Tails of Foreign Exchange at Risk (FEaR):
Exchange Rate Disasters and Dollar Liquidity Yields*

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Abstract

This paper first builds a heterogeneous-financier model, with currency speculators and hedgers, to draw testable implications for exchange rate dynamics during global disaster events. Second, it develops a novel empirical framework centered on *signed* quantile Uncovered Interest Parity (UIP) regressions to test the model's main predictions. Reflecting the behavior of currency speculators, I find strong evidence in support of the disaster-risk theory of exchange rates for all currencies: high-interest-rate currencies suffer large "disaster-state" depreciations against low-interest-rate currencies in the left tail of the exchange rate distribution, but appreciate mildly at the median. Reflecting the behavior of currency hedgers, I find that the currency with the greatest liquidity yield, the U.S. dollar, tends to experience a left-tail appreciation in disasters against all other currencies—a safe-haven effect. Ultimately, and different from other currencies, the behavior of the U.S. dollar during disasters reflects a balance between these two forces, which reinforce each other when the U.S. interest rate is relatively low but offset each other when the U.S. interest rate is relatively high.

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1 Introduction

The disaster risk theory of exchange rate predicts that the interest rate differential has a non-linear impact on exchange rate dynamics. This non-linearity is a function of the "state of the world": normal times versus disasters. During normal times when perceived risk is low, high-interest-rate currencies tend to appreciate (or only mildly depreciate) against low-interest-rate currencies. Since normal times are near-ubiquitous in the data, this empirical regularity seems a violation of the Uncovered Interest Parity (UIP) condition, which under risk neutrality predicts that high-interest-rate currencies should experience depreciations *equal* to their interest rate differentials. The failure of UIP in normal times, known as the Fama (1984) puzzle, allows speculators to make expected profits by taking long positions in high-yield currencies financed by shorting low-yield currencies, known as the carry trade. However, when risk aversion spikes in a rare disaster event, high-interest-rate currencies suffer severe depreciations in excess of interest rate differentials, which generates carry trade losses (Farhi and Gabaix, 2016).

Absent from this theory is a particular role for the U.S. dollar (USD) as the safe-haven currency of the international monetary system. Gourinchas et al. (2010) and Maggiori (2017) highlight that investors' desire for safe assets in global crises leads to a flight to U.S. Treasuries and, consequently, a dollar appreciation. This appetite for safety is captured by the liquidity yield, measured by the wedge in the covered interest parity (CIP) condition, on the grounds that deviations from CIP reflect the lower credit risk, greater collateral value and ease of resale (liquidity) of U.S. Treasuries relative to other government bonds (Du et al., 2018). While Engel and Wu (2018) and Jiang et al. (2021) investigate the liquidity yield's effect on the *mean* exchange rate, this paper is the first to assess its impact in the *disaster-state*, periods where the dollar's safety premium is highest (see Figure 1).

The first contribution of this paper is to develop a heterogeneous-financier model of exchange rate determination that integrates disaster-risk theory and the United States' unique role as the global safe asset provider. In the model, currency speculators generate dynamics consistent with the disaster risk theory of exchange rates. As in Gabaix and Maggiori (2015), speculators intermediate global imbalances and earn a positive expected return as compensation for holding currency risk. Since this expected return, the UIP deviation, is increasing in the interest rate differential, speculators will tend to take long positions in the high-interest-rate currency financed by shorting the low-interest-rate currency. The size of speculators' carry trade portfolio, however, is limited by their ability to raise funds, modelled as a credit constraint.

In addition to speculators, my setup includes a second type of financial agent, currency hedgers, who imbue the USD with its safe-haven status. As in Jiang (2021), hedgers are required by a reserve constraint to hold USD bonds as a safe store of value to complement their investments in risky foreign assets. While Jiang (2021) posits that the strictness of the reserve constraint is tied to the size of the U.S. government's budget deficit, I model the stringency as being driven by the USD liquidity yield. My choice is consistent with the behavior of currency hedgers, as classified by the Commodity Futures Trading Commission (CFTC), in the Chicago Board of Exchange's currency futures markets, who fly to dollar liquidity in disasters.

The disaster state in my model is defined as a sudden period of extreme illiquidity in currency funding markets, which results in a pronounced tightening in speculators' credit constraints, as in Brunnermeier et al. (2009). As speculators are net long high-yield currencies, these currencies must excessively appreciate (or insufficiently depreciate) relative to UIP, conditional on no-disaster, to provide speculators with positive expected returns. However, conditional on a disaster, speculators are forced to unwind their carry trades to limit the risk on their balance sheets. These retrenchment flows generate depreciations of the high-interest-rate currency *in excess* of the interest rate differential, implying losses on the carry trade. Thus, reflecting the behavior of currency speculators in each state, my model's first two predictions are consistent with the disaster risk theory of exchange rates.

I assume that a crisis in speculators' funding market generates a spike in the USD liquidity yield, since reduced funding opportunities limit investors' capacity to arbitrage CIP deviations. This is consistent with models linking funding liquidity and market liquidity, as in Brunnermeier and Pederson (2008), and with Figure 1, which highlights that the three-month USD liquidity yield spikes during episodes of global stress. As a result, in periods where speculators are forced to unwind carry trades, the spike in the liquidity yield triggers a large flight to USD bonds by currency hedgers, appreciating the U.S. dollar. Thus, my model's third prediction highlights that the USD liquidity yield is an important additional driver of the dollar's exchange rate dynamics in disasters.

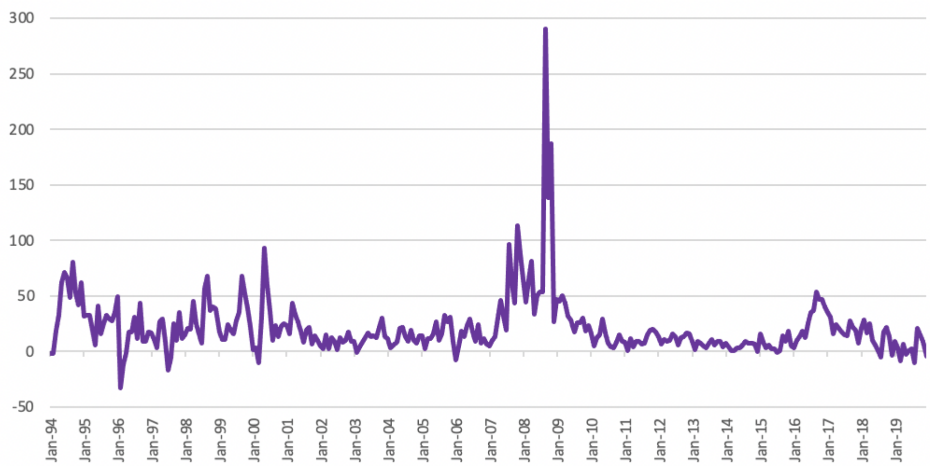

Figure 1: 3-month USD liquidity yield averaged across 8 major currencies, JPY, CHF, EUR, CAD, GBP, AUD, NZD and SEK, in an unbalanced panel from 1994:M2 to 2019:M12

This paper's second contribution is to develop a novel empirical framework to test these predictions. My method, which I call *signed* quantile UIP regressions, accounts for two key features of the disaster risk theory: the state-dependence (disaster versus calm) and the interest-differential sign-dependence (positive or negative) of exchange rate movements. As normal time movements are concentrated in the center of the exchange rate distribution while extreme crisis dynamics manifest in the distribution's tails, I account for state-dependence by estimating the UIP relationship using fixed effect panel quantile regression. Which tail to focus on depends on the sign of the interest rate differential since high-yield currencies suffer large (left-tail) depreciations in disasters while low-yield currencies experience large (right-tail) appreciations. To manage this sign dependence, I interact each term in the UIP regression with the sign of the interest rate differential. This transformation, a more-flexible version of portfolio sorting based on relative interest rates, rearranges the exchange rate distribution such that all disaster-state exchange rate movements appear in the left (disaster-state) tail, which facilitates the analysis.

Using this approach, in panels for each of the 9-most-traded global currencies, I find strong evidence consistent with the first two predictions of my model. High-interest-rate currencies tend to appreciate (or only mildly depreciate) at the median, but suffer severe depreciations in excess of interest rate differentials at the 1^{st} percentile of the distribution, which I term the Foreign Exchange at Risk (FEaR)—the Value at Risk (VaR) of the signed exchange rate distribution. This novel result demonstrates the existence of *in-sample* interest-rate-driven exchange rate disasters for all major currencies, whereas most of the previous literature has focused on the U.S. dollar's *out-of-sample* disaster risk implied by options prices.

I test my model's third prediction by augmenting the USD's signed quantile UIP regression with the contemporaneous USD liquidity yield.[1] I find that a higher contemporaneous USD liquidity yield predicts a significant dollar appreciation against all other currencies in the disaster state, as measured by the variable's marginal effect on the FEaR. Thus, different from other currencies, the U.S. dollar's disaster-state exchange rate reflects a balance between speculators' interest-rate-driven deleveraging flows and hedgers' liquidity-driven safety flows. The net effect of these forces implies an amplified USD appreciation in disasters against high-interest-rate currencies, such as the Australian dollar, and a dampened USD depreciation in disasters relative to low-interest-rate currencies, such as the Japanese yen. This highlights an important asymmetry in the disaster dynamics of the USD exchange rate due to its role as the global safe asset.

To complement the exchange rate (price) regressions of my empirical framework, I also perform portfolio flow (quantity) regressions for each type of financial agent in my setup using CFTC currency positions data, which sorts agents trading currency futures into hedgers and speculators. First, I show that, while speculators use currency futures for carry trades, their largest portfolio adjustments correspond to carry trade unwindings and are driven by the interest rate differential. This is consistent with the prediction that speculators' carry trade activity bolsters the value of high-interest-rate currencies in normal times, but deleveraging in disaster-states drives these currencies to significantly depreciate. Furthermore, I highlight that increases in the USD liquidity yield drive the largest adjustments to hedgers' currency portfolios, which correspond to large flights to the dollar. This is consistent with the predicted behavior of hedgers in my framework, which generates a unique tendency for the USD to appreciate in disasters.

Literature Review: My paper is at the intersection of several strands in the literature. First, this paper relates to the disaster risk theory of exchange rates, an asset pricing framework in which deviations from UIP (see Hansen and Hodrick, 1980, and Fama, 1984)

[1] This variable is also interacted with the sign of the interest rate differential to fit into the framework.

arise due to the risk of extreme exchange rate movements in rare disasters.[2] Closed economy disaster risk models to account for the equity premium puzzle (Mehra and Prescott, 1985) were introduced by Reitz (1988) and Barro (2006) and have been extended to explain a wide array of asset pricing anomalies by Gabaix (2012) and Gourio (2012). Farhi et al. (2015) and Farhi and Gabaix (2016) both develop structural open-economy models with rare disasters to account for UIP deviations, as well as other puzzles in international finance, which they calibrate using options prices. Relative to them, my empirical framework directly tests for exchange rate *disasters* in-sample, based on a financier-driven theory of exchange rate determination, instead of using the *disaster risk* embedded in options prices.

A separate literature studies in-sample currency crash risk. Brunnermeier Nagel and Pederson (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 test only for skewness, their method cannot address whether relative interest rates predict high-interest-rate currencies to depreciate *in excess* of interest differentials in disasters, as the disaster risk theory predicts, whereas my empirical framework can.[3] Furthermore, in addition to studying speculators' portfolio positions, I show that hedgers fly to dollar liquidity in disasters, which generates a tendency for the dollar to appreciate.

A related literature focuses on the properties of safe-haven currencies, defined as currencies that appreciate in times of (currency) market turmoil (Ranaldo and Söderlind, 2010, Menkhoff et al., 2012, Habib and Stracca (2012), and Cenedese et al., 2014). Based on this definition, this literature seldom identifies the dollar as a safe-haven currency since it tends to depreciate against lower interest rate currencies in tumultuous times.[4] For example, using a downside beta CAPM model, Dobrynskaya (2014) shows that carry trades short the dollar do poorly in times of negative market returns only when the investment currency has a relatively high interest rate. This is true even in an "extreme downside beta" variant of the model that conditions on periods where market returns are very negative.[5]

[2] This echoes an earlier literature on "Peso Problems", see Krasker (1980), Burnside et al. (2011).

[3] Relatedly, Corsetti and Marin (2020) use a century of dollar-pound exchange rates to show the UIP coefficient spiked in several crises over this period, indicating a disaster. See also Bussière et al., 2018.

[4] A notable exception is Maggiori (2013) who uses an instrumental variable approach to identify a dollar safety premium that spikes in times of global stress, although it is statistically insignificant.

[5] Using a database of 22 episodes of natural disasters and terror/war (14/22) as well as financial crashes (8/22) from 1993-2010, from Ranaldo and Söderlind (2010), she does find evidence that the downside market factor predicts falls in *mean* carry trade returns for low-interest-rate currencies against the dollar.

My innovation, aside from my novel method, is to show that the dollar's safe-haven status, due to safe-asset demand, can be appreciated *only* in the context of the disaster risk theory.

The vast literature on the U.S.'s role as the world's safe-asset supplier and the dollar's safe-haven status originates with Bernanke (2005) and Caballero et al. (2008), who argue the U.S.'s comparative advantage in generating safe assets relative to the rest of the world rationalizes its current account deficit. Gourinchas et al. (2010) and Maggiori (2017) then attribute the dollar's appreciation in global crises to a flight to U.S. safe assets.

Until recently, this inherent safe asset demand 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 using U.S. credit spreads. The breakthrough comes with Du et al. (2018), 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 Engel and Wu (2018) and Jiang et al. (2021) show that increases in this U.S. dollar liquidity yield predict instantaneous dollar appreciations at the mean, my paper studies this relationship during global disasters.[6]

To discipline my empirical analysis, I build on the growing literature modelling exchange rates dynamics in imperfect financial markets (see e.g. Kouri (1976), Jeanne and Rose (2002), Pavlova and Rigobon (2007, 2008) and Akinci and Queralto (2019)). My model is most-closely related to Gabaix and Maggiori (2015) and Jiang (2021) but has a different focus: I study the role of U.S. safe asset demand and speculative carry trade activity in driving exchange rate dynamics in disasters.

Finally, my empirical framework is related to Adrian et al. (2018, 2019) who use quantile regression to show deteriorating domestic financial conditions increase downside GDP growth risk. Eguren-Martin and Sokol (2019) apply this methodology to study the impact of tighter global financial conditions on the exchange rate distribution by sorting currencies according to the safe-haven characteristics previously identified in the literature. Relative to them, my empirical framework is designed to test the disaster risk theory of exchange rates and studies the role of the U.S. dollar liquidity yield in disasters. Quantile regression has its roots in the seminal work of Koenker and Bassett (1978). Building on

These episodes, however, do not always correspond to episodes of carry trade disasters for developed countries and so are a step removed from the disaster risk theory of exchange rates.

[6] Engel and Wu (2018) show this liquidity yield channel exists, but is weaker, for other currencies.

this, Kato et al. (2012) provide conditions under which the estimated coefficients from pooled-panel quantile regression with fixed effects are consistent and asymptotically normal while Parente and Santos Silva (2016) and Yoon and Galvao (2020) develop associated cluster-robust inference methods to account for heteroskedasticity and autocorrelation. I implement these techniques by adapting the statistical module of Machado et al. (2011).

The remainder of this paper is organized as follows. Section 2 presents my model and discusses its key predictions. Section 3 describes my data and presents some relevant cross-sectional evidence. Section 4 outlines my empirical strategy. The paper's main empirical results are presented in Section 5. Section 6 concludes.

2 Model

In this section, I develop a heterogeneous agent model of exchange rate determination that features two types of global financiers: speculators and hedgers. The setup is adapted from Gabaix and Maggiori (2015) and Jiang (2021), with departures that highlight the role of the USD liquidity yield in capturing the demand for dollars during "disaster" events. Appendix I solves the model in full and Appendix II provides proofs.

2.1 Model Preliminaries

Time is discrete, indexed by t, and there are 3 periods $t \in \{0, 1, 2\}$. There are two countries: the home country (H) is the U.S. and the foreign country (F) is a second advanced economy, either Australia or Japan. I define the real exchange rate ε_t to have units of U.S. dollars (USD) per unit of foreign currency, such that an increase in the exchange rate, $\varepsilon_t \uparrow$, implies a real appreciation of foreign currency relative to the USD. Stars (*) denote foreign variables.

2.2 U.S. Households

In this section, I present the U.S. household problem. The foreign household problem, presented in Appendix I, is analogous except for that foreign households are rebated financial sector profits, which simplifies the exposition. 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 good (H), which can be frictionlessly traded across borders. The household maximizes its expected utility as defined by:

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

where $C_t = [(C_{NT,t})^{\chi_t}(C_{H,t})^{a_t}(C_{F,t})^{\iota_t}]^{\frac{1}{\theta_t}}$ is a consumption basket and $\chi_t + a_t + \iota_t = \theta_t$.

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 in each period are given by:

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

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

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

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

2.3 Two Types of Global Financiers: Speculators and Hedgers

As in Jiang (2021), my model features heterogeneous global financiers. The first type, currency speculators, are modelled as the financial intermediaries introduced in the seminal paper by Gabaix and Maggiori (2015). These currency speculators are permitted to hold bonds denominated in both currencies, and, as a result, are in a position to facilitate time and currency intermediation between the households in each country.

Following Gabaix and Maggiori (2015), as speculators have zero net worth, their balance sheets in periods $t \in \{0, 1\}$ will consist of q_t USD bonds and $-q_t/\varepsilon_t$ foreign currency bonds. If $q_t > 0$, then speculators are long the USD and short the foreign currency. This portfolio's expected 1-period U.S. dollar profit, in both $t = 0$ and 1, is given by

$$V_t = \mathbb{E}_t\Big[\beta\{R - R^* \frac{\varepsilon_{t+1}}{\varepsilon_t}\}q_t\Big] \tag{5}$$

The creditors (home or foreign households), who finance speculators' currency investments, rationally anticipate that speculators may divert a fraction $\Gamma_t|\frac{q_t}{\varepsilon_t}|$ of their total portfolio position $|\frac{q_t}{\varepsilon_t}|$ for personal use. This agency friction gives rise to the following credit constraint for speculators in both $t = 0$ and 1:

$$\frac{V_t}{\varepsilon_t} \geq \Big|\frac{q_t}{\varepsilon_t}\Big| \times \Gamma_t \Big|\frac{q_t}{\varepsilon_t}\Big| \implies V_t \geq \Gamma_t \Big(\frac{q_t^2}{\varepsilon_t}\Big) \tag{6}$$

where $\Gamma_t = \gamma \cdot var(\varepsilon_t)^\alpha > 0$. This highlights that speculators are able to divert a larger share as the complexity of their balance sheet, proxied by the volatility of the exchange rate, increases. Intuitively, a higher Γ_t implies greater funding market frictions or, equivalently, lower funding market liquidity, which tightens speculators' credit constraints.

Since speculators' objective function V_t is linear in q_t but their credit constraint is quadratic in q_t, the constraint always binds. Thus, speculators' optimal holding of USD bonds in $t = 0$ and 1 is

$$q_t = \frac{1}{\Gamma_t}\mathbb{E}_t\Big[\beta\{R\varepsilon_t - R^*\varepsilon_{t+1}\}\Big] \tag{7}$$

Next, I augment the three-period version of the Gabaix and Maggiori (2015) model introduced thus far with a three-period version of the risky asset financiers introduced by Jiang (2021), which I term currency hedgers.

At both $t = 0$ and 1, currency hedgers are endowed with one unit of a risky asset paying $\tilde{X}^*_{t+1}$ units of the foreign NT good at $t + 1$. In the period the asset is endowed, it can be partially liquidated for X^*_t units of NT good. Thus, if a share $(1 - v_t)$ of the period t endowment is liquidated, the payout is $(1 - v_t)X^*_t$ units of foreign NT at t and $v_t\tilde{X}^*_{t+1}$ units of NT good at t+1.

To ensure their risky investments are well-hedged, currency hedgers are subject to a liquidity constraint that stipulates that they must hold κ times the expected value of the unliquidated portion of their risky asset in the high-liquidity-yield currency each period:

$$\frac{w_t}{\varepsilon_t} \geq \kappa_t \times v_t\mathbb{E}_t[\tilde{X}^*_{t+1}] \tag{8}$$

where w_t is the hedgers position in the USD bond, which is greater than zero if $\kappa > 0$.[7]

[7] $\kappa > 0 \iff$ USD is the high-liquidity-yield currency will be formalized in the next section.

As the purchase of high-liquidity-yield bonds at t is financed by liquidating the newly endowed risky asset at t, $\frac{w_t}{\varepsilon_t} = (1 - v_t)X_t^*$, hedgers realized profit on this endowment at t + 1 is $(1 - v_t)X_t^* R \frac{\varepsilon_t}{\varepsilon_{t+1}} + v_t \tilde{X}_{t+1}^*$ in units of the foreign NT good. Assuming $X_t^* \mathbb{E}_t[R \frac{\varepsilon_t}{\varepsilon_{t+1}}] < \mathbb{E}_t[\tilde{X}_{t+1}^*]$, the liquidity constraint always binds and we can solve for hedgers optimal USD bond holdings for $t = 0$ and 1 as

$$\frac{w_t}{\varepsilon_t} = \frac{\kappa_t \mathbb{E}_t[\tilde{X}_{t+1}^*]}{\kappa_t \mathbb{E}_t[\tilde{X}_{t+1}^*]/X_t^* + 1} \tag{9}$$

2.4 Liquidity Yields, Financial Constraints and Disaster States

My model departs from the previous literature by emphasizing the importance of the U.S. dollar liquidity yield in global disaster events. To this end, I define the USD liquidity yield, λ_t, as the deviation from the CIP condition between the U.S. and the foreign country

$$\lambda_t = f_t - e_t + i_t^* - i_t \tag{10}$$

where f_t, e_t, i_t, and i_t^* are, respectively, the forward rate, the nominal exchange rate and the home and foreign interest rates under the log transform (as in Du et al. (2018)).

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. bond must be greater than that on the foreign bond. This non-pecuniary return is termed the USD liquidity yield. As mentioned previously, a positive USD liquidity yield reflects the greater safety and liquidity of U.S. Treasuries relative to other government bonds.

I define the disaster state as a sudden period of extreme illiquidity in currency speculators' funding market, which manifests as a large tightening in their credit constraints, as in the empirical work of Brunnermeier et al. (2009). Specifically, while Γ_0 is fixed and low, meant to capture calm "normal times" (ND) where funding liquidity is abundant and speculators are able to take on lots of risk, Γ_1 is stochastic and, with a small probability p, it spikes, signifying a disaster (D) in the speculator's funding market that forces them to drastically limit the risk on their balance sheets. This can be summarized as

$$\Gamma_0 = \Gamma_L > 0 \quad \text{and} \quad \Gamma_1 = \begin{cases} \Gamma_L & \text{ND} \\ \Gamma_H >> \Gamma_L & \text{D} \end{cases} \tag{11}$$

Although forward contracts are not held by speculators in this setup, I assume that the USD liquidity yield is positive and is increasing in funding market illiquidity:

$$\lambda_t = \lambda(\Gamma_t) \geq 0 \quad \text{and} \quad \lambda^{'}(\Gamma_t) > 0 \tag{12}$$

This maps the stochastic process for Γ_t in (11) to a similar one for the USD liquidity yield:

$$\lambda_0 = \lambda_L \geq 0 \quad \text{and} \quad \lambda_1 = \begin{cases} \lambda_L & \text{ND} \\ \lambda_H >> \lambda_L & \text{D} \end{cases} \tag{13}$$

While a deeper foundation for the assumptions in (13) are outside the scope of this paper, they are consistent with models linking funding liquidity and market liquidity as in Brunnermeier and Pederson (2008). Specifically, one can envision a set of global arbitrageurs whose ability to arbitrage away CIP deviations depends on their ability to borrow in funding markets. As a result, when funding market conditions deteriorate, they construct fewer arbitrage portfolios, which leads CIP deviations to widen. Further, the dynamics in (13) match those in Figure 1, where the USD liquidity yield is on-average small, less than 20 basis points, but, during rare crises, it spikes to anywhere from 5 to 15 times this average value.[8]

Finally, I assume that the parameter κ, which governs the tightness of currency hedgers' liquidity constraints in (8), is positive if $\lambda_t > 0$ and is increasing in the USD liquidity yield:

$$\kappa_t = \kappa(\lambda_t) > 0 \iff \lambda_t > 0 \quad \text{and} \quad \kappa^{'}(\lambda_t) > 0 \tag{14}$$

Again, this maps the stochastic process for Γ_t, via λ_t, to a similar one for κ_t:

$$\kappa_0 = \kappa_L \geq 0 \quad \text{and} \quad \kappa_1 = \begin{cases} \kappa_L & \text{ND} \\ \kappa_H >> \kappa_L & \text{D} \end{cases} \tag{15}$$

In light of this, one could interpret currency hedgers as foreign banks whose balance sheets

[8] These spikes tend to coincide with spikes to the VIX, an index that is known to capture conditions in funding markets or the general risk aversion of creditors.

feature currency mismatch, with safe low-interest dollar-denominated liabilities and risky high-yield foreign currency assets, as in Gopinath and Stein (2020). In Jiang et al. (2020), when the USD liquidity yield spikes, the dollar appreciates, which results in losses for mismatched local banks. These losses would force hedgers to decrease the size of their balance sheets, which is equivalent to the flight to the dollar dynamics induced by κ in (15). Alternatively, spikes in the USD liquidity yield may signal a global disaster in which the future returns on hedger's risky assets will be low. As a result, they fly towards the safest store of value and liquidity—USD bonds.

2.5 Market Clearing

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

$$q_t + w_t + b_{H,t} = 0 \quad \text{and} \quad \frac{-q_t}{\varepsilon_t} + b^*_{F,t} = 0 \tag{16}$$

Goods market clearing in $t \in \{0, 1, 2\}$ for tradables (17) and non-tradables (18)-(19) is:

$$Y_{H,t} = C_{H,t} + C^*_{H,t} \quad \text{and} \quad Y^*_{F,t} = C_{F,t} + C^*_{F,t} \tag{17}$$

$$Y_{NT,t} = C_{NT,t} \quad \text{and} \quad Y^*_{NT,0} + (1 - v_0)X^*_0 = C^*_{NT,0} \tag{18}$$

$$Y^*_{NT,1} + (1 - v_1)X^*_1 + v_0\tilde{X}^*_1 = C^*_{NT,1} \quad \text{and} \quad Y^*_{NT,2} + v_1\tilde{X}^*_2 = C^*_{NT,2} \tag{19}$$

As in Gabaix and Maggiori (2015), I make two further assumptions that allow the model to be solved analytically. First, I assume that households' preference parameter for non-tradable goods, in each country, is equal to the total supply of non-tradables each period. As Appendix I shows, this implies that the expenditure on non-tradable goods is determined solely by households' preference parameters. Second, as in the three-period model with a "long run" last period in Gabaix and Maggiori (2015), I assume that currency speculators and hedgers intermediate only *new* flows and so wait to unwind their $t = 0$ currency positions until $t = 2$, a period where financial frictions are assumed to be very small relative to trade in the goods market. As shown in detail in Appendix I, this implies that periods t = 0 and t = 1 become identical up to the shock to Γ_t in t = 1, while the exchange rate in the long run final period is now determined solely by fundamentals i.e. countries' relative marginal propensities to import.

2.6 Model Characterization

The model's solution, which is derived in detail in Appendix I, gives rise to three equilibrium conditions that equate U.S. net imports with U.S. net borrowing in each period.

$$\iota_0 - \varepsilon_0 \xi_0 = q_0 + w_0 \qquad \iota_1 - \varepsilon_1 \xi_1 = q_1 + w_1 \qquad \iota_2 - \varepsilon_2 \xi_2 = 0 \tag{20}$$

These highlight that when the U.S. is a net importer in $t \in \{0, 1\}$, $\iota_t > \varepsilon_t \xi_t$, market segmentation requires U.S. net borrowing to be intermediated by speculators or accommodated by hedgers, such that the financial sector is net long the USD: $q_t + w_t > 0$. Notice that the long-run final period assumption implies U.S. net borrowing is zero at t = 2, and so trade is balanced: $\iota_2 = \varepsilon_2 \xi_2$.

The Euler equations from the U.S. and foreign household problems are

$$R = \frac{1}{\beta} \qquad R^* = \frac{1}{\beta^*} \tag{21}$$

Substituting these into the equation for speculators' optimal USD bond holdings (7) gives

$$q_t = \frac{1}{\Gamma_t} \mathbb{E}_t \Big[\varepsilon_t - \frac{R^*}{R} \varepsilon_{t+1} \Big] \tag{22}$$

where the expectation is taken over capital flow shocks in the subsequent period, ι_{t+1} and ξ_{t+1} and, in particular, over funding market shocks in t = 1, Γ_1.

Substituting speculators and hedgers optimal holdings of USD bonds (9, 22) into the net foreign asset equations in (20), we can solve for the equilibrium exchange rate in each period. Beginning with the final period, we have

$$\varepsilon_2 = \frac{\iota_2}{\xi_2} \tag{23}$$

Thus, the exchange rate such under financial autarky is driven by the relative marginal propensity to import between countries.

For the middle period, the exchange rate is solved as a function of Γ_1 and $\kappa_1(\lambda_1(\Gamma_1))$:

$$\varepsilon_1 = \frac{\iota_1 + \frac{1}{\Gamma_1} \frac{R^*}{R} \mathbb{E}_1[\varepsilon_2]}{\xi_1 + \frac{1}{\Gamma_1} + \frac{\kappa_1 E_1[\tilde{X}_2^*]}{\kappa_1 E_1[\tilde{X}_2^*]/X_1^* + 1}} = \frac{\iota_1 + \frac{1}{\Gamma_1} \frac{R^*}{R} \mathbb{E}_1[\frac{\iota_2}{\xi_2}]}{\xi_1 + \frac{1}{\Gamma_1} + \frac{\kappa_1 E_1[\tilde{X}_2^*]}{\kappa_1 E_1[\tilde{X}_2^*]/X_1^* + 1}} \tag{24}$$

where the second equality uses the conditional expectation of (23) as $\mathbb{E}_1[\varepsilon_2]$.

Similarly, the first period exchange rate is given by

$$\varepsilon_0 = \frac{\iota_0 + \frac{1}{\Gamma_0}\frac{R^*}{R}\mathbb{E}_0[\varepsilon_1]}{\xi_0 + \frac{1}{\Gamma_0} + \frac{\kappa_0 E_0[\tilde{X}_1^*]}{\kappa_0 E_0[\tilde{X}_1^*]/X_0^*+1}} \tag{25}$$

where, from (24), the conditional expectation of Γ_1 and $\kappa_1(\lambda_1(\Gamma_1))$ affect ε_0 through $\mathbb{E}_0[\varepsilon_1]$.

2.7 Exchange Rates in Disaster States

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

$$\frac{\partial\varepsilon_1}{\partial\Gamma_1} = \frac{1}{A}\Big[\underbrace{\iota_1 - \frac{R^*}{R}\mathbb{E}_1(\iota_2)(1 + \frac{\kappa_1 E_1[\tilde{X}_2^*]}{\kappa_1 E_1[\tilde{X}_2^*]/X_1^* + 1})}_{\text{Speculator Direct Effect through }\partial\Gamma_1} - \underbrace{\Gamma_1\frac{\mathbb{E}_1[\tilde{X}_2]}{B}\frac{\partial\kappa_1}{\partial\Gamma_1}(\Gamma_1\iota_1 + \frac{R^*}{R}\mathbb{E}_1(\iota_2))}_{\text{Hedger Indirect effect through }\partial\kappa_1}\Big] \tag{26}$$

where $A = \left(\Gamma_1 + 1 + \frac{\kappa_1 E_1[\tilde{X}_2^*]}{\kappa_1 E_1[\tilde{X}_2^*]/X_1^*+1}\right)^2$, $B = (\kappa_1 E_1[\tilde{X}_2^*]/X_1^* + 1)^2$ and $\frac{\partial\kappa_1}{\partial\Gamma_1} = \frac{\partial\kappa_1}{\partial\lambda_1}\cdot\frac{\partial\lambda_1}{\partial\Gamma_1}$.[9]

Equation (26) decomposes the overall response of the exchange rate into a direct effect, which captures the impact of the tightening of speculators' credit 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. dollar 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 arises because a spike in Γ_1 triggers a similar jump in the USD liquidity yield by (13), $\frac{\partial\lambda_1}{\partial\Gamma_1} > 0$, and thus a tightening in hedgers reserve constraints by (15), $\frac{\partial\kappa_1}{\partial\lambda_1} > 0$, such that $\frac{\partial\kappa_1}{\partial\Gamma_1} > 0$.[10] This "indirect" exchange rate response stems from hedgers' flight to the dollar in disasters, as evidenced by

$$\frac{\partial w_1/\varepsilon_1}{\partial\Gamma_1} = \frac{\partial\kappa_1}{\partial\Gamma_1}\frac{\mathbb{E}_1[\tilde{X}_2]}{B} > 0 \tag{27}$$

Importantly, the size of this dollar flight, like the indirect effect, is increasing in $\frac{\partial\kappa_1}{\partial\Gamma_1}$ 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

[9] Since I allow ι_t to move freely, I set $\xi_t = 1$ in (23), (24) and (25) without loss of generality

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

magnitudes of R^* and R. This is because relative interest rates determine the composition of speculators' balance sheets:

$$q_t = \frac{1}{\Gamma_t}\mathbb{E}_t\Big[\varepsilon_t - \frac{R^*}{R}\varepsilon_{t+1}\Big] > 0 \iff R > R^* \frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t} \tag{28}$$

Thus, speculators are long the USD bond and short the foreign currency bond if and only if the U.S. interest rate is sufficiently high to generate positive expected returns to this portfolio. 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:

$$\frac{\partial q_1}{\partial \Gamma_1} = \frac{1}{\Gamma_1^2}\Big(\frac{R^*}{R}\mathbb{E}_1(\varepsilon_2) - \varepsilon_1\Big) + \frac{1}{\Gamma_1}\frac{\partial \varepsilon_1}{\partial \Gamma_1} \tag{29}$$

Proposition 1: For a sufficiently small $\frac{\partial \kappa_1}{\partial \Gamma_1}$ 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, $|q_1| \uparrow \implies |\frac{\partial q_1}{\partial \Gamma_1}| \uparrow$.[11]

Since speculators' are net-long the dollar when U.S. interest rates are relatively high, $R > R^* \frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t}$, Proposition 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.

Speculators' interest-rate-dependent response in disasters explains why relative interest rates determine the sign of the direct effect, which I formalize in the following proposition.

Proposition 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 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.

[11] Proofs for all propositions and predictions can be found in Appendix II

2.8 Model Predictions and Deviations from Disaster Risk Theory

My model makes three predictions for exchange rate dynamics, which are best understood in the context of the disaster-risk theory of exchange rates. To make this mapping, I adopt

Assumption 1: $$R^* > R \iff R^* \frac{\mathbb{E}[\varepsilon_{t+1}]}{\varepsilon_t} > R$$

Consistent with the data, this assumption implies, by (28), that net-long positions in high-interest-rate currencies offer positive expected returns. This can be easily parameterized in my model since interest rates, as defined in (21), are determined by household discount factors. As a result, speculators enact a carry trade that is the long high-interest-rate currency and short the low-interest-rate currency, which has an ex-post return

$$Z_{t+1} = R_t^* \frac{\varepsilon_{t+1}}{\varepsilon_t} - R_t \tag{30}$$

where, for now, I parameterize the foreign currency to have the high interest rate.[12] Then, by the law of total expectations, the "traditional" Uncovered Interest Parity (UIP) no-arbitrage condition can be decomposed as

$$\mathbb{E}_t[Z_{t+1}] = 0 = (1-p)\ \mathbb{E}_t[Z_{t+1}|\ ND\ ] + p\ \mathbb{E}_t[Z_{t+1}|\ D\ ] \tag{31}$$

where D denotes the disaster state, ND denotes the non-disaster state or normal times and p denotes the small probability of a disaster occurring in t+1. I then rearrange this equation for the expected discounted carry trade return in normal times:

$$\mathbb{E}_t\Big[R_t^* \frac{\varepsilon_{t+1}}{\varepsilon_t} - R_t\Big|\ ND\ \Big] = \frac{-p}{1-p}\ \mathbb{E}_t\Big[R_t^* \frac{\varepsilon_{t+1}}{\varepsilon_t} - R_t\Big|\ D\ \Big] \tag{32}$$

The first two predictions of my model are consistent with this disaster-risk-adjusted UIP condition, which posits that the interest rate differential, $\frac{R_t^*}{R_t}$, has a non-linear effect on exchange rate movements, $\frac{\varepsilon_{t+1}}{\varepsilon_t}$, as a function of the state, disasters or non-disasters. Recall that I define the disaster state as a severe shock to funding market liquidity at t = 1

$$D \iff \Gamma_1 = \Gamma_H \tag{33}$$

First, due to speculators' net-long position in high-yield currencies under assumption 1, my model predicts that high-interest-rate currencies will experience excessive appreciations

[12] Predictions 1 and 2 are invariant to whether the foreign country or the U.S. has the high interest rate.

(or insufficient depreciations) relative to UIP. Ex-post, however, positive UIP deviations (positive carry trade returns) only occur conditional on no-disaster in t = 1:

Prediction 1: *Under assumption 1, for a sufficiently small p, we have*

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

These expected returns, which grow with the interest rate differential, arise because speculators' require compensation for holding the capital-flow risk (ι_1) and funding liquidity risk (Γ_1) associated with their net-long positions in high-interest-rate currencies. This prediction is consistent with the disaster risk theory of exchange rates as captured by the left-hand-side of (32): $\mathbb{E}_t\Big[R_t^*\frac{\varepsilon_{t+1}}{\varepsilon_t} - R_t\Big|\ ND\ \Big] > 0$ when $R_t^* > R_t$.

Second, the direct effect in (26) highlights that currency speculators' unwinding of their carry trade in a disaster triggers a large depreciation of the high-yield currency. Prediction 2 below provides the conditions under which this depreciation is *in excess* of the interest rate differential, thereby delivering large ex-post carry trade losses for speculators.[13]

Prediction 2: *Abstracting away from currency hedgers*[14]*, for a sufficiently small p, a sufficiently small* Γ_L *and a sufficiently large* Γ_H *, we have*

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

where if $\frac{R_0^*}{R_0}\uparrow$, $\Gamma_H \uparrow$ *or* $\Gamma_L \downarrow$ *we have* $\mathbb{E}_0\Big[R_0^*\frac{\varepsilon_1}{\varepsilon_0} - R_0\Big|\ \Gamma_1 = \Gamma_H\ \Big]\downarrow$

That $\frac{R_0^*}{R_0}$, Γ_H and Γ_L affect the size of the disaster-state depreciation of the high-interest-rate currency arises because exchange rate dynamics in crisis episodes are driven by speculator deleveraging. Since a higher interest rate differential, $\frac{R_0^*}{R_0}\uparrow$, or greater initial funding market liquidity, $\Gamma_L \downarrow$, permit speculators to take larger carry trade positions (more risk) at t = 0, they increase the amount of risk that speculators must be shed in disasters, leading to larger depreciations of the investment currency. Similarly, as the size of the funding market shock at t = 1 worsens, $\Gamma_H \uparrow$, speculators are also forced to deleverage more, worsening carry trade losses. Again, the prediction of disaster-state carry trade losses is consistent with the disaster risk theory, as captured by the right-hand-size of (32): $\mathbb{E}_t\Big[R_t^*\frac{\varepsilon_{t+1}}{\varepsilon_t} - R_t\Big|\ D\ \Big] << 0$ when $R_t^* > R_t$

[13]These losses are large as compared to the size of the positive profits conditional on no disaster.

[14]whose effect will be taken into account in Prediction 3

The disaster risk theory, exhibited in (32), frames the positive returns on net-long position in high interest rate currencies in normal times as compensation for the rare but large losses on these positions in the disaster-state. A similar intuition exists in my model since larger interest rate differentials predict greater carry trade profits in normal times at the expense of more severe losses in disasters. Thus, as in the disaster risk theory, predictions 1 and 2 of my model show that, for both states, the *sign* of the interest rate differential determines the *sign* of carry trade returns, while the *magnitude* of the interest rate differential drives the *magnitude* of carry trade returns.

My model has, until now, proposed symmetric dynamics for the USD-foreign currency exchange rate in disasters, which depends only on the relative interest rates. Reintroducing currency hedgers breaks this symmetry, which can be understood as a deviation from the disaster risk theory of exchange rates:

Prediction 3: *When the U.S. is the home country, we have*

$$\frac{\partial}{\partial \lambda_1}\mathbb{E}_0\Big[R_0^*\frac{\varepsilon_1}{\varepsilon_0} - R_0^{US}\Big|\ \Gamma_1 = \Gamma_H\ \Big] < 0$$

such that for $R_0^{*,high} - R_0^{US} = R_0^{US} - R_0^{*,low} > 0$ and sufficiently small λ_0, we have

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

Spikes in the USD liquidity yield trigger safety flows to dollar liquidity by hedgers, which are orthogonal to the interest-rate-driven deleveraging flows of speculators. These forces amplify each other when the dollar is the low-interest-rate currency but are offsetting when the dollar is the high-interest-rate currency, resulting in asymmetric disaster-state exchange rate dynamics involving the dollar. Thus, different from other currencies, the dollar is predicted to experience an amplified appreciation in disasters relative to high-interest-rate currencies ($R_0^{*,high}$), such as the Australian dollar, and a dampened depreciation relative to low-interest-rate currencies ($R_0^{*,low}$), such as the Japanese yen.

3 Data, Definitions and Cross-Sectional Evidence

To test the model's first 2 predictions, I construct a monthly sample, from 1986:M1 to 2020:M12, of exchange rates and interest rates for the 9-most-traded global currencies:

Australia (AUD), Canada (CAD), the Euro area (EUR), Japan (JPY), New Zealand (NZD), Sweden (SEK), Switzerland (CHF), the United Kingdom (GBP), and the United States (USD).[15] I study the three-month (overlapping) exchange rate movements of each of these currencies relative to the remaining eight 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; data sources can be found in Figure 10 in Appendix III.

I denote by e_t the logarithm of the nominal exchange rate at time t in units of domestic currency per unit of foreign currency:

$$e_t = log(\varepsilon_t) \tag{34}$$

such that an appreciation of the foreign currency corresponds to an increase in e_t.[16] The logarithm of the domestic and foreign gross nominal interest rates at time t are given by $i_t = log(R_t)$ and $i_t^* = log(R_t^*)$, respectively. Then, the carry trade return from investing in the foreign currency financed by borrowing in the domestic currency is given by

$$z_{t+1} = i_t^* - i_t + \Delta e_{t+1} \tag{35}$$

where $\Delta e_{t+1} = e_{t+1} - e_t$ is the appreciation of the foreign currency.[17] Under risk-neutrality, the UIP condition predicts that $E[z_{t+1}] = 0$, such that high-interest-rate currencies should depreciate relative to low-interest-rate currencies to exactly offset the difference in their interest rates.

Figure 2 presents the first and third moments of the realized distribution of carry trade returns (z) and exchange rate changes (Δe), plotted against the average interest rate differential ($\mathbb{E}[i^* - i]$), with the U.S. dollar (USD) serving as the base currency.

Panel A highlights that, in general, investing in currencies with on-average higher (lower) interest rates than the U.S. earns carry traders a positive (negative) expected return, which grows linearly with the interest rate differential. This is due to the significant

[15] According to the BIS's "Turnover of foreign exchange instruments, by currency".

[16] A long literature, beginning with Mussa (1986), has shown that, in logs, the correlation between nominal exchange rates (e_t) and real exchange rates ($log(\varepsilon_t)$) is very near 1, due to nominal rigidities.

[17] Equation (35) is the logarithm of Equation (30) from Section 2 under risk-neutrality.

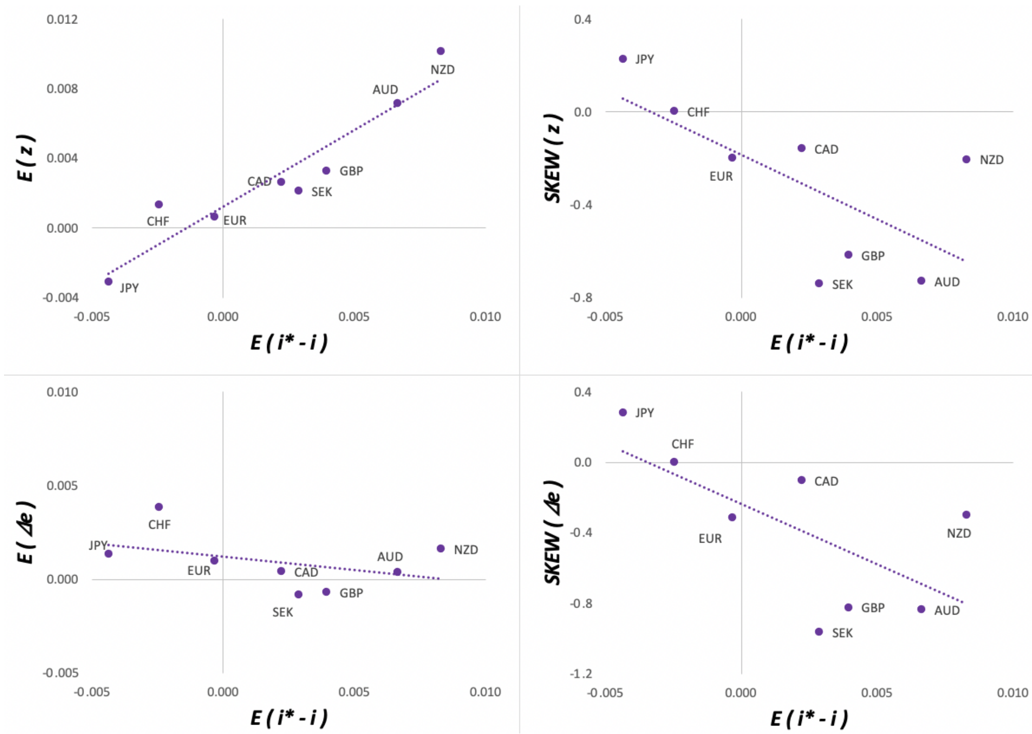

Figure 2: Mean and skewness of the realized distribution of overlapping 3-month carry trade returns (z) and exchange rate changes (Δe) for 8 currencies (JPY, CHF, EUR, CAD, SEK, GBP, AUD, NZD) relative to the USD, plotted against the average interest rate differential, $\mathbb{E}[i^* - i]$. Data is monthly from 1986:M1 to 2020:M12. See Figure 11 for details.

underreaction of the exchange rate relative to the prediction of UIP, which manifests as a slope of near 0 for the best-fit line in Panel C, as opposed to a UIP-consistent slope of -1.

As compensation for their positive expected returns, Panel B demonstrates that long positions in on-average high-interest-rate currencies are left-skewed, suggesting that these carry trades occasionally experience large losses. The opposite is true for long positions in on-average low-interest-rate currencies, whose carry trade return distribution tend to be more right-skewed. The skewness of the return distribution is driven by the skewness of exchange rate movements (Panel D) since carry trade losses are driven by large depreciations of high-interest-rate currencies in excess of interest rate differentials.

Figure 3 again plots the mean and skewness of the carry trade return and exchange rate change distributions against the average interest rate differential, but now with the Japanese yen as the base currency. The key new insight is that, despite the positive U.S.-Japan interest rate differential, the USD-JPY carry trade return distribution is nearly symmetric (Panel B) rather than left-skewed. This symmetry is driven by a lack of left-skewness of the exchange rate change distribution (Panel D), suggesting that USD crash risk may not be fully captured by relative interest rates, as in Prediction 3.[18]

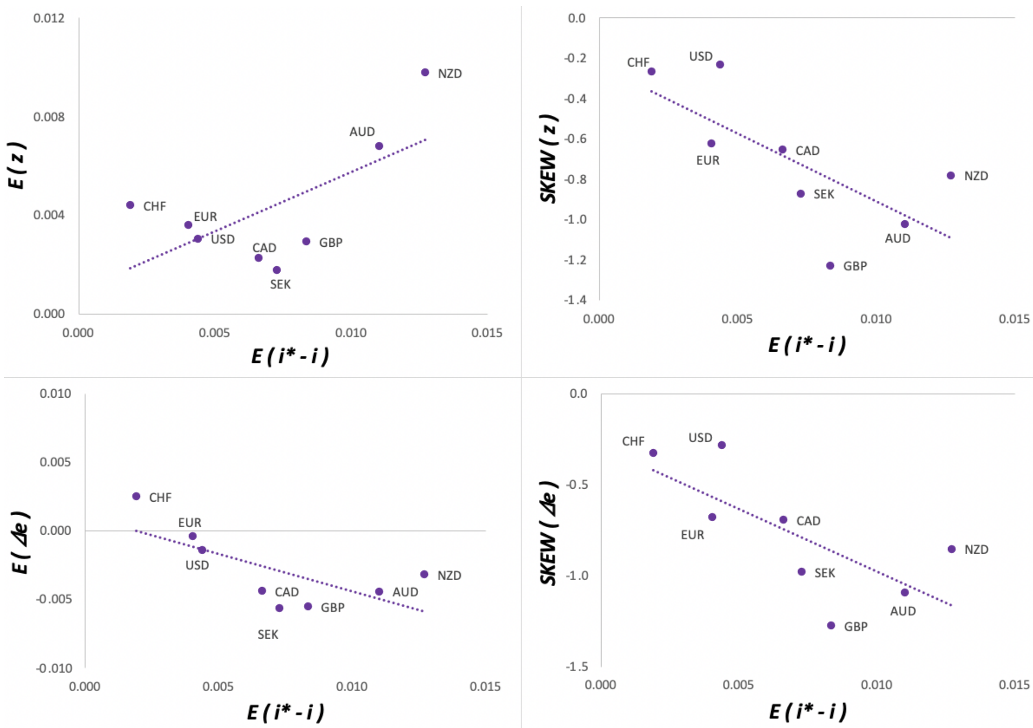

Figure 3: Mean and skewness of the realized distribution of overlapping 3-month carry trade returns (z) and exchange rate changes (Δe) for 8 currencies (CHF, EUR, USD, CAD, SEK, GBP, AUD, NZD) relative to the JPY, plotted against the average interest rate differential, $\mathbb{E}[i^* - i]$. Data is monthly from 1986:M1 to 2020:M12.

To test my model's third prediction, I additionally use the Du, Im and Schreger (2018) data on the USD liquidity yield, measured as the wedge in the 3-month CIP condition between currency j and the dollar:

$$\lambda_{j,t} = (f_{j,t} - e_{j,t}) + (i^*_{j,t} - i_t) \tag{36}$$

where $f_{j,t}$ is the logarithm of the three-month forward exchange rate for currency j relative to the USD at time t. Figure 11 in Appendix III provides summary statistics for the USD

[18]Similar anomalies appear when using base currencies other than the JPY. For example, the USD-AUD exchange rate distribution is more right-skewed than its interest rate differential would predict.

liquidity yield relative to each of the eight other currencies in my sample, which form an unbalanced panel spanning 1991:M4 to 2019:M12. The statistics highlight that the average USD liquidity yield is positive, reflecting the safety and liquidity of U.S. Treasuries, but is small. In addition, the USD liquidity yield exhibits strong right skewness, highlighting that the perceived safety of U.S. bonds can occasionally spike. These cross-sectional results hold for each currency I study over the full sample period, except for the New Zealand dollar, where it holds in a slightly-shortened sample from 1994:M4 to 2019:M12.[19]

Finally, to investigate if quantity adjustments by speculators and hedgers are consistent with my model's predictions, I use data from the Commodity Futures Trading Commission (CFTC) to construct

$$Spec\_Pos_{j,t} \equiv \frac{Long^S_{j,t} - Short^S_{j,t}}{Open\_Interest_{j,t}} \qquad Hedge\_Pos_{j,t} \equiv \frac{Long^H_{j,t} - Short^H_{j,t}}{Open\_Interest_{j,t}} \tag{37}$$

the net (long minus short) portfolio position of speculators and hedgers, respectively, in the Chicago Board of Exchange's (CBOE's) futures market for currency j relative to the USD, normalized by the total open interest of all traders for currency j futures. A positive speculator or hedger position implies they are net-long currency j (and net-short the USD)—they implement a long currency j-short USD carry trade. The data to construct these quantities is available only for six currencies (JPY, CHF, EUR, CAD, GBP and AUD) relative to the USD in a balanced panel from 1993:M1 to 2020:M12.[20] Figure 11 in Appendix III provides summary statistics for $Spec\_Pos$ and $Hedge\_Pos$.

The CFTC classifies traders in the CBOE's currency futures market as either non-commercial—those I term speculators—who use futures for non-hedging purposes or commercial—those I call hedgers—who use futures as a hedge. Importantly, the sum of speculators and hedgers net positions does not equal 0, highlighting that not all traders in the futures market are sorted into one of these two groups. The (small) residual group can be thought of as the households from my model. While this data may not capture the full market for U.S. dollar futures trades, much of which occurs in the over-the-counter market, it still likely forms a representative sample.

[19] This sample discounts NZD-specific capital flow surges which took place from 1992:M3 to 1994:M3. In my analysis, however, I work with the full sample.

[20] Data for the AUD is available beginning in 1993, rather than 1986 for the other currencies. Prior to 1993, the market is less liquid for all currencies, so the balanced 1993:M1 to 2020:M12 sample serves as my baseline. An unbalanced sample starting in 1986 with each currency entering once its market is sufficiently liquid (defined as having no further zeros for Long or Short positions) yields similar results.

4 Empirical Strategy

In this section, I build my empirical framework, which I term signed quantile UIP regressions, to test the predictions of my model. The starting point is the time-series UIP regression of Fama (1984), which tests for UIP under risk-neutrality: $E[z_{t+1}] = 0$.

$$\Delta e_{t+1} = \beta_0 + \beta_1 (i_t^* - i_t) + u_{t+1} \tag{38}$$

The null hypothesis is that $\beta_0 = 0$ and $\beta_1 = -1$. At short horizons, estimating (38) by least squares produces estimated coefficients of $\hat{\beta}_1 \geq 0$, such that one can clearly reject the null hypothesis.

This result is unsurprising when viewed in the context of the disaster risk theory of exchange rates, as captured by (32), which I reproduce below in log form:[21]

$$\mathbb{E}_t\left[i_t^* - i_t + \Delta e_{t+1} \middle| \; ND \right] = \frac{-p}{1-p} \; \mathbb{E}_t\left[i_t^* - i_t + \Delta e_{t+1} \middle| \; D \right] \tag{39}$$

For $i_t^* > i_t$, this disaster-risk-adjusted UIP relation highlights that positive expected carry trade returns in normal times—the left-hand-side of equation (39)—serve as compensation for the large carry trade losses in rare disasters—the right-hand-side of equation (39). As the least-squares coefficient from (38) estimates the marginal effect of the interest rate differential on the *mean* exchange rate movement, it captures only the mild currency movements that occur conditional on no-disaster, rationalizing $\hat{\beta}_1 \geq 0$.

To take full account of the state-dependence (disaster versus calm) and interest-differential sign-dependence (positive or negative) of exchange rate movements, as predicted by my model and the disaster risk theory, I make two modifications to the standard UIP regression in (38). I perform these in turn.

4.1 Quantile UIP Regressions

First, as mild, normal time movements are concentrated in the center of the exchange rate distribution while extreme crisis dynamics manifest in the distribution's tails, I account for

[21] This analysis carries over to the most general asset pricing setup (dropping the assumption of risk neutrality): for an investor with stochastic discount factor $M_{t,t+1}$, the UIP condition $\mathbb{E}_t[M_{t,t+1} \; z_{t+1}] = 0$ can be decomposed as $\mathbb{E}_t\left[M_{t,t+1} \left\{ (i_t^* - i_t) + \Delta e_{t+1} \right\} \middle| \; ND \right] = \frac{-p}{1-p} \; \mathbb{E}_t\left[M_{t,t+1} \left\{ (i_t^* - i_t) + \Delta e_{t+1} \right\} \middle| \; D \right]$

state-dependence by estimating the UIP relationship using quantile regression:

$$\Delta e_{t+1} = \beta_0^\tau + \beta_1^\tau (i_t^* - i_t) + u_{t+1} \tag{40}$$

In the simple univariate, time-series case above, estimation by quantile regression minimizes the sum of quantile-weighted absolute errors according to:

$$\hat{\beta}^\tau = argmin_{\{\beta \in \mathbf{R}^2\}} \sum_{t=1}^{T-1} \Big[\tau * \mathbf{1}_{\{\Delta e_{t+1} > \beta_0 + \beta_1 (i_t^* - i_t)\}} \mid \Delta e_{t+1} - \beta_0 - \beta_1 (i_t^* - i_t) \mid + (1-\tau) * \mathbf{1}_{\{\Delta e_{t+1} < \beta_0 + \beta_1 (i_t^* - i_t)\}} \mid \Delta e_{t+1} - \beta_0 - \beta_1 (i_t^* - i_t) \mid \Big] \tag{41}$$

where τ denotes the quantile and $\mathbf{1}_{(.)}$ denotes the indicator function. By varying τ and thus changing the weighting scheme of the loss function, I can estimate the marginal effect of the interest rate differential on the different quantiles of the exchange rate change distribution. Importantly, the estimated marginal effects ($\hat{\beta}^\tau$) are quantile-specific. For example, setting $\tau = 0.5$ collapses the loss function into the absolute value function such that $\hat{\beta}_1^{\tau=0.5}$ is the estimated marginal effect of the interest rate differential on the median change in the exchange rate. In section 5, I report a selection of quantile regression coefficients from the left-tail—$\tau = \{0.005, 0.01, 0.025, 0.05\}$—from the right-tail—$\tau = \{0.95, 0.975, 0.99, 0.995\}$—and from the center—$\tau = \{0.1, 0.3, 0.5, 0.7, 0.9\}$—of the exchange rate change distribution[22].

To illustrate the advantage of this first modification, I estimate (40) using quantile regression for three currencies—the JPY, the USD and the AUD. Figure 4 displays the estimated quantile regression coefficients for the interest rate differential ($\hat{\beta}_1^\tau$), for the quantiles $\tau = \{0.005, 0.5, 0.995\}$, for each of the six permutations of currency pairs. Standard errors, reported in the appendix, are computed using 500 bootstrapped samples. As is the case for all results in this paper, the full regression table is in Appendix IV.

The key takeaway from this example is that the sign of the *average* interest rate differential determines in which tail of the exchange rate distribution the disaster state movement *generally* appears. Take, for instance, the United States, whose average interest rate lies between that of Japan (with a relatively low average interest rate) and that of Australia (with a relatively high average interest rate). When the USD is the domestic

[22] The selection of quantiles I estimate in the tails are less spread out than in the center of the distribution to ensure my results are robust, as tail quantiles weigh relatively few extreme observations heavily.

Regression Coefficients from Quantile UIP Regressions

Domestic Currency	JPY		USD		AUD	
Foreign Currency (*)	*AUD*	*USD*	*JPY*	*AUD*	*JPY*	*USD*
Quantiles (τ)	β_1^{τ} *for* $i_t^* - i_t$					
0.005	-19.32***	-7.44***	2.56	-9.28**	-4.04	-3.04
0.5	0.28	2.72***	2.72***	1.40***	0.28	1.40***
0.995	-4.04	2.56	-7.44***	-3.04	-19.32***	-9.28**

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Figure 4: Bilateral quantile regression coefficients for the interest rate differential from the quantile UIP regression. Currencies are the JPY, USD and AUD; quantiles are $\tau = \{0.005, 0.5, 0.995\}$. Data is monthly from 1986:M1 to 2020:M12. Standard errors (see Table 2.1 in Appendix IV) are computed using 500 bootstrapped samples.

currency in the quantile UIP regression (columns 3 and 4), the dollar's disaster state exchange rate movement tends to be a large right-tail appreciation against the yen (in blue) but a large left-tail depreciation against the AUD (in purple). In both cases, the marginal effect has a magnitude significantly more extreme than -1 such that a higher interest rate differential predicts a disaster-state exchange rate movement in excess of the interest rate differential, implying a loss on the carry trade.

Of note, when looking at the marginal effect in the 'incorrect' tail as defined by the disaster risk theory—the left tail for the JPY-USD exchange rate and the right tail for the AUD-USD exchange rate—one finds that the effects are statistically insignificant. This suggests that the interest rate differential provides little information on the large appreciations (depreciations) of on-average high- (low-) interest-rate currencies.

A second takeaway from this example is that the interest rate differential's marginal effect on the left-tail depreciation of a high-interest-rate currency is equal to its marginal effect on the right-tail appreciation of a low-interest-rate currency. For instance, when the JPY is the domestic currency and the AUD is the foreign currency (column 1), the disaster-state marginal effect in the left tail (in red) is identical to the disaster-state marginal effect in the right tail (also in red) when the AUD is the domestic currency and the JPY is the foreign currency (column 5). This is because the AUD-JPY quantile UIP regression is the JPY-AUD quantile UIP regression multiplied by a factor of -1. Thus, a variable's marginal effect at the τ^{th}quantile in one UIP regression will be equal to its marginal effect at the $(1-\tau)^{th}$ quantile in the other.

This -1 transformation, however, leaves the median effect unchanged. This explains why the interest rate differential's marginal effects at the median are the same for any pair of currencies regardless of which acts as the domestic and which acts as the foreign. Consistent with the Fama puzzle, the interest rate differential's marginal effects at the median (row 2) are significantly different from -1, implying an exchange rate underreaction relative to UIP in normal times that generates positive returns to the carry trade.

4.2 *Signed* Quantile UIP Regressions

The quantile UIP regression, however, does not adjust for the interest-differential sign-dependence of exchange rate movements. Specifically, UIP regressions estimate the impact of the foreign-minus-domestic interest rate differential on the appreciation of the foreign currency i.e. they predict exchange rate movements using a foreign/domestic currency classification system. However, Predictions 1 and 2, as well as the disaster risk theory, highlight that exchange rate movements depend on the sign of the interest rate differential at time t: a high-interest-rate currency should excessively appreciate (or insufficiently depreciate) relative to UIP in normal times but experience severe depreciations in disasters relative to a low-interest-rate currency. The opposite is predicted for low-interest-rate currencies relative to high-interest-rate currencies. Thus, currency movements should instead be analyzed under a classification system that distinguishes between high/low-interest-rate currencies.

To address this, I interact the interest rate differential and the exchange rate movement from the quantile UIP regression in (40) with the sign of the interest rate differential:

$$\Delta e_{t+1} \times sign(i_t^* - i_t) = \beta_0^\tau + \beta_1^\tau (i_t^* - i_t) \times sign(i_t^* - i_t) + u_{t+1} \tag{42}$$

Each period, this *signed* quantile UIP regression re-classifies the foreign currency as either the high- or low-interest rate currency as compared to the domestic currency.[23]

[23] The panel version of this sign transform is similar to portfolio sorting (see Lustig and Verdlhan (2007), Lustig et al. (2011), which allocates currencies to n portfolios based on their interest rate differentials with the domestic currency, but has three added benefits: 1. I can analyze my entire sample of currencies together, rather than separately studying n subsets of my currency sample (individual portfolios) where n is arbitrary and where the results may be sensitive to different groupings; 2. Portfolio sorting analyzes equally-weighted currency excess returns within a portfolio, whereas my method remains agnostic as to the exact weighting of investors' positions; and 3. In my method, I can study the impact of the variable used to sort the portfolios, the interest rate differential, which is crucial to test the disaster risk theory in sample.

Specifically, if the interest differential is positive at time t, $sign(i_t^* - i_t) = 1$, then the signed UIP regression reduces to the standard UIP regression as the foreign currency has the higher interest rate. Conversely, if the interest rate differential is negative at time t, $sign(i_t^* - i_t) = -1$, then the signed UIP regression estimates the effect of the domestic-minus-foreign interest rate differential on the appreciation of the domestic currency, as now the domestic currency has the higher interest rate. Thus, consistent with the disaster risk theory and speculator behavior in my model, this transformation allows me to investigate the impact of the (always-positive) high-minus-low interest rate differential on the appreciation of the high-interest-rate currency.

A key advantage of this transformation is it "re-organizes" the exchange rate change distribution such that all large depreciations (appreciations) that occur when the interest rate differential is positive (negative) are placed in the left tail of the new, signed exchange rate change distribution. I term this tail the "disaster-state tail". This result will be crucial when I extend the method to study panels of currencies. Further, the transformation places all large exchange rate movements that occur when the interest rate differential has the incorrect sign according to the disaster risk theory in the right tail. Figure 5 highlights this by estimating (42) for the same quantiles and currency pairs as in Figure 4.

Regression Coefficients from Signed Quantile UIP Regressions

Domestic Currency	JPY		USD		AUD	
Foreign Currency (*)	*AUD*	*USD*	*JPY*	*AUD*	*JPY*	*USD*
Quantiles (τ)	β_1^τ *for* $(i_t^* - i_t) \times$ *sign*$(i_t^* - i_t)$					
0.005	-19.32***	-7.44***	-7.44***	-12.96***	-19.32***	-12.96***
0.5	0.28	3.12***	3.12***	0.52	0.28	0.52
0.995	-4.04	2.56	2.56	-3.04	-4.04	-3.04

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Figure 5: Bilateral quantile regression coefficients for the signed interest rate differential from the signed quantile UIP regression. Currencies are the JPY, USD and AUD; quantiles are $\tau = \{0.005, 0.5, 0.995\}$. Data is monthly from 1986:M1 to 2020:M12. Standard errors (see Table 2.2 in Appendix IV) are computed using 500 bootstrapped samples.

As expected, the disaster state exchange rate movements for all currency pairs appear in the left tail, as evidenced by the marginal effects in red, blue and purple in row 1. The interpretation of these marginal effects is nuanced. Since $(i_t^* - i_t) \times sign(i_t^* - i_t)$ is always positive, β_1^τ measures the marginal effect of the interest rate differential's *magnitude* on the appreciation of the foreign (high-interest-rate) currency when the interest differential is positive and the depreciation of the foreign (low-interest-rate) currency when the interest differential is negative. Thus, the large negative marginal effects in the left tail highlight that a greater magnitude predicts a greater depreciation of high-interest-rate currencies and greater appreciation of low-interest-rate currencies in disasters. These results demonstrate that the sign of the interest rate differential is crucial to determining the sign of exchange rate movements in disasters.

Furthermore, the interest-rate differential's marginal effects at each quantile from the AUD-JPY signed quantile UIP regression in Figure 5 are the same as those from the AUD-JPY standard quantile UIP regression in Figure 4. This is because the AUD-JPY interest rate differential is always positive, so the sign transformation has no effect. In the case of the USD-JPY signed UIP regression, the marginal effect at the median has increased slightly compared to the effect in the standard UIP regression, but the effects in the tails remain the same. This indicates that there has been some mild re-classification based on relative interest rates at the center of the distribution, but not in the tails. Finally, a more extreme re-classification occurs in the AUD-USD case, where, in particular, the marginal effect at the $\tau = 0.005$ quantile has increased substantially under the sign transform, from $\hat{\beta}_1^{\tau=0.005} = -9.28$ to $\hat{\beta}_1^{\tau=0.005} = -12.96$, with the effect becoming more statistically significant. This implies that several disaster-state exchange rate movements, which were previously misclassified as non-disaster based on the fact that Australia has a higher *average* interest rate than the U.S., are now correctly classified as disasters based on the AUD-USD interest rate differential in each period (or vice versa).

An additional insight is that the U.S. dollar's disaster-state marginal effect is nearly twice as large against the AUD as it is against the JPY. Thus, for the same magnitude interest differential, the USD is predicted to appreciate twice as much against the generally high-interest-rate AUD as it is predicted to depreciate against the generally low-interest-rate JPY. These univariate regressions already point to an asymmetric response of the dollar to low versus high interest rate currencies in disasters, which highlights its safe-haven status.

In the results section that follows, I make two more adjustments to the time-series signed quantile UIP regression from (42). First, I estimate pooled-panel signed quantile UIP regressions with fixed effects, which are estimated analogously to the time-series case.

Second, I augment the regression with the U.S. dollar liquidity yield. I leave the precise details of the specification for section 5.

Finally, I implicitly define the Foreign Exchange at Risk—the FEaR—as:

$$Pr\Big[\Delta e_{t+1} \times \widehat{sign(i_t^* - i_t)} \mid \vec{x_t} \;\le FEaR_{t+1}\Big] = 0.01 \tag{43}$$

The FEaR, the Value at Risk (VaR) of the signed exchange rate change distribution, corresponds to the left-tail exchange rate movement for which only 1% of disaster-state exchange rate movements[24] are more extreme, conditional on the vector of regressors $\vec{x_t}$. The conditioning vector is the signed interest rate differential, $(i_t^* - i_t) \times sign(i_t^* - i_t)$, when estimating (42) and in an augmented regression would also include the interest-rate-signed dollar liquidity yield. The $FEaR_{t+1}$ will serve as my baseline measure of the disaster-state exchange rate movement $E[\Delta e_{t+1} | \ D\ ]$, although my results are robust to threshold probabilities (quantiles) $\tau = 0.005$, $\tau = 0.025$ and $\tau = 0.05$.

5 Empirical Results

5.1 Testing the Disaster Risk Theory of Exchange Rates

I begin by using my empirical framework to test the first two predictions of my model, which amounts to a test of the disaster risk theory of exchange rates. To do so, I estimate pooled-panel signed quantile UIP regressions with currency fixed effects:

$$\Delta e_{j,t+1} \times sign(i_{j,t}^* - i_t) = \beta_1^\tau (i_{j,t}^* - i_t) \times sign(i_{j,t}^* - i_t) + f_j^\tau + u_{j,t+1} \tag{44}$$

This relation is estimated using a sample of the 9-most-traded global currencies, which each serve once as the fixed domestic currency vis-a-vis the remaining 8 foreign (variable) currencies. Figure 6 presents the quantile regression coefficients for the signed interest rate differential ($\hat{\beta}_1^\tau$) from (44) for each currency. The quantiles estimated range from $\tau = 0.005$ to $\tau = 0.995$, which run (evenly-spaced) from lowest to highest along the x-axis in each panel.[25] The yellow columns represent the marginal effects, measured along the

[24] large depreciations of high-interest-rate currencies or large appreciations of low-interest-rate currencies

[25] Figure 16 provides an alternate representation of Figure 6 with the quantiles spaced in proportion to their values, which accentuates the rarity of disaster episodes.

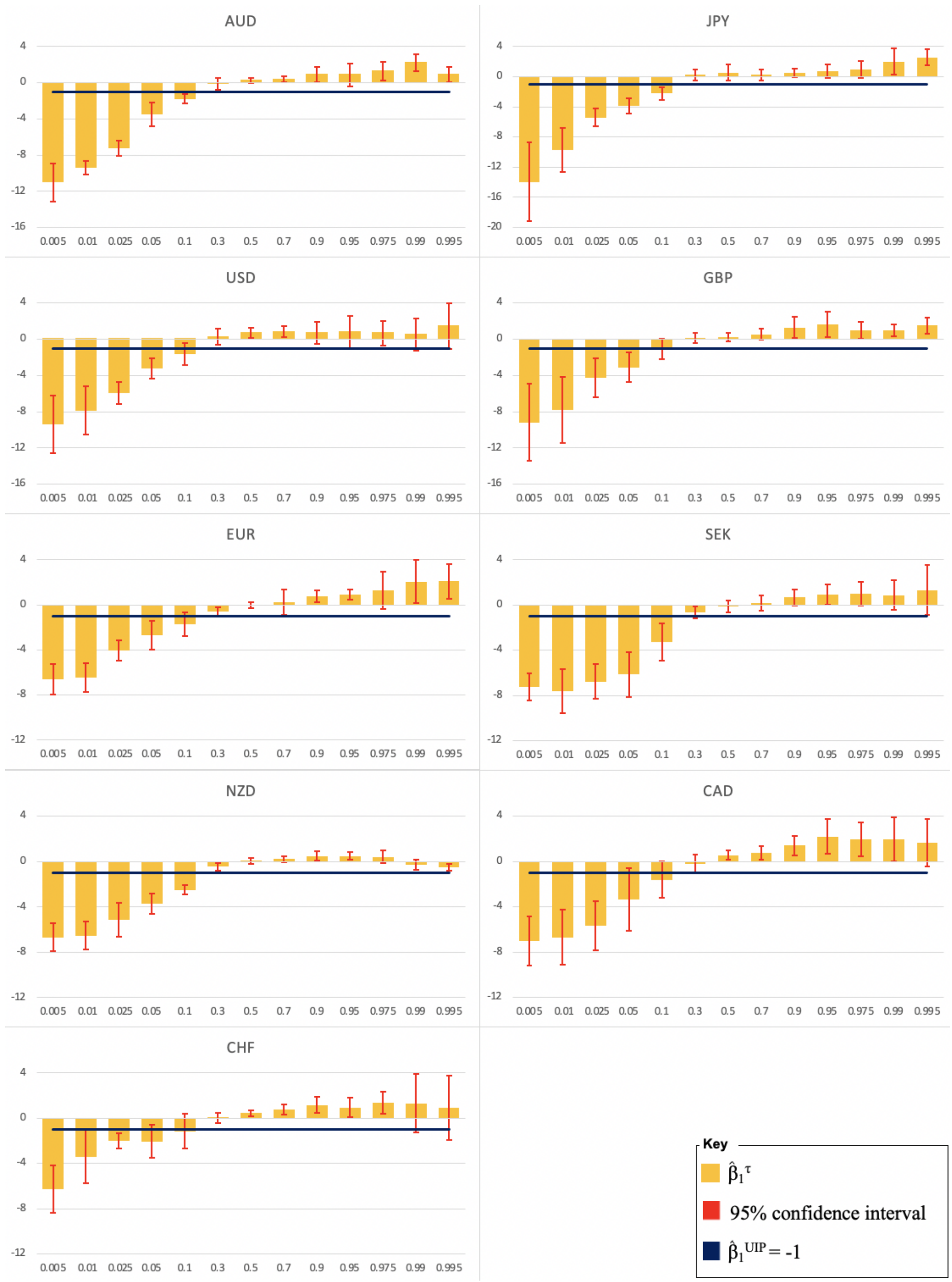

Figure 6: Quantile regression coefficients for the signed interest rate differential, $\hat{\beta}_1^\tau$, from (44). Currencies: AUD, JPY, USD, GBP, EUR, SEK, NZD, CAD, CHF; quantiles: $\tau = \{0.005,\ 0.01,\ 0.025,\ 0.05,\ 0.1,\ 0.3,\ 0.5,\ 0.7,\ 0.9,\ 0.95,\ 0.975,\ 0.99,\ 0.995\}$; Sample period: 1986:M1 to 2020:M12. Error bars are 95% confidence intervals. For full results, see Tables 3.1-3.9 in Appendix IV. Figure 16 remodels Figure 6 to have the quantiles spaced in proportion to their values.

y-axis, while the red error bars correspond to 95% confidence intervals constructed using cluster robust standard errors for quantile regression to account for heteroskedasticity and autocorrelation. The blue horizontal line at -1 indicates the marginal effect for which UIP holds, $\hat{\beta}_1^{UIP} = -1$.

Figure 6 showcases the highly non-linear relationship between relative interest rates and exchange rate dynamics for the world's most traded currencies. If UIP held each period, then the marginal effects at each quantile would equal the UIP line at -1: high-interest-rate currencies would experience depreciations equal to their interest rate differential with low-interest-rate currencies. Instead, in the disaster-state (left) tail, the marginal effects are significantly more extreme than -1: high-interest-rate currencies are predicted to suffer depreciations in excess of interest rate differentials. By construction, the opposite holds for low-interest-rate currencies, which are predicted to appreciate in excess of their interest rate differential in the left tail. These disaster-state marginal effects, with magnitudes more extreme than -1 at the 97.5% one-sided confidence level, manifest at both the 0.5^{th} percentile, the 1^{st} percentile (the FEaR), and the 2.5^{th} percentile for all currencies, except for the Swiss Franc, where they appear only at the first two. Further, for most currencies, the disaster-state marginal effects are additionally present at the 5^{th} percentile,[26] implying the interest rate differential predicts that carry trades involving these currencies will earn large losses roughly once every two years.[27] This provides strong evidence consistent with model Prediction 2.

Furthermore, high-interest-rate currencies are (point-)predicted to appreciate at the median against low interest rate currencies. More generally, the interest rate differential predicts that high-interest-rate currencies will insufficiently depreciate (or excessively appreciate) relative to UIP, at the 97.5% one-sided confidence level, for all quantiles larger than $\tau = 0.3$. In other words, high-minus-low carry trades implemented using any of these currencies will be profitable most the time. This is consistent with model prediction 1 and, along with prediction 2, provides strong evidence in support of the disaster risk theory of exchange rates.[28]

[26]For the AUD, JPY, SEK and NZD, disaster-state marginal effects exist also at the 10^{th} percentile.

[27]Importantly, however, as disaster-state exchange rate movements generally group together, they are much rarer than this figure suggests.

[28]Figure 17 in Appendix V shows the results in Figure 6, from estimating (44), are robust to excluding the 2008 Global Financial Crisis.

My model posits that the non-linear exchange rate dynamics presented in Figure 6 are driven by currency speculators' carry trade activity in normal times and their deleveraging in disasters. To test this, I estimate by quantile regression two specifications using $Spec\_Pos_{j,t}$, the normalized net-long position of speculators in currency j relative to the dollar, as the dependent variable. To investigate the interest rate differential's effect on speculators' currency positions during normal times, I estimate:

$$Spec\_Pos_{j,t+1} = \beta_1^{\tau}(i_{j,t}^{*} - i_t^{USD}) + f_{j,t}^{\tau} + u_{j,t+1} \tag{45}$$

To investigate the interest rate differential's impact on *changes* to speculators' currency positions in disasters, I estimate:

$$\Delta Spec\_Pos_{j,t+1} \times sign(i_{j,t}^{*} - i_t^{USD}) = \beta_1^{\tau}(i_{j,t}^{*} - i_t^{USD}) \times sign(i_{j,t}^{*} - i_t^{USD}) + f_{j,t}^{\tau} + u_{j,t+1} \tag{46}$$

Figure 7 presents the quantile regression coefficients for the interest rate differential from (45) in Panel A and for the signed interest rate differential from (46) in Panel B.

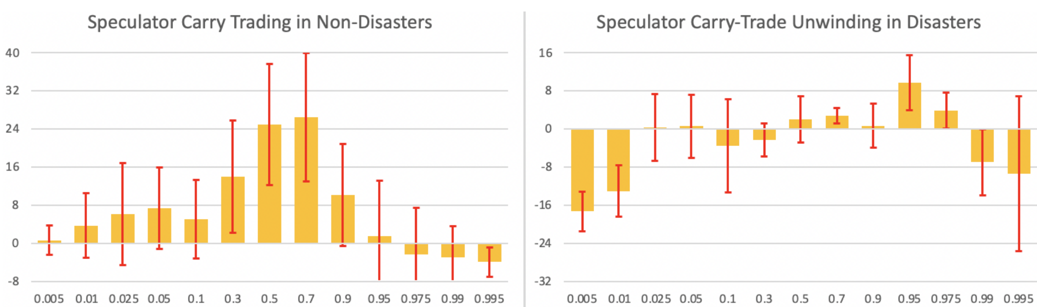

Figure 7: Quantile regression coefficients for the interest rate differential from (45) in Panel A and for the signed interest rate differential from (46) in Panel B. Fixed domestic currency is the USD relative to: JPY, AUD, GBP, CAD, EUR, CHF. Sample period: balanced from 1993:M1 to 2020:M12. Error bars are 95% confidence intervals. For full results, see Tables 4.1 and 4.2 in Appendix IV.

The positive regression coefficients in the center of the distribution in Panel A highlight that, for the most part, speculators are long high-interest-rate currencies and short low-interest-rate currencies—they implement the carry trade. Thus, speculator behavior in normal times is consistent with exchange rate movements in normal times, as in the model.

The regression estimated in (46) is analogous to the signed UIP regression in (44) but with the (signed) change in speculators' currency positions as the dependent variable. I term the left tail of the $\Delta Spec\_Pos_{j,t+1} \times sign(i^*_{j,t} - i^{USD}_t)$ 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 in Panel B highlight that the interest rate differential drives these carry trade unwindings: a higher interest rate differential predicts a substantial decrease in speculators' holdings of the high-interest-rate currency. Figure 12 in Appendix IV shows that, for each currency, the time series of $\Delta e_{j,t+1} \times sign(i^*_{j,t} - i^{USD}_t)$ and $\Delta Spec\_Pos_{j,t+1} \times sign(i^*_{j,t} - i^{USD}_t)$ co-move, including in the left tail, such that the large depreciations of high-interest-rate currencies occur in the same periods in which speculators drastically unwind their carry trades. This points to a causal relation between quantity adjustments and price corrections in disasters, as my model predicts.[29]

5.2 Liquidity Yields, Disasters and the Safe-Haven Dollar

Motivated by the cross-sectional and time-series-regression evidence presented earlier, I adapt my empirical framework to study the unique safe-haven properties of the U.S. dollar in disaster events. Model prediction 3 conjectures that this safe-haven benefit results from hedgers' desire for the safety and liquidity of U.S. Treasuries, encoded in the dollar liquidity yield, $\lambda_{j,t+1}$. To test this, I first estimate a liquidity yield-augmented version of (44):

$$\Delta e_{j,t+1} \times sign(i^*_{j,t} - i^{USD}_t) = \beta^\tau_1 (i^*_{j,t} - i^{USD}_t) \times sign(i^*_{j,t} - i^{USD}_t) + \beta^\tau_2 \lambda_{j,t+1} \times sign(i^*_{j,t} - i^{USD}_t) + f^\tau_j + u_{j,t+1} \quad (47)$$

According to prediction 3, the liquidity yield's effect should be independent of the sign of the interest rate differential. To capture this within the signed quantile UIP framework, I interact $\lambda_{j,t+1}$ with $sign(i^*_{j,t} - i^{USD}_t)$. As the exchange rate change is also interacted with the sign of the interest rate different, the $sign(i^*_{j,t} - i^{USD}_t)$ terms on either side of the regression effectively cancel. This strategy allows me to study the liquidity yield's impact on exchange rate movements in the disaster-state (left) tail, without imposing an interest-differential sign-dependence on the effect.[30]

[29] Only with high-frequency exchange rate and speculator positions data can we assess causality.

[30] Interacting the interest rate differential, $i^*_{j,t} - i^{USD}_t$, with $sign(i^*_{j,t} - i^{USD}_t)$ *does* impose an interest-differential sign-dependence since these two terms always have the same sign i.e. their interaction is always positive. Thus, β^τ_1 is interpreted as the impact of an always always positive quantity on

Figure 8 presents the quantile regression coefficients for the signed interest rate differential (β_1^τ) in Panel A and the signed liquidity yield (β_2^τ) in Panel B, where the U.S. dollar is the fixed domestic currency:

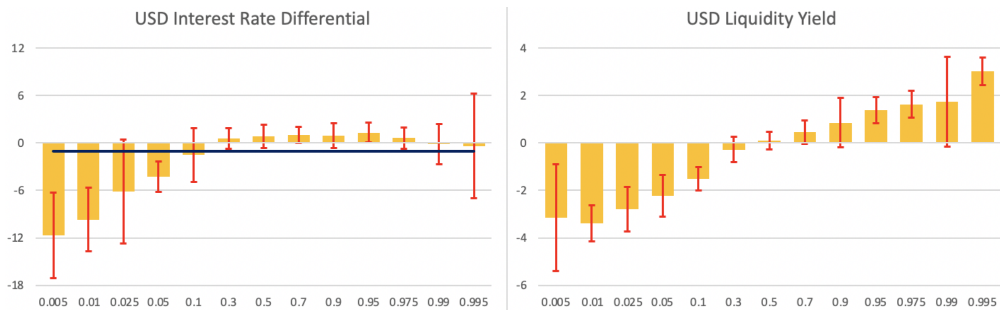

Figure 8: Quantile regression coefficients for the signed interest rate differential (β_1^τ) in Panel A and the signed liquidity yield (β_2^τ) in Panel B from (47). Fixed domestic currency is the USD relative to AUD, USD, JPY, GBP, SEK, CAD, EUR, CHF, NZD; Sample period: unbalanced from 1991:M4 to 2019:M12. Error bars are 95% confidence intervals. For full results, see Table 5.1 in Appendix IV.

Panel A again provides evidence in support of the disaster risk theory: the interest rate differential predicts that high-interest-rate currencies will suffer depreciations in excess of interest rate differentials in the left tail, but, throughout the rest of the distribution, will insufficiently depreciate (or excessively appreciate) relative to UIP. Thus, model predictions 1 and 2 are robust to augmenting the signed quantile UIP regression with the liquidity yield.

The large, negative marginal effects in the left tail of Panel B imply that an increase in the contemporaneous USD liquidity yield, $\lambda_{j,t+1} \uparrow$, predicts a larger depreciation of the foreign currency in disasters, and thus a larger appreciation of the U.S. dollar, regardless of their relative interest rates. By contrast, this liquidity yield effect is not present when the relationship in (47) is estimated with currencies other than the dollar as the fixed domestic currency. Thus, consistent with model prediction 3, the U.S. dollar experiences pressure to appreciate in disasters due to the safety and liquidity of U.S. Treasuries.[31] To assuage endogeneity concerns, I re-estimate (47) by instrumental variable quantile regression using the VIX index, an exogenous measure of funding liquidity implied by options prices, as the

$\Delta e_{j,t+1} \times sign(i^*_{j,t} - i_t^{USD})$ such that the sign terms on each side *don't* cancel, in contrast to the λ case.

[31] Figure 18 in Appendix V shows the results in Figure 8 are robust to excluding the largest spike in the dollar liquidity yield, which occurred at the height of the Global Financial crisis in 2008:M9 (see Figure 1).

instrument for the dollar liquidity yield, as in Engel and Wu (2018). Figure 13 in Appendix IV shows this generates similar results to those in Figure 8.[32]

Together, Panels A and B highlight that different from other currencies, the U.S. dollar's disaster-state exchange rate reflects a balance between the interest rate differential and the liquidity yield. The net effect of these forces implies an amplified USD appreciation in disasters against high-interest-rate currencies, such as the Australian dollar, and a dampened USD depreciation in disasters relative to low-interest-rate currencies, such as the Japanese yen. This points to an important asymmetry in the disaster dynamics of the dollar due to its role as the global safe asset. Interestingly, this safe-haven effect does not seem to be a free lunch—in the non-disaster (right) tail, a higher USD liquidity yield actually predicts a dollar depreciation. Understanding this tradeoff is an interesting avenue for future research.

Finally, my model conjectures that this liquidity-driven safety force, which predicts a USD appreciation in disasters, is due to a flight to the dollar by currency hedgers. To test this, I use $Hedge\_Pos_{j,t}$, the normalized net-long position of hedgers in currency j relative to the dollar, to estimate:

$$\Delta Hedge\_Pos_{j,t+1} = \beta_1^{\tau}(\lambda_{j,t+1}) + f_j^{\tau} + u_{j,t+1} \tag{48}$$

The marginal effects for the dollar liquidity yield, presented in Figure 9, indicate that

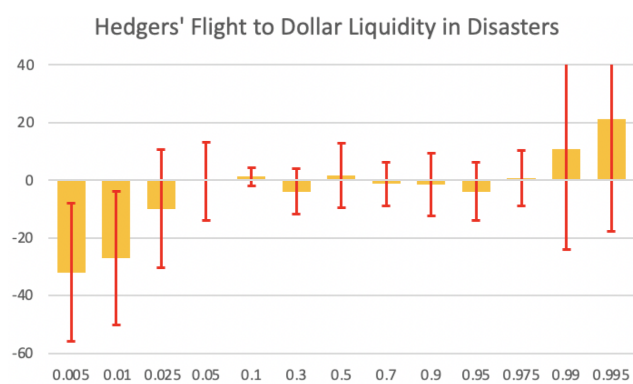

Figure 9: Quantile regression coefficients the liquidity yield from (48). Fixed currency is the USD relative to: JPY, AUD, GBP, CAD, EUR, CHF. Sample period: unbalanced from 1993:M1 to 2019:M12. Error bars are 95% confidence intervals. For full results, see Table 6.1 in Appendix IV.

[32]Figure 14 shows that proxying the dollar liquidity yield in (47) with the VIX gives very similar results.

hedgers' largest flights towards the dollar, which occur in the left tail ($\Delta Hedge\_Pos_{j,t+1} \downarrow$), are driven by the liquidity yield: a higher dollar liquidity yield predicts a larger flight to the dollar by hedgers. Using an augmented regression that includes the interest rate differential, Figure 15 in Appendix IV shows that hedgers' largest flights to the dollar occur in the same periods in which they accommodate the large carry trade unwindings of speculators (the marginal effects occur in the same tail). This is consistent with model prediction 3, where spikes in the dollar liquidity yield induce a flight to the dollar by hedgers that puts pressure on the USD to appreciate in disasters.

6 Conclusion

In this paper, I first develop a model of exchange rate determination that unifies the disaster risk theory of exchange rates and the unique role of the U.S. as the global safe asset provider. Then, I test the model's main predictions using a novel empirical strategy. Reflecting speculators' carry trades in normal times and deleveraging in disasters, I present compelling evidence that supports the disaster risk theory of exchange rates for the 9-most traded global currencies. Further, I show that, in disasters, safety flows by hedgers towards high-liquidity-yield U.S. Treasuries pushes the dollar to appreciate regardless of its relative interest rate. This encapsulates the safe-haven status of the U.S. dollar and represents a deviation from disaster risk theory, which predicts symmetric exchange rate dynamics based on relative interest rates alone.

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Appendix I: Model Solution

As in Gabaix and Maggiori (2015) and Jiang (2021), for analytical tractability 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 $\chi_2^* = Y_{NT,2}^* + v_1\tilde{X}_2^*$.

I begin to solve the model by considering the household problem, in each country, in two stages: a static (intratemporal) stage—households choose how to split their consumption expenditure in a given period between the different types of goods; and a dynamic (intertemporal) stage—households decide on their consumption-savings decision across periods.

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 (2) - (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:

$$\eta_t = 1 \quad \text{and} \quad p_{H,t}C_{H,t} = a_t \quad \text{and} \quad p_{F,t}C_{F,t} = \iota_t \tag{49}$$

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 (2) - (4)) between the periods t and $t+1$. Solving gives the first order conditions (FOCs) below

$$\frac{\chi_t}{C_{NT,t}} = \nu_t p_{NT,t} \quad \& \quad \beta \mathbb{E}_t\Big[\frac{\chi_{t+1}}{C_{NT,t+1}}\Big] = \frac{\nu_t p_{NT,t+1}}{R} \tag{50}$$

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

$$1 = \beta R \tag{51}$$

This implies that speculators' policy function becomes:

$$q_t = \frac{1}{\Gamma}\mathbb{E}_t\Big[\varepsilon_t - \frac{R^*}{R}\varepsilon_{t+1}\Big] \tag{52}$$

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 $t \in \{1,2\}$:

$$\max_{\{C_t^*, b_{F,t}^*\}} \mathbb{E}_0[U(C_0^*, C_1^*, C_2^*)] = \theta_0^* log(C_0^*) + \beta^* \mathbb{E}_0[\theta_1^* log(C_1)] + (\beta^*)^2 \mathbb{E}_0[\theta_2^* log(C_2^*)] \tag{53}$$

$$\textit{such that} \quad Y_{NT,0}^* + p_{F,0}^* Y_{F,0}^* = C_{NT,0}^* + p_{H,0}^* C_{H,0}^* + p_{F,0}^* C_{F,0}^* + b_{F,0}^* \tag{54}$$

$$Y_{NT,1}^* + p_{F,1}^* Y_{F,1}^* + \Pi_1 = C_{NT,1}^* + p_{H,1}^* C_{H,1}^* + p_{F,1}^* C_{F,1}^* + b_{F,1}^* - R^* b_{F,0}^* \tag{55}$$

$$Y_{NT,2}^* + p_{F,2}^* Y_{F,2}^* + \Pi_2 = C_{NT,2}^* + p_{H,2}^* C_{H,2}^* + p_{F,2}^* C_{F,2}^* - R^* b_{F,1}^* \tag{56}$$

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:

$$\chi_t^* = C_{NT,t}^* \implies \eta_t^* = 1 \quad , \quad p_{F,t}^* C_{F,t}^* = a_t^* \quad , \quad p_{H,t}^* C_{H,t}^* = \xi_t \quad \& \quad 1 = \beta^* R^* \tag{57}$$

Solving the Model

Beginning with the household's budget constraints in each period (equations (2) - (4)

and (54) - (56)), substitute in the market clearing conditions for bonds (16):

$$Y_{NT,0} + p_{H,0}Y_{H,0} = C_{NT,0} + p_{H,0}C_{H,0} + p_{F,0}C_{F,0} - q_0 - w_0 \tag{58}$$

$$Y_{NT,1} + p_{H,1}Y_{H,1} = C_{NT,1} + p_{H,1}C_{H,1} + p_{F,1}C_{F,1} - q_1 - w_1 - R(-q_0 - w_0) \tag{59}$$

$$Y_{NT,2} + p_{H,2}Y_{H,2} = C_{NT,2} + p_{H,2}C_{H,2} + p_{F,2}C_{F,2} - R(-q_1 - w_1) \tag{60}$$

$$Y^*_{NT,0} + p^*_{F,0}Y^*_{F,0} = C^*_{NT,0} + p^*_{H,0}C^*_{H,0} + p^*_{F,0}C^*_{F,0} + \frac{q_0}{\varepsilon_0} \tag{61}$$

$$Y^*_{NT,1} + p^*_{F,1}Y^*_{F,1} + \Pi_1 = C^*_{NT,1} + p^*_{H,1}C^*_{H,1} + p^*_{F,1}C^*_{F,1} + \frac{q_1}{\varepsilon_1} - R^*\frac{q_0}{\varepsilon_0} \tag{62}$$

$$Y^*_{NT,2} + p^*_{F,2}Y^*_{F,2} + \Pi_2 = C^*_{NT,2} + p^*_{H,2}C^*_{H,2} + p^*_{F,2}C^*_{F,2} - R^*\frac{q_1}{\varepsilon_1} \tag{63}$$

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

Next, substitute in the market clearing conditions for NT goods ((18) and (19)):

$$p_{H,0}Y_{H,0} = p_{H,0}C_{H,0} + p_{F,0}C_{F,0} - q_0 - w_0 \tag{64}$$

$$p_{H,1}Y_{H,1} = p_{H,1}C_{H,1} + p_{F,1}C_{F,1} - q_1 - w_1 - R(-q_0 - w_0) \tag{65}$$

$$p_{H,2}Y_{H,2} = p_{H,2}C_{H,2} + p_{F,2}C_{F,2} - R(-q_1 - w_1) \tag{66}$$

$$p^*_{F,0}Y^*_{F,0} = (1 - v_0)X^*_0 + p^*_{H,0}C^*_{H,0} + p^*_{F,0}C^*_{F,0} + \frac{q_0}{\varepsilon_0} \tag{67}$$

$$p^*_{F,1}Y^*_{F,1} + \Pi_1 = (1 - v_1)X^*_1 + v_0\tilde{X}^*_1 + p^*_{H,1}C^*_{H,1} + p^*_{F,1}C^*_{F,1} + \frac{q_1}{\varepsilon_1} - R^*\frac{q_0}{\varepsilon_0} \tag{68}$$

$$p^*_{F,2}Y^*_{F,2} + \Pi_2 = v_1\tilde{X}^*_2 + p^*_{H,2}C^*_{H,2} + p^*_{F,2}C^*_{F,2} - R^*\frac{q_1}{\varepsilon_1} \tag{69}$$

Next, plug in the market clearing for T goods (20), household FOCs (49) and (57), and the law of one price. Then, the t = 0 conditions (equations (64) and (67)) can each be reduced to:[33]

$$\varepsilon_0\xi_0 - \iota_0 = -q_0 - w_0 \tag{70}$$

The t = 1 conditions (equations (65) and (68)) can each be reduced to:[34]

$$\varepsilon_1\xi_1 - \iota_1 = -q_1 - w_1 + R(q_0 + w_0) \tag{71}$$

[33] since $(1 - v_0)X^*_0 = \frac{w_0}{\varepsilon_0}$ in (67)

[34] substitute the definition of Π_1 into (68)

And the t = 2 conditions (equations (66) and (69)) can each be reduced to:[35]

$$\varepsilon_2\xi_2 - \iota_2 = R(q_1 + w_1) \tag{72}$$

Following Gabaix and Maggiori (2015), I make two additional simplifications that streamline the analysis, but do not change the underlying economics. First, I assume that the currency speculators intermediate and currency 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' stocks of bonds in t = 1 arising from t = 0 flows are held passively until period t = 2.[36] This accounting exercise implies that households can be thought of as long term investors. This adjusts the t = 1 flow demand equation (71) to $\varepsilon_1\xi_1 - \iota_1 = -q_1 - w_1$ and the t = 2 flow demand equation (72) 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 (72) becomes $T(\varepsilon_2\xi_2 - \iota_2) = R(q_1 + w_1) + R^2(q_0 + w_0)$.[37] 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 $T \to \infty$, we can now write the USD bond flow demand equations in each period as:

$$\varepsilon_0\xi_0 - \iota_0 = -q_0 - w_0 \quad \varepsilon_1\xi_1 - \iota_1 = -q_1 - w_1 \quad \varepsilon_2\xi_2 = \iota_2 \tag{73}$$

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

Appendix II: Model Proofs

Proposition 1 Proof:

First, let $\frac{\partial \kappa_1}{\partial \Gamma_1} \to 0$ such that the indirect effect in (26) tends to 0 as well.[38] Thus, the $\frac{\partial \varepsilon_1}{\partial \Gamma_1}$

[35] substitute the definition of Π_2 into (69)

[36] As a result, financial sector profits at t = 1, Π_1, are not channelled to households until t = 2

[37] 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.

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

term in (29) is now composed only of the direct effect. Notice that the second term in (29), $\frac{1}{\Gamma_1}\frac{\partial \varepsilon_1}{\partial \Gamma_1}$, is proportional to $\frac{1}{\Gamma_1^3}$ while the first term in (29) 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 (28) $q_1 > 0$ and by (29) $\frac{\partial q_1}{\partial \Gamma_1} < 0$. Similarly, if the foreign interest rate is sufficiently high, $R < R^* \frac{\mathbb{E}_t[\varepsilon_2]}{\varepsilon_1}$, then by (28) $q_1 < 0$ and by (29) $\frac{\partial q_1}{\partial \Gamma_1} > 0$. ■

Proposition 2 Proof:

Assume that $R > R^* \frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t}$. By (28), this implies that $q_t > 0$, which, by market clearing (20) 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 $R < R^* \frac{\mathbb{E}_t[\varepsilon_{t+1}]}{\varepsilon_t}$. ■

Prediction 1 Proof:

Under assumption 1, we have that $R_0^* > R_0 \implies q_0 > 0$. By (28), since $\Gamma_0 = \Gamma_L > 0$ we have that $R_0^* > R_0 \implies \mathbb{E}_0\left[R_0^* \frac{\varepsilon_1}{\varepsilon_0} - R_0\right] > 0$, 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. ■[39]

Prediction 2 Proof:

In (23), (24) and (25) 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 (24) and (25), 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 (24) with $\Gamma_1 = \Gamma_H$.[40] ε_0 is as defined in (29) 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

[39] The second claim of Prediction 1 is proved in Prediction 2's proof, see below.

[40] I also can define ε_1^{ND} as the t = 1 exchange rate as defined in (24) with $\Gamma_1 = \Gamma_L$, which will be useful to prove the second implication of Prediction 1.

currency hedgers, whose impact will be taken into account in prediction 3.

Thus, prediction 2 can be rewritten as $R^* > R \implies \frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} < 1$. The second inequality can be rewritten as:

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

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

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

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.

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 implication in prediction 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* $\Gamma_L = 0.1$ *and consider two cases, both of which satisfy* $A(\Gamma_L, \Gamma_H, \eta) < 0$*:*

Case 1: $\frac{R^*}{R} = \frac{1.06}{1.01}$*, a* 5% *interest rate differential. In this case,* $\frac{\varepsilon_1^D}{\varepsilon_0} = 0.93$*, indicating a* 7% *disaster state depreciation. The maps to a* $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} = 0.98$*, a* 2% *loss on the carry trade. For context, these losses dwarf the expected carry trade profits conditional on no-disaster:* $\frac{\varepsilon_1^{ND}}{\varepsilon_0}\frac{R^*}{R} = 1.008$*, a* 0.8% *profit on the carry trade. These disaster-state losses are driven by the endogenous unwinding of speculators long positions in the high-interest-rate foreign currency:* $q_0 = -0.035$ *and* $q_1^D = -0.0066$*, using* $\iota = 0.5$

Case 2: $\frac{R^*}{R} = \frac{1.02}{1.01}$*, a* 1% *interest rate differential. In this case,* $\frac{\varepsilon_1^D}{\varepsilon_0} = 0.985$*, indicating a* 1.5% *disaster state depreciation. The maps to a* $\frac{\varepsilon_1^D}{\varepsilon_0}\frac{R^*}{R} = 0.995$*, a* 0.5% *loss on the carry trade. For context, these losses dwarf the expected carry trade profits conditional on no-disaster:* $\frac{\varepsilon_1^{ND}}{\varepsilon_0}\frac{R^*}{R} = 1.002$*, a* 0.2% *profit on the carry trade. These disaster-state losses are driven by the endogenous unwinding of speculators long positions in the high-interest-rate foreign currency:* $q_0 = -0.009$ *and* $q_1^D = -0.0017$*, using* $\iota = 0.5$

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 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 3 Proof:

The first claim follows immediately from the hedgers' indirect effect in (26), noticing that only $\mathbb{E}_0[\varepsilon_1 | \ \Gamma_1 = \Gamma_H \ ] \equiv \varepsilon_1^D$ depends on λ_1. With $\lambda_0 \to 0$, by (14) we have $\kappa_0 \to 0$ such that hedgers don't hold USD except in disaster states. As a result, prediction 2 holds except for the effect of hedgers demand for USD in disasters, captured by the effect of the spike in $\lambda_1 = \lambda_H > 0$. Thus, since prediction 2 stipulates that carry trades that are long the high-interest-rate currency make large losses in disasters due to the severe depreciation of the high-interest-rate currency while the first claim in prediction 3 highlights that the USD is pressured to appreciate by the spike in the liquidity yield, these effects are reinforcing when the USD is the low-interest-rate funding currency but offsetting when the USD is the high-interest-rate investment currency for the carry trade. This implies claim 2 of prediction 3. ■

Appendix III: Data Sources and Summary Statistics

Table 0: Data Sources

Data	Government Bond Interest Rates	Exchange Rates	Liquidity Yields	Speculator and Hedger Positions	VIX (Robustness)
Source	Global Financial Data	Global Financial Data	Du et al. (2018)	Commodity Futures Trading Commission	Chicago Board of Exchange
Sample Period	1986:M1 - 2020:M12 (balanced)	1986:M1 - 2020:M12 (balanced)	1991:M4 - 2019:M12 (unbalanced)	1993:M1 - 2020:M12 (balanced)	1990:M1 - 2020:M12 (balanced)

Figure 10: All data correspond to end-of-month figures. Speculator and Hedger Futures Positions data available only for AUD, CAD, CHF, EUR, GBP, JPY relative to USD. The liquidity yield data from Du et al. (2018) is unbalanced: AUD and GBP start 1991:M4, CAD starts 1991:M6, NZD starts 1992:M3, JPY starts 1992:M9, CHF and SEK start 1994:M2, and EUR starts 1998:M12.

Table 1.1: U.S. Dollar Base Summary Statistics

	JPY	CHF	EUR	CAD	SEK	GBP	AUD	NZD
	Panel A: Mean							
$i^* - i$	-0.004	-0.002	0.000	0.002	0.003	0.004	0.007	0.008
Δe	0.001	0.004	0.001	0.000	-0.001	-0.001	0.000	0.002
z	-0.003	0.001	0.001	0.003	0.002	0.003	0.007	0.010
Spec_Pos	-0.104	-0.083	0.001	0.012	-	-0.025	0.097	-
Hedge_Pos	0.160	0.120	-0.029	-0.111	-	0.016	-0.156	-
λ	35.449	36.224	23.472	24.610	19.803	10.581	16.269	-9.003
	Panel B: Skewness							
Δe	0.284	0.002	-0.309	-0.102	-0.962	-0.822	-0.833	-0.298
z	0.230	0.004	-0.196	-0.155	-0.737	-0.615	-0.726	-0.202
Spec_Pos	0.281	0.215	-0.217	0.084	-	0.321	-0.113	-
Hedge_Pos	-0.224	-0.359	0.190	0.039	-	-0.297	0.231	-
λ	6.524	2.655	6.002	1.493	1.294	1.412	1.057	-2.283

Figure 11: USD Base Summary Statistics: Mean (Panel A) and Skewness (Panel B)

Appendix IV: Regression Tables

Table 2.1: Regression Coefficients from Quantile UIP Regressions (Figure 4)

Domestic Currency	JPY		USD		AUD	
Foreign Currency (*)	*AUD*	*USD*	*JPY*	*AUD*	*JPY*	*USD*
Quantiles (τ)	β_1^{τ} *for* $i_t^* - i_t$					
0.005	-19.32***	-7.44***	2.56	-9.28**	-4.04	-3.04
	(5.72)	(2.32)	(1.96)	(4.64)	(3.52)	(3.04)
0.5	0.28	2.72***	2.72***	1.40***	0.28	1.40***
	(0.60)	(0.64)	(0.64)	(0.36)	(0.60)	(0.36)
0.995	-4.04	2.56	-7.44***	-3.04	-19.32***	-9.28**
	(3.52)	(1.96)	(2.32)	(3.04)	(5.72)	(4.64)

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Sample Size: T = 420

Table 2.2: Regression Coefficients from Signed Quantile UIP Regressions (Figure 5)

Domestic Currency	JPY		USD		AUD	
Foreign Currency (*)	*AUD*	*USD*	*JPY*	*AUD*	*JPY*	*USD*
Quantiles (τ)	β_1^{τ} *for* $(i_t^* - i_t) \times \mathit{sign}(i_t^* - i_t)$					
0.005	-19.32***	-7.44***	-7.44***	-12.96***	-19.32***	-12.96***
	(5.72)	(2.56)	(2.56)	(4.92)	(5.72)	(4.92)
0.5	0.28	3.12***	3.12***	0.52	0.28	0.52
	(0.60)	(0.64)	(0.64)	(0.52)	(0.60)	(0.52)
0.995	-4.04	2.56	2.56	-3.04	-4.04	-3.04
	(3.52)	(2.44)	(2.44)	(2.88)	(3.52)	(2.88)

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Sample Size: T = 420

Table 3.1: AUD Panel Signed Quantile UIP Regression (Figure 6)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	-11.02***	1.06	0.28
0.01	-9.42***	0.40	0.21
0.025	-7.23***	0.43	0.11
0.05	-3.52***	0.67	0.06
0.1	-1.76***	0.26	0.04
0.3	-0.18	0.33	0.01
0.5	0.20	0.14	0.00
0.7	0.36**	0.16	0.01
0.9	0.88**	0.44	0.02
0.95	0.87	0.64	0.03
0.975	1.30**	0.52	0.05
0.99	2.18***	0.48	0.07
0.995	0.90	0.44	0.11

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*
Sample Size $(T \times n)$: 3357

Table 3.2: JPY Panel Signed Quantile UIP Regression (Figure 6)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	-13.94***	2.69	0.14
0.01	-9.77***	1.49	0.11
0.025	-5.40***	0.58	0.07
0.05	-3.90***	0.50	0.04
0.1	-2.22***	0.44	0.01
0.3	0.27	0.37	0.00
0.5	0.56	0.52	0.00
0.7	0.23	0.35	0.00
0.9	0.50	0.31	0.01
0.95	0.74	0.47	0.01
0.975	0.92	0.57	0.01
0.99	2.00**	0.87	0.04
0.995	2.54***	0.54	0.08

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*
Sample Size $(T \times n)$: 3357

Table 3.3: USD Panel Signed Quantile UIP Regression (Figure 6)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	-9.38***	1.62	0.21
0.01	-7.86***	1.38	0.14
0.025	-5.94***	0.61	0.07
0.05	-3.25***	0.58	0.04
0.1	-1.67***	0.62	0.03
0.3	0.27	0.43	0.01
0.5	0.69**	0.29	0.01
0.7	0.84***	0.29	0.01
0.9	0.72	0.61	0.03
0.95	0.80	0.90	0.02
0.975	0.68	0.69	0.02
0.99	0.49	0.90	0.03
0.995	1.45	1.71	0.03

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Sample Size ($T \times n$) : 3357

Table 3.4: GBP Panel Signed Quantile UIP Regression (Figure 6)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	-9.17***	2.15	0.19
0.01	-7.80***	1.93	0.13
0.025	-4.28***	1.10	0.07
0.05	-3.11***	0.82	0.05
0.1	-1.10*	0.56	0.02
0.3	0.16	0.29	0.00
0.5	0.23	0.23	0.00
0.7	0.54*	0.33	0.01
0.9	1.28**	0.58	0.03
0.95	1.66**	0.71	0.04
0.975	0.95**	0.48	0.05
0.99	0.97***	0.35	0.05
0.995	1.51***	0.44	0.04

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Sample Size ($T \times n$) : 3357

Table 3.5: EUR Panel Signed Quantile UIP Regression (Figure 6)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo* R^2
Quantiles	Coefficient	Standard Error	
0.005	-6.60***	0.74	0.19
0.01	-6.46***	0.66	0.12
0.025	-4.02***	0.45	0.09
0.05	-2.70***	0.65	0.08
0.1	-1.75***	0.54	0.06
0.3	-0.60***	0.18	0.01
0.5	-0.05	0.13	0.00
0.7	0.24	0.17	0.03
0.9	0.76***	0.27	0.07
0.95	0.92***	0.23	0.09
0.975	1.26	0.84	0.11
0.99	2.04	1.32	0.14
0.995	2.08***	0.79	0.15

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*
Sample Size $(T \times n)$: 3336

Table 3.6: SEK Panel Signed Quantile UIP Regression (Figure 6)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo* R^2
Quantiles	Coefficient	Standard Error	
0.005	-7.27***	0.61	0.34
0.01	-7.62***	0.98	0.30
0.025	-6.77***	0.77	0.21
0.05	-6.16***	1.00	0.14
0.1	-3.28***	0.83	0.06
0.3	-0.68**	0.26	0.01
0.5	-0.13	0.27	0.01
0.7	0.15	0.35	0.02
0.9	0.67	0.37	0.05
0.95	0.94**	0.46	0.07
0.975	1.00*	0.54	0.09
0.99	0.88	0.68	0.11
0.995	1.30	1.13	0.16

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*
Sample Size $(T \times n)$: 3357

Table 3.7: NZD Panel Signed Quantile UIP Regression (Figure 6)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	-6.69***	0.62	0.28
0.01	-6.52***	0.63	0.21
0.025	-5.12***	0.76	0.13
0.05	-3.71***	0.46	0.10
0.1	-2.52***	0.21	0.05
0.3	-0.46***	0.16	0.01
0.5	0.06	0.13	0.00
0.7	0.21*	0.12	0.01
0.9	0.49**	0.22	0.02
0.95	0.48***	0.16	0.02
0.975	0.42	0.28	0.03
0.99	-0.31	0.24	0.04
0.995	-0.51***	0.14	0.08

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Sample Size ($T \times n$) : 3357

Table 3.8: CAD Panel Signed Quantile UIP Regression (Figure 6)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	-7.02***	1.11	0.19
0.01	-6.69***	1.23	0.13
0.025	-5.68***	1.10	0.09
0.05	-3.37**	1.40	0.05
0.1	-1.60*	0.84	0.03
0.3	-0.19	0.41	0.01
0.5	0.54***	0.21	0.00
0.7	0.75**	0.31	0.01
0.9	1.40***	0.43	0.02
0.95	2.21***	0.76	0.04
0.975	1.94**	0.75	0.04
0.99	1.96**	0.99	0.06
0.995	1.63	1.07	0.10

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Sample Size ($T \times n$) : 3357

Table 3.9: CHF Panel Signed Quantile UIP Regression (Figure 6)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	-6.26***	1.06	0.12
0.01	-2.29***	1.20	0.07
0.025	-2.03***	0.34	0.06
0.05	-2.05***	0.74	0.05
0.1	-1.14	0.80	0.04
0.3	0.04	0.22	0.01
0.5	0.44***	0.14	0.00
0.7	0.77***	0.21	0.02
0.9	1.17***	0.36	0.07
0.95	0.94**	0.43	0.09
0.975	1.34***	0.50	0.11
0.99	1.32	1.33	0.13
0.995	0.9	1.45	0.14

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Sample Size $(T \times n)$: 3357

Table 4.1: USD Panel Quantile Spec_Pos Regression (Figure 7)

Dependent Variable: $Spec\_Pos_t$	$i_t^* - i_t$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	0.64	1.59	0.10
0.01	3.68	3.47	0.06
0.025	6.08	5.47	0.04
0.05	7.35*	4.32	0.03
0.1	5.07	4.19	0.04
0.3	13.99**	6.04	0.06
0.5	24.92***	6.52	0.08
0.7	26.40***	6.88	0.08
0.9	10.08*	5.47	0.07
0.95	1.56	5.90	0.07
0.975	-2.36	4.97	0.08
0.99	-3.02	3.38	0.11
0.995	-3.96**	1.55	0.15

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Sample Size $(T \times n)$: 2016

Table 4.2: USD Panel Signed Quantile ΔSpec_Pos Regression (Figure 7)

Dependent Variable: $\Delta Spec\_Pos_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	-17.34***	2.12	0.05
0.01	-13.08***	2.74	0.04
0.025	0.35	3.56	0.02
0.05	0.57	3.38	0.02
0.1	-3.54	4.98	0.01
0.3	-2.34	1.78	0.00
0.5	2.02	2.50	0.00
0.7	2.77***	0.86	0.01
0.9	0.66	2.38	0.02
0.95	9.73***	2.94	0.04
0.975	3.84**	1.90	0.05
0.99	-7.00**	3.52	0.05
0.995	-9.41	8.26	0.06

*Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Sample Size $(T \times n)$: 2010

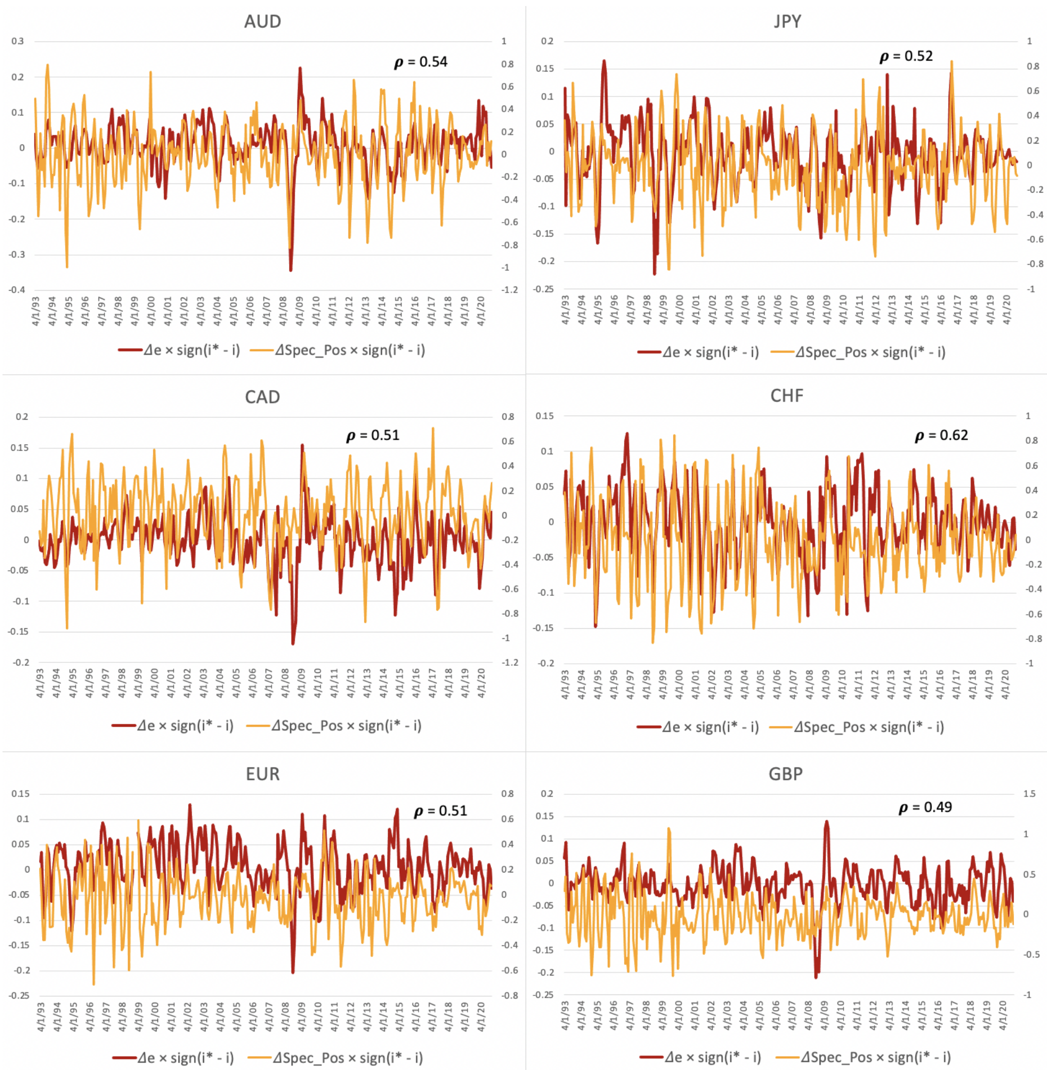

Figure 12: Additional Material for Figure 7: Time series of $\Delta e_{j,t+1} \times sign(i^*_{j,t} - i^{USD}_t)$ in red and $\Delta Spec\_Pos_{j,t+1} \times sign(i^*_{j,t} - i^{USD}_t)$ in yellow for j $\in$ {AUD, JPY, CAD, CHF, EUR, GBP} from 1993:M4 to 2020:M12. ρ refers to the correlation coefficient between the two series.

Table 5.1: USD Liquidity Yield-Augmented Panel Signed Quantile UIP Regression (Figure 8)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		$\lambda_{t+1} \times sign(i_t^* - i_t)$		*Pseudo* R^2
Quantiles	Coefficient	Standard Error	Coefficient	Standard Error	
0.005	-11.71***	2.76	-3.16***	1.14	0.28
0.01	-9.70***	2.04	-3.39***	0.39	0.19
0.025	-6.14*	3.36	-2.79***	0.48	0.10
0.05	-4.29***	0.97	-2.22***	0.45	0.06
0.1	-1.52	1.74	-1.52***	0.25	0.03
0.3	0.56	0.65	-0.28	0.27	0.01
0.5	0.79	0.75	0.10	0.19	0.01
0.7	0.99*	0.53	0.47*	0.25	0.02
0.9	0.92	0.81	0.85	0.53	0.03
0.95	1.31	0.65	1.38***	0.28	0.03
0.975	0.64	0.69	1.63***	0.29	0.04
0.99	-0.13	1.28	1.75*	0.96	0.05
0.995	-0.41	3.37	3.02***	0.30	0.06

Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sample Size $(T \times n)$ *: 2567*

Table 5.2: USD Liquidity-Yield-Instrumented by VIX Panel Signed IV Quantile UIP Regression (Additional Regression for Figure 8)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign\,(i_t^* - i_t)$		$\lambda_{t+1}(VIX) \times sign\,(i_t^* - i_t)$	
Quantiles	Coefficient	Standard Error	Coefficient	Standard Error
0.005	-5.38***	1.18	-5.82***	1.25
0.01	-4.11***	0.91	-4.58***	0.95
0.025	-3.26***	0.72	-3.77***	0.75
0.05	-2.58***	0.60	-3.11***	0.64
0.1	-1.92*	0.51	-2.47**	0.56
0.3	-0.62	0.36	-1.22	0.53
0.5	0.04	0.32	-0.58	0.58
0.7	0.68**	0.32	0.03	0.65
0.9	1.73***	0.41	1.05	0.83
0.95	2.26***	0.48	1.56	0.93
0.975	2.67***	0.53	1.96*	1.01
0.99	3.47***	0.66	2.73**	1.19
0.995	3.92***	0.75	3.16**	1.30

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Sample Size (T × n) : 2567

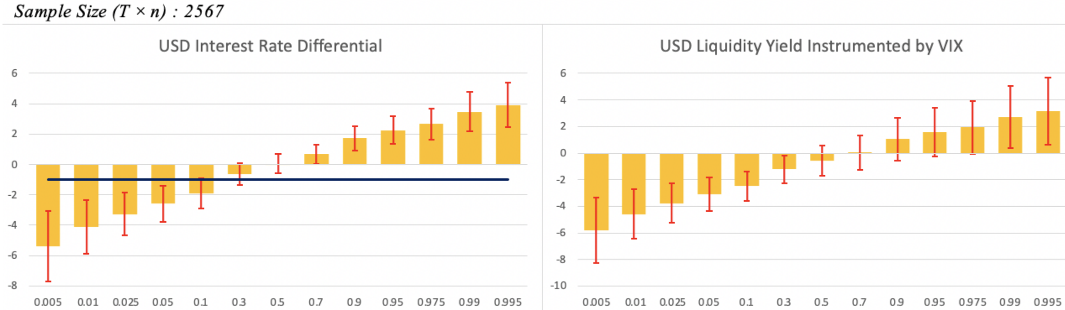

Figure 13: Additional Regression for Figure 8: Estimates (47) using Panel IV Quantile Regression, where the VIX serves as the instrument for the dollar liquidity yield.

Table 5.3: USD VIX-Augmented Panel Signed Quantile UIP Regression (Additional Regression for Figure 8)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign(i_t^* - i_t)$		$VIX_{t+1} \times sign(i_t^* - i_t)$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	Coefficient	Standard Error	
0.005	-8.28***	2.48	-12.08***	3.60	0.30
0.01	-7.26***	2.33	-11.30***	2.91	0.22
0.025	-6.10***	1.48	-8.69***	2.05	0.12
0.05	-3.51***	0.59	-7.08***	1.92	0.07
0.1	-1.65*	0.92	-5.22***	1.62	0.04
0.3	0.17	0.48	-2.47**	1.13	0.01
0.5	0.30	0.51	-1.29	1.29	0.01
0.7	0.53	0.56	0.62	1.02	0.01
0.9	0.81	0.70	1.11	1.11	0.03
0.95	1.11	0.85	1.65	1.27	0.03
0.975	0.98	0.76	3.66***	1.10	0.03
0.99	0.56	1.09	4.25**	1.97	0.04
0.995	0.52	1.21	5.79***	1.27	0.06

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Sample Size (T × n) : 2917

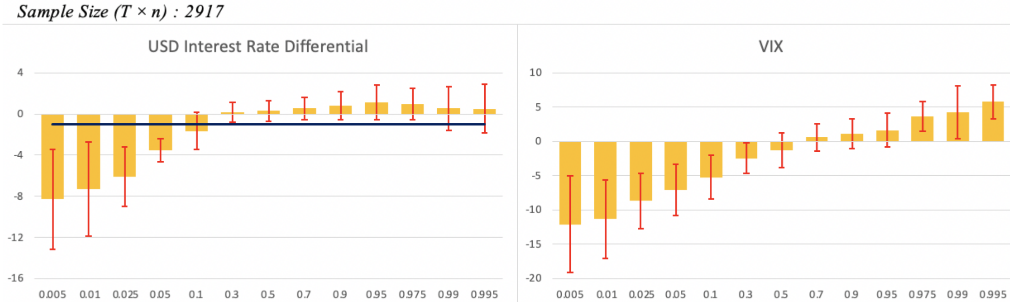

Figure 14: Additional Regression for Figure 8: Estimates (47) with the VIX index proxying for the dollar liquidity yield.

Table 6.1: USD Panel Quantile ΔHedge_Pos Regression (Figure 9)

Dependent Variable: $\Delta Hedge\_Pos_{t+1}$	$\tilde{\lambda}_{t+1}$		*Pseudo R^2*
Quantiles	Coefficient	Standard Error	
0.005	-31.99***	12.25	0.14
0.01	-27.05**	11.80	0.10
0.025	-9.92	10.49	0.07
0.05	-0.39	6.89	0.06
0.1	1.22	1.60	0.03
0.3	-3.89	4.05	0.00
0.5	1.62	5.74	0.00
0.7	-1.32	3.80	0.01
0.9	-1.48	5.56	0.03
0.95	-3.92	5.14	0.05
0.975	0.74	4.92	0.07
0.99	10.65	17.68	0.07
0.995	21.13	19.87	0.08

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Sample Size ($T \times n$) : 1854

Table 6.2: USD Interest Differential-Augmented Panel Signed Quantile ΔHedge_Pos Regression (Additional Regression for Figure 9)

Dependent Variable: ΔHedge_Pos $_{t+1}$ × *sign*(i_t^* - i_t)	$[i_t^* - i_t]$ × *sign* (i_t^* - i_t)		λ_{t+1} × *sign* (i_t^* - i_t)		*Pseudo* R^2
Quantiles	Coefficient	Standard Error	Coefficient	Standard Error	
0.005	9.00	8.19	-14.72	8.83	0.14
0.01	11.04	7.60	-2.94	8.12	0.11
0.025	-4.25	9.04	-5.58	8.48	0.09
0.05	-1.96	8.39	0.91	6.73	0.06
0.1	3.64	6.58	1.63	5.14	0.04
0.3	0.88	2.99	2.72	2.89	0.01
0.5	0.49	1.87	1.47	2.24	0.00
0.7	-0.39	2.32	-1.81	2.64	0.00
0.9	3.06	8.15	-0.71	2.67	0.02
0.95	-1.00	4.41	1.20	8.08	0.04
0.975	-2.27	5.05	1.87	4.51	0.06
0.99	10.41	17.53	3.06	18.48	0.07
0.995	18.04***	6.37	10.64***	1.49	0.09

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*
Sample Size (T × n) : 1854

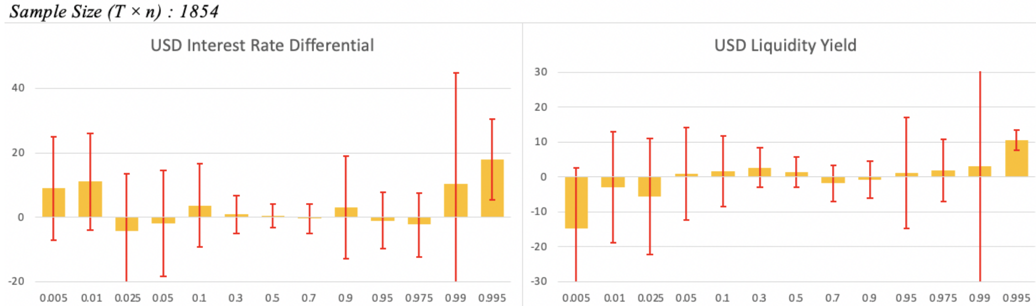

Figure 15: Additional Regression for Figure 9: Estimates an interest rate differential-augmented version of (48). The results highlight that hedgers flight to dollar liquidity (Panel B) occurs in the same periods as they accommodate speculators carry trade unwinding (Panel A), as the effects are in the same (right) tail.

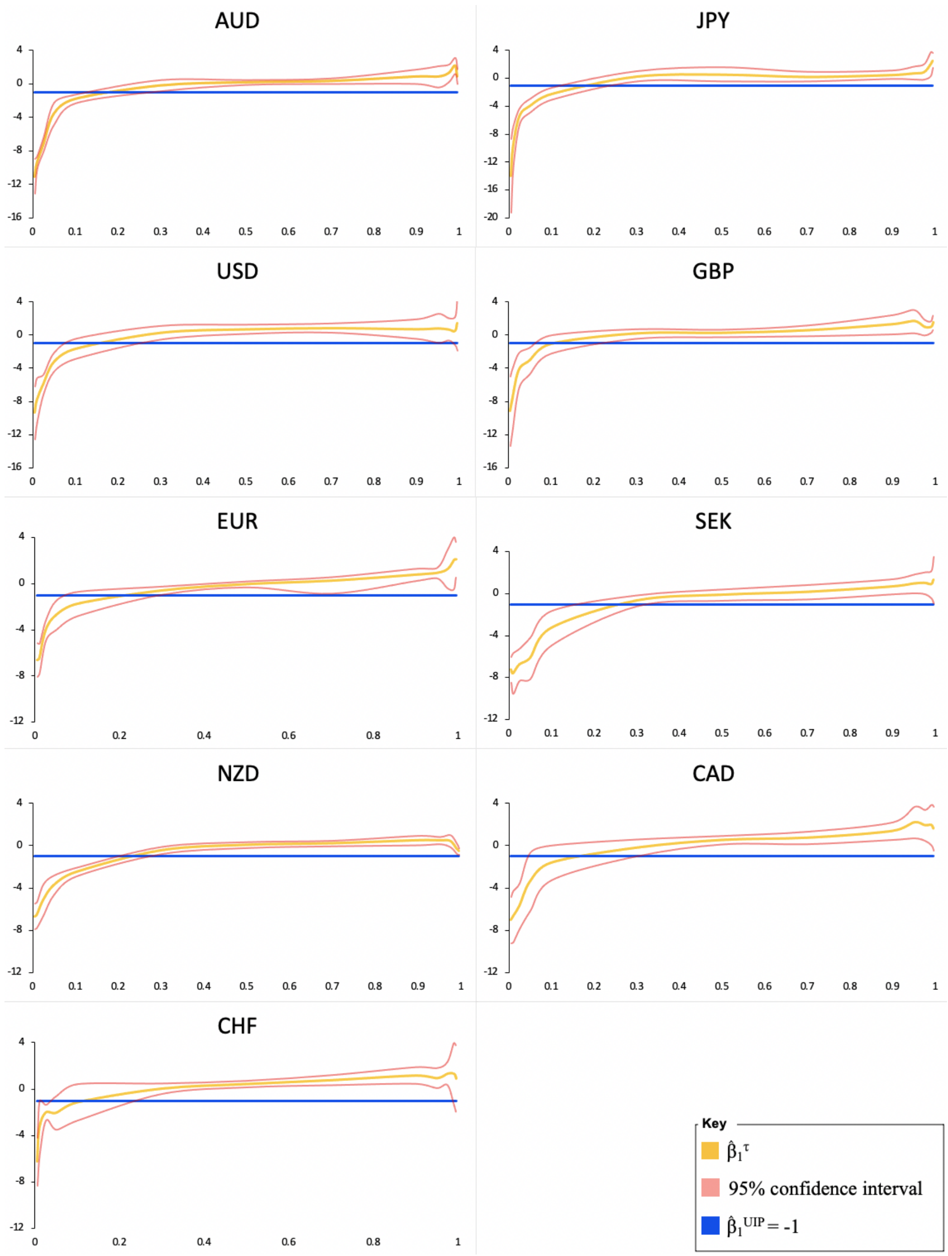

Figure 16: Instead of placing the unevenly spaced quantiles evenly along the x-axis of each panel, as in Figure 6, this chart spaces the quantiles in proportion to their values. The yellow line corresponds to the marginal effects (which are smoothed between the quantiles I estimate: $\tau = \{0.005,\ 0.01,\ 0.025,\ 0.05,\ 0.1,\ 0.3,\ 0.5,\ 0.7,\ 0.9,\ 0.95,\ 0.975,\ 0.99,\ 0.995\}$). The red lines correspond to the same 95% confidence intervals from Figure 6, but are again smoothed between quantiles. And the blue horizontal line at -1 corresponds to the marginal effect for which UIP holds.

Appendix V: Excluding the Global Financial Crisis

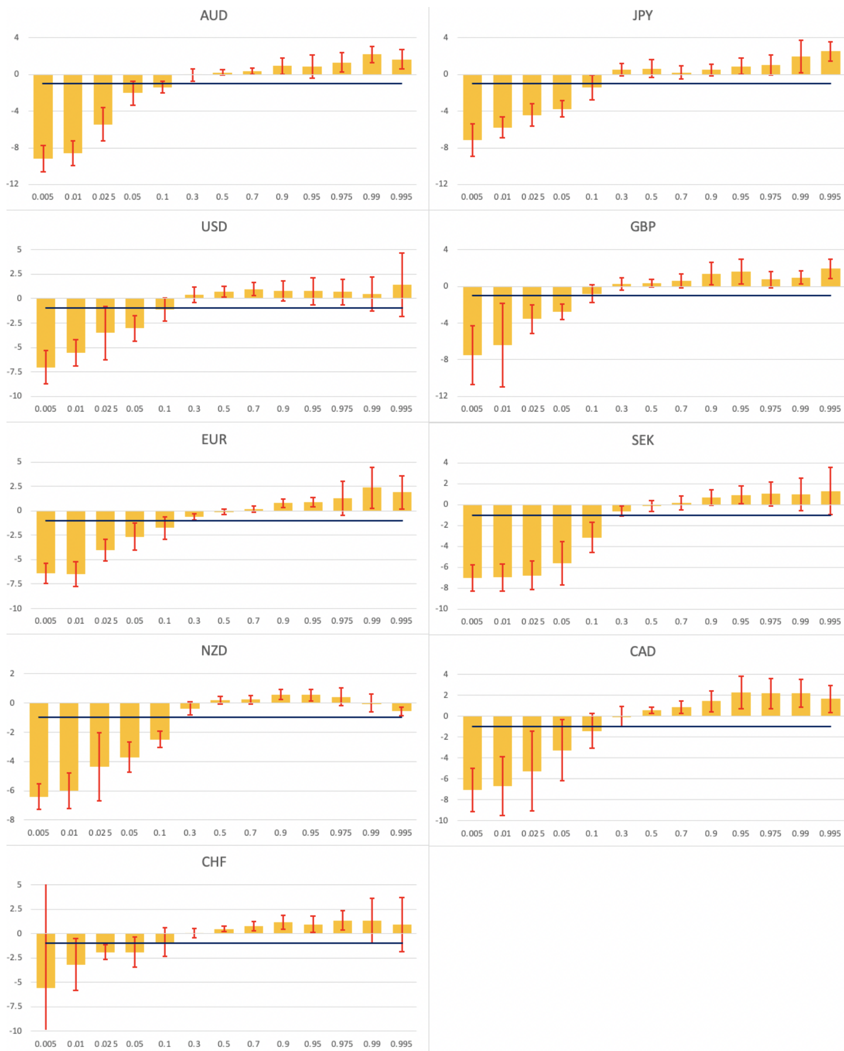

Figure 17: Additional Regression for Figure 6: Re-estimating the signed quantile UIP regression for each currency excluding the 2008 Global Financial Crisis, which I define as 2008:M1 to 2008:M12.

Table 5.4: USD Liquidity Yield-Augmented Panel Signed Quantile UIP Regression, Excluding Liquidity Yield Spike 2008:M9 (Robustness for Figure 8)

Dependent Variable: $\Delta e_{t+1} \times sign(i_t^* - i_t)$	$[i_t^* - i_t] \times sign\ (i_t^* - i_t)$		$\lambda_{t+1} \times sign\ (i_t^* - i_t)$	
Quantiles	Coefficient	Standard Error	Coefficient	Standard Error
0.005	-11.71***	2.78	-3.16***	1.16
0.01	-10.08***	2.11	-3.56***	0.38
0.025	-6.08*	3.50	-2.86***	0.53
0.05	-4.18***	1.13	-2.09***	0.57
0.1	-0.99	1.25	-1.00**	0.42
0.3	0.56	0.64	-0.00	0.42
0.5	0.88	0.72	0.34	0.26
0.7	1.10**	0.52	0.62**	0.27
0.9	0.97	0.80	0.87*	0.49
0.95	1.31	0.65	1.38***	0.28
0.975	0.64	0.69	1.63***	0.29
0.99	-0.14	1.28	1.75*	0.98
0.995	-0.41	3.36	3.02***	0.30

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Sample Size (T × n) : 2559

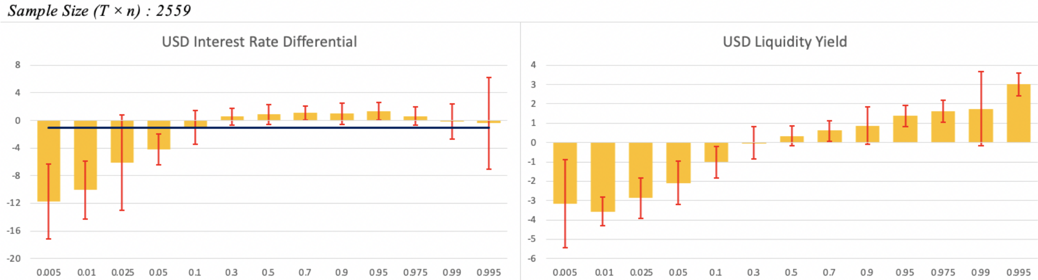

Figure 18: Additional Regression for Figure 8: Re-estimating the liquidity-yield-augmented signed quantile UIP regression excluding the largest spike in the dollar liquidity yield, which occured in 2008:M9.