

## Annex 1. Surges in Capital Inflows and Domestic Investment

This annex looks at the association between capital inflows surges and investment booms. The evidence suggests that large inflows and capital formation are highly positively correlated in LAC but not in other EMEs. This pattern is particularly evident during the commodity super-cycle, and suggests that a dry-up of external financing triggered by exogenous shocks (like a spike in global financial market volatility) may hamper investment even when the domestic economy is performing well.

Surges in gross capital inflows are identified using a modified version of the Hausmann, Pritchett and Rodrik (2005) algorithm. The methodology classifies an episode of high capital flow growth as a surge if it satisfies the following two conditions: (i) the growth rate of inflows in the years following the episode must exceed the growth rate in the preceding years, and (ii) gross capital inflows have to be positive at the start of the episode. More technically, the following variables are computed:

For every 4-year window, the average growth rate of yearly gross capital inflows (GKF) is computed as:

$$\bar{g}_{it}^{KF} = \frac{1}{4} \sum_{j=t}^{t+4} \left( \frac{GKF_j - GKF_{j-1}}{GKF_{j-1}} \right)$$

Then, for every date  $t$ , the difference between the average growth rate in the previous four years and the average growth rate in the four years starting in  $t$ , is defined as  $\text{dif } g_{it}^{KF} = \bar{g}_{it}^{KF} - \bar{g}_{it-4}^{KF}$

A surge in gross capital inflows is identified when the following conditions are satisfied: (a)  $\bar{g}_{it}^{KF} \geq \bar{g}_{75}^{KF}$  (the growth rate is higher than the 75th percentile of the growth distribution); (b)  $\text{dif } g_{it}^{KF} \geq \text{dif } g_{75}^{KF}$  (the growth acceleration is higher than 75 percentile of the distribution of growth accelerations); (c)  $GKF_t \geq 0$  (gross capital inflows are positive at the beginning of the episode).

Having identified the surges in gross capital inflows, the following simple OLS regression is estimated:

$$\text{Investment growth}_{it} = \alpha + \beta * \text{Post Surge}_{it} + \varepsilon_{it} \quad (1)$$

The parameter  $\beta$  captures the difference in investment growth between the pre-surge and post-surge periods. The relation should not be interpreted as causal, as both investment and capital flows affect each other and depend on other factors not included in the analysis. This equation is estimated for several time periods, country samples, and windows around the capital flow surge.

Annex Table 1 shows that real investment growth accelerates around episodes of strong capital inflows, but the size and significance of the accelerations vary across samples and time periods. For the average EME, investment growth increases by 1.7 percentage points after a capital flow surge, but the effect is not statistically significant (Panel A, Column (1)). In contrast, the LA7 countries experience a sharp and statistically significant acceleration in investment growth by 11 percentage points in the years following surges of gross capital inflows (Panel A, Column (2)).

The difference in the response of investment in LAC versus other EMEs is even larger in the post-2000 period. Columns (3)-(4) show that surges in capital flows in the 1990s were not associated with higher investment growth in the LAC-7 countries, while columns (5)-(6) show that in the post-2000s they were associated with large increases. This difference may be due to the factors underlying the episodes of strong capital inflows in each period. In the 1990s, strong capital inflows were associated with optimism on the reforms in the region, which faded quickly as many countries experienced severe economic and financial turmoil. In contrast, the inflows of the 2000s were driven by more persistent improvements in macro-financial frameworks and favorable external conditions, including high commodity prices.

The acceleration of investment growth is largest during the first few years following the capital flow surge (Panel B). The estimated difference between pre and post capital flow surge investment growth is larger when analyzing the smaller window (2 years post vs. 2 years prior) than when using the longer window

(4 years post vs. 4 years prior) in all cases, and many of the estimated growth differences that were not significant at the 4-year window, become significant at the 2-year window. However, the stronger increase in investment growth after capital flow surges in the LA7 countries relative to other EMEs remains.

Annex Table 1 also shows that the LA7 countries typically have lower investment rates in the pre-surge years compared to other EMEs, suggesting that investment growth in the LA7 countries is intimately tied to the availability of external financing.

**Annex Table 1. Investment Growth Around Episodes of Capital Flows Surges**

<b>Panel A. 4 years prior vs. 4 years post</b>						
Real Investment Growth						
	1990–2018		1990–2000		2000–18	
	EMEs (1)	LAC (2)	EMEs (3)	LAC (4)	EMEs (5)	LAC (6)
Post Capital Flows Surge	1.698 (1.828)	11.03** (4.236)	5.179* (2.821)	-4.156 (7.230)	0.553 (2.261)	16.09*** (4.981)
Constant	6.047*** (1.365)	1.515 (3.157)	1.949 (2.140)	8.530 (5.389)	7.421*** (1.678)	-0.823 (3.712)
Observations	504	72	132	18	372	54
R-squared	0.002	0.088	0.025	0.020	0.000	0.167
<b>Panel B. 2 years prior vs. 2 years post</b>						
Real Investment Growth						
	1990–2018		1990–2000		2000–18	
	EMEs (1)	LAC (2)	EMEs (3)	LAC (4)	EMEs (5)	LAC (6)
Post Capital Flows Surge	2.868 (1.967)	17.36*** (5.684)	7.494** (3.282)	8.516 (9.900)	1.107 (2.407)	20.31*** (6.884)
Constant	5.127*** (1.513)	-0.432 (4.403)	1.194 (2.531)	2.169 (7.669)	6.620*** (1.850)	-1.299 (5.333)
Observations	267	40	74	10	193	30
R-squared	0.008	0.197	0.068	0.085	0.001	0.237

Sources: IMF, Financial Flows Analytics database; IMF, World Economic Outlook database; and IMF staff calculations.

Note: Standard errors in parentheses.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

## Annex 2. Determinants of Capital Flows: Data and Methodology

To study the drivers of capital flows, econometric specifications are estimated over two sample periods, 2000–18 and 2012–18. The analysis uses the data from the Financial Flows Analytics (FFA) database (Bluedorn et al., 2013) for 165 countries at a quarterly frequency starting in 1990, complemented with data from the IMF's Balance of Payments Statistics, Haver Analytics, CEIC and EMED databases.<sup>1</sup> The FFA database has data on private capital flows within the "other investment" category, which exclude flows to the general government and monetary authorities as well as IMF lending and reserve asset accumulation. Thus, the FFA data allows the analysis to focus on flows that respond to market forces.

The empirical literature on the determinants of capital flows typically splits the control variables into "pull" and "push" factors (Calvo et al., 1996, Koepke, 2019). The former refers to domestic forces that attract capital flows to the country (domestic growth, structural reforms, etc.), while the latter refers to exogenous external factors driving capital flows to EMEs (lower rates of return in advanced economies, lower global risk aversion). More specifically, the analysis this chapter includes the following push factors: (i) growth in advanced economies; (ii) US 10-year government bond yields; and (iii) global risk aversion measured by the CBOE VIX index. It also includes domestic growth as a pull factor. Domestic interest rates were not included as pull factors because of endogeneity considerations.

Since investment decisions are not fully reversible in the short term, the lagged dependent variable was added as an explanatory variable, in addition to the pull and push factors mentioned above, which is also useful to attenuate possible omitted variable biases. The inclusion of lagged dependent variable, however, implies biased standard fixed-effects estimators, and thus the chapter reports results from system-GMM regressions instead (Arellano-Bond estimator).

---

<sup>1</sup>The FFA data on capital flows starts in 1970, but data on other variables included in the analysis start only in the 1990s.

### Annex 3. A Brief Overview of Duration Analysis

To investigate what lies behind the duration of a sudden stop one cannot resort to traditional linear methods because the distribution of the variable “time to an event” is almost certainly non-symmetric, hence normality of the residuals is unlikely to be an adequate assumption. Therefore, ordinary least squares estimation of the parameters would not be appropriate.

In duration models, survival time is assumed to follow a distribution with a certain underlying density function,  $f(t)$ . The so-called survival function,  $S(t)$  is given by:  $S(t) = P(T > t) = \int_t^{\infty} f(z)dz$ .

From this, the hazard function can be derived,  $h(t) = -\frac{dS(t)}{S(t)}$ , which is the instantaneous probability of failure at  $t$  given non-failure up to that point in time. In general, the hazard will be a function of a vector  $x$  of (possibly country-specific) controls. This allows for analysis of how a change from  $x_i$  to  $x_{i+1}$  affects the probability of failure.

There are three types of survival analysis models: non-parametric, semi parametric and fully parametric. Non-parametric models assume a universal survival distribution for all units of observation in the sample and does not depend on any controls. Semi parametric models assume the existence of a non-parametric common baseline distribution that shifts multiplicatively according to the controls included in the regression. In fully parametric models, different functional forms for the shape of the baseline distribution are tested and estimated.

The chapter uses parametric models. Proportional hazard (PH) models estimate the hazard function:

$$h(t_j|x_j) = h_0(t)exp(x_j\beta)$$

In which  $h(t_j|x_j)$  is the hazard function and  $h_0(t)$  is the baseline hazard function (the hazard function when all explanatory variables are assumed to have zero value) and  $x_j$  is a vector of covariates.

Alternative formulations of the PH models make varied assumptions about the distribution of the baseline hazard. If the data exhibits duration dependence, i.e. if the hazard rate is expected to increase or decrease with time, the Weibull distribution is frequently used. This distribution assumes that the baseline hazard function is given by  $h_0(t) = \theta t^{\theta-1}$ , where the parameter  $\theta$  captures the duration dependence.

## Annex 4. Data Sources and Definitions for Sudden Stops Analysis

**Capital flows.** Total Gross Non-Official Flows (ICAPFLP) in U. S. dollars from the IMF's Financial Flows Analytics (FFA) database. Capital flows in nominal dollar terms were deflated using the US GDP deflator.

**Real GDP in national currency units.** For most countries we rely on quarterly data from IMF's International Financial Statistics Database (IFS). Nevertheless, we use data from Haver Analytics when information in the IFS was missing or with more limited availability. This is the case for the following countries: AZE; BHR; BLR; BLZ; BRA; CHN; CMR; COL; DEU; DNK; FIN; GHA; GTM; HND; IDN; IND; ITA; JOR; JPN; KAZ; KWT; LKA; LSO; MEX; MNE; MNG; MOZ; NAM; NGA; NIC; PAN; SLV; UGA; URY; VNM; ZAF; ZMB.

**Real GDP per capita.** Data from the Maddison Project database (Bolt et al., 2018).

**International reserves.** Official reserve assets in millions of US dollars from the IMF's IFS database.

**Monetary policy rates.** We rely on policy rates from Thomson Reuters Datastream. Nevertheless, we use information from the IMF's IFS Database for money market rates and for discount rates when data on policy rates is not available. The real (ex-post) interest rate is calculated using CPI inflation data from the IMF's IFS database.

**Fiscal balance.** General government primary net lending/borrowing as a share of GDP from the IMF's World Economic Outlook (WEO) database. In the regressions, the measure of fiscal policy is constructed using the residuals from a simple OLS regression of a constant and on real GDP growth and growth in the commodity terms of trade series in order to control for the effect of automatic stabilizers on the balance.

**Capital account restrictions.** Index of de jure capital account openness constructed by Chinn and Ito (2006) based on information from the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). Higher levels of the index indicate a more open capital account.

**Terms of trade.** Log of the commodity net export price index constructed by Gruss (2014).

**Exchange rate regimes.** Coarse de facto exchange rate regime classification from Ilzetzki, Reinhart, and Rogoff (2017). Categories 1 and 2 were classified as fixed-exchange rate regimes and categories 3 and 4 as floating exchange rate regimes.