Working paper 3
Exchange Rate Risk

1. Introduction

Multilateral development banks (MDBs) consider exchange rate risk the most significant risk associated with local currency (LC) lending in low- and middle-income countries (LMICs), and typically hedge their currency exposure in full. Moreover, a key risk—particularly for long-term oriented MDBs—is the risk of sudden and significant exchange rate depreciations, often referred to as 'crash risk'. Recent literature suggests that with increased financial integration, this crash risk is driven by global economic conditions and is exacerbated by the substantial presence of non-resident investors in LC markets.

This paper examines two central questions. First, it considers the historical returns on LC lending to LMICs and whether, on average, such lending would have been profitable across a broad set of LMICs. By analysing the historical volatility of exchange rates to estimate the unhedged returns on LC loans, the paper demonstrates that these returns are generally positive. However, it also highlights that periods of negative excess returns are not uncommon and often occur concurrently across multiple countries, indicating the presence of significant tail depreciation or crash risk.

Second, this paper explores the determinants of tail risks. The hypothesis is that the co-movement of currencies is driven by common global factors. Departing from much of the existing literature, global commodity prices are used as a proxy for these factors, given the critical role commodities play in the production and export structures of many LMICs. The findings suggest that global commodity prices are a significant determinant of large exchange rate movements, with commodity price booms, in particular, showing predictive power for future depreciations. Additionally, the role of non-resident investors in domestic bond markets is examined as a major driver of depreciation risks. The paper finds that, alongside interest rate and inflation differentials, the participation of these investors can significantly amplify depreciations triggered by commodity price shocks.

This paper proceeds as follows. Section 2 analyses the excess returns on unhedged positions in LMICs. Section 3 motivates and reviews the literature on tail risks in LMIC currencies and outlines the regression methodology. Section 4 discusses the data and stylised facts used in the quantile regression approach. Section 5 presents the regression results. Section 6 offers concluding remarks.

2. Exchange rates and excess returns

An increase in MDBs' LC financing with partially unhedged positions could impact the profitability of these institutions in the event of adverse (depreciating) exchange rate movements. Currency depreciation may result in capital losses on their asset side, which, in turn, generate losses on their capital positions. MDBs consider these risks to be excessive and utilise risk management models that typically prevent any exposure to currency risk. As a result, MDBs tend to hedge such risks fully, insulating themselves against potential losses. Nevertheless, despite their general aversion or inability to take on currency risk, our findings indicate that many MDBs do assess currency risk, often employing in-house quantitative models.

One way for MDBs to assess the impact of currency risk is by calculating the return on financing positions in different currencies, comparing their own lending rates with their cost of capital. An excess return exists when the interest rates of risk-free financial instruments in local currencies, minus the depreciation against another currency (usually the US dollar), exceed the interest rates of risk-free financial instruments in that other currency. In our analysis, if interest rates in LC exceed those in US dollars, minus the depreciation of the LC, MDBs could achieve positive excess returns.

Formally, the (approximate) excess return on a (risk-free) LC LMIC asset is:

$$excess\ return_t = (i_t^{LMIC} - i_t) + \frac{e_{t+1} - e_t}{e_t} \tag{1}$$

Where $i_t^{LMIC} - i_t$ represents the current interest rate differential between the LMIC and the US, e_t is the current exchange rate quoted as US dollars per unit of LC (where an increase in e implies a LC appreciation), and e_{t+1} is the exchange rate one period (e.g. a month) ahead.

Equation (1) shows the 'ex-post' excess return, i.e., the realised returns from an unhedged position in LC, with e_{t+1} being the actual realised exchange rate in the following period. Alternatively, excess returns can be calculated 'ex-ante' using expected depreciation from surveys or derivative markets (or implicit in other asset prices), or the forward/futures exchange rate observed in derivative markets (where e_{t+1} is replaced by an approximation of the expected exchange rate).

This approach relates to Persaud's work, where he compares the cost of hedging, reflected in the difference between the forward rate (f) and the actual observed exchange rate (e_{t+1}).[1] Reformulating equation (2), he tests whether:

$$(i_t^{LMIC} - i_t) + \frac{e_{t+1} - f_t}{e_t} < (i_t^{LMIC} - i_t) + \frac{e_{t+1} - e_t}{e_t} \tag{2}$$

In essence, he examines whether the excess return on a hedged position is lower than on an unhedged one. Persaud shows that this inequality holds on average in five key emerging markets,[2] over five-year periods from 1999 to 2018. He demonstrates that this is the case when $f_t < e_{t+1}$, i.e., when the exchange rate depreciation implied by the forward rate exceeds the actual depreciation. From another perspective, investors tend to pay a premium in forward markets to protect themselves against exchange rate depreciation that consistently exceeds actual depreciation. Persaud refers to these as 'overpayments' and shows that they are more substantial during periods of financial turmoil, such as the Global Financial Crisis and the Fed's taper tantrum in 2015.[3]

Persaud's findings align with existing literature on excess returns, which primarily focuses on advanced economy currencies.[4] Besides Persaud, an exception is Gilmore and Hayashi, who find that investors have historically obtained profits by borrowing in US dollar markets and investing in LMIC currencies, even considering short-term losses during global crises.[5] However, empirical studies on excess returns in LMICs are limited, and, to our knowledge, there are no studies using panels of countries rather than focusing on single-country analyses.

Adopting an ex-post approach, we estimate excess returns based on the approach shown in equation (1). Using data from the International Financial Statistics of the International Monetary

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[1] A Persaud, *Unblocking the Green Transformation in Developing Countries with a Partial Foreign Exchange Guarantee* (2023) https://www.climatepolicyinitiative.org/wp-content/uploads/2023/06/An-FX-Guarantee-Mechanism-for-the-Green-Transformation-in-Developing-Countries.pdf accessed 11 October 2024.

[2] These are Brazil, Colombia, Indonesia, Mexico, and South Africa.

[3] Persaud (n 1).

[4] C Burnside, 'Carry Trades and Risk' in J James, IW Marsh, and L Sarno (eds), *Handbook of Exchange Rates* (Wiley 2012) 283; K Daniel and others, *The Carry Trade: Risks and Drawdowns* (National Bureau of Economic Research, 2014); G Bekaert and G Panayotov, 'Good Carry, Bad Carry' (2020) 55(4) Journal of Financial and Quantitative Analysis 1063; S Abankwa and LP Blenman, 'Measuring Liquidity Risk Effects on Carry Trades Across Currencies and Regimes' (2021) 60 Journal of Multinational Financial Management 100683; T Maurer and others, 'Pricing Implications of Covariances and Spreads in Currency Markets' (2021) 12(1) The Review of Asset Pricing Studies 336.

[5] S Gilmore and F Hayashi, 'Emerging Market Currency Excess Returns' (2011) 3(4) American Economic Journal: Macroeconomics 85.

Fund (see Table A-1), we examine excess returns in a broader sample of 110 LMICs from 1990 onwards.[6] We approximate these returns using the deposit rates in local currencies and US dollars, as well as changes in the bilateral nominal exchange rate:

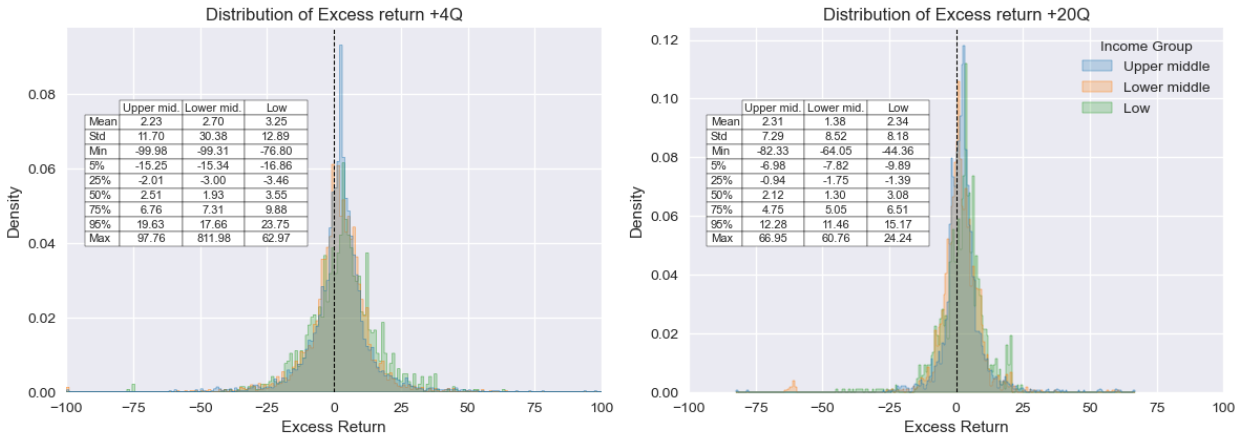
$$r_{t+h}^{j} = \frac{1 + i_t^j}{1 + i_t^{USD}} / \left(\frac{xr_{t+h}^{USD/j}}{xr_t^{USD/j}}\right)^{\frac{4}{h}} - 1 \qquad (3)$$

Where r_{t+h}^{j} represents the excess returns in the LC j calculated h quarters ahead, using the LC deposit interest rate i_t^j, the deposit rate in US dollars in the United States i_t^{USD} , and the annualised variation h quarters ahead of the bilateral nominal exchange $xr_t^{USD/j}$ between the currency j and the US dollar. Our ex-post approach uses realised—that is, historically observed—nominal exchange rates and interest rates. In this context, $t + h$ refers to the evaluation of excess returns h quarters after period t, based on actual historical exchange rates and deposit interest rates. This equation is the non-approximated equivalent of equation (1).

Focusing on the average values since 2000, our results, shown in Figure 1, confirm that, on average, and over a time horizon greater than one year, excess returns have been positive in the LMICs studied. Both the 1-year and 5-year horizons (in line with the longer maturity of MDBs' financing) show that mean and median returns are positive for all income groups. The results are statistically and economically significant: mean yearly returns are 2.23% for upper-middle-income countries, and 2.70% and 3.25% for low-income countries over the 1-year horizon. Notably, low-income countries report the highest mean and median returns across both time horizons, despite a lower standard deviation than lower-middle-income countries.

[6] For this analysis, we consider LMICs with all types of exchange rate regimes. As discussed in more detail below, we later exclude permanently fixed regimes from our econometric analysis to allow for sufficient variation in the data.

Figure 1 Distribution of excess returns

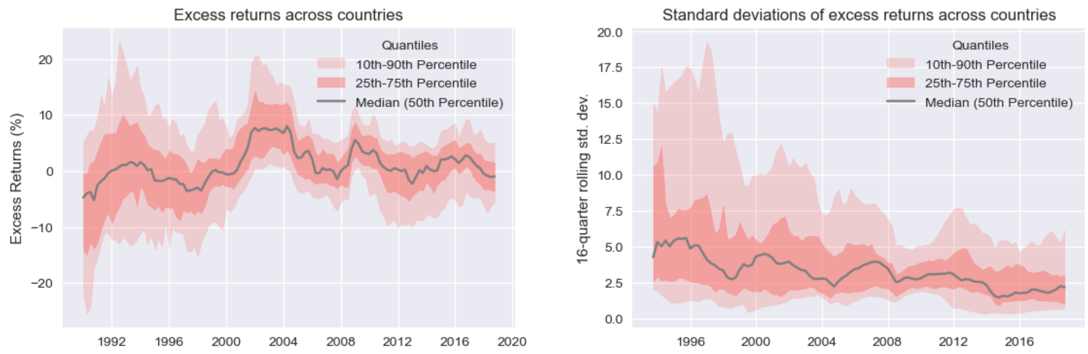


However, the distributions also reveal considerable volatility, with particularly large standard deviations for lower-middle-income countries. Tail risks, mainly driven by significant depreciations, indicate that negative returns can be substantial. Nevertheless, the distribution is not overly asymmetrical, as the 5th percentile shows smaller negative returns compared to the high positive returns at the 95th percentile.

The next charts display the distribution of excess returns across currencies and their volatility over time, showing the median values, interquartile ranges, and extreme bounds (5th to 95th percentiles). Figure 2a shows that positive excess returns are more common than exceptions: median excess returns have remained mostly positive over time, while median negative returns have become less frequent and shorter in duration. Moreover, negative excess returns are generally concentrated during periods of global financial stress, such as the US and European financial crises and COVID-19. Figure 2a indicates that the cross-country dispersion of these excess returns has been declining in recent years, suggesting a stronger co-movement across currencies.

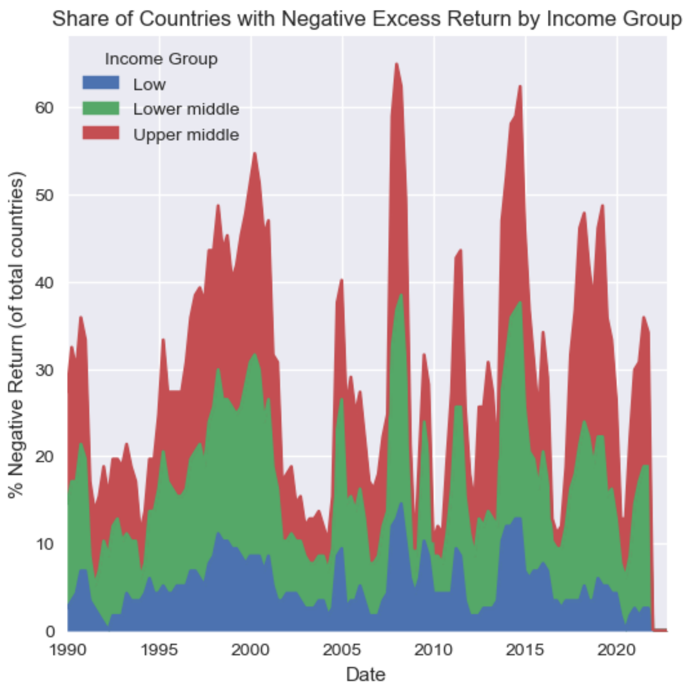
Figure 2b illustrates two key dynamics. First, in line with the previous chart, the volatility of excess returns across currencies is time-varying and has increasingly been linked to global financial conditions. Second, Figure 2b shows that large volatility events in LMIC currencies have declined in recent years: excess median returns in these currencies have become less volatile (as shown by the grey line), and this trend holds across the entire distribution, as indicated by the narrowing shaded areas.

Figure 2 Excess returns 16-quarters ahead and their rolling standard deviations (16-quarters)



We next focus specifically on negative excess returns to understand their timing, magnitude, and cross-country co-movement. Figure 3a shows the share of countries with negative excess returns over time, disaggregated by income group. Figure 3b further breaks down the results by income group and by the magnitude of the negative excess returns.

Figure 3 Share of countries with negative excess returns by income group



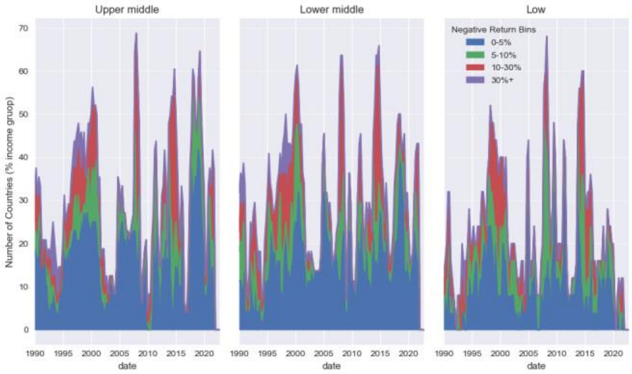
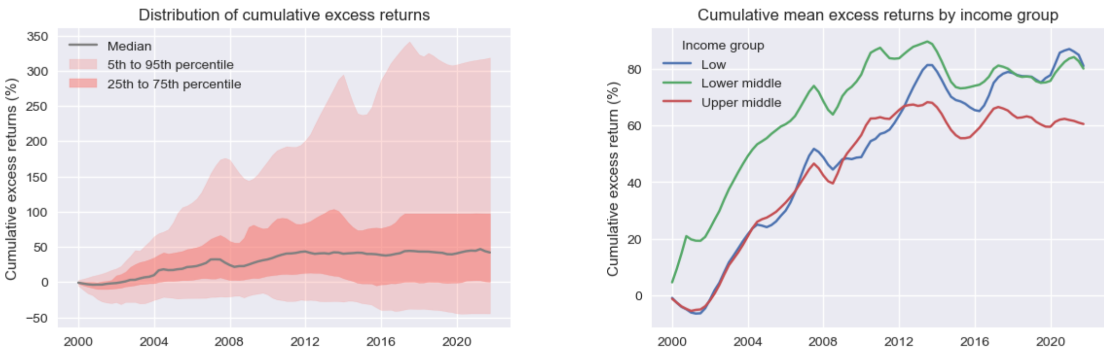


Figure 3 shows that after 2002, the share of countries with negative excess returns has generally decreased, although it increases during periods of global financial turmoil. This common cyclicality is evident across upper-, lower-middle-, and low-income economies. Additionally, during periods when a larger share of countries experiences negative returns, the magnitude of these negative returns also tends to increase. This suggests that the risk of large depreciations is correlated across currencies, confirming the growing importance of common global factors driving tail risks in LMICs.

However, our data also indicate that over longer horizons, the mean positive excess returns of LMIC currencies can compensate for these common depreciation events. Focusing on the post-2000 period, Figure 4a plots the cross-currency distribution of the cumulative excess returns, showing that, within our sample of LMICs, the median and interquartile range exhibit non-negative cumulative returns between 2000 and 2021. In other words, only systematically selecting the worst-performing 25% of currencies would yield negative cumulative excess returns. Additionally, the tails of this distribution are asymmetric: while the 5th percentile (lower excess returns) records a cumulative loss of less than 50%, the 95th percentile reflects a cumulative gain of over 300%. This highlights that long-term exposure to LC can significantly boost returns and supports earlier conclusions that, although large negative returns are possible, even larger positive returns are achievable.

Furthermore, these negative returns appear to be primarily concentrated in upper-middle-income economies. When differentiating by income group, Figure 4b reveals that cumulative mean excess returns in low- and lower-middle-income countries outperform those in upper-middle-income economies. This suggests that focusing on unhedged loans to LMICs could indeed enhance returns.

Figure 4 Cumulative excess returns



Note: The chart on the left only includes 84 currencies for which data are available for the entire sample period since 2000.

It is important to note that these analyses do not reflect any attempt at currency diversification. The cumulative mean returns shown in Figure 4 are in a way an equally weighted portfolio across LMIC currencies. These returns could be further boosted through strategic diversification. Evidence from shows that their portfolio, which is diversified across 100 currencies, earned a positive return on average[7]. Our results point to further potential diversification benefits of including more low-income countries.

In summary, our analysis shows that excess returns on unhedged LMIC currencies are generally positive and have become less volatile over time. During periods of global financial turmoil, excess returns are more likely to turn negative and become significant across multiple countries, underscoring the persistent relevance of tail risks arising from currency depreciations. Nevertheless, over the long term, cumulative excess returns remain positive. Notably, low-income countries present the highest positive returns, suggesting that their lower financial integration reduces their vulnerability to global financial shocks.

3. An investigation of tail risk: motivation and literature review

This section discusses and provides the rationale for our regression analysis on the predictors of tail currency risk. Section 2 has demonstrated that, although the likelihood of large negative tail events has declined on average, these events have become more correlated and seem to be driven by a common global factor. We test this hypothesis by analysing the determinants of

[7] They calculated a 1.6% annualised return based on actual executed deals, or 2.4% based on all their quoted prices. These figures are comparable to our results, as shown in Figure 1. See TCX, *Scaling Up Currency Risk Hedging for Low and Lower Middle-Income Countries: A Proposal to Mitigate Currency Risk at Scale and Mobilize Private Finance for Sustainable Development* (September 2023).

currency risk, specifically focusing on the right tail of the distribution of depreciation rates against the US dollar. For a panel of up to 90 countries, we explore how global shocks affect the 95th quantile of depreciation rates in a panel of low- to middle-income countries. Additionally, we consider structural country-specific factors that mediate the impact of these global shocks on tail risk. In line with recent literature on 'original sin redux',[8] we pay particular attention to the role of non-resident investors in domestic bond markets as a key channel through which global financial conditions are transmitted into exchange rate instability in LMICs.

Unlike previous research, which has primarily focused on global financial conditions as predictors of currency risk,[9] we investigate the role of commodity price fluctuations as risk factors. Commodity prices are well-established drivers of exchange rates, particularly for low- and middle-income countries that are often commodity exporters.[10] However, their role in influencing tail risks has been explored to a much lesser extent. We focus on the cyclical properties of commodity prices, examining the potential asymmetric effects between booms and busts. Commodity price busts tend to be sharp and sudden, often accompanied by depreciations, but due to their short-lived nature, they offer limited predictive power. In contrast, commodity price booms typically last longer and are usually associated with currency appreciation. Our findings confirm the conventional understanding that commodity price expansions tend to appreciate currencies at the median of the distribution. However, we also report a novel finding: in low- to middle-income countries, commodity price booms increase future currency risk at the tail of the distribution, raising the likelihood of a significant depreciation following the expansion.

In terms of mediating effects, contrary to expectations, this effect is not related to the share of commodities in exports. Instead, we find that the share of non-bank foreign investors in domestic bond markets amplifies the risk-enhancing effect of commodity price booms. This points to the presence of a financial channel in which currency depreciations following commodity price booms are exacerbated by the behaviour of 'impatient' foreign investors. This result aligns with the 'original sin redux' literature, highlighting the ongoing vulnerability of LMICs due to the increasing presence of foreign investors in domestic financial markets.

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[8] A Kaltenbrunner and JP Painceira, 'Developing Countries' Changing Nature of Financial Integration and New Forms of External Vulnerability: The Brazilian Experience' (2015) 39(5) Cambridge Journal of Economics 1281; M Onen, HS Shin, and G von Peter, 'Macroprudential Policy in Developing Economies' (BIS Working Papers No 1075, 21 February 2023) https://www.bis.org/publ/work1075.htm accessed 11 October 2024; LF de Paula, B Fritz, and D Prates, 'The Metamorphosis of External Vulnerability from "Original Sin" to "Original Sin Redux": Currency Hierarchy and Financial Globalization in Emerging Economies' (2024) 15(2) Review of International Political Economy 1-28.

[9] F Eguren-Martin and A Sokol, 'Attention to the Tail(s): Global Financial Conditions and Exchange Rate Risks' (2022) 70(3) *IMF Economic Review* 487.

[10] Y Chen and K Rogoff, 'Commodity Currencies' (2003) 60(1) *Journal of International Economics* 133; P Cashin, LF Céspedes and R Sahay, 'Commodity Currencies and the Real Exchange Rate' (2004) 75(1) *Journal of Development Economics* 239; S Van Huellen and RB Palazzi, 'Commodity Currencies: Unpicking the Asymmetric Relationship Between Commodity Prices and Exchange Rates' (2023), Unpublished Manuscript.

3.1. Literature review

Research on currency crash risk has traditionally focused on identifying the factors that increase the likelihood of a currency crisis.[11] These crises are often treated as binary events, with their probability being estimated through logit or probit models.[12] This body of work has primarily identified weak domestic macroeconomic fundamentals—such as foreign reserves, exchange rate overvaluation, domestic credit growth, public debt, and inflation—as key determinants of currency crashes.

More recent studies have shifted towards exploring extreme macroeconomic events, often referred to as 'tail risk'.[13] One notable approach, the growth-at-risk framework, utilises quantile regressions to estimate the distribution of GDP growth based on risk factors, including the deterioration of global and domestic financial conditions. This method enables the assessment of how changes in macroeconomic indicators affect the tails of the GDP growth distribution—specifically, how they alter the size of a recession at particular quantiles, typically the left tail represented by the 5th quantile.[14] Adrian, Boyarchenko, and Giannone applied this framework to a panel of advanced economies, finding that looser financial conditions initially boost median GDP growth but subsequently increase the left tail of the GDP growth distribution after about 10 quarters, signalling a heightened risk of a significant recession.[15]

Eguren-Martin and Sokol extended the growth-at-risk framework to exchange rates, focusing on global financial conditions as a key determinant of tail risks.[16] A substantial body of literature suggests that short-term currency fluctuations are largely driven by capital flows resulting from portfolio reallocations, making global financial conditions a critical factor in exchange rate

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[11] A Berg and C Pattillo, 'Predicting Currency Crises' (1999) 18(4) *Journal of International Money and Finance* 561; JA Frankel and AK Rose, 'Currency Crashes in Emerging Markets: An Empirical Treatment' (1996) 41 *Journal of International Economics* 351; TM Boonman and others, 'Early Warning Systems for Currency Crises with Real-Time Data' (2019) 30(4) *Open Economies Review* 813.

[12] Events are defined based on specific criteria, for example, an annual rate of depreciation of 25% or more.

[13] T Adrian, N Boyarchenko and D Giannone, 'Vulnerable Growth' (2019) 109(4) *American Economic Review* 1263; M Gächter, M Geiger and H Hasler, 'On the Structural Determinants of Growth-at-Risk' (2023) 19(2) *International Journal of Central Banking* 251.

[14] The quantile is the point in the distribution at which a given proportion of the data is less than or equal to that value.

[15] Adrian, Boyarchenko, and Giannone (n 13).

[16] Their global financial conditions index is based on a principal component analysos of monthly financial indicators for 43 countries comprising term, sovereign, interbank, and coporate spreads, long-term interest rates, equity returns and volatility a well as relative market capitalisation of the financial sector. The index is strongly correlated with the US stock market volatility index VIX (correlation coefficient: 0.81). See Eguren-Martin and Sokol (n 9).

risk.[17] Eguren-Martin and Sokol estimated quantile regressions for 61 advanced and emerging economies, using the growth rate of the nominal exchange rate as the dependent variable and a global financial conditions index as the key explanatory variable. They found that tightening global financial conditions increases tail risk in most countries, with exceptions for safe-haven currencies such as the Swiss Franc and the US dollar. To examine cross-country differences, they sorted currencies into three portfolios based on characteristics such as interest rate differentials, current account balances, fiscal balances, net foreign assets, and international reserves. The results indicated that currencies in high-risk portfolios, particularly in terms of interest rate differentials, international reserves, and fiscal balances, respond more strongly to tightening financial conditions than those in low-risk portfolios.

However, Eguren-Martin and Sokol (2022) did not consider the role of non-resident investors in shaping the transmission of global shocks in domestic financial markets. Cerutti, Claessens, and Puy, along with Kohler, Bonizzi, and Kaltenbrunner, show that countries with a larger share of domestic bonds held by non-bank foreign investors are more vulnerable to global financial shocks.[18] This suggests that a significant portion of currency fluctuations in response to global risk factors may be driven by the behaviour of institutional investors, who tend to be more sensitive to changes in risk perceptions.

Another important determinant of exchange rate tail risks overlooked by Eguren-Martin and Sokol is commodity prices. Commodity prices are particularly relevant for low- to middle-income countries, given their reliance on concentrated trade structures, either as commodity exporters or importers. Earlier literature on the commodity-exchange rate nexus has primarily focused on the real exchange rate of commodity-exporting countries (so-called ‘commodity currencies’), examining how exogenous changes in commodity prices affect relative prices.[19] Typically, rising commodity prices are expected to lead to a real appreciation of the currency. More recent studies, however, highlight financial channels in the relationship between commodity prices and nominal exchange rates. Some studies argue that commodity prices are inversely related to the risk premium on local-currency liabilities of commodity exporters.[20]

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[17] E.g., V Bruno and HS Shin, ‘Cross-Border Banking and Global Liquidity’ (2015) 82(2) *The Review of Economic Studies* 535; X Gabaix and M Maggiori, ‘International Liquidity and Exchange Rate Dynamics’ (2015) 130(3) *The Quarterly Journal of Economics* 1369; C Engel and SPY Wu, ‘Liquidity and Exchange Rates: An Empirical Investigation’ (2023) 90(5) *The Review of Economic Studies* 2395.

[18] E Cerutti, S Claessens and D Puy, ‘Push Factors and Capital Flows to Emerging Markets: Why Knowing Your Lender Matters More than Fundamentals’ (2019) 119 Journal of International Economics 133; K Kohler, B Bonizzi and A Kaltenbrunner, ‘Global Financial Uncertainty Shocks and External Monetary Vulnerability: The Role of Dominance, Exposure, and History’ (2023) 88 Journal of International Financial Markets, Institutions and Money 101818.

[19] Chen and Rogoff (n 10); Cashin, Céspedes and Sahay (n 10).

[20] T Drechsel and S Tenreyro, ‘Commodity Booms and Busts in Emerging Economies’ (2018) 112 *Journal of International Economics* 200; A Fernández, A González and D Rodríguez, ‘Sharing a Ride on the Commodities Roller Coaster: Common Factors in Business Cycles of Emerging Economies’ (2018) 111 Journal of International Economics 99; S Van Huellen and RB Palazzi, ‘Commodity Currencies: Unpicking the Asymmetric Relationship Between Commodity Prices and Exchange Rates’ (2023), Unpublished Manuscript.

Commodity price booms would then reduce the risk premium, attracting financial inflows and appreciating the currency.

Van Huellen and Palazzi integrate this financial channel into an exchange rate model that assumes foreign investors follow different expectational rules. In their model, fundamentalist traders expect the exchange rate to revert to its fundamental value, while positive feedback traders extrapolate past trends. The presence of feedback traders can cause the exchange rate to overshoot temporarily in response to commodity price shocks, resulting in sharper reversals towards the fundamental value compared to a market that was dominated by fundamentalists only.[21] Sockin and Xiong demonstrate in their model how informational frictions can lead market participants to misinterpret commodity demand, making commodity markets highly susceptible to volatility.[22] Nalin and Yajima's macroeconomic model further highlights the destabilising effects of commodity price fluctuations, showing that price booms attract financial inflows into domestic bond markets, increasing currency sensitivity when the boom ends.[23]

Motivated by this recent theoretical work on the interaction between commodity prices, exchange rates, and foreign investor behaviour, we empirically investigate whether the presence of foreign investors in domestic bond markets amplifies future currency crash risks stemming from commodity price shocks. Our approach builds on recent literature on exchange rate tail risks but departs from it in several key respects. First, unlike Eguren-Martin and Sokol, who conducted country-by-country regressions and reported results primarily for advanced economies,[24] we use panel quantile regressions for low- to middle-income countries. Second, we focus on commodity prices, rather than financial conditions, as the primary global shock variable. Commodity prices are especially pertinent to exchange rates in developing countries, yet have been overlooked in studies on exchange rate tail risks. Third, instead of concentrating on standard macroeconomic fundamentals such as current account balances and fiscal positions, we explore the role of international financial integration, specifically the influence of foreign investors in domestic bond markets.[25] Finally, we give greater attention to prediction by examining the determinants of elevated currency tail risks up to four quarters ahead.

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[21] Van Huellen and Palazzi (n 10).

[22] M Sockin and W Xiong, 'Informational Frictions and Commodity Markets' (2015) 70(5) The Journal of Finance 2063.

[23] L Nalin and GT Yajima, 'Commodities Fluctuations, Cross-Border Flows and Financial Innovation: A Stock-Flow Analysis' (2021) 72(3) Metroeconomica 539.

[24] Eguren-Martin and Sokol (n 9).

[25] Cerutti, Claessens and Puy (n 18); Kohler, Bonizzi and Kaltenbrunner (n 18).

3.2. Methodology

Following the growth-at-risk literature,[26] we apply quantile regressions to assess the determinants of currency tail risk in low- to middle-income countries. While Ordinary Least Squares (OLS) regressions estimate the mean of a dependent variable conditional on a set of regressors, quantile regressions estimate any quantile of interest of the dependent variable based on the same regressors.[27] Panel quantile regression (PQR) extends this approach to panel datasets, allowing for quantile-specific fixed effects.[28] PQR can also be combined with the local projections approach to estimate how current changes in explanatory variables affect future tail risks.[29]

Our dependent variable is the quarterly rate of depreciation of the nominal US dollar (USD) exchange rate, denoted as ΔXR_{it} for currency i. Applying the local projections approach, we estimate the coefficients of the following quantile function:

$$Q_{\Delta XR_{it+h}}(\tau | X_t, Z_{it}, Y_{it}) = \alpha_{i\tau} + \sum_{k=0}^{p} \beta_{k\tau} X_{t-k} + \delta_\tau Z_{it-1} X_t + \gamma_\tau Z_{it-1} + \theta_\tau' Y_{it-1} \tag{4}$$

where Q is the τ-th quantile of the distribution of ΔXR_{it}, $h = 0, \ldots, 4$ is the forecast horizon, $\alpha_{i\tau}$ is a quantile-specific country fixed effect, X_t is a common global shock, Z_{it} is a (structural) country-specific characteristic that may mediate the effect of the global shock on the quantile of the rate of depreciation, and Y_{it} is a vector of country-specific macroeconomic control variables.

Parameter estimates are obtained by solving the following optimisation problem:

[26] Adrian, Boyarchenko, and Giannone (n 13); Gächter, Geiger and Hasler (n 13).

[27] R Koenker and G Bassett, 'Regression Quantiles' (1978) 46(1) *Econometrica* 33.

[28] R Koenker, 'Quantile Regression for Longitudinal Data' (2004) 91(1) *Journal of Multivariate Analysis* 74.

[29] T Adrian and others, 'The Term Structure of Growth-at-Risk' (2022) 14(3) *American Economic Journal: Macroeconomics* 283; J Baruník and F Čech, 'Measurement of Common Risks in Tails: A Panel Quantile Regression Model for Financial Returns' (2021) 52 *Journal of Financial Markets* 100562.

$$\min_{\alpha_{i\tau},\beta_\tau,\delta_\tau,\gamma_\tau,\theta'_\tau} \sum_{t=1}^{T-h}\sum_{i=1}^{N}\rho_\tau\left(\Delta XR_{it+h}-\alpha_{i\tau}-\sum_{k=0}^{p}\beta_{k\tau}X_{t-k}-\delta_\tau Z_{it-1}X_t-\gamma_\tau Z_{it-1}-\theta'_\tau Y_{it-1} + \lambda\sum_{i=1}^{N}|\alpha_{i\tau}|\right), \tag{5}$$

where $\rho_\tau(u)=u(\tau-\mathbf{1}(u\leq 0))$ is the quantile loss function[30] and $\sum_{i=1}^{N}|\alpha_{i\tau}|$ is a penalty for the potentially large number of estimated fixed effect parameters with penalty term λ. For $\lambda=0$, a full set of country-specific fixed effects is estimated; for $\lambda>0$, the fixed effects for some countries shink towards zero and as $\lambda\to\infty$, the model drops any fixed effects. In our estimations, we set $\lambda=1$ given the relatively large number of countries in our dataset relative to the number of periods.[31] We also check the robustness of our results with respect to this assumption.

As common in the quantile regressions literature, we obtain standard errors through bootstrap resampling.[32] We employ the random-weighted bootstrap proposed by Galvao, Parker, and Xiao for PQR with fixed effects.[33] This method performs well in small samples and preserves the temporal structure of the panel data, a key consideration for our application, which utilises the dynamic properties of the dataset for local projections.

To determine an appropriate lag structure, we initially estimated equation (4) with a lagged dependent variable. However, this variable proved statistically insignificant across various specifications and was subsequently excluded from the model. We also tested different lag lengths for the global shock variable, ultimately finding that a lag of $p=1$ was statistically significant in most cases.

Van Huellen and Palazzi allow for asymmetric effects of global commodity price booms and busts on exchange rates, hypothesising that investors, being loss-averse, may respond more strongly to negative shocks than positive ones. However, their analysis focuses on the conditional mean of the exchange rate, while our approach examines the right tail of the

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[30] This is also called the „check function“ whose value depends on the sign of the residuals $u=\Delta XR_{it+h}-\alpha_{i\tau}-\sum_{k=0}^{p}\beta_{k\tau}X_{t-k}-\delta_\tau Z_{it-1}X_t-\gamma_\tau Z_{it-1}-\theta'_\tau Y_{it-1}+\lambda\sum_{i=1}^{N}|\alpha_{i\tau}|$, which is measured by the indicator function $\mathbf{1}(u<0)$.

[31] On this issue, see Baruník and Čech (n 29).

[32] Adrian and others (n 29); Baruník and Čech (n 29).

[33] The random-weighted bootstrap relies on cross-sectional resampling, where in each bootstrap iteration a different nonngeative random weight ω_i is applied to each cross-section i. The random weights have mean and variance of unity. See AF Galvao, T Parker and Z Xiao, 'Bootstrap Inference for Panel Data Quantile Regression' (2024) 42(2) *Journal of Business & Economic Statistics* 628.

distribution. It is not clear a priori whether asymmetry exists in the response of exchange rate tail risks to booms or busts in the global shock variable. We assess the existence of asymmetric effects by additionally estimating the following augmented quantile regression:

$$\begin{aligned} Q_{\Delta XR_{it+h}} = \alpha_{i\tau} + I_t^+ \left(\sum_{k=0}^{p} \beta_{k\tau}^+ X_{t-k} + \delta_\tau^+ Z_{t-1} X_t + \gamma_\tau^+ Z_{it-1} + \theta_t'^+ Y_{it-1} \right) \\ + I_t^- \left(\sum_{k=0}^{p} \beta_{k\tau}^- X_{t-k} + \delta_\tau^- Z_{t-1} X_t + \gamma_\tau^- Z_{it-1} + \theta_t'^- Y_{it-1} \right) \end{aligned} \tag{6}$$

where I_t^+ is a dummy variable for $\Delta X_t > 0$ and I_t^- for $\Delta X_t \leq 0$.[34] This specification allows the estimated coefficients to differ depending on whether the global shock variable is experiencing expansions or contractions.

4. Data and stylized facts

Our dataset consists of quarterly data with a maximum period of 1990Q1 – 2022Q4. Besides being constrained by data availability, our country selection is based on two criteria. First, we include all countries classified by the World Bank in 2019 as low-, lower-middle-, or upper-middle-income. Second, we exclude countries classified as hard pegs for the entire sample period according to the exchange rate regime classification by Ilzetzki, Reinhart, and Rogoff, countries with no variation in the dependent variable, and those with significant gaps in the dependent variable. This results in an unbalanced panel of up to 90 low- to middle-income countries.[35]

The dependent variable is the quarterly depreciation rate of the nominal USD exchange rate (ΔXR).[36] As global shock variables, we use the (logged) global commodity price index (*CMP*) and, for comparison, the (logged) VIX index (*VIX*), which measures market expectations of near-term volatility conveyed by stock index option prices. We also explore alternative commodity price indices, such as an energy commodity index (*CMP_EN*), an index excluding energy commodities (*CMP_NEN*), and country-specific indices based on commodity export (*CMP_EXP*)

[34] See, e.g., N Ben Zeev, VA Ramey and S Zubairy, 'Do Government Spending Multipliers Depend on the Sign of the Shock?' (2023) 113 *AEA Papers and Proceedings* 382; Van Huellen and Palazzi (n 10).

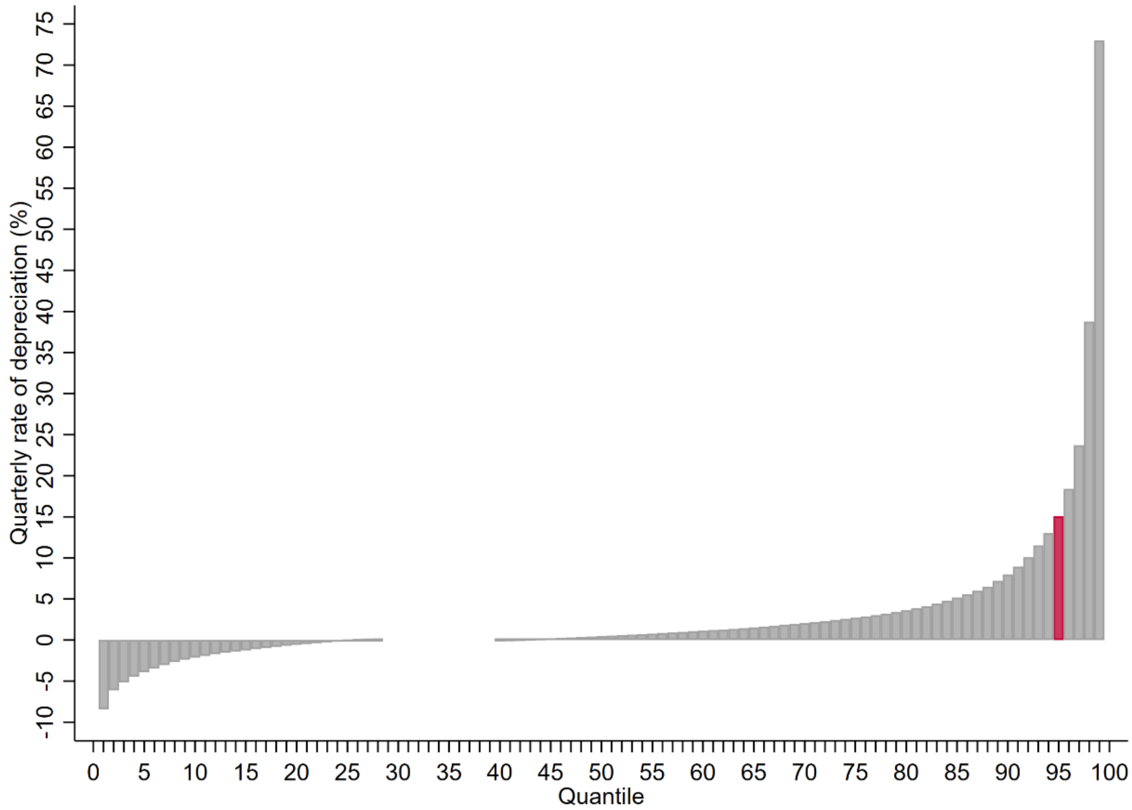
[35] The number of countries may vary across regressions due to country-specific data availability constraints on the control variables. See E Ilzetzki, CM Reinhart and KS Rogoff, 'Exchange Arrangements Entering the Twenty-First Century: Which Anchor Will Hold?' (2019) 134(2) *The Quarterly Journal of Economics* 599.

[36] For a comprehensive overview of the data, please refer to Table A-1 in the appendix.

or import (*CMP_IMP*) shares. Our key country characteristic is the ownership of government debt, measured by the share held by foreign investors (*FI*), including both bank (*BFI*) and non-bank (*NBFI*) investors, based on data from Arslanalp and Tsuda.[37] To explore potential effects that take place via the trade channel, we test the effect of adding the median share of commodities in total export ($CMEX\_MED$) and the median economic complexity index (ECI) to the estimation. All regressions control for domestic interest rate differentials relative to the US Federal Funds rate (*INTDIFF*) and the inflation differential between the domestic economy and the US (*INFLDIFF*).

Figure 5 displays the unconditional quantile function of the quarterly depreciation rate for the full sample. The quantile function, which is the inverse of the cumulative distribution function, shows the probability that the depreciation rate will be less than or equal to a specific value. The distribution is highly right-skewed, indicating that depreciations are more frequent and severe than appreciations. The quantile function from a quarterly rate of appreciation of 8% at the 1st quantile to a rate of depreciation of 73% at the 99th quantile. It is close to zero (0.5%) at the median and 15% at the 95th quantile.

Figure 5 Unconditional quantile function of the quarterly rate of depreciation

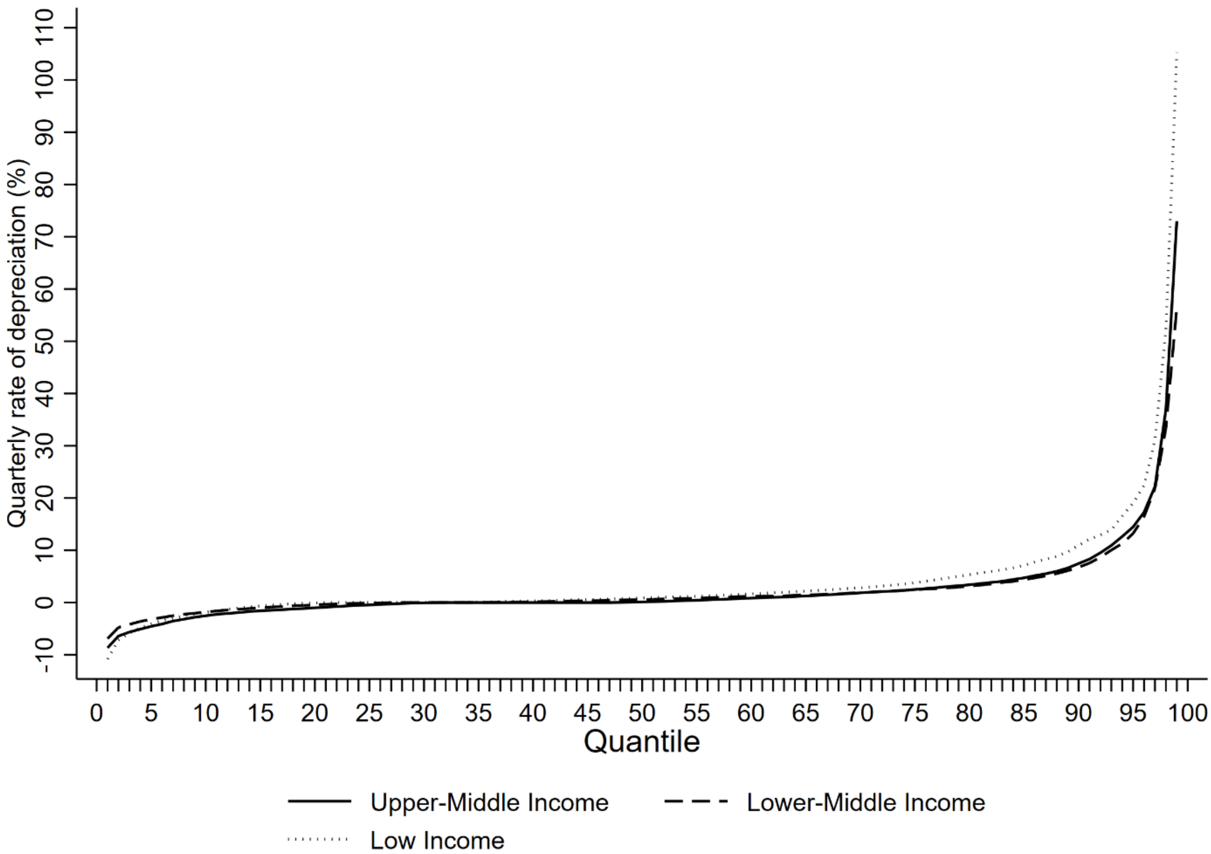


[37] S Arslanalp and T Tsuda, 'Tracking Global Demand for Emerging Market Sovereign Debt' (2014) *IMF Working Paper* No. 14/39.

Note: Quarterly rate of depreciation of nominal US dollar exchange rate; unbalanced panel of 90 countries, 1990Q1 – 20122Q4. Quantiles range from 1st to 99th. Highlighted bar demarks the 95th quantile.

Figure 6 presents quantile functions by income group based on the 2019 World Bank country classification. While the middle of the distribution is quite similar across the three country groups, low-income countries display a slightly thicker right tail at the 25th percentile, a somewhat larger 95th quantile of approximately 19%, and a significantly elevated 99th quantile of 105%, indicating that low-income countries experience higher tail risks compared to middle-income countries.

Figure 6 Unconditional quantile function of the quarterly rate of depreciation by income group



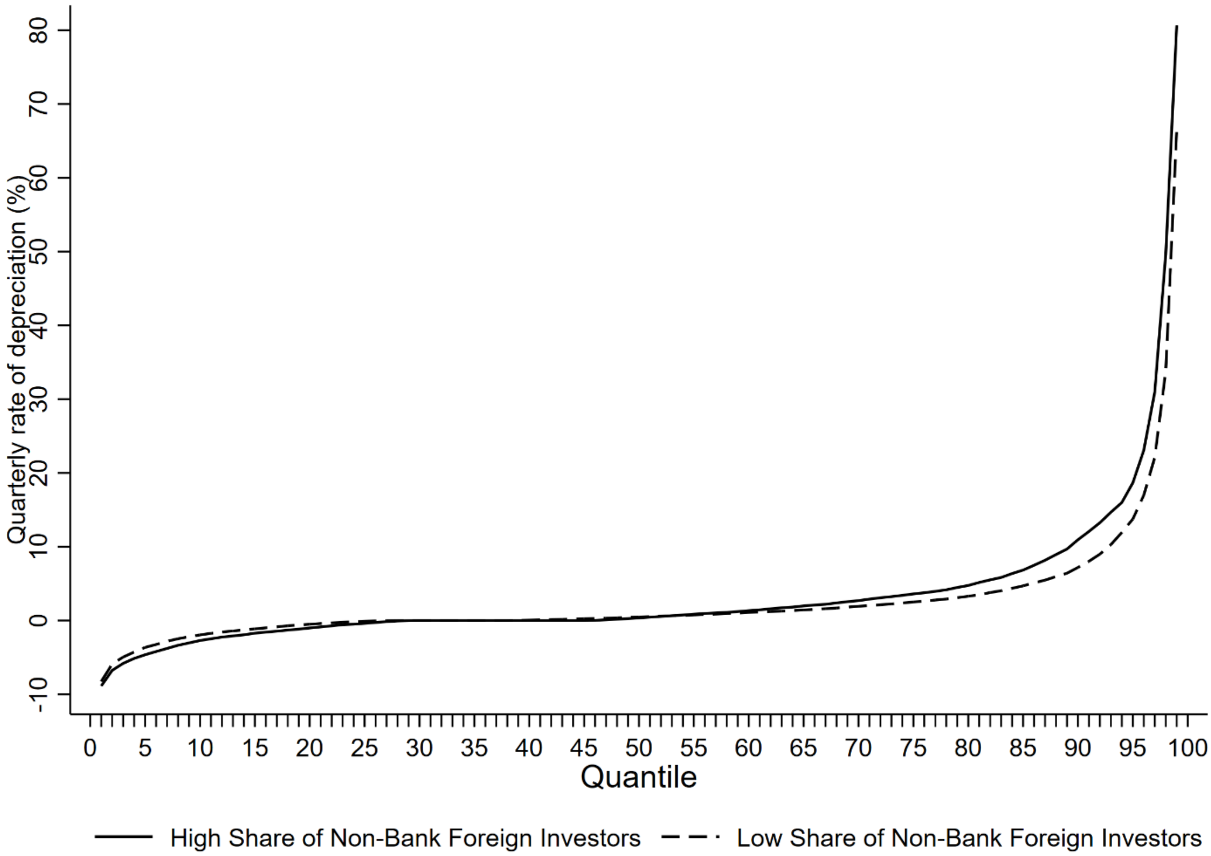
Note: Quarterly rate of depreciation of the nominal US dollar exchange rate; unbalanced panel of 90 countries, 1990Q1 – 2022Q4; grouped based on the 2019 WB classification. Quantiles range from 1% to 99%.

Finally, Figure 7 compares the quantile functions of two country groups defined by whether the median share of domestic government debt held by non-bank foreign investors is above ('high') or below ('low') 10%.[38] While the quantile functions are largely identical in the middle of the

[38] The sample average is 7%, and the 75th quantile is 11.5%.

distribution, the group with a high share of non-bank foreign investors exhibits a markedly thicker right tail, with the 95th quantile being approximately 5 percentage points larger. This provides some preliminary evidence that the presence of non-bank foreign investors in domestic bond markets amplifies currency risk. The following section explores the role of foreign investor exposure in greater detail using regression analysis.

Figure 7 Unconditional quantile function of the quarterly rate of depreciation by share of non-bank foreign investors in domestic bond markets



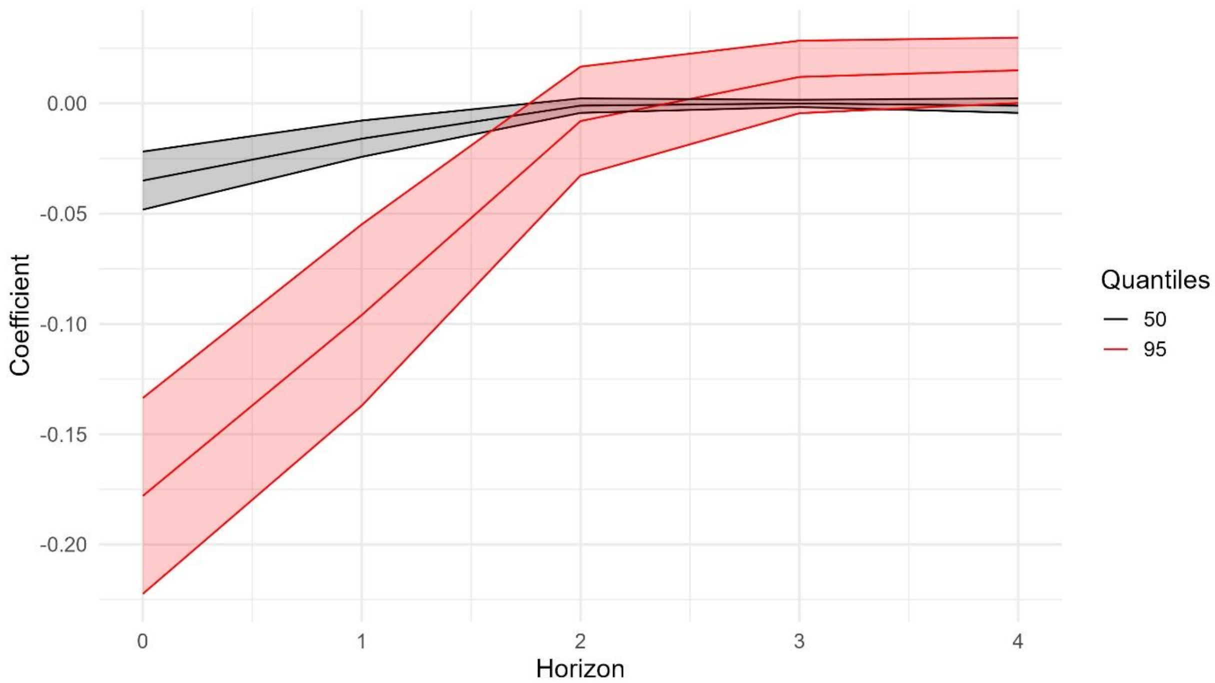
Note: Quarterly rate of depreciation of the nominal US dollar exchange rate; unbalanced panel of 90 countries, 1990Q1–2022Q4, grouped based on whether the median share of non-bank foreign investors in the domestic bond market is above or below 10%. Quantiles range from 1% to 99%.

5. Results

We start by estimating a restricted version of equation (4) that excludes the structural country characteristic (i.e. we set $\delta_\tau = \gamma_\tau = 0$) for the 50th and 95th quantiles. Figure 8 plots the estimated coefficients on CMP along with a 90% confidence band over the horizon $h = 0,..,4$. It can be observed that an increase in CMP significantly reduces the rate of depreciation on impact. The effect persists for about two quarters and is generally much stronger for the 95th tail of the distribution, with a 1% increase in commodity prices reducing the rate of depreciation by approximately 0.18 percentage points on impact. To gauge the economic significance of this effect, it is important to note that the standard deviation of the quarterly growth rate of commodity prices is around 10%, indicating that quarterly changes in commodity prices of this magnitude are relatively common. The finding that commodity price increases tend to appreciate the currencies of low- and middle-income countries aligns with the terms-of-trade and risk-premium channels discussed earlier.

To further compare the magnitude of the effect of CMP on the rate of depreciation, we run an additional regression where we add the US stock market volatility index VIX as a second global shock variable. We normalise both CMP and VIX to have zero means and standard deviations of unity to be able to compare the estimated coefficients. The results are presented in Figure B-1 in the appendix. It can be seen that the magnitude of CMP exceeds that of VIX across all horizons. Only for CMP do we observe a reversal of the sign of the effect over the forecasting horizon, pointing to a boom-bust-cycle pattern that is absent from the VIX. The relative importance of commodity prices compared to the more familiar effects of global financial shocks corroborates our focus on commodities and their cyclical properties as predictors of currency tail risk.

Figure 8 Estimated coefficients on CMP for 50th and 95th percentile of nominal rate of depreciation

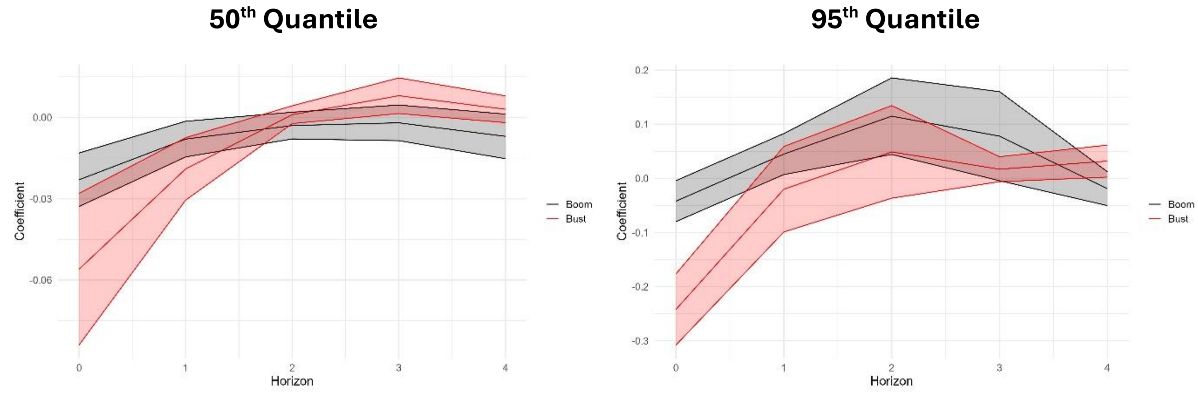


Notes: Estimated coefficients on CMP_t ($\beta_{0,50}$ and $\beta_{0,95}$ in equation 1) from panel quantile regressions with nominal rate of depreciation as dependent variable (in %) with horizon $h = 0, \dots, 4$. Regression includes control variables but excludes structural country characteristics (i.e. $\delta_\tau = \gamma_\tau = 0$). Confidence bands represent the 90% confidence interval based on bootstrapped standard errors. Number of observations: 7,586.

Next, following Van Huellen and Palazzi,[39] we allow for asymmetric effects of commodity price booms and busts. To this end, we first estimate a restricted version of equation (6) where, as before, we exclude the structural country characteristic (i.e. we set $\delta_\tau^i = \gamma_\tau^i = 0$ for all i). Figure 9 plots the estimated coefficients on the commodity price boom and bust terms, respectively, for both the 50th and the 95th quantile. For the 50th quantile, the impact of commodity prices on exchange rates is stronger for commodity price booms than busts, but the difference is not statistically significant.

By contrast, the results for the 95th quantile are strongly asymmetric. The impact effect appears to be largely driven by commodity price busts that exert immediate and strong effects on the right tail of depreciation rates. However, from the first quarter onwards, the effect becomes statistically insignificant, suggesting that it plays out rapidly. Interestingly, the effect of commodity price booms on currency tail risk behaves rather differently. While commodity price booms lower tail risks on impact, they *raise* future tail risk between the first and third quarters. The effect peaks in the second quarter where a one percent increase in commodity prices during booms raises future tail risks by about 0.12 percentage points. With quarterly commodity prices rising by more than 10% during some boom episodes, the effect is economically sizeable. The asymmetric nature of this effect being confined to the tails of the distribution is consistent with the idea that some, but not all, commodity price booms end with sharp depreciations. Commodity price expansions thus carry predictive information about elevated tail risks.

Figure 9 Estimated coefficients on CMP for 50th and 95th quantile of nominal rate of depreciation, separated into commodity price booms and busts



Notes: Estimated coefficients on CMP_t for commodity price booms and busts (β_0^+ and β_0^- in equation 2) from panel quantile regressions with nominal rate of depreciation as dependent variable (in %) with horizon $h = 0, \dots, 4$. Regression includes control variables but excludes structural country characteristics (i.e. $\delta_\tau^i = \gamma_\tau^i = 0$ for all i). Confidence bands represent the 90% confidence interval based on bootstrapped standard errors. Number of observations: 7,586.

[39] Van Huellen and Palazzi (n 10).

Next, we assess the role of non-bank foreign investors in domestic bond markets by estimating the unrestricted version of equation (6), i.e. we allow for $\delta_\tau^i \neq \gamma_\tau^i \neq 0$ during both commodity price booms and busts. Results are presented in Table 1. Our main interest is in the interaction term between CMP and $NBFI$. During commodity price booms, the interaction amplifies currency tails risks at all horizons. Thus, a higher share of non-bank foreign investors in domestic bond markets increases the predicted future tail risk from commodity price booms. To assess the size of the effect, consider a country with a share of non-bank foreign investors of 10% ($NBFI = 10$) undergoing a quarterly increase of commodity prices of 10% ($\Delta CMP = 10$). The marginal effect two quarters ahead is around 2.9, i.e. the rate of depreciation at the 95$^{\text{th}}$ percentile is predicted to increase by 2.9 percentage points, which is economically sizable. Table B-2 in the appendix reports analogous results for the 50$^{\text{th}}$ quantile, for which the estimated effect on the interaction term is either much smaller or less significant.

These results are consistent with the theoretical argument discussed above whereby commodity price booms that are accompanied by increased exposure to fickle foreign investors can result in deeper busts.

Table 1 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.044**	0.028	0.09*	0.045	-0.018
	(0.021)	(0.021)	(0.052)	(0.048)	(0.02)
CMP x BUST	-0.233***	-0.026	0.006	0.017	0.02
	(0.039)	(0.05)	(0.051)	(0.014)	(0.016)
L1.CMP x BOOM	0.015	-0.047**	-0.108**	-0.062	0.002
	(0.02)	(0.021)	(0.051)	(0.047)	(0.019)
L1.CMP x BUST	0.206***	0.018	-0.018	-0.032**	-0.034**
	(0.038)	(0.047)	(0.051)	(0.014)	(0.014)
CMP X L1.NBFI x BOOM	0.001***	0.001***	0.002***	0.002**	0.001**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
CMP x L1.NBFI x BUST	-0.001	-0.001	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
L1.NBFI x BOOM	-0.508***	-0.499***	-0.731***	-0.779***	-0.674**
	(0.179)	(0.171)	(0.256)	(0.279)	(0.307)
L1.NBFI x BUST	0.431	0.272	-0.317	-0.139	-0.352
	(0.492)	(0.53)	(0.362)	(0.169)	(0.22)
L1.INFLDIFF x BOOM	0.118***	0.122***	0.056	-0.004	-0.005
	(0.017)	(0.015)	(0.062)	(0.033)	(0.041)
L1.INFLDIFF x BUST	0.082	0.049	0.123**	0.079	0.031
	(0.094)	(0.063)	(0.062)	(0.053)	(0.042)
L1.INTDIFF x BOOM	0.001	-0.001	0.033	0.099***	0.12***
	(0.135)	(0.064)	(0.074)	(0.028)	(0.034)
L1.INTDIFF x BUST	0.02	0.022	0.000	0.035	0.069

Variable	h=0	h=1	h=2	h=3	h=4
	(0.202)	(0.219)	(0.146)	(0.101)	(0.132)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \ldots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,079.

Table 2 reports analogous results for a restricted sample that only includes countries that were classified by the WB as low- or lower-middle income countries in 2019. The main results become stronger: commodity price booms predict an even larger increase in currency tails risks two and three quarters ahead, and the amplifying effect of non-bank foreign investors is between two and four times stronger.

Table 2 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, low- and lower-middle income countries

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.047**	0.001	0.134*	0.133*	0.025
	(0.023)	(0.038)	(0.079)	(0.076)	(0.044)
CMP x BUST	-0.219***	-0.145**	0.019	0.048	0.022
	(0.049)	(0.058)	(0.043)	(0.032)	(0.021)
L1.CMP x BOOM	0.012	-0.02	-0.15*	-0.145*	-0.038
	(0.024)	(0.041)	(0.079)	(0.076)	(0.045)
L1.CMP x BUST	0.185***	0.128**	-0.033	-0.062**	-0.036**
	(0.047)	(0.056)	(0.04)	(0.03)	(0.018)
CMP X L1.NBFI x BOOM	0.004***	0.003**	0.004*	0.009***	0.008**
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
CMP x L1.NBFI x BUST	0.000	0.006	0.004	0.001	0.003
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)
L1.NBFI x BOOM	-1.688***	-1.546**	-1.839*	-3.834***	-3.606**
	(0.535)	(0.694)	(1.005)	(1.198)	(1.439)
L1.NBFI x BUST	0.046	-2.658	-1.751	-0.712	-1.231
	(1.347)	(1.729)	(1.852)	(1.342)	(1.071)

Variable	h=0	h=1	h=2	h=3	h=4
L1.INFLDIFF x BOOM	0.083***	0.101***	-0.004	-0.004	-0.004
	(0.013)	(0.019)	(0.058)	(0.014)	(0.02)
L1.INFLDIFF x BUST	-0.006	-0.001	-0.001	-0.009	0.017
	(0.087)	(0.074)	(0.022)	(0.038)	(0.033)
L1.INTDIFF x BOOM	0.555***	0.36***	0.481***	0.117	0.065
	(0.164)	(0.129)	(0.148)	(0.077)	(0.085)
L1.INTDIFF x BUST	0.71***	0.696***	0.741***	0.862***	0.569***
	(0.216)	(0.194)	(0.239)	(0.235)	(0.192)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \dots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. The sample is restricted to countries that were classified by the WB as low- or lower-middle income in 2019. Number of observations: 3,642.

In Table 3, we replace the time-varying $NBFI$ with the median value over time for each country (denoted as $NFBFI\_MED$). This adjustment removes any within-country variation, allowing us to isolate the between-country effect. Compared to the main results in Table 1, the mediating effect of the share of non-bank foreign investors becomes somewhat weaker but remains statistically significant in the first and second quarters. This suggests that the main results capture both between- and within-country effects. In other words, countries with higher median shares of non-bank foreign investors in domestic bond markets are not only more exposed to future currency tail risks from commodity price booms, but dynamic increases in those shares during commodity price booms also contribute to heightened risk.

Table 3 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, median value of NBFI

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.03	0.032	0.089*	0.049	-0.017
	(0.021)	(0.023)	(0.046)	(0.052)	(0.02)
CMP x BUST	-0.224***	-0.037	0.039	0.023*	0.021
	(0.031)	(0.05)	(0.046)	(0.012)	(0.017)

Variable	h=0	h=1	h=2	h=3	h=4
L1.CMP x BOOM	0.006	-0.05**	-0.101**	-0.064	0.006
	(0.02)	(0.023)	(0.046)	(0.051)	(0.021)
L1.CMP x BUST	0.202***	0.028	-0.045	-0.035***	-0.031**
	(0.03)	(0.049)	(0.046)	(0.011)	(0.015)
CMP X NBFI_MED x BOOM	0.001	0.001**	0.001**	0.001	0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
CMP x NBFI_MED x BUST	-0.002*	-0.001	-0.001	0.000	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
NBFI_MED x BOOM	-0.322	-0.364*	-0.521**	-0.53	-0.212
	(0.234)	(0.215)	(0.261)	(0.439)	(0.384)
NBFI_MED x BUST	1.182*	0.718	0.52	0.14	0.334
	(0.649)	(0.709)	(0.782)	(0.388)	(0.654)
L1.INFLDIFF x BOOM	0.118***	0.122***	0.198***	-0.004	-0.005
	(0.018)	(0.018)	(0.042)	(0.034)	(0.033)
L1.INFLDIFF x BUST	0.062	0.041	0.131**	0.081	0.028
	(0.093)	(0.063)	(0.063)	(0.055)	(0.037)
L1.INTDIFF x BOOM	0.002	-0.001	-0.015	0.1***	0.121***
	(0.145)	(0.073)	(0.069)	(0.036)	(0.031)
L1.INTDIFF x BUST	0.023	0.026	0.001	0.034	0.072
	(0.182)	(0.2)	(0.169)	(0.139)	(0.142)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \ldots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,095.

5.1. Additional exercises

In this section, we conduct a couple of additional exercises to shed further light on our main findings.

First, we replace the generic commodity price index once with an energy commodity price index (CMP_EN) and once with a non-energy index (CMP_NEN). Results are reported in Tables B-3 and B-4 in the appendix. The main results are weaker, but the interaction term between commodity sub-indices and $NBFI$ is significant and positive for most horizons during commodity price booms. The fact that the results are weaker when using more fine-grained commodity price indices suggests that booms of the generic commodity price index carry greater predictive power for elevated currency tail risk.

Second, to contrast the financial channel captured by $NBFI$ more directly with the conventional terms of trade channel, we replace in the regression reported in Table 4 $NBFI$ with the median share of commodities in total export ($CMEX\_MED$). The interaction between commodity prices and ($CMEX\_MED$ is consistently insignificant for commodity price booms. For commodity price busts, there is a statistically significant effect on impact, whereby a higher share of commodities in total exports amplifies the contractionary effect of commodity price busts on exchange rates, consistent with the terms-of-trade channel.[40] When using instead the median economic complexity index (ECI), a measure of the diversity and rarity of a country's exports, the coefficient on the interaction term is again statistically insignificant, lending further support to the finding that export structure does not seem to be relevant for the predictive power of commodity price booms for currency risk (see Table B-5 in the appendix).

[40] The results reported in Table 4 are qualitatively similar for the subsample of low- and lower-middle income countries.

Table 4 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, median share of commodities in total exports (CMEX_MED)

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.035	0.024	0.137**	0.131**	-0.029
	(0.027)	(0.028)	(0.057)	(0.051)	(0.035)
CMP x BUST	-0.221***	-0.023	0.006	0.04**	0.015
	(0.042)	(0.063)	(0.057)	(0.018)	(0.023)
L1.CMP x BOOM	0.035	-0.02	-0.144**	-0.138***	0.014
	(0.023)	(0.026)	(0.058)	(0.051)	(0.031)
L1.CMP x BUST	0.223***	0.033	-0.01	-0.046***	-0.031*
	(0.039)	(0.061)	(0.055)	(0.012)	(0.018)
CMP X CMEX_MED x BOOM	-0.026	-0.024	0.008	0.015	0.019
	(0.017)	(0.02)	(0.023)	(0.023)	(0.026)
CMP x CMEX_MED x BUST	-0.077***	-0.042	-0.037	-0.035	-0.008
	(0.024)	(0.03)	(0.025)	(0.026)	(0.032)
CMEX_MED x BOOM	14.471**	14.403	-0.594	-3.99	-5.036
	(7.316)	(8.916)	(9.847)	(9.955)	(11.357)
CMEX_MED x BUST	37.438***	24.771*	20.563*	19.056	9.351
	(11.131)	(13.436)	(11.73)	(11.767)	(14.304)
L1.INFLDIFF x BOOM	0.175***	0.121***	0.181***	0.007	0.022
	(0.041)	(0.019)	(0.068)	(0.049)	(0.023)
L1.INFLDIFF x BUST	0.047	0.087***	0.101***	0.088***	0.111*
	(0.061)	(0.029)	(0.031)	(0.013)	(0.057)
L1.INTDIFF x BOOM	-0.015	0.01	-0.01	0.092*	0.103***
	(0.133)	(0.057)	(0.054)	(0.05)	(0.021)

Variable	h=0	h=1	h=2	h=3	h=4
L1.INTDIFF x BUST	0.108	0.008	0.031	0.028	0.021
	(0.221)	(0.123)	(0.106)	(0.077)	(0.102)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \dots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 6,675.

Third, we further explore the terms-of-trade channel by replacing the global commodity price index with an index with country-specific weights based on the share of commodities in total exports or imports (CMP_EXP and CMP_IMP, respectively).[41] Results are reported in Tables B-6 and B-7 in the appendix. Similar to the results with $CMEX\_MED$ in Table 4, the impact effects of commodity price busts on exchange rates are stronger for commodity exports. Commodity price booms alone, without the interaction with $NBFI$, do not exhibit statistically significant predictive power for future currency tail risks. However, the interaction between the weighted commodity price indices and $NBFI$ is positive and statistically significant for commodity price booms in both cases, supporting the main results.

Taken together, the additional regressions on the role of the terms-of-trade channel suggest that commodity dependence does increase tail risks from commodity price downturns on impact, but unlike dependence on non-bank foreign investors, it seems to carry little predictive power for future risk. This suggests that the predictive power of commodity price booms for future currency tail risk is indeed driven by the financial channel as captured by $NBFI,$ which reflects foreign investor behaviour rather than trade in commodities.

Fourth, to check that it is indeed *non-bank* foreign investors that are particularly prone to speculative behaviour,[42] we report results in Tables B-8 and B-9 in the appendix where we used instead the combined share of foreign investors (FI) and the share of bank foreign investors (BFI) only, respectively. For FI, the interaction term with commodity prices during booms is positive and statistically significant, but the size of the fact is smaller. By contrast, with BFI the effect is not statistically significant. This confirms that the effect is indeed driven by non-bank foreign investors.

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[41] The main difference to the specification with $CMEX\_MED$ reported in Table 4 is that CMP_EXP and CMP_IMP are time-varying and based on the data compiled by the IMF, whereas $CMEX\_MED$ is calculated based on data from the Penn World Table. Furthermore, in the specifications with CMP_EXP and CMP_IMP reported in Tables B-5 and B-6, we consider the interaction with $NBFI$.

[42] Cerutti, Claessens and Puy (n 18); Kohler, Bonizzi and Kaltenbrunner (n 18).

Finally, we explore the role of global financial shocks by replacing CMP with the US stock market volatility index VIX (see Table 5). As the VIX displays higher frequency fluctuations than commodity prices, we report results without allowing for asymmetric effects during booms and busts (i.e. we estimate equation 1 with the *VIX* as the global shock).[43] Spikes in the VIX represent increased global financial uncertainty and are indeed associated with increased currency risk, both on impact and over the entire four-quarter horizon. This is consistent with the results in Eguren-Martin's and Sokol's work and extends them to a longer forecast horizon.[44] Importantly, the interaction with $NBFI$ is mostly statistically insignificant, except for the third quarter, where it *lowers* crash risk. When estimating the same regression with the median of $NBFI$ (see Table C-11 in the appendix), the coefficient on the interaction term becomes statistically insignificant across all horizons, suggesting that the statistically significant effect in the third quarter in Table 5 is entirely driven by within-country dynamics rather than between-country differences.

Table 5 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, VIX

Variable	h=0	h=1	h=2	h=3	h=4
VIX	0.081***	0.061***	0.021**	0.028**	0.017*
	(0.011)	(0.016)	(0.01)	(0.012)	(0.01)
L1.VIX	-0.034***	-0.03**	0.005	-0.002	0.000
	(0.009)	(0.012)	(0.008)	(0.008)	(0.006)
VIX x NBFI	0.000	0.000	-0.001	-0.001*	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
L1.NBFI	0.112	0.084	0.12	0.153	0.079
	(0.171)	(0.114)	(0.113)	(0.118)	(0.132)
L1.INFLDIFF	0.119***	0.122***	0.07	-0.003	-0.005
	(0.041)	(0.016)	(0.056)	(0.052)	(0.044)
L1.INTDIFF	0.014	0.003	0.025	0.085	0.1**
	(0.168)	(0.139)	(0.109)	(0.074)	(0.047)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \dots, 4$ (see equation 1). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,079.

[43] We also experimented with a specification as in equation (2) but the results appeared to be less meaningful, consistent with the visible frequencies in the VIX series.

[44] Eguren-Martin and Sokol (n 9) only consider impact effects on currency tail risks. Their main explanatory variable is a novel global financial conditions index, which is however highly correlated with the VIX.

5.2. Robustness tests

We perform several robustness test on the main results in Table 1. The relevant regression tables are reported in the appendix. First, we check the sensitivity of the results to the sample. Table C-11 reports results when setting the sample start to 2000Q1 so as to exclude the 1990s and Table C-12 when setting the sample end to 2019Q4 to exclude the Covid-19 pandemic. The interaction term between CMP and $NBFI$ during commodity price booms becomes insignificant for some horizons but does remain significant in at least two horizons.

Second, we set the shrinkage parameter to $\lambda = 0.5$, thereby allowing a larger number of countries to have non-zero fixed effects (at the expense of estimation precision) (Table A-13). The estimated coefficients and standard errors on the interaction term of interest are not visibly affected by this. We get very similar results when decreasing the shrinkage parameter further to $\lambda = 0.01$.

Third, instead of Koenker's penalised fixed effects PQR estimator,[45] we use Canay's estimator which allows for individual fixed effects for all countries but assumes that the fixed effects are invariant across quantiles.[46] As for the main results, we use the random-weigthed bootstrap to obtain standard errors.[47] Results are reported in Table A-14. Compared to the baseline, the estimated coefficients on the commodity price boom and on the interaction term of interest tend to be larger. However, the standard errors are larger as well. Nevertheless, the interaction with $NBFI$ is statistically at the first, third, and fourth horizon, confirming the main results.

6. Conclusion

This paper has presented the results of an econometric analysis of currency tail risks. It utilised panel quantile regressions to investigate the role of global commodity prices in predicting future currency risk, as measured by the right tail of depreciation rates against the US dollar. The findings reveal a strong connection between commodity prices and currency tail risk. In line with conventional theory, commodity price busts have immediate and significant effects on tail risks, with these impacts being more pronounced for commodity exporters. However, the

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[45] Koenker (n 28).

[46] IA Canay, 'A Simple Approach to Quantile Regression for Panel Data' (2011) 14(3) *The Econometrics Journal* 368. For an application of this estimator to growth-at-risk, see D Aikman and others, 'Credit, Capital and Crises: A GDP-at-Risk Approach' (2019) *Bank of England Staff Working Paper* 824.

[47] AF Galvao, T Parker and Z Xiao, 'Bootstrap Inference for Panel Data Quantile Regression' (2024) 42(2) *Journal of Business & Economic Statistics* 628.

paper's main contribution is novel: it demonstrates that commodity price booms predict elevated crash risks several quarters ahead. The analysis provides evidence that this effect is not driven by commodity dependence or export structure but by the behaviour of foreign investors in domestic bond markets. The predictive effect of commodity price booms on future currency tail risk is stronger when there is a higher share of non-bank foreign investors in these markets. Furthermore, this effect is found to be specifically related to non-bank foreign investors, as opposed to foreign banks, which is consistent with the view that non-bank investors are less patient and more sensitive to global factors.[48]

The finding that exposure to non-bank foreign investors is associated with commodity price booms is novel and supports theoretical claims that such booms tend to attract speculative foreign investment.[49] While these dynamics may generally lead to currency appreciation, they can also result in extreme depreciations when commodity price booms end. Importantly, we find no evidence of a similar interaction between non-bank foreign investors and global uncertainty shocks, as measured by the VIX. This suggests that the channel identified is specific to global commodity price dynamics, which may act as a key information signal for institutional investors, guiding their portfolio choices in low- and middle-income countries.

From a policy perspective, the findings suggest that periods of commodity price booms should be viewed as opportunities to prepare for increased currency risk, particularly when such booms are accompanied by capital inflows into domestic bond markets. Although commodity price expansions may initially appear advantageous due to local currency appreciation, they also raise the potential for substantial depreciation in the future. This implies that precautionary measures should be considered during periods of sustained commodity price increases. Additionally, the findings highlight the risks of financing sustainable transitions through yield-seeking non-resident institutional investors, such as asset managers. This reinforces the importance of patient institutions, such as MDBs, which provide counter-cyclical lending, and it underscores the risks of relying on global institutional investors to assume financial risks.

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[48] Cerutti, Claessens and Puy (n 18); Kohler, Bonizzi and Kaltenbrunner (n 18); Onen, Shin and von Peter (n 18); de Paula, Fritz, Prates (n 8).

[49] L Nalin and GT Yajima, 'Commodities Fluctuations, Cross-Border Flows and Financial Innovation: A Stock-Flow Analysis' (2021) 72(3) *Metroeconomica* 539.

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Appendix: Data Description and Additional Estimation Results

A. Data Description

Table A-1 Data definitions and sources

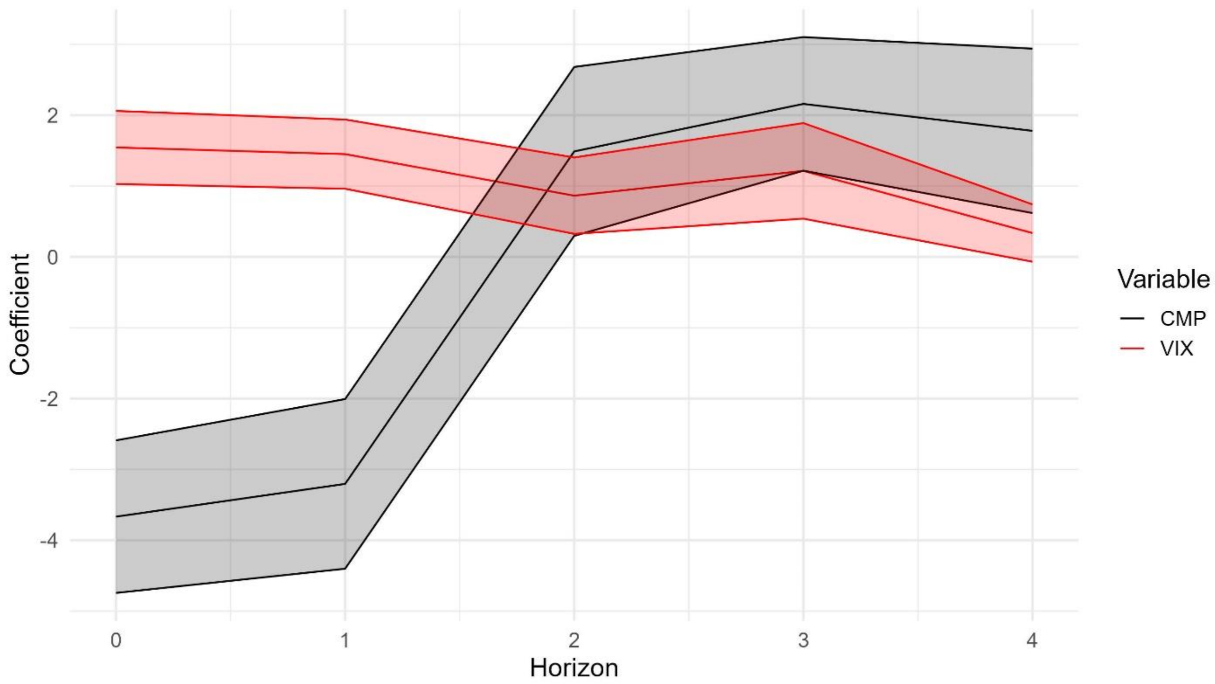
Variable	Definition	Description and unit	Source
BFI	Share of bank foreign investors	Share of government debt held by foreign banks. Percent.	Arslanalp and Tsuda (2014)*
CMEX_MED	The median share of commodities in total export	Share of commodities (food and beverages, fuels and lubricants, industrial supplies) of exports. Percent.	Feenstra and others (2015). Penn World Table.
CMP_EN	Energy commodity price index	Includes prices of coal, crude oil, natural gas. Natural log.	World Bank Commodity Price Data (The Pink Sheet)
CMP_EXP	Index with country-specific weights based on the share of commodities in total exports	Commodity Export Price Index, Individual Commodities Weighted by Ratio of Exports to Total Commodity Exports. Natural log.	International Monetary Fund (IMF)
CMP_IMP	Index with country-specific weights based on the share of commodities in total imports	Commodity Import Price Index, Individual Commodities Weighted by Ratio of Imports to Total Commodity Imports. Natural log.	International Monetary Fund (IMF)
CMP_NEN	Non-energy commodity price index	Includes agriculture, fertilizers and metals and minerals. Natural log.	World Bank Commodity Price Data (The Pink Sheet)
CMP	Commodity Price	Includes energy and non-energy commodities, and precious metals. Natural log.	World Bank Commodity Price Data (The Pink Sheet)
ECI	Economic Complexity Index	Na index based on how diversified and complex a country export basket is.	The Growth Lab at Harvard University. The Atlas of Economic Complexity
FI	Share of foreign investors	Share of government debt held by foreign investors (includes foreign banks, nonbanks, and official sector). Percent.	Arslanalp and Tsuda (2014)*
FX_RES	Foreign exchange reserves as a share of GDP	Foreign exchange reserves (minus gold) as a share of GDP	Lane and Milesi-Ferretti (2018)
INTDIFF	Interest rate difference	Difference between extrapolated deposit rate using policy rate and Federal Funds rate. The baseline level of domestic interest rate is given by the deposit rate level, which is extrapolated, when necessary, by the change in the policy rate. Percent.	International Financial Statistics (IFS), IMF. Board of Governors of the Federal Reserve System (US).
NBFI	Share of domestic government held by non-bank foreign investors	Share of government debt held by foreign nonbanks. Percent.	Arslanalp and Tsuda (2014)*
INFLDIFF	Difference in inflation	Difference in domestic and US inflation (Headline consumer price index). Percent.	World Bank. Jongrim and others (2023)

VIX	CBOE S&P 500 Volatility Index	VIX measures market expectation of near term volatility conveyed by stock index option prices. Natural log.	Chicago Board Options Exchange, CBOE Volatility Index: VIX, retrieved from FRED, Federal Reserve Bank of St. Louis
ΔXR_i	Quarterly rate of depreciation of the nominal USD dollar exchange rate of a currency i	Nominal US dollar exchange rate. Percent.	IMF-IFS

Source: International Monetary Fund (IMF), Version Updated on 15 December 2023 https://www.imf.org/~/media/Websites/IMF/imported-datasets/external/pubs/ft/wp/2014/Data/wp1439.ashx accessed 14 October 2024.

B. Additional estimation results

Figure B-1 Estimated coefficients on normalised CMP and normalised VIX, 95th percentile of nominal rate of depreciation



Notes: Estimated coefficients on normalised CMP and normalised VIX from panel quantile regressions with nominal rate of depreciation as dependent variable (in %), 95th quantile, with horizon $h = 0, \ldots, 4$. CMP and VIX are normalised to have zero mean and unit standard deviation. Regression includes control variables but excludes structural country characteristics (i.e. $\delta_\tau = \gamma_\tau = 0$ in equation 1). Confidence bands represent the 90% confidence interval based on bootstrapped standard errors. Number of observations: 7,586.

Table B-2 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 50th quantile

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.026***	-0.013**	-0.006*	-0.006	-0.011**
	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)
CMP x BUST	-0.07***	-0.025***	-0.001	0.013***	0.006
	(0.019)	(0.008)	(0.003)	(0.004)	(0.004)
L1.CMP x BOOM	0.021***	0.009**	0.004	0.003	0.007*
	(0.006)	(0.005)	(0.003)	(0.004)	(0.004)

Variable	h=0	h=1	h=2	h=3	h=4
L1.CMP x BUST	0.064***	0.021***	-0.002	-0.016***	-0.009**
	(0.019)	(0.008)	(0.003)	(0.005)	(0.004)
CMP X L1.NBFI x BOOM	0.000	0.000	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CMP x L1.NBFI x BUST	0.000**	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L1.NBFI x BOOM	-0.039	-0.054	-0.103	-0.138**	-0.128**
	(0.06)	(0.073)	(0.076)	(0.069)	(0.06)
L1.NBFI x BUST	-0.17**	-0.173**	-0.063	-0.047	-0.083
	(0.075)	(0.078)	(0.059)	(0.065)	(0.066)
L1.INFLDIFF x BOOM	0.01	0.000	0.000	0.000	0.000
	(0.013)	(0.001)	(0.001)	(0.001)	(0.002)
L1.INFLDIFF x BUST	0.014***	-0.002	-0.002	0.002	0.000
	(0.004)	(0.01)	(0.007)	(0.002)	(0.004)
L1.INTDIFF x BOOM	0.016	0.004	0.000	0.000	0.000
	(0.019)	(0.022)	(0.022)	(0.013)	(0.014)
L1.INTDIFF x BUST	0.04**	0.045***	0.046***	0.011	0.001
	(0.019)	(0.017)	(0.011)	(0.023)	(0.026)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 50th quantile, with horizon $h = 0, \ldots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,079.

Table B-3 Estimated coefficients from panel quantile regression of nominal rate of depreciation, energy commodity price index (CMP_EN)

Variable	h=0	h=1	h=2	h=3	h=4
CMP_EN x BOOM	-0.028	0.024	0.031	-0.023	-0.031
	(0.018)	(0.026)	(0.028)	(0.017)	(0.019)
CMP_EN x BUST	-0.206***	-0.047**	0.001	0.001	-0.015
	(0.024)	(0.022)	(0.015)	(0.011)	(0.013)
L1.CMP_EN x BOOM	0.006	-0.042*	-0.045*	0.009	0.016
	(0.018)	(0.024)	(0.027)	(0.015)	(0.018)
L1.CMP_EN x BUST	0.183***	0.031	-0.012	-0.016	0.000
	(0.021)	(0.021)	(0.015)	(0.011)	(0.012)
CMP_EN x NBFI x BOOM	0.001	0.001**	0.001**	0.001*	0.001**
	(0.000)	(0)	(0.001)	(0.000)	(0.000)
CMP_EN x NBFI x BUST	0.001	0.001**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
NBFI x BOOM	-0.275	-0.587***	-0.613**	-0.451**	-0.516**
	(0.214)	(0.223)	(0.279)	(0.205)	(0.211)
NBFI x BUST	-0.289*	-0.377**	-0.246	-0.164	-0.263
	(0.174)	(0.165)	(0.178)	(0.225)	(0.188)
L1.INFLDIFF x BOOM	0.118***	0.122***	0.022	-0.005	-0.005
	(0.016)	(0.014)	(0.044)	(0.038)	(0.044)
L1.INFLDIFF x BUST	0.045	0.087**	0.168**	0.006	0.018
	(0.081)	(0.044)	(0.074)	(0.058)	(0.023)
L1.INTDIFF x BOOM	0.001	-0.002	0.058	0.099***	0.119***
	(0.154)	(0.075)	(0.084)	(0.033)	(0.036)
L1.INTDIFF x BUST	0.027	0.009	-0.007	0.086	0.078

Variable	h=0	h=1	h=2	h=3	h=4
	(0.194)	(0.164)	(0.183)	(0.112)	(0.057)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \ldots, 4$. Estimated coefficients are allowed to differ depending on whether energy commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,079.

Table B-4 Estimated coefficients from panel quantile regression of nominal rate of depreciation, non-energy commodity price index (CMP_NEN)

Variable	h=0	h=1	h=2	h=3	h=4
CMP_NEN x BOOM	-0.052**	-0.096*	0.18	-0.056	-0.04
	(0.026)	(0.058)	(0.118)	(0.051)	(0.048)
CMP_NEN x BUST	-0.571***	-0.23***	-0.071	0.027	0.005
	(0.101)	(0.074)	(0.086)	(0.024)	(0.033)
L1.CMP_NEN x BOOM	0.018	0.08	-0.199*	0.044	0.032
	(0.025)	(0.061)	(0.118)	(0.054)	(0.049)
L1.CMP_NEN x BUST	0.537***	0.211***	0.053	-0.039**	-0.012
	(0.097)	(0.073)	(0.086)	(0.02)	(0.029)
CMP_NEN x NBFI x BOOM	0.002***	0.002**	0.002***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CMP_NEN x NBFI x BUST	-0.002	0.001	0.001	0.001	0.002**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
NBFI x BOOM	-0.681***	-0.684**	-1.02***	-0.649	-0.574
	(0.262)	(0.28)	(0.327)	(0.479)	(0.352)
NBFI x BUST	0.945	-0.507	-0.323	-0.477	-0.76**
	(0.94)	(0.554)	(0.42)	(0.351)	(0.321)
L1.INFLDIFF x BOOM	0.118**	0.037	0.081	-0.007	0.019
	(0.052)	(0.043)	(0.059)	(0.045)	(0.035)

Variable	h=0	h=1	h=2	h=3	h=4
L1.INFLDIFF x BUST	0.039	0.112***	0.019	-0.001	-0.006
	(0.045)	(0.029)	(0.076)	(0.041)	(0.058)
L1.INTDIFF x BOOM	0.001	0.043	0.019	0.094***	0.078***
	(0.115)	(0.11)	(0.079)	(0.036)	(0.026)
L1.INTDIFF x BUST	0.162	0.16	0.12	0.095	0.199
	(0.239)	(0.179)	(0.145)	(0.109)	(0.154)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \ldots, 4$. Estimated coefficients are allowed to differ depending on whether non-energy commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,079.

Table B-5 Estimated coefficients from panel quantile regression of nominal rate of depreciation, median economic complexity index (ECI_MED)

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.054**	-0.003	0.068	0.101*	-0.02
	(0.026)	(0.023)	(0.042)	(0.055)	(0.033)
CMP x BUST	-0.288***	-0.104	0.055	0.026	0.046**
	(0.046)	(0.064)	(0.041)	(0.017)	(0.022)
L1.CMP x BOOM	0.031	-0.007	-0.068*	-0.105*	0.019
	(0.024)	(0.022)	(0.04)	(0.056)	(0.031)
L1.CMP x BUST	0.267***	0.103	-0.049	-0.03*	-0.046**
	(0.045)	(0.063)	(0.04)	(0.017)	(0.02)
CMP X ECI_MED x BOOM	0.003	0.008	0.006	-0.007	0.001
	(0.008)	(0.006)	(0.009)	(0.012)	(0.013)
CMP x ECI_MED x BUST	0.01	0.027	0.018	0.022	0.023
	(0.013)	(0.018)	(0.018)	(0.016)	(0.017)
ECI_MED x BOOM	-0.338	-2.847	-1.279	3.736	-0.231

Variable	h=0	h=1	h=2	h=3	h=4
	(3.592)	(2.614)	(3.789)	(5.074)	(5.84)
ECI_MED x BUST	-1.696	-8.597	-7.621	-9.061	-8.938
	(5.542)	(7.7)	(7.497)	(6.911)	(7.344)
L1.INFLDIFF x BOOM	0.089**	0.106***	0.187***	-0.005	-0.005
	(0.04)	(0.028)	(0.035)	(0.005)	(0.006)
L1.INFLDIFF x BUST	-0.007	-0.002	0.002	0.002	0.017
	(0.153)	(0.083)	(0.061)	(0.093)	(0.058)
L1.INTDIFF x BOOM	0.451***	0.273***	0.223**	0.182***	0.126**
	(0.14)	(0.083)	(0.113)	(0.065)	(0.062)
L1.INTDIFF x BUST	0.624***	0.576***	0.409	0.405*	0.359*
	(0.195)	(0.174)	(0.271)	(0.22)	(0.199)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \ldots, 4$. Estimated coefficients are allowed to differ depending on whether non-energy commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 5,659.

Table B-6 Estimated coefficients from panel quantile regression of nominal rate of depreciation, export-share weighted commodity price index (CMP_EXP)

Variable	h=0	h=1	h=2	h=3	h=4
CMP_EXP x BOOM	-0.036	-0.013	-0.025	-0.059*	-0.091**
	(0.039)	(0.022)	(0.022)	(0.036)	(0.042)
CMP_EXP x BUST	-0.339***	-0.201***	-0.092	0.02	-0.006
	(0.062)	(0.053)	(0.07)	(0.024)	(0.02)
L1.CMP_EXP x BOOM	-0.008	-0.02	-0.012	0.021	0.056
	(0.038)	(0.026)	(0.025)	(0.031)	(0.042)
L1.CMP_EXP x BUST	0.294***	0.17***	0.056	-0.058**	-0.029

Variable	h=0	h=1	h=2	h=3	h=4
	(0.059)	(0.051)	(0.072)	(0.027)	(0.019)
CMP_EXP x NBFI x BOOM	0.002**	0.002***	0.002***	0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CMP_EXP x NBFI x BUST	0	0.001	0.002**	0.002*	0.002**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
NBFI x BOOM	-0.689**	-1***	-1.144***	-1.272***	-0.868**
	(0.296)	(0.326)	(0.366)	(0.41)	(0.4)
NBFI x BUST	0.196	-0.4	-0.799**	-0.741**	-0.796**
	(0.745)	(0.678)	(0.367)	(0.358)	(0.311)
L1.INFLDIFF x BOOM	0.119***	0.122***	0.021	-0.005	-0.004
	(0.019)	(0.012)	(0.049)	(0.034)	(0.017)
L1.INFLDIFF x BUST	0.112	0.102	0.096	0.024	0.016
	(0.096)	(0.072)	(0.063)	(0.056)	(0.058)
L1.INTDIFF x BOOM	0.001	0.001	0.059	0.09***	0.06***
	(0.158)	(0.092)	(0.087)	(0.026)	(0.022)
L1.INTDIFF x BUST	0.085	0.173	0.042	0.121	0.137
	(0.188)	(0.201)	(0.157)	(0.092)	(0.123)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \ldots, 4$. Estimated coefficients are allowed to differ depending on whether export-share weighted commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,043.

Table B-7 Estimated coefficients from panel quantile regression of nominal rate of depreciation, import-share weighted commodity price index (CMP_IMP)

Variable	h=0	h=1	h=2	h=3	h=4
CMP_IMP x BOOM	-0.047*	0.009	0.05	0.006	-0.038
	(0.027)	(0.025)	(0.041)	(0.039)	(0.025)

Variable	h=0	h=1	h=2	h=3	h=4
CMP_IMP x BUST	-0.259***	-0.07	-0.017	0.006	0.005
	(0.043)	(0.047)	(0.047)	(0.01)	(0.013)
L1.CMP_IMP x BOOM	0.005	-0.037	-0.072*	-0.025	0.019
	(0.023)	(0.023)	(0.041)	(0.039)	(0.022)
L1.CMP_IMP x BUST	0.219***	0.049	-0.002	-0.025***	-0.024*
	(0.041)	(0.045)	(0.047)	(0.01)	(0.013)
CMP_IMP x NBFI x BOOM	0.002***	0.002***	0.003***	0.002**	0.001
	(0)	(0)	(0.001)	(0.001)	(0.001)
CMP_IMP x NBFI x BUST	-0.001	0.002	0.001	0.001*	0.001
	(0.001)	(0.002)	(0.001)	(0)	(0.001)
NBFI x BOOM	-0.717***	-0.705***	-1.181***	-0.852**	-0.718*
	(0.222)	(0.216)	(0.306)	(0.365)	(0.392)
NBFI x BUST	0.566	-0.674	-0.302	-0.417**	-0.344
	(0.517)	(0.741)	(0.314)	(0.209)	(0.27)
L1.INFLDIFF x BOOM	0.119***	0.122***	0.073	-0.004	-0.006
	(0.02)	(0.03)	(0.065)	(0.056)	(0.062)
L1.INFLDIFF x BUST	0.035	0.045	0.089	0.012	0.018**
	(0.083)	(0.067)	(0.069)	(0.04)	(0.008)
L1.INTDIFF x BOOM	0.001	-0.002	0.019	0.099**	0.121***
	(0.124)	(0.05)	(0.087)	(0.047)	(0.045)
L1.INTDIFF x BUST	0.029	0.029	0.023	0.08	0.077
	(0.208)	(0.238)	(0.177)	(0.088)	(0.095)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \ldots, 4$. Estimated coefficients are allowed to differ depending on whether import-share weighted commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,043.

Table B-8 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, combined share of foreign investors (FI)

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.043**	0.033	0.095*	0.047	-0.016
	(0.02)	(0.022)	(0.051)	(0.049)	(0.021)
CMP x BUST	-0.234***	-0.03	0.033	0.012	0.017
	(0.037)	(0.046)	(0.051)	(0.015)	(0.015)
L1.CMP x BOOM	0.016	-0.051**	-0.11**	-0.063	0.001
	(0.019)	(0.022)	(0.051)	(0.048)	(0.02)
L1.CMP x BUST	0.209***	0.021	-0.042	-0.027*	-0.03**
	(0.036)	(0.044)	(0.051)	(0.015)	(0.013)
CMP X L1.FI x BOOM	0.001*	0.001***	0.001**	0.001*	0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
CMP x L1.FI x BUST	-0.001	-0.001	0.000	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0)	(0.001)
L1.FI x BOOM	-0.428*	-0.464***	-0.549**	-0.69*	-0.399
	(0.241)	(0.165)	(0.247)	(0.377)	(0.344)
L1.FI x BUST	0.477	0.558	-0.076	0	-0.211
	(0.588)	(0.714)	(0.51)	(0.174)	(0.222)
L1.INFLDIFF x BOOM	0.118***	0.122***	0.056	-0.004	-0.005
	(0.018)	(0.015)	(0.065)	(0.032)	(0.04)
L1.INFLDIFF x BUST	0.083	0.052	0.125**	0.077	0.03
	(0.091)	(0.074)	(0.063)	(0.056)	(0.036)
L1.INTDIFF x BOOM	0.002	-0.001	0.034	0.1***	0.122***
	(0.146)	(0.068)	(0.099)	(0.031)	(0.033)
L1.INTDIFF x BUST	0.019	0.02	0.000	0.037	0.071

Variable	h=0	h=1	h=2	h=3	h=4
	(0.181)	(0.204)	(0.193)	(0.127)	(0.115)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \dots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,079.

Table B-9 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, share of bank foreign investors (BFI)

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.036*	0.043*	0.103**	0.083*	-0.011
	(0.021)	(0.025)	(0.051)	(0.047)	(0.023)
CMP x BUST	-0.26***	-0.043	0.038	0.026**	0.026
	(0.038)	(0.043)	(0.045)	(0.013)	(0.018)
L1.CMP x BOOM	0.019	-0.051**	-0.107**	-0.089*	0.008
	(0.02)	(0.025)	(0.051)	(0.047)	(0.022)
L1.CMP x BUST	0.244***	0.042	-0.038	-0.031***	-0.028*
	(0.038)	(0.042)	(0.045)	(0.012)	(0.016)
CMP X L1.BFI x BOOM	-0.004	-0.003	-0.003	-0.007	-0.008
	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
CMP x L1.BFI x BUST	-0.016***	-0.016***	-0.016**	-0.009	-0.011
	(0.005)	(0.005)	(0.007)	(0.006)	(0.007)
L1.FI x BOOM	1.983	1.446	1.619	3.099	3.503
	(2.338)	(2.503)	(2.993)	(3.298)	(3.112)
L1.FI x BUST	7.651***	7.199***	7.702**	4.412	4.907
	(2.424)	(2.54)	(3.2)	(2.94)	(3.392)
L1.INFLDIFF x BOOM	0.119***	0.123***	0.043	-0.004	-0.002
	(0.016)	(0.014)	(0.063)	(0.031)	(0.037)
L1.INFLDIFF x BUST	0.078	0.027	0.068	0.082	0.028

Variable	h=0	h=1	h=2	h=3	h=4
	(0.095)	(0.065)	(0.057)	(0.055)	(0.035)
L1.INTDIFF x BOOM	-0.003	-0.003	0.04	0.092***	0.111***
	(0.136)	(0.066)	(0.09)	(0.033)	(0.033)
L1.INTDIFF x BUST	0.009	0.026	0.01	0.028	0.065
	(0.171)	(0.171)	(0.141)	(0.125)	(0.122)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \dots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,079.

Table B-10 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, VIX and median share of non-bank foreign investors (NBFI_MED)

Variable	h=0	h=1	h=2	h=3	h=4
VIX	0.074***	0.056***	0.02**	0.026**	0.015
	(0.014)	(0.016)	(0.009)	(0.012)	(0.01)
L1.VIX	-0.032***	-0.027**	0.008	0.001	0.004
	(0.009)	(0.012)	(0.009)	(0.008)	(0.007)
VIX x NBFI_MED	0.001	-0.001	-0.001	-0.001	0
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NBFI_MED	-0.154	0.318*	0.378**	0.399**	0.174
	(0.295)	(0.189)	(0.161)	(0.191)	(0.167)
L1.INFLDIFF	0.119***	0.122***	0.195***	0.037	-0.005
	(0.032)	(0.017)	(0.038)	(0.038)	(0.041)
L1.INTDIFF	0.014	0.004	-0.01	0.059	0.101*
	(0.164)	(0.135)	(0.095)	(0.095)	(0.056)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \dots, 4$ (see equation 1). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Number of observations: 7,079.

C. Robustness tests

Table C-11 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, sample start 2000Q1

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.056**	0.033	0.155***	0.095*	0.006
	(0.023)	(0.025)	(0.054)	(0.051)	(0.036)
CMP x BUST	-0.283***	-0.177***	-0.075	0.004	0.005
	(0.044)	(0.062)	(0.047)	(0.02)	(0.013)
L1.CMP x BOOM	0.046**	-0.037	-0.145***	-0.086*	0.001
	(0.023)	(0.024)	(0.052)	(0.052)	(0.036)
L1.CMP x BUST	0.271***	0.174***	0.087*	0.003	0.001
	(0.043)	(0.061)	(0.046)	(0.02)	(0.011)
CMP X L1.NBFI x BOOM	0.001*	0.001	0.001	0.002*	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
CMP x L1.NBFI x BUST	0.001	0.003***	0.002**	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
L1.NBFI x BOOM	-0.247	-0.282	-0.218	-0.676*	-0.457
	(0.16)	(0.215)	(0.311)	(0.365)	(0.433)
L1.NBFI x BUST	-0.393	-1.084***	-0.714**	-0.01	-0.294
	(0.376)	(0.41)	(0.326)	(0.192)	(0.323)
L1.INFLDIFF x BOOM	0.229**	0.097***	0.126***	0.04	0.024
	(0.089)	(0.033)	(0.044)	(0.036)	(0.025)
L1.INFLDIFF x BUST	0.218**	0.225***	0.024	0.015	-0.037
	(0.1)	(0.076)	(0.051)	(0.037)	(0.032)
L1.INTDIFF x BOOM	0.354***	0.258***	0.196*	0.053	0.05
	(0.127)	(0.084)	(0.103)	(0.073)	(0.081)
L1.INTDIFF x BUST	0.42***	0.384**	0.256**	0.192**	0.278***
	(0.126)	(0.154)	(0.116)	(0.095)	(0.103)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \dots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Sample start was set to 2000Q1. Number of observations: 5,939.

Table C-12 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, sample end 2019Q4

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.086**	-0.019	0.139**	0.069	-0.048
	(0.034)	(0.028)	(0.065)	(0.061)	(0.035)
CMP x BUST	-0.283***	-0.058	-0.007	0.015	0.012
	(0.044)	(0.063)	(0.057)	(0.017)	(0.016)
L1.CMP x BOOM	0.051*	-0.005	-0.159**	-0.088	0.032
	(0.03)	(0.027)	(0.063)	(0.06)	(0.036)
L1.CMP x BUST	0.248***	0.044	-0.007	-0.031*	-0.026*
	(0.042)	(0.061)	(0.057)	(0.016)	(0.014)
CMP X L1.NBFI x BOOM	0.001*	0.001***	0.002**	0.002**	0.001
	(0.001)	(0)	(0.001)	(0.001)	(0.001)
CMP x L1.NBFI x BUST	-0.001	-0.001	0.001	0	0.001**
	(0.002)	(0.002)	(0.001)	(0)	(0)
L1.NBFI x BOOM	-0.421*	-0.538***	-0.762**	-0.796**	-0.571*
	(0.23)	(0.177)	(0.305)	(0.32)	(0.325)
L1.NBFI x BUST	0.713	0.317	-0.357	-0.184	-0.594***
	(0.796)	(0.701)	(0.508)	(0.195)	(0.2)
L1.INFLDIFF x BOOM	0.118***	0.122***	0.056	-0.004	-0.005
	(0.017)	(0.011)	(0.06)	(0.035)	(0.039)
L1.INFLDIFF x BUST	0.111	0.033	0.123*	0.066	0.021
	(0.103)	(0.073)	(0.063)	(0.062)	(0.04)
L1.INTDIFF x BOOM	0	-0.002	0.034	0.099***	0.12***

Variable	h=0	h=1	h=2	h=3	h=4
	(0.128)	(0.07)	(0.069)	(0.032)	(0.031)
L1.INTDIFF x BUST	0.014	0.03	0	0.043	0.076
	(0.172)	(0.203)	(0.151)	(0.117)	(0.135)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \dots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Sample start was set to 2000Q1. Number of observations: 6,388.

Table C-13 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, λ=0.5

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.043**	0.032	0.076	0.037	-0.018
	(0.021)	(0.021)	(0.052)	(0.043)	(0.023)
CMP x BUST	-0.229***	-0.017	0.005	0.019	0.02
	(0.036)	(0.051)	(0.051)	(0.012)	(0.015)
L1.CMP x BOOM	0.015	-0.05**	-0.092*	-0.054	0.002
	(0.019)	(0.021)	(0.051)	(0.042)	(0.022)
L1.CMP x BUST	0.203***	0.009	-0.016	-0.034***	-0.034***
	(0.035)	(0.048)	(0.05)	(0.012)	(0.013)
CMP X L1.NBFI x BOOM	0.001***	0.001***	0.001**	0.002***	0.001*
	(0)	(0)	(0.001)	(0.001)	(0.001)
CMP x L1.NBFI x BUST	-0.001	-0.001	0.001	0	0.001
	(0.001)	(0.001)	(0.001)	(0)	(0)
L1.NBFI x BOOM	-0.486***	-0.523***	-0.686**	-0.782***	-0.647*
	(0.171)	(0.17)	(0.29)	(0.27)	(0.334)
L1.NBFI x BUST	0.446	0.325	-0.318	-0.136	-0.316
	(0.469)	(0.613)	(0.448)	(0.16)	(0.209)
L1.INFLDIFF x BOOM	0.118***	0.122***	0.022	-0.004	-0.005

Variable	h=0	h=1	h=2	h=3	h=4
	(0.017)	(0.017)	(0.062)	(0.03)	(0.043)
L1.INFLDIFF x BUST	0.087	0.035	0.123*	0.066	0.02
	(0.094)	(0.069)	(0.067)	(0.049)	(0.036)
L1.INTDIFF x BOOM	0.001	-0.002	0.056	0.099***	0.12***
	(0.127)	(0.072)	(0.075)	(0.024)	(0.035)
L1.INTDIFF x BUST	0.019	0.029	0	0.044	0.076
	(0.182)	(0.208)	(0.165)	(0.093)	(0.135)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95th quantile, with horizon $h = 0, \dots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Shrinkage parameter was set to $\lambda = 0.5$. Number of observations: 7,079.

Table C-14 Estimated coefficients from panel quantile regression of nominal rate of depreciation, 95th quantile, Canay (2011) estimator

Variable	h=0	h=1	h=2	h=3	h=4
CMP x BOOM	-0.148**	0.011	0.127	0.161**	0.139*
	(0.054)	(0.051)	(0.221)	(0.073)	(0.063)
CMP x BUST	-0.289***	-0.207*	0.021	0.058	0.027
	(0.062)	(0.083)	(0.464)	(0.055)	(0.045)
L1.CMP x BOOM	0.116*	-0.031	-0.154	-0.179**	-0.161**
	(0.049)	(0.049)	(0.261)	(0.077)	(0.063)
L1.CMP x BUST	0.255***	0.193	-0.041	-0.068	-0.046
	(0.057)	(0.079)	(0.521)	(0.06)	(0.046)
CMP X L1.NBFI x BOOM	0.002	0.003*	0.001	0.003**	0.003**
	(0.001)	(0.001)	(0.051)	(0.001)	(0.001)
CMP x L1.NBFI x BUST	0.001	0.002	0	0	0.001
	(0.002)	(0.002)	(0.036)	(0.001)	(0.001)
L1.NBFI x BOOM	-0.778	-1.157*	-0.207	-1.366**	-1.387**
	(0.553)	(0.606)	(24.16)	(0.562)	(0.567)
L1.NBFI x BUST	-0.303	-0.757	0.249	-0.096	-0.483
	(0.699)	(0.727)	(19.182)	(0.595)	(0.456)
L1.INFLDIFF x BOOM	0.14	0.136***	0.092	0.113*	0.071*
	(0.107)	(0.038)	(3.689)	(0.054)	(0.039)
L1.INFLDIFF x BUST	0.212	0.096	0.148	0.117*	0.127
	(0.124)	(0.097)	(0.848)	(0.062)	(0.095)
L1.INTDIFF x BOOM	-0.015	-0.014	0.021	0.014	0.051
	(0.211)	(0.188)	(6.245)	(0.156)	(0.091)
L1.INTDIFF x BUST	-0.014	-0.001	0.003	0.011	0.011
	(0.236)	(0.247)	(2.633)	(0.277)	(0.227)

Notes: Estimated coefficients from panel quantile regression of nominal rate of depreciation (in %), 95^{th} quantile, with horizon $h = 0, \dots, 4$. Estimated coefficients are allowed to differ depending on whether commodity prices are in a boom or bust (see equation 2). Bootstrapped standard errors in parentheses. *, **, and ***, indicate 10%, 5%, and 1% level of statistical significance, respectively. Based on Canay's (2011) fixed effects panel quantile estimator that allows for individual fixed effects for all countries but assumes that the fixed effects are invariant across quantiles. Number of observations: 7,079.