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Essays in International Macroeconomics

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Economics

by

Bangyu He

2026

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2026

ABSTRACT OF THE DISSERTATION

Essays in International Macroeconomics

by

Bangyu He

Doctor of Philosophy in Economics

University of California, Los Angeles, 2026

Professor Pierre-Olivier Weill, Co-Chair

Professor Oleg Itskhoki, Co-Chair

This dissertation studies how financial frictions, market structure, and policy interventions shape exchange rate dynamics and capital flows across countries at different stages of financial development. The three chapters jointly provide a unified perspective on international macroeconomics by emphasizing the role of constrained arbitrage, financial market depth, and official capital flows in determining macroeconomic outcomes. Chapter 1 revisits the uncovered interest parity (UIP) puzzle using daily data on exchange rates and interest differentials for both developed and emerging market economies over the past two to three decades. The large number of observations allows for a detailed analysis of the dynamics of the Fama coefficient and its response to major global events, including the global financial crisis, the European sovereign debt crisis, and the COVID-19 pandemic. Using a decomposition approach, the chapter evaluates several leading explanations of UIP deviations. The

results suggest that different theoretical channels explain different dimensions of the data, while models based on financial market frictions are particularly well suited to account for the high-frequency dynamics of the Fama coefficient. Chapter 2 develops a theoretical framework to study the role of arbitrageurs in foreign exchange markets. The chapter highlights two opposing forces generated by arbitrage activity: a substitution effect that stabilizes exchange rates by absorbing shocks, and a wealth effect that can amplify exchange rate fluctuations when arbitrageurs incur losses. The model shows that the relative importance of these effects depends on the level of arbitrageur wealth and market depth. In advanced economies with deep and liquid foreign exchange markets, the substitution effect dominates and exchange rates remain relatively stable. In emerging market economies with thinner markets and limited arbitrageur capital, the wealth effect becomes more important, contributing to larger deviations from uncovered interest parity and more frequent foreign exchange interventions by central banks. Chapter 3 studies the catalytic impact of IMF lending on official development assistance (ODA) in low-income countries. Using a country-year panel dataset and an instrumental variables strategy to address selection bias in IMF program participation and lending size, the chapter estimates the causal effect of IMF disbursements on external financing. The findings show that IMF lending significantly increases ODA inflows and that larger IMF disbursements catalyze more substantial external financing. At the same time, the catalytic effect exhibits diminishing returns with respect to program size. The results highlight the important role of IMF programs in mobilizing official capital flows in economies where private financial markets remain underdeveloped. Taken together, the chapters demonstrate that financial frictions and constraints on capital allocation are central to understanding exchange rates, capital flows, and policy interventions in

the international economy. While advanced economies, emerging market economies, and low-income countries differ substantially in financial market depth and the composition of capital flows, the dissertation shows that a unified framework centered on market frictions and risk-bearing capacity can help explain macroeconomic outcomes across these diverse settings.

The dissertation of Bangyu He is approved.

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2026

To my family, for their love, encouragement, and support throughout this journey.
To my advisors, teachers, and mentors, for their guidance, patience, and inspiration.
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¹This chapter is based on joint work with Phil Johnston and Agustin Velasquez at the International Monetary Fund. The views expressed are those of the author(s) and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

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INTRODUCTION

International financial markets differ substantially across countries in terms of depth, liquidity, and the composition of capital flows. These differences shape how exchange rates adjust, how capital is allocated, and how policymakers respond to external shocks. In advanced economies, foreign exchange markets are deep and liquid, supported by a large base of arbitrageurs and financial intermediaries. In contrast, emerging market economies are characterized by thinner markets and more limited arbitrage capacity, making exchange rates more volatile and policy intervention more frequent. At an even lower level of financial development, low-income countries rely predominantly on official capital flows rather than private financial markets. Understanding how these structural differences affect macroeconomic outcomes is a central challenge in international economics.

This dissertation, *Essays in International Macroeconomics*, studies how financial frictions, market structure, and policy interventions jointly determine exchange rate dynamics and capital flows across these different economic environments. A unifying theme is that the depth of financial markets and the availability of arbitrage capital are key determinants of both market outcomes and the role of policy. By combining high-frequency empirical analysis, structural modeling, and causal inference, the dissertation sheds new lights on understanding international macroeconomic phenomena across advanced economies, emerging market economies, and low-income

countries.

Chapter 1 examines the uncovered interest parity (UIP) puzzle using high-frequency data on exchange rates and interest differentials. By leveraging daily data over the past two to three decades, the chapter documents the time-varying behavior of the Fama coefficient across both advanced and emerging market economies. The analysis highlights that UIP deviations are pervasive but exhibit systematic variation over time and across countries. Using a decomposition approach, the chapter evaluates competing explanations and finds that financial market frictions provide the most consistent account of the data. Importantly, the results reveal common patterns between advanced and emerging market economies, suggesting that differences in market outcomes are not driven by fundamentally different mechanisms, but rather by differences in the severity of financial frictions and market depth.

Chapter 2 builds on this insight by developing a theoretical framework that explicitly models the role of arbitrageurs in foreign exchange markets. The chapter introduces a continuous-time model in which arbitrageur wealth evolves endogenously and affects their ability to absorb shocks. A key contribution is the distinction between the substitution effect, which stabilizes markets, and the wealth effect, which can amplify exchange rate movements and generate instability. The model shows that in economies with deep markets and abundant arbitrage capital—such as advanced economies—the stabilizing substitution effect dominates. In contrast, in emerging market economies with limited arbitrageur wealth, the destabilizing wealth effect becomes more important, leading to larger exchange rate fluctuations and more frequent deviations from UIP. These findings provide a structural explanation for why central banks of emerging market economies intervene more frequently in foreign

exchange markets. The analysis also suggests that policies aimed at deepening financial markets and expanding arbitrageur capital can significantly reduce the need for intervention.

Chapter 3 shifts the focus to low-income countries, where financial markets are underdeveloped and external financing primarily takes the form of official capital flows. In this context, the chapter studies the catalytic impact of IMF lending on official development assistance (ODA). Using an instrumental variables approach to address selection bias, the analysis estimates the causal effect of IMF disbursements on external financing. The results show that IMF lending plays a significant role in mobilizing additional resources from international donors. Unlike advanced and emerging market economies, where private capital markets and arbitrage activity dominate, low-income countries rely heavily on coordinated official support, highlighting a fundamentally different mechanism of international financial integration.

Taken together, the three chapters provide a unified perspective on international macroeconomics across different levels of financial development. They show that while the underlying mechanisms—such as financial frictions and constraints on risk-bearing capacity—are common across countries, their implications depend critically on market structure and the availability of capital. This perspective helps bridge the gap between the behavior of exchange rates in advanced economies, the policy challenges faced by emerging market economies, and the financing constraints of low-income countries.

CHAPTER 1

The Dynamics of the Uncovered Interest Parity: A Unified Story of Developed and Emerging Market Economies

1.1 Introduction

In the field of international macroeconomics, a renowned relationship between exchange rates and interest rates is the uncovered interest parity (UIP) condition, which is

$$E_t \hat{s}_{t+1} - s_t = i_t - i_t^*, \quad (1.1)$$

where $s_t \equiv \log S_t$ and S_t denotes the number of home currency per unit of foreign currency, i_t denotes the interest rate on home currency, and i_t^* denotes the interest rate on foreign currency. So, if the UIP condition holds, then when we run the Fama regression as follows,

$$s_{t+1} - s_t = \alpha + \beta(i_t - i_t^*) + \varepsilon_{t+1}, \quad (1.2)$$

we should expect $\alpha = 0$ and $\beta = 1$ in the data.

However, Fama (1984) establishes the UIP puzzle in an empirical work where $\alpha = 0$ is

not rejected while $\beta = 1$ is rejected. More importantly, the estimated β , which is then known as the Fama coefficient, is even negative for all of the 9 developed economies in the study. To be specific, the Fama coefficients range from -1.58 to -0.29. Since then, a broad literature both empirical and theoretical has been developed to explore and explain this puzzle.

Several empirical studies such as Lewis (1995) and Engle (2016) test the UIP condition with Fama regressions using up-to-date monthly data. They mainly focus on developed countries and document negative Fama coefficients for most of those economies.¹ However, the values of the Fama coefficients in these two studies are not agreed. To be specific, Lewis (1995) reports Fama coefficients ranging from -3.33 to -2.31 for 3 countries in a period of 15 years between 1975 and 1989, while the numbers in Engle (2016) range from -2.71 to 0.66 instead. More interestingly, in Lewis (1995), the value of the Fama coefficient depends on the sampling period significantly. The range is from -1.33 to 1.06 in a five-year sub-sample between 1975 and 1979, while is from -12.05 to -9.70 in another five-year sub-sample between 1984 to 1989. In addition to the study on developed economies, Bansal and Dahlquist (2000) test the UIP condition on emerging market economies with weekly data in the 1990s and 2000s. They outline a different story that although the Fama coefficients are negative in most of the developed economies, they are typically positive in emerging market economies where inflation, inflation volatility, and credit risk are higher.

Numerous theories have been proposed as well to explain the UIP puzzle. The

¹Lewis (1995) tests the UIP condition between the United States and each of the developed economies, including Germany, Japan, and United Kingdom. Engle (2016) includes three more developed economies to the list, including Canada, France, and Italy.

theories can be classified into four broad categories, namely risk premium channel, expectations channel, liquidity premium channel, and financial market frictions channel. First, one of the classic arguments blames the risk premium for causing the UIP puzzle. To reconcile the puzzle, models without frictions are proposed in a series of studies, including Colacito (2009), Backus et al. (2010), Lustig, Roussanov, and Verdelhan (2011), Bansal and Shaliastovich (2013), and Corsetti and Marin (2020). Second, since the UIP condition incorporates the expectations about the future exchange rate, then distortions in the expectations can contribute to the violations of that condition. Gourinchas and Tornell (2004), Bacchetta and van Wincoop (2010), and Stavrageva and Tang (2018) highlight the importance of the information friction on the UIP puzzle. They argue that the actions of the agents are indirectly affected and it is their distorted belief or biased behavior that generates the UIP deviations. Third, Engle (2016) points out the liquidity premium as a potential factor that contributes to the UIP puzzle by distorting asset prices. Finally, instead of focusing on the asset price itself, Gabaix and Maggiori (2015) and Itskhoki and Mukhin (2021) consider the imperfections of the international asset markets. They propose a modeling framework that features segmented financial markets with noise traders and arbitrage restrictions, which is capable to explain the UIP puzzle.

This chapter is an empirical study based on the techniques from four of the most influential studies, including Fama (1984), Bansal and Dahlquist (2000), Engle (2016), and Itskhoki and Mukhin (2021). It contributes to the literature in four aspects. First, most of the previous studies use weekly or monthly data in a period of 5 to 30 years. They typically have tens or hundreds of observations in their regressions. I collect daily data on exchange rate changes and interest differentials in the past two

to three decades for analysis. Then, the number of observations is significantly increased to around 6000 compared to the weekly data in Bansal and Dahlquist (2000). This enables me to get more accurate results from regressions without using some compensation techniques such as pooling in Bansal and Dahlquist (2000). Second, I characterize the dynamics of the Fama coefficient over time. The benefit of more observations from daily data is that the window size of the rolling regressions can be shrunk from 5 years to 1 year. This allows me to identify and separate the influences of a sequence of events in the past 15 years. To be specific, there are at least four influential events in the global financial markets in that period, including the financial crisis in 2007 and 2008, the Greek government-debt crisis from 2010 to 2014, the interest rate hike of the Federal Reserve in 2016, and the pandemic starting from 2020. Third, by applying a decomposition technique inspired by Engle (2016), the empirical results highlight that different modeling frameworks capture distinct aspects of the data. In particular, models based on risk premia, expectations, and liquidity considerations provide useful insights into medium- to low-frequency movements, while models within the financial market frictions channel are well suited to account for the high-frequency dynamics of the Fama coefficient. This finding is consistent with Itskhoki and Mukhin (2021) and suggests that these approaches are complementary in understanding exchange rate behavior. Fourth, with the help of the decomposition technique, a unified explanation of developed and emerging market economies regarding the UIP puzzle becomes possible.

The rest of the chapter is organized in the following 5 sections. Section 1.2 describes the data used in the empirical analysis. Section 1.3 summarizes the empirical findings about the UIP puzzle. Section 1.4 discusses the implications of those empirical

findings on the theoretical models aiming to explain the puzzle. Section 1.5 points out several directions for further research. Section 1.6 concludes. The figures are attached to the end of this chapter.

1.2 Exchange Rate Changes and Interest Differentials

In this section, I first describe the data used for the empirical analysis thereafter, and then summarize their descriptive statistics. Table 1.1 presents the key information about the data.

1.2.1 The Data

I use daily data on exchange rate changes $s_{t+1} - s_t$ and interest differentials $i_t - i_t^*$ for 26 economies against the United States. Among these 26 economies, 11 economies are classified as developed economies, while the other 15 economies are considered as emerging market economies. The sampling periods range from 14 years to 25 years. The detailed information is summarized in the first four columns of Table 1.1. The daily exchange rate changes are derived from the daily exchange rate data. The interest differentials are calculated by the differences of the 1 year London Interbank Offered Rate (LIBOR) between the United States dollar (USD) and the currency in each of the 26 economies on a daily basis. The daily data on exchange rates and interest rates are obtained from Federal Reserve Economic Data (FRED), Intercontinental Exchange (ICE), Investing.com, Wenxin Du's website, and Yahoo Finance.

1.2.2 Descriptive Statistics

The last five columns of Table 1.1 display the descriptive statistics of the exchange rate changes and the interest differentials. The exchange rate changes are more drastic in emerging market economies than in developed economies. The standard deviations of the exchange rate changes are in the same magnitude on average, but they vary a lot across emerging market economies. To be specific, emerging market economies such as India, Malaysia, and Peru have standard deviations less than 8%, while Brazil and South Africa recorded standard deviations more than 20%. The interest differentials are in general smaller in the developed economies than in the emerging market economies. This is because the emerging market economies typically have higher interest rates.

The descriptive statistics of the exchange rate changes and the interest differentials reported in Table 1.1 are in the same magnitude of those in Bansal and Dahlquist (2000). So, replacing weekly data with daily data does not add more volatility in the exchange rate changes and the interest differentials, the two key variables in the Fama regression.

The following two groups of figures depict the variance of the exchange rate changes and that of the interest differentials across the sampling period in each of the 26 economies respectively. The variance at a particular time is calculated with the most recent 260 observations by that time. Since there are approximately 260 observations or trading days every calendar year, then choosing 260 as the sample size to calculate variances gives us the annual variance at each point of time.

Table 1.1: Summary statistics of the exchange rate changes and the interest differentials

	Currency	Group	Date	$s_{t+1} - s_t$		$i_t - i_t^*$		Obs
				Mean	SD	Mean	SD	
Australia	AUD	Developed	6/21/96-3/9/21	-0.12	14.87	-1.57	1.67	6443
Canada	CAD	Developed	8/27/99-3/9/21	1.08	10.36	-0.27	0.73	5615
Switzerland	CHF	Developed	6/21/96-3/9/21	1.76	12.98	1.65	1.43	6442
Denmark	DKK	Developed	6/21/96-3/9/21	-0.31	11.42	0.45	1.40	6439
European Union	EUR	Developed	1/4/99-3/9/21	0.05	11.51	0.54	1.35	5785
United Kingdom	GBP	Developed	1/23/97-3/9/21	-0.91	10.87	-0.44	1.17	6288
Japan	JPY	Developed	6/21/96-3/9/21	0.04	12.58	2.20	1.99	6434
South Korea	KRW	Developed	8/20/99-3/9/21	0.36	12.13	-1.64	1.36	5614
Norway	NOK	Developed	7/10/98-3/9/21	-0.56	14.56	-0.88	1.68	5845
New Zealand	NZD	Developed	6/21/96-3/9/21	0.34	14.97	-2.02	1.53	6432
Sweden	SEK	Developed	6/21/96-3/9/21	-1.36	14.01	0.39	1.53	6439
Brazil	BRL	Emerging	3/27/07-3/9/21	-10.12	20.73	-8.80	3.54	3637
Chile	CLP	Emerging	10/19/05-3/9/21	-2.78	12.79	-2.59	1.88	3955
Colombia	COP	Emerging	6/14/05-3/9/21	-3.74	15.30	-4.27	1.68	4087
Hungary	HUF	Emerging	2/15/00-3/9/21	-1.10	16.87	-3.76	3.51	5492
Indonesia	IDR	Emerging	2/25/03-3/9/21	-3.76	8.96	-5.88	1.93	4684
India	INR	Emerging	12/11/98-3/9/21	-3.37	7.61	-5.10	1.99	5796
Mexico	MXN	Emerging	9/23/02-3/9/21	-5.40	14.71	-4.61	1.32	4807
Malaysia	MYR	Emerging	11/22/06-3/9/21	-1.21	7.84	-1.89	1.12	3716
Peru	PEN	Emerging	7/7/06-3/9/21	-1.24	6.49	-2.48	1.61	3822
Philippines	PHP	Emerging	12/19/00-3/9/21	0.23	7.58	-3.42	2.31	4949
Poland	PLN	Emerging	2/11/02-3/9/21	0.69	16.57	-2.20	2.22	4976
Russia	RUB	Emerging	4/13/06-3/9/21	-9.29	17.88	-5.71	2.74	3838
Thailand	THB	Emerging	11/22/06-3/9/21	1.73	9.04	-1.07	1.28	3726
Turkey	TRY	Emerging	5/25/05-3/9/21	-14.96	18.04	-10.98	3.69	4119
South Africa	ZAR	Emerging	12/31/96-3/9/21	-6.77	20.65	-6.30	2.15	6304

Figure 1.1 presents 26 plots of the variance of exchange rate changes across the sample economies. The plots indicate that developed and emerging market economies exhibit a broadly similar time-series pattern: the variance remains relatively stable over time but experiences sharp systematic spikes during major global financial events, including the financial crisis in 2007 and 2008, the Greek government-debt crisis from 2010 to 2014, the Federal Reserve interest rate hike in 2016, and the pandemic beginning in 2020, along with occasional smaller idiosyncratic spikes. However, the magnitude of these spikes is substantially larger in emerging market economies, where the peaks are several times higher than those observed in developed economies. This finding is consistent with Table 1.1, which shows that the variance of exchange rate changes is generally higher in emerging market economies than in developed economies.

Figure 1.2 presents the variance of interest differentials for the same 26 economies. Similar to the variance of exchange rate changes, the variance of interest differentials displays a stable long-run pattern interrupted by pronounced spikes during the major global financial events between 2007 and 2020, together with occasional idiosyncratic increases. Emerging market economies again exhibit substantially larger spikes than developed economies, with peak values several times higher on average. This result is also consistent with Table 1.2, which shows that the variance of interest differentials is generally higher in emerging market economies than in developed economies.

1.3 Empirical Analysis

In this section, I run two types of regressions, namely the Fama regression following Fama (1984) and Bansal and Dahlquist (2000) and the rolling regression inspired by Itskhoki and Mukhin (2021). The Fama regressions are used to estimate the long-run

Fama coefficients, while the rolling regressions help to detect the dynamics of the Fama coefficients over the sampling period.

1.3.1 Fama Regression

To test the UIP condition, a classic technique in the literature is running a regression on Equation (1.2). I run that regression for each of the 26 economies with the data. The results are shown in Table 1.2. From those regressions, α is estimated to be 0 for all economies, which is consistent with the UIP condition. However, the hypothesis of $\beta = 1$ is rejected for many of the economies. More importantly, the Fama coefficients are estimated to be negative for all developed economies except Canada and South Korea. The finding here that negative Fama coefficients are pervasive in developed economies is square with the results from previous empirical studies such as Fama (1984), Lewis (1995), Bansal and Dahlquist (2000), and Engle (2016). Interestingly, 10 out of 15 emerging market economies have negative Fama coefficients, which is different from the findings by Bansal and Dahlquist (2000). To be specific, they report positive Fama coefficients for most of the emerging market economies and therefore point out a dichotomy in the Fama coefficient between developed and emerging market economies. However, the Fama regressions with more recent data suggest a weaker dichotomy.

Table 1.2: Fama coefficients

	Currency	Group	Date	α		β		Obs
				Est	SD	Est	SD	
Australia	AUD	Developed	6/21/96-3/9/21	0.00	0.00	-3.23	2.12	6443
Canada	CAD	Developed	8/27/99-3/9/21	0.00	0.00	0.94	3.62	5615
Switzerland	CHF	Developed	6/21/96-3/9/21	0.00	0.00	-3.86	2.16	6442
Denmark	DKK	Developed	6/21/96-3/9/21	0.00	0.00	-2.89	1.94	6439
European Union	EUR	Developed	1/4/99-3/9/21	0.00	0.00	-2.77	2.14	5785
United Kingdom	GBP	Developed	1/23/97-3/9/21	0.00	0.00	-0.62	2.24	6288
Japan	JPY	Developed	6/21/96-3/9/21	0.00	0.00	-0.52	1.51	6434
South Korea	KRW	Developed	8/20/99-3/9/21	0.00	0.00	1.16	2.28	5614
Norway	NOK	Developed	7/10/98-3/9/21	0.00	0.00	-1.06	2.16	5845
New Zealand	NZD	Developed	6/21/96-3/9/21	0.00	0.00	-1.81	2.32	6432
Sweden	SEK	Developed	6/21/96-3/9/21	0.00	0.00	-2.90	2.18	6439
Brazil	BRL	Emerging	3/27/07-3/9/21	0.00	0.00	-0.61	1.86	3637
Chile	CLP	Emerging	10/19/05-3/9/21	0.00	0.00	2.59	2.07	3955
Colombia	COP	Emerging	6/14/05-3/9/21	0.00	0.00	-0.39	2.73	4087
Hungary	HUF	Emerging	2/15/00-3/9/21	0.00	0.00	-2.00	1.24	5492
Indonesia	IDR	Emerging	2/25/03-3/9/21	0.00	0.00	-0.18	1.29	4684
India	INR	Emerging	12/11/98-3/9/21	0.00	0.00	2.58	0.96	5796
Mexico	MXN	Emerging	9/23/02-3/9/21	0.00	0.00	-1.30	3.06	4807
Malaysia	MYR	Emerging	11/22/06-3/9/21	0.00	0.00	4.58	2.20	3716
Peru	PEN	Emerging	7/7/06-3/9/21	0.00	0.00	-0.29	1.25	3822
Philippines	PHP	Emerging	12/19/00-3/9/21	0.00	0.00	-0.08	0.89	4949
Poland	PLN	Emerging	2/11/02-3/9/21	0.00	0.00	-0.06	2.02	4976
Russia	RUB	Emerging	4/13/06-3/9/21	0.00	0.00	3.24	2.02	3838
Thailand	THB	Emerging	11/22/06-3/9/21	0.00	0.00	3.24	2.22	3726
Turkey	TRY	Emerging	5/25/05-3/9/21	0.00	0.00	-1.84	1.45	4119
South Africa	ZAR	Emerging	12/31/96-3/9/21	0.00	0.00	-2.82	2.31	6304

In addition to the classic Fama regressions, Bansal and Dahlquist (2000) propose an augmented Fama regression. To be specific, they run regressions on the following equation.

$$s_{t+1} - s_t = \alpha + \beta^+(i_t - i_t^*)^+ + \beta^-(i_t - i_t^*)^- + \varepsilon_{t+1}, \quad (1.3)$$

where

$$(i_t - i_t^*)^+ = \begin{cases} i_t - i_t^* & \text{if } i_t - i_t^* > 0 \\ 0 & \text{if } i_t - i_t^* \leq 0, \end{cases}$$

$$(i_t - i_t^*)^- = \begin{cases} 0 & \text{if } i_t - i_t^* > 0 \\ i_t - i_t^* & \text{if } i_t - i_t^* \leq 0. \end{cases}$$

This technique is useful to test if the relationship between changes of exchange rates and interest rate differentials is the same for both positive and negative interest rate differentials.

I run the augmented Fama regressions with the full sample for every economy. The results are summarized in Table 1.3. Some economies have "—" instead because their interest rate differentials never switch signs during the sampling period. If this is the case, then Equation (1.3) becomes either of the following two equations.

$$s_{t+1} - s_t = \begin{cases} \alpha + \beta^+(i_t - i_t^*)^+ + \varepsilon_{t+1} & \text{if } i_t - i_t^* > 0 \text{ for all } t \\ \alpha + \beta^-(i_t - i_t^*)^- + \varepsilon_{t+1} & \text{if } i_t - i_t^* \leq 0 \text{ for all } t. \end{cases}$$

Table 1.3: Augmented Fama coefficients

	Currency	Group	Date	β^+		β^-		Obs
				Est	SD	Est	SD	
Australia	AUD	Developed	6/21/96-3/9/21	-28.94	15.52	-0.38	2.72	6443
Canada	CAD	Developed	8/27/99-3/9/21	7.09	10.54	-1.94	5.85	5615
Switzerland	CHF	Developed	6/21/96-3/9/21	—	—	—	—	—
Denmark	DKK	Developed	6/21/96-3/9/21	-3.58	3.42	-1.84	4.74	6439
European Union	EUR	Developed	1/4/99-3/9/21	-2.48	3.30	-3.41	6.04	5785
United Kingdom	GBP	Developed	1/23/97-3/9/21	0.15	5.78	-0.94	3.15	6288
Japan	JPY	Developed	6/21/96-3/9/21	—	—	—	—	—
South Korea	KRW	Developed	8/20/99-3/9/21	-25.30	19.76	3.37	2.80	5614
Norway	NOK	Developed	7/10/98-3/9/21	1.72	7.48	-1.87	3.00	5845
New Zealand	NZD	Developed	6/21/96-3/9/21	-10.31	17.99	-0.97	2.90	6432
Sweden	SEK	Developed	6/21/96-3/9/21	-2.50	4.16	-3.45	5.22	6439
Brazil	BRL	Emerging	3/27/07-3/9/21	—	—	—	—	—
Chile	CLP	Emerging	10/19/05-3/9/21	—	—	—	—	—
Colombia	COP	Emerging	6/14/05-3/9/21	—	—	—	—	—
Hungary	HUF	Emerging	2/15/00-3/9/21	4.47	8.11	-2.84	1.62	5492
Indonesia	IDR	Emerging	2/25/03-3/9/21	—	—	—	—	—
India	INR	Emerging	12/11/98-3/9/21	—	—	—	—	—
Mexico	MXN	Emerging	9/23/02-3/9/21	—	—	—	—	—
Malaysia	MYR	Emerging	11/22/06-3/9/21	-2.12	8.62	6.71	3.44	3716
Peru	PEN	Emerging	7/7/06-3/9/21	24.78	29.34	-0.21	0.90	3822
Philippines	PHP	Emerging	12/19/00-3/9/21	—	—	—	—	—
Poland	PLN	Emerging	2/11/02-3/9/21	0.52	2.62	-5.79	16.22	4976
Russia	RUB	Emerging	4/13/06-3/9/21	—	—	—	—	—
Thailand	THB	Emerging	11/22/06-3/9/21	-0.47	9.39	4.17	3.20	3726
Turkey	TRY	Emerging	5/25/05-3/9/21	—	—	—	—	—
South Africa	ZAR	Emerging	12/31/96-3/9/21	—	—	—	—	—

The β^+ or β^- here serves the same role as the β in Equation (1.2). Then, the augmented Fama regressions provide no additional information. So, their results are marked as "—" in Table 1.3. Another case when the results are marked as "—" is due to lack of observations. Without sufficient amount of observations, a point estimation can have large variance. This does not provide valuable information as well and its result is not recorded.

Bansal and Dahlquist (2000) argue that the most rejections of the UIP condition occur when $i_t - i_t^* > 0$ instead of when $i_t - i_t^* \leq 0$. However, using the same technique with a more recent and longer data set, the findings are different. Although the standard deviations of the estimates are relatively large, which is also the case in Bansal and Dahlquist (2000), there is no clear pattern that more rejections take place when $i_t - i_t^* > 0$ or $i_t - i_t^* \leq 0$. What is consistent with Bansal and Dahlquist (2000) is that the estimated Fama coefficients for the two scenarios, $i_t - i_t^* > 0$ and $i_t - i_t^* \leq 0$, are different. More importantly, the magnitude of the differences varies country by country.

To sum up, the long-run Fama coefficient has the following features in the data. First, it is negative for most of the developed economies and for some of the emerging market economies. Second, although the Fama coefficient is often negative, its estimated value depends on the sampling period and the sampling frequency. To be specific, my results and the findings in previous studies, including Fama (1984), Lewis (1995), Bansal and Dahlquist (2000), and Engle (2016) are different from each other. Third, even in the same study, the estimated Fama coefficients are different country by country. In other words, in terms of the Fama coefficient, heterogeneity appears across countries. Fourth, even for the same economy, the estimated Fama

coefficient depends on the sign of the interest rate differentials.

1.3.2 Rolling Regression

Inspired by the second feature that the long-run Fama coefficients are time-varying, the dynamics of the Fama coefficients can provide more information on the UIP puzzle. I study the dynamics of the Fama coefficients with the help of the rolling regression, a technique applied in numerous previous empirical studies such as Itskhoki and Mukhin (2021). To derive the dynamics of the Fama coefficients for the 26 economies, I run rolling regressions using a window of 260 observations, which approximately corresponds to the average number of trading days in one calendar year.

The results of the rolling regressions are plotted in Figure 1.3. In the set of 26 plots, the x-axis indicates the end-point of the corresponding window. The red line plots the estimated Fama coefficient over time. The two blue lines in every plot denote the 10% and 90% percentiles of the estimation. The horizontal green line serves as the reference line with value equals to 1.

In general, the Fama coefficients are more stable in developed economies than in emerging market economies. The Fama coefficients have experienced a series of sharp turbulence since the outbreak of the global financial crisis in 2007 and 2008. In particular, the turbulence is systematic during the four influential events in the global financial markets mentioned before. During those periods, the estimated Fama coefficient can be as low as -1000 and as high as 1000.

To sum up, the dynamics of the Fama coefficient has the following features in the

data. First, it varies across time for all of the 11 developed economies and the 15 emerging market economies. Second, it stays nowhere close to 1 most of the time. More importantly, the estimated Fama coefficient can be extreme when influential events in the global financial markets take place. The emerging market economies tend to realize more extreme values on the Fama coefficients than the developed economies. Third, contrary to the long-run estimate of negative Fama coefficient, the Fama coefficient can stay above 1 for an extended period. Fourth, the turbulence in the Fama coefficient can be systematic and idiosyncratic. However, when the turbulence in the Fama coefficient is systematic, some economies can be unaffected. For instance, in terms of the Fama coefficient, the financial crisis in 2007 and 2008 has limited influence on Chile and the Greek government-debt crisis from 2010 to 2014 has minor impact on Australia.

The features of the dynamics of the Fama coefficient can explain several findings of the empirical studies on the long-run Fama coefficient. First, since the Fama coefficient varies across time and can take extreme value sometimes, its long-run estimate should depend on the sampling period. This provides an explanation why my results and the findings in previous studies, including Fama (1984), Lewis (1995), Bansal and Dahlquist (2000), and Engle (2016) are all different. Moreover, the long-run Fama coefficients are different country-by-country because the turbulence of the Fama coefficients can be idiosyncratic and their values vary even the turbulence is systematic.

1.4 Implications

To test if the theories of risk premium, expectation, liquidity, and financial market friction are consistent with the data, the Fama coefficient is decomposed. To begin with, the literature defines the return on carry trade as

$$\rho_{t+1} \equiv s_{t+1} - s_t + i_t^* - i_t. \quad (1.4)$$

Then, Equation (1.2) can be rewritten as

$$\rho_{t+1} = \alpha + (1 - \beta)(i_t - i_t^*) + \varepsilon_{t+1}. \quad (1.5)$$

By Equation (1.5), I get

$$1 - \beta = \frac{\text{Cov}(\rho_{t+1}, i_t - i_t^*)}{\text{Var}(i_t - i_t^*)}. \quad (1.6)$$

This allows me to decompose the Fama coefficient as

$$1 - \beta = \text{Corr}(\rho_{t+1}, i_t - i_t^*) \frac{\sigma(\rho_{t+1})}{\sigma(i_t - i_t^*)}. \quad (1.7)$$

The first term $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ is the correlation coefficient between the return on carry trade and the interest differential. It has a sense of normalization because its value is between -1 and 1. This correlation coefficient is used to test the models of risk premium in Engle (2016). The second term $\frac{\sigma(\rho_{t+1})}{\sigma(i_t - i_t^*)}$ is the ratio of the standard deviation of the return on carry trade to that of the interest differential. Since its value must be a strictly positive number in the data, the sign of $1 - \beta$ is determined

by the sign of $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$. To be specific, we have the following three cases.

$$\beta \begin{cases} > 1 & \text{if } \text{Corr}(\rho_{t+1}, i_t - i_t^*) < 0 \\ = 1 & \text{if } \text{Corr}(\rho_{t+1}, i_t - i_t^*) = 0 \\ < 1 & \text{if } \text{Corr}(\rho_{t+1}, i_t - i_t^*) > 0. \end{cases} \quad (1.8)$$

The following two groups of plots depict the dynamics of the two terms resulting from the decomposition in each of the 26 economies respectively. The first group, Figure 1.4, depicts the dynamics of the first term $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$, while the second group, Figure 1.5, depicts the dynamics of the second term $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$. The order of the figures within each of these two groups is the same as the order of previous ones. By comparing these two groups of figures, a striking fact is that the first term is more noisy than the second term. Moreover, the second term has high spikes, which magnifies the first term by multiplication. This leads to the sharp hikes observed in the Fama coefficients. So, a unified story of developed and emerging market economies is that the first term $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ follows a similar volatile and noisy pattern, while the second term $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ magnifies the first term. The reason why the emerging market economies tend to realize more extreme values on the Fama coefficients than the developed economies is that the spikes of the second term are higher in emerging market economies.

The decomposition provides useful insights into how different modeling frameworks relate to the data. In particular, the empirical finding that the correlation between carry trade returns and the interest differential, $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$, is noisy, frequently changes sign, and exhibits substantial time variation is informative for evaluating existing theories. Rather than ruling out specific approaches, these patterns suggest

that different mechanisms may be more relevant at different frequencies.

First, models within the risk premium channel, such as those proposed by Colacito (2009), Backus et al. (2010), Lustig, Roussanov, and Verdelhan (2011), Bansal and Shaliastovich (2013), and Corsetti and Marin (2020), are typically built in frictionless environments where equilibrium relationships are tightly linked to structural parameters. These models are well suited to explain long-run features of the data, including the average negative Fama coefficient. However, their relatively stable structure makes it more challenging to capture the high-frequency fluctuations and occasional extreme realizations observed in the data.

Second, models in the expectations channel, including Gourinchas and Tornell (2004), Bacchetta and van Wincoop (2010), and Stavrakeva and Tang (2018), incorporate information frictions and can generate both positive and negative Fama coefficients. These models provide a flexible framework for understanding how beliefs and information affect exchange rates. At the same time, matching the high-frequency variation in $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ would require substantial time variation in underlying parameters or belief distortions, suggesting that these mechanisms may be more relevant for lower-frequency dynamics.

Third, the liquidity premium channel, as emphasized by Engle (2016), highlights the role of liquidity in shaping asset prices and can also generate variation in the correlation between returns and interest differentials. This framework is particularly useful for understanding how holding horizons and market liquidity conditions influence exchange rate dynamics. However, the empirical evidence that short-run correlations can take both positive and negative values indicates that additional sources of

variation may be important at higher frequencies.

In contrast, models within the financial market frictions channel, such as those developed by Gabaix and Maggiori (2015) and Itskhoki and Mukhin (2021), provide a natural way to account for the high-frequency features of the data. In these models, wedges in international asset pricing arise from segmented markets, noise traders, and limits to arbitrage. These mechanisms generate endogenous variation that is noisy, time-varying, and capable of switching sign, aligning closely with the observed dynamics of $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$.

Overall, the results suggest that while risk premia, expectations, and liquidity considerations remain important for understanding medium- to low-frequency movements in exchange rates, financial market frictions play a particularly central role in explaining high-frequency dynamics.

1.5 Discussion

The challenge of explaining the UIP puzzle stems from the complex features of the Fama coefficient. The complexity in the Fama coefficient is mainly due to its heterogeneity across economies and its volatility across time. However, the empirical findings in this chapter suggest that a unified theory to explain the UIP puzzle for both of the developed and emerging market economies are possible. On one hand, the dichotomy in the Fama coefficient between developed and emerging market economies documented by Bansal and Dahlquist (2000) seems to be weakened in the most recent data. On the other hand, the dichotomy does not appear in the component $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ but due to $\frac{\sigma(\rho_{t+1})}{\sigma(i_t - i_t^*)}$ and its correlation with $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$. So,

further research can first focus on the explanation of the volatile and noisy nature of $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$. Itskhoki and Mukhin (2021) provide a good point to begin with. Then, the explanation of the dichotomy between developed and emerging market economies on $\frac{\sigma(\rho_{t+1})}{\sigma(i_t - i_t^*)}$ in the crisis periods can be attempted.

Another challenge to resolve the UIP puzzle is the variety of factors causing this puzzle. Factors such as risk premium, expectations, liquidity premium, and financial market frictions are proved to be relevant in the empirical literature. However, theories based on those channels except the financial market frictions channel are inconsistent with the dynamics of the Fama coefficient. Moreover, according to Bansal and Dahlquist (2000), several fundamental macroeconomic variables, including inflation, inflation volatility, country credit risk, and openness to trade, may also at play. To achieve a unification in the explanation, further research can start with a baseline model and enrich it with additional features.

1.6 Conclusion

In the past four decades since the discovery of the UIP puzzle, numerous efforts have been devoted to explore and explain it empirically and theoretically. The literature has made huge progresses in this topic. Empirically, a number of factors driving the UIP deviations have been identified. For instance, factors including but not limited to risk premium, expectations, liquidity premium, financial market frictions, monetary policy shocks, inflation, inflation volatility, country credit risks, openness to trade are proved to potentially cause the UIP puzzle. Theoretically, the implications of risk aversion, distorted beliefs, biased behavior, asset liquidity, asset market segmentation, borrowing limits are discussed in the corresponding models in the four

broad categories, including risk premium channel, expectations channel, liquidity premium channel, and financial market frictions channel.

This chapter is built upon the techniques of four of the most influential studies, namely Fama (1984), Bansal and Dahlquist (2000), Engle (2016), and Itskhoki and Mukhin (2021), to explore the UIP puzzle empirically with most recent daily data on exchange rate changes and interest differentials. Thanks to the large number of observations, this chapter is able to trace the dynamics of the Fama coefficients in the past two to three decades for each of the 11 developed economies and 15 emerging market economies. The increasing volatility in the Fama coefficients starting from the outbreak of the global financial crisis in 2007 and 2008 is identified. The significance of several influential events in the global financial markets in that period, including the financial crisis in 2007 and 2008, the Greek government-debt crisis from 2010 to 2014, the interest rate hike of the Federal Reserve in 2016, and the pandemic starting from 2020, is also recognized. By applying a decomposition technique inspired by Engle (2016), this chapter explains why the models in three of the four categories, namely risk premium channel, expectations channel, and liquidity premium channel fail to match the data and recognize the desirable features of the models in the category of financial market frictions channel over the models in the other three categories.

The chapter sheds light on the possibility to reconcile the theories of developed and emerging market economies by pointing out several common features in the data. First, the similar pattern of the dynamics of the Fama coefficients are identified. Another common feature is discovered in the dynamics of $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ with the help of the decomposition technique. These findings can serve as a starting point to

build up a unified model to resolve the UIP puzzle in both developed and emerging market economies.

More work need to be done to explain the dynamics of $\frac{\sigma(\rho_{t+1})}{\sigma(i_t - i_t^*)}$ and its correlation with $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$, especially in the crisis periods. Further research is also needed in unifying the factors that contribute to the UIP puzzle. To achieve this goal, a baseline model needs to be proposed at first to keep the factors to a minimum and then enrich it with additional features to match the data better.

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Figure 1.1: $\text{Var}(s_{t+1} - s_t)$ with a window of 260 observations

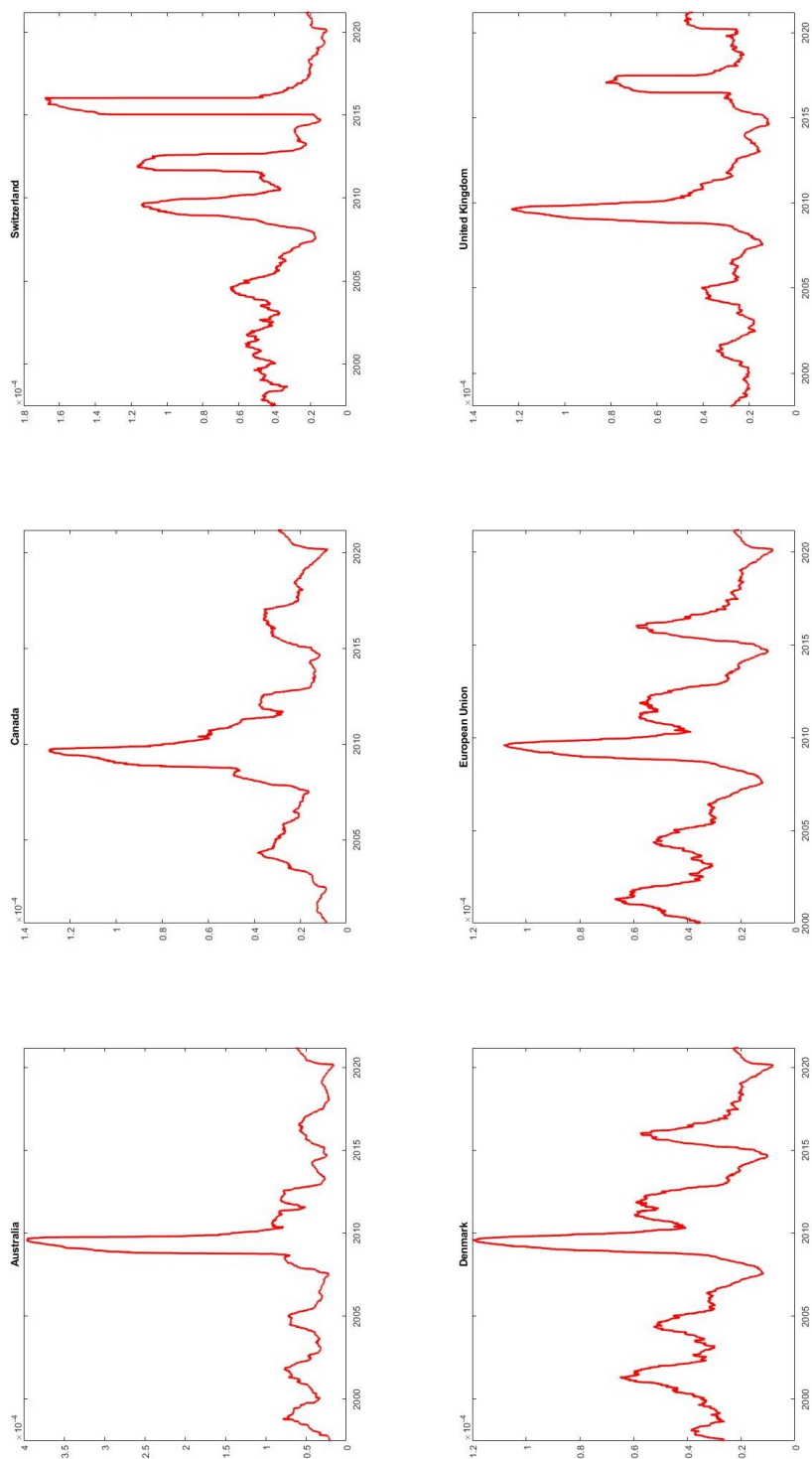


Figure 1.1: $\text{Var}(s_{t+1} - s_t)$ with a window of 260 observations (cont.)

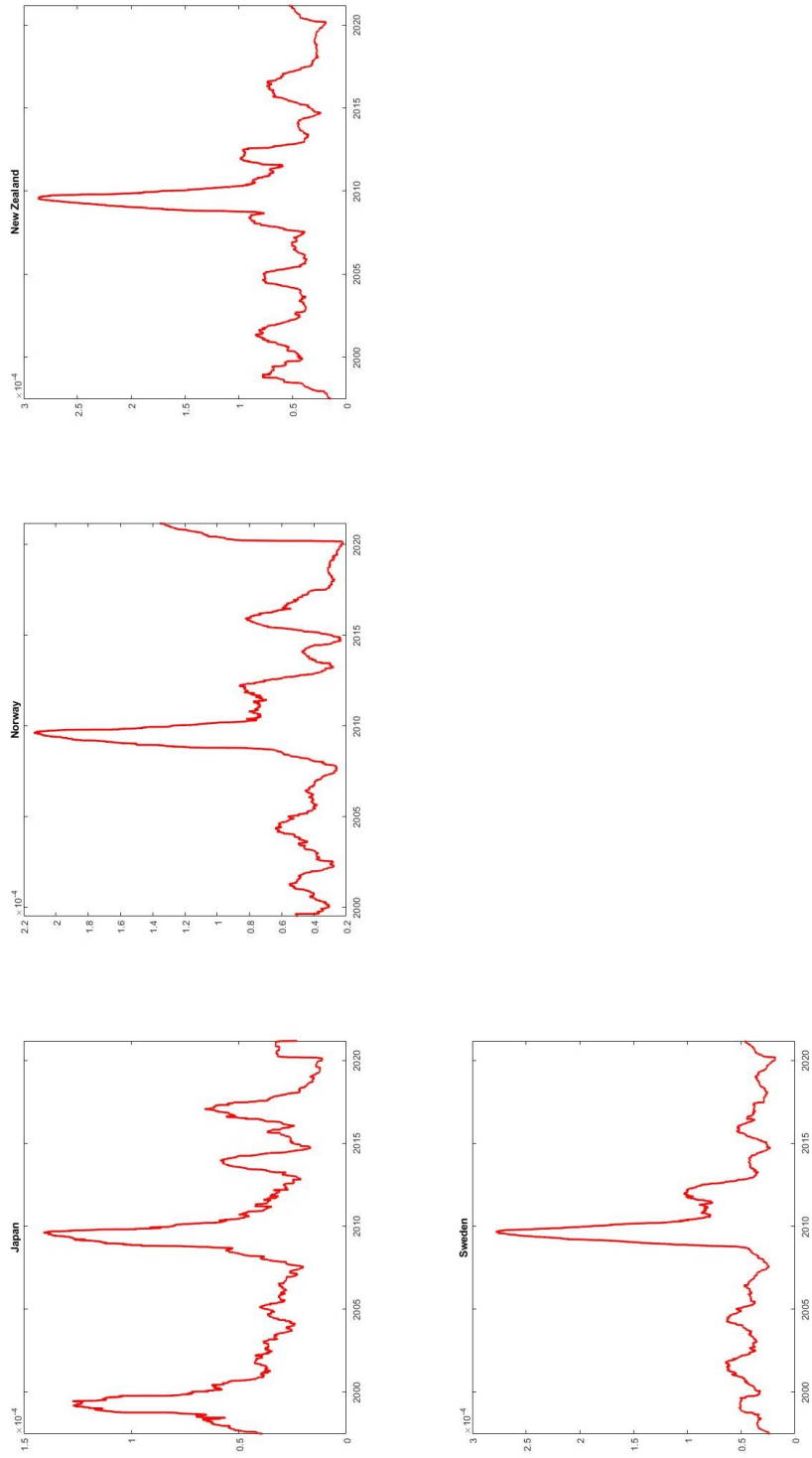


Figure 1.1: $\text{Var}(s_{t+1} - s_t)$ with a window of 260 observations (cont.)

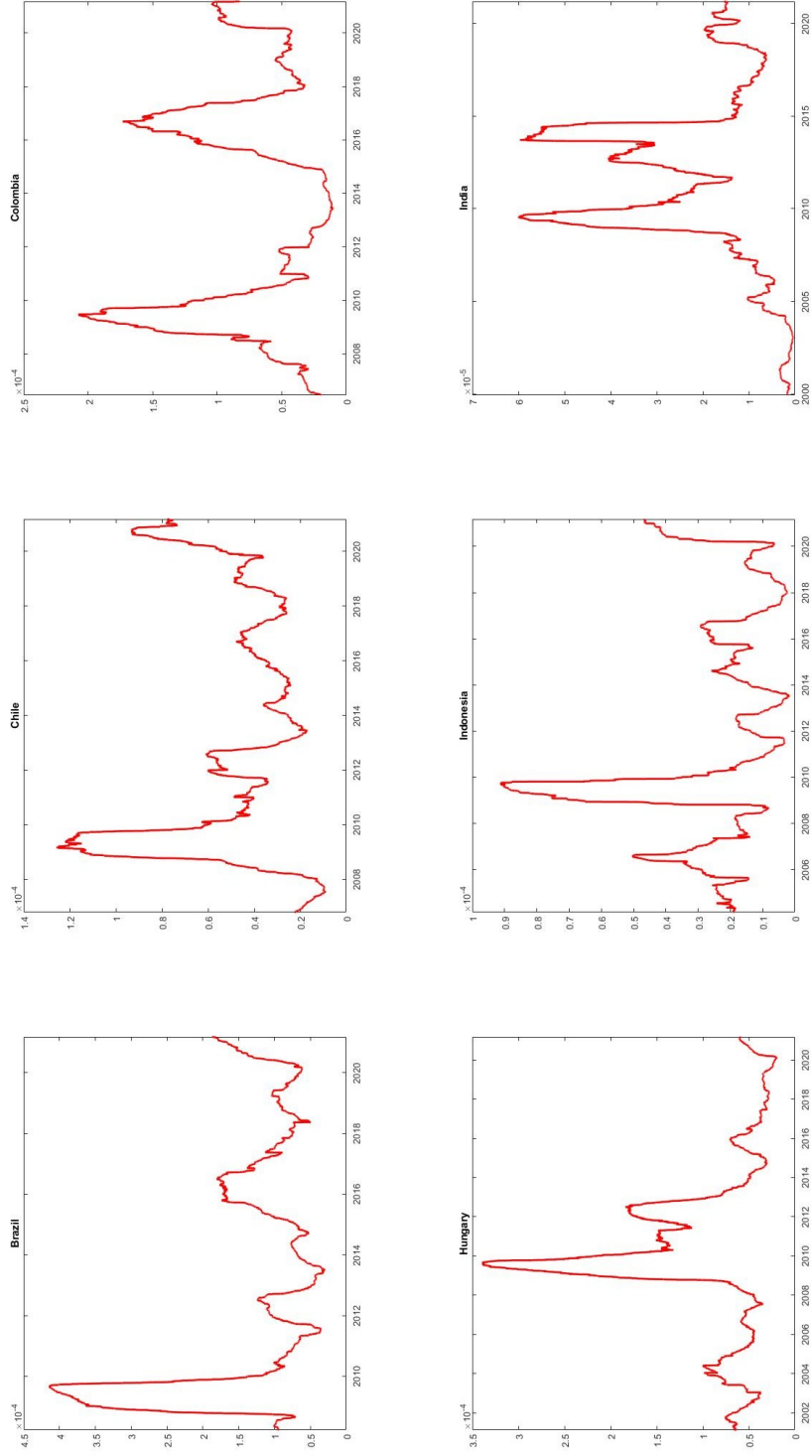


Figure 1.1: $\text{Var}(s_{t+1} - s_t)$ with a window of 260 observations (cont.)

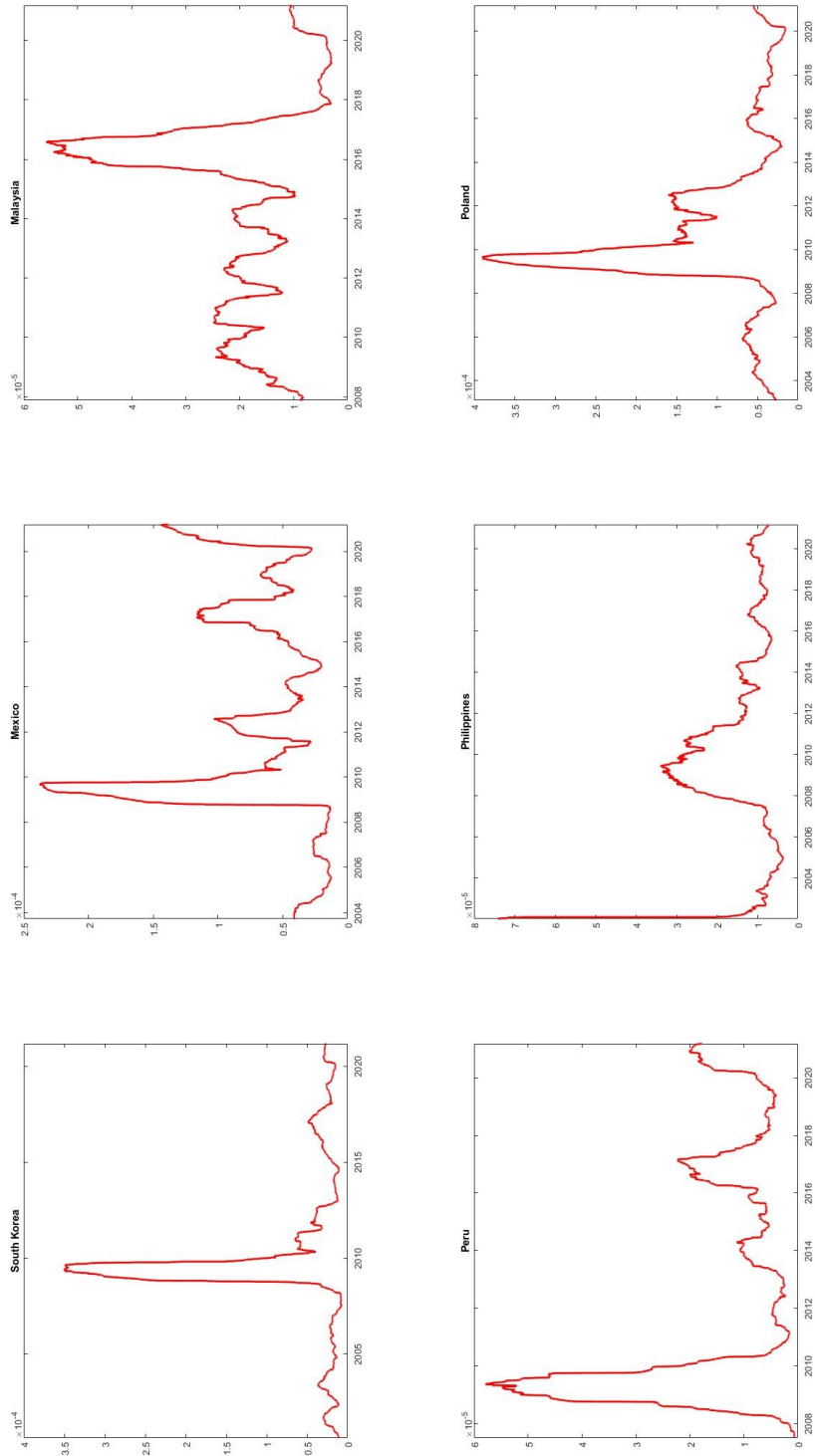


Figure 1.1: $\text{Var}(s_{t+1} - s_t)$ with a window of 260 observations (cont.)

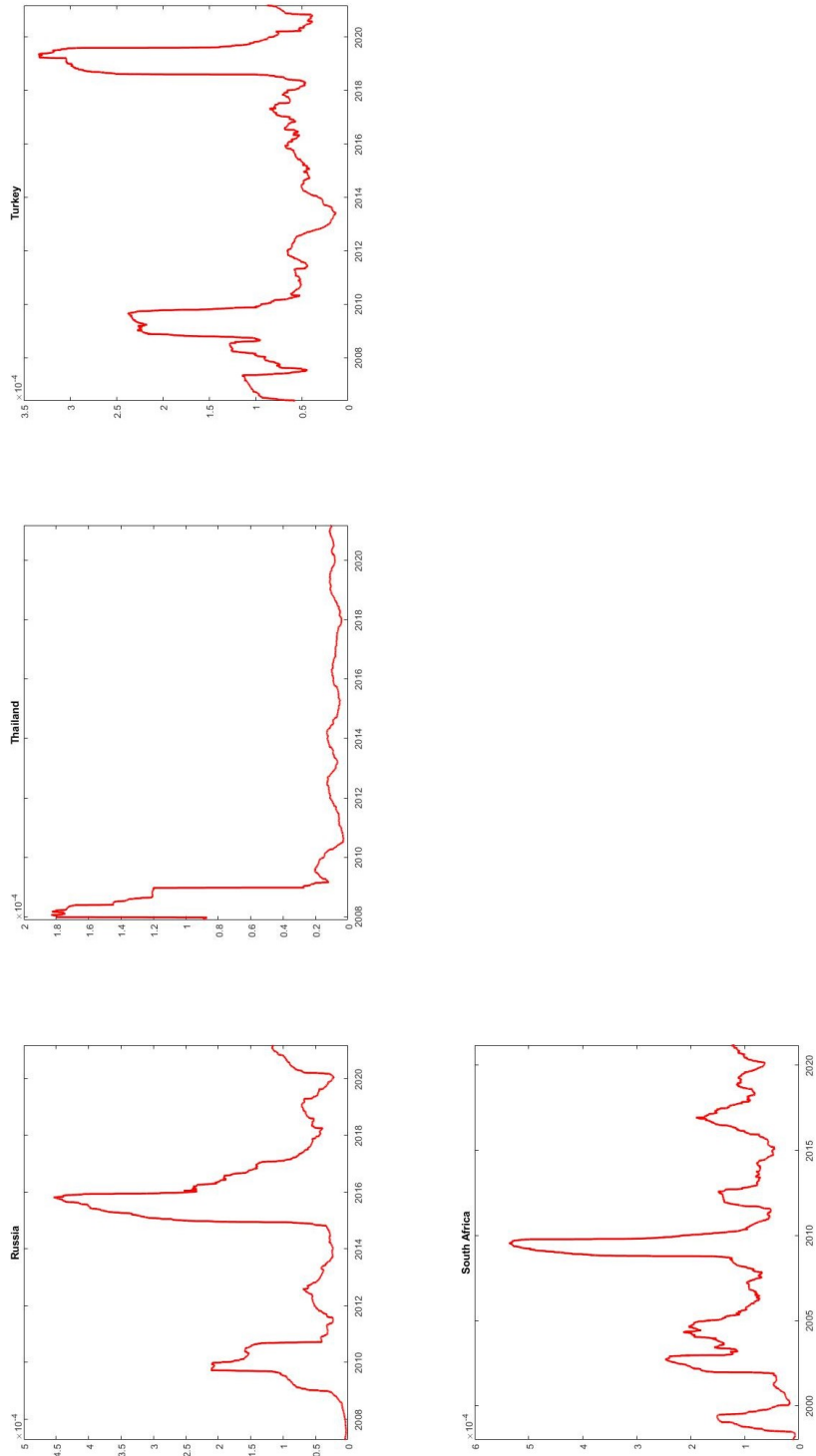


Figure 1.2: $\text{Var}(i_t - i_t^*)$ with a window of 260 observations

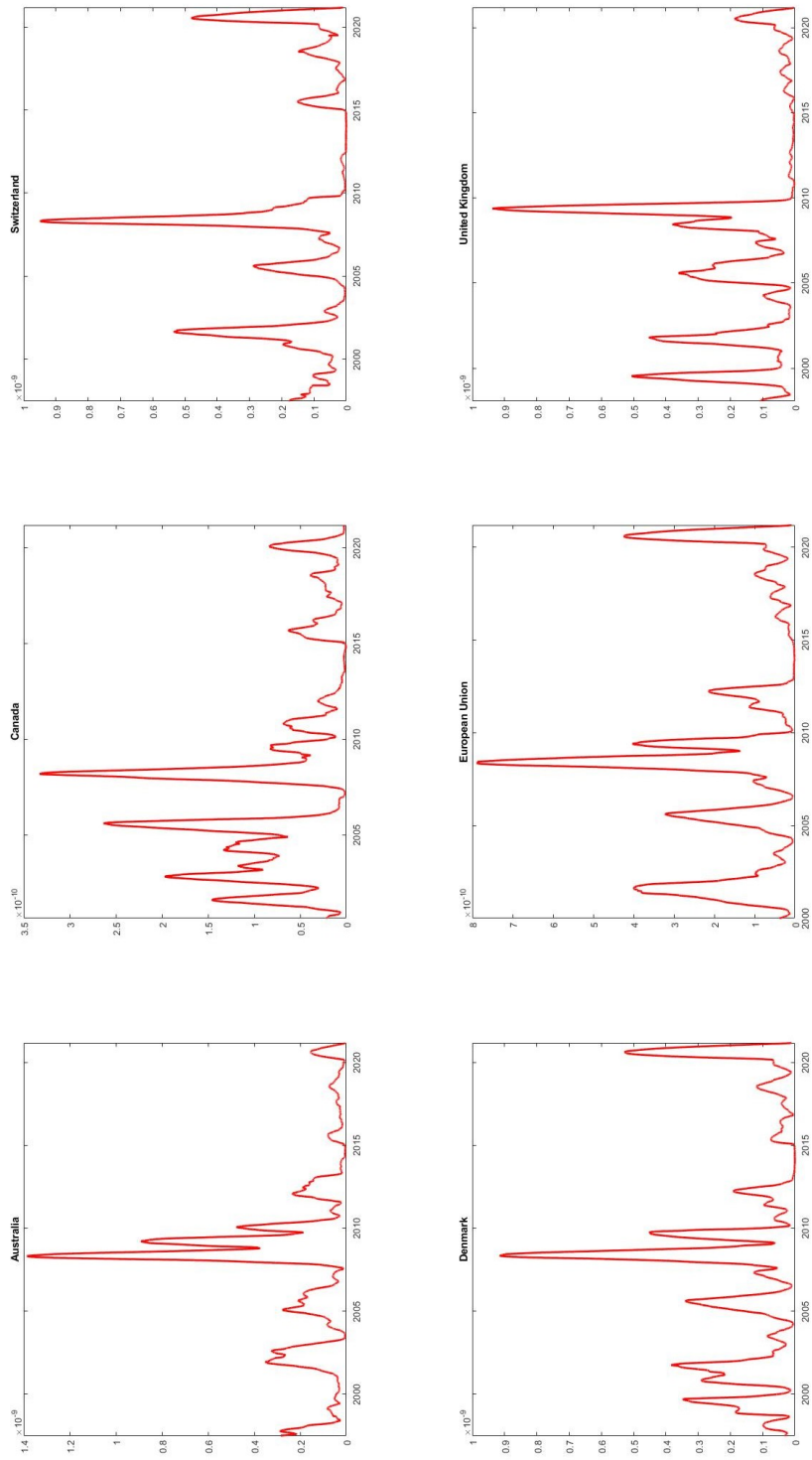


Figure 1.2: $\text{Var}(i_t - i_t^*)$ with a window of 260 observations (cont.)

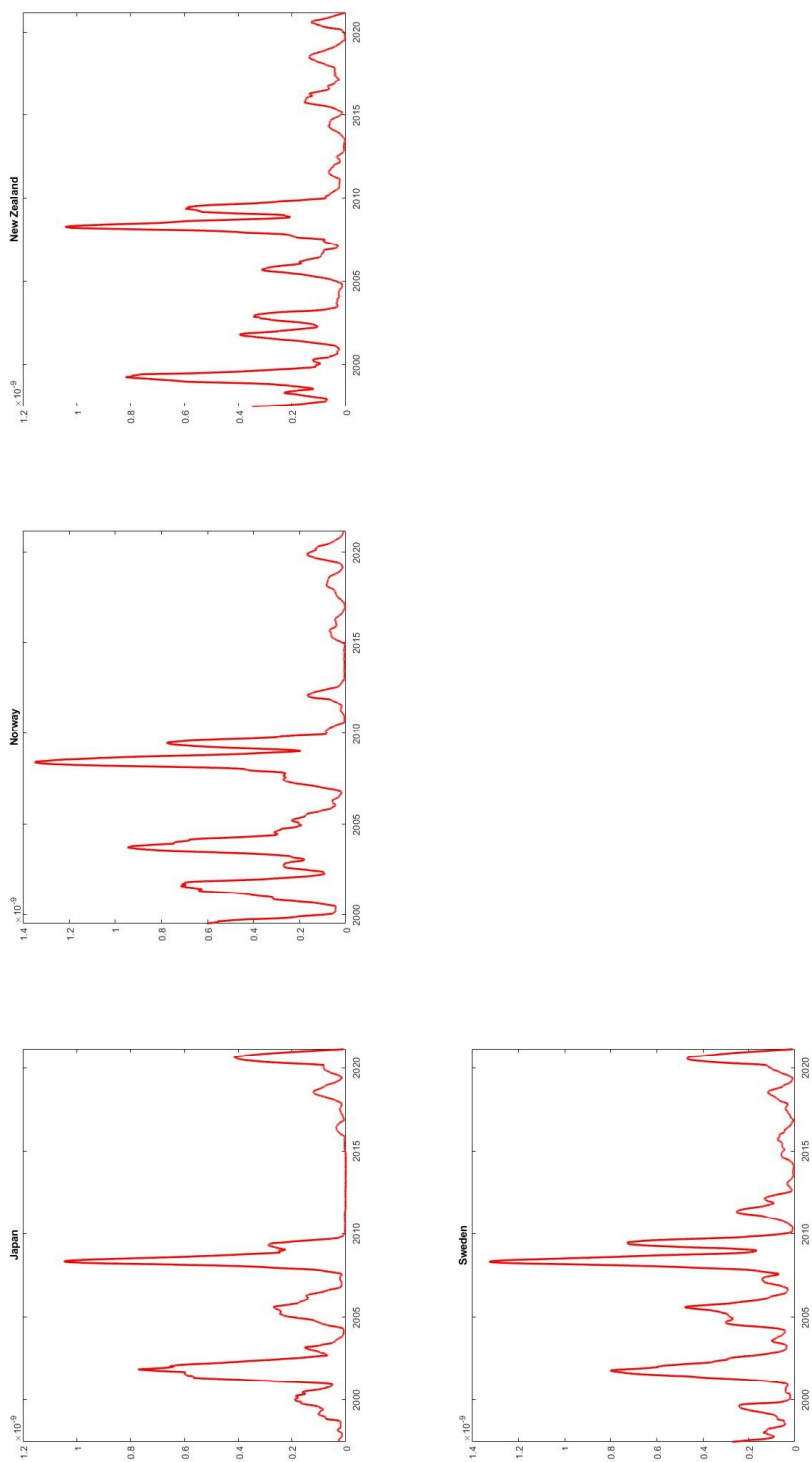


Figure 1.2: $\text{Var}(i_t - i_t^*)$ with a window of 260 observations (cont.)

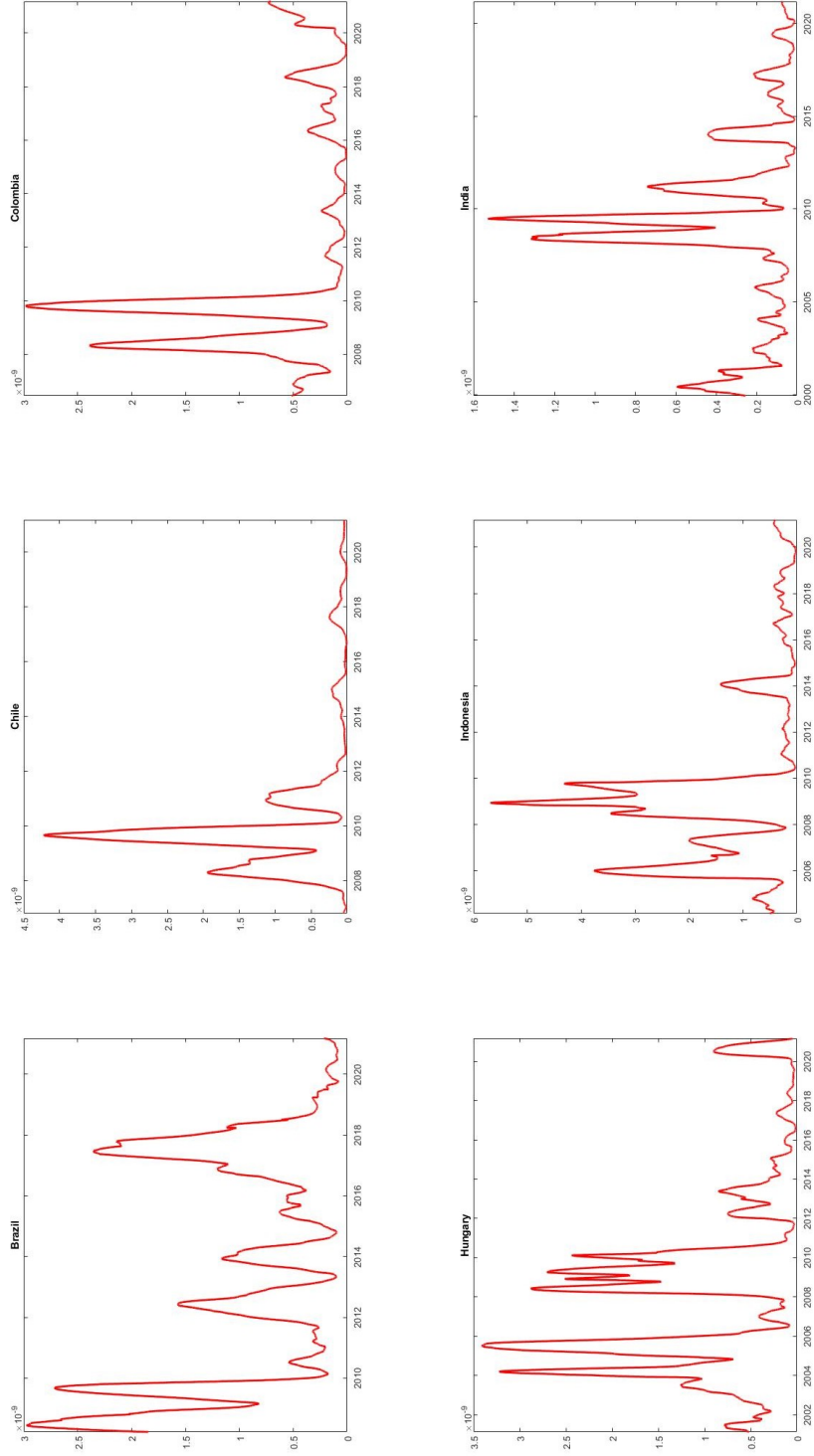


Figure 1.2: $\text{Var}(i_t - i_t^*)$ with a window of 260 observations (cont.)

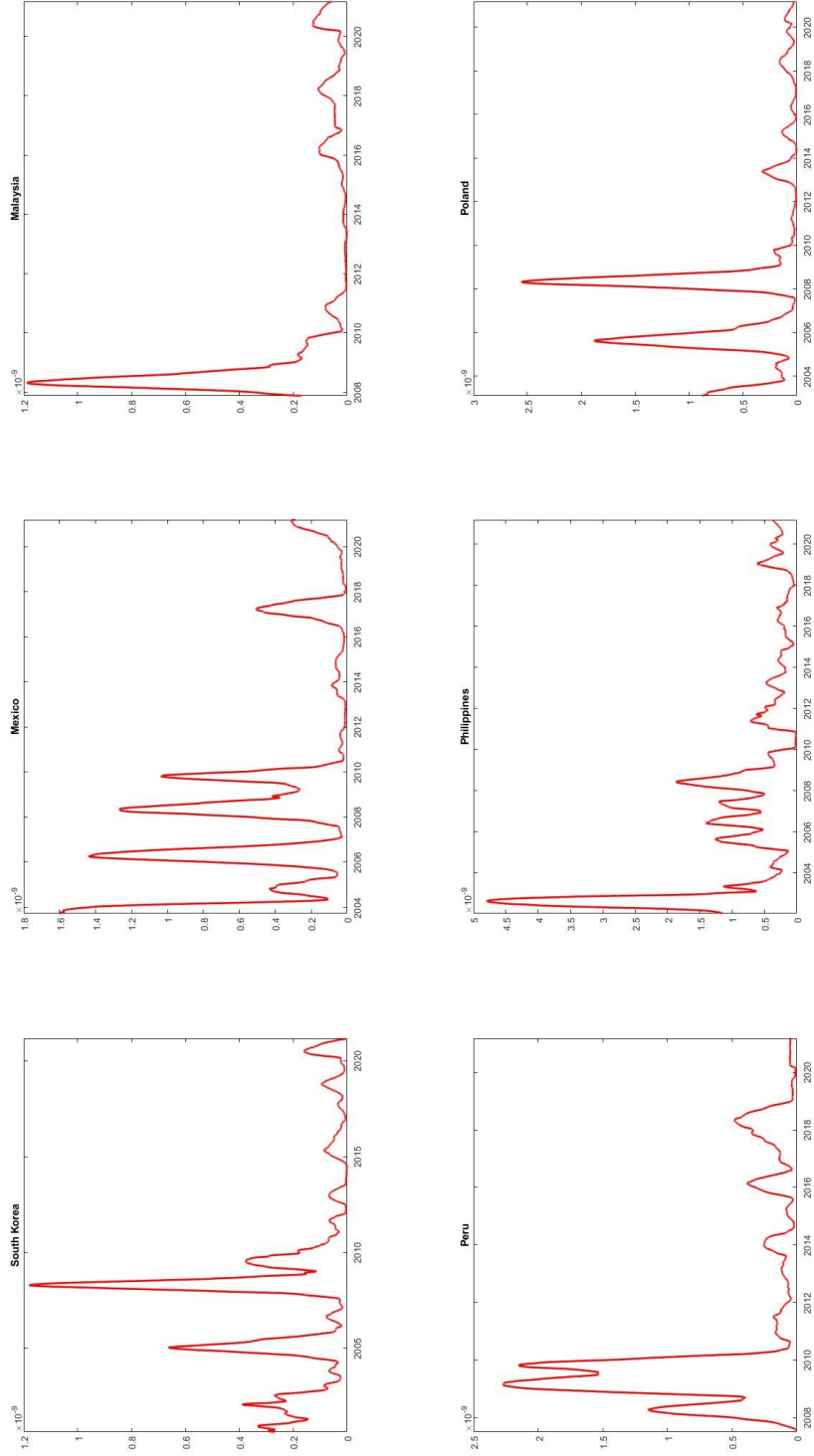


Figure 1.2: $\text{Var}(i_t - i_t^*)$ with a window of 260 observations (cont.)

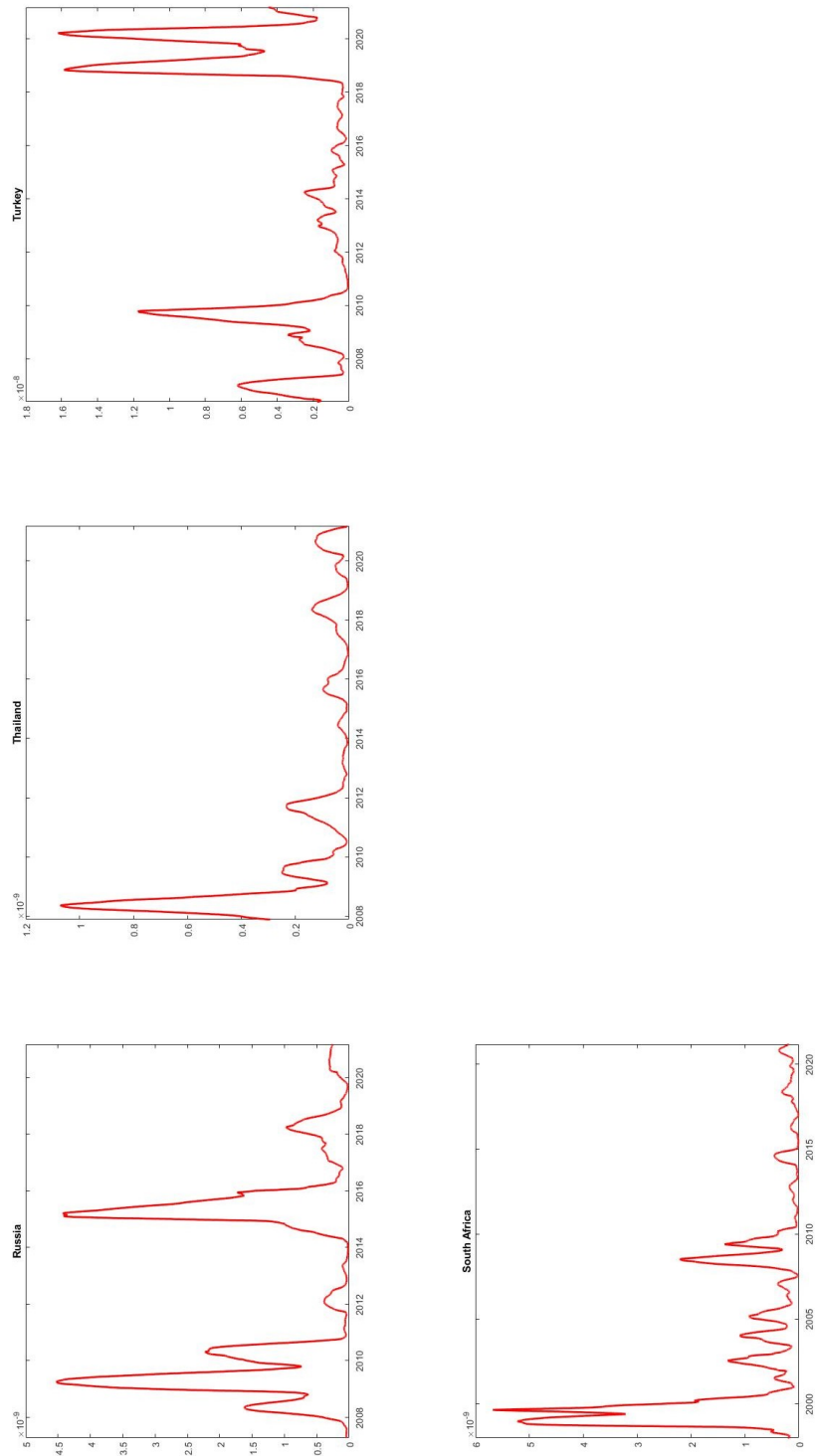


Figure 1.3: Rolling regressions with a window of 260 observations

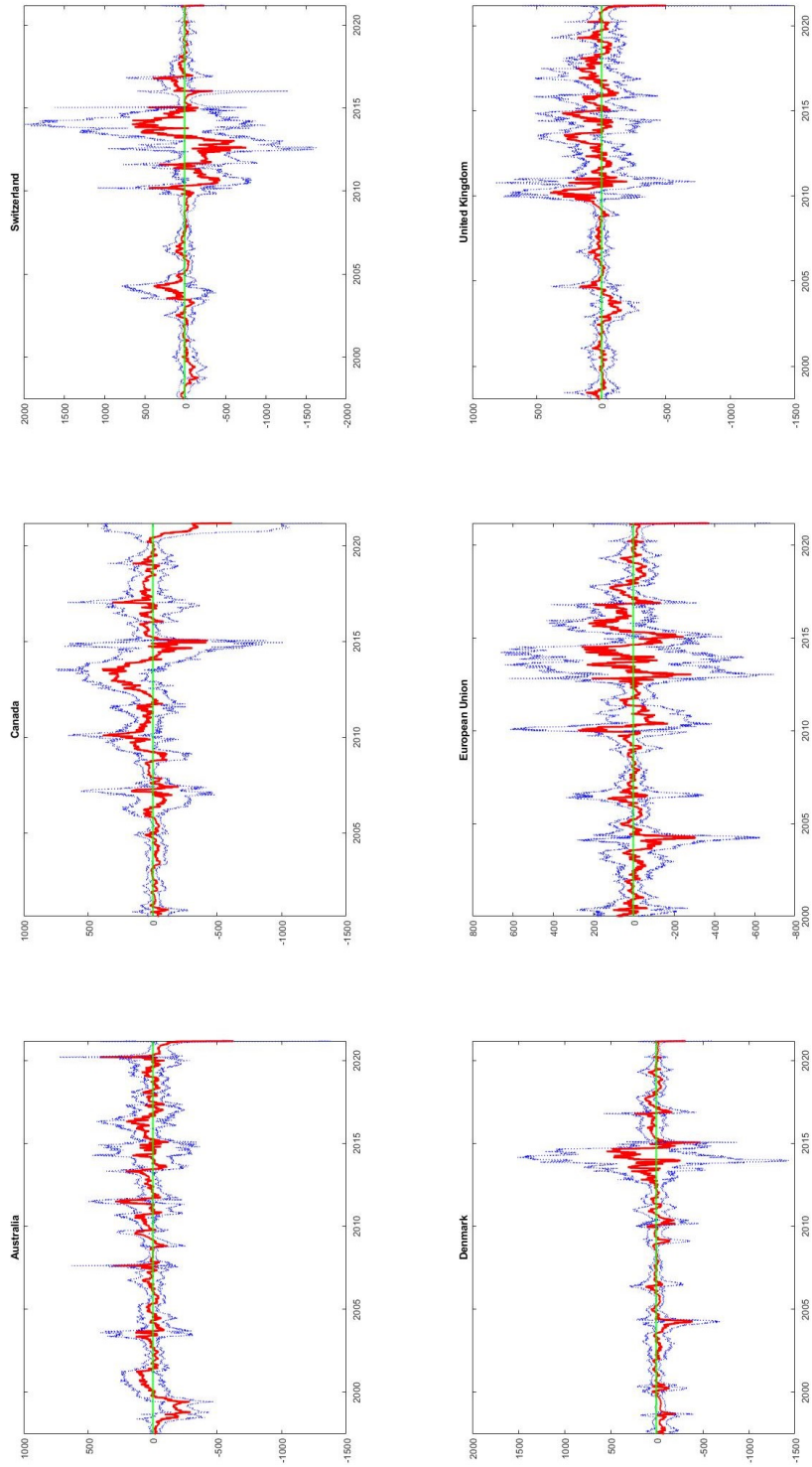


Figure 1.3: Rolling regressions with a window of 260 observations (cont.)

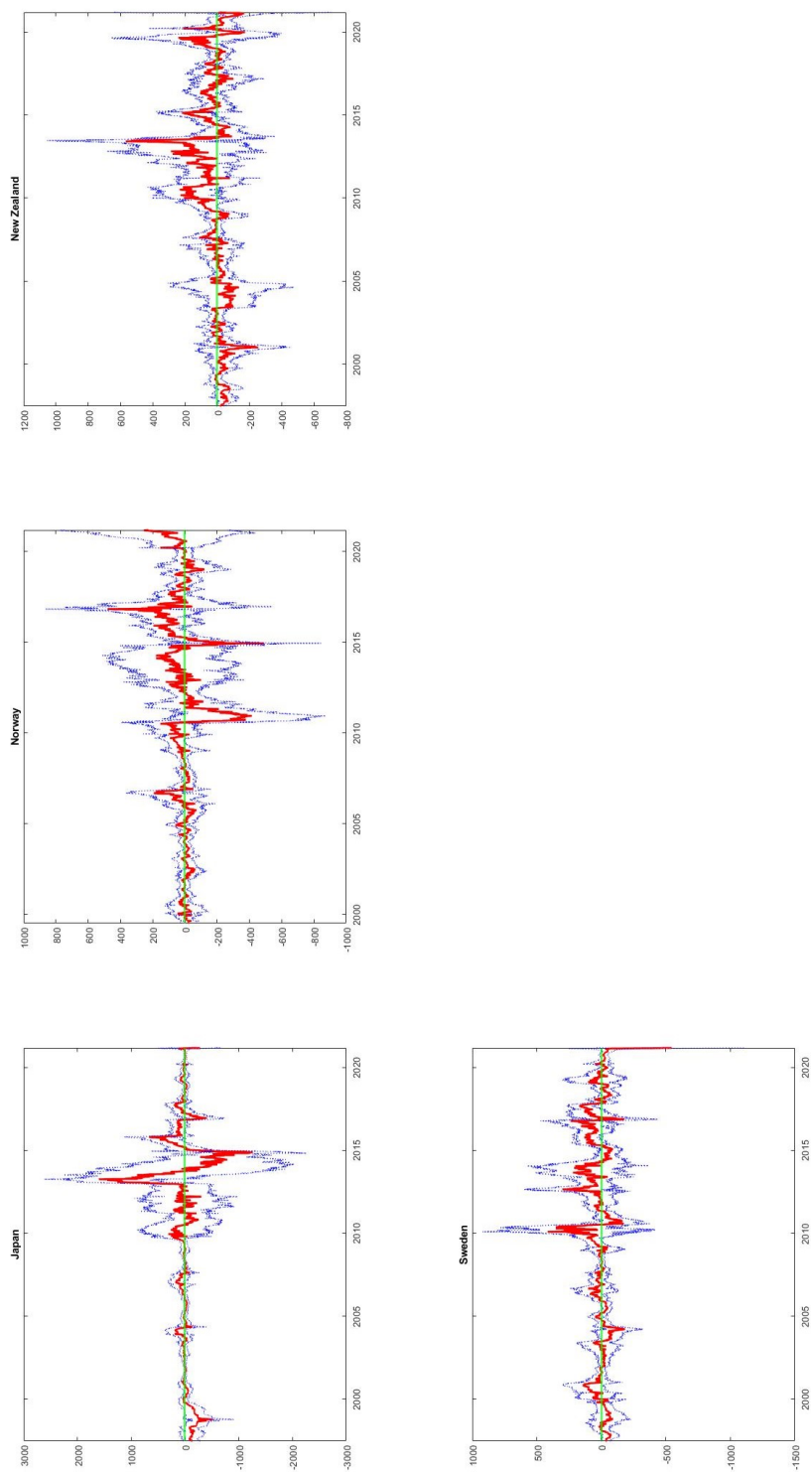


Figure 1.3: Rolling regressions with a window of 260 observations (cont.)

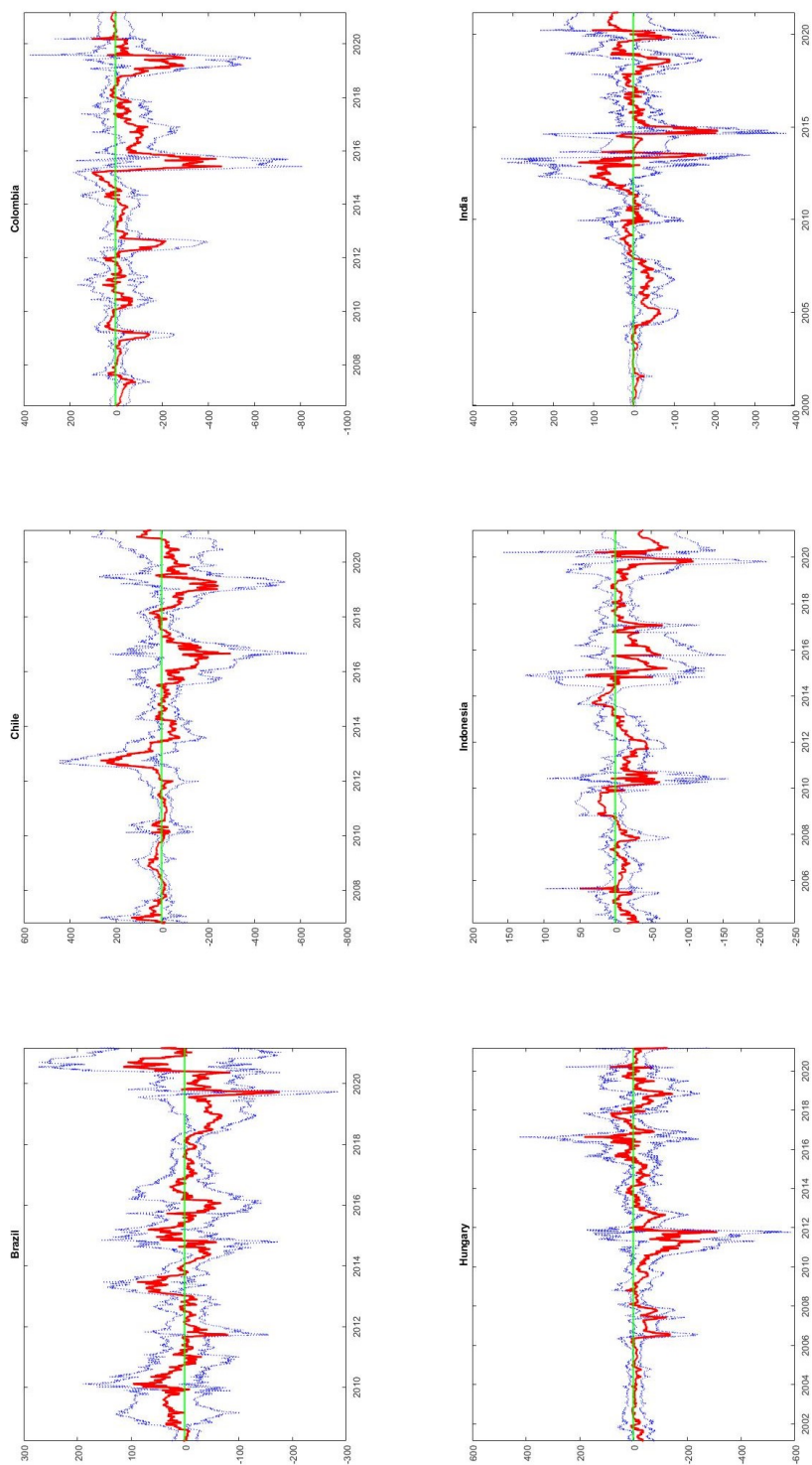


Figure 1.3: Rolling regressions with a window of 260 observations (cont.)

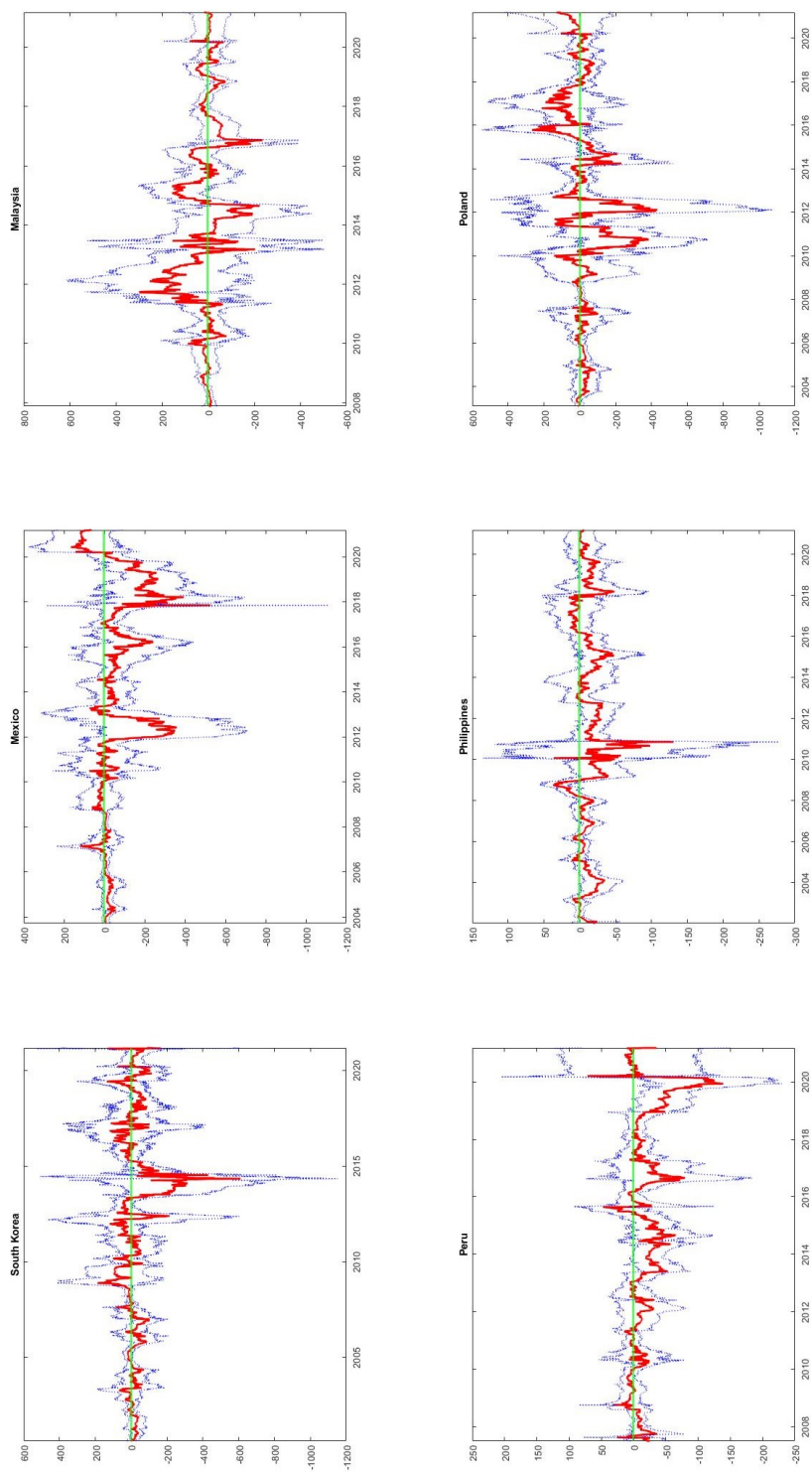


Figure 1.3: Rolling regressions with a window of 260 observations (cont.)

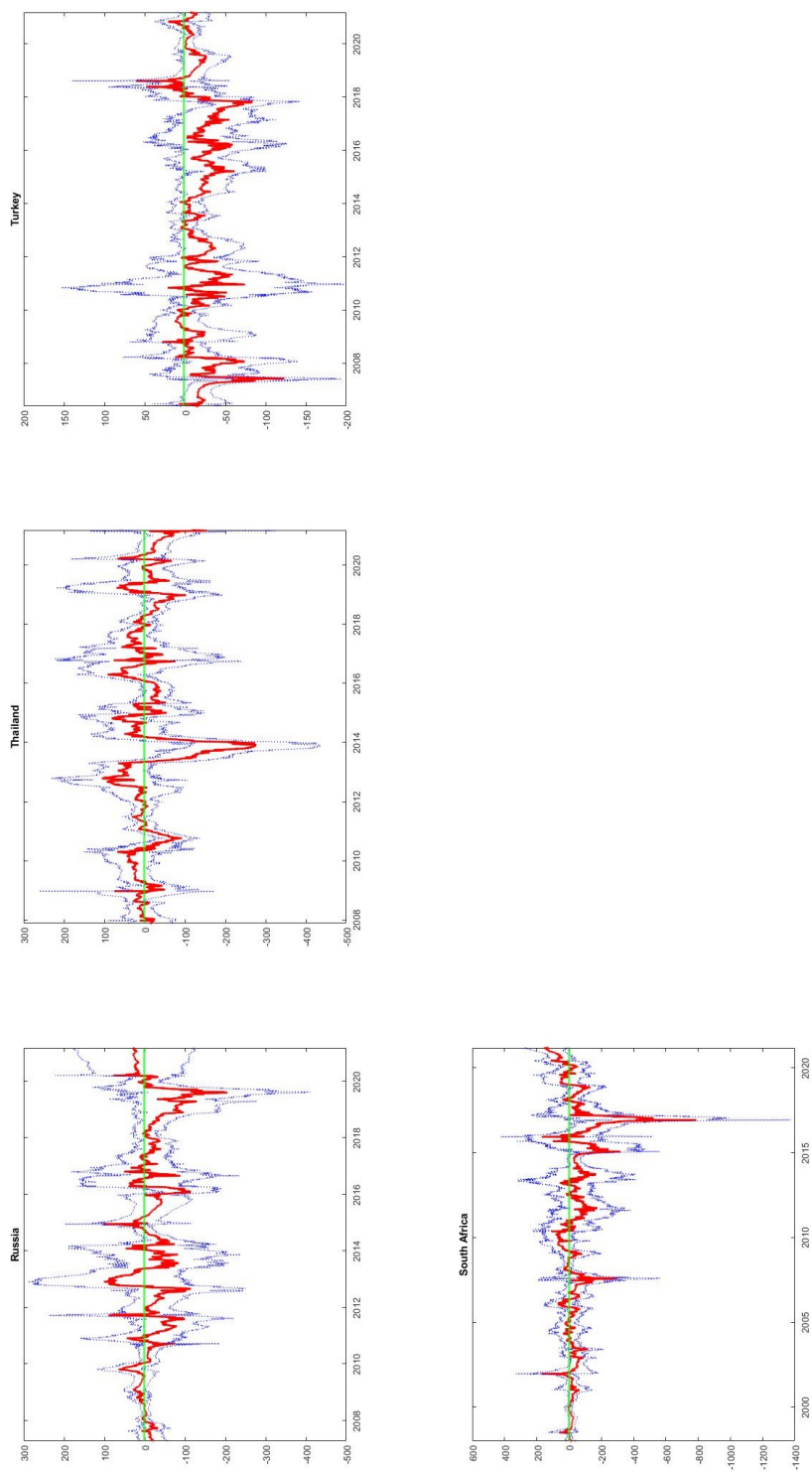


Figure 1.4: $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ with a window of 260 observations

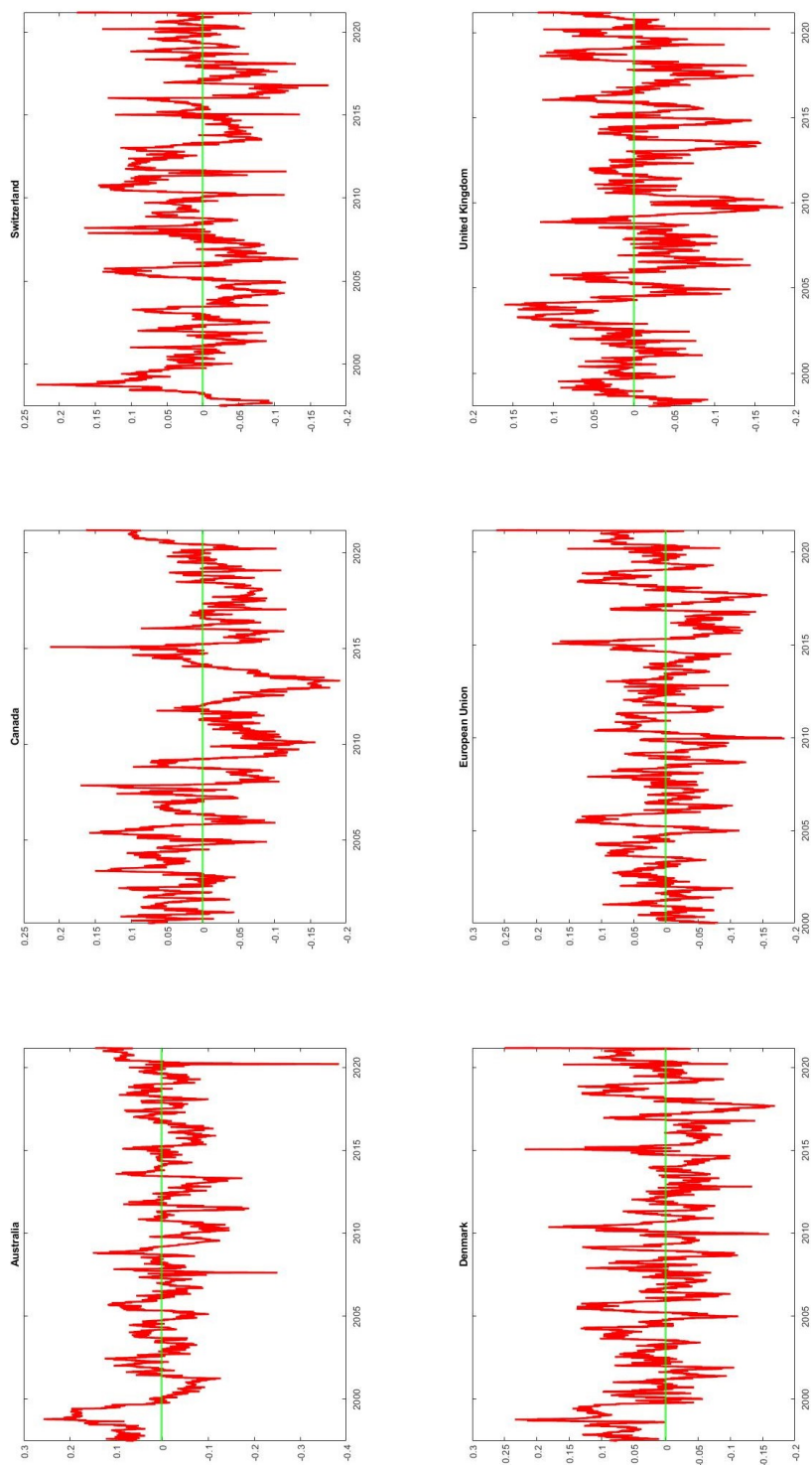


Figure 1.4: $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ with a window of 260 observations (cont.)

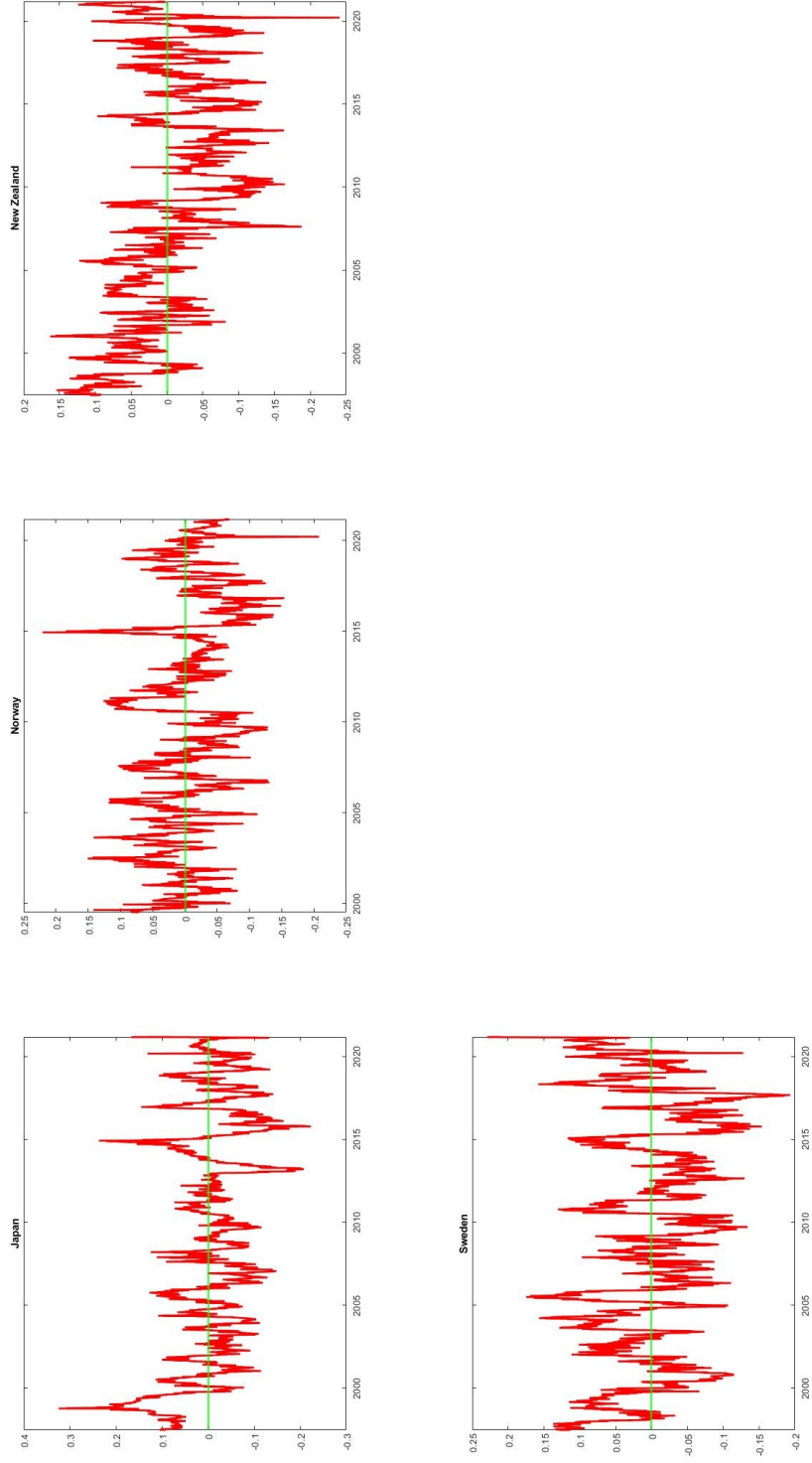


Figure 1.4: $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ with a window of 260 observations (cont.)

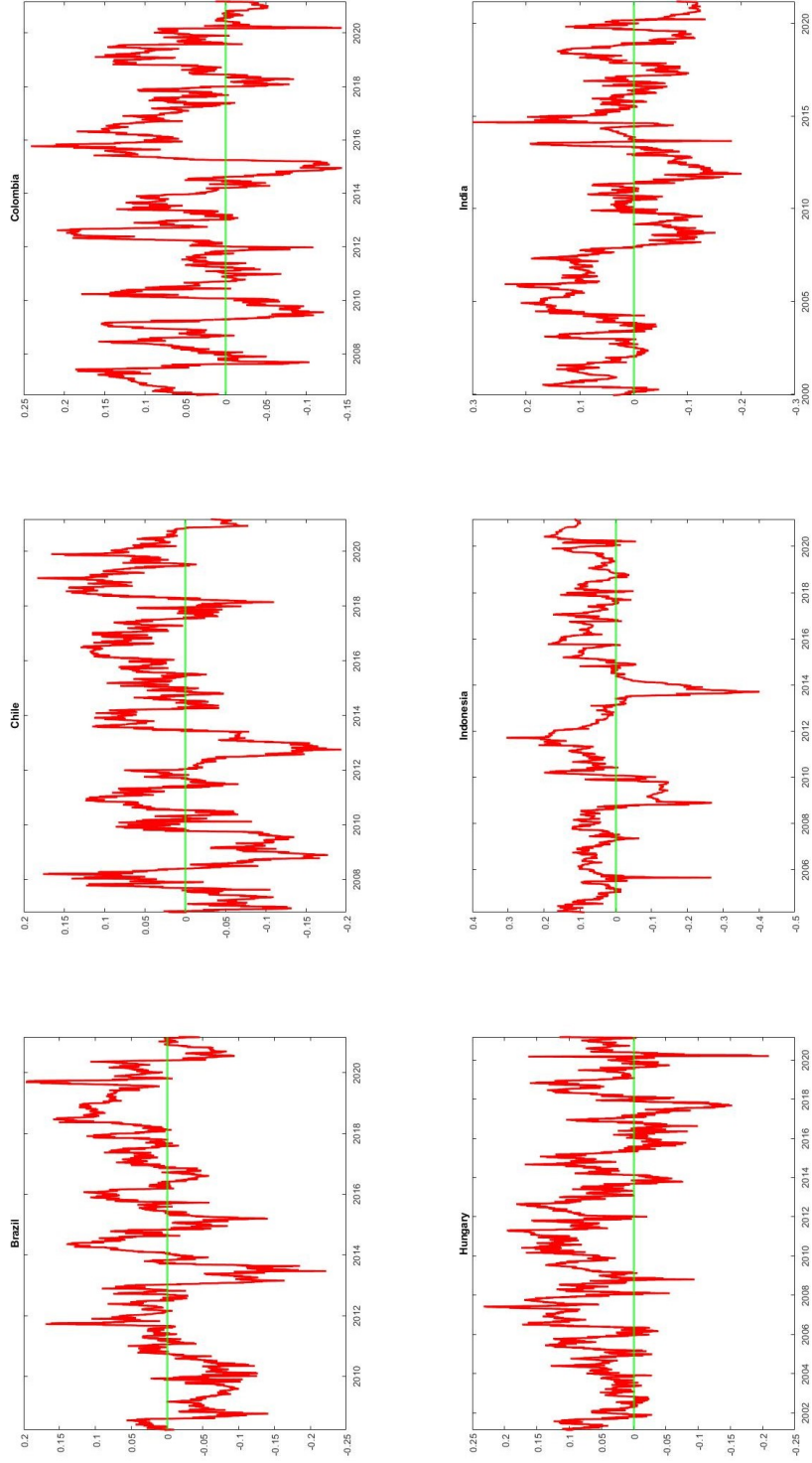


Figure 1.4: $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ with a window of 260 observations (cont.)

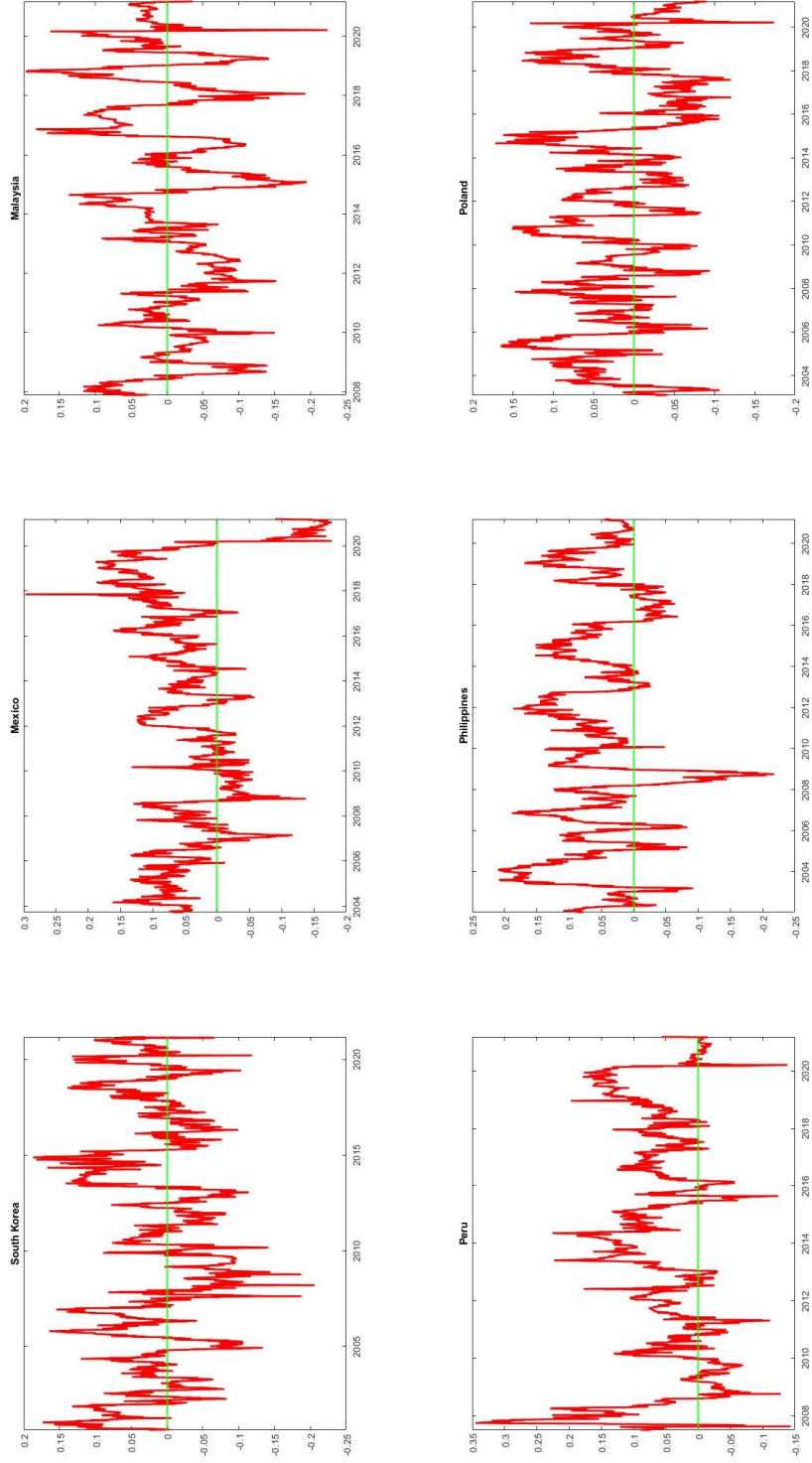


Figure 1.4: $\text{Corr}(\rho_{t+1}, i_t - i_t^*)$ with a window of 260 observations (cont.)

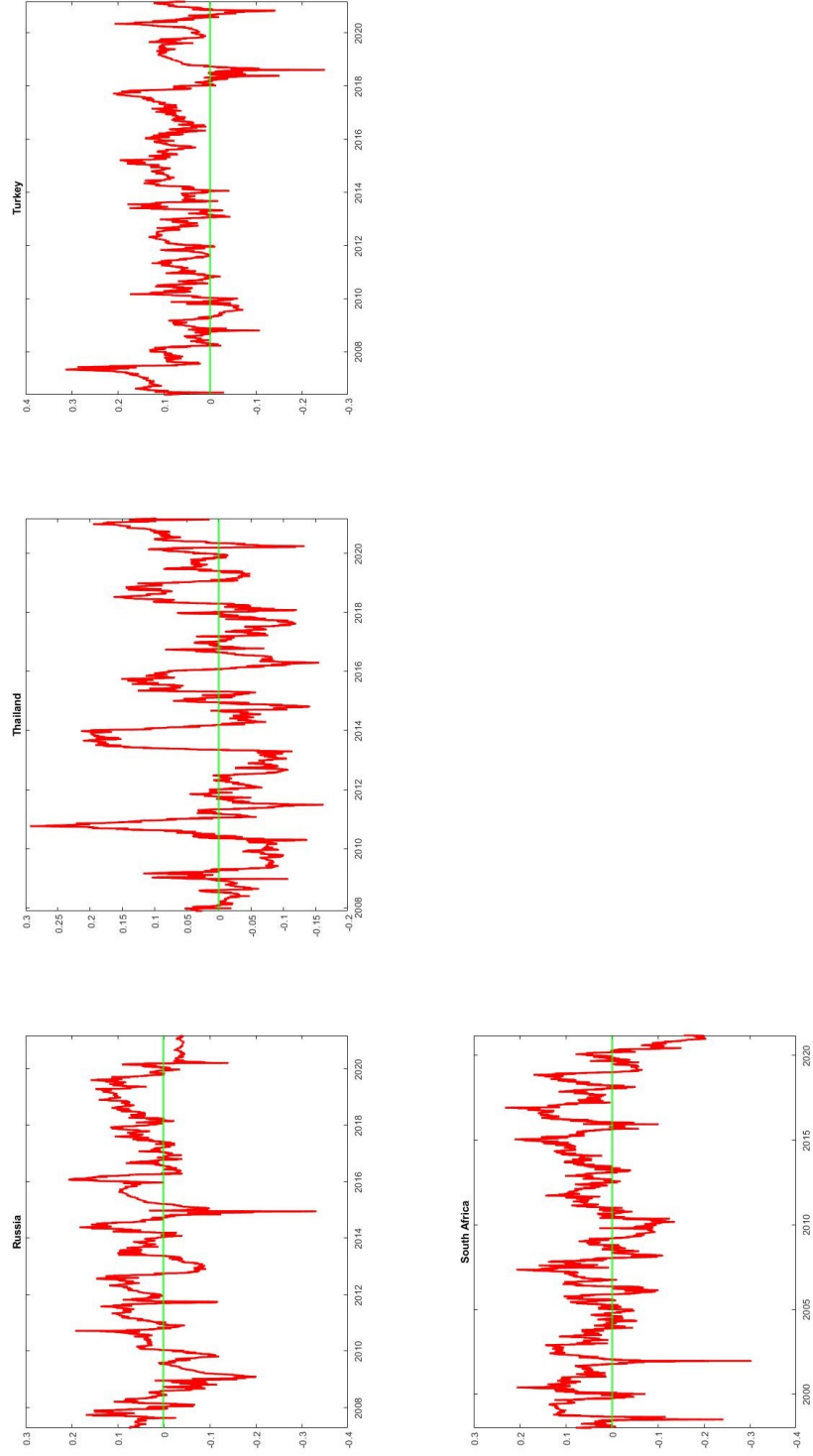


Figure 1.5: $\frac{\sigma(\rho_{t+1})}{\sigma(i_t - i_t^*)}$ with a window of 260 observations

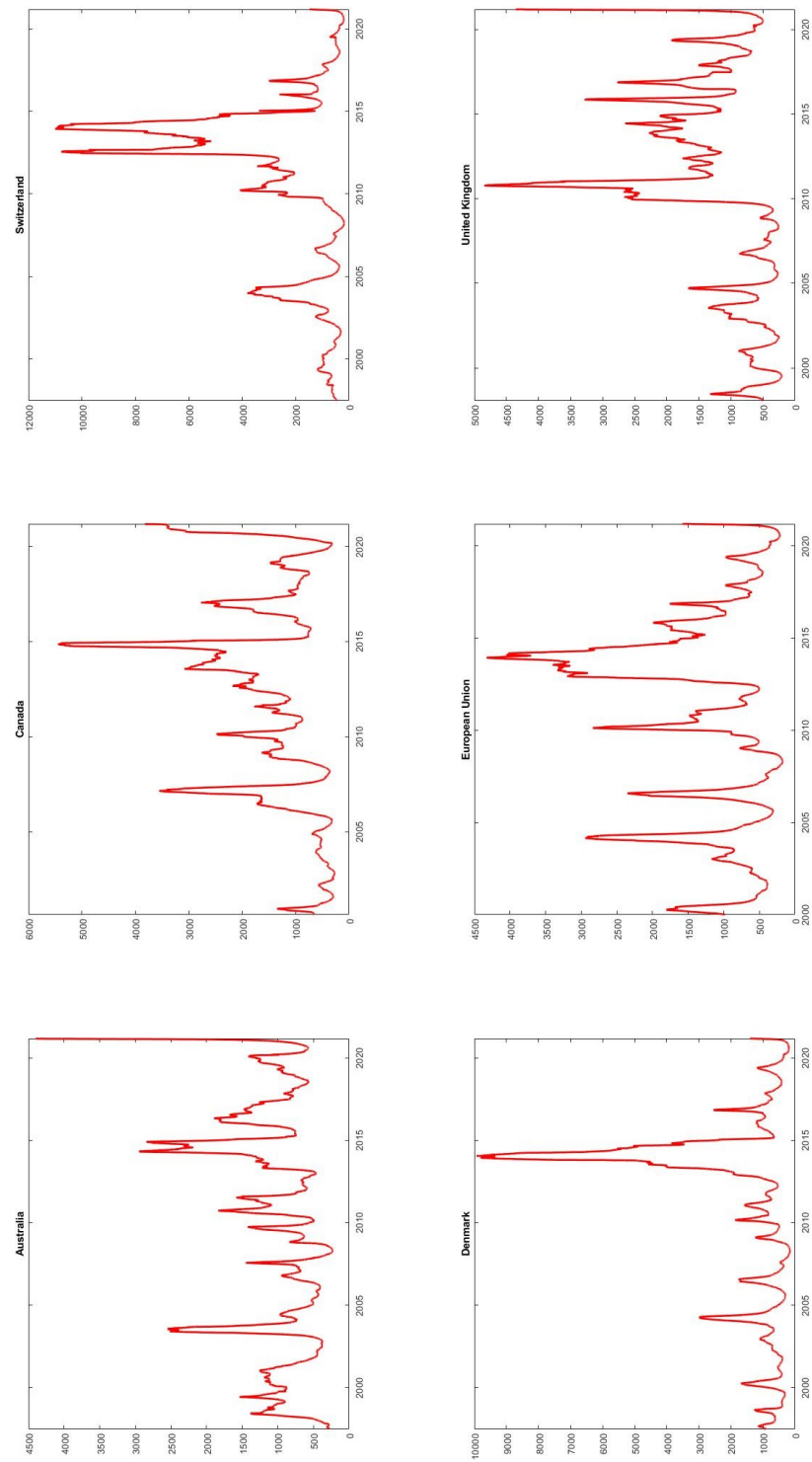


Figure 1.5: $\frac{\sigma(\rho_{t+1})}{\sigma(i_t - \ell_t^*)}$ with a window of 260 observations (cont.)

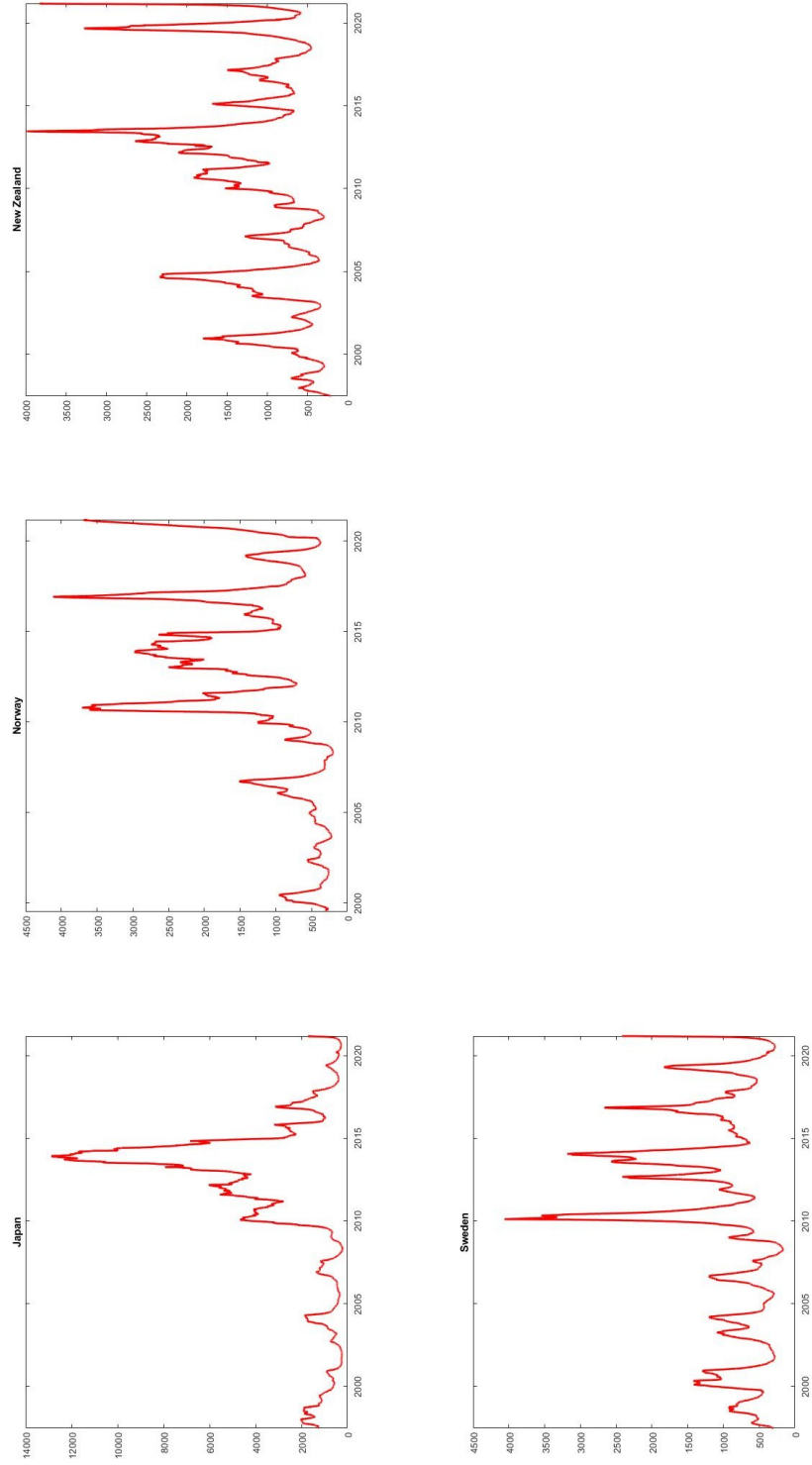


Figure 1.5: $\frac{\sigma(\rho_{t+1})}{\sigma(i_t - \ell_t^*)}$ with a window of 260 observations (cont.)

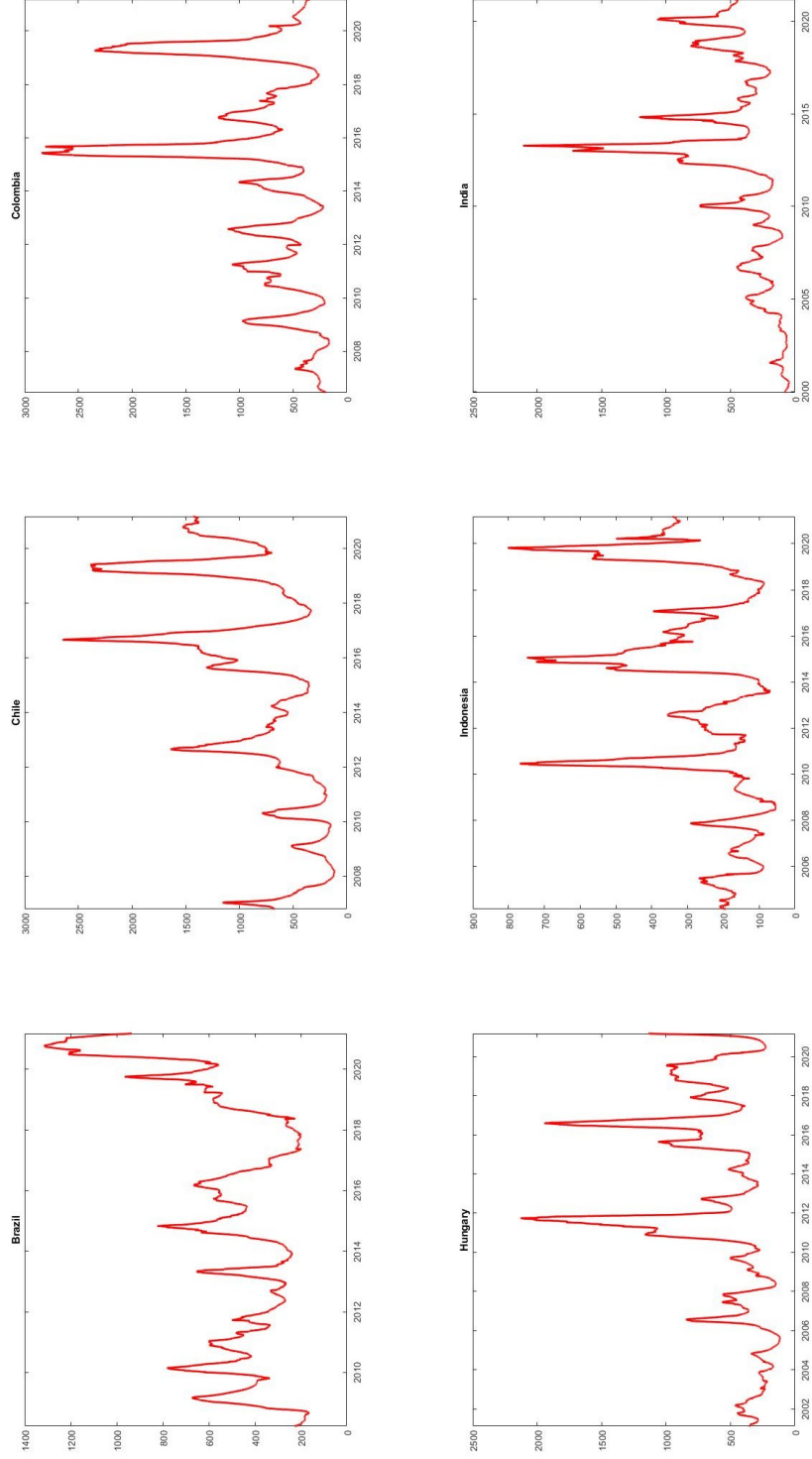


Figure 1.5: $\frac{\sigma(\rho_{t+1})}{\sigma(i_t - \ell_t^*)}$ with a window of 260 observations (cont.)

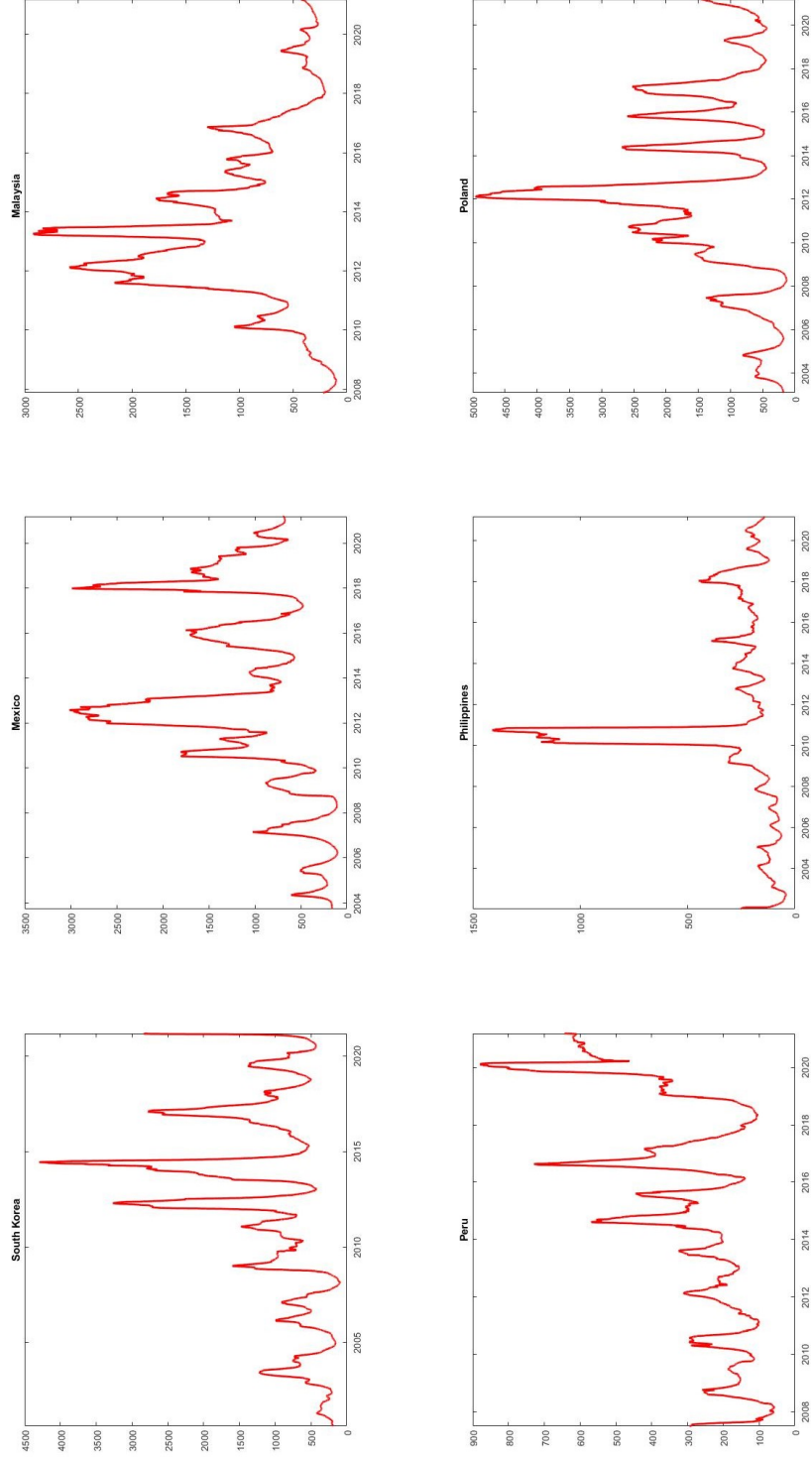
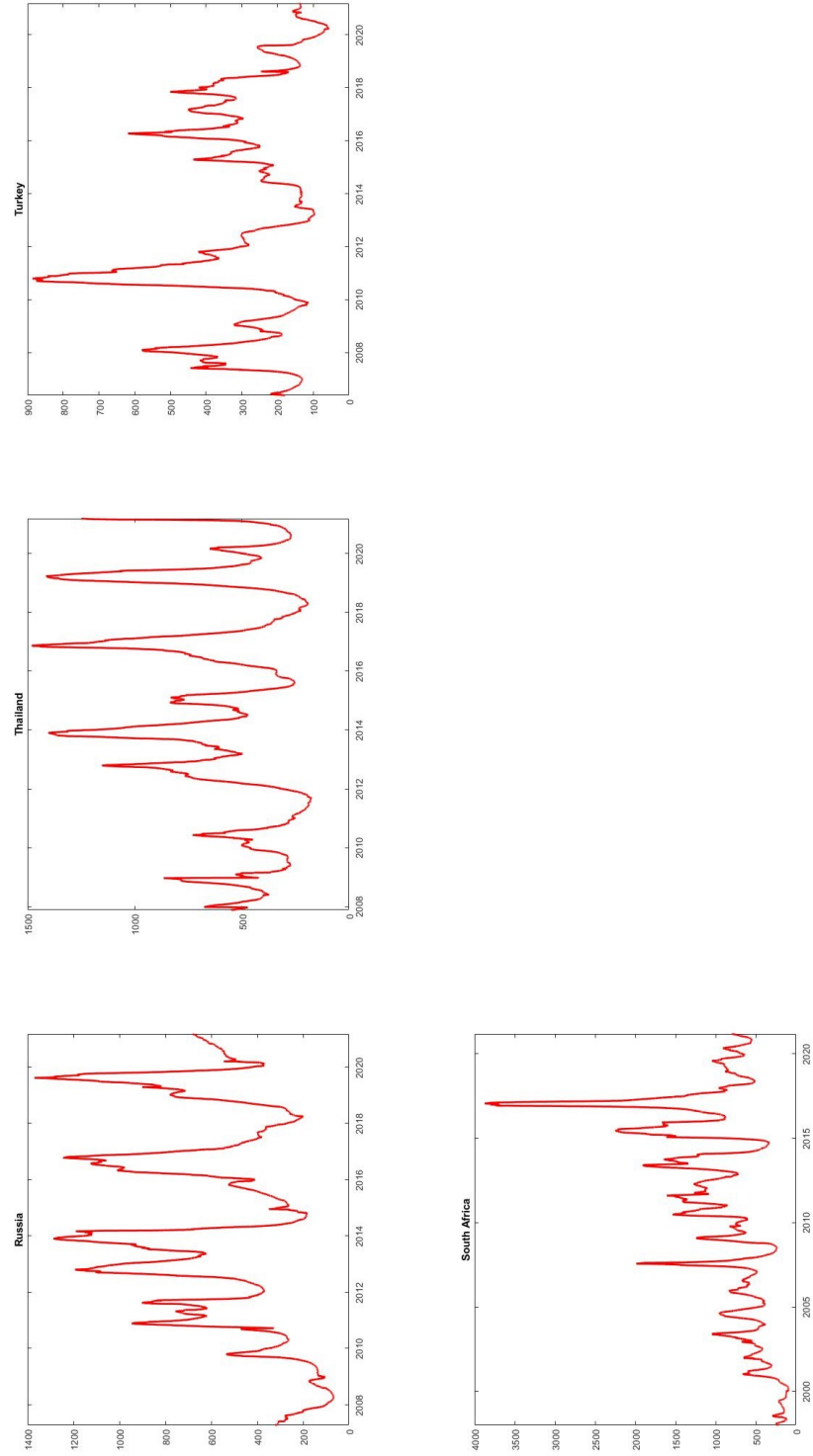


Figure 1.5: $\frac{\sigma(\rho_{t+1})}{\sigma(i_t - \ell_t^*)}$ with a window of 260 observations (cont.)



CHAPTER 2

Beyond Substitution: The Wealth Effect of Arbitrageurs in Foreign Exchange Markets

2.1 Introduction

There is a growing acknowledgment that financial frictions within foreign exchange markets can provide insights into several conundrums in international macroeconomics highlighted by Obstfeld and Rogoff (2000). A key source of these frictions is the constrained arbitrage capacity of arbitrageurs in foreign exchange markets. Recent studies by Gabaix and Maggiori (2015), Greenwood et al. (2020), Itskhoki and Mukhin (2021), and Gourinchas, Ray, and Vayanos (2022) have emphasized that these financial frictions, particularly those arising from the limited ability of arbitrageurs to act, offer explanations for various puzzles in international macroeconomic data, notably deviations from the uncovered interest parity (UIP).

Under the UIP framework, the interest rate differential between two currencies should equal the expected change in the exchange rate between them. Arbitrageurs, such as global banks and hedge funds, typically exploit arbitrage opportunities through carry trades, where they hold long-short positions in two currencies if there is a

deviation from UIP. In theory, these activities should connect global financial markets and uphold the UIP. However, due to their profit-driven and risk-averse nature, arbitrageurs face limitations that restrict their arbitrage capacity (Greenwood et al., 2020; Itskhoki and Mukhin, 2021; Gourinchas, Ray, and Vayanos, 2022; Itskhoki and Mukhin, 2024). While arbitrageurs seek to maximize profits through carry trades, they also demand a risk premium to compensate for the uncertainties in future exchange rates. As a result, arbitrage often falls short of maintaining UIP, leading to persistent deviations (Fama, 1984; Hodrick, 1989; Froot and Thaler, 1990; Lewis, 1995; Engel, 2016).

While existing studies primarily focus on the substitution effect of arbitrageurs—how they absorb or respond to shocks by adjusting their portfolios—this chapter aims to complement these studies by investigating the wealth effect of arbitrageurs in foreign exchange markets. The substitution effect underscores arbitrageurs’ role in stabilizing markets by absorbing shocks, aligning with the traditional view of arbitrage improving market efficiency. In contrast, this study explores how fluctuations in arbitrageurs’ wealth impact exchange rate dynamics and stability, offering a novel perspective on the interplay between arbitrage capacity and market outcomes. By incorporating the wealth effect, this chapter contributes to a deeper understanding of the dual forces at play in foreign exchange markets and their influence on market efficiency and stability.

The ability of arbitrageurs to exploit opportunities in foreign exchange markets is influenced by both the risk of future exchange rates and their wealth. De Long et al.’s (1990) model demonstrates that in financial markets, the ability to arbitrage is closely tied to the wealth of arbitrageurs. This model suggests that the impact of supply or

demand shocks on asset prices is diminished when arbitrageurs are wealthier and hold significant stakes in the asset. Itskhoki and Mukhin (2021, 2024) have integrated this principle into international finance models, showing that wealthier arbitrageurs face reduced risks associated with future exchange rates. However, their model assumes that arbitrageurs' wealth is exogenously determined and constant. In reality, the wealth of arbitrageurs fluctuates based on the realized returns of carry trades. This has significant implications, especially during abrupt and substantial depreciations of exchange rates, where arbitrageurs may incur substantial losses, posing risks to market stability and increasing future exchange rate risks.

Recognizing the critical role of arbitrageurs' wealth in linking arbitrage activities to UIP deviations and affecting exchange rates underscores the importance of integrating this factor into foreign exchange market models. However, there are three main challenges when incorporating wealth dynamics into the modeling framework.

First, a two-period setting is commonly adopted in previous studies of portfolio problems in international finance, such as Jeanne and Rose (2002) and Gabaix and Maggiori (2015), because it can derive key insights while keeping the model simple and tractable. This study, however, focuses on wealth dynamics, which requires a dynamic rather than a static setting. In an infinite horizon context, models are often consumption-based rather than wealth-based, complicating the model since the real sector influences the portfolio choices of arbitrageurs. To address this challenge, this chapter assumes that arbitrageurs have log-utility, which implies a constant consumption-wealth ratio, effectively transforming a consumption-based model into a wealth-based one and segregating the influences from the real sector.

Second, wealth dynamics is a second-order term often ignored when studying arbitrageurs in foreign exchange markets. The literature primarily focuses on first-order terms, such as changes in exchange rates and changes in arbitrageurs' portfolios. The wealth effect, which is the product of return and portfolio, is a second-order term. Many previous studies use linearization techniques to make the modeling framework more tractable and derive closed-form solutions (Itskhoki and Mukhin, 2021, 2024). However, these linearization techniques cannot be applied to study second-order terms. To overcome the nonlinearity challenge while keeping the model tractable, this chapter adopts a continuous time framework similar to Kyle and Xiong (2001), Xiong (2001), and Gourinchas, Ray, and Vayanos (2022).

Third, the autocorrelation in exchange rate returns is often ignored in the literature because models focusing on first-order terms naturally omit these second-order terms. However, this is not applicable to this modeling framework, as the change in wealth is also a second-order term. According to Campbell and Viceira (2002), the dynamic portfolio choice problem of long-term investors is reduced to a sequence of two-period portfolio choice problems if the investors have log-utility. In other words, investors with log-utilities will be myopic, and the autocorrelation in exchange rates will not influence their portfolio choices. Thus, the choice of log-utility in this modeling framework resolves this issue.

Therefore, this study explores the interactions among arbitrage activities, arbitrageurs' wealth, and exchange rates through a continuous-time model. The findings reveal that the wealth effect operates contrary to the substitution effect. While substitution effects tend to reduce deviations from the UIP, wealth effects exacerbate deviations from the UIP. In terms of market stability, substitution effects generally

stabilize the market as arbitrageurs absorb shocks, whereas wealth effects tend to destabilize it. This dual impact underscores the nuanced influence of arbitrageurs' wealth on the efficiency and stability of foreign exchange markets.

The remaining sections of this chapter are organized as follows: Section 2.2 summarizes the related literature. Section 2.3 presents the modeling framework. Section 2.4 performs the equilibrium analysis to derive optimal consumption and portfolio choices of the representative arbitrageur, the implied dynamics of carry trade returns and exchange rates, and evolution of arbitrageur wealth. Section 2.5 conducts quantitative analysis to solve the equilibrium in levels. Section 2.6 discusses the policy implications for foreign exchange interventions. Section 2.7 concludes this chapter.

2.2 Related Literature

This chapter contributes to three strands of literature: wealth effects of financial intermediaries on asset prices, financial friction as an explanation for UIP deviations, and the analysis of policies concerning foreign exchange interventions.

2.2.1 Wealth Effects of Financial Intermediaries

The wealth effects of financial intermediaries on asset prices have been widely studied in the context of stock and bond markets. The fundamental idea is that the wealth of financial intermediaries influences their ability to take positions, thereby affecting asset prices.

One of the seminal works in this area is by Xiong (2001), who developed a model showing that sudden and sharp drops in stock prices lead to significant losses for

arbitrageurs, forcing them to sell off the stock to rebalance their portfolios. This selling pressure feeds back into the stock price, causing further declines.

Further contributions by Kyle and Xiong (2001) highlight that in a context with more than one stock, sudden and sharp drops in the price of one stock can cause arbitrageurs to liquidate other stocks in their portfolios during the rebalancing process. This liquidation leads to price drops in those other stocks as well. Thus, the sudden and sharp price drops in one asset can become contagious, ultimately leading to inefficiencies and instabilities in the stock market as a whole.

While the wealth effects of financial intermediaries are commonly studied in stock and bond markets (Kyle and Xiong, 2001; Xiong, 2001; Gromb and Vayanos, 2002; Guimaraes and Morris, 2007; Lizarazo, 2009; Petmezas and Santamaria, 2014; Bayona and Peia, 2022), the wealth effects in the foreign exchange market are relatively underexplored. In the context of foreign exchange markets, Itskhoki and Mukhin (2021, 2024) integrate arbitrageurs' wealth into their models. However, their assumption of exogenously determined and constant wealth limits the understanding of how fluctuations in arbitrageurs' wealth dynamically influence exchange rates.

This chapter builds on these studies by explicitly modeling the wealth effect of arbitrageurs in foreign exchange markets. It posits that changes in exchange rates affect the realized returns of carry trades, impacting arbitrageurs' wealth. This, in turn, influences their portfolio choices and further affects exchange rate dynamics. By incorporating the wealth effect, this study provides a more comprehensive understanding of the dual forces shaping the dynamics and stability of foreign exchange markets.

2.2.2 Financial Friction and UIP Deviations

Previous research has identified four main channels that contribute to persistent deviations from the UIP: the risk premium channel, the information frictions channel, the liquidity premium channel, and the financial frictions channel. The risk premium channel, explored in models by Colacito (2009), Backus et al. (2010), Lustig, Roussanov, and Verdelhan (2011), Bansal and Shaliastovich (2013), and Corsetti and Marin (2020), posits a frictionless environment where arbitrageurs receive compensation for the risk tied to carry trades. These models highlight that the presence of carry trade risk curtails the arbitrage activities of risk-averse arbitrageurs, leading to arbitrage opportunities. The information frictions channel, as developed by Gourinchas and Tornell (2004), Bacchetta and van Wincoop (2010), and Stavrakeva and Tang (2018), integrates information frictions and links UIP deviations to delayed overshooting or delayed reactions, suggesting that these deviations may result from arbitrageurs' misjudgments in the foreign exchange market. The liquidity premium channel, proposed by Engle (2016), argues that the UIP framework overlooks liquidity premiums in short-term assets, which can explain the observed deviations.

The financial frictions channel, outlined in theories by Gabaix and Maggiori (2015), Greenwood et al. (2020), Itskhoki and Mukhin (2021), and Gourinchas, Ray, and Vayanos (2022), contends that various financial frictions hinder arbitrageurs' capacity to adjust to supply or demand shocks in foreign exchange markets, thus contributing to UIP deviations. On the empirical side, Barbiero et al. (2024) leverage supervisory microdata and find that shocks to dealers' risk limits can trigger UIP deviations. The financial frictions channel stands out as a prevalent explanation because it can account for various puzzles in international macroeconomic data besides deviations

from UIP (Itskhoki and Mukhin, 2021).

This chapter focuses on the financial frictions channel and contributes to this strand of literature by highlighting wealth as another type of financial friction that can cause deviations from UIP. Existing studies on the financial frictions channel primarily address the ability of arbitrageurs to absorb or respond to shocks by adjusting their portfolios—the substitution effect. This chapter aims to augment these studies by investigating the wealth effect of arbitrageurs in foreign exchange markets. Specifically, it points out that changes in the foreign exchange rate affect the realized returns of carry trades, impacting the wealth of arbitrageurs. This results in adjustments to the portfolios of arbitrageurs, as their portfolio choices depend on their wealth, further influencing the foreign exchange rate. This has significant implications, especially during abrupt and substantial depreciations of exchange rates, where arbitrageurs may incur substantial losses, posing risks to market stability and increasing future exchange rate risks.

2.2.3 Foreign Exchange Interventions

Previous research has underscored the critical role of foreign exchange interventions in enhancing the efficiency and stability of foreign exchange markets. Scholars such as Aizenman and Lee (2007), Caballero and Panageas (2007), Alfaro and Kanczuk (2009), Jeanne and Ranciere (2011), and Bianchi and Lorenzoni (2022) have highlighted the significance of accumulating foreign exchange reserves as a defensive strategy against abrupt devaluations and surges in volatility in the exchange rate of home currency. Additionally, researchers like Fanelli and Straub (2021) and Itskhoki and Mukhin (2024) have explored the strategic deployment of international reserves in

foreign exchange interventions.

This chapter contributes to this area by emphasizing the importance of considering the wealth of arbitrageurs in foreign exchange interventions, both in terms of its level—arbitrageurs’ wealth—and its change—wealth effects.

In terms of the level of wealth, it posits that in economies where arbitrageurs possess greater wealth, the exchange rate exhibits reduced sensitivity to noise trader shocks, diminishing the necessity for foreign exchange intervention. This observation aligns with empirical data that show that emerging market economies engage more frequently in foreign exchange interventions compared to advanced economies. It is also consistent with the trend of rapidly growing foreign exchange reserves in emerging market economies relative to advanced economies. This chapter suggests that the more frequent intervention needs in emerging market economies necessitate the accumulation of substantial foreign exchange reserves to enable effective market interventions.

2.3 Model Setup

The modeling framework draws inspiration from five pivotal studies: De Long et al. (1990), Kyle and Xiong (2001), Xiong (2001), Campbell and Viceira (2002), and Itskhoki and Mukhin (2021). The model is set over an infinite horizon with continuous time. There are two countries in this model: the home country, which is an advanced economy, and a foreign country, which is an emerging market economy. There are three types of participants in the foreign exchange markets: noise traders, who take random positions in home and foreign currencies; arbitrageurs, who perform

carry trades to exploit arbitrage opportunities between home and foreign currencies; and households, who are lenders supplying home and foreign currencies. To keep the model tractable, agents of each type are assumed to be identical, resulting in a homogeneous agent model.

2.3.1 Noise Traders

The representative noise trader takes short positions in the home currency. The supply of the home currency, denoted as n , follows the Ornstein-Uhlenbeck process described below:

$$dn = -\lambda_n (n - \bar{n}) dt + \sigma_n dz_n \quad (2.1)$$

with constant rates of mean reversion $\lambda_n \in (0, 1)$, constant volatility σ_n , and long-run average $\bar{n}$. Both the noise traders' position n and its long-run average $\bar{n}$ can be negative, indicating the noise traders are demanding the home currency instead.

2.3.2 Arbitrageurs

The representative arbitrageur chooses a consumption c and an investment x in carry trade to maximize their lifetime utility:

$$J(n, w) = \max_{x, c} \mathbb{E} \int_0^{+\infty} e^{-\rho t} \log c \, dt, \quad (2.2)$$

subject to

$$dw = x \, dq + (iw - c) \, dt, \quad (2.3)$$

$$dq = ds + (i^* - i) \, dt, \quad (2.4)$$

where ρ is the arbitrageur's time-preference, w is the arbitrageur's wealth, q is the return from carry trade, i is the risk-free home interest rate, i^* is the risk-free foreign interest rate, and s is the logarithm of the nominal exchange rate.

To maintain model tractability, home and foreign interest rates are assumed to be constant over time and fixed at their long-run levels. This assumption is also supported by the empirical evidence in Chapter 1, which shows that exchange rates are substantially more volatile than interest rate differentials, suggesting that most of the relevant variation in the model is driven by exchange rate dynamics rather than interest rate movements. Additionally, inflation is assumed to be constant over time and normalized to 1, making the nominal exchange rate identical to the real exchange rate. The assumption of log-utility further ensures that wealth remains strictly positive in this setup.

2.3.3 Net Foreign Asset

The demand for foreign currency from arbitrageurs should equal the total supply for foreign currency in the foreign exchange market, which is the sum of the supply from noise traders and the net foreign asset b . Thus, the market-clearing condition is:

$$b + n + x = 0. \tag{2.5}$$

The relationship between the net foreign asset and the logarithm of the nominal exchange rate, as described in Hau and Rey (2006), Itskhoki and Mukhin (2021), and Gourinchas, Ray, and Vayanos (2022), can be rewritten in continuous time as follows:

$$b = \theta (\tilde{s} - s), \tag{2.6}$$

and

$$d\tilde{s} = (i^* - i) dt + \sigma_{\tilde{s}} dz_{\tilde{s}}, \quad (2.7)$$

$$db = \theta (d\tilde{s} - ds). \quad (2.8)$$

According to Equation (2.6), an appreciation of the home currency, reflected in a decrease in s , is associated with an increase in net foreign assets, or equivalently, in the supply of the home currency b . Equation (2.6) therefore implies an upward-sloping supply curve with slope θ , which captures the elasticity of the foreign exchange market. A higher value of θ corresponds to lower elasticity, as it implies smaller exchange rate adjustments in response to a given change in quantity demanded. Conversely, a lower value of θ indicates greater elasticity. In addition, the volatility of net foreign assets, σ_b , is assumed to be constant.

2.4 Equilibrium Analysis

This section presents the results of the equilibrium analysis. It begins by characterizing the optimal consumption and portfolio choices of the representative arbitrageur. It then examines the implied dynamics of carry trade returns and exchange rates. Finally, it analyzes the evolution of arbitrageur wealth.

2.4.1 Arbitrageur's Optimal Consumption and Portfolio

Since dz_n in Equation (2.1) and $dz_{\tilde{s}}$ in Equation (2.7) are the sources of risk, the process for the carry trade return can be specified as:

$$dq = \mu_q(n, w) dt + \sigma_{q,n}(n, w) dz_n + \sigma_{q,\tilde{s}}(n, w) dz_{\tilde{s}}, \quad (2.9)$$

where $\mu_q(n, w)$ is the drift term, and $\sigma_q(n, w)$ and $\sigma_{q,\tilde{s}}(n, w)$ are diffusion terms. These three terms are functions of two state variables: the supply of home currency from noise traders n and the wealth of the representative arbitrageur w , which are undetermined coefficients to be derived in the later part of this section.

As is shown in Appendix A, under the assumption of log-utility, the arbitrageur's optimal consumption is:

$$c = \rho w. \quad (2.10)$$

Using Equation (2.10), the model is restructured from a consumption-based framework to a wealth-based one. Importantly, the use of log-utility reduces the dynamic portfolio choice problem for long-term investors to a sequence of two-period portfolio choice problems. As demonstrated in Appendix B, the arbitrageur's optimal portfolio is:

$$x = \frac{\mu_q(n, w)}{\sigma_{q,n}^2(n, w) + \sigma_{q,\tilde{s}}^2(n, w)} w. \quad (2.11)$$

The representative arbitrageur's optimal portfolio x is proportional to the level of wealth, increasing in the expected return from the carry trade, and decreasing in the associated risks.

2.4.2 Carry Trade Return

As is shown in Appendix C, the drift and diffusions in the carry trade return process specified in Equation (2.9) are:

$$\begin{aligned} \mu_q(n, w) = \frac{1}{\theta - \Gamma(n, w)} & \left\{ (1 - \Psi(n, w)) [-\lambda_n (n - \tilde{n})] + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \\ & \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\tilde{s}}^2(n, w)] + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right\}, \end{aligned} \quad (2.12)$$

$$\sigma_{q,n}(n, w) = \frac{1}{\theta - \Gamma(n, w)} (1 - \Psi(n, w)) \sigma_n, \quad (2.13)$$

$$\sigma_{q,\tilde{s}}(n, w) = \frac{\theta}{\theta - \Gamma(n, w)} \sigma_{\tilde{s}}, \quad (2.14)$$

respectively, where

$$\Gamma(n, w) = \frac{\partial x}{\partial w} x \quad (2.15)$$

is defined as the wealth effect and

$$\Psi(n, w) = \frac{\partial x}{\partial(-n)} = -\frac{\partial x}{\partial n} \quad (2.16)$$

is defined as the substitution effect.

The substitution and wealth effects are structured analogously to Slutsky's equation. In this setting, both are non-negative.

The substitution effect $\Psi(n, w)$ captures the responsiveness of arbitrageurs' portfolios to noise trader shocks. It dampens volatility arising from such shocks and mitigates their impact on carry trade returns, thereby contributing to the stabilization of the

foreign exchange market. The substitution effect is stronger when $\Psi(n, w)$ is larger, reflecting greater absorption of noise trader shocks by arbitrageurs, and weakest when it approaches zero, indicating limited absorption.

The wealth effect $\Gamma(n, w)$ captures the sensitivity of arbitrageurs' portfolios to their wealth. In contrast to the substitution effect, the wealth effect amplifies volatility and tends to destabilize the foreign exchange market. It becomes stronger as $\Gamma(n, w)$ increases, implying that portfolio choices are more sensitive to changes in wealth, and weakest when it approaches zero, in which case portfolio choices are effectively independent of wealth.

Importantly, the drift term in Equation (2.12) measures deviations from uncovered interest parity (UIP). As shown in Equation (2.12), the drift decreases with the substitution effect $\Psi(n, w)$ and increases with the wealth effect $\Gamma(n, w)$. This highlights their opposing roles: the substitution effect reduces deviations from UIP, whereas the wealth effect amplifies UIP deviations.

2.4.3 Exchange Rate

The exchange rate process can be derived from Equation (2.4). It is the carry trade return minus the interest rate differential, which is the difference between foreign and home interest rates. As is shown in Appendix D, the exchange rate process is:

$$ds = \mu_s(n, w)dt + \sigma_{s,n}(n, w)dz_n + \sigma_{s,\tilde{s}}(n, w)dz_{\tilde{s}}, \quad (2.17)$$

where

$$\begin{aligned} \mu_s(n, w) = \frac{1}{1 - \frac{1}{\theta}\Gamma(n, w)} & \left\{ \frac{1}{\theta}\Gamma(n, w) (i^* - i) + \frac{1}{\theta} \left[(1 - \Psi(n, w)) \lambda_n (n - \bar{n}) + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 \right. \right. \\ & \left. \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 (\sigma_{q,n}^2(n, w) + \sigma_{q,b}^2(n, w)) + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right] \right\}, \quad (2.18) \end{aligned}$$

$$\sigma_{s,n}(n, w) = \frac{\frac{1}{\theta} (1 - \Psi(n, w))}{1 - \frac{1}{\theta}\Gamma(n, w)} \sigma_n, \quad (2.19)$$

$$\sigma_{s,\tilde{s}}(n, w) = \frac{\frac{1}{\theta}}{1 - \frac{1}{\theta}\Gamma(n, w)} \sigma_{\tilde{s}}, \quad (2.20)$$

respectively, where $\Gamma(n, w)$ and $\Psi(n, w)$ are the wealth and substitution effects defined in Equations (2.15) and (2.16) respectively.

The diffusion terms specified in Equations (2.19) and (2.20) measure the volatility of the foreign exchange rate or the stability of the foreign exchange market. According to these equations, the diffusion terms decrease with the substitution effect $\Psi(n, w)$ and increase with the wealth effect $\Gamma(n, w)$. This indicates that, in terms of foreign exchange market stability, the wealth effect acts in the opposite direction of the substitution effect: while substitution effects generally stabilize the market as arbitrageurs absorb shocks, wealth effects tend to destabilize it.

Combining the discussions from Sections 2.4.2 and 2.4.3, the dual impact of the substitution and wealth effects underscores the nuanced influence of arbitrageurs' wealth on the UIP and stability of foreign exchange markets. The total effect, comprising the sum of the substitution and wealth effects, represents the impact of arbitrageurs on the exchange rate in response to noise trader shocks. Of these two effects, the

wealth effect is often omitted in linearization and discrete-time models. However, the wealth effect can be substantial, especially during episodes of sharp and sudden foreign exchange depreciation where arbitrageurs incur significant losses in their wealth.

2.4.4 Arbitrageur's Wealth

As is shown in Appendix E, the arbitrageur's wealth process is:

$$\frac{dw}{w} = \mu_w(n, w)dt + \sigma_{w,n}(n, w)dz_n + \sigma_{w,\tilde{s}}(n, w)dz_{\tilde{s}}, \quad (2.21)$$

where

$$\begin{aligned} \mu_w(n, w) = & i - \rho + \frac{1}{\left[\frac{1}{\theta}(1 - \Psi(n, w))\right]^2 \sigma_n^2 + \left(\frac{1}{\theta}\right)^2 \sigma_{\tilde{s}}^2} \\ & \times \left\{ i^* - i + \frac{1}{\theta} \left[(1 - \Psi(n, w)) \lambda_n (n - \bar{n}) + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \right. \\ & \left. \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 (\sigma_{q,n}^2(n, w) + \sigma_{q,\tilde{s}}^2(n, w)) + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right] \right\}^2, \quad (2.22) \end{aligned}$$

$$\begin{aligned} \sigma_{w,n}(n, w) = & \frac{\frac{1}{\theta} (1 - \Psi(n, w)) \sigma_n}{\left[\frac{1}{\theta}(1 - \Psi(n, w))\right]^2 \sigma_n^2 + \left(\frac{1}{\theta}\right)^2 \sigma_{\tilde{s}}^2} \\ & \times \left\{ i^* - i + \frac{1}{\theta} \left[(1 - \Psi(n, w)) \lambda_n (n - \bar{n}) + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \right. \\ & \left. \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 (\sigma_{q,n}^2(n, w) + \sigma_{q,\tilde{s}}^2(n, w)) + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right] \right\}, \quad (2.23) \end{aligned}$$

$$\begin{aligned}
\sigma_{w,\bar{s}}(n, w) = & \frac{\frac{1}{\theta}\sigma_{\bar{s}}}{\left[\frac{1}{\theta}(1 - \Psi(n, w))\right]^2 \sigma_n^2 + \left(\frac{1}{\theta}\right)^2 \sigma_{\bar{s}}^2} \\
& \times \left\{ i^* - i + \frac{1}{\theta} \left[(1 - \Psi(n, w)) \lambda_n (n - \bar{n}) + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \right. \\
& \left. \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 (\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)) + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right] \right\}, \quad (2.24)
\end{aligned}$$

respectively, where $\Gamma(n, w)$ and $\Psi(n, w)$ are the wealth and substitution effects defined in Equations (2.15) and (2.16) respectively.

According to Equation (2.22), a non-explosive solution is possible only if the home interest rate i is smaller than the arbitrageur's time-preference ρ . This is because the home interest rate represents the risk-free return that the arbitrageur can earn on their wealth, while the arbitrageur's time preference, as specified in Equation (2.10), corresponds to the consumption-wealth ratio and can be viewed as the rate of wealth depreciation. Consequently, if the home interest rate exceeds the arbitrageur's time preference, wealth accumulation will surpass depreciation, resulting in explosive wealth dynamics.

2.5 Quantitative Analysis

To solve the equilibrium, it is necessary to address the nonlinear PDE specified in Equation (2.11). The calibration for the quantitative analysis closely follows the methodology of Kojen and Yogo (2019) and Itskhoki and Mukhin (2021). The iterative relaxation method is used to solve the nonlinear PDE.

2.5.1 The Boundary Value Problem (BVP)

Solving the arbitrageurs' optimal portfolio requires solving a second-order nonlinear PDE specified by:

$$x = \frac{\mu_q(n, w)}{\sigma_{q,n}^2(n, w) + \sigma_{q,\tilde{s}}^2(n, w)} w, \quad (2.11)$$

where

$$\begin{aligned} \mu_q(n, w) = \frac{1}{\theta - \Gamma(n, w)} & \left\{ (1 - \Psi(n, w)) [-\lambda_n(n - \tilde{n})] + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \\ & \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\tilde{s}}^2(n, w)] + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right\}, \end{aligned} \quad (2.12)$$

$$\sigma_{q,n}(n, w) = \frac{1}{\theta - \Gamma(n, w)} (1 - \Psi(n, w)) \sigma_n, \quad (2.13)$$

$$\sigma_{q,\tilde{s}}(n, w) = \frac{\theta}{\theta - \Gamma(n, w)} \sigma_{\tilde{s}}, \quad (2.14)$$

$$\Gamma(n, w) = \frac{\partial x}{\partial w} x \quad (2.15)$$

$$\Psi(n, w) = -\frac{\partial x}{\partial n} \quad (2.16)$$

In fact, the PDE is in the format:

$$f(x, x_n, x_w, x_{nn}, x_{ww}, x_{nw}) = 0,$$

where

$$x_n \equiv \frac{\partial x}{\partial n}, \quad x_w \equiv \frac{\partial x}{\partial w}, \quad x_{nn} \equiv \frac{\partial^2 x}{\partial n^2}, \quad x_{nw} \equiv \frac{\partial^2 x}{\partial n \partial w}, \quad x_{ww} \equiv \frac{\partial^2 x}{\partial w^2}.$$

In particular, by substituting Equations (2.12), (2.13), (2.14), (2.15), and (2.16) into Equation (2.11), the arbitrageurs' optimal portfolio is given by the solution to this PDE:

$$\begin{aligned} & \frac{1}{\theta - x_w x} \left[(1 + x_n)^2 \sigma_n^2 + \theta^2 \sigma_s^2 \right] \frac{x}{w} + (1 + x_n) [-\lambda_n (n - \bar{n})] - x_w (i - \rho) w - \frac{1}{2} x_{nn} \sigma_n^2 \\ & - \left(\frac{1}{\theta - x_w x} \right)^2 \left[(1 + x_n)^2 \sigma_n^2 + \theta^2 \sigma_s^2 \right] \frac{1}{2} x_{ww} x^2 - x_{nw} x \frac{1}{\theta - x_w x} (1 + x_n) \sigma_n^2 = 0. \end{aligned} \quad (2.11')$$

This PDE has two boundary conditions according to the level of arbitrageurs' wealth. On one hand, if arbitrageurs have no wealth, they would not be able to enter a carry trade such that their carry trade portfolio is 0:

$$x(n, 0) = 0. \quad (2.25)$$

On the other hand, if arbitrageurs have infinite wealth, they will absorb all the trading flows from noise traders:

$$x(n, \infty) = -n. \quad (2.26)$$

2.5.2 Transformation of Variables and the PDE

However, $n \in (-\infty, +\infty)$, $w \in (0, +\infty)$, and solving the PDE numerically requires the domain to be finite. Therefore, we make the following transformations.

Noise trader shock follows a normal distribution:

$$n \sim \mathcal{N}\left(\bar{n}, \frac{\sigma_n^2}{2\lambda_n}\right).$$

We obtain the transformed noise trader shocks as:

$$\tilde{n} = \frac{n - \bar{n}}{5\sigma_n/\sqrt{2\lambda_n}} \in [-1, 1]. \quad (2.27)$$

The transformed noise trader shocks are truncated to be within ± 5 standard deviations around their long-run average $\bar{n}$, with $\tilde{n} = 1$ being the noise trader shock 5 standard deviations above while $\tilde{n} = -1$ is 5 standard deviations below. The truncation is reasonable because it is extremely rare for the noise trader shock to deviate the long-run average by 5 standard deviations:

$$\mathbb{P}(\{\tilde{n} : \tilde{n} \notin [-1, 1]\}) \approx 6 \times 10^{-7}.$$

The transformed arbitrageurs' wealth is:

$$\tilde{w} = 1 - e^{-w} \in [0, 1]. \quad (2.28)$$

Given the transformations in Equations (2.27) and (2.28):

$$n = \bar{n} + \tilde{n} \cdot \frac{5\sigma_n}{\sqrt{2\lambda_n}}, \quad (2.27')$$

$$w = -\ln(1 - \tilde{w}). \quad (2.28')$$

Therefore, the transformed derivatives are:

$$\begin{aligned}
x_n &= \tilde{x}_n \cdot \frac{\sqrt{2\lambda_n}}{5\sigma_n}, \\
x_w &= \tilde{x}_w \cdot (1 - \tilde{w}), \\
x_{nn} &= \tilde{x}_{nn} \cdot \frac{2\lambda_n}{25\sigma_n^2}, \\
x_{ww} &= \tilde{x}_{ww} \cdot (1 - \tilde{w})^2 - \tilde{x}_w \cdot (1 - \tilde{w}), \\
x_{nw} &= \tilde{x}_{nw} \cdot (1 - \tilde{w}) \cdot \frac{\sqrt{2\lambda_n}}{5\sigma_n}.
\end{aligned}$$

With these transformations in place, the PDE is now in the format:

$$\tilde{f}(x, x_{\tilde{n}}, x_{\tilde{w}}, x_{\tilde{n}\tilde{n}}, x_{\tilde{w}\tilde{w}}, x_{\tilde{n}\tilde{w}}) = 0.$$

In particular, the arbitrageurs' optimal portfolio is now given by the solution to this transformed PDE:

$$\begin{aligned}
&\frac{1}{\theta - x_{\tilde{w}}\gamma(1 - \tilde{w})x} \left[\left(1 + x_{\tilde{n}} \frac{\sqrt{2\lambda_n}}{5\sigma_n} \right)^2 \sigma_n^2 + \theta^2 \sigma_s^2 \right] \frac{x}{\frac{1}{\gamma} \ln \frac{1}{1-\tilde{w}}} + \left(1 + x_{\tilde{n}} \frac{\sqrt{2\lambda_n}}{5\sigma_n} \right) \left(-\lambda_n \tilde{n} \frac{5\sigma_n}{\sqrt{2\lambda_n}} \right) \\
&\quad - x_{\tilde{w}}\gamma(1 - \tilde{w})(i - \rho) \frac{1}{\gamma} \ln \frac{1}{1 - \tilde{w}} - \frac{1}{2} x_{\tilde{n}\tilde{n}} \frac{2\lambda_n}{25\sigma_n^2} \sigma_n^2 \\
&- \left(\frac{1}{\theta - x_{\tilde{w}}\gamma(1 - \tilde{w})x} \right)^2 \left[\left(1 + x_{\tilde{n}} \frac{\sqrt{2\lambda_n}}{5\sigma_n} \right)^2 \sigma_n^2 + \theta^2 \sigma_s^2 \right] \frac{1}{2} [x_{\tilde{w}\tilde{w}}\gamma^2(1 - \tilde{w})^2 - x_{\tilde{w}}\gamma^2(1 - \tilde{w})] x^2 \\
&\quad - x_{\tilde{n}\tilde{w}}\gamma(1 - \tilde{w}) \frac{\sqrt{2\lambda_n}}{5\sigma_n} x \frac{1}{\theta - x_{\tilde{w}}\gamma(1 - \tilde{w})x} \left(1 + x_{\tilde{n}} \frac{\sqrt{2\lambda_n}}{5\sigma_n} \right) \sigma_n^2 = 0, \quad (2.11'')
\end{aligned}$$

with boundary conditions:

$$x(\tilde{n}, 0) = 0, \quad (2.25')$$

$$x(\tilde{n}, 1) = -\bar{n} - \tilde{n} \frac{5\sigma_n}{\sqrt{2\lambda_n}}. \quad (2.26')$$

2.5.3 Calibration

Table 2.1 summarizes the baseline calibration of the model parameters.

Table 2.1: Calibration

Parameter		Value	Comment
Average noise trader shock	$\bar{n}$	0	Normalization
Mean-reversion of the noise trader shock	λ_n	0.125	Itskhoki and Mukhin (2021)
Arbitrageur's time-preference	ρ	0.04	Itskhoki and Mukhin (2021)
Elasticity of FX demand	θ	0.5	Koijen and Yogo (2019)
Average home interest rate	i	0.01	Data from Chapter 1
Average foreign interest rate	i^*	0.05	Data from Chapter 1
Volatility of UIP-consistent exchange rate	$\sigma_{\bar{s}}$	0.15	Data from Chapter 1
Volatility of noise trader shock	σ_n	0.1	Data from Chapter 1

The average noise trader shock $\bar{n}$ is normalized to zero, implying that noise traders are not systematically biased toward buying or selling foreign currency. Their demand fluctuates around zero over time.

The mean-reversion parameter of the noise trader shock, λ_n , is calibrated using evidence from Itskhoki and Mukhin (2021). In their paper, the noise trader shock follows a highly persistent quarterly process with persistence approximately 0.97. Translating this persistence into the continuous-time mean-reversion parameter of the Ornstein–Uhlenbeck process used in this chapter yields

$$\lambda_n = -\frac{\ln(0.97)}{1/4} \approx 0.125.$$

The arbitrageur's time-preference parameter ρ is also calibrated using Itskhoki and Mukhin (2021). They assume a quarterly discount factor of 0.99. Converting this into a continuous-time discount rate implies

$$\rho = -\frac{\ln(0.99)}{1/4} \approx 0.04.$$

The elasticity of foreign exchange demand θ follows the evidence in Koijsen and Yogo (2019), who document that the demand for financial assets is relatively inelastic. Their estimates suggest that micro-level elasticities are around one, while macro-level elasticities are typically smaller due to general equilibrium effects. To capture this relatively inelastic demand in the foreign exchange market, this chapter sets $\theta = 0.5$.

The home country in the model represents a typical advanced economy in the context of carry trade. Consistent with the low interest rate environment observed after the Global Financial Crisis, the average home interest rate is set to $i = 0.01$. The foreign country represents a typical emerging market economy used as the investment currency in carry trades. Emerging market economies generally exhibit higher interest rates, so the average foreign interest rate is set to $i^* = 0.05$, which is broadly consistent with the data.

To calibrate the volatility of the UIP-consistent exchange rate, we rely on empirical evidence from currency returns. The carry trade return for a foreign currency against the U.S. dollar typically has a daily standard deviation of around 0.01 for advanced economies and around 0.015 for emerging market economies. These correspond to

annualized volatilities of

$$0.01 \times \sqrt{252} \approx 0.16$$

for advanced economies and

$$0.015 \times \sqrt{252} \approx 0.24$$

for emerging market economies. Based on these magnitudes, the model sets the annualized volatility of the UIP-consistent exchange rate to $\sigma_{\tilde{s}} = 0.15$.

Finally, the volatility of the noise trader shock is assumed to be smaller than that of the fundamental shock that drives the UIP-consistent exchange rate. Accordingly, the annualized volatility of the noise trader shock is set to $\sigma_n = 0.1$, which provides a reasonable magnitude relative to the fundamental volatility in the model.

2.5.4 Numerical Methods

The arbitrageurs' optimal portfolio policy $x(\tilde{n}, \tilde{w})$ is characterized by a nonlinear partial differential equation. Since an analytical solution is not available, the equation is solved numerically using a finite difference method combined with an iterative relaxation algorithm.

The state space of the model is defined over the domain

$$(\tilde{n}, \tilde{w}) \in [-1, 1] \times [0, 1],$$

where $\tilde{n}$ represents the noise trader shock and $\tilde{w}$ represents the arbitrageur wealth share. The domain is discretized into a grid of 201×1001 points, resulting in ap-

proximately 200,000 grid points. Specifically, the noise trader shock $\tilde{n} \in [-1, 1]$ is discretized into 201 equally spaced points with grid width $\Delta\tilde{n} = 0.01$, while the wealth share $\tilde{w} \in [0, 1]$ is discretized into 1001 equally spaced points with grid width $\Delta\tilde{w} = 0.001$.

Spatial derivatives of the policy function $x(\tilde{n}, \tilde{w})$ are approximated using finite difference methods. At interior grid points (i, j) , the first derivatives are approximated by

$$\begin{aligned} x_{\tilde{n}} &\approx \frac{x_{i+1,j} - x_{i-1,j}}{2\Delta\tilde{n}}, \\ x_{\tilde{w}} &\approx \frac{x_{i,j+1} - x_{i,j-1}}{2\Delta\tilde{w}}, \end{aligned}$$

while the second derivatives are approximated by

$$\begin{aligned} x_{\tilde{n}\tilde{n}} &\approx \frac{x_{i+1,j} - 2x_{i,j} + x_{i-1,j}}{\Delta\tilde{n}^2}, \\ x_{\tilde{w}\tilde{w}} &\approx \frac{x_{i,j+1} - 2x_{i,j} + x_{i,j-1}}{\Delta\tilde{w}^2}. \end{aligned}$$

The cross-partial derivative is computed using

$$x_{\tilde{n}\tilde{w}} \approx \frac{x_{i+1,j+1} - x_{i+1,j-1} - x_{i-1,j+1} + x_{i-1,j-1}}{4\Delta\tilde{n}\Delta\tilde{w}}.$$

At the boundaries where $\tilde{n} = \pm 1$, one-sided finite difference approximations are used.

The boundary conditions imposed in the model are

$$x(\tilde{n}, 0) = 0$$

and

$$x(\tilde{n}, 1) = -\bar{n} - \tilde{n} \frac{5\sigma_n}{\sqrt{2\lambda_n}}.$$

Given the discretized derivatives, the partial differential equation can be written in terms of a residual function

$$\tilde{f}_{i,j}(x, x_{\tilde{n}}, x_{\tilde{w}}, x_{\tilde{n}\tilde{n}}, x_{\tilde{w}\tilde{w}}, x_{\tilde{n}\tilde{w}})$$

evaluated at each grid point (i, j) , where $0 \leq i \leq 200$ and $0 \leq j \leq 1000$. The numerical solution is obtained using an iterative relaxation method that updates the policy function to reduce the PDE residual. Starting from an initial guess for $x(\tilde{n}, \tilde{w})$, the solution at each grid point is updated according to

$$x_{i,j}^{(k+1)} = x_{i,j}^{(k)} - \lambda \tilde{f}_{i,j}^{(k)}(x, x_{\tilde{n}}, x_{\tilde{w}}, x_{\tilde{n}\tilde{n}}, x_{\tilde{w}\tilde{w}}, x_{\tilde{n}\tilde{w}}),$$

where $\lambda = 10^{-5}$ is the relaxation parameter.

The procedure iterates until the maximum absolute residual across the grid satisfies

$$\max_{0 \leq i \leq 200, 0 \leq j \leq 1000} \left| \tilde{f}_{i,j}(x, x_{\tilde{n}}, x_{\tilde{w}}, x_{\tilde{n}\tilde{n}}, x_{\tilde{w}\tilde{w}}, x_{\tilde{n}\tilde{w}}) \right| \leq 10^{-6}.$$

Upon convergence, the resulting function $x(\tilde{n}, \tilde{w})$ provides a numerical approximation to the arbitrageurs' optimal portfolio policy over the state space. ¹

¹The stopping criterion is based on the absolute residual of the discretized PDE. Since the policy function satisfies $x_{i,j} \in [0, 1]$ across the grid, this condition also implies a bound on the relative residual. In particular,

$$\max_{i,j} \frac{|\tilde{f}_{i,j}|}{1 + |x_{i,j}|} \leq 10^{-6},$$

2.5.5 Arbitrageurs' Optimal Portfolio

This subsection presents the quantitative results obtained from solving the boundary value problem (BVP). We first describe the arbitrageurs' optimal portfolio policy and then examine how arbitrageurs respond to noise trader shocks. In equilibrium, the response of arbitrageurs determines how effectively the market absorbs noise trader shocks. Following an intuition similar to Slutsky's equation, the total response can be decomposed into a substitution effect and a wealth effect.

Arbitrageurs' Optimal Portfolio. Figure 2.1 illustrates the arbitrageurs' optimal portfolio x as a function of the transformed noise trader shock $\tilde{n}$ and transformed wealth $\tilde{w}$.

Three main findings emerge from the figure. First, arbitrageurs take positions opposite to those of noise traders. When noise traders are short the home currency (corresponding to a positive noise trader shock n), arbitrageurs take a long position in the home currency (a negative value of x), and vice versa. Second, the ability of arbitrageurs to engage in carry trades depends crucially on their wealth. When arbitrageurs have no wealth, their optimal portfolio is zero because they cannot take positions in the carry trade. In contrast, if arbitrageurs have effectively unlimited

because $|\tilde{f}_{i,j}| \leq 10^{-6}$ and $|x_{i,j}| \in [0, 1]$ everywhere on the grid. Moreover, the relaxation update step

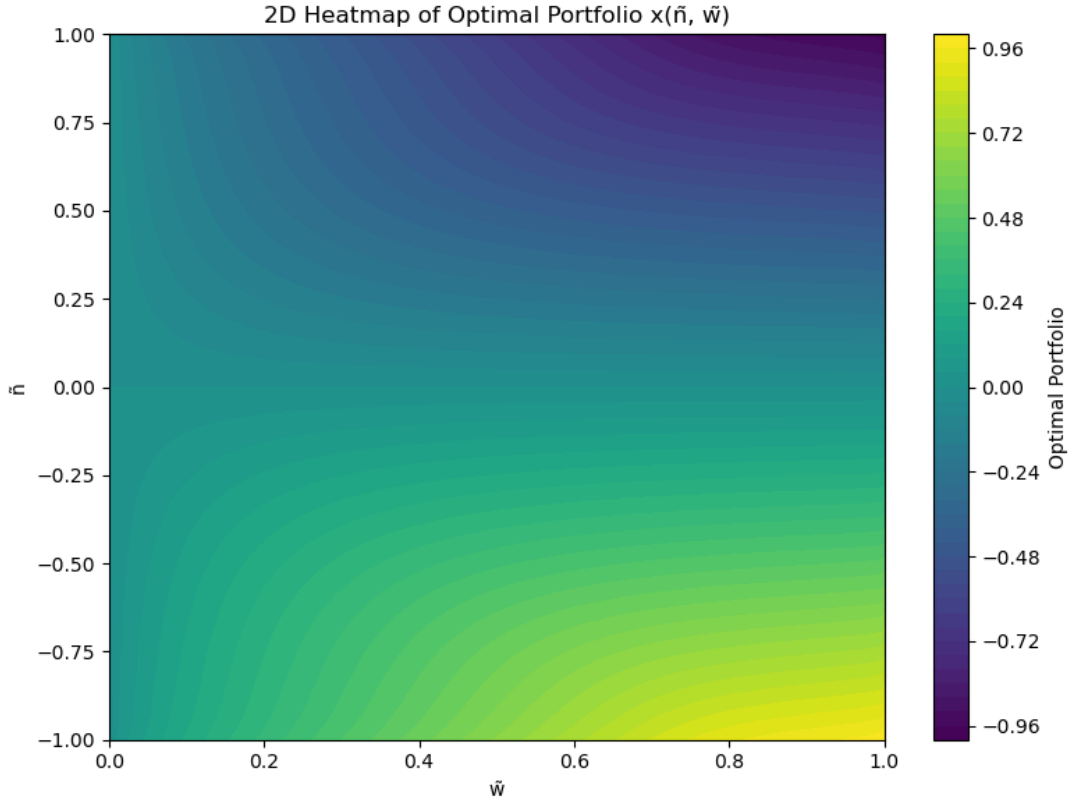
$$x_{i,j}^{(k+1)} = x_{i,j}^{(k)} - \lambda \tilde{f}_{i,j}^{(k)},$$

with relaxation parameter $\lambda = 10^{-5}$, implies that the change in the policy function between successive iterations satisfies

$$|x_{i,j}^{(k+1)} - x_{i,j}^{(k)}| \leq 10^{-5} \times 10^{-6} = 10^{-11}.$$

Therefore, once the residual tolerance is reached, the solution changes only negligibly across further iterations, indicating numerical convergence.

Figure 2.1: 2D heatmap of arbitrageurs' optimal portfolio x

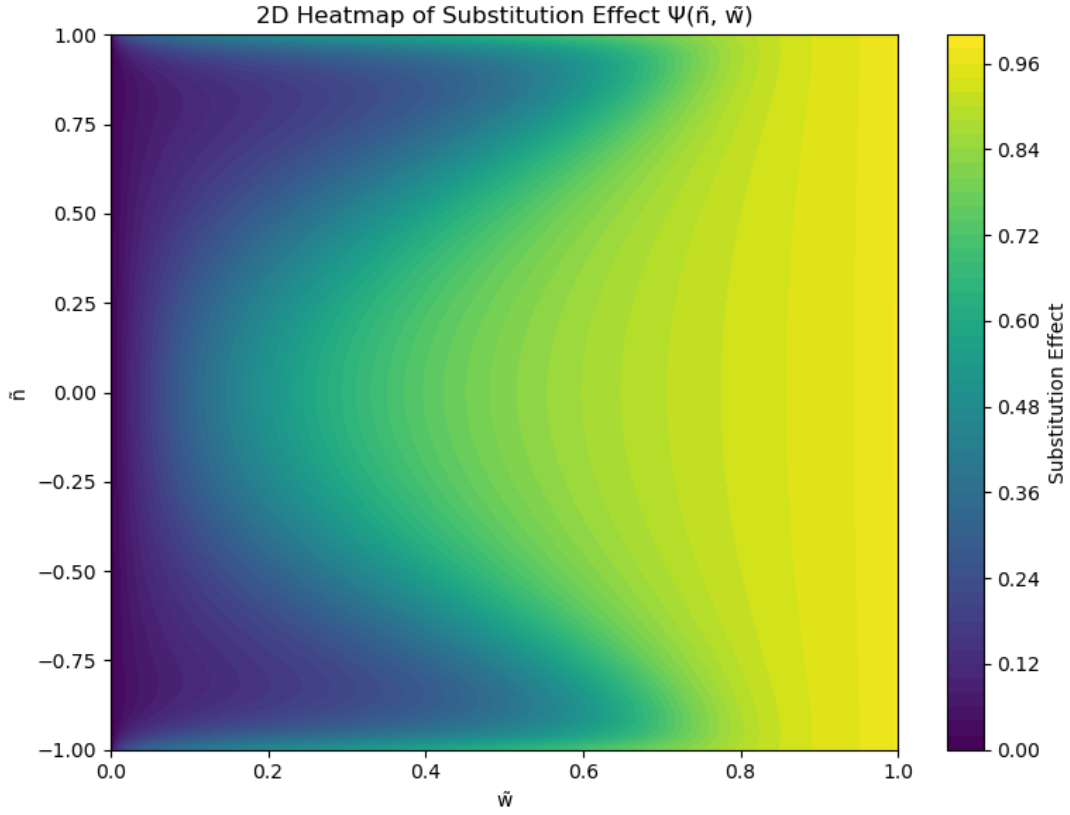


wealth, their optimal portfolio approaches $x = -n$, meaning that they fully absorb the trading flows generated by noise traders. Third, the magnitude of the arbitrageurs' optimal portfolio increases with both the size of the noise trader shock and the level of arbitrageur wealth.

Substitution Effect. Figure 2.2 shows the substitution effect Ψ across the state space. The substitution effect is defined as

$$\Psi = -\frac{\partial x}{\partial n}.$$

Figure 2.2: 2D heatmap of the substitution effect Ψ

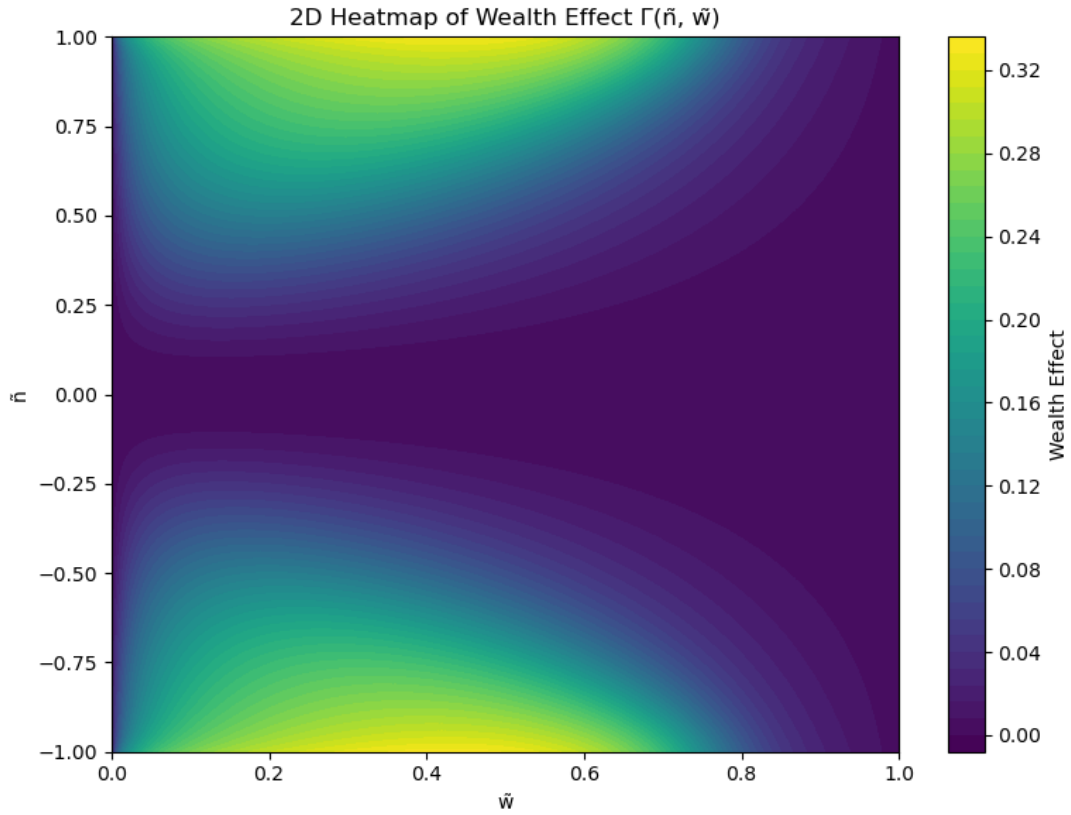


It measures how strongly arbitrageurs adjust their portfolio positions in response to changes in noise trader demand.

The substitution effect increases monotonically with arbitrageur wealth. Importantly, the substitution effect is always positive, reflecting the fact that arbitrageurs consistently take positions opposite to those of noise traders. In other words, arbitrageurs are always willing to “bet” against noise trader demand. However, their ability to do so depends on their available wealth. When arbitrageurs have no wealth, they cannot take positions, and the substitution effect is therefore zero. As arbi-

trageur wealth increases, they become increasingly capable of absorbing noise trader shocks, and the substitution effect approaches one. The substitution effect varies only slightly with the noise trader shock $\tilde{n}$, indicating that it is primarily driven by the wealth of arbitrageurs rather than the size of the shock.

Figure 2.3: 2D heatmap of the wealth effect Γ



Wealth Effect. Figure 2.3 presents the wealth effect Γ , defined as

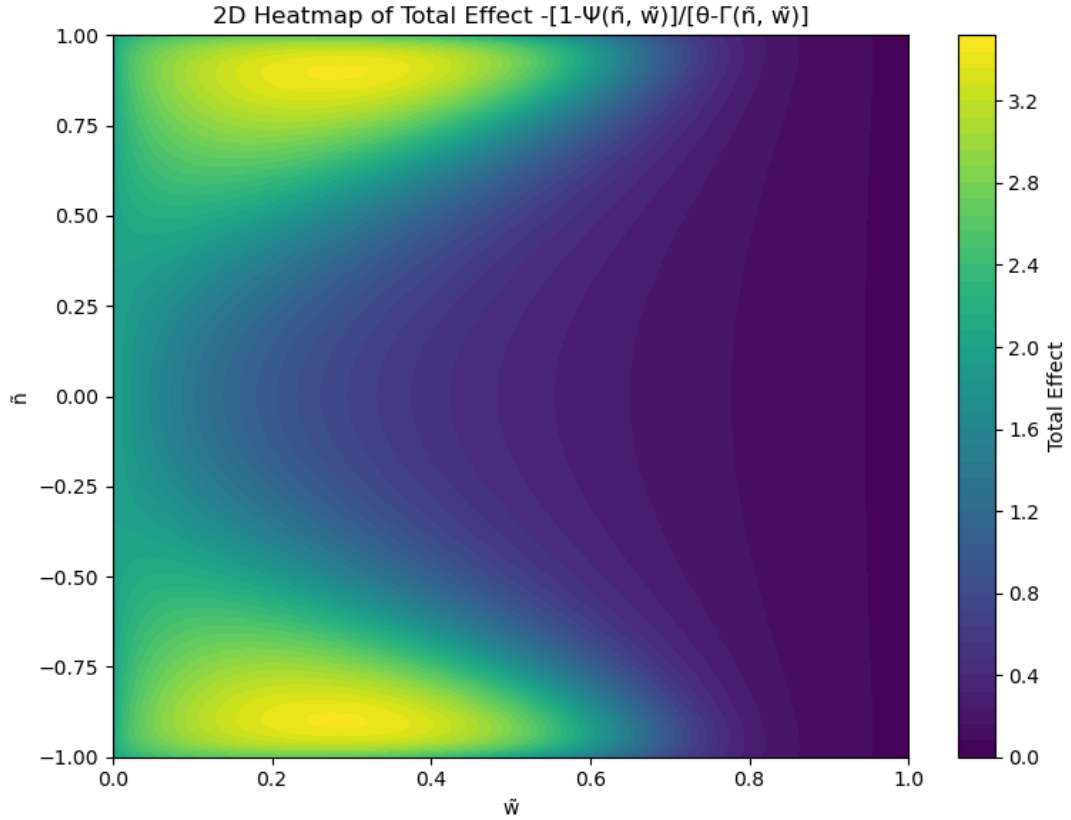
$$\Gamma = \frac{\partial x}{\partial w} x.$$

The wealth effect captures how changes in arbitrageur wealth influence their portfolio

positions.

The wealth effect depends on two components: the size of the carry trade position x and the marginal sensitivity of the portfolio to wealth, $\partial x/\partial w$. It is strongest when noise trader shocks are large in magnitude, which leads to a large portfolio position x , and when arbitrageur wealth is at an intermediate level, where the marginal sensitivity $\partial x/\partial w$ remains high. As arbitrageur wealth becomes very large, the marginal sensitivity declines, since additional wealth has a diminishing impact on the optimal portfolio choice.

Figure 2.4: 2D heatmap of the total effect $-(1 - \Psi)/(\theta - \Gamma)$



Total Effect. Figure 2.4 illustrates the total effect,

$$-\frac{1 - \Psi}{\theta - \Gamma},$$

which measures how effectively arbitrageurs absorb noise trader shocks in equilibrium.

A total effect of zero implies that arbitrageurs can fully absorb noise trader shocks, which occurs when arbitrageur wealth becomes sufficiently large. A total effect between zero and one implies that arbitrageurs stabilize the foreign exchange market by dampening exchange rate volatility. In contrast, a total effect greater than one implies that arbitrageurs amplify market volatility and therefore destabilize the foreign exchange market.

As shown in Figure 2.4, destabilizing dynamics may arise when arbitrageur wealth is relatively low and noise trader shocks are large. In such circumstances, arbitrageurs are unable to absorb market imbalances, potentially creating a role for central bank intervention to stabilize the foreign exchange market. This situation is more likely to occur in emerging market economies, where arbitrage capital is relatively limited. By contrast, when arbitrageur wealth is high and noise trader shocks are moderate, arbitrageurs absorb shocks more effectively and help stabilize the market. This situation is more typical of advanced economies. Policy implications of these results are discussed in the next section. At high levels of arbitrageur wealth, the substitution effect dominates, keeping the total effect close to its maximum stabilizing value.

2.5.6 Impulse Responses

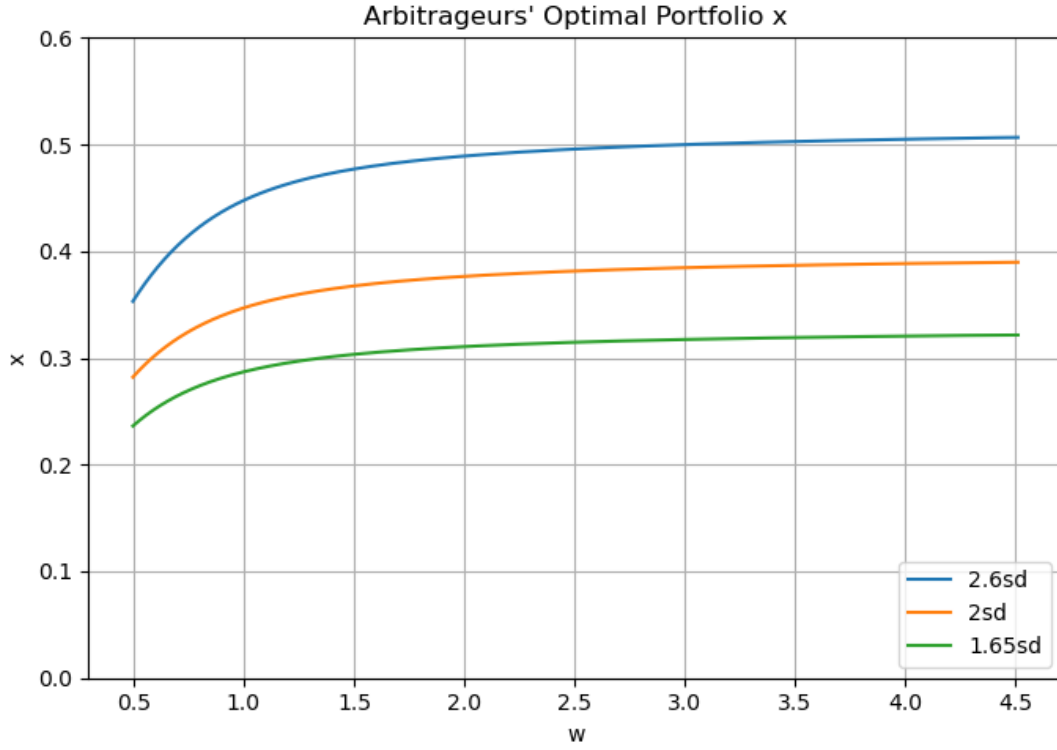
In this subsection, we study the impact of noise trader shocks on arbitrageurs' optimal portfolio x and the gap between the exchange rate and its UIP-consistent level, $s - \tilde{s}$. We focus on how these effects vary across different levels of arbitrageur wealth and over time.

Impulse Responses across Wealth. We first examine the impact of three negative noise trader shocks, $\tilde{n} = -0.33, -0.4, -0.52$, on arbitrageurs' optimal portfolio x and the deviation of the exchange rate from its UIP-consistent level, $s - \tilde{s}$. These shocks correspond to 1.65, 2, and 2.6 standard deviations, representing the 90%, 95%, and 99% percentiles, respectively.

Figure 2.5 plots the arbitrageurs' optimal portfolio x as a function of their wealth w , ranging from 0.5 to 4.5, corresponding to transformed wealth $\tilde{w}$ between 0.393 and 0.989. Arbitrageurs take long positions in the carry trade, partially offsetting the positions of noise traders. Across all wealth levels, their positions remain smaller in magnitude than the corresponding noise trader shocks. The optimal portfolio is strictly increasing in wealth, indicating that wealthier arbitrageurs absorb a larger share of the shock. When wealth is low, around $w = 0.5$, arbitrageurs absorb approximately 70% of the shock. When wealth exceeds $w = 4$, they nearly fully offset it.

Figure 2.6 illustrates the deviation $s - \tilde{s}$ as a function of arbitrageur wealth over the same range. Because arbitrageurs only partially absorb the shocks, the foreign currency faces excess selling pressure, leading to depreciation in all cases. Although incomplete absorption always results in depreciation, the magnitude varies substan-

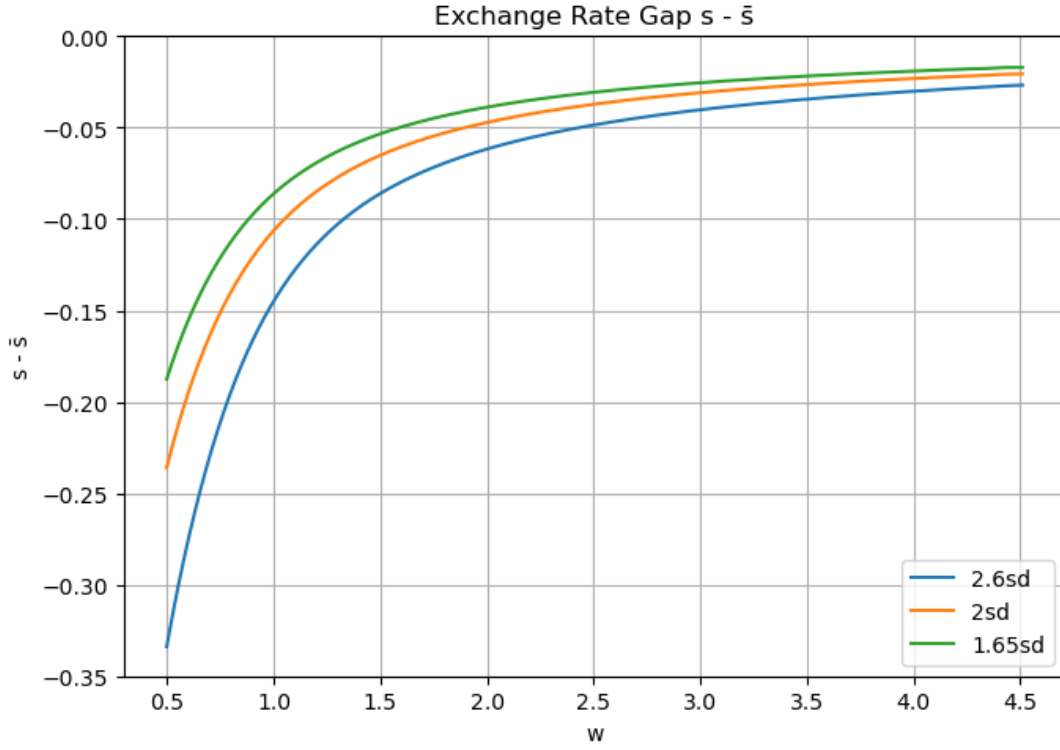
Figure 2.5: Arbitrageurs' optimal portfolio x across wealth levels



tially. It increases with the size of the noise trader shock and decreases with arbitrageur wealth. For example, following a two-standard-deviation negative shock, the exchange rate depreciates by approximately 23% when wealth is low, around $w = 0.5$, but only by about 2–3% when wealth exceeds $w = 4$. For a fixed wealth level of $w = 1$, shocks of 1.65, 2, and 2.6 standard deviations generate depreciations of roughly 8%, 11%, and 14%, respectively.

Impulse Responses over Time. We next examine the dynamic impact of a two-standard-deviation negative noise trader shock, $\tilde{n} = -0.4$, on arbitrageurs' optimal portfolio x and the exchange rate deviation $s - \tilde{s}$ over a horizon of 30 years. We

Figure 2.6: Exchange rate gap $s - \bar{s}$ across wealth levels

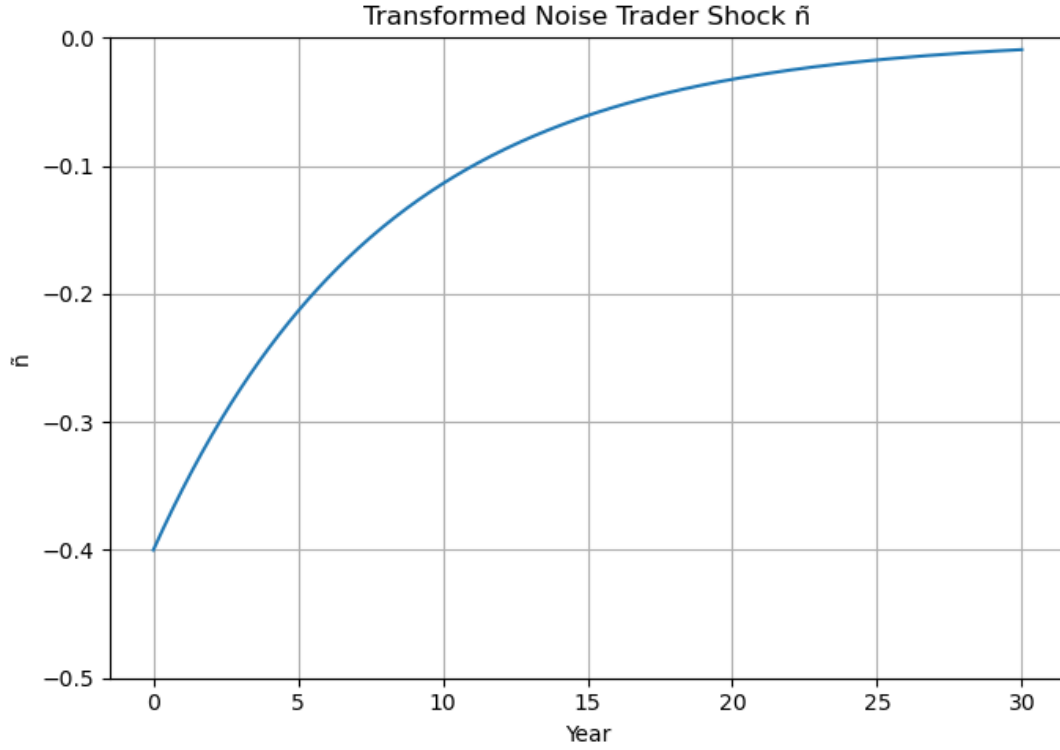


first describe the evolution of the shock itself, and then study its effects under three initial wealth levels, $w_0 = 0.5, 1, 2$.²

Figure 2.7 shows the path of the shock $\tilde{n} = -0.4$ from year 0 to year 30. The shock decays over time because it follows the Ornstein–Uhlenbeck process described

²For simplicity, this analysis considers a single noise trader shock and treats initial wealth as given. In this partial equilibrium setting, arbitrageur wealth declines over time as the shock dissipates and consumption dominates carry trade gains. A more complete approach would simulate a sequence of shocks to obtain the long-run equilibrium distribution of arbitrageur wealth, which depends on the volatility of noise trader shocks σ_n . Impulse responses could then be derived by varying σ_n in a general equilibrium framework.

Figure 2.7: Transformed noise trader shock $\tilde{n}$ over time



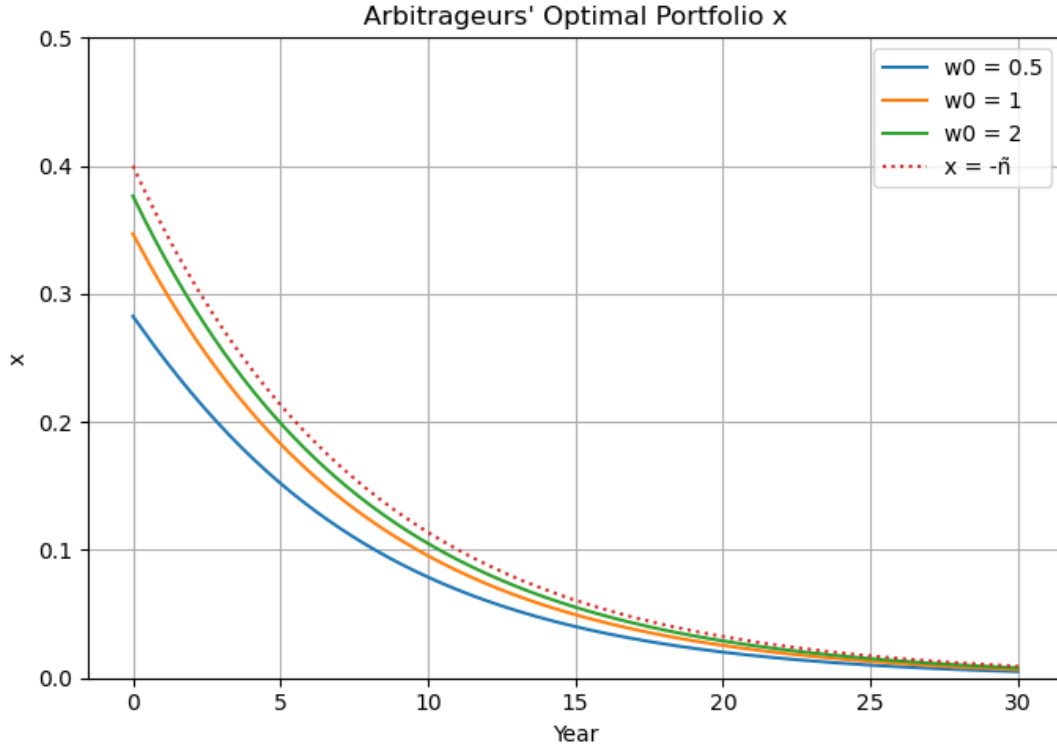
in Equation (2.1). With $\lambda_n = 0.125$, the implied half-life is

$$\frac{\log 2}{\lambda_n} = \frac{\log 2}{0.125} \approx 5.5 \text{ years},$$

which is consistent with Figure 2.7, where the magnitude of the noise trader shock declines from -0.4 to approximately -0.2 around years 5-6.

Figure 2.8 plots the evolution of arbitrageurs' optimal portfolio x over time under the three initial wealth levels. Arbitrageurs take long positions in the carry trade, partially offsetting noise trader positions. The optimal portfolio is increasing in wealth at all times. However, for all wealth levels and at every point in time, the position

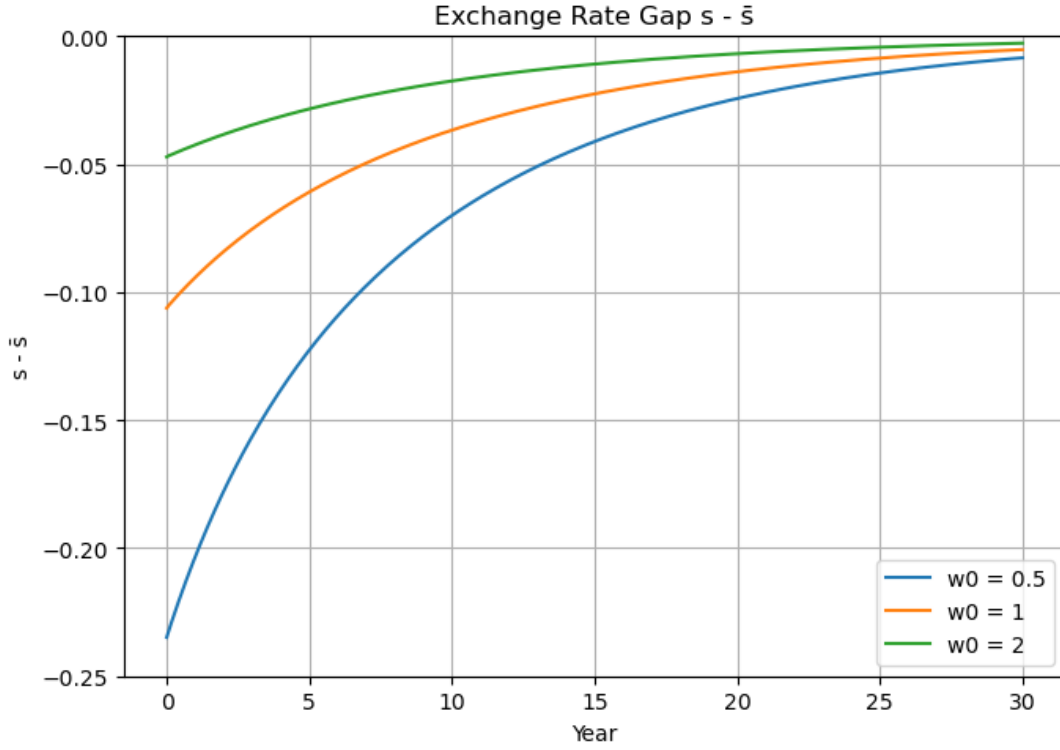
Figure 2.8: Arbitrageurs' optimal portfolio x over time



remains smaller in magnitude than the noise trader shock. In year 0, following the shock $\tilde{n} = -0.4$, the optimal portfolio is approximately 0.28, 0.35, and 0.38 for initial wealth levels of 0.5, 1, and 2, respectively. The ordering of the lines reflects this pattern: the lowest wealth level lies below the higher wealth levels, and all remain below the red dotted line corresponding to full absorption. As the shock decays to zero, the optimal portfolio gradually converges to zero.

Figure 2.9 plots the exchange rate gap $s - \tilde{s}$ over time under the same initial wealth levels. Because arbitrageurs only partially absorb the shock at all times, the foreign currency experiences persistent selling pressure and depreciates throughout the ad-

Figure 2.9: Exchange rate gap $s - \tilde{s}$ over time



justment process. The magnitude of depreciation depends on both the size of the shock and the level of arbitrageur wealth. For example, immediately after the shock, the exchange rate depreciates by about 23% when $w = 0.5$, around 11% when $w = 1$, and slightly below 5% when $w = 2$. At every point in time, lower wealth is associated with larger deviations from the UIP-consistent level. As the noise trader shock decays, the exchange rate gap gradually closes and converges to zero.

2.6 Policy Implications

This section discusses the policy implications of the model for foreign exchange intervention.

When a central bank intervenes in the foreign exchange market, it buys or sells foreign currency in an amount f . The market-clearing condition for the foreign exchange market in Equation (2.5) becomes:

$$b + n + x + f = 0, \quad (2.29)$$

which implies, using Equation (2.6),

$$f + n + x = \theta(s - \tilde{s}). \quad (2.30)$$

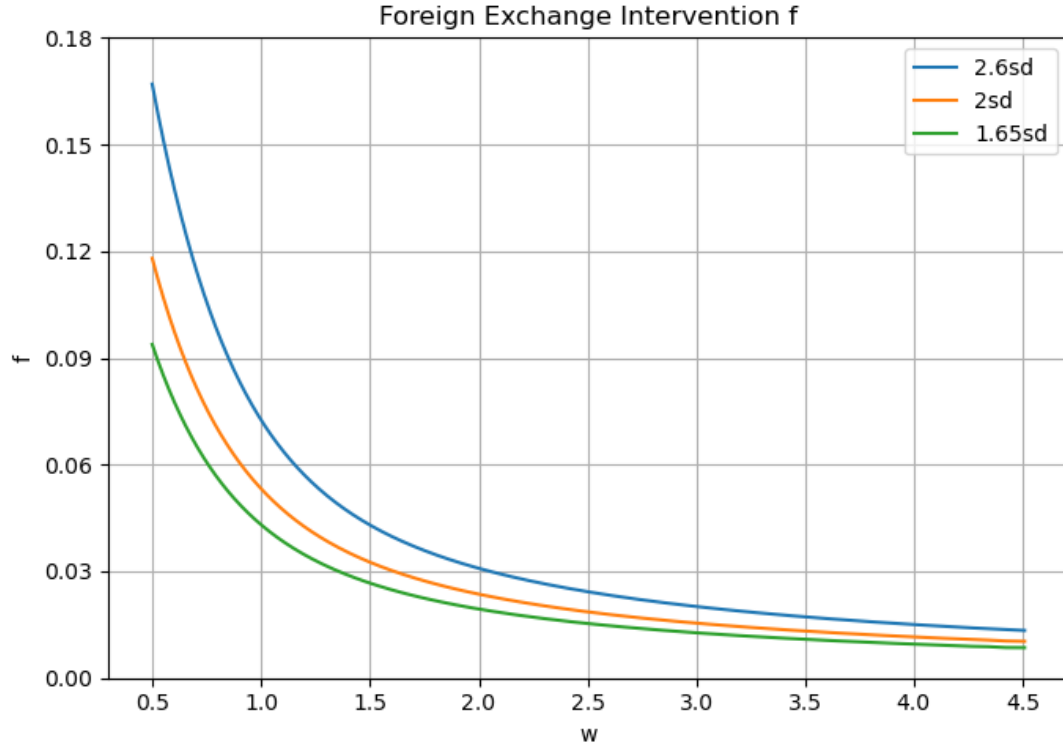
To maintain the exchange rate at its UIP-consistent level, that is, to set $s = \tilde{s}$, the central bank must absorb the portion of the noise trader shock that is not absorbed by arbitrageurs:

$$f = -n - x. \quad (2.31)$$

The scale of the required foreign exchange intervention therefore depends directly on the share of the noise trader shock that remains unabsorbed by arbitrageurs.

Figure 2.10 plots the level of foreign exchange intervention required to restore UIP, f , as a function of arbitrageurs' wealth w , ranging from 0.5 to 4.5, corresponding to transformed wealth $\tilde{w}$ between 0.393 and 0.989. The required intervention increases with the magnitude of the noise trader shock and decreases with arbitrageur wealth, reflecting the extent of unabsorbed shocks. For example, following a two-standard-

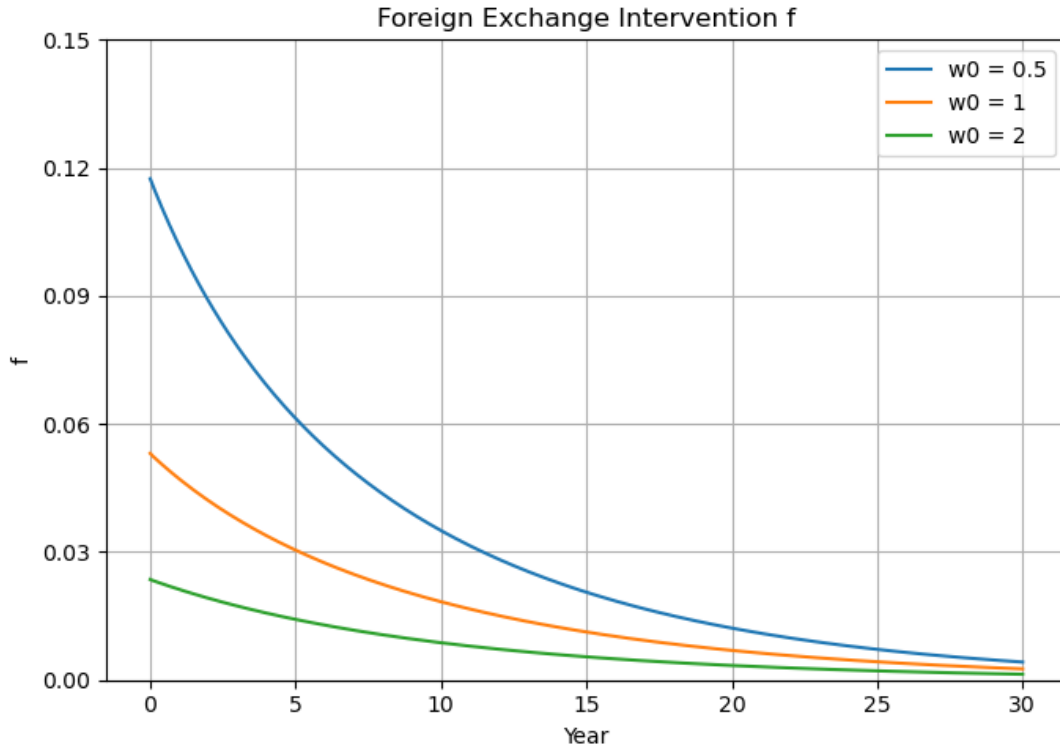
Figure 2.10: Foreign exchange intervention f across wealth levels



deviation negative noise trader shock, the required intervention under low arbitrageur wealth ($w = 0.5$) is approximately eight times larger than under high wealth ($w = 4$), declining from about 0.12 to 0.015.

Figure 2.11 plots the time path of the foreign exchange intervention required to restore UIP under the same initial wealth levels. Because arbitrageurs only partially absorb the shock at all times, the foreign currency is subject to persistent selling pressure and depreciates throughout the adjustment process. The required intervention depends on both the size of the shock and the level of arbitrageur wealth. Immediately after the shock, the required intervention is approximately 0.12 when

Figure 2.11: Foreign exchange intervention f over time



$w = 0.5$, about 0.05 when $w = 1$, and slightly above 0.02 when $w = 2$. At every point in time, lower wealth is associated with greater intervention needs. As the noise trader shock decays, the required intervention gradually declines and converges to zero.

This framework provides a natural explanation for the well-documented observation that central banks in emerging market economies intervene more frequently and on a larger scale than those in advanced economies. Advanced economies typically feature deeper and more liquid foreign exchange markets, with greater arbitrageur capital available to absorb noise trader shocks, thereby reducing the need for official

intervention. In contrast, emerging market economies are characterized by thinner markets and lower arbitrageur wealth, which leads to larger deviations from UIP and higher intervention requirements. The model suggests that this asymmetry arises not only from differences in shock magnitudes, but also from structural differences in the depth of arbitrageur capital.

As illustrated in Figure 2.10, even modest increases in arbitrageur wealth can substantially reduce intervention needs. For example, in an economy with low arbitrageur wealth ($w = 0.5$), increasing wealth by 50% to $w = 0.75$ reduces the required intervention f by approximately 40%. From a policy perspective, fostering deeper foreign exchange markets and expanding arbitrageur capital can significantly reduce reliance on foreign exchange intervention as a tool for exchange rate stabilization.

2.7 Conclusions

This chapter develops a continuous-time model to analyze how fluctuations in arbitrageurs' wealth shape exchange rate dynamics and stability in foreign exchange markets. The model features noise traders, whose stochastic positions generate deviations from uncovered interest parity, and arbitrageurs who exploit carry trade opportunities. The key innovation is the explicit treatment of the wealth effect—the feedback from exchange rate movements to arbitrageurs' realized returns, and from there to their portfolio choices and back to the exchange rate.

The equilibrium analysis shows that the substitution effect and the wealth effect operate in opposite directions. The substitution effect is stabilizing: as arbitrageurs absorb noise trader shocks, it dampens exchange rate volatility and reduces UIP

deviations, enhancing market efficiency. The wealth effect is destabilizing: losses incurred by arbitrageurs reduce their capacity to absorb shocks, amplifying exchange rate volatility and widening UIP deviations. These two forces are analogous to the substitution and wealth effects in Slutsky's Equation.

The relative strength of these two effects depends on the level of arbitrageur wealth. In normal times or in economies with deep and broad foreign exchange markets—as in advanced economies—the substitution effect dominates the wealth effect, and markets remain relatively stable. In crisis times or in economies with thin markets and limited arbitrageur capital—as in emerging market economies—the wealth effect can become dominant, amplifying exchange rate devaluations and increasing market instability. The quantitative experiments demonstrate that arbitrageurs can amplify the impact of noise trader shocks by as much as $2.7\times$ when FX elasticity is high and arbitrageur wealth is limited.

These findings have direct implications for foreign exchange intervention policy. The required scale and frequency of intervention increase when arbitrageur wealth is low, noise trader shocks are large or persistent, and FX elasticity is high. This provides a structural explanation for the observation that central banks of emerging market economies intervene more frequently and at greater scale than their advanced economy counterparts. Policies that support the development of deeper foreign exchange markets—expanding the base of arbitrageur capital—can reduce the need for official intervention and improve exchange rate stability.

Several directions for future research emerge from this analysis. First, extending the model to incorporate an endogenous policy response by the central bank—where the

intervention rule itself is optimized—would provide richer guidance for policymakers. Second, introducing heterogeneous arbitrageurs with different wealth levels and risk tolerances could capture realistic distributional dynamics in arbitrageur capital. Third, empirically estimating the substitution and wealth effects using micro-level data on arbitrageur positions and wealth would allow a direct quantitative assessment of the mechanism identified in this chapter.

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Appendix

A Derivation of the Arbitrageur's Optimal Consumption

Substituting Equation (2.9) into Equation (2.3),

$$\begin{aligned} dw &= x[\mu_q(n, w) dt + \sigma_{q,n}(n, w) dz_n + \sigma_{q,\bar{s}}(n, w) dz_{\bar{s}}] + (iw - c) dt \\ &= [x\mu_q(n, w) + (iw - c)] dt + x\sigma_{q,n}(n, w) dz_n + x\sigma_{q,\bar{s}}(n, w) dz_{\bar{s}}. \end{aligned} \quad (\text{A1})$$

Therefore, the arbitrageur's problem can be rewritten as:

$$J(n, w) = \max_{x, c} \mathbb{E} \int_0^{+\infty} e^{-\rho t} \log c dt, \quad (2.2)$$

subject to

$$dw = [x\mu_q(n, w) + (iw - c)] dt + x\sigma_{q,n}(n, w) dz_n + x\sigma_{q,\bar{s}}(n, w) dz_{\bar{s}}. \quad (\text{A1})$$

The Hamilton–Jacobi–Bellman (HJB) equation is:

$$\begin{aligned} \rho J(n, w) = \max_{x, c} \Big\{ & \log c + \frac{\partial J}{\partial w} [x\mu_q(n, w) + (iw - c)] + \frac{1}{2} \frac{\partial^2 J}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] \\ & + \frac{\partial J}{\partial n} [-\lambda_n(n - \tilde{n})] + \frac{1}{2} \frac{\partial^2 J}{\partial n^2} \sigma_n^2 \Big\}. \end{aligned} \quad (\text{A2})$$

Guess and verify:

$$J(n, w) = J_0(n) + \kappa \log w. \quad (\text{A3})$$

The first-order condition of the HJB equation with respect to consumption c is:

$$\frac{1}{c} = \frac{\partial J(n, w)}{\partial w}. \quad (\text{A4})$$

By Equations (A3) and (A4),

$$c = \frac{w}{\kappa}. \quad (\text{A5})$$

Substituting Equations (A3) and (A5) into the HJB equation:

$$\begin{aligned} \rho[J_0(n) + \kappa \log w] &= \log w - \log \kappa + \frac{\kappa}{w} \left[x\mu_q(n, w) + \left(iw - \frac{w}{\kappa} \right) \right] \\ &+ \frac{1}{2} \left(-\frac{\kappa}{w^2} \right) x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] \\ &+ \frac{\partial J_0(n)}{\partial n} [-\lambda_n(n - \tilde{n})] + \frac{1}{2} \frac{\partial^2 J_0(n)}{\partial n^2} \sigma_n^2 n^2. \end{aligned} \quad (\text{A6})$$

By matching the terms involving $\log w$,

$$\kappa = \frac{1}{\rho}. \quad (\text{A7})$$

Then, by Equation (A5), the optimal consumption is:

$$c = \rho w. \quad (2.10)$$

B Derivation of the Arbitrageur's Optimal Portfolio

The first-order condition of the HJB equation with respect to portfolio x is:

$$\frac{\partial J(n, w)}{\partial w} \mu_q(n, w) = -\frac{\partial^2 J(n, w)}{\partial w^2} x [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)]. \quad (\text{B1})$$

Using the guess for the value function specified in Equation (A3), Equation (B1) becomes:

$$\frac{\kappa}{w} \mu_q(n, w) = \frac{\kappa}{w^2} x [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)]. \quad (\text{B2})$$

Therefore, the arbitrageur's optimal portfolio is:

$$x = \frac{\mu_q(n, w)}{\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)} w. \quad (2.11)$$

C Derivation of the Carry Trade Return

Substituting Equation (2.10) into Equation (2.3),

$$dw = x dq + (i - \rho)w dt. \quad (\text{C1})$$

Substituting Equation (2.4) into Equation (C1),

$$\begin{aligned} dw &= x[ds + (i^* - i) dt] + (i - \rho)w dt \\ &= x ds + [x(i^* - i) + (i - \rho)w] dt. \end{aligned} \quad (\text{C2})$$

Substituting Equation (2.7) into Equation (2.8),

$$ds = -\frac{1}{\theta} db - (i^* - i) dt + \sigma_{\bar{s}} dz_{\bar{s}}. \quad (\text{C3})$$

Then, by the market clearing condition in Equation (2.5),

$$db = -dx - dn. \quad (\text{C4})$$

Substituting Equation (C4) into Equation (C3),

$$ds = \frac{1}{\theta}(dx + dn) - (i^* - i) dt + \sigma_{\bar{s}} dz_{\bar{s}}. \quad (\text{C5})$$

Plugging Equation (C5) into Equation (C2),

$$dw = \frac{x}{\theta}(dx + dn) + x\sigma_{\bar{s}} dz_{\bar{s}} + (i - \rho)w dt. \quad (\text{C6})$$

By applying Itô's Lemma to the arbitrageur's optimal portfolio x in Equation (2.11),

$$dx = \frac{\partial x}{\partial n} dn + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \mathbb{E}(dn)^2 + \frac{\partial x}{\partial w} dw + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} \mathbb{E}(dw)^2 + \frac{\partial^2 x}{\partial w \partial n} \mathbb{E}(dw dn). \quad (\text{C7})$$

By substituting Equation (C1) into Equation (C7),

$$\begin{aligned}
dx = & \frac{\partial x}{\partial n} dn + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \mathbb{E}(dn)^2 + \frac{\partial x}{\partial w} x dq + \frac{\partial x}{\partial w} (i - \rho) w dt \\
& + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] dt + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n dt. \quad (C8)
\end{aligned}$$

By substituting Equation (C8) into Equation (C5),

$$\begin{aligned}
ds = & \frac{1}{\theta} \left\{ \left(1 + \frac{\partial x}{\partial n} \right) dn + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \mathbb{E}(dn)^2 + \frac{\partial x}{\partial w} x dq + \frac{\partial x}{\partial w} (i - \rho) w dt \right. \\
& \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] dt + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n dt \right\} - (i^* - i) dt + \sigma_{\bar{s}} dz_{\bar{s}}. \quad (C9)
\end{aligned}$$

By substituting Equation (2.1) into Equation (C9),

$$\begin{aligned}
ds = & \frac{1}{\theta} \left\{ \left(1 + \frac{\partial x}{\partial n} \right) [-\lambda_n(n - \tilde{n}) dt + \sigma_n dz_n] + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 dt + \frac{\partial x}{\partial w} x dq + \frac{\partial x}{\partial w} (i - \rho) w dt \right. \\
& \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] dt + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n dt \right\} - (i^* - i) dt + \sigma_{\bar{s}} dz_{\bar{s}}. \quad (C10)
\end{aligned}$$

Therefore, by substituting Equation (C10) into Equation (2.4),

$$\begin{aligned}
dq &= \frac{1}{\theta} \left\{ \left(1 + \frac{\partial x}{\partial n} \right) [-\lambda_n(n - \tilde{n}) dt + \sigma_n dz_n] + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 dt + \frac{\partial x}{\partial w} x dq + \frac{\partial x}{\partial w} (i - \rho) w dt \right. \\
&\quad \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] dt + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n dt \right\} + \sigma_{\bar{s}} dz_{\bar{s}} \\
&= \frac{1}{\theta} \frac{\partial x}{\partial w} x dq + \frac{1}{\theta} \left\{ \left(1 + \frac{\partial x}{\partial n} \right) [-\lambda_n(n - \tilde{n}) dt + \sigma_n dz_n] + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 dt + \frac{\partial x}{\partial w} (i - \rho) w dt \right. \\
&\quad \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] dt + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n dt \right\} + \sigma_{\bar{s}} dz_{\bar{s}}.
\end{aligned}$$

Collecting and moving terms with dq to the left-hand side,

$$\begin{aligned}
\left(1 - \frac{1}{\theta} \frac{\partial x}{\partial w} x \right) dq &= \frac{1}{\theta} \left\{ \left(1 + \frac{\partial x}{\partial n} \right) [-\lambda_n(n - \tilde{n})] + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \\
&\quad \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right\} dt \\
&\quad + \frac{1}{\theta} \left(1 + \frac{\partial x}{\partial n} \right) \sigma_n dz_n + \sigma_{\bar{s}} dz_{\bar{s}}.
\end{aligned}$$

Therefore,

$$\begin{aligned}
dq &= \frac{1/\theta}{1 - \frac{1}{\theta} \frac{\partial x}{\partial w} x} \left\{ \left(1 + \frac{\partial x}{\partial n}\right) [-\lambda_n(n - \tilde{n})] + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \\
&\quad \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right\} dt \\
&\quad + \frac{(1/\theta)(1 + \frac{\partial x}{\partial n})}{1 - \frac{1}{\theta} \frac{\partial x}{\partial w} x} \sigma_n dz_n + \frac{1}{1 - \frac{1}{\theta} \frac{\partial x}{\partial w} x} \sigma_{\bar{s}} dz_{\bar{s}} \\
&= \frac{1}{\theta - \frac{\partial x}{\partial w} x} \left\{ \left(1 + \frac{\partial x}{\partial n}\right) [-\lambda_n(n - \tilde{n})] + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \\
&\quad \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right\} dt \\
&\quad + \frac{1 + \frac{\partial x}{\partial n}}{\theta - \frac{\partial x}{\partial w} x} \sigma_n dz_n + \frac{\theta}{\theta - \frac{\partial x}{\partial w} x} \sigma_{\bar{s}} dz_{\bar{s}}. \tag{C11}
\end{aligned}$$

Define

$$\Gamma(n, w) = \frac{\partial x}{\partial w} x \tag{2.15}$$

as the wealth effect and

$$\Psi(n, w) = \frac{\partial x}{\partial(-n)} = -\frac{\partial x}{\partial n} \tag{2.16}$$

as the substitution effect. Then, the drift and diffusion in the carry trade return process are:

$$\begin{aligned}
\mu_q(n, w) &= \frac{1}{\theta - \Gamma(n, w)} \left\{ (1 - \Psi(n, w)) [-\lambda_n(n - \tilde{n})] + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \\
&\quad \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 [\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)] + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right\}, \tag{2.12}
\end{aligned}$$

$$\sigma_{q,n}(n, w) = \frac{1}{\theta - \Gamma(n, w)} (1 - \Psi(n, w)) \sigma_n, \quad (2.13)$$

$$\sigma_{q,\bar{s}}(n, w) = \frac{\theta}{\theta - \Gamma(n, w)} \sigma_{\bar{s}}, \quad (2.14)$$

respectively.

D Derivation of the Exchange Rate Process

By Equation (2.4),

$$ds = dq - (i^* - i) dt. \quad (D1)$$

Substituting Equation (2.9) into Equation (D1),

$$\begin{aligned} ds &= \mu_q(n, w) dt + \sigma_{q,n}(n, w) dz_n + \sigma_{q,\bar{s}}(n, w) dz_{\bar{s}} - (i^* - i) dt \\ &= [\mu_q(n, w) - (i^* - i)] dt + \sigma_{q,n}(n, w) dz_n + \sigma_{q,\bar{s}}(n, w) dz_{\bar{s}}. \end{aligned} \quad (D2)$$

Then, substituting Equations (2.12), (2.13), and (2.14) into Equation (D2), the drift and diffusion in the exchange rate return process are:

$$\begin{aligned} \mu_s(n, w) &= \mu_q(n, w) - (i^* - i) \\ &= \frac{1}{1 - \frac{1}{\theta}\Gamma(n, w)} \left\{ \frac{\Gamma(n, w)}{\theta} (i^* - i) + \frac{1}{\theta} \left[(1 - \Psi(n, w)) \lambda_n(n - \bar{n}) + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 \right. \right. \\ &\quad \left. \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 \sigma_q^2(n, w) + \frac{\partial^2 x}{\partial w \partial n} x \sigma_q(n, w) \sigma_n \right] \right\}, \end{aligned} \quad (2.18)$$

$$\sigma_{s,n}(n, w) = \sigma_{q,n}(n, w) = \frac{\frac{1}{\theta}(1 - \Psi(n, w))}{1 - \frac{1}{\theta}\Gamma(n, w)} \sigma_n, \quad (2.19)$$

$$\sigma_{s,\tilde{s}}(n, w) = \sigma_{q,\tilde{s}}(n, w) = \frac{\frac{1}{\theta}}{1 - \frac{1}{\theta}\Gamma(n, w)} \sigma_{\tilde{s}}, \quad (2.20)$$

respectively, where $\Gamma(n, w)$ and $\Psi(n, w)$ are the wealth and substitution effects defined in Equations (2.15) and (2.16) respectively.

E Derivation of the Arbitrageur's Wealth Accumulation

Substituting the arbitrageur's optimal consumption derived from Equation (2.10) into the arbitrageur's wealth dynamics specified in Equation (A1),

$$dw = [x\mu_q(n, w) + (i - \rho)w] dt + x\sigma_q(n, w) dz_n. \quad (E1)$$

Then,

$$\frac{dw}{w} = \left[\frac{x}{w} \mu_q(n, w) + (i - \rho) \right] dt + \frac{x}{w} \sigma_q(n, w) dz_n. \quad (E2)$$

Plugging in the arbitrageur's optimal portfolio derived from Equation (2.11),

$$\frac{dw}{w} = \left[\frac{\mu_q^2(n, w)}{\sigma_q^2(n, w)} + (i - \rho) \right] dt + \frac{\mu_q(n, w)}{\sigma_q(n, w)} dz_n. \quad (E3)$$

Therefore, the arbitrageur's wealth process is:

$$\frac{dw}{w} = \mu_w(n, w) dt + \sigma_{w,n}(n, w) dz_n + \sigma_{w,\tilde{s}}(n, w) dz_{\tilde{s}}, \quad (2.21)$$

where

$$\begin{aligned} \mu_w(n, w) = i - \rho + \frac{1}{\left[\frac{1}{\theta}(1 - \Psi(n, w))\right]^2 \sigma_n^2 + \left(\frac{1}{\theta}\right)^2 \sigma_{\bar{s}}^2} \\ \times \left\{ i^* - i + \frac{1}{\theta} \left[(1 - \Psi(n, w)) \lambda_n (n - \bar{n}) + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \right. \\ \left. \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 (\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)) + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right] \right\}^2, \quad (2.22) \end{aligned}$$

$$\begin{aligned} \sigma_{w,n}(n, w) = \frac{\frac{1}{\theta}(1 - \Psi(n, w)) \sigma_n}{\left[\frac{1}{\theta}(1 - \Psi(n, w))\right]^2 \sigma_n^2 + \left(\frac{1}{\theta}\right)^2 \sigma_{\bar{s}}^2} \\ \times \left\{ i^* - i + \frac{1}{\theta} \left[(1 - \Psi(n, w)) \lambda_n (n - \bar{n}) + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \right. \\ \left. \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 (\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)) + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right] \right\}, \quad (2.23) \end{aligned}$$

$$\begin{aligned} \sigma_{w,\bar{s}}(n, w) = \frac{\frac{1}{\theta} \sigma_{\bar{s}}}{\left[\frac{1}{\theta}(1 - \Psi(n, w))\right]^2 \sigma_n^2 + \left(\frac{1}{\theta}\right)^2 \sigma_{\bar{s}}^2} \\ \times \left\{ i^* - i + \frac{1}{\theta} \left[(1 - \Psi(n, w)) \lambda_n (n - \bar{n}) + \frac{1}{2} \frac{\partial^2 x}{\partial n^2} \sigma_n^2 + \frac{\partial x}{\partial w} (i - \rho) w \right. \right. \\ \left. \left. + \frac{1}{2} \frac{\partial^2 x}{\partial w^2} x^2 (\sigma_{q,n}^2(n, w) + \sigma_{q,\bar{s}}^2(n, w)) + \frac{\partial^2 x}{\partial w \partial n} x \sigma_{q,n}(n, w) \sigma_n \right] \right\}, \quad (2.24) \end{aligned}$$

respectively, where $\Gamma(n, w)$ and $\Psi(n, w)$ are the wealth and substitution effects defined in Equations (2.15) and (2.16) respectively.

CHAPTER 3

The Catalytic Impact of IMF Lending on Official Development Assistance¹

3.1 Introduction

Official Development Assistance (ODA) represents a primary source of external financing for Low-Income Countries (LICs). In contrast to emerging markets, LICs' domestic savings are typically low and their access to portfolio flows is limited (International Monetary Fund, 2023b). In 2019, international development partners disbursed around USD 52.4 billion of ODA to LICs, representing 6.3 percent of GDP for the average LIC.²

In situations where external balances come under pressure, LICs often turn to the International Monetary Fund (IMF) for financial support. To address external pressures of individual LICs, IMF-supported programs lay out an agreed roadmap for policy actions and structural reforms complemented by granting financing to miti-

¹This chapter is based on joint work with Phil Johnston and Agustin Velasquez at the International Monetary Fund. The views expressed are those of the author(s) and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

²Own estimations based on OECD ODA database.

gate the adverse effects of the adjustment policies. In doing so, these IMF-supported programs and the related IMF financing are expected to catalyze external financing from multilateral and official bilateral donors. The importance of the magnitude of the catalytic impact of IMF lending is underscored by LICs' large financing needs as they strive to achieve the Sustainable Development Goals in the aftermath of the COVID-19 pandemic, and amid the tightening of financial conditions in advanced economies in response to the post-pandemic surge in inflation.

In this chapter we analyze the catalytic effect of IMF programs on ODA for LICs. We ask the following questions: Is there a catalytic effect of IMF programs on ODA? If so, how large is it and how has it evolved over the past decades? Which donors contribute the most and through which aid type (grants vs concessional loans)? Does the size of IMF disbursements matter for the amounts catalyzed?

Before answering these questions, it is important to address important identification challenges for IMF program participation: selection bias. Countries typically borrow from the IMF when they are facing economic hardship. This fact, combined with the alignment between LICs, donors, and the IMF means that econometric methods that do not correctly account for the non-random selection of LICs requesting IMF programs will likely lead to biased estimation results. Some studies have attempted to address selection bias by relying on *selection on observables* methods to identify the catalytic effects of IMF programs (Bird and Rowlands, 2007).

Instead, in this chapter we rely on two instrumental variables (IVs) to address different dimensions of selection bias. The first one addresses potential biases of program participation. Following Lang (2021), Gehring and Lang (2020) and Krahne (2023),

we employ an instrument that combines cross-sectional variation in a country’s probability of requesting an IMF program (based on past requests) and the temporal variation in the IMF’s liquid resources. The second IV addresses potential biases of program size. Larger amounts of IMF lending and ODA are likely to be provided in tandem to countries in deep economic crises. As in Krahne (2023), we use the IMF’s pre-determined institutional changes to borrowing limits, also known as ‘access limits’, as an IV for lending amounts. Variation in these IVs are largely driven by pre-determined periodic revisions to the IMF rules and regulations (such as the review of country quotas), which are exogenous to the traditional determinants of ODA in LICs.

Equipped with these IVs, we estimate the impact of IMF disbursements on the amounts of ODA inflows (as percent of GDP) using a country-year panel of 63 LICs over the 1990-2019 period. Unlike other studies that use binary variables to capture the impact of IMF programs, we estimate the impact of IMF disbursements to decouple the extensive margin (program participation) from the intensive margin (program size). These disbursement data, sourced from IMF administrative accounts, correspond to all traditional IMF arrangements (such as the Extended and Stand-by Credit Facilities).³

Our findings present evidence that IMF lending catalyzes ODA. We find that a one percentage point (henceforth pp) increase in IMF disbursements (relative to GDP) catalyzes an increase in ODA by 2.7 pp of GDP. Given the average size of annual disbursements (0.8 pp of GDP), the average country in an IMF program is expected

³We only include programs with upper credit tranche quality conditionality. In other words, all emergency financing arrangements are excluded.

to observe additional ODA flows of 2.2 pp of GDP per year. In other words, for each dollar disbursed, the IMF would cover (*ex-post*) approximately 27 percent of total donor flows in active programs.⁴ We also document that the magnitude of the catalytic effects in LICs has remained broadly stable throughout the 1990-2019 period.

We find that IMF programs catalyze most ODA flows from multilateral donors (1.4 pp of GDP) and traditional bilateral donors (0.7 pp of GDP). As expected, among multilaterals the largest contributions are from the World Bank followed by the European Union. Our findings also show that these catalytic effects are more pronounced for grants than for concessional loans.

We find that larger disbursements catalyze larger ODA flows. When decomposing between program participation effects and lending amounts (identifying each margin with our IVs), we report that the size of disbursements is, on average, more (statistically) relevant than simple program participation.⁵ When comparing across active programs, we also document that larger disbursements catalyze more ODA. However, we find a nonlinear effect between the two, implying there are diminishing catalytic effects in the amount of IMF financing.

This chapter builds on the limited literature which analyses the impact of traditional IMF-supported programs on ODA for LICs. The few other papers that have looked into this topic have relied on *selection on observables* methods. Gündüz and

⁴If 1 pp of GDP in IMF disbursements catalyzes 2.7 GDP points of ODA, then the IMF would be covering $1/(1+2.7) \approx 27$ percent of total new donor flows to the average program country.

⁵Note that this finding is not informative about the catalytic impact of IMF programs not included in this study, including non-financial ones.

Crystallin (2018) adopt a Propensity Score Matching and find that IMF programs increase net ODA disbursements by 2.4 percent of GDP. Along the same line, Schiavone and Maurini (2023) use an entropy balancing method and report that IMF programs boost ODA in LICs by 1.6 pp of GDP per year. Stubbs, Kentikelenis, and King (2016) focus on the catalytic effect of IMF programs on bilateral contributions. Complementing the findings of traditional programs, Cohen-Setton and Toni (2024) also find catalytic effects for IMF emergency financing throughout the COVID-19 pandemic. Other studies, which do not have an explicit IV strategy, also find a strong positive correlation between traditional IMF programs and ODA (Bird and Rowlands, 2007; Dabla-Norris, Minoiu, and Zanna, 2010; Stubbs, Kentikelenis, and King, 2016).

We also contribute to a wider range of studies that have explored the impact of IMF programs on capital flows in emerging market (non-LIC) economies (Díaz-Cassou, García-Herrero, and Molina, 2006; Erce and Riera-Crichton, 2015). Some studies find that IMF programs have played a catalytic role depending on borrower's initial conditions (Mody and Saravia, 2006), while others have reported elusive effects (Jensen, 2004). Krahne (2023) and Maurini and Schiavone (2021) finds that large IMF lending amounts play an anti-catalytic effect on private capital flows in emerging market economies. Additional studies have reported that IMF programs have a catalytic impact on Foreign Direct Investment flows (Al-Sadiq, 2015; Woo, 2013) and lower the cost of borrowing (Chahine, Panizza, and Suedekum, 2024).

The remainder of the chapter is organized as follows. Section 3.2 describes stylized facts regarding ODA and IMF programs in LICs. Section 3.3 presents the methodology to estimate the catalytic effects, including the identification strategy and the

construction of the IVs. Section 3.4 details the data employed for the econometric analysis. Section 3.5 describes the main econometric results while section 3.6 presents a sensitivity analysis of the findings. Finally, section 3.7 provides a summary and conclusions.

3.2 ODA and IMF Lending to LICs: Stylized Facts

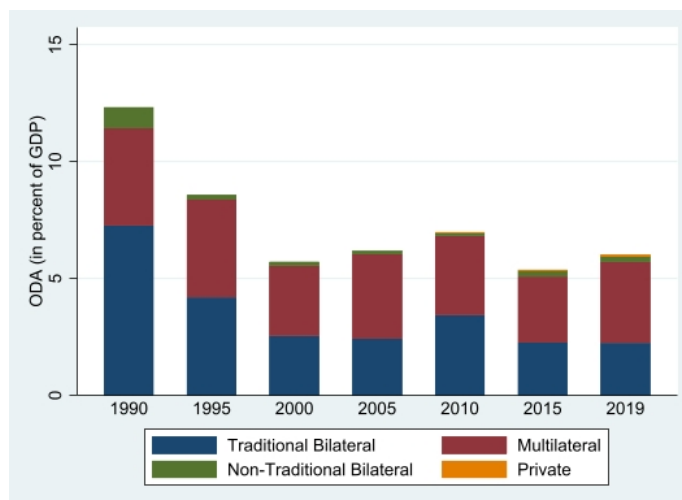
This section discusses stylized facts about ODA and IMF lending to LICs and the positive sorting between the two.

ODA represents a principal source of external financing for LICs, which are constrained by their limited access to private capital markets and have low domestic savings. By helping to address external financing needs, ODA can limit the size of the needed fiscal adjustments thereby helping to protect the poorest and most vulnerable. In this sense, ODA can act as a buffer aiding the recipient country facing an economic shock (Dabla-Norris, Minoiu, and Zanna, 2010). While the absolute amount of ODA flows to LICs has increased from USD 13.4 billion to 52.4 billion from 1990-2019, its magnitude in relation to the size of the economy for the average LIC has nearly halved, falling from 12.7 to 6.3 pp of GDP over the same period. Figure 3.1 depicts total ODA flows to LICs (in percent of GDP) broken down by donor type in 5-year intervals from 1990 to 2019. Although ODA flows have declined in real terms, they have consistently remained above 5 pp of GDP, thereby providing important financing to LICs.

The composition of ODA to LICs has shifted over time. The share provided by traditional bilateral donors fell from 63 to 43 percent of ODA between 1990 and

2019 while conversely the multilateral donors' share of ODA rose from 32 to 51 percent. The share of ODA provided by non-traditional bilateral donors showed an upward trajectory since 2009 but it still remained small at 4 percent of total ODA flows in 2019.⁶

Figure 3.1: ODA flows (in percent of GDP) to LICs



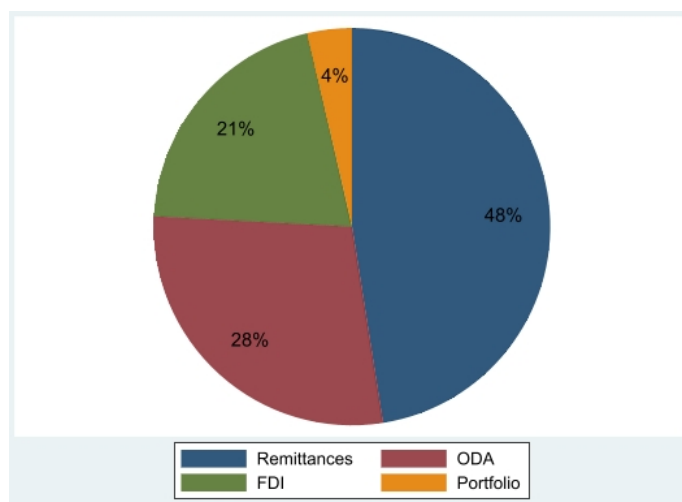
Source: Authors' estimates based on the OECD ODA database (OECD, 2023).

LICs significantly rely on ODA flows to balance their external financing needs. Figure 3.2 shows the composition of external financing flows to LICs in 2019. ODA represents about 28 percent of external financing flows. Remittances comprise 48 percent of external financial flows. By contrast, private capital flows, in the form of FDI and portfolio flows have expanded in past years but still account for less flows than ODA. FDI flows represent 21 percent of external financing flows. Reflecting

⁶Data on non-traditional bilateral donors only captures non-OECD countries that voluntarily report to the OECD Development Assistance Committee. This excludes important partners such as China. Data on non-traditional bilateral donor support is thus likely to be an underestimate even though many Chinese financial flows may not meet the ODA criteria. See Appendix A for a full list of non-traditional bilateral donors that report to the OECD.

LICs limited access to external capital markets, private portfolio flows made a small contribution to LICs external financing worth only 4 percent in 2019.

Figure 3.2: Composition of selected external financing flows to LICs in 2019



Source: Authors calculations based on OECD ODA database (OECD, 2023) and the World Bank's WDI (World Bank, 2024).

IMF concessional lending to LICs is designed to assist countries with protracted balance of payments needs. Its goal is to facilitate the implementation of economic policy actions to restore external balance while supporting strong growth and poverty reduction. The size of IMF lending to LICs is determined on a case-by-case basis taking into account the size of the balance of payments gap, the strength of the program, capacity to repay the IMF and the borrowing country's past record of policy implementation.

LICs often request IMF-supported programs when they suffer economic hardship and external sector pressures emerge. In IMF program negotiations, the program's size, length, schedule of disbursements and policy actions are discussed and agreed

prior to its approval by the IMF's Executive Board. Once the program is approved, the policy actions envisaged in the program as well as the schedule and amount of disbursements are publicly communicated such that international investors and other development partners have clarity on the way forward. Disbursements over the duration of the program can be front-, even-, or back-loaded depending on each country's balance of payments situation and the phasing of the adjustment measures and the expected timing of their impact.

Prior to disbursing, the IMF's Executive Board verifies that the program is 'on-track' through formal program reviews. In most cases, the timing and amounts of disbursements follow the schedule agreed upon approval. However, in some cases the amount of financing may deviate. Amounts may be brought forward or delayed depending on macroeconomic conditions and progress on policy reforms/actions. In some cases, when countries encounter additional financing needs, they can request an 'augmentation'. Programs can go 'off-track' for various reasons. In those cases, program reviews are not completed and disbursements are stopped.

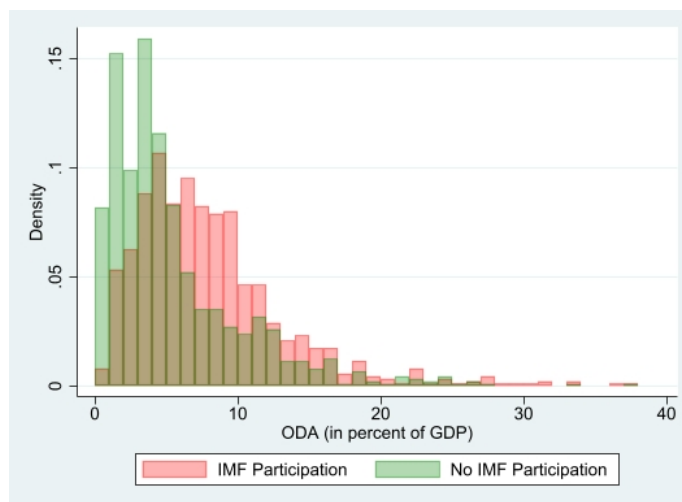
In this study we estimate the (ex-post) catalytic effect from IMF-supported programs. As per IMF institutional rules, the approval of a program request (and subsequent reviews) require the IMF's *financing assurances policy* to hold. This policy requires that an IMF-supported program has adequate external donor financing to fill program financing gaps, such that the program is (ex-ante) fully financed for the next 12 months and with good prospects for the remainder of the program period. This means that other donors, mainly the World Bank and other traditional bilateral and multilateral donors, should indicate that they will provide additional new financing to the member country to support the efforts to restore macroeco-

conomic stability. Nonetheless, these indications from other donors are not binding. Some may not always materialize, whereas some donors may contribute throughout the program without prior announcement to the IMF. In this way, in this chapter we refer to the catalytic effect as the (ex-post) materialized support from the donor community in response to the IMF financing.

The IMF's catalytic effect is expected to be achieved through two channels. First, the conditionality associated with an IMF program entails the implementation of a wide range of reforms which can both act as a signal regarding the authorities' intentions and strengthen the recipient government's ability to withstand economic shocks. Failure to comply with these conditions can lead to loss of financial assistance. The second channel is the direct provision of liquidity associated with an IMF program, which can ease the burden of adjustment to an economic shock (Bird and Rowlands, 2000; Bird and Rowlands, 2007; Stubbs, Kentikelenis, and King, 2016). Both channels can boost ODA as donors may perceive their aid to become more effective with the recipient country's enhanced resilience and more robust expected macro-economic outcomes. In this way, IMF-supported programs serve as a coordination mechanism amongst donors (Gündüz and Crystallin, 2018).

Participation in IMF programs and ODA are highly correlated in LICs. Figure 3.3 depicts the annual ODA-to-GDP ratio for LICs splitting the sample between LICs in and out of IMF-supported programs. On average LICs engaged in an IMF-supported program receive nearly double the annual amount of ODA (10.2 pp of GDP) compared to those that are not (5.8 pp of GDP). The ODA-to-GDP ratio varies widely across LICs and its distribution has a long right tail. As expected, ODA is positively correlated with IMF programs, as macroeconomic and structural reforms

Figure 3.3: Distribution of ODA (in percent of GDP) across IMF program participation status



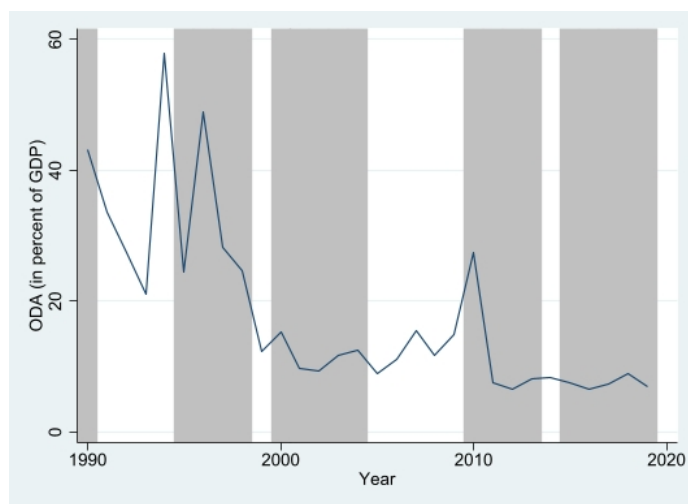
Note: Observations are country-year values.

undertaken to address balance of payments pressures and boost growth and poverty reduction may trigger both engagement from the IMF and more ODA support from other donors.

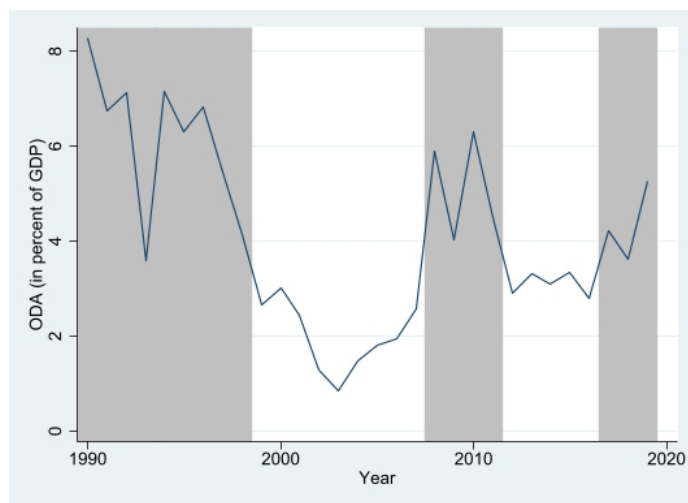
Another way of visualizing this correlation is through time series. For example, Figure 3.4 shows that Guinea-Bissau participated in five IMF programs between 1990 and 2019. In each, the ODA-to-GDP ratio is on average higher in each program period compared to off-program years. The amount of ODA (net of debt relief) received was large, exceeding 20 pp of GDP in years prior to 2000. Similar dynamics are observed in Togo.

Figure 3.4: ODA (in percent of GDP) in selected countries (program participation in shaded areas)

Panel A. Guinea-Bissau



Panel B. Togo



Source: Authors' calculations based on OECD ODA database (OECD, 2023).

3.3 Methodology

This section discusses the econometric approach to identify the catalytic effects of IMF lending. Section 3.3.1 describes the identification strategy to address selection biases of program participation and size. Section 3.3.2 describes the econometric specifications.

A simple OLS regression of ODA flows on IMF financing would most certainly deliver biased estimates. LICs typically turn to IMF lending when external financing needs are on the rise and alternative sources of financing are not available. On the other hand, LICs receive a continuous flow of ODA from multiple donors. As shown in Figure 3.3, these flows increase, on average, when countries are engaged in an IMF program. Therefore, it is challenging to identify which ODA flows were actually catalyzed by IMF programs, and which ones were not.

The difficulty arises because the same drivers for a request of an IMF program could also potentially explain heightened receipt of ODA flows from other development partners, e.g., recessions, widening current account deficits, adverse terms of trade shocks, supporting a new reform minded government, to name a few. To provide a clear identification strategy of the catalytic impact of IMF programs we rely on IVs.

3.3.1 Identification Strategy

We build two IVs. One to address bias from selection into programs and another to address bias from program size. To this aim, we use the same IV approach described in Lang (2021), Gehring and Lang (2020), and Krahnke (2023).

The first IV that addresses bias from selection into programs comprises the inter-

action between past participation in IMF programs and temporal variation in IMF lending resources. Based on Lang (2021) and Krahne (2023), we construct our first IV as

$$\text{IMFProbability}_{it} \times \log(\text{IMFLiquidity}_t), \quad (3.1)$$

which is the interaction between country i 's specific probability of having participated in an IMF program in the past, $\text{IMFProbability}_{it}$, defined as past number of years under programs, and the (log of) disposable amounts of IMF resources that are available for lending IMFLiquidity_t .⁷

The literature generally finds that past participation in IMF programs is a good predictor of future participation (Bird, Hussain, and Joyce, 2004; Sturm, Berger, and De Haan, 2005). One of the reasons put forward pertains to the balance of payments pressures caused by repayments to the IMF on earlier loans exacerbated by new domestic or external shocks, as is not uncommon among LICs (Conway, 2007). Another view points at 'recidivism' or political favoritism (Bird, Hussain, and Joyce, 2004; Sturm, Berger, and De Haan, 2005)). Furthermore, LICs tend to be repeat borrowers from the IMF, as they often face protracted balance of payments needs that cannot be addressed over the duration of a single program.

For these reasons, countries with a track record of frequent requests of IMF programs tend to have a higher probability of requesting an IMF program today. However, the interaction with the level of IMF resources should provide additional predictive power, as argued and shown in Lang (2021), Gehring and Lang (2020), and

⁷We take the log of IMFLiquidity but we omit this fact in the rest of the chapter to simplify notation.

Krahnke (2023). During periods of relatively low IMF liquidity, countries with past program participation are likely to increase their probability of having an IMF-supported program compared to those who infrequently borrow from the IMF. The rationale provided in the literature is that the IMF, as any other financial institution, is likely to become more conservative in its lending when liquidity levels are relatively low, and vice-versa. Therefore, conditional on past use of IMF financing - which indicates potential future requests - the interaction of IMFProbability and IMFLiquidity should be a good predictor of program participation.

The IMFLiquidity variable we use in this study reflects available financing resources in the IMF's General Resources Accounts (GRA). All IMF members are eligible to borrow from these accounts. In contrast to non-LICs, LICs can also borrow from the IMF's Poverty Reduction and Growth Trust (PRGT) at concessional rates. The PRGT receives contributions from IMF members and the IMF itself. Its funds are not directly linked to the GRA, however in practice they are correlated.⁸

Using a measure of IMF Liquidity from the GRA instead of the PRGT reinforces the instrument's exogeneity assumption. Given that the amount of lending resources in the PRGT is donor based—and therefore donors may make additional contributions in times of need—variations in PRGT financing may not fully reflect real constraints on potential available financing. In contrast, we favor the use of IMF resources from the GRA which is largely financed by country's quotas which are subject to rules-based reviews every few years.

⁸The correlation between the uncommitted assets from the PRGT and the GRA is 0.57, for the years with overlapping data (2001-2019). The correlation between non-borrowed PRGT resources and available liquidity in the GRA is 0.7.

Within the IMF, an important principle guiding all lending operations is “equality of treatment” between members. Except for the borrowing rate, maturity, and a more tailored approach towards poverty reduction, IMF programs for LICs and non-LICs are largely similar (in terms of timing of negotiations, requiring the approval of the Board to disburse, and other institutional aspects). Similarities are such that some LICs can ‘blend’ and borrow from both the PRGT and GRA in the same program.

Variations in availability of resources in the GRA are largely driven by factors that are independent from idiosyncratic economic drivers in LICs. Key examples are quota reviews (more on this below) or large pre-determined repayments from individual high-access IMF programs (Krahnke, 2023). Therefore, the interaction between IMFProbability and IMFLiquidity (conditioning on IMFProbability) is likely to satisfy the exclusion restriction. We provide evidence that the exclusion restriction holds by controlling for other potential drivers of ODA in our baseline results (see Section 3.6). In Appendix 3.7 we show that this IV method does not suffer from spurious trends.

The second IV to address biases related to program size is

$$\frac{\text{AccessLimits}_{it}}{\text{GDP}_{it}} = \frac{\text{IMFQuota}_{it} \times \text{Limits}_t}{\text{GDP}_{it}} \quad (3.2)$$

where IMFQuota_{it} is the size of the IMF quota of country i in year t expressed in USD. Limits_t is the maximum amount of resources (in percent of quota) that a country can borrow in a single IMF arrangement without triggering exceptional

access policies.⁹ Thus, AccessLimits/GDP displays the *real* amount (in GDP terms) of lending that a requesting country can potentially borrow in a single arrangement.¹⁰

AccessLimits is an institutional nominal cap on the maximum amount of borrowing (in SDRs) from the IMF available to each LIC. Therefore, it is a good predictor of the overall program size and its disbursements. The size of each program, together with the timing and policy requirements are negotiated and agreed at the time of the program request (see section 3.2). AccessLimits also satisfies the IV's exclusion restriction. These are reviewed by the IMF Board at least every five years. However, delays are common. The reviews of quotas often follow a specific formula for each country, and thus are uncorrelated with the short-run performance of macro-variables that are key in attracting ODA and overall capital flows (we provide empirical evidence on this in section 3.6).

Limits are also revised periodically, sometimes along with quotas, every few years to help ensure access to borrowing evolves broadly in line with demand based on macro developments such as the size of the economy and trade openness. These limits apply equally to all LICs (PRGT-eligible countries). Therefore, they are simpler and faster to adjust in periods of more demand for IMF financing (for example, in response to the COVID-19 pandemic) than quotas.

⁹We use Limits specifically for borrowing from PRGT resources. These limits are more technically known as PRGT Cumulative Access Limits.

¹⁰From within IMF guidelines, the amount of lending a country eventually receives is generally driven by the balance of payment gap, the strength of the proposed policy actions and capacity to repay (International Monetary Fund, 2023a).

3.3.2 Econometric Specifications

We now move on to show the empirical estimation used to identify the catalytic impact of IMF lending on ODA flows. We first focus on a baseline estimation to capture the total catalytic effects (intensive plus extensive margin). Then we provide a decomposition for each margin. Finally, we discuss a decomposition of the analysis by donor and aid type and the possible non-linear effects of the catalytic effects.

3.3.2.1 Total catalytic effects

Relying on the described IVs, we set a two-stage least squares (2SLS) specification. The second stage of our baseline is given by:

$$\log\left(\frac{\text{ODA}_{it}}{\text{GDP}_{it}}\right) = \beta_1 \frac{\widehat{\text{Disbursement}_{it}}}{\text{GDP}_{it}} + \beta_2 \text{IMFProbability}_{it} + \delta_i + \gamma_t + \varepsilon_{it}, \quad (3.3)$$

where ODA/GDP is the total flows of ODA (in percent of nominal GDP) that country i received in year t . Disbursement/GDP is the total amount of IMF disbursements measured in percent of nominal GDP borrower i received in year t . This may represent one or more individual disbursements received in year t . IMFProbability $_{it}$ is country i 's rolling probability of requesting an IMF program based on past IMF programs. The specification includes country- δ_i and year- γ_t fixed effects. ε_{it} is the error term.^{11 12}

The coefficient β_1 measures the percentage change in the amount of ODA flows trig-

¹¹We take the log of ODA-to-GDP ratio due right-skewness of its distribution (see Figure 3.3), and to have normally distributed residuals.

¹²The ODA-to-GDP ratio may over-fluctuate given the decline of GDP in economic crises. Using alternative time composition of GDP, we find that the denominator does not drive our results.

gered by one pp change in annual disbursements. β_1 captures the total catalytic effect, the sum of the intensive and the extensive margins of participation in IMF programs. In other words, Disbursement/GDP can be seen as the interaction between participation in an IMF program and the average disbursement amount (as by definition no disbursement can occur outside an active program). Below we show how we can decompose these margins.

The first-stage regression is

$$\begin{aligned} \frac{\text{Disbursement}_{it}}{\text{GDP}_{it}} = & \alpha_1 \text{IMFProbability}_{it} \times \text{IMFLiquidity}_t + \alpha_2 \text{IMFProbability}_{it} \\ & + \alpha_3 \frac{\text{AccessLimits}_{it}}{\text{GDP}_{it}} + \delta_i + \gamma_t + u_{it}, \end{aligned} \quad (3.4)$$

where the interaction of IMFProbability and IMFLiquidity discussed in Section 3.3.1 is the main instrument to address edogeneity concerns regarding program participation. It is important to highlight that IMFProbability is included in the first and second stage, which means that the sole source of exogenous variation to identify program participation is the interaction term. According to our discussion, we would expect that past participation in IMF programs would lead to a higher probability of a new program request today ($\alpha_2 > 0$). But, when IMF resources are low (high), we expect to have a higher (lower) probability of an IMF program for more frequent users of IMF financing ($\alpha_1 < 0$).

In addition to addressing selection into programs, the first stage (3.4) also includes AccessLimits/GDP. This is our instrument to address biases related to program size, and thus, disbursement size. When the IMF increases its AccessLimits, countries have more capacity to borrow, in terms of GDP. We expect to observe $\alpha_3 > 0$.

While β_1 in (3.3) is of interest because it measures the percentage change in ODA following an increase in disbursements, an alternative measure to quantify the magnitude of the catalytic effects is to measure them in pp of GDP. To this aim, we compute the average marginal effects (AME) of the disbursements (at sample means) using the following formula:

$$\begin{aligned} \text{AME} &= \frac{\partial \mathbb{E} \left(\frac{\text{ODA}}{\text{GDP}} \middle| \frac{\text{Disbursement}}{\text{GDP}} \right)}{\partial \frac{\text{Disbursement}}{\text{GDP}}} \\ &= \frac{\partial \exp \left(\widehat{\beta_1} \frac{\overline{\text{Disbursement}_{it}}}{\overline{\text{GDP}_{it}}} + \widehat{\beta_2} \overline{\text{IMFProbability}_{it}} + \overline{\widehat{\delta}_i} + \overline{\widehat{\gamma}_t} \right)}{\partial \frac{\overline{\text{Disbursement}_{it}}}{\overline{\text{GDP}_{it}}}}, \end{aligned} \quad (3.5)$$

where the numerator is the natural exponent of expression (3.3) with the estimated coefficients from the 2SLS. The variables with bars refer to sample means. Equation (3.5) allows us to compute how ODA in pp of GDP would change in response to a one pp increase in disbursement (in percent of GDP). In addition, it allows us to study how this magnitude has evolved over time by computing the AME at different time periods.

3.3.2.2 Catalytic effects decomposed by margin

The catalytic impact can be further decomposed into the magnitude of program participation (extensive margin) and disbursement amounts (intensive margin). The

second stage is set up as:

$$\log\left(\frac{\text{ODA}_{it}}{\text{GDP}_{it}}\right) = \beta_1 \frac{\widehat{\text{Disbursement}_{it}}}{\text{GDP}_{it}} + \beta_2 \widehat{\text{IMFParticipation}_{it}} + \beta_3 \widehat{\text{IMFProbability}_{it}} + \delta_i + \gamma_t + \varepsilon_{it}, \quad (3.6)$$

where IMFParticipation is a dummy variable valued as one when the country is in an active program. Now β_1 quantifies the catalytic impact of disbursements on ODA while controlling for program participation. On the other hand, β_2 measures the catalytic effect of participation into programs conditional on how much is disbursed. To identify the catalytic effect of each margin, we will employ one instrument at a time. IMFParticipation is instrumented with the interaction of IMFProbability and IMFLiquidity, and Disbursement/GDP instrumented with AccessLimits/GDP.

3.3.2.3 Decomposition of ODA and non-linear effects

Our analysis also expands to decompose the catalytic effects of IMF lending through different dimensions of ODA. We decompose the response of ODA flows by donors and type of assistance. In terms of donors, we distinguish three groups: i) traditional bilateral donors, ii) non-traditional bilateral donors and iii) multilateral organizations. Traditional donors refer to countries with OECD membership. See Appendix 3.7 for details. Given that multilateral organizations are the primary contributors of ODA in LICs, we further decompose this category into contributions from the European Union (EU), Regional Development Banks, the United Nations, the World Bank, and other multilateral organizations. Regarding aid types, we decompose ODA flows between concessional loans and grants.

Finally, we explore possible non-linearity in terms of the catalytic effects. For this we

restrict our attention to a sample with active IMF programs. We set the following specification for the second stage of the 2SLS:

$$\log\left(\frac{\text{ODA}_{it}}{\text{GDP}_{it}}\right)\bigg|_{\text{IMFProgram}=1} = \beta_1 \frac{\widehat{\text{Disbursement}_{it}}}{\text{GDP}_{it}} + \beta_2 \left(\frac{\widehat{\text{Disbursement}_{it}}}{\text{GDP}_{it}}\right)^2 + \delta_i + \gamma_t + \varepsilon_{it}. \quad (3.7)$$

We specifically aim to determine whether the size of the disbursement exhibits increasing, constant, or decreasing returns to scale by incorporating an additional quadratic term in our regression conditional on strictly positive disbursement years. Given this conditionality, we no longer need nor can use the interaction of IMFProbability and IMFLiquidity, and are left with a single instrument: AccessLimits/GDP.¹³

3.4 Data

Data for ODA is from the OECD Development Assistance Committee dataset (OECD, 2023). These are aid flows, in the form of grants, concessional loans with the purpose of promoting economic development and welfare. Loans must include a grant element of at least 25 percent calculated at a discount rate of 10 percent to qualify as ODA. For our dependent variable we utilize gross disbursements of ODA and follow Schiavone and Maurini (2023) and Gündüz and Crystallin (2018) in excluding certain flows from ODA. We exclude food and humanitarian aid, and technical cooperation as these are usually driven by event-specific factors. In addition, we also subtract aid in the form of debt forgiveness and debt rescheduling's forgiven and rescheduled, as

¹³To estimate a quadratic linear regression such as (3.7), which presents two endogenous variables and one IV, we follow the steps in Wooldridge (2010). We first run the first stage regression regressing Disbursements/GDP on AccessLimits/GDP. We then perform its linear projection. Then the squared of the projection, and use it as an instrument for (Disbursement/GDP)².

our main interest is new sources of financing.¹⁴ Finally, we also subtract from ODA flows all loans and debt relief provided by the IMF.

Data on IMF disbursements is sourced from the Finance Department of the IMF. These data are accounting records of actual financial transactions between the IMF and its member countries and thereby present minimal measurement error. Our yearly measurement of disbursements is built by adding all disbursements to each country in a given calendar year. If the ongoing IMF program receives an augmentation, it is also recorded in the disbursement variable. With less than one percent of the sample composed of disbursements to blended borrowers the data includes very few blender country cases.¹⁵ Disbursements are recorded in Special Drawing Rights (SDR). We transform them into USD at the recorded SDR/USD exchange rate. In terms of IMF program coverage, we only consider Upper Credit Tranche quality programs. These include the Stand-by and Extended Credit Facilities, and older versions of such programs. Our sample does not include disbursements from emergency financing programs.

The first IV employed in the econometric analysis is the interaction of IMFProbability and IMFLiquidity. IMFProbability is constructed as a 20-year rolling probability. It represents the percent of years in which country i participated in an IMF program in the 20 years preceding year t . Specifically, it is calculated as follows:

$$\text{IMFProbability}_{it} = \frac{1}{20} \sum_{\tau=t-19}^t \text{IMFParticipation}_{i\tau},$$

¹⁴Overall debt relief is not large compared to gross ODA flows, and our main results are not significantly affected by their exclusion.

¹⁵These are LICs that borrow from the IMF General Resources Accounts on top of the PRGT.

where

$$\text{IMFParticipation}_{it} = \begin{cases} 1 & \text{if country } i \text{ is in an IMF program in year } t \\ 0 & \text{otherwise.} \end{cases}$$

IMFLiquidity is a measure for the amount of resources that are the available for lending. As in Krahne (2023), we use the IMF’s forward commitment capacity (FCC) as a measure of IMF liquidity. The FCC reflects the annual available resources from its GRA.¹⁶

AccessLimits is the interaction between IMF quotas and cumulative access limits to the PRGT. Both variables are sourced from historic IMF records on country quotas and cumulative access limits to PRGT resources. The latter is a cap on borrowing amounts for each country, as a percent of quota, before triggering Exceptional Access policies. IMF programs under this policy often come with more stringent conditions and are subject to a higher level of scrutiny by the IMF’s Executive Board, which could discourage such requests.

Additional data for the sensitivity analysis is collected for different sources. GDP growth and current account balance data are from the IMF World Economic Outlook indicators. For the degree of capital account openness we employ the Chinn-Ito

¹⁶The FCC measures the IMF’s ability to make new financial commitments from the GRA to its members over the next 12 months. The FCC indicates how much the IMF has available for new lending from its regular financial resources and is adjusted downwards to account for resources already committed to members under existing IMF arrangements. A further downward adjustment is made to ensure that the Fund retains a prudential balance intended to safeguard the liquidity of creditors’ claims and take account of the potential erosion of the IMF’s resource base. Projected repayments from IMF borrowers over the next 12 months are then added to the total to derive the IMF’s stock of usable resources.

index (Chinn and Ito, 2023). We also use a proxy for political stability. From the World Banks' Database on Political Institutions (World Bank, 2020), we employ the percentage of veto players (those with influence in political rulings) who drop from a government in a given year as a proxy for political stability.¹⁷

Our final data sample covers 63 LICs from 1990 to 2019. We focus on LICs that were eligible to receive concessional loans from the PRGT in 2019. We exclude countries that used to be PRGT eligible, but graduated from PRGT eligibility prior to 2019. More details on the sample coverage are provided in Appendix 3.7.

3.5 Empirical Results

In this section we show the estimation results of the catalytic effects of IMF programs in LICs. We show first the total catalytic effects of disbursements and later decompose the results by the intensive and extensive margins. We then move on to analyze catalytic effects by donor and aid type. Finally we focus on possible non-linear effects of large disbursements.

3.5.1 Total Catalytic Effects

We begin our analysis by showing the OLS estimation results of regressions of ODA on disbursements as set up in specification (3.3). Table 3.1 presents the results.

¹⁷Veto players are defined as the president, largest party in the legislature, for a presidential system; and as the prime minister and the parties in the government coalition in a parliamentary system. The control variable captures the extent of turnover in any one year of a government's key decision makers. The variable is computed by dividing the number of exits between year t and $t + 1$ by the total number of veto players in year t as specified in World Bank (2020). The control variable is a share with zero representing no exits and one representing the exit and replacement of all veto players (World Bank, 2020).

Column 1-3 show results for pooled OLS, and controlling for country and year fixed effects. The estimated coefficient exhibits a positive and statistically significant value, even in the absence of fixed effects. An increase of one pp in disbursements (in percent of GDP) is associated with a 13.6 percent increase in ODA-to-GDP flows. In terms of pp of GDP (AME), this translates into additional ODA flows worth 0.69 pp of GDP. When we control for country and year fixed effects, the magnitude of the estimated coefficient becomes smaller. An increase of disbursements of one pp raises ODA flows by an average of 7 percent, or 0.35 pp of GDP.

Columns 4-6 show the 2SLS results. Column 4 displays the results of instrumenting disbursements with *only* the interaction of IMFProbability and IMFLiquidity. The coefficient retains a positive sign but has a significantly larger magnitude compared to the OLS one. An increase in disbursements by one pp of GDP leads to a 61.2 percent rise in ODA-to-GDP flows. The AME quantifies that a 1 pp of GDP increase in disbursements leads to an additional increase of ODA of 3 pp of GDP. The Kleiberg-Paap Wald F-stat for weak identification is 14.2, well above the usual threshold of weak instrument (Stock and Yogo, 2005).

Column 5 replicates the same estimation, but using only AccessLimits/GDP as the instrument instead of the interaction of IMFProbability and IMFLiquidity. The estimated coefficient is highly significant and slightly smaller than the one in column 4. The 2SLS presents a F-stat of 13.16, which reflects that AccessLimits/GDP is not a weak instrument for disbursements.

Independently, columns 4 and 5 show that using different IVs to address biases from program participation and size is important to isolate the catalytic effects of IMF

Table 3.1: Total catalytic effects of IMF programs on ODA

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Second stage:</i>						
	Dependent variable: $\log(\text{ODA}/\text{GDP})$					
	OLS	OLS	OLS	IV	IV	IV
Disbursement/GDP	0.136*** (0.046)	0.087*** (0.033)	0.070** (0.029)	0.612*** (0.204)	0.528*** (0.161)	0.534*** (0.158)
Marginal Effects (in pp of GDP)	0.69	0.44	0.35	3.01	2.67	2.70
R ²	0.05	0.05	0.03			
<i>First stage:</i>						
	Dependent variable: Disbursement/GDP					
IMFProbability				0.145*** (0.005)	-0.004*** (0.001)	0.009** (0.004)
IMFProbability $\times$ IMFLiquidity				-0.004*** (0.001)		-0.003*** (0.001)
AccessLimit/GDP					0.095*** (0.026)	0.094*** (0.026)
First stage R ²				0.14	0.18	0.18
Country FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
F-stat				14.24	13.16	8.23
J-stat (p-value)						0.63
Countries	63	63	63	63	63	63
Observations	1746	1746	1746	1746	1746	1746

Note: This table reports OLS and IV estimates of regressing $\log(\text{ODA}/\text{GDP})$ on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. The IV regressions use IMFProbability $\times$ IMFLiquidity and AccessLimit/GDP are constructed based on (3.1) and (3.2) respectively. All regressions control for IMFProbability (not shown). The F-stat is Kleiberg-Paap Wald F-stat for weak identification. The J-stat is Hansen J-stat for over-identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

programs. In column 6 we employ both IVs at the same time to *simultaneously* control for these biases. The results show that a statistically significant coefficient of 0.53, implying that disbursements increase ODA-to-GDP ratio flows by 53 percent. In absolute terms, an increase in disbursements of 1 pp of GDP catalyzes ODA by 2.7 pp of GDP. Column 6 constitutes our most preferred specification for the rest of this study.

The first-stage results confirm the discussion in Section 3.3.1. The OLS coefficient of IMFProbability on disbursements is estimated to be positive in columns 4 and 6. These results imply that past users of IMF programs are more likely to request programs and receive disbursements today. While controlling for IMFProbability, column 4 displays the estimated coefficient of the interaction between IMFProbability and IMFLiquidity. It is negative and highly significant. As discussed, when IMF resources are low (high), it is more likely that more (less) frequent users of IMF programs request programs and receive disbursements.

Column 5 shows the results of regressing disbursements on AccessLimits/GDP. As expected, the estimated coefficient is positive and significant. Larger lending capacity (in GDP terms) leads to larger programs and larger disbursements. One common source of variation in AccessLimits and IMFLiquidity is the review of IMF quotas, which simultaneously creates more resources and borrowing capacity (see Section 3.4). Even if there is a common source of variation in these instruments, column 6 shows that each IV is still significant in explaining disbursements when the other one is included in the specification. In addition, the p-value of Hansen J-stat for over-identification is 0.63, which indicates that each of our instruments is valid on

its own right.¹⁸¹⁹

The 2SLS effectively shows that there is a downward bias in the OLS results. The average amount of yearly disbursements (in percent of GDP) is 0.8, which implies that a program-requesting country could expect to receive additional ODA of 2.16 pp of GDP through each year under the program. This is in line with Gündüz and Crystallin (2018) who report that net ODA disbursements increase by 2.4 percent of GDP in countries with IMF programs. Schiavone and Maurini (2023) report that for each year under an IMF program there is a catalytic effect on ODA in LICs worth 1.6 pp of GDP.

Using the estimated coefficients from column 6 in Table 3.1, we now analyze how the catalytic effects evolved across time. For this, we compute the AME for different years. The results in Figure 3.5 demonstrates that the catalytic effects of IMF programs on ODA have remained broadly constant at around 2.7 pp of GDP in LICs during 1990-2019. There is a slight larger catalytic impact for 1990, but not statistically different than in other years.

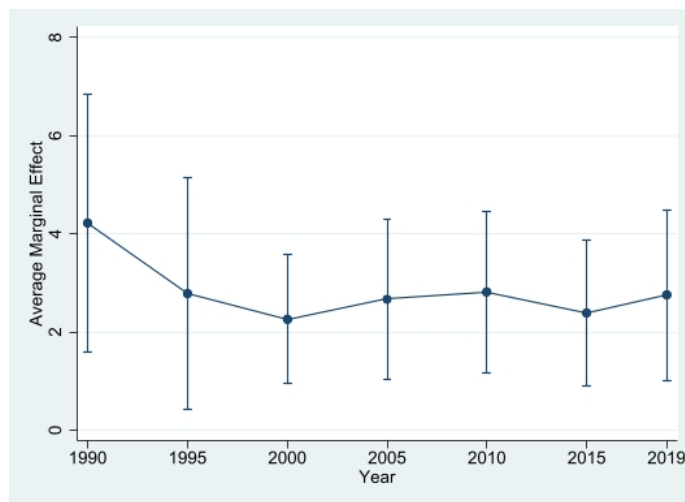
3.5.2 Decomposing the Catalytic Effects by the Intensive and Extensive Margins

We have shown that LICs in an active IMF program attracted larger ODA flows than what would otherwise have been the case. Next, we assess how relatively important

¹⁸In other words, the null hypothesis that the over-identifying restrictions are valid cannot be rejected.

¹⁹These first-stage results are similar to those in Krahne (2023), who run the same set of instruments but on a panel of emerging (non-LIC) countries.

Figure 3.5: Catalytic effect over time



Source: Authors' calculations based on OECD ODA database (OECD, 2023).

Note: This figure shows the average marginal effects of disbursements on ODA (as percent of GDP). 95 percent CIs are computed using the Delta method.

program participation and lending size were in catalyzing ODA. In other words, did participation in an IMF program play a larger role than the actual lending amount received or was it the inverse? Fortunately, we have two IVs to aim at identifying each margin to answer this question.

Table 3.2 decomposes the IMF's catalytic effects by margins. We begin with a simple OLS regression in column 1 to set up a baseline for comparisons. The column presents the OLS estimates of regressing ODA on disbursements (in percent of GDP) and country and year fixed effects.²⁰ Column 2 introduces a dummy variable, IMF-Participation, which is equal to one when a country is in an IMF-supported program.

²⁰This regression is the same as the one in column 3 in Table 3.1, which displays a positive and significant coefficient.

The coefficient of IMFParticipation captures the average catalytic effect of program participation, conditional on the average disbursed amount. Both coefficients for disbursements and participation are positive and statistically significant. As expected, the magnitude of the disbursement coefficient becomes slightly smaller.

Table 3.2: The catalytic effects by margin

	(1)	(2)	(3)	(4)
<i>Second stage:</i>				
	Dependent variable: log (ODA/GDP)			
	OLS	OLS	IV	IV
Disbursement/GDP	0.070** (0.029)	0.044** (0.021)	0.539*** (0.177)	0.502*** (0.184)
IMFParticipation		0.284*** (0.031)	-0.075 (0.114)	0.199 (0.418)
R ²	0.03	0.08		
Marginal Effects (in pp of GDP) of Disbursement/GDP	0.35	0.22	2.72	2.53
Country and Year FE	Yes	Yes	Yes	Yes
IV: IMFProbability x IMFLiquidity			No	Yes
IV: AccessLimits/GDP			Yes	Yes
F-statistic			11.55	9.42
Countries	63	63	63	63
Observations	1746	1746	1746	1746

Note: This table reports OLS and IV estimates of regressing log (ODA/GDP) on Disbursement/GDP and IMFParticipation. The panel comprises annual data between 1990 and 2019 for 63 countries. IMFParticipation is instrumented with IMFProbability $\times$ IMFLiquidity (eq. 3.1), and Disbursement/GDP with AccessLimit/GDP (eq. 3.2), respectively. All regressions control for IMFProbability (not shown). First stage results are presented in Appendix 3.7. The F-stat is Kleiberg-Paap Wald F-stat for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Columns 3 and 4 in Table 3.2 introduce our 2SLS approach to isolate the different margins. First stage results are presented in Appendix 3.7. Column 3 uses AccessLimits/GDP as an instrument for disbursement amounts, while IMFParticipation is not instrumented. The results show that the coefficient on disbursements increases from 0.044 (OLS) to 0.539 (2SLS), which is essentially the same magnitude

as in column 6 in Table 3.1.

In column 4 we replicate the 2SLS regression of column 3 but instrument IMFParticipation with the interaction of IMFProbability and IMFLiquidity. The magnitude of the coefficient on IMF participation changes from negative to positive, but remains not statistically significant at the 10 percent level. On the other hand, the coefficient of disbursement declines compared to column 3, from 0.539 to 0.502. It remains highly significant. These results suggest that the amounts disbursed play a more important role in attracting ODA than the simple dummy of program participation. The first stage results of column 4 can be found in Appendix 3.7.

3.5.3 Decomposing the Catalytic Effects by Donor and Aid Type

Next, we analyze the breakdown of the total catalytic effects of IMF programs on ODA by donor type and type of aid. Table 3.3 shows the catalytic effects of IMF programs on different donors using both IVs as in specification (3.3). Column 1 shows the catalytic effects on all donors.²¹ Column 2 focuses on ODA provided only from traditional bilateral donors. The results suggest that a 1 pp increase in disbursements (in percent of GDP) leads to an average increase of ODA of 0.65 pp of GDP. Column 3 displays the catalytic effects on multilateral organizations. We observe the largest impact on these donors. Its coefficient shows that a 1 pp increase in IMF disbursements (in percent of GDP) raises ODA from multilateral organizations by 56 percent. In level terms, an increase in disbursements of one pp of GDP leads to an average increase of the ODA-to-GDP ratio in 1.4 pp.

²¹These results are the same as in column 6 in Table 3.1

Finally, column 4 shows the catalytic impact on non-traditional bilateral donors. The marginal impact is large, a one percent increase in disbursements leads to a 127 percent increase in ODA flows. However, this large marginal impact can be explained by the small ODA amounts usually contributed by these donors (as displayed in Figure 3.1). When we compute the AME, we find that one pp of disbursements (in percent of GDP) catalyzes only 0.05 GDP points of ODA.²²

Table 3.3: The catalytic effect by donor type

	(1) Total	(2) Traditional bilateral	(3) Multilateral Organiza- tions	(4) Non- Traditional bilateral
<i>Second stage:</i>				
	Dependent variable: $\log(\text{ODA}/\text{GDP})$			
Disbursement/GDP	0.534*** (0.158)	0.331*** (0.109)	0.558*** (0.166)	1.271** (0.498)
Marginal Effect (in pp of GDP)	2.70	0.65	1.40	0.05
Country and Year FE	Yes	Yes	Yes	Yes
Countries	63	63	63	63
Observations	1746	1745	1745	1565

Note: This table reports IV estimates of regressing $\log(\text{ODA}/\text{GDP})$ on $\text{Disbursement}/\text{GDP}$ with a breakdown by donor type. The panel comprises annual data between 1990 and 2019 for 63 countries. $\text{Disbursement}/\text{GDP}$ is instrumented using the interaction of IMFPrbability and IMFLiquidity (3.1) and $\text{AccessLimits}/\text{GDP}$ (3.2). All regressions control for IMFProbability in the second stage (not shown). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We further decompose the catalytic effects of IMF programs among multilateral organizations. Table 3.4 presents the catalytic effects of IMF programs on different multilaterals using the same specification (3.3). Column 2 presents the results for the catalytic effects on contributions by the European Union (EU). We find a positive and significant coefficient. A one pp increase in disbursements (in percent of GDP)

²²We omitted analyzing contributions from private donors because they are not large enough to be representative.

increases ODA from the EU by 0.17 pp of GDP. Column 3 shows the impact on regional development banks. Surprisingly, we find no significant catalytic effects on these donors.²³ Column 4 shows the catalytic impact on the UN agencies. Overall, the IMF programs do catalyze a small amount of ODA from the UN at around 0.04 pp of GDP.

The catalytic impact of IMF lending on World Bank financing is presented in column 5. Both in percent changes and pp of GDP, we observe a large catalytic impact of IMF disbursements on the World Bank Group's ODA flows. On average, an increase in disbursements of 1 pp of GDP catalyzes ODA from the World Bank by 0.72 pp of GDP, increasing its ODA flows by 87 percent. Finally, column 6 studies the impact of IMF lending on other multilateral organizations not grouped in the above categories (see Appendix 3.7). A positive and significant catalytic effect is found for this category, albeit with a small marginal effect.

Finally, we decompose ODA flows into concessional loans and grants. Table 3.5 displays the results. Column 1 shows the regression outcomes on total ODA flows, column 2 on concessional loans and column 3 on grants, respectively. Overall, we observe that a 1 pp increase in disbursements (in percent of GDP) increases concessional loans by 53.1 percent and grants by 37.2 percent. However, LICs receive more grants than concessional loans. When computing the AME, we observe that an increase in disbursements of 1 pp of GDP catalyzes concessional loans amounting to 0.66 pp of GDP, on average, and 1.17 pp of GDP in grants.

²³One reason why we may not observe catalytic effects is because RDBs usually provide more project financing than budget support, which may be less influenced by IMF financing.

Table 3.4: The catalytic effect by multilateral organizations

	(1) Total Multi- lateral	(2) EU	(3) Regional Dev. Banks	(4) UN	(5) World Bank Group	(6) Others
<i>Second stage:</i>						
	Dependent variable: log (ODA/GDP)					
Disbursement/GDP	0.558*** (0.166)	0.339** (0.113)	0.162 (0.140)	0.227** (0.113)	0.871*** (0.240)	0.231* (0.139)
Marginal Effects (in pp of GDP)	1.40	0.17	-	0.04	0.72	0.04
Country and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	63	63	63	63	63	63
Observations	1745	1718	1418	1646	1594	1587

Note: This table reports IV estimates of regressing log (ODA/GDP) on Disbursement/GDP with a breakdown by multilateral organizations. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFPrability and IMFLiquidity (3.1) and AccessLimits/GDP (3.2). All regressions control for IMFProbability in the second stage (not shown). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.5: The catalytic effect by donor type

	(1) Total	(2) Concessional Loans	(3) Grants
<i>Second stage:</i>			
	Dependent variable: log (ODA/GDP)		
Disbursement/GDP	0.534*** (0.158)	0.531*** (0.192)	0.372*** (0.116)
Marginal Effects (in pp of GDP)	2.70	0.66	1.17
Country and Year FE	Yes	Yes	Yes
Countries	63	62	63
Observations	1746	1693	1744

Note: This table reports IV estimates of regressing log (ODA/GDP) on Disbursement/GDP with a breakdown by aid type. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFPrability and IMFLiquidity (3.1) and AccessLimits/GDP (3.2). All regressions control for IMFProbability in the second stage (not shown). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.5.4 Decomposing the Catalytic Effects within IMF Programs

So far we have explored different dimensions of how IMF lending attracts ODA flows into a program country. In this subsection we restrict our attention by comparing the catalytic effects across active programs to analyze the relationship between the magnitude of disbursements and the amount catalyzed. To this end, we restrict our sample to countries that are actively receiving disbursements, following specification (3.7). Different from past regressions, we do not condition on IMFprobability (as it is not needed) and rely solely on $\text{AccessLimits}/\text{GDP}$ as our instrument for amount of IMF lending.²⁴

Table 3.6 reports the results. Columns 1 and 2 show the OLS and IV results of regressing ODA (in percent of GDP) flows on IMF disbursements, respectively, while controlling for country and year fixed effects. As previously discussed, OLS estimates suffer from a significant downward bias. The 2SLS coefficient shows that an increase in disbursements of 1 pp of GDP increases ODA flows (in percent of GDP) by 26 percent. In levels, this amounts to 1.8 pp of GDP. Larger disbursements (and programs) attract larger ODA flows, even when comparing across IMF programs.

Columns 3 and 4 test possible non-linearities of these catalytic effects. In column 3 we instrument $\text{Disbursement}/\text{GDP}$ with $\text{AccessLimits}/\text{GDP}$, and control for $\text{Disbursement}/\text{GDP}$ squared but do not instrument it. The estimated coefficient associated with disbursement squared reflects a negative and significant coefficient, although small compared to the linear term. In column 4 we replicate the results of column 3, but instrument disbursement and disbursement squared using $\text{AccessLimits}/\text{GDP}$

²⁴Reduced-form results are presented in the Appendix 3.7.

following the steps in Wooldridge (2010).²⁵ The results confirm that there is a quadratic (inverted U-shape) effect of disbursements on ODA flows for LICs that receive IMF lending.

We find that larger programs catalyze more ODA. However, each additional SDR in access catalyzes less ODA than the previous one (decreasing marginal effects). There is a theoretical threshold beyond which additional disbursements could potentially reduce the catalytic effects of IMF lending to LICs in absolute terms. Nonetheless, based on the estimation results of Table 3.6, conservative estimates of such a threshold are around annual disbursements worth 12 pp of GDP, which is far from being reached in practice.²⁶

3.6 Sensitivity Analysis

The previous section estimated the catalytic impact of IMF programs on ODA flows in LICs. In this section we conduct a sensitivity analysis to i) provide evidence that the exclusion restriction of the IVs hold and ii) to show that the estimated catalytic effects are robust to various modifications to the estimation sample, and inclusion of other potential drivers of ODA, such as debt relief.

We begin by showing that the IVs we use to identify the causal impact of IMF programs on ODA are not correlated with other determinants of ODA flows (as

²⁵We first run the first-stage regression regressing Disbursements/GDP on AccessLimits/GDP. We then perform its linear projection. Then we square such projection and use it as an instrument for (Disbursement/GDP)². See Section 3.3.2 for details.

²⁶In Appendix 3.7 we further explore whether this quadratic effect is increasing in the stock of public debt. We do not find evidence that the diminishing returns to catalytic effects are more pronounced when debt levels are higher.

Table 3.6: The catalytic effect and disbursement size

	(1)	(2)	(3)	(4)
<i>Second stage:</i>				
	Dependent variable: $\log(\text{ODA}/\text{GDP})$			
	OLS	IV	OLS	IV
Disbursement/GDP	0.0272** (0.013)	0.257*** (0.097)	0.101*** (0.032)	0.662*** (0.135)
(Disbursement/GDP) ²			-0.003*** (0.001)	-0.026*** (0.007)
Marginal Effects (in pp of GDP)	0.19	1.80	Non-Linear	Non-Linear
Country and Year FE	Yes	Yes	Yes	Yes
F-stat		7.57		7.28
Countries	51	51	51	51
Observations	702	702	702	702

Note: This table reports OLS and IV estimates of regressing $\log(\text{ODA}/\text{GDP})$ on Disbursement/GDP and $(\text{Disbursement}/\text{GDP})^2$ conditional on a sample of countries receiving disbursements. The panel comprises annual data between 1990 and 2019 for 51 countries. Disbursement/GDP is instrumented with AccessLimit/GDP (eq. 3.2). The F-stat is the Kleiberg-Paap Wald F-statistics for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

discussed in Section 3.3.1). In other words, we provide evidence that the exclusion restriction of our IVs holds. To this aim, we estimate our baseline specification (3.3) and include different control variables that are usual determinants of ODA flows (Rabehajaina, Gueyie, and Sedzro, 2023).

Table 3.7 presents the results. Column 1 shows the baseline results of regressing ODA flows on IMF disbursements (in percent of GDP). Column 2 includes real GDP growth as a control. One could expect that low and negative growth could be a good predictors of ODA and IMF program requests. The estimated coefficient for Disbursement/GDP remains unchanged. In column 3 we include current account balance (which is simultaneously a predictor of ODA flows and IMF programs) and find that our estimated coefficient still remains broadly unchanged at 0.534.

In column 4 we control for capital account openness (Chinn and Ito, 2023). Countries that have more open capital account are expected to attract more capital flows (ODA among them). We find support for this claim but controlling for capital account openness does not significantly change the instrumented coefficient of disbursements. In column 5 we include a proxy for political stability and good governance. Countries with robust institutional environments and better governance are more likely to attract more ODA (Dabla-Norris, Minoiu, and Zanna, 2010). Our estimated coefficient on the response of ODA flows to IMF disbursements (column 1) remains significantly constant when including each of these controls separately, and even all at the same time (column 6). These results support our selection for IVs that are largely based on rules-based institutional changes at the IMF and that do not depend on the current macroeconomic performance of LICs.

Finally, we also conducted a sensitivity analysis on variations in the estimation sample, e.g., we excluded countries by region and export structure, and used the lag of GDP to assess the influence of the denominator in the estimated results. These results are presented in Appendix 3.7.

3.7 Conclusions

In this study, we examine the catalytic impact of IMF programs on ODA for LICs and answer the following questions: How large is the catalytic effect of IMF programs on ODA? How has it evolved over the past decades? Which donors contribute the most and through which aid type (grants vs concessional loans)? Does the size of IMF disbursements matter for the amounts of catalyzed financial assistance?

Table 3.7: The catalytic effects of IMF programs and other determinants of ODA

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Second stage:</i>						
	Dependent variable: $\log(\text{ODA}/\text{GDP})$					
Disbursement/GDP	0.534** (0.158)	0.537*** (0.175)	0.534*** (0.159)	0.601*** (0.155)	0.501*** (0.149)	0.569*** (0.157)
Real GDP growth		0.000 (0.005)				0.002 (0.002)
Current Account balance			0.000 (0.002)			- 0.001 (0.005)
Capital Account Openness (Chinn and Ito index)				0.163* (0.085)		0.142 (0.100)
Political Stability					- 0.033 (0.052)	- 0.006 (0.058)
Marginal Effects (in pp of GDP)	2.70	2.70	2.99	2.67	2.51	2.75
Country and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	8.23	7.52	8.19	9.72	7.93	10.72
Countries	63	63	63	63	59	59
Observations	1746	1671	1746	1675	1615	1481

Note: This table reports IV estimates of regressing $\log(\text{ODA}/\text{GDP})$ on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFProbability and IMFLiquidity (3.1) and AccessLimits/GDP (3.2). All regressions control for IMFProbability in the second stage (not shown). The F-stat is the Kleiberg-Paap Wald F-statistic for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To answer these questions, we rely on the use of IVs to address the challenges of selection bias stemming from participation into IMF programs and program size. Unlike previous studies that relied on *selection on observables*, this chapter employs two distinct IVs aimed at addressing each of these biases.

Our findings highlight a significant catalytic impact of IMF lending on ODA in LICs. We quantify that an increase in IMF disbursements of 1 pp of GDP catalyzes additional ODA flows worth 2.7 pp of GDP. Given the typical size of IMF disbursements, this implies that, on average, a LIC engaged in an IMF-supported program can expect to receive an additional 2.2 pp of GDP annually in ODA.

Multilateral organizations, with the World Bank and the European Union at the forefront, emerge as the primary contributors to the catalytic effects, together with traditional bilateral donors. Additionally, our analysis indicates that the catalytic effect of IMF programs pertains more to grants than to concessional loans, emphasizing the importance of aid modalities in shaping the impact of IMF programs on ODA. With LICs' external financing needs exacerbated by a series of global shocks amid tighter market conditions, the catalytic impact of IMF lending has regained importance in closing financing gaps and cushioning adjustment needs.

Furthermore, our exploration into the size of IMF disbursements reveals that larger amounts catalyze more substantial ODA flows. While program participation remains a relevant factor, the amount of lending is more statistically relevant, suggesting that the sheer magnitude of IMF support plays a crucial role in attracting additional external financing. Finally, we also document that the catalytic effects are declining in the size of the IMF programs.

Appendix

A Details on Sample Coverage

A1 Key variables and sources of data

Table 3.8: Main variables: coverage and sources of data

Variable	Coverage	Source
ODA	1990-2019	OECD DAC database
Disbursements	1990-2019	IMF Financial Data Query Tool
PRGTParticipation	1990-2019	IMF Financial Data Query Tool
IMFProbability	1971-2019	IMF Annual Financial Reports
IMFLiquidity (FCC)	1990-2019	IMF
Quotas	1990-2019	IMF Financial Data Query Tool
Cumulative Access Limits to the PRGT	1990-2019	IMF
Nominal GDP	1990-2019	WB World Development Indicators

A2 List of 63 LICs in the baseline sample

Afghanistan, Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Democratic Republic of Congo, Republic of Congo, Cote d'Ivoire, Djibouti, Dominica, Ethiopia, The Gambia, Ghana, Grenada, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Kenya, Kyrgyz Republic, Lao People's Democratic Republic, Lesotho, Liberia, Madagascar, Malawi, Maldives, Mali, Mauritania, Republic of Moldova, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Papua New Guinea, Rwanda, Samoa, Sao Tome & Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, St. Lucia, St. Vincent and the Grenadines, Sudan, Republic of Tajikistan, Tanzania, Togo, Tonga, Uganda, Republic of Uzbekistan, Vanuatu, Republic of Yemen, Zambia, Zimbabwe.

A3 Composition of donors

Traditional bilateral donors: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom and the United States.

Non-Traditional bilateral donors: Azerbaijan, Bulgaria, Chinese Taipei, Croatia, Cyprus, Estonia, Israel, Kazakhstan, Kuwait, Latvia, Liechtenstein, Lithuania, Malta, Monaco, Qatar, Romania, Russian Federation, Saudi Arabia, Thailand, Timor-Leste, Türkiye and United Arab Emirates.

Multilateral Organizations:

- **EU Institutions**
- **Regional Development Banks:** African Development Bank (AfDB), Asian Development Bank (AsDB), Inter-American Development Bank (IDB), Asian Infrastructure Investment Bank (AIIB), Arab Bank for Economic Development in Africa (BADEA), Central American Bank for Economic Integration (CABEI), Caribbean Development Bank (CarDB), Council of Europe Development Bank (CEB), European Bank for Reconstruction and Development (EBRD), Islamic Development Bank (IsDB), North American Development Bank (NADB).
- **United Nations:** Central Emergency Response Fund (CERF), Food and Agriculture Organisation (FAO), IFAD, International Atomic Energy Agency

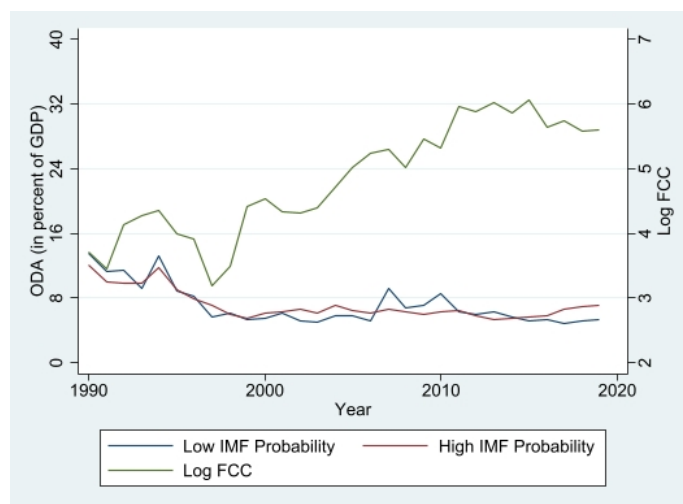
(IAEA), International Labour Organisation (ILO), Joint Sustainable Development GOals Fund (Joint SDG Fund), UN Capital Development Fund (UNCDF), UN Institute for Disarmament Research (UNIDIR), UN Peacebuilding Fund (UNPBF), UN Women, UNAIDS, UNDP, UNECE, UNEP, UNFPA, UNHCR, UNICEF, United Nations Conference on Trade and Development (UNCTAD), United Nations Industrial Development Organization (UNIDO), UNRWA, UNTA, WFP, WHO-Strategic Preparedness and Response Plan (SPRP), World Health Organisation (WHO), World Tourism Organisation (UNWTO), WTO - International Trade Centre (ITC).

- **World Bank Group:** International Bank for Reconstruction and Development (IBRD), International Development Association (IDA) and the International Finance Corporation (IFC).
- **Other Multilateral:** Adaptation Fund, Arab Fund (AFESD), Asian Forest Cooperation Organisation (AFoCO), Center of Excellence in Finance (CEF), CGIAR, Climate Investment Funds (CIF), Global Alliance for Vaccines and Immunization (GAVI), Global Environment Facility (GEF), Global Fund, Global Green Growth Institute (GGGI), Green Climate Fund (GCF), International Centre for Genetic Engineering and Biotechnology (ICGEB), International Commission on Missing Persons (ICMP), Montreal Protocol, Nordic Development Fund (NDF), OPEC Fund for International Development (OPEC Fund), OSCE, World Organisation for Animal Health (WOAH).

B Checking for Spurious Correlations in the Identification Strategy

One potential concern with the first IV is that it may be suffer from spurious trends, as discussed in Christian and Barrett (2017). This would be the case if countries with higher IMFprobability receive proportionally more ODA as IMF liquidity increases over time. We show that this is not the case by separating LICs into a group with a low probability of IMF program (below 50 percentile of IMFProbability), and another one with high probability (above 50 percentile of IMFProbability). Figure 3.6 shows these trends. There is no apparent overlap in long-run trends in any of these groups with the IMF liquidity time series. Using other percentiles yields similar results. This evidence suggest the absence of spurious trends in our IV approach.

Figure 3.6: The IMF's liquidity and trends in ODA



Note: The blue line plots the mean of ODA for countries that have a low probability of participation in IMF programs in the most recent 20-year period (below 50th percentile). The red line plots the mean of ODA for countries that have a high probability of participation in IMF programs in the most recent 20-year period (above 50th percentile). The green line plots the logarithm of the FCC variable. Source: Authors' calculations based on OECD ODA database (OECD, 2023).

C Empirical Results (Additional Tables)

C1 First Stage Regressions of Table 3.2

Table 3.9: First stage results of Table 3.2

	(1)	(2)
	Dependent variable:	
	Disbursement/GDP	IMFParticipation
IMFProbability	0.009** (0.004)	0.012*** (0.002)
IMFProbability $\times$ IMFLiquidity	-0.004*** (0.001)	-0.002*** (0.000)
AccessLimit/GDP	0.094*** (0.026)	0.012*** (0.004)
R ²	0.18	0.41
Country FE	Yes	Yes
Year FE	Yes	Yes
Countries	63	63
Observations	1746	1746

Note: This table reports the first stage (OLS) results of Table 3.2. The panel comprises annual data between 1990 and 2019 for 63 countries. IMFProbability $\times$ IMFLiquidity and AccessLimit/GDP are constructed based on (3.1) and (3.2) respectively. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.10: Reduced form evidence of catalytic effects and program size (based on Table 3.6)

	(1)	(2)
	Dependent variable: $\log(\text{ODA}/\text{GDP})$	
AccessLimit/GDP	0.0425*** (0.00956)	0.0913*** (0.0102)
(AccessLimit/GDP) ²		-0.000949*** (0.000177)
Country FE	Yes	Yes
Year FE	Yes	Yes
Countries	51	51
Observations	702	702

Note: This table reports the reduced-form (OLS) results of Table 3.6 by regressing $\log(\text{ODA}/\text{GDP})$ (for observations with positive disbursements) on the IVs AccessLimit/GDP and (AccessLimit/GDP)². The panel comprises annual data between 1990 and 2019 for 63 countries. AccessLimit/GDP is constructed based on (3.2). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Sensitivity Analysis (Additional Results)

Here we extend our sensitivity analysis to show that our main results are not sensitive to the exclusion of potential events and variations in the country sample.

D1 Special events

Column 1 in Table 3.11 shows our baseline results as a benchmark for comparisons. These are the same results as in column 6 in Table 3.1. In column 2 we show that these baseline results are robust to a series of modifications to the sample. In column 2 we exclude the years following the Global Financial Crisis (2008-2010 period). During this period, there was a large decline in global demand and a spike in uncertainty that challenged LICs' capacity to attract capital inflows. We find that the magnitude of the estimated catalytic effects is not significantly driven by the global developments in this period. In Column 3, we exclude a few cases where

Table 3.11: The catalytic effects of IMF programs excluding regions with sample variations

	(1) Baseline	(2) Excluding GFC years	(3) Excluding precaution- ary programs	(4) Controlling for IMF debt relief
<i>Second stage:</i>				
	Dependent variable: $\log(\text{ODA}/\text{GDP})$			
Disbursement/GDP	0.534*** (0.158)	0.510*** (0.149)	0.533*** (0.159)	0.523*** (0.155)
IMF Debt Relief/GDP				0.039*** (0.011)
Marginal Effects (in pp of GDP)	2.70	2.59	2.70	2.64
Country and Year FE	Yes	Yes	Yes	Yes
F-stat	8.23	8.25	8.02	8.15
Countries	63	63	63	63
Observations	1746	1563	1738	1746

Note: This table reports IV estimates of regressing $\log(\text{ODA}/\text{GDP})$ on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. The instruments $\text{IMFProbability} \times \text{IMFLiquidity}$ and $\text{AccessLimit}/\text{GDP}$ are constructed based on Equations (3.1) and (3.2) respectively. All regressions control for IMFProbability in the second stage (not shown). The F-statistic is the Kleiberg-Paap Wald F-statistics for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

IMF programs were requested for precautionary reasons. The estimated coefficient does not change much. In column 4 we control for the amount of IMF-provided debt relief. Through the Heavily Indebted Poor Countries (HIPC) Initiative, which began in 1996, the IMF provided debt relief to several LICs. This relief was typically granted in tandem with IMF-supported programs. We control for the amount of debt relief provided per year (not-instrumented) and find almost no changes to our baseline results.

D2 Regional and export-type heterogeneity

We also show that our results are robust to variations in the country composition. First, we group LICs in five regions: Europe and Central Asia, Latin America and Caribbean, Middle East and North Africa, Asia and Pacific, and sub-Saharan Africa. Then we run our baseline regression and remove one region at a time. In Table 3.12 we find that our results are not driven by one particular region. More than half of our main sample is composed by sub-Saharan Africa countries. When we remove these countries from the sample the magnitude of the catalytic effect on ODA declines by half from 2.7 to 1.3 pp of GDP. This result implies that catalytic effects of IMF programs in sub-Saharan African countries is larger than the average 2.7 pp of GDP for this group of countries.

We also conduct a sensitivity analysis to show that our results are robust to variations in the main source of export earnings. First, we separate LICs into five groups by source of export earnings: fuel, manufactures, primary products (excluding fuel), services, and diversified products. Then, we run our baseline regression and remove one group at a time. In Table 3.13 we find that our results are not driven by any

Table 3.12: The catalytic effects of IMF programs excluding regions

Excluding countries in	(1) None	(2) Europe and Central Asia	(3) Latin Amer- ica and Caribbean	(4) Middle East North Africa	(5) South Asia	(6) Sub- Saharan Africa
<i>Second stage:</i>						
	Dependent variable: $\log(\text{ODA}/\text{GDP})$					
Disbursement/GDP	0.534*** (0.158)	0.544*** (0.166)	1.205* (0.658)	0.530*** (0.158)	0.554*** (0.165)	0.338*** (0.095)
Marginal Effects (in pp of GDP)	2.70	2.83	6.46	2.68	2.86	1.32
Country and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	8.23	8.77	3.90	8.05	7.63	11.66
Countries	63	59	55	61	59	28
Observations	1746	1654	1510	1687	1638	719

Note: This table reports IV estimates of regressing $\log(\text{ODA}/\text{GDP})$ on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFProbability and IMFLiquidity (3.1) and AccessLimits/GDP (3.2). All regressions control for IMFProbability in the second stage (not shown). The F-stat is the Kleiberg-Paap Wald F-statistic for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Europe and Central Asia (ECA):** Kyrgyz Republic, Republic of Moldova, Republic of Tajikistan, Republic of Uzbekistan. **Latin America and Caribbean (LAC):** Dominica, Grenada, Guyana, Haiti, Honduras, Nicaragua, St. Lucia, St. Vincent and the Grenadines. **Middle East North Africa (MNA):** Djibouti, Republic of Yemen. **South Asia (SAR):** Afghanistan, Bangladesh, Maldives, Nepal. **Sub-Saharan Africa (SSA):** Benin, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Democratic Republic of Congo, Republic of Congo, Cote d'Ivoire, Ethiopia, The Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Rwanda, Sao Tome & Principe, Senegal, Sierra Leone, Somalia, South Sudan, Sudan, Tanzania, Togo, Uganda, Zambia, Zimbabwe. **East Asia and Pacific (EAP):** Cambodia, Chad, Comoros, Lao People's Democratic Republic, Myanmar, Papua New Guinea, Samoa, Solomon Islands, Tonga, Vanuatu.

Table 3.13: The catalytic effects of IMF programs excluding countries based on their main source of exports

Excluding countries with main source of export earnings from	(1) None	(2) Fuel	(3) Manuf.	(4) Primary Products	(5) Services	(6) Diversified Products
<i>Second stage:</i>						
	Dependent variable: $\log(\text{ODA}/\text{GDP})$					
Disbursement/GDP	0.534*** (0.158)	1.012* (0.546)	0.523*** (0.155)	0.442*** (0.125)	0.498*** (0.156)	0.459*** (0.137)
Marginal Effects (in pp of GDP)	2.70	5.30	2.75	1.99	2.40	2.45
Country and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	8.23	5.34	8.14	18.65	6.13	6.86
Countries	63	58	58	42	45	49
Observations	1746	1628	1601	1178	1220	1357

Note: This table reports IV estimates of regressing $\log(\text{ODA}/\text{GDP})$ on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFProbability and IMFLiquidity (3.1) and AccessLimits/GDP (3.2). All regressions control for IMFProbability in the second stage (not shown). The F-stat is the Kleiberg-Paap Wald F-statistic for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Main source of export based on WEO definition: **Fuel:** Chad, Republic of Congo, Guyana, South Sudan, Republic of Yemen. **Manufactures:** Bangladesh, Cambodia, Cote d'Ivoire, Haiti, Lesotho. **Primary Products (Excluding Fuel):** Afghanistan, Benin, Burkina Faso, Burundi, Central African Republic, Democratic Republic of Congo, Ghana, Guinea, Guinea-Bissau, Liberia, Malawi, Mali, Mauritania, Papua New Guinea, Sierra Leone, Solomon Islands, Somalia, Sudan, Republic of Tajikistan, Zambia, Zimbabwe. **Services:** Cape Verde, Comoros, Djibouti, Dominica, Ethiopia, The Gambia, Grenada, Kyrgyz Republic, Maldives, Nepal, Niger, Rwanda, Samoa, Sao Tome & Principe, St. Lucia, St. Vincent and the Grenadines, Tonga, Vanuatu. **Diversified Products:** Cameroon, Honduras, Kenya, Lao People's Democratic Republic, Madagascar, Republic of Moldova, Mozambique, Myanmar, Nicaragua, Senegal, Tanzania, Togo, Uganda, Republic of Uzbekistan.

particular group.

D3 GDP denominator

One concern regarding ODA in percent of GDP, is that countries are more likely to request an IMF program when GDP contracts. We show that our results are not especially sensitive to its denominator. In Table 3.14, we re-estimate the regressions in Table 3.1 using a one-year lag of GDP in all our variables measured in GDP terms. Column 1-3 show results for pooled OLS, and controlling for country and year fixed effects, while Columns 4-6 show the 2SLS results. The estimated coefficients still exhibit are positive and statistically significant. The Kleiberg-Paap Wald F-stat for weak identification is still well above the usual threshold of weak instrument (Stock and Yogo, 2005). In Column 6, our most preferred specification, an increase of one pp in disbursements (in percent of GDP in time (t-1)) is associated with an additional ODA flows worth 2.58 pp of GDP in time (t-1) instead of the 2.7 in Column 6 of Table 3.1.

D4 Intensive margin and government debt

In this subsection we investigate if the catalytic effect of disbursement size, as illustrated in Table 3.6, is affected by sovereign debt levels. We would like to know if the quadratic term is affected when controlling by government debt. The rationale being that large debt pressures (here proxies by debt to GDP ratio) may encourage more ODA when debt to help a struggling LIC. Conversely, high levels of debt could also deter ODA after Fund lending comes in due to the higher likelihood of a potential restructuring case.

Table 3.14: Total catalytic effects using one-year lag of GDP

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Second stage:</i>	Dependent variable: log (ODA/GDP(t-1))					
	OLS	OLS	OLS	IV	IV	IV
Disbursement/GDP(t-1)	0.122** (0.040)	0.074** (0.026)	0.061** (0.026)	0.701*** (0.263)	0.471*** (0.170)	0.487*** (0.171)
Marginal Effects (in pp of GDP(t-1))	0.64	0.39	0.32	3.71	2.49	2.58
R ²	0.05	0.05	0.02			
<i>First stage:</i>	Dependent variable: Disbursement/GDP					
IMFProbability				0.011** (0.006)	-0.005*** (0.002)	0.007 (0.005)
IMFProbability × IMFLiquidity				-0.003*** (0.001)		-0.002*** (0.001)
AccessLimit/GDP(t-1)					0.086*** (0.027)	0.084*** (0.027)
Country FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
F-stat				10.11	10.14	6.03
Countries	63	63	63	63	63	63
Observations	1682	1682	1682	1682	1682	1682

One empirical challenge here is that Table 3.6 employed a double-instrument approach to IMF disbursements. Adding a further interaction may pose econometric challenges. To simplify, we decided to apply the "reduced-form" approach and use the instrument $\text{AccessLimits}/\text{GDP}$ as the proxy for disbursements. Table 3.15 shows the ordinary least squares (OLS) outcomes with government debt included as a control variable. The initial two columns reaffirm the baseline reduced-form outcomes, where there is a quadratic effect of access limits on ODA. The introduction of government debt as a control variable in Column 3, and the inclusion of an interaction term between Debt/GDP and the square of $\text{AccessLimit}/\text{GDP}$ in Column 4, do not alter the overarching conclusion: program size is positively and significantly related to the outcomes, whereas the square of program size has a negative and significant causal effect. Nonetheless, we observe that the interaction between $\text{AccessLimits}/\text{GDP}$ squared and government debt is positive and significant. This means that the so called decreasing catalytic effects become "less concave" when debt levels are high. We replicated the analysis on ODA from bilateral and multilateral creditors separately (not shown). Both display the similar results as in column 4.

Further evidence is presented in Table 3.16, where we replicate Table 3.6 by separating the data sample into two categories based on the annual median Debt-to-GDP ratio. Columns 1 and 2 revisit the primary findings from Table 3.6. Subsequent analyses in Columns 3 and 4 apply the regression model from Column 2 separately to the groups characterized by high and low Debt-to-GDP ratios. For both divisions, we observe that the coefficients associated with program size remain positively significant, and those related to the squared program size are negatively significant.

Table 3.15: Reduced form evidence of catalytic effects and program size controlling government debt

	(1)	(2)	(3)	(4)
	Dependent variable: $\log(\text{ODA}/\text{GDP})$			
AccessLimit/GDP	0.0425*** (0.00956)	0.0913*** (0.0102)	0.0854*** (0.0105)	0.110*** (0.0163)
(AccessLimit/GDP) ²		- 0.000949*** (0.000177)	- 0.000921*** (0.000179)	-0.00201*** (0.000546)
Debt/GDP			0.000991* (0.000512)	0.000222 (0.000671)
Debt/GDP $\times$ (AccessLimit/GDP) ²				0.00000259** (0.00000115)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Countries	51	51	51	51
Observations	702	702	681	681

Note: This table reports the reduced-form (OLS) results of Table 3.6 by regressing $\log(\text{ODA}/\text{GDP})$ (for observations with positive disbursements) on the IVs AccessLimit/GDP and (AccessLimit/GDP)² controlling government debt. The panel comprises annual data between 1990 and 2019 for 51 countries. AccessLimit/GDP is constructed based on (3.2). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.16: The catalytic effects and program size by high and low government debt levels

	(1) Baseline	(2) Baseline	(3) Low Debt/GDP	(4) High Debt/GDP
<i>Second stage:</i>				
	Dependent variable: $\log(\text{ODA}/\text{GDP})$			
	OLS	IV	IV	IV
Disbursement/GDP	0.101*** (0.0318)	0.662*** (0.135)	1.153** (0.524)	0.758** (0.343)
(Disbursement/GDP) ²	-0.003*** (0.001)	-0.026*** (0.007)	-0.033** (0.015)	-0.062** (0.0256)
Country and Year FE	Yes	Yes	Yes	Yes
F-stat		7.28	3.14	2.55
Countries	51	51	42	40
Observations	702	702	346	351

Note: This table reports OLS and IV estimates of regressing $\log(\text{ODA}/\text{GDP})$ on Disbursement/GDP and $(\text{Disbursement}/\text{GDP})^2$ conditional on a sample of countries receiving disbursements. The panel comprises annual data between 1990 and 2019 for 51 countries. Disbursement/GDP is instrumented with AccessLimit/GDP (Equation (3.2)). The cutoff between low and high Debt/GDP in Columns (3) and (4) is the median Debt/GDP across all countries in each year. The sum of the number of countries in low and high Debt/GDP groups is larger than the total number of countries because a country can switch between these two groups over time. All regressions control for IMFProbability in the second stage (not shown). The F-stat is the Kleiberg-Paap Wald F-statistics for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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CONCLUSION

This dissertation studies how financial frictions, market structure, and policy interventions shape exchange rate dynamics and capital flows across countries at different stages of financial development. A central message is that the depth of financial markets and the availability of arbitrage capital are key determinants of macroeconomic outcomes. While advanced economies, emerging market economies, and low-income countries operate under different institutional environments, the underlying mechanisms are closely related. The three chapters together provide a unified framework to understand how these mechanisms manifest differently depending on market structure and the composition of capital flows.

In Chapter 1, I provide new empirical evidence on the uncovered interest parity (UIP) puzzle using daily data on exchange rates and interest differentials. The high-frequency data allow me to trace the dynamics of the Fama coefficient over time and across both advanced and emerging market economies. The findings show that UIP deviations are pervasive and highly time-varying, with significant shifts around major global events such as financial crises and changes in monetary policy. By applying a decomposition technique, I show that models based on financial market frictions provide a better fit to time-varying behavior of the Fama coefficient than traditional explanations based on risk premia, expectations, and liquidity. Importantly, the results reveal common patterns across countries, suggesting that differences between

advanced and emerging market economies arise from differences in the magnitude of frictions rather than fundamentally different mechanisms.

In Chapter 2, I develop a continuous-time model to study how arbitrageur behavior shapes exchange rate dynamics. The key insight is that arbitrageurs generate two opposing forces: a substitution effect that stabilizes markets and a wealth effect that can amplify shocks. The relative strength of these effects depends on the level of arbitrageur wealth. In advanced economies with deep and liquid foreign exchange markets, abundant arbitrage capital allows the substitution effect to dominate, resulting in more stable exchange rates and smaller deviations from UIP. In contrast, in emerging market economies with thinner markets and limited arbitrageur wealth, the wealth effect becomes more prominent, leading to greater exchange rate volatility and more frequent deviations from UIP. This framework provides a natural explanation for why central banks of emerging market economies intervene more frequently and at larger scale. It also implies that policies aimed at increasing market depth and expanding arbitrageur capital can substantially reduce the need for foreign exchange intervention.

In Chapter 3, I examine the catalytic impact of IMF lending on official development assistance (ODA) in low-income countries. Using an instrumental variables approach to address selection bias, I find that IMF disbursements have a strong positive effect on ODA inflows. The results show that larger IMF lending amounts catalyze more substantial external financing, and that the size of disbursements plays a more important role than program participation alone. At the same time, the analysis uncovers diminishing returns to IMF lending, with catalytic effects declining at higher levels of disbursements. These findings highlight the importance of IMF programs

in mobilizing external resources in environments where private capital markets are limited, and underscore the distinct role of official financing in low-income countries.

Overall, the dissertation demonstrates that financial frictions and constraints on capital allocation are central to understanding international macroeconomic outcomes. In advanced economies, deep financial markets mitigate these frictions and promote stability. In emerging market economies, limited arbitrage capacity amplifies shocks and necessitates policy intervention. In low-income countries, the absence of developed financial markets shifts the burden of adjustment to official capital flows and international institutions. Recognizing these differences, while maintaining a unified analytical framework, is essential for understanding global financial dynamics and for designing effective economic policies.