UNIVERSITY OF CAMBRIDGE
Faculty of Economics

JANEWAY INSTITUTE CAMBRIDGE

CAMBRIDGE WORKING PAPERS IN ECONOMICS
JANEWAY INSTITUTE WORKING PAPERS

Tails of Foreign Exchange-at-Risk (FEaR)

Daniel A. Ostry
University of Cambridge

Abstract

I build a model in which speculators unwind carry trades and hedgers fly to relatively liquid U.S. Treasuries during global financial disasters. The net effect of these flows produces an amplified U.S. dollar appreciation against high-yield currencies in disasters and a dampened depreciation, or even an appreciation, against low-yield ones. I verify this prediction by examining deviations from uncovered interest parity (UIP) within a novel quantile-regression framework. In the tail quantiles, I show that interest differentials predict high-yield currencies to suffer depreciations ten times as large as suggested by UIP, while spikes in Treasury liquidity premia meaningfully appreciate the dollar regardless of the U.S. relative interest rate. A complementary analysis of speculators' and hedgers' currency futures positions substantiates my model's mechanism and highlights that hedging agents imbue the U.S. dollar with its unique safe-haven status.

Reference Details

2343	Cambridge Working Papers in Economics
2311	Janeway Institute Working Paper Series
Published	7 June 2023
Revised	16 July 2023
Keywords	Exchange Rates, Disaster Risk, U.S. Safety, Liquidity Yields, Quantile Regression
JEL-codes	C22, F31, G15
Websites	www.econ.cam.ac.uk/cwpe www.janeway.econ.cam.ac.uk/working-papers

Tails of Foreign Exchange-at-Risk (FEaR)*

Daniel A. Ostry†

July 16, 2023

Abstract

I build a model in which speculators unwind carry trades and hedgers fly to relatively liquid U.S. Treasuries during global financial disasters. The net effect of these flows produces an amplified U.S. dollar appreciation against high-yield currencies in disasters and a dampened depreciation, or even an appreciation, against low-yield ones. I verify this prediction by examining deviations from uncovered interest parity (UIP) within a novel quantile-regression framework. In the tail quantiles, I show that interest differentials predict high-yield currencies to suffer depreciations ten times as large as suggested by UIP, while spikes in Treasury liquidity premia meaningfully appreciate the dollar regardless of the U.S. relative interest rate. A complementary analysis of speculators' and hedgers' currency futures positions substantiates my model's mechanism and highlights that hedging agents imbue the U.S. dollar with its unique safe-haven status.

Key Words: Exchange Rates, Disaster Risk, U.S. Safety, Liquidity Yields, Quantile Regression.
JEL Codes: C22; F31; G15.

*I am very grateful to Giancarlo Corsetti and Simon Lloyd for their guidance and support, as well as to Barbara Rossi (discussant), Balduin Bippus, Vasco Carvalho, Ambrogio Cesa-Bianchi, Nuno Coimbra, Rustam Jamilov, Seung Jung Lee, Benjamin Knox, Niklas Kroner, Karen Lewis, Sai Ma, Emile Marin, Dmitry Mukhin, Hélène Rey, Tim Schmidt-Eisenlohr, Vania Stavrakeva, Liliana Varela, Tony Zhang and seminar participants at the 2023 BoE-CfM-EUI-LSE Workshop on International Macroeconomics and Finance, 2022 EEA, 2022 FMND, University of Cambridge, Federal Reserve Board and Bank of England for useful comments and discussion. I am also thankful to the Cambridge Endowment for Research in Finance (CERF) for recognizing this paper with the 2021 Cambridge Finance Best Student Paper Award. First Draft: May 31, 2021.

†University of Cambridge. Email Address: dao33@cam.ac.uk.

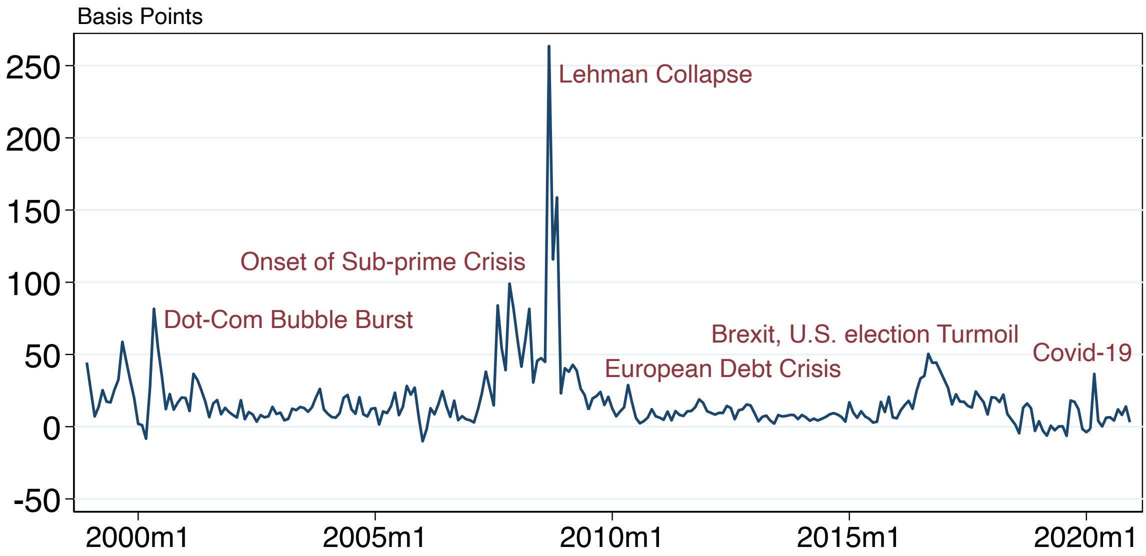
1 Introduction

Beginning with Rietz (1988) and Barro (2006), models with rare disasters have been used to explain a wide array of anomalies in macro-finance, including numerous exchange rate puzzles. From this research have emerged two competing theories of exchange rates during global disasters. The first is that the U.S. is special in the international system due the relative safety of its assets, and so the U.S. dollar appreciates against all other currencies in crisis times (e.g. Gourinchas, Rey, and Govillot, 2010; Maggiori, 2017). The second is that interest rate differentials reflect countries' relative exposure to disaster risk, and so high-interest-rate currencies suffer large depreciations in disasters (e.g., Brunnermeier, Nagel, and Pedersen, 2009; Farhi and Gabaix, 2016). Since the U.S. tends not to have the lowest interest rate among advanced economies—e.g., relative to Japan, Switzerland and Germany—these two theories often make divergent predictions for the U.S. dollar exchange rate during periods of global financial stress. Moreover, recent models that feature safe dollar assets overlook the role of relative interest rates, which obscures the extent and the source of the U.S. dollar's safe-haven status.

In this paper, I unify the two competing theories by showing that exchange rate dynamics in disasters reflect currency flows by two distinct types of financial agent: speculators and hedgers. While speculators' flows push high-yield currencies to depreciate in disasters—consistent with the theory centered on relative interest rates—I uncover that it is hedging agents' flight to liquid U.S. dollar assets that is responsible for the dollar's unique tendency to appreciate in disasters. Together, these flows imply a significant asymmetry between the dollar's exchange-rate dynamics in disasters against high-interest-rate and low-interest-rate currencies. Using a novel quantile-regression framework, I then estimate the explanatory power of interest differentials and U.S. safe-asset demand for disaster-state exchange-rate movements. I find that while high-interest-rate currencies are predicted to suffer depreciations *ten times as large* as suggested by uncovered interest parity (UIP) in disasters, Treasury liquidity premia also play a quantitatively important role in explaining the dollar's disaster-state exchange rate. Finally, applying the quantile-regression approach to speculators' and hedgers' currency futures positions reveals that their flows in disasters can indeed reconcile disaster-state exchange rate movements.

I begin by building a model that features two types of financial agent—speculators and hedgers—and makes testable predictions for exchange rate dynamics during global financial disasters. In normal times, as in Gabaix and Maggiori (2015), speculators intermediate capital flows between the U.S. and the foreign country by performing the carry trade, i.e., by taking long positions in the high-interest-rate country's bond financed by shorting the low-interest-

Figure 1: Time Series of Average 3-Month U.S. Treasury Liquidity Yield



Note. Figure 1 reports the time series of annualized 3-month U.S. Treasury liquidity yields, measured as the deviation from covered interest parity (CIP) from government bonds, as an average across G10 currencies (AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, relative to the USD) from 1998:M12 (when the EUR series becomes available) until 2020:M12, using data from Du, Im, and Schreger, 2018a. Annotated in red are major events surrounding the 6 largest episodes of elevated Treasury liquidity yields over this period.

rate country's bond. Hedgers, on the other hand, earn a non-pecuniary liquidity yield from hedging their exposure to risky foreign assets with the global reserve asset—the U.S. dollar bond.[1] Disasters are characterized by a severe disruption in funding markets (Brunnermeier et al., 2009) and an increase in the perceived quality—liquidity and safety—of the reserve asset (Jiang, Krishnamurthy, and Lustig (2021) and see Figure 1). As a result of the funding market disruption, speculators are forced to deleverage in disasters by unwinding carry trades, which pushes the high-interest-rate currency to suffer a large depreciation relative to the low-interest-rate one. In addition, the spike in the liquidity of the reserve asset induces a flight to the U.S. dollar bond by hedgers, which generates a unique tendency for the dollar to appreciate in the disaster. In all, when the U.S. interest rate is relatively low, the unwinding of carry trades by speculators and the flight to dollar liquidity by hedgers reinforce each other, leading to an amplified appreciation of the dollar in disasters. Conversely, when the U.S. interest rate is relatively high, the dollar experiences a dampened depreciation, or may even appreciate, in a disaster, since portfolio adjustments by speculators and hedgers partially offset each other. The relative magnitude of these two flows is an empirical question, which I tackle below.

[1] Speculators are typically large institutional investors such as commercial banks, investment banks, hedge funds and pension funds. Hedgers are financial institutions who hedge currency mismatch on their balance sheets.

The model makes several testable predictions for exchange rate dynamics. First, due to the possibility of a rare disaster, exchange rate dynamics are state-dependent. Second, high-interest-rate currencies suffer depreciations in disasters that (a) are increasing in the size of the interest rate differential and (b) may be larger than the interest rate differential, implying losses on the carry trade for speculators. Third, spikes in the Treasury liquidity yield appreciate the dollar in disasters, regardless of the U.S. relative interest rate. As a result, the dollar experiences an amplified appreciation against high-yield currencies in disasters and a dampened depreciation, or sometimes may even appreciate, against low-yield ones. Turning now to quantities, speculators perform the carry trade in normal times and unwind carry trades in disasters, with both of these proportional to the size of interest differentials. Further, hedgers' flight to the dollar in disasters is proportional to the rise in the U.S. Treasury liquidity yield. Finally, in normal times, (a) high-yield currencies excessively appreciate relative to interest differentials and (b) the dollar has a unique tendency to depreciate, both of which compensate speculators for their exposure to disaster risk. This latter prediction can rationalize the puzzling size of the dollar's risk premium (Lustig, Roussanov, and Verdelhan, 2014).

The empirical strategy I use to evaluate these predictions rests on what I term the 'signed quantile UIP regression', a novel approach to modelling tail exchange rate movements that is crucial to properly assess dynamics in disasters. To start, the approach modifies the UIP regression (Fama, 1984) to account for two key features of exchange rate dynamics in the data that arise from speculators' behavior in my model: (i) state-dependence (disasters versus normal times) and (ii) symmetry (between high- and low- interest-rate currencies). First, since speculator carry trades in normal times imply mild exchange rate movements—which manifest at the center of the exchange rate change distribution—while their carry trade unwindings in disasters lead to extreme swings in exchange rates that manifest in the distribution's tails, I flexibly allow for state-dependence by estimating the UIP relationship using quantile regression. Second, since speculator behavior implies that high- (low-) interest-rate currencies mildly appreciate (depreciate) in normal times but suffer large depreciations (appreciations) in disasters, I account for this symmetry by interacting each term in the quantile UIP regression with the sign of the interest differential. This interaction transposes exchange rate movements about the vertical axis when interest differentials are negative (i.e., when the sign is -1) and so groups together the depreciations of high-yield currencies and the appreciations of low-yield currencies—which are two sides of the same coin in the context of speculator carry trading in my model. Importantly, interacting the interest differential also with its sign ensures the regression coefficients from the signed quantile UIP regression still estimate the marginal effect of relative interest rates on exchange rate movements, as in the standard UIP regression, but at the quantiles of the conditional 'signed' distribution of exchange rate movements.

In particular, the left tail of the 'signed' distribution of exchange rate movements holds the largest depreciations of high-yield currencies and the largest appreciations of low-yield currencies, that is, the exchange rate movements that, in my model, are driven by speculators' unwinding of carry trades in disasters. Therefore, the conditional 1^{st} percentile of this distribution, which I term 'speculator's Foreign Exchange-at-Risk' (FEaR^{S}), serves as my baseline measure of exchange rate movements in disasters. On the other hand, the right tail of this signed distribution holds all large depreciations (appreciations) of low- (high-) yield currencies. As I discuss in detail shortly, because hedgers' flight to liquidity can push the dollar to appreciate in disasters even when it has a relatively high interest rate, I refer to the 99^{th} percentile of the distribution as 'hedger's Foreign Exchange-at-Risk' (FEaR^{H}).[2]

I begin by estimating signed quantile UIP regressions using a sample of G-10 currencies to assess the elasticity of exchange rate movements to interest rate differentials both inside and outside of disaster periods. I find that while high-yield currencies are predicted to mildly appreciate at the *median*, my empirical proxy for normal times, they suffer large depreciations at the FEaR^{S}, that is, in disasters. Specifically, I estimate that a 1 percentage point (pp) wider interest differential between the U.S. and a second G-10 currency area predicts a 1 pp greater appreciation of the high-yield currency conditional on no-disaster but a 10 pp larger depreciation of the high-yield currency in disasters. The elasticities are similar for the other 9 currencies in my sample and imply mild profits in normal times and large losses in disasters for speculators performing the carry trade.

Next, I build on the signed quantile UIP approach in two ways. First, I augment the regression with the change in the U.S. Treasury liquidity yield, using data from Du, Im, and Schreger (2018a). I show that a rise in the U.S. Treasury liquidity yield predicts a significant appreciation of the dollar in <u>both</u> tails of the signed exchange rate change distribution, regardless of the U.S.'s relative interest rate. Importantly, unlike for the interest differential, whose effects hold across all currencies in my sample, this liquidity yield channel appears unique to the U.S. dollar exchange rate. Quantitatively, I find that a 75 basis point rise in the Treasury liquidity yield, which corresponds to the spike during the bursting of the "Dot-Com" bubble in 2000 (see Figure 1), predicts a dollar appreciation of up to 3 percent.

The structure imposed by the signed quantile UIP approach helps interpret the net effect of interest differentials and liquidity yields on exchange rates in each tail. When the U.S. interest

[2] Of course, the right-tail also holds large depreciations of low-yield currencies.

rate is relatively low, spikes in the Treasury liquidity yield reinforce the interest-differential channel, generating an amplified appreciation of the low-yield dollar in disasters. Thus, disaster dynamics remain in the left-tail. On the other hand, when the U.S. interest rate is relatively high, the two channels partially offset each other, leading to two cases. When the interest-rate channel dominates, the high-yield dollar's depreciation in disasters is dampened, but the dynamics remain in the left tail. Conversely, when the liquidity-yield force dominates, the high-yield dollar appreciates in the disaster, which pushes the disaster dynamics into the right tail. Overall, this points to a fundamental asymmetry between the dollar's exchange-rate dynamics in disasters against high-interest-rate and low-interest-rate currencies.

Second, to test whether my model's mechanisms underlie these exchange rate dynamics, I use data on the currency futures positions of both speculators and hedgers trading on the Chicago Board of Exchange to estimate signed quantile *portfolio-flow* regressions for each type of financier.[3] I first show that while speculators use currency futures to carry trade in normal times, interest differentials predict large carry trade unwindings by speculators in disasters. Next, I find that a rise in the liquidity yield on U.S. Treasuries induces hedgers to substantially increase their holdings of U.S. dollars in disasters. In all, as they do in my model, portfolio adjustments by speculators and hedgers seem to drive the disaster-state exchange rate dynamics we see in the data. Furthermore, they suggest that hedgers imbue the U.S. dollar with its unique safe-haven status.

Literature Review: My paper relates to theories of exchange rates with disaster risk, an asset pricing framework in which deviations from UIP (see Hansen and Hodrick, 1980, Fama, 1984, Hassan and Mano, 2019 and Kalemli-Özcan and Varela, 2021) arise due to the risk of extreme exchange rate movements in rare disasters. Farhi and Gabaix (2016) develop a model in which countries' differential exposures to exogenous productivity disasters, which determine interest differentials in their setup, explain the magnitude of UIP deviations and rationalize other exchange-rate puzzles.[4] Relative to them, my paper investigates what drives these differential exposures to disaster risk. Specifically, I show that both interest differentials and the liquidity yield on U.S. Treasuries are needed to account for the dollar's exchange rate dynamics in disasters and that these dynamics arise due to endogenous portfolio adjustments by financiers.

A related literature studies in-sample currency crash risk and the properties of safe-haven

[3]The data come from the Commodity Futures Trading Commission, which sorts traders on the Chicago Board of Exchange into those who use currency futures to hedge—hedgers—and those who do not—speculators.

[4]This echoes an earlier literature on "Peso Problems" (Krasker, 1980). See also Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), who argue investors value returns much more in disasters, and Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2009), who show over a third of the UIP premium is from disaster risk.

currencies, defined as currencies that appreciate in times of (currency) market turmoil (e.g. Menkhoff, Sarno, Schmeling, and Schrimpf, 2012).[5] Brunnermeier et al. (2009) show that higher interest differentials predict greater left-skewness of the within-month distribution of carry trade returns and that increases in the VIX predict a fall in average carry trade returns and an unwinding of speculator carry trades. However, as they look only at skewness, their method cannot estimate the elasticity of exchange rate movements to interest differentials or other factors, whereas my empirical framework can. Further, I uncover a second type of financier—hedgers—whose flight to liquid U.S. dollar bonds in disasters is necessary to fully capture the dollar's disaster-state exchange rate dynamics.

The literature linking the U.S.'s comparative advantage in generating safe assets (Farhi and Maggiori, 2018) with the dollar's safe-haven status originates with Gourinchas et al. (2010).[6] Maggiori (2017) then argues that this comparative advantage arises due to the greater risk-bearing capacity of the U.S. financial sector. Until recently, this demand for U.S. safe assets was difficult to quantify empirically in an international context, although Krishnamurthy and Vissing-Jorgensen (2012) show investors value U.S. Treasuries for their safety and liquidity relative to other U.S. assets. The breakthrough comes with Du et al. (2018a) and Du, Tepper, and Verdelhan (2018b), who document persistent CIP deviations pre- and post-crisis, highlighting that U.S. Treasuries offer greater liquidity and safety compared to other countries' government bonds. While Jiang et al. (2021), Engel and Wu (2018), Valchev (2020) and Lloyd and Marin (2020) show that increases in this U.S. Treasury liquidity yield predict instantaneous dollar appreciations at the mean, my paper studies this relationship during global disasters and compares its importance to that of relative interest rates. Further, consistent with my mechanism, Liao and Zhang (2020) show that currency hedging can explain the dynamics of CIP deviations.

To discipline my empirical analysis, I build on the growing literature modelling exchange rates dynamics in imperfect financial markets (Itskhoki and Mukhin, 2021).[7] My model extends the work of Gabaix and Maggiori (2015) and Jiang (2021) in two respects: (i) a formal modelling of financial market disasters; and (ii) that hedgers value the dollar for its non-pecuniary liquidity yield, which spikes in disasters. Relative to existing models, this framework nests theories

[5]See also important works by Ranaldo and Söderlind (2010), Habib and Stracca (2012), Cenedese, Sarno, and Tsiakas (2014), Dobrynskaya (2014), Corsetti and Marin (2020) and Cesa-Bianchi and Eguren Martin (2021).

[6]Bernanke (2005), Gourinchas and Rey (2007) and Caballero, Farhi, and Gourinchas (2008) also argue the U.S.'s role as the world's safe-asset supplier explains its current account deficit. It may explain the extent of U.S. monetary policy's effect on capital flows and asset prices (Rey, 2015, Miranda-Agrippino and Rey, 2020) and why the information effect of U.S. monetary policy appreciated the dollar in the GFC (Stavrakeva and Tang, 2019).

[7]See also Jeanne and Rose (2002), Evans and Lyons (2002), Pavlova and Rigobon (2007), Jiang, Krishnamurthy, and Lustig (2020), Greenwood, Hanson, Stein, and Sunderam (2020), Koijen and Yogo (2020), Kekre and Lenel (2021), Georgiadis, Müller, and Schumann (2021), Bianchi, Bigio, and Engel (2021), Gourinchas, Ray, and Vayanos (2022), Devereux, Engel, and Wu (2023), Fukui, Nakamura, and Steinsson (2023).

of exchange rate dynamics in disasters tied to both interest differentials and U.S. safe-asset demand, making it the appropriate laboratory with which to draw testable predictions.

Finally, my empirical approach relates to Adrian, Boyarchenko, and Giannone (2019), who use quantile regression (Koenker and Bassett Jr, 1978) to show deteriorating domestic financial conditions predict greater downside GDP growth risk.[8] Eguren-Martin and Sokol (2020) apply this methodology to study the impact of tighter global financial conditions on the exchange rate distribution by sorting currencies by interest differentials, international reserves and fiscal deficits. Rather than conditioning on financial conditions, my empirical approach estimates the direct effect of interest differentials (and liquidity yields) on exchange rate movements as in the standard UIP regression of Fama (1984), but uses quantile regression to account for state-dependence and a 'sign' interaction to account for symmetric movements for high- versus low-yield currencies.[9] In addition to studying tail exchange rate movements, I also evaluate tail movements in the portfolio adjustments of speculators and hedgers to understand the mechanisms underlying these results.

The remainder of this paper is organized as follows. Section 2 develops a model of exchange rates with rare disaster. In section 3, I discuss the novel empirical strategy I use to evaluate my model. Section 4 presents the empirical results and section 5 concludes.

2 Speculators, Hedgers and Exchange Rates in Disasters

In this section, I develop a model of exchange rate dynamics with rare disasters and two types of global financier: speculators and hedgers. The setup builds on the models of Gabaix and Maggiori (2015) and Jiang (2021) but, different to them, studies how portfolio adjustments by speculators and hedgers jointly determine exchange rate dynamics during periods of stress in global financial markets. Appendix A solves the model in full and Appendix B provides proofs.

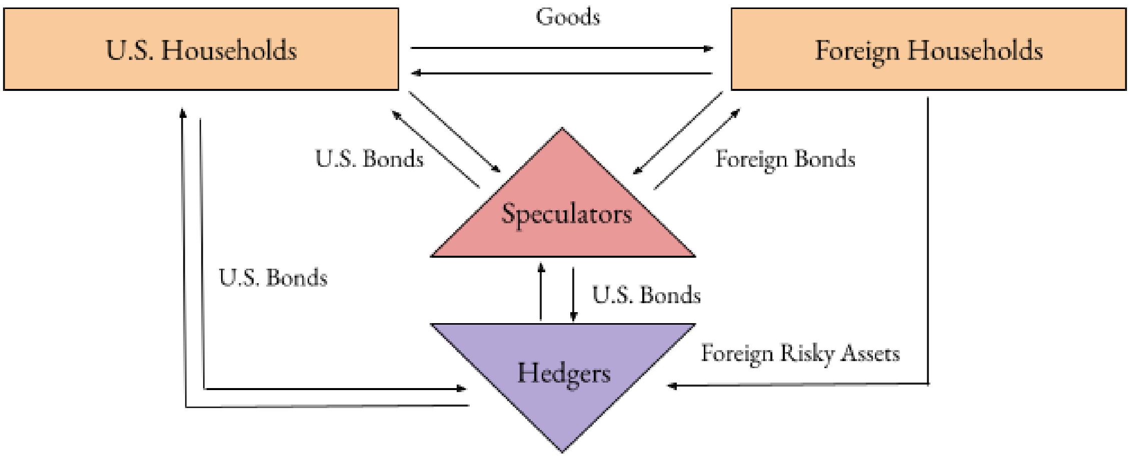
2.1 Model Structure

The structure of international financial markets is displayed in Figure 2. There are two countries each populated by a unit mass of identical households: the home country (H) is the U.S. and the foreign country (F) is a second advanced economy. Stars (*) denote foreign variables.

[8] See also Lloyd, Manuel, and Panchev (2021) who link foreign financial conditions to downside risks to growth.

[9] In appendix F, I show there are challenges with interpreting the *direction* of the effects of global financial conditions on exchange rate movements. This is an added reason I opt for my strategy.

Figure 2: International Financial Market Structure



Note. Figure 2 displays the agents and international financial market structure of the model.

Households in each country are endowed with both tradable and non-tradable (NT) goods and have access to a one-period risk-free bond. While trade in goods between countries is assumed to be frictionless, financial markets are segmented such that U.S. households can trade only the U.S. bond and foreign households can trade only the foreign bond. This form of market segmentation provides the opportunity for global financiers to intermediate cross-border flows.

2.2 Two Types of Global Financier: Speculators and Hedgers

Exchange rate dynamics in the model depend on the behavior of two types of global financier. The first type, currency speculators, are modelled as the financial intermediaries introduced by Gabaix and Maggiori (2015). Specifically, speculators are born with zero net worth, exist for one period, and can hold both U.S. and Foreign bonds. Their balance sheet in period t consists of q_t U.S. bonds and $-q_t/\varepsilon_t$ Foreign bonds, where ε_t denotes the real exchange rate, defined such that an increase corresponds to a real appreciation of foreign currency against the U.S. dollar (USD).[10] If $q_t > 0$, then speculators are long the U.S. bond and short the foreign bond. Their expected profit in dollars from this currency trade is the scaled deviation from uncovered interest parity (UIP):

$$V_t^S = \mathbb{E}_t\Big[\beta\{R_t - R_t^* \frac{\varepsilon_{t+1}}{\varepsilon_t}\}q_t\Big], \tag{1}$$

[10]Throughout, I sometimes use nominal terms (exchange rate, currency or dollar-denominated) while I have in mind their real counterparts (real exchange rate, claim to the economy's numeraire or valued in units of the U.S. numeraire). The numeraire in each country is the non-tradable good.

where R_t and R_t^* denote the real interest rate on U.S. and Foreign risk-free bonds, respectively, and β is the U.S. household discount factor. As shown in Appendix A, households' Euler equations imply $R_t = 1/\beta$ and $R_t^* = 1/\beta^*$.

Creditors (home or foreign households), who finance speculators' currency investments, rationally anticipate that speculators may abscond with $\Gamma_t|\frac{q_t}{\varepsilon_t}|$ of their total portfolio position $|\frac{q_t}{\varepsilon_t}|$. This agency friction gives rise to the following funding constraint for speculators:

$$\frac{V_t^S}{\varepsilon_t} \geq \left|\frac{q_t}{\varepsilon_t}\right| \times \Gamma_t \left|\frac{q_t}{\varepsilon_t}\right| \implies V_t^S \geq \Gamma_t\Big(\frac{q_t^2}{\varepsilon_t}\Big), \tag{2}$$

where $\Gamma_t > 0$. A higher Γ_t exacerbates frictions in funding market, and thereby tightens speculators' funding constraints. As speculators' constraints bind, their optimal holding of U.S. dollar bonds is given by:

$$q_t = \frac{1}{\Gamma_t}\mathbb{E}_t\Big[\varepsilon_t - \frac{R^*}{R}\varepsilon_{t+1}\Big], \tag{3}$$

which highlights that speculators must decrease the size of their balance sheets ($|q_t| \downarrow$) when funding frictions tighten ($\Gamma_t \uparrow$) or when the expected return (UIP deviation) falls.

The second type of financial agent, hedgers, are modelled in a similar fashion to the risky-asset financiers in Jiang (2021). In period t, hedgers are endowed with one unit of a risky asset paying $\mathbb{E}_t[\tilde{X}_{t+1}^*]$ units of the foreign NT good in $t+1$. In the period the asset is endowed, it can be partially liquidated for X_t^* units of the NT good, which can then be used to purchase U.S. bonds. Therefore, if a share $(1 - v_t)$ of the period t endowment is liquidated, the expected 1-period pecuniary payoff in foreign currency terms is:

$$V_t^H = (1 - v_t)X_t^*\mathbb{E}_t[R\frac{\varepsilon_t}{\varepsilon_{t+1}}] + v_t\mathbb{E}_t[\tilde{X}_{t+1}^*]. \tag{4}$$

In addition to valuing the pecuniary return on U.S. dollar bonds, I assume hedgers also derive a non-pecuniary "liquidity yield" λ_t from hedging their holdings of foreign risky assets with the reserve asset. This is modelled as a reserve constraint that requires hedgers to hold λ_t times the expected value of the unliquidated portion of their risky asset in the USD bond:

$$\frac{w_t}{\varepsilon_t} \geq \lambda_t \times v_t\mathbb{E}_t[\tilde{X}_{t+1}^*] \tag{5}$$

where w_t is the hedgers' position in the USD bond and $\lambda_t \geq 0$. A greater liquidity benefit to holding U.S. dollar bonds, $\lambda_t \uparrow$, or a larger expected return on the foreign risky asset,

$\mathbb{E}_t[\tilde{X}^*_{t+1}] \uparrow$, tightens hedgers' reserve constraint, and so induces hedgers to rebalance their portfolios towards U.S. dollar bonds. This constraint captures the idea that the degree to which hedgers "hedge" their exposure to foreign risky assets is tied to the quality of the reserve asset—e.g., its safety, liquidity and convenience—as measured by the U.S. bond's liquidity yield (Di Tella, 2020). Assuming $X^*_t \mathbb{E}_t[R \frac{\varepsilon_t}{\varepsilon_{t+1}}] < \mathbb{E}_t[\tilde{X}^*_{t+1}]$, the constraint binds and hedgers optimal USD bond holdings are:

$$\frac{w_t}{\varepsilon_t} = \frac{\lambda_t \mathbb{E}_t[\tilde{X}^*_{t+1}]}{\lambda_t \mathbb{E}_t[\tilde{X}^*_{t+1}]/X^*_t + 1}, \tag{6}$$

which is increasing in the U.S. bond's liquidity yield.

An important distinction between speculators and hedgers is that while hedgers' portfolio positions are tied to the liquidity yield on the world's reserve asset, speculators' portfolios are determined by expected returns such that, to them, U.S. bonds are a priori no different from foreign bonds. As a result, in what follows, predictions for exchange rate dynamics that arise due to speculator behavior should hold for all currency pairs, whereas those arising from hedger behavior should hold only for the dollar vis-à-vis other currencies.[11]

2.3 Disaster States, Financial Constraints and the Liquidity Yield

Central to my analysis is the possibility of a financial-market disaster, defined as a sudden period of extreme illiquidity in speculators' funding market.[12] For ease of exposition, in what follows, I assume there are three periods $t \in \{0, 1, 2\}$. In $t = 0$, Γ_0 is fixed and low, meant to capture calm non-disaster (ND) periods where funding liquidity is abundant and speculators are able to take on lots of risk. In $t = 1$, however, Γ_1 is stochastic and, with a small probability p, it spikes, signifying a disaster (D) in speculators' funding market that forces them to drastically limit the risk on their balance sheets.[13] This is summarized by the following process for Γ_t:

$$\Gamma_0 = \Gamma_L > 0 \quad \text{and} \quad \Gamma_1 = \begin{cases} \Gamma_L & \text{ND} \\ \Gamma_H >> \Gamma_L & \text{D.} \end{cases} \tag{7}$$

As I discuss in detail shortly, the parameters governing the likelihood and severity of disasters, $\{p, \Gamma_L, \Gamma_H\}$, determine the extent of the exchange rate response to disaster shocks.

[11] Formally, in a model where the home country is not the U.S., hedgers do not derive a non-pecuniary benefit from holding either bond, and so face no reserve constraint and do not hold bonds in either currency.

[12] This is the definition of a disaster used by Brunnermeier et al., 2009.

[13] I describe the final period $t = 2$ in the next section.

In addition, consistent with models linking funding liquidity (Γ_t) to market liquidity (λ_t), such as Brunnermeier and Pedersen (2009), the liquidity yield on U.S. bonds is assumed to be an increasing function of funding illiquidity:

$$\lambda_t = \lambda(\Gamma_t) \geq 0 \quad \text{and} \quad \lambda^{'}(\Gamma_t) > 0 \tag{8}$$

This maps the process for Γ_t in (7) to a similar one for the U.S. liquidity yield:

$$\lambda_0 = \lambda_L \geq 0 \quad \text{then} \quad \lambda_1 = \begin{cases} \lambda_L & \text{ND} \\ \lambda_H >> \lambda_L & \text{D} \end{cases} \tag{9}$$

That is, the liquidity yield on U.S. bonds spikes in disasters, consistent with its dynamics in Figure 1. While a deeper foundation for (8) is outside the scope of this paper, there are several potential mechanisms underlying this assumption. For example, one can envision a set of global arbitrageurs whose ability to arbitrage away non-pecuniary returns depends on their ability to borrow in funding markets. As a result, when funding market conditions deteriorate in disasters, they construct fewer arbitrage portfolios, which leads the liquidity yield to increase. Alternatively, a more interesting rationale is that episodes of funding market illiquidity serve as a signal that induces hedgers' to fly to U.S. bonds in disasters, regardless of their return. This may endogenously widen the liquidity yield on U.S. bonds.[14]

2.4 Equilibrium

Equilibrium in international financial markets is characterized by a condition that equates U.S. net imports with U.S. net borrowing each period:

$$\iota_t - \varepsilon_t \xi_t = q_t + w_t, \tag{10}$$

where ι_t and ξ_t denote U.S. imports denominated in dollars and foreign imports denominated in foreign currency, respectively (see Appendix A for details).[15] That is, when the U.S. is a net importer, $\iota_t > \varepsilon_t \xi_t$, market segmentation requires U.S. net borrowing to be intermediated by

[14] In the empirical sections to come, I measure the liquidity yield on U.S. Treasuries as the deviation from CIP. By flying to dollars and hedging their positions with a swap back into foreign currency, hedgers may appreciate the dollar in the spot market and depreciate it in the forward market, consistent with a widening of CIP. This would be in-line with the findings of Liao and Zhang (2020).

[15] This equation assumes that financiers intermediate only new flows at t, with the repayment of stocks arising from previous flows, that is, $R_t(q_{t-1} + w_{t-1})$, held passively by households until the "long-run period", which I define momentarily. As emphasized by Gabaix and Maggiori (2015), this makes the algebra less cumbersome, but does not alter the underlying economics. See Appendix A for the details.

speculators or accommodated by hedgers, such that the financial sector is net long the USD: $q_t + w_t > 0$. Condition (10) also pins down the equilibrium exchange rate for each $t \in \{0, 1, 2\}$:

$$\varepsilon_t = \frac{\iota_t - q_t - w_t}{\xi_t} = \frac{\iota_t + \frac{1}{\Gamma_t}\frac{R^*}{R}\mathbb{E}_t[\varepsilon_{t+1}]}{\xi_t + \frac{1}{\Gamma_t} + \frac{\lambda_t E_t[\tilde{X}^*_{t+1}]}{\lambda_t E_t[\tilde{X}^*_{t+1}]/X^*_t + 1}}, \tag{11}$$

where the exchange rate at $t = 1$, ε_1, depends on the realization of the disaster shock Γ_1, and thus $\lambda_1(\Gamma_1)$, while the exchange rate at $t = 0$, ε_0, is influenced by disaster *risk* through $\mathbb{E}_0[\varepsilon_1]$.

Finally, to improve clarity, I assume that the final period is the "long-run" without financial frictions so that trade is balanced at $t = 2$: $\iota_2 = \varepsilon_2 \xi_2$. Thus, the exchange rate in the final period is determined solely by fundamentals, i.e. countries' relative import demand, which is consistent with the empirical findings of Froot and Ramadorai (2005). As discussed in Gabaix and Maggiori (2015), this anchors the exchange rate in the final period, but does not affect exchange rate dynamics between the first two periods, which are the focus of my analysis.

2.5 Exchange Rates in Disaster States

To understand how exchange rates respond to funding market disasters, I first study the comparative statics of ε_1 to changes in Γ_1:

$$\frac{\partial \varepsilon_1}{\partial \Gamma_1} = \frac{1}{A}\Big[\underbrace{\iota_1 - \frac{R^*}{R}\mathbb{E}_1(\iota_2)(1 + \frac{\lambda_1 E_1[\tilde{X}^*_2]}{\lambda_1 E_1[\tilde{X}^*_2]/X^*_1 + 1})}_{\text{Speculator Direct Effect through } \partial\Gamma_1} - \underbrace{\Gamma_1 \frac{\mathbb{E}_1[\tilde{X}_2]}{B}\frac{\partial \lambda_1}{\partial \Gamma_1}(\Gamma_1 \iota_1 + \frac{R^*}{R}\mathbb{E}_1(\iota_2))}_{\text{Hedger Indirect effect through } \partial\lambda_1}\Big] \tag{12}$$

where $A = \left(\Gamma_1 + 1 + \frac{\lambda_1 E_1[\tilde{X}^*_2]}{\lambda_1 E_1[\tilde{X}^*_2]/X^*_1 + 1}\right)^2$ and $B = (\lambda_1 E_1[\tilde{X}^*_2]/X^*_1 + 1)^2$.[16]

Equation (12) decomposes the overall response of the exchange rate into a direct effect, which captures the impact of the tightening of speculators' funding constraints when hedgers' constraints are fixed, and an indirect effect, which captures the impact of the tightening of hedgers' reserve constraints due to the spike in the U.S. Treasury liquidity yield.

First, the sign of the indirect effect is unambiguously negative such that $\Gamma_1 \uparrow$ predicts $\varepsilon_1 \downarrow$, a USD appreciation. This is because a spike in Γ_1 triggers a similar jump in the USD liquidity

[16] Since I allow ι_t to move freely, I set $\xi_t = 1$ without loss of generality

yield by (8), $\frac{\partial \lambda_1}{\partial \Gamma_1} > 0$, which induces a flight to the dollar by hedgers:[17]

$$\frac{\partial w_1/\varepsilon_1}{\partial \Gamma_1} = \frac{\partial \lambda_1}{\partial \Gamma_1} \frac{\mathbb{E}_1[\tilde{X}_2]}{B} > 0 \tag{13}$$

Importantly, the size of this dollar flight, like the indirect effect, is increasing in $\frac{\partial \lambda_1}{\partial \Gamma_1}$ such that larger spikes in the liquidity yield predict a greater indirect appreciation of the dollar.

Conversely, the sign of the direct effect is ambiguous and depends on the relative magnitudes of R^* and R. This is because relative interest rates determine the composition of speculators' balance sheets:

$$q_t = \frac{1}{\Gamma_t} \mathbb{E}_t \Big[\varepsilon_t - \frac{R^*}{R} \varepsilon_{t+1} \Big] > 0 \iff R > R^* \frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t} \tag{14}$$

Thus, speculators are long the USD bond and short the foreign currency bond ($q_t > 0$) if and only if the return on the U.S. bond is larger than the return on an uncovered position in the foreign currency. Furthermore, as the expected return to a net-long position in the USD bond grows, $R - R^* \frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t} \uparrow$, so too do speculators' USD bond holdings, $q_t \uparrow$.

As relative interest rates determine speculators' portfolio positions in "normal times", they also drive speculators' portfolio adjustments in the disaster state:

$$\frac{\partial q_1}{\partial \Gamma_1} = \frac{1}{\Gamma_1^2} \Big(\frac{R^*}{R} \mathbb{E}_1(\varepsilon_2) - \varepsilon_1 \Big) + \frac{1}{\Gamma_1} \frac{\partial \varepsilon_1}{\partial \Gamma_1} \tag{15}$$

Lemma 1: For a sufficiently small $\frac{\partial \lambda_1}{\partial \Gamma_1}$ and sufficiently large Γ_1, if $q_1 > 0$ then $\frac{\partial q_1}{\partial \Gamma_1} < 0$ and if $q_1 < 0$ then $\frac{\partial q_1}{\partial \Gamma_1} > 0$. Also, $|q_1| \uparrow \implies |\frac{\partial q_1}{\partial \Gamma_1}| \uparrow$.

Since speculators' are net-long the dollar when U.S. interest rates are relatively high, $R > R^* \frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t}$, Lemma 1 highlights that speculators' decrease their holdings of the currency with the relatively high interest rate as their constraints tighten in disasters. The extent of this portfolio adjustment grows with the size speculators' initial positions (which grows as $|R - R^* \frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t}| \uparrow$), since larger positions imply more balance sheet risks that must be shed in a disaster.

Finally, as the direction of speculators' flows in disasters depends on relative interest rates, so does the "direct" exchange rate response:

Lemma 2: If $R > R^* \frac{\mathbb{E}_1[\varepsilon_2]}{\varepsilon_1}$, the sign of the direct effect is positive ($\Gamma_1 \uparrow \implies \varepsilon_1 \uparrow$, a dollar depreciation) and increasing in $R - R^* \frac{\mathbb{E}_1[\varepsilon_2]}{\varepsilon_1}$. If $R < R^* \frac{\mathbb{E}_1[\varepsilon_2]}{\varepsilon_1}$, the sign of the direct effect is

[17] Note also that the parameters ι_t, Γ_t, B, R, R^*, $\mathbb{E}_1(\iota_2)$ and $\mathbb{E}_t[\tilde{X}_{t+1}]$ are always greater than zero.

negative ($\Gamma_1 \uparrow \implies \varepsilon_1 \downarrow$, a dollar appreciation) and increasing in $R^* \frac{\mathbb{E}_1[\varepsilon_2]}{\varepsilon_1} - R$.

Reflecting the behavior of currency speculators, a shock to funding liquidity predicts a direct depreciation of the dollar when the U.S. interest rate is relatively high but predicts a direct dollar appreciation when the U.S. interest rate is relatively low.

2.6 Model Predictions

In this section, I outline my model's two predictions for exchange rate dynamics in disasters, which together form the paper's main theoretical result. I also discuss two corollaries that pertain to exchange rate dynamics in normal times. While proofs can be found in Appendix B, I illustrate these predictions here with model-simulated exchange rate distributions.

Before proceeding, I amend (14) by assuming that speculators perform the carry trade when intermediating flows across borders. That is, they take net-long positions in the high-interest-rate currency: $q_t > 0 \iff R > R^*$. This can be easily parameterized in my model since interest rates are determined by household discount factors.[18]

I begin by considering how speculators' behavior shapes exchange rate dynamics in normal times. Since speculators perform the carry trade, net-long positions in high-yield currencies must offer positive expected returns. Ex-post, however, carry trades only earn positive returns conditional on no-disaster in t = 1, that is, conditional on $\Gamma_1 = \Gamma_L$:

Corollary 1: *Abstracting from hedgers, for a sufficiently small disaster probability p, we have*

$$R_0^* > R_0 \implies \mathbb{E}_0\left[R_0^* \frac{\varepsilon_1}{\varepsilon_0} - R_0 \middle| \; \Gamma_1 = \Gamma_L \right] > 0 \quad \textit{and} \quad \frac{\partial}{\partial \frac{R_0^*}{R_0}} \mathbb{E}_0\left[R_0^* \frac{\varepsilon_1}{\varepsilon_0} - R_0 \middle| \; \Gamma_1 = \Gamma_L \right] > 0.$$

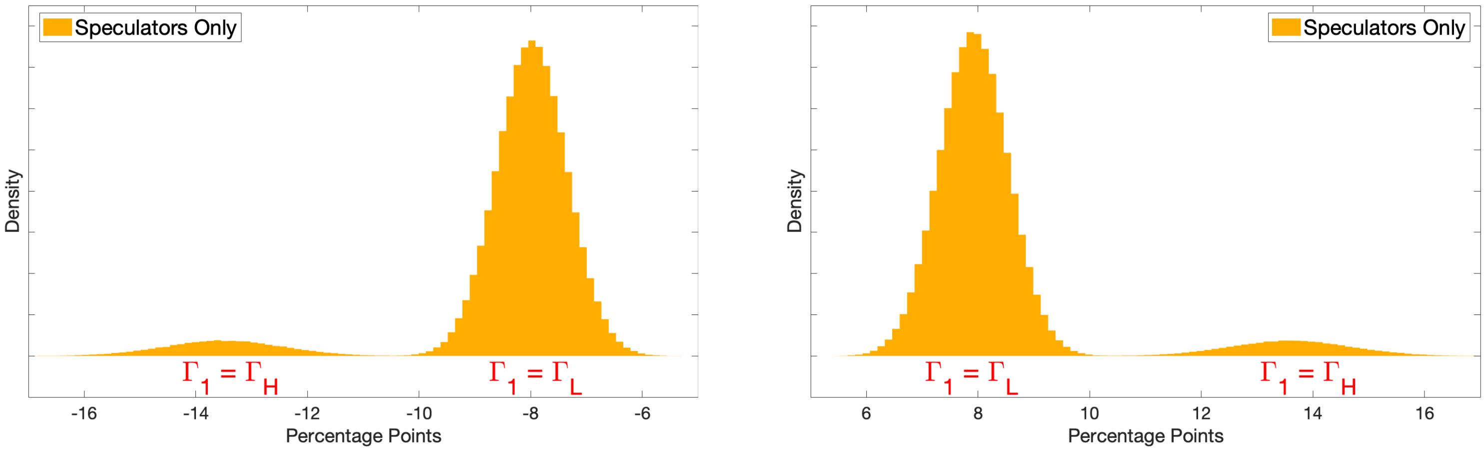
A positive carry trade return implies an excessive appreciation, relative to interest differentials, of the high-interest-rate currency against the low-interest-rate currency. These returns, which grow with the interest differential, arise to compensate speculators for holding the disaster risk (Γ_1) associated with their net-long positions in high-interest-rate currency.

Next, I show how speculators' behavior shapes exchange rate dynamics in disasters. Relative to Gabaix and Maggiori (2015), I prove two new results. First, I show that high-interest-rate currencies can suffer depreciations far larger than interest differentials in disasters, implying ex-post losses on the carry trade. Second, I show that the size of this disaster-state depreciation

[18] The assumption matches the unconditional pattern of UIP deviations we see in the data: high-interest-rate currencies offer speculators a positive expected returns across all states. The distinct exchange rate dynamics in each state, normal times and disasters, are the focus of the remainder of this section.

Figure 3: Simulated Exchange Rate Change Distribution due to Speculators

(a) $R^* - R > 0$ (b) $R^* - R < 0$



Note. Figure 3 displays simulated distributions of exchange rate changes, $log(\frac{\varepsilon_1}{\varepsilon_0})$, which take into account only the behavior of speculators (formally $\lambda_0 = \lambda_1 = 0$), from simulating the model and aggregating exchange rate movements into histograms. In panel 3a, the foreign interest rate is 10% and the home interest rate is 1%. In panel 3b, the foreign interest rate is 1% and the home interest rate is 10%. The full parameterization is available in Appendix C. Exchange rate movements in the small mode in each panel, labeled $\Gamma_1 = \Gamma_H$, refer to exchange rate movements conditional on a disaster, whereas movements in the large mode, labeled $\Gamma_1 = \Gamma_L$, are movements conditional on no-disaster.

is *increasing* in the magnitude of the interest differential:

Prediction 1: *Abstracting from hedgers, for a sufficiently small disaster probability p, a sufficiently small* Γ_L *and a sufficiently large* Γ_H *, we have*

$$R_0^* > R_0 \implies \mathbb{E}_0\left[R_0^*\frac{\varepsilon_1}{\varepsilon_0} - R_0 \middle| \; \Gamma_1 = \Gamma_H \; \right] << 0$$

where if $\frac{R_0^*}{R_0} \uparrow$ (and if $\Gamma_H \uparrow$ *or* $\Gamma_L \downarrow$ as well) *we have* $\mathbb{E}_0\left[R_0^*\frac{\varepsilon_1}{\varepsilon_0} - R_0 \middle| \; \Gamma_1 = \Gamma_H \; \right] \downarrow$

$\frac{R_0^*}{R_0}$, as well as Γ_L and Γ_H, affect the size of the high-yield currency's depreciation because exchange rate dynamics in disasters are driven by speculator deleveraging. Since a higher interest rate differential, $\frac{R_0^*}{R_0} \uparrow$, or greater initial funding market liquidity, $\Gamma_L \downarrow$, permits speculators to take larger carry trade positions (more risk) at t = 0, as outlined in Corollary 1, they increase the amount of risk that speculators must shed in disasters. Similarly, as the size of the funding market disaster at t = 1 worsens, $\Gamma_H \uparrow$, speculators are also forced to deleverage more, worsening carry trade losses.

Together, Corollary 1 and Prediction 1 imply a state-dependent relationship between relative interest rates and exchange rate dynamics. This state-dependence is visible in the exchange rate change ($log(\frac{\varepsilon_1}{\varepsilon_0})$) distributions in Figure 3, which I construct by simulating my model and aggregating exchange rate movements into histograms. In addition, Corollary 1 and Prediction 1 highlight that the direction of exchange rate movements in each state is tied to the sign of the interest differential. This feature is also visible in the simulations in Figure 3. Specifically, the exchange rate change distribution in panel 3a, in which the foreign currency is parameterized to have the high-interest-rate, is the transposition of the one in Panel 3b, in which the foreign currency has the low-interest-rate. The empirical framework I develop in section 3 is informed by the state-dependence and interest-rate symmetry of exchange rate movements predicted by speculators in my model.

Next, I reintroduce hedgers into the analysis. As such, the remaining results in this section hold for the dollar vis-à-vis other currencies. Hedgers' flight to the dollar in disasters, due to spikes in the Treasury liquidity yield λ_1, imply that:

Prediction 2: *For a sufficiently small p and λ_0, when the U.S. is the home country, we have*

$$\frac{\partial}{\partial(\lambda_1 - \lambda_0)}\mathbb{E}_0\left[R_0^*\frac{\varepsilon_1}{\varepsilon_0} - R_0^{US}\middle|\ \Gamma_1 = \Gamma_H\ \right] < 0.$$

That is, the U.S. dollar has a unique tendency to appreciate in disasters, regardless of interest differentials.

When accounting for the behavior of both speculators and hedgers in disasters (Predictions 1 and 2), we arrive at the paper's main theoretical result:

Main Result: *For a sufficiently small p and λ_0, if $R_0^{*,high} - R_0^{US} = R_0^{US} - R_0^{*,low} > 0$,* we have

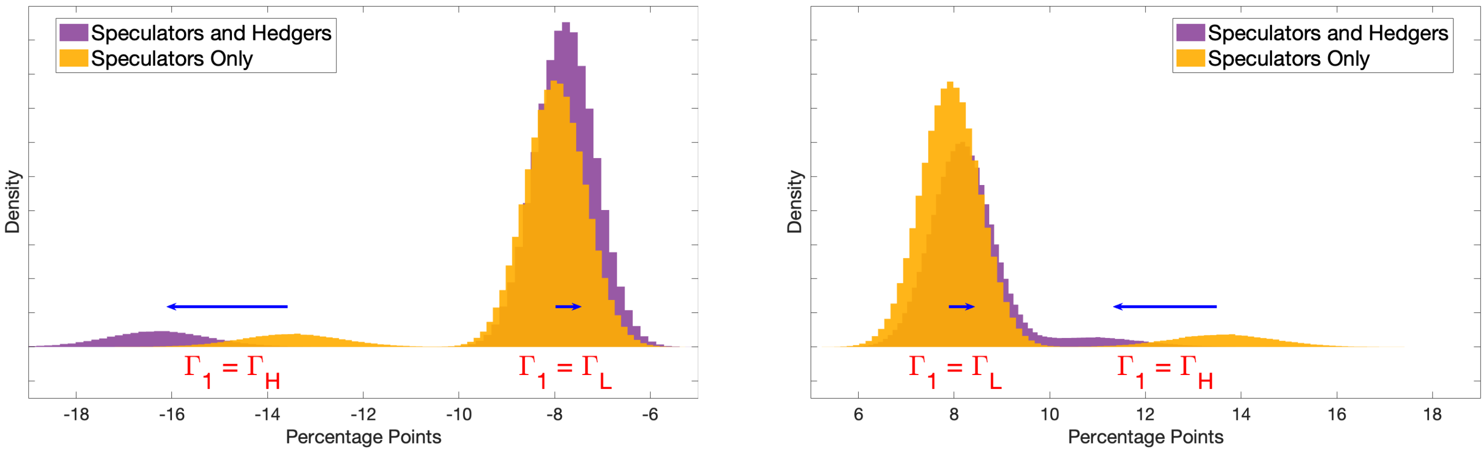
$$\left|\ \mathbb{E}_0\left[R_0^{*,high}\frac{\varepsilon_1}{\varepsilon_0} - R_0^{US}\middle|\ \Gamma_1 = \Gamma_H\ \right]\ \right| \quad >> \quad \left|\ \mathbb{E}_0\left[R_0^{US}\frac{\varepsilon_0}{\varepsilon_1} - R_0^{*,low}\middle|\ \Gamma_1 = \Gamma_H\ \right]\ \right|$$

Speculators' unwinding of carry trades and hedgers' flight to the dollar reinforce each other when the U.S. interest rate R_0^{US} is low, as compared to the foreign rate $R_0^{*,high}$, leading to an amplified appreciation of the dollar in disasters. Conversely, the two effects offset each other when the U.S. interest rate R_0^{US} is high, as compared to the foreign rate $R_0^{*,low}$, leading to a dampened depreciation, or even an appreciation, of the dollar in disasters. In this latter case, which effect dominates depends on two factors: (i) the magnitude of the interest differential R_0^*/R_0 and the spike in the U.S. Treasury liquidity yield $\Delta\lambda_1$; and (ii) the relative elasticity of exchange rates to interest differentials versus changes in Treasury liquidity, $\partial e_1/\partial\frac{R_0^*}{R_0}$ and $\partial e_1/\partial\Delta\lambda_1$, respectively. In the data, I find that both forces can dominate.

This amplification or dampening of the dollar's exchange rate movement in disasters due to

Figure 4: Simulated Exchange Rate Change Distribution due to Speculators and Hedgers

(a) $R^* - R^{US} > 0$ (b) $R^* - R^{US} < 0$



Note. In each panel of Figure 4, I present 2 simulated distributions of exchange rate changes, $log(\frac{\varepsilon_1}{\varepsilon_0})$, constructed by simulating the model and aggregating exchange rate movements into histograms. The first, in yellow, accounts only the behavior of speculators (formally $\lambda_0 = \lambda_1 = 0$), and is the same as in Figure 3. The second, in purple, accounts for the behavior of both speculators and hedgers. In panel 4a, the foreign interest rate is 10% and the U.S. interest rate is 1%. In panel 4b, the foreign interest rate is 1% and the U.S. interest rate is 10%. The full parameterization is available in Appendix C. Exchange rate movements in the small mode in each panel, labeled $\Gamma_1 = \Gamma_H$, refer to exchange rate movements conditional on a disaster, whereas movements in the large mode, labeled $\Gamma_1 = \Gamma_L$, are movements conditional on no-disaster. Blue arrows indicate to how the exchange rate change distribution changes when hedgers behavior is accounted for.

hedgers is large (>>) as compared to the compensation that speculators require to fund carry trades in dollars, due to the dollar's tendency to appreciate in disasters:

Corollary 2: *For* $R_0^{*,high} - R_0^{US} = R_0^{US} - R_0^{*,low} > 0$, we have

$$\left| \mathbb{E}_0 \left[R_0^{*,high} \frac{\varepsilon_1}{\varepsilon_0} - R_0^{US} \middle| \Gamma_1 = \Gamma_L \right] \right| \quad > \quad \left| \mathbb{E}_0 \left[R_0^{US} \frac{\varepsilon_0}{\varepsilon_1} - R_0^{*,low} \middle| \Gamma_1 = \Gamma_L \right] \right|$$

This highlights that the dollar tends to depreciate conditional on no disaster to compensate speculators for the greater risks from funding carry trades in dollars. Thus, carry trades long high-yield currencies and short the dollar should offer greater returns conditional on no-disaster compared to carry trades long the dollar and short low-yield currencies. This may help explain the size of the risk premium on the dollar carry trade, which Lustig et al. (2014) show cannot be fully accounted for by a calibrated no-arbitrage model that does not adjust for the dollar's reserve-currency status.

My main result, as well as Corollary 2, are visible in the simulations in Figure 4, which compares, in each panel, the exchange rate change distribution when considering only the behavior of currency speculators with one that also accounts for the behavior of hedgers. The main takeaway here is that the inclusion of hedgers breaks the symmetry result that was visible in Figure 3. This asymmetry can be made even more stark, as shown in in Appendix C, if the interest differential is small and the spike in the Treasury liquidity yield is large.[19] In this case, hedgers' flight to dollar pushes the disaster state from the right-tail into the left-tail, implying an appreciation of the high-yield U.S. dollar in the disaster. This possibility will be considered in my empirical framework.

In all, my model bridges the gap between competing interest-rate theories (Brunnermeier et al., 2009 and Farhi and Gabaix, 2016) and U.S.-centric theories (Gourinchas et al., 2010 and Maggiori, 2017) of exchange rates in disasters by showing that exchange-rate dynamics reflect the currency flows of speculators and hedgers.

3 Empirical Strategy

In this section, I discuss the empirical strategy I use to test my model's predictions. I first outline my data and define key variables. Next, I develop the signed quantile UIP regression, a novel approach to modelling exchange rate dynamics relative to interest differentials in disasters, and show how it can be used to test Prediction 1. Finally, I highlight how a variation of the signed quantile UIP regression can be used to test Prediction 2.

3.1 Data and Definitions

In this paper, I consider a monthly sample, from 1986:M1 to 2020:M12, of interest rates and exchange rates for "G-10" currencies: Australia (AUD), Canada (CAD), Germany (EUR), Japan (JPY), Norway (NOK), New Zealand (NZD), Sweden (SEK), Switzerland (CHF), the United Kingdom (GBP), and the United States (USD). I study the three-month (overlapping) exchange rate movements of each of these currencies relative to the remaining nine currencies. Interest rate data correspond to three-month government bond yields. The German mark substitutes for the Euro in the period prior to the Euro's introduction in 1999:M1 and Euro area interest rates are from German bonds. All data used correspond to end-of-month figures.

I denote by e_t the logarithm of the nominal exchange rate ε_t at time t in units of domestic currency per unit of foreign currency, $e_t \equiv log(\varepsilon_t)$, such that an appreciation of the foreign

[19] Alternatively, the elasticity of exchange rates to changes in liquidity yields (interest differentials) can be increased (decreased).

currency corresponds to an increase in e_t.[20] The logarithm of the domestic and foreign gross nominal interest rates at time t are given by $i_t \equiv log(R_t)$ and $i_t^* \equiv log(R_t^*)$, respectively.[21] Then, the uncovered interest parity condition predicts that, in-expectation, high-interest-rate currencies should depreciate relative to low-interest-rate currencies to exactly offset the difference in their countries' interest rates:

$$\mathbb{E}_t[i_t^* - i_t + \Delta e_{t+1}] \equiv \mathbb{E}_t[z_{t+1}] = 0, \tag{16}$$

where $\Delta e_{t+1} = e_{t+1} - e_t$ is the three-month (log) appreciation of the foreign currency and z_{t+1} is the three-month (log) carry trade return. Summary statistics for interest differentials, exchange rates and carry trade returns are presented in Appendix D. In particular, Figure D.1 uses the cross-sectional skewness of exchange rate movements to show that while currencies with higher average interest rates face a greater risk of extreme depreciations, the dollar carries significant upside risk against all other currencies after controlling for interest differentials. These cross-sectional results are consistent with the predictions of my model.

To verify whether my model's mechanisms are behind the findings in Figure D.1, I use two further pieces of data. First, I use data on the U.S. Treasury liquidity yield (Du et al., 2018a), denoted by λ_t, which is defined as the deviation from covered interest parity (CIP) between the U.S. and the foreign country:

$$\lambda_t = f_t - e_t + i_t^* - i_t \tag{17}$$

where f_t is the nominal three-month forward rate in logs. The data form an unbalanced panel spanning 1991:M4 to 2020:M12.

When $\lambda_t > 0$, the pecuniary return on a synthetic USD bond, $f_t - e_t + i_t^*$, is greater than the pecuniary return on a U.S. Treasury, i_t. Since arbitraging CIP deviations is riskless, this implies the non-pecuniary return on the U.S. dollar bond must be greater than that on the foreign currency bond. This non-pecuniary return is termed the USD liquidity yield. Positive USD liquidity yields reflect the relative safety and liquidity, as perceived by investors, of dollar-denominated Treasuries as compared to other foreign-currency-denominated government bonds.

Second, I use data on the long and short currency futures positions of both speculators and hedgers trading on the Chicago Board of Exchange (CBOE) from the Commodity Futures

[20]In the previous section, ε_t referred to the *real* exchange rate. Beginning with Mussa (1986), studies have shown the correlation between nominal and real exchange rates in logs to be very near 1, due to nominal rigidities.

[21]Again, I make a mapping from the real interest rates used in my model to nominal ones in the data.

Trading Commission (CFTC). The CFTC sorts agents based on expert knowledge of their businesses into those who use futures for non-hedging purposes—those I term speculators—and those who use futures as a hedge—those I call hedgers.[22] The data are available for six currencies (AUD, CAD, CHF, EUR, GBP, JPY) relative to the USD in a balanced panel from 1993:M1 to 2020:M12.[23] Using this data, I construct:

$$Pos^S_{j,t} \equiv \frac{Long^S_{j,t} - Short^S_{j,t}}{Open\_Interest_{j,t}} \qquad Pos^H_{j,t} \equiv \frac{Long^H_{j,t} - Short^H_{j,t}}{Open\_Interest_{j,t}} \tag{18}$$

the net (long minus short) currency position of speculators and hedgers, respectively, in the Chicago Board of Exchanges' futures market for currency j relative to the USD, normalized by the total open interest of all traders for currency j futures.[24] A positive speculator or hedger position implies they are net-long currency j and net-short the USD. If an agent is net-long currency j when its interest rate is greater than the U.S.'s, this agent implements a long currency j–short USD carry trade. Summary statistics for the liquidity yield and financiers' positions are again shown in Appendix D.

3.2 *Signed* Quantile UIP Regressions

In this section, I outline the signed quantile UIP regression. The approach accounts for two key features of exchange rate movements in the data that arise due to speculators in my model: state-dependence (disasters versus normal times) and symmetry (for high- and low-interest-rate currencies). I will use this regression to test Corollary 1 and Prediction 1.

The starting point is the time-series UIP regression of Fama (1984), which regresses exchange rate movements on interest differentials:

$$\Delta e_{t+1} = \beta_0 + \beta_1(i^*_t - i_t) + u_{t+1} \tag{19}$$

The null (UIP) hypothesis is $\beta_0 = 0$ and $\beta_1 = -1$. As is well-known, estimating (19) (at short-horizons) by least squares produces estimates of $\hat{\beta}_1 > -1$, implying that high-interest-rate

[22]The CFTC refers to speculators as non-commercial traders and hedgers are commercial traders. While this data does not capture the full market for U.S. dollar trades, much of which occurs over-the-counter, it has several advantages. First, the data is available at a relatively high frequency, which allows me to study flows in sudden crises. Second, the maturity of the contracts is three months, which matches the horizon of exchange rate movements I study. Third, the CFTC sorts agents into speculators or hedgers, such that I don't have to take a stand on this myself. And fourth, the data captures the entire market for currency futures trades on one of the world's largest commodity exchanges, meaning the data likely constitutes a representative sample.

[23]Data from 1986:M1 to 1992:M12 are not used to data errors, as noted by the CFTC.

[24]The variables defined in (18) are, strictly speaking, speculators' and hedgers' "net-long-to-total positions" in currency j, respectively. With a slight abuse of language, I refer to them as "net-long positions" for short.

currencies insufficiently depreciate (and sometimes even appreciate) against low-interest-rate currencies. This result is unsurprising since the OLS coefficient $\hat{\beta}_1$ measures the marginal effect of interest differentials on the conditional *mean* exchange rate movement, which cannot fully offset interest differentials in my model else speculators will not earn a positive expected return.

As highlighted in Figure 3, this mean exchange rate movement masks considerable state-dependence. In particular, speculator carry trades in normal times imply mild exchange rate movements that manifest at the center of the exchange rate change distribution, while their deleveraging in disasters lead to extreme exchange rate swings that manifest in the distribution's tails. To account for this, I estimate the UIP relationship by quantile regression (Koenker and Bassett Jr (1978)): $\Delta e_{t+1} = \beta_0^\tau + \beta_1^\tau (i_t^* - i_t) + u_{t+1}^\tau$, where τ denotes the quantile.

The quantile UIP regression, however, does not account for the interest-rate symmetry of exchange rate movements (see Panels 3a and 3b). That is, as shown in Appendix E, the quantile UIP regression chooses a single quantile marginal effect β_1^τ for the interest differential to explain 'sets' of exchange rate movements that ought not to be grouped together according to my model. For example, a single β_1^τ to explain both the depreciations of high-yield currencies, which are due to the unwinding of carry trades by speculators in disasters, and the depreciations of low-yield currencies, which are due to speculator carry trades in normal times. To address this deficiency, I develop the signed quantile UIP regression:

Proposition 1: *The signed quantile UIP regression interacts each term in the quantile UIP regression with the sign of the interest rate differential,* $S_t \equiv sign(i_t^* - i_t) = \begin{cases} 1 & if \quad i_t^* \geq i_t \\ -1 & if \quad i_t^* < i_t \end{cases}$:

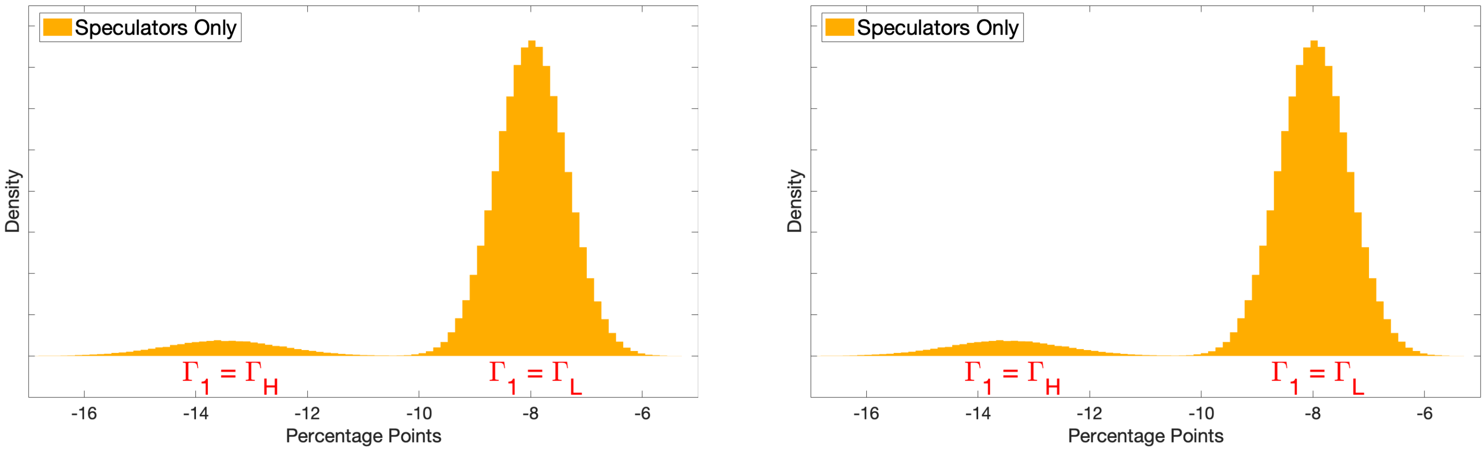
$$\Delta e_{t+1} \times S_t = \beta_0^\tau S_t + \beta_1^\tau (i_t^* - i_t) \times S_t + u_{t+1}^\tau. \tag{20}$$

β_1^τ captures the marginal effect of $i_t^* - i_t$ on Δe_{t+1}, as in the least-squares UIP regression, but at the τ^{th} quantile of the conditional signed exchange rate change distribution, which is formed by weighting errors by $1-\tau$ if the depreciation of the high-interest-rate foreign currency or appreciation of the low-interest-rate foreign currency is sufficiently large (i.e. $\Delta e_{t+1} \times S_t < \beta^\tau X_t^S$), where $X_t^S = \{S_t, (i_t^* - i_t) \times S_t\}$, and by τ otherwise. On the other hand, the quantile UIP regression weights errors by $1-\tau$ if the foreign currency's depreciation is sufficiently large and by τ otherwise. As such, the signed quantile UIP regression adjusts for the interest-rate symmetry of exchange rate movements. This interpretation is not unique to $i_t^* - i_t$; it holds for any conditioning variable in X_t^S, provided they too are interacted with S_t.

Appendix E provides a proof for proposition 1. The intuition, however, is presented in

Figure 5: Simulated *Signed* Exchange Rate Change Distribution due to Speculators

(a) $R^* - R > 0$ (b) $R^* - R < 0$



Note. Figure 5 displays simulated distributions of signed exchange rate change, $log(\frac{\varepsilon_1}{\varepsilon_0}) \times sign(R_t^* - R_t)$, which take into account only the behavior of speculators (formally $\lambda_0 = \lambda_1 = 0$), from simulating the model and aggregating exchange rate movements into histograms. In panel 5a, the foreign interest rate is 10% and the home interest rate is 1%. In panel 5b, the foreign interest rate is 1% and the home interest rate is 10%. The full parameterization is available in Appendix C. Exchange rate movements in the small mode in each panel, labeled $\Gamma_1 = \Gamma_H$, refer to exchange rate movements conditional on a disaster, whereas movements in the large mode, labeled $\Gamma_1 = \Gamma_L$, are movements conditional on no-disaster.

Figure 5, which displays simulated *signed* exchange rate change, $\Delta e_{t+1} \times S_t$, distributions when the interest differential is positive (in Panel 5a) and when the the interest differential is negative (in Panel 5b).[25] When the interest differential is positive, the sign interaction is akin to multiplying Δe_{t+1} by 1 such that the simulated signed exchange rate change distribution in Panel 5a is identical to the simulate exchange rate change distribution in Panel 3a. However, when the interest differential is negative, the sign interaction multiplies Δe_{t+1} by -1, thereby transposing the exchange rate change distribution from Panel 3b about the vertical axis. Thus, by leveraging the symmetry of exchange rate movements imposed by speculators, the sign-transform allows me to recover the same (signed) exchange rate change distribution for both high- (Panel 5a) and low- (Panel 5b) interest-rate currencies. Interacting the interest rate differential with its sign ensures I continue to estimate the marginal effect of interest differentials on exchange rate movements, as in the traditional Fama (1984) regression.

Importantly, the sign interaction places all speculator-driven disaster-state exchange rate movements—large depreciations (appreciations) of high- (low-) interest-rate currencies—into the left tail. I then define the 1^{st} percentile of the *conditional* signed exchange rate change distribution, my baseline measure for the disaster-state, as speculators' "Foreign Exchange-at-

[25]Since the distribution comes from the model, it actually corresponds to $log(\frac{\varepsilon_1}{\varepsilon_0}) \times sign(R_t^* - R_t)$.

Risk", $FEaR^S$:

$$Pr\Big[\widehat{\Delta e_{t+1} \times S_t} \mid X_t^S \ \le FEaR_{t+1}^S\Big] = 0.01, \tag{21}$$

where the conditioning vector X_t^S is $\{S_t, (i_t^* - i_t) \times S_t\}$ in (20).

3.3 Building on the Signed Quantile UIP Regression

To capture the effects of hedgers and empirically test Prediction 2, I augment (20) with the change in the U.S. Treasury liquidity yield, $\Delta\lambda_{t+1}$:

$$\Delta e_{t+1} \times S_t = \beta_0^\tau S_t + \beta_1^\tau (i_t^* - i_t) \times S_t + \beta_2^\tau \Delta\lambda_{t+1} \times S_t + u_{t+1}^\tau, \tag{22}$$

where the base currency is the U.S. dollar and $\Delta\lambda_{t+1}$ is interacted with the sign of the interest differential. As stated in Proposition 1 and proved in Appendix E, the interaction with S_t allows me to study the liquidity yield's impact on exchange rate movements without imposing sign-dependence on the effect: a negative β_2 implies that an increase in the Treasury liquidity yield predicts a fall in Δe_{t+1}, a U.S. dollar appreciation, regardless of interest differentials.[26]

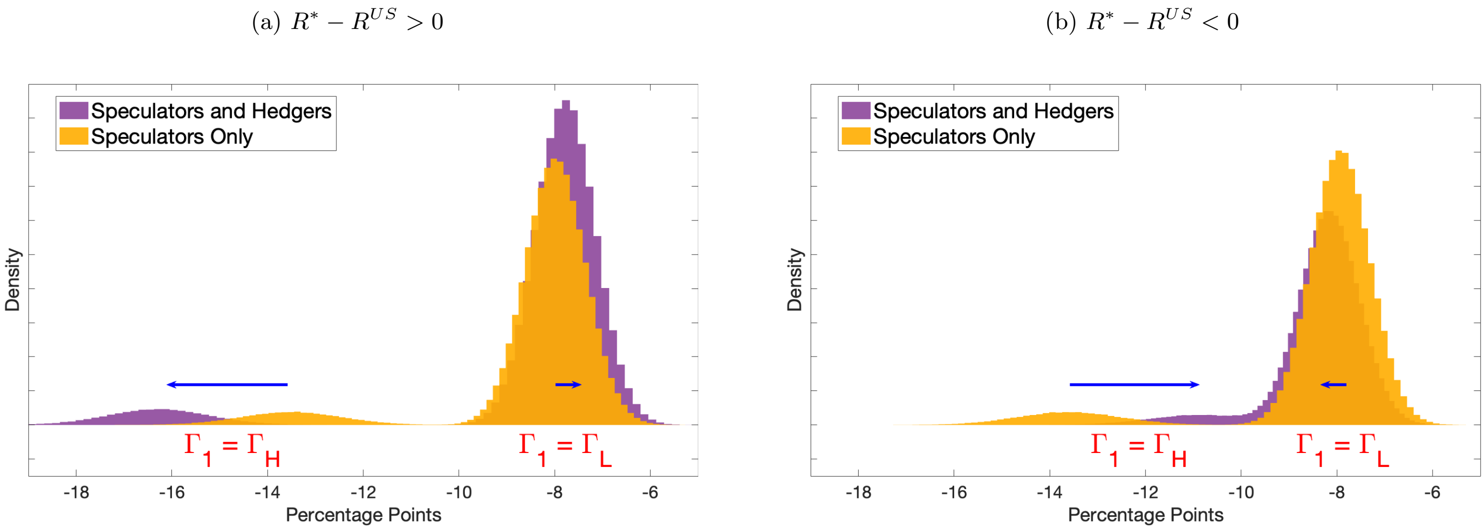
My model predicts the Treasury liquidity yield is an important driver of exchange rate movements in disasters. To understand in which tail of the signed exchange rate change distribution these effects should materialize, Figure 6 displays simulated distributions of signed exchange rate changes, $\Delta e_{t+1} \times S_t$, which now account also for the behavior of hedgers (in purple). It displays the distributions when the interest differential is positive in Panel 6a and when the the interest differential is negative in Panel 6b.

When additionally accounting for the behavior of hedgers, the signed exchange rate change distributions are no longer identical for high- and low-interest rate currencies. Still, the disaster-state outcomes materialize in the left-tail in both panels of Figure 6. In Panel 6a, this occurs because speculators' and hedgers' effects reinforce one another, leading to an amplified appreciation of the low-interest-rate U.S. dollar. Conversely, in Panel 6b, this occurs because, although the two financiers' portfolio adjustments offset each other, the model has been parameterized such that speculators' effect dominates and the high-interest-rate U.S. dollar experiences a dampened depreciation in the disaster. In these two cases, one would expect to find the U.S. Treasury liquidity yield's effect present in the left-tail, that is, at speculators' FEaR ($FEaR^S$).

A third possibility, which is shown in Appendix C, is that, if the U.S. interest rate differential is not too wide, the spike in Treasury liquidity is large enough, and the elasticity of exchange

[26]Intuitively, the S_t terms on either side of the regression cancel.

Figure 6: Simulated *Signed* Exchange Rate Change Distribution with Speculators and Hedgers



Note. In each panel of Figure 6, I present 2 simulated distributions of *signed* exchange rate changes, $log(\frac{\varepsilon_1}{\varepsilon_0}) \times sign(R_t^* - R_t^{US})$, constructed by simulating the model and aggregating exchange rate movements into histograms. The first, in yellow, accounts only the behavior of speculators (formally $\lambda_0 = \lambda_1 = 0$). The second, in purple, accounts for the behavior of both speculators and hedgers. In panel 6a, the foreign interest rate is 10% and the U.S. interest rate is 1%. In panel 6b, the foreign interest rate is 1% and the U.S. interest rate is 10%. The full parameterization is available in Appendix C. Exchange rate movements in the small mode in each panel, labeled $\Gamma_1 = \Gamma_H$, refer to exchange rate movements conditional on a disaster, whereas movements in the large mode, labeled $\Gamma_1 = \Gamma_L$, are movements conditional on no-disaster. Blue arrows indicate to how the exchange rate change distribution changes when hedgers behavior is accounted for.

rates to liquidity yields is sufficiently high, hedgers' effect overcomes that of speculators and pushes the disaster-state into the right-tail of the signed-exchange rate change distribution, implying an appreciation of the high-yield U.S. dollar.[27] This leads me to define the 99^{th} percentile of the *conditional* signed exchange rate change distribution as hedgers' "Foreign Exchange-at-Risk" $FEaR^H$:

$$Pr\left[\widehat{\Delta e_{t+1} \times S_t} \mid X_t^S \leq FEaR_{t+1}^H\right] = 0.99, \tag{23}$$

where the conditioning vector X_t^S is $\{S_t, (i_t^* - i_t^{US}) \times S_t, \Delta\lambda_{t+1} \times S_t\}$ when estimating (22). In this third case, one would expect to find liquidity yield's effect manifesting at hedgers' FEaR ($FEaR^H$).[28]

Finally, to test the mechanisms of my model, I will replace the signed exchange rate movement $\Delta e_{t+1} \times S_t$ in (20) and (22) with the signed change in speculators' and hedgers' portfolio

[27] The final possibility is the knife-edge case in which speculators' and hedgers' effects (exactly) cancel one another, such that the disaster-state exchange rate movement would manifest in the center of the signed exchange rate change distribution. In this case, one would expect to find the liquidity yield's effect at the central quantiles of the distribution.

[28] Of note, the right tail of $\Delta e_{t+1} \times S_t$ also holds all large depreciations of the dollar when the U.S. has a relatively high interest rate. These episodes, on the other hand, need not be driven by hedgers' flight to the dollar, although this flight to safety would dampen the extent of the dollar's depreciation.

positions, $\Delta Pos^S_{t+1} \times S_t$ and $\Delta Pos^H_{t+1} \times S_t$, respectively, where financiers' portfolio positions are as defined in (18). I leave the precise details to section 4.

4 Empirical Results

In this section, I use the empirical strategy developed in Section 3 to test the predictions of my model. Further, I test whether my model's mechanisms underlie these exchange rate dynamics by studying the portfolio adjustments of speculators and hedgers. In 4.1, I test Corollary 1 and Prediction 1, which, in my model, arise due to speculator behavior. In 4.2, I focus on Prediction 2, which arises due to hedgers in my framework, and discuss Corollary 2 as well. Robustness is discussed at the end of each sub-section.

4.1 Interest Differentials, Exchange Rates and Speculator (De)Leveraging

I begin by estimating panel signed quantile UIP regressions with currency fixed effects for the case where the U.S. is the domestic currency vis-a-vis the remaining G-10 currencies:

$$\Delta e_{j,t+1} \times S_{j,t} = \beta_0^\tau S_{j,t} + \beta_1^\tau (i^*_{j,t} - i_t) \times S_{j,t} + f_j^\tau + u^\tau_{j,t+1}. \tag{24}$$

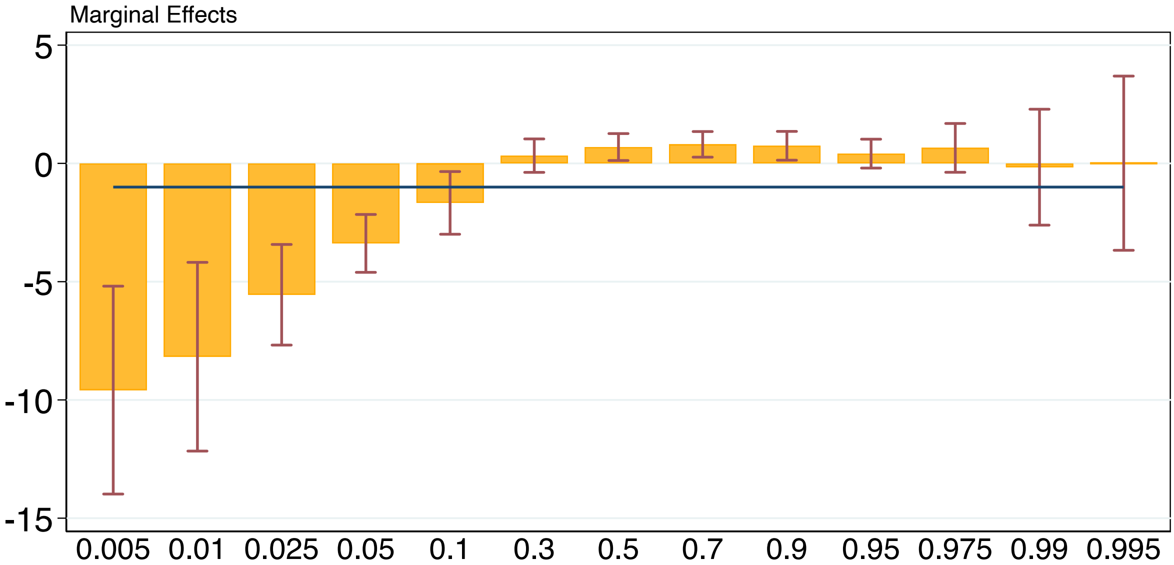
Figure 7 presents the quantile marginal effects for the signed interest rate differential ($\hat{\beta}_1^\tau$) from estimating regression (24) at different quantiles τ. The quantiles estimated range from $\tau = 0.005$ to $\tau = 0.995$ and run from lowest to highest along the horizontal axis.[29] The yellow bars represent the marginal effects, measured along the vertical axis, while the red error bars correspond to 90% confidence intervals constructed using an overlapping block bootstrap procedure that accounts for heteroskedasticity and autocorrelation, as in Adrian et al. (2022) (see Appendix E.1 for details). The blue horizontal line at -1 indicates the marginal effect for which UIP holds, $\hat{\beta}_1^{UIP} = -1$. In each regression, the sample size is 3780 observations (9 currencies times 420 months).[30]

The results showcase the highly state-dependent relationship between relative interest rates and U.S. dollar exchange rate movements. If UIP held each period, the marginal effects at each quantile would be on the UIP line at -1. Instead, the interest rate differential's marginal

[29] For robustness, I estimate a large number of left-tail quantiles ($\tau \in \{0.005, 0.01, 0.025, 0.05, 0.1\}$) and right-tail quantiles ($\tau \in \{0.9, 0.95, 0.975, 0.99, 0.995\}$) as these tail quantiles weight fewer observations a relatively large amount, compared to the central quantiles ($\tau \in \{0.3, 0.5, 0.7\}$).

[30] This is a large sample compared to many other studies in macro-finance that use quantile regression, which often feature quarterly GDP data for a single country.

Figure 7: The U.S. Signed Quantile UIP Regression

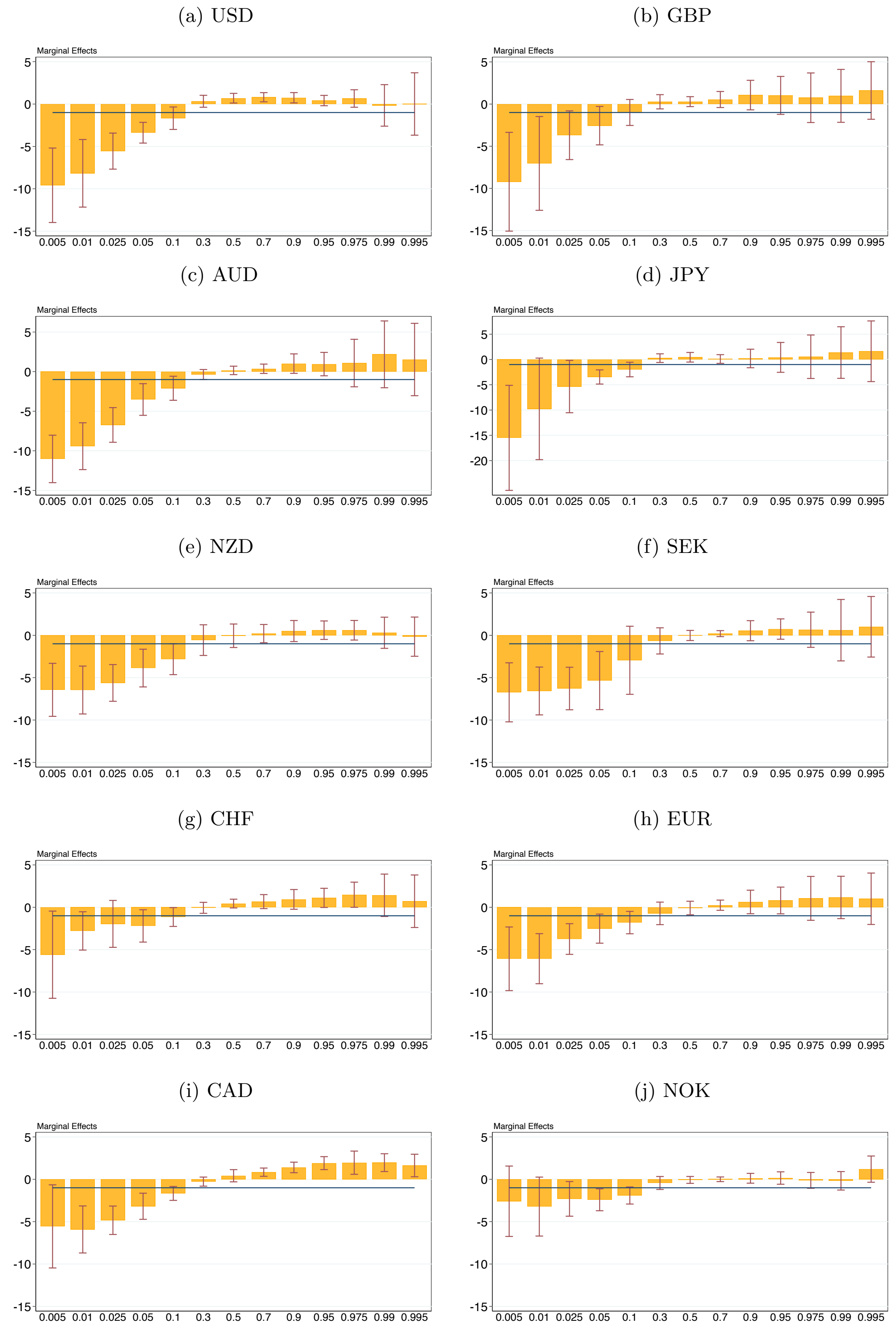


Note. Figure 7 presents panel quantile regression coefficients for the signed interest rate differential on the signed exchange rate change, ($\hat{\beta}_1^\tau$) from estimating (24) using the USD as the domestic currency vis-à-vis the remaining G-10 currencies. The sample period is 1986:M1 to 2020:M12. Quantiles $\tau = \{0.005, 0.01, 0.025, 0.05, 0.1, 0.3, 0.5, 0.7, 0.9, 0.95, 0.975, 0.99, 0.995\}$ range along the horizontal axis. The blue line is the "UIP line". Red error bars are 90% confidence intervals constructed using a block bootstrap with 500 bootstrap samples.

effect at the median is larger than -1, implying that high-interest-rate currencies are predicted to *excessively* appreciate, relative to interest differentials, against low-interest-rate currencies. Specifically, a 1 percentage point (pp) increase in the U.S. relative interest rate predicts about a 1 pp greater dollar appreciation at the median, my empirical proxy for conditional on no-disaster. Conversely, the marginal effects at the 1^{st} percentile of the distribution are signicantly below -1, implying depreciations of high-yield currencies in disasters that are far greater that interest differentials. Quantitatively, a 1 pp increase in the U.S. relative interest rate predicts about an 8 pp larger dollar depreciation at the FEaR^S. Further, these 'disaster-state' marginal effects are also present at other left-tail percentiles I estimate (the 0.5^{th}, 2.5^{th} and 5^{th}). Altogether, the results in Figure 7 match the predictions of my model.

This state-dependent relationship between relative interest rates and exchange rate dynamics appears also when other G-10 currencies serve as the domestic currency in the panel signed quantile UIP regression (24). Alongside the U.S. dollar results in Panel 8a, the other panels of Figure 8 presents quantile marginal effects for the signed interest rate differential ($\hat{\beta}_1^\tau$) from estimating (24) for the remaining G-10 currencies, with the labels atop each panel denoting the domestic currency. As in the U.S. dollar case, for most G-10 currencies, interest differentials predict high-interest-rate currencies to excessively appreciate relative to UIP at the median but

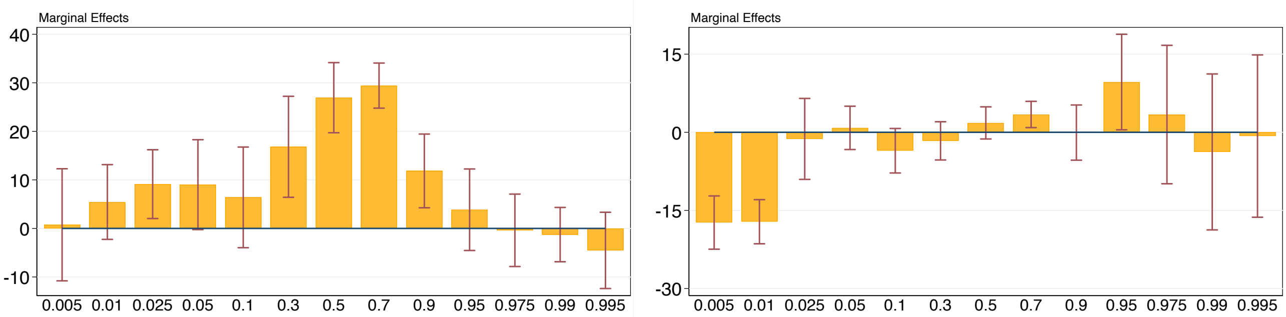
Figure 8: State-Dependent Uncovered Interest Parity Relations for G-10 Currencies



Note. Figure 8 presents panel quantile regression coefficients for the signed interest rate differential on the signed exchange rate change, ($\hat{\beta}_1^\tau$) from estimating (24) for each G-10 currency. The labels atop each panel denote the domestic currency vis-à-vis the remaining G-10 currencies. The sample period is 1986:M1 to 2020:M12. Quantiles $\tau = \{0.005,\ 0.01,\ 0.025,\ 0.05,\ 0.1,\ 0.3,\ 0.5,\ 0.7,\ 0.9,\ 0.95,\ 0.975,\ 0.99,\ 0.995\}$ range along the horizontal axis in each panel. The blue line is the “UIP line”. Red error bars are 90% confidence intervals constructed using a block bootstrap with 500 bootstrap samples.

Figure 9: The State-Dependence of Speculators' Carry Trade Positions

(a) Carry Trading in Normal Times (b) Unwinding in Disasters



Note. Panel 9a of Figure 9 presents panel quantile regression coefficients for the interest rate differential ($\hat{\beta}_1^\tau$) on speculator positions from estimating (25). Panel 9b presents panel quantile regression coefficients for the signed interest rate differential ($\hat{\beta}_1^\tau$) on the signed change in speculator positions from estimating (26). The USD is the base (domestic) currency vis-à-vis 6 major currencies from 1993:M1 to 2020:M12. Quantiles $\tau = \{0.005,\ 0.01,\ 0.025,\ 0.05,\ 0.1,\ 0.3,\ 0.5,\ 0.7,\ 0.9,\ 0.95,\ 0.975,\ 0.99,\ 0.995\}$ range along the horizontal axis in each panel. The blue line is the "zero line" in each panel. Red error bars are 90% confidence intervals constructed using a block bootstrap with 500 bootstrap samples.

to experience large depreciations far in-excess of interest differentials in the left-tail.[31] These findings are consistent with Corrollary 1 and Prediction 1: according to interest differentials, while carry trades implemented using any of these currencies tend to be profitable in normal times, they earn large losses in disasters.

Next, I test whether speculators' state-dependent behavior may be behind the exchange rate dynamics presented in Figure 8. To do so, I estimate by quantile regression two specifications using $Pos^S_{j,t}$, the net-long position of speculators in currency j relative to the dollar, as the dependent variable.

First, to investigate the relation between interest differentials and speculators' currency positions in normal times, I estimate:

$$Pos^S_{j,t} = \beta_0^\tau + \beta_1^\tau(i^*_{j,t} - i_t) + f_j^\tau + u^\tau_{j,t+1} \tag{25}$$

The positive coefficient at the median in Panel 9a, from estimating (25), implies that an increase in country j's relative interest rate predicts an increase in speculators' net-long position in currency j. That is, speculators use currency futures to carry trade in normal times. The estimated elasticity is also quite large: a 1 pp increase in country j's relative interest rate predicts over a 25 pp increase in speculators' net-long positions in currency j, as a fraction the total open interest in j.

[31] The exceptions are the CHF and NOK in the left-tail, although the point-estimates are still large and negative, and the NZD at the median.

Second, to investigate the relation between interest differentials and *changes* in speculators' currency positions in disasters, I estimate:

$$\Delta Pos^{S}_{j,t+1} \times S_{j,t} = \beta^{\tau}_{0} S_{j,t} + \beta^{\tau}_{1}(i^{*}_{j,t} - i_{t}) \times S_{j,t} + f^{\tau}_{j} + u^{\tau}_{j,t+1}. \tag{26}$$

This regression is the speculator positions analogue of the signed quantile UIP regression in (24). Specifically, it replaces $\Delta e_{j,t+1} \times S_{j,t}$ as the dependent variable with the signed change in speculators' currency positions. I term the left tail of the $\Delta Pos^{S}_{j,t+1} \times S_{j,t}$ distribution the carry-trade-unwinding tail, since it stores the largest decreases (increases) in speculators' net-long positions in currency j when currency j has the relatively high (low) interest rate.

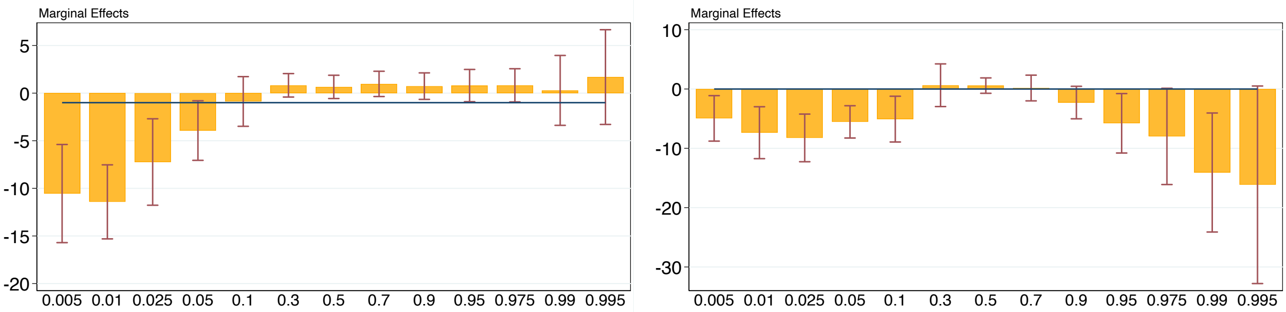
The large, negative coefficients in the left-tail of Panel 9b highlight that interest differentials predict these large carry trade unwindings. Quantitatively, a 1 pp increase in country j's relative interest rate predicts a more than 15 pp *larger* decline in speculators' net-long position in currency j. And since speculators unwind their carry trades in the same periods in which high-yield currencies suffer large depreciations, as shown in Figure F.9, these results suggest that speculator deleveraging may be driving, or at least amplifying, these disaster-state exchange rate movements, as they do in my model.

Robustness and Additional Results: In Appendix F, I show that the exchange rate results from this section are robust to many variations of my empirical approach. In F.4, I show they are little changed once I control for investors' interest rate expectations, an important concern raised by Hassan and Mano (2019). In F.8, I show my results are robust to controlling for a 'signed' currency fixed effects, which controls for time-invariant factors that may push the domestic currency to appreciate, in addition to the currency fixed effect used in my baseline specification that controls for time-invariant factors that may push the high-yield currency to appreciate. I show in F.9 that my results are not driven exclusively by the largest disaster episode in my sample, the collapse of Lehman Brothers in September 2008. Finally, in F.10, I show that the state-dependent relation between interest differentials and exchange rate dynamics holds also on a currency-by-currency basis. Robustness to the speculator positions regression is discussed at the end of Section 4.2.

Appendix F also provides some additional empirical results to supplement the ones from this section. In F.1, I present results from estimating quantile UIP regressions without the sign interaction and showcases this specification's deficiencies relative to (24). In F.2, I present the quantile analogue of the R^2, $R^1(\tau)$, and highlight the strong fit of my model in the left-tail of the signed exchange rate change distribution. And finally, in F.7, I estimate quantile regression

Figure 10: Interest Differentials, Treasury Liquidity Premia and Tail Exchange Rate Dynamics

(a) Interest Rate Differential (b) Δ U.S. Treasury Liquidity Yield



Note. Figure 10 presents panel quantile regression coefficients for the signed interest rate differential ($\hat{\beta}_1^\tau$ in Panel 10a) and the signed liquidity yield ($\hat{\beta}_2^\tau$ in Panel 10b) on the signed exchange rate change, from estimating (27) with the USD as the base (domestic) currency vis-a-vis the remaining G-10 currencies. The sample period is from 1991:M4 to 2020:M12 (unbalanced). Quantiles $\tau = \{0.005, 0.01, 0.025, 0.05, 0.1, 0.3, 0.5, 0.7, 0.9, 0.95, 0.975, 0.99, 0.995\}$ range along the horizontal axis in each panel. The blue line is the 'UIP line" in Panel 10a and the "zero line" in Panel 10b. Red error bars are 90% confidence intervals constructed using a block bootstrap with 500 bootstrap samples.

models that include the VIX index to demonstrate the drawbacks of using measures of financial market stress to explain exchange rate dynamics in disasters

4.2 Treasury liquidity, Exchange Rates and Hedger Portfolios in Disasters

To test Prediction 2, I augment the U.S.'s signed quantile UIP regression in (24) with the signed change in the U.S. Treasury liquidity yield $\Delta\lambda_{j,t+1} \times S_{j,t}$:

$$\Delta e_{j,t+1} \times S_{j,t} = \beta_0^\tau S_{j,t} + \beta_1^\tau (i_{j,t}^* - i_t) \times S_{j,t} + \beta_2^\tau (\Delta\lambda_{j,t+1}) \times S_{j,t} + f_j^\tau + u_{j,t+1}^\tau \tag{27}$$

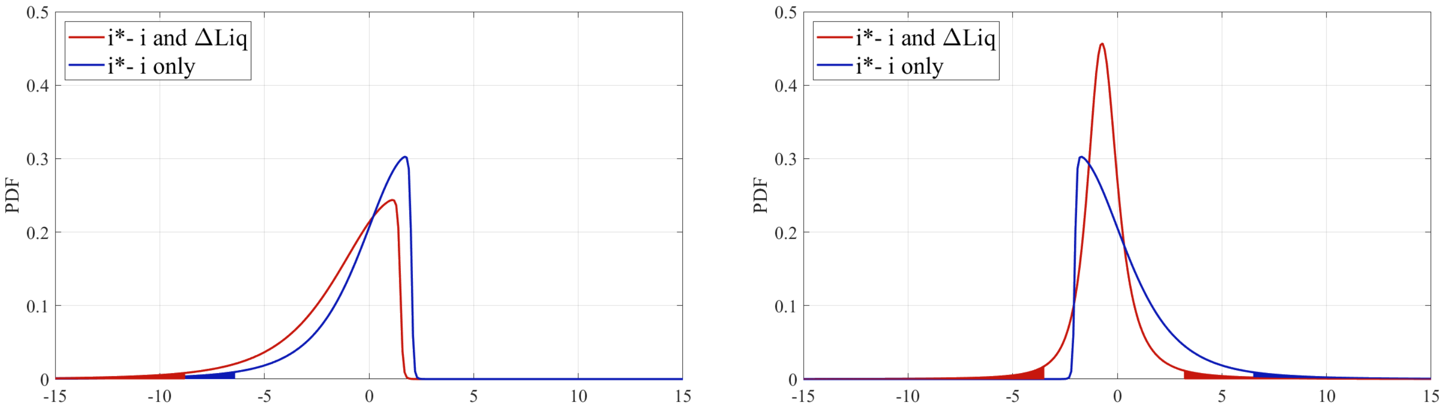
Figure 10 presents the quantile regression coefficients for the signed interest rate differential (β_1^τ) in Panel 10a and the signed liquidity yield (β_2^τ) in Panel 10b. The negative marginal effects at the $FEaR^S$ in Panel 10a highlight that the inclusion of the liquidity yield does not distort the interest-differential's effect on exchange rates in disasters. In fact, the left-tail marginal effects become even larger: a 1 pp widening of interest differentials now predicts over a 10 pp depreciation of the high-yield currency in disasters.[32]

As expected, the liquidity yield has effects in <u>both</u> tails of the conditional signed exchange rate change distribution (Panel 10b). The large negative marginal effects indicate that an increase in the liquidity yield on U.S. Treasuries predicts a sizeable appreciation of the dollar

[32]The interest differential's effect at the median is also little changed when including the Treasury liquidity yield.

Figure 11: Conditional U.S. dollar Exchange Rate Change Distribution

(a) $R^* > R^{US}$ (b) $R^* < R^{US}$



Note. Figure 11 presents conditional U.S. dollar exchange rate change distributions when the U.S. interest rate is relatively low (Panel 11a) and when the U.S. interest rate is relatively high (Panel 11b). Following the methodology of Adrian et al. (2019), the PDFs are estimated by fitting the empirical conditional quantiles ($\hat{\beta}^{\tau} X_t$) constructed using the coefficients from Figure 10 to the theoretical quantiles of the Skew-T distribution. In terms of X_t, the magnitude of the interest differential is set to 1% and the change in the Treasury liquidity yield is 75 basis points. The blue PDFs in each panel condition only on interest differentials while the red PDFs condition also on the change in the U.S. Treasury liquidity yield. See Appendix E.2 for details.

in disasters, regardless of the U.S.'s relative interest rate. Importantly, while the interest-differential channel was present for all currencies in my sample, this liquidity yield channel appears unique to the U.S. dollar. The tail marginal effects imply that a 75 basis point rise in Treasury liquidity, which corresponds to the spike during the bursting of the "Dot-Com" bubble in 2000 (see Figure 1), predicts a dollar appreciation of between 1.5 percent at the 1^{st} percentile and 3 percent at the 99^{th} percentile (the FEaR^H).

The structure imposed by the signed quantile UIP approach, as discussed in Section 3, helps interpret the net effect of interest differentials and liquidity yields on exchange rates in each tail. When the U.S. interest rate is relatively low, spikes in the Treasury liquidity yield reinforce the interest-differential channel, generating an amplified appreciation of the low-yield dollar in disasters. Thus, disaster dynamics remain in the left-tail. On the other hand, when the U.S. interest rate is relatively high, the two channels offset each other, leading to two cases. When the interest-rate channel dominates, the high-yield dollar's depreciation in disasters is dampened, but the dynamics remain in the left tail. Conversely, when the liquidity-yield force dominates, the high-yield dollar appreciates in the disaster, which pushes the disaster dynamics into the right tail.[33]

The dollar's amplified appreciation against high-yield currencies and dampened depreci-

[33] Of note, some of these right-tail episodes occur when the U.S. dollar has a relatively low interest rate, in which case spikes in dollar liquidity dampen the extent of the dollar's depreciation.

ation, or appreciation, against low-yield ones in disasters is unmistakable in the conditional exchange rate change distributions displayed in Figure 11. These distributions are estimated following the methodology of Adrian et al. (2019), using as inputs the quantile marginal effects displayed in Figure 10 (see Appendix E.2 for details). Each panel compares two Δe_{t+1} distributions, where recall that an increase in Δe_{t+1} implies an appreciation of the foreign currency vis-à-vis the dollar. The first, in blue, accounts only for the effect of a 1 pp interest differential. The second, in red, considers also the effect of a 75 basis point spike in the Treasury liquidity yield.

The key takeaway is that while the distributions accounting only for interest differentials are transpositions of each other about the vertical axis, with the high-yield currency at risk of a large "disaster-state" depreciation, the inclusion of the Treasury liquidity yield breaks this symmetry. In Panel 11a, where the U.S. interest rate is relatively low, spikes in Treasury liquidity extend the left-tail of the distribution, reflecting an amplified appreciation of the low-yield dollar in disasters. In Panel 11b, where the U.S. interest rate is relatively high, spikes in Treasury liquidity shorten the right-tail of the distribution and move probability mass to the left-tail, reflecting a dampened depreciation or even an appreciation of the high-yield dollar in disasters.[34] In all, these findings are consistent with the "Main Result" from my model and demonstrate the significant asymmetry between the dollar's exchange-rate dynamics in disasters against high-interest-rate and low-interest-rate currencies.

Finally, I investigate whether hedgers' flight to Treasury liquidity may be behind the dollar's unique tendency to appreciate in disasters. To do so, I use $Pos^H_{j,t}$, the normalized net-long position of hedgers in currency j relative to the dollar, to estimate:

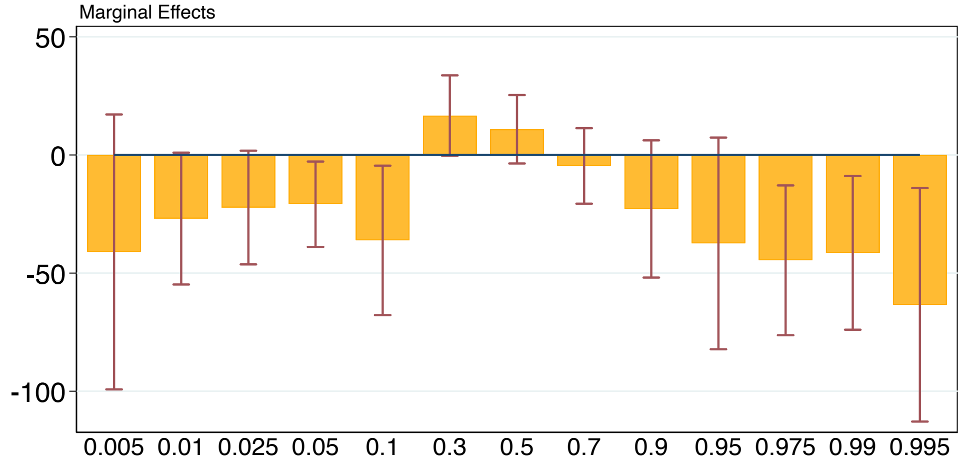
$$\Delta Pos^H_{j,t+1} \times S_{j,t} = \beta_0^\tau S_{j,t} + \beta_1^\tau (i^*_{j,t} - i_t) \times S_{j,t} + \beta_2^\tau (\Delta\lambda_{j,t+1}) \times S_{j,t} + f_j^\tau + u^\tau_{j,t+1} \tag{28}$$

The regression in (28) is the hedger positions analogue of regression (27). Specifically, it replaces $\Delta e_{j,t+1} \times S_{j,t}$ as the dependent variable with the signed change in hedgers' currency positions $\Delta Pos^H_{j,t+1} \times S_{j,t}$. Since hedgers and speculators trade with each other in the CBOE's currency futures market, changes in their positions are inversely correlated, as shown in Figure F.10.[35] As a result, speculators' carry trade unwindings in disasters, which occurred in the left tail of their position distribution (Panel 9b) are accommodated by hedgers in the right tail of

[34] Due to the symmetry imposed by the signed quantile UIP regression, the right tail in Panel 11a shifts to the left as well.

[35] The correlation coefficient is about -0.95. It isn't exactly -1 since some agents are classified as neither hedgers nor speculators by the CFTC. This third category of agents is small in the data and can be thought of as the households of my model.

Figure 12: Treasury Liquidity Yields and Hedgers' Flight to U.S. Dollars



Note. Figure 12 presents panel quantile regression coefficients for the signed U.S. liquidity yield ($\hat{\beta}_2^{\tau}$) from estimating (28). The USD is the base (domestic) currency vis-à-vis 6 major currencies from 1993:M1 to 2020:M12. Quantiles $\tau = \{0.005, 0.01, 0.025, 0.05, 0.1, 0.3, 0.5, 0.7, 0.9, 0.95, 0.975, 0.99, 0.995\}$ range along the horizontal axis in each panel. The blue line is the "zero line" in each panel. Red error bars are 90% confidence intervals constructed using a block bootstrap with 500 bootstrap samples.

the $\Delta Pos^H_{j,t+1} \times S_{j,t}$ distribution.

Figure 12 displays the marginal effects for the U.S. Treasury liquidity yield from estimating (28). The large negative marginal effects in the right tail indicate that an increase in the U.S. Treasury liquidity yield is associated with a significant flight to U.S. dollars by hedgers in disasters. The magnitude implies that a 75 basis point rise in the liquidity yield on U.S. Treasuries predicts a 7.5 percent increase in hedgers' dollar holdings. Consistent with my model, this flight to the liquidity by hedgers would appreciate the dollar in disasters against all other currencies, regardless of relative interest rates.

Robustness and Additional Results: In Appendix F, I show that the exchange rate results from this section are robust to many variations of my empirical approach, including 'signed' fixed effects (F.8), excluding the largest spike in the Treasury liquidity yield in September 2008 (F.9), and a currency-by-currency analysis (F.10). Further, in F.2, I show that including the Treasury liquidity yield improves the goodness of fit $R^1(\tau)$ in both tails of the signed exchange rate change distribution.

I also provide additional empirical results to reinforce the conclusions from this section. First, in Appendix F.5, I tease out the causal effect of spikes in the U.S. Treasury liquidity yield on dollar appreciations in disasters using instrumental variable quantile regression. Following Engel and Wu (2018), I instrument the Treasury liquidity yield with the VIX index, which is a measure of equity market volatility that is not mechanically related to exchange rates. I find that the instrument is highly relevant and that the causal marginal effects are larger and more significant than in my baseline. Second, I show explicitly in F.6 that speculators' accommodate hedgers' flights to the dollar and hedgers' accommodate speculators' carry trade unwinding in disasters. Finally, in Figure D.2 of Appendix D, I provide evidence consistent with Corollary 2: the dollar has a tendency to depreciate conditional on no-disaster (at the median) against all other currencies.

5 Conclusion

In this paper, I show that exchange rate dynamics in disasters reflect portfolio adjustments by two distinct types of financial agent: speculators and hedgers. While speculators unwind carry trades in disasters, pushing high-yield currencies to depreciate, it is hedgers' desire for safe, liquidity and convenient U.S. Treasuries that imbues the U.S. dollar with its unique tendency to appreciate in disasters.

Due to the resilience of the U.S. economy, the Federal Reserve has been able to tighten monetary policy aggressively in 2022-23 to combat inflation such that U.S. interest rates now eclipse those of other advanced economies. According to my results, this makes the U.S. dollar more of an investment currency for speculators' carry trade and so increases its downside exchange-rate risk in the event of a disaster. Still, this downside risk should be dampened, and even more than fully offset, by hedgers' desire for U.S. Treasuries during periods of financial stress.

As the recent bank failures in the U.S. have made clear, higher interest rates matter not just for exchange rate dynamics *in the event* of financial market stress, but may also serve as the *catalyst* for the next disaster event. This underscores the pressing need for a flexible and interpretable approach with which to track currencies' ever-evolving exposure to disaster risk, which the signed quantile UIP framework I develop here provides.

References

Adrian, T., N. Boyarchenko, and D. Giannone (2019): "Vulnerable growth," *American Economic Review*, 109, 1263–89.

Adrian, T., F. Grinberg, N. Liang, S. Malik, and J. Yu (2022): "The term structure of growth-at-risk," *American Economic Journal: Macroeconomics*, 14, 283–323.

Azzalini, A. and A. Capitanio (2003): "Distributions generated by perturbation of symmetry with emphasis on a multivariate skew t-distribution," *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 65, 367–389.

Barro, R. J. (2006): "Rare disasters and asset markets in the twentieth century," *The Quarterly Journal of Economics*, 121, 823–866.

Bernanke, B. (2005): "The global saving glut and the US current account deficit," Tech. rep., Board of Governors of the Federal Reserve System (US).

Bianchi, J., S. Bigio, and C. Engel (2021): "Scrambling for dollars: International liquidity, banks and exchange rates," Tech. rep., National Bureau of Economic Research.

Brunnermeier, M. K., S. Nagel, and L. H. Pedersen (2009): "Carry Trades and Currency Crashes," in *NBER Macroeconomics Annual 2008, Volume 23*, National Bureau of Economic Research, Inc, NBER Chapters, 313–347.

Brunnermeier, M. K. and L. H. Pedersen (2009): "Market liquidity and funding liquidity," *The review of financial studies*, 22, 2201–2238.

Burnside, C., M. Eichenbaum, I. Kleshchelski, and S. Rebelo (2011): "Do peso problems explain the returns to the carry trade?" *The Review of Financial Studies*, 24, 853–891.

Caballero, R. J., E. Farhi, and P.-O. Gourinchas (2008): "An Equilibrium Model of "Global Imbalances" and Low Interest Rates," *American Economic Review*, 98, 358–393.

Cenedese, G., L. Sarno, and I. Tsiakas (2014): "Foreign exchange risk and the predictability of carry trade returns," *Journal of Banking & Finance*, 42, 302–313.

Cesa-Bianchi, A. and F. Eguren Martin (2021): "Dash for dollars," .

Chernozhukov, V., I. Fernández-Val, and A. E. Kowalski (2015): "Quantile regression with censoring and endogeneity," *Journal of Econometrics*, 186, 201–221.

Corsetti, G. and E. A. Marin (2020): "A century of arbitrage and disaster risk pricing in the foreign exchange market," .

Devereux, M. B., C. Engel, and S. P. Y. Wu (2023): "Collateral Advantage: Exchange Rates, Capital Flows and Global Cycles," Tech. rep., National Bureau of Economic Research.

Di Tella, S. (2020): "Risk premia and the real effects of money," *American Economic Review*, 110, 1995–2040.

Dobrynskaya, V. (2014): "Downside market risk of carry trades," *Review of Finance*, 18, 1885–1913.

Du, W., J. Im, and J. Schreger (2018a): "The U.S. Treasury Premium," *Journal of International Economics*, 112, 167–181.

Du, W., A. Tepper, and A. Verdelhan (2018b): "Deviations from covered interest rate parity," *The Journal of Finance*, 73, 915–957.

Eguren-Martin, F. and A. Sokol (2020): "Attention to the tail (s): global financial conditions and exchange rate risks," .

Engel, C. and S. P. Y. Wu (2018): "Liquidity and Exchange Rates: An Empirical Investigation," NBER Working Papers 25397, National Bureau of Economic Research, Inc.

Evans, M. D. and R. K. Lyons (2002): "Order flow and exchange rate dynamics," *Journal of political economy*, 110, 170–180.

Fama, E. F. (1984): "Forward and spot exchange rates," *Journal of monetary economics*, 14, 319–338.

Farhi, E., S. P. Fraiberger, X. Gabaix, R. Ranciere, and A. Verdelhan (2009): "Crash risk in currency markets," Tech. rep., National Bureau of Economic Research.

Farhi, E. and X. Gabaix (2016): "Rare disasters and exchange rates," *The Quarterly Journal of Economics*, 131, 1–52.

Farhi, E. and M. Maggiori (2018): "A model of the international monetary system," *The Quarterly Journal of Economics*, 133, 295–355.

Froot, K. A. and T. Ramadorai (2005): "Currency returns, intrinsic value, and institutional-investor flows," *The Journal of Finance*, 60, 1535–1566.

Fukui, M., E. Nakamura, and J. Steinsson (2023): "The Macroeconomic Consequences of Exchange Rate Depreciations," Tech. rep., National Bureau of Economic Research.

Gabaix, X. and M. Maggiori (2015): "International Liquidity and Exchange Rate Dynamics," *The Quarterly Journal of Economics*, 130, 1369–1420.

Georgiadis, G., G. J. Müller, and B. Schumann (2021): "Global risk and the dollar," .

Gourinchas, P.-O., W. D. Ray, and D. Vayanos (2022): "A Preferred-Habitat Model of Term Premia, Exchange Rates, and Monetary Policy Spillovers," Tech. rep., National Bureau of Economic Research.

Gourinchas, P.-O. and H. Rey (2007): "International financial adjustment," *Journal of Political Economy*, 115, 665–703.

Gourinchas, P.-O., H. Rey, and N. Govillot (2010): "Exorbitant Privilege and Exorbitant Duty," IMES Discussion Paper Series 10-E-20, Institute for Monetary and Economic Studies, Bank of Japan.

Greenwood, R., S. G. Hanson, J. C. Stein, and A. Sunderam (2020): "A quantity-driven theory of term premia and exchange rates," Tech. rep., National Bureau of Economic Research.

Habib, M. M. and L. Stracca (2012): "Getting beyond carry trade: What makes a safe haven currency?" *Journal of International Economics*, 87, 50–64.

Hansen, L. P. and R. J. Hodrick (1980): "Forward exchange rates as optimal predictors of future spot rates: An econometric analysis," *Journal of political economy*, 88, 829–853.

Hassan, T. A. and R. C. Mano (2019): "Forward and spot exchange rates in a multi-currency world," *The Quarterly Journal of Economics*, 134, 397–450.

Itskhoki, O. and D. Mukhin (2021): "Exchange rate disconnect in general equilibrium," *Journal of Political Economy*, 129, 2183–2232.

Jeanne, O. and A. K. Rose (2002): "Noise trading and exchange rate regimes," *The Quarterly Journal of Economics*, 117, 537–569.

Jiang, Z. (2021): "US Fiscal cycle and the dollar," *Journal of Monetary Economics*, 124, 91–106.

Jiang, Z., A. Krishnamurthy, and H. Lustig (2020): "Dollar Safety and the Global Financial Cycle," NBER Working Papers 27682, National Bureau of Economic Research, Inc.

——— (2021): "Foreign safe asset demand and the dollar exchange rate," *The Journal of Finance*, 76, 1049–1089.

Kalemli-Özcan, nd L. Varela (2021): "Five facts about the uip premium," Tech. rep., National Bureau of Economic Research.

Kekre, R. and M. Lenel (2021): "The flight to safety and international risk sharing," Tech. rep., National Bureau of Economic Research.

Koenker, R. and G. Bassett Jr (1978): "Regression quantiles," *Econometrica: journal of the Econometric Society*, 33–50.

Koenker, R. and J. A. Machado (1999): "Goodness of fit and related inference processes for quantile regression," *Journal of the american statistical association*, 94, 1296–1310.

Koijen, R. S. and M. Yogo (2020): "Exchange rates and asset prices in a global demand system," Tech. rep., National Bureau of Economic Research.

Krasker, W. S. (1980): "The 'peso problem'in testing the efficiency of forward exchange markets," *Journal of Monetary Economics*, 6, 269–276.

Krishnamurthy, A. and A. Vissing-Jorgensen (2012): "The aggregate demand for treasury debt," *Journal of Political Economy*, 120, 233–267.

Liao, G. and T. Zhang (2020): "The Hedging Channel of Exchange Rate Determination," International Finance Discussion Papers 1283, Board of Governors of the Federal Reserve System (U.S.).

Lloyd, S., E. Manuel, and K. Panchev (2021): "Foreign vulnerabilities, domestic risks: The global drivers of GDP-at-risk," .

Lloyd, S. and E. Marin (2020): "Exchange rate risk and business cycles," Bank of England Staff Working Papers 872, Bank of England.

Lustig, H., N. Roussanov, and A. Verdelhan (2014): "Countercyclical currency risk premia," *Journal of Financial Economics*, 111, 527–553.

Maggiori, M. (2017): "Financial intermediation, international risk sharing, and reserve currencies," *American Economic Review*, 107, 3038–71.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2012): "Carry trades and global foreign exchange volatility," *The Journal of Finance*, 67, 681–718.

Miranda-Agrippino, S. and H. Rey (2020): "US monetary policy and the global financial cycle," *The Review of Economic Studies*, 87, 2754–2776.

Mussa, M. (1986): "Nominal exchange rate regimes and the behavior of real exchange rates: Evidence and implications," in *Carnegie-Rochester Conference series on public policy*, Elsevier, vol. 25, 117–214.

Pavlova, A. and R. Rigobon (2007): "Asset prices and exchange rates," *The Review of Financial Studies*, 20, 1139–1180.

Ranaldo, A. and P. Söderlind (2010): "Safe haven currencies," *Review of finance*, 14, 385–407.

Rey, H. (2015): "Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence," NBER Working Papers 21162, National Bureau of Economic Research, Inc.

Rietz, T. A. (1988): "The equity risk premium a solution," *Journal of monetary Economics*, 22, 117–131.

Stavrakeva, V. and J. Tang (2019): "The dollar during the great recession: US monetary policy signaling and the flight to safety," .

Stock, J. H. and M. Yogo (2002): "Testing for weak instruments in linear IV regression," .

Valchev, R. (2020): "Bond convenience yields and exchange rate dynamics," *American Economic Journal: Macroeconomics*, 12, 124–66.

Yoon, J. and A. F. Galvao (2020): "Cluster robust covariance matrix estimation in panel quantile regression with individual fixed effects," *Quantitative Economics*, 11, 579–608.

Appendix

A Model Solution

In the main text, I solved for optimal U.S. dollar bond holdings of speculators and hedgers. In this section, I solve the rest of the model as follows. First, I setup and solve the U.S. and Foreign household problems. Second, I state the market clearing conditions for bonds and goods. Third, I input the equilibrium and market clearing conditions into household's budget constraints until I arrive at the net foreign asset flow demand equations (10) in each period.

Household Problem Setup:

Time is discrete, indexed by t, and there are 3 periods $t \in \{0, 1, 2\}$. Each country is populated by a unit mass of households. Each period, the representative U.S. household is endowed with $Y_{NT,t}$ units of a country-specific non-tradable (NT) good and $Y_{H,t}$ units of the U.S. tradable (H) good. The setup is analogous for the foreign household.[36] The U.S. household maximizes its expected utility over consumption across the three periods:

$$\mathbb{E}_0[U(C_0, C_1, C_2)] = \theta_0 log(C_0) + \beta\mathbb{E}_0[\theta_1 log(C_1)] + \beta^2\mathbb{E}_0[\theta_2 log(C_2)] \tag{A.1}$$

where $C_t = [(C_{NT,t})^{\chi_t}(C_{H,t})^{a_t}(C_{F,t})^{\iota_t}]^{\frac{1}{\theta_t}}$ and the preference parameters satisfy $\chi_t + a_t + \iota_t = \theta_t$.

While trade in goods is frictionless, financial markets are segmented such that U.S. households can trade only the U.S. bond and foreign households can trade only the foreign bond. Let $b_{H,t}$ for $t \in \{0, 1\}$ be the quantity of USD bonds held by U.S. households in each of the first two periods and denote by R the gross U.S risk free rate in units of the NT good. Then, the U.S. households' budget constraints are given by:

$$Y_{NT,0} + p_{H,0}Y_{H,0} = C_{NT,0} + p_{H,0}C_{H,0} + p_{F,0}C_{F,0} + b_{H,0} \tag{A.2}$$

$$Y_{NT,1} + p_{H,1}Y_{H,1} = C_{NT,1} + p_{H,1}C_{H,1} + p_{F,1}C_{F,1} + b_{H,1} - Rb_{H,0} \tag{A.3}$$

$$Y_{NT,2} + p_{H,2}Y_{H,2} = C_{NT,2} + p_{H,2}C_{H,2} + p_{F,2}C_{F,2} - Rb_{H,1}, \tag{A.4}$$

where I set as numeraire the non-tradable good in each country $p_{NT,t} = p^*_{NT,t} = 1$. I further assume the law of one price for goods holds, $p_{H,t} = p^*_{H,t}\varepsilon_t$ and $p_{F,t} = p^*_{F,t}\varepsilon_t$.

[36] The only difference is that financiers' profits are rebated to foreign households to simplify the exposition.

U.S. Household static problem:

$$\mathcal{L}_{\{C_{NT,t},C_{H,t},C_{F,t}\}} = \theta_t log[(C_{NT,t})^{\chi_t}(C_{H,t})^{a_t}(C_{F,t})^{\iota_t}]^{\frac{1}{\theta_t}} - \eta_t[Exp_t - C_{NT,t} - p_{H,t}C_{H,t} - p_{F,t}C_{F,t}]$$

where Exp_t denotes the U.S. household's optimal expenditure on consumption in period t (solved for in the dynamic stage) and η_t is the Lagrange multiplier on the intratemporal portion of the U.S. household's budget constraint (from (A.2), (A.3), and (A.4)). Under the assumption on U.S. household's NT preference parameter ($\chi_t = Y_{NT,t}$), market clearing implies $\chi_t = C_{NT,t}$. Then, the first order conditions of the static problem are:

$$\eta_t = 1 \quad \text{and} \quad p_{H,t}C_{H,t} = a_t \quad \text{and} \quad p_{F,t}C_{F,t} = \iota_t \tag{A.5}$$

Thus, U.S. household's expenditure share on imports ι_t is actually equal to their expenditure on imports.

U.S. Household intertemporal problem:

Since the U.S. bond pays in the U.S. NT good, the U.S. Household's intertemporal problem solves for the optimal allocation of non-tradable consumption between periods:

$$\mathcal{L}_{\{C_{NT,t},C_{NT,t+1}\}} = \theta_t log(C_t) + \beta\mathbb{E}_t[\theta_{t+1}log(C_{t+1})] + \nu_t(p_tY_t + \frac{1}{R}p_{t+1}Y_{t+1} - p_tC_t - \frac{1}{R}p_{t+1}C_{t+1})$$

where ν_t is the Lagrange multiplier on the intertemporal portion of the U.S. household's budget constraint (from (A.2), (A.3), and (A.4)) between the periods t and $t+1$. Solving gives the first order conditions (FOCs) below

$$\frac{\chi_t}{C_{NT,t}} = \nu_t p_{NT,t} \quad \& \quad \beta\mathbb{E}_t\Big[\frac{\chi_{t+1}}{C_{NT,t+1}}\Big] = \frac{\nu_t p_{NT,t+1}}{R} \tag{A.6}$$

Recalling that $\chi_t = C_{NT,t}$ and $p_{NT,t} = 1 \;\forall t$, the first FOC implies $\nu_t = 1$ such that the second gives rise to the Euler equation:

$$1 = \beta R \tag{A.7}$$

That is, because non-tradable consumption is risk-free and equal to households' desired expenditure share, households have no precautionary or consumption-smoothing motives and so interest rates are driven by the rate of time preference, as in Gabaix and Maggiori (2015).

Foreign Household static and intertemporal problems:

As discussed, the foreign household problem is analogous to the U.S. case, except that foreign households are rebated the complete financial sector's profits Π_t for $t \in \{1,2\}$:

$$\max_{\{C_t^*, b_{F,t}^*\}} \mathbb{E}_0[U(C_0^*, C_1^*, C_2^*)] = \theta_0^* log(C_0^*) + \beta^* \mathbb{E}_0[\theta_1^* log(C_1)] + (\beta^*)^2 \mathbb{E}_0[\theta_2^* log(C_2^*)] \tag{A.8}$$

$$such\ that \quad Y_{NT,0}^* + p_{F,0}^* Y_{F,0}^* = C_{NT,0}^* + p_{H,0}^* C_{H,0}^* + p_{F,0}^* C_{F,0}^* + b_{F,0}^* \tag{A.9}$$

$$Y_{NT,1}^* + p_{F,1}^* Y_{F,1}^* + \Pi_1 = C_{NT,1}^* + p_{H,1}^* C_{H,1}^* + p_{F,1}^* C_{F,1}^* + b_{F,1}^* - R^* b_{F,0}^* \tag{A.10}$$

$$Y_{NT,2}^* + p_{F,2}^* Y_{F,2}^* + \Pi_2 = C_{NT,2}^* + p_{H,2}^* C_{H,2}^* + p_{F,2}^* C_{F,2}^* - R^* b_{F,1}^* \tag{A.11}$$

where $C_t^* = [(C_{NT,t}^*)^{\chi_t^*}(C_{F,t}^*)^{a_t^*}(C_{H,t}^*)^{\xi_t}]^{\frac{1}{\theta_t^*}}$ with $\chi_t^* + a_t^* + \xi_t = \theta_t^*$, $b_{F,t}^*$ for $t \in \{0,1\}$ is quantity of foreign currency bonds held by foreign households and R^* is the gross foreign risk free rate.

Separating the problem into static and dynamic stages as before, the solution to the foreign household problem can be summarized by the following FOCs:

$$\chi_t^* = C_{NT,t}^* \implies \eta_t^* = 1 \quad , \quad p_{F,t}^* C_{F,t}^* = a_t^* \quad , \quad p_{H,t}^* C_{H,t}^* = \xi_t \quad \& \quad 1 = \beta^* R^* \tag{A.12}$$

Market Clearing

As hedgers hold only U.S. bonds, home and foreign bond market clearing for $t \in \{0,1\}$ is:

$$q_t + w_t + b_{H,t} = 0 \quad \text{and} \quad \frac{-q_t}{\varepsilon_t} + b_{F,t}^* = 0 \tag{A.13}$$

Goods market clearing in $t \in \{0,1,2\}$ for tradables (A.14) and non-tradables (A.15)-(A.16) is:

$$Y_{H,t} = C_{H,t} + C_{H,t}^* \quad \text{and} \quad Y_{F,t}^* = C_{F,t} + C_{F,t}^* \tag{A.14}$$

$$Y_{NT,t} = C_{NT,t} \quad \text{and} \quad Y_{NT,0}^* + (1-v_0)X_0^* = C_{NT,0}^* \tag{A.15}$$

$$Y_{NT,1}^* + (1-v_1)X_1^* + v_0\tilde{X}_1^* = C_{NT,1}^* \quad \text{and} \quad Y_{NT,2}^* + v_1\tilde{X}_2^* = C_{NT,2}^* \tag{A.16}$$

As in Gabaix and Maggiori (2015) and Jiang (2021), I assume that the households preference parameter for non-tradable goods, in each country, is equal to the total supply of non-tradables each period: $\chi_t = Y_{NT,t}$, $\chi_0^* = Y_{NT,0}^* + (1-v_0)X_0^*$, $\chi_1^* = Y_{NT,1}^* + (1-v_1)\tilde{X}_1^* + v_0 X_1^*$, and $\chi_2^* = Y_{NT,2}^* + v_1\tilde{X}_2^*$. As will become more clear shortly, this assumption ensures households have no consumption smoothing or precautionary motives, since their endowments of non-tradables (in which their bonds are denominated) are risk-free and equal to their desired expenditure share. This assumption allows me to isolate for how speculators and hedgers jointly determined exchange rates in financial markets, while relegating to the background the behavior of households.

Solving the Model

Beginning with the household's budget constraints in each period (equations (A.2), (A.3), and (A.4) and (A.9), (A.10), and (A.11)), substitute in the market clearing conditions for bonds (A.13):

$$Y_{NT,0} + p_{H,0}Y_{H,0} = C_{NT,0} + p_{H,0}C_{H,0} + p_{F,0}C_{F,0} - q_0 - w_0 \tag{A.17}$$

$$Y_{NT,1} + p_{H,1}Y_{H,1} = C_{NT,1} + p_{H,1}C_{H,1} + p_{F,1}C_{F,1} - q_1 - w_1 - R(-q_0 - w_0) \tag{A.18}$$

$$Y_{NT,2} + p_{H,2}Y_{H,2} = C_{NT,2} + p_{H,2}C_{H,2} + p_{F,2}C_{F,2} - R(-q_1 - w_1) \tag{A.19}$$

$$Y^*_{NT,0} + p^*_{F,0}Y^*_{F,0} = C^*_{NT,0} + p^*_{H,0}C^*_{H,0} + p^*_{F,0}C^*_{F,0} + \frac{q_0}{\varepsilon_0} \tag{A.20}$$

$$Y^*_{NT,1} + p^*_{F,1}Y^*_{F,1} + \Pi_1 = C^*_{NT,1} + p^*_{H,1}C^*_{H,1} + p^*_{F,1}C^*_{F,1} + \frac{q_1}{\varepsilon_1} - R^*\frac{q_0}{\varepsilon_0} \tag{A.21}$$

$$Y^*_{NT,2} + p^*_{F,2}Y^*_{F,2} + \Pi_2 = C^*_{NT,2} + p^*_{H,2}C^*_{H,2} + p^*_{F,2}C^*_{F,2} - R^*\frac{q_1}{\varepsilon_1} \tag{A.22}$$

where $\Pi_{t+1} = q_t(R - R^*\frac{\varepsilon_{t+1}}{\varepsilon_t})\frac{1}{\varepsilon_{t+1}} + (1 - \upsilon_t)X^*_t R\frac{\varepsilon_t}{\varepsilon_{t+1}} + \upsilon_t\tilde{X}^*_{t+1}$ for $t \in \{0, 1\}$.

Next, substitute in the market clearing conditions for NT goods ((A.15) and (A.16)):

$$p_{H,0}Y_{H,0} = p_{H,0}C_{H,0} + p_{F,0}C_{F,0} - q_0 - w_0 \tag{A.23}$$

$$p_{H,1}Y_{H,1} = p_{H,1}C_{H,1} + p_{F,1}C_{F,1} - q_1 - w_1 - R(-q_0 - w_0) \tag{A.24}$$

$$p_{H,2}Y_{H,2} = p_{H,2}C_{H,2} + p_{F,2}C_{F,2} - R(-q_1 - w_1) \tag{A.25}$$

$$p^*_{F,0}Y^*_{F,0} = (1 - \upsilon_0)X^*_0 + p^*_{H,0}C^*_{H,0} + p^*_{F,0}C^*_{F,0} + \frac{q_0}{\varepsilon_0} \tag{A.26}$$

$$p^*_{F,1}Y^*_{F,1} + \Pi_1 = (1 - \upsilon_1)X^*_1 + \upsilon_0\tilde{X}^*_1 + p^*_{H,1}C^*_{H,1} + p^*_{F,1}C^*_{F,1} + \frac{q_1}{\varepsilon_1} - R^*\frac{q_0}{\varepsilon_0} \tag{A.27}$$

$$p^*_{F,2}Y^*_{F,2} + \Pi_2 = \upsilon_1\tilde{X}^*_2 + p^*_{H,2}C^*_{H,2} + p^*_{F,2}C^*_{F,2} - R^*\frac{q_1}{\varepsilon_1} \tag{A.28}$$

Next, plug in the market clearing for T goods (A.14), household FOCs (A.5) and (A.12), and the law of one price. Then, the t = 0 conditions (equations (A.23) and (A.26)) can each be reduced to:[37]

$$\varepsilon_0\xi_0 - \iota_0 = -q_0 - w_0 \tag{A.29}$$

[37] since $(1 - \upsilon_0)X^*_0 = \frac{w_0}{\varepsilon_0}$ in (A.26)

The t = 1 conditions (equations (A.24) and (A.27)) can each be reduced to:[38]

$$\varepsilon_1\xi_1 - \iota_1 = -q_1 - w_1 + R(q_0 + w_0) \tag{A.30}$$

And the t = 2 conditions (equations (A.25) and (A.28)) can each be reduced to:[39]

$$\varepsilon_2\xi_2 - \iota_2 = R(q_1 + w_1) \tag{A.31}$$

Following Gabaix and Maggiori (2015), I make two additional assumptions to anchor the exchange rate in the final period. This is done solely for ease of exposition; the assumptions have no effect on exchange rate dynamics in the model, as pointed out in section 2. First, I assume that currency speculators intermediate and hedgers accommodate only *new* flows in period t = 1 and so wait until t = 2 to unwind their t = 0 currency positions. In effect, this implies that households', who can now be viewed as long-term investors, stocks of bonds in t = 1 arising from t = 0 flows are held passively until period t = 2.[40] This adjusts the t = 1 flow demand equation (A.30) to $\varepsilon_1\xi_1 - \iota_1 = -q_1 - w_1$ and the t = 2 flow demand equation (A.31) to $\varepsilon_2\xi_2 - \iota_2 = R(q_1 + w_1) + R^2(q_0 + w_0)$. Second, I assume that t = 2 is the "long run" period, which lasts T-times as long as the first two periods, such that the t = 2 flow demand equation (A.31) becomes $T(\varepsilon_2\xi_2 - \iota_2) = R(q_1 + w_1) + R^2(q_0 + w_0)$.[41] In effect, speculation and hedging behavior in the currency market is assumed to be very small relative to trade in the goods market in the long run. Dividing through by T and letting $T \to \infty$, one can now write the US net foreign asset flow demand equations in each period as:

$$\varepsilon_0\xi_0 - \iota_0 = -q_0 - w_0 \quad \varepsilon_1\xi_1 - \iota_1 = -q_1 - w_1 \quad \varepsilon_2\xi_2 = \iota_2 \tag{A.32}$$

Thus, the long run exchange rate is the exchange rate under financial autarky and is determined solely by fundamentals—countries relative import shares—while short run exchange rates are determined both by fundamentals as well as financial frictions.

Finally, substituting speculators' and hedgers' optimal holdings of USD bonds, (3) and (6), into the net foreign asset equations in (A.32), one can solve for the equilibrium exchange rate

[38] substitute the definition of Π_1 into (A.27)
[39] substitute the definition of Π_2 into (A.28)
[40] As a result, financial sector profits at t = 1, Π_1, are not channelled to households until t = 2
[41] The T multiplies only the left-hand-side since interest income from previous lending/borrowing is channelled to households at the start of the period while trade in goods occurs evenly throughout the long run period.

in each period. Beginning with the final period, we have

$$\varepsilon_2 = \frac{\iota_2}{\xi_2}. \tag{A.33}$$

For the middle period, the exchange rate is solved as a function of Γ_1 and $\lambda_1(\Gamma_1)$:

$$\varepsilon_1 = \frac{\iota_1 + \frac{1}{\Gamma_1}\frac{R^*}{R}\mathbb{E}_1[\varepsilon_2]}{\xi_1 + \frac{1}{\Gamma_1} + \frac{\lambda_1 E_1[\tilde{X}_2^*]}{\lambda_1 E_1[\tilde{X}_2^*]/X_1^*+1}} = \frac{\iota_1 + \frac{1}{\Gamma_1}\frac{R^*}{R}\mathbb{E}_1[\frac{\iota_2}{\xi_2}]}{\xi_1 + \frac{1}{\Gamma_1} + \frac{\lambda_1 E_1[\tilde{X}_2^*]}{\lambda_1 E_1[\tilde{X}_2^*]/X_1^*+1}} \tag{A.34}$$

where the second equality uses the conditional expectation of (A.33) as $\mathbb{E}_1[\varepsilon_2]$.

Similarly, the first period exchange rate is given by

$$\varepsilon_0 = \frac{\iota_0 + \frac{1}{\Gamma_0}\frac{R^*}{R}\mathbb{E}_0[\varepsilon_1]}{\xi_0 + \frac{1}{\Gamma_0} + \frac{\lambda_0 E_0[\tilde{X}_1^*]}{\lambda_0 E_0[\tilde{X}_1^*]/X_0^*+1}} \tag{A.35}$$

where, from (A.34), the conditional expectation of Γ_1 and $\lambda_1(\Gamma_1)$ affect ε_0 through $\mathbb{E}_0[\varepsilon_1]$.

B Model Proofs

Lemma 1 Proof:

First, let $\frac{\partial\lambda_1}{\partial\Gamma_1} \to 0$ such that the indirect effect in (12) tends to 0 as well.[42] Thus, the $\frac{\partial\varepsilon_1}{\partial\Gamma_1}$ term in (15) is now composed only of the direct effect. Notice that the second term in (15), $\frac{1}{\Gamma_1}\frac{\partial\varepsilon_1}{\partial\Gamma_1}$, is proportional to $\frac{1}{\Gamma_1^3}$ while the first term in (15) is proportional to $\frac{1}{\Gamma_1^2}$. Thus, for sufficiently large Γ_1, the first term will dominate. Then, if the U.S. interest rate is sufficiently high, $R > R^*\frac{\mathbb{E}_t[\varepsilon_2]}{\varepsilon_1}$, then by (14) $q_1 > 0$ and by (15) $\frac{\partial q_1}{\partial\Gamma_1} < 0$. Similarly, if the foreign interest rate is sufficiently high, $R < R^*\frac{\mathbb{E}_t[\varepsilon_2]}{\varepsilon_1}$, then by (14) $q_1 < 0$ and by (15) $\frac{\partial q_1}{\partial\Gamma_1} > 0$. ■

Lemma 2 Proof:

Assume that $R > R^*\frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t}$. By (14), this implies that $q_t > 0$, which, by market clearing (10) implies that $\iota_t - \varepsilon_t > w_t$, where I have set $\xi = 1$ without loss of generality. Rearranging gives $\frac{\iota_t}{\varepsilon_t} - 1 > \frac{w_t}{\varepsilon_t}$. Setting t = 1, we have the direct effect $\iota_1 - \frac{R^*}{R}\mathbb{E}_1[\varepsilon_2](1+w_1/\varepsilon_1) > \iota_1 - \frac{R^*}{R}\mathbb{E}_1[\varepsilon_2](\frac{\iota_1}{\varepsilon_1}) = \iota_1[1 - \frac{R^*}{R}\frac{\mathbb{E}_1[\varepsilon_2]}{\varepsilon_1}] > 0$, where the first $>$ comes from inputting $\frac{\iota_t}{\varepsilon_t} - 1 > \frac{w_t}{\varepsilon_t}$ and the second $>$ comes from the initial assumption of $R > R^*\frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t}$. From $\iota_1[1 - \frac{R^*}{R}\frac{\mathbb{E}_1[\varepsilon_2]}{\varepsilon_1}] > 0$ we see that the direct effect's magnitude in this case is increasing in $R - R^*\frac{\mathbb{E}_1[\varepsilon_2]}{\varepsilon_1}$. A similar procedure gives the result for the case $R < R^*\frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t}$. ■

[42] I abstract away from hedgers since we are focused for now on speculators' direct effect.

Corollary 1 Proof:

Corollary 1 includes two claims. First, under ingredient 3, we have that $R_0^* > R_0 \iff q_0 > 0$. By (14), since $\Gamma_0 = \Gamma_L > 0$ we have that $R_0^* > R_0 \iff \mathbb{E}_0\left[R_0^* \frac{\varepsilon_1}{\varepsilon_0} - R_0\right] > 0$, which holds unconditionally. As the probability of a disaster tends to 0, $p \to 0$, we have $\mathbb{E}_0[\Gamma_1] \to \Gamma_L$, and the unconditional expected return tends to the expected return conditional on ND. The converse proof (where $R_0^* < R_0$ is proved analogously). See the proof of Corollary 2 for a proof when $p > 0$. ■

I prove the second claim of Corollary 1 in Prediction 1's proof, see below.

Prediction 1 Proof:

In (A.35), (A.34) and (A.33) with $\xi = 1$, to ensure the result is not driven by changes in household preference parameters, I assume $\iota_0 = \iota_1 = \iota_2 = \iota$ and is deterministic. From (A.35), (A.34), the t = 1 disaster state exchange rate, ε_1^D and the exchange rate at t = 0, ε_0, are

$$\mathbb{E}_0[\varepsilon_1 |\ \Gamma_1 = \Gamma_H\ ] \equiv \varepsilon_1^D = \frac{\iota(1 + \frac{1}{\Gamma_H}\frac{R^*}{R})}{1 + \frac{1}{\Gamma_H}} \quad \text{and} \quad \varepsilon_0 = \frac{\iota + \frac{1}{\Gamma_L}\frac{R^*}{R}\left[\frac{\iota + \iota\frac{R^*}{R}\frac{1}{\Gamma_L}}{1+\frac{1}{\Gamma_L}}\right]}{1 + \frac{1}{\Gamma_L}}$$

ε_1^D is the t = 1 exchange rate as defined in (A.34) with $\Gamma_1 = \Gamma_H$.[43] ε_0 is as defined in (A.35) with $\Gamma_0 = \Gamma_L$ and with $\mathbb{E}_0[\Gamma_1] = \Gamma_L$ since the disaster probability is assumed near zero, formally: $p \to 0$. In both cases, I have set $w_t = 0$ to study exchange rate dynamics without hedgers, whose impact will be taken into account in prediction 2.

Thus, prediction 1 can be rewritten as $R^* > R \implies \frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} < 1$. The second inequality can be rewritten as:

$$\frac{1}{\Gamma_H\Gamma_L^2}\left[\left(\frac{R^*}{R}\right)^2[\Gamma_L^2 + 2\Gamma_L - \Gamma_H] + \frac{R^*}{R}[\Gamma_H\Gamma_L^2 + \Gamma_H + \Gamma_H\Gamma_L - \Gamma_L] + [-\Gamma_L^2 - \Gamma_H\Gamma_L - \Gamma_L]\right] < 1$$

Notice that when $\frac{R^*}{R} = 1$, the left-hand-side (LHS) of this inequality reduces to 1: $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} = 1$. Consider now $\frac{R^*}{R} = 1 + \eta > 1$ such that $\eta > 0$ is the interest rate differential. Relative to the $\frac{R^*}{R} = 1$ case, $\frac{R^*}{R} = 1 + \eta$ implies the LHS of the inequality grows by $\frac{1}{\Gamma_H\Gamma_L^2}\{(\eta^2 + 2\eta)[\Gamma_L^2 + 2\Gamma_L - \Gamma_H] + \eta[\Gamma_H\Gamma_L^2 + \Gamma_H + \Gamma_H\Gamma_L - \Gamma_L]\}$. Thus, the condition $R^* > R \implies \frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} < 1$ is satisfied if and only if

$$\eta > 0 \implies (\eta^2 + 2\eta)[\Gamma_L^2 + 2\Gamma_L - \Gamma_H] + \eta[\Gamma_H\Gamma_L^2 + \Gamma_H + \Gamma_H\Gamma_L - \Gamma_L] < 0$$

[43] I also can define ε_1^{ND} as the t = 1 exchange rate as defined in (A.34) with $\Gamma_1 = \Gamma_L$, which will be useful to prove the second claim of Corollary 1.

which can be rewritten as

$$\eta > 0 \implies A(\Gamma_L, \Gamma_H, \eta) \equiv \Gamma_L^2[2+\eta] + \Gamma_L[3+2\eta] + \Gamma_H(-1-\eta) + \Gamma_L\Gamma_H[\Gamma_L+1] < 0$$

To understand this result, notice that for a given $\eta > 0$, whether this condition is satisfied depends on the values of Γ_H and Γ_L. The impact of changing Γ_L is summarized by:

$$\frac{\partial A(\Gamma_L, \Gamma_H, \eta)}{\partial \Gamma_L} = 2\Gamma_L(2+\eta) + 3 + 2\eta + 2\Gamma_L\Gamma_H + \Gamma_H > 0 \quad \frac{\partial^2 A(\Gamma_L, \Gamma_H, \eta)}{\partial \Gamma_L^2} = C(\Gamma_H, \eta) > 0$$

The always positive first derivative implies that decreasing Γ_L makes satisfying the condition $A(\Gamma_L, \Gamma_H, \eta) < 0$ easier for $\eta > 0$. Put differently, $\Gamma_L \downarrow \implies \frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} \downarrow$. Furthermore, as the first derivative is increasing in η and Γ_H, larger interest rate differentials or more extreme disaster state funding market shocks increase the responsiveness of $A(\Gamma_L, \Gamma_H, \eta) \downarrow$ to $\Gamma_L \downarrow$, making the condition easier to satisfy. Similarly, the positive second derivative implies that further decreases in Γ_L lead to progressively larger falls $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R}$, again making it easier to satisfy $A(\Gamma_L, \Gamma_H, \eta) < 0$.

The impact of changing Γ_H is summarized by:

$$\frac{\partial A(\Gamma_L, \Gamma_H, \eta)}{\partial \Gamma_H} = (-1-\eta) + \Gamma_L^2 < 0 \iff \Gamma_L^2 < (1+\eta) \quad \frac{\partial^2 A(\Gamma_L, \Gamma_H, \eta)}{\partial \Gamma_H^2} = 0$$

Thus, when the funding market is sufficiently liquid in t = 0, as compared to the interest rate differential ($\Gamma_L^2 < \frac{R^*}{R}$), an increase in disaster-state funding market illiquidity in t = 1, $\Gamma_H \uparrow$, leads to a larger disaster state depreciation and $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} \downarrow$. This makes satisfying $A(\Gamma_L, \Gamma_H, \eta) < 0$ easier for $\eta > 0$. Furthermore, as the first derivative is increasing in η and decreasing in Γ_L, larger interest rate differentials and lower funding market liquidity in t = 0 increase the responsiveness of $A(\Gamma_L, \Gamma_H, \eta) \downarrow$ to $\Gamma_H \uparrow$, making the condition easier to satisfy. In addition, as the second derivative is zero, there are no decreasing gains to $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} \downarrow$ from increasing Γ_H that would make $A(\Gamma_L, \Gamma_H, \eta) < 0$ more difficult to satisfy.

In addition to this intuition, the condition $\eta > 0 \implies A(\Gamma_L, \Gamma_H, \eta) < 0$ can be rewritten in two illuminating ways:

$$\eta > 0 \implies \Gamma_H > \frac{\Gamma_L^2(2+\eta) + \Gamma_L(3+2\eta)}{1+\eta-\Gamma_L^2-\Gamma_L}$$
$$\eta > 0 \implies \Gamma_L < \frac{-\Gamma_H - 2\eta - 3 + \Big((\Gamma_H + 2\eta + 3)^2 + 4\Gamma_H(1+\eta)(2+\eta+\Gamma_H)\Big)}{2(2+\eta+\Gamma_H)}$$

which highlight that Γ_H must be sufficiently high and Γ_L must be sufficiently low for the exchange rate depreciation of the high-interest-rate currency to more than offset the magnitude of the interest rate differential.

The final comparative static captures the impact of changing $\eta > 0$ for fixed Γ_H and Γ_L and is summarized by:

$$\frac{\partial A(\Gamma_L, \Gamma_H, \eta)}{\partial \eta} = \Gamma_L^2 + 2\Gamma_L - \Gamma_H < 0 \iff \Gamma_H > \Gamma_L^2 + 2\Gamma_L$$

Thus, when disaster state funding market frictions are sufficiently large relative to normal times, ($\Gamma_H > \Gamma_L^2 + 2\Gamma_L$), a higher interest rate differential implies a larger disaster state depreciation of the high-interest-rate foreign currency and thus a larger fall in the carry trade return, $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R}$. In this case, $\eta \uparrow$ makes satisfying $A(\Gamma_L, \Gamma_H, \eta) < 0$ easier.

As a brief aside, notice that, if the disaster does not materialize in t = 1, $\varepsilon_1 = \varepsilon_1^{ND}$, then by following the same procedure as above with $\varepsilon_1^D = \varepsilon_1^{ND}$, we arrive at the quantity $A(\Gamma_L, \Gamma_L, \eta)$, where the only difference is $\Gamma_H = \Gamma_L$. Thus, we can show that $\frac{\partial A(\Gamma_L, \Gamma_L, \eta)}{\partial \eta} = \Gamma_L^2 + 2\Gamma_L - \Gamma_L > 0 \iff \Gamma_L > 0$, which is always true in this model. Thus, an increase in the interest rate differential implies a higher expected return conditional on no disaster, formalizing the proof of the second claim in Corollary 1.

Finally, to complete the proof, it is possible that the condition $\eta > 0 \implies A(\Gamma_L, \Gamma_H, \eta) < 0$ cannot be satisfied for $\Gamma_L > 0$ and Γ_H finite. This can be ruled out by a numerical example:

Let $\Gamma_H = 2$ and $\Gamma_L = 0.01$ and consider two cases, both of which satisfy $A(\Gamma_L, \Gamma_H, \eta) < 0$:

Case 1: $\frac{R^*}{R} = \frac{1.10}{1.01}$, a 9% interest rate differential. In this case, $\frac{\varepsilon_1^D}{\varepsilon_0} = 0.87$, indicating a 13% disaster state depreciation of the high-interest-rate foreign currency in the disaster. The maps to $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} = 0.947$, about a 5% loss on the carry trade. For context, these losses dwarf the expected carry trade profits conditional on no-disaster: $\frac{\varepsilon_1^{ND}}{\varepsilon_0}\frac{R^*}{R} = 1.0015$, a 0.15% profit on the carry trade. In addition, the results are unchanged if the probability of a disaster, as perceived by speculators (and in reality) is non-zero. For example, setting $p = 0.075$, a 7.5% disaster probability, we have $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} = 0.952$, still about a 5% loss on the carry trade in disasters, while $\frac{\varepsilon_1^{ND}}{\varepsilon_0}\frac{R^*}{R} = 1.0056$, a 0.56% profit on the carry trade in normal times.

Case 2: $\frac{R^*}{R} = \frac{1.05}{1.01}$, a 4% interest rate differential. In this case, $\frac{\varepsilon_1^D}{\varepsilon_0} = 0.94$, indicating a 6% disaster state depreciation of the high-interest-rate foreign currency in the disaster. The maps to $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} = 0.976$, about a 2% loss on the carry trade. For context, these losses dwarf the expected carry trade profits conditional on no-disaster: $\frac{\varepsilon_1^{ND}}{\varepsilon_0}\frac{R^*}{R} = 1.0007$, a 0.07% profit on the carry trade. In addition, the results are unchanged if the probability of a disaster, as perceived by speculators (and in reality) is non-zero. For example, setting $p = 0.075$, a 7.5% disaster *probability, we have* $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} = 0.978$*, still about a* 2% *loss on the carry trade in disasters, while* $\frac{\varepsilon_1^{ND}}{\varepsilon_0}\frac{R^*}{R} = 1.0026$*, a* 0.26% *profit on the carry trade in normal times.*

Thus, for sufficiently small disaster probability $p \to 0$, there exists a region, with a sufficiently small Γ_L and a sufficiently large Γ_H, where, for a fixed positive interest rate differential $\frac{R^*}{R}$, carry trade profits in disasters are negative $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} < 1$. In a subset of this region, these losses grow as $\frac{R^*}{R}\uparrow$, as $\Gamma_L \downarrow$ and as $\Gamma_H \uparrow$. ■

Prediction 2 Proof:

With $\lambda_0 \to 0$, hedgers only hold USD in disaster states. Further, if $p \to 0$, then ε_0 unaffected by disaster risk. Then, the result follows immediately from the hedgers' indirect effect in (12) since only $\mathbb{E}_0[\varepsilon_1 | \ \Gamma_1 = \Gamma_H\ ] \equiv \varepsilon_1^D$ depends on λ_1 and $\lambda_1 \uparrow \implies \varepsilon_1^D \downarrow$, a dollar appreciation. ■

Main Result Proof:

The proof for the paper's main theoretical result combines elements of Predictions 1 and 2. Formally, let $p \to 0$ such that ε_0 is unaffected by disaster risk, as explicitly shown in the proof of prediction 1. Denote the exchange rate in a disaster that accounts only for the behavior of speculators by $\varepsilon_1^{D,spec}$, which is as defined in the proof of prediction 1 (although it was denoted simply by ε_1^D in that case). Under a symmetric parameterization, with $R_0^{*,high} - R_0^{US} = R_0^{US} - R_0^{*,low} > 0$, we know that:

$$\left| \ \mathbb{E}_0 \underbrace{\left[R_0^{*,high}\frac{\varepsilon_1^{D,spec}}{\varepsilon_0} - R_0^{US}\right]}_{<<0} \ \right| \quad = \quad \left| \ \mathbb{E}_0 \underbrace{\left[R_0^{US}\frac{\varepsilon_0}{\varepsilon_1^{D,spec}} - R_0^{*,low}\right]}_{<<0} \right|$$

That is, when accounting only for the behavior of speculators, the depreciation of a high-interest-rate currency vis-à-vis the dollar in a disaster is equal in magnitude to the appreciation of a low-interest-rate currency against the dollar in a disaster.

Next, denote by $\varepsilon_1^{D,all}$ the exchange rate in a disaster that accounts for the behavior of both speculators and hedgers. Assuming $\lambda_0 \to 0$ such that hedgers only hold dollars in disasters, we know from prediction 2 that $\varepsilon_1^{D,all} < \varepsilon_1^{D,spec}$, since the dollar appreciates in disasters due to $\lambda_1 > 0$ regardless of relative interest rates. Since $p \to 0$, the spike in the liquidity yield in disasters has no effect on ε_0 such that:

$$\left| \ \mathbb{E}_0\left[R_0^{*,high}\frac{\varepsilon_1^{D,all}}{\varepsilon_0} - R_0^{US}\right] \ \right| \quad > \quad \left| \ \mathbb{E}_0\left[R_0^{US}\frac{\varepsilon_0}{\varepsilon_1^{D,all}} - R_0^{*,low}\right]\right|$$

which completes the proof. ■

Corollary 2 Proof:

Like the proof of the main result, this proof combines elements of Corollary 1, Prediction 1 and Prediction 2. First, Corollary 1 shows that, when taking into account only the behavior of speculators, high-interest-rate currencies excessively appreciate conditional on no-disaster. Denoting the exchange rate at t=0 and at t=1 conditional on no-disaster due to speculators as ε_0^{spec} and $\varepsilon_1^{ND,spec}$, respectively, then under a symmetric parameterization with $R_0^{*,high} - R_0^{US} = R_0^{US} - R_0^{*,low} > 0$, we have that:

$$\left| \underbrace{\mathbb{E}_0 \left[R_0^{*,high} \frac{\varepsilon_1^{ND,spec}}{\varepsilon_0^{spec}} - R_0^{US} \right]}_{>0} \right| = \left| \underbrace{\mathbb{E}_0 \left[R_0^{US} \frac{\varepsilon_0^{spec}}{\varepsilon_1^{ND,spec}} - R_0^{*,low} \right]}_{>0} \right|$$

As a brief aside, Corollary 1 was proven with $p \to 0$, whereas this proof requires that $p > 0$. So, consider the case where $R_0^* > R_0$ (the converse case is entirely analogous). From prediction 1, the possibility of a disaster causes $\mathbb{E}_0[\varepsilon_1] \downarrow$ and so $\mathbb{E}_0 \left[R_0^* \frac{\varepsilon_1}{\varepsilon_0} - R_0 \right] \downarrow$ such that $\mathbb{E}_0 \left[R_0^* \frac{\varepsilon_1}{\varepsilon_0} - R_0 \right] > 0$ may not hold anymore, as was needed for the proof of corollary 1. However, ε_0 also falls by (A.35), with this fall proportional to $\frac{1}{\Gamma_0} \frac{R_0^*}{R_0} / 1 + \frac{1}{\Gamma_0}$. Thus, for a sufficiently low Γ_0 relative to $\frac{R_0^*}{R_0}$, the fall in ε_0 is larger than the fall in $\mathbb{E}_0[\varepsilon_1]$ such that $R_0^* > R_0 \implies \mathbb{E}_0 \left[R_0^* \frac{\varepsilon_1}{\varepsilon_0} - R_0 \right] > 0 \implies \mathbb{E}_0 \left[R_0^* \frac{\varepsilon_1}{\varepsilon_0} - R_0 \middle| \, \Gamma_1 = \Gamma_L \right] > 0$.

Again, consider two different exchange rates conditional on a disaster in period 1: $\varepsilon_1^{D,spec}$, which accounts only the behavior of speculators in the disaster; and $\varepsilon_1^{D,all}$, which additionally accounts for the behavior of hedgers. From Prediction 2, we know that $\varepsilon_1^{D,all} < \varepsilon_1^{D,spec}$ since hedgers flight to the dollar generates a tendency for the dollar to appreciate in disasters ($\varepsilon_1^D \downarrow$). From (A.35), we see that $\varepsilon_1^D \downarrow \implies \mathbb{E}_0[\varepsilon_1] \downarrow \implies \varepsilon_0 \downarrow$. Thus, $\varepsilon_0^{all} < \varepsilon_0^{spec}$. Since hedgers only hold dollars conditional on a disaster at $t = 1$, then $\varepsilon_1^{ND,all} = \varepsilon_1^{ND,spec}$. Combining these two facts with the expression for exchange rate dynamics conditional on no-disaster accounting only for speculators, we see that:

$$\left| \mathbb{E}_0 \left[R_0^{*,high} \frac{\varepsilon_1^{ND,all}}{\varepsilon_0^{all}} - R_0^{US} \right] \right| > \left| \mathbb{E}_0 \left[R_0^{US} \frac{\varepsilon_0^{all}}{\varepsilon_1^{ND,all}} - R_0^{*,low} \right] \right|$$

That is, there is a tendency for the dollar to depreciate conditional on no-disaster to compensate for the dollar's tendency to appreciate in disasters. It is worth noting the mechanics behind this: $R_0^* \frac{\varepsilon_1^{ND,all}}{\varepsilon_0^{all}} - R_0 > R_0^* \frac{\varepsilon_1^{ND,spec}}{\varepsilon_0^{spec}} - R_0 \implies q_0^{all} < q_0^{spec}$, that is, the tendency for the dollar to depreciate conditional on no disaster arises because speculators tilt their portfolios away from USD (the dollar becomes the dominant funding currency for the carry trade). ■

C Model Parameterization and Additional Simulations

In this section, I discuss how I simulate my model to produce exchange rate change $log(\varepsilon_1/\varepsilon_0)$ distributions. First, Table C.1 displays the parameterizations I use in the baseline simulation. The interest rate differential is set to 9% ($log(R^*/R) = log(1.1/1.01)$. In the table, the foreign currency has the high-interest-rate, but I also simulate the model when the U.S. has the high-interest-rate, in which case the interest differential is -9% ($log(R^*/R) = log(1.01/1.1)$. I focus for now, without loss of generality, on the case where $R^* > R$.

Table C.1: Benchmark Model Parameterization

Parameter	Value	Description	Target
β	0.99	U.S. Discount Factor	1% interest rate
β^*	0.91	Foreign Discount Factor	10% interest rate
Γ_L	0.01	Elasticity of Specs. Demand in ND	Liquid Funding in ND
Γ_H	2	Elasticity of Specs. Demand in D	Illiquid Funding in D
λ_L	0	Liquidity Yield in ND	Treasuries not special in ND
λ_H	0.05	Liquidity Yield in D	Treasury liquidity spikes in D
p	0.075	Disaster Probability	From Figure 7
$\iota = \xi$	1	Import Share (relative to θ)	Symmetric and neutral
$\tilde{X}^*$	1	Hedgers' Risky Asset Return	Neutral
X^*	0.5	Liquidation value of Risky Asset	Sufficiently low vs. $\tilde{X}$

The extent of the disaster is captured by two state-dependent parameters, Γ and λ, where $\Gamma_H >> \Gamma_L > 0$ and $\lambda_H >> \lambda_L = 0$. The probability of a disaster is set to 7.5%, which I infer from the quantile regression results in Figure 8: interest differentials predict exchange rate depreciations of high-yield currencies in excess of interest differentials up to between the 5^{th} and 10^{th} percentile of the distribution. Finally, the remaining parameters including household import shares and hedgers' risky asset returns are chosen so as not to have an impact on the results i.e. "neutral". The liquidation value of hedgers' risky asset is sufficiently low to ensure hedgers' constraint binds.

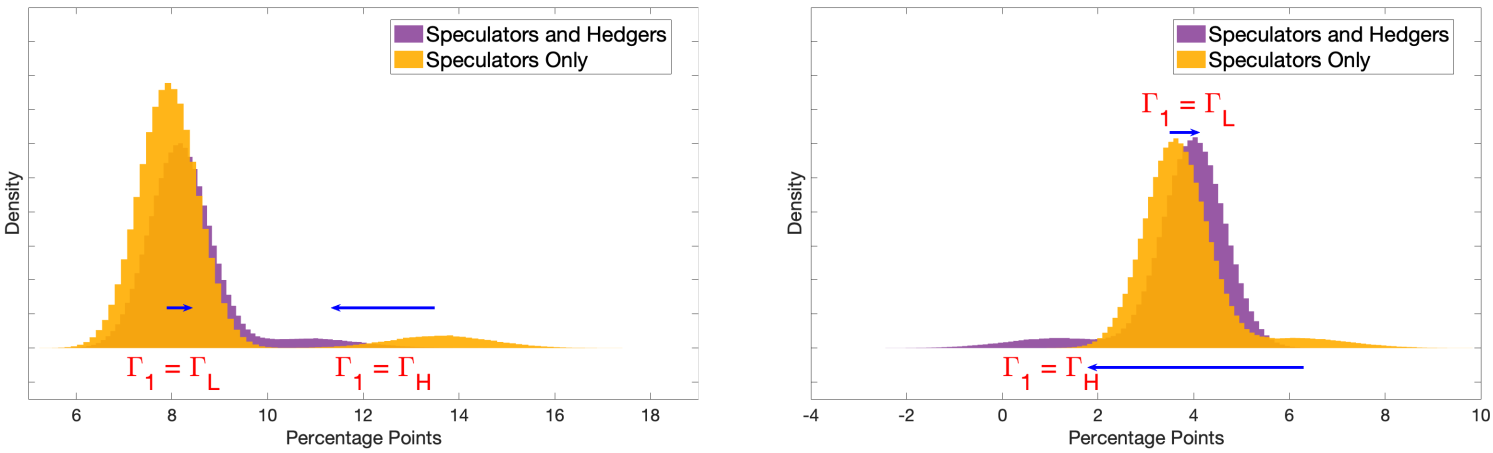
To output the exchange rate change $log(\varepsilon_1/\varepsilon_0)$ distributions, I first calculate ε_0, given the parameters from Table C.1 using equation (A.35), which tailors equation (11) to the t = 0 exchange rate. Note that the expected exchange rate in $t = 1$ is a weighted average of the exchange rate that prevails in a disaster and a non-disaster. Since relative interest rates are not constant in practice, I generate foreign and domestic interest rates, to use in equation (A.35), according to $R^* \sim \mathbb{N}(1.1, 0.005)$ and $R \sim \mathbb{N}(1.01, 0.005)$, respectively. I then generate a vector of length n of simulated ε_0 where each entry draws a new iid R^* and R from their respective normal distributions. This is what generates the hump-shaped modes in the simulated $log(\varepsilon_1/\varepsilon_0)$ distributions; with a constant R^* and R, each modes' mass would be concentrated at a single value.

Unlike ε_0, the value of ε_1 depends on the realization of the disaster shock, which follows a binomial distribution with success probability p = 7.5%. I simulated a vector of n realizations of the disaster shock and use these to generate a vector of ε_1s using (A.34), which tailors equation (11) to the t = 1 exchange rate, conditional on the disaster realization. Interest rates are the same as those in period 0; parameters depend on the realization of the disaster shock, as detailed in Table C.1. Given length-n vectors for ε_1 and ε_0, I can output a vector of $log(\varepsilon_1/\varepsilon_0)$. Setting $n = 1$ million, I aggregate these exchange rate movements together into a histogram, generating the exchange rate change distributions that appear in the main text.

Next, when discussing the asymmetry that arises due to the behavior of hedgers in the main text, I mentioned that, when the U.S. interest rate is relatively high, if the interest differential is not too wide, the spike in Treasury liquidity is large enough, and the elasticity of exchange rates to liquidity yields is sufficiently high, hedgers' effect can overcome that of speculators and push the U.S. dollar to appreciate in the disaster. I show this below in Panel C.1b of Figure C.1. Relative to Panel C.1a of Figure C.1, the interest differential goes from about -9% ($log(1.01/1.1)$ to -4% ($log(1.01/1.05)$ and the spike in the liquidity yield in a disaster doubles from $\lambda_H - \lambda_L = 0.05$ to 0.1. In this case, the disaster moves from the right-tail to the left-tail.

Figure C.1: Simulated Exchange Rate Change Distribution due to Speculators and Hedgers

(a) $R^* - R^{US} > 0$ (b) $R^* - R^{US} < 0$

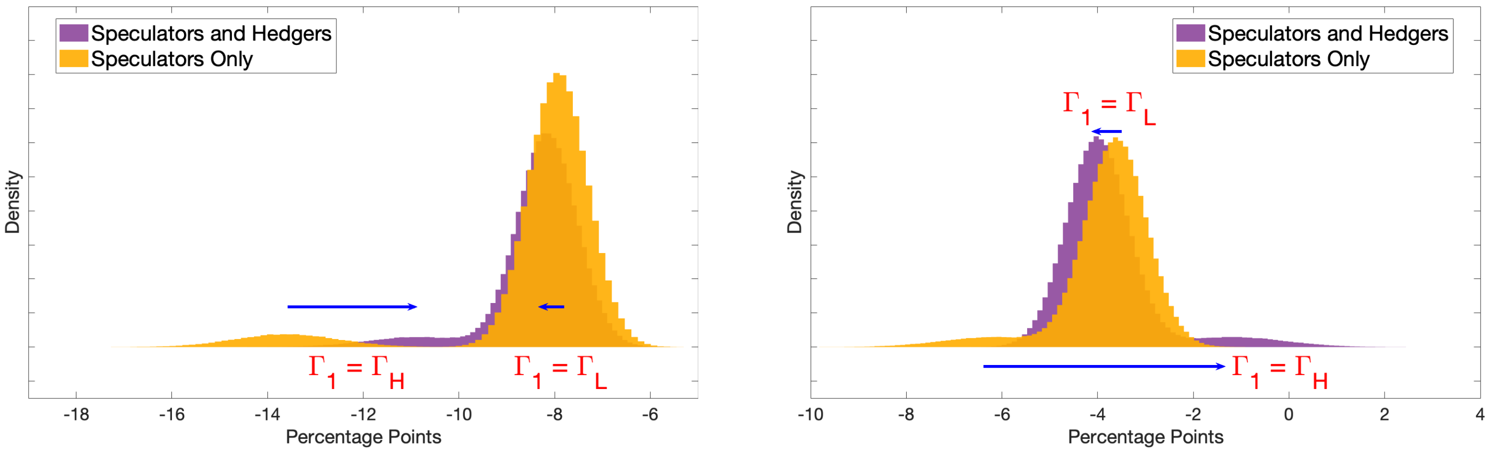


Note. In each panel of Figure C.1, I present 2 simulated distributions of exchange rate changes, $log(\frac{\varepsilon_1}{\varepsilon_0})$, constructed by simulating the model and aggregating exchange rate movements into histograms. The first, in yellow, accounts only the behavior of speculators (formally $\lambda_0 = \lambda_1 = 0$), and is the same as in Figure 3. The second, in purple, accounts for the behavior of both speculators and hedgers. In panel C.1a, the foreign interest rate is 10% and the U.S. interest rate is 1%. In panel C.1b, the foreign interest rate is 1% and the U.S. interest rate is 10%. The full parameterization is available in Appendix C. Exchange rate movements in the small mode in each panel, labeled $\Gamma_1 = \Gamma_H$, refer to exchange rate movements conditional on a disaster, whereas movements in the large mode, labeled $\Gamma_1 = \Gamma_L$, are movements conditional on no-disaster. Blue arrows indicate to how the exchange rate change distribution changes when hedgers behavior is accounted for.

Finally, to generate the signed exchange rate change distributions, $log(\varepsilon_1/\varepsilon_0) \times sign(R^* - R)$, I simply multiply the exchange rate change by 1 if $R^* - R \geq 0$ and by -1 otherwise. Using this procedure on the distributions in Figure C.1 yields those in Figure C.2 below. As discussed in the main text, these results highlight that, when the U.S. interest rate is relatively low, disasters can manifest in either tail of the signed exchange rate change distribution. If speculators' effect dominates, the disasters remain in the left-tail, as shown in Panel C.2a, implying a dampened depreciation of the dollar in the disaster, while if hedgers' effect dominates, the disasters move to the right-tail, as shown in Panel C.2b, implying an appreciation of the high-yield U.S. dollar in the disaster.

Figure C.2: Simulated *Signed* Exchange Rate Change Distribution with Speculators and Hedgers

(a) $R^* - R^{US} > 0$ (b) $R^* - R^{US} < 0$



Note. In each panel of Figure C.2, I present 2 simulated distributions of *signed* exchange rate changes, $log(\frac{\varepsilon_1}{\varepsilon_0}) \times sign(R_t^* - R_t)$, constructed by simulating the model and aggregating exchange rate movements into histograms. The first, in yellow, accounts only the behavior of speculators (formally $\lambda_0 = \lambda_1 = 0$). The second, in purple, accounts for the behavior of both speculators and hedgers. In panel C.2a, the foreign interest rate is 10% and the U.S. interest rate is 1%. In panel C.2b, the foreign interest rate is 1% and the U.S. interest rate is 10%. The full parameterization is available in Appendix C. Exchange rate movements in the small mode in each panel, labeled $\Gamma_1 = \Gamma_H$, refer to exchange rate movements conditional on a disaster, whereas movements in the large mode, labeled $\Gamma_1 = \Gamma_L$, are movements conditional on no-disaster. Blue arrows indicate to how the exchange rate change distribution changes when hedgers behavior is accounted for.

D Data Sources and Summary Statistics

In this section, I discuss my data sources and provide some cross-sectional summary statistics. As shown in Table D.1, interest rate and exchange rate data are from “Global Financial Data”. Liquidity yields are from Du et al. (2018a). Speculator and hedger currency futures positions data is from the Commodity Future Trading Commission. And finally, the VIX index is from the Chicago Board of Exchange.

Table D.1: Data Sources and Sample Period

Data	**Source**	**Sample Period**
3M Government Yields (i)	Global Financial Data	1986M1—2020M12
Exchange Rates (e)	Global Financial Data	1986M1—2020M12
3M Liquidity Yields (λ)	Du et al. (2018a)	1991M4—2020M12
Speculator, Hedger Positions ($Pos^{S,H}$)	Commodity Future Trading Commission	1993M1—2020M12
VIX	Chicago Board of Exchange	1990M1—2020M12

Notes: All data correspond to end-of-month figures. Speculator and Hedger position available only for AUD, CAD, CHF, EUR (DEM), GBP, JPY relative to USD. Liquidity yield data from Du et al. (2018a) and is unbalanced: AUD and GBP start 1991M14; CAD starts 1991M6; NZD starts 1992M3; JPY starts 1992M9; CHF and SEK start 1994M2, NOK starts 1998M7 and EUR starts 1998M12.

In Table D.2, I provide a full-set of cross-sectional summary statistics—including the mean, median, variance, skewness and kurtosis—for my main variables of interest. Exchange rate skewness—a measure of asymmetric crash risk for currencies in disasters—and median exchange rate movements—a measure of exchange rate dynamics conditional on no-disaster—are of particular interest for this paper.

My model from section 2 made two key predictions for exchange rate dynamics in disasters: (1) high- (low-) interest-rate currencies tend to experience large depreciations (appreciations); and (2) the U.S. dollar tends to appreciate against all other currencies. These effects can either reinforce or offset one another depending on the sign of a country's interest differential with the U.S.. The two predictions are visible in Figure D.1, which plots the realized *skewness* of 3-month exchange rate movements Δe (Panel D.1a) and carry trade returns z (Panel D.1b) for each currency in my sample vis-à-vis the dollar against each country's average interest differential against the U.S. ($\mathbb{E}[i^* - i]$).[44] A negatively skewed exchange rate change distribution implies the foreign currency has tended to experience more extreme left-tail depreciations as compared to extreme right-tail appreciatons. Similarly, a negatively skewed carry trade return distribution implies carry trades long the foreign currency have tended to suffer more extreme left-tail losses as compared to extreme right-tail gains.

The negative slope of the best-fit lines in Figure D.1 indicates that the distributions of exchange rate movements and carry trade returns become more left-skewed as average interest differentials relative to the U.S. increase. Consistent with Prediction 1, this suggests that high-interest-rate currencies occasionally experience very large depreciations, whose magnitudes are proportional to (average) interest differentials. At the same time, the negative intercept terms

[44] These values are taken from Table D.2

Table D.2: Cross-Sectional Summary Statistics with U.S. dollar as Base Currency

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
					Mean				
$i^* - i$	0.0066	0.0022	-0.0028	-0.0008	0.0039	-0.0044	0.0047	0.0083	0.0029
Δe	0.0004	0.0004	0.0060	0.0035	-0.0007	0.0048	-0.0012	0.0017	-0.0008
z	0.0072	0.0027	0.0031	0.0027	0.0033	0.0004	0.0037	0.0102	0.0021
Pos^S	0.0968	0.0121	-0.0830	0.0014	-0.0254	-0.1037	.	.	.
Pos^H	-0.1561	-0.1109	0.1201	-0.0318	0.0163	0.1605	.	.	.
λ	4.272	6.213	8.633	5.511	2.753	8.221	3.993	-1.701	4.629
					Median				
$i^* - i$	0.0060	0.0016	-0.0027	-0.0014	0.0022	-0.0033	0.0034	0.0070	0.0021
Δe	0.0034	-0.0004	0.0056	0.0033	0.0007	0.0019	0.0033	0.0077	0.0021
z	0.0098	0.0017	0.0015	0.0026	0.0052	-0.0029	0.0034	0.0142	0.0046
Pos^S	0.0946	-0.0003	-0.1314	0.0217	-0.0463	-0.1345	.	.	.
Pos^H	-0.2049	-0.1296	0.2143	-0.0535	0.0663	0.1958	.	.	.
λ	3.202	4.082	7.298	4.297	1.642	6.288	2.995	0.956	4.219
					Variance				
$i^* - i$	3.4e-5	1.3e-5	2.1e-5	1.9e-5	2.3e-5	2.2e-5	4.4e-5	5.1e-5	4.4e-5
Δe	0.0034	0.0013	0.0030	0.0029	0.0025	0.0033	0.0033	0.0033	0.0035
z	0.0035	0.0014	0.0031	0.0029	0.0026	0.0033	0.0033	0.0034	0.0035
Pos^S	0.0907	0.0627	0.0733	0.0534	0.0605	0.0705	.	.	.
Pos^H	0.1997	0.1199	0.1773	0.1080	0.1261	0.1224	.	.	.
λ	67.54	63.94	82.12	57.42	54.41	81.33	72.67	385.8	122.6
					Skewness				
$i^* - i$	0.9030	0.8141	0.7424	0.7746	0.7958	-0.3256	0.8880	2.0618	0.8808
Δe	-0.8330	-0.1022	0.002	-0.2044	-0.8218	0.3229	-0.6575	-0.2975	-0.9619
z	-0.7260	-0.1553	0.0625	-0.1372	-0.6151	0.2679	-0.5276	-0.2019	-0.7371
Pos^S	-0.1133	0.0837	0.2150	-0.2174	0.3213	0.2807	.	.	.
Pos^H	0.2310	0.0393	-0.3585	0.1935	-0.2975	-0.2244	.	.	.
λ	1.157	1.943	2.524	5.984	1.577	6.141	2.636	-2.314	1.448
					Kurtosis				
$i^* - i$	3.874	3.515	3.588	3.540	2.954	1.939	3.298	9.091	4.094
Δe	7.190	5.951	3.253	3.343	6.693	3.829	5.057	4.422	6.373
z	6.523	5.702	3.128	3.156	6.070	3.621	4.645	4.141	5.273
Pos^S	1.855	1.937	1.978	2.268	2.349	1.860	.	.	.
Pos^H	1.775	1.805	1.889	2.096	1.989	1.767	.	.	.
λ	13.26	20.06	16.16	60.74	12.91	69.15	17.91	11.30	18.55

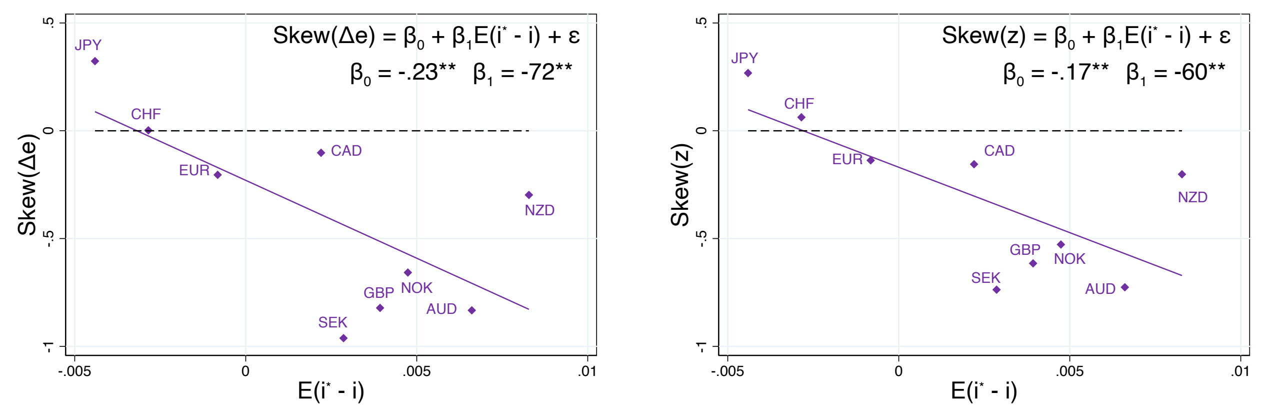
Notes: USD base summary statistics.

to these best-fit lines indicate that, controlling for average interest differentials, the distributions of exchange rate movements and carry trade returns are left-skewed. That is, the U.S. dollar carries significant upside risk against all currencies ceteris paribus, which is consistent with Prediction 2. As a result, high-interest-rate currencies, such as the AUD, carry amplified risks of large depreciations whereas low-interest-rate currencies, such as the CHF, see their upside risks vis-à-vis the dollar dampened. In fact, the dollar, due to the relatively small gap between U.S. and German interest rates, actually carries upside exchange rate risk against the low-interest-rate euro.

In addition, my model made 2 predictions for exchange rate dynamics in normal times: (1) high- (low-) yield currencies excessively appreciate (depreciate) relative to interest differentials;

Figure D.1: Realized U.S. Exchange Rate and Carry Trade Skewness by Interest Differentials

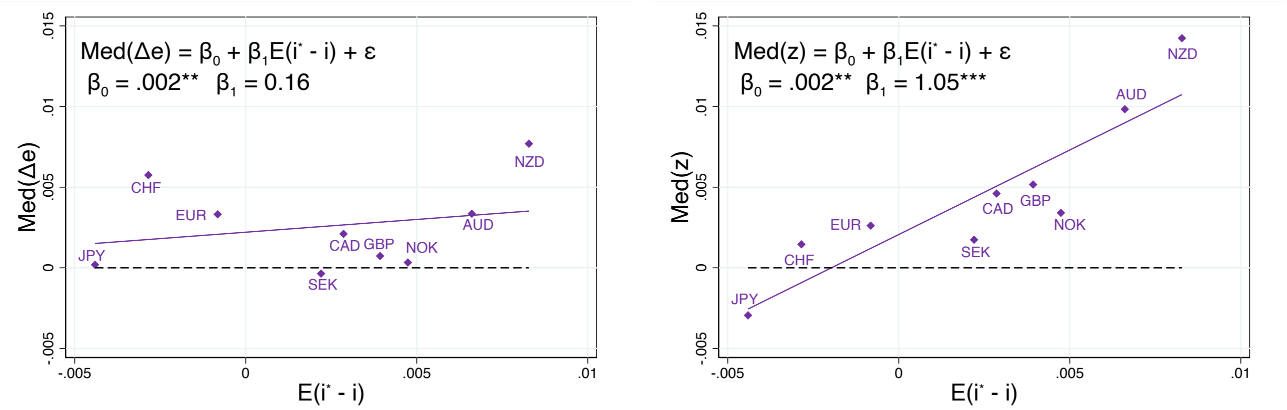
(a) Skewness of Exchange Rate Movements (b) Skewness of Carry Trade Returns



Note. Figure D.1 presents the unconditional skewness of 3-month exchange rate movements $\Delta e_{t+1} = e_{t+1} - e_t$ in Panel D.1a and of 3-month carry trade returns $z_{t+1} = \Delta e_{t+1} + i^* - i$ in Panel D.1b for 9 currencies (AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK) relative to the USD, plotted against each currencies' average interest differential with the U.S. $\mathbb{E}[i^* - i]$. e_t is the log dollar exchange rate defined such that an increase is a depreciation of the USD while i^* is the (log) foreign 3-month government bond interest rate and i is the 3-month U.S. Treasury rate. Data is monthly from 1986:M1 to 2020:M12.

Figure D.2: Median US Exchange Rate Movement, Carry Trade Return by Interest Differentials

(a) Median Exchange Rate Movement (b) Median Carry Trade Return



Note. Figure D.2 presents the unconditional median of 3-month exchange rate movements $\Delta e_{t+1} = e_{t+1} - e_t$ in Panel D.2a and of 3-month carry trade returns $z_{t+1} = \Delta e_{t+1} + i^* - i$ in Panel D.2b for 9 currencies (AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK) relative to the USD, plotted against each currencies' average interest differential with the U.S. $\mathbb{E}[i^* - i]$. e_t is the log dollar exchange rate defined such that an increase is a depreciation of the USD while i^* is the (log) foreign 3-month government bond interest rate and i is the 3-month U.S. Treasury rate. Data is monthly from 1986:M1 to 2020:M12.

and (2) the U.S. dollar depreciates against all other currencies. These two effects can either reinforce or offset one another depending on the sign of a country's interest differential with the U.S.. The two predicitions are visible in Figure D.2, which plots the cross-sectional median exchange rate movement Δe (Panel D.2a) and carry trade return z (Panel D.2b) for each currency in my sample vis-à-vis the dollar against each country's average interest differential with to the U.S. ($\mathbb{E}[i^* - i]$). The positive slope of the best-fit lines in each panel indicate that median appreciation of the foreign currency against the U.S. dollar increases as the foreign country's average interest rate relative to the U.S. rises. Furthermore, the positive intercept terms of the best-fit lines in each panel indicate that, after controlling for (average) interest differentials, the U.S. dollar tends to depreciate at the median, my proxy for conditional on no-disaster. These effects reinforce one another when the U.S. interest rate is relatively low, e.g. compared to Australia's, and (partially) offset each other when the U.S. interest rate is relatively high, e.g. compared to Switzerland's. As a result, there are larger carry trade returns when going long high-yield currencies and short the dollar, conditional on no-disaster, as compared to returns when going long the dollar and short low-yield currencies. This is exactly the prediction of Corollary 2.

E The Signed Quantile UIP Regression: A Proof

In this section, I provide a proof for the signed quantile UIP regression from Proposition 1:

$$\Delta e_{t+1} \times sign(i_t^* - i_t) = \beta_0^\tau sign(i_t^* - i_t) + \beta_1^\tau (i_t^* - i_t) \times sign(i_t^* - i_t) + u_{t+1}^\tau \tag{E.1}$$

Specifically, I show that β_1^τ measures the quantile marginal effect of the interest differential $i_t^* - i_t$ on exchange rate movements Δe_{t+1} at the τ^{th} quantile of the conditional signed exchange rate change distribution $\Delta e_{t+1} \times sign(i_t^* - i_t) | X_t^S$, where the conditioning vector X_t^S when estimating E.1 includes the intercept $sign(i_t^* - i_t)$ and the signed interest differential $(i_t^* - i_t) \times sign(i_t^* - i_t)$. As shown in the simulations in section 3, this signed exchange rate change distribution is the correct distribution with which to analyze exchange rate dynamics in light of my model. I will make this clear formally below. Importantly, the proof that follows can be easily generalized to include other conditioning variables in X_t^S, such as the change in the U.S. Treasury liquidity yield $\Delta\lambda_{t+1}$, provided these too are interacted with the sign of the interest differential.

As a starting point, consider the signed UIP regression estimated by least squares:

$$\Delta e_{t+1} \times sign(i_t^* - i_t) = \beta_0 sign(i_t^* - i_t) + \beta_1 (i_t^* - i_t) \times sign(i_t^* - i_t) + u_{t+1}. \tag{E.2}$$

For clarity, let $X_t = \{1, (i_t^* - i_t)\}$ and $X_t^S = \{sign(i_t^* - i_t), (i_t^* - i_t) \times sign(i_t^* - i_t)\}$. Then, the OLS-estimated marginal effects $\hat{\beta} = \{\hat{\beta}_0, \hat{\beta}_1\}$ are given as the solution to the minimization problem:

$$
\begin{aligned}
\hat{\beta} &= argmin_{\{\beta \in \mathbf{R}^2\}} \sum_{t=1}^{T-1} \Big[\ (\Delta e_{t+1} \times sign(i_t^* - i_t) - \beta X_t^S)^2 \Big] \\
&= argmin_{\{\beta \in \mathbf{R}^2\}} \sum_{t=1}^{T-1} \Big[\ \underbrace{(sign(i_t^* - i_t))^2}_{1} (\Delta e_{t+1} - \beta X_t)^2 \Big]
\end{aligned} \tag{E.3}
$$

Thus, the marginal effects $\hat{\beta}$ from estimating the signed UIP regression by OLS are identical to those from estimating the traditional Fama (1984) UIP regression. In particular, $\hat{\beta}_1$ estimates the marginal effect of the interest differential on the *mean* exchange rate movement. The reason for this is that: (1) the loss-function is quadratic; and (2) both the dependent and independent variables are interacted with the $sign(i_t^* - i_t)$ term.

Next, lets consider the quantile UIP regression without the sign transformation:

$$
\Delta e_{t+1} = \beta_0^\tau + \beta_1^\tau (i_t^* - i_t) + u_{t+1}^\tau \tag{E.4}
$$

The estimated quantile-regression marginal effects $\hat{\beta}^\tau = \{\hat{\beta}_0^\tau, \hat{\beta}_1^\tau\}$ are given as the solution to the minimization problem:

$$
\begin{aligned}
\hat{\beta}^\tau = argmin_{\{\beta^\tau \in \mathbf{R}^2\}} \sum_{t=1}^{T-1} \Big[& \ \tau * \mathbf{1}_{\{\Delta e_{t+1} > \beta^\tau X_t\}} \mid \Delta e_{t+1} - \beta^\tau X_t \mid \\
& + (1-\tau) * \mathbf{1}_{\{\Delta e_{t+1} < \beta^\tau X_t\}} \mid \Delta e_{t+1} - \beta^\tau X_t \mid \Big]
\end{aligned} \tag{E.5}
$$

$\hat{\beta}^\tau$ measures the marginal effect of X_t on exchange rate movements Δe_{t+1} at the τ^{th} quantile of the conditional exchange rate distribution $\Delta e_{t+1}|X_t$. In this case, the loss function weights observations (by τ or $1-\tau$) based on whether or not the appreciation of the foreign currency is sufficiently large ($e_{t+1} > \beta^\tau X_t$ or $e_{t+1} < \beta^\tau X_t$). According to my model, however, this is not the appropriate weighting scheme as it weights large appreciations of high-interest-rate currencies (when $i_t^* > i_t$) and large appreciations of low-interest-rate currencies (when $i_t^* < i_t$) by the same amount τ, provided they both satisfy ($e_{t+1} > \beta^\tau X_t$). That is, the minimization problem selects a single $\hat{\beta}_1^\tau$ to explain exchange rate movements that ought not be grouped together. For example, in my model, appreciations of high-yield currencies are due to speculators' carry-trading while appreciations of low-yield currencies are due to speculators' unwinding of carry trades.

The signed quantile UIP regression (E.1), on the other hand, corrects for this problem. The estimated quantile-regression marginal effects, which I again denote by $\hat{\beta}^\tau = \{\hat{\beta}_0^\tau, \hat{\beta}_1^\tau\}$, are given as the solution to the minimization problem:

$$\hat{\beta}^{\tau} = argmin_{\{\beta^{\tau}\in\mathbf{R}^2\}} \sum_{t=1}^{T-1} \Big[\tau * \mathbf{1}_{\{\Delta e_{t+1}\times sign(i_t^*-i_t)>\beta^{\tau}X_t^S\}} \mid \Delta e_{t+1} \times sign(i_t^* - i_t) - \beta^{\tau} X_t^S \mid$$
$$+ (1-\tau) * \mathbf{1}_{\{\Delta e_{t+1}\times sign(i_t^*-i_t)<\beta^{\tau}X_t^S\}} \mid \Delta e_{t+1} \times sign(i_t^* - i_t) - \beta^{\tau} X_t^S \mid \Big]$$

Factoring out the $sign(i_t^* - i_t)$ terms from within the absolute value, we arrive at:

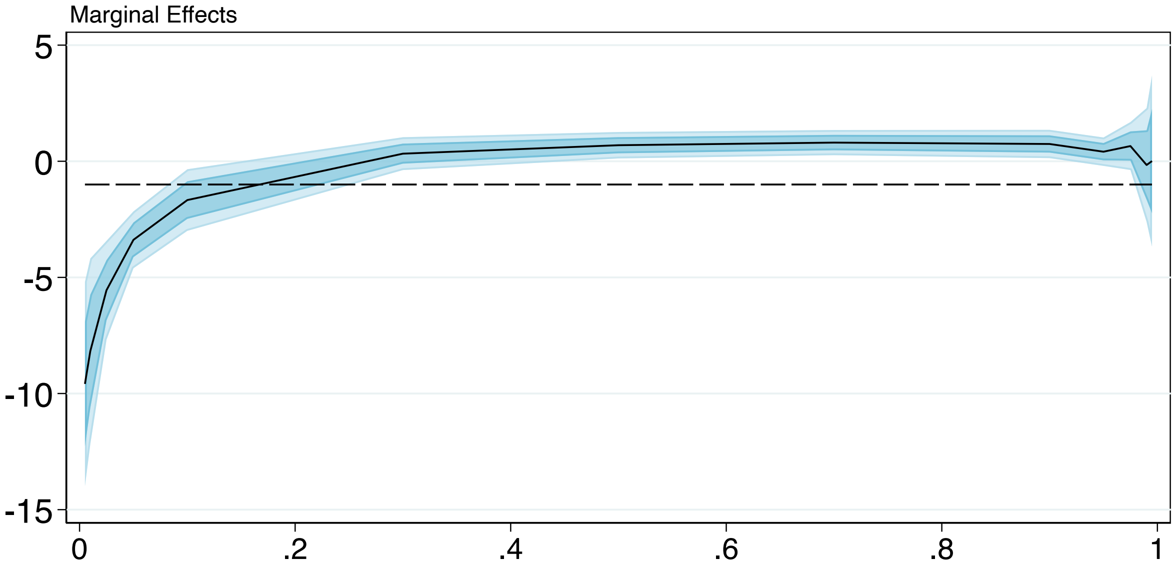
$$\hat{\beta}^{\tau} = argmin_{\{\beta^{\tau}\in\mathbf{R}^2\}} \sum_{t=1}^{T-1} \Big[\tau * \mathbf{1}_{\{\Delta e_{t+1}\times sign(i_t^*-i_t)>\beta^{\tau}X_t^S\}} \overbrace{\mid sign(i_t^* - i_t) \mid}^{1} \mid \Delta e_{t+1} - \beta^{\tau} X_t \mid$$
$$+ (1-\tau) * \mathbf{1}_{\{\Delta e_{t+1}\times sign(i_t^*-i_t)<\beta^{\tau}X_t^S\}} \underbrace{\mid sign(i_t^* - i_t) \mid}_{1} \mid \Delta e_{t+1} - \beta^{\tau} X_t \mid \Big]$$

Thus, like in the OLS-estimated case above, the error-term is $e_{t+1} - \beta^{\tau} X_t$ such that the quantile-specific coefficients from estimating (E.1) capture the marginal effects of X_t on exchange rate movements Δe_{t+1}. This is because both the dependent and independent variables are interacted with the $sign(i_t^* - i_t)$ term. However, unlike the OLS case, the conditioning distribution matters since observations above ($\Delta e_{t+1} \times sign(i_t^* - i_t) > \beta^{\tau} X_t^S$) or below ($\Delta e_{t+1} \times sign(i_t^* - i_t) < \beta^{\tau} X_t^S$) the best fit line are weighted differently. That is, more specifically, β_1^{τ} measures the marginal effects of X_t on exchange rate movements Δe_{t+1} at the τ^{th} quantile of the conditional signed exchange rate distribution $\Delta e_{t+1} \times sign(i_t^* - i_t)|X_t^S$. To provide an intuition for this distribution, notice that the loss function can be rewritten as:

$$\hat{\beta}^{\tau} = argmin_{\{\beta^{\tau}\in\mathbf{R}^2\}} \sum_{t=1}^{T-1} \Big[\tau * \mathbf{1}_{\{\{\Delta e_{t+1}>\beta^{\tau}X_t \mid sign(i_t^*-i_t)=1)\cup(\Delta e_{t+1}<\beta^{\tau}X_t \mid sign(i_t^*-i_t)=-1\}\}} \mid \Delta e_{t+1} - \beta^{\tau} X_t \mid$$
$$+ (1-\tau) * \mathbf{1}_{\{\{\Delta e_{t+1}>\beta^{\tau}X_t \mid sign(i_t^*-i_t)=-1)\cup(\Delta e_{t+1}<\beta^{\tau}X_t \mid sign(i_t^*-i_t)=1\}\}} \mid \Delta e_{t+1} - \beta^{\tau} X_t \mid \Big] \tag{E.6}$$

In this case, β^{τ} is estimated by weighting observations where the appreciation of the high-interest-rate currency is sufficiently large ($\Delta e_{t+1} > \beta^{\tau} X_t$ and $sign(i_t^* - i_t) = 1$) and observations where the depreciation of the low-interest-rate currency is sufficiently large ($\Delta e_{t+1} < \beta^{\tau} X_t$ and $sign(i_t^* - i_t) = -1$) by the same amount τ. Similarly, it weights observations where the depreciation of the high-interest-rate currency is sufficiently large ($\Delta e_{t+1} < \beta^{\tau} X_t$ and $sign(i_t^* - i_t) = 1$) and observations where the appreciation of the low-interest-rate currency is sufficiently large ($\Delta e_{t+1} > \beta^{\tau} X_t$ and $sign(i_t^* - i_t) = -1$), by the same amount $1 - \tau$. Thus, this weighting scheme accounts for the interest-rate symmetry of exchange rate movements predicted by my model. ■

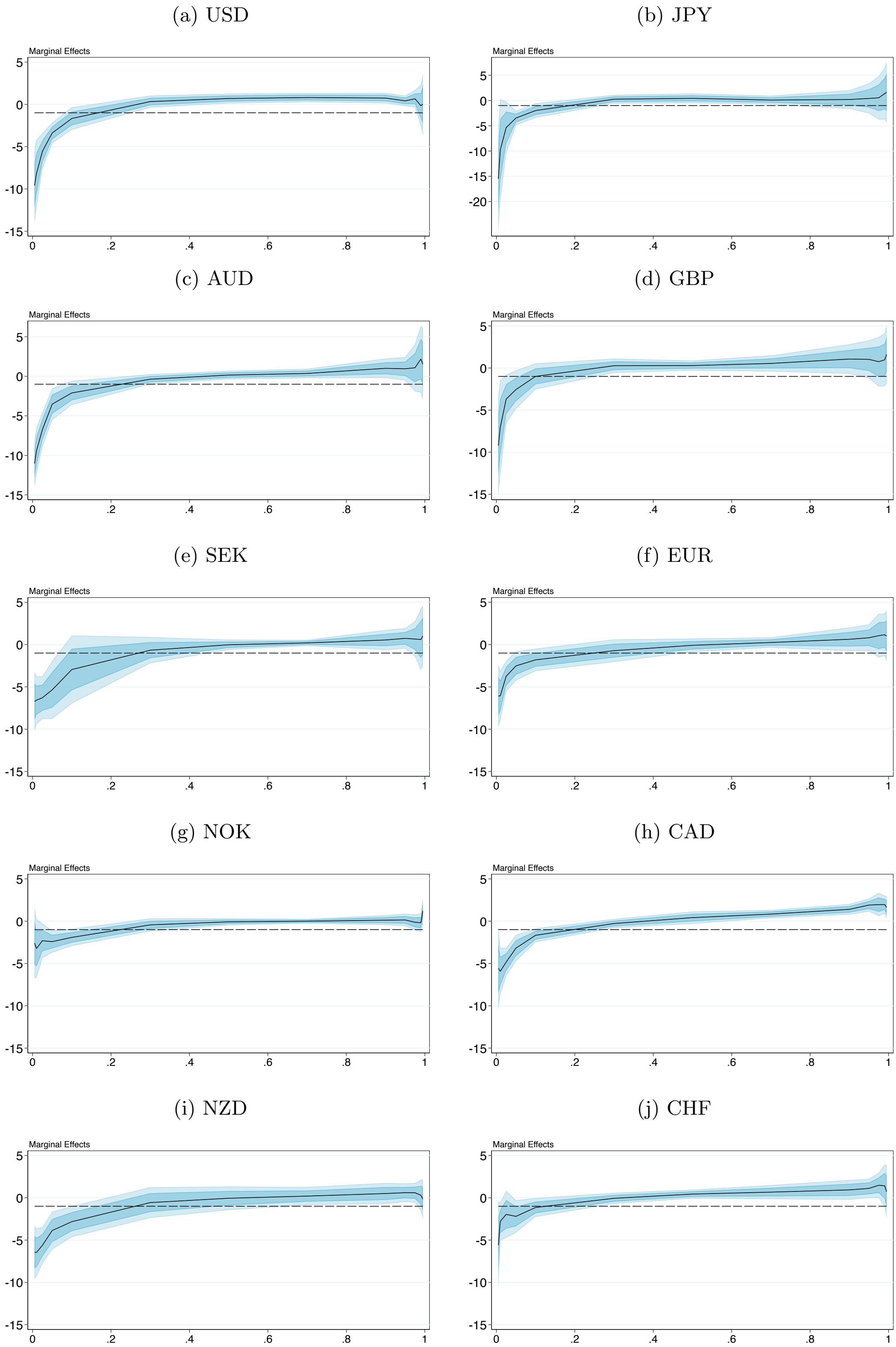
Figure E.1: The U.S. Signed Quantile UIP Regression



Note. Figure E.1 presents the same results as Figure 7, but with the estimated quantiles on the horizontal axis spaced in proportion to their value. The black dashed line is the "UIP line". Light and dark shaded regions are 90% and 68% confidence intervals constructed using a block bootstrap with 500 bootstrap samples.

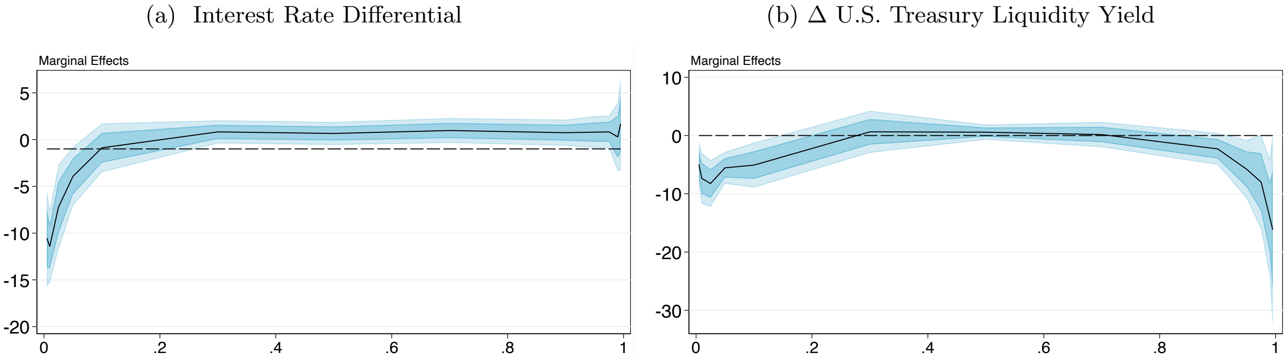
Finally, below I re-plot the marginal effects displayed in Figures 7, 8 and 10 in the main text, but with the estimated quantiles on the horizontal axis spaced in proportion to their value, rather than evenly spaced. These results highlight the relative rarity of the disaster state in the data.

Figure E.2: The State-Dependent Uncovered Interest Parity Condition



Note. Figure E.2 presents the same results as Figure 8, but with the estimated quantiles on the horizontal axis of each panel spaced in proportion to their value. The black dashed line is the "UIP line" in each panel. Light and dark shaded regions in each panel are 90% and 68% confidence intervals constructed using a block bootstrap with 500 bootstrap samples.

Figure E.3: Interest Differentials, Treasury Liquidity Premia and Tail Exchange Rate Dynamics



Note. Figure E.3 presents presents the same results as Figure 10, but with the estimated quantiles on the horizontal axis of each panel spaced in proportion to their value. The black dashed line is the "UIP line" in Panel E.3a and the "zero line" in Panel E.3b. Light and dark shaded regions are 90% and 68% confidence intervals constructed using a block bootstrap with 500 bootstrap samples.

E.1 Details on the Block Bootstrap Procedure

In this section, I provide details on the block bootstrap procedure that I use to compute the confidence intervals in this paper, which correct for heteroskedasticity and autocorrelation. Following Adrian et al. (2022), I first split the panel with time-series length T into contiguous overlapping blocks of length t. I then construct a bootstrap sample by randomly sampling s of these blocks of length t, where $s \times t = T$.[45] Using the resulting panel bootstrap sample, I re-estimate a given panel quantile regression specification, for example (24), at a given quantile τ and output a new vector of marginal effects $\widehat{\beta}^{\tau}_{BS}$. Repeating this procedure x times produces a distribution of $\widehat{\beta}^{\tau}_{BS}$s which can be used to construct confidence intervals around the marginal effects estimated using the original panel $\widehat{\beta}^{\tau}$. In particular, I construct an $1-\alpha\%$ two-sided confidence interval around $\widehat{\beta}^{\tau}$ as:

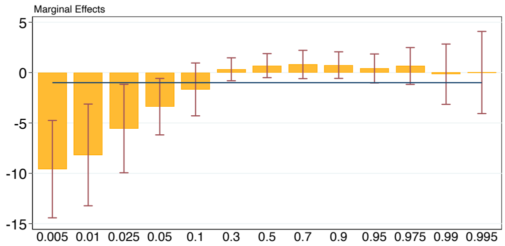
$$[\widehat{\beta}^{\tau} - \Phi^{-1}(1-\alpha/2) \times \sigma(\widehat{\beta}^{\tau}_{BS}), \widehat{\beta}^{\tau} + \Phi^{-1}(1-\alpha/2) \times \sigma(\widehat{\beta}^{\tau}_{BS})], \tag{E.7}$$

where $\sigma(\widehat{\beta}^{\tau}_{BS})$ is the standard deviation of the distribution of $\widehat{\beta}^{\tau}_{BS}$s and Φ^{-1} is the inverse cdf of the standard normal distribution. In my baseline, I use 2 non-overlapping blocks per bootstrap sample i.e., $s = 2$. Figures E.4 and E.5 show that my results are similar if I set $s = 3$. Further, I show in section F.3 that my results are robust to a parametric clustering method of computing standard errors that account for heteroskedasticity and autocorrelation.

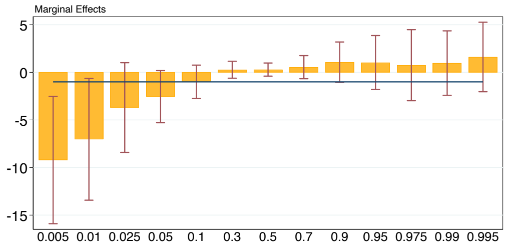
[45]Of note, the sample size of the resulting bootstrapped panel may differ slightly from the size of the original panel since the sample is unbalanced. Thus, the bootstrapped sample may sample more or less missing values in the original dataset.

Figure E.4: The State-Dependent UIP Condition: Inference with Alternative Block Length

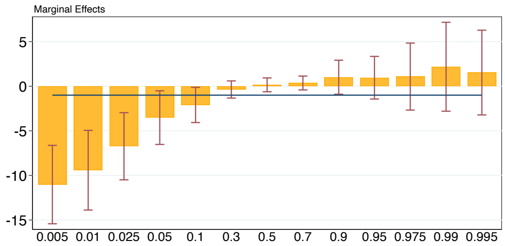
(a) USD



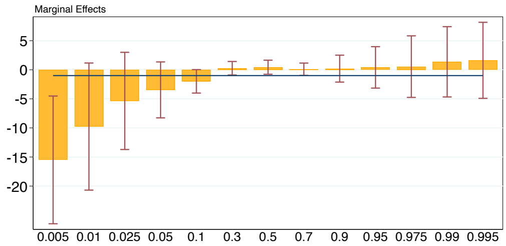
(b) GBP



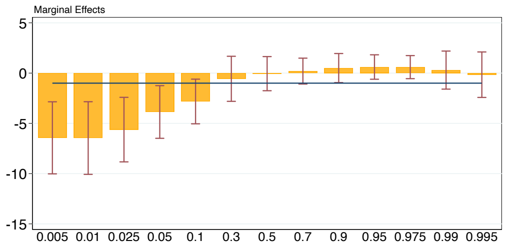
(c) AUD



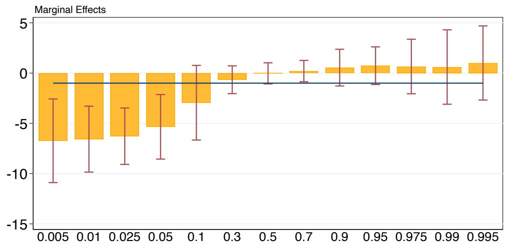
(d) JPY



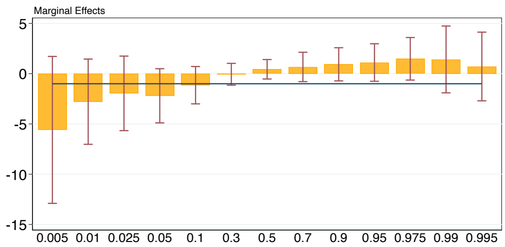
(e) NZD



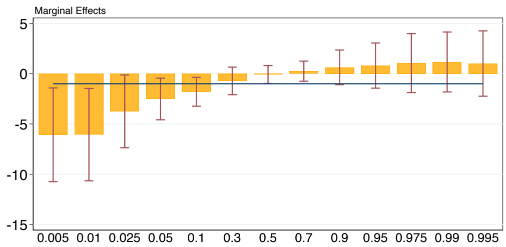
(f) SEK



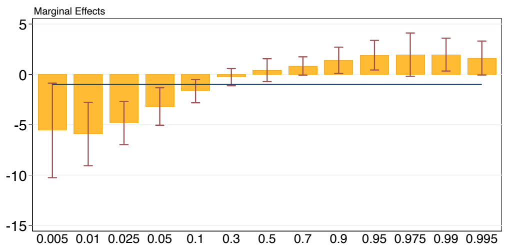
(g) CHF



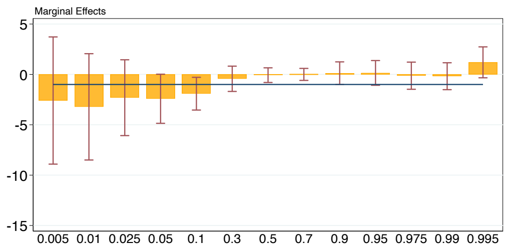
(h) EUR



(i) CAD

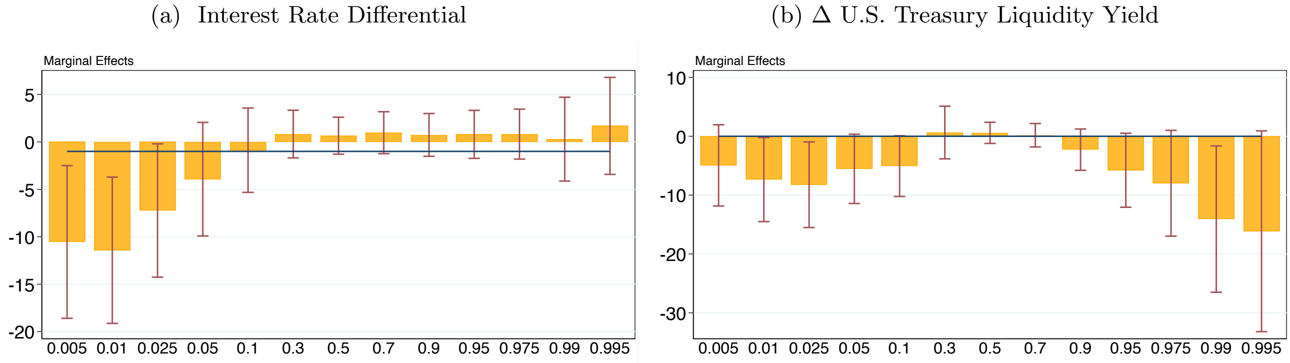


(j) NOK



Note. Figure E.4 is the analogue of Figure 8 but with confidence intervals constructed from a block bootstrap procedure with a block length of $T/3$ rather than the $T/2$ used in the baseline. The remainder of the notes in Figure 8 apply here as well.

Figure E.5: Interest Differentials, Liquidity Premia and Tail Exchange Rate Dynamics with Alternative Block Length



Note. Figure E.5 is the analogue of Figure 10 but with confidence intervals constructed from a block bootstrap procedure with a block length of $T/3$ rather than the $T/2$ used in the baseline. The remainder of the notes in Figure 10 apply here as well.

E.2 Details on the Fitted Exchange Rate Change Distribution Procedure

In this section, I discuss how I implement the procedure of Adrian et al. (2019) to output the conditional exchange rate change distributions in Figure 11. For now, assume that the interest differential is positive such that $sign(i_t^* - i_t) = 1$. I discuss the case of $sign(i_t^* - i_t) = -1$ shortly. When $sign(i_t^* - i_t) = 1$, the $\widehat{\beta}^{\tau}$s associated to $i_t^* - i_t \times sign(i_t^* - i_t)$ and $\Delta\lambda_{t+1} \times sign(i_t^* - i_t)$ from estimating (27) (which are displayed in Figure 10) measure the marginal effects of $X_{t,t+1} = \{i_t^* - i_t, \Delta\lambda_{t+1}\}$ on the τ^{th} quantile Δe_{t+1}. Thus, they can be used to predict the conditional quantiles of the exchange rate change distribution as follows:

$$\widehat{\Delta e_{t+1}}^{\tau} | X_{t,t+1} = \widehat{\beta}^{\tau} X_{t,t+1}, \tag{E.8}$$

where, in Figure 11, I set $X_{t,t+1} = \{i_t^* - i_t, \Delta\lambda_{t+1}\} = \{1pp, 75bp\}$. I use this procedure to output 7 conditional quantiles of Δe_{t+1}, namely, the $\tau \in \{0.005, 0.01.0.025, 0.3, 0.5, 0.7, 0.975\}$ quantiles. Next, I fit these empirical quantiles to the theoretical quantiles $Q^{\tau}(\mu, \sigma, \alpha, \nu)$ of the skew-T distribution (Azzalini and Capitanio (2003)) by selecting parameters $\{\mu, \sigma, \alpha, \nu\}$ of the skew-T to minimize the sum of squared deviations across quantiles between $\widehat{\Delta e_{t+1}}^{\tau} | X_{t,t+1}$ and $Q^{\tau}(\mu, \sigma, \alpha, \nu)$. Once the four parameters of the skew-T distribution are selected, they can be substituted into the pdf for the skew-T to output the conditional exchange rate change distributions displayed in Panel 11a of Figure 11.

When $sign(i_t^* - i_t) = -1$, as in Panel 11b of Figure 11, I adapt the above procedure as follows. Since the coefficients at the τ^{th} quantile for $i_t^* - i_t \times sign(i_t^* - i_t)$ and $\Delta\lambda_{t+1} \times sign(i_t^* - i_t)$ in Figure 10 measure their marginal effects on the τ^{th} quantile $\Delta e_{t+1} \times sign(i_t^* - i_t)$, they measure the marginal effects of $i_t^* - i_t$ and $\Delta\lambda_{t+1}$ on the $1-\tau^{th}$ quantile Δe_{t+1} when $sign(i_t^* - i_t) = -1$, such that:

$$\widehat{\Delta e_{t+1}}^{1-\tau} | X_{t,t+1} = \widehat{\beta}^{\tau} X_{t,t+1} \tag{E.9}$$

where, for symmetry, I set $X_{t,t+1} = \{i_t^* - i_t, \Delta\lambda_{t+1}\} = \{-1pp, 75bp\}$. I again use (E.9) to output 7 conditional quantiles $\tau \in \{0.005, 0.01.0.025, 0.3, 0.5, 0.7, 0.975\}$ of the exchange rate change distribution. The remainder of the procedure is the same as the case where $sign(i_t^* - i_t) = 1$, and yields Panel 11b of Figure 11.

F Additional Empirical Results and Robustness

F.1 The Quantile UIP Regression

To demonstrate the clear improvement of the signed quantile UIP regression over the standard UIP relationship estimated by quantile regression (F.1) in capturing exchange rate movements in disasters, I estimate the panel quantile UIP regression:

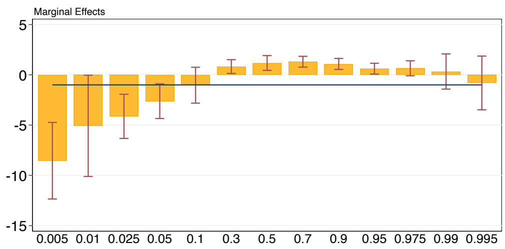
$$\Delta e_{j,t+1} = \beta_0^\tau + \beta_1^\tau (i_{j,t}^* - i_{j,t}) + f_j^\tau + u_{j,t+1}^\tau. \tag{F.1}$$

The results are displayed in Figure F.1. There are a few things to highlight. First, notice that negative marginal effects tend to appear in the left-tail for low-yield currencies such as the JPY, USD while they tend to appear in the right-tail for high-yield currencies such as the GBP, SEK and NZD. The reason is that, without the sign interaction, large appreciations of the base currency $\Delta e_{t+1} \downarrow$ manifest in the left tail and large depreciations of the base currency $\Delta e_{t+1} \uparrow$ manifest in the right tail of the exchange rate distribution. Second, these marginal effects are much smaller, less-precisely estimated and not present for all currencies as compared to those coming from the signed quantile UIP regression from Figure 8.

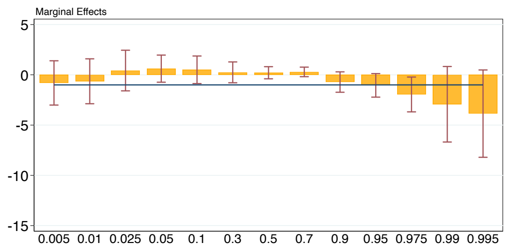
The reason is that the quantile UIP regression does not account for the interest-rate symmetry of exchange rate movements, an important feature of the data that arises due to speculators in my model. A good case study is AUD, which tends to have a relatively high interest rate. As a result, one would expect it to experience a large depreciation in a disaster, which would manifest in the right tail. While we do see evidence of this, large negative marginal effects are even more stark in the left-tail, indicating that interest differentials also predict the large appreciations of AUD. When inspecting the AUD panel in Figure 8, we see all the large negative marginal effects are present in the left-tail, indicating that interest differential's predict the AUD to suffer large depreciations when its interest rate is relatively high and large appreciations when its interest rate is relatively low. This highlights the key issue with the quantile UIP regression: it allocates disaster-state exchange rate movements, which ought to be grouped together, to different tails depending on the sign of the interest differential. The signed quantile UIP regression corrects for this. Importantly, this is not a phenomenon unique to the AUD. We see negative marginal effects, albeit smaller, in the opposite tail to what we would expect based on each currencies' *average* interest rate for the USD, GBP, NZD as well, not to mention the improvement in terms of magnitude and precision of the estimated coefficients in the left-tail of

Figure F.1: The State-Dependent UIP Condition Without $sign(i^*_{j,t} - i_t)$ Adjustment

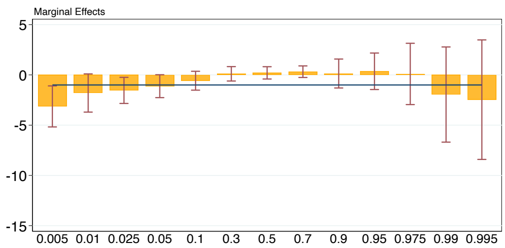
(a) USD



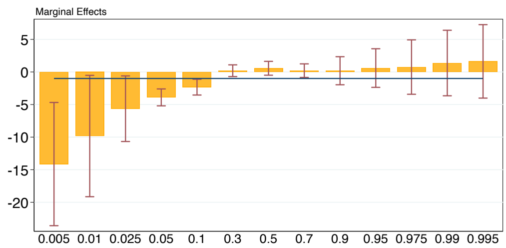
(b) GBP



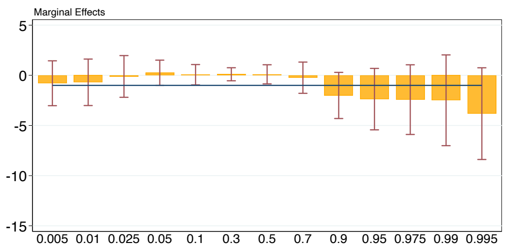
(c) AUD



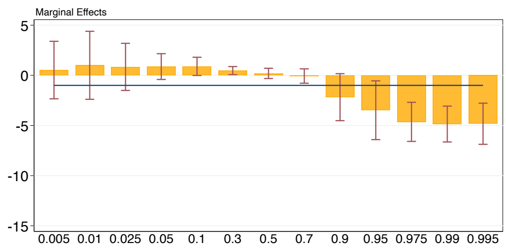
(d) JPY



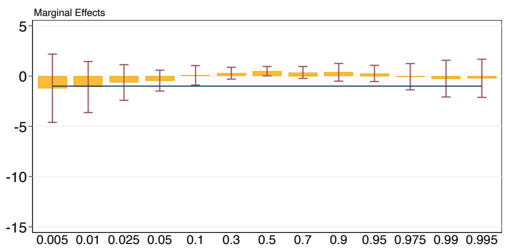
(e) NZD



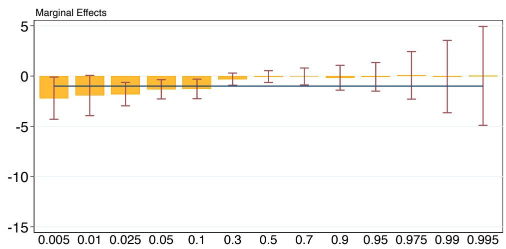
(f) SEK



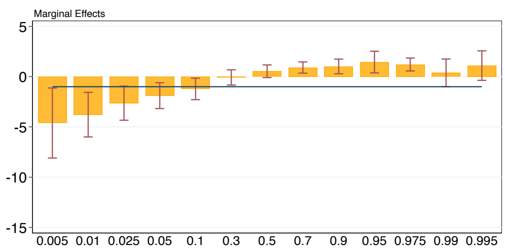
(g) CHF



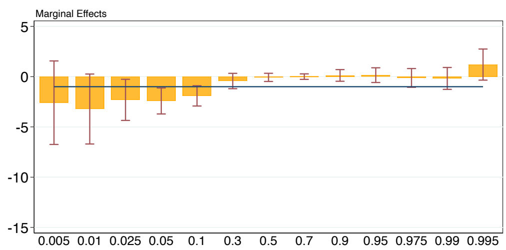
(h) EUR



(i) CAD

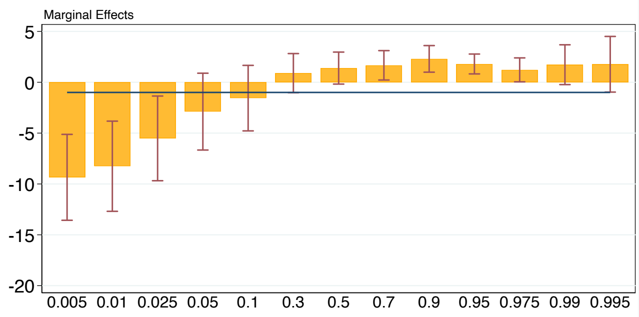


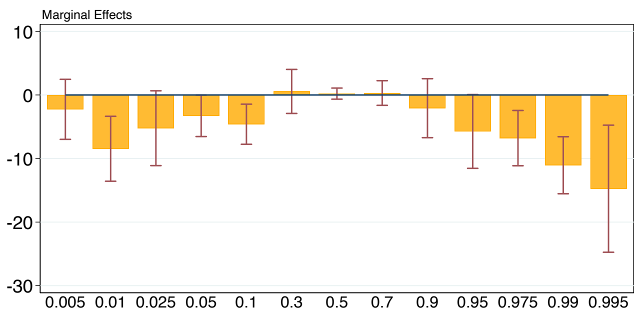
(j) NOK



Note. Figure F.1 is the analogue of Figure 8 but without the $sign(i^*_{j,t} - i_t)$ interaction. Specifically, it presents coefficient estimates from regression (F.1). The remainder of the notes in Figure 8 apply here as well.

Figure F.2: Interest Differentials, Liquidity Yields and Exchange Rates Without $sign(i^*_{j,t} - i_t)$ Adjustment





Note. Figure F.2 is the analogue of Figure 10 but without the $sign(i^*_{j,t} - i_t)$ interaction. Specifically, it presents coefficient estimates from regression (F.2). The remainder of the notes in Figure 10 apply here as well.

Figure 8 for all currencies.

$$\Delta e_{j,t+1} = \beta_0^\tau + \beta_1^\tau(i^*_{j,t} - i_{j,t}) + \beta_2^\tau \Delta\lambda_{t+1} + f_j^\tau + u^\tau_{j,t+1}. \tag{F.2}$$

Figure F.2 presents the quantile regression coefficients from estimating the standard UIP relationship augmented with the U.S. Treasury liquidity yield (F.1). The main takeaway is that the lef-tail marginal effects are significantly more-precisely estimated in Figure 10 than those in Figure F.2, while the effects in the right-tail are (mildly) larger in Figure 10 relative to those in Figure F.2. This again highlights the improvement of the signed quantile UIP approach.

F.2 Goodness of Fit of Signed Quantile UIP Regression

I measure the goodness of fit of the signed quantile UIP regression using the $R^1(\tau)$ measure developed by Koenker and Machado (1999):

$$R^1(\tau) = 1 - \frac{\hat{V}(\tau)}{\tilde{V}(\tau)} \tag{F.3}$$

where $\hat{V}(\tau)$ is the sum of quantile-weighted absolute residuals from regression (24):

$$\begin{aligned}\hat{V}(\tau) =& min_{\{\beta^\tau\}} \sum_{t=1}^{T-1} \Big[\tau * \mathbf{1}_{\{\Delta e_{t+1} \times sign(i^*_t - i_t) > \beta^\tau X^S_t\}} \mid \Delta e_{t+1} \times sign(i^*_t - i_t) - \beta^\tau X^S_t \mid \\ &+ (1-\tau) * \mathbf{1}_{\{\Delta e_{t+1} \times sign(i^*_t - i_t) < \beta^\tau X^S_t\}} \mid \Delta e_{t+1} \times sign(i^*_t - i_t) - \beta^\tau X^S_t \mid \Big]\end{aligned} \tag{F.4}$$

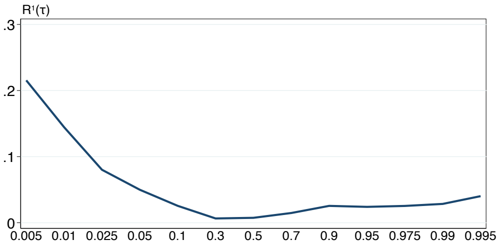
and $\tilde{V}(\tau)$ is the sum of quantile-weighted absolute residuals from a model that includes only a constant, which provides an estimate of the unconditional quantile. Like the R^2 from a least-squares estimated model, $R^1(\tau) \in [0, 1]$. While the definition of $R^1(\tau)$ in (F.3) is analogous to the definition of the standard R^2—a ratio of explained variance to total variance—$R^1(\tau)$ is a local measures of goodness of fit at a particular quantile τ of the conditional distribution, whereas R^2 is a global measure of goodness of fit over the entire distribution, proxied by the conditional mean.

In Figure F.3, I report the $R^1(\tau)$s for the panel signed quantile UIP regression (24) for each base currency in my sample, and for each quantile I estimate. The main takeaway is that the $R^1(\tau)$ is largest in the left-tail, with a magnitude generally greater than or equal to 20%, implying that interest differentials explain the variation in exchange rate movements predominately in disaster episodes. This value dwarfs the $R^1(\tau)$s at the center of the distribution, which are essentially 0 at the median (the R^2s in the OLS UIP regression are also about 0 (Fama (1984)), as well as in the right-tail, where their magnitude is generally not larger than 10%.

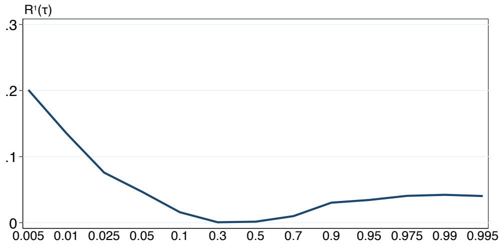
Next, I evaluate the $R^1(\tau)$ from the U.S.'s signed quantile UIP regression that additionally includes the U.S. Treasury liquidity yield (27) and compare its value to the $R^1(\tau)$ from estimating equation (24). The results are displayed in Figure F.4 and highlight that the inclusion of the Treasury liquidity yield improves the goodness of fit of the model in both the left tail and in right tail.

Figure F.3: $R^1(\tau)$: Goodness of Fit of Signed Quantile UIP Regression

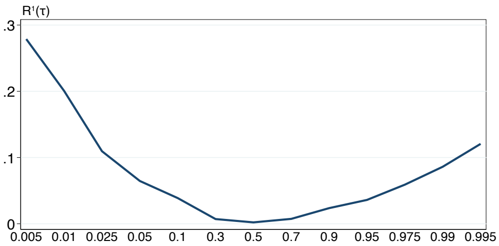
(a) USD



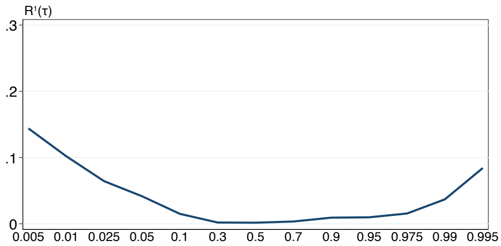
(b) GBP



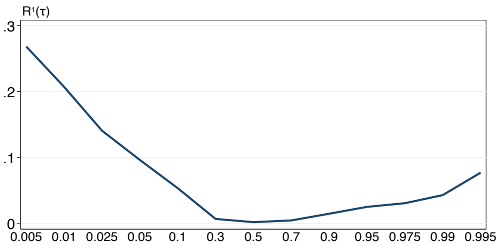
(c) AUD



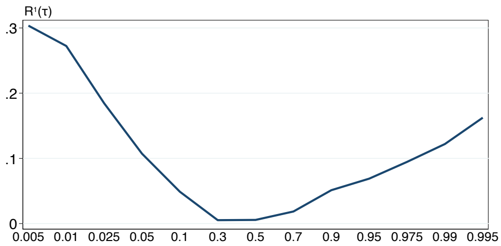
(d) JPY



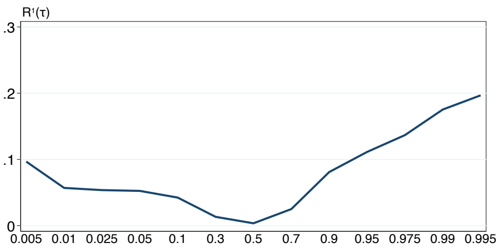
(e) NZD



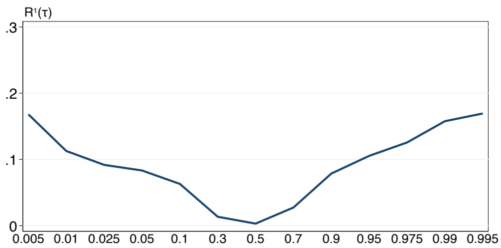
(f) SEK



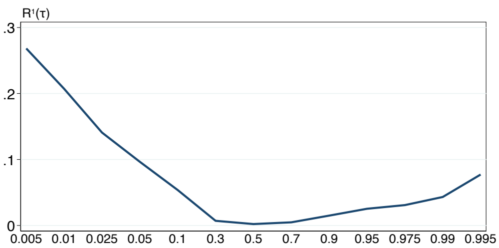
(g) CHF



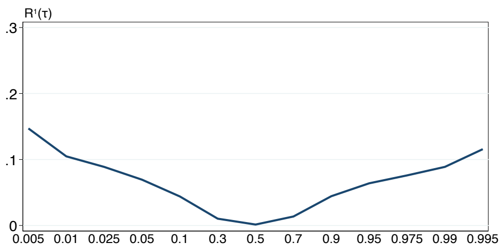
(h) EUR



(i) CAD

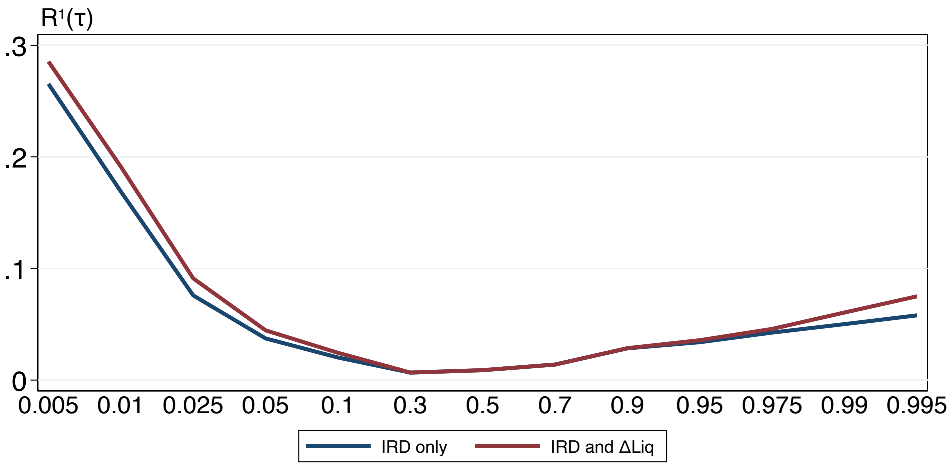


(j) NOK



Note. Figure F.3 displays the goodness of fit measure $R^1(\tau)$ for the signed quantile UIP regressions (24) estimated in Figure 8.

Figure F.4: Goodness of Fit Improvement with U.S. Liquidity Yield



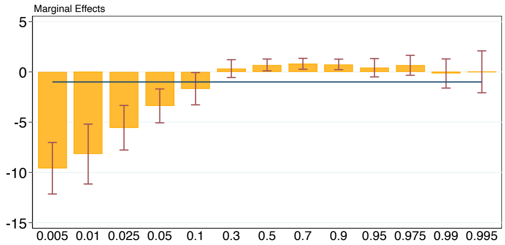
Note. Figure F.4 displays the goodness of fit ($R^1(\tau)$) of the U.S.'s signed quantile UIP regression with (equation (27))and without (equation (24)) the U.S. Treasury liquidity yield.

F.3 Inference using a Time-Clustered Bootstrap Procedure

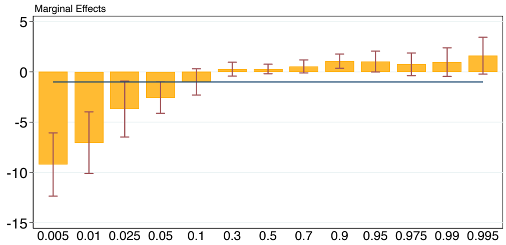
In this section, I show my results are robust to computing standard errors that account for heteroskedasticity and autocorrelation by clustering by time period (Yoon and Galvao (2020)). I implement this procedure again via the bootstrap, as in Chernozhukov et al. (2015). The results are displayed in Figures F.5 and F.6.

Figure F.5: The State-Dependent UIP Condition With Time-Clustered Standard Errors

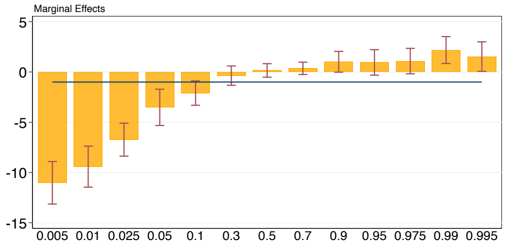
(a) USD



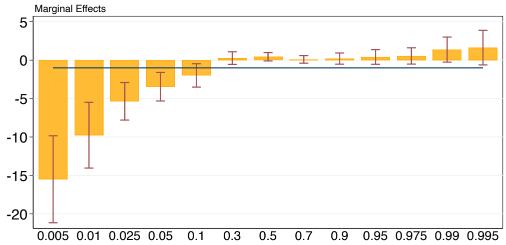
(b) GBP



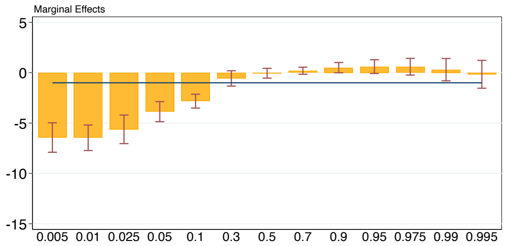
(c) AUD



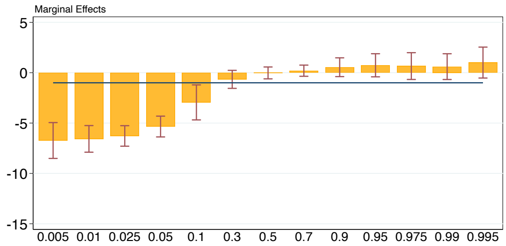
(d) JPY



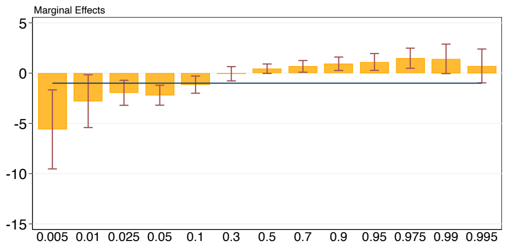
(e) NZD



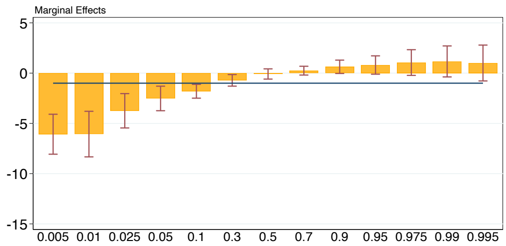
(f) SEK



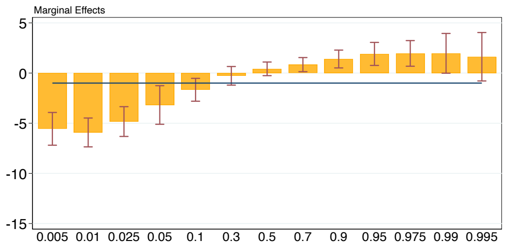
(g) CHF



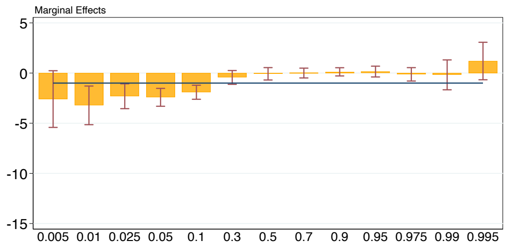
(h) EUR



(i) CAD



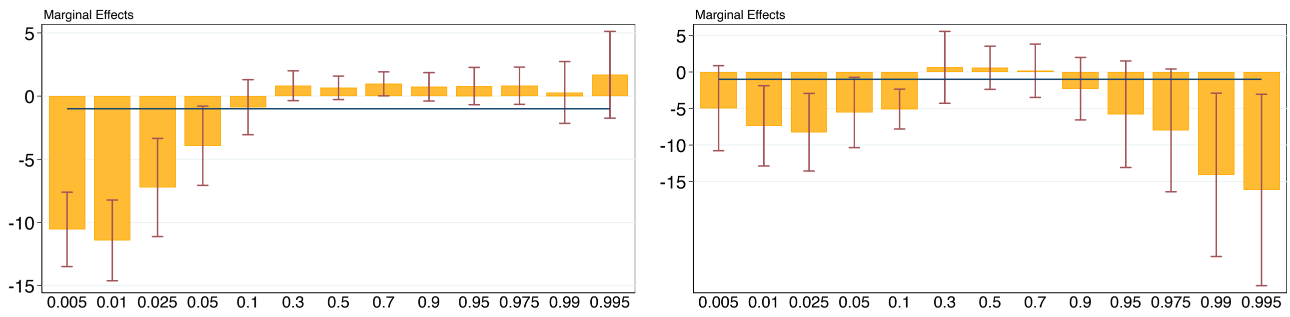
(j) NOK



Note. Figure F.5 is the analogue of Figure 8 but with confidence intervals constructed using a time-clustered bootstrap as in Chernozhukov et al. (2015) The remainder of the notes in Figure 8 apply here as well.

Figure F.6: Interest Differentials, Treasury Liquidity Premia and Tail Exchange Rate Dynamics With Time-Clustered Standard Errors

(a) Interest Rate Differential (b) Δ U.S. Treasury Liquidity Yield



Note. Figure F.6 is the analogue of Figure 10 but with confidence intervals constructed using a time-clustered bootstrap as in Chernozhukov et al. (2015) The remainder of the notes in Figure 10 apply here as well.

F.4 Accounting for Interest Rate Expectations

In Hassan and Mano (2019), the authors argue that a share of the deviation from UIP that one observes when estimating the UIP regression of Fama (1984):

$$\Delta e_{j,t+1} = \beta_1(i^*_{j,t} - i_t) + f_j + u_{j,t+1}, \tag{F.5}$$

is due to the imperfect foresight of investors on the path of future interest rate differentials. To see how this, eliminate the currency fixed effect f_j from (F.5) by de-meaning each variable by its time-series average, which I denote by $\overline{x_j} = \frac{1}{T}\sum_t x_{j,t}$ for an arbitrary variable $x_{j,t}$:

$$\Delta e_{j,t+1} - \overline{\Delta e_j} = \beta_1[(i^*_{j,t} - i_t) - \overline{(i^*_j - i)}] + u_{j,t+1} - \overline{u_j}, \tag{F.6}$$

The UIP regression is meant to capture the marginal effect of interest differentials on *expected* exchange rate movements under rational expectations (such that we proxy this expectation with *realized* exchange rate movements), conditional on information available at date t. The issue is that the inclusion of currency fixed effects, which, as shown in (F.6), requires information that is not available ex-ante to investors, namely the time series average interest differential $\overline{(i^*_j - i)}$. When investors do not have perfect foresight about the path of future interest differentials (or at least if the variance of their forecast errors for future interest differentials does not converge in probability to the true variance), Hassan and Mano (2019) show that the marginal effect β_1 should be understood as the elasticity of realized exchange rate movements to interest differentials as β_1 becomes an inconsistent estimator of the elasticity of expected exchange rate movements to interest differentials.

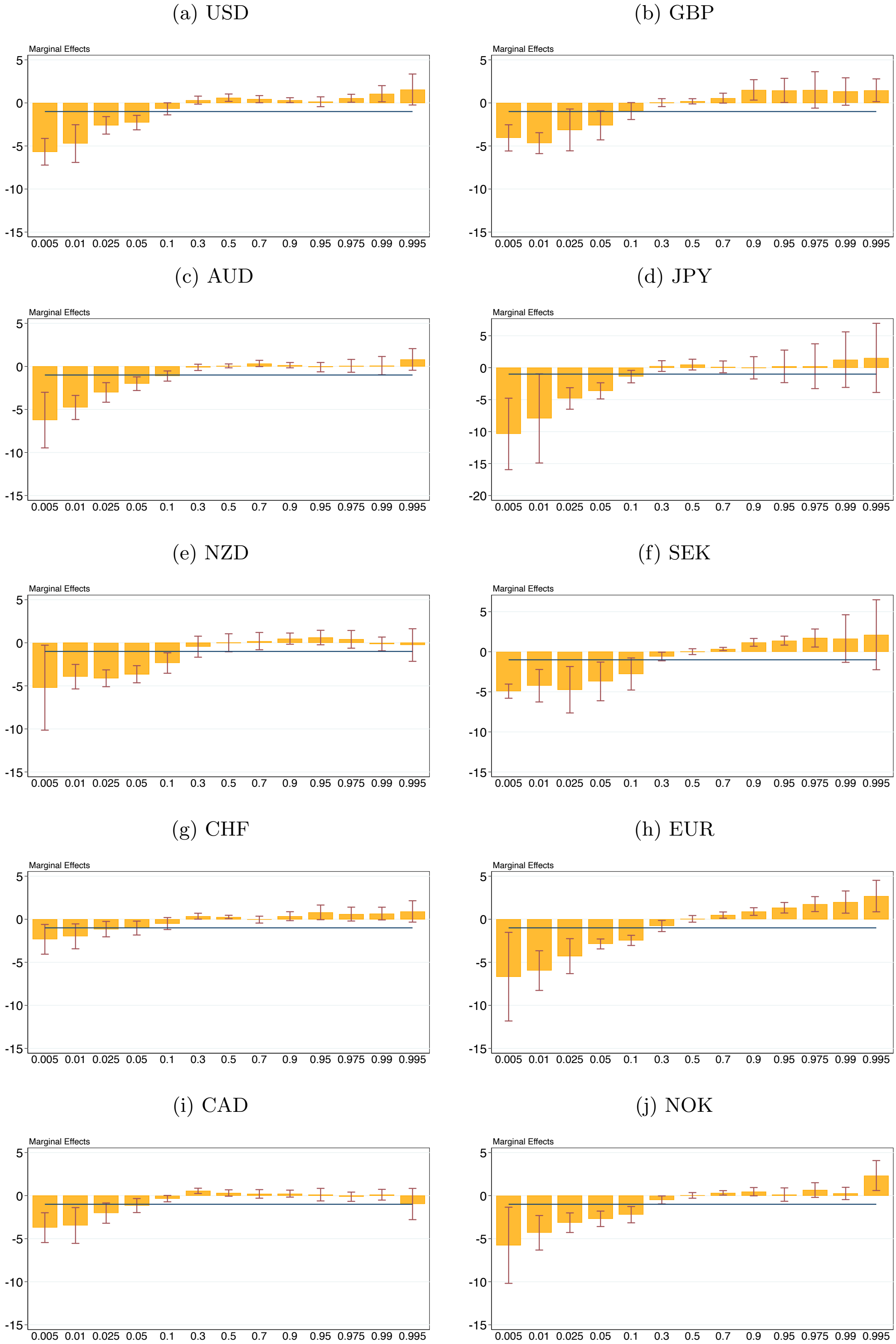
To interpret the findings in terms of expected exchange rate movements, Hassan and Mano (2019) show it is necessary to ensure all conditioning variables are known ex-ante to carry traders and so they replace $\overline{(i_j^* - i)}$ with a plausible value for investors' beliefs for $\overline{(i_j^* - i)}$ prior to the implementation of the carry trade, denoted by $\overline{(i_j^* - i)}^e$. Specifically, they use for $\overline{(i_j^* - i)}^e$ the time-series average interest differential prior to the start of the sample period. While they continue to find deviations from UIP $\beta_1 > -1$, these deviations are no longer larger than 0, as they were before accounting for investors' imperfect foresight on the path of interest differentials.

To ensure my results are not driven by the imperfect foresight of carry traders, I re-estimate the signed quantile UIP regression with the Hassan and Mano (2019) fixed effect adjustment $\overline{(i_j^* - i)}^e$, which I estimate using monthly interest rate data from 1970:M1 to 1985:M12. To make the notation less cumbersome, I denote $sign(i_{j,t}^* - i_t)$ as $S_{j,t}$, $\overline{sign(i_j^* - i)}$ as $\overline{S_j}$ and $\overline{sign(i_j^* - i)}^e$ as $\overline{S_j}^e$. I then estimate:

$$\Delta e_{j,t+1} \times S_{j,t} - \overline{\Delta e_j \times S_j} = \beta_0^\tau (S_{j,t} - \overline{S_j}^e) + \beta_1^\tau ((i_{j,t}^* - i_t) \times S_{j,t}) - [\overline{i_j^* - i) \times S_j}]^e) + u_{j,t+1}^\tau - \overline{u_j^\tau} \tag{F.7}$$

The marginal effects for the signed interest differential are displayed in Figure F.7. Like in Hassan and Mano (2019), the marginal effects for the interest differential are smaller in magnitude when estimating specification F.7, but, we still see clear evidence, for most currencies, that high-yield currencies are expected to suffer depreciations far in excess of interest differentials disasters in the left-tail but are expected to excessively appreciate relative to interest differentials at the median, that is, conditional on no-disaster.

Figure F.7: State-Dependent UIP Accounting for Interest Rate Expectations

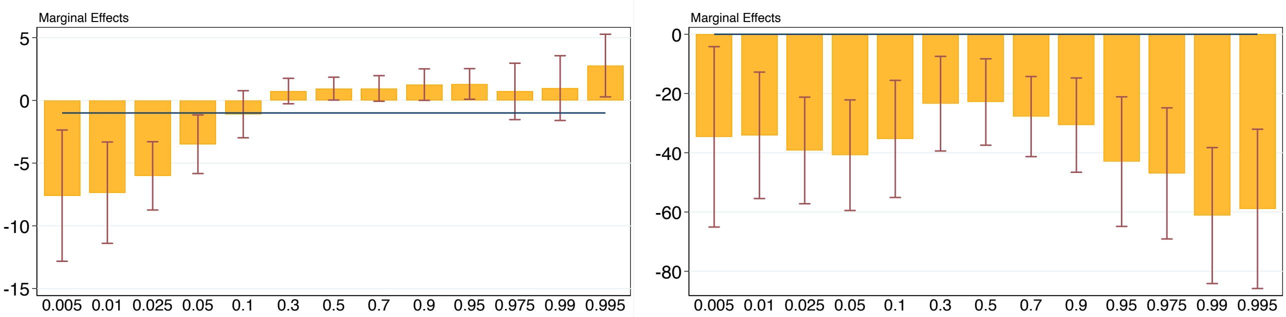


Note. Figure F.7 is the analogue of Figure 8 but accounts for interest rate expectations, as emphasized by Hassan and Mano (2019), by estimating currency fixed effects using interest rate data from 1970:M1 to 1985:M12. Specifically, it displays coefficients from estimating (F.7). Remainder of notes from Figure 8 apply here.

Figure F.8: Interest Differentials, U.S. Liquidity Yields and Exchange Rates

(a) Interest Rate Differential

(b) Instrumented Δ U.S. Treasury Liquidity Yield



Note. Figure F.8 is the analogue of Figure 10, but instruments the change in the U.S. Treasury liquidity yield with the change in the VIX. Confidence intervals are constructed via a time-clustered bootstrap. The remainder of the notes in Figure 10 apply.

F.5 Treasury liquidity and the VIX: An Instrumental Variable Approach

In this section, I highlight the causal impact of spikes in Treasury liquidity on exchange rate dynamics using an instrumental variable approach. Because the U.S. Treasury liquidity yield is measured as the deviation from covered interest parity, which is defined as a function of spot and forward exchange rates, the effect of Treasury liquidity yields on exchange rates may simply reflect a correlation. Since spikes in the Treasury liquidity yield in my model generate a flight to the dollar by hedgers, which causes the dollar to appreciate, I address this concern, following Engel and Wu (2018), by instrumenting the change in the Treasury liquidity yield with the change in the VIX, an index that measures volatility in U.S. equity markets, ensuring it is not mechanically related to exchange rate movements. Further, the VIX is a measure of global uncertainty, and, as argued by Engel and Wu (2018), has an effect on bilateral exchange rate movements only through its effect on the relative liquidity yield on dollar bonds.

The ΔVIX is also highly relevant as an instrument for ΔLiq, with an F-statistic of excluding it as an instrument in the first-stage regression of 100 (that is, a t-statistic of 10), which is far larger than the rule-of-thumb cut-off value of 10 advocated for by Stock and Yogo (2002).

The results for the second stage of the regression are displayed in Figure F.8. First, the marginal effects associated to the interest differential are little changed relative to the baseline in Figure 10. Second, the instrumented liquidity yield's marginal effects are largest in the tails, as they are in Figure 10. The magnitude of the instrumented effects, though, is considerably larger, and there are even significant effects in the center of the distribution. In all, these findings point to a causal relation between the liquidity yield on U.S. Treasuries and exchange rate dynamics in disasters.

F.6 Exchange Rate Dynamics and Financiers' Currency Positions

In this section, I provide further supportive evidence for the tight link between exchange rate dynamics and the portfolio adjustments by speculators and hedgers.

First, Figure F.9 highlights the strong correlation between exchange rate movements and changes in speculators positions. Specifically, when the high-yield foreign currency depreciates, speculators unwind their positions in the high-yield foreign currency. This is particularly true in the left-tail, which holds the largest depreciations (appreciations) of high- (low-) yield currencies and speculators' largest decreases (increases) in their positions in the high- (low-) yield currency.[46]

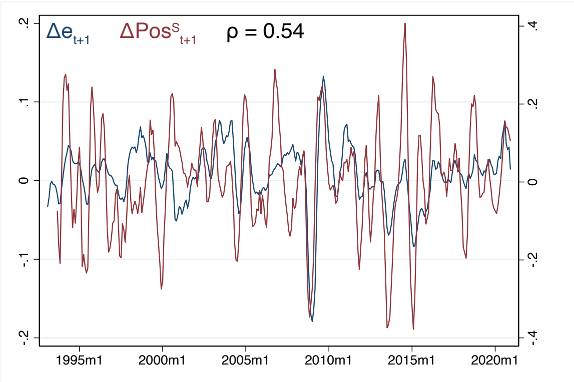
Next, Figure F.10 shows that changes in speculators' and hedgers' currency positions are highly inversely correlated with one another. This is because speculators and hedgers trade with each other in currency markets. The correlation is not perfect because there is a smaller third set of small, retail speculative investors who do not meet the reporting requirements of the CFTC. You can think of these less-sophisticated investors as the households of my model.

The trading of speculators and hedgers in currency markets has important implications for the behavior of exchange rates in disasters. In Figure F.11, I re-estimate the baseline signed quantile portfolio-flow regression for speculators but augment it with the U.S. Treasury liquidity yield $\Delta\lambda_{j,t+1} \times sign(i^*_{j,t} - i_t)$. There are a couple things to point out. First, the left-tail effects for the signed interest differential are essentially unchanged: greater interest differentials predict a larger unwinding of carry trades by speculators in disasters. Second, we see that interest differentials also seem to have an effect in the right-tail, when conditioning also on the liquidity yield. This may be due to the fact that speculators must at least partially accommodate hedgers' flight to the more-liquid dollar in disasters. We see this in Panel F.12. In both the left and right tails, a greater liquidity yield on U.S. Treasuries induces speculators to increase their holdings of the foreign currency and decrease their holding of the U.S. dollar. This is because they accommodate hedgers' flight to the dollar, which they are happy to do since these agents value pecuniary returns (CIP deviations), which widen when the non-pecuniary liquidity yield, which hedgers' value, rises. Interestingly, speculators' seem more willing to accommodate hedgers' flight to the dollar in the right-tail, suggesting that in many disaster outcomes, it is households and smaller retail investors who accommodate hedgers' flight.

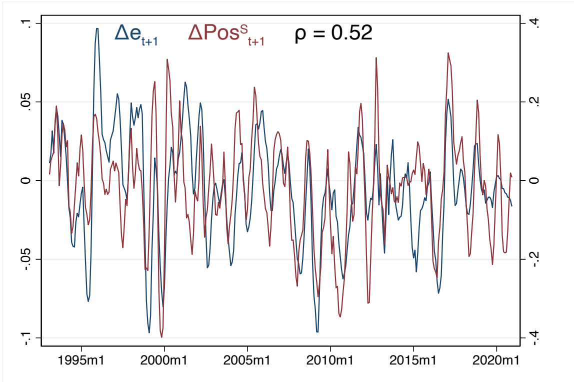
[46] Since both the exchange rate movement and changes in speculator positions are interacted with $sign(i^*_{j,t} - i_t)$ in Figure F.9, there is no effect from the $sign(i^*_{j,t} - i_t)$ terms other than putting disasters and carry-trade unwindings in the left tail.

Figure F.9: Correlation between Exchange Rate Changes and Speculator Changes

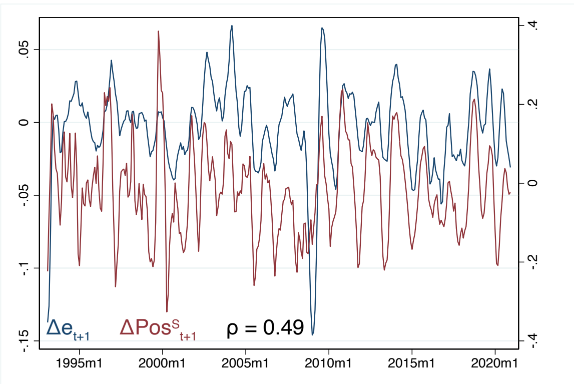
(a) AUD



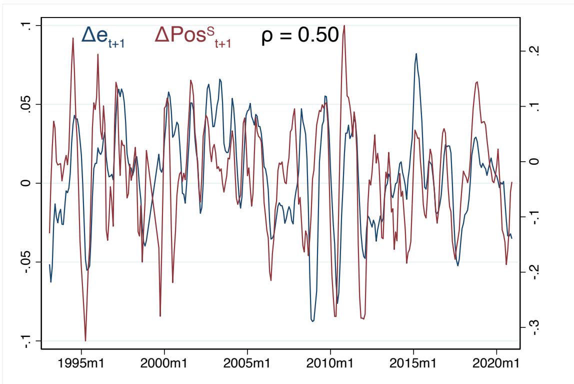
(b) JPY



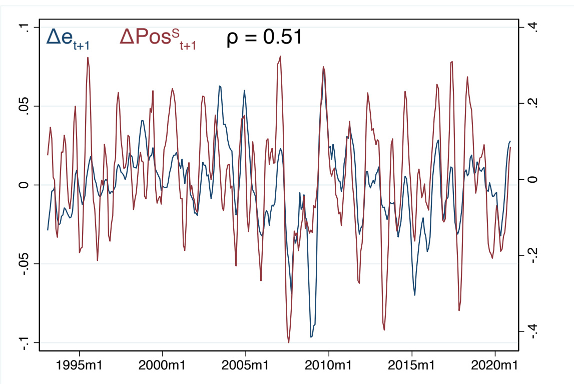
(c) GBP



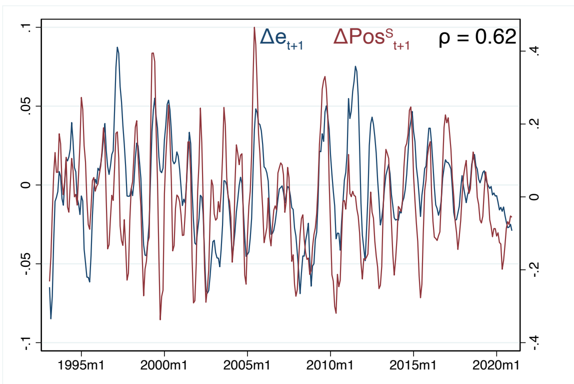
(d) EUR



(e) CAD



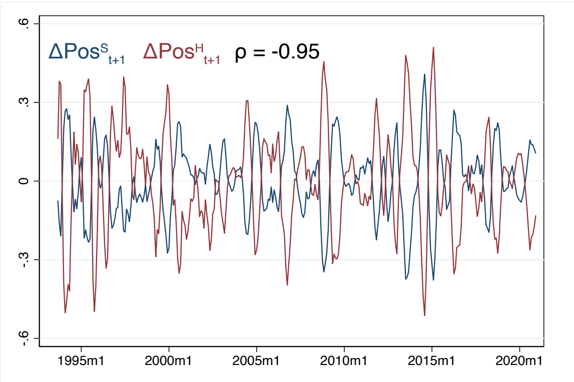
(f) CHF



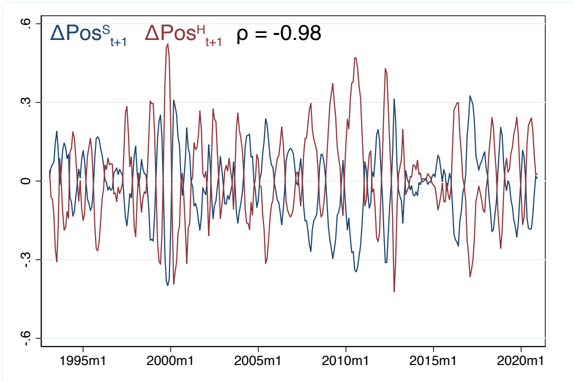
Note. Figure F.9 shows the time series correlation between $\Delta e_{j,t+1} \times sign(i^*_{j,t} - i_t)$ in navy blue and $\Delta Pos^S_{t+1} \times sign(i^*_{j,t} - i_t)$ in maroon. ρ refers to the correlation coefficient.

Figure F.10: Correlation between Speculators' and Hedgers' Position Changes

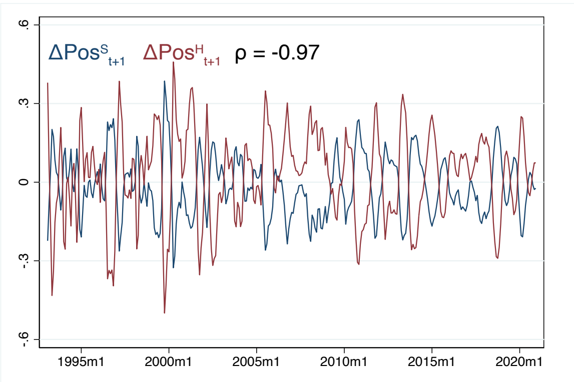
(a) AUD



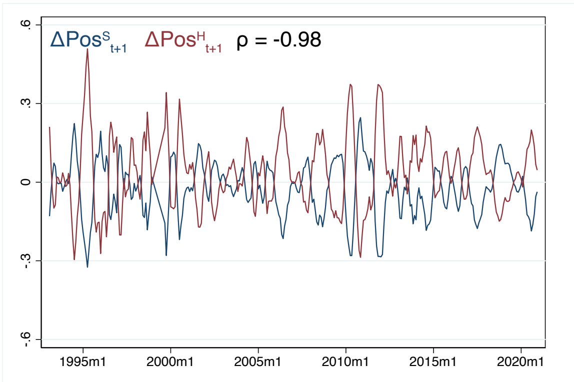
(b) JPY



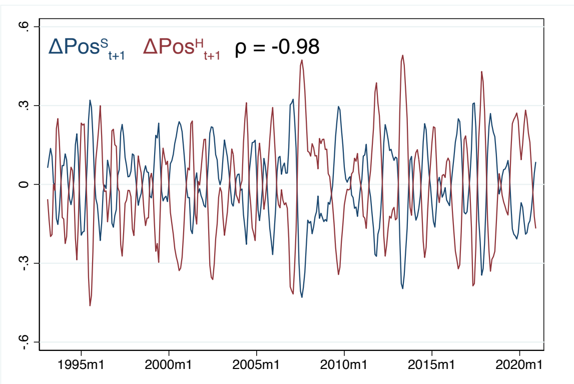
(c) GBP



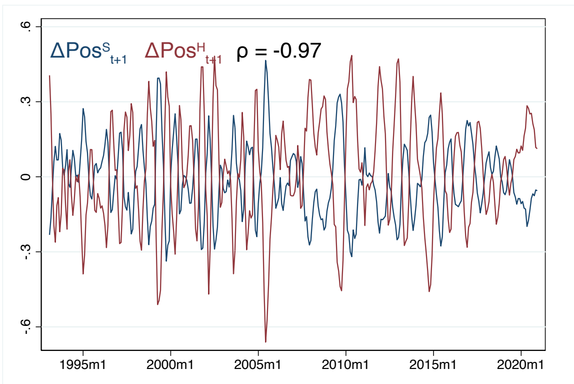
(d) EUR



(e) CAD



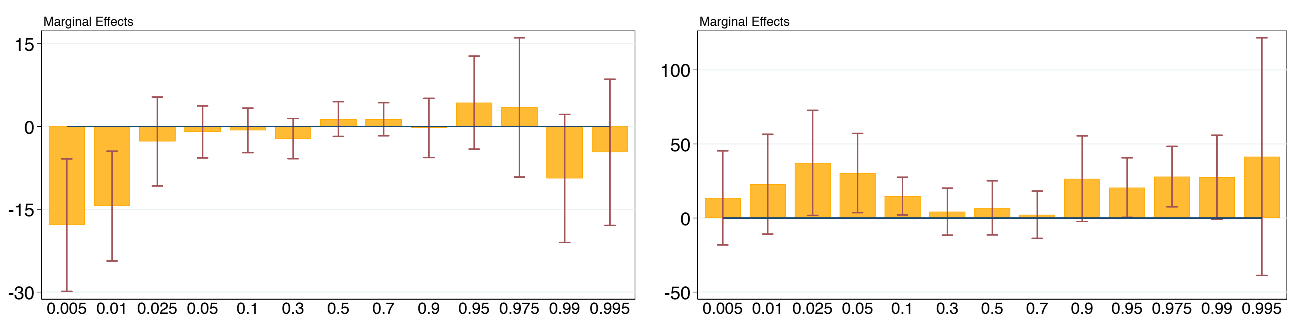
(f) CHF



Note. Figure F.10 shows the time series correlation between $\Delta Pos^S_{t+1} \times sign(i^*_{j,t} - i_t)$ in navy blue and $\Delta Pos^H_{t+1} \times sign(i^*_{j,t} - i_t)$ in maroon. ρ refers to the correlation coefficient.

Figure F.11: Speculators Unwind Carry Trades While Accommodating Hedgers' Dollar Flight

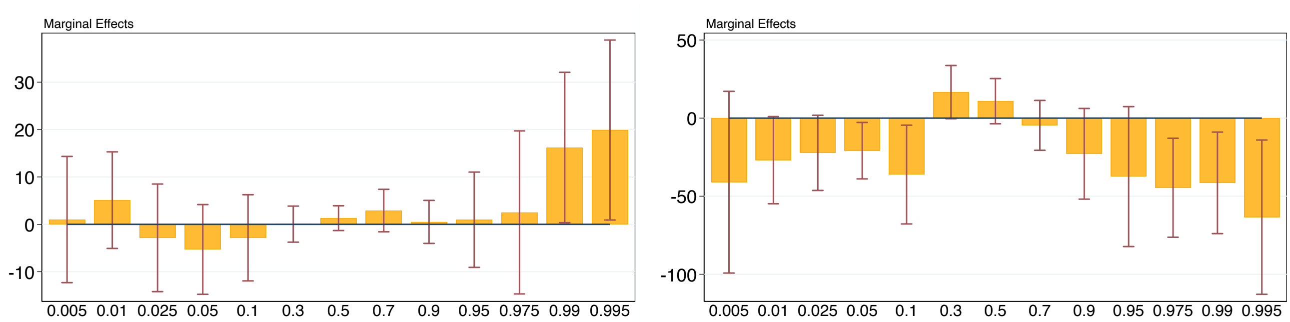
(a) Interest Rate Differentials (b) Δ U.S. Treasury Liquidity Yield



Note. Figure F.11 builds on the results displayed in Panel 9b of Figure 9 by augmenting the regression with $\Delta\lambda_{j,t+1} \times sign(i^*_{j,t} - i_t)$. The remainder of the notes associated with Panel 9b of Figure 9 apply here as well.

Figure F.12: Hedgers Fly-to-Dollar While Accommodating Speculators' Deleveraging

(a) Interest Rate Differentials (b) Δ U.S. Treasury Liquidity Yield



Note. Figure F.12 displays the results from same regression estimated for Figure 12, but now also shows the effects of the interest differential. The same notes as in Figure 12 apply here.

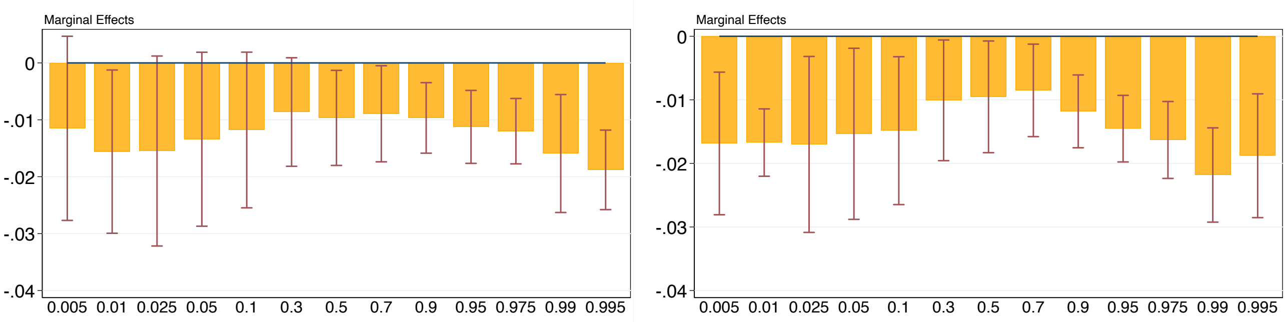
Finally, Figure F.12 highlights that while hedgers' fly to the dollar in disasters, they accommodate speculators' carry trade unwindings.

F.7 Exchange Rate Dynamics and the VIX

In this section, I highlight challenges associated with using measures of global financial market stress, namely the VIX index, for understanding the direction of exchange rate movements in disasters. To do so, I consider two potential specifications. The first, equation (F.8), is akin to

Figure F.13: Financial Market Distress and Exchange Rates

(a) ΔVIX's Effect on High-Yield Currency (b) ΔVIX's Effect on the Dollar



Note. Figure F.13 presents panel quantile regression coefficients for the signed change in the VIX on the exchange rate change in Panel F.13a from estimating (F.8) and on the signed exchange rate change in Panel F.13b from estimating (F.9), respectively, with the USD as the base (domestic) currency vis-à-vis 9 major currencies from 1990:M1 to 2020:M12. Quantiles $\tau = \{0.005, 0.01, 0.025, 0.05, 0.1, 0.3, 0.5, 0.7, 0.9, 0.95, 0.975, 0.99, 0.995\}$ range along the horizontal axis in each panel. Red error bars are 90% confidence intervals constructed using a block bootstrap with 500 bootstrap samples.

the specification used in Brunnermeier et al. (2009):[47]

$$\Delta e_{j,t+1} = \beta_0^\tau + \beta_1^\tau(\Delta VIX_{t+1}) \times sign(i_{j,t}^* - i_t^{US}) + f_j^\tau + u_{j,t+1}^\tau \tag{F.8}$$

The key feature of this specification is that $\Delta e_{j,t+1}$ is not interacted with the sign of the interest differential while ΔVIX_{t+1} is. Thus, β_1^τ captures the marginal effect of an increase in the VIX on the appreciation of the foreign currency when the foreign currency has the high interest rate $(i_{j,t}^* - i_t^{US} > 0)$ is positive and the depreciation of the foreign currency when it has the low interest rate $(i_{j,t}^* - i_t^{US} < 0)$. In other words, β_1^τ measures the effect of an increase in the VIX index on the appreciation of the high-interest-rate currency.

On the other hand, the specification in (F.9) interacts both the exchange rate movement and the VIX with the sign of the interest differential:

$$\Delta e_{j,t+1} \times sign(i_{j,t}^* - i_t) = \beta_0^\tau sign(i_{j,t}^* - i_t) + \beta_1^\tau(\Delta VIX_{t+1}) \times sign(i_{j,t}^* - i_t) + f_j^\tau + u_{j,t+1}^\tau. \tag{F.9}$$

As a result, β_1^τ measures the marginal effect of an increase in the VIX index on the appreciation of the U.S. dollar, regardless of interest differentials.

The marginal effects for the VIX, β_1^τ, from each specification are presented in Figure F.13

[47] Brunnermeier et al. (2009) use the carry trade return rather than the exchange rate movement as the dependent variable.

(specification (F.8) in Panel F.13a and specification (F.9) in Panel F.13b). The main takeaway here is that, from these marginal effects, it is unclear which specification is the "correct" one. The negative marginal effects in each panel imply that an increase in the VIX predicts both a depreciation of the high-interest-rate currency (Panel F.13a) and an appreciation of the U.S. dollar (Panel F.13b). Thus, it seems that financial market distress predicts large exchange rate swings, but is unable to distinguish the direction of these swings. Conversely, the liquidity yield-augmented signed quantile UIP regression estimated in Section 4.2 is able to predict this direction: the interest differential captures the large depreciations of high-yield currencies in disasters while the liquidity yield captures the large appreciations of the dollar.

F.8 Signed Quantile UIP Regression with Additional *Signed* Fixed Effect

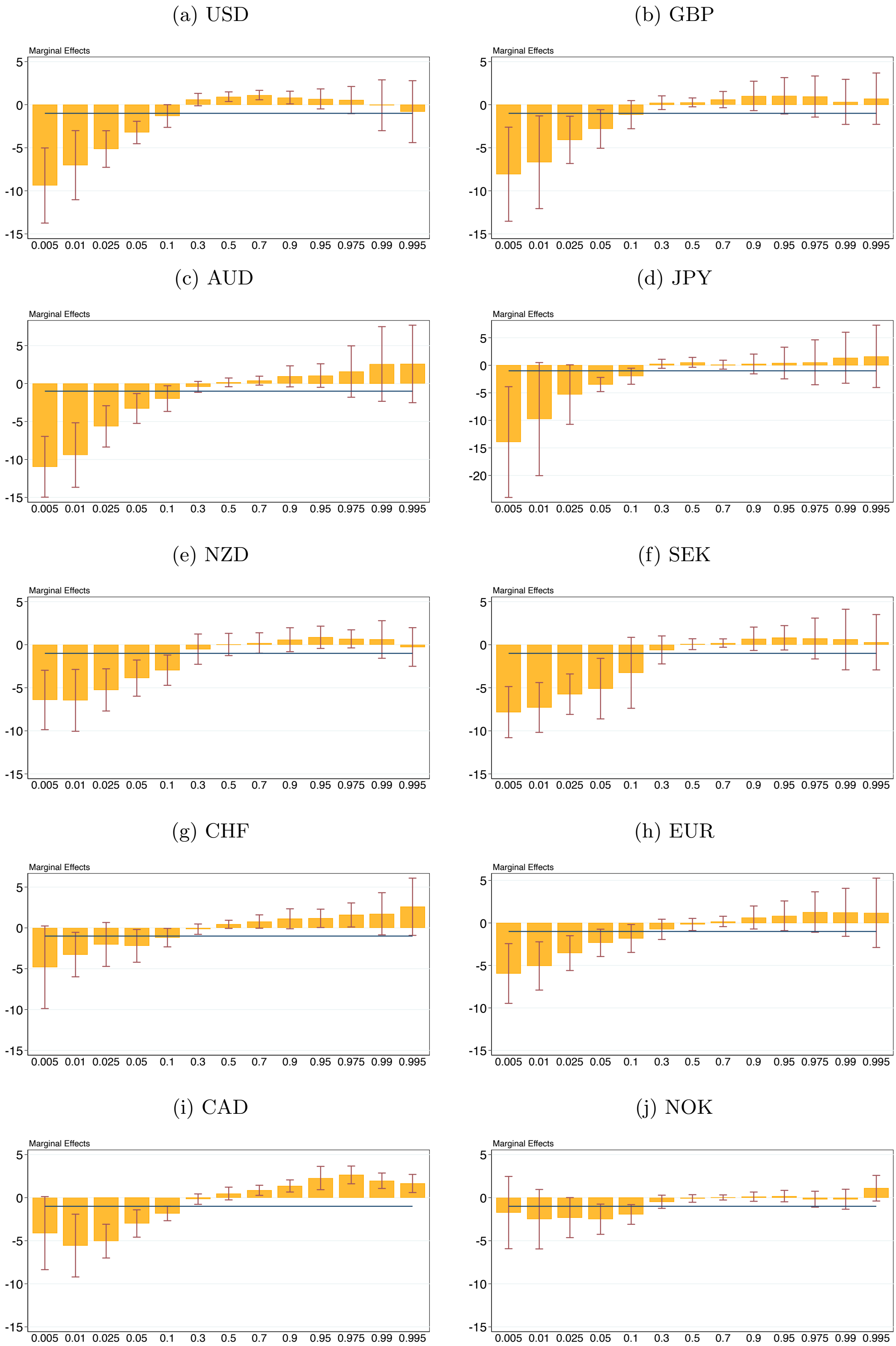
The standard UIP regression of Fama (1984) includes currency fixed effects that control for unobserved time-invariant confounding factors that may push the foreign currency to appreciate against the domestic currency. In my signed quantile UIP regression, informed by my model, I include a different type of fixed effect, one that controls for unobserved time-invariant confounding factors that may push the high-yield currency to appreciate and the low-yield currency to depreciate. In this section, I include both of these types of fixed effects in tandem, in effect controlling for two potential models for exchange rate dynamics, and show that my empirical results are little changed. Specifically, I estimate:

$$\Delta e_{j,t+1} \times sign(i^*_{j,t} - i_t) = \beta^\tau_j \times sign(i^*_{j,t} - i_t) + \beta^\tau_1 (i^*_{j,t} - i_t) \times sign(i^*_{j,t} - i_t) + f^\tau_j + u^\tau_{j,t+1}, \tag{F.10}$$

which replaces the intercept term from my baseline specification $\beta^\tau_0 \times sign(i^*_{j,t} - i_t)$ with a fixed-effect version $\beta^\tau_j \times sign(i^*_{j,t} - i_t)$. To be explicit, f^τ_j controls for factors that may push the high-yield currency to appreciate and the low-yield currency to depreciate, since it is not interacted with the $sign(i^*_{j,t} - i_t)$ while the dependent variable is, while $\beta^\tau_j \times sign(i^*_{j,t} - i_t)$ controls for factors that may push the foreign currency to appreciate against the domestic currency.

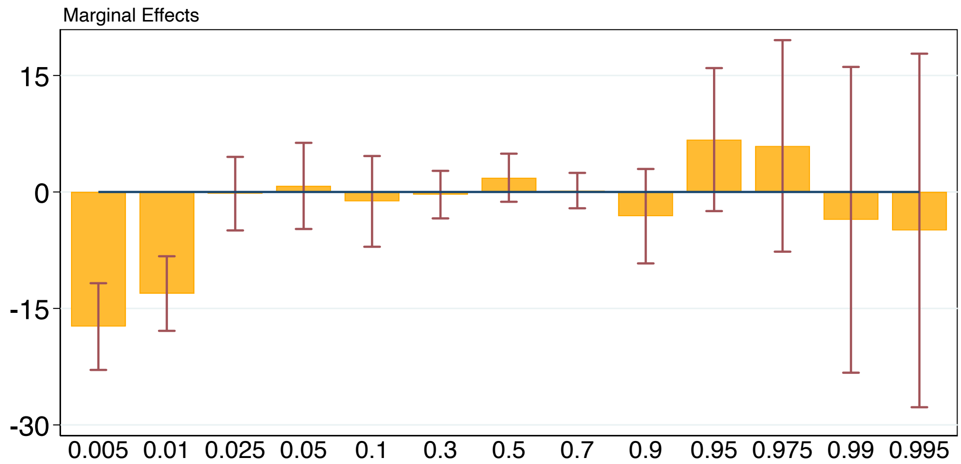
The results are displayed in Figure F.14 and highlight that my results are robust to including this alternative type of fixed effect. I also show the remainder of my results are robust to additionally controlling for this signed fixed effect. In Figure F.15, interest differentials continue to predict carry trade unwindings in the left-tail. In Figure F.16, an increase in the U.S. Treasury liquidity yield's continues to predict a large appreciation of the dollar in disasters, as measured at the FEaR^S and FEaR^H. And finally, liquidity yields continue to predict a flight to the dollar by hedgers' in disasters, as shown in the right-tail of Figure F.17.

Figure F.14: State-Dependent UIP Estimated with 2 Types of Fixed Effect



Note. Figure F.14 is the analogue of Figure 8 but includes the signed fixed effect (equation (F.10)). The remainder of the notes from Figure 8 apply here as well.

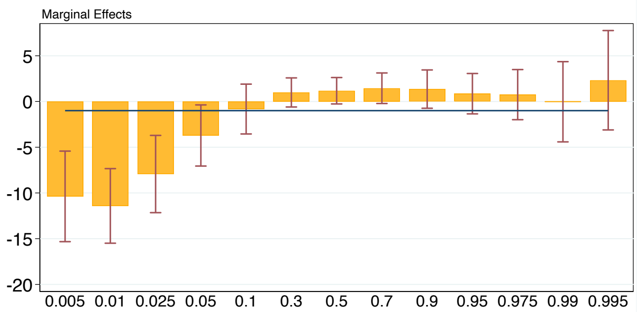
Figure F.15: Speculator Carry Trade Unwindings with 2 Types of Fixed Effect



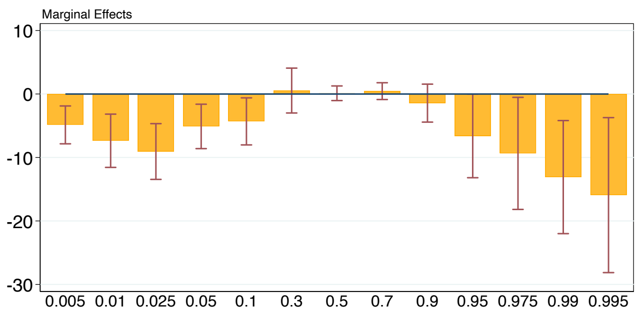
Note. Figure F.15 is the analogue of Panel 9b, but additionally includes the signed fixed effect. The remainder of the notes from Panel 9b apply here as well.

Figure F.16: Interest Differentials, U.S. Liquidity Yields and Exchange Rates with 2 Types of Fixed Effect

(a) Interest Rate Differential

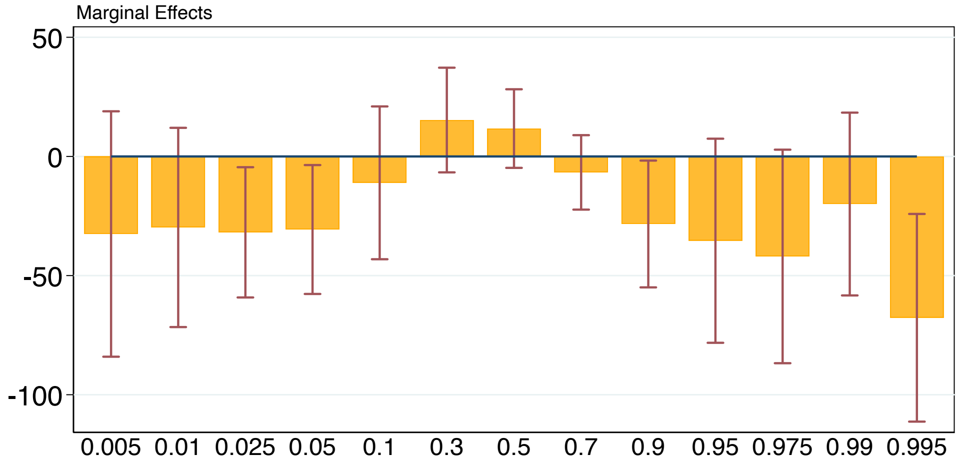


(b) Δ U.S. Treasury Liquidity Yield



Note. Figure F.16 is the analogue of Figure 10, but additionally includes the signed fixed effect. The remainder of the notes from Figure 10 apply here as well.

Figure F.17: U.S. Liquidity Yields and Hedgers' Flight to Safety with 2 Types of Fixed Effect



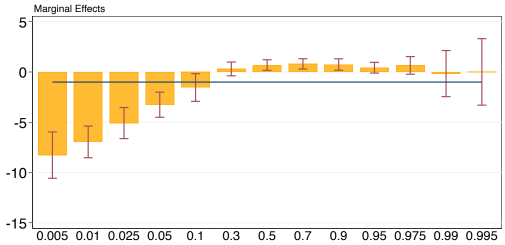
Note. Figure F.17 is the analogue of 12, but additionally includes the signed fixed effect. The remainder of the notes from Figure 12 apply here as well.

F.9 Disaster-State Exchange Rate Dynamics Excluding Lehman Collapse

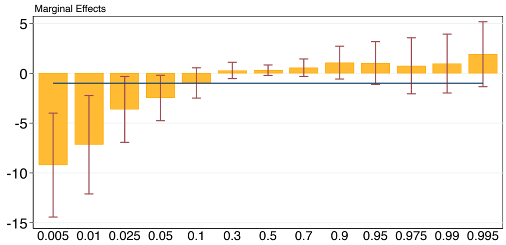
In this section, I highlight that my results regarding exchange rate dynamics in disasters are not driven by the largest disaster in my sample—the collapse of Lehman Brothers at the height of the Global Financial Crisis in September 2008—which led to the largest spike in the U.S. Treasury liquidity yield. I show this first for the interest-differential regressions in Figure F.18. These results are nearly-identical to those in Figure 8. The same is true for the U.S. Treasury liquidity yield in Figure F.19.

Figure F.18: The State-Dependent Uncovered Interest Parity Condition ex. 2008:M9

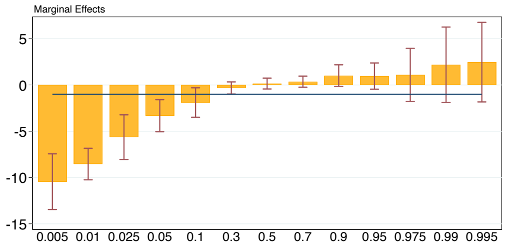
(a) USD



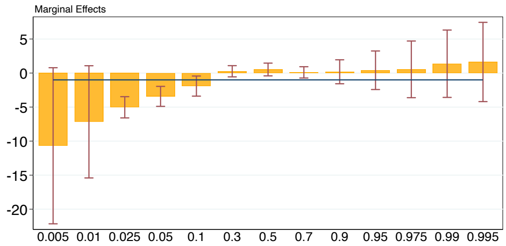
(b) GBP



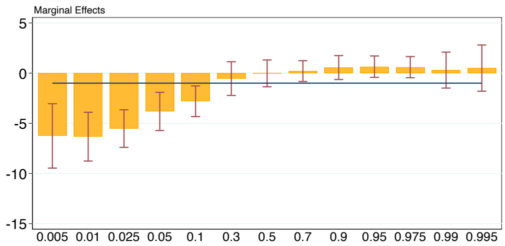
(c) AUD



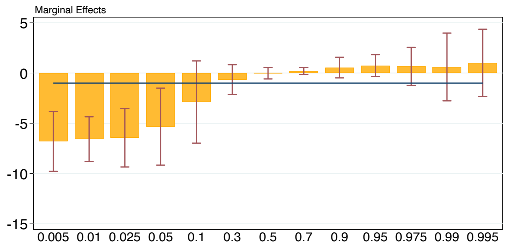
(d) JPY



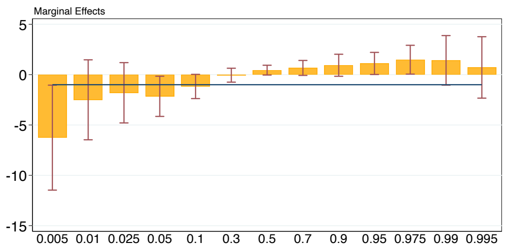
(e) NZD



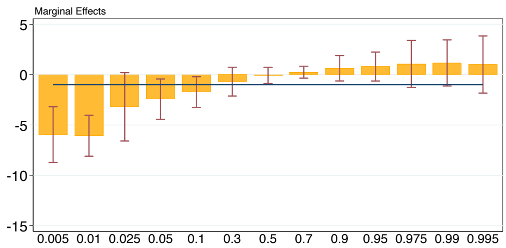
(f) SEK



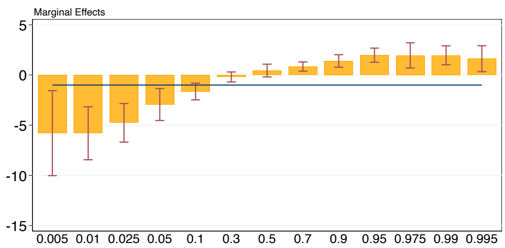
(g) CHF



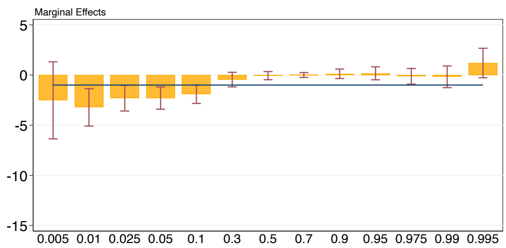
(h) EUR



(i) CAD

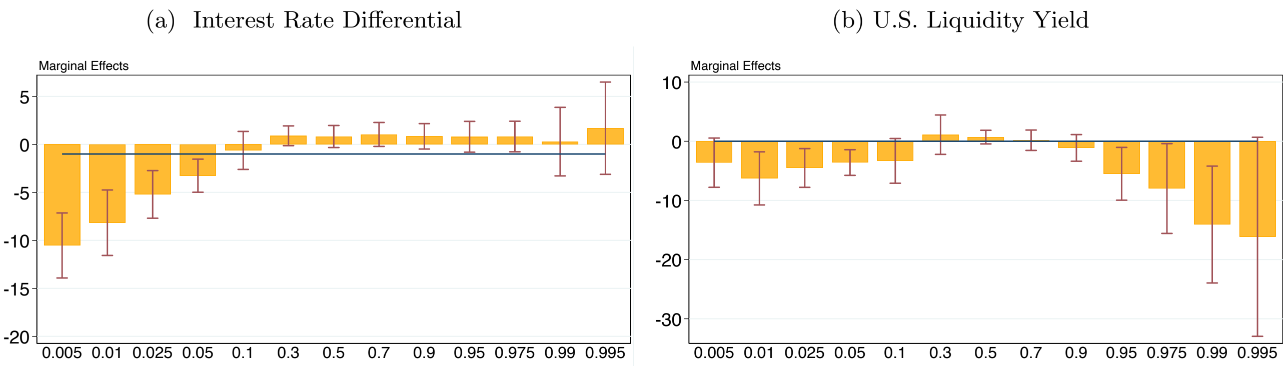


(j) NOK



Note. Figure F.18 is the analogue of Figure 8 but excluding the Global Financial Crisis from 2008:M9.

Figure F.19: Interest Differentials, U.S. Liquidity Yields and Exchange Rates ex. 2008:M9



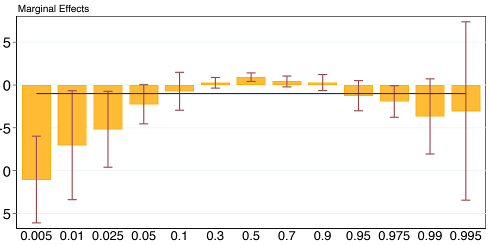
Note. Figure F.19 is the analogue of Figure 10 excluding the Global Financial Crisis from 2008:M9.

F.10 U.S. Exchange Rate Dynamics Country-by-Country

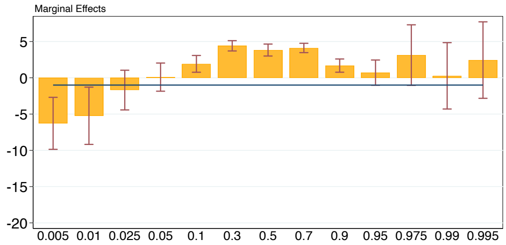
In this section, I estimate the time-series signed quantile UIP regression for the U.S. on a country-by-country basis against the other countries/jurisdictions in my sample. I show that my results are not tied just to the panel specifications, but are visible in the time-series for most currencies in my sample.

Figure F.20: The U.S. State-Dependent Uncovered Interest Parity Condition by-Country

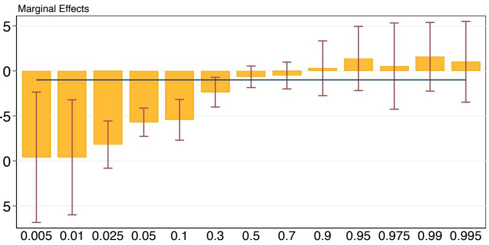
(a) AUD



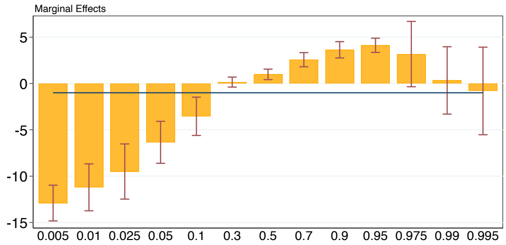
(b) JPY



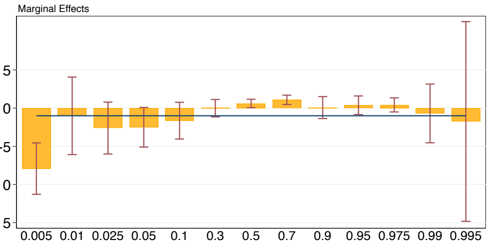
(c) EUR



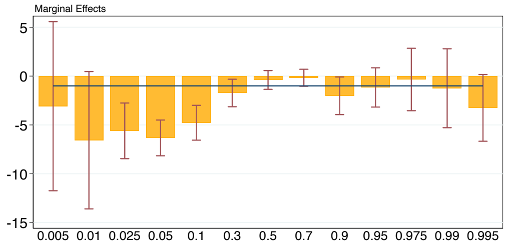
(d) GBP



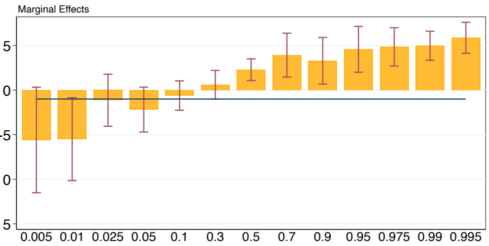
(e) NZD



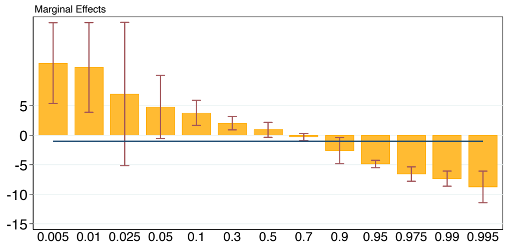
(f) SEK



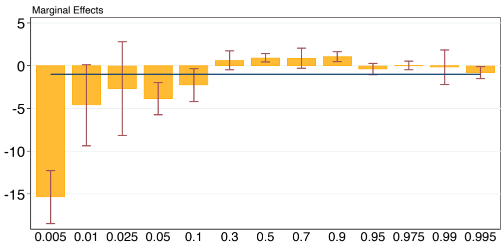
(g) CHF



(h) CAD



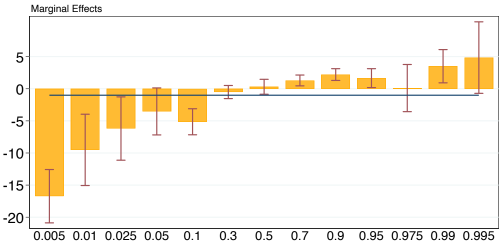
(i) NOK



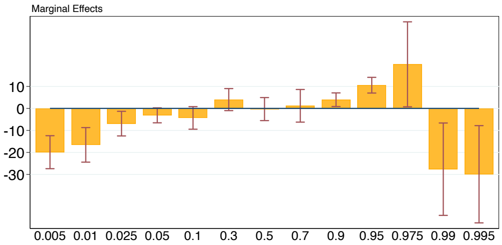
Note. Figure F.20 is the analogue of Figure 8 country-by-country with the U.S. as the base currency. Standard errors are computed via the block bootstrap and red error bars correspond to 68% confidence intervals.

Figure F.21: U.S. Interest Differentials, Liquidity Yields and Exchange Rates by Country Pt. 1

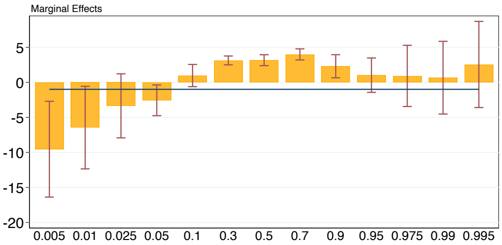
(a) AUD: Interest Differentials



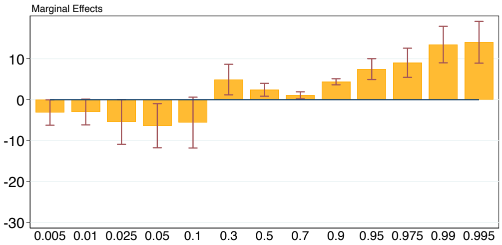
(b) AUD: Liquidity Yields



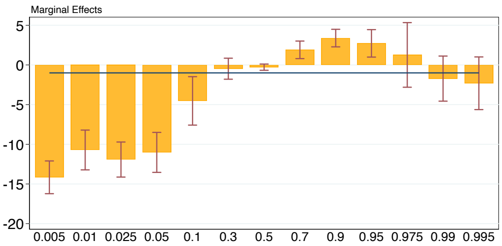
(c) JPY: Interest Differentials



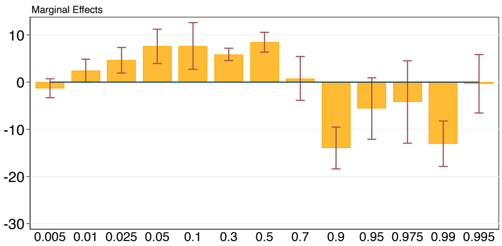
(d) JPY: Liquidity Yields



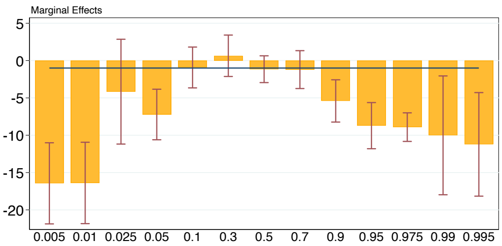
(e) GBP: Interest Differentials



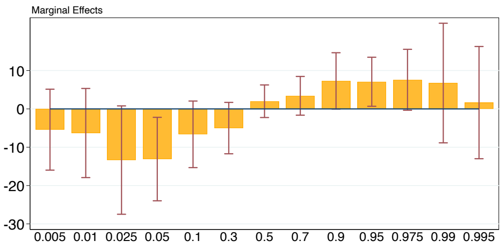
(f) GBP: Liquidity Yields



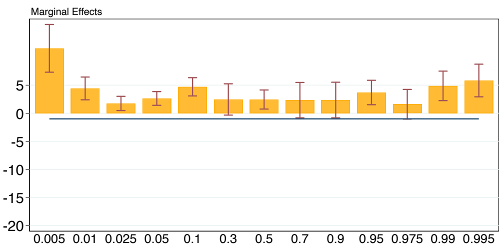
(g) EUR: Interest Differentials



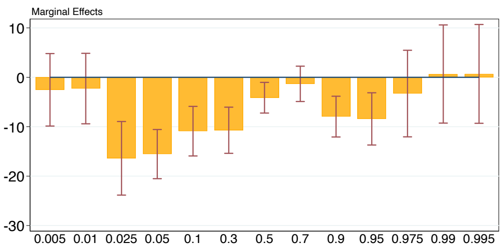
(h) EUR: Liquidity Yields



(i) CHF: Interest Differentials



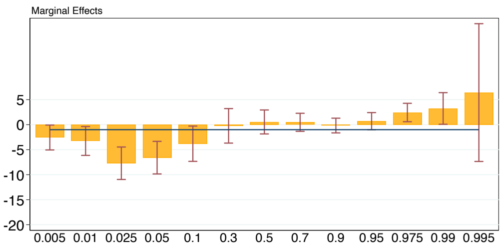
(j) CHF: Liquidity Yields



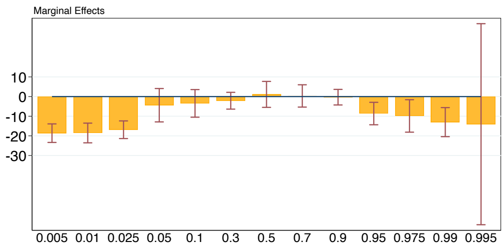
Note. Figure F.21 is the analogue of Figure 10 on a country-by-country basis with the USD as the base currency. Standard errors are computed via the block bootstrap and red error bars correspond to 68% confidence intervals.

Figure F.22: U.S. Interest Differentials, Liquidity Yields and Exchange Rates by Country Pt. 2

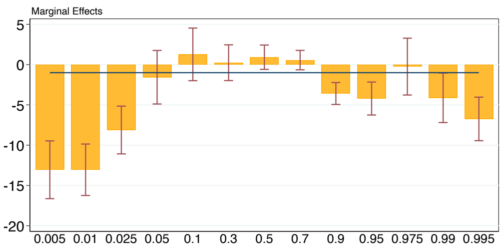
(a) NZD: Interest Differentials



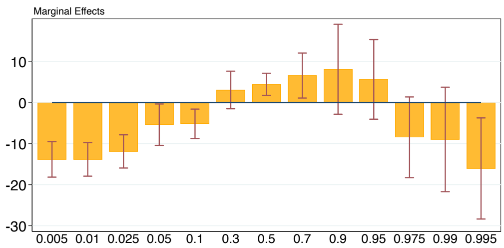
(b) NZD: Liquidity Yields



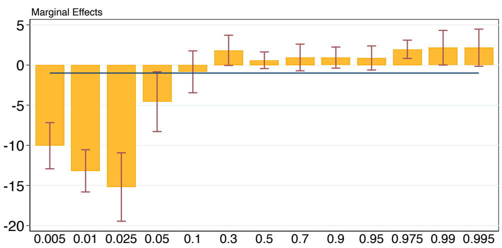
(c) SEK: Interest Differentials



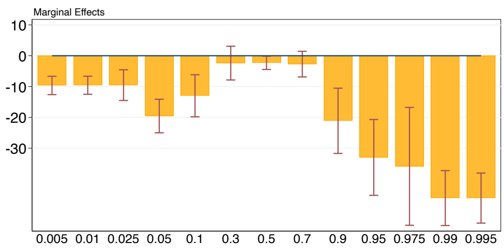
(d) SEK: Liquidity Yields



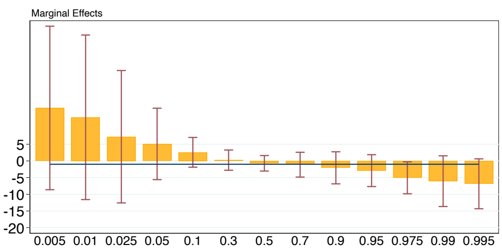
(e) NOK: Interest Differentials



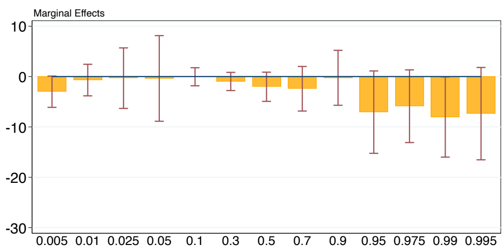
(f) NOK: Liquidity Yields



(g) CAD: Interest Differentials



(h) CAD: Liquidity Yields



Note. Figure F.22 is the analogue of Figure 10 on a country-by-country basis with the USD as the base currency. Standard errors are computed via the block bootstrap and red error bars correspond to 68% confidence intervals.