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Opening Up: Capital Flows and Financial Sector Dynamics in Low-Income Developing Countries

by Sebastian Horn and Futoshi Narita

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Opening Up: Capital Flows and Financial Sector Dynamics in Low-Income Developing Countries [*]

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Abstract

Over the past two decades, many low-income developing countries have substantially increased openness towards external financing and have received large capital inflows. Using bank-level micro data, this paper finds that capital inflows have been associated with financial deepening through increases in bank loans, deposits, and wholesale funding. Domestic banks increase loans more than foreign banks. There are only modest signs of a build-up in financial vulnerabilities. Causality is examined through an instrumental variable approach and an augmented inverse-probability weighting estimator. These approaches indicate only limited evidence for global push effects, pointing towards the importance of domestic pull factors.

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Keywords: Capital flows, credit growth, low-income developing countries, capital account liberalization, financial stability

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I. Introduction

Prior to the COVID-19 crisis many low-income developing countries (LIDCs) experienced almost two decades of strong economic growth. Average real GDP growth in LIDCs exceeded 6 percent since the year 2000 until commodity prices started to collapse in mid-2014. During this period of high growth, many LIDCs initiated institutional reforms and have gradually taken off restrictions on cross-border capital transactions and have opened up toward non-traditional forms of capital inflows.

With their continuous liberalization of the capital account, LIDCs have been enjoying large capital inflows from more diversified sources than in the past. While de jure capital account openness does not necessarily lead to an increase in capital flows, total capital inflows to LIDCs more than doubled from 2 percent of GDP on average in the early 2000s to 5 percent of GDP during the period of 2005 to 2015, with a temporary decline during the global financial crisis (IMF, 2015, 3rd chapter). This increase in capital inflows has come along with a diversification of funding sources. For decades, capital flows to LIDCs had been dominated by loans from traditional bilateral and multilateral donors as well as by foreign direct investment (FDI). Since the onset of the global financial crisis, however, highly accommodative monetary policy stances in financial centers and ample global liquidity supported the flow of non-FDI private capital into financial markets in LIDCs. Several frontier markets—the most open and developed LIDCs—were able to issue sovereign bonds in international capital markets for the first time in decades (Presbitero and others, 2016). At the same time, lending to LIDCs from non-Paris Club bilateral creditors has surged (Cerutti, Koch and Pradhan, 2018; Horn, Reinhart and Trebesch, 2019).

Capital inflows to LIDCs have the advantage of supplementing scarce domestic savings in capital-constrained economies. They can promote financial deepening by stimulating private credit creation through banks, which—in the absence of deep domestic financial markets—usually represent one of the key sources of domestic financing (Gori, Li, and Presbitero, 2015). In a macroeconomic environment severely constrained by low levels of financial development, such an increase in credit extension can have significant welfare effects by creating employment opportunities and alleviating poverty (Banerjee and Duflo, 2014).

At the same time, however, the experiences of emerging market economies (EMEs) give rise to concerns about increased financial vulnerabilities due to volatile capital flows. A broad empirical and theoretical literature shows how surges in capital flows can trigger boom-and-bust cycles in recipient economies and lead to the build-up of financial vulnerabilities (Reinhart and Reinhart, 2008; Jordà, Schularick, and Taylor, 2011; Ghosh, Ostry, and Qureshi, 2016;

Reinhart, Reinhart, and Trebesch, 2016; Korinek, 2018; Eberhardt and Presbitero, 2021). Non-FDI capital flows to LIDCs are generally pro-cyclical (Araujo and others, 2017a, b), and for the subgroup of frontier markets now closely resemble those to EMEs in terms of volatility and synchronicity with global factors (Abidi, Hacibedel, and Mwanza, 2016). As a consequence, the experiences of EMEs in managing capital flows are becoming increasingly relevant to LIDCs.

With these contrasting mechanisms in mind, this paper uses bank-level micro data from *Fitch Fundamental Financial Data* to analyze LIDC financial sector dynamics under capital inflows. Micro data allow us to generate a more granular picture of financial developments and potential financial vulnerabilities in LIDCs by studying the effects of capital inflows on both the asset and the liability sides of the financial sector. The micro data also allow to analyze to what extent banks with different characteristics respond differently to capital inflows. The banking systems in LIDCs strongly differ from those in more financially developed countries in terms of bank size, ownership, and funding structures (Barajas and others, 2013; Agarwal, Duttagupta and Presbitero, 2019), and these LIDC-specific bank characteristics may help understand the overall financial sector dynamics.

Our results show that gross capital inflows to LIDCs were associated with economically and statistically significant financial deepening, with only modest signs of a build-up in financial vulnerabilities. Capital flows were associated with increases in loans, deposits, and wholesale funding. Interestingly, the credit expansion upon capital inflows is more substantial at domestic banks than at foreign banks. We find a marginal increase in the loan-to-deposit ratio—a measure of liquidity risk—but only limited evidence for statistically significant worsening in other financial soundness indicators. These results emphasize the important role that capital flows can play in promoting financial deepening of low-income countries, while pointing towards only weak evidence on a potential increase in financial vulnerabilities. We still note, however, that it is in general difficult to capture financial stability risks ex ante. In particular, our results need to be revisited in the light of the COVID-19 crisis, once financial sector data for 2020 becomes available.

We also examine causality of our main findings, employing two distinct approaches. In exploring the implications of capital flows, a key challenge is to disentangle the push effect of global capital flows from the pull effects of local credit demand, i.e., to identify a causal effect from global capital flows to the local financial sector. We tackle this issue of two-way causalities by first using an instrumental variable strategy based on the synchronicity of international capital flows to regions. Second, we use the augmented inverse-probability weighting (AIPW) estimator, originally credited to biostatisticians (Robins, Rotnitzky and Zhao 1994), introduced to social science (e.g., Glynn and Quinn, 2010), and recently used in macroeconomic empirical analyses (Jordà and Taylor, 2016; Alam and others, 2019). While both estimation procedures have caveats, they suggest only weak evidence of a causal effect from global capital flows to domestic financial conditions (see details in Section IV). In other words, the observed financial deepening may not be mainly caused by global push but rather by domestic pull factors.

Our analysis is related to the growing literature on credit booms and financial development. Starting from the seminal contribution by Mendoza and Terrones (2008), a large number of papers have investigated drivers, correlates, and consequences of credit growth (Jordà, Schularick, and Taylor, 2011; Schularick and Taylor, 2012). Particularly relevant to our paper are the existing contributions on foreign determinants of domestic credit growth. Lane and McQuade (2014) show that in European countries net debt inflows were strongly correlated with domestic credit growth prior to the euro crisis. Likewise, Calderon and Kubota (2012) show for many advanced and emerging countries that surges in gross debt inflows are good predictors for subsequent credit booms for the period of 1975 to 2010. In the context of LIDCs, credit booms are mostly regarded as elements of financial deepening rather than crises predictors. Meng and Gonzalez (2017) show that in low-income countries credit booms much less frequently lead to financial crises than in advanced and emerging economies. At the country level, Gori, Li, and Presbitero (2015) use an instrument variable estimation to show that capital inflows have causal effects on the level of domestic credit in LIDCs and are thus an important driver of financial development. In contrast to these existing contributions on LIDCs, we make use of bank-level micro data to provide a more granular analysis of financial sector developments in LIDCs when capital flows in. In this sense, our analysis complements a recent study by Agarwal, Duttagupta and Presbitero (2019) that uses bank-level balance sheet data to study the effects of global commodity price shocks on the LIDC banking sector.

Our paper also informs the literature on the international transmission of economic shocks through capital flows and cross-border banking. The key idea in this literature is that fluctuations in U.S. monetary policy and global risk aversion drive the time variation in international capital flows and thus lead to synchronized responses in asset prices and local credit cycles across the globe (Calvo, Leiderman, and Reinhart, 1993, 1996; Forbes and Warnock, 2012; Rey, 2016; Miranda-Agrippino and Rey, 2020). To understand the mechanism behind this process, Bruno and Shin (2015b) formulate a model in which global banks pass on financial conditions in the center by pro-cyclically adjusting their leverage and by lending to foreign subsidiaries and local banks. Various papers provide empirical support for this mechanism in the context of advanced and emerging economies. Bruno and Shin (2015b) find that a contractionary shock to U.S. monetary policy leads to lower leverage and lower cross-border bank lending. Cecchetti and others (2020) also find that the leverage ratio increases for banks and non-banks outside of the U.S. when U.S. monetary policy easing persists. Using credit register data for Mexico, Morais and others (2019) show that changes in foreign monetary policy alter domestic credit supply through changes in foreign bank lending to local corporates. Baskaya and others (2017a, b) use loan-level data from Turkey to analyze how different types of banks differ in the transmission of flows. They show that larger, well-capitalized banks respond particularly strongly to cross-border capital inflows and emphasize that both foreign and domestic banks participate in this transmission process. Our paper adds to this literature by analyzing the role that the banking sector plays in the transmission of global liquidity conditions to LIDCs.

The paper proceeds as follows. Section II sets the stage by providing updated evidence on the current state of capital account liberalization in LIDCs. Section III introduces our data sources and presents the main results on the effect of capital inflows on financial conditions in LIDCs.

Section IV turns to the identification of causal effects. Section V concludes with policy implications.

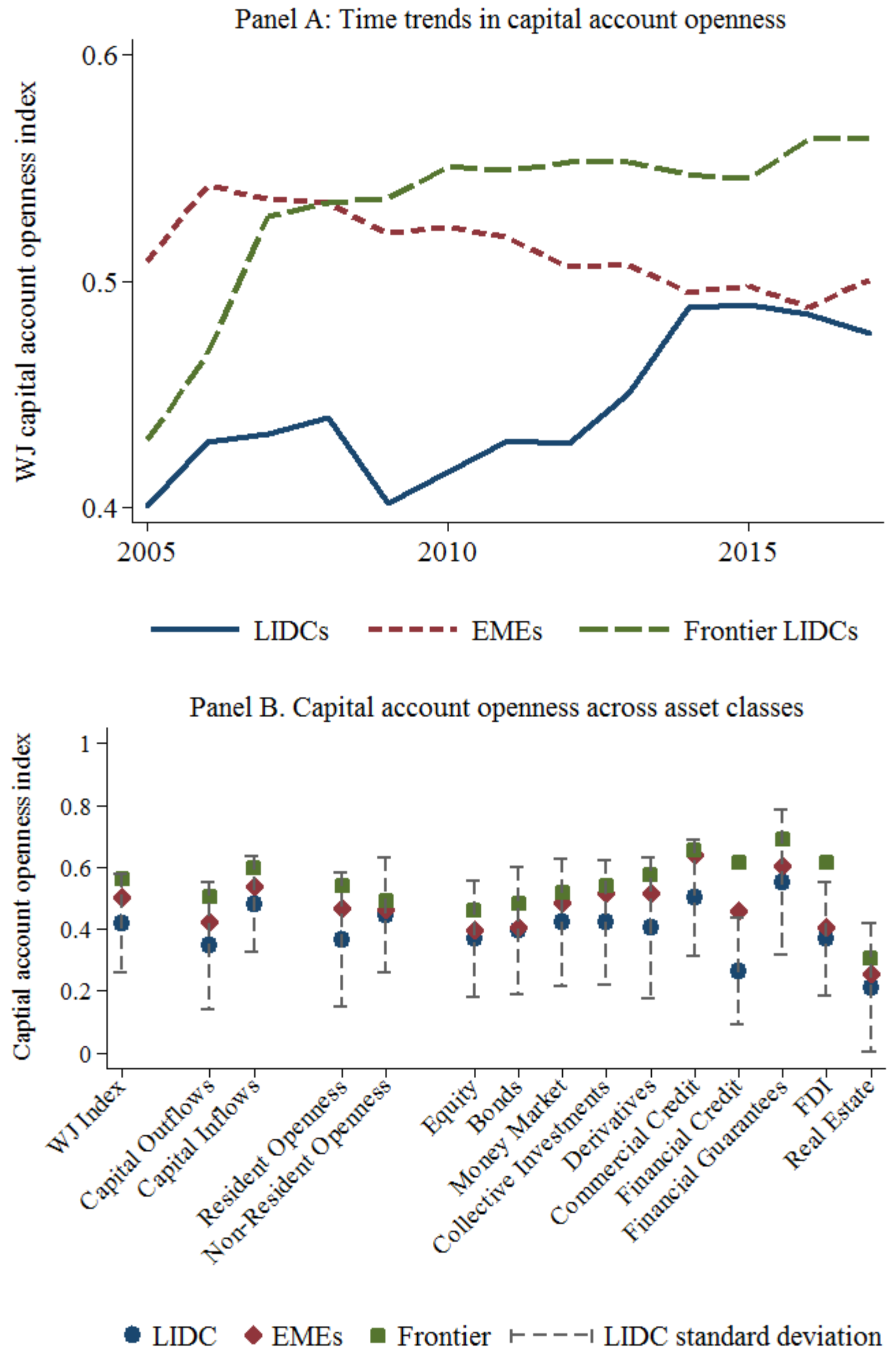
II. Opening Up: Capital Account Liberalization in LIDCs

To assess the current state of capital account openness, we update the Wang-Jahan Index of capital account openness until 2017. The Wang-Jahan Index measures de jure capital account openness based on survey data from the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER, IMF, 2019a).[1] A main advantage of the index is the wide coverage of LIDCs. Another advantage is that it does not only capture overall openness, but also provides a break-down of openness across twelve different types of cross-border transactions and thus offers a granular picture of capital account liberalization. The original time series by Jahan and Wang (2016) is available until 2013. We extend coverage until 2017, following the same methodology (Appendix I, Section B).

The Wang-Jahan Index shows that many LIDCs have gradually liberalized their capital accounts in the past decade. Average capital account openness in frontier market LIDCs has surpassed average EME openness during the global financial crisis, in response to which certain EMEs have tightened capital controls (Figure 1, Panel A). At the same time, non-frontier LIDCs have also gradually moved toward greater capital account openness, although average openness for overall LIDCs is still significantly lower than openness in EMEs. While LIDCs have opened up fairly evenly across all types of cross-border financial transactions, the interquartile ranges for LIDCs indicate a high degree of heterogeneity, which is concealed at the average. This emphasizes how strongly capital account configurations differ even within country groups (Figure 1, Panel B).

[1] There are several indices based on the IMF's AREAER. For a comparison, see for example Cerdeiro and Komaromi (2019).

Figure 1. Opening-up of capital accounts in LIDCs

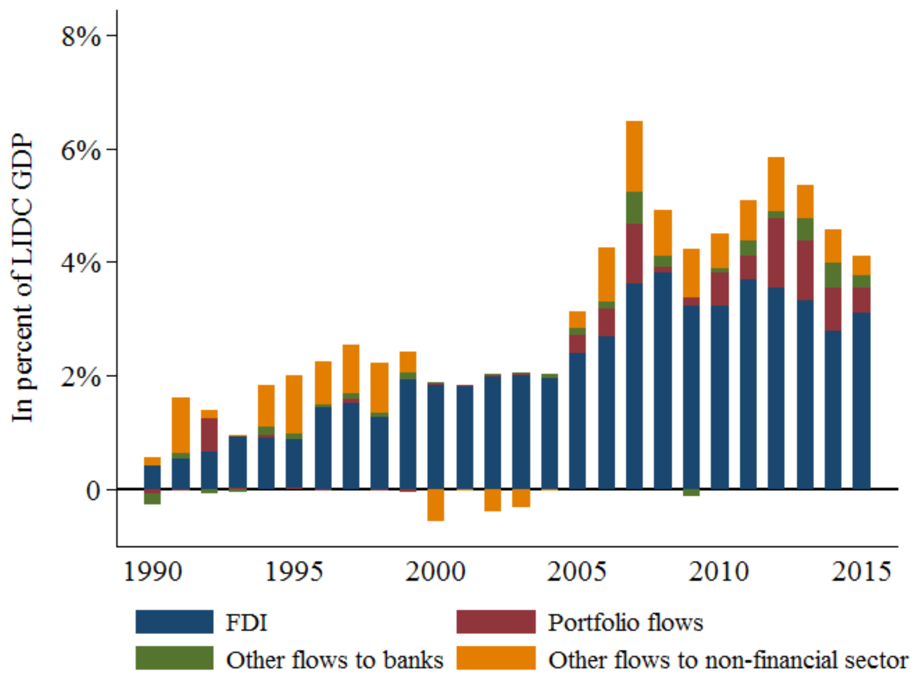


Sources: Jahan and Wang (2016) and AREAER database (IMF, 2019a).

Note: See Appendix I, Section B for details on the Wang-Jahan Index of capital account openness. Panel A shows the main indicator, which is the simple average over all 12 subcategories, ranging from 0 in the case of a fully closed capital account, to 1 if cross-border transactions are unrestricted in all 12 sub-categories. In panel B, dots represent averages per subcategory for each country group, and the vertical dashed lines show the standard deviation for LIDCs. Small and fragile countries are excluded. EMEs: emerging market economies; LIDCs: low-income developing countries.

The recent episode of LIDC capital account liberalization has been accompanied by an increase in gross capital inflows (Figure 2). In general, *de jure* capital account openness may not necessarily invite capital flows, because it may not reflect the degree to which capital account restrictions are actually enforced. In the case of LIDCs, however, *de jure* capital account liberalization was indeed accompanied by an unprecedented amount of capital inflows, particularly to frontier market LIDCs. In addition to FDI flows that have always played an important part in foreign financing, LIDCs have received a growing amount of portfolio and other flows. This change in the composition of capital inflows has important implications, because private non-FDI flows exhibit volatile and pro-cyclical dynamics similar to those experienced by EMEs (Abidi, Hacibedel, and Mwanza, 2016; Araujo and others, 2017b).

Figure 2. Gross capital flows to LIDCs



Source: Financial Flows Analytics (FFA, IMF, 2021a).
Note: This figure shows total gross capital flows to private recipients in LIDCs in percent of the total GDP of LIDCs. Other flows mainly comprise direct loans and trade credit.

III. Financial Sector Dynamics under Large Capital Inflows

The increased openness of LIDCs toward capital flows raises two closely related questions: Do capital inflow surges translate into financial deepening in capital-constrained economies? And to what extent do they pose risks to financial market stability? In this section we provide evidence on these questions by combining bank-level balance sheet data from *Fitch Fundamental Financial Data* with country-level capital flow data.

A. Bank-level data from Fitch Fundamental Financial Data

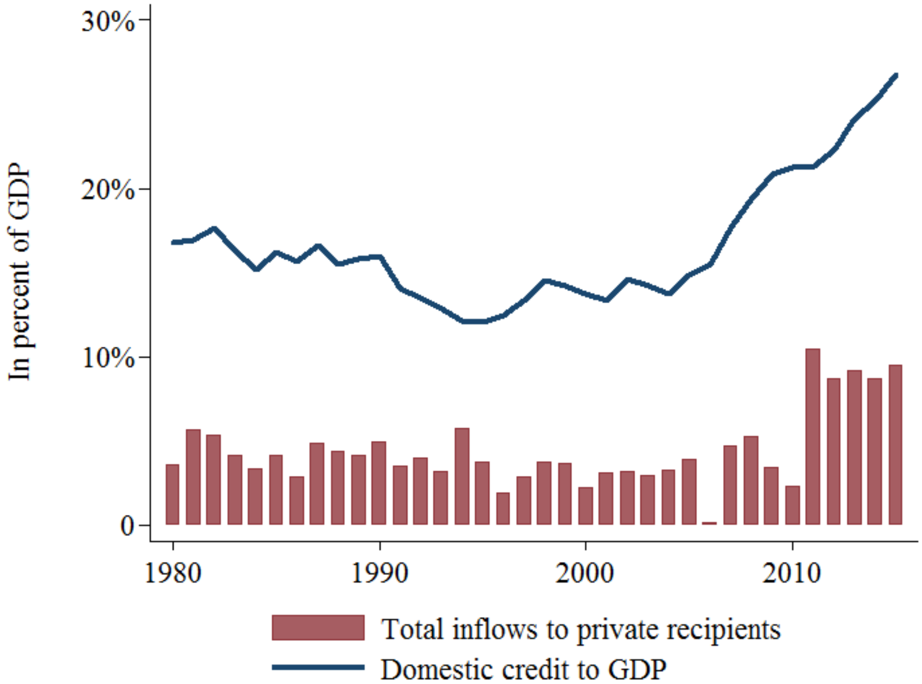
The use of bank-level micro data can provide more insights than analyses based on aggregate-level data. While the existing literature on credit growth in LIDCs has mostly relied on aggregate measures of credit to GDP (e.g., Gori, Li, and Presbitero, 2015; Meng and Gonzalez, 2017), our analysis makes use of bank-level balance sheet data from *Fitch Fundamental Financial Data*, which allow us to examine loan extension and funding choices as well as other characteristics of banks. For example, a strong increase in the loan-to-deposit ratio or an increased reliance on short-term funding might signal possible balance-sheet mismatches and thus could enlarge crisis susceptibility. Furthermore, responses could differ across banks with different characteristics such as ownership or size.

Our dataset covers banks in LIDCs over the period from 1989 to 2019. It contains a total of 584 banks from 32 LIDCs in our baseline specification, while the number varies depending on variables used in regression estimation. Appendix I, Section C shows how we construct the bank-level dataset. As Appendix III shows, a large share of banks in our sample is from frontier market LIDCs, such as Vietnam, Kenya, and Nigeria. Most of the represented countries are not heavily reliant on commodity exports. It is therefore important to note that our sample of micro data is not representative of all LIDCs. Due to the large share of banks in frontier market LIDCs, the sample represents those that are more open than the LIDC average and that receive more non-FDI private capital flows. Tables A1 and A3 in Appendix I give a detailed overview of our sample and of the main descriptive statistics.

We examine the relationships between bank-level variables and country-level capital flows, while controlling for other macroeconomic variables. Capital flow data are taken from the IMF's Financial Flows Analytics database (FFA, IMF, 2021a) and all other macroeconomic variables are from the IMF's International Financial Statistics (IFS; IMF, 2021b) and World Economic Outlook (WEO; IMF, 2021c) databases. Table A2 in Appendix I lists all variables and data sources.

An inspection of the raw data suggests that at the country level, domestic credit and gross capital inflows to the private sector move in tandem in LIDCs on average. Figure 3 uses data from the World Bank's Global Financial Development database to show that after being relatively constant for more than two decades, the average level of domestic credit to GDP has substantially increased in the early 2000s. This rise in financial deepening has therefore emerged at the same time as the above documented capital inflow surge.

Figure 3. Domestic credit and gross capital inflows to LIDCs



Sources: World Bank's Global Financial Development database and Financial Flows Analytics (FFA, IMF, 2021a).
Note. The figure shows sample averages over 36 LIDCs based on aggregate macro data.

B. Financial sector dynamics under large capital inflows

We first examine whether capital flows were associated with financial deepening in LIDCs in a panel regression framework that allows to control for other covariates. Our full-form specification estimates a regression of bank-level variable $Y_{j,i,t}$ (e.g., gross loans) of bank j in country i at time t on capital inflows $K_{i,t}$ to country i at time t, with lags of these variables, macro-level and bank-level controls, time dummies, and bank-fixed effects:

$$Y_{j,i,t} = \beta K_{i,t} + \phi X_{i,t-1} + \psi B_{j,i,t-1} + D_t + \alpha_j + \varepsilon_{j,t},$$

where $X_{i,t}$ represents a group of macro-level control variables (including lagged capital inflows $K_{i,t-1}$); $B_{j,i,t}$ represents a set of bank-level, time-varying control variables (including lagged dependent variable $Y_{i,j,t-1}$); D_t represents the year dummy; α_j represents bank fixed effects (which also absorb country fixed effects); and $\varepsilon_{j,t}$ is the error term. We include all control variables with a one-year lag. Other Greek letters represent parameters of this linear model.

We use the standard errors proposed by Driscoll and Kraay (1998), to take into account both arbitrary cross-sectional dependence and some degree of autocorrelation in the error term. This way, both within-country correlation due to country-level capital flows and cross-country correlation due to synchronicity of capital flows across LIDCs are reflected, as well as some degree of persistence over time in the error term. The use of this standard error formula is suggested by previous studies on capital flows to LIDCs (Araujo and others, 2017b, c) and motivated by the importance of common global and regional factors in driving bond and portfolio flows to developing countries (Puy, 2016).

We begin by estimating the above regression model through Ordinary Least Squares (OLS) despite a variety of methodological caveats with the OLS approach. First, there is an issue of reverse causality, which we further discuss in Section IV. On the one hand, capital inflows provide credit supply to the destination economy, causing credit growth. On the other hand, growth in domestic credit demand might attract foreign funds, resulting in a reverse causality from credit growth to capital inflows. Not taking this reverse causality into account would result in bias toward overestimation (Appendix III, Section A). The inclusion of a lagged dependent variable further creates the Nickell bias (Nickell, 1981), and the small number of clusters might lead to over rejection or spurious significance of coefficients. In Appendix II, we discuss these issues and conduct robustness checks on the Nickell bias, by GMM estimation of dynamic panel data models, by performing Nickell bias correction through a panel-split jackknife approach, and by restricting the sample to have a minimum number of observations for each bank (4 and 8 years). These additional analyses, however, indicate that the Nickell bias has still non-negligible influence on the OLS results.

The OLS results show that capital flows are associated with sizeable increases in bank loans in LIDCs (Table 1). A one percent increase in capital flows was associated with about 6 basis point increase in gross loans at banks on average. Because of the high volatility of capital flows, the magnitude of this estimated increase is sizeable from an economic point of view. A one (within) standard deviation increase in capital inflows is associated with an increase of 5 percent in annual loan growth. This is significantly larger than the corresponding impact of 2.6 percent from real GDP growth (based on the sum of the effects from both the level and growth terms). Replacing time fixed effects by global control variables leads to only a marginal change in the results (Table 1, column 4).

Most of our control variables show intuitive associations with bank loans. Higher lagged domestic interest rates (on the funding side) are associated with lower loan growth. Higher levels of real GDP and stronger institutional quality are associated with higher loan growth. Positive correlation with export prices may reflect more investment opportunities and more financing needs for higher imports. A banking crisis is associated with lower loans, while the association with a currency crisis is not significant.

We proceed by analyzing whether different types of capital inflows are associated with different dynamics in the recipient country's banking sector (Table 2). First of all, the results do not change much if we focus on capital flows to the private sector only. This may reflect that capital flows to the official sector substitute governments' domestic borrowing and unlock resources at banks for private sector lending. Our results further show that both FDI and non-FDI inflows are associated with higher loan growth, although the associations are weak (Table 2, column 5). Given the strong emphasis that the existing literature has placed on debt flows in driving domestic credit cycles, the significant result for FDI flows might be considered surprising. The fact that a sizable portion of FDI flows to LIDCs are indeed debt instruments can partly reconcile this finding. Also, FDI flows may be received by foreign owned banks in LIDCs (which also takes the form of retained earnings of foreign banks if profits are not distributed to share-holding companies abroad). Another explanation could be that FDI flows have second-round effects on economic activity and generate positive spillovers to domestic firms by easing credit constraints (Harrison, Love, and McMillan, 2004).

With respect to potential financial vulnerabilities, a key question is whether banks have also changed the composition of funding sources in response to capital inflows. Newly extended loans could be backed by pure wholesale funding through capital inflows or might be funded by an increase in deposits due to an associated boost in domestic economic activity financed by these new loans. As deposits are considered to be a more stable funding source than wholesale funding, a shift in the funding composition would have important implications for financial sector risks.

Regression results show that, while wholesale funding was increased in response to capital inflows, bank deposits also grew (Table 3). As both loans and deposits increased, the loan-to-deposit ratio—a typical indicator for financial vulnerability—saw only a moderate increase of 0.74 percent. The changes in the regulatory capital ratio and the leverage ratio (measured as the total asset to equity ratio) are only weakly significant, but they indicate the build-up of financial vulnerabilities, to some extent.[2]

We also examine the relationship of other financial soundness indicators with capital inflows in LIDCs but find no significant results (Table 4, first three columns). So far, the average asset quality, measured by nonperforming loans (NPLs) or returns to assets, has not significantly changed, nor has the average net interest margin. Only the liquid asset to short-term funding ratio shows a statistically significant decline. Note, however, that these relatively benign results only capture the average response and might therefore miss the build-up of vulnerabilities in the tails of the bank distribution.[3]

Examining bank employee statistics provides new insights to bank business dynamics when receiving capital flows (Table 4, last two columns). The number of employees shows a significant increase, indicating an expansion of bank business, while personnel cost increases only insignificantly. This has important implications for financial inclusion. Loan growth upon capital inflows could have just been concentrated to large companies that already have had banking relationships, which would not require an expansion of labor input at banks. The estimated results go opposite and imply that loans may be extended to new customers, necessitating more labor input at banks. If this is the case, capital flows to LIDCs have contributed to financial inclusion by expanding financial access.

[2] Note that due to data availability our leverage measure is based on the book value of equity. As discussed by Cecchetti and others (2021), a market-value based leverage measure would be preferable to examine financial vulnerabilities. Nonetheless, a book-value based measure can contain valuable information, in particular if banks follow accounting standards that require marked-to-market valuation.

[3] We return to the analysis of non-average responses in subsection III.C below where we present results of quantile regressions. Appendix II, Section C further presents regression analyses that focus on the effects of capital flow surges (bonanzas).

Table 1. Gross loans and capital flows in LIDCs

	(1) Gross loans log	(2) Gross loans log	(3) Gross loans log	(4) Gross loans log
Total gross capital inflows (log)	0.12***	0.07***	0.06***	0.07***
	(0.03)	(0.02)	(0.01)	(0.01)
Total gross capital inflows (log), lag		0.01	-0.00	-0.02*
		(0.01)	(0.01)	(0.01)
Gross loans (log), lag		0.68***	0.57***	0.57***
		(0.02)	(0.03)	(0.03)
Deposits (log), lag			0.12***	0.12***
			(0.02)	(0.02)
Real GDP (log), lag			0.37***	0.33***
			(0.10)	(0.09)
Real GDP growth (log), lag			0.28	0.34
			(0.22)	(0.21)
Domestic interest rate, lag			-0.41*	-0.53**
			(0.21)	(0.21)
Banking crisis, lag			-0.31***	-0.34***
			(0.08)	(0.07)
Currency crisis, lag			-0.01	-0.00
			(0.07)	(0.07)
REER (log difference), lag			0.04	0.06
			(0.08)	(0.08)
ICRG quality of government, lag			0.46**	0.36
			(0.20)	(0.22)
Trade partner's growth, lag			-0.46	-0.44
			(0.88)	(0.71)
Export commodity price growth, lag			1.00***	0.97***
			(0.29)	(0.24)
Import commodity price growth, lag			0.31	0.28
			(0.37)	(0.31)
VIX (log), lag				0.07
				(0.04)
Global financial crisis dummy, lag				0.01
				(0.03)
US policy rate, lag				-0.00
				(0.01)
US inflation, lag				6.11***
				(2.10)
Trend term				0.01**
				(0.00)
Bank fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	NO
Sample period	1989-2019	1989-2019	1989-2019	1991-2019
Observations	5,279	5,279	5,279	5,271
Adjusted within R^2	-0.107	0.633	0.655	0.883

Sources: Cboe (2021); Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (clustering by years with the bandwidth of 4) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), implemented by the Stata command ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010). The estimation sample includes 32 countries and 584 banks.

Table 2. Gross loans and capital flows by type of capital flows

	(1)	(2)	(3)	(4)	(5)
	Gross loans	Gross loans	Gross loans	Gross loans	Gross loans
	Log	Log	Log	Log	Log
Total gross capital inflows (log)	0.06***				
	(0.01)				
Total gross capital inflows (log), lag	-0.00				
	(0.01)				
Gross inflows to private sector (log)		0.07***			
		(0.02)			
Gross inflows to private sector (log), lag		-0.03			
		(0.02)			
Gross FDI inflows (log)			0.02		0.02*
			(0.01)		(0.01)
Gross FDI inflows (log), lag			-0.00		-0.00
			(0.01)		(0.01)
Gross non-FDI inflows (log)				0.04*	0.04*
				(0.02)	(0.02)
Gross non-FDI inflows (log), lag				0.01	0.01
				(0.01)	(0.01)
# of countries	32	32	31	30	29
# of banks	584	582	579	569	564
Observations	5,279	5,198	5,166	4,786	4,693
Adjusted within R^2	0.655	0.666	0.654	0.650	0.652

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (with the bandwidth of 4 and the number of clusters—years—is 31) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), implemented by the Stata command ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010). The sample period is 1989 to 2019. All specifications include the lagged dependent variable, bank- and country-level controls, and bank and year fixed effects.

Table 3. Banks' funding sources and capital flows in LIDCs

	(1) Wholesale funding Log	(2) Deposits Log	(3) Loan-to-deposit ratio Winsorized at 5 percent	(4) Regulatory capital ratio Winsorized at 5 percent	(5) Total assets to equity Winsorized at 5 percent
Total gross capital inflows (log)	0.07**	0.05***	0.74**	-0.27*	0.17*
	(0.03)	(0.01)	(0.35)	(0.15)	(0.08)
Total gross capital inflows (log), lag	0.04	-0.00	0.37	-0.27	-0.03
	(0.04)	(0.01)	(0.31)	(0.23)	(0.09)
Wholesale funding (log), lag	0.38***				
	(0.05)				
Deposits (log), lag	0.05	0.63***	-2.82	-2.24	0.36**
	(0.04)	(0.05)	(2.26)	(1.50)	(0.14)
Loan-to-deposit ratio, winsorized, lag			0.48***		
			(0.05)		
Reg. capital. ratio, winsorized, lag				0.44***	
				(0.05)	
Total assets to equity, winsorized, lag					0.50***
					(0.04)
Gross loans, log = L,	0.26***	0.06*	4.23**	0.53	-0.09
	(0.06)	(0.03)	(1.86)	(1.11)	(0.13)
Real GDP (log), lag	0.46	0.08	2.48	4.85**	-1.31
	(0.36)	(0.10)	(3.56)	(2.24)	(0.80)
Real GDP growth (log), lag	0.68	-0.05	18.28	-0.51	2.24
	(0.52)	(0.31)	(12.44)	(5.68)	(2.04)
Domestic interest rate, lag	-0.39	0.07	-21.92***	2.31	-1.37
	(0.33)	(0.19)	(6.42)	(2.47)	(0.88)
Banking crisis, lag	-0.38	-0.20**	-8.19***	1.36*	0.11
	(0.39)	(0.09)	(1.54)	(0.78)	(0.50)
Currency crisis, lag	-0.23*	0.01	0.05	-1.79***	0.04
	(0.12)	(0.04)	(1.66)	(0.58)	(0.27)
REER (log difference), lag	-0.38**	0.05	2.78	-3.57**	0.28
	(0.14)	(0.09)	(5.65)	(1.72)	(0.70)
ICRG quality of government, lag	0.42	0.47**	7.56	3.48	-1.86*
	(0.72)	(0.22)	(7.74)	(4.19)	(1.01)
Trade partner's growth, lag	0.52	-0.09	-36.42	-5.43	11.96
	(3.51)	(0.74)	(29.07)	(19.89)	(7.62)
Export commodity price growth, lag	0.72	0.99**	-0.08	-3.19	2.61
	(1.07)	(0.38)	(13.21)	(6.24)	(2.48)
Import commodity price growth, lag	-2.54**	0.16	-11.19	0.46	12.73***
	(1.11)	(0.28)	(16.83)	(9.70)	(3.82)
Bank and year fixed effects	YES	YES	YES	YES	YES
# of countries	31	32	32	27	32
# of banks	508	584	584	324	584
Sample period	1992-2019	1989-2019	1989-2019	1993-2018	1989-2019
Observations	4,020	5,279	5,279	2,251	5,279
Adjusted within R^2	0.123	0.582	0.253	0.165	0.216

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (clustering by years, with the bandwidth of 4) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), implemented by the Stata command ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010).

Table 4. Banks' soundness and business dynamics upon capital inflows in LIDCs

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-performing loans	Return on assets	Net interest margin	Liquid asset to short-term funding ratio	Personnel expenses per overhead	Number of employees
	Winsorized at 5 percent	Winsorized at 5 percent	Winsorized at 5 percent	Winsorized at 5 percent	Log	Log
Total gross capital inflows (log)	-0.35	0.04	-0.01	-0.79**	0.01	0.02***
	(0.23)	(0.05)	(0.01)	(0.35)	(0.01)	(0.01)
# of countries	30	32	32	32	32	31
# of banks	445	541	528	584	530	345
Sample period	1994-2019	1993-2019	1993-2019	1989-2019	1993-2019	1994-2019
Observations	3,295	4,706	4,538	5,278	4,521	2,124
Adjusted within R^2	0.240	0.129	0.265	0.173	0.212	0.644

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (clustering by years, with the bandwidth of 4) are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$), implemented by the Stata command ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010). All specifications include the lagged dependent variable, bank- and country-level controls, and bank and year fixed effects.

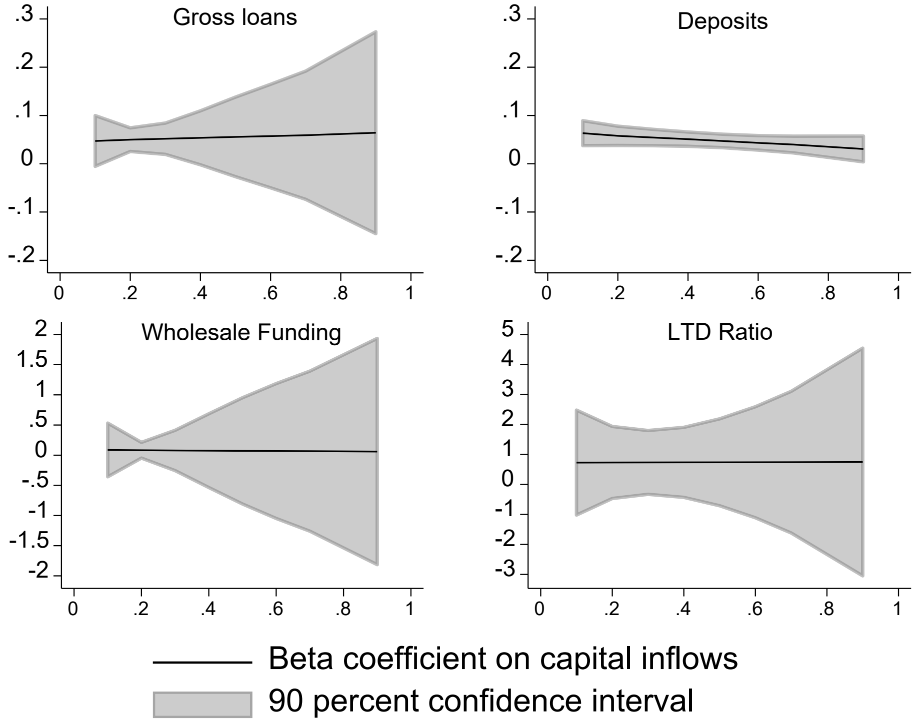
C. Quantile regressions

To assess whether financial vulnerabilities are building up in LIDCs when capital flows in, it is important to analyze the banking distribution in more detail. A particular concern is that financial stability risks might be concentrated in the upper tail of the distribution of bank riskiness and might not be adequately captured by the conditional mean, i.e., the average financial sector response to capital inflows. In this subsection, we therefore employ quantile regressions to study how responses in loans and funding sources differ across the different quantiles of the distribution. Specifically, we employ a method-of-moments estimator recently developed by Machado and Santos Silva (2019) that allows estimating regression quantiles in panel data models with fixed effects.

The results indicate an increase in the skewness of the banking distribution for loans and the loan-to-deposit ratio when international capital flows in (Figure 4). Capital inflows were associated with a right shift of the loan distribution. A one percentage point increase in gross capital inflows was associated with an increase in loans of 6.4 basis points for the highest decile, but with a smaller increase of 4.7 basis points for the lowest decile. Interestingly, the opposite pattern is evident for deposits, where the lowest decile exhibits stronger correlation with capital inflows (6.3 basis points) than the highest decile (3.1 basis points). Consequently, the estimates for the loan-to-deposit ratio increase from the lowest decile to the highest decile, within a very narrow range of 0.73-0.75, though. Wholesale funding shows a decreasing pattern from 8.7 basis points to 6.1 basis points.

Taken together, these results reveal different dynamics across the bank distribution. Some banks have responded particularly strongly to capital inflows and have therefore experienced stronger increases in their loan-to-deposit ratios. These dynamics should be surveilled closely, as they might signal potential tail risks. It needs to be noted, however, that differences between estimated coefficients across quantiles are not statistically significant.

Figure 4. Financial sector dynamics across different quantiles



Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note: This figure shows the results of quantile regressions, implemented by the Stata command xtqreg (Machado and Santos Silva, 2019). All regressions include bank- and year-fixed effects and the same set of control variables as in Tables 1 and 3. The black lines indicate beta coefficients on capital inflows over different quantiles. Grey shaded areas show the corresponding 90 percent confidence intervals. LTD ratio: loan-to-deposit ratio.

D. Roles of foreign banks and large banks

We further examine differential effects by ownership and size of banks. The literature has emphasized the role of foreign banks in the transmission of global liquidity conditions to local financial markets (Bruno and Shin, 2015a). One reason is that cross-border financing may be more readily available to foreign-owned banks, either through the parent company or through better market access due to lower information asymmetries. Similarly, large banks may have better access to cross-border financing due to stronger fundamentals or established trustworthiness. In this regard, the channels through which capital flows affect banks may differ by ownership and size of banks.

As for ownership, an indicator available in *Fitch Fundamental Financial Data* shows three categories: foreign, domestic, or no information available. The last case likely indicates that these banks are domestically owned, because foreign ownership might have been clearly declared. Still, we keep these three categories separate to make sure our identification of foreign ownership does not suffer from mismeasurement. In our sample, there is no bank that changes the residency of ownership. Foreign banks, with this definition, tend to be larger—the correlation between foreign bank ownership and bank asset size is weakly positive (about 10 percent—significant at 1 percent level). To identify large banks, we divide banks into four groups by size of their total assets, splitting the estimation sample at the quartiles. Using these indicators, we re-run the above presented regressions with additional interaction terms and study potentially different effects of capital flows by bank size and ownership.

The results show that foreign banks extended fewer loans than domestically owned banks (Table 5). The estimated coefficients on the interaction terms of capital inflows and the bank-ownership dummies show that the association between foreign banks' loans and capital inflows is less than a half of that for domestic banks. The difference is statistically significant at the 1 percent level. The increases in wholesales funding and in deposits are also higher for domestic banks, although the differences are not statistically significant. NPLs also significantly decline for domestic banks, and the difference compared to foreign banks is also significant at the 5 percent level. Domestic banks also see statistically significant increases in personnel expenses per overhead and the number of employees. These results imply that domestic banks expand their business by facing more credit demand. Note that banks in our sample are rather evenly split by residency of ownership, with a slightly larger number of (identifiable) domestic banks, leaving little concern about small sample issues.

As for the bank size, the results indicate that smaller banks extend more loans when receiving capital inflows (Table 6). The estimated coefficients on the interaction terms of capital inflows and the bank-size indicator show a monotone decrease as bank size increases, measured by bank asset quartiles in the previous year. The differences between the estimated coefficients are not statistically significant. While some significant results indicate increased financial vulnerabilities, especially for the lower middle-sized banks, caution is warranted, because these results might also reflect that some observations may become highly leveraged due to the splicing of the sample by slope dummies.

Overall, our empirical analysis finds little evidence for increasing financial vulnerabilities in response to capital inflows. We still note, however, that it is in general difficult to capture financial stability risks ex ante, in particular due the time lag between capital inflows and an observable build-up of vulnerabilities. An omission that deserves particular mention is the lack of data on foreign currency liabilities and loans. In addition to maturity mismatches, past financial crises in developing countries have often been triggered by currency mismatches on bank balance sheets. Currency mismatches occur, when banks borrow in foreign currency and re-lend to customers in domestic currency. This has been particularly common under fixed exchange rate regimes (Magud, Reinhart, and Vesperoni, 2014) that are widespread among LIDCs. Unfortunately, it is not possible to test for changes in the currency composition of bank assets and liabilities, because for the large majority of banks in LIDCs such data is not available.

Table 5. Results by ownership

Panel A: Banks' balance sheets

Interaction term with gross capital inflows	(1) Gross loans log	(2) Wholesale funding log	(3) Deposits log	(4) Loan-to-deposit ratio winsorized at 5 percent	(5) Regulatory capital ratio winsorized at 5 percent	(6) Total assets to equity winsorized at 5 percent
Domestically owned banks	0.088***	0.166**	0.091***	0.129	-0.518	-0.021
	(0.014)	(0.080)	(0.025)	(0.704)	(0.312)	(0.226)
Foreign owned banks	0.043***	0.055**	0.050***	0.215	0.496	0.177
	(0.011)	(0.026)	(0.014)	(0.653)	(0.481)	(0.116)
No information available	0.047**	0.029	0.020	1.445***	-0.563**	0.278**
	(0.019)	(0.047)	(0.016)	(0.373)	(0.249)	(0.132)
# of countries	32	31	32	32	27	32
# of domestic banks	147	135	147	147	107	147
# of foreign banks	148	136	148	148	97	148
# of banks with no information	289	237	289	289	120	289
Asset share of domestic banks	68.0	67.5	68.0	68.0	68.7	68.0
Sample period	1989-2019	1992-2019	1989-2019	1989-2019	1993-2018	1989-2019
Observations	5,279	4,020	5,279	5,279	2,251	5,279
Adjusted within R^2	0.658	0.126	0.585	0.255	0.167	0.218

Panel B: Banks' soundness indicators and business dynamics

Interaction term with gross capital inflows	(1) Non-performing loans winsorized at 5 percent	(2) Return on assets winsorized at 5 percent	(3) Net interest margin winsorized at 5 percent	(4) Liquid asset to short-term funding ratio winsorized at 5 percent	(5) Personnel expenses per overhead log	(6) Number of employees log
Domestically owned banks	-0.934***	0.149	0.000	-0.108	0.023*	0.055***
	(0.248)	(0.097)	(0.010)	(0.570)	(0.011)	(0.019)
Foreign owned banks	-0.015	0.074	-0.004	-0.655*	0.007	0.018**
	(0.231)	(0.075)	(0.012)	(0.385)	(0.015)	(0.008)
No information available	-0.265	-0.047	-0.012	-1.267**	0.013	0.006
	(0.348)	(0.050)	(0.013)	(0.524)	(0.009)	(0.010)
# of countries	30	32	32	32	32	31
# of domestic banks	133	146	146	147	143	106
# of foreign banks	122	140	138	148	145	93
# of banks with no information	190	255	244	289	242	146
Sample period	1994-2019	1993-2019	1993-2019	1989-2019	1993-2019	1994-2019
Observations	3,295	4,706	4,538	5,278	4,521	2,124
Adjusted within R^2	0.245	0.137	0.274	0.177	0.213	0.645

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (clustering by years, with the bandwidth of 4) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), implemented by the Stata package ivreghdfe (Correia, 2014, 2017; Baum, Schaffer, and Stillman, 2010). All specifications include the lagged dependent variable, bank- and country-level controls, bank and year fixed effects, and the lag of the interaction terms.

Table 6. Results by total asset size

Panel A: Banks' balance sheets

Interaction term with capital inflows	(1) Gross loans log	(2) Wholesale funding log	(3) Deposits log	(4) Loan-to-deposit ratio winsorized at 5 percent	(5) Regulatory capital ratio winsorized at 5 percent	(6) Total assets to equity winsorized at 5 percent
Assets below 25th percentile	0.065***	0.036	0.051***	0.322	0.260	0.377***
	(0.020)	(0.096)	(0.018)	(0.864)	(0.538)	(0.076)
Assets between 25th and 50th percentiles	0.062*	0.129***	0.028	2.011**	-1.206***	0.363***
	(0.030)	(0.035)	(0.026)	(0.759)	(0.286)	(0.104)
Assets between 50th and 75th percentiles	0.050**	0.067	0.048*	0.651	-0.078	0.037
	(0.023)	(0.045)	(0.026)	(0.574)	(0.646)	(0.132)
Assets above 75th percentile	0.040	0.091	0.037	0.761	0.335	-0.011
	(0.026)	(0.069)	(0.023)	(0.881)	(0.392)	(0.156)
# of Countries	28	28	28	28	25	28
# of Banks	464	401	464	464	283	464
Sample period	1991-2019	1994-2019	1991-2019	1991-2019	1996-2018	1991-2019
Observations	3,614	2,787	3,614	3,614	1,798	3,614
Adjusted within R^2	0.637	0.059	0.592	0.218	0.103	0.217

Panel B: Banks' soundness indicators and business dynamics

Interaction term with capital inflows	(1) Non-performing loans winsorized at 5 percent	(2) Return on assets winsorized at 5 percent	(3) Net interest margin winsorized at 5 percent	(4) Liquid asset to short-term funding ratio winsorized at 5 percent	(5) Personnel expenses per overhead log	(6) Number of employees log
Assets below 25th percentile	0.314	0.086	-0.011	-2.597***	0.006	0.001
	(0.534)	(0.069)	(0.011)	(0.812)	(0.013)	(0.018)
Assets between 25th and 50th percentiles	-0.305	0.117	-0.005	-2.221***	0.002	0.006
	(0.371)	(0.075)	(0.011)	(0.782)	(0.013)	(0.009)
Assets between 50th and 75th percentiles	-0.355	0.153**	-0.013	0.293	0.018	0.034***
	(0.339)	(0.058)	(0.013)	(0.698)	(0.011)	(0.008)
Assets above 75th percentile	-0.524	0.184**	0.022*	0.538	0.017	0.055*
	(0.452)	(0.085)	(0.012)	(0.767)	(0.010)	(0.028)
# of Countries	27	28	28	28	28	27
# of Banks	366	462	452	463	436	282
Sample period	1996-2019	1994-2019	1994-2019	1991-2019	1994-2019	1996-2019
Observations	2,495	3,538	3,429	3,612	3,229	1,571
Adjusted within R^2	0.199	0.111	0.240	0.141	0.140	0.663

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (clustering by years, with the bandwidth of 4) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), implemented by the Stata package ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010). All specifications include the lagged dependent variable, bank- and country-level controls, bank and year fixed effects, and the lag of the interaction terms. Asset percentiles are evaluated as of the previous year.

IV. Examining Causality

A. Two-way causalities

Estimating the causal effect of capital inflows on domestic credit growth is complicated by the existence of different confounding factors, in particular reverse causality. On the one hand, capital inflows provide credit supply to the destination economy, causing credit growth. On the other hand, growth in domestic credit demand might attract foreign funds, resulting in reverse causality from credit growth to capital inflows. In addition, there are other factors that affect both capital flows and domestic credit in LIDCs, such as the country's income level and population (Lane, 2015; Araujo, Lastauskas, and Papageorgiou, 2017c), which indirectly reinforce two-way causalities. These two-way causalities pose a challenge in estimating the effects of one of the two causal channels. In this case, both effects imply positive correlation between domestic credit growth and capital inflows, and thus, the direction of bias would be upward (Appendix III, Section A).

While causal inference is challenging, we aim to address reverse causality in two approaches. One is to use an instrumental variable based on the regional synchronicity of capital flows (Blanchard, Adler, and de Carvalho Filho, 2015). The other is to estimate treatment effects through the augmented inverse-probability weighted (AIPW) estimator, originally credited to biostatisticians (Robins, Rotnitzky, and Zhao, 1994). Appendix III presents more details on these two methodologies.

B. Instrument variable estimation

Our first approach to identify causal effects relies on an instrumental variable that has been used in the international finance literature (Blanchard, Adler, and de Carvalho Filho, 2015; Blanchard and others, 2016; Ghosh and Qureshi, 2016, Ghosh, Ostry, and Qureshi, 2017). This approach makes use of the synchronicity of international capital flows to developing and emerging countries and uses capital flows to the region of a recipient economy as an instrument for direct capital flows to that recipient economy. Specifically, the instrument is constructed by adding up all gross capital flows to a given region in a given year excluding capital flows to the country itself.[4]

A key identification assumption of this instrument is the idea that the sum of gross capital flows to a region is mainly driven by financial conditions in advanced economies, instead of those of individual recipient countries in the region. Under this view, gross capital flows to a region can be considered exogenous from the perspective of a small, developing economy in the region. This idea is consistent with the high correlation observed in capital flows across the countries in the same region. This high cross-county correlation can help capture the changes in capital flows due to exogeneous "push" factors, instead of domestic "pull" factors that are endogenous.

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[4] The regions are defined as the following seven areas: (1) East Asia and Pacific; (2) Middle East and Central Asia; (3) Latin America and Caribbean; (4) Middle East and North Africa; (5) North America; (6) South Asia; and (7) sub-Saharan Africa. Reserve currency issuers (euro area, Japan, Switzerland, United Kingdom, United States) are excluded from the calculation. See Appendix III, Section B for a detailed discussion.

In practice, however, ensuring the instrument to be both exogenous and strong is challenging. To ensure the instrument to be fully exogenous, there should not be any economic or financial spillovers within the region except for capital flows to the region (see Appendix III, Section B for a formal discussion of the identification assumption). This condition could be satisfied in our regressions once we control for country-specific terms of trade (Gruss and Kebhaj, 2019) and for country-specific foreign demand.[5] However, controlling for regional spillover effects also reduces the initially high cross-country correlation in capital flows among the countries in the region and thus weakens the instrument.

This challenge in fact seems to be pronounced in our analysis, especially when we include year fixed effects in the estimation. For our sample of LIDCs, this regional capital-flow instrument has little region-specific variations, leading to little country-specific variation. Therefore, most of the variation in the instrument is absorbed by year fixed effects. In other words, including year dummies not only controls for sample-wide factors in general but also removes the useful and arguably exogenous variation in global capital flow cycles, on which our identification relies. The lack of region- or country-specific variations is consistent with the conjecture that capital inflows to LIDCs as a whole are mostly driven by global financial conditions or risk appetites of international investors that affect all LIDCs regardless of their regions.

Indeed, for our sample, using the regional capital-flow instrument with year fixed effects does not indicate a causal effect from capital inflows to bank lending. The size of coefficient reduces to 2 basis points from the baseline result of 6 basis points, losing statistical significance. There is also evidence of weak instruments. The first stage F value is 11.80, which is lower than the non-i.i.d. case benchmark of 23 with a 10 percent worst-case bias (Montiel Olea and Pflueger, 2013; Pflueger and Wang, 2015). The auxiliary regression method that is robust to weak instruments, proposed by Anderson and Rubin (1949), also suggests no impact from capital inflows to bank loans (Table 7, column 3).

To avoid the problem of limited region-specific variation in the instrument, we replace year fixed effects by variables that control for global effects. More specifically, we include U.S. stock market volatility index, a dummy for the global financial crisis, U.S. policy rate, and U.S. inflation, all with one year lag, as well as the trend term (see Table 1, column 4). Without year fixed effects, the strength of the instrument increases significantly, with the F value of 61.64. We find a larger impact from capital inflows to bank loans of 14 basis points, although this is contrary to the expected correction of overestimation bias (Appendix III, Section A). It also needs to be kept in mind that the instrument might no longer be fully exogenous, if year fixed effects were able to control for unobserved spillover effects that are common to the sample countries and unrelated to regional capital flows.

Overall, the instrument variable approach does not significantly indicate a causal effect from capital flows to bank loans. It may be partially due to limited region-specific variation in the regional capital-flow instrument for our sample, leading to weak instruments. But it may also be the case that macroeconomic fundamentals in LIDCs had strengthened during the sample period, inviting more capital inflows, together with financial deepening and credit expansion.

[5] Specifically, we use export-weighted real GDP growth in trading partners. We thank Felicia Belostecinic and Gruss, Nabar, and Poplawski-Ribeiro (2017) for their help in data construction.

Table 7. Instrument variable estimation

	(1) Gross loans 2SLS	(2) Total gross capital inflows 1st stage	(3) Gross loans OLS (AR)	(4) Gross loans 2SLS	(5) Total gross capital inflows 1st stage	(6) Gross loans OLS (AR)
Total gross capital inflows (log)	0.02			0.14**		
	(0.10)			(0.06)		
Total gross capital inflows to the region (log)		0.20***	0.00		0.30***	0.04*
		(0.06)	(0.02)		(0.04)	(0.02)
Year fixed effects	YES	YES	YES	NO	NO	NO
Global control variables	-	-	-	YES	YES	YES
# of countries	32	32	32	32	32	32
# of banks	583	583	583	583	583	583
Sample period	1989-2019	1989-2019	1989-2019	1991-2019	1991-2019	1991-2019
Observations	5,207	5,207	5,207	5,199	5,199	5,199
F statistic (2SLS) or R^2 (1st stage/OLS)	F: 11.80	R^2: 0.090	R^2: 0.685	F: 61.64	R^2: 0.634	R^2: 0.893

Sources: Cboe (2021); Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. Driscoll-Kraay standard errors (clustering by years, with the bandwidth of 4) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), implemented by the Stata package ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010). All specifications include the lagged dependent variable, bank- and country-level controls, and bank fixed effects. The lag of the instrument variable is included as an exogenous regressor. Using the lag of the instrument variable as another instrument leads to similar results. The global control variables are the same as in Table 1. Adjusted within R^2 are reported. 2SLS: two-stage least squares; AR: Anderson-Rubin.

C. Augmented inverse-probability weighting (AIPW) estimator

Our second approach to examine causality follows Jordà and Taylor (2016) and Alam and others (2019) and applies the AIPW estimator to model capital inflows as treatments and to estimate their causal effects. A main advantage of the AIPW estimator in comparison to the OLS is its flexibility in parametric assumptions together with double robustness, while maintaining the same conditional independence assumption that, once controlling for other observable conditions (e.g., economic growth, interest rate), residual capital inflows do not correlate to residual bank loans (or other bank-level dependent variables). Appendix III, Section C provides more details on the AIPW estimator.

Since our treatment variable—capital inflows—takes a continuous value, we use the quantile binning approach to categorize capital flows into three distinct groups, based on the findings of Naimi and others (2014). The quantiles of our baseline choice are 0.15 and 0.85, leading to three treatment levels. This classification is ad hoc but an attempt to strike a balance between capturing different natures by the size of capital flows and ensuring enough observations for estimation of models by treatment level.[6] Results with other quantile thresholds are also reported.

The AIPW estimation proceeds in three steps to estimate average treatment effects (ATEs). In the first step, we estimate the ordered logit model as our treatment model to obtain propensity scores for each treatment, i.e., the probabilities of receiving little, moderate, and large capital inflows, in our application. In the second step, the OLS is used to estimate the outcome models for different treatment levels. The outcome models provide the estimates on how bank loans (or other dependent variables) respond to control variables (e.g., macro conditions except for capital flows), which can potentially differ across the cases when capital inflows are little, moderate, or large. Our choice of covariates for both models is the same as the baseline OLS regressions, excluding capital inflows (while retaining the lag of capital inflows). In the third step, ATEs are derived by combining the estimates from both treatment and outcome models in a formula that misspecification bias from one model will vanish if the other model provides consistent estimates.

ATEs are estimated against the base case where capital inflows are between the 15th percentile and the 85th percentile. To ease interpretation, we follow the literature and rescale ATEs in the following way. We divide the ATEs by the difference between the average levels of capital flows in each group to obtain per-unit ATEs, which can be interpreted as the impact per one percentage point increase in capital inflows (Jordà and Taylor, 2016; Alam et al., 2019).

The results show, in some cases, significant impacts from capital inflows to bank loans and deposits, but they are not robust across threshold specifications (Table 8). Under the baseline thresholds of [0.15, 0.85], bank loans are estimated to be increased by 3 basis points, which is half of the OLS estimates, in line with the expected correction of overestimation bias from reverse causality. The estimated increase in deposits is slightly smaller than the OLS estimates when capital inflows are large, while it is larger when capital inflows are little. Both size and statistical significance of the results vary across the threshold specifications (Table 8, columns 2, 3, 5, and 6).

As in the case of the instrument variable approach, we only find weak evidence of a causal effect from capital flows to bank loans and deposits. The instability of the AIPW results possibly stems from the small number of observations relative to the number of parameters to be estimated.[7] But it may also be the case that, as discussed regarding the instrument variable approach, global push may not be the main driver of the increases in loans and deposits, even though there may be a causal impact. Rather, domestic pull factors and strengthened macroeconomic fundamentals may have attracted large capital inflows in LIDCs during this sample period.

[6] The number of parameters estimated in the AIPW estimator for three treatment levels is four times larger than that of the OLS regression, roughly speaking. For the same reason, estimates become unstable if the sample is divided into more than three treatment levels.

[7] On the instability of the AIPW estimator, see, e.g., Kang and Schafer (2007), Kahn and Tamer (2010), and Qin, Zhang, and Leung (2017).

Table 8. Estimating treatment effects using the AIPW estimator

ATEs relative to the medium level of capital inflows, per one ppt of capital inflows	(1) Gross loans log	(2) Gross loans log	(3) Gross loans log	(4) Deposits log	(5) Deposits log	(6) Deposits log
Low levels of capital inflows	0.03	0.07**	0.02	0.09**	0.02	0.01
	(0.05)	(0.03)	(0.03)	(0.03)	(0.01)	(0.03)
High levels of capital inflows	0.03**	0.02*	-0.02	0.04***	0.02**	-0.00
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)
Percentile thresholds	[15,85]	[20,80]	[25,75]	[15,85]	[20,80]	[25,75]
Observations	5,279	5,279	5,279	5,279	5,279	5,279

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (with the bandwidth of 4 and the number of clusters—years—is 31) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), based on the formula assuming that the estimates from both treatment and outcome models are consistent. All specifications include the lagged dependent variable, bank- and country-level controls, and bank- and year-fixed effects. The sample period is 1989 to 2019, the number of countries is 32, and the number of banks is 584. The observations are grouped into three categories—low, medium, or high levels of capital inflows—based on the location in the sample distribution of total gross capital flows, as specified in the percentile thresholds line. For example, [15, 85] means that the observations below the 15th percentile are classified as low, the observations above or equal to the 85th percentile are classified as high, and the rest of the observations are classified as medium. The treatment model is the ordered logit model, and the outcome models are linear regressions. Per-unit ATEs are calculated by dividing ATEs by the difference between the average levels of capital inflows in each group. The estimation of the outcome models are implemented by the Stata package ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010). ATE: average treatment effect.

V. Conclusion

Many LIDCs have gradually opened up to external financial flows during the past two decades. Funds flowing into these countries may contribute to financial deepening in capital-constrained economies but may also come with stability risks to the financial sector. To shed light on how the domestic financial sector responded to large capital inflows, we examined the association between capital inflows and bank-level balance sheet variables across these countries.

The empirical analysis in this paper finds suggestive links between capital inflows and domestic financial development in a sample of 32 LIDCs. Overall, domestic credit extension, bank deposits, and wholesale funding are positively associated with capital inflows. We further document that the expansion of domestically owned banks exhibits stronger correlation with capital inflows than that of foreign owned banks.

We also try to identify causal relationships from capital flows to banks' balance sheets (driven by "push" factors), taking into account the reverse causality (i.e., "pull" factors). Subject to technical caveats, our results using two different approaches—the instrument variable and the AIPW estimations—indicate only weak evidence on the causal effect. Therefore, even though there is a causal effect from capital flows to bank lending and other behaviors, domestic financial market dynamics in response to capital flows may not be mainly driven by global "push" factors but rather by local "pull" factors.

The results in this paper do not indicate significant increases in financial vulnerabilities, but caution is still warranted. Looming financial vulnerabilities may primarily be seen in the increase in the loan-to-deposit ratio that is strongest for the upper tail of banks that increase loans the most and deposits the least. There is the possibility that time lags in observing financial vulnerabilities make empirical identification difficult ex ante. This is the case for potential declines in profitability, decreases in regulatory capital ratios, or increases in non-performing loans. A point of omission that deserves particular attention are potential currency mismatches on LIDC bank balance sheets. Currency mismatches have played important roles in past EME financial crises and, due to a lack of data, are particularly hard to track in LIDCs. Further research and active micro- and macro-prudential surveillance should therefore remain a policy priority.

There are several policy implications from the empirical analyses in this paper. First, the finding that the implied fluctuations in domestic credit associated with capital flows are larger than those associated with domestic real economic activity indicates the need for a sound macroprudential framework when capital accounts are liberalized. This point is well noted in the literature examining capital flows to EMEs, and we confirm its importance for LIDCs. Second, the finding that both loans and deposits increase upon the external capital inflows implies that a loan expansion funded by a deposit increase may not necessarily be driven by domestic factors that can be associated with healthy financial deepening along with expanding fundamentals. In this regard, the loan-to-deposit ratio may not serve as a strong warning sign of financial vulnerabilities, which is consistent with a finding by Eberhardt and Presbitero (2021) that high loan-to-deposit ratio do not significantly correlate with crises. In this sense, the ultimate question is not how loans are funded, but whether the financial sector is heating up too much relative to the economic fundamentals.

Policy responses to capital flows need to strike the right balance between promoting financial deepening and addressing financial vulnerabilities. Even caused by external “push” factors, a financial sector expansion could be a sound deepening that allows domestic firms and individuals to access financial services, given the capital constraints in LIDCs. That said, “push” factors are likely to be uncorrelated with domestic fundamentals and can be a cause of concern for financial stability. Policy makers therefore need to carefully judge whether financial expansion upon the receipt of large capital inflows does exceed the level consistent with the developments of economic fundamentals.

How to effectively respond to capital flows is still under active debates among researchers and policy makers. Not only the issue on when capital controls are justifiable (e.g., Taylor, 2019), but also other related issues are still open to active debates, including monetary policy autonomy when capital accounts are open (e.g., Rey, 2016); the use and the implications of macroprudential policies (e.g., Akinci and Olmstead-Rumsey, 2018; Alam and others, 2019; Nier, Olafsson, and Rollinson, 2020); and foreign exchange interventions and their implications on the domestic financial sector (e.g., Arce, Bengui, and Bianchi, 2019). The IMF has been working on the “Integrated Policy Framework” to form policy guidance under these interactions (IMF, 2020). The results in our paper provide some insights to this area of research, although further efforts are needed to distill policy guidance.

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APPENDIX I. DATA DESCRIPTIONS

A. Country groups and variable definitions

Table A1. Groupings of the economies

Panel A. Full list of countries

Low-income developing countries (LIDCs; 59)[1]
Afghanistan, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Comoros, Democratic Republic of the Congo, Republic of the Congo, Côte d'Ivoire, Djibouti, Eritrea, Ethiopia, The Gambia, Ghana, Guinea, Guinea-Bissau, Haiti, Honduras, Kenya, Kiribati, Kyrgyz Republic, Lao P.D.R., Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Moldova, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Nigeria, Papua New Guinea, Rwanda, São Tomé and Príncipe, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, Sudan, Tajikistan, Tanzania, Timor-Leste, Togo, Uganda, Uzbekistan, Vietnam, Yemen, Zambia, Zimbabwe
Emerging market economies (EMEs; 95)[2]
Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Azerbaijan, The Bahamas, Bahrain, Barbados, Belarus, Belize, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Cabo Verde, Chile, China, Colombia, Costa Rica, Croatia, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eswatini, Fiji, Gabon, Georgia, Grenada, Guatemala, Guyana, Hungary, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kosovo, Kuwait, Lebanon, Libya, Malaysia, Maldives, Marshall Islands, Mauritius, Mexico, Micronesia, Mongolia, Montenegro, Morocco, Namibia, Nauru, North Macedonia, Oman, Pakistan, Palau, Panama, Paraguay, Peru, Philippines, Poland, Qatar, Romania, Russia, Samoa, Saudi Arabia, Serbia, Seychelles, South Africa, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Suriname, Syria, Thailand, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Tuvalu, Ukraine, United Arab Emirates, Uruguay, Vanuatu, Venezuela
Advanced economies (AEs; 39)
Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong S.A.R. of China, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Macao S.A.R. of China, Malta, Netherlands, New Zealand, Norway, Portugal, Puerto Rico, San Marino, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Taiwan Province of China, United Kingdom, United States

Panel B. The countries with the number of banks in our sample (32 LIDCs)

Country	Number of banks	Country	Number of banks
Bangladesh	55	Moldova	17
Burkina Faso	9	Mozambique	16
Cameroon	12	Myanmar	1
Democratic Republic of the Congo	16	Nicaragua	16
Republic of the Congo	3	Niger	6
Côte d'Ivoire	14	Nigeria	41
Ethiopia	2	Papua New Guinea	1
The Gambia	5	Senegal	16
Ghana	50	Sierra Leone	9
Guinea	3	Tanzania	39
Guinea-Bissau	1	Togo	10
Honduras	31	Uganda	29
Kenya	63	Vietnam	54
Liberia	5	Yemen	8
Madagascar	8	Zambia	22
Malawi	12		
Mali	10	**Total**	**584**

Sources: Fitch Fundamental Financial Data (Fitch Solutions, 2020); World Economic Outlook (IMF, 2019c); and the data compiled by the authors (Table A2).

[1] See also IMF (2018, Appendix I) for the update of the classification of the LIDCs.

[2] EMEs are defined as the residual group of economies that are not included in AEs nor LIDCs.

Table A2. Variable definitions and data sources

Variable	Transformation	Series code	Database
Loans	Natural logarithm	Gross Loans	Fitch Fundamental Financial Data
Wholesales funding	Natural logarithm	Wholesale Funding	Fitch Fundamental Financial Data
Deposits	Natural logarithm	Total Deposits	Fitch Fundamental Financial Data
Loan-to-deposit ratio	Winsorized at 5 percent	Net Loans / Total Deposits	Fitch Fundamental Financial Data
Regulatory capital ratio	Winsorized at 5 percent	Total Regulatory Capital Ratio	Fitch Fundamental Financial Data
Total asset to equity ratio	Winsorized at 5 percent	100 / (Equity / Total Assets)	Fitch Fundamental Financial Data
Nonperforming loans	Winsorized at 5 percent	Impaired Loans (NPLs) / Gross Loans	Fitch Fundamental Financial Data
Return on assets	Winsorized at 5 percent	Operating ROAA	Fitch Fundamental Financial Data
Net interest margin	Winsorized at 5 percent	Net Interest Margin	Fitch Fundamental Financial Data
Liquid asset to short-term funding ratio	Winsorized at 5 percent	Liquid Assets / Deposits and ST Funding	Fitch Fundamental Financial Data
Personnel expenses per overhead	Natural logarithm	Personnel Expenses / Overheads	Fitch Fundamental Financial Data
Number of employees	Natural logarithm	Number of Employees	Fitch Fundamental Financial Data
Total capital inflows	Natural logarithm	ICAPFL	FFA
Private capital inflows	Natural logarithm	ICAPFLP	FFA
Foreign direct investment (FDI) inflows	Natural logarithm	IFDI	FFA
Non-FDI private inflows	Natural logarithm	ICAPFLP minus IFDI	FFA
Total inflows to the region	Natural logarithm	The sum of ICAPFL for the countries in the same regions, excluding the country itself	FFA
Real GDP, level	Natural logarithm	NGDP_R	WEO
Domestic interest rate	None	The following five interest rates are combined in this order, when not available: money market rate (FIMM_PA), discount rate (FID_PA), central bank policy rate (FPOLM_PA), deposit rate (FIDR_PA), and government T-bill rate (FITB_PA).	IFS
Banking crisis dummy	None	Banking	Laeven and Valencia (2020)
Currency crisis dummy	None	Currency	Laeven and Valencia (2020)
Real effective exchange rate (REER)	Percent change	EREER_IX	IFS
Wang-Jahan capital account openness index	None	WJ_ka_new	Jahan and Wang (2016), updated by the authors.

(Continued)

Table A2. (continued)

Variable	Transformation	Series code	Database
ICRG, quality of government (QoG) index	None	icrg_qog	Dahlberg and others (2021), PRS Group, Inc., International Country Risk Guide (ICRG)
Trading partners' growth (export-value weighted average of real GDP growth in export destination countries)	Percent change	NGDP_R_WX001	WEO (GEE)
Export commodity prices	Natural logarithm	x_gdp	Gruss and Kebhaj (2019)
Import commodity prices	Natural logarithm	m_gdp	Gruss and Kebhaj (2019)
Volatility Index (VIX)	Natural logarithm	The Cboe Volatility Index	Chicago Board Options Exchange (Cboe, 2021)
U.S. policy rate	None	111FPOLM_PA	IFS
U.S. deflator	Percent change	111NGDP_D	WEO

Sources: Cboe (2021); Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Jahan and Wang (2016); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. Percent changes are calculated as a difference in natural logarithm of the level. The FFA database is compiled from the IMF's Balance of Payments Statistics, IFS, and WEO databases, World Bank's WDI database, Haver Analytics, CEIC Asia database, and CEIC China database. GEE: Global Economic Environment; LIDCs: low-income developing countries.

Table A3. Summary statistics for LIDCs

Variable	Percentiles 25th	50th	75th	Mean	S.D.	Within S.D.	# of Observations	# of Banks or Countries	Average T
Bank-level variables									
Loan	3.78	4.89	6.01	4.91	1.69	0.79	5,279	584	9
Wholesale funding	1.71	3.09	4.41	2.99	2.25	1.29	4,293	559	8
Deposits	4.19	5.27	6.38	5.26	1.68	0.76	5,279	584	9
Loan-to-deposit ratio	53.21	68.41	82.71	72.52	35.17	17.15	5,279	584	9
Regulatory capital ratio	13.00	18.24	26.00	22.11	12.97	6.61	2,541	364	7
Total asset to equity ratio	5.87	8.38	12.14	9.51	5.10	2.90	5,279	584	9
Nonperforming loans	2.24	5.22	11.94	8.84	9.36	6.15	3,671	494	7
Return on assets	0.89	2.22	3.94	2.46	2.62	1.66	5,171	583	9
Net interest margin	1.38	1.86	2.27	1.83	0.61	0.26	5,028	570	9
Liquid asset to short-term funding ratio	18.58	30.07	47.31	36.13	23.12	14.47	5,278	584	9
Personnel expenses per overhead	3.63	3.81	3.96	3.77	0.33	0.21	4,690	552	8
Number of employees	5.24	6.21	7.11	6.21	1.37	0.46	2,492	405	6
Country-level variables									
Total capital inflows	-1.24	-0.32	0.60	-0.32	1.49	0.98	481	32	15
Private capital inflows	-1.19	-0.35	0.59	-0.31	1.47	0.97	474	32	15
FDI inflows	-2.24	-1.02	0.05	-1.17	1.80	1.28	458	32	14
Non-FDI inflows	-1.77	-0.90	-0.01	-0.92	1.42	1.02	437	31	14
Total capital inflows to the region	2.93	4.20	4.70	3.96	1.16	0.86	477	32	15
Real GDP, level	5.29	8.27	9.66	7.84	2.96	0.33	481	32	15
Real GDP, growth	0.03	0.05	0.06	0.04	0.04	0.04	481	32	15
Domestic interest rate	0.05	0.09	0.14	0.11	0.09	0.06	474	32	15
Banking crisis dummy	0.00	0.00	0.00	0.01	0.10	0.10	481	32	15
Currency crisis dummy	0.00	0.00	0.00	0.04	0.19	0.18	481	32	15
REER	-0.04	0.01	0.04	-0.00	0.12	0.12	481	32	15
Wang-Jahan capital account openness index	0.13	0.33	0.69	0.41	0.33	0.10	337	29	12
ICRG, quality of government index	0.33	0.40	0.47	0.40	0.10	0.05	481	32	15
Trading partners' growth	0.03	0.04	0.05	0.04	0.02	0.01	481	32	15
Export commodity prices	4.58	4.60	4.61	4.58	0.05	0.04	481	32	15
Import commodity prices	4.55	4.57	4.60	4.57	0.04	0.03	481	32	15
VIX	2.66	2.86	3.19	2.93	0.31	0.30	480	32	15
U.S. policy rate	0.13	1.25	4.25	1.94	2.09	1.95	481	32	15
U.S. deflator, growth	0.01	0.02	0.02	0.02	0.01	0.01	481	32	15

Sources: Cboe (2021); Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Jahan and Wang (2016); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. Sample period:1989-2019. See Table A1 for country groupings and Table A2 for variable definitions (most of variables are in natural logarithm or percent change) and data sources. LIDCs: low-income developing countries; REER: real effective exchange rate.

B. Update of the Wang-Jahan index

The Wang-Jahan index of capital account openness (Jahan and Wang, 2016) features a broad coverage of LIDCs with complete coding of all 12 subcategories available in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) database (IMF, 2019a) and thus provides the most complete assessment of de jure capital account openness in LIDCs. For each subcategory, a dummy taking zero or one is constructed to indicate whether in a given year restrictions on cross-border financial transactions were in place (note that the intensity of the control is not captured). Adjacent text information, if available, is used to verify the dummy variable and overrules it in the rare cases of contradicting information. The main indicator is the simple average over all 12 subcategories, ranging from 0 in the case of a fully closed capital account, to 1 if cross-border transactions are unrestricted in all 12 subcategories. The 12 subcategories refer to transactions in shares or other securities, bonds and other debt, money market instruments, collective investment securities, financial credits, direct investment and its liquidation, derivatives, real estate, financial guarantees and commercial credit.

We update the index following the methodology outlined in Jahan and Wang (2016). The original dataset covers 1996 until 2013. We extend the coverage until 2017.

C. Bank-level data construction

We extract bank-level balance sheet data from the records of financial statements stored in *Fitch Fundamental Financial Data*. For many financial institutions, there is more than one financial statement because of many reasons. In such cases, we identify one record among multiple financial statements per financial institution per year, by choosing the one with the following characteristics, if applicable, in this order: (1) the end-year report, instead of quarterly or interim reports; (2) the one that covers 12 months; (3) the one that is not consolidated, because consolidated statements may mix the situations in more than one country in the case of international companies; (4) the one in international accounting standards; (5) the one that is audited; and (6) the one reported as of end-December, in line with macroeconomic variables. We further select the financial institutions whose market sector level 3 description is "Banks" or whose issuer name includes "bank" or its variants, using Stata's regexm command with the following regular expression search to capture some language differences: "[B|b]ank|BANK|[B|b]anco|BANCO|[B|b]anque|BANQUE|[B|b]anca|BANCA." We then exclude central banks and bank holding companies. Finally, we further restrict the sample for the ones in LIDCs and the ones with positive entries for gross loans and deposits.

APPENDIX II. ROBUSTNESS CHECK

In our baseline specifications, there is so-called Nickell bias, which results in bias toward zero on the coefficient of the lagged dependent variable, when we include the lagged dependent variable and bank-level fixed effects. Bias on the coefficients on other variables would depend on the correlation between these variables and the lagged dependent variables. As the Nickell bias is known to be proportional to the inverse of the length of the time dimension, it would not be too large in our sample with the average length of 9 years and the minimum of 4 years. Lastly, we face the problem of the small number of clusters, which has two counteracting implications, one of which enlarges standard errors but the other of which reduces standard errors mechanically.

A. Nickell bias

To address the estimation issue due to the use of the lagged dependent variable and fixed effects in the regression, we employ the standard panel technique. We estimate our baseline regression models by generalized method of moments (GMM), using lagged variables as instruments (Table A1), following Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). While we try the system GMM specifications, the rejection of the AR (1) test invalidates the lagged instruments for the level equation for all cases. Therefore, we focus on the one-equation specification (i.e., columns with “One eq.” in Table A4), for which the AR (2) test supports the validity of instruments for all cases.

The results are broadly similar to the baseline OLS results, with weaker evidence on deposits (Table A4). On loans, the coefficient on capital flows becomes slightly larger than the OLS results, indicating some correction of the Nickell bias toward zero. In contrast, significance is lost for wholesale funding and deposits. The loan-to-deposit ratio still shows weak evidence of an increase when capital flows come in. As is generally the case, the results are not very robust to alternative specifications of the panel GMM settings.

As another robustness check against the Nickell bias, we also use the spilt-panel jackknife bias correction. We apply the half-panel jackknifed likelihood estimator proposed by Dhaene and Jockmans (2015), basically following Sun and Dhaene (2019)’s Stata implementation xtspj with model(regress) method(likelihood) options, while we follow Chudik, Pesaran, and Yang (2018) on how to deal with unbalanced panel data. Specifically, we halve the sample into two over time for each panel in calculating the jackknifed log likelihood. Some banks have an odd number of observations, and in these cases, we take the average over the two possible divisions. The estimator is derived as the maximizer of the jackknifed log likelihood, while we use the Driscoll-Kraay standard error formula (with bandwidth of 4). While the asymptotic theories in the cited papers do not allow for data gaps within a panel, our calculations allow for such gaps. Arguably, similar asymptotic results could be obtained if the frequency of such gaps are minor. We report the results excluding observations with any data gaps, as well.

We also apply the half-panel parameter jackknife estimator, with a shortcut to reduce computational burdens. Specifically, we do not exhaustively include all possible combinations of sample splits among unbalanced data, regarding the two possible divisions for banks with an odd number of observations. Instead, we choose the only one way that entails the former half sample with one more observation (e.g., if a bank has 9 observations from 2001 to 2009, we split the sample into 2001-2005 and 2006-2009 for this bank). Also, for standard errors, we ignore cross-equation correlations.

With these split-panel jackknife estimators, we find that the baseline result (Table 1, column 3) of 6.7 basis points only slightly change to 7.5 basis points, but the point estimate is no longer statistically significant. Namely, the size of the bias is very small, estimated at 12 percent of the size of the coefficient, but estimation precision declines in the face of the Nickell bias (Table A5). The results for other variables also indicate corrections of downward bias.

Finally, we restrict the sample to have at least four (or eight) observations per bank. This restriction reduces the sample to 5,020 (or 4,125) observations with 480 (or 313) banks in 29 (or 26) countries, in the case of the main regression with gross loans. The results with both 4-year and 8-year restrictions are broadly similar to the baseline results.

In sum, these robustness checks tend to indicate non-negligible influence of the Nickell bias. The challenge mainly stems from limited data availability for long time series of bank-level data in LIDCs.

Table A4. Panel GMM estimation results

	Loan		Wholesale funding		Deposits		Loan-to-deposit ratio	
	One eq.	System	One eq.	System	One eq.	System	One eq.	System
DIF	0.08***	0.07	0.17***	-0.08	0.02	0.04	3.63***	3.38
FOD	0.07	0.06	0.13**	0.21*	0.02	0.02	2.94**	3.85*
FOD/BOD	0.05	0.03	0.17**	0.12	0.03	0.02	2.99**	3.52**

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. Each cell shows the coefficient of total gross capital flows, with significant levels (*** p<0.01, ** p<0.05, * p<0.1) based on the cluster-robust standard error, clustering by years, to account for cross-country correlation on capital inflows, implemented by the Stata command xtabond2 (Roodman, 2009). Specifications are the same as Table 1, column 3, and Table 3, with all bank-level and country-level controls included, as well as year dummies. The sample size depends on the specifications, but it is the same as in Tables 1 and 3, except for any differences caused by additional lags. The loan-to-deposit ratio is winsorized at 5 percent on both sides. Each row corresponds to how variables are transformed to eliminate bank-level fixed effects. DIF means first-differencing. FOD means forward-orthogonalization. FOD/BOD means that regressors are transformed by forward-orthogonalization and instruments are transformed by backward-orthogonalization (Hayakawa, 2009). Each two set of columns corresponds to one dependent variable. The two columns for each dependent variable show results depending on whether the transformed equation only is estimated (One eq.) or the level equation is also included to be estimated as a system of equations (System). Only capital flows and lagged dependent variables are treated as endogenous, while all other lagged control variables are treated as exogenous. The instruments for these endogenous variables are the second and third lags of the level of the regressors for the transformed equation and the lag of transformed regressors for the level equation if included. Although we limit the number of lags to be the same as the number of endogenous variables, the number of instruments is still large (more than 200, compared with 15-16 regressors and 31 year-dummies) because separate instruments are created for each period. Hansen's J test is accepted at the 5 percent level for all specifications except for the one-equation FOD and FOD/BOD cases of wholesale funding, while the test may be weakened by many weak instruments, and Sargan's test (not robust to heteroskedasticity or autocorrelation but robust to many weak instruments) is all rejected, potentially indicating invalid instruments. The AR(1) test is rejected for all specifications, indicating that the results under the "System" columns are invalid. The AR(2) test is accepted at the 5 percent significance level for all cases except for wholesale funding, for which the tests are still accepted at the 1 percent significance level, supporting the validity of instruments for the transformed equation. All estimations are done by one step, instead of the two-step optimal weighting. GMM: generalized method of moment.

Table A5. Correction to the Nickell bias by split-panel jackknife

	(1) Gross loans	(2) Wholesale funding log	(3) Deposits log	(4) Loan-to-deposit ratio Winsorized at 5 percent
Baseline (Table 1, col. 3, Table 3)	0.055***	0.073**	0.047***	0.739**
Half-panel jackknifed likelihood	0.057	0.087	0.054	0.543
Half-panel jackknifed likelihood, excluding observations with any data gaps over time	0.061	0.083	0.078	0.709
Half-panel parameter jackknife	0.061*	0.121*	0.058**	0.322*

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. Each cell shows the coefficient of total gross capital flows, with significant levels (*** p<0.01, ** p<0.05, * p<0.1) based on the Driscoll-Kraay standard error (clustering by years, with bandwidth of 4), although the standard errors for the half-panel parameter jackknife estimates do not properly reflect cross-equation correlations. We follow Dhaene and Jockmans (2015) and apply the half-panel jackknife estimators, basically as in the Stata command xtspj implemented by Sun and Dhaene (2019), while we follow Chudik, Pesaran, and Yang (2018) on how to deal with unbalanced panel data. Specifications and sample sizes are the same as Table 1, column 3, and Table 3, with all bank-level and country-level controls included, as well as year dummies.

B. Small number of clusters

A small number of clusters is a matter of concern for cluster-robust standard errors, including Driscoll and Kraay (1998) standard errors that we use in this paper. There have been active developments on the issue of a small number of clusters in using the cluster-robust standard errors, as discussed in a seminal paper by Cameron, Gelbach, and Miller (2008). As in the case of the cluster-robust standard error, Driscoll and Kraay (1998) standard errors are based on the asymptotic where the number of clusters goes infinite. The Driscoll-Kraay standard error clusters error terms by the time variable (year), while applying Newey and West (1996)'s kernel formula to take into account autocorrelation (Baum, Schaffer and Stillman, 2010). Namely, in this case, the number of clusters means the number of sample periods, i.e., years, which needs to be sufficiently large. Our unbalanced panel data cover 31 years, which may still be insufficient. MacKinnon and Webb (2017) note that even the rule of thumb of 42 is not enough for unbalanced panel data. Note that the number of clusters would remain similar by clustering by country (as at 32), which takes into account arbitrary cross-correlation within a country and arbitrary autocorrelation but assumes no correlation across countries (which may be too restrictive given the synchronicity of capital flows among LIDCs).

Standard errors based on a small number of clusters may result in over-rejection and spurious significance of estimated coefficients. At first glance, a small number of clusters seems to result in large standard errors in the same way of a small number of observations, leading to under-rejection of the null hypothesis. However, as pointed out by Young (2019), a small number of clusters tends to result in highly leveraged observations, because, if there are only few observations, there are likely to be some observations that look like outliers. Although highly leveraged observations should not be automatically considered as erroneous, their mechanical consequences are too small standard errors, leading to over-rejection. The root of the issue dates back to the original formula of the heteroskedasticity-robust standard error, whose bias depends largely on the degree of leverages of observations (MacKinnon and White, 1985). The literature on cluster-robust standard error is mainly concerned about over-rejection.

While bootstrap methods have been proposed to alleviate the problem, a consensus has not yet been formed for the Driscoll-Kraay standard error. For the cluster-robust standard error, Young (2019) advocates the use of a coefficient-based bootstrap method to alleviate the problem, based on Monte Carlo simulations. However, a similar simulation analysis for the Driscoll-Kraay standard error has not yet been popularly conducted, and thus, whether bootstrap works in this case or not is still under investigation.

C. Capital flow surges and non-averages responses

The literature has examined the effects of capital-flow "bonanzas" or "surges"—periods of unusually large amounts of capital flows, to explore any nonlinear effects or to sharpen the identification of the effects of capital flows.

We find that capital-flow surges are associated with similar results to those based on the log level of capital inflows. We follow one of the methods proposed by Caballero (2016) to identify 10 capital-inflow surge episodes in the estimation sample that includes 481 country-year observations. A surge is identified if the HP-filtered gap of capital inflows is higher than two standard errors calculated country by country. We use a version of the HP filter that allows for missing observations (Schlicht, 2008; Yamada, 2021). With this baseline surge specification, results are broadly similar to those obtained by the log levels of capital inflows (Tables A6, A7), although the results are not robust across the methods to identify surges (Table A8).

Table A6. Gross loans and capital-flow bonanzas in LIDCs

	(1) Gross loans log	(2) Gross loans log	(3) Gross loans log	(5) Gross loans log
Total inflows bonanza – two S.D.	0.04	0.08*	0.07**	0.12***
	(0.06)	(0.04)	(0.03)	(0.03)
Total inflows bonanza – two S.D. (lag)		0.04	0.04	0.03
		(0.06)	(0.06)	(0.07)
Gross loans (log), lag		0.69***	0.57***	0.58***
		(0.02)	(0.03)	(0.03)
Deposits (log), lag			0.12***	0.12***
			(0.02)	(0.02)
Real GDP (log), lag			0.39***	0.34***
			(0.11)	(0.10)
Real GDP growth (log), lag			0.34	0.35
			(0.21)	(0.21)
Domestic interest rate, lag			-0.36*	-0.49**
			(0.20)	(0.22)
Banking crisis, lag			-0.34***	-0.36***
			(0.07)	(0.05)
Currency crisis, lag			-0.00	0.01
			(0.06)	(0.07)
REER (log difference), lag			0.06	0.07
			(0.07)	(0.08)
ICRG quality of government, lag			0.47**	0.37
			(0.21)	(0.24)
Trade partner's growth, lag			-0.40	-0.54
			(0.98)	(0.85)
Export commodity price growth, lag			1.10**	1.18***
			(0.29)	(0.24)
Import commodity price growth, lag			0.48	0.66*
			(0.38)	(0.34)
VIX (log), lag				0.06
				(0.05)
GFC, lag				0.01
				(0.04)
US policy rate, lag				-0.00
				(0.01)
US inflation, lag				4.94**
				(2.44)
Trend term				0.01***
				(0.01)
Bank fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	NO
Sample period	1989-2019	1989-2019	1989-2019	1991-2019
Observations	5,279	5,279	5,279	5,271
Adjusted within R^2	-0.124	0.628	0.652	0.882

Sources: Cboe (2021); Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (clustering by years with the bandwidth of 4) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), implemented by the Stata command ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010). The estimation sample includes 32 countries and 584 banks. S.D.: standard deviations.

Table A7. Banks' soundness and business dynamics upon capital-flow bonanzas/surges

	(1) Non-performing loans Winsorized at 5 percent	(2) Return on assets Winsorized at 5 percent	(3) Net interest margin Winsorized at 5 percent	(4) Liquid asset to short-term funding ratio Winsorized at 5 percent	(5) Personnel expenses per overhead Log	(6) Number of employees Log
Total inflows bonanza – two S.D.	0.37	-0.14	0.04*	2.51***	-0.04	0.09**
	(0.29)	(0.32)	(0.02)	(0.78)	(0.04)	(0.03)
# of countries	30	32	32	32	32	31
# of banks	445	541	528	584	530	345
Sample period	1994-2019	1993-2019	1993-2019	1989-2019	1993-2019	1994-2019
Observations	3,295	4,706	4,538	5,278	4,521	2,124
Adjusted within R^2	0.239	0.129	0.264	0.174	0.211	0.645

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (clustering by years, with the bandwidth of 4) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), implemented by the Stata command ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010). All specifications include the lagged dependent variable, bank- and country-level controls, and bank and year fixed effects. S.D.: standard deviations.

Table A8. Comparison across different definitions of capital-flow bonanzas/surges

	(1) Gross loans log	(2) Gross loans log	(3) Gross loans log	(4) Gross loans log
Total inflows bonanza – one S.D.	0.03			
	(0.02)			
Total inflows bonanza – one S.D., lag	0.01			
	(0.03)			
Total inflows bonanza – two S.D.		0.07**		
		(0.03)		
Total inflows bonanza – two S.D., lag		0.04		
		(0.06)		
Total inflows surge – top 30 percent			0.04*	
			(0.02)	
Total inflows surge – top 30 percent, lag			-0.01	
			(0.02)	
Total inflows surge – top 30 percent for t-1, t, and t+1				0.00
				(0.02)
Total inflows surge – top 30 percent for t-1, t, and t+1, lag				0.03
				(0.02)
# of countries	32	32	32	32
# of banks	584	584	584	584
Observations	5,279	5,279	5,279	5,279
Adjusted within R^2	0.652	0.652	0.652	0.651

Sources: Financial Flows Analytics (FFA, IMF, 2021a); Fitch Fundamental Financial Data (Fitch Solutions, 2020); Gruss and Kebhaj (2019); International Financial Statistics (IFS, IMF, 2021b); Laeven and Valencia (2020); Quality of Government Basic Dataset (Dahlberg and others, 2021; PRS Group, Inc., 2021); and World Economic Outlook (WEO, IMF, 2021c).

Note. The Driscoll-Kraay standard errors (with the bandwidth of 4 and the number of clusters—years—is 31) are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1), implemented by the Stata command ivreghdfe (Correira, 2014, 2017; Baum, Schaffer, and Stillman, 2010). The sample period is 1989 to 2019. All specifications include the lagged dependent variable, bank- and country-level controls, and bank and year fixed effects. S.D.: standard deviations.

APPENDIX III. METHODOLOGIES TO ADRESS REVERSE CAUSALITY

We employ two approaches to address reverse causality: the use of an instrument variable based on regional synchronicity of capital flows and the application of a treatment effect estimator named the augmented inverse-probability weighting estimator.

A. Consequences of reverse causality

Formally, the two-way causality problem can be presented as a simultaneous system of equations. We consider credit $C_{j,i,t}$ of bank j in country i at time t and capital inflows $K_{i,t}$ to country i at time t to satisfy the following system of equations:

$$\begin{aligned} C_{j,i,t} &= \beta K_{i,t} + \phi X_{i,t} + \psi B_{j,i,t} + \alpha_j + \varepsilon_{j,i,t}, \\ K_{i,t} &= \gamma \sum_j C_{j,i,t} + \theta X_{i,t} + \rho Z_{i,t} + \mu_i + \eta_{i,t}, \end{aligned}$$

where $X_{i,t}$ represents a group of country-level control variables; $B_{j,t}$ represents a set of bank-level, time-varying control variables; α_j represents bank fixed effects (which also absorb country fixed effects) and μ_i represents country fixed effects for the second equation; and $\varepsilon_{j,t}$ and $\eta_{j,t}$ are innovation (or shock) terms to the respective equations. Variable $Z_{i,t}$ is key in our identification strategy, which is assumed to be correlated with capital inflows $K_{i,t}$, but which does not affect credit growth of bank j through any other channel conditional on our bank-level and other control variables. Other Greek letters represent parameters of this linear model.

To demonstrate how the reverse causality affects the estimation, let's consider a simplified case with only one bank and one country and without controls or fixed effects. Namely, the system of equations become:

$$\begin{aligned} C_t &= \beta K_t + \varepsilon_t, \\ K_t &= \gamma C_t + \eta_t, \end{aligned}$$

where both subscript i for a country and subscript j for a bank are dropped. To separately identify the two equations, further assumptions are needed because otherwise the second equation would be the same as the first one with $\gamma = \beta^{-1}$ and $\eta_t = -\beta^{-1}\varepsilon_t$. It is natural to assume that an increase ε_t will increase C_t keeping other things constant. Such an assumption is made by restricting $1 - \beta\gamma$ to be positive, because we can solve for C_t and K_t to obtain:

$$\begin{pmatrix} C_t \\ K_t \end{pmatrix} = \frac{1}{1-\beta\gamma} \begin{pmatrix} \varepsilon_t & + & \beta\eta_t \\ \gamma\varepsilon_t & + & \eta_t \end{pmatrix}.$$

This assumption would hold automatically if the signs of the slopes of the two equations are opposite (which is the case of the standard demand and supply equations). But in our case, both β and γ are considered to be positive—domestic credit growth invites capital inflows and capital inflows lead to domestic credit growth. Therefore, $1 - \beta\gamma > 0$ is an additional assumption needed to identify this simple model.

We further assume that ε_t and η_t are both independently and identically distributed with mean zero and variance σ_ε^2 and σ_η^2, respectively. In this case, the OLS estimate of β, denoted by $\hat{\beta}$, satisfies:

$$\operatorname*{plim}_{N\to\infty} \hat{\beta} = \frac{E[K_t C_t]}{E[K_t^2]} = \gamma^{-1}\left(\frac{\gamma^2\sigma_\varepsilon^2}{\gamma^2\sigma_\varepsilon^2 + \sigma_\eta^2}\right) + \beta\left(\frac{\sigma_\eta^2}{\gamma^2\sigma_\varepsilon^2 + \sigma_\eta^2}\right).$$

Namely, $\hat{\beta}$ is a mixture of β and γ^{-1}. In other words, the OLS regression would draw a line with a mixture of the slopes of the first and the second equations in the CK-plane.

The direction of the OLS bias is positive in our case. The bias of the OLS estimate satisfies:

$$\operatorname*{plim}_{N\to\infty} \hat{\beta} - \beta = (\gamma^{-1} - \beta)\left(\frac{\gamma^2\sigma_\varepsilon^2}{\gamma^2\sigma_\varepsilon^2 + \sigma_\eta^2}\right).$$

In our case, $\gamma^{-1} > \beta$ holds because both β and γ are positive and the model is identified by assuming $1 - \beta\gamma$ to be positive. Therefore, the bias is positive, and the OLS estimation would overstate the magnitude of the slope β.

B. Instrumental variable based on regional synchronicity

To disentangle the reverse effects and to identify the causal effect β of capital inflows on credit of bank j, we use an instrumental variable $Z_{i,t}$, utilizing the synchronicity of capital flows to countries in the same region, following Blanchard, Adler, and de Carvalho Filho (2015). Formally, instrument exogeneity requires: $E(Z_{i,t}\varepsilon_{j,i,t} | X_{i,t}, B_{j,i,t}, \alpha_j) = 0$. At the same time, $Z_{i,t}$ must be highly correlated with capital inflows $K_{i,t}$ to reduce small-sample bias (Stock and Yogo, 2005). Specifically, we construct a measure of regional capital inflows $K_{i,t}^*$, which is constructed as follows:

$$K_{i,t}^* = \sum_{j\in\{\Theta_i:\ j\neq i\}} K_{j,t},$$

where Θ_i is the set of countries in the same region as country i, excluding reserve currency issuers (euro area, Japan, Switzerland, United Kingdom, United States). Capital flows to the region of the country are calculated by adding up all gross capital flows to a given region in a given year excluding capital flows to the country itself. While Blanchard, Adler, and de Carvalho Filho (2015) use a share to the previous year's GDP, we use U.S. dollar levels and take the natural logarithm in empirical analysis, to avoid the influences of GDP.

An important aspect in the construction of the instrument is the definition of suitable regions. The granularity of the country grouping needs to take the right balance. The more granular the grouping is, the more likely the instrument may capture shocks specific to the country of interest, making the instrument invalid. The coarser the grouping is, the more likely the instrument may be weak, because it may mix up unrelated countries.[8] Our approach follows the World Bank's region classification: (1) East Asia and Pacific; (2) Europe and Central Asia; (3) Latin America and Caribbean; (4) Middle East and North Africa; (5) North America; (6) South Asia; and (7) sub-Saharan Africa.

Exogeneity of this instrument requires that capital inflows to the region affect domestic credit in a given country only by their correlation with capital flows to that country itself. This points to two requirements as follows:

- First, it requires to fully control for other channels through which the regional capital flows could be correlated with domestic credit. Such channels include foreign demand for domestically produced goods and services (including regional spillovers) and changes in market prices of the country's import or export goods.

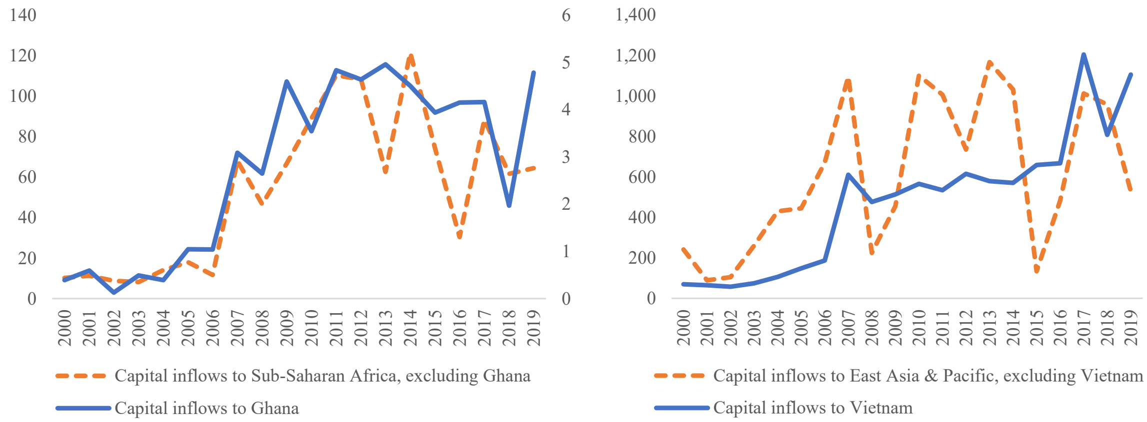
- Second, it requires that domestic economic conditions in any given country in our sample do not affect capital flows to the region as a whole. This assumption can be satisfied if foreign investors first set the total amount to invest to similar countries in a region and then decide on its allocation depending on individual countries' economic conditions, and thus, changes in individual countries' conditions do not affect the total amount of the investment to the region.

To control for these potentially diluting channels for the exogeneity of our instrument variable, we include two country-specific measures of foreign demand and prices. Our foreign demand measure is the change in real GDP of main trading partners weighted by their export shares. Our measure of foreign prices is the change in the prices of commodity exports and imports, weighted by export and import volumes (Gruss and Kebhaj, 2019). Conditional on these variables and other controls, we argue that capital flows to the region are exogenous from the perspective of each single LIDC.

The strength of this instrument—the explanatory power of capital flows to the region for capital flows to a country—builds on the synchronicity of capital flows across the world that are predominantly driven by macroeconomic and financial conditions in the center of the international financial system, as argued in the literature of "global financial cycles" (e.g., Rey, 2016; Reinhart, Reinhart, and Trebesch, 2016). Figure A1 illustrates this point with the examples of Ghana and Vietnam. The correlation coefficient between this instrument variable and gross capital inflows (both in the natural logarithm) is significantly positive for a majority of LIDCs (35 out of 43 countries in our dataset), with the 1 percent significance, ranging from 46 percent to 90 percent.

[8] In theory, we can construct more than one instrumental variable using different country groups based on other similarities than regions. However, for our dataset, it tends to result in highly correlated instruments, such that one of the two instruments would be insignificant in the first stage regression, making the test of overidentifying restrictions unreliable. We conjecture that this happens because two instruments rely on the same synchronicity, based on foreign investors' supply of funds and thus contain mostly the same information.

Figure A1. Synchronicity of capital flows to LIDCs: the cases of Ghana and Vietnam
(In billions of U.S. dollars)



Sources: Financial Flows Analytics (FFA, IMF, 2021a), and the authors' calculations.

A sufficient (and easy-to-digest) condition to these requirements above is the following set of equations:

$$E\left[\varepsilon_{j_1,i_1,t}\varepsilon_{j_2,i_2,t}\right] = 0, E\left[\eta_{i_1t}\varepsilon_{j_2,i_2,t}\right] = 0, E\left[\eta_{i_1t}\eta_{i_2t}\right] \neq 0, \quad i_1 \neq i_2, \forall i_1, i_2 \in \Omega, \forall j_1, j_2, t.$$

The first equation does not allow any cross-country correlation in innovations $\{\varepsilon_{j,i,t}\}_{i\in\Omega}$. Although this would not be satisfied as it is, it might be satisfied if we could fully capture all common factors for $\{C_{j,i,t}\}_{i\in\Omega}$ across countries by $K_{i,t}$ and $X_{i,t}$. This is why we include country-specific terms of trade and trade partners' growth as part of $X_{i,t}$. The second equation requires zero correlation across innovations $\varepsilon_{j,i,t}$ and $\eta_{i,t}$, that is, domestic credit in country i should not directly affect capital flows to country j in the same region, and vice versa. For this condition, our controls need to capture any spillover effects so that any remaining spillover effects are limited in the residuals. Finally, the third equation requires non-zero cross-country correlation in innovations $\{\eta_{it}\}_{i\in\Omega}$, which means that there is regional synchronicity in capital flows.

In other words, to validate this instrument, we need to control for all cross-country common factors for $C_{j,i,t}$ but still retain some cross-country common factors for $K_{i,t}$. This is very challenging in practice. We conjecture that, with our sample, including year fixed effects would have controlled not only for cross-country common factors $C_{j,i,t}$, but also absorbed cross-country common factors for $K_{i,t}$, resulting in a weak instrument and more generally little identifying power of this instrument variable.

C. Methodological note on the AIPW estimator

We employ a methodology from the literature of treatment effect estimation. Glynn and Quinn (2010) provide a clear exposition of the AIPW estimator to the social science literature, which has also been adopted in the macroeconomic literature, for example, by Jordà and Taylor (2016) and Alam and others (2019), to examine macroeconomic policy effects. Similar propensity weighted estimators have also been used in the same context of macroeconomic policy evaluation (Angrist, Jordà, and Kuersteiner, 2016; Asonuma, Chamon and Sasahara, 2016; IMF, 2019b; Kuvshinov and Zimmermann, 2019; Richter, Schularick, and Shim, 2019), while the propensity score matching estimator was already popularly used (see, e.g., Bal Gündüz, 2016).

The AIPW estimator combines two semiparametric estimators for treatment effects. One is the inverse-probability weighting (IPW) estimator that calculates the weighted average of the outcome variable for each treatment level, using the inverse of estimated propensity scores as the weights. This way, the IPW estimator puts more weights on the observations that are less likely to be affected by reverse causality. The other one is the regression adjustment (RA) estimator that estimates the outcome models—the statistical relations between the outcome variable and the control variables—for each level of the treatment separately, to impute unobserved outcomes in hypothetical counterfactual situations where the treatment were to be different from the actual treatment.

A main advantage of the AIPW estimator to the OLS is its flexibility on parametric assumptions, together with double robustness. The underlying necessary assumptions for the AIPW estimator (as well as the IPW and the RA estimators) include conditional mean independence, which is also part of the assumptions where the OLS can validly provide estimates of causal effects. In fact, the OLS can be seen as a special case of the RA estimator, restricting all parameter coefficients except for the one on the constant term are the same across the outcome models for all treatment levels. To put it the other way around, the RA estimator provides more parametric flexibility than the OLS, without restricting parameters across outcome models. The same applies to the IPW estimator, which avoid assuming any parametric form for the outcome models by, instead, assuming a parametric form for the treatment model. The AIPW estimator inherits this flexibility from the RA and the IPW estimators, while providing additional robustness to misspecification in parametric forms.

The AIPW estimator is doubly robust and the most efficient among semiparametric models with the doubly robust property. Double robustness means that it is consistent if either the treatment model or the outcome model is consistent. The AIPW estimator attains the semiparametric efficiency in the class of the doubly robust estimators when both specifications are correct (i.e., its asymptotic variance is equal to the theoretical lower bound). The proof of these claims is credited to the work on missing observation models (Robins, Rotnitzky, and Zhao, 1994). Note that the treatment effect model can be seen as a missing observation model, because it is based on the recovery of information about unobserved potential outcomes in the counterfactual state (i.e., the treated outcome for nontreated observations and the nontreated outcome for treated observations), and thus, there is a translation from one estimation setting to the other. Glynn and Quinn (2010, Appendix A.2) provides a more accessible proof on double robustness.

We follow the quantile binning approach in the continuous treatment effect literature, by creating a categorical variable that indicates the location separated at the quantiles of the whole sample (country-level) distribution of capital inflows. Naimi and others (2014), a paper in epidemiology, finds that this nonparametric approach is simple but robust in various specifications of the data generating process used in their simulation study, whether the distribution is normal with a constant variance or markedly non-normal with a nonconstant variance.[9] We separate locations at the 0.15 and 0.85 quantiles, resulting in three treatment levels. The choice is rather ad hoc but we intend to separate and compare the cases with very high and very low capital inflows while keeping enough observations for each category to ensure reliable estimates for each outcome model estimation done by category. This choice is critical in identification, and the results largely depend on the choice of quantiles, naturally because this choice determines which part of observations should be compared with which other part, and if the choice is irrelevant, the estimation cannot identify treatment effects.

Once assembling continuous values into the three discrete categories, the estimation procedure follows the same procedure for multiple discrete treatments. We use the ordered logit model as the treatment model and the linear regression model as the outcome models for each treatment level. Our choice of covariates for both models is the same as the baseline OLS regressions, excluding capital inflows (while retaining the lag of capital flows). The treatment model is estimated at the country level. The estimation of the two models and the subsequent calculations of (per unit) average treatment effects (ATEs) are done sequentially.

As in the previous studies, the standard errors are calculated in the last step, i.e., when ATEs are estimated based on the estimates from the treatment and outcome models. It is based on the formula when the point estimates of both treatment and outcome models are consistent. Since the AIPW estimator proceeds in three steps, in principle, its standard errors need to be derived from a one-step joint estimation formula to reflect estimation uncertainty of all three steps. However, the one-step formula reduces to the simple standard error formula that can be obtained from only the last step of the sequential estimation if both treatment and outcome models produce consistent estimates (regardless of weak dependence or heteroscedasticity).

Even in the case where one of the two models is mis-specified, the standard errors based on the one-step formula may not be necessarily larger than those obtained from the last step only. It depends on the degree of misspecification. Note that, in general, the standard errors from the one-step formula are larger in the case of the RA estimator but are smaller in the case of the IPW estimator than those based only on the last step of sequential estimation procedures of these estimators.[10] The AIPW estimator combines these two that have opposite natures, and furthermore, its one-step standard error formula is also structured such that estimation errors from earlier steps will vanish if the point estimates are consistent.

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[9] See, e.g., Zhao, van Dyk, and Imai (2020) for other methods for continuous treatment effects.

[10] For this reduction in standard errors in the one-step IPW estimation, see Kim (2019) and papers cited therein, for the property of the IPW estimator that using the estimated propensity scores leads to a smaller asymptotic variance even when the true propensity scores are known. See also Wooldridge (2010).