# Inelastic Financial Markets and Foreign Exchange Interventions*

Paula Beltran
IMF

Chang He
UCLA, **Job Market Paper**

January 29, 2024
(click here for the latest version)

**Abstract**

Are foreign exchange interventions effective at moving exchange rates? In this paper, we leverage the rebalancings of a local-currency government bonds index for emerging countries as a quasi-natural experiment to identify the required size of foreign exchange interventions to stabilize exchange rates. We show that the rebalancings create large and exogenous currency demand shocks that move exchange rates. Our results provide empirical support for models of inelastic financial markets where foreign exchange intervention serves as an additional policy tool to effectively stabilize exchange rates. Under inelastic financial markets, a managed exchange rate does not have to compromise monetary policy independence even in the presence of free capital mobility, relaxing the classical trilemma constraint. Our results show that to achieve a 1% exchange rate appreciation, the average required intervention is about 0.4% of annual GDP. We also show that countries with a free-floating exchange rate regime (free floaters) are more than three-fold more effective at stabilizing exchange rates than are countries with a managed exchange rate regime. This is because the volatile exchange rates for the free floaters lead to more inelastic financial markets and generate further departure from the trilemma.

*Previously circulated as "Identifying the Size of Open Market Operations in Foreign Exchange Interventions." Beltran (PBeltranSaavedra2@imf.org): International Monetary Fund (IMF), 700 19th Street, N.W. Washington D.C. USA 20431. He (hec@ucla.edu): University of California, Los Angeles (UCLA) Department of Economics, 8283 Bunche Hall, 315 Portola Plaza, Los Angeles, CA. USA 90095. The views expressed herein are those of the authors and should not be attributed to the IMF, its executive board, or its management. Chang He is indebted to her doctoral committee members Oleg Itskhoki (advisor), Andy Atkeson, Tyler Muir, and Pierre-Olivier Weill for their continuous support. We are grateful to Patrick Adams, David Baqaee, Ariel Burstein, Saki Bigio, Marcos Chamon, Mikhail Chernov, Wenxin Du, Andres Fernandez, Miguel Faria-e-Castro, Joao Guerreiro, Valentin Haddad, Bernard Herskovic, Sun Yong Kim (discussant), Annie Lee, Fernando Martin, Chris Neely, Matteo Maggiori, Dimitry Mukhin, Lee Ohanian, Stavros Panageas, Avanidhar Subra, Anand Systla, and Tomas Williams for insightful discussions at different stages of this paper. We thank the research teams at EPFR, J.P. Morgan Markets and IMF for help with data; special thanks to Tomas Williams for guiding us through the data. We also benefited from useful conversations with numerous participants in various seminars and conferences.

# 1 Introduction

Are foreign exchange interventions effective at moving exchange rates? And if so, how large should the size of interventions be to stabilize exchange rates? Policymakers frequently resort to large-scale foreign exchange interventions. For example, during the post-"taper-tantrum" episode[1], the inflation-targeting Latin American countries engaged in massive sales of foreign reserves to defend the value of their home currencies. In this episode, Mexico (managed float) sold foreign reserves worth more than 30 billion USD (3% of GDP), and Peru (crawling peg) sold about 10 billion USD worth of foreign reserves (5% of GDP) (IMF, 2019).

Assessing the effectiveness of the foreign exchange intervention is empirically challenging, because exchange rates, the prevailing macroeconomic conditions, and the intervention itself are jointly endogenous. Several papers have provided empirical evidence on the effects of foreign exchange interventions by resorting to confidential and high-frequency data on intervention episodes (Adler et al., 2019; Fratzscher et al., 2019). Yet, a valid identification calls for a natural experiment that exogenously changes the currency composition of the government bonds in an economy.

In this paper, we overcome the identification challenge addressed above and estimate the required size of intervention to stabilize exchange rates through a quasi-natural experiment. We leverage our exogenous currency demand shock from the mechanical rebalancings of the Government Bond Index Emerging Market (GBI-EM) Global Diversified. Our empirical results provide evidence for models of inelastic financial markets where foreign exchange intervention serves as an effective policy tool to stabilize exchange rates. Through the lens of the model, we identify the required size of intervention to stabilize exchange rates for countries with different exchange rate regimes.

The exogenous currency demand shock created by the mechanical rebalancings of the GBI-EM Global Diversified index is crucial for our identification. This is the most widely tracked benchmark index by mutual funds that invest in local-currency government bonds in emerging markets, with an estimated value of the assets under management exceeding 200 billion USD in 2019. The monthly rebalancings cap the benchmark

[1] Taper tantrum refers to the episode with falling capital inflows in emerging countries following the 2013 Federal Reserve announcement of tapering down quantitative easings. The announcement set off a market reaction affecting the U.S. and other countries.

weight of each country in the index at 10%, and any excess weight above the cap is redistributed to smaller countries so that all the weights add up to 1. At the rebalancing dates, countries *not* at the cap experience positive weight increase not because of an improvement in their economic conditions, but purely as a result of the bigger countries hitting the cap. Thus, the rebalancing feature gives rise to large and exogenous cross-border capital flows for countries not at the weight cap.

We construct our exogenous currency demand shock as the percentage change in the country weights before and after a rebalancing event. Intuitively, the shock captures the change in quantity (face amount) of local-currency sovereign bonds in the index purely implied by the mechanical rebalancings, independent of the market prices and macroeconomic conditions. For clean identification, we use currency demand shocks only from countries not at the 10% weight cap at the rebalancing dates. A one standard deviation of the shock equals 21% of market value (a weight change from 5 to 6% for a medium country, or equivalently 2.5 billion USD flows) of a country's government bonds in the GBI-EM Global Diversified index.

We show that exchange rates respond significantly to the currency demand shock and the effects are persistent for at least three months. On average, a one standard deviation of the currency demand shock appreciates local currencies by 1% in the days following a rebalancing event. We show that despite the significant response of exchange rates, central bank monetary policy rates do not respond to the currency demand shock. This implies that the macroeconomic conditions are smooth around the index rebalancing events, consistent with the exogeneity assumptions.

The fact that exchange rates respond significantly to the currency demand shock is consistent with models of inelastic financial markets (e.g., Gabaix and Maggiori, 2015; Itskhoki and Mukhin, 2021). Under these markets, a currency demand shock changes arbitrageurs' holdings and gives rise to endogenous deviations in the uncovered interest parity (UIP) condition. By comparison, standard macroeconomic models (e.g., Mundell, 1962; Gali and Monacelli, 2005; Farhi and Werning, 2012) assume perfectly elastic financial markets or UIP holds. If financial markets were truly elastic, a currency demand shock would have no impact on the path of exchange rates or the UIP condition.

Inelastic financial markets have important implications for the effectiveness of foreign exchange interventions at stabilizing exchange rates. Under models of inelastic financial markets, foreign exchange interventions shift arbitrageurs' risk-bearing capacity in a similar way to the currency demand shock, leading to endogenous deviations in the uncovered interest parity condition. Therefore, foreign exchange interventions serve as an additional policy tool to effectively stabilize exchange rates, whereas the monetary policies can be entirely inward-focused on domestic inflation and output gap. Even under free capital flows, an economy can simultaneously have an independent monetary policy and a managed exchange rate through foreign exchange interventions. We refer to this condition as the "relaxed trilemma" (Basu et al., 2023; Itskhoki and Mukhin, 2023a).

We show that the more inelastic the financial markets, the more effective the foreign exchange interventions. This would imply that the interventions are more effective for countries with a free-floating currency exchange regime (free floaters). Through the lens of our model, the higher exchange rates' volatility for free floaters makes the financial markets more inelastic and generates further departure from the trilemma constraint. At the other extreme, where exchange rates are fully pegged (i.e., in countries with a fixed exchange rate regime, or peggers), we are back to the elastic financial markets model under the trilemma constraint where foreign exchange interventions are ineffective.

Our estimates suggest that foreign exchange interventions are more than three-fold more effective for free floaters than for either managed floaters or peggers. This can be seen from the larger response of exchange rates to the currency demand shock for free floaters. We convert the estimates of the response of exchange rates to the USD flows by computing the mutual funds flows implied by the rebalancings of the index. Through the lens of our model, the counterfactual size of intervention required to stabilize exchange rates would have to exactly offset the impact from the currency demand shock. Our findings suggest that the required size of intervention (as a share of GDP) is more than three times smaller for free floaters than for managed floaters or peggers, meaning that the interventions work more effectively for the free floaters.

We find that to achieve a 1 percent exchange rate appreciation, the average required foreign reserves that the central bank needs to sell in foreign exchange interventions is about 0.4% of GDP (or about 2.5 billion USD on average) for the emerging countries in our sample. Our results are largely consistent with the early literature on estimating the size of foreign exchange intervention using event studies (Adler et al., 2019; Fratzscher et al., 2019) and the asset-pricing literature that identifies demand elasticities for currencies (e.g., Evans and Lyons, 2002; Hau, Massa, and Peress, 2009; Camanho, Hau and Rey, 2021).

**Related Literature.** Our results contribute to various strands of literature in both macroeconomics and finance and are informative to central bank policymakers. First, we contribute to the large empirical literature on the effects of foreign exchange interventions, including Fatum and Hutchison (2003), Blanchard et al. (2015), Fratzscher et al. (2019) and Adler, Lisack and Mano (2019) and the foreign exchange policy framework in Jeanne (2012), Amador, Bianchi, Bocola, and Perri (2019), Cavallino (2019), Fanelli and Straub (2021), Basu et al., (2023) and Itskhoki and Mukhin (2023a). We add to this literature by finding a plausible exogenous currency demand shock through leveraging the rebalancings of a local currency government bond index as a quasi-natural experiment.

Moreover, our paper connects with the broad finance literature on asset demand estimation and evidence for inelastic financial markets. Empirical studies using index rebalancings to estimate asset demand curves date back to Shleifer (1986), followed by a series of studies with refined identification strategies by Lynch and Mendenhall (1997), Kaul, Mehrotra and Morck (2000), and Chang, Hong and Liskovich (2014), as well as theoretical contributions on models of benchmark investments including Basak and Pavlova (2013) and Kashyap et al. (2021, 2023). More recent work, including Hau, Massa, and Peress (2009), Pandolfi and Williams (2019), Koijen and Yogo (2019, 2020) and Camanho, Hau and Rey (2021), Bacchetta, Tieche, and Van Wincoop (2023), estimates the (global) asset pricing demand system, and Gabaix and Koijen (2022) discusses policy implications for inelastic financial markets. Our paper applies the empirical strategy of index rebalancing traditionally used to estimate asset demand in a new context: the elasticity of currencies and its implications for foreign exchange interventions.

In addition, our paper speaks to the macro-finance literature on exchange rates dynamics in segmented markets with frictional financial markets. The segmented financial market model we use in this paper builds on Alvarez, Atkeson and Kehoe (2009), Gabaix and Maggiori (2015), Gourinchas, Ray and Vayanos (2019), Cavallino (2019), Greenwood, Hanson, Stein, and Sunderam (2020), Itskhoki and Mukhin (2021), and Basu, Boz, Gopinath, Roch and Unsal (2023). Another recent work, by Jiang, Krishnamurthy and Lustig (2022), produces similar exchange dynamics but features incomplete rather than segmented financial markets.

Finally, our work is related to the large literature on exchange rates prediction. The related papers to ours include Fama (1984), Evans and Lyons (2002), Tornell and Gourinchas (2004), Lustig and Verdelhan (2007), Engel (2016), Jiang, Krishnamurthy and Lustig (2022), and more recently Kremens, Martin, and Liliana (2023) and Candian and De Leo (2023). While these works mostly leverage taste shocks or expectation errors in forecasting exchange rates, our currency demand shocks for predicting exchange rates rely on a quantity shock from the mechanical index rebalancings.

**Outline**. The rest of the paper is structured as follows. In the first part of the paper, we introduce the exogenous currency demand shock and illustrate its relation to the dynamics of exchange rates and interest rates. To interpret these stylized empirical facts, in the second part of the paper we present an inelastic financial market model where a currency demand shock leads to endogenous deviations in the uncovered interest parity condition. In the third and last part of the paper, we introduce foreign exchange interventions into the inelastic financial market model and estimate the required size of intervention to stabilize exchange rates.

# 2 Introducing the Currency Demand Shock

We leverage the mechanical rebalancing features of a local-currency government bond index for emerging countries to construct an exogenous currency demand shock. We document in detail the rebalancing rules of the index and introduce our measure for the currency demand shock as well as the implied flows from the shock.

## 2.1 Mechanical Rebalancings of the GBI-EM Global Diversified Index

Our empirical strategy relies on the mechanical rebalancings of the Government Bond Index Emerging Market (GBI-EM) Global Diversified published by J.P. Morgan. This is the largest local currency government bonds index for emerging countries. An estimated assets under management of more than 200 billion USD of mutual funds track the index in 2019.[2] There are currently 19 emerging countries in the index, with each country

[2] The 200 billion USD is a large number for the emerging market sovereign bonds market, because the total new issuance of the emerging market sovereign bonds is merely 160 billion USD in 2019 (Refinitiv

weight equal to the share of its market value of the local-currency sovereign bonds in the index. A larger country, such as Brazil, has a larger weight in the index than a smaller country, such as Peru or Chile.

The mechanical rebalancings by the GBI-EM Global Diversified index on the country weight cap are crucial for the identification in this paper. The country weight fluctuates daily as the market price of the sovereign bonds moves up or down. However, at the rebalancing date (which is the end of the last business day of each month), the index mechanically caps the country weight at 10% for all countries to limit concentration risk. Any excess weight above the cap is redistributed to smaller countries that are below the cap proportionally so that all country weights add up to 100%. The rebalancings can continue recursively for multiple rounds until all the country weights are either at or below the 10% cap.[3]

We argue that for countries not at the 10% country-weight cap, their change in weights in the GBI-EM Global Diversified index creates currency demand shocks that are uninformative to the macroeconomic fundamentals of the sovereign. For example, if Brazil's country weight is rebalanced from 15% to 10% and leads to an increase in Peru's country weight, those benchmarked mutual funds have to sell local-currency sovereign bonds of Brazil and buy Peruvian sol in order to purchase local-currency sovereign bonds of Peru. In this rebalancing example, a smaller country experienced a positive currency demand shock on its local-currency bonds *independent* of its own macroeconomic conditions and purely as a result of a larger country hitting the 10% cap. Table 2.1 gives a simplified rebalancing example.

In our empirical identification, we focus on the change in country weights at the rebalancing date mechanically implied by the rebalancing algorithm. That is, the part where smaller countries' weights go up due to the bigger countries at the cap being rebalanced downwards rather than how countries arrive at the weights before rebalancing (15% for Brazil, 4% for Colombia and 1% for Peru). An above-the-cap weight (e.g. Brazil at 15%) at the rebalancing date doesn't necessarily mean that the market price goes up every month for the country. A bigger country's market price appreciates compared to

data).

[3]The rebalancings are done in three layers in order and the country-weight rebalancing is the last layer following the face-amount inclusion and bond maturity threshold. Appendix A discusses the first two layers of rebalancings and how the countries are chosen to enter or exit the index.

Table 2.1: A simplified rebalancing example at 10% weight cap

| | $\omega_{c,t}^{before}$ | | $\omega_{c,t}^{after}$ | $\mu_{c,t}$ |
|---|---|---|---|---|
| **Brazil** | **15** | **-5** | **10** | - |
| **Colombia** | **4** | **+4** | **8** | 1/2 |
| **Peru** | **1** | **+1** | **2** | 1/2 |

**Note**: This table presents a simplified rebalancing example that caps the country weight at 10%. For simplicity, assume there are 11 countries in the index and 8 of them are already at 10%. The rebalancings therefore only apply to Brazil (with weight 15%) above the cap and Peru (with weight 1%) and Columbia (with weight 4%) below the cap. Each round of rebalancing takes the excess weight of the country and redistributes it to the smaller countries below the cap proportionally to the weight of each country. The rebalancings continue recursively until all the country weights are either at or below the 10% cap. In this example, the currency demand shock $\mu_{c,t}$ for both Colombia and Peru are 1/2 (computed as 4/8 and 1/2, respectively).

the smaller ones only in *relative* sense because all the weights add up to 100%, and also because a larger weight for the bigger country is closer to its true market share in an investment portfolio that's unconstrained by the rebalancing cap.

## 2.2 Measuring the Currency Demand Shock

We introduce $\mu_{c,t}$ to capture the currency demand shock from the mechanical rebalancings of the GBI-EM Global Diversified index, for country $c$ at the rebalancing date $t$. As shown in equation (1), we define $\omega_{c,t}^{\text{before}}$ and $\omega_{c,t}^{\text{after}}$ as the country weight before and after the rebalancing event, respectively, at the rebalancing date. Taken market price $P_{c,t}$ as given, J.P. Morgan adjusts the country weights (from $\omega_{c,t}^{\text{before}}$ to $\omega_{c,t}^{\text{after}}$) through changing the face amount ($\hat{Q}_{c,t}$) of the local-currency sovereign bonds of the country included in the index:

$$\mu_{c,t} = \frac{\omega_{c,t}^{\text{after}} - \omega_{c,t}^{\text{before}}}{\omega_{c,t}^{\text{after}}}, \tag{1}$$

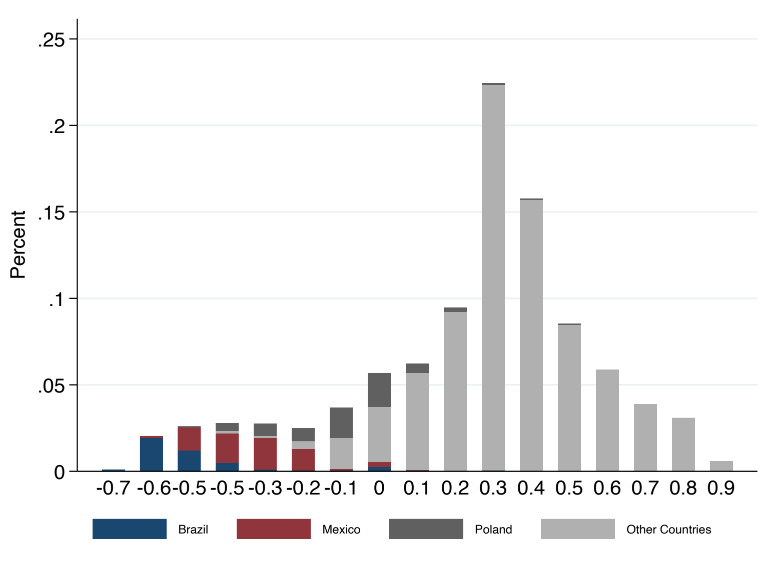
where $\omega_{c,t}^{\text{before}} = \frac{P_{c,t}\hat{Q}_{c,t-1}}{\sum_c' P_{c',t}\hat{Q}_{c',t}}$ and $\omega_{c,t}^{\text{after}} = \frac{P_{c,t}\hat{Q}_{c,t}}{\sum_c' P_{c',t}\hat{Q}_{c',t}}$; $P_{c,t}$ is the aggregate market price of the local-currency sovereign bonds for country $c$ at the rebalancing date; $\hat{Q}_{c,t-1}$ and $\hat{Q}_{c,t}$ are the face amount of the local-currency sovereigns bonds included in the index from the last rebalancing and the current rebalancing, respectively.[4] Intuitively, $\mu_{c,t}$ captures purely the quantity (face amount) change in sovereign bonds implied by the mechanical rebalancings.[5] We construct $\mu_{c,t}$ as the change in weights as a share of a country's own weight, because countries have different "depth" (reflected in the size of the market value and therefore the weight of the country) in the sovereign bonds market. Table 2.1 gives a simplified rebalancing example and computes the currency demand shock in this example.

Our main empirical analysis focus on currency demand shocks from countries that do *not* meet the 10% cap at the rebalancing dates. These countries have to change their weights as a result of the bigger countries meeting the cap, and therefore their change in weight is independent of their macro-fundamentals, which are smooth around the rebalancing date. In the example in Table 2.1, we would use only the change in weights from Peru and Columbia for the identification. Table 2.2 shows the summary statistics and histogram of the currency demand shocks for the countries in our sample. While most of the countries experience positive currency demand shocks ($\mu_{c,t} > 0$), a few bigger countries (namely, Brazil, Mexico and Poland) have mostly negative shocks ($\mu_{c,t} < 0$) throughout the sample as a result of being rebalanced downwards when their weights exceed the 10% cap. Table B.6 in Appendix reports the time series of shock for each country.

[4] It is important to distinguish the face amount of sovereign bonds included in the index ($\hat{Q}_{c,t}$) from the face amount of the actual issuance ($Q_{c,t}$) by the sovereign.

[5] If the expression for country weights $\omega_{c,t}^{\text{before}}$ and $\omega_{c,t}^{\text{after}}$ is written out, the market price $P_{c,t}$ will be cancelled and $\mu_{c,t}$ will be left with the quantity effects only. See appendix A.3 for the derivation.

Table 2.2: Distribution of the Currency Demand Shock ($\mu_{c,t}$)




**Note**: This table reports the summary statistics on the currency demand shock ($\mu_{c,t}$) implied by the monthly rebalancings of the GBI-EM Global Diversified index. The figure plots the distribution $\mu_{c,t}$ across time for each country; $\mu_{c,t}$ for Brazil, Poland and Mexico are labeled and in navy, red, and dark grey respectively. The vertical axis is the precent share in the entire sample as indicated by the labels on the horizontal axis. For example, -0.7 indicates the value range (-0.7, -0.6) and 0.9 indicates the value range (0.9, 1). A negative $\mu_{c,t}$ ($< 0$) implies that the country is rebalanced downwards when it hits the 10% cap. In the empirical analysis below, we drop the countries at the 10% cap, for cleaner identification. A full histogram of all countries can be found in Table B.5 in the appendix.

## 2.3 Flows Implied by the Currency Demand Shock

The mechanical rebalancings of the GBI-EM Global Diversified index create large demand shocks on the local-currency government bonds. We show that the mutual funds tracking the index passively and with large asset positions comply with the rebalancing rules, as seen by their high-performance R-squared against the returns of the GBI-EM Global Diversified index. We select from the Emerging Portfolio Fund Research (EPFR) dataset all emerging market bond funds whose benchmark indices are the GBI-EM Global Diversified index[6] and regress the monthly returns of each fund on the returns on the index[7]. This gives us a large median R-squared, of 0.92 (Table B.7a in the

[6]Details on how we selected mutual funds into the data are reported in appendix A.

[7]We follow Amihud and Goyenko (2013) and Pandolfi and Williams (2019) and use the return regression to test the performance of mutual funds. The method regresses the fund-level monthly returns on the monthly returns of the GBI-EM Global Diversified: $r_{i,t} = \alpha + \beta r_{B,t}$, where $r_{i,t}$ is the monthly returns from fund $i$ at time $t$ and $r_{B,t}$ is the monthly returns from the benchmark – in this case, the J.P. Morgan GBI-EM

appendix). We also construct the weighted average return (by asset under management) of these mutual funds and regress the weighted return on the index returns, which results in an even higher R-squared, of 0.97 (Table B.7b).

To convert the currency demand shocks to USD flows, we estimate the total assets under management of the mutual funds tracking the GBI-EM Global Diversified index globally. Figure B.4 panel (a) plots the assets under the management of funds tracking the GBI-EM Global Diversified index in the EPFR data from 2016 to 2022. Figure B.4 panel (b) shows the representation of EPFR data in the total mutual funds population as estimated by the Investment Company Institute (ICI) Global. The figures show that EPFR data represent about 60% of the worldwide mutual funds population in 2019.

## 2.4 Data Sources

The main data source we use is the Index Composition and Statistics reports from J.P. Morgan. These reports include monthly information on benchmark weights and rebalancing for their sovereign bonds benchmarks, including the GBI-EM Global Diversified index. Our sample includes a panel of 17 countries from 2010 to 2021: Argentina, Brazil, Chile, Colombia, Czech Republic (Czechia), Hungary, Indonesia, Malaysia, Mexico, Peru, the Philippines, Poland, Romania, Russia, South Africa, Thailand and Turkey.[8] These reports allow us to construct our currency demand shock as introduced above.

The second main data source we use is the EPFR data on the asset positions of the emerging market bond funds. We show that the currency demand shock is correlated with the changes in the asset positions of the mutual funds tracking the GBI-EM Global Diversified index in the EPFR data. Moreover, we use the EPFR data to compute the flows in US dollars implied by the rebalancings by our currency demand shock.

Finally, we combine J.P. Morgan reports and EPFR fund flows data with daily data of exchange rates and data on central bank policy rates from the Bank for International Settlements. We complement these data with sovereign bonds yields for various maturities for each country from Du and Schruger (2016), with the dataset updated until 2021.

Global Diversified index. We then collect the fitted R-squared from each return regression. A higher fitted R-squared indicates the fund tracks the benchmark index more closely.

[8] We exclude China from the current analysis because there are limited time series on this country in the data, as China entered the GBI-EM Global Diversified index only in 2020; we exclude Nigeria from the analysis because there are limited data on exchange rates for this country.

# 3 Currency Demand Shocks and Exchange Rates

In this section, we present four novel empirical facts on how the currency demand shocks affect exchange rates and interest rates.

**Empirical Fact 1.** *The currency demand shock moves exchange rates in the short run. A one standard deviation increase of the shock appreciates exchange rates by an average of 1%.*

Figure 1 reports the estimated coefficients of cumulative exchange rate changes on our currency demand shock as measured by $\mu_{c,t}$ in equation (1). The regression takes the following form:

$$\Delta e_{c,t+d} = \beta_0 + \beta_\mu \, \mu_{c,t} + \phi \, X_{c,t} + \epsilon_{c,t}, \tag{2}$$

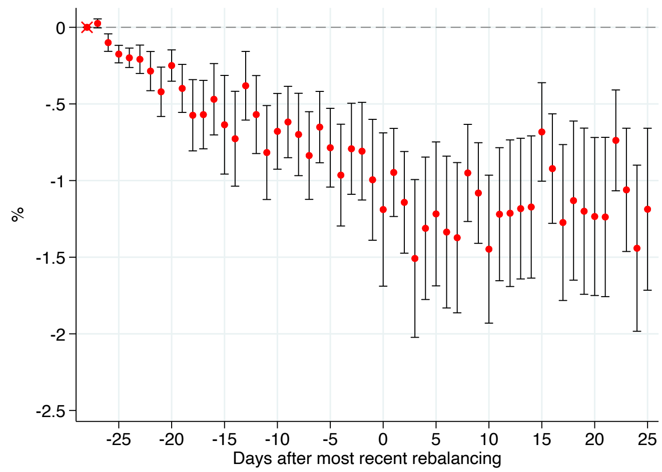
where $\mu_{c,t}$ is the currency demand shock defined in equation (1); $\beta_0$ is the constant and $X_{c,t}$ is a set of dummies that control for country, month, and year fixed effects, respectively. Standard errors are clustered at the country level. We include year fixed effects to account of the cyclicality of the global financial cycle (Rey, 2013) and month fixed effects to account of the documented tighter balance sheet constraints for banks towards the quarter ends (Du, Tepper and Verhelhan, 2018).

Exchange rates are measured in local currencies per US dollar, and the exchange rate change $\Delta e_{c,t+d}$ is the cumulative change from the interval beginning 28 days before the rebalancing date 0 until $d$ days after this date ($d < 0$ for days before the rebalancing date 0; if $d > 0$, vice versa). As discussed, our main empirical analysis drops all country-month observations that exceed the 10% threshold from the regression to ensure the currency demand shock is information-free and independent of the macro-fundamentals. Nevertheless, we report the regression results that include countries at the 10% threshold in Table B.14 in the appendix, which shows that the estimates are largely identical as in Fact 1. [9]

The pooled OLS regression shows that a one standard deviation increase of $\mu_{c,t}$ (21% increase in the market value of the country in the index, or an average of 2.5 billion USD flows) appreciates local currency exchange rates significantly by 1%, after a rebalancing

[9] There's also concern on the time-series correlation of the currency demand shock, which displays an AR(1) structure. Tables B.16 in the appendix reproduce Fact 1 using $\Delta\mu_{c,t} \equiv \mu_{c,t} - \mu_{c,t-1}$ instead and show that this alternative definition does not change our main results.

Figure 1:
Fact 1: Currency demand shock moves exchange rates in the short run




**Note**: This figure presents the estimated regression coefficient of the change in exchange rates on the currency demand shock measured by $\mu_{c,t}$ in equation (1); $\mu_{c,t}$ is standardized by its mean and standard deviation in the regression. The change in exchange rates (local currencies per US dollar) is measured as the cumulative change starting from 28 days before the recent rebalancing at day 0. The regression is performed in a pooled OLS using time- and country-fixed effects with standard errors clustered at the country level. The results are shown as point estimates (red) with a 90% confidence interval (black).

event.[10] Our estimates are consistent with the literature on currency demand elasticities, including Hau, Massa, and Peress (2009) and Camanho, Hau and Rey (2021).

**Remark 1.** *Why do exchange rates start to move before the rebalancing date 0?*

As shown in Figures 1 and 2, exchange rates respond significantly to the currency demand shock $\mu_{c,t}$ before the rebalancing date at 0 arrives. We state that these dynamics are expected and strongly support the "efficient market hypothesis" (Fama, 1970). Change in country weights is predicted before the rebalancing dates as J.P. Morgan Markets announces its mid-month projections.[11] The mutual funds tracking the index would buy or sell government bonds almost immediately as new information about the next rebalancing feeds in, and exchange rates would move before the rebalancing happens, which is exactly what the efficient market hypothesis predicts. The fact that exchange rates start to move before the rebalancing date is also consistent with the movements of stock

[10] See appendix A.3 for details on backing out the flows implied by the currency demand shock $\mu_{c,t}$.

[11] Nevertheless, those predictions are imprecise, especially for smaller countries that would not meet the 10% cap.

prices in other works on index rebalancings (Kaul, Mehrotra and Morck, 2000; Duffie, 2010).

**Remark 2.** *Can other local-currency emerging market sovereign bonds indices also contribute to the observed exchange rate movements?*

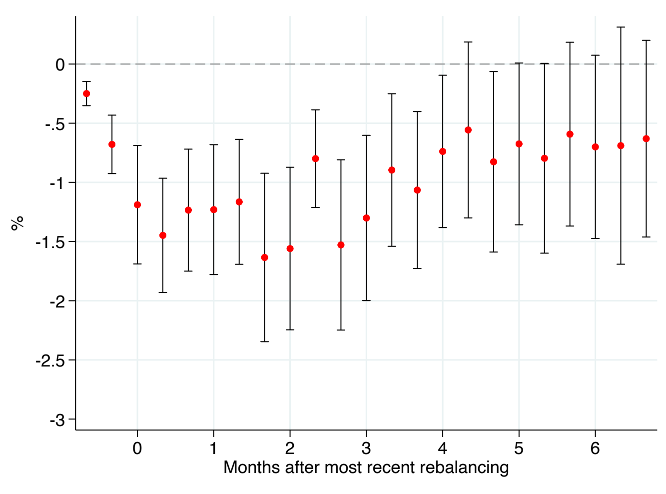
One potential concern on identification is that other local-currency emerging market sovereign bonds indices (apart from the J.P. Morgan GBI-EM Global Diversified) may also contribute to the variation in exchange rates. We examine carefully the rebalancing mechanisms of all leading local currency government bonds indices for emerging countries. We find that most of them have different rebalancing schemes and timing compared to the GBI-EM Global Diversified index, with the exception of Russell FTSE Emerging Markets Government Bond Index (EMGBI-Capped).[12] However, a simple aggregation exercise shows that the total asset positions of the funds tracking the EMGBI-Capped are not even 10% of the positions of the GBI-EM Global Diversified index in our EPFR dataset. Therefore, we consider the variation in exchange rates created by the EMGBI-Capped negligible compared to the rebalancings of the GBI-EM Global Diversified.

**Remark 3.** *Could the co-movements of macro-fundamentals across countries contaminate the results on identification?*

Another potential concern on identification is whether the macro-fundamentals and sovereign bond prices co-move systematically across countries. For example, one might suspect that the inflation-targeting Latin American countries in our sample – namely Argentina, Brazil, Colombia, Mexico and Peru – would have strong and positive co-movements in sovereign bond prices. We show in Table B.8 in the appendix that even within the Latin American countries, there are a lot of heterogeneity in their correlations of aggregate local-currency sovereign bond prices at the rebalancing dates. In addition, one should note that the index rebalancings happen at monthly frequency (rather than one time) over our sample of 11 years. Thus, it's unlikely for any two countries' sovereign bond prices to move in the same direction at every rebalancing date.

[12]FTSE fixed income EMGBI by Russell was introduced in 2018 as a rebranding of an older Citi Group WGBI index. It is an emerging market local-currency government bonds index and has an end-of-month country weight cap at 10%.

Figure 2:
Fact 2: Currency demand shock has persistent effects on exchange rates




**Note**: This figure plots the estimated coefficients of the change of cumulative exchange rate on the currency demand shock measured by $\mu_{c,t}$ in the six-month horizon after a rebalancing event; $\mu_{c,t}$ is standardized by its mean and standard deviation in the regression. The dependent variable is the change in cumulative exchange rates starting from 28 days prior to the first rebalancing event. All regressions are performed in a pooled OLS using time- and country-fixed effects with standard errors clustered at the country level. The results are shown as point estimates (red) with a 90% confidence interval (black).

**Empirical Fact 2.** *The currency demand shock has a persistent effect on exchange rates, lasting for more than three months after a rebalancing event.*

Figure 2 shows that the effects of rebalancings on exchange rates do not disappear immediately; instead, they remain significant for at least three months after a rebalancing event. Compared to the level of exchange rates before the first rebalancing event, the cumulative exchange rates on average appreciate about 1.5% in response to a one standard deviation increase in $\mu_{c,t}$. Reversion to the mean starts three months after the first rebalancing event, with the effects then gradually losing significance. The regression results are with time- and country-fixed effects with standard errors clustered at the country level.[13]

**Remark 4.** *Why does the currency demand shock have persistent effects on exchange rates?*

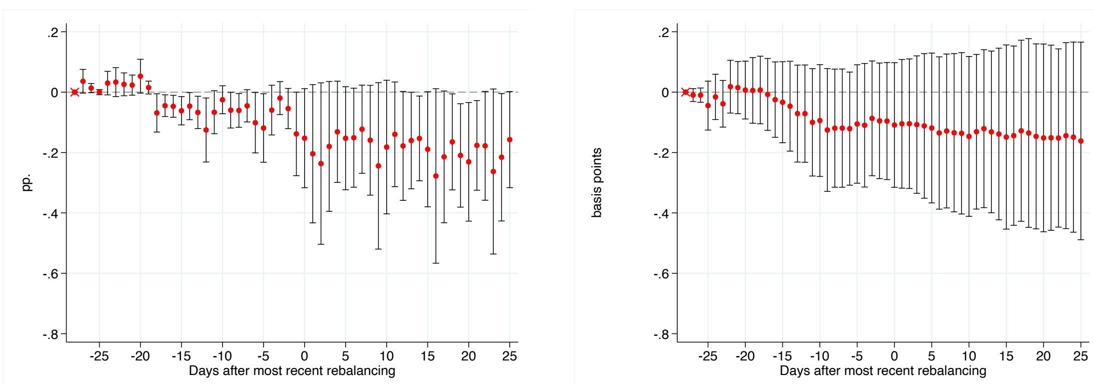
[13]We do not control for macro-fundamentals because our variables (such as GDP and net foreign asset positions) are much more slow-moving compared to exchange rates, and including them does not alter the baseline results. We also show in Table 4.1 that the macro-fundamentals (GDP and net foreign asset positions) are immune to the currency demand shock.

As shown in Figure 2, exchange rates have a significant and persistent response to the currency demand shock for at least three months. The fact that it takes time before exchange rates reversal is consistent with the "slow-moving capital" argument (Duffie, 2010) that the price reversal happens gradually over time as additional capital becomes available following the initial currency shock. Another reason that the effects are long-lasting is due to the persistence of the shock; as reported in Table B.13 in the appendix, the average currency demand shock $\mu_{c,t}$ follows an AR(1) process with persistence 0.66. Finally, our regression captures a level shift in exchange rates (starting 28 days before a rebalancing event) and there are no gains of excess returns for arbitrageurs in the financial market.

**Empirical Fact 3.** *Policy rates and yields do not respond to the currency demand shock.*

Figure 3:
Fact 3: Policy rates and yields do not respond to the currency demand shock

(a) Policy Rates (b) One-Year Yields Relative to USD




**Note**: Pooled regression coefficients of change in monetary policy rates (in percentage point, left panel) and change in three-month local-currency government bonds yields relative to synthetic USD yields ($i_{c,t} - i^*_{c,t}$) in basis points, not annualized, right panel) with 90% confidence interval. Monetary policy rates and one-month government bonds yields are provided at the daily frequency are defined as the cumulative change from 28 days before the rebalancing date.

Another concern for identification is that central bank policy rates might respond to the rebalancings of the GBI-EM Global Diversified index. If the policy rates were to move, the macro-fundamentals and exchange rates would also respond, violating the exogenous nature of the currency demand. We show that this is not the case.

Central bank policy rates and yields are not responsive to the exogenous currency demand shock.[14] The OLS regression using changes in central bank policy rates (starting from 28 days before the rebalancing event) on the currency demand shock gives insignificant coefficients for all countries in our sample, as shown in Figure 3 and Table B.9 for the country-by-country regression. The results make clear that the central banks are not using monetary policy rates to offset the exchange rates moves due to the rebalancings of the index. In addition, Figure 3 shows that changes in short-term local-currency government bond yields relative synthetic USD yields ($i_{c,t} - i^*_{c,t}$) have insignificant response to the currency demand shock. Country-specific regressions in Table B.10 show that a few countries demonstrate borderline significant estimates for policy rates and yields. However, those numbers (in less than half a percentage point for policy rates, and less than one basis point for yields) are negligibly small in magnitudes compared to the response of exchange rates to the currency demand shocks.

**Empirical Fact 4.** *Country-specific exchange rate response to the currency demand shocks differs by exchange rate regime, with free floaters being much more responsive compared to peggers.*

We find heterogenous responses of exchange rates to the currency demand shock across countries, as shown in Figure 4. We repeat the exercise in Figure 1 for each country and collect the estimated coefficients at the horizon 0 days after rebalancing [15] in the empirical specification below:

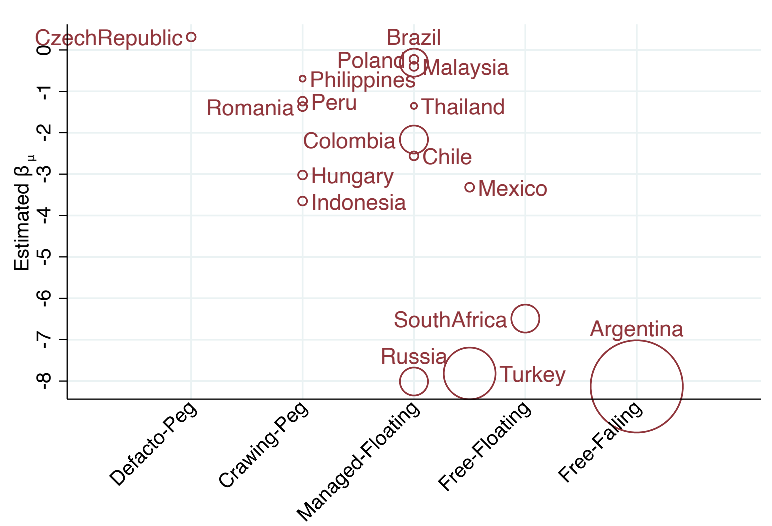
$$\Delta e_{c,t+d} = \beta_{0,c} + \beta_{\mu,c}\ \mu_{c,t} + \phi_c\ X_{c,t} + \epsilon_{c,t}, \tag{3}$$

where we now estimate the country-specific exchange rates response $\beta_{\mu,c}$. The regression includes constants as in the pooled regression and $X_{c,t}$ is a set of dummies that control for month, and year fixed effects, respectively. Standard errors are clustered at the country level.

[14] Pandolfi and Williams (2019) find that a one standard deviation in the flows implied by rebalancings of the GBI-EM Global Diversified index leads to small increase in sovereign debt prices of 8 basis points in the window -5 to +5 days of the rebalancing date 0 for long-term government bonds. Different from their regression, our regressor is the short-term yields rather than long-term, and we use the change in local-currency yields relative to synthetic USD yields.

[15] We choose the window right after the rebalancing date as Facts 1 and 2 to make clear that the lion share of exchange rates movements occurs before the rebalancing date at time 0.

Figure 4:
Fact 4: Free Floaters respond more to the currency demand shocks




**Note**: This figure presents the relation between country-specific exchange rate response to the currency demand shock (measured by $\mu_{c,t}$) and the exchange rates regimes classified by Ilzetzki, Reinhart and Rogoff (2021). The y-axis is the estimated exchange rate response to $\mu_{c,t}$ at the horizon 0 days after rebalancing, with time fixed effects (with the exception of Brazil and Mexico, which are with year fixed effects owing to limited observations); the x-axis is the exchange rate regimes ranging from de facto peg (left) to free falling (right). All regression estimates are significant at the 1% level except for Czech Republic, Brazil, Malaysia and Poland. The circle size is proportional to the exchange rates volatility of the currency.

Most countries respond to $\mu_{c,t}$ with 1% significance, and all countries (except Czech Republic) predict the right sign.[16] Specifically, a positive local-currency demand shock (an increase in $\mu_{c,t}$) appreciates local currency exchange rates and decreases the price of US dollars in units of local currency. Czech Republic, Brazil, Malaysia and Poland do not have significant coefficients. Tables B.11 and B.12 in the Appendix give the country-specific exchange rate response.

There is a clear relation between the country-specific exchange rate response and the exchange rates regimes, as illustrated by the downward trend in Figure 4. The y-axis is the country-specific estimated exchange rate response to the currency demand shock ($\mu_{c,t}$); the x-axis is the coarse exchange rate regimes ranging from de facto peg to free falling as classified by Ilzetzki, Reinhart and Rogoff (2021). The figure makes clear that free floaters (e.g., Argentina, South Africa and Turkey) are much more responsive to $\mu_{c,t}$ compared to either managed floaters (e.g., Malaysia, Poland, and Thailand) or peggers (e.g., Czech Republic, Romania and Peru). In addition, floaters have much larger exchange rate volatility, as indicated by their larger circle size.

# 4 Currency Demand Shocks in Inelastic Financial Markets

In this section, we review major classes of models in international finance where the uncovered interest parity condition does not hold. We show that models with endogenous deviations in the uncovered interest parity condition in inelastic financial markets can explain the observed empirical facts on our currency demand shocks and exchange rate dynamics.

## 4.1 Inelastic Markets and Uncovered Interest Parity (UIP)

Our empirical facts that currency demand shocks move exchange rates significantly are the most direct evidence suggesting that the foreign exchange markets are not perfectly elastic. Similar as the "inelastic markets hypothesis" (Gabaix and Koijen, 2022) for the aggregate equity markets, the foreign exchange markets are also inelastic in that flows

[16] Czech Republic does not because it has a de facto pegged exchange rate regime. We will discuss this point in more detail in Section 6.2.

and demand shocks affect asset prices and expected returns in a quantitatively important way. On the other hand, the currency demand shock should have no traction on exchange rates if the markets were perfectly elastic.

The simplest model where the foreign exchange markets are perfectly elastic is when uncovered interest parity holds. We define the uncovered interest party (UIP) condition as follows. Let $i_{c,t}$ and $i^*_{c,t}$ be the returns of home- and foreign-currency bonds, respectively; $e_{c,t}$ is the exchange rate measured in the number of home currencies per US dollar (foreign); $\mathbb{E}_t \Delta e_{c,t+1}$ is the expected change of exchange rates from $t$ to $t+1$. The UIP condition implies zero excess return in the currency carry trade on home- and foreign-currency bonds. In other words, the expected exchange rate change is fully offset by return differentials and thus no arbitrageur profits.

**Definition 1.** *UIP holds if the following equation holds:*

$$(i_{c,t} - i^*_{c,t}) - \mathbb{E}_t \Delta e_{c,t+1} = 0. \tag{4}$$

Classical macroeconomic models (e.g., Mundell, 1962; Obstfeld and Rogoff, 1995; Gali and Monacelli, 2005) typically assume UIP condition in equation (4) holds. In these models, a currency demand shock plays no role in determining the path of exchange rates nor short-term interest rates differentials as the financial markets are assumed to be perfectly elastic.

However, the assumption of perfectly elastic financial markets does not require UIP condition to hold. Another class of macroeconomic models with capital control taxes and exogenous risk-premium shocks (Devereux and Engel 2002; Farhi and Werning, 2012) or convenience yields (Jiang, Krishnamurthy, and Lustig, 2018) violate the UIP condition in equation (4) but not the assumption of perfectly elastic financial markets. In this class of models, exogenous shocks deviate UIP condition (i.e., *exogenous UIP shocks*) and move exchange rates but do not change the equilibrium allocation of assets. Similar as in the classical macroeconomic models where UIP holds, currency demand shocks play no role in models with exogenous UIP shocks.

Only in models with inelastic foreign exchange markets would a currency demand shock have traction on exchange rates. In this class of models (e.g., Gabaix and Maggiori, 2015; Itskhoki and Mukhin, 2021), a currency demand shock changes the risk-bearing capacity of arbitrageurs who conduct currency carry trade in a segmented financial market that is not perfectly elastic. As the risk-bearing capacity of the arbitraguers is limited, a currency demand shock translates into movements in exchange rates, changes in the equilibrium allocation of assets, and endogenous deviations of UIP condition. We therefore also refer to the currency demand shocks in inelastic financial markets as *endogenous UIP shocks*.

## 4.2 Empirical Evidence for Inelastic Financial Markets

We argue that a model of perfectly elastic markets cannot square with the observed empirical facts on our currency demand shocks and exchange rates dynamics. Markets are perfectly elastic both in models where UIP holds and in models with exogenous UIP shocks. We provide empirical evidence that our exogenous currency demand shock would have no bearing on exchange rate movements these markets.

We start with the modified UIP condition below that includes both the exogenous and endogenous UIP shocks below.

**Definition 2.** *The modified UIP condition is given by:*

$$i_{c,t} - i^*_{c,t} - \mathbb{E}_t \Delta e_{c,t+1} = \underbrace{\tau_{c,t} + \psi_{c,t}}_{exogenous} + \underbrace{\Lambda_{c,t}}_{endogenous}, \tag{5}$$

*where we denote capital control taxes by $\tau_{c,t}$, exogenous risk-premium shock by $\psi_{c,t}$, and endogenous risk-premium shock by $\Lambda_{c,t}$. Both $\tau_{c,t}$ and $\psi_{c,t}$ are exogenous UIP shocks, and $\Lambda_{c,t}$ is the endogenous UIP shock.*

Strictly speaking, there should be separate capital taxes for both home and foreign capital. Without loss of generality, we use net capital tax defined as the difference between home and foreign capital tax. An example of risk-premium shock ($\psi_{c,t} > 0$) is a sudden increase in the world interest rate that makes investors deem home assets more risky than foreign assets without changing the equilibrium allocation of assets and exchange rates.

We show that a model with only exogenous UIP shocks cannot square with our stylized empirical facts. Intuitively, both capital control taxes and risk premium for macroeconomic conditions are slow-moving variables compared to the exogenous currency demand shocks, which arrive at monthly frequency. We provide formal econometrics to

Table 4.1: Capital controls and macro-fundamentals are not responsive to $\mu_{c,t}$

| | (1) Capital controls | (2) GDP | (3) Consumption | (4) NFA | (5) Net exports | (6) Inflation |
|---|---|---|---|---|---|---|
| $\mu_{c,t}$ | 0.0111 | -2.000 | -435.8 | 7.671 | -1.735 | 0.1710 |
| | (0.0212) | (1.697) | (338.0) | (6.058) | (1.801) | (0.1151) |
| Constant | 0.516*** | 1.373*** | 339.4*** | 1.940 | 0.759 | 0.2865*** |
| | (0.00579) | (0.478) | (90.03) | (1.685) | (0.495) | (9.0320) |
| Observations | 1956 | 2170 | 1241 | 1777 | 1675 | 1777 |
| $R^2$ | 0.9779 | 0.9310 | 0.9415 | 0.8715 | 0.1629 | 0.0815 |
| Adjusted $R^2$ | 0.978 | 0.930 | 0.940 | 0.870 | 0.149 | 0.0673 |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.02$, $^{***}$ $p < 0.01$

**Note**: This table shows the OLS regression results of the following independent variables on the currency demand shock ($\mu_{c,t}$): capital control measures (Fernandez et. al., 2016), nominal GDP, consumption, net foreign asset positions (NFA), net exports and inflation. Capital controls and GDP (billions of local currency) are in annual frequency. NFA, consumption and net exports are in trillions of local currency and of quarterly frequency. Inflation level is computed from the consumer price index that treats year 2010 as the base year and is of quarterly frequency. All regressions include country and year fixed effects with standard errors clustered at the country level.

attest to this idea by using capital control index data from Fernandez et al., 2016 (with dataset updated to 2021) to proxy $\tau_{c,t}$ and variables of macroeconomic fundamentals (e.g., inflation, consumption, output, net exports) to proxy $\psi_{c,t}$. As shown in Table 4.1 in the appendix, both measures for capital taxes $\tau_t$ and risk-premium shock $\psi_{c,t}$ are immune to our exogenous currency demand shock $\mu_{c,t}$. Taken together with the results on interest rates (Fact 3), the evidence suggests that models with exogenous UIP shocks cannot explain the observed dynamics in exchange rates (Facts 1 and 2).

## 4.3 A Model of Endogenous UIP Shocks in Inelastic Financial Markets

Our empirical facts point to a model with endogenous UIP shocks. In this section, we present a simple model featuring the financial sector only where a currency demand shock shifts arbitrageurs' holdings and gives rise to endogenous deviations in UIP. There are two types of agents in the model. Arbitrageurs demand home- and foreign-currency bonds and derive profits from the excess returns in currency carry trades; noise traders have a constant supply schedule of home- and foreign-currency bonds with their positions $n_{c,t}$ subject to the currency demand shocks $\mu_{c,t}$. Importantly, shocks to noise traders' positions are orthogonal to macroeconomic fundamentals.

The arbitrageurs' holdings and market clearing condition with noise traders' positions are as follows:

$$i_{c,t} - i^*_{c,t} - \mathbb{E}_t \Delta e_{c,t+1} - (\tau_{c,t} + \psi_{c,t}) = \lambda_{c,t}\, d_{c,t} \tag{6}$$

$$n_{c,t} + d_{c,t} = 0, \tag{7}$$

where in (6), we follow Gabaix and Maggiori (2015) and rewrite the endogenous UIP component $\Lambda_t$ in equation (5) as the arbitrageurs' holdings in local-currency bonds ($d_{c,t}$) times the arbitrageurs' risk-bearing capacity ($\lambda_{c,t}$). The larger the $\lambda_{c,t}$, the lower the arbitrageurs' risk-bearing capacity and the steeper their demand curve. In the limit that $\lambda_t \to \infty$, the international bonds market is completely segmented, with financial autarky. On the other extreme, when $\lambda_{c,t} = 0$, the arbitrageurs are able to take infinite positions and absorb any nonzero excess returns in the currency carry trade. In the case when $\lambda_{c,t} \in (0, \infty)$, the model endogenously generates UIP deviations given by arbitrageurs' risk taking.

An exogenous local-currency demand shock[17] (an increase in $\mu_{c,t}$) shifts noise traders' positions $n_{c,t}$ and affects arbitrageurs' holdings through the market clearing condition (7). In other words, the exogenous currency demand shock traces out the slope of the demand curve and arbitrageurs' risk-bearing capacity. The steeper the demand curve (a larger $\lambda_{c,t}$), the more inelastic the financial market and the lower the arbitrageurs' risk-bearing capacity.

#### 4.3.1 Drivers of Risk-Bearing Capacity in Endogenous UIP Models

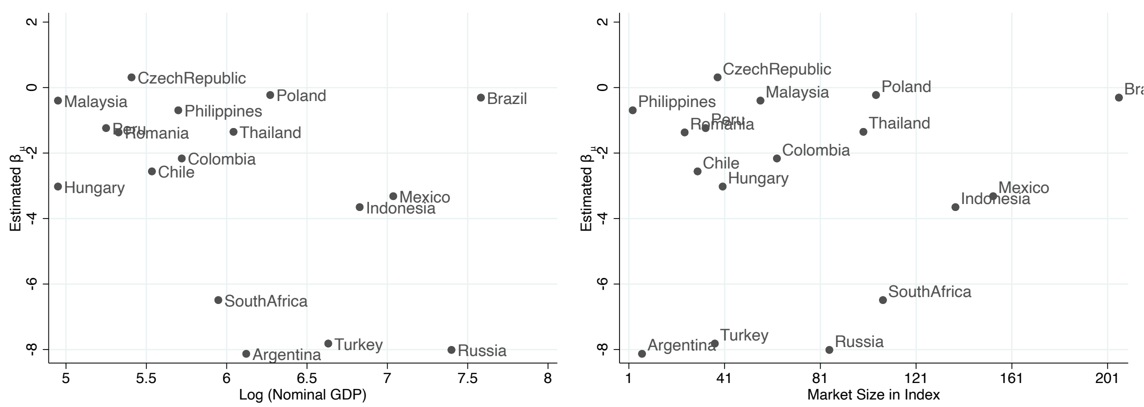
Given that our currency demand shock does not move interest rates nor exogenous UIP shocks (capital control taxes and risk-premium shocks), the exchange rate responses can identify the arbitrageurs' risk-bearing capacity $\lambda_{c,t}$. The only caveat is that our measure of currency demand shocks $\mu_{c,t}$ is in the share of market size, whereas the measure of

[17] As shown below in the model, a currency demand shock shifts noise traders' positions and would be seen as shifts in *supply* from the perspective of arbitrageurs. That is why we say the currency demand shock traces out the *demand* curve for arbitrageurs.

the noise traders' positions is in flows of local currencies. We show in appendix A.3 and A.3.2 how to convert the currency demand shocks $\mu_{c,t}$ into flows (as in noise traders' positions) and the relation between the estimated $\beta_{\mu_{c,t}}$ and the arbitrageurs' risk-bearing capacity $\lambda_{c,t}$.

To understand the drivers of risk-bearing capacity across countries, we collect the estimated exchange rate responses to the currency demand shock ($\beta_{c,t}$) and plot them against different metrics ranging from macroeconomic fundamentals to the depth of financial markets. We find no correlation between $\beta_{c,t}$ and macroeconomic or financial metrics such as outputs and market size (Table 4.2), but only a strong correlation with the exchange rates regime (and the volatility of exchange rates).

Table 4.2: Exchange Rates Response do not correlate with macro/financial metrics

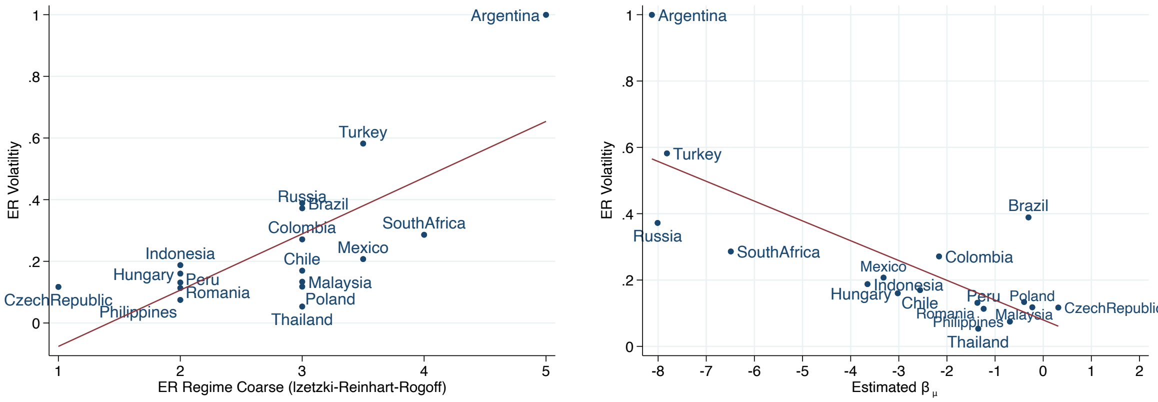



(a) Nominal GDP

(b) Sovereign bond market size

**Note**: This Figure presents the relation between the country-specific response to currency demand shock to nominal GDP and sovereign bonds market size in the GBI-EM Global Diversified index. Nominal GDP and market size are in billions of USD and take the average of the sample years from 2009 to 2021.

Table 4.3: Exchange Rate Response Correlates with Exchange Rates Volatility




(a) Exchange rate vol. and regime

(b) Exchange rate vol. and $\beta_\mu$

**Note**: This figure presents the relation between (a) the country-specific exchange rate response to the currency demand shock (measured by $\mu_{c,t}$) and the exchange rates volatility and (b) the relation between the exchange rates regime and exchange rates volatility. The red line is the fitted regression for the x- and y-axis variables.

As shown in Empirical Fact 4, floaters have a much larger exchange rate response and much larger exchange volatility compared to peggers, as illustrated by the clear downward trend in Figure 4 and the relation with exchange rates volatility in Table 4.3. The more floating the exchange rates, the larger the exchange rates volatility, the lower the arbitrageurs' risk-bearing capacity (higher $\lambda_{c,t}$), and the more inelastic the financial market. The next section formally builds a model where the arbitrageurs' risk-bearing capacity endogenously depends on the volatility of exchange rates.

# 5 Interventions in Inelastic Foreign Exchange Markets

In this section, we introduce foreign exchange interventions in our model of inelastic financial markets with endogenous UIP deviations. We show that under inelastic financial markets, foreign exchange interventions serve as an additional policy tool to stabilize exchange rates without compromising monetary policy independence, regardless of the capital controls.

## 5.1 Endogenous UIP Model with Foreign Exchange Interventions

Consider a small open economy, denoted by $c$. There are four types of agents in the partially segmented financial market where both home and foreign households can hold only government bonds of their own currency. Households demand home-currency bonds $b_{c,t}$, which are shaped by the macroeconomic fundamentals in the economy. There are also three types of agents who can trade both home and foreign currency bonds in the international financial market, namely, noise traders, arbitrageurs and the government, and we assume without loss of generality that they all reside in the home country. We describe the problem of these agents below.

Risk-averse arbitrageurs hold a zero-capital portfolio for home- and foreign-currency bonds $(d_{c,t}, d^*_{c,t})$, with the returns on one local-currency unit holding of such portfolio given by $\tilde{i}_{c,t+1} = i_{c,t} - i^*_{c,t} - \mathbb{E}_t \Delta e_{c,t+1}$. Arbitrageurs choose $(d_{c,t}, d^*_{c,t})$ to maximize the mean-variance preferences over profits in the currency carry trade

$$d_{c,t} = \frac{1}{\lambda_{c,t}}\left(i_{c,t} - i^*_{c,t} - \mathbb{E}_t \Delta e_{c,t+1} - (\tau_{c,t} + \psi_{c,t})\right), \tag{8}$$

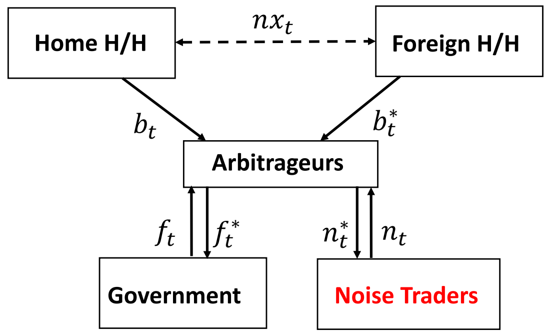
where $\lambda_{c,t} = \omega\ \sigma^2_{e_{c,t}}$ governs the risk-bearing ability of the arbitrageurs; parameter $\omega$ is the risk-aversion coefficient of the arbitrageurs, and $\sigma^2_{e_{c,t}}$ is the equilibrium volatility of exchange rates. The larger the $\lambda_{c,t}$ (or $\omega$ and $\sigma^2_{e_{c,t}}$), the lower the arbitrageurs' risk-bearing capacity. We model the risk-bearing capacity to be endogenously dependent on the equilibrium volatility of exchange rates, because our empirical evidence on risk-bearing capacity strongly correlates with exchange rates volatility (Fact 4).

Noise traders hold a zero-capital portfolio $(n_{c,t}, n^*_{c,t})$ and are subject to liquidity demand for local-currency bonds $\mu_{c,t}$. Importantly, $\mu_{c,t}$ is a random variable uncorrelated with the macroeconomic fundamentals. A positive $\mu_{c,t}$ means that noise traders sell foreign-currency (US dollar) bonds and buy local-currency bonds.

The government holds a portfolio of $(f_{c,t}, f^*_{c,t})$ units of home- and foreign-currency bonds, where $f_{c,t}$, and $f^*_{c,t}$ are policy instruments corresponding to open market operations in foreign exchange interventions for home- and foreign-currency bonds, respectively. A positive (resp., negative) $f_{c,t}$ means buying (resp., selling) local-currency bonds in the foreign exchange interventions.

We also define $b^*_{c,t}$ as the net foreign asset (NFA) position of the home households

Figure 5: Segmented International Bonds Market




**Note**: This figure presents the four types of agents in a segmented international bonds market, where home and foreign households (home H/H and foreign H/H, respectively) can hold only government bonds in their own currency. Noise traders' positions are subject to exogenous currency demand shocks that are uncorrelated with the macroeconomic fundamentals.

and government. In our model with only home and foreign countries, $b^*_{c,t}$ is the foreign households' holdings of foreign-currency bonds, as foreign households cannot hold home currency bonds, owing to the segmented financial market. In Figure 5 we use a simple diagram to present the four types of agents and their positions in a segmented market.

The market clearing condition for home-currency bond states

$$b_{c,t} + n_{c,t} + d_{c,t} + f_{c,t} = 0. \tag{9}$$

Using the zero-capital position of the noise traders and arbitrageurs, one can arrive at the following expression for net foreign assets: $b^*_{c,t} = f^*_{c,t} + n^*_{c,t} + d^*_{c,t}$.

Combining equation (9) with equation (8) and putting exchange rates on the left-hand-side of the equation, we have

$$\mathbb{E}_t \Delta e_{c,t+1} = i_{c,t} - i^*_{c,t} - (\tau_{c,t} + \psi_{c,t}) \; + \; \lambda_{c,t} \left( b_{c,t} + n_{c,t} + f_{c,t} \right), \tag{10}$$

where $\lambda_{c,t} = \omega \; \sigma^2_{e_{c,t}}$, and we substitute the arbitrageurs' holdings using the market clearing condition. A currency demand shock $\mu_{c,t}$ on the local-currency bonds moves the noise traders' holdings $n_{c,t}$ and in turn the position of the arbitrageurs, which then leads to movements in exchange rates and endogenous deviations in UIP. Specifically, a positive local-currency demand shock (an increase in $\mu_{c,t}$) appreciates exchange rates levels tomorrow (a decrease in $e_{c,t+1}$), with the size of the appreciation governed by the risk-bearing capacity of the arbitrageurs $\lambda_{c,t} = \omega\ \sigma^2_{e_{c,t}}$.

### 5.1.1 Policy Function of Foreign Exchange Interventions

Holding all else constant in equation (10), the foreign exchange interventions $f_{c,t}$ stabilize exchange rates by exactly offsetting the noise trader shocks, at the same magnitude and persistence; that is, $f_{c,t} = -n_{c,t}$ to ensure $\partial e_{c,t}/\partial f_{c,t} = -\partial e_{c,t}/\partial n_{c,t}$. This condition requires all variables on the right-hand side of equation (10) to be immune to the currency demand shock that moves noise traders' positions $n_{c,t}$. We have already shown that interest rates differentials ($i_{c,t} - i^*_{c,t}$) and exogenous UIP shocks ($\tau_{c,t}$, $\psi_{c,t}$) do not respond to $\mu_{c,t}$. In addition, variables indicating macroeconomic fundamentals $b_{c,t}$ are slow-moving compared to the currency demand shock and would not contaminate the identification. We summarize this statement in the Proposition 1 below.

**Proposition 1.** *Foreign exchange interventions that use open market operations to stabilize exchange rates need to offset the noise trader shocks with the exact same magnitude and persistence, that is, $f_{c,t} = -n_{c,t}$. This requires that interest rates differentials and macroeconomic fundamentals (as well as capital control taxes, etc) to be slow moving.*

**Proof**: See Appendix C.

We show empirically that foreign exchange interventions do not respond to the currency demand shocks. Using monthly foreign exchange intervention data from Adler el al. (2021), we find no correlation between spot foreign exchange intervention data (as a share of GDP) and our exogenous currency demand shock $\mu_{c,t}$, as shown in Table 5.1. This lack of correlation suggests the central banks are not actively using foreign exchange interventions to offset the noise trader shocks from the exogenous currency demand in equation (10). Thus, it is valid to assume $f_{c,t}$ to be independent of the noise traders' positions $n_{c,t}$ in the empirical analysis of this paper.

To arrive at the closed-form expression of the policy function of foreign exchange intervention, we provide solutions from two model examples – a partial equilibrium model under Taylor rule (Engel and West, 2005) and a general equilibrium model with fully specified goods market and the country's intertemporal budget constraint (Itskhoki

Table 5.1: FX Interventions are not responsive to $\mu_{c,t}$

| | FXI over GDP |
|---|---|
| Currency Demand Shock ($\mu_{c,t}$) | 0.124 |
| | (0.109) |
| Constant | 0.0447* |
| | (0.0314) |
| Observations | 2144 |
| $R^2$ | 0.0315 |
| Adjusted $R^2$ | 0.024 |

Standard errors in parentheses

$^{*}$ $p < 0.2$, $^{**}$ $p < 0.10$, $^{***}$ $p < 0.05$

**Note**: This table shows the OLS regression results of the FX interventions data on the currency demand shock ($\mu_{c,t}$): capital control measures (Fernandez et. al., 2016), net foreign asset positions and nominal GDP. Interventions data are measured in spot FX interventions over GDP at monthly frequency. The regression includes country fixed effects with standard errors clustered at the country level.

and Mukhin, 2021). Through solving these models, one can then match the estimated regression coefficient in the empirical specification in equation (3) with the impulse response function of exchange rates in response to the noise trader shocks.

**Example 1.** *In the Taylor-rule model (Engel and West, 2005) with exchange rate target* $\bar{e}_c$, *the home- and foreign monetary policy rates follow the form:*

$$
\begin{aligned}
i_{c,t} =& \beta_0\ (e_{c,t} - \bar{e}_c) + \beta_1\ y_{c,t} + \beta_2\ \pi_{c,t} + \nu_{c,t} \quad , \beta_0 \in (0,1) \\
i^*_{c,t} =& \beta_1\ y^*_{c,t} + \beta_2\ y^*_{c,t} + \nu^*_{c,t}.
\end{aligned}
$$

*where* $\bar{e}_c$ *is the exchange rate target,* $\pi_{c,t} = p_{c,t} - p_{c,t-1}$ *is the inflation rate, and* $y_{c,t}$ *the output gap of home country c. The policy function of foreign exchange intervention is given by:*

$$
\frac{\partial e_{c,t}}{\partial f_{c,t}} = \frac{\partial e_{c,t}}{\partial n_{c,t}} = \frac{1}{(1 + \beta_0 - \rho)} \lambda_{c,t},
$$

*where* $\lambda_{c,t} = \omega\ \sigma^2_{e_{c,t}}$, *under the assumptions that* $n_{c,t} \sim AR(1)$ *with persistence* $\rho$, $n_{c,t} \perp f_{c,t}$, *and macro-fundamentals are slow-moving compared to noise trader shocks.*

**Proof**: See Appendix C.

**Example 2.** *In the general equilibrium model of Itskhoki and Mukhin (2021) that specifies the budget constraint of a country c,* $\beta\ b^*_{c,t} - b^*_{c,t-1} = nx_{c,t} = \gamma\ e_{c,t} + \xi_{c,t}$, *where* $nx_{c,t}$ *is the net* *exports and $b^*_{c,t}$ the net foreign assets of the home country. The policy function of foreign exchange intervention is given by:*

$$\frac{\partial e_{c,t}}{\partial f_{c,t}} = \frac{\partial e_{c,t}}{\partial n_{c,t}} = \frac{\beta}{(1-\rho\beta)}\lambda_{c,t},$$

*where $\lambda_{c,t} = \omega\ \sigma^2_{e_{c,t}}$, under the assumptions that $n_{c,t} \sim AR(1)$ with persistence $\rho$, $n_{c,t} \perp f_{c,t}$, and macro-fundamentals are slow-moving compared to noise trader shocks.*

**Proof**: See Appendix C.

## 5.2 Implications of Foreign Exchange Interventions and the Relaxed Trilemma

In this section, we discuss the implications of foreign exchange interventions under inelastic financial markets. We define the relaxed trilemma condition following Itskhoki and Mukhin (2023a) for endogenous UIP models with inelastic financial markets. Under inelastic financial markets, foreign exchange intervention serves as an effective policy tool to stabilize exchange rates without compromising monetary policy independence, regardless of the capital controls.

**Definition 3.** *The relaxed trilemma constraint states that it is possible to have all three of the following conditions simultaneously: an independent monetary policy (inward focused on domestic inflation and output gap), free capital mobility (absence of capital control taxes), and a managed exchange rate. By contrast, under the classical trilemma constraint it's only possible to have two of the three conditions simultanously.*

**Definition 4.** *Trilemma type models are UIP models that bind under the classical trilemma constraint; non-trilemma–type models are UIP models that hold under the relaxed trilemma constraint.*

Definition 3 contradicts the classical trilemma constraint (Mundell, 1962), which states that it is *not* possible to have all three conditions in definition 3. The models where the UIP condition holds and the models with exogenous UIP shocks are subject to the classical trilemma constraint; thus, we refer to these models as *trilemma type* models. If UIP holds, there is free capital mobility by construction and the economy faces the direct trilemma trade-off between an independent monetary policy and a fixed exchange rate, as seen in equation (10). If the UIP deviations came from exogenous shocks, monetary policy rates would have to move one on one with exchange rates unless capital control taxes ($\tau_{c,t}$) and exogenous risk premium ($\psi_{c,t}$) can both be used as policy instruments to offset exchange rates; however, this is clearly not feasible. Thus, under the trilemma constraint, exchange rates stabilization comes at the cost of compromising monetary policy independence.

By contrast, models with endogenous UIP shocks can have all three conditions in the trilemma met, because they have an additional policy instrument to stabilize exchange rates: foreign exchange interventions. As shown in equation (10), foreign exchange interventions conduct open market operations that shift the arbitrageurs' positions, which then lead to endogenous deviations in UIP and move exchange rates. Therefore, the central bank[18] can now stabilize exchange rates through foreign exchange (FX) interventions while the monetary policy is entirely domestically focused to close the output gap. In other words, even under perfectly mobile capital flows, the economy no longer has to compromise monetary policy independence to stabilize exchange rates, relaxing the classical trilemma constraint. We thus refer to the endogenous UIP models as the *non-trilemma–type* models.

### 5.2.1 Empirical Evidence for the Relaxed Trilemma

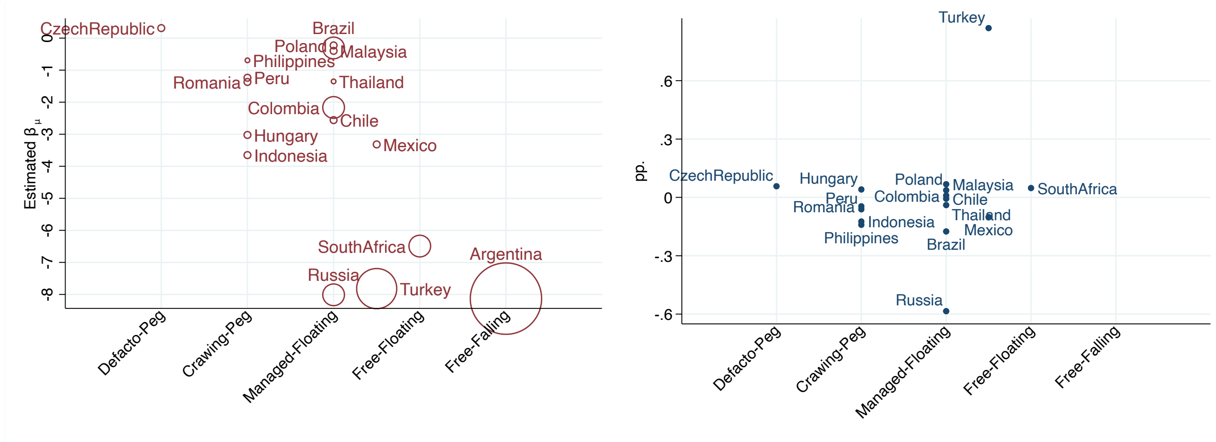
Empirical Facts 3 and 4 show that there is a significant exchange rate response to the exogenous currency demand shock of almost all currencies but no response of the policy rates. Under trilemma-type models, the movements in exchange rates must be offset one on one by monetary policy rates for exchange rates to be fixed, for any given capital control taxes ($\tau_{c,t} \geq 0$ in equation (10)). Our evidence provides empirical support for non-trilemma–type models and implies that countries under managed exchange rates regimes (namely, de facto peg, crawling peg and managed floaters) have used instruments other than monetary policies to manage their exchange rates. We view this finding as the most direct piece of evidence supporting the relaxed trilemma constraint discussed above.

Table 5.2 puts both the response of exchange rates and policy rates to the currency

[18] The central bank's objective is to minimize the international risk-sharing wedge and domestic output gap.

Table 5.2: Empirical Support for Relaxed Trilemma

(a) exchange rates (b) policy rates




**Note**: Scatterplot of country-specific exchange rates (left) and policy rates (right) response to the currency demand shock $\mu_{c,t}$ against the exchange rates regime (from strict to relaxed) as classified by Ilzetzki, Reinhart and Rogoff (2021). Policy rates of Argentina is not plotted in the right diagram as its in the magnitude of 10 times larger than other countries.

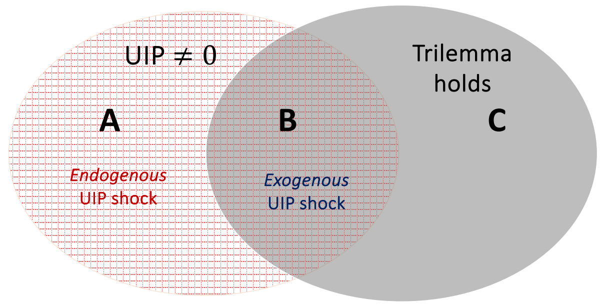
demand shock side by side and summarizes this result. While there's a clear downsward

### 5.2.2 Discussion on Non-Trilemma-Type Models and UIP

In this section, we discuss the implications of the major classes of literature in international finance on the trilemma constraint, the UIP condition and inelastic financial markets. We start with the trilemma-type models where UIP either holds or is subject to exogenous shocks only, and then compare them with non-trilemma–type models with endogenous UIP shocks where FX interventions are effective.

The models where UIP holds or the models with exogenous UIP shocks are subject to the classical trilemma constraint. This is because either the models where UIP holds (e.g., Mundell, 1962; Obstfeld and Rogoff, 1995) or the models with exogenous UIP shocks (e.g., Devereux and Engel, 2002; Farhi and Werning, 2012) assume financial markets are perfectly elastic and thus a quantity shock would have no bearing on exchange rates. Even if FX interventions were implemented, they would be ineffective in these models, because they lack the channel where a demand shock endogenously shifts arbitrageurs' holdings that in turn leads to deviations in UIP. Therefore, these models are subject to the trilemma trade-off between monetary policy rates and exchange rates, as discussed

Table 5.3: Trilemma Constraint and UIP




| Model | Financial market | Papers |
|---|---|---|
| endogenous UIP shock | (imperfectly) inelastic | Gabaix and Maggiori (2015), Cavallino (2019), Itskhoki and Mukhin (2021), Fanelli and Straub (2021), Basu et al. (2023) |
| exogenous UIP shock | perfectly elastic | Devereux and Engel (2002), Farhi and Werning (2012), Jiang, Krishnamurthy and Lustig (2018) |
| classic trilemma (UIP = 0) | perfectly elastic | Mundell (1962), Dornbusch (1976), Obstfeld and Rogoff (1995), Gali and Monacelli (2005) |

**Note**: This diagram presents the relation between models where UIP fails (left circle) and models where the trielamma constraint holds (right circle). Region A refers to models under the relaxed trilemma and UIP fails (endogenous UIP shock); region B refers to models where UIP fails but the trilemma holds (exogenous UIP shock); region C represents the classic trilemma models where UIP holds. The references for each type of models are listed.

in the previous section.

Only in non-trilemma–type models with endogenous UIP deviations (e.g., Gabaix and Maggiori, 2015; Itskhoki and Mukhin, 2021) can FX interventions effectively stabilize exchange rates. In these models, financial markets are inelastic. FX intervention serves as an additional policy tool to stabilize exchange rates, because demand shocks can have traction on exchange rates under inelastic markets. Thus, FX interventions can now work together with independent monetary policy with no capital controls. Table 5.3 presents the relation between classical trilemma models, models with exogenous UIP shocks, and models with endogenous UIP shocks.

# 6 Identifying the Size of Foreign Exchange Interventions

In this section, we identify the required size of FX intervention to stabilize exchange rates and discuss its effectiveness across different exchange rate regimes. We find that free floaters are more the effective at stabilizing exchange rates on average compared to managed floaters or peggers, with the free floaters require much less amount of reserves to stabilize exchange rates.

## 6.1 Converting the Estimates to the Size of the Intervention

We convert the estimates from the currency demand shock into implied capital flows in US dollars. We first use the cross-country estimates (Empirical Fact 1) on the average exchange rates in response to the shock and show how to compute the implied flows of the mutual funds tracking the GBI-EM Global Diversified index. We report the average counterfactual required size of FX interventions to stabilize exchange rates and compare it with the estimates from the literature.

The caveat in this exercise is that our currency demand shock is measured in shares of market values, whereas the required size of intervention is in capital flows. Our regression results show that a one standard deviation of $\mu_{c,t}$ (21% change in market value, by Table 2.2) moves exchange rates by 1% (at horizon of 0 days after rebalancing) for the pooled OLS regression with country and time fixed effects. We also know that the average market value of local-currency government bonds in the GBI-EM Global Diversified index for all countries is 68 billion USD in 2019, with the total index value equal to 1221 billion USD in the same year (Table B.1). In addition, we estimate that the total positions of mutual funds in the EPFR dataset tracking the index are 113.6 billion USD, whereas the EPFR dataset represents about 60% of the global mutual funds population in the Investment Company Institutes (ICI) facts book (reported in Table B.4 in the Appendix).

We can therefore write the following equation to back out our estimates into flows required to stabilize exchange rates by 1%:

Required flows to move exchange rates by 1% =

$$\frac{1}{\beta_{\mu_c}} \times \text{std.}(\mu_{c,t}) \times \frac{\text{avg. country-level market value}}{\text{total market value of the index}} \times \frac{\text{EPFR mutual funds positions}}{\text{Share of EPFR funds in ICI}}.$$

Our pooled OLS regression results imply that the average required flows to move exchange rates by 1% is $1 \times 0.21 \times \frac{68}{1221} \times \frac{113.6}{0.6} = 2.5$ billion USD, or about 0.38% of the average annual GDP in 2019 (the average annual nominal GDP in 2019 is 586 billion USD, reported in Table B.1).

Our results are largely consistent with both the foreign exchange intervention literature using event studies and the asset pricing literature using index rebalancings. Adler et al (2019) focus on FX intervention episodes for a group of advanced and emerging market economies and estimate the effects of the intervention by relying on an instrumental-variable panel approach. They find that FX intervention with a magnitude of 1% of GDP results in exchange rate depreciation in the range of 1.7–2 percent. In other words, the average required size of the intervention needed to move exchange rates by 1% is about 0.5% of GDP, which is very similar to our results.

Our estimates are also aligned with the asset pricing literature on measuring the demand elasticities of currencies. For example, Hau, Massa, and Peress (2009) use the reweighting of 33 countries in MSCI's global index as an exogenous shock to estimate currency supply elasticity. Their estimates suggest that an average 2.6 billion USD is needed for a 1% change in exchange rates in a six-day window around the announcement of the index reweighting. This is almost exactly the same as our results. By comparison, Evans and Lyons (2002) use order flows data and estimate that a 1 billion USD daily FX order flows moves exchange rates by 0.5%.[19]

**Remark 5.** *How do our estimates of currency demand elasticities advance our understanding on FX interventions compared to the early work in the literature?*

We believe our estimates on currency demand elasticities from the rebalancings of the GBI-EM Global Diversified index are more suitable for drawing inferences on FX interventions compared to early work for the following reasons: First, as shown below in

[19] Camanho, Hau and Rey (2021) is the only paper with much larger estimates. Using quarterly rebalancings from the equity funds, they find that an average capital flow of 5.5 billion USD amounts to moving exchange rates by 1%, in a quarterly window. We therefore claim that the estimates from Evans and Lyons (2002) and Hau, Massa, and Peress (2009) mentioned above are more comparable to ours owing to the similar window of exchange rate movements.

section 6.2, we uncover the heterogenous responses across currency regimes between free floaters and managed floaters or peggers. A cross-sectional OLS that includes peggers would bias the elasticities downwards. Second, the long time series gives us ample variation in our estimation and the persistence of our currency demand shock matches well with the actual intervention episodes, which typically take place repeatedly over a longer intervention period.[20] By comparison, Hau, Massa, and Peress (2009) use a one-time index reweighting shock to recover currency demand elasticities.

### 6.2 Size of Foreign Exchange Interventions for Different Currency Regimes

We use the country-specific estimates (Empirical Fact 4) to compute the required size of the FX intervention (in US Dollar flows) needed to stabilize exchange rates. To do so, we repeat the exercise in section 6.1 but with the country-specific estimates to the currency demand shock, as well as the country-specific market value of the local currency government bonds in the GBI-EM Global Diversified index. The counterfactual required size of intervention as a share of GDP to stabilize exchange rates for each country is reported in Table 6.1. Table B.2 in the appendix reports the required size of intervention as a share of broad money measures (M2).

We find that countries with floating exchange rates regimes require much less intervention (and thus are more effective at using FX intervention) to stabilize exchange rates compared to countries with pegged regimes. For example, the required FX intervention over GDP to move exchange rates by 1% is about 0.38% of GDP for Peru (crawling peg). The number is about three times larger than South Africa (Free floating), which only requires reserves worth 0.136% of GDP to stabilize exchange rates by 1%. The pattern also holds within floaters, with free floaters require much smaller size of reserves to stabilize exchange rates than managed floaters.

The average required intervention for country-specific estimates in Table B.1 (less than 0.2% GDP) is much smaller than the average required intervention using pooled OLS as reported in section 6.1 (about 0.4% GDP). We believe the difference comes from the fact that the inclusion of peggers and managed floaters in the pooled regression biases the OLS estimates. When dropping insignificant estimates such as those of Czech Republic (de facto peg), Brazil, Malaysia and Poland (all managed floaters), the required

[20] See Fratzscher et al. (2019) for detailed characteristics of foreign exchange interventions.

Table 6.1: Foreign exchange intervention required to induce 1% exchange rate change

| Country | ER regime (code) | ER Vol. | FXI | FXI / GDP (%) |
|---|---|---|---|---|
| Peru | crawling peg (2) | 0.113 | 0.875 | 0.380 |
| Hungary | crawling peg (2) | 0.160 | 0.435 | 0.269 |
| Romania | crawling peg (2) | 0.131 | 0.582 | 0.233 |
| Indonesia | crawling peg (2) | 0.187 | 1.34 | 0.108 |
| Philippines | crawling peg (2) | 0.074 | 0.124 | 0.032 |
| Thailand | managed floating (3) | 0.053 | 2.397 | 0.428 |
| Chile | managed floating (3) | 0.169 | 0.380 | 0.145 |
| Colombia | managed floating (3) | 0.271 | 0.950 | 0.295 |
| Russia | managed floating (3) | 0.372 | 0.346 | 0.020 |
| Mexico | managed/free floating (3.5) | 0.207 | 1.511 | 0.116 |
| Turkey | managed floating/free falling (3.5) | 0.582 | 0.154 | 0.021 |
| South Africa | free floating (4) | 0.286 | 0.540 | 0.135 |
| Argentina | free falling (5) | 0.999 | 0.026 | 0.007 |
| | Group Average | | | |
| | crawling peg | | 0.65 | 0.21 |
| | managed floating | | 1.02 | 0.22 |
| | free floating/falling | | 0.56 | 0.07 |

**Note**:

The estimates for Czechia (de facto peg, code 1), Brazil, Malaysia and Poland (all managed floating, code 3) are insignificant and we do *not* report them in this table.

This table reports the country-specific required size of foreign exchange (FX) intervention to stabilize exchange rates by 1% in billion US dollars (column 4) and as a share (%) of each country's 2019 nominal GDP (column 5). The exchange rates volatility, measured as the standard deviation of the log exchange rate level by country, as reported in column 3. We sort countries by their coarse exchange rate regimes (column 2, as classified by Iltzetki, Rogoff and Reinhart 2021) from de facto peg to free floating or falling. For countries having multiple exchange rate regime codes during our sample period (2010–2021), as for Mexico and Turkey, we take the average regime code across time.

The required size of intervention is computed using the country-specific exchange rate response to the currency demand shock at the horizon of 0 days after the rebalancing date. All estimates are significant at the 1% level. A table with the country's GDP and market value can be found in the appendix (Table B.1).

size of intervention becomes much smaller, because the sample is weighted more towards free floaters.

Why are floaters more effective than peggers at stabilizing exchange rates? These empirical results are consistent with the model mechanism in section 5. The risk-bearing capacity $\lambda_{c,t} \equiv \omega\sigma^2_{e_{c,t}}$ governs the elasticity of the exchange rate response to the currency demand shock. A more stable or managed exchange rate would therefore imply a smaller exchange rate volatility ($\sigma^2_{e_{c,t}}$) and thus a more elastic market. In the limit of exchange rates being fully pegged, we are back to the elastic financial market model under the trilemma constraint where exchange rates are immune to currency demand shocks. In other words, FX interventions are more effective for floaters precisely because they have larger exchange rate volatility (Empirical Fact 4) and a more inelastic financial market, and are thus further away from the trilemma constraint.

Our results on the interventions being more effective for free floaters are consistent with the findings of Fratzscher et al (2019). Using confidential FX intervention data from 33 countries, they determine the *success* of FX interventions (defined as the consistency in the movement of exchange rates during the intervention and its intended direction) across different regimes. They find that FX interventions are most effective for free floaters, with a success rate of 0.53 through pure purchase or sale of FX reserves. By comparison, the success rate for broad band, narrow band, and other exchange rates regimes are significantly lower (Table 5 in Fratzscher et al., 2019).

**Remark 6.** *What types of foreign exchange interventions can our quasi-natural experiment best speak to?*

The exogenous currency demand shock from our quasi-natural experiment would be most analogous to a sterilized foreign exchange intervention in the spot exchange market. Similar as the open market operations in the spot exchange markets, the index rebalancings create currency demand shocks that move exchange rates as the mutual funds investors buy or sell their positions of local-currency government bonds. The fact that we find the monetary policy rates are not moving with respect to the currency demand shock makes the experiment most suitable for understanding the effects of sterilized intervention. Nevertheless, our estimates allow one to separately identify the effects from open market operations in an unsterilized intervention that also employs monetary policy as an instrument.

### 6.3 Additional Counterfactual Exercise

We provide additional counterfactual exercise on the implied movements in exchange rates in response to a capital inflow shock in the size of 1% GDP. The exercise uses the estimated country-specific OLS coefficient as in Table 6.1 and the results are reported in Table B.3 in the Appendix. Consistent with the model intuition of inelastic financial markets, we find that free floaters have much larger exchange rates movements in response to capital inflow shock compared to managed floater or peggers. In response to a capital flow shock in the size of 1% GDP, the exchange rates for free floaters move on average 50%, about five times larger than managed floaters (15%) and crawling peggers (10%).

Appendix C.3 relaxes the assumption that foreign exchange interventions are independent of the currency demand shock and estimate the country-specific intervention intensity $\alpha_{c,f}$. That is, $f_{c,t} = -\alpha_{c,f}\ n_{c,t}$, where $\alpha_{c,f} \in [0,1]$ and is the share of noise trader shocks offset by open market operations through foreign exchange interventions to stabilize exchange rates. We find that our estimated invention intensities and their relation with the exchange rate regime display a similar trend as the actual spot market intervention data (Adler et al (2021)), as shown in Table C.1.

# 7 Conclusion

In this paper, we use a well-identified currency demand shock on noise traders that gives rise to endogenous uncovered interest parity deviations under an inelastic financial market. Our results show that the exogenous currency demand shock moves exchange rates significantly both in the short- and long-run but not monetary policy rates, providing direct support for models with inelastic financial markets and the relaxed trilemma constraint. We assess the effectiveness of FX interventions for an emerging-market central bank for stabilizing exchange rates under the inelastic financial market hypothesis. When markets are inelastic, foreign exchange rate intervention works as an additional policy tool to move exchange rates without compromising monetary policy independence, providing evidence relaxing the classical trilemma constraint. Our results contribute to various strands of literature including those on foreign exchange intervention and asset demand estimation, and are informative to policymakers at emerging market central banks.

# References


1. Alvarez, Fernando, Andrew Atkeson, and Patrick J. Kehoe. "Time-varying risk, interest rates, and exchange rates in general equilibrium." *The Review of Economic Studies* 76.3 (2009): 851-878.

2. Amihud, Yakov, and Ruslan Goyenko. "Mutual fund's $R^2$ as predictor of performance." The Review of Financial Studies 26.3 (2013): 667-694.

3. Amador, Manuel, Javier Bianchi, Luigi Bocola, and Fabrizio Perri. "Exchange rate policies at the zero lower bound." *The Review of Economic Studies* 87, no. 4 (2020): 1605-1645.

4. Adler, Gustavo, Noemie Lisack, and Rui C. Mano. "Unveiling the effects of foreign exchange intervention: A panel approach." *Emerging Markets Review* 40 (2019): 100620.

5. Adler, Gustavo, Kyun Suk Chang, Rui Mano, and Yuting Shao. "Foreign exchange intervention: A dataset of public data and proxies." International Monetary Fund, (2021).

6. Arslanalp, Serkan, Dimitris Drakopoulos, Rohit Goel, and Robin Koepke. "Benchmark-driven investments in emerging market bond markets: taking stock." IMF Working Paper, (2020).

7. Bacchetta, Philippe, Simon Tieche, and Eric Van Wincoop. "International portfolio choice with frictions: Evidence from mutual funds." *The Review of Financial Studies* 36, no. 10 (2023): 4233-4270.

8. Basak, Suleyman, and Anna Pavlova. "Asset prices and institutional investors." *American Economic Review* 103, no. 5 (2013): 1728-1758.

9. Basu, Suman Sambha, Emine Boz, Gita Gopinath, Francisco Roch, and Filiz Unsal. "Integrated Monetary and Financial Policies for Small Open Economies." IMF Working Paper, (2023).

10. Blanchard, Olivier J., Gustavo Adler, and Irineu de Carvalho Filho. "Can foreign exchange intervention stem exchange rate pressures from global capital flow shocks?." IMF Working Paper, (2015).

11. Cavallino, Paolo. "Capital flows and foreign exchange intervention." *American Economic Journal: Macroeconomics* 11, no. 2 (2019): 127-170.

12. Camanho, Nelson, Harald Hau, and Helene Rey. "Global portfolio rebalancing and exchange rates." *The Review of Financial Studies* 35, no. 11 (2022): 5228-5274.

13. Candian, Giacomo, and Pierre De Leo. "Imperfect exchange rate expectations." *Review of Economics and Statistics* (2023): 1-46.

14. Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich. "Regression discontinuity and the price effects of stock market indexing." *The Review of Financial Studies* 28, no. 1 (2015): 212-246.

15. Devereux, Michael B., and Charles Engel. "Exchange rate pass-through, exchange rate volatility, and exchange rate disconnect." *Journal of Monetary Economics* 49, no. 5 (2002): 913-940.

16. Dornbusch, Rudiger. "Expectations and Exchange Rate Dynamics." *Journal of Political Economy* 84, no. 6 (1976): 1161 - 76.

17. Du, Wenxin, and Jesse Schreger. "Local currency sovereign risk." *The Journal of Finance* 71, no. 3 (2016): 1027-1070.

18. Du, Wenxin, Alexander Tepper, and Adrien Verdelhan. "Deviations from covered interest rate parity." *The Journal of Finance* 73, no. 3 (2018): 915-957.

19. Duffie, Darrell. "Presidential address: Asset price dynamics with slow?moving capital." *The Journal of Finance* 65, no. 4 (2010): 1237-1267.

20. Engel, Charles. "Exchange rates, interest rates, and the risk premium." *American Economic Review* 106, no. 2 (2016): 436-474.

21. Engel, Charles, and Kenneth D. West. "Exchange rates and fundamentals." *Journal of political Economy* 113, no. 3 (2005): 485-517.

22. Evans, Martin DD, and Richard K. Lyons. "Order flow and exchange rate dynamics." *Journal of political economy* 110, no. 1 (2002): 170-180.

23. Fama, Eugene F. "Efficient capital markets: A review of theory and empirical work." *The Journal of Finance* 25, no. 2 (1970): 383-417.

24. Fama, Eugene F. "Forward and spot exchange rates." *Journal of Monetary Economics* 14, no. 3 (1984): 319-338.

25. Fanelli, Sebastian, and Ludwig Straub. "A theory of foreign exchange interventions." *The Review of Economic Studies* 88, no. 6 (2021): 2857-2885.

26. Farhi, Emmanuel, and Xavier Gabaix. "Rare disasters and exchange rates." *The Quarterly Journal of Economics* 131, no. 1 (2016): 1-52.

27. Farhi, Emmanuel, and Ivan Werning. "Dealing with the trilemma: Optimal capital controls with fixed exchange rates." No. w18199. National Bureau of Economic Research, (2012).

28. Fatum, Rasmus, and Michael M. Hutchison. "Is sterilised foreign exchange intervention effective after all? An event study approach." *The Economic Journal* 113, no. 487 (2003): 390-411.

29. Fratzscher, Marcel, Oliver Gloede, Lukas Menkhoff, Lucio Sarno, and Tobias Stohr. "When is foreign exchange intervention effective? Evidence from 33 countries." *American Economic Journal: Macroeconomics* 11, no. 1 (2019): 132-156.

30. Fernandez, Andres, Michael Klein, Alessandro Rebucci, Martin Schindler, and Martin Uribe, "Capital Control Measures: A New Dataset," *IMF Economic Review* 64, (2016): 548-574.

31. Kashyap, Anil K., Natalia Kovrijnykh, Jian Li, and Anna Pavlova. “The benchmark inclusion subsidy.” *Journal of Financial Economics* 142, no. 2 (2021): 756-774.

32. Kashyap, Anil K., Natalia Kovrijnykh, Jian Li, and Anna Pavlova. “Is there too much benchmarking in asset management?.” *American Economic Review* 113, no. 4 (2023): 1112-1141.

33. Gabaix, Xavier, and Matteo Maggiori. “International liquidity and exchange rate dynamics.” *The Quarterly Journal of Economics* 130, no. 3 (2015): 1369-1420.

34. Gabaix, Xavier, and Ralph Koijen. “In search of the origins of financial fluctuations: The inelastic markets hypothesis.” No. w28967. National Bureau of Economic Research, 2021.

35. Gali, J., and T. Monacelli (2005): “Monetary Policy and Exchange Rate Volatility in a Small Open Economy,” *Review of Economic Studies*, 72(3), 707 – 734.

36. Gourinchas, Pierre-Olivier, and Aaron Tornell. “Exchange rate puzzles and distorted beliefs.” *Journal of International Economics* 64, no. 2 (2004): 303-333.

37. Gourinchas, Pierre-Olivier, Walker Ray, and Dimitri Vayanos. “A preferred-habitat model of term premia and currency risk.” University of California–Berkeley, working paper (2020).

38. Greenwood, Robin, Samuel Hanson, Jeremy C. Stein, and Adi Sunderam. “A quantity-driven theory of term premia and exchange rates.” *The Quarterly Journal of Economics* 138, no. 4 (2023): 2327-2389.

39. Hau, Harald, Massimo Massa, and Joel Peress. “Do demand curves for currencies slope down? Evidence from the MSCI global index change.” *The Review of Financial Studies* 23, no. 4 (2010): 1681-1717.

40. Hau, Harald, and Helene Rey. “Exchange rates, equity prices, and capital flows.” *The Review of Financial Studies* 19, no. 1 (2006): 273-317.

41. Jiang, Zhengyang, Arvind Krishnamurthy, Hanno N. Lustig, and Jialu Sun. ”Beyond incomplete spanning: Convenience yields and exchange rate disconnect.” (2022).

42. Jiang, Zhengyang, Arvind Krishnamurthy, and Hanno Lustig. ”Foreign safe asset demand for us treasurys and the dollar.” *AEA Papers and Proceedings*, vol. 108, pp. 537-541. (2014)

43. Jeanne, Olivier, and Andrew K. Rose. “Noise trading and exchange rate regimes.” *The Quarterly Journal of Economics* 117, no. 2 (2002): 537-569.

44. Jeanne, Olivier. ”Capital account policies and the real exchange rate.” In NBER International Seminar on Macroeconomics, vol. 9, no. 1, pp. 7-42. Chicago, IL: University of Chicago Press, 2013.

45. Kremens, Lukas and Martin, Ian W. R. and Varela, Liliana, Long-Horizon Exchange Rate Expectations (August 19, 2023). Available at SSRN: https://ssrn.com/abstract=4545603

46. Lustig, Hanno, and Adrien Verdelhan. “The cross section of foreign currency risk premia and consumption growth risk.” American Economic Review 97, no. 1 (2007): 89-117.

47. Mundell, Robert A. "A theory of optimum currency areas." *The American Economic Review* 51, no. 4 (1961): 657-665.

48. Mundell, Robert A. "The appropriate use of monetary and fiscal policy for internal and external stability." Staff Papers 9 (1962): 70-79.

49. Kaul, Aditya, Vikas Mehrotra, and Randall Morck. "Demand curves for stocks do slope down: New evidence from an index weights adjustment." *The Journal of Finance* 55, no. 2 (2000): 893-912.

50. Koijen, Ralph SJ, and Motohiro Yogo. "A demand system approach to asset pricing." *Journal of Political Economy* 127, no. 4 (2019): 1475-1515.

51. Ilzetzki, Ethan, Carmen M. Reinhart, and Kenneth S. Rogoff. "Exchange arrangements entering the twenty-first century: Which anchor will hold?." *The Quarterly Journal of Economics* 134, no. 2 (2019): 599-646.

52. Ilzetzki, Ethan, Carmen M. Reinhart, and Kenneth S. Rogoff. "Rethinking exchange rate regimes." *Handbook of International Economics*, vol. 6, pp. 91-145. Elsevier, 2022.

53. Itskhoki, Oleg, and Dmitry Mukhin. "Exchange rate disconnect in general equilibrium." *Journal of Political Economy* 129, no. 8 (2021): 2183-2232.

54. Itskhoki, Oleg, and Dmitry Mukhin. "Optimal Exchange Rate Policy." (2023). Working Paper: https://itskhoki.com/papers/ERpolicy.pdf.

55. Itskhoki, Oleg, and Dmitry Mukhin. "Mussa Puzzle Redux." (2023). Working paper: https://itskhoki.com/papers/Mussa.pdf.

56. International Monetary Fund (IMF) (2019). "Foreign Exchange Intervention in Inflation Targeters in Latin America."

57. Lynch, Anthony W., and Richard R. Mendenhall. "New evidence on stock price effects associated with changes in the S&P 500 index." *The Journal of Business* 70, no. 3 (1997): 351-383.

58. Obstfeld, Maurice, and Kenneth Rogoff. "Exchange rate dynamics redux." *Journal of Political Economy* 103, no. 3 (1995): 624-660

59. Pandolfi, Lorenzo, and Tomas Williams. "Capital flows and sovereign debt markets: Evidence from index rebalancings." *Journal of Financial Economics* 132, no. 2 (2019): 384-403.

60. Raddatz, Claudio, Sergio L. Schmukler, and Tomas Williams. "International asset allocations and capital flows: The benchmark effect." *Journal of International Economics* 108 (2017): 413-430.

61. Rey, Helene. "Dilemma not trilemma: the global financial cycle and monetary policy independence." No. w21162. National Bureau of Economic Research, 2015..

62. Shleifer, Andrei. "Do demand curves for stocks slope down?." The Journal of Finance 41, no. 3 (1986): 579-590.

# Appendix

## A Data Description and Background

### A.1 More on GBI-EM Global Diversified Index

#### The GBI-EM Family

Published by J.P. Morgan in 2005, the GBI-EM Global Diversified index is the largest local-currency government bonds index for emerging countries. It's also the most popular index among the GBI-EM family of a total of six different indexes of local-currency emerging market government bonds indices. These are the three basic versions plus their respective diversified version: GBI-EM Broad and its diversified version, GBI-EM Global and its diversified version, and GBI-EM Narrow and its diversified version. Each diversified version is created from the corresponding basic version by maintaining the same set of countries but with different country weights to reduce the market concentration risks. Among all basic versions, GBI-EM broad has the broadest coverage of countries, followed by GBI-EM Global, and then GBI-EM Narrow. A simple comparison between the three basic versions are reported in Table A.1.

Table A.1: Comparison between three basic versions of GBI-EM indices by JP Morgan

| | GBI-EM Broad | GBI-EM Global | GBI-EM Narrow |
|---|---|---|---|
| Explicit Capital control | ✓ | | |
| Tax/Regulatory constraints | ✓ | ✓ | |
| Direct access by foreigners | ✓ | ✓ | ✓ |
| No. Countries as of 2021 | 21 | 19 | 16 |
| Country criteria | GNI per capita below the IIC[a] for 3 consecutive years | | |
| Instrument Criteria | Fixed/Zero coupon; Maturity $>$ 13 months<br>Minimum Face Amount $>$ US $1 bn. | | |

**Source**: JP Morgan Market Reports.

[a]Index Income Ceiling for emerging countries

Apart from different restrictions on capital controls and tax regulations for different versions of the GBI-EM index, all versions of the index have the same control on income capita and credit ratings. A country is chosen to enter (and remain in) the GBI-EM Global diversified if its Gross National Income (GNI) per capita is *below* the J.P. Morgan defined Index Income Ceiling (IIC) for three consecutive years. A country is chosen to exit the index if its GNI per capita is *above* the IIC or three consecutive years as well as the country's long term local currency sovereign credit rating (the available ratings from all three agencies: S&P, Moody's & Fitch) is A-/A3/A- (inclusive) or above for three consecutive years. In addition, the government bonds included in the index have to be local currency and have month-to-maturity of over 13 months as the threshold.

We choose to analyze the rebalancings of the GBI-EM Global Diversified index as it's the largest and most popular index in its family. According to the J.P. Morgan Market Survey, the asset under management for the mutual funds tracking the GBI-EM Global Diversified is more than 200 billion US Dollars in 2019. The 200 billion USD is a large number for the emerging market sovereign bonds market, as the total new issuance of the emerging market sovereign bonds is merely 160 billion USD in the same year, according to Refinitiv data.

There are currently 19 emerging countries in the GBI-EM Global Diversified index as of 2021. They are Brazil, Chile, Czech Republic, China, Colombia, Dominican Republic, Hungary, Indonesia, Malaysia, Mexico, Peru, the Philippines, Poland, Romania, Russia, South Africa, Thailand, Turkey and Uruguay. We exclude Dominican Republic and Uruguay in the sample due to their limited exchange rates data. We also exclude China as it just entered the GBI-EM Global diversified index in 2020. We include Argentina in our sample as it was in the index between 2018 and 2020.

**More Details on the Rebalancings Methodology**

The monthly rebalancings of the GBI-EM Global Diversified index have three layers, which are done in order on the last weekday of the month. The first layer uses a diversification methodology that includes only a portion of a country's current face amount outstanding into the index. The included face amount outstanding – called the adjusted face amount – is based on the respective country's relative size in the index and the average size of all countries. The adjusted face amount is then used to compute the market value of each country in the index. The second layer focuses on the bonds maturity threshold that drops bonds with less than 13 months to maturity from the index. As the third and last layer of control, the index rebalancing caps the weight of each country, computed using the adjusted face amount, at 10%.

We provide more details on first layer of rebalancing on the country's face amount, which is not discussed in the main texts. The face amount in the *diversified* version is created from its corresponding basic version with different weighting strategies for countries and aims to reduce concentration risks. Specifically, the following formula is used to construct the "Diversified Country Face Amount" $FA_c^D$ for country $c$:

$$FA_c^D = \begin{cases} ICA \times 2 & \text{if} \quad FA_{\max} \\ ICA + \frac{ICA}{FA_{\max} - ICA}\left(FA_c - ICA\right) & \text{if} \quad FA_c > ICA \\ FA_c & \text{if} \quad FA_c \leq ICA \end{cases}$$

where $FA_c$ is the face amount of country $c$. $ICA$ is the average face amount of countries (or currencies) in the index

$$ICA = \frac{\sum_c \text{Country face amount}}{\text{No. countries in the index}}$$

How are $FA^D$ used to compute the country-level weights in the index? These diversified face amounts ($FA^D$) are multiplied by the dirty price (price + accrued interests) to compute market value for each country, which is then divided by the total market value of the entire index to compute weights. If we were to compare the the diversified and non-diversified version GBI-EM, the diversified version would have a much smaller total market value of the entire index compared to the non-diversified version. Small countries $(FA_c \leq ICA)$ have the same market value in both indices, although their weights are bigger in the diversified version. For other countries, their market value is smaller in diversified version, but their reduction comes from two possible layers of control: the control on country-level face amount and the country weight cap of 10% as they are more likely to hit the cap.

**How often are the weights adjusted?**

The weights are updated on a daily frequency level, both for the diversified and non-diversified version. This is because the market value of the bonds (which uses dirty price) changes everyday and all versions use dirty price to compute country weights. However, the rebalance on the country's diversified face amount, as well as the additional layer of rebalance on the weight cap of 10% is done only at the end of each month. This rebalance at the end of the month creates additional change on the weight in additional to the daily adjustments due to price change. The diversified face amount will be held fixed after rebalancing until the next rebalance arrives. Therefore, the change in weights in the diversified version before the end of the month reflects the change in market return (or dirty price) only.

How are bonds deleted from the index? Can bonds be deleted both from the maturity threshold (13 months) and from rebalancing of face amount on the country-level? In fact, only rebalancing on the maturity threshold can lead to bonds to be dropped from index. The rebalancing on face amount keeps the same bonds in the diversified and non-diversified version, while reducing the face amount of bonds from country above the ICA in the diversified version.

Therefore, the bonds (both the number and its name) should be the same in both the diversified and non-diversified version for each country. For example, if we compare a Chinese bond in the GBI-EM Broad with its diversified version in Jan 2022, the bond should have the exact same yield and returns in both versions. However, the market value outstanding is smaller in the diversified version for this bond particularly due to the reduction in face amount rather prices (since China's face amount $>$ ICA). Also, if we compare a Philippines bond in the two indices, they should have the same metrics on everything including market value since its face amount is below ICA so they are intact from rebalancing on the country level.

## A.2 More on the Currency Demand Shock $\mu_{c,t}$

Two facts worth pointing out on the country-level dynamics: First, while most countries experience persistent positive $\mu_{c,t}$ (for example, Argentina, Chile, Hungary, etc.), some countries (for example, Brazil and Mexico) have negative $\mu_{c,t}$ in most of their episodes. This is because large countries like Brazil and Mexico are more likely to hit the 10% country weight cap during rebalancings. Their excess weights are redistributed to smaller countries that are below the cap such that the weights of all countries in the index sum up to 100%. This can be clearly seen from the plots country-specific currency demand shocks as reported in Table 2.2 in the main texts.

Second, data for some countries (for example, Argentina) are available only in a small number of months between 2010 and 2021 for the reason(s) that these countries fail to meet either the income ceiling or the credit rating requirement of the index in those episodes. A big country like Brazil can also be excluded from the GBI-EM Global Diversified index from time to time – as shown by the discontinuous MIR time-series for Brazil from 2010 to 2019. In those months, Brazil was included the GBI-EM Broad (another more inclusive index of the J.P Morgan GBI-EM family) instead possibly due to its explicit and intensive capital control policies.

## A.3 Converting the Currency Demand Shock into Flows

We can re-write the expression the currency demand shock $\mu_{c,t}$ as the percentage change in market value implied from the rebalancing:

$$\begin{aligned}\mu_{c,t} &= \frac{\omega_{c,t}^{\text{after}} - \omega_{c,t}^{\text{before}}}{\omega_{c,t}^{\text{after}}} \\ &= \frac{\frac{P_{c,t}\hat{Q}_{c,t}}{\sum_c' P_c \hat{Q}_c} - \frac{P_{c,t}\hat{Q}_{c,t-1}}{\sum_c' P_c \hat{Q}_c}}{\frac{P_{c,t}\hat{Q}_{c,t}}{\sum_c' P_c \hat{Q}_c}} \\ &= \left(\omega_{c,t}^{\text{after}} - \omega_{c,t}^{\text{before}}\right) \times \frac{\sum_c \text{market value}}{\text{market value country c}}\end{aligned}$$

where $\hat{Q}_{c,t}$ is the face-amount (or quantity) of the local-currency sovereign bonds of country $c$ included in the GBI-EM Global Diversified index at rebalancing date $t$; $P_{c,t}$ is the aggregate market price of the local-currency sovereign bonds of country $c$. Once $\hat{Q}_{c,t}$ is chosen at a rebalancing date, it will be fixed for the next month until the end of the business day of the next month when the next rebalancing comes in. The product of face-amount and market price $P_{c,t}\hat{Q}_{c,t}$ is the market value of the sovereign bonds included in the index.

After showing $\mu_{c,t}$ essentially represents the change in market value, we can back out the change in the flows of mutual funds positions implied by rebalancings:

$$\text{Average Implied flows from rebalancings (FIR) } \mu_{c,t} = \frac{\text{avg. country-level market value}}{\text{total market value of the index}} \times \frac{\text{EPFR mutual funds positions}}{\text{Share of EPFR funds in ICI}} \tag{11}$$

In the definition above, EPFR mutual funds positions is the asset-under-management (AUM) of the the mutual funds that are passively tracking the GBI-EM Global Diversified Index at time $t$. However, EPFR doesn't report the universe of mutual funds globally that track GBI-EM Global Diversified Index. We therefore need to scale the positions reported by EPFR by its population share in the mutual funds universe, as reported by the Investment Company Institutes (ICI). We show how to compute the aggregate flows based on EPFR mutual funds data below.

### A.3.1 Estimating the aggregate flows from EPFR

We report the estimated AUM of EPFR mutual funds passively tracking the GBI-EM Global Diversified index in panel (a) of Table B.4 and the population share of EPFR data in ICI database in panel (b) of Table B.4. Scaling up the total AUM of mutual funds in EPFR tracking the index (panel a) using its population share in ICI (panel b), we arrive at the total mutual funds in the industry tracking the index. Below, we start with explaining how to estimate the mutual funds tracking the index in the EPFR dataset.

We first use EPFR fund flows data to select the mutual funds that closely track the GBI- EM Global Diversified index. To do so, we first filter out all the emerging market bond funds from the EPFR dataset whose benchmark indices are JP Morgan GBI-EM Global Diversified. This include JP Morgan GBI-EM Global Diversified, GBI-EM Global Diversified composite indices, GBI- EM Global Diversified ESG, or GBI-EM Global Diversified Europe (or LATUM, Asia). Funds whose benchmark names are other indices in the GBI-EM family only (ie: "GBI-EM Broad") and the investment grade version of GBI-EM Global Diversified are not included.

We then regress the monthly returns of each bond fund in the EPFR dataset on the returns of GBI-EM Global Diversified and select those funds whose performance R-squared (Amihud and Goyenko, 2013) are at least 0.9. Our final dataset merges the funds whose benchmark indices are GBI-EM Global Diversified with those funds whose performance R-squared at at least 0.9. This gives us 2113 unique funds.

The mutual funds performance R-squared method developed by Amihud and Goyenko (2013) is meant to determine the passivism of the mutual funds in our dataset. The method regresses the fund-level monthly returns on the monthly returns of GBI-EM Global Diversified. To test the passivism of mutual funds we selected, we preform the regression in equation (2) on a rolling window of 12-month from January 2016 to January 2022 to record the R-squared of each regression. The histogram of the estimated R-squared is presented in Table B.7a. We use the rolling window rather than the entire time series to gauge the mutual fund performance as the mutual fund's passivism could be time varying. Our regression results show that the mutual funds in our data gives a medium R-squared performance of 0.9.

As an additional test for the passivism of mutual funds, we construct a hypothetical fund whose return is the weighted average (by assets under management) of all mutual funds in our sample identified as closely tracking the GBI-EM Global Diversified index. We find that the monthly returns of the "constructed" fund closely track the returns of the GBI-EM Global Diversified, as illustrated in Table B.7b. A simple OLS regression using the returns of "constructed" fund and the index returns give a R-squared of 0.97.

Taken together, Table B.7a and B.7b makes clear that at the rebalancing dates, these funds have to buy or sell their asset positions to match the returns of GBI-EM Global Diversified that uses the rebalancing scheme discussed above. Table B.4 panel (a) plots the AUM of funds tracking the GBI-EM Global Diversified index in the EPFR data from 2016 to 2022.

The final step in computing the global flows of mutual funds tracking the index is to estimate the EPFR data's population share in ICI dataset. Investment Company Institute (ICI) Global Facts Sheet reports the global mutual funds data population. We aggregate equity, bonds, and money market end-of month assets for both industrialized and emerging markets from the EPFR data and divide that number with investment Company Institute (ICI) Global Facts Sheet. This gives the the population presentation of the EPFR data in the world-wide mutual funds industry, as reported in panel (b) of Table B.4.

### A.3.2 Converting the currency demand shocks into noise trader shocks

We show below how to connect the flows implied by rebalancings (FIR) with the noise trader positions. As we do not observe the entire variation in the noise trader shocks, we decompose noise trader positions $n_{c,t}$ into two components: the first component is the buy-and-hold portfolio of benchmark invesments who are subject to mechanical rebalancings ($\tilde{n}_{c,t}$); the second component is the part of noise trader positions unexplained by rebalancings ($\tilde{e}_{c,t}$). The two components are *additive* and *orthogonal* to each other.

$$n_{c,t} = \tilde{n}_{c,t} + \tilde{e}_{c,t}, \qquad \text{where} \quad \tilde{n}_{c,t} \perp \tilde{e}_{c,t}$$

Holdings of benchmark investments ($\tilde{n}_t$) are subject to noise trader shocks ($\tilde{\psi}_t$) when rebalancing happens. Noise traders shocks are orthogonal to macroeconomic fundamentals just as illustrated in the model. The position $\tilde{n}_t$ at time $t$ is:

$$\tilde{n}_{c,t} = \begin{cases} \left(\frac{\tilde{n}_{c,t-1}}{R_{c,t-1}}\right) R_{c,t} & \text{o.w} \\ \tilde{\psi}_t R_{c,t} & \text{if} \quad t = \text{rebalancing date} \end{cases} \tag{12}$$

At the rebalancing date:

$$\begin{aligned} \tilde{n}_{c,t} = \tilde{\psi}_{c,t} R_{c,t} &= \underbrace{\tilde{\psi}_{c,t} R_{c,t} - \left(\frac{\tilde{n}_{c,t-1}}{R_{c,t-1}}\right) R_{c,t}}_{\text{flows implied by rebalancings}} + \underbrace{\left(\frac{\tilde{n}_{c,t-1}}{R_{c,t-1}}\right) R_{c,t}}_{\text{market value buy-and-hold}} \\ &= \quad \text{FIR}_{c,t} \qquad\qquad + \qquad \text{market value}^{BH}_{c,t} \end{aligned}$$

where market value$^{BH}_{c,t}$ is buy-and-hold market value that equates the faceamount of previous rebalancing $t-1$ times the market price at time $t$. The flows-implied-by-rebalancings (FIR) can be connected with our currency demand shock as shown in equation (11). We can therefore re-write the noise trader shocks $n_{c,t}$ as:

$$n_{c,t} = \text{FIR}_{c,t} + \quad \text{market value}^{BH}_{c,t} + \quad \tilde{e}^{n}_{c,t} \tag{13}$$

where $\tilde{e}^{n}_{c,t} \perp \text{FIR}_{c,t}$, that is, the components of noise trader shocks unexplained by rebalancings are orthogonal to the flows implied by rebalancings of the GBI-EM Global Diversified.

# B Additional Figures and Tables

Table B.1: Country Statistics for Computing Required Size of Intervention

| Country | 2019 mkt value | 2019 GDP | 2019 broad money (M2) |
|---|---|---|---|
| Argentina | 6.65 | 360.57 | . |
| Brazil | 205.72 | 1833.49 | 1761.21 |
| Chile | 29.72 | 262.98 | 221.51 |
| Colombia | 62.86 | 321.81 | 157.54 |
| CzechRepublic | 38.09 | 256.02 | 211.28 |
| Hungary | 40.20 | 161.72 | 94.05 |
| Indonesia | 137.43 | 1138.96 | 441.46 |
| Malaysia | 55.98 | 369.14 | 454.31 |
| Mexico | 153.18 | 1297.19 | 490.13 |
| Peru | 33.07 | 229.93 | 112.80 |
| Philippines | 2.63 | 384.63 | 294.62 |
| Poland | 104.24 | 602.6 | 412. 15 |
| Romania | 24.33 | 249.67 | . |
| Russia | 84.76 | 1764.64 | 1042.48 |
| South Africa | 107.15 | 400.25 | 268.35 |
| Thailand | 98.98 | 560.20 | 691.15 |
| Turkey | 36.91 | 725.20 | 426.82 |
| Average | 68 | 586 | 472 |
| Median | 48 | 383 | 412 |

**Note**: Column 2 gives the average market value of the local-currency government bonds of each country in the GBI-EM Global Diversified in 2019 (with the except of Argentina that we use the average between 2017-2019 due to limited data). Column 3 gives the annual nominal GDP of 2019. Column 4 gives the annual broad money supply (M2) in 2019. All values are in billions of US Dollars. We used the market value and GDP to compute the required size of foreign exchange interventions in Table 6.1 in the main texts.

Table B.2: Foreign exchange intervention required to induce 1% exchange rate change

| Country | ER regime (code) | ER Vol. | FXI | FXI over M2 (%) |
|---|---|---|---|---|
| Peru | crawling peg (2) | 0.113 | 0.875 | 0.775 |
| Hungary | crawling peg (2) | 0.160 | 0.435 | 0.463 |
| Romania | crawling peg (2) | 0.131 | 0.582 | . |
| Indonesia | crawling peg (2) | 0.187 | 1.34 | 0.279 |
| Philippines | crawling peg (2) | 0.074 | 0.124 | 0.042 |
| Thailand | managed floating (3) | 0.053 | 2.397 | 0.347 |
| Chile | managed floating (3) | 0.169 | 0.380 | 0.172 |
| Colombia | managed floating (3) | 0.271 | 0.950 | 0.603 |
| Russia | managed floating (3) | 0.372 | 0.346 | 0.033 |
| Mexico | managed/free floating (3.5) | 0.207 | 1.511 | 0.308 |
| Turkey | managed floating/free falling (3.5) | 0.582 | 0.154 | 0.036 |
| South Africa | free floating (4) | 0.286 | 0.540 | 0.201 |
| Argentina | free falling (5) | 0.999 | 0.026 | . |
| | Group Average | | | |
| | crawling peg | | 0.65 | 0.400 |
| | managed floating | | 1.02 | 0.289 |
| | free floating/falling | | 0.56 | 0.182 |

**Note**:

The estimates for Czechia (de facto peg, code 1), Brazil, Malaysia and Poland (all managed floating, code 3) are insignificant and we do not report them in this table. Also we lack the data for Argentina and Romania on their broad money (M2) measure.

This table reports the country-specific required size of foreign exchange (FX) intervention to stabilize exchange rates by 1% in billion US dollars (column 4) and as a share (%) of each country's broad money supply (column 5). The exchange rates volatility, measured as the standard deviation of the log exchange rate level by country, as reported in column 3. We sort countries by their coarse exchange rate regimes (column 2, as classified by Iltzetki, Rogoff and Reinhart 2021) from de facto peg to free floating or falling. For countries having multiple exchange rate regime codes during our sample period (2010–2021), as for Mexico and Turkey, we take the average regime code across time.

The required size of intervention is computed using the country-specific exchange rate response to the currency demand shock at the horizon of 0 days after the rebalancing date. All estimates are significant at the 1% level. A table with the country's GDP and market value, as well as M2 can be found in the appendix (Table B.1).

Table B.3: Exchange rates movements as a result of 1% GDP capital inflow

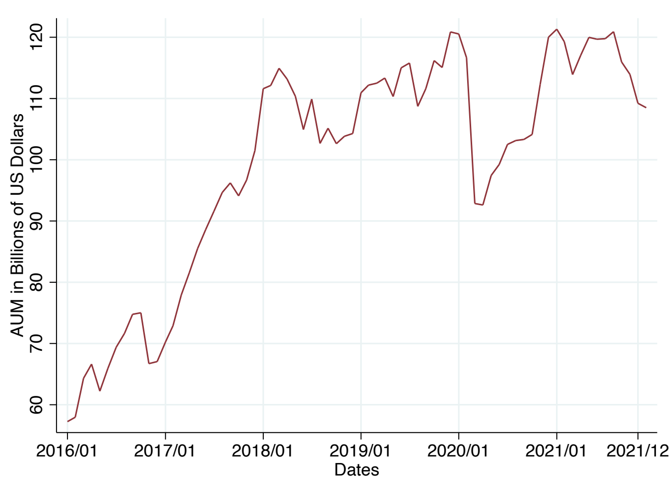
| Country | ER regime (code) | ER Vol. | Flow size | Δ ER (%) |
|---|---|---|---|---|
| Peru | crawling peg (2) | 0.113 | 2.30 | 2.63 |
| Hungary | crawling peg (2) | 0.160 | 1.62 | 3.72 |
| Romania | crawling peg (2) | 0.131 | 2.50 | 4.29 |
| Indonesia | crawling peg (2) | 0.187 | 11.39 | 9.25 |
| Philippines | crawling peg (2) | 0.074 | 3.85 | 31.0 |
| Thailand | managed floating (3) | 0.053 | 5.60 | 2.34 |
| Chile | managed floating (3) | 0.169 | 2.63 | 6.92 |
| Colombia | managed floating (3) | 0.271 | 3.22 | 3.39 |
| Russia | managed floating (3) | 0.372 | 17.65 | 51.0 |
| Mexico | managed/free floating (3.5) | 0.207 | 12.97 | 8.56 |
| Turkey | managed floating/free falling (3.5) | 0.582 | 7.25 | 46.94 |
| South Africa | free floating (4) | 0.286 | 4.00 | 7.41 |
| Argentina | free falling (5) | 0.999 | 3.61 | 137.53 |
| | Group Average | | | |
| | crawling peg | | | 10.18 |
| | managed floating | | | 15.91 |
| | free floating/falling | | | 50.12 |

**Note**:

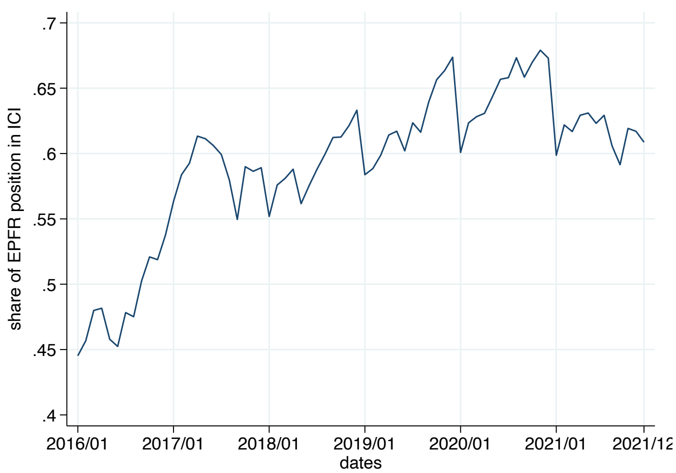
The estimates for Czechia (de facto peg, code 1), Brazil, Malaysia and Poland (all managed floating, code 3) are insignificant and we do not report them in this table.

This table reports the country-specific exchange rates movements (in percent) in response to an exogenous capital flow in the size of 1% of its nominal GDP (column 5). Column 4 reports of size of the country-specific capital flow shock that equals 1% nominal GDP of the country in 2019. The exchange rates volatility, measured as the standard deviation of the log exchange rate level by country, as reported in column 3. We sort countries by their coarse exchange rate regimes (column 2, as classified by Iltzetki, Rogoff and Reinhart 2021) from de facto peg to free floating or falling. For countries having multiple exchange rate regime codes during our sample period (2010–2021), as for Mexico and Turkey, we take the average regime code across time.

Table B.4: AUM of the GBI-EM index in EPFR data and Its Share in ICI




(a) AUM of Funds tracking GBI-EM Global Diversified in EPFR Data

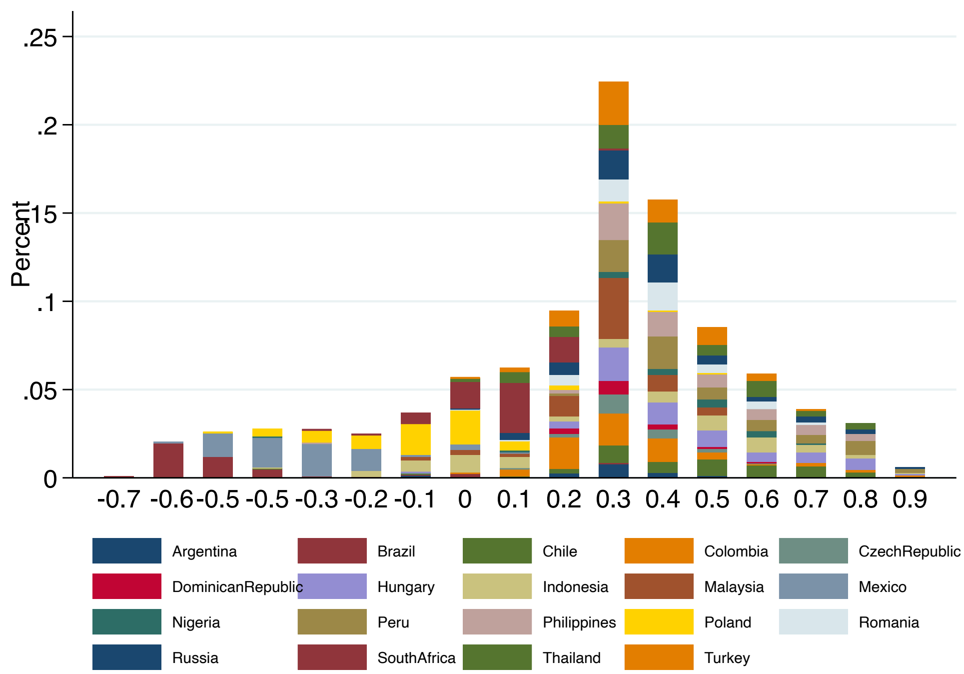



(b) EPFR Mutual Funds Population Share in ICI Data

**Note**: This figure reports the total asset under management of bond funds that track the GBI-EM Global Diversified index in the EPFR dataset (panel a) and the share of total EPFR data representation for the entire mutual funds industry (panel b). The bonds funds aggregated in panel (a) are in Billions of USD and are selected from mutual funds whose benchmark indices track the JP Morgan GBI-EM Global Diversified or their performance R-squared are at least 0.9. Observations are in monthly frequency from January 2016 to December 2021.

For the share of mutual funds representation in panel (b), we aggregate equity, bonds, and money market end-of month assets for both industrialized and emerging markets from the EPFR data and divide that number with investment Company Institute (ICI) Global Facts Sheet. This gives the the population presentation of the EPFR data in the world-wide mutual funds industry.

Table B.5: Histogram for the Country-Specific Currency Demand Shock $\mu_{c,t}$




**Note**: This figure presents the distribution of currency demand shock ($\mu_{c,t}$) across countries. Each country is represented by a different color, as indicated in the legend of the figure. The vertical axis is the precent share in the entire sample as indicated by the labels on the horizontal axis. For example, -0.7 indicates the value range (-0.7, -0.6) and 0.9 indicates the value range (0.9, 1).

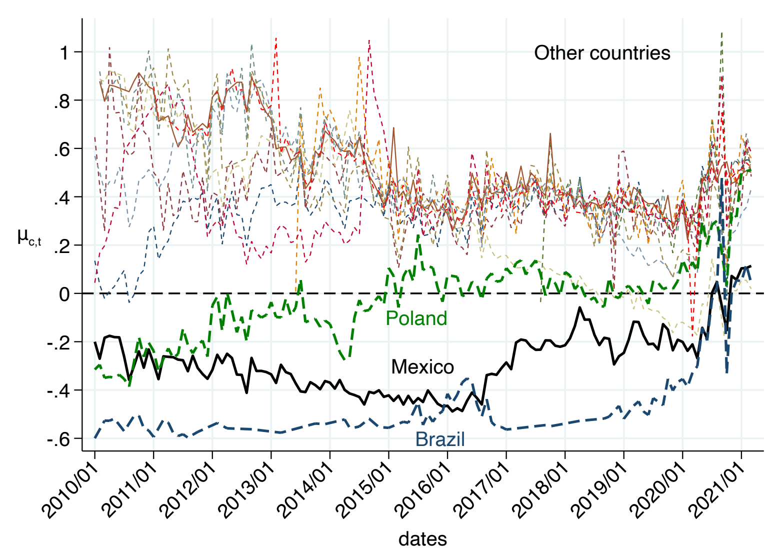
Table B.6: Summary of Statistics of the Currency Demand Shock $\mu_{c,t}$

$\mu_{c,t}$, *including* observations at 10% cap

| Obs. | Mean | Std. | Min | Max | Median | 90% | 10% |
|---|---|---|---|---|---|---|---|
| 2,044 | 0.292 | 0.315 | -0.58 | 0.91 | 0.36 | 0.65 | -0.21 |

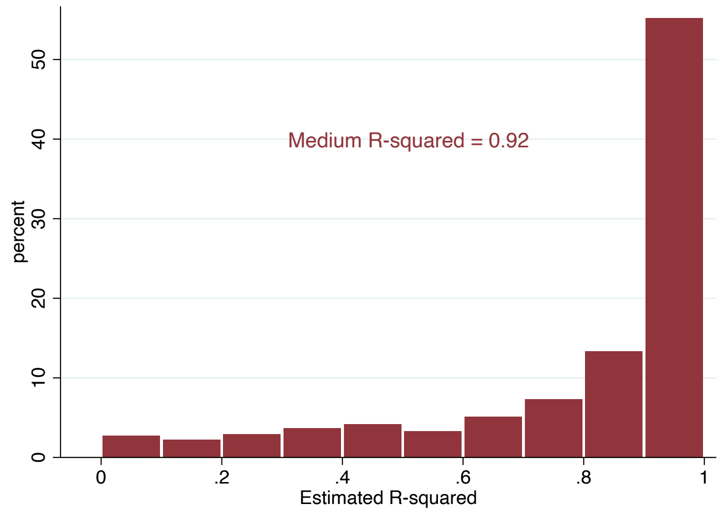
$\mu_{c,t}$, *excluding* observations at 10% cap

| Obs. | Mean | Std. | Min | Max | Median | 90% | 10% |
|---|---|---|---|---|---|---|---|
| 1,436 | 0.405 | 0.211 | -0.43 | 0.91 | 0.39 | 0.70 | 0.13 |

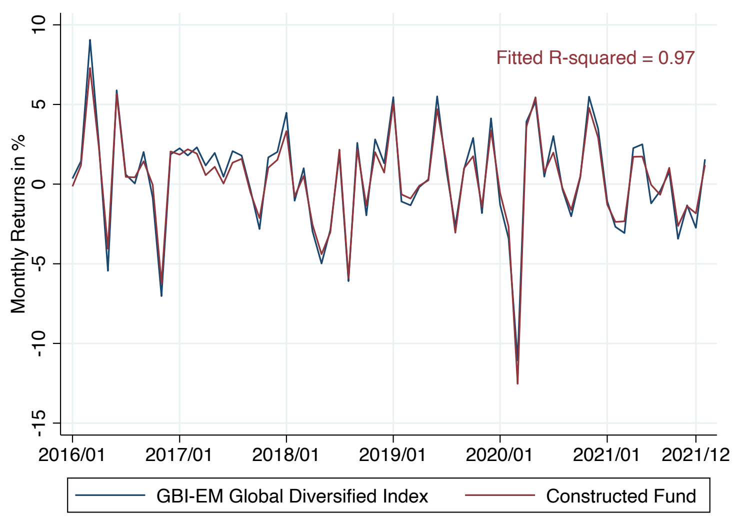



**Note**: This table reports the summary statistics on the currency demand shock ($\mu_{c,t}$) implied by the monthly rebalancings of the GBI-EM Global Diversified index. The figure plots the time series of the $\mu_{c,t}$ across time for each country. Each line represents country.

Table B.7: Return performance of mutual funds in the data




(a) Histogram of fund performance $R^2$




(b) Weighted (by positions) average returns

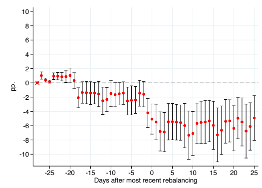
**Note**: This left panel reports the histogram of estimated R-squared of12-month rolling window regressions of monthly fund returns on the returns of GBI-EM Global Diversified index; the median R-squared is 0.92. The right panel plots the returns of GBI-EM Global Diversified index and the returns of weighted (by asset under management) of all mutual funds tracking the index; the performance R-squared here is 0.97.

Table B.8: Correlation matrix of sovereign bond prices across countries

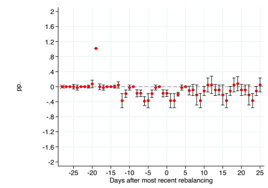
| | Argentina | Brazil | Chile | Colombia | Czech Republic | Hungary | Indonesia | Malaysia | Mexico | Peru | Phillippines | Poland | Romania | Russia | South Africa | Thailand | Turkey |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Argentina** | 1 | -0.8667 | -0.8342 | 0.2055 | 0.5164 | 0.1163 | 0.4792 | -0.8014 | -0.0187 | -0.3778 | -0.0916 | -0.8158 | 0.4812 | -0.152 | 0.119 | -0.569 | 0.4134 |
| **Brazil** | -0.8667 | 1 | 0.8659 | 0.1942 | -0.0728 | -0.1368 | 0.1808 | 0.6966 | -0.3609 | 0.7603 | 0.4262 | -0.0838 | -0.7315 | 0.7327 | -0.2318 | 0.4274 | -0.2363 |
| **Chile** | -0.8342 | 0.8659 | 1 | -0.1281 | -0.0991 | 0.2982 | 0.0342 | 0.7773 | 0.2081 | 0.5126 | 0.6267 | 0.606 | -0.1286 | 0.6171 | -0.3057 | 0.6206 | 0.0442 |
| **Colombia** | 0.2055 | 0.1942 | -0.1281 | 1 | 0.4053 | -0.6548 | 0.7185 | 0.3287 | 0.477 | 0.6826 | 0.1958 | -0.0446 | -0.2871 | 0.4116 | 0.803 | -0.5452 | 0.4848 |
| **Czech Republic** | 0.5164 | -0.0728 | -0.0991 | 0.4053 | 1 | 0.5746 | 0.5731 | -0.0654 | 0.2933 | 0.0762 | 0.1848 | -0.0742 | 0.7641 | 0.0734 | 0.0455 | 0.0894 | 0.5688 |
| **Hungary** | 0.1163 | -0.1368 | 0.2982 | -0.6548 | 0.5746 | 1 | -0.6249 | -0.306 | -0.117 | -0.3587 | 0.2331 | 0.5308 | 0.6694 | -0.4758 | -0.5827 | 0.3045 | -0.1248 |
| **Indonesia** | 0.4792 | 0.1808 | 0.0342 | 0.7185 | 0.5731 | -0.6249 | 1 | 0.494 | 0.4165 | 0.605 | 0.1923 | -0.2212 | -0.058 | 0.4223 | 0.6708 | -0.1097 | 0.4343 |
| **Malaysia** | -0.8014 | 0.6966 | 0.7773 | 0.3287 | -0.0654 | -0.306 | 0.494 | 1 | 0.3731 | 0.6203 | 0.5879 | 0.1779 | -0.2167 | 0.6014 | 0.075 | 0.3943 | 0.1972 |
| **Mexico** | -0.0187 | -0.3609 | 0.2081 | 0.477 | 0.2933 | -0.117 | 0.4165 | 0.3731 | 1 | 0.3078 | 0.5318 | 0.5108 | 0.5711 | -0.09 | 0.5411 | -0.057 | 0.7291 |
| **Peru** | -0.3778 | 0.7603 | 0.5126 | 0.6826 | 0.0762 | -0.3587 | 0.605 | 0.6203 | 0.3078 | 1 | 0.5845 | 0.1084 | -0.5196 | 0.6308 | 0.4414 | -0.1035 | 0.3259 |
| **Phillippines** | -0.0916 | 0.4262 | 0.6267 | 0.1958 | 0.1848 | 0.2331 | 0.1923 | 0.5879 | 0.5318 | 0.5845 | 1 | 0.6392 | 0.1009 | 0.3058 | 0.043 | 0.3197 | 0.4332 |
| **Poland** | -0.8158 | -0.0838 | 0.606 | -0.0446 | -0.0742 | 0.5308 | -0.2212 | 0.1779 | 0.5108 | 0.1084 | 0.6392 | 1 | 0.4257 | -0.3521 | -0.1133 | 0.0005 | 0.2222 |
| **Romania** | 0.4812 | -0.7315 | -0.1286 | -0.2871 | 0.7641 | 0.6694 | -0.058 | -0.2167 | 0.5711 | -0.5196 | 0.1009 | 0.4257 | 1 | -0.7123 | 0.2355 | 0.1476 | 0.6135 |
| **Russia** | -0.152 | 0.7327 | 0.6171 | 0.4116 | 0.0734 | -0.4758 | 0.4223 | 0.6014 | -0.09 | 0.6308 | 0.3058 | -0.3521 | -0.7123 | 1 | 0.0026 | 0.1857 | -0.0248 |
| **South Africa** | 0.119 | -0.2318 | -0.3057 | 0.803 | 0.0455 | -0.5827 | 0.6708 | 0.075 | 0.5411 | 0.4414 | 0.043 | -0.1133 | 0.2355 | 0.0026 | 1 | -0.423 | 0.5578 |
| **Thailand** | -0.569 | 0.4274 | 0.6206 | -0.5452 | 0.0894 | 0.3045 | -0.1097 | 0.3943 | -0.057 | -0.1035 | 0.3197 | 0.0005 | 0.1476 | 0.1857 | -0.423 | 1 | -0.0057 |
| **Turkey** | 0.4134 | -0.2363 | 0.0442 | 0.4848 | 0.5688 | -0.1248 | 0.4343 | 0.1972 | 0.7291 | 0.3259 | 0.4332 | 0.2222 | 0.6135 | -0.0248 | 0.5578 | -0.423 | 1 |

**Note**: This table reports the correlation coefficient in aggregate local-currency sovereign bond prices at the rebalancing date ($P_{c,t}$ in the equation (1) on the currency demand shock) across countries. Each entry in the matrix is the time-series correlation in prices between the two countries over the sample period from 2010 to 2021 at the monthly frequency. The red entries are price positive correlations and the blue entries are negative correlations, with the darker shade implying a stronger correlation in magnitudes. Off-diagonal entries are in darkest shade in red as they all have correlation coefficients that equal 1.

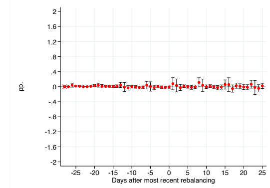
Table B.9: Cumulative Change in Policy Rates in on $\mu_{c,t}$



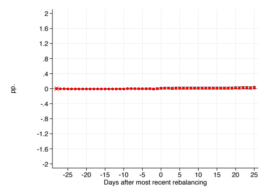
(a) Argentina



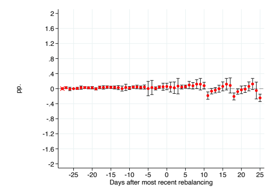
(b) Brazil



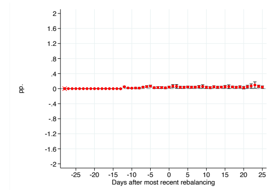
(c) Chile



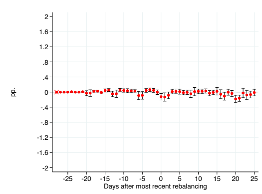
(d) Colombia



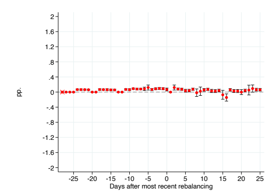
(e) Czech Republic



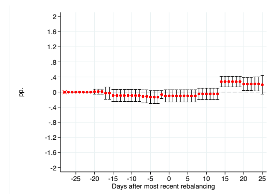
(f) Hungary



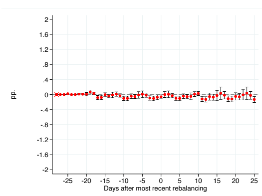
(g) Indonesia



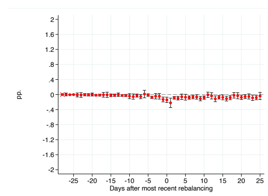
(h) Malaysia



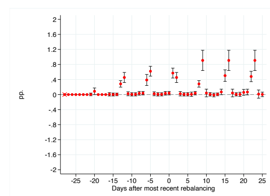
(i) Mexico



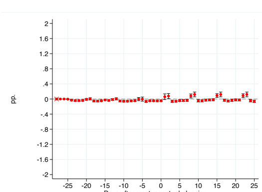
(j) Peru



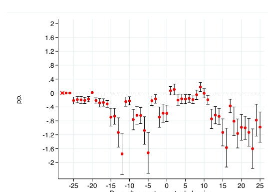
(k) Philippines



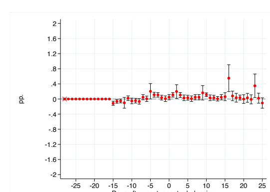
(l) Poland



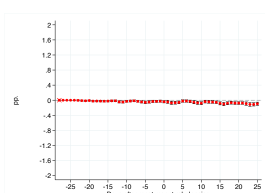
(m) Romania



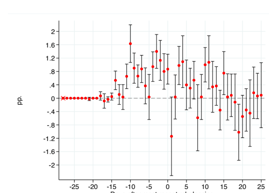
(n) Russia



(o) South Africa



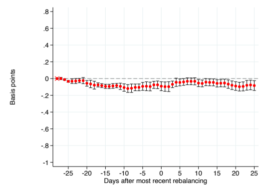
(p) Thailand



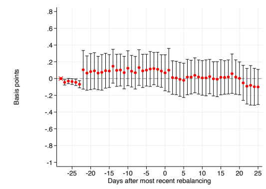
(q) Turkey

**Note**: This panel of figures provide the regression coefficients of country-specific central bank policy rates (in percentage points) in response to the currency demand shock $\mu_{c,t}$. The black line indicates 90% confidence interval. The change in central bank policy rates are provided by Bank of International Settlements (BIS) and measured as the change since 28 before rebalancing dates. All countries have the same scale for vertical axis except for Argentina.

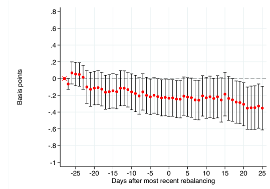
Table B.10: Cumulative interest rate (3-month) difference on $\mu_{ct}$



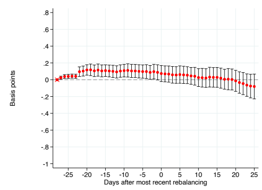

(a) Brazil



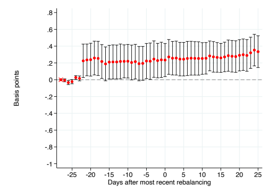

(b) Chile



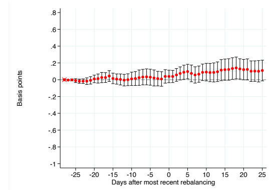

(c) Colombia



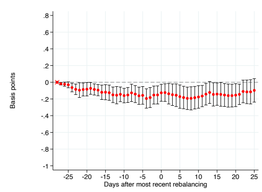

(d) Hungary



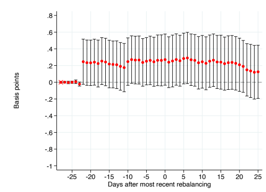

(e) Indonesia



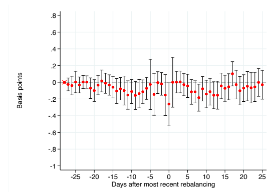

(f) Malaysia



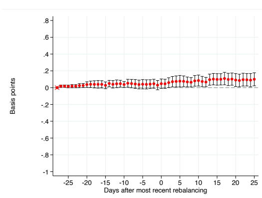

(g) Mexico



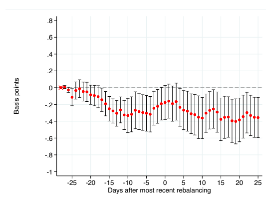

(h) Peru



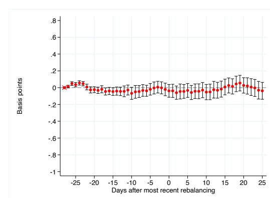

(i) Philippines



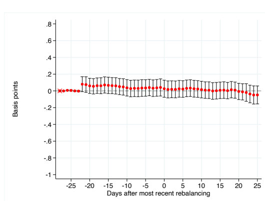

(j) Poland



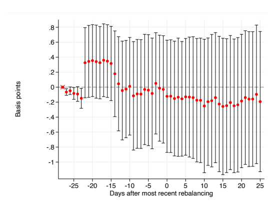

(k) Russia




(l) South Africa



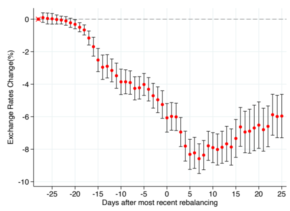

(m) Thailand



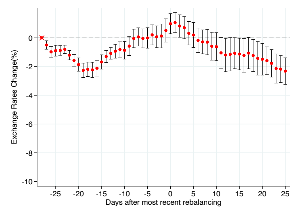

(n) Turkey

**Note**: This panel of figures reports the regression coefficient of "double-interest-rates-differentials" of 3-month tenor (in basis points, not annualized) on our currency demand shock $\mu_{ct}$. The black line indicates 90% confidence interval. We define "double-interest-rates-differentials" as change in the yield differentials on home and foreign (USD) government bonds since -28 before rebalancing. All countries have the same scale for vertical axis.

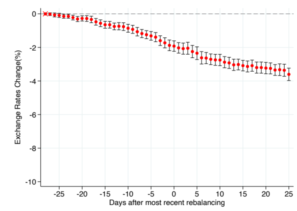
Table B.11: Exchange Rates Change on $\mu_{c,t}$ with year and month fixed effects



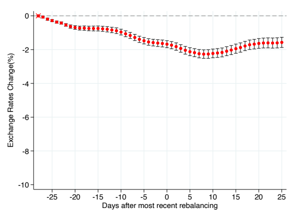
(a) Argentina



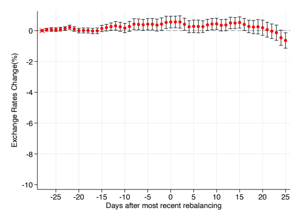
(b) Brazil



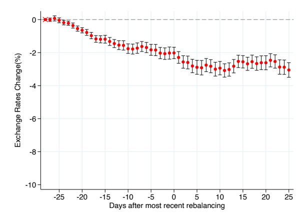
(c) Chile



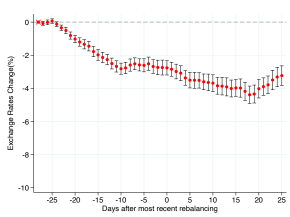
(d) Colombia



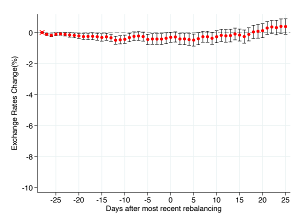
(e) Czech Republic



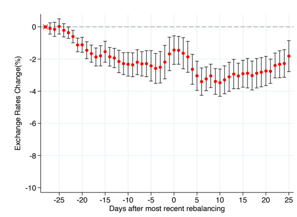
(f) Hungary



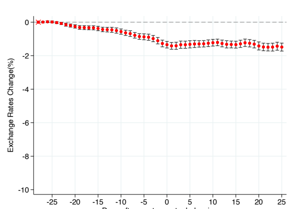
(g) Indonesia



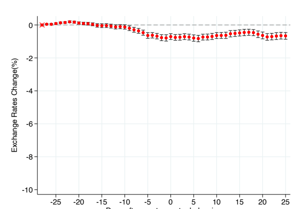
(h) Malaysia



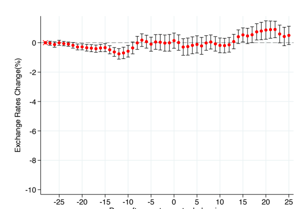
(i) Mexico



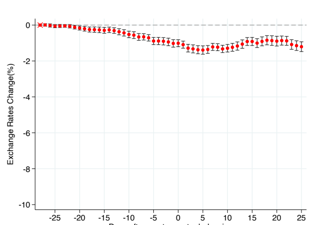
(j) Peru



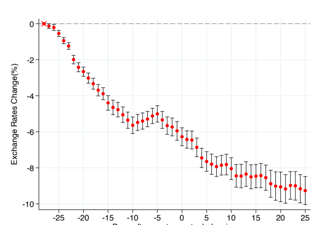
(k) Philippines



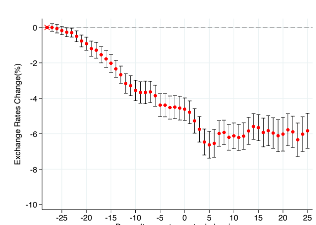
(l) Poland



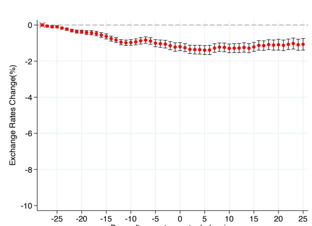
(m) Romania



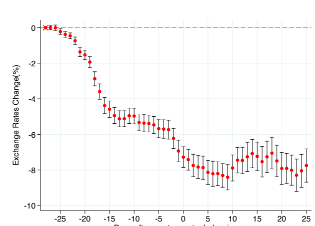
(n) Russia



(o) South Africa



(p) Thailand



(q) Turkey

**Note**: This panel of figures reports the regression coefficient of country-level cumulative exchange rates change (in % or $100 \times \Delta \log(.)$) in response to $\mu_{c,t}$. Exchange rates change are defined as the change since 28 days before the current rebalancing. Black lines indicate confidence interval of 90%. Regressions of Mexico and Brazil have year fixed effects due to limited observations.

Table B.12: Exchange Rates Change on $\mu_{c,t}$ with year and month fixed effects

| | (1) Argentina | (2) Brazil | (3) Chile | (4) Colombia | (5) CzechRepublic | (6) Hungary | (7) Indonesia | (8) Malaysia | (9) Mexico |
|---|---|---|---|---|---|---|---|---|---|
| $\mu_{c,t}$ | -8.130*** | -0.306 | -2.559*** | -2.164*** | 0.313 | -3.022*** | -3.651*** | -0.397 | -3.317*** |
| | (0.676) | (0.690) | (0.265) | (0.183) | (0.281) | (0.305) | (0.355) | (0.286) | (0.652) |
| Constant | 0.668 | -0.451 | 1.292*** | 0.0458 | -0.469*** | 1.951*** | -0.673*** | 0.139 | -8.295*** |
| | (0.437) | (1.381) | (0.182) | (0.103) | (1.338) | (0.191) | (0.119) | (0.111) | (0.121) |
| Obs. | 228 | 61 | 627 | 1386 | 313 | 932 | 574 | 468 | 75 |
| $R^2$ | 0.6608 | 0.0033 | 0.3201 | 0.2162 | 0.3819 | 0.2581 | 0.4808 | 0.2683 | 0.5426 |
| Adj. $R^2$ | 0.638 | -0.014 | 0.296 | 0.203 | 0.351 | 0.239 | 0.460 | 0.239 | 0.523 |

| | (1) Peru | (2) Philippines | (3) Poland | (4) Romania | (5) Russia | (6) South Africa | (7) Thailand | (8) Turkey |
|---|---|---|---|---|---|---|---|---|
| $\mu_{c,t}$ | -1.237*** | -0.693*** | -0.227 | -1.368*** | -8.011*** | -6.490*** | -1.351*** | -7.817*** |
| | (0.152) | (0.134) | (0.398) | (0.164) | (0.430) | (0.543) | (0.179) | (0.518) |
| Constant | 0.800*** | 0.340*** | -0.431 | 0.356*** | 1.865*** | -9.672*** | 0.196*** | 0.449** |
| | (0.0928) | (0.0724) | (0.611) | (0.0722) | (0.169) | (0.845) | (0.0583) | (0.199) |
| Obs. | 841 | 886 | 301 | 665 | 724 | 435 | 845 | 549 |
| $R^2$ | 0.3242 | 0.1886 | 0.3533 | 0.3078 | 0.4849 | 0.4401 | 0.2268 | 0.3769 |
| Adj. $R^2$ | 0.305 | 0.168 | 0.319 | 0.287 | 0.469 | 0.417 | 0.207 | 0.353 |

Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Note**: This panel of figures reports the regression coefficient of country-level cumulative exchange rates change (in % or $100 \times \Delta \log(.)$) in response to $\mu_{c,t}$. Exchange rates change are defined as the change since 28 days before the current rebalancing to the horizon 0-10 days after rebalancing. Regressions of Mexico and Brazil have year fixed effects due to limited observations.

Table B.13: Autocorrelation Tests for country-specific time-series of $\mu_{c,t}$

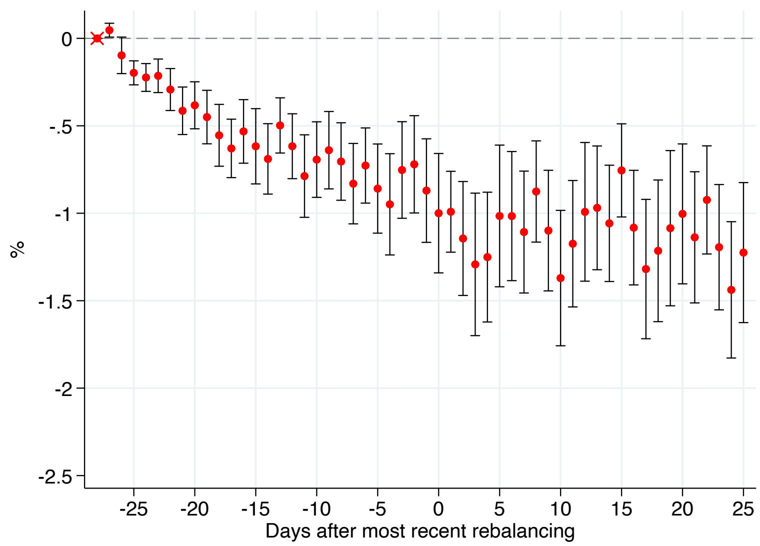
| | (1) Argentina | (2) Chile | (3) Colombia | (4) Czech Republic | (5) Hungary | (6) Indonesia | (7) Malaysia |
|---|---|---|---|---|---|---|---|
| Auto-corr. Coef. | 0.009 | 0.66 | 0.71 | 0.58 | 0.27 | 0.76 | 0.91 |
| Portmanteau test | | | | | | | |
| test-statistics | .003 | 37.6 | 47.4 | 43.7 | 2.40 | 77.26 | 108 |
| p-value | 0.96 | 0.0 | 0.0 | 0.0 | 0.12 | 0.0 | 0.0 |

| | (1) Peru | (2) Philippines | (3) Romania | (4) Russia | (5) South Africa | (6) Thailand | (7) Turkey |
|---|---|---|---|---|---|---|---|
| Auto-corr. Coef. | 0.70 | 0.81 | 0.37 | 0.83 | 0.82 | 0.74 | 0.48 |
| Portmanteau test | | | | | | | |
| test-statistics | 67.1 | 89.5 | 5.13 | 90.8 | 85.3 | 74.6 | 22.5 |
| p-value | 0.0 | 0.0 | 0.02 | 0.0 | 0.0 | 0.0 | 0.01 |

**Note**: This panel of figures the autocorrelation tests for the currency demand shocks ($\mu_{c,t}$) of countries not at the weight cap of 10% in the monthly rebalancing events of the GBI-EM Global Diversified index (tests for Brazil, Mexico and Poland are therefore not reported). We report the estimated auto-correlation for the fitting country-specific $\mu_{c,t}$ with AR(1) and the Portmanteau white noise test on the residuals after fitting. The null hypothesis of the Portmanteau test is that the error terms are white noise.

All Portmanteau white noise tests give significant coefficient except for Argentina. The average auto-correlation coefficient of all countries with significant coefficients is 0.66.

Table B.14: Cumulative Exchange rate change on $\mu_{c,t}$ (including those at 10% cap)




**Note**: This figure presents the estimated regression coefficient of exchange rates change on the currency demand shock measured by $\mu_{c,t}$, which is standardized by its mean and standard deviation in the regression. Different from the Fact 1 in the main texts of the paper, this regression includes observations at the 10% threshold. Exchange rates change (local currencies per USD) is measured as the cumulative change starting from 28 days before the recent rebalancing at day 0. The regression is performed in a pooled OLS using time- and country-fixed effects with standard errors clustered at the country level. The results are reported in point estimates (red) with 90% confidence interval (black).

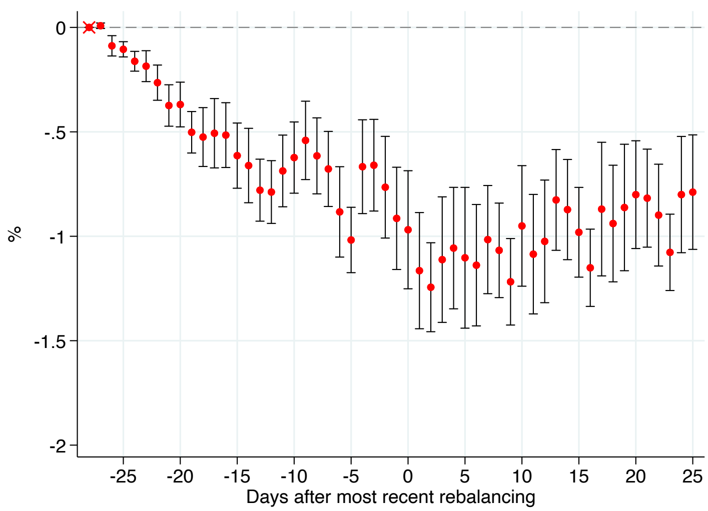
Table B.15: Summary Statistics of the $\Delta\mu_{c,t}$

$\Delta\mu_{c,t}$, *excluding* observations at 10% cap

| Obs | Mean | Std. | Min | Max | Median | 90% | 10% |
|---|---|---|---|---|---|---|---|
| 1,416 | -.0002 | .113 | -.790 | 1.210 | -.006 | .098 | -.093 |

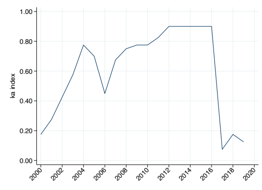
**Note**: Summary statistics of $\Delta\mu_{c,t}$, defined as $\Delta\mu_{c,t} \equiv \mu_{c,t} - \mu_{c,t-1}$. We exclude observations that hit 10% weight cap at the rebalancing dates in this table.

Table B.16: Exchange rate change on $\Delta\mu_{c,t}$

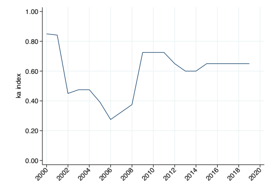



**Note**: This figure presents the estimated regression coefficient of exchange rates change on the *change* in currency demand shock measured by $\Delta\mu_{c,t}$, which is standardized by its mean and standard deviation in the regression. Exchange rates change (local currencies per USD) is measured as the cumulative change starting from 28 days before the recent rebalancing at day 0. The regression is performed in a pooled OLS using time- and country-fixed effects with standard errors clustered at the country level. The results are reported in point estimates (red) with 90% confidence interval (black).

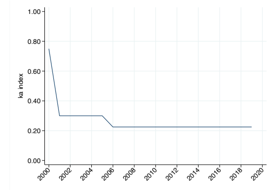
Table B.17: Capital Controls Overall Restriction Index



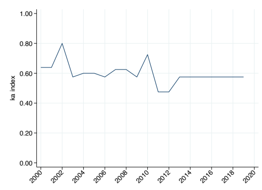
(a) Argentina



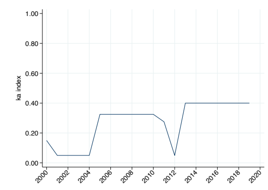
(b) Brazil



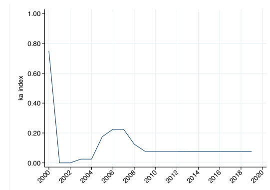
(c) Chile



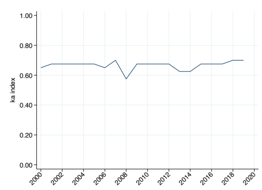
(d) Colombia



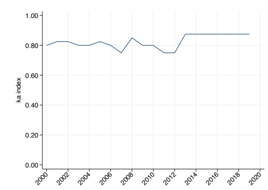
(e) Czech Republic



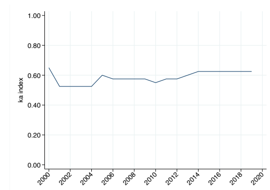
(f) Hungary



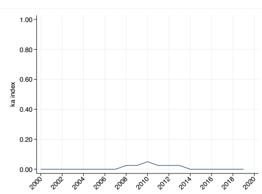
(g) Indonesia



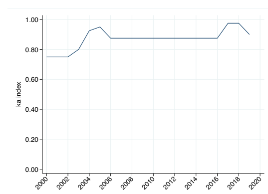
(h) Malaysia



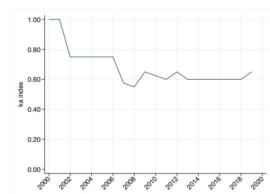
(i) Mexico



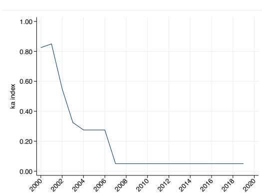
(j) Peru



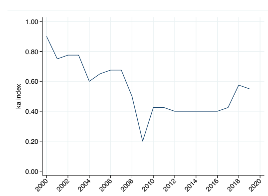
(k) Philippines



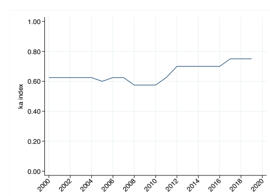
(l) Poland



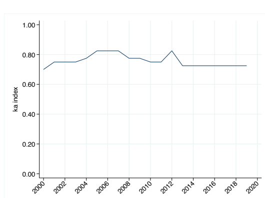
(m) Romania



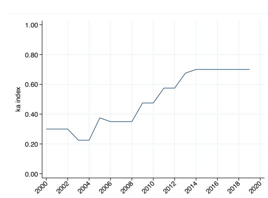
(n) Russia



(o) South Africa



(p) Thailand



(q) Turkey

**Note**: This panel of figures presents the overall capital restriction index (the average of capital inflow and outflow restriction) for each country provided by Fernandez-Klein-Rebucci-Schindler-Uribe dataset. The measure is in annual frequency.

Table B.18: Summary Statistics of Control Restriction Index

| Obs | Mean | Std. | Min | Max | median | 90% | 10% |
|---|---|---|---|---|---|---|---|
| 340 | 0.513 | 0.28 | 0 | 1 | 0.6 | 0.85 | 0.05 |

**Note**: This table presents the summary of statistics on the overall capital restriction index provided by Fernandez-Klein-Rebucci-Schindler-Uribe dataset. Data are in annual frequency.

Table B.19: Summary Statistics of Spot FXI over GDP

| | Mean | Std. | Min | Max | median | 90% | 10% | Obs. |
|---|---|---|---|---|---|---|---|---|
| Argentina | .013 | .51 | -3.08 | 1.49 | .01 | -.49 | .58 | 276 |
| Brazil | .065 | .29 | -1.06 | 1.53 | .01 | -.21 | .41 | 276 |
| Chile | -.0006 | .42 | -2.11 | 2.75 | .005 | -.35 | .34 | 276 |
| Colombia | .048 | .238 | -1.29 | 1.13 | .04 | -.15 | .29 | 276 |
| Czech Republic | .248 | 1.584 | -4.53 | 10.82 | .125 | -1.14 | 1.66 | 276 |
| Hungary | .04 | 1.47 | -4.96 | 8.46 | -.06 | -1.35 | 1.89 | 275 |
| Indonesia | .041 | .42 | -1.64 | 2.78 | .01 | -.38 | .42 | 276 |
| Malaysia | .117 | 1.138 | -6.38 | 5.64 | .06 | -.79 | 1.33 | 276 |
| Mexico | .048 | .215 | -1.47 | 1.05 | .04 | -.17 | .27 | 276 |
| Peru | .106 | .71 | -2.81 | 3.48 | .04 | -.61 | .94 | 276 |
| Philippines | .134 | .49 | -1.82 | 3.17 | .08 | -.36 | .71 | 276 |
| Poland | .074 | .842 | -2.94 | 3.99 | .03 | -.73 | 1.02 | 276 |
| Romania | .091 | 1.02 | -6.12 | 5.29 | .09 | -.66 | .87 | 273 |
| Russia | .257 | .808 | -3.86 | 3.77 | .215 | -.42 | 1.11 | 276 |
| South Africa | .036 | .182 | -1.26 | .99 | .02 | -.11 | .21 | 276 |
| Thailand | .19 | .707 | -2.02 | 3.38 | .18 | -.58 | 1.03 | 275 |
| Turkey | -.022 | .481 | -1.89 | 1.36 | -.01 | -.62 | .52 | 276 |

**Note**: This table reports the summary statistics of spot FXI over (3 year average) GDP for the countries in our sample for the year 2000 to 2021. FXI data are at monthly frequency and from Adler-Chang-Mano-Shao (2021).

# C Derivation and Proofs

## C.1 Optimal Policies of the Central Bank

The policy objective of the central bank is to maintain the tradeoff between output gap ($x_{c,t}$) stabilization and international risk sharing wedge ($z_{c,t}$):

$$\begin{aligned} \min_{x_{c,t}, z_{c,t}, e_{c,t}, b^*_{c,t}, f^*_{c,t}, \sigma^2_{e_{c,t}}} \quad & \frac{1}{2}\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[ \gamma\, z^2_{c,t} + (1-\gamma) x^2_{c,t} \right] \\ \text{subject to} \quad & \beta b^*_{c,t} = b^*_{c,t-1} - z_{c,t} \\ & \mathbb{E}\Delta z_{c,t+1} = -\omega \sigma^2_{e_{c,t}} (b^*_{c,t} - n^*_{c,t} - f^*_{c,t}) \end{aligned}$$

where the two constraints are the country's budget constraint and the international risk-sharing wedge. $b^*_{c,t}$ is the net foreign asset position of home country and the international risk-sharing wedge is measured as the deviations from the uncovered interest parity (UIP) condition. Parameter $\gamma$ is the weight on the international risk-sharing wedge and a measure of the degree of openness of the economy. Given initial net foreign assets $b^*_{c,-1}$ and the exogenous path of noise trader shocks $n^*_{c,t}$, monetary policy chooses the direct path of output gap $x_{c,t}$ while FX intervention $f^*_{c,t}$ chooses the path of risk sharing wedge $z_{c,t}$. The goal of the policymaker is thus to minimize the weighted average of the volatility of the output gap $x_{c,t}$ and the risk sharing wedge $z_{c,t}$.

If both policy instruments are available and unconstrained, the optimal policy fully stabilizes both wedges, the output gap $x_{c,t} = 0$ and the risk sharing wedge $z_{c,t} = 0$. The demand for currency with foreign exchange interventions through the open market operations is given by $f^*_{c,t} = -n^*_{c,t}$ (or $f_{c,t} = -n_{c,t}$) , as stated in Proposition 1.

To see this, note that the constrained optimum allocation (derivation omitted) features $x_t = z_t = 0$ for all $z_t$. Such allocation can be delivered by a combination of monetary policy and FX policies with monetary policy stabilizing output gap ($x_{c,t} = 0$) and optimal FX interventions $f^*_{c,t} = -n^*_{c,t}$ to ensure $z_{c,t} = 0$. As a result, the risk sharing wedge is fully offset, and the optimal international risk sharing is restored independently of the currency demand shocks $n^*_{c,t}$.

Optimal policies above can be implemented using a conventional Taylor interest rule targeting the output gap and a similar policy rule for FX interventions that target UIP deviations. Specifically, FX interventions $f^*_{c,t} = -\mathbb{E}_t \Delta z_{c,t+1}$ and $f^*_{c,t} = -n^*_{c,t}$. That is, the optimal FX interventions should lean against the wind intensively until UIP wedge is fully eliminated. The implementation doesn't require observing the shocks and distinguishing between macro-fundamental and non-fundamental sources of variations in the exchange rates.

## C.2 Proof of Example 1 and 2

In this section, we provide two model examples and their solutions of exchange rates in response to the noise trader shocks (or currency demand shocks). These impulse responses of exchange rates can be directly mapped into the estimated coefficient from our empirical results. We start with a model with endogenous deviation from uncovered interest parity (UIP) with inelastic financial markets can rationalize the observed dynamics on exchange rates. We then combine the UIP equation with both a partial equilibrium model (Engel and West, 2005) and a general equilibrium models (Itskhoki and Mukhin, 2021) to solve for exchange rates as well as their impulse response functions to the noise trader shocks.

The modified UIP equation with endogenous UIP shocks as given in equation (5) is:

$$i_{c,t} - i^*_{c,t} - \mathbb{E}_t \Delta e_{c,t+1} = \tau_{c,t} + \psi_{c,t} - \omega\, \sigma^2_{e_{c,t}} \left( b_{c,t} + n_{c,t} + f_{c,t} \right) \tag{14}$$

where we have substituted the risk-bearing capacity $\lambda_{c,t} = \omega\, \sigma^2_{e_{c,t}}$. Capital control taxes ($\tau_{c,t}$) and risk-premium shock ($\psi_{c,t}$) impose exogenous UIP deviations. We can re-arrange equation (14) as:

$$\mathbb{E}_t \Delta e_{c,t+1} = \underbrace{(i_{c,t} - i^*_{c,t}) - \tau_{c,t} - \psi_{c,t}}_{\equiv -x_{c,t}} \quad + \quad \underbrace{\omega\, \sigma^2_{e_{c,t}} \left( b_{c,t} + n_{c,t} + f_{c,t} \right)}_{\equiv -u_{c,t}} \tag{15}$$

where $x_t$ is the component of exchange rate $e_t$ where the classical trilemma constraint holds. The term $u_t$ is the additional component for models endogenous UIP deviation when the classical trilemma constraint no longer binds, as foreign exchange interventions $f_{c,t}$ can now work as an additional policy tool to stabilize exchange rates under inelastic financial markets. Specifically, under trilemma models where the classical Trilemma constraint holds, the risk-bearing capacity of the arbitrageurs $\lambda_{c,t} = 0$, due to either the risk-aversion of the arbitrageurs $\bar{\omega} = 0$ or exchange rates are fixed (so that $\sigma^2_{e_c} = 0$). The term non-trilemma term $u_t$ therefore vanishes under trilemma models, whose UIP deviations can only come from exogenous UIP shocks.

If we keep iterate equation (15) forward, we have:

$$e_{c,t} = \mathbb{E}_t \, e_{c,\infty} + \mathbb{E}_t \sum_{j=0}^{\infty} x_{c,t+j} + \mathbb{E}_t \sum_{j=0}^{\infty} u_{c,t+j} \tag{16}$$

and the expectation term vanishes as $e_{c,\infty} = 0$ if exchange rate $e_{c,t}$ follows a stationary process.

**Example 1: Engel and West (2005) Taylor Rule Model**

We solve for the impulse response of exchange rates to the noise trader shocks under a partial equilibrium model with Taylor rule as specified by Engel and West (2005). Let $\pi_{c,t} = p_{c,t} - p_{c,t-1}$ be the inflation rate and $y_{c,t}$ the output gap of home country $c$. Monetary policy in the home country (emerging country) follows a Taylor rule of the form:

$$i_{c,t} = \beta_0(e_{c,t} - \bar{e}_{c,t}) + \beta_1 \, y_{c,t} + \beta_2 \, \pi_{c,t} + v_{c,t}$$

where exchange rate target $\bar{e}_t$ ensures PPP so that $\bar{e}_{c,t} = p_{c,t} - p^*_{c,t}$ and $\beta_0 \in (0, 1)$.

Monetary policy in the foreign country (US) follows the Tylor rule of the form:

$$i^*_{c,t} = \beta_1 \, y^*_{c,t} + \beta_2 \pi^*_{c,t} + v^*_{c,t}$$

Interest rate difference $i_{c,t} - i^*_{c,t}$ can thus be written as:

$$i_{c,t} - i^*_{c,t} = \beta_0 \, (e_{c,t} - \bar{e}_{c,t}) + \beta_1(y_{c,t} - y^*_{c,t}) + \beta_2(\pi_{c,t} - \pi^*_{c,t}) + (v_{c,t} - v^*_{c,t}) \tag{17}$$

Now combine the interest rates differential expression in equation (17) with the UIP condition in equation (15) to substitute out $(i_{c,t} - i^*_{c,t})$:

$$
\begin{aligned}
\mathbb{E}_t\, e_{c,t+1} &= e_{c,t} - \tau_{c,t} - \psi_{c,t} + \beta_0\,(e_{c,t} - \bar{e}_{c,t}) + \beta_1(y_{c,t} - y^*_{c,t}) + \beta_2(\pi_{c,t} - \pi^*_{c,t}) + (v_{c,t} - v^*_{c,t}) - u_{c,t} \\
\Rightarrow (1+\beta_0)e_{c,t} &= \tau_{c,t} + \psi_{c,t} + \mathbb{E}_t e_{c,t+1} + \beta_0(p_{c,t} - p^*_{c,t}) - \beta_1(y_{c,t} - y^*_{c,t}) - \beta_2(\pi_{c,t} - \pi^*_{c,t}) - (v_{c,t} - v^*_{c,t}) + u_{c,t} \\
\Rightarrow e_{c,t} &= \frac{1}{1+\beta_0}(\tau_{c,t} + \psi_{c,t}) + \frac{\beta_0}{1+\beta_0}(p_{c,t} - p^*_{c,t}) - \frac{\beta_1}{1+\beta_0}(y_{c,t} - y^*_{c,t}) - \frac{\beta_2}{1+\beta_0}(\pi_{c,t} - \pi^*_{c,t}) - \cdots \\
&\quad - \frac{1}{1+\beta_0}(v_{c,t} - v^*_{c,t}) + \frac{1}{1+\beta_0}u_{c,t} + \frac{1}{1+\beta_0}\mathbb{E}_t e_{c,t+1}
\end{aligned}
$$

We can write the solution of exchange rate under Taylor rule in the similar manner as equation (15) by separating out its trilemma and non-trilemma component:

$$
e_{c,t} = X_{c,t} + U_{c,t} + \frac{1}{1+\beta_0}\mathbb{E}_t\, e_{c,t+1} \tag{18}
$$

where $\beta_0 \in (0,1)$, $U_{c,t} = \frac{1}{1+\beta_0}u_{c,t} = -\frac{1}{1+\beta_0}\,\omega\sigma^2_{e_{c,t}}(b_{c,t} + n_{c,t} + f_{c,t})$ is the non-trilemma component and $X_t = \frac{1}{1+\beta_0}(\tau_{c,t} + \psi_{c,t}) + \frac{\beta_0}{1+\beta_0}(p_{c,t} - p^*_{c,t}) - \frac{\beta_1}{1+\beta_0}(y_{c,t} - y^*_{c,t}) - \frac{\beta_2}{1+\beta_0}(\pi_{c,t} - \pi^*_{c,t}) + \frac{1}{1+\beta_0}(v_{c,t} - v^*_{c,t})$ is the trilemma component.

Iterate equation (18) forward, we have:

$$
e_{c,t} = \mathbb{E}_t \sum_{j=1}^{\infty} \frac{1}{(1+\beta_0)^j} X_{c,t+j} \;+\; \mathbb{E}_t \sum_{j=1}^{\infty} \frac{1}{(1+\beta_0)^j} U_{c,t+j} \;+\; \mathbb{E}_t \lim_{j\to\infty} \frac{1}{(1+\beta_0)^j} e_{c,\infty}
$$

where $\lim_{j\to\infty} \frac{1}{(1+\beta_0)^j} = 0$ in the limit, together with $e_{c,\infty} = 0$ under stationary process, the expectation term of exchange rates vanishes.

If we impose the assumption that $n_{c,t}$ inside the non-trilemma component $U_{c,t}$ is an AR(1) process with persistence $\rho$, foreign exchange interventions are independent of noise trader shocks $f_{c,t} \perp n_{c,t}$, and that macro-fundamentals are slow-moving compared to noise trader shocks $n_{c,t}$, we can solve for the impulse response of exchange rate $e_{c,t}$ in response to $n_{c,t}$ as:

$$
\frac{\partial e_{c,t}}{\partial n_{c,t}} = \frac{-\omega\sigma^2_{e_{c,t}}}{(1+\beta_0-\rho)} < 0 \tag{19}
$$

On impact, a positive noise trader shock (or a positive local currency demand shock from the increase of country weight in the GBI-EM Global Diversified index) appreciates home currency and leads to a decrease in exchange rate $e_{c,t}$, which is defined in the number of local currencies per USD. Therefore, the model prediction gives the right sign as suggested by our empirical evidence. To match the estimated empirical coefficient $\beta_{\mu_{c},t}$ in response to the currency demand shock with the impulse reponse $\frac{\partial e_{c,t}}{\partial n_{c,t}}$ from the model, one needs to repeat the exercise as illustrated in section A.3.2. This is because our currency demand shock is measured in shares of market value while the noise trader positions are measured in USD flows.

**Example 2: Itskhoki and Mukhin (2021) General Equilibrium Model**

We now solve for the impulse response of exchange rates to the noise trader shocks under a general equilibrium model with the country's intertemporal budget constraint as specified by Itskhoki and Mukhin (2021). The log-linearized intertemporal budget constraint in Itskhoki and Mukhin (2021) states:

$$\beta b^{*}_{c,t} - b^{*}_{c,t-1} = nx_{c,t} = \lambda \, e_{c,t} + \xi_{c,t} \tag{20}$$

where $b^{*}_{c,t}$ is the net foreign asset position of country $c$ at time $t$; $nx_{c,t}$ is the net export and $e_{c,t}$ is level of exchange rates. Parameter $\beta$ is the discount factor; $\lambda$ ($> 0$) is a structural parameter pinned down from the price equations in the equilibrium goods market; and $\xi_{c,t}$ is shock to the net export $nx_{c,t}$ and is orthogonal to $e_{c,t}$.

We iterate the country budget constraint forward and get:

$$b^{*}_{c,t-1} + \mathbb{E}_t \, \lambda \sum_{j=0}^{\infty} \beta^{j} e_{c,t+j} = \lim_{T \to \infty} \beta^{T} b^{*}_{c,t+T-1} = 0 \tag{21}$$

where we imposed the No-Ponzi Game Condition (NPGC) on the country's intertemporal budget constraint.

The country's intertemporal budget constraint uses the net foreign asset position $b^{*}_{c,t}$ of home households (which equals foreign households' holding of foreign-currency bonds), while the UIP condition in equation (15) uses home households' holding of home-currency bonds. We therefore need re-write equation (15) using $b^{*}_{c,t}$:

$$\mathbb{E}_t \Delta e_{c,t+1} = \underbrace{(i_{c,t} - i^*_{c,t}) - \tau_{c,t} - \psi_{c,t}}_{\equiv -x_{c,t}} \quad + \quad \underbrace{\omega\, \sigma^2_{e_{c,t}} \left(\cancel{-b^*_{c,t}} + n^*_{c,t} + f^*_{c,t}\right)}_{\equiv -u^*_{c,t}} \tag{22}$$

where we used the market clearing condition of home- and foreign-currency bonds to substitute the zero-capital position of arbitrageurs holdings. In addition, we normalize $b^*_{c,t} = 0$ without loss of generality to simplify the derivations below. We use notation $u^*_{c,t}$ (rather than $u_{c,t}$) to represent the non-trilemma component as carry-trade returns are now for the holdings of foreign currency.

We iterate equation (22) forward in a similar way as we did for equation (15) to derive an expression of $\mathbb{E}_t\, e_{t+j}$:

$$\mathbb{E}_t\, e_{t+j} = \mathbb{E}_t\, e_{c,\infty} + \mathbb{E}_t \sum_{k=0}^{\infty} x_{c,t+j+k} + \mathbb{E}_t \sum_{k=0}^{\infty} u^*_{c,t+j+k} \tag{23}$$

We can then combine equation (23) with country's budget constraint in equation (21):

$$\begin{aligned}
& b^*_{c,t-1} + \lambda \sum_{j=0}^{\infty} \beta^j\, \mathbb{E}_t e_{c,t+j} = 0 \\
\Rightarrow & b^*_{c,t-1} + \lambda \sum_{k=0}^{\infty} \beta^j \left( \mathbb{E}_t\, e_{c,\infty} + \mathbb{E}_t \sum_{k=0}^{\infty} x_{c,t+j+k} + \mathbb{E}_t \sum_{j=0}^{\infty} u^*_{c,t+j+k} \right) = 0 \\
\Rightarrow & b^*_{c,t-1} + \frac{\lambda}{1-\beta} \mathbb{E}_t\, e_{c,\infty} + \lambda\, \mathbb{E}_t \sum_j \sum_k \beta^j x_{c,t+j+k} + \lambda\, \mathbb{E}_t \sum_j \sum_k \beta^j u^*_{c,t+j+k} = 0 \\
\Rightarrow & b^*_{c,t-1} + \frac{\lambda}{1-\beta} \underbrace{\left( e_{c,t} - \mathbb{E}_t \sum_{j=0}^{\infty} x_{c,t+j} - \mathbb{E}_t \sum_{j=0}^{\infty} u^*_{c,t+j} \right)}_{=\mathbb{E}_t\, e_{c,\infty}} + \lambda\, \mathbb{E}_t \sum_j \sum_k \beta^j x_{c,t+j+k} + \lambda\, \mathbb{E}_t \sum_j \sum_k \beta^j u^*_{c,t+j+k} = 0
\end{aligned}$$

where the last line substituted the expression of $\mathbb{E}_t\, e_{c,\infty}$ from equation (23).

From above, we have the relation between $e_{c,t}$ and $b^*_{c,t-1}$:

$$\frac{\lambda}{1-\beta} e_{c,t} + b^*_{c,t-1} + X_{c,t} + U^*_{c,t} = 0 \tag{24}$$

where $X_{c,t} \equiv -\frac{\lambda}{1-\beta} \sum_j\ \mathbb{E}_t x_{c,t+j} + \lambda \sum_j \sum_k \beta^j\ \mathbb{E}_t x_{c,t+j+k}$ is the Trilemma component of

UIP equation and $U^*_{c,t} \equiv -\frac{\lambda}{1-\beta}\sum_j \ \mathbb{E}_t u^*_{c,t+j} + \lambda \sum_j \sum_k \beta^j \ \mathbb{E}_t u^*_{c,t+j+k}$ is the non-trilemma component the UIP equation and generates endogenous UIP deviations from the noise trader shocks.

To arrive at the closed-form solution of exchange rate response to the noise trader shock, we impose the following assumptions similar as in the model example 1 under Taylor rule: we assume that noise trader positions $n^*_{c,t}$ inside the non-trilemma component follows an AR(1) process with persistence $\rho$, foreign exchange interventions in foreign-currency bonds $f^*_{c,t}$ are independent of noise trader shocks ( $f^*_{c,t} \perp n^*_{c,t}$), and that macro-fundamentals are slow-moving compared to noise trader shocks $n^*_{c,t}$.

Under these three assumptions, we can simplify equation (24) to the following:

$$\frac{\lambda}{1-\beta} e_{c,t} + b^*_{c,t-1} + X_{c,t} - \frac{\beta\lambda \ \omega\sigma^2_{e_{c,t}}}{(1-\rho\beta)(1-\beta)} \ n^*_t + \tilde{U}^*_{c,t} = 0 \tag{25}$$

where $\tilde{U}^*_{c,t} \equiv U^*_{c,t} + \frac{\beta\lambda \ \omega\sigma^2_{e_{c,t}}}{(1-\rho\beta)(1-\beta)} \ n^*_t$ are the residuals of the non-trilemma component of $U^*_{c,t}$ , such as foreign exchange interventions $f^*_{c,t}$, that are independent of the noise trader positions $n^*_{c,t}$.

We can therefore compute the impulse response of exchange rate level $e_t$ in response to the noise trader shock to holdings of foreign currency holdings $n^*_{c,t}$:

$$\frac{\partial e_{c,t}}{\partial n^*_{c,t}} = \frac{\beta \ \omega\sigma^2_{e_{c,t}}}{(1-\rho\beta)} > 0 \tag{26}$$

as $\rho, \beta \in (0,1)$. This is consistent with the empirical evidence as here the noise trader positions $n^*_{c,t}$ are measured in foreign currency rather than local currency. A positive foreign currency demand shock appreciates foreign currency and depreciates local currency as the relative demand for local currency drops, resulting in an increase in local-currency exchange rate level $e_{c,t}$ that is measured in the number of local currencies per dollar. Thus, the inequality in equation (26) is equivalent as saying $\frac{\partial e_{c,t}}{\partial n_{c,t}} < 0$, same as the prediction from model example 1 under Taylor rule.

## C.3 Estimating Intervention intensity $\alpha_f$

Throughout the main texts of the paper, we have made our analysis based on the assumption that foreign exchange interventions $f_{c,t}$ are independent of the noise trader shocks (or currency demand shocks) from the mechanical rebalancings of the GBI-EM Global Diversified index. The assumption is supported by the empirical evidence that the data on foreign exchange interventions in the spot exchange markets display no correlation with our currency demand shock (Table 5.1).

In this section, we relax the assumption that FX interventions $f_{c,t}$ are independent of the shocks to noise trader positions $n_{c,t}$. One could argue that the monthly FX interventions data from Adler el al. (2021) used in Table 5.1) give the monthly average and do not align well with the rebalancing windows of the GBI-EM Global Diversified index, which happen at the last business day of the month. Such measurement error could potentially result in the poor correlation between FX interventions data and our currency demand shock.

We allow open market operations for country $c$ to offset part of the noise trader shocks. That is, $f_{c,t} = -\alpha_{c,f}\, n_{c,t}$, where $\alpha_{c,f} \in [0,1]$ and is the share of noise trader shocks offset by open market operations through foreign exchange interventions to stabilize exchange rates. In addition, the FX interventions $f_{c,t}$ follows the same persistence over time as the noise trader shocks.

The exact value of $\alpha_{c,f}$ is unobservable in the data. In this section, we seek to identify the value of $\alpha_{c,f}$ using the country-specific estimates on exchange rates responses to the currency demand shocks from empirical results. Intuitively, a country with more floating exchange rate regime is expected to have a smaller $\alpha_{c,f}$; and vice versa for countries with more stringent (or pegged) exchange rate regime.

Under the assumption that FX interventions offsets partially the noise trader shocks, the impulse response of exchange rates in response to noise trader shocks in equation (19) under model example 1 with Tylor rule becomes:

$$\frac{\partial e_{c,t}}{\partial n_{c,t}} = \frac{-\omega \sigma^2_{e_{c,t}}}{(1+\beta_0-\rho)}\,(1-\alpha_{c,f}) \tag{27}$$

where $\beta_0$ is the intensity of the Taylor rule; $\rho$ the persistence of the AR (1) process of the noise trade shocks and the persistence of FX interventions (as $f_{c,t}$ is assumed to follow the same persistence as $n_{c,t}$); $\omega$ the risk aversion parameter of the arbitrageurs that conduct currency carry trade; $\sigma^2_{e_{c,t}}$ the volatility of exchange rates; and $\alpha_{c,f} \in [0,1]$ is the share of noise trade shocks offset by open market operations in foreign exchange interventions. The only addition in equation (27) compared to (19) is the term $(1-\alpha_{c,f})$.

For any two countries $c_1$ and $c_2$, if parameters $\rho, \omega$ and $\beta_0$ are homogenous across countries, then exchange rates volatility $\sigma^2_{e_{c,t}}$ and the intensity of FX intervention $\alpha_{c,f}$ are the only source of heterogeneity across countries in their exchange rate responses to noise trader shocks. Define $\beta_{c,f} \equiv \frac{\omega\, \sigma^2_{e_{c,t}}}{1+\beta_0-\rho}(1-\alpha_{c,f})$ and $\hat{\beta}_{c,\mu}$ as the estimated regression coefficient of exchange rates response to the currency demand shock $\mu_{c,t}$. Using equation (11) for converting the currency demand shock $\mu_{c,t}$ into flows of noise trader shocks, we arrive at the following relation for exchange rates response of country $c_1$ and $c_2$:

$$\frac{\hat{\beta}_{c_1,\mu}}{\hat{\beta}_{c_2,\mu}} = \frac{\kappa_{c_2}}{\kappa_{c_1}} \times \frac{\sigma^2_{e_{c_1,t}}(1-\alpha_{c_1,f})}{\sigma^2_{e_{c_2,t}}(1-\alpha_{c_2,f})} \tag{28}$$

where $\kappa_c = \text{market value}_c \times \frac{\text{AUM}}{\sum_{c'} \text{market value}_{c'}}$; market value$_c$ is the market value of the local currency sovereign bonds in the GBI-EM Global Diversified index; AUM is the asset under management of all the mutual funds that track the index closely and passively. Equation (28) suggests that countries with larger market size, more volatile exchange rates, and more floating exchange rates regime (less foreign exchange intervention) should expect a larger coefficient of exchange rates in response to the currency demand shock $\mu_{c,t}$.

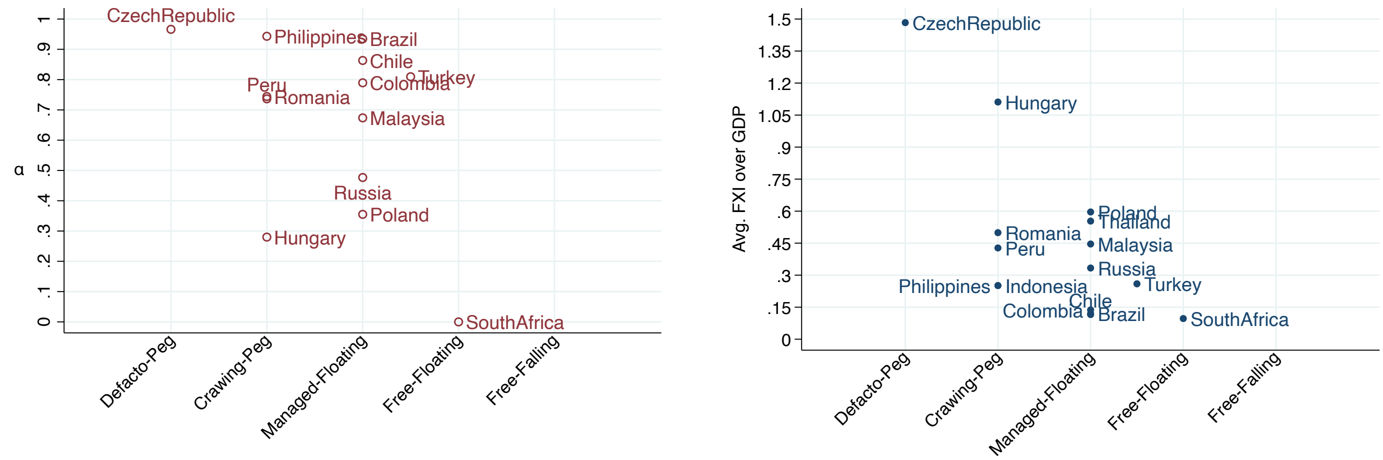
Consider two countries with different exchange rate regimes. Fix country $c_2$ as the benchmark country with free-floating (or free-falling) exchange rate regime and define $\alpha^* \equiv \alpha_{c_2} = 0$. For any country $c$ that doesn't have a free-floating (or free-falling) exchange rate regime, we can therefore identify its $\alpha_c$ below following equation (28):

$$\alpha_c = 1 - \left( \frac{\beta_{\mu,c}/\sigma^2_{e_{c,t}}}{\beta_{\mu,c^*}/\sigma^2_{e_{c^*,t}}} \times \frac{\kappa_{c_1}}{\kappa_{c^*}} \right) \tag{29}$$

where $k^* = \text{market value}_{c^*} \times \frac{\text{AUM}}{\sum_{c'} \text{market value}_{c'}}$ for the benchmark country under free-floating (or free-falling) exchange rates regime and the central bank does not intervene with exchange rates at all ($\alpha^* = 0$).

We choose South Africa as the benchmark country with $\alpha^* = 0$ in our sample. South Africa is classified as "free-floating" through out some sample years from 2009 to 2021 under the exchange rates regime classification by Ilzetzki, Reinhart and Rogoff (2019, 2021). Another country, Argentina ("free-falling" exchange regime), also qualifies as our benchmark country by its exchange rate regime classification. However, Unlike South

Table C.1: Calibrated Intervention $\alpha_f$ and Actual Intervention




**Note**: This table (left panel) gives the calibrated intervention $\alpha_f$ and their relation to exchange rates regimes, with South Africa chosen as the benchmark country with $\alpha^* = 0$. The right panel reports the average spot FXI as a share of country's GDP for each country as provided by Adler et al (2021). Estimates for Argentina, Poland and Mexico are not reported.

Africa, Argentina has very short time series in our sample is only included in the GBI-EM Global Diversified index from early 2018 to 2020.

Using South Africa as the benchmark country, we report the estimated intervention $\alpha_f$ in Table C.1 (left panel). The relation of estimated $\alpha_f$ displays a clear downward trend in relation with exchange rate regimes: the more floating the exchange rates, the smaller the intervention $\alpha_f$ from the central banks to offset the noise trader shocks. The calibrated intervention $\alpha_f$ reported in Table C.1 are all between 0 and 1, as expected by theory.

The calibrated intervention $\alpha_f$ for each country is largely consistent with the actual historical intervention data, as reported in the right panel of Table C.1. The intervention data is the monthly spot foreign exchange intervention as a percentage share of 3-year moving average annual GDP of the country, as provided by Adler et al (2021). We average the intervention data for each country over 2010 - 2021 for the months the country is included the J.P Morgan GBI-EM Global Diversified index. To measure the magnitude of intervention, we also take the absolute value of the interventions data rather than distinguishing the purchase (positive FXI in the data) or sale (negative) of reserves.

There are, however, some disparities in the rankings of $\alpha_f$ among countries and the rankings of actual intervention data, as shown in Table C.1. For example, we estimate that Romania has a higher intervention $\alpha_f$ than Hungary while the data shows that Hungary does more FX interventions relative to its size of GDP, even though both countries are under the crawling peg exchange rate regime. We contribute these disparities to the heterogeneity in parameters that were assumed to be the same across countries in equation (29). That is, the difference in the persistence of the noise trader shocks, monetary policy intensity in the Taylor rule, or the relative risk aversion parameter of the international arbitrageurs across countries could also contribute to the heterogeneities in the estimated exchange rate response to the currency demand shock.