Replication of Forbes and Warnock 2012

Danil Agafiev Macambira* Pierre-Antoine Etienne† Mohamed Baraa Lafi‡

May 29, 2026

Abstract

This paper replicates and extends Forbes and Warnock (2012). Using quarterly data for 60 countries over 1980–2024, we reconstruct the original dataset, reproduce the identification of surge, stop, flight, and retrenchment episodes and re-estimate binary prediction models with a cloglog specification.

Our replication broadly confirms the main findings of the original paper. Global factors, particularly global risk and financial contagion, remain the most important predictors of capital-flow episodes, while domestic factors generally play a limited role.

We extend the analysis in three directions. First, we update the sample through 2024, covering major events such as the European sovereign debt crisis and the COVID-19 pandemic. Second, we examine heterogeneity across income groups and find that the relative importance of global and domestic factors varies with the level of development. Third, we estimate local projections to assess the effects of episodes on economic activity.

Finally, robustness checks based on alternative episode-identification thresholds show that the main conclusions remain largely unchanged.

*Paris School of Economics. Email: danil.agafiev.macambira@ens.psl.eu
†Paris School of Econoimcs. Email: pierre-antoine.etienne@ens.psl.eu
‡Paris School of Economics. Email: lafibarra11@gmail.com

Contents

1 Introduction

Understanding the determinants of large fluctuations in international capital flows is a central question in international macroeconomics. Episodes of sharp increases or reversals in capital movements can affect financial stability, economic growth, and the transmission of external shocks. Forbes and Warnock (2012) contribute to this literature by examining the determinants of extreme capital flow episodes using gross rather than net capital flows. This distinction enables them to separate the behaviour of foreign investors from that of domestic residents and to identify four types of episodes: surges, stops, flight, and retrenchment. Using quarterly data for a large cross-country sample over the period 1980–2010, they find that global factors, particularly global risk, play a more important role than domestic characteristics in explaining these episodes.

The objective of this report is to replicate and extend the analysis of Forbes and Warnock (2012). First, we reconstruct the original dataset using publicly available primary sources and reproduce the episode-identification procedure and estimation framework as closely as possible. Second, we extend the sample period from 2010 to 2024, allowing us to assess whether the main findings remain valid in the presence of major global events, including the European sovereign debt crisis and the COVID-19 pandemic. Finally, we develop two additional extensions. We investigate the dynamic effects of capital flow episodes on economic activity using the Local Projections methodology from Jordà (2005), and we evaluate the sensitivity of the results to alternative episode-identification thresholds.

The remainder of the report is organised as follows. Section 2 presents the data, variable construction, and empirical methodology. Section 3 discusses the replication and extension results, including the determinants of capital flow episodes and the effects of shocks. Section 4 reports robustness exercises based on alternative episode-identification thresholds. Section 5 concludes.

2 Data and Methods

2.1 Data

To replicate the findings in Forbes and Warnock (2012), we use the same primary sources as detailed in the main paper. All primary sources in Forbes and Warnock (2012) are publicly available and most can be accessed through dedicated Application Programming Interfaces (APIs) reducing data mishaps. We draw data from seven different sources including both institutional sources such as the IMF or World Bank and datasets created by various authors. The data cover 60 countries over 180 quarters, from 1980Q1 to 2024Q4. This refers to our primary "extended sample" of 8,677 country $\times$ quarter observations which accounts for missing data in gross capital inflows.

Although the sources are identical, the data are not necessarily so. Macro public data often gets updated over time and we do not have any information with respect to the exact "vintage" of the data Forbes and Warnock use. This difference in data should not drastically affect the replication;

data revision are, on average, minor and mostly affect recent data. GDP data from the 1980s is very likely to be stable, forty five years later. Data revision do however indicate that we should not expect to find the same point estimates. Rather, we should expect our results to be in the same general direction and provide the same general interpretation. To make our results as comparable as possible as those in Forbes and Warnock (2012), we subset the "extended sample" to 1980Q1-2010Q4. This sample is the "Forbes 2012 sample": 59 countries and 124 quarters for a total of 5,369 country × quarter observations. An important deviation from the original paper is that we have a very slightly different sample: we do not include Taiwan as data are generally hard to access, we separate Benelux into two separate observations and we include China, Nicaragua and Costa Rica. This leads to 60 versus 58 countries in the original paper.[1] Other than these changes, the sample is identical.

As mentioned in Forbes and Warnock (2012), both panels are not balanced. Data are scarcer the older they are. Most countries, however, have a balanced panel. For instance, Argentina, the Netherlands and the US all have a full series on capital flows starting in 1980Q1 and ending in 2010Q4 whereas countries such Croatia or Latvia only start in 1993Q1 with several missing values in between. (See Appendix Table A1 for more details.) Missing data explains the smaller than expected sample size.

2.2 Empirical strategy

2.2.1 Extreme episodes in international capital flows

A key methodological contribution of Forbes and Warnock (2012) is the shift from *net* to *gross* capital flows in identifying episodes of extreme international capital movements. Earlier work, mainly Calvo (1998) and Calvo et al. (2004), defined extreme capital episodes with *net* private capital inflows.[2] The weakness of the net inflows measure is that it cannot disentangle counteracting flows (an increase in foreign capital might be "cancelled out" by a decrease in domestic capital) and as well as the source of flows (a sudden increase in net flows might be driven by foreign capital or by residents liquidating foreign positions and repatriating funds). Figure 1 showcases this issue for Brazil. In 1999, Brazil experienced both a sharp decrease in gross capital inflows (green dotted line) and a sharp decrease in gross capital outflows (red dashed line; outflows are depicted as negative as per convention but should be understood as a positive flow). On net however, there seems to be no movement in capital (black solid line) thus hiding some of the volatility in capital flows. Focusing on gross flows solves both of these problems and thus allows for a more precise study of extreme episodes as well as their determinants. As gross flows have grown relative to net flows since the 1990s, this issues has become all the more problematic.

Whereas Calvo (1998) and Calvo et al. (2004) could only classify capital flows into two categories (surges or stops in net flows), Forbes and Warnock (2012) are able to classify extreme capital flow episodes into four distinct types, each tracking a separate dimension of the capital account:

[1] This different sample reflects the changes the authors conducted in their updated 2021.

[2] Net capital flows are typically proxied by subtracting changes in international reserves from the current account balance.

- **Surge.** A sharp increase in gross capital inflows, i.e., a rapid acceleration of net foreign purchases of domestic assets. Surges reflect decisions by foreign investors to increase their exposure to the domestic economy.

- **Stop.** A sharp decrease in gross capital inflows. Foreigners abruptly reduce or reverse their net purchases of domestic assets. This is the gross-flow analogue of the classical "sudden stop".

- **Flight.** A sharp increase in gross capital outflows, i.e., an acceleration of net domestic-resident purchases of foreign assets. Flight reflects decisions by domestic investors to move capital abroad.

- **Retrenchment.** A sharp decrease in gross capital outflows. Domestic investors liquidate foreign holdings and bring capital home. During the GFC, retrenchment was widespread and, because it offset stop episodes, frequently caused net-flow measures to misclassify countries as experiencing surges.

Surges and stops are driven by the decisions of foreigners; flight and retrenchment are driven by domestic investors. The four episodes together span the full cycle of extreme capital flow movements. Importantly, they need not coincide. A country can simultaneously undergo a stop (foreigners pulling out) and a retrenchment (residents also pulling out of foreign markets).

Whereas previous literature constructed proxies for net flows through changes in international reserves, Forbes and Warnock (2012) use Balance of Payments data to measure gross capital flows. These quarterly data at the country level come from the IMF's Balance-of-Payments (BOP) dataset.[3] Following standard BOP conventions, gross inflows aggregate the net foreign purchases of domestic assets across the direct-investment, portfolio, and other investment accounts (the liability side). Gross inflows aggregate the net domestic-resident purchases of foreign assets (the asset side).[4] Because BOP convention records outflows as negative values, the replication code sign-standardises outflows [5] so that larger positive values unambiguously indicate larger outward flows by residents.

The statistic used to characterise episodes is a year-over-year change in the rolling mean of either gross inflows or gross outflows. Let F_t denote either gross inflows or (sign-adjusted) gross outflows for a given country in quarter t. Following Forbes and Warnock (2012), the detection statistic is:

$$C_t = \sum_{i=0}^{3} F_{t-i}, \qquad \Delta C_t = C_t - C_{t-4}. \tag{2.2.1}$$

Summing over four quarters eliminates seasonal fluctuations while preserving the annual flow signal. The year-over-year difference ΔC_t then measures the change in the pace of capital movements relative to the corresponding period one year earlier. Extreme deviations are then judged relative to the rolling mean and standard deviation of ΔC_t computed over the preceding 20 quarters, and a

[3] Forbes and Warnock (2012) use the same IMF data but these were pulled from the now deprecated International Financial Statistics (IFS) dataset. The underlying data should be identical.

[4] Assets and liabilities follow the IMF's definitions. See Appendix Section A.1 for more details.

[5] (`outflows_std` = − `outflows`)

minimum of 5 years of history is thus required before an episode can be identified. Though multiple methods can be used to characterise extreme capital flow episodes from this statistic, Forbes and Warnock (2012) use the following criteria:

1. **Persistence.** An episode is characterised when ΔC_t crosses one standard deviation above (surge or flight) or below (stop or retrenchment) the rolling mean for at least two consecutive quarters.

2. **Extreme movement.** At some quarter within the episode, ΔC_t reaches at least two standard deviations from the rolling mean in the same direction. This ensures that episodes reflect genuinely extreme movements and unexpected deviations.

3. **Exit criterion.** The episode continues for all consecutive quarters in which ΔC_t remains beyond the one-standard-deviation threshold, and it ends when ΔC_t re-crosses that boundary.

Each country's episodes are detected independently, i.e., the detection statistic is calculated at the country level, so that thresholds adapt to the idiosyncratic volatility of that country's capital flows. Figure 2 provides an illustration of the characterisation algorithm for Chile. Between 2005 and 2010, only one episode is recorded as the 2 SD band is only crossed by the first surge in gross inflows, while the sharp decrease in 2008 only approached the 2 SD band. The same goes for the following peak in gross inflows: as inflows were very volatile over the past years, the 2 SD band expands and makes it so that huge movements that would have been characterised as episodes had they happened 10 years before are now considered standard and predictable by agents, who adapt to the increase in volatility.

2.2.2 Variable definitions

To determine the drivers of extreme episodes, Forbes and Warnock (2012) (and Forbes and Warnock (2021)) classify explanatory variables into three categories: global factors, domestic factors and transmission factors

- **Global factors**. Global drivers are measured through four variables. Global liquidity is the year-over-year growth in the *braod* money supply of the United States, euro area (EU19), Japan, and the United Kingdom (all converted to USD).[6,7,8,9] Global interest rates are the average long-term government bond yield across the same four economies.[10] Global growth is the quarterly

[6]Broad money is a term coined by the IMF in an effort to homogenise money supply definitions across economies. See Cartas and Harutyunyan (2017) for more information.

[7]We were not able to find the exact same data as mentioned in Forbes and Warnock (2012) on money supply. We thus chose to use the OECD "broad money M3" series in the MONAGG dataset.

[8]We use the OECD's "euro-area" definition which allows for the EU-19 to evolve over time. Data prior to 2001 refers to EU11 (Belgium, Germany, Ireland, Spain, France, Italy, Luxembourg, the Netherlands, Austria, Portugal and Finland). Data from 2001 to 2006 refers to EU12 (EU11 plus Greece). Starting in January 2007, data refers to EU13 (EU12 plus Slovenia). Data refers to EA19 with Malta and Cyprus joining the euro area in 2008, Slovak Republic in 2009, Estonia in 2011, Latvia in 2014 and Lithuania in 2015.

[9]To convert the EU19 money supply into US dollar, we use the OECD's composite exchange rate for EU19, in the FINMARK dataset.

[10]We use the OECD's series on "Interest Rate Long Term" in the FINMARK database.

change in world real economic activity measured through global GDP data from the IMF's Quarterly National Economic Accounts (QNEA) dataset. Finally, global risk is measured by the VXO index from the Chicago Board Options Exchange on S&P 100 options. The VXO (formerly the VIX) captures both investor risk aversion and economic uncertainty.[11]

- **Domestic factors.** Domestic drivers are measured through three measures. Stock market capitalisation relative to GDP drawn from the World Bank[12] Capital controls with Chinn and Ito (2006)'s KAOPEN index of domestic financial openness. Lastly, to account for local economic activity and constraints, we include domestic growth shocks, defined as the cyclical component of year-over-year real GDP growth extracted via a Hodrick-Prescott (HP) filter.[13]

- **Transmission factors.** We use three different variables to measure transmission (or contagion). The first variable measures transmission of extreme episodes through trade exposure. Simply, the trade-linkage variable weights the episode incidence of trading partners by their share of country x's exports, further scaled by trade openness.[14] The second variable measures transmission through cross-country financial ties. Analogously to the trade-linkage variable, financial-linkages is GDP-weighted average using bilateral bank-claims data from the BIS's Locational banking statistics (LBS) dataset. (See Appendix A.2 for more details.) Lastly, we use a simple categorical for regions to capture geographic proximity.[15]

2.2.3 CLOGLOG regression specification

To determine the drivers of extreme episodes, without asserting a causal relationship, Forbes and Warnock (2012) estimate a binary response model of the form

$$\Pr(e_{it} = 1) \;=\; F\left(\Phi_{t-1}^{\text{Global}}\,\beta_G + \Phi_{i,t-1}^{\text{Contagion}}\,\beta_C + \Phi_{i,t-1}^{\text{Domestic}}\,\beta_D\right), \tag{2.2.2}$$

where e_{it} is a binary indicator equal to one if country i is in an episode in quarter t; $\Phi_{t-1}^{\text{Global}}$ is a vector of global variables (global risk, global liquidity, global interest rates, and global growth); $\Phi_{i,t-1}^{\text{Contagion}}$ captures contagion through regional proximity, trade linkages, and financial linkages; and $\Phi_{i,t-1}^{\text{Domestic}}$ includes country-level variables comprising financial system depth, capital controls, public debt, a

[11] In our analysis, we combine both measures to create a complete series from from 1980Q1 to 2024Q4. Particularly, we use the newer VXO series to extend that VIX series that was deprecated in 2017. Hence, this has no effect on the "Forbes 2012 sample".

[12] See Beck et al. (2009) for more details.

[13] Growth shocks are calculated as the cyclical component of year-over-year real GDP growth, computed using constant-price, non-seasonally adjusted quarterly data from the IMF's (QNEA). Growth rates are calculated relative to the same quarter of the previous year to eliminate seasonality, and the cyclical shock is extracted via a Hodrick-Prescott (HP) filter with a standard quarterly smoothing parameter of $\lambda = 1600$. To ensure statistical validity, the filter is only applied to country series where a minimum of 10 historical growth observations are available.

[14] Trade data is drawn from the IMF's International Trade in Goods (IMTS) dataset whereas GDP data comes from the QNEA.

[15] In the international trade literature, distance still explains a large portion of trade flows.

domestic growth shock, and GDP per capita.[16] All regressors are lagged one quarter to limit simultaneity concerns. The four episode equations are estimated jointly using seemingly unrelated estimation, allowing for cross-episode correlation in the error terms, with standard errors clustered by country. The model is estimated using a complementary log-log (cloglog) specification, which relies on the cumulative distribution function $F(z) = 1 - \exp[-\exp(z)]$. Unlike the symmetric logistic or probit links, the cloglog CDF is right-skewed. This asymmetric property makes the cloglog specification a robust choice when the event of interest is rare, as it avoids the structural distortions that symmetric links introduce when zeros heavily dominate the outcome variable.

2.2.4 Local Projections

Following Jordà (2005), we apply the Local Projections (LP) framework to estimate the effect of each episode type (surge, stop, flight, and retrenchment) on real GDP over a horizon of $H = 16$ quarters in the form of Impulse Response Functions. The outcome variable is the cumulative log change in real GDP, $\Delta^h y_{i,t} = \log Y_{i,t+h} - \log Y_{i,t-1}$. The treatment variable $e_{i,t}$ is the binary episode indicator constructed in Section 2. Controls include an AR(4) term for GDP growth, alongside lagged values of public debt, capital openness, inflation, and the Forbes and Warnock (2012) trade-linkage variable ($\mathbf{Z}_{i,t-1}$). Including country fixed effects (α_i), time fixed effects (γ_t), and seasonal dummies, our specification is:

$$\log Y_{i,t+h} - \log Y_{i,t-1} = \alpha_i^h + \gamma_t^h + \beta^h e_{i,t} + \lambda^h \sum_{p=1}^{4} \Delta y_{i,t-p} + \mathbf{\Gamma}^h \mathbf{Z}_{i,t-1} + \varepsilon_{i,t}^h, \qquad h = 0, 1, \ldots, 16 \quad (2.2.3)$$

Standard errors follow Driscoll and Kraay (1998) with four lags to account for cross-sectional dependence and serial correlation. This lag structure and rich set of controls ensure that $\hat{\beta}^h$ isolates the specific output effect of an episode from domestic macroeconomic vulnerabilities and synchronized external shocks.

3 Results

Table 1 reports summary statistics for the four episode types over the full sample of the original paper. Following Forbes and Warnock (2012), the dummy variable $e_{i,t}$ from Equation (2.2.2) equals one whenever country i is currently experiencing an episode in quarter t, that is, it flags every quarter within an episode's duration. The four episode types occur with broadly similar frequency. Surge and flight episodes are each active in roughly 11% of country-quarter observations, while stops and retrenchments are slightly less prevalent at around 10%, somewhat below the 15–18% reported by Forbes and Warnock (2012) for their 1980–2010 sample (Table 1, Panels A and B). This difference

[16] We use public debt from the World Bank's Quarterly Public Sector Debt (QPSD) series and the IMF's Historical Public Debt (HPD) database when the World Bank data were not available.

is fairly hard to explain as we used the very same data sources as the authors.[17] Average episode duration is uniform across types and income groups, hovering close to four quarters (one year) for almost every subgroup, suggesting that once an extreme capital flow movement is underway its persistence is broadly invariant to whether it is driven by foreigners or residents and to the level of development of the host country. The main exception is Eastern Europe, where episodes tend to be somewhat longer than elsewhere, with flight episodes there average five quarters, possibly consistent with the region's history of prolonged capital flow cycles tied to EU accession dynamics and recurring balance-of-payments pressures. Latin America displays the opposite pattern, with retrenchment episodes averaging only 3.4 quarters, the shortest of any region-type subgroup, possibly reflecting the historically abrupt and short-lived nature of domestic investor responses to external shocks in that region.

3.1 Drivers of Extreme episodes

3.1.1 Replication of the Determinants of Episodes

Table 4 compares our replication estimates with those reported in Forbes and Warnock (2012) for all four episode types. Our estimates are based the "Forbes 2012 sample". The specification used is the cloglog from Equation (2.2.2).

The replication broadly confirms the central finding of Forbes and Warnock (2012): global and contagion factors dominate domestic ones. Global risk is significantly negative for surge and flight in both exercises, though we lose significance for stop and retrenchment, likely reflecting the smaller sample (2,017 vs. 3,446 observations). Financial contagion emerges strongly in our replication for stop and retrenchment episodes, consistent in sign with the Forbes and Warnock (2012) though larger in magnitude, possibly due to differences in the banking-linkage matrix construction. Trade linkages, significant in Forbes and Warnock (2012) for stops and retrenchments, are not significant in our sample. Domestic factors remain broadly insignificant in both exercises, and capital controls show no robust association with surge or stop episodes in either, supporting the authors' conclusion that controls do not insulate economies from foreign-driven capital flow volatility.

As a complement to the gross flows analysis, Forbes and Warnock (2012) re-estimate the determinants of episodes defined using the net flows methodology from Calvo et al. (2004) (Table 5 in Forbes and Warnock (2012)). We replicate this exercise on our "Forbes 2012 sample". The results in table 9 reinforce the main message of the paper. When episodes are constructed with net flows, global risk loses significance in the original. In our replication, however, global risk is statistically significant at the 5% level for both surge ($\hat{\beta} = -0.068^{**}$) and stop ($\hat{\beta} = 0.042^{**}$) episodes. Regional contagion is also statistically significant at the 5% level in both episode types ($\hat{\beta} = 0.765^{**}$ and $\hat{\beta} = 0.811^{**}$), while domestic factors remain largely irrelevant, consistent with the gross flows results. Overall, net flows

[17] For a closer comparison, we replicated Table 1 using the author's own datasets from their updated paper, Forbes and Warnock (2021). This paper simply updates the original 2012 paper, given some very small changes. When using these posed data, we recovered similar summary statistics as those described in Table 1, Panel B.

hide valuable variation for not added benefit.

3.1.2 Sensitivity Analysis

Forbes and Warnock (2012) subject their baseline results to an extensive battery of robustness checks (their Tables 8a–8d), covering each of the four episode types separately. The specifications include dropping the crisis period (2008Q3–2009Q2), adding country fixed effects, controlling for the exchange-rate regime, replacing global liquidity with private credit growth, and using an alternative measure of financial system strength. Across all these variations, the significance of global risk and contagion variables remains stable in the original, while domestic factors stay largely uninformative. We replicate this sensitivity analysis on our sample and report the full results in Tables 10– 13.

The sensitivity replication analysis (1980–2010) reveals a broadly consistent picture with the Forbes sample replication, though with some noteworthy differences across episode types. Global risk is the single most robust result in the extended sample. For *surge* episodes (Table 10), global risk is negative and significant at 1% across all five specifications, replicating the original paper's finding with high fidelity. Similarly, for *flight* episodes (Table 12), global risk remains negative and significant at 1% in all five columns, making it equally robust for both outflow episode types. For *stop* episodes (Table 11), global risk is significant in three out of five columns (Add ER regime, global credit, and financial system), suggesting a moderate degree of stability. By contrast, for *retrenchment* episodes (Table 13), global risk is significant in only one specification (financial system), representing the weakest result across all four episode types.

Financial contagion through banking linkages retains its robustness for *stop* and *retrenchment* episodes. For *stop* (Table 11), the financial linkage coefficient is positive and significant at 1% in four out of five columns, with the drop-crisis column the only exception. For *retrenchment* Table 13, financial linkages are significant at 1% in four out of five columns (fixed effects, ER regime, global credit, and financial system), making it the dominant and most consistent predictor for this episode type. By contrast, for *surge* (Table 10) and *flight* (Table 12), financial linkages are never significant in any specification. Regional contagion remains a strong and consistent predictor of *surge* episodes, significant at 1% across all five specifications, reinforcing the pattern observed in the baseline replication.

Among global factors, global interest rates emerge as a robust predictor of *stop* episodes, positive and significant at 1% or 5% in four out of five columns (all except fixed effects). Liquidity is a significant predictor of *flight* at 1% or 5% in three out of five columns (drop crisis, fixed effects, and ER regime). Global growth is negatively and significantly associated with *retrenchment* in two columns (drop crisis and financial system), consistent with the baseline finding.

Domestic factors remain largely uninformative throughout. Growth shock is negatively significant for *stop* in the drop-crisis specification and for *retrenchment* in the drop-crisis column, but these results do not hold across the full battery of checks. Capital controls show no significant association with surge or stop episodes in any specification. Overall, the extended sample confirms that global risk and regional contagion are the dominant drivers of surge episodes, global risk and financial linkages jointly characterise stop episodes, global risk and liquidity drive flight episodes, and financial linkages together with global growth characterise retrenchment episodes across all robustness specifications.

3.1.3 Global vs Local Drivers

The estimates in Table 4 point to a clear hierarchy: global factors, and to a lesser extent contagion, drive extreme capital flow episodes, while domestic characteristics play a secondary and largely insignificant role. This is consistent with the central conclusion of Forbes and Warnock (2012), who argue that waves of capital flows are primarily associated with changes in global risk rather than country-specific fundamentals. Our replication corroborates this picture — global risk is the variable most robustly significant across episode types, and capital controls, fiscal positions, and financial system depth are generally uninformative once global and contagion channels are accounted for.

That said, this conclusion should be taken with some caution. The sample pooled across all countries treats the cross-section as homogeneous, which it clearly is not. High-income, middle-income, and lower-income economies differ substantially in their degree of financial openness, the depth of their capital markets, and their exposure to global risk sentiment. Pooling them together may mask important heterogeneity: global factors may dominate the full-sample estimates simply because they are overwhelmingly relevant for advanced economies, which account for the bulk of the observations, while domestic fundamentals could play a more meaningful role in emerging or lower-income countries. As we show in the extensions below, splitting the sample by income group yields noticeably different patterns, suggesting that the primacy of global drivers is not uniform across country groups.

The full-sample results are therefore best read as a useful but incomplete summary. They confirm that global factors — particularly risk — are a first-order determinant of capital flow volatility at the aggregate level, in line with Forbes and Warnock (2012). But the underlying group heterogeneity means that a single set of coefficients cannot tell the whole story, and policy conclusions drawn from the pooled estimates alone may not translate equally well across different types of economies.

3.2 What are the effects of shocks?

The local projection estimates reveal a clear and symmetric pattern for episodes driven by foreign investors, and a null result for those driven by domestic investors, as reported in Figure 1. Surge episodes are associated with a cumulative increase in real GDP of up to 1.2 percentage points, with the effect building gradually and peaking approximately two years after the onset of the episode, consistent with the hypothesis that surges' growth effect are channelled through investment. Stop episodes produce a mirror-image response: gross inflows falling sharply below trend are associated with a cumulative output loss of up to 1.5 percentage points over the same horizon, consistent with the view that a sudden withdrawal of foreign capital tightens domestic financial conditions, raises the cost of external finance, and depresses investment. Stops therefore seem to have a little worse impact on GDP than surges, though the difference is not statistically significant. By contrast, the estimated response functions for flight and retrenchment episodes are small in magnitude and not statistically different from zero at all horizons at the 90% confidence interval, suggesting that sharp movements in gross outflows by domestic investors carry little explanatory power for subsequent output dynamics.

These null results for domestic-investor episodes are consistent with the literature preceding Forbes and Warnock (2012) that built on the idea that macroeconomic outcomes are primarily driven by the net flow of capital, which is itself largely determined by gross inflows from foreigners rather than by gross outflows from residents. When domestic investors retrench—liquidating foreign holdings and repatriating funds, usually because of higher global risk as the CLOGLOG model showed—the increase in net inflows this generates tends to offset the simultaneous stop in foreign capital, leaving aggregate financing conditions and, ultimately, output relatively unchanged. Flight episodes are similarly self-contained: when residents send capital abroad, e.g. if they are investing in a particular sector such as the US tech sector, this need not signal or cause domestic distress if foreign investors continue to supply capital on the inflow side. The output response to capital flow episodes therefore appears to operate primarily through the foreign-investor channel, with domestic investor behaviour playing a secondary and largely offsetting role. This is consistent with the literature on international capital markets that highlights how financial globalisation has made gross inflows from abroad, rather than the portfolio decisions of residents, the dominant force in determining domestic financing conditions.

A key caveat is that the estimates in equation (2.2.3) should not be interpreted as causal effects. Episode incidence is not randomly assigned across country-quarters: surges, for instance, may occur precisely when a country's growth prospects are improving, while stops may coincide with the onset of domestic or regional crises. This reverse causality, i.e. output dynamics driving the probability of an episode rather than the other way around, means that the coefficient sequence $\{\hat{\beta}^h\}$ is likely to be upward biased for surges and downward biased for stops. Although the inclusion of country and time fixed effects, AR(4) output lags, and a set of pre-determined macroeconomic controls absorbs the most salient sources of confounding, they do not fully resolve the endogeneity of episode timing. In the absence of a credible instrument for the onset of extreme capital flow episodes, the estimates are best interpreted as conditional correlations that characterise the average output trajectory associated with each type of episode, rather than as policy-relevant causal parameters.

4 Robustness

4.1 Income-Group Heterogeneity and Sample Extension (1980–2024)

The previous analysis pooled all countries into a single sample, implicitly assuming that the determinants of capital-flow episodes are homogeneous across economies. This assumption may be restrictive. Financial markets, institutional quality, capital-account openness, and exposure to global shocks differ substantially across countries at different stages of development. To investigate whether the drivers identified by Forbes and Warnock (2012) are equally relevant across countries, we extend the original sample through 2024 and split the dataset into three income groups: high-income, middle-income, and low-income economies.

This extension serves two purposes. First, it allows us to evaluate whether the original conclusions remain valid in a substantially different global environment, encompassing the European sovereign debt crisis, the COVID-19 pandemic, and the subsequent tightening cycle of major central banks. This objective closely follows Forbes and Warnock (2021), who revisit the original analysis using post-crisis data to assess the stability of the main findings. Second, it enables us to examine whether the relative importance of global, contagion, and domestic factors varies across levels of development.

Rather than estimating a single average effect for all countries, the income-group approach allows for heterogeneous responses to global financial conditions. If the dominance of global risk documented in the pooled sample is primarily driven by advanced economies, then the estimated coefficients should weaken in lower-income groups. Conversely, if global factors remain dominant across all income categories, this would strengthen the argument that capital-flow episodes are fundamentally driven by external conditions rather than domestic fundamentals.

Tables 6–8 report the results for the three income groups. Several differences emerge across groups, suggesting that the pooled estimates mask meaningful heterogeneity. While global factors continue to play an important role, their magnitude and significance vary across income levels. Likewise, some contagion channels become more relevant for certain groups, whereas domestic variables remain largely insignificant in others. These results indicate that the relative importance of global and local drivers depends on the level of economic development and caution against interpreting the pooled estimates as universally applicable.

Overall, the extended sample confirms the central message of Forbes and Warnock (2012): external factors remain key determinants of capital-flow episodes. However, the income-group analysis reveals that the strength and transmission of these effects differ across countries, highlighting the importance of accounting for heterogeneity when assessing the drivers of international capital flows.

This heterogeneity is economically intuitive. High-income economies are generally more integrated into global financial markets and therefore appear more sensitive to global risk conditions, particularly during surge episodes. In contrast, middle- and low-income countries display a greater role for contagion channels and domestic characteristics. For example, regional contagion is significant for surge episodes in middle-income economies and for stop and retrenchment episodes in low-income economies, while several domestic variables, including financial-system depth, debt levels, and capital controls, become significant only in the lower-income groups. These findings suggest that as countries become less financially integrated and more exposed to regional shocks, domestic and regional characteristics play a larger role in shaping capital-flow dynamics.

4.2 Sensitivity to the Episode Cutoff

The identification of capital-flow episodes relies on a statistical threshold defining what constitutes an extreme movement. Forbes and Warnock (2012) classify episodes using a cutoff of two standard deviations above or below the historical mean. Although this threshold is widely used, it remains somewhat arbitrary. To assess whether our results depend on this choice, we re-estimate the episode-identification procedure using cutoffs ranging from 1.5 to 3 standard deviations.

Figure 5 reports the number of detected episodes for each threshold. As expected, the number of episodes declines monotonically as the cutoff becomes more restrictive. Across all episode types, increasing the threshold from 1.5 to 3 standard deviations reduces the number of identified episodes by roughly an order of magnitude. Importantly, the baseline threshold of 2 standard deviations lies near the middle of the distribution and does not appear to generate either an unusually large or unusually small number of episodes.

Figures 6 and 7 examine the stability of the estimated coefficients for gross-flow and net-flow episodes, respectively. The vertical dashed line marks the baseline threshold used by Forbes and Warnock (2012). Several patterns emerge.

First, the signs of the main coefficients remain remarkably stable across alternative cutoffs. Global risk continues to display the same qualitative relationship with episode occurrence over a wide range of thresholds. Similarly, regional and financial contagion variables preserve their general patterns. This stability suggests that the economic interpretation of the results does not depend on a particular choice of cutoff.

Second, coefficient uncertainty increases as the threshold becomes more restrictive. Higher cutoffs identify fewer episodes, reducing the effective sample size and generating wider confidence intervals. At the same time, a higher threshold focuses on increasingly severe capital-flow episodes, which are by construction rarer events. This creates a natural trade-off between precision and extremity: lower cutoffs provide more observations but include less extreme movements, whereas higher cutoffs isolate the most pronounced episodes at the cost of greater estimation uncertainty. This effect is particularly visible beyond 2.5 standard deviations, where estimates become noticeably more volatile. Nevertheless, the broad qualitative conclusions remain unchanged, suggesting that the main findings are not driven by the inclusion of moderately large capital-flow movements but also characterize the most extreme episodes.

Third, domestic variables continue to exhibit limited explanatory power regardless of the threshold used. Their coefficients remain small, unstable, and rarely distinguishable from zero. By contrast, global and contagion variables continue to account for most of the explanatory content of the regressions.

Taken together, these results indicate that the main findings are not driven by the particular episode-definition rule adopted in the baseline specification. While the exact number of episodes naturally depends on the cutoff selected, the overall hierarchy of determinants remains largely unchanged. Global risk and contagion channels continue to emerge as the most informative predictors of extreme capital-flow episodes, whereas domestic factors play a comparatively limited role.

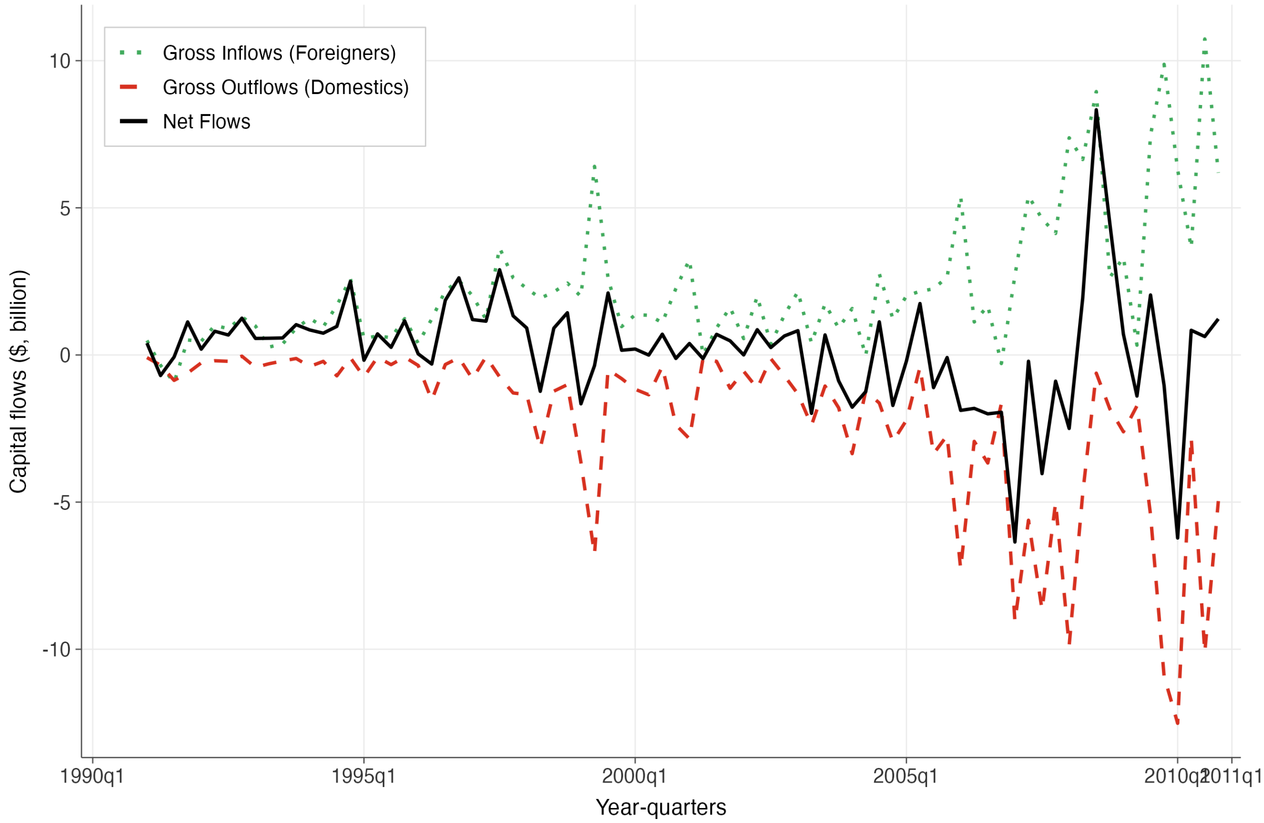
5 Conclusion

Replicating the results of Forbes and Warnock (2012) from the same primary sources proved more difficult than expected. Publicly available data do not exactly reproduce the panel used by the authors, and successive revisions to balance of payments statistics introduce discrepancies which, although generally minor, affect the point estimates. The results are therefore not identical to those of the original paper. Nevertheless, the core conclusions on the causes of extreme capital flow episodes remain valid: global risk is the most robust and consistently significant determinant of extreme episodes, while domestic factors such as capital controls, public debt, and financial depth remain largely uninformative once global financial conditions are controlled for.

Our extensions support this interpretation. Robustness checks using alternative identification thresholds show that the hierarchy of determinants is stable over a wide range of values, and that the choice of the two-standard-deviation threshold used by Forbes and Warnock (2012) does not drive the qualitative conclusions. Furthermore, the analysis by income group indicates that the primacy of global factors, while verified across the entire sample, is more pronounced in advanced economies. One also has to keep in mind that the extended sample we used to extend the original paper of Forbes and Warnock (2012) covers a very long period, during which investors' behaviour may have changed overtime.

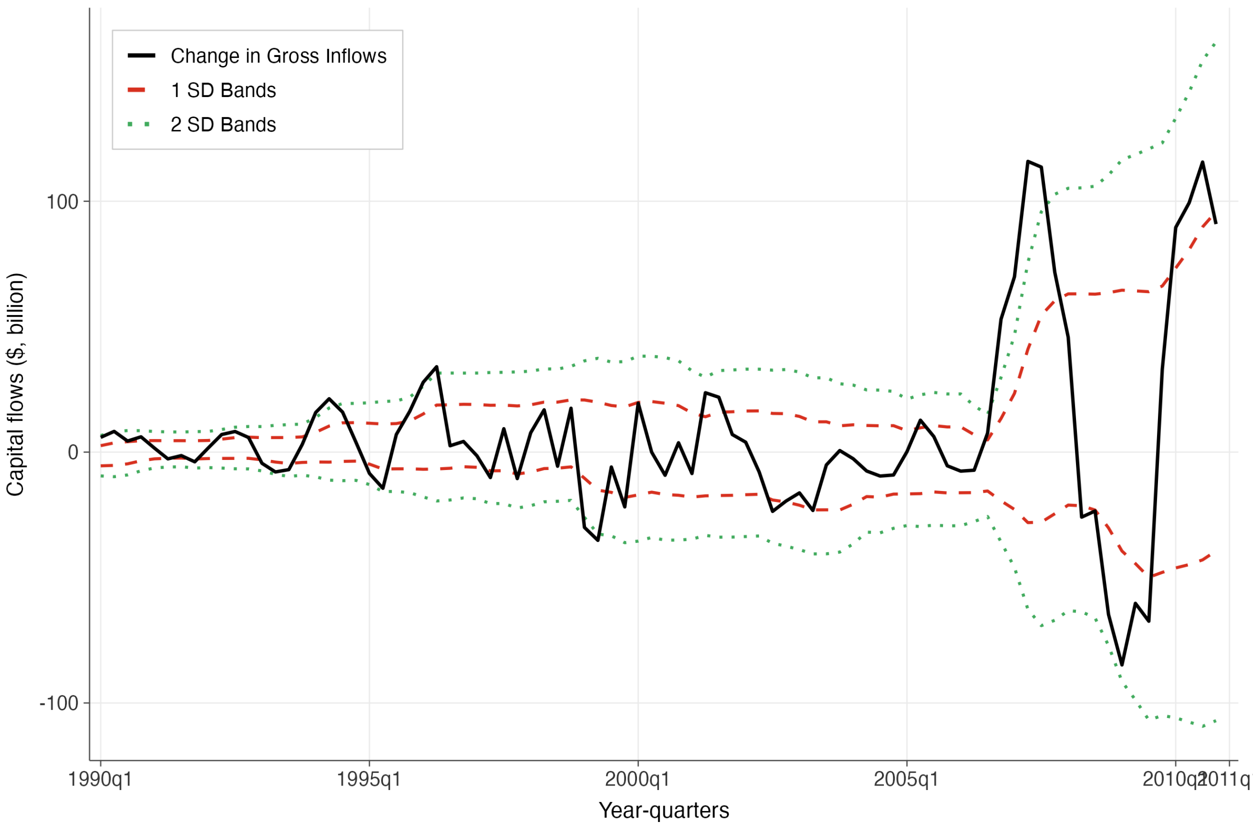
Several extensions remain to be explored. On the one hand, the role of institutions—governance quality, stability of the regulatory framework, credibility of macroeconomic policies—could explain part of the residual heterogeneity observed in low-income economies, where domestic factors appear more active than elsewhere. On the other hand, the causal interpretation of the effects on output remains fragile in the absence of a credible identification strategy: since the incidence of episodes is not random, the estimates from local projections remain conditional correlations. Identifying valid instrumental variables for the onset of these episodes would constitute a promising avenue to settle the question of causality.

Figure 1: Net flows, gross inflows and gross outflows for Brazil



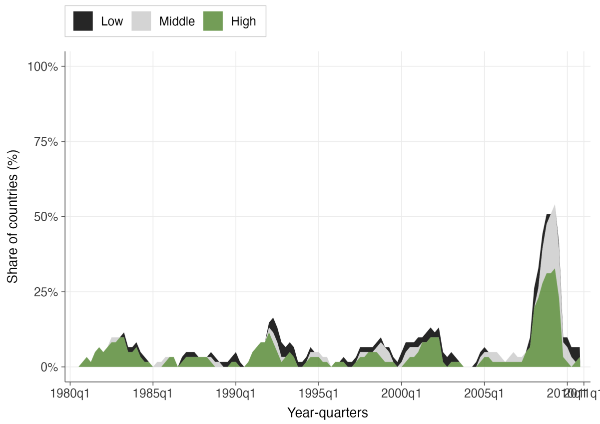
Note: The figure presents the evolution of net capital flows, gross capital inflows and gross capital outflows for Brazil between 1990 and 2011. Time, in quarters, is on the horizontal axis. Net and gross capital flows (inflows and outflows) in billions of USD are plotted on the y-axis.

Figure 2: Gross inflows for Chile and episode characterisation visualisation

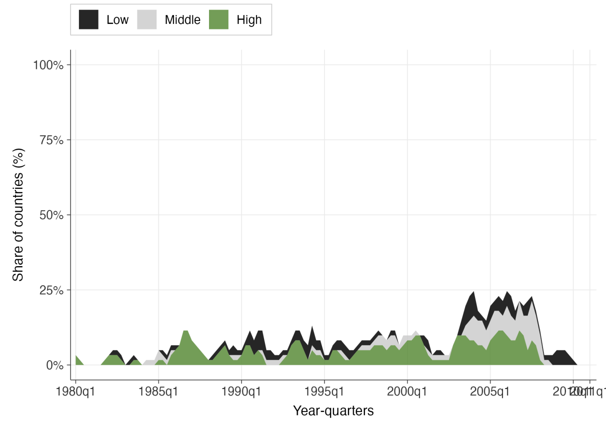


Note: The figure presents the evolution of gross inflows for Chile between 1990 and 2011 together with the 1 standard deviation and 2 standard deviations bands of the one-year rolling mean. Time, in quarters, is on the horizontal axis. Gross capital flows (inflows and outflows) in billions of USD are plotted on the y-axis. An episode is characterised whenever gross inflows cross the 2 SD band for at least one quarter and the 1 SD band for at least one preceding or following quarter.

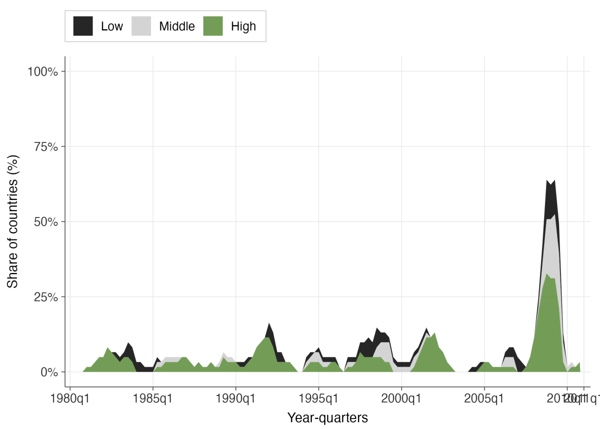
Figure 3: Density of extreme capital flow episodes by income group



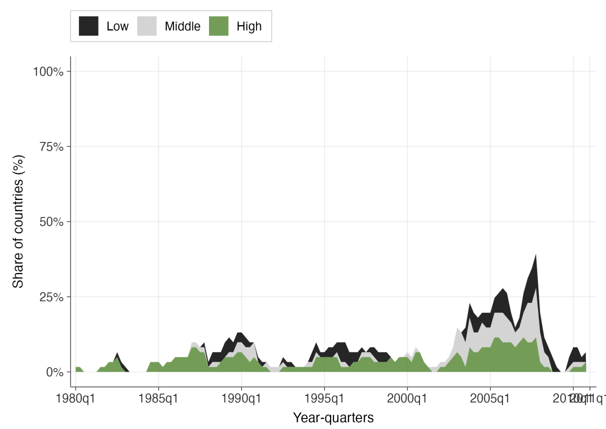
(a) Density of Retrenchment Episodes by Income Group



(b) Density of Flight Episodes by Income Group



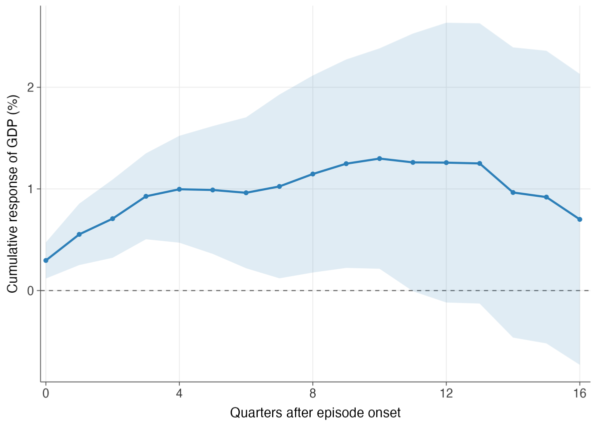
(c) Density of Stop Episodes by Income Group



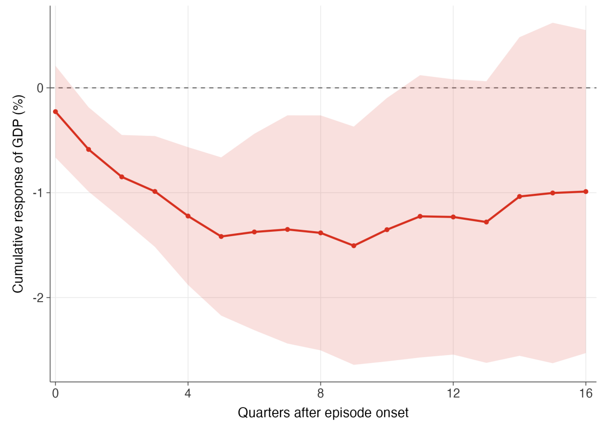
(d) Density of Surge Episodes by Income Group

Note: The graphs display the distribution of extreme capital flow episodes across income groups in the Forbes sample. Kernel density estimates are reported separately for each income group. The four panels correspond to surge, stop, flight, and retrenchment episodes. Higher density values indicate a greater concentration of episodes within a given income group.

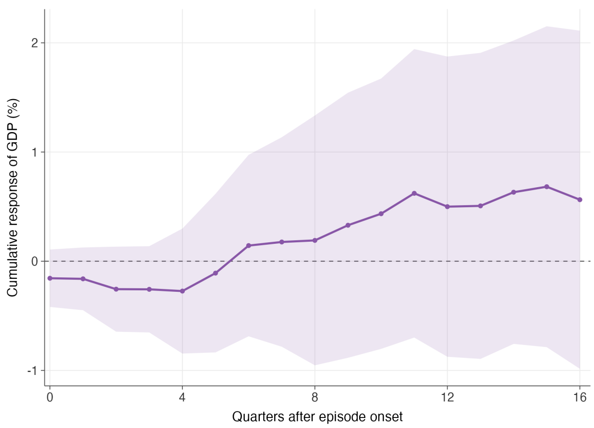
Figure 4: Cummulative evolution of output growth after the start of an episode



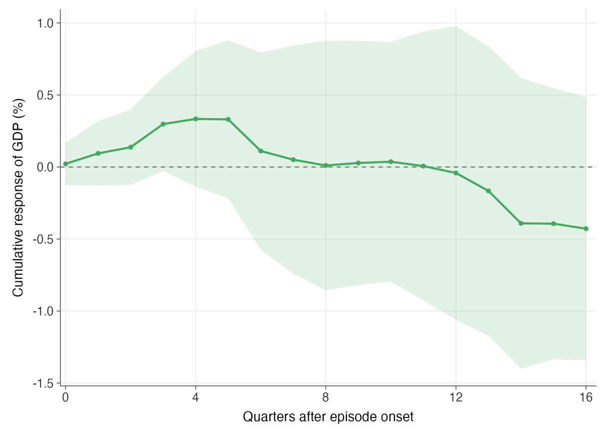
(a) Evolution of output after a surge



(b) Evolution of output after a stop



(c) Evolution of output after a retrenchment



(d) Evolution of output after a flight

Note: The graphs present the Impulse Response Functions of real GDP growth after the start of an extreme capital flow episode at $t = 0$. The IRFs are estimated using local projections method, following Jordà (2005). Estimates should not be taken as causal parameters as the incidence of an episode is endogenous to the economic situation of a country.

Figure 5: Number of Detected Episodes across Alternative Cutoff Thresholds

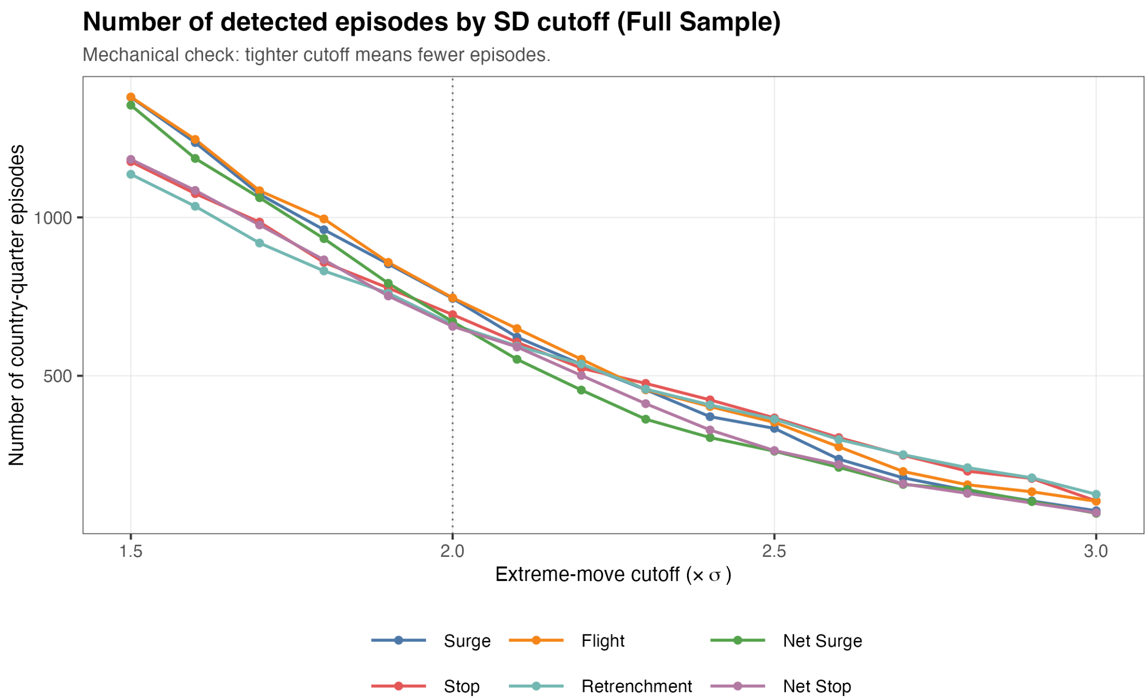


Figure 6: Robustness of Gross-Flow Coefficients to Alternative Episode Definitions

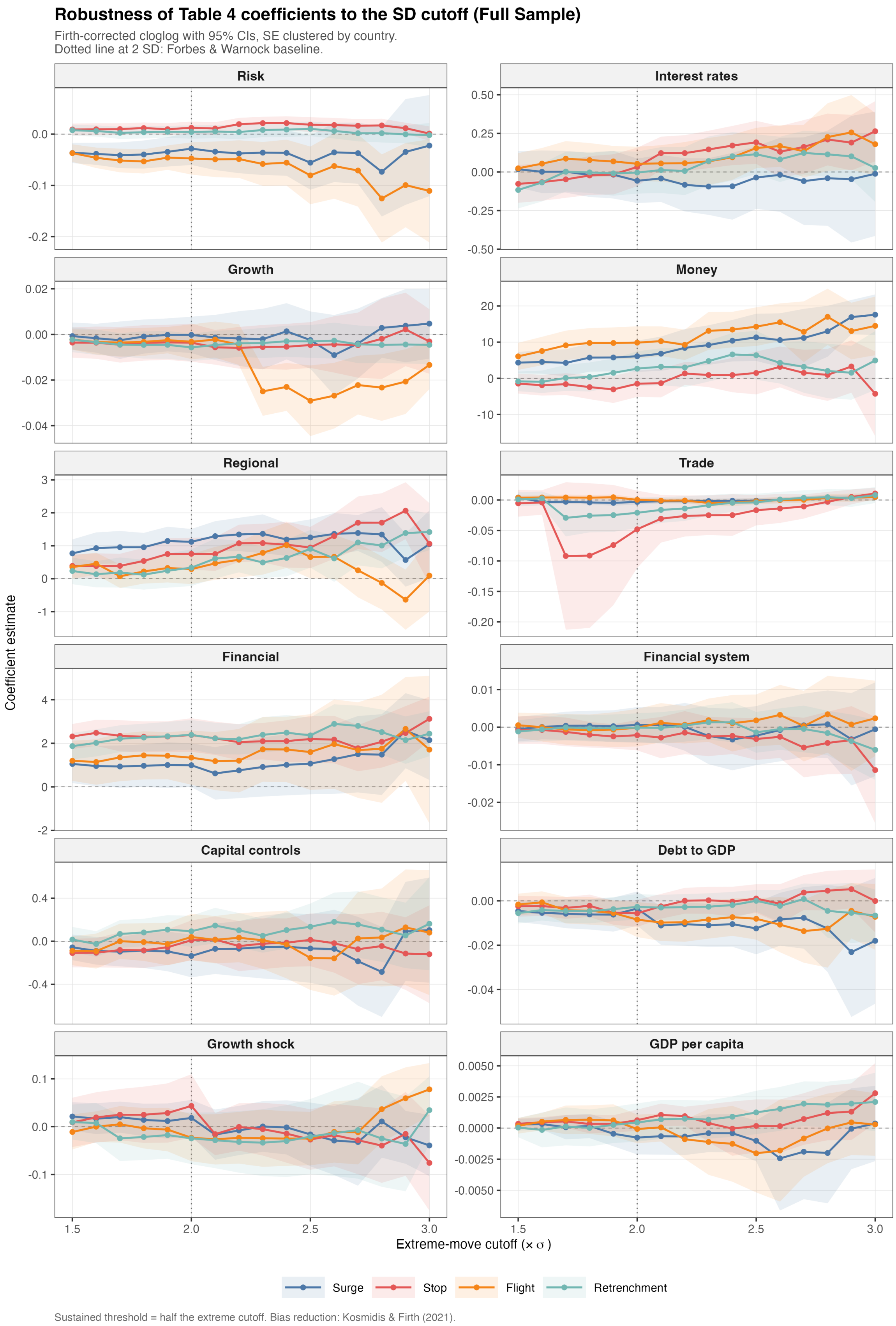


Figure 7: Robustness of Net-Flow Coefficients to Alternative Episode Definitions

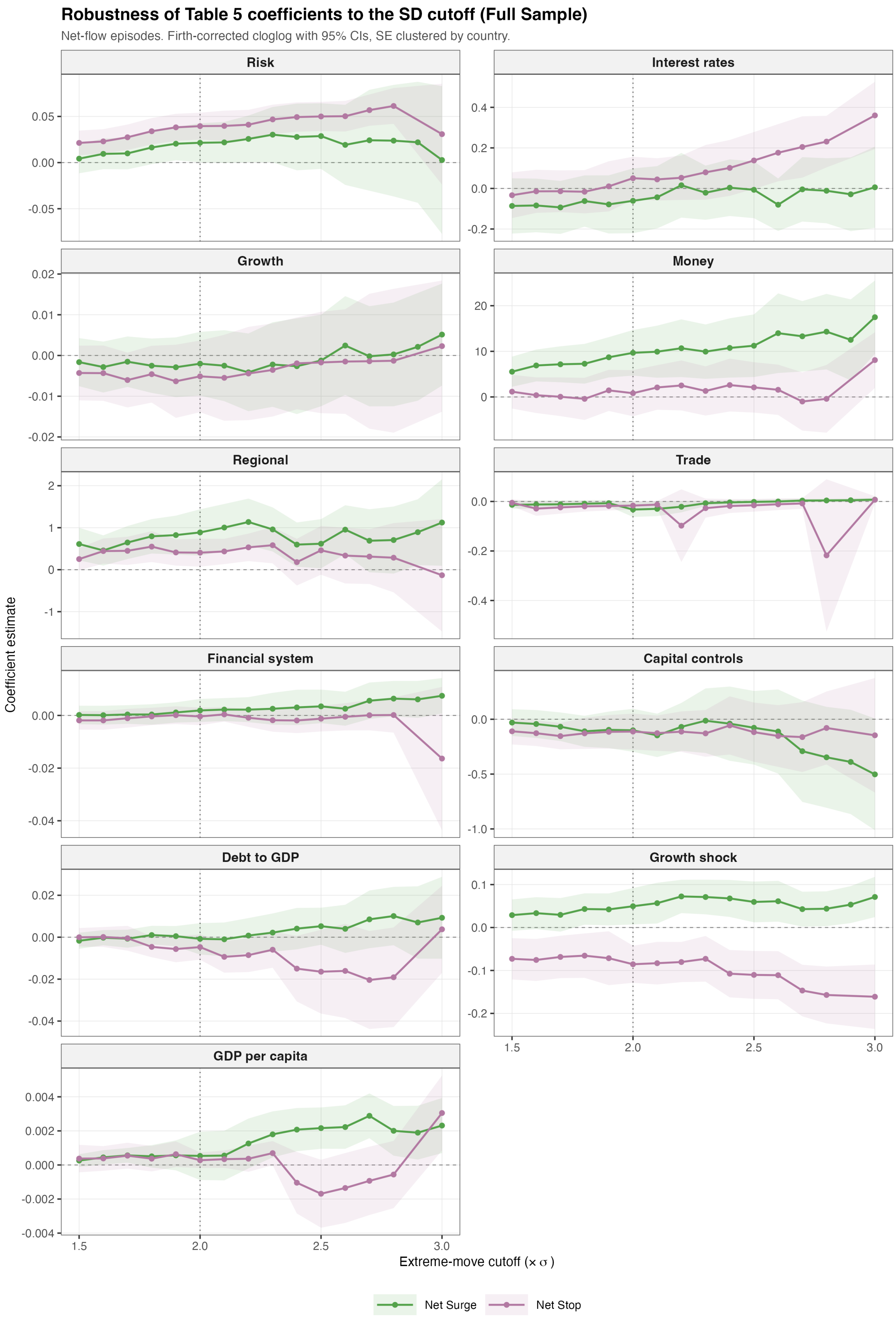


Table 1: Table 1 (Reproduction)

	Surge	Stop	Flight	Retrenchment
Panel A. Forbes and Warnock 2012				
% of country x quarters in episode	15	18	17	17
Number of episodes	167	221	196	214
Panel B. Forbes 2012 Sample				
% of country x quarters in episode	11.3	10.3	11.2	10.1
Number of episodes	148	134	145	133
Episodes per country, unconditional	2.4	2.2	2.4	2.2
Episodes per country, conditional	2.8	2.5	3	2.5
Average length, quarters	4.1	4.1	4.2	4.1
Panel C. Average length, quarters, by income group				
High income	4	4.3	4	4.4
Middle income	4.4	4	4.5	3.6
Lower income	4	3.8	4.1	3.7
Panel D. Average length, quarters, by region				
North America	3.8	4	4.2	4.4
Western Europe	4.1	4.2	4.2	4.3
Asia	3.8	4	4.2	4
Eastern Europe	4.8	4.4	5	4.2
Latin America	4	3.9	3.7	3.4
Other	4	4.5	3.6	4.3

Notes: Table presents summary statistics for the incidence of extreme capital flow episodes across the same sample as Forbes and Warnock (2012). Incidence is defined as currently being in an episode.

Table 2: Episodes during the GFC based on net and gross capital flows

Surges		**Stops**	
Net flows	Gross flows	Net flows	Gross flows
Belgium	Bangladesh	Argentina	Belgium
Canada	Bolivia	Brazil	Canada
Chile	Nicaragua	CostaRica	CostaRica
France		Croatia	CzechRepublic
Iceland		Estonia	Denmark
Israel		Greece	Estonia
Luxembourg		Iceland	France
Mexico		India	Germany
Nicaragua		Korea	Guatamala
Slovenia		Latvia	HongKong
Venezuela		Lithuania	Hungary
		Malaysia	Iceland
		NewZealand	India
		Norway	Italy
		Peru	Japan
		Poland	Korea
		Romania	Latvia
		Russia	Lithuania
		SouthAfrica	Luxembourg
		Spain	Malaysia
		Sri Lanka	Mexico
		Thailand	Netherlands
		Turkey	NewZealand
			Norway
			Panama
			Peru
			Philippines
			Poland
			Romania
			Russia
			Slovenia
			SouthAfrica
			Spain
			Sri Lanka
			Sweden
			Switzerland
			Thailand
			Turkey
			UK
			US

Notes: The "net flows" columns report episodes identified using net capital flows, following the traditional sudden stops and bonanzas literature. The "gross flows" columns report episodes identified using gross capital flows, as in Forbes and Warnock (2012). The key difference is that net-flow episodes incorporate the behavior of domestic investors, who retrenched in many countries during the global financial crisis. The crisis period is defined as 2008Q4 and 2009Q1.

Table 3: Correlation between probability of each type of episode

	Surge	Stop	Flight	Retrenchment
Surge	1.000			
Stop	−0.121	1.000		
Flight	0.393	−0.064	1.000	
Retrenchment	−0.081	0.497	−0.119	1.000

Table 4: Determinants of Gross Capital-Flow Episodes: Replication of Forbes and Warnock (1980–2010)

	Surge	**Stop**	**Flight**	**Retrenchment**
Global factors				
Global Risk	–0.051**	0.010	–0.060**	0.008
	(0.015)	(0.005)	(0.018)	(0.006)
Global Interest Rates	–0.154	0.187**	0.024	0.051
	(0.105)	(0.066)	(0.081)	(0.086)
Global Growth	0.005	–0.004	–0.002	–0.005
	(0.004)	(0.004)	(0.004)	(0.003)
Global Money Supply (USD)	3.207	–0.657	6.510**	2.589
	(1.974)	(1.497)	(1.950)	(2.358)
Contagion				
Regional Contagion	0.889**	0.519*	0.118	0.125
	(0.206)	(0.258)	(0.244)	(0.306)
Trade Linkages	–0.004	–0.031	0.000	–0.021
	(0.002)	(0.017)	(0.002)	(0.012)
Financial Contagion	–0.258	2.273**	0.069	2.110**
	(0.541)	(0.423)	(0.793)	(0.378)
Domestic factors				
Financial System Depth	0.003	–0.002	0.002	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Capital Controls	–0.157	0.104	0.091	0.121
	(0.088)	(0.106)	(0.103)	(0.072)
Debt to GDP	0.001	–0.001	–0.005	0.002
	(0.003)	(0.003)	(0.005)	(0.003)
Growth Shock	0.056	–0.037	–0.004	–0.046
	(0.034)	(0.029)	(0.033)	(0.035)
GDP per Capita	–0.002	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2.017	2.017	2.017	2.017

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Table 5: Determinants of Gross Capital-Flow Episodes: Replication of Forbes and Warnock (1980–2024)

	Surge	**Stop**	**Flight**	**Retrenchment**
Global factors				
Global Risk	−0.029*	0.012*	−0.039**	0.005
	(0.014)	(0.006)	(0.015)	(0.007)
Global Interest Rates	0.044	0.122*	0.174**	0.106
	(0.061)	(0.057)	(0.050)	(0.065)
Global Growth	0.004	−0.004	−0.002	−0.006
	(0.004)	(0.005)	(0.004)	(0.003)
Global Money Supply (USD)	4.971*	−1.536	8.769**	2.194
	(2.073)	(1.760)	(2.330)	(2.262)
Contagion				
Regional Contagion	1.082**	0.698**	0.109	0.324
	(0.198)	(0.242)	(0.223)	(0.269)
Trade Linkages	−0.003	−0.036	0.000	−0.017
	(0.002)	(0.022)	(0.002)	(0.010)
Financial Contagion	0.726	2.355**	1.384*	2.276**
	(0.504)	(0.415)	(0.633)	(0.352)
Domestic factors				
Financial System Depth	0.002	−0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Capital Controls	−0.082	0.045	0.134	0.134*
	(0.094)	(0.088)	(0.104)	(0.065)
Debt to GDP	0.000	−0.004	−0.004	−0.001
	(0.003)	(0.002)	(0.004)	(0.002)
Growth Shock	0.012	0.041	−0.026	−0.037
	(0.020)	(0.038)	(0.027)	(0.028)
GDP per Capita	−0.001	0.001	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)
Observations	3.107	3.107	3.107	3.107

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Table 6: Determinants of Gross Capital-Flow Episodes: Replication of Forbes and Warnock (1980–2024): High income

	Surge	**Stop**	**Flight**	**Retrench.**
Global factors				
Global Risk	−0.054**	0.007	−0.030	0.009
	(0.017)	(0.007)	(0.018)	(0.008)
Global Interest Rates	−0.226*	−0.031	−0.092	−0.092
	(0.114)	(0.082)	(0.099)	(0.103)
Global Growth	0.006	−0.004	0.002	−0.002
	(0.005)	(0.005)	(0.004)	(0.003)
Global Money Supply (USD)	2.389	−0.372	2.309	1.911
	(2.267)	(1.690)	(2.070)	(2.611)
Contagion				
Regional Contagion	0.381	0.393	0.173	0.292
	(0.252)	(0.283)	(0.284)	(0.385)
Trade Linkages	−0.003	−0.026	−0.001	−0.014
	(0.002)	(0.018)	(0.002)	(0.011)
Financial Contagion	−0.633	2.147**	0.554	2.230**
	(0.888)	(0.599)	(1.156)	(0.526)
Domestic factors				
Financial System Depth	0.003	−0.005	0.001	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Capital Controls	−0.555**	−0.322	−0.419*	−0.236
	(0.134)	(0.186)	(0.181)	(0.214)
Debt to GDP	0.004	−0.001	−0.002	0.001
	(0.003)	(0.003)	(0.005)	(0.004)
Growth Shock	0.107	−0.014	0.048	−0.040
	(0.061)	(0.042)	(0.044)	(0.064)
GDP per Capita	−0.005**	−0.001	−0.002*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1.248	1.248	1.248	1.248

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Table 7: Determinants of Gross Capital-Flow Episodes: Replication of Forbes and Warnock (1980–2024): Middle income

	Surge	Stop	Flight	Retrench.
Global factors				
Global Risk	−0.025		−0.125**	0.004
	(0.035)		(0.045)	(0.019)
Global Interest Rates	−0.401		−0.009	0.034
	(0.341)		(0.351)	(0.415)
Global Growth	0.013		−0.009	−0.018**
	(0.009)		(0.012)	(0.006)
Global Money Supply (USD)	4.491		12.350*	−4.004
	(3.246)		(4.904)	(5.180)
Contagion				
Regional Contagion	0.916*		0.343	0.138
	(0.366)		(0.626)	(0.497)
Trade Linkages	−0.010		−0.064	−0.010
	(0.016)		(0.051)	(0.019)
Financial Contagion	0.690		−1.077	1.778*
	(0.975)		(0.965)	(0.782)
Domestic factors				
Financial System Depth	0.008**		0.008**	0.002
	(0.002)		(0.003)	(0.005)
Capital Controls	0.153		0.442	0.261
	(0.184)		(0.378)	(0.181)
Debt to GDP	0.014*		0.003	0.012
	(0.006)		(0.009)	(0.012)
Growth Shock	−0.012		−0.068	−0.067
	(0.042)		(0.040)	(0.039)
GDP per Capita	0.003		0.000	0.000
	(0.004)		(0.007)	(0.007)
Observations	573	NA	573	573

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Table 8: Determinants of Gross Capital-Flow Episodes: Replication of Forbes and Warnock (1980–2024): Low income

	Surge	**Stop**	**Flight**	**Retrench.**
Global factors				
Global Risk	−0.147**	−0.019	−0.131	−0.025
	(0.041)	(0.013)	(0.068)	(0.033)
Global Interest Rates	0.162	0.628**	−1.193	0.216
	(0.406)	(0.180)	(0.908)	(0.386)
Global Growth	0.003	−0.010	−0.038	−0.015
	(0.012)	(0.018)	(0.044)	(0.018)
Global Money Supply (USD)	1.718	1.377	11.037	26.121**
	(8.578)	(5.587)	(5.735)	(9.195)
Contagion				
Regional Contagion	0.466	1.925**	0.388	1.936**
	(0.299)	(0.405)	(0.657)	(0.595)
Trade Linkages	−1.267	0.109	0.945	1.622
	(0.680)	(0.871)	(1.007)	(1.081)
Financial Contagion	−0.721	2.561**	−2.410	1.092
	(0.894)	(0.921)	(1.519)	(1.089)
Domestic factors				
Financial System Depth	0.024**	−0.028**	0.006	0.011
	(0.008)	(0.007)	(0.012)	(0.016)
Capital Controls	0.070	0.223*	−0.110	0.557**
	(0.163)	(0.098)	(0.177)	(0.171)
Debt to GDP	−0.036*	0.008	−0.046**	0.022
	(0.015)	(0.015)	(0.012)	(0.017)
Growth Shock	0.097	−0.021	−0.060	0.098
	(0.063)	(0.023)	(0.077)	(0.074)
GDP per Capita	−0.003**	−0.010*	−0.003*	−0.008
	(0.001)	(0.004)	(0.002)	(0.005)
Observations	196	196	196	196

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Table 9: Determinants of Net Capital-Flow Episodes: Replication of Forbes and Warnock (1980–2010): Low income

	Surge	**Stop**
Global factors		
Global Risk	–0.068**	0.042**
	(0.019)	(0.006)
Global Interest Rates	0.030	0.117
	(0.085)	(0.069)
Global Growth	0.000	–0.005
	(0.003)	(0.003)
Global Money Supply (USD)	2.906	0.148
	(1.596)	(1.903)
Contagion		
Regional Contagion	0.765**	0.811**
	(0.252)	(0.222)
Trade Linkages	–0.002	–0.032*
	(0.001)	(0.016)
Domestic factors		
Financial System Depth	0.002	0.000
	(0.002)	(0.002)
Capital Controls	–0.080	0.083
	(0.073)	(0.108)
Debt to GDP	–0.004	0.001
	(0.004)	(0.002)
Growth Shock	0.031	–0.097**
	(0.038)	(0.024)
GDP per Capita	–0.002**	0.001
	(0.001)	(0.001)
Observations	2.017	2.017

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Table 10: Robustness of Surge Determinants in the Forbes Sample (1980–2010)

	Baseline	Drop crisis	Fixed effects	Add ER regime	Global credit	Financial system
Global factors						
Global Risk	-0.052**	-0.045**	-0.045**	-0.051**	-0.054**	-0.046**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
Global Interest Rates	-0.159	-0.201	-0.154	-0.176	-0.162	-0.266
	(0.109)	(0.114)	(0.128)	(0.107)	(0.124)	(0.316)
Global Growth	0.005	0.005	0.007	0.005	0.006	0.009
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Liquidity	3.241	1.869	1.473	3.208	0.002	1.122
	(2.014)	(2.092)	(1.918)	(1.995)	(0.019)	(3.163)
Contagion						
Regional contagion	0.901**	0.794**	1.120**	0.895**	0.945**	1.036**
	(0.213)	(0.246)	(0.233)	(0.213)	(0.234)	(0.279)
Trade linkage	-0.007	-0.008	-0.012**	-0.009*	-0.006	-0.005
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Financial linkage	-0.272	-0.505	-0.242	-0.230	-0.016	0.041
	(0.551)	(0.568)	(0.582)	(0.555)	(0.598)	(0.460)
Domestic factors						
Financial system	0.003	0.003	0.011	0.003	0.004	0.056**
	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.013)
Capital Controls	-0.156	-0.141	-0.089	-0.158	-0.189	-0.039
	(0.089)	(0.099)	(0.207)	(0.089)	(0.099)	(0.096)
Debt to GDP	0.001	-0.001	0.002	0.001	0.002	-0.003
	(0.003)	(0.004)	(0.016)	(0.003)	(0.003)	(0.004)
Growth Shock	0.057	0.062	0.043	0.057	0.057	0.044
	(0.035)	(0.036)	(0.035)	(0.035)	(0.037)	(0.039)
GDP per Capita	-0.002*	-0.002*	-0.008**	-0.002*	-0.002*	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Exchange-rate regime (peg)				0.357		
				(0.341)		
Observations	2,017	1,716	1,849	2,017	1,883	1,599

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Table 11: Robustness of Stop Determinants in the Forbes Sample (1980–2010)

	Baseline	Drop crisis	Fixed effects	Add ER regime	Global credit	Financial system
Global factors						
Global Risk	0.010	0.026	0.004	0.010*	0.010*	0.019**
	(0.005)	(0.017)	(0.006)	(0.005)	(0.005)	(0.005)
Global Interest Rates	0.185**	0.272**	0.010	0.211**	0.165**	0.693*
	(0.067)	(0.079)	(0.119)	(0.072)	(0.063)	(0.290)
Global Growth	-0.005	-0.006	-0.007	-0.005	-0.004	-0.006
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)
Liquidity	-0.698	-3.648	-0.828	-0.807	0.073*	1.241
	(1.533)	(2.725)	(1.490)	(1.503)	(0.030)	(3.269)
Contagion						
Regional contagion	0.532*	0.457	0.493	0.545*	0.490	0.604
	(0.265)	(0.289)	(0.268)	(0.262)	(0.278)	(0.319)
Trade linkage	-0.071	-0.143	-0.050	-0.048	-0.126	-0.018
	(0.045)	(0.091)	(0.034)	(0.034)	(0.064)	(0.010)
Financial linkage	2.304**	1.531**	2.439**	2.232**	2.269**	2.397**
	(0.432)	(0.555)	(0.464)	(0.432)	(0.441)	(0.459)
Domestic factors						
Financial system	-0.002	-0.001	-0.018**	-0.002	-0.002	-0.004
	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.009)
Capital Controls	0.109	0.082	0.095	0.106	-0.004	0.279*
	(0.108)	(0.117)	(0.202)	(0.107)	(0.092)	(0.123)
Debt to GDP	-0.001	0.001	-0.005	-0.001	0.001	-0.001
	(0.003)	(0.005)	(0.013)	(0.003)	(0.003)	(0.003)
Growth Shock	-0.037	-0.128**	-0.066*	-0.037	-0.044	-0.027
	(0.030)	(0.042)	(0.028)	(0.029)	(0.028)	(0.028)
GDP per Capita	-0.000	-0.000	-0.001	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Exchange-rate regime (peg)				-0.981*		
				(0.453)		
Observations	2,017	1,716	1,761	2,017	1,883	1,599

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Table 12: Robustness of Flight Determinants in the Forbes Sample (1980–2010)

	Baseline	Drop crisis	Fixed effects	Add ER regime	Global credit	Financial system
Global factors						
Global Risk	-0.061**	-0.054**	-0.064**	-0.061**	-0.063**	-0.096**
	(0.018)	(0.018)	(0.021)	(0.018)	(0.021)	(0.023)
Global Interest Rates	0.021	-0.055	-0.078	0.029	0.012	0.497
	(0.083)	(0.102)	(0.096)	(0.086)	(0.101)	(0.322)
Global Growth	-0.002	-0.001	-0.000	-0.002	-0.001	-0.006
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.008)
Liquidity	6.533**	4.682*	5.629**	6.500**	-0.022	2.077
	(1.990)	(2.174)	(1.976)	(2.007)	(0.027)	(3.937)
Contagion						
Regional contagion	0.124	-0.229	0.380	0.135	0.207	-0.100
	(0.250)	(0.240)	(0.330)	(0.253)	(0.240)	(0.345)
Trade linkage	-0.001	-0.001	-0.005**	-0.000	-0.001	-0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Financial linkage	0.051	-0.399	0.418	0.008	-0.388	-0.688
	(0.809)	(0.878)	(0.953)	(0.820)	(0.981)	(0.632)
Domestic factors						
Financial system	0.002	0.001	0.005	0.002	0.002	0.058**
	(0.002)	(0.002)	(0.006)	(0.002)	(0.003)	(0.016)
Capital Controls	0.094	0.120	-0.136	0.094	0.089	0.297*
	(0.104)	(0.103)	(0.194)	(0.104)	(0.124)	(0.121)
Debt to GDP	-0.006	-0.006	-0.015	-0.006	-0.006	-0.010*
	(0.005)	(0.005)	(0.011)	(0.005)	(0.005)	(0.005)
Growth Shock	-0.003	0.029	-0.015	-0.003	-0.016	-0.054
	(0.034)	(0.031)	(0.037)	(0.034)	(0.039)	(0.054)
GDP per Capita	0.000	0.001	-0.002*	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Exchange-rate regime (peg)				-0.260		
				(0.239)		
Observations	2,017	1,716	1,683	2,017	1,883	1,599

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Table 13: Robustness of Retrenchment Determinants in the Forbes Sample (1980–2010)

	Baseline	Drop crisis	Fixed effects	Add ER regime	Global credit	Financial system
Global factors						
Global Risk	0.008	0.030	0.003	0.008	0.007	0.014*
	(0.007)	(0.018)	(0.009)	(0.007)	(0.006)	(0.007)
Global Interest Rates	0.046	0.060	-0.057	0.045	0.052	0.496
	(0.090)	(0.095)	(0.157)	(0.094)	(0.090)	(0.327)
Global Growth	-0.006*	-0.008*	-0.008*	-0.006	-0.005	-0.007**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Liquidity	2.594	0.032	2.124	2.593	0.023	4.381
	(2.424)	(2.779)	(2.746)	(2.426)	(0.025)	(3.815)
Contagion						
Regional contagion	0.130	0.290	0.334	0.130	0.108	0.044
	(0.315)	(0.308)	(0.307)	(0.315)	(0.310)	(0.327)
Trade linkage	-0.056	-0.135	-0.097	-0.056	-0.061	-0.012
	(0.037)	(0.082)	(0.068)	(0.041)	(0.043)	(0.012)
Financial linkage	2.138**	0.986	2.414**	2.140**	2.136**	2.304**
	(0.385)	(0.571)	(0.469)	(0.392)	(0.395)	(0.353)
Domestic factors						
Financial system	-0.000	0.001	-0.010	-0.000	-0.000	0.000
	(0.002)	(0.003)	(0.007)	(0.002)	(0.002)	(0.007)
Capital Controls	0.125	0.005	0.242	0.125	0.089	0.218**
	(0.073)	(0.090)	(0.248)	(0.073)	(0.073)	(0.077)
Debt to GDP	0.002	0.003	-0.011	0.002	0.003	0.006
	(0.003)	(0.005)	(0.014)	(0.003)	(0.003)	(0.004)
Growth Shock	-0.046	-0.109*	-0.054	-0.046	-0.045	-0.021
	(0.036)	(0.044)	(0.042)	(0.036)	(0.040)	(0.031)
GDP per Capita	-0.000	-0.000	0.001	-0.000	-0.000	-0.010
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)
Exchange-rate regime (peg)				0.015		
				(0.339)		
Observations	2,017	1,716	1,834	2,017	1,883	1,599

Notes: Robust standard errors clustered by country. ** significant at 1%; * significant at 5%.

Appendix for: Replication of Forbes and Warnock 2012

A Data and Methods

A.1 Data

To measure capital flow data, we use the Balance-of-Payment (BOP) dataset from the IMF. Following the IMF's BOP standard nomenclature, we use the same set of instrument codes for both sides of the balance sheet. Gross outflows (assets) are defined as the Net Acquisition of Financial Assets (`A_NFA_T`), while gross inflows (liabilities) are defined as the Net Incurrence of Liabilities (`L_NIL_T`). The exact financial instruments used to construct our capital flow measures are

- **D_F5**: Direct investment, equity
- **D_FL**: Direct investment, debt instruments
- **P_F5**: Portfolio investment, equity and investment fund shares
- **P_F3**: Portfolio investment, debt securities
- **O_F2**: Other investment, currency and deposits
- **O_F81**: Other investment, trade credit and advances
- **O_F4**: Other investment, loans
- **O_F8AR**: Other investment, other accounts receivable
- **O_F8AP**: Other investment, other accounts payable (contra-entry)
- **O_F6**: Other investment, insurance, pension and standardised guarantee schemes
- **O_F12_S1N**: Financial derivatives and employee stock options, net

Gross inflows are thus the sum of the liabilities for all the instruments listed above, and gross outflows are the sum of the assets for these exact same instruments.

Because BOP outflows are recorded as negative numbers, the replication code passes $-$ `outflows_std` to the detection function for flight and retrenchment. After this sign flip, the series is positive and larger values correspond to more outward investment by residents. A flight episode is therefore detected as a surge in this sign-adjusted outflow series, and a retrenchment as a stop, preserving a single detection function (`detect_episode`) for all four episode types.

A.2 Methods

A.2.1 Construction of Trade Linkage (TL) Variables

To capture trade-based contagion channels following Forbes and Warnock (2012), we construct trade linkage (TL_{xt}) metrics for each gross capital flow episode type $E \in \{\text{surge}, \text{stop}, \text{flight}, \text{retrench}\}$. We also compute for net flow episodes $E \in \{\text{net-surge}, \text{net-stop}\}$ for a comparison with Calvo (1998) and

Calvo et al. (2004). The variable weights foreign episodes by bilateral export intensity and scales the aggregate exposure by the country's overall trade openness $\frac{\text{Total Exports}_{x,t}}{\text{GDP}_{x,t}}$

$$TL_{x,t}^{E} = \left[\frac{\sum_{i=1}^{n} \left(\text{Exports}_{x,i,t} \times \text{Episode}_{i,t}^{E} \right)}{\sum_{i=1}^{n} \text{Exports}_{x,i,t}} \right] \times \frac{\text{Total Exports}_{x,t}}{\text{GDP}_{x,t}} \tag{A.2.1}$$

where:

- x denotes the home country and t denotes the year-quarter.
- $i \in \{1, \ldots, n\}$ indexes the subset of n available in-sample countries with which country x trades.
- $\text{Exports}_{x,i,t}$ represents the nominal FOB export volume from country x to receiving country i, sourced from the IMF.
- $\text{Episode}_{i,t}^{E}$ is a binary indicator (1 if country i is experiencing extreme episode E in quarter t, and 0 otherwise).
- $\text{Total Exports}_{x,t}$ reflects country x's aggregate nominal exports globally (encompassing both in-sample and out-of-sample destinations).
- $\text{GDP}_{x,t}$ represents nominal non-seasonally adjusted national GDP denominated in USD.

Trade data are drawn from the IMF's IMTS dataset and GDP data are drawn from the IMF's QNEA dataset. Episodes are computed using the methodology described in the main paper.

By construction, the first bracketed term isolates the export-weighted intensity of episode exposure purely among primary trading partners within our sample panel. The second term rescales this intensity relative to the country's total export-to-GDP footprint to capture macroeconomic vulnerability to global trade shocks. Gaps in bilateral trade and GDP reporting are treated as missing at random, and summations omit missing cells dynamically.

A.2.2 Construction of Financial Linkage (FL) Variables

Following Forbes and Warnock (2012), we construct financial linkage (FL_{xt}) variables to capture contagion transmitted through cross-border banking relationships. As for trade linkages, the measure is computed separately for each gross-flow episode type $E \in \{\text{surge}, \text{stop}, \text{flight}, \text{retrench}\}$, and for net-flow episodes $E \in \{\text{net-surge}, \text{net-stop}\}$.

The variable weights foreign episodes by bilateral banking exposure and scales the aggregate exposure by the country's overall financial openness:

$$FL_{x,t}^{E} = \left[\frac{\sum_{i=1}^{n} \left(BANK_{x,i,t} \times Episode_{i,t}^{E} \right)}{\sum_{i=1}^{n} BANK_{x,i,t}} \right] \times \frac{Total\ BANK_{x,t}}{GDP_{x,t}} \tag{A.2.2}$$

where:

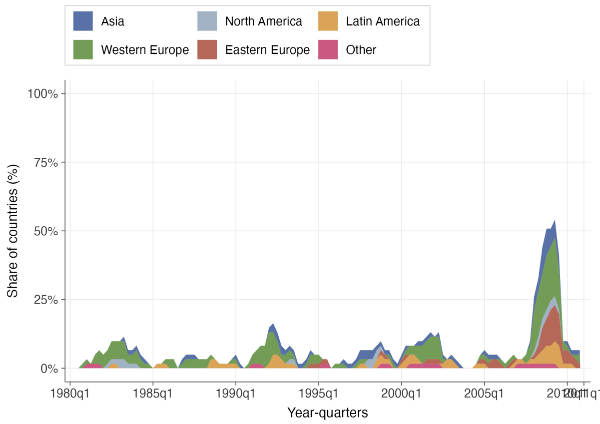
- x denotes the home country and t denotes the year-quarter.

- $i \in \{1, \ldots, n\}$ indexes the subset of n available in-sample countries with which country x maintains cross-border banking relationships.
- $BANK_{x,i,t}$ represents bilateral banking claims from country x to country i, obtained from the BIS Locational Banking Statistics.
- $Episode^{E}_{i,t}$ is a binary indicator (1 if country i experiences episode E in quarter t, and 0 otherwise).
- $Total\ BANK_{x,t}$ denotes the total stock of foreign banking claims held by country x.
- $GDP_{x,t}$ represents nominal non-seasonally adjusted national GDP denominated in USD.

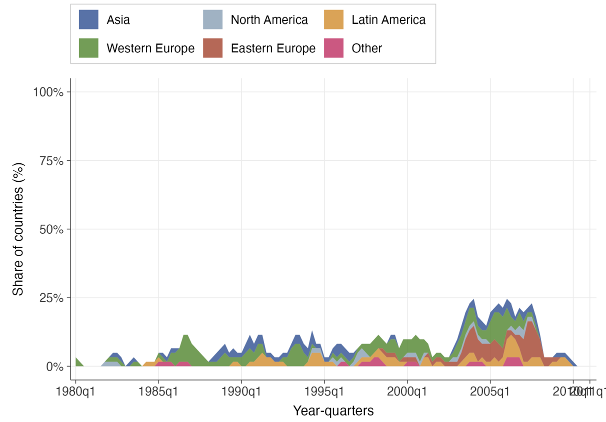
Bilateral banking claims are obtained from the BIS Locational Banking Statistics. Episodes are computed using the methodology described in the main paper.

By construction, the first bracketed term measures the banking-claims-weighted exposure of country x to foreign episode occurrences within the sample. The second term rescales this exposure by the country's aggregate foreign banking claims relative to GDP, capturing the degree of financial openness and potential vulnerability to international financial shocks. Missing observations in bilateral banking claims are treated as missing at random, and summations dynamically omit unavailable country pairs.

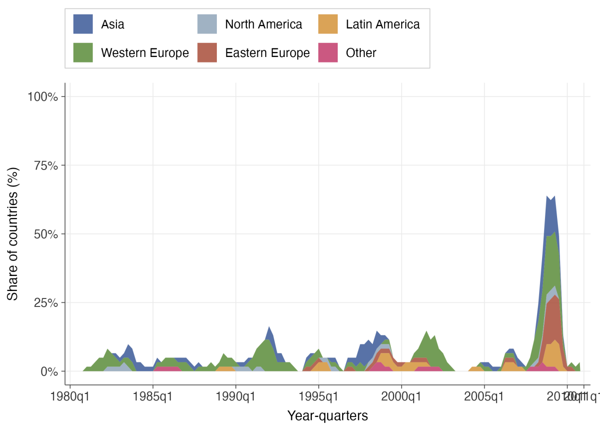
Appendix Figure A1: Density of extreme capital flow episodes by region group



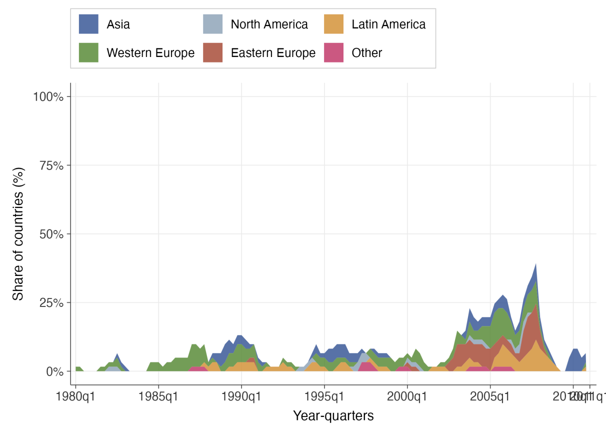
(a) Density of Retrenchment Episodes by Region Group



(b) Density of Flight Episodes by Region Group



(c) Density of Stop Episodes by Region Group



(d) Density of Surge Episodes by Region Group

Note: The graphs display the distribution of extreme capital flow episodes across region groups in the Forbes sample. Kernel density estimates are reported separately for each region group. The four panels correspond to surge, stop, flight, and retrenchment episodes. Higher density values indicate a greater concentration of episodes within a given region group.

Appendix Table A1: Samples are not balanced though most countries have balanced data

Data start	Data end	Number of observations	Share of missing	Country
1980Q1	2010Q4	124	0	Argentina, Bangladesh, Brazil, Canada, Denmark, Finland, France, Guatamala, Iceland, India, Israel, Italy, Korea, Mexico, Netherlands, Philippines, Portugal, SouthAfrica, Spain, Sri Lanka, Sweden, Thailand, UK, US
1980Q1	2010Q4	120	3	Greece
1980Q1	2010Q4	116	6	Norway
1980Q1	2010Q4	100	19	Peru
1980Q1	2010Q4	92	26	Germany
1981Q1	2010Q4	120	3	Indonesia
1984Q1	2010Q4	108	13	Turkey
1988Q1	2010Q4	92	26	Bolivia
1989Q1	2010Q4	88	29	Australia
1989Q4	2010Q4	85	31	Hungary
1991Q1	2010Q4	80	35	Chile, Romania
1992Q1	2010Q4	76	39	Estonia, Nicaragua, Slovenia
1993Q1	2010Q4	72	42	Croatia, CzechRepublic, Latvia, Lithuania, SlovakRep
1994Q1	2010Q4	68	45	Russia, Venezuela
1996Q1	2010Q4	60	52	Colombia, Japan
1998Q1	2010Q4	52	58	Panama
1999Q1	2010Q4	48	61	CostaRica, HongKong, Switzerland
2000Q1	2010Q4	44	65	NewZealand, Poland
2001Q1	2010Q4	40	68	Malaysia
2002Q1	2010Q4	36	71	Belgium, Luxembourg
2005Q1	2010Q4	24	81	Austria, China, Ireland

Notes: The table reports the availability of quarterly observations for each country in the replication sample. Although the dataset is not fully balanced, most countries provide nearly complete coverage over the 1980Q1–2010Q4 period. The share of missing observations is calculated relative to the maximum number of quarters available in the sample (124 observations). Countries are grouped according to their data coverage.

References

Beck, T., A. Demirguc-Kunt, and R. Levine (2009, May). Financial institutions and markets across countries and over time - data and analysis. Policy Research Working Paper Series 4943, The World Bank.

Calvo, G. A. (1998). Capital flows and capital-market crises: The simple economics of sudden stops. *Journal of Applied Economics 1*(1), 35–54.

Calvo, G. A., A. Izquierdo, and L.-F. Mejía (2004, May). On the empirics of sudden stops: The relevance of balance-sheet effects. Working Paper 10520, National Bureau of Economic Research.

Cartas, J. M. and A. Harutyunyan (2017). *Monetary and Financial Statistics Manual and Compilation Guide*. USA: International Monetary Fund.

Chinn, M. D. and H. Ito (2006). What matters for financial development? capital controls, institutions, and interactions. *Journal of Development Economics 81*(1), 163–192.

Driscoll, J. C. and A. C. Kraay (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics 80*(4), 549–560.

Forbes, K. J. and F. E. Warnock (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics 88*(2), 235–251. NBER Global.

Forbes, K. J. and F. E. Warnock (2021). Capital flow waves—or ripples? extreme capital flow movements since the crisis. *Journal of International Money and Finance 116*, 102394.

Jordà, O. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.