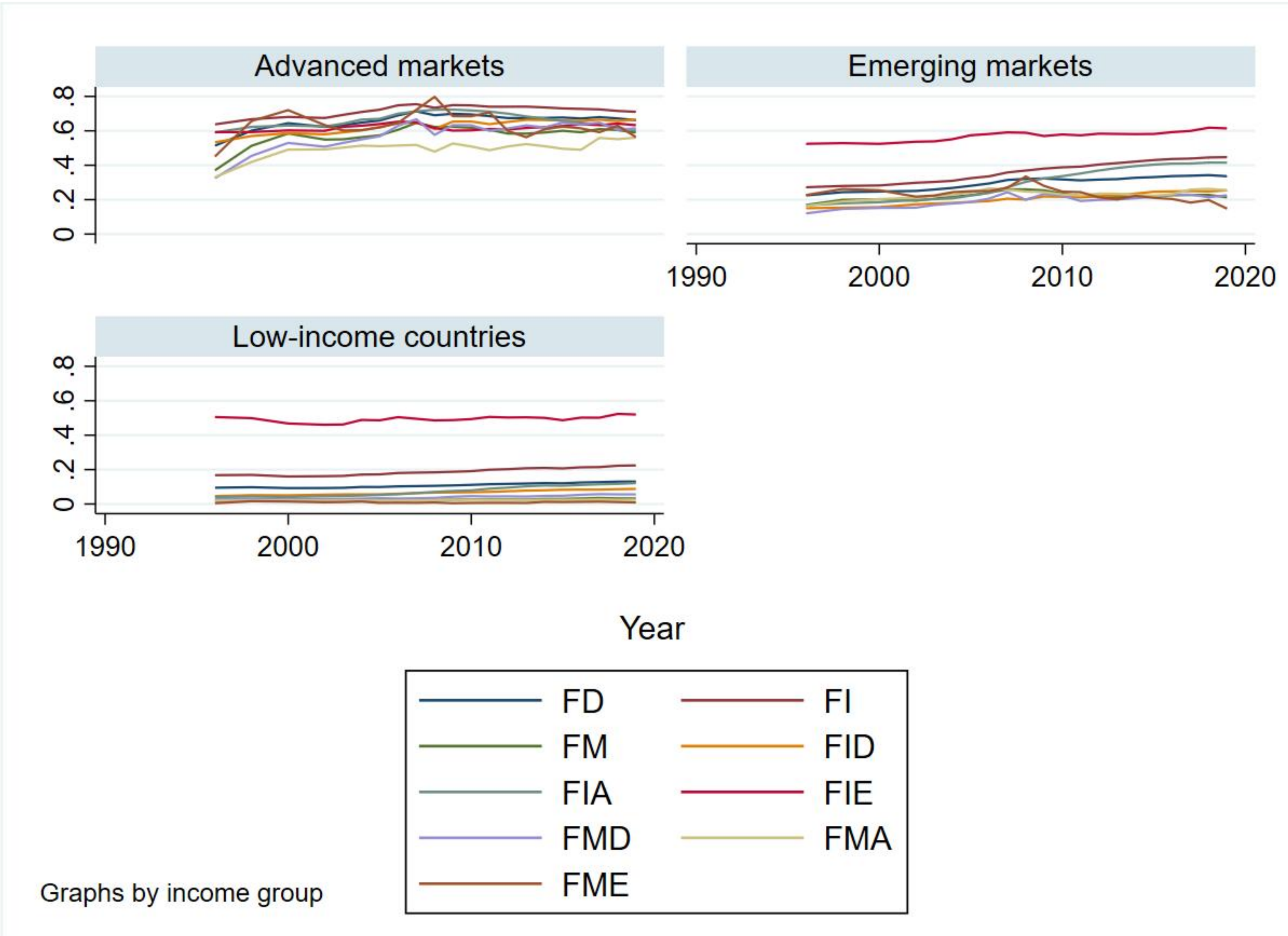

Figure 2: Broad-based financial development indexes by income group. Source: Authors' work.

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