The global financial cycle and debt capital flows to latin america: An ARDL bounds testing approach

Rouven Beiner

December 15, 2024

Abstract

This study analyzes the dynamics of net debt capital flows in Brazil, Chile, and Mexico, focusing on both long-run and short-run relationships using an Error Correction Model (ECM). Using the ARDL bounds testing approach, I found evidence of a long-run relationship for Chile and Mexico, but not for Brazil.

Contents

List of Figures

List of Tables

1 Introduction and Motivation

Capital inflows are critical for financial stability, investment, and growth in Emerging markets (EMs). These economies are particularly vulnerable to external shocks like the Global Financial Cycle (GFC), which can drive volatile swings in capital availability. As Rey (2015) highlights, "as capital flows respond to US monetary policy, they may not be appropriate for the cyclical conditions of many economies", often misaligning with domestic cyclical conditions and causing excessive credit growth in booms or retrenchment in downturns. Such dynamics limit the effectiveness of local policymaking and may necessitate capital controls or macroprudential instruments to mitigate adverse effects (Cerutti et al. (2015)). Portfolio debt and equity flows, as types of capital flows, carry significant risks. Their net flows are closely linked to asset price and exchange rate fluctuations, making them particularly dependent on central bank policy decisions. Additionally, when portfolio debt is borrowed in foreign currencies, it introduces currency and default risks for domestic banks.

While capital inflows pose risks, they also offer significant benefits, and different types of capital flows affect growth in different ways. Among the various forms of capital flows, portfolio debt directly increases the domestic capital supply, thereby lowering interest rates, which in turn stimulates consumption and investment. Other types, such as foreign direct investments (FDIs) or portfolio equity flows, influence domestic growth indirectly through knowledge spillovers and externalities.

While countries can influence certain domestic factors, global push factors are largely beyond their control. Policymakers in EMs must therefore understand the impact of specific push factors to manage the risks associated with volatile capital flows.

This study investigates the impact of push factors that approximate the GFC on portfolio debt flows to EMs, focusing specifically on Brazil, Chile, and Mexico. The GFC, an unobservable phenomenon, is approximated by directly observable push factors from the U.S..

The paper is structured as follows. Section 2 reviews related work, and Section 3 outlines the push/pull framework. Section 4 presents the data and descriptive statistics, followed by the ARDL reparameterization in Section 5 and model estimation in Section 6. Section 7 discusses the results, and Section 8 concludes with key findings and implications.

2 Related Work

The determinants of capital flows have been extensively studied, with the literature distinguishing between global "push" factors and domestic "pull" factors, as well as their respective transmission channels. The seminal works of Calvo, Leiderman, and Reinhart (1993) and Fernandez-Arias (1996) laid the foundation for this distinction, introducing the push-pull framework as a useful tool for understanding the behavior of capital flows.

Recent contributions to the literature include Fratzscher (2011), Forbes and Warnock (2012), and Cerutti et al. (2015). Cerutti et al. (2015) found that global push factors drive co-movement of capital inflows in 34 emerging markets, with sensitivity varying by flow type and market structure. Fratzscher (2011) showed that global risk and liquidity dominate capital flows during crises, while pull factors matter more in recovery. Forbes and Warnock (2012) identified global risk as key in extreme capital flow episodes, with limited influence from domestic factors. M2 money supply, while reflective of liquidity conditions, was found to have an statistically insignificant impact on debt capital flows to Latin American countries (Cerutti et al. (2017)).

In a meta-study by Koepke (2015) reviewed over 40 studies and summarized the main drivers of capital flows to emerging markets, focusing on the components of portfolio equity, portfolio debt, banking flows, and foreign direct investment (FDI). Koepke (2015) found that worsening global risk conditions and higher interest rates in mature economies tend to reduce portfolio equity, portfolio debt, and banking flows. However, the impact of these push factors on FDI is less clear, with mixed evidence reported across studies. A positive relationship between mature economy output growth and portfolio equity and portfolio debt is found, while the evidence on a relationship between mature economy output growth and banking flows and FDI are mixed. Regarding the pull factors: while domestic growth and asset returns are positively associated with all forms of capital flows, country risk indicators typically have a negative relationship with inflows. Summarizing the results, both push and pull factors play a significant role in driving capital flows to emerging markets, although the relative importance of these factors remains a subject of debate. Country risk indicators have a negative relationship on most capital flow drivers, and evidence on the effect of US monetary policy on EM capital flows is more mixed.

Hannan (2018), in a literature survey, highlights that while the occurrence and riskiness of capital flows is primarily influenced by external factors, the extent to which a particular emerging market economy benefits from these surges depends on domestic conditions. These include the level of financial market liberalization and integration into global financial markets. Furthermore, the specific determinants of capital flows vary by flow type (net or gross), and specific channels of capital flows like FDI, portfolio debt or portfolio equity.

3 Determinants of Capital Flows: The Push/Pull Framework

The modern literature on capital flows began in the early 1970s, when international bank lending to developing countries increased significantly, partly due to the oil price shock. However, this growth was disrupted by the Latin American debt crisis in the early 1980s, which led to a sharp decline in capital flows. In the late 1980s and early 1990s, flows to Latin America recovered, supported by a recession in the United States and improvements in macroeconomic fundamentals in recipient countries. This upward trend continued until the late 1990s, when the Asian Financial Crisis caused another significant contraction in flows. In the early 2000s, capital flows revived once more, only to be interrupted by the Global Financial Crisis (GFC) in 2008. After a brief recovery following the GFC, flows slowed between 2011 and 2016 before picking up again in 2017.

A central question in the literature on capital flows is whether these flows are primarily driven by external "push" conditions or domestic "pull" characteristics. Pull factors, which are demand-side determinants, include institutional quality, income per capita, capital and trade openness or the financial development. In many emerging markets, domestic savings are insufficient to meet the demand for capital, creating a "deflationary gap" that results in high interest rates and macroeconomic instability.

While high interest rates generally attract foreign capital and form a necessary condition for capital inflows, they are not sufficient. For capital flows to materialize, stability must also be achieved through domestic policies and economic reforms that reduce investment risks. Push factors are supply-side determinants that affect the availability of global liquidity. These include global risk aversion, commodity prices, U.S. economic growth, and U.S. interest rates. Monetary policy, particularly in advanced economies, is a key push factor. For instance, Bhattarai et al. (2021) shows that expansionary U.S. quantitative easing (QE) shocks significantly increase capital flows into emerging markets, with inflows peaking at approximately 2% of GDP during such periods. The federal funds rate, another primary tool of U.S. monetary policy, influences global interest rate differentials, making it a determinant of flows seeking yield in emerging economies. Similarly, the ex-post real policy interest rate accounts for the inflation-adjusted return on U.S. assets, providing a more direct measure of the opportunity cost of investing abroad. The TED spread is included as a measure of liquidity and credit risk in global financial markets, while the slope of the yield curve captures market expectations about future economic conditions and monetary policy. The REER reflects the competitiveness of the U.S. dollar, which affects the attractiveness of dollar-denominated investments. The VIX, often referred to as the "fear index," measures implied volatility in the U.S. stock market and is widely regarded as the key proxy for the global financial cycle. Higher VIX levels typically signaling risk aversion and triggering capital outflows from riskier EM assets, while lower levels indicate greater risk appetite and increased inflows.

The effect of pull or push factors is usually estimated using panel, VAR or VEC models. While Cerutti et al. (2017) suggests that omitting pull factors and regressand dynamics can highlight the maximal impact of the global financial cycle (GFCy), including pull factors as controls is important and a common practice in the literature, as noted by Hannan (2017). Moreover, Fratzscher (2011) found that since the recovery period of March 2009, domestic pull factors have increasingly dominated as drivers of capital flows, particularly in regions like Emerging Asia and Latin America, reducing the relative importance of common global factors.

4 Data

Monthly capital debt flow data for Brazil, Mexico and Chile are obtained from the IMF dataset on international capital flows, that includes observations for Brazil and Mexico from 1995 to 2022 and for Chile from 2003 to 2022.

For the push factors, the analysis focuses on a selected set of variables that are theoretically and empirically relevant for explaining capital flows into emerging markets. Specifically, the variables included in the analysis are the U.S. nominal policy interest rate (the federal funds rate), the ex-post real policy interest rate (calculated as the nominal rate minus U.S. CPI inflation), the TED spread (the difference between the three-month LIBOR and the three-month U.S. treasury bill rate), the slope of the U.S. yield curve (10-year minus 3-month treasury rates), the real effective exchange rate (REER) of the U.S., and the VIX (volatility index).

The VIX data was obtained from the Chicago Board Options Exchange. The three-month LIBOR rate is obtained from the ECB's data repository. The 10-year treasury rate, the 3-month treasury bill rate, the nominal federal funds rate and the U.S. CPI are obtained from FRED. The REER data was acquired from the Bruegel database.

Figures 1 and 2 plot the debt capital flows for Brazil, Chile, and Mexico alongside the selected U.S. push variables on a level basis. Correlations show that the U.S. real effective exchange rate (REER) has a negative correlation with debt capital flows to Brazil (-0.36)

and Mexico (-0.35), while no correlation for Chile is found (0.1). Interestingly no notable correlation is found for the VIX.

5 ARDL reparameterization

Dynamic relationships among variables are usually analyzed using vector autoregressive (VAR) or vector error-correction (VEC) models. However, when variables have a natural ordering that excludes contemporaneous feedback from the response variable to the explanatory variables, a single-equation autoregressive distributed lag (ARDL) model offers a simpler and more efficient approach.

The ARDL model can be reparameterized into an error-correction (EC) form, allowing a clear distinction between the long-run relationships and the short-run dynamics.

Pesaran and Shin (1998) and Hassler and Wolters (2006) highlight some advantages of the ARDL approach over alternative strategies for cointegration analysis. It allows for the inclusion of both stationary and nonstationary variables without requiring pretests for integration order. Additionally, short-run and long-run coefficients are consistently estimated simultaneously. However, the ARDL framework assumes that the dependent variable does not influence simultaneously the long-run equilibrium of explanatory variables, which would cause endogeneity issues. In cases where such feedback exists, the VAR or VEC framework is more appropriate.

If we expect the existence of a long run equilibrium relationship between y and a set of K explanatory variable, a baseline model would be given by:

$$y_t = b_0 + b_1 t + \mathbf{x}_t' \boldsymbol{\theta} + e_t \tag{1}$$

However, this model is only a valid regression if yt and some of or all the variables xt are cointegrated such that the error term et is integrated of order I(0). In the short run, the process might divert from this equilibrium, but the above equation is silent about the dynamic evolution of the process when it is off the equilibrium path. The inclusion of lags of the dependent and independent variables, we can model the dynamic evolution of the process when it is off the equilibrium path. Such a model would be given by a general ARDL(p,q,..,q) model with intercept, linear trend and lag orders p,q.:

$$y_t = c_0 + c_1 t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=0}^{q} \beta_i' x_{t-i} + u_t \tag{2}$$

in which the regression error term u_t is free of serial correlation.

To gain a better interpretability of the model's coefficients, we can reformulate the ARDL model in EC representation Hassler and Wolters (2006):

$$\Delta y_t = c_0 + c_1 t - \alpha(y_{t-1} - \boldsymbol{\theta}\mathbf{x}_t) + \sum_{i=1}^{p-1} \psi_{y_i} \Delta y_{t-i} + \sum_{i=0}^{q-1} \psi_{x_i}' \Delta \mathbf{x}_{t-i} + u_t \tag{3}$$

Because of the nonlinear interaction between the coefficients α and $\boldsymbol{\theta}$, we cannot directly fit (3) with OLS. However, we can fit the following model:

$$\Delta y_t = c_0 + c_1 t + \pi_y y_{t-1} + \pi_x \mathbf{x}_t + \sum_{i=1}^{p-1} \psi_{y_i} \Delta y_{t-i} + \sum_{i=0}^{q-1} \psi_{x_i}' \Delta \mathbf{x}_{t-i} + u_t \tag{4}$$

and easily recover the so-called speed-of-adjustment coefficient $\alpha = -\pi_y$ and the long-run coefficients $\boldsymbol{\theta} = \frac{\pi_x}{\alpha}$. The corresponding standard errors can be computed with the delta method (Pesaran and Shin (1998)). The speed-of-adjustment coefficient α indicates how quickly y_t reverts to its long-run equilibrium after a distortion. $\alpha = 1$ implies full correction in the next period, while $\alpha = 0$ means no return to equilibrium. Values between 0 and 1 reflect partial adjustment, with the gap closing gradually over time. For a long-run level relationship to exist, we need both $\boldsymbol{\theta} \neq 0$ and $\alpha > 0$, as shown by Kripfganz. The remaining coefficients ψ_{y_i}, ψ_{x_i} capture the short-run dynamics that are not prescribed by the equilibrium-reverting forces.

The ARDL-EC representation models long-run and short-run effects and should be used if a long-run levels relationship is found by the popular bounds-test procedure from Pesaran et al. (2001). If there is evidence against a long-run level relationship, a ARDL in first differences is estimated:

$$\Delta y_t = c_0 + c_1 t + \sum_{i=1}^{p-1} \psi_{y,i} \Delta y_{t-i} + \sum_{i=0}^{q-1} \psi'_{x,i} \Delta x_{t-i} + \gamma' z_t + u_t$$

6 Model estimation

As explained in Section 4, the analysis focuses on three Latin American countries important push factors: TED spread (`TED_spread_US`), global market volatility (`VIX`), ex-post real policy interest rate in the U.S. (`ex_post_real_pol_int_US`), U.S. Treasury yield (`yield_US`), U.S. nominal interest rate (`nom_int_rate_US`) and the real effective exchange rate of the U.S. dollar (`REER_US`).

First, I tested the order of integration with an augmented dickey fuller test, shown in 1. No variable in the dataset is integrated of order $I(d > 1)$, making it suitable for

Table 1: Order of Stationarity for Variables

Variable	**Order**
nom_int_rate_US	I(1)
TED_spread_US	I(1)
VIX	I(0)
ex_post_real_pol_int_US	I(1)
yield_US	I(0)
REER_US	I(1)
Brazil_Debt_inf	I(0)
Chile_Debt_inf	I(1)
Mexico_Debt_inf	I(1)

the ARDL-EC model. As Brazil's debt capital flows are stationary at level, no test for a long-run relationship is needed, allowing the direct use of ARDL in differences. Long-run relationships must still be tested for Chile and Mexico.

As a preliminary step, I tested for multicollinearity. In an ECM, multicollinearity testing should focus on the short-run variables (Δx_t), as multicollinearity in the long-run relationship is inherent and effectively addressed in the ARDL-EC. Table 2 presents the VIF value, indicating that no multicollinearity exists among the push factors.

Table 3 shows the number of cointegration relationships among the analyzed variables, including capital flows for each country. The ARDL-EC model assumes a single

Variable	VIF
TED_spread_US	1.4307
VIX	1.3404
ex_post_real_pol_int_US	1.0957
nom_int_rate_US	2.0665
yield_US	2.3331
REER_US	1.1199

Table 2: Variance Inflation Factor (VIF) for Variables

cointegration relationship involving y_t. However, as noted by Kripfganz and Schneider (2023) and Pesaran et al. (2001), a cointegration rank greater than one (e.g. for Chile) does not violate this assumption if cointegration exists only among the elements of x_t. Additionally, the absence of feedback effects from y to x is assumed, which is reasonable since EM capital flows are unlikely to influence the global financial cycle.

Table 3: Cointegration Rank Results for Analyzed Countries

Country	Number of Cointegrations
Brazil_Debt	1
Chile_Debt	2
Mexico_Debt	1

To determine whether to estimate the "long-run" error correction form or the short-run standard ARDL in differences, I performed the ARDL bounds test. Test case 4, including an intercept and a linear time trend, was selected. The optimal lag structure was chosen by minimizing the AIC with a maximum of 6 lags. The null hypothesis of the ARDL bounds test is that there is no long-run level relationship. Conclusive evidence occurs when the test statistic lies outside the bounds: below the lower bound indicates no rejection, above the upper bound indicates rejection, and values between the bounds are inconclusive. The 95% critical values for the bounds test are $CV_l = 2.65$ and $CV_u = 3.62$, with estimated F-statistics of $F_{\text{Chile}} = 4.47$ and $F_{\text{Mexico}} = 5.61$. The results indicate that the null hypothesis of no long-run relationship can be rejected for both, Chile and Mexico, and the ARDL-EC form is appropriate for these countries

Tables 4,5 and 6 show the model results for Brazil, Chile and Mexico.

For Brazil, the autoregressive components are highly significant, indicating a strong dependence of current capital flows on their past values. A capital flow shock in period t is expected to reduce capital flows in subsequent periods. Among the explanatory variables, the VIX has a negative and significant impact on capital flows, indicating that increases in market volatility reduce capital flows to Brazil. The real effective exchange rate (`D.REER_US.L0` = -260.3987) shows a significant and negative short-run effect, suggesting that a stronger U.S. dollar relative to other currencies recudes capital inflows into Brazil. Other variables, such as the TED spread, U.S. real policy interest rates, and U.S. yield, do not show statistically significant effects in this model.

In the case of chile, the coefficient of the lagged dependent variable (`capital_flow.L1` = -0.8231) indicates a strong error correction mechanism, suggesting that approximately 82.3% of the deviation from the long-run equilibrium is corrected in the subsequent period. In the short run, the second lag of nominal interest rate changes (`D.nom_int_rate_US.L2`

Table 4: Regression Summary for Brazil

Dependent Variable:	D.capital_flow
Number of Observations:	332
Model:	ARDL(5, 1, 2, 1, 1, 2, 1)
Method:	Conditional ML, HAC robust
AIC:	6074.625
Variable	**Coefficient (SE)**
const	94.02 (290.71)
trend	-0.09 (1.51)
D.capital_flow.L1	-0.814 (0.056) ***
D.capital_flow.L2	-0.671 (0.068) ***
D.capital_flow.L3	-0.422 (0.071) ***
D.capital_flow.L4	-0.314 (0.065) ***
D.capital_flow.L5	-0.162 (0.053) ***
D.TED_spread_US.L0	-714.10 (977.87)
D.TED_spread_US.L1	491.50 (956.40)
D.VIX.L0	-103.41 (39.78) **
D.VIX.L1	-112.03 (40.15) ***
D.VIX.L2	-82.29 (37.68) **
D.ex_post_real_pol_int_US.L0	406.17 (397.07)
D.ex_post_real_pol_int_US.L1	323.00 (391.89)
D.yield_US.L0	637.20 (613.20)
D.yield_US.L1	51.69 (631.53)
D.REER_US.L0	-259.29 (117.34) **
D.REER_US.L1	-166.90 (128.19)
D.REER_US.L2	167.65 (118.84)
D.nom_int_rate_US.L0	757.42 (1443.30)
D.nom_int_rate_US.L1	1452.98 (1429.70)
Significance Levels:	* p<0.05, ** p<0.01, *** p<0.001

= -2065.093) exhibits a negative and significant effect, suggesting that previous changes in U.S. nominal interest rates have a short-term impact on capital flows. Consistent with theoretical expectations, the VIX coefficients are negative in both the long and short run, but they are not statistically significant.

The coefficient of the lagged dependent variable (`capital_flow.L1` = -0.6796) indicates a moderate error correction mechanism, with approximately 67.96% of deviations from the long-run equilibrium corrected in the following period. In the long run, the real effective exchange rate (`REER_US.L1` = -51.8280) has a significant and negative impact, suggesting that a stronger U.S. dollar relative to other currencies reduces capital inflows to Mexico. In the short run, the VIX (`D.VIX.L0` = -79.7228) has a negative and significant effect, indicating that increased market volatility reduces capital flows to Mexico. Additionally, real effective exchange rate (`D.REER_US.L0` = -155.2300, $p = 0.054$) is marginally significant, implying a short-run sensitivity of capital flows to exchange rate changes.

The comparison of AIC values provides insight into how well the models explain debt capital flows driven by U.S. push factors for each country. Given that $AIC_{Chile} = 3914 < AIC_{Mexico} = 5856 < AIC_{Brazil} = 6074$, and assuming the models are correctly specified,

Table 5: Regression Summary for Chile

Dependent Variable:	D.Net Debt flow Chile
Number of Observations:	236
Model:	UECM(5, 1, 1, 1, 1, 1, 5)
Method:	Conditional ML, HAC robust
AIC:	3913.808
Variable	**Coefficient (SE)**
const	2125.06 (954.48) **
trend	2.19 (1.81)
capital_flow.L1	-0.823 (0.131) ***
TED_spread_US.L1	-361.87 (374.43)
VIX.L1	-21.58 (14.04)
ex_post_real_pol_int_US.L1	-120.84 (83.55)
yield_US.L1	-163.98 (129.73)
REER_US.L1	-10.88 (7.01)
nom_int_rate_US.L1	-204.94 (234.60)
D.capital_flow.L1	-0.294 (0.118) **
D.capital_flow.L2	-0.090 (0.160)
D.capital_flow.L3	0.126 (0.199)
D.capital_flow.L4	0.168 (0.104)
D.TED_spread_US.L0	-384.99 (395.49)
D.VIX.L0	-1.70 (17.89)
D.ex_post_real_pol_int_US.L0	-7.76 (116.04)
D.yield_US.L0	175.34 (208.75)
D.REER_US.L0	-53.10 (51.50)
D.nom_int_rate_US.L0	401.57 (760.85)
D.nom_int_rate_US.L1	179.38 (551.67)
D.nom_int_rate_US.L2	-2065.09 (931.25) **
D.nom_int_rate_US.L3	-845.21 (665.67)
D.nom_int_rate_US.L4	1044.30 (592.20) *
Significance Levels:	* p<0.05, ** p<0.01, *** p<0.001

this suggests that debt capital flows to Chile are more strongly influenced by U.S. push factors compared to flows to Mexico or Brazil.

7 Discussion and Conclusion

Chile, Brazil, and Mexico share similarities as emerging markets in Latin America, making them partially comparable. Additionally, they are all commodity exporters, which exposes their economies to external shocks. However, they also exhibit differences. Brazil has a strong industrial and agricultural base, while Chile's economy is smaller and heavily dependent on copper exports. Mexico, in contrast, is a trade-oriented economy with strong ties to the U.S., driven by trade agreements.

This study provides insights into the long-run dynamics of capital flows by employing an Error Correction Model (ECM), which captures both short-run adjustments and long-run equilibrium relationships. The analysis reveals a moderate to strong error correction mechanism for both Chile and Mexico. While not all long-run relationships are statistically significant, the signs of the coefficients are consistent across models. Specifically, a negative long-run relationship is observed between debt capital flows and the VIX, the ex-post real policy interest rate, the U.S. yield, the REER, and the nominal interest rates. In the short run, the majority of coefficients are also consistent across all three models.

Further improvements could involve incorporating pull factors, such as domestic economic conditions, and considering not only U.S.-based push factors but also those from other major economies, such as the EMU, the UK, or Japan.

References

Bhattarai, S., Chatterjee, A., and Park, W. Y. (2021). Effects of us quantitative easing on emerging market economies. *Journal of Economic Dynamics and Control*, 122:104031.

Cerutti, E., Claessens, S., and Puy, D. (2015). Push factors and capital flows to emerging markets: Why knowing your lender matters more than fundamentals. IMF Working Paper WP/15/127, International Monetary Fund.

Cerutti, E., Claessens, S., and Rose, A. K. (2017). How important is the global financial cycle? evidence from capital flows. NBER Working Paper 23699, National Bureau of Economic Research.

Forbes, K. J. and Warnock, F. E. (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics*, 88(2):235–251. Available online 29 March 2012.

Fratzscher, M. (2011). Capital flows, push versus pull factors and the global financial crisis. Working Paper Series 1364, European Central Bank.

Hannan, S. A. (2017). The drivers of capital flows in emerging markets post global financial crisis. IMF Working Paper WP/17/52, International Monetary Fund.

Hannan, S. A. (2018). Revisiting the determinants of capital flows to emerging markets—a survey of the evolving literature. IMF Working Paper WP/18/214, International Monetary Fund.

Hassler, U. and Wolters, J. (2006). Autoregressive distributed lag models and cointegration. *Allgemeines Statistisches Archiv*, 90:59–74.

Koepke, R. (2015). What drives capital flows to emerging markets? a survey of the empirical literature. MPRA Paper 62770, Institute of International Finance, University of Wurzburg. Posted 25 Apr 2015 04:20 UTC.

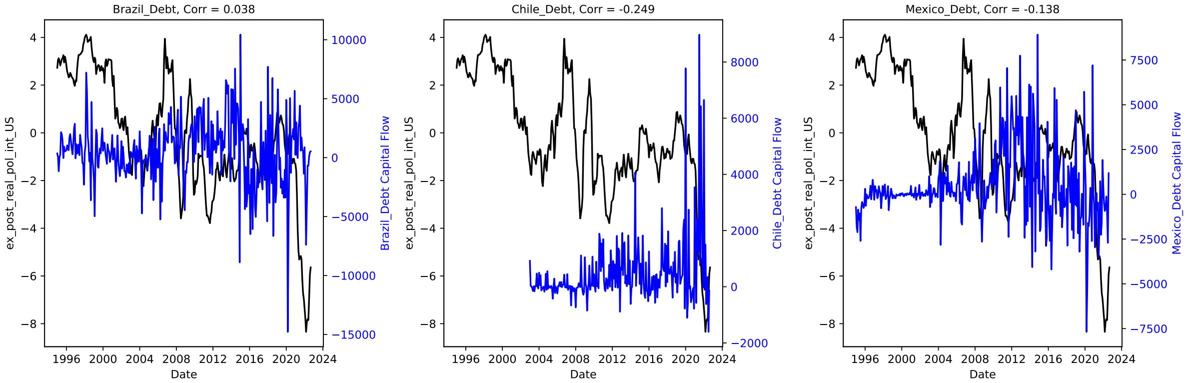
Kripfganz, S. and Schneider, D. C. (2023). ardl: Estimating autoregressive distributed lag and equilibrium correction models. *The Stata Journal*, 23(4):983–1019.

Pesaran, M. H. and Shin, Y. (1998). An autoregressive distributed-lag modelling approach to cointegration analysis. In Steiner, S., editor, *Econometrics and Economic Theory in the Twentieth Century: The Ragnar Frisch Centennial Symposium*, pages 371–413. Cambridge University Press, Cambridge.

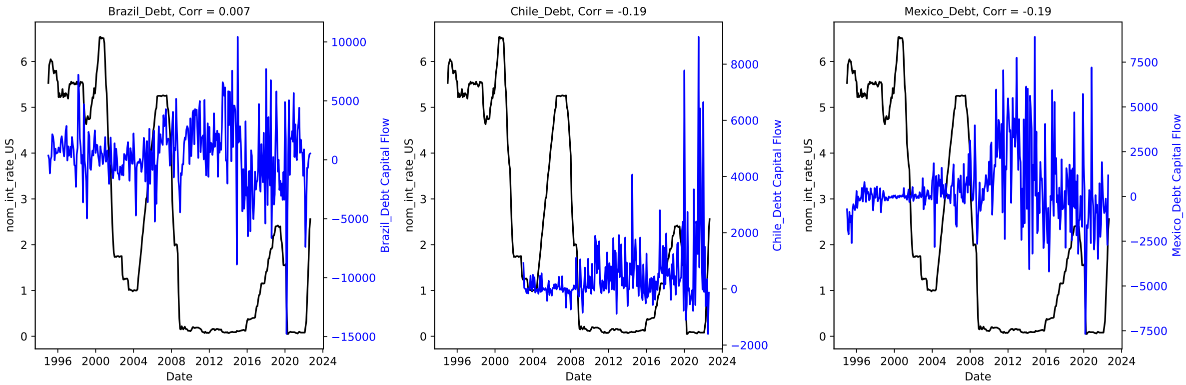
Pesaran, M. H., Shin, Y., and Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16:289–326.

Rey, H. (2015). International channels of transmission of monetary policy and the mundellian trilemma. *IMF Economic Review*, 64(1):6–35. Mundell Fleming Lecture.

(a) Debt Capital Flows and Ex-Post Real Policy Interest Rate.



(b) Debt Capital Flows and Nominal US Interest Rate.



(c) Debt Capital Flows and REER.

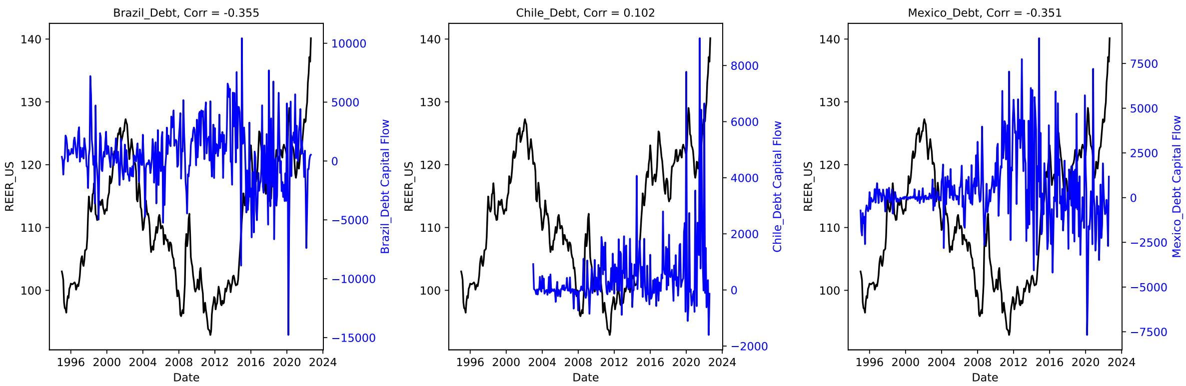
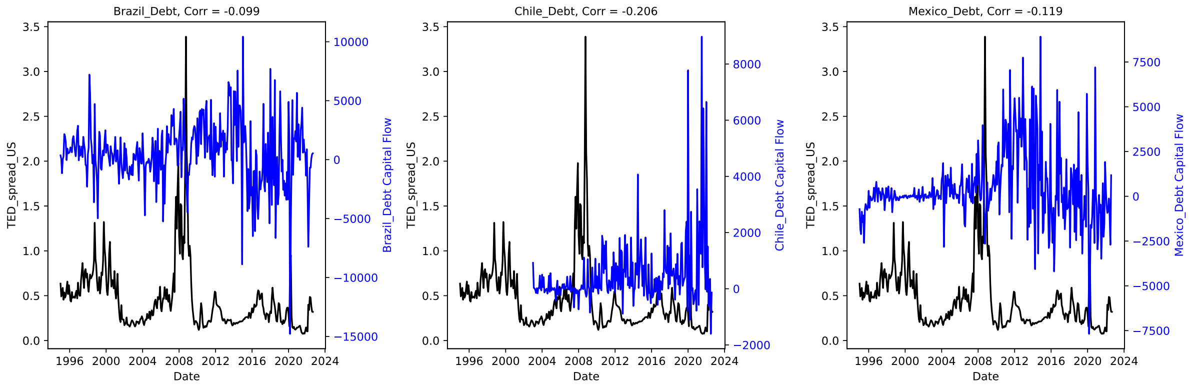
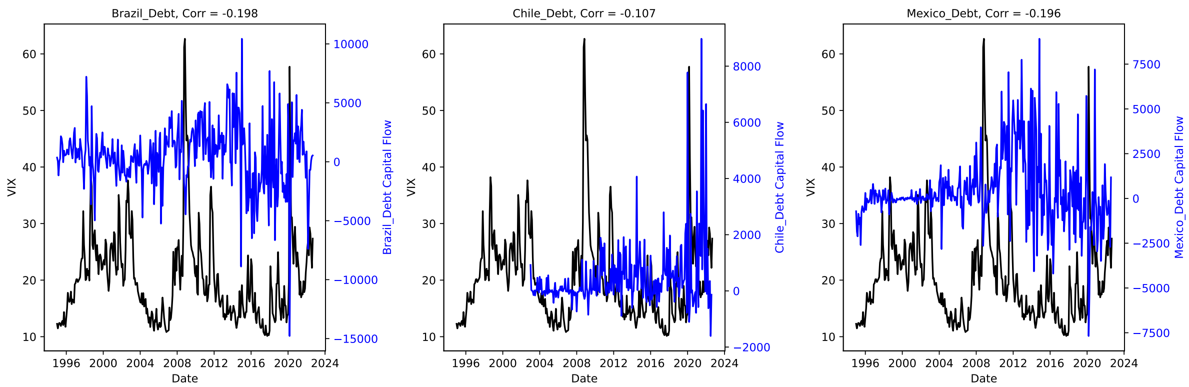


Figure 1: Debt Capital Flows and Selected Push Factors (Part 1).

(a) Debt Capital Flows and TED Spread.



(b) Debt Capital Flows and VIX.



(c) Debt Capital Flows and US Yield Curve.

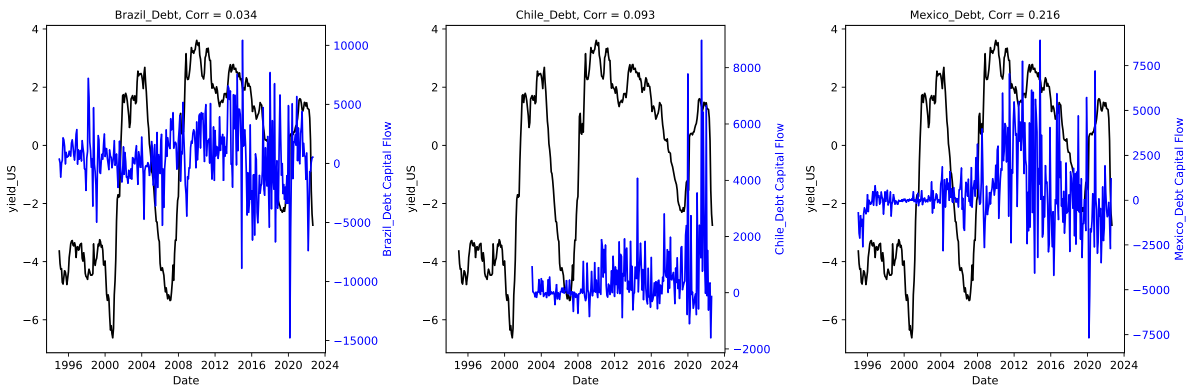


Figure 2: Debt Capital Flows and Selected Push Factors (Part 2).

Table 6: Regression Summary for Mexico

Dependent Variable:	D.Net Debt flow Mexico
Number of Observations:	332
Model:	UECM(5, 1, 1, 1, 1, 1, 5)
Method:	Conditional ML, HAC robust
AIC:	5856.456
BIC:	5947.415
HQIC:	5892.750
Variable	**Coefficient (SE)**
const	7585.07 (2090.01) ***
trend	-2.27 (3.26)
capital_flow.L1	-0.680 (0.125) ***
TED_spread_US.L1	84.94 (449.19)
VIX.L1	-29.01 (22.22)
ex_post_real_pol_int_US.L1	-71.69 (55.62)
yield_US.L1	-138.77 (238.31)
REER_US.L1	-51.83 (14.78) ***
nom_int_rate_US.L1	-285.77 (395.64)
D.capital_flow.L1	-0.236 (0.104) **
D.capital_flow.L2	-0.110 (0.107)
D.capital_flow.L3	-0.102 (0.109)
D.capital_flow.L4	-0.073 (0.061)
D.TED_spread_US.L0	-189.05 (547.29)
D.VIX.L0	-79.72 (27.35) ***
D.ex_post_real_pol_int_US.L0	-3.44 (217.88)
D.yield_US.L0	288.95 (356.52)
D.REER_US.L0	-155.23 (79.84) *
D.nom_int_rate_US.L0	1352.61 (1000.33)
D.nom_int_rate_US.L1	86.96 (693.87)
D.nom_int_rate_US.L2	-666.76 (562.37)
D.nom_int_rate_US.L3	420.11 (456.27)
D.nom_int_rate_US.L4	-1002.85 (524.70) *
Significance Levels:	* p<0.05, ** p<0.01, *** p<0.001