Essays on International Finance and Macroeconomics

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DISSERTATION ACCEPTANCE CERTIFICATE

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A dissertation presented

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Abstract

This dissertation is composed of three essays on international macroeconomics and finance. The essays center on the interrelationship between asset prices, risk premia, and financial purchases. The first documents a stark change in correlation between exchange rates and equity market returns at the start of the Great Recession, and proposes the zero lower bound as a cause of the break. The second examines the markups paid by the Federal Reserve for the intermediation of large-scale Treasury Bond purchases during the four iterations of Quantitative Easing over the last decade. The third demonstrates that U.S. purchases of foreign bonds began to strongly comove with the US dollar from 2007.

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To my parents, Garry and Maha, and to my wife Giselle.

Introduction

This dissertation is composed of three essays on international macroeconomics and finance. The essays center on the interrelationship between asset prices, risk premia, and financial purchases.

The first chapter, coauthored with Gianluca Rinaldi, documents that the relationship between currencies and risk premia has changed dramatically since the financial crisis. While exchange rates had no strong relationship with risk premia in the first three decades after Bretton Woods, the covariance of exchange rates with equity returns increased sharply in magnitude after the Great Recession. We show that this change is consistent with a decrease in the responsiveness of interest rate spreads to risk premia after the crisis. This development is particularly important given the role of the nominal exchange rate in determining international purchasing power and relative wealth, and the constraints for monetary policy to counteract movements in global risk premia at the zero lower bound.

The second chapter, coauthored with Gianluca Rinaldi, measures the cost of implementing permanent open monetary operations in the United States. Large Scale Asset Purchases have become a permanent fixture of monetary policy, with over four trillion purchases of Treasury bonds completed in the last decade. In this paper, we provide an estimate for the cost of these transactions, and show that it increased starkly in 2020. We analyze the factors which drive the costs paid for intermediation, and provide guidance on minimizing the markups charged for intermediating these purchases.

The third chapter is coauthored with Matteo Maggiori, Brent Neiman, and Jesse Schreger. We demonstrate that U.S. purchases of foreign bonds, which did not co-move with exchange rates prior to the Great Recession, have provided significant explanatory power for currencies since then. We show that several proxies for global risk factors also start to co-move strongly with the dollar and with U.S. purchases of foreign bonds around 2007, suggesting that risk plays a key role in this finding. We use security-level data on U.S. portfolios to demonstrate that the reconnect of U.S. foreign bond purchases to exchange rates is largely driven by investment in dollar-denominated assets rather than by foreign currency exposure alone. Our results support an emerging narrative that the US dollar's role as an international and safe-haven currency has surged since the global financial crisis.

Chapter 1

Currency Betas and Interest Rate Spreads[1]

1.1 Introduction

Uncovered interest parity does not hold in the data: exchange rates do not move to offset interest rate differentials on average (Fama, 1984). This finding highlights the importance of risk premia in explaining currency returns. Yet if currencies are indeed risky, it is surprising that high return currencies did not co-move with other risky asset prices: Lustig and Verdelhan (2007) find that equity returns can only explain 4 percent of the variation in the monthly returns to a long-short portfolio of currencies sorted on their interest rate, in the 1971-2002 period. In this paper, we show that the relationship between currencies and risk premia has changed since the recent financial crisis.

Focusing on the ten most traded currencies of developed countries, we document that the covariance of exchange rates with equity returns has increased substantially. For each currency, we estimate yearly rolling regressions of its daily appreciation on the contemporaneous return on the S&P 500 index, a proxy for changes in risk premia, and find that while the conditional beta estimates are noisy and close to zero before the financial crisis, they have become persistently different from zero afterward. For instance, the average conditional beta of the Japanese yen and the Australian dollar vis-à-vis the US

[1] Co-authored with Gianluca Rinaldi

dollar are -0.24 and 0.35 respectively since 2008, but were indistinguishable from zero before. The High-Minus-Low carry factor described by Lustig *et al.* (2011a) similarly becomes strongly correlated with equity prices after 2007.

The emergence of this relationship between currency returns and risk premia is important because it opens an avenue for the resolution of the Meese and Rogoff (1983a) puzzle: that exchange rate moves are unexplainable by both macro and financial variables.[2] We show that a regression of exchange rates against the US dollar on conditional currency betas (estimated out of sample, using one year of trailing data) interacted with the contemporaneous return on the US stock market has an R-squared of 20% after the crisis, but only 1% before.

A broad literature, following Meese and Rogoff (1983a) and summarized in Rossi (2013a), has established the failure of nearly all models to deliver comparable explanatory power for exchange rates at short horizons. Recent exceptions include Kremens and Martin (2018) who find out of sample forecastability for currency appreciations from 2007 to 2017 from the pricing of S&P 500 futures in foreign currencies, and Lilley *et al.* (2019) who, in subsequent work, confirm our finding that currency returns became explainable by changes in risk attitudes after the crisis, using additional proxies for risk premia including foreign bond purchases from the United States. Gourinchas and Rey (2007) have previously shown predictability over medium term horizons using the country's net external balance.[3]

The post-crisis conditional betas reflect the risk in carry trades, though the betas measured before the crisis did not, providing a useful measure of currency risk. We show that the average post-crisis beta is strongly correlated with the returns for each currency carry trade prior to the financial crisis. Similarly, the crash risk premium priced in currency options (Farhi *et al.*, 2015) is also strongly related to post-crisis betas. This cross sectional relationship between pre-crisis currency risk proxies and post-crisis equity betas is consistent with currency riskiness being persistent, as has been suggested by Hassan and Mano (2019). Moreover, post-crisis conditional market betas are a measure of risk which

[2] This puzzle is not merely about the inability for models to make informative forecasts, but that estimating a model in-sample, and then projecting on the future realized values of the regressors, performs as well as or worse than a forecast of no change.

[3] At decade-long horizons, purchasing power parity differentials and differential inflation are related to exchange rates between developed countries. (Rogoff, 1996).

is not spanned by interest rate differentials. For instance, the US dollar has had the highest interest rate of the G10 currencies since 2018, but its conditional beta still reflects its safety.

We propose an explanation for the change in the covariance of exchange rates and equity prices based on a change in the dynamics of interest rate spreads. Consider a trade investing in a risky currency and funding the position in a safe currency. The return on this trade can be decomposed into interest rate spread and expected currency appreciation. If a central bank responds to an increase in the risk premium of its currency by increasing its interest rate, investors are compensated for holding the currency through the interest rate, and accept a relatively higher exchange rate. If instead interest rate spreads are unresponsive to risk changes, then exchange rates adjust to compensate investors through expected appreciation.

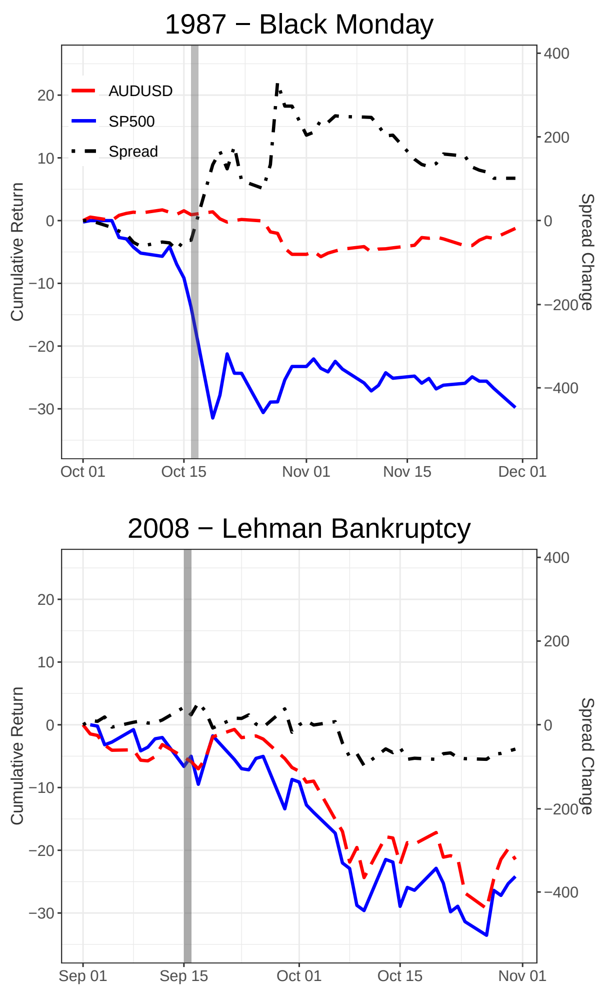
Therefore, if risk premia change with the value of the stock market, and interest rate spreads don't respond to risk premia changes, a regression of currency returns on market returns delivers non zero betas. Our explanation relies on risk premia moving together with equity returns. Standard asset pricing models, such as external habit formation (Campbell and Cochrane (1999), Verdelhan (2010)), time varying disaster risk (Barro (2006), Gabaix (2012), Wachter (2013)), or long run risk (Colacito and Croce (2011)) predict that the required compensation per unit of risk increases at the same time as equity prices decrease.

As an example, consider the changes in the Australian dollar exchange rate and interest rate spread with respect to the US dollar around the stock market crash of 1987 and Lehman's 2008 bankruptcy, reported in Figure 1.1. The stock market declined by approximately 30% in both periods, increasing the required compensation per unit of risk, and therefore the risk premia for all risky payoffs, including that of the Australian dollar carry trade.[4]

After the crash of 1987, the US central bank immediately eased monetary conditions, lowering the federal funds rate by more than 100bps over the subsequent two days, while the Australian central bank raised its policy rate by 150bps. The market expected this change to be persistent - the three month interest spread between the two currencies widened by as much as 300 basis points, while the ten

[4]Aside from the theoretical justification above, the fact that risk premia increased in those two periods is confirmed empirically by standard valuation measures (Campbell and Shiller (1988), Lettau and Ludvigson (2001)) and by more recent measures of expected returns based on option prices (Martin, 2017).

Figure 1.1: *Australian dollar exchange rate with the US dollar and interest rate spread, and the S&P 500 in two equity market crashes*



The left axes are the AUDUSD and S&P 500 cumulative returns in percentages, and the right axes measure the change in the AUD 3M - US 3M spread in basis points. The left panel reports data for two months around Black Monday 1987 and the right panel for the 2008 Lehman bankruptcy.

year spread increased by 100bps. During this panic episode, the Australian dollar did not depreciate materially, and did not move together with the S&P 500.

Conversely, central banks were not expected to respond differently to the risk premium shock after the failure of Lehman Brothers in the fall of 2008. The Federal Reserve and the Australian central bank lowered interest rates to a similar extent, so that interest rate spreads didn't move substantially, as shown in the bottom panel of Figure 1.1. At the same time, the Australian dollar suffered a dramatic depreciation of around 20% in this two month period, mirroring the return on the S&P 500 and reflecting the increase in currency betas we document in this paper.

This example is representative of interest rate spreads behavior before the financial crisis. We regress changes in the two year government bond yield spread on movements in the S&P 500, and show that in the two decades prior to the 2008 crisis, central banks of risky currencies like the Australian dollar were expected to increase their policy rates relative to the US dollar policy rate when risk premia were rising (equity prices fell). The opposite was true for central banks of safe currencies, like the Japanese yen. We also show that this has not been the case in the period after the financial crisis, in which interest rate spreads have been much less volatile. Therefore, the increase in currency betas is at least partly due to central banks being unwilling or unable to respond to changes in currency risk in the period since the financial crisis.

To quantitatively assess the importance of this change, we bring to bear a decomposition of exchange rate moves into future expected carry trade returns and expected interest rate spreads (Froot and Ramadorai, 2005). We cannot reject the null hypothesis that, notwithstanding the large change in currency equity betas, the sensitivity of carry trade expected returns to risk premia remained unchanged between the two periods.

From this perspective, the empirical failure to explain carry trade returns with measured currency equity betas is not surprising. During times in which interest spreads are unresponsive to risk premia, large currency betas will emerge and currencies will display more expected appreciation: the expected return to holding risky currencies comes through expected appreciation rather than the interest rate differential. Conversely if interest spreads adjust to absorb risk premia variation, currency betas are small.

The paper proceeds as follows: in section 2, we expound upon the emergence of the conditional betas of exchange rates, and use various out of sample tests to validate their meaningfulness; in section 3 we provide a decomposition of currency equity betas and provide evidence that the behavior of interest rate spreads has changed since the crisis. Section 4 concludes.

Relation to previous literature. This paper bridges the literature on currency risk premia with the literature on central banks' management of exchange rates. Given the widely documented failure of uncovered interest rate parity, researchers have attempted to link the returns to the carry trade to standard risk factors (Lustig and Verdelhan, 2007). A classic approach has been to sort currencies into portfolios by their interest rate level in order to capture the conditional risk within currencies. The returns on those portfolios have been linked to their CAPM beta, which showed that high interest rate currencies displayed a positive beta, but their magnitudes were too low to justify the expected returns on the carry trade.[5]

Three recent papers have related exchange rate movements to financial market measures of investor attitudes. Kremens and Martin (2018) use the forward price of the S&P 500 in foreign currency to extract the implied risk premia within each currency, and show that it forecasts the future return of the currency. These measures are available since 2007, but not beforehand. Jiang *et al.* (2018b) use the treasury basis, i.e. the excess return of currency hedged foreign government bonds (in US dollars) to US treasuries, to explain current and future movements in the dollar using changes in treasury convenience premia. Kalemli-Ozcan and Varela (2019) also link currency returns and equity risk premia, showing that future carry trade returns are higher versus the US dollar when investor risk aversion is high, as proxied by the level of the VIX.

Another strand of literature following Lustig *et al.* (2011a) demonstrates that a high share of cross-sectional variation in total currency returns can be explained by one or few common exchange rate factors, though these factors had a low correlation with other measures of risk premia. We also contribute to the literature on foreign exchange stability as an objective of monetary policy, broadly reviewed in Ilzetzki *et al.* (2019). In particular, we focus on the impact of central bank behavior on measures of currency risk and the expected appreciation of currencies. Central banks have an objective of smoothing their exchange rates, and tend to lean against foreign currency flows using their own foreign exchange reserves - a fact documented in Fratzscher *et al.* (2018). We consider

[5] Carry trade returns have been better explained using conditional models of risk: these returns display higher comovements with the market during periods of bad market returns (Lettau *et al.*, 2014); they are more vulnerable to crashes, and particularly so when the price of protection against stock market crashes is high (Brunnermeier *et al.*, 2008; Fan *et al.*, 2019); the risk premium in the dollar, vis-à-vis the currencies of the rest of the world, is lower in US recessions, when risk premia are high (Lustig *et al.*, 2014); as is the case with the equity market, currencies which depreciate during periods of low cross-sectional foreign exchange correlations have positive excess returns (Mueller *et al.*, 2017); countries with more cyclical budget surpluses have currency returns which are more predictable by the carry factor (Jiang, 2019).

the parallel role of using their policy rate to this end, first suggested in Taylor (2001) as a tool to reducing inflation volatility. Mertens *et al.* (2017) show that a fiscal policy which appreciates one's own currency in bad times will raise the capital-labor ratio of a country by lowering its risk premium mechanically.[6] Our work complements a growing literature on the specialness of the US dollar, to which our contribution is in documenting foreign central banks' preference for currency stability against the US dollar specifically.[7] We also add to a nascent literature on the impact of the effective lower bound on asset prices.[8]

1.2 Stock Market Betas of Currencies

We document a new fact: the conditional equity market betas of all developed market currencies display a structural break around the recent financial crisis. We define the conditional beta of each currency (with respect to the US dollar) as follows: we measure the price of each G10 currency in terms of US dollars, such that a foreign currency appreciation corresponds to an increase in the exchange rate. We then regress the daily log appreciation of each of the nine exchange rates against the daily log return of the S&P 500, again in US dollars, using rolling regressions of one year of history, and show these conditional betas in the top panel of Figure 1.2. A positive beta indicates that a positive return for the S&P 500 corresponds to an appreciation of the foreign currency versus the US dollar - for example, the value of 0.5 for the Australian dollar for December 2009 says that a 1% return in the S&P 500 corresponded to a 0.5% appreciation of the Australian dollar against the US dollar over the calendar

[6] In related empirical work, Inoue and Rossi (2018) show that central banks can influence their currencies through monetary policy shocks which depreciate their currencies via expectations of future policy spreads, and Valchev (2019) considers the interplay of monetary and fiscal policy in determining carry trade returns. Calomiris and Mamaysky (2019a) show that the major foreign central banks can use their language to affect the price of their currencies vis-à-vis to the US dollar.

[7] Various authors have documented this special role in the form of a lower return on dollar denominated assets, including work by Caballero *et al.* (2008a), Mendoza *et al.* (2009), Gourinchas *et al.* (2010), Maggiori (2017a), Farhi and Maggiori (2018a). Previous work has demonstrated the dollar's role as a global unit of account, as in Chahrour and Valchev (2018) and Gopinath and Stein (2018).

[8] Ferrari *et al.* (2017) document that monetary policy shocks have had larger impacts on currencies in the era of low rates. In other asset classes, recent work by Datta *et al.* (2018) links the constraint of the effective lower bound to a significant change in the correlation of US equities and oil prices; Ngo and Gourio (2016) find a similar sign reversal between US equities and inflation swaps; Bilal (2017) document the decrease in correlation between stock and nominal bond returns, associating these changes to shifts in central bank policy.

year of 2009.

The change in conditional betas after the crisis is equally clear for both real and nominal exchange rates. We use nominal exchange rates for most of our analysis as we can measure them daily: inflation measures in most countries are only available at the monthly frequency. In Appendix Figure A.7 we show that the conditional betas constructed using 5 years of monthly data are very close for real and nominal exchange rates.

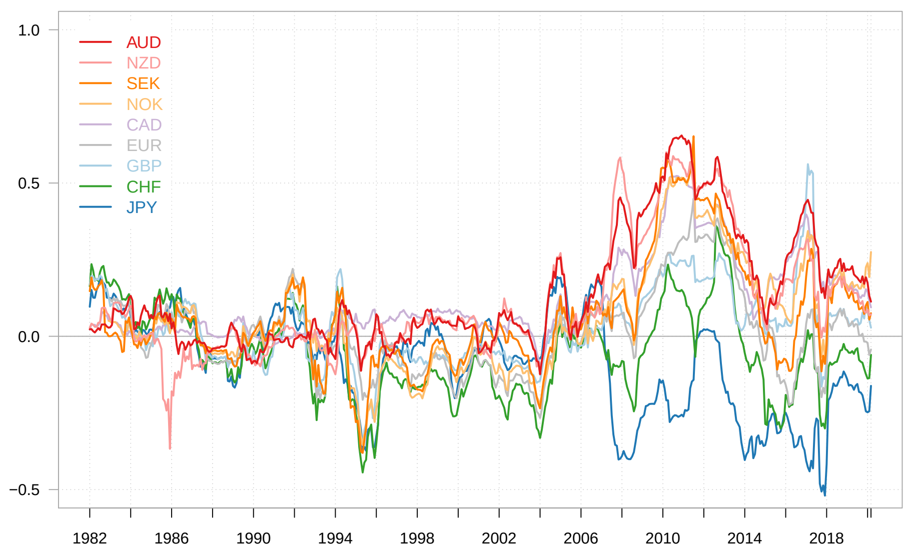
The well-known exchange rate disconnect with macroeconomic variables is mirrored here for equity returns: all G10 exchange rates showed little co-variation with equity returns prior to the recent financial crisis. Immediately after the onset of the crisis, large betas emerged and have not receded. The fact that the conditional betas fan out, rather than increase by the same quantity, implies that the increase is not merely a consequence of an increase in the role of the US dollar as a risk factor (Jiang *et al.*, 2018b, 2019b). Moreover, when we repeat the analysis using the Japanese yen as the base currency, rather than the US dollar, we find the same structural break at the start of the crisis, as shown in the bottom panel of Figure 1.2.[9] The break is equally apparent for the High Minus Low carry factor constructed by Lustig *et al.* (2011a). In Appendix Table A.6, we show the R^2 of the HML factor regressed against the monthly return on the S&P500 is 29% after the crisis, compared to 3% beforehand. Furthermore, this structural break is not due to a change in the variance of currency returns: the same break can be observed in the corresponding conditional correlations, reported in Appendix Figure A.6.

While the magnitudes of betas differ when defining exchange rates in terms of US dollars and Japanese yen, the ordering remains the same. The covariation between the exchange rate of any two currencies and the return to the S&P 500 can be summarized by their relative positions on a single risk spectrum. In Table 1.1, we summarize the covariation in all G10 exchange rates. In addition to defining exchange rates with respect to a single base currency, as we do in Figure 1.2, we also define

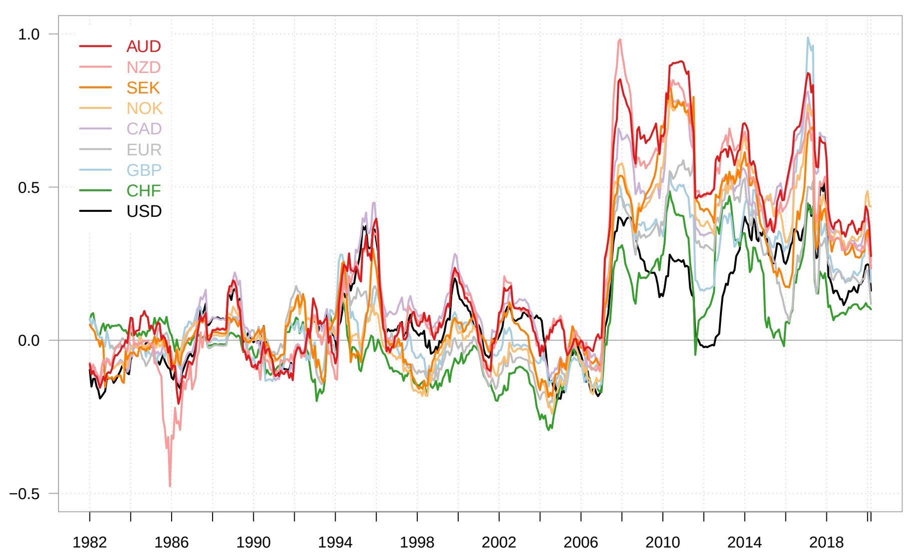
[9]The fact that the S&P 500 return covaries with the exchange rate between the Japanese yen and non-US currencies suggests the relationship is not being driven by US specific news in the S&P 500, but rather by changes in risk premia. To cement this point, in Appendix Table A.5, we regress currency appreciations against the corresponding local equity market returns, as well as the first principal component of all G10 equity market returns. We find the first principal component of all G10 equity market returns dominates the local country's equity market, suggesting the relationship is driven by a common risk factor, and not by country-specific news.

Figure 1.2: *Conditional exchange rate betas with the S&P 500*

(a) *Exchange rates bilaterally with the US dollar*



(b) *Exchange rates bilaterally with the Japanese yen*



Panel (a) shows the conditional betas of each exchange rate with respect to the US dollar against the log return on the S&P 500, and Panel (b) shows the conditional betas for each exchange rates defined with respect to the Japanese yen. Conditional betas are estimated by the following regression:

$$\Delta e_t^i = \alpha_{i,t} + \beta^i r_t^m + \varepsilon_{i,t}$$

A positive Δe_t^i is an appreciation of the non-base currency. Each beta is estimated using one year (252 trading days) of data, with one coefficient estimated per currency per month. Data are from Jan 1981 to June 2019, from Bloomberg.

Table 1.1: *Average conditional betas before and after the Financial Crisis*

(a) *Jan 1982-Dec 2007.*

	AUD	NZD	CAD	NOK	SEK	GBP	EUR	USD	CHF	JPY
AUD										
NZD	0.02									
CAD	-0.01	-0.02								
NOK	0.07	0.05	0.07							
SEK	0.05	0.03	0.05	-0.02						
GBP	0.06	0.04	0.06	0.00	0.01					
EUR	0.07	0.05	0.07	0.00	0.01	0.00				
USD	0.03	0.02	0.04	-0.03	-0.01	-0.02	-0.03			
CHF	0.10	0.08	0.11	0.04	0.05	0.04	0.04	0.07		
JPY	0.05	0.04	0.06	-0.01	0.01	0.00	-0.01	0.02	-0.05	
G10 Basket	0.05	0.03	0.05	-0.02	-0.01	-0.02	-0.02	0.01	-0.06	-0.01

(b) *Jan 2008-Mar 2020.*

	AUD	NZD	CAD	NOK	SEK	GBP	EUR	USD	CHF	JPY
AUD										
NZD	0.05									
CAD	0.08	0.03								
NOK	0.10	0.06	0.02							
SEK	0.14	0.09	0.06	0.03						
GBP	0.22	0.17	0.14	0.11	0.08					
EUR	0.25	0.21	0.17	0.15	0.12	0.04				
USD	0.35	0.30	0.27	0.25	0.21	0.13	0.10			
CHF	0.38	0.33	0.30	0.27	0.24	0.16	0.13	0.03		
JPY	0.59	0.55	0.51	0.49	0.46	0.38	0.34	0.24	0.21	
G10 Basket	0.21	0.18	0.13	0.10	0.08	0.00	-0.04	-0.14	-0.16	-0.38

Panel (a) shows the average conditional betas from January 1982 through December 2007, Panel (b) from January 2008 through June 2019. Average betas estimated from a rolling annual regression (252 trading days) of the daily log appreciation of each G10 currency for every exchange rate pair e^{ij}, defined as the price of the currency in column i in terms of the currency in row j, against the daily log return of the S&P 500 in US dollars. The final row of each Table defines the exchange rate e^i as an equally weighted basket against all other G10 currencies.

$$\Delta e_t^{i,j} = \alpha_{i,t} + \beta^{i,j} r_t^m + \varepsilon_{i,t}$$

A positive value for $\beta^{i,j}$ signifies that the currency in column i appreciates by more against row j when the S&P 500 has a positive return. Each beta is estimated using one year (252 trading days) of historical data, with one coefficient estimated per currency per month, and then averaged over their respective periods. Data are from Jan 1981 to June 2019, from Bloomberg.

each exchange rate relative to an equally weighted basket of its log appreciation against all other G10 exchange rates.[10] We order currencies left to right (and top to bottom) on the basis of the average conditional beta for its exchange rate basket, from the most risky (Australian dollar, with a β of 0.21) to the most safe (Japanese yen, with a β of -0.38). Since we use log appreciations, the β between the Australian dollar and Japanese yen exchange rate and the return on the market must be equal to the

[10] See Figure A.5 in the appendix for the corresponding time series graph of conditional equity betas of exchange rates defined against the equal-weighted basket of G10 currencies.

difference in their baskets' β with the return on the market, i.e. the β for this pair is 0.59. For this reason, the degree to which the exchange rate between any two currencies covaries with the return on the market depends on their relative position on the risk spectrum - the British pound, when measured against the G10 basket, shows no covariation with risky assets, though its beta when measured against the Australian dollar, or the Japanese yen, are -0.21 and 0.38 respectively.

To establish the statistical significance of the structural break of currency betas with the stock market displayed in Figure 1.2, we test the null hypothesis of no change in the beta versus a single change at an unknown date, using the $Sup-F$ statistic of Andrews (1993). For each currency against the US dollar, we report the month in which the test estimates a break, as well as the associated p-value. Table 1.2 shows that every pair displays a strongly statistically significant break around the start of the financial crisis. Results are analogous when repeating the exercise using the Japanese yen instead of the US dollar as the base currency.

While the rank ordering of conditional betas remains largely fixed throughout the post-2008 sample, two exceptions to this rule are worth mentioning. The Euro became risky (vis-à-vis the US dollar) during the sovereign debt crisis of 2010, and returned to being safe at the crisis' resolution in 2015; the British pound switched from being a safe currency to the riskiest in the sample during the lead-up to the Brexit vote, and then returned to being safe once the uncertainty around the vote was resolved. In both of these cases, the risks which were driving the currencies were also significant global risk factors.

1.2.1 Out of sample explanatory power

The increase in market betas we document suggests a simple explanatory model for currency returns: the appreciation of a currency against the US dollar on a given month should be partially explained by the interaction of its conditional beta and the contemporaneous return on the S&P 500. To evaluate this model using the long-standing benchmark of the Meese-Rogoff test, we measure the out-of-sample performance of our model by estimating model parameters with a hold-out sample, and then hand the model the realized values of the next period's regressors. Of course, this is not equivalent to a true out of sample forecast, since we use information about the regressors which was not ex-ante available at

Table 1.2: *Structural break estimates*

	AUD	NZD	SEK	NOK	CAD	EUR	GBP	CHF	JPY
Month of Break	2006-Jun	2007-Feb	2008-Oct	2008-Oct	2006-Dec	2008-Oct	2008-Oct	2008-Oct	2007-Mar
Sup-Wald statistic	850	592	530	735	911	249	253	75	268
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

This Table shows the selected date of a structural break for the relationship between each currency pair and the return on the S&P500. Following Andrews (1993), the break date is $\tau = \lambda T$ such that

$$\lambda = \arg\sup_{\lambda \in [\pi_0, 1-\pi_0]} W(\lambda)$$

and T is the sample length. The Wald statistics $W(\lambda)$ are obtained from regressions in which the dependent variable is the daily log appreciation of each exchange rate with respect to the US dollar, and the independent variable is the log return on the S&P 500. In the unrestricted regression, the beta of each currency i appreciation on the market return is estimated both before and after the unknown break date, λT, as follows:

$$\Delta e_t^i = \alpha_t^i + \beta_1^i r_t^m + \beta_2^i r_t^m \cdot \mathbb{1}(t > \lambda T) + \varepsilon_{i,t}.$$

In the restricted regression, the β_2^i term is dropped from the estimation. p-values are calculated using the critical values in Andrews (1993) using $\tau_0 = .15$. Data are from Jan 1982 to March 2020, from Bloomberg.

the time to make the forecast. Notwithstanding this, the framework is useful to provide a bar which establishes that the relationship observed in-sample was meaningful, and contains information about the future relationship.

We summarize the performance of these out of sample predictions for all G10 currencies against the US dollar in Table 1.3, using five separate tests. For each test, we compare their outcomes between the post-crisis period, and three pre-financial crisis periods of equal length. Each test shows a vastly improved explanatory power during the post-crisis period.

In the first metric, we show the R^2 of an in-sample regression. We take our conditional estimates of betas from the methodology underlying Figure 1.2, which are estimated using 1 year of historical daily information, and use them to explain the next one month exchange rate appreciation by interacting this measure of risk with the future return on the market, under a pooled regression. The right hand side term can be thought of as an expected appreciation if these betas were stable, and the entire expected return came from appreciation. We estimate parameters over the full sample, as a benchmark. In the regime prior to the effective lower bound, this specification has little explanatory power, with an R^2 of at most 1 percent. In post-crisis sample, we find an R^2 of 21 percent.

The second exercise uses a similar methodology to the first, but restricts the parameter estimation to be out of sample. Again, we take the conditional estimates of betas from the methodology underlying

Table 1.3: *Tests of informativeness of conditional betas*

		Pre-financial crisis			Post-financial crisis
	Test	1983-1994	1990-2001	1996-2007	2008-2019
R^2	In-sample	0.01	0.00	0.02	0.20
pseudo-R^2	Meese-Rogoff	0.01	0.00	0.02	0.19
True Positive	Meese-Rogoff	0.56	0.51	0.56^{***}	0.58^{***}
t-stat		(1.63)	(0.49)	(3.04)	(4.5)
True Negative	Meese-Rogoff	0.49	0.53	0.54	0.67^{***}
t-stat		(0.72)	(1.83)	(1.84)	(7.68)
RMSE Ratio	Meese-Rogoff	0.99	1.00	0.99	0.90

The Table summarizes the informational content of the conditional betas for four sample windows of equal size: Jan 1983-Dec 1994, Jan 1990-Dec 2001, Jan 1996-Dec 2007, and Jan 2008-Dec 2019.
In-sample. *R^2:* We run pooled regressions of the following form:

$$\Delta e^i_{t+1} = \alpha + \gamma(\hat{\beta}^i_t \cdot r^m_{t+1}) + \varepsilon^i_{t+1}$$

for each of the samples listed in the first row of the table. Δe^i_{t+1} is the log appreciation of each currency versus the US dollar, and $\hat{\beta}^i_t$ are the estimates of conditional beta for each currency in Figure 1.2. α and γ are estimated once per sample, rather than one per currency, since we are only interested in the informational content of the conditional betas.
Meese-Rogoff. We follow the standard Meese-Rogoff procedure for making forecasts of each exchange rate for the next out of sample period. We predict every exchange rate's monthly appreciation versus the US dollar (i.e. we make 9 predictions per month) by taking the betas for each currency appreciation against the S&P 500 in rolling samples, and then taking these parameters out of sample, and including the next period's actual return of the S&P 500:

$$\widehat{\Delta e^i_{t+1}} = \widehat{\beta}^i_t r^m_{t+1}$$

pseudo-R^2: We then calculate the pseudo-R^2 for these pooled predictions according to the following statistic, in which T is the final month of each 11 year window, and outer sum is over all all G10 exchange rates with respect to the US dollar:

$$\text{pseudo-}R^2 = 1 - \sum_{i \in G10} \sum_{t=T-132}^{T} \frac{(\widehat{\Delta e^i_{t+1}} - \Delta e^i_{t+1})^2}{(\Delta e^i_{t+1} - \overline{\Delta e^i_{t+1}})^2}$$

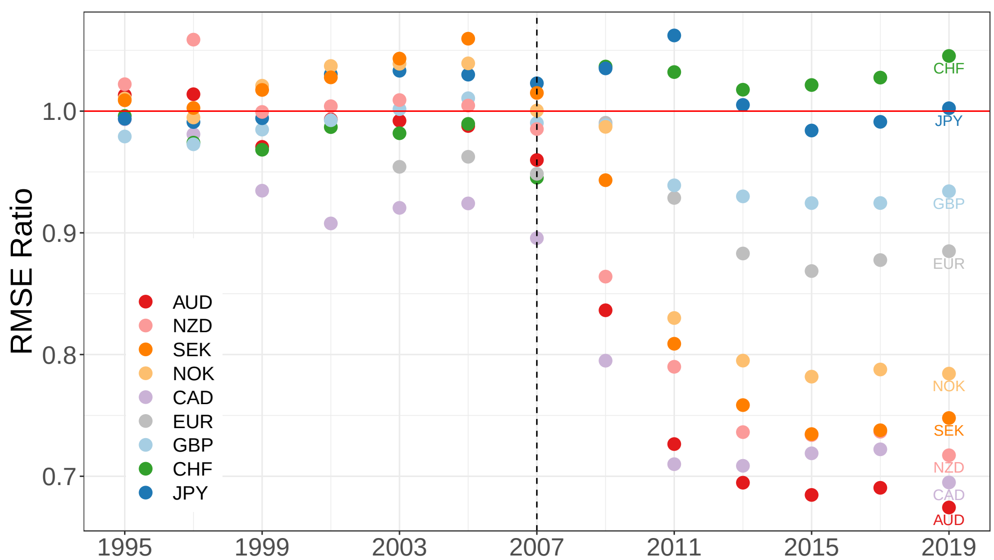
True positive (True negative): We measure the proportion of the time that the currency appreciated (depreciated) over the subsequent month when the model predicted an appreciation (depreciation) and report these proportions as the true positive (negative) rates. We report the t-statistic for a hypothesis test of no forecastability ($H_0 : p = 0.5$). **p<0.1* ***p<0.05* ****p<0.01.*
RMSE Ratio: We calculate the ratio of root mean squared error for the above forecasts versus a random walk model (a forecast of no change), pooled as a single summary statistic.

Figure 1.2 and interact them with the next period's return on the market. In this case, we do not allow for any further parameter estimation, but rather use the conditional beta directly to construct the forecasted appreciation. We evaluate these forecasts by constructing a pseudo-R^2 of the forecasts. As in the first exercise, we find a jump in explanatory power from at most 1 percent in the earlier regimes, to 19 percent in the post-crisis regime.

We then take the estimates from these exercises, and construct three more forecast metrics. Following Jorda and Taylor (2012), we use a forecast metric which is less sensitive to outlier events -

that of the true positive and true negative rates. This metric tests for the ability to predict the direction but not the magnitude of appreciations. Forecasted appreciations are correct 59 percent of the time in the post-crisis period, which is a significant improvement over an uninformed guess at the 1 percent level, compared to at best 54 percent in the pre-crisis windows. Forecasts are even more accurate when it comes to depreciations in the recent sample, with a 67 percent accuracy rate. Finally, we measure the ratio of the root mean squared error (RMSE) between the model forecast, and that of no change. The model barely outperforms a random walk in the pre-financial crisis samples, but in the recent sample, it outperforms the random walk with a 10 percent lower RMSE.

Figure 1.3: *Out of sample Meese-Rogoff tests by currency*



We make out of sample predictions of each exchange rate for the next out of sample period using the conditional beta, and compare the forecast accuracy to that of a random walk. We predict every exchange rate's monthly appreciation versus the US dollar (i.e. we make 9 predictions per month) by taking the betas for each currency appreciation against the S&P 500 in rolling samples, and then taking these parameters out of sample, and including the next period's actual return of the S&P 500:

$$\widehat{\Delta e^i_{t+1}} = \widehat{\beta}^i_t r^m_{t+1}$$

Using each forecast, we calculate the ratio of root mean squared error for the above forecasts versus a random walk model over the prior 12 years. We find the average root mean squared error of our prediction was 75% as large as that of the random walk model.

$$RMSE\ Ratio : \sqrt{\sum_{i \in G10} \sum_{t=T-132}^{T} \frac{(\widehat{\Delta e^i_{t+1}} - \Delta e^i_{t+1})^2}{(\Delta e^i_{t+1})^2}}$$

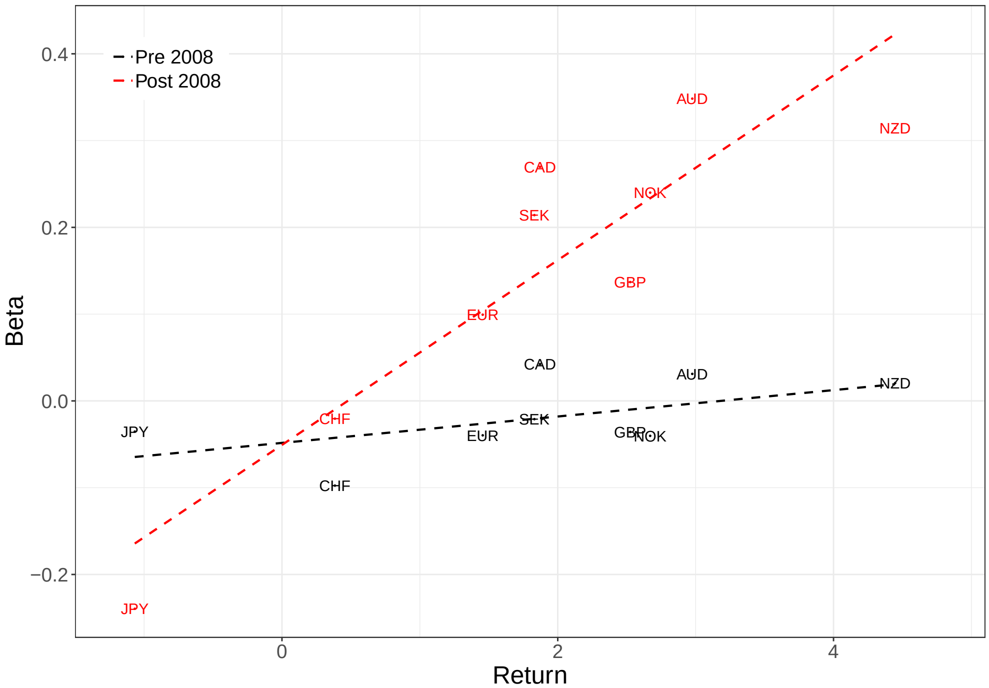
In order to understand which of these exchange rates are explainable, we switch from a pooled approach to predicting each currency separately. For each exchange rate against the US dollar, we take the forecasts from the out of sample exercise and calculate the RMSE ratio between the forecast and that of no change each 10 year sample. We plot the RMSE ratio for each currency and the end of the sample window in Figure 1.3. For example, the data point for 2018 corresponds to the forecast window of January 2009 to December 2018. For this window, the riskiest currencies (with respect to the US dollar) have the best forecasting performance, e.g. the Australian dollar exchange rate has a RMSE ratio of 0.68. Two patterns emerge - the first is that forecasts over a 10 year window begin to beat that of a random walk once the forecast window begins to include the sample of 2008 onward. The second is that the forecastability of each currency broadly matches the ranking of in-sample betas. In Appendix Figure A.8 we report the results of a Diebold-Mariano test of forecast accuracy for each window, and find that for the most recent sample, the forecasts outperform those of a random walk with a p-value below 0.1 for a majority of currencies.

1.2.2 Currency betas and risk

Having established the meaningfulness of post-crisis betas in explaining future exchange rate moves, we now turn to the question of what explains the cross-section of betas. A natural hypothesis is that riskier currencies have higher equity betas. Since, as displayed in Figure 1.2, the rank ordering of betas, while having little persistence in the early sample, remains stable in the post-crisis sample, we take the average beta after 2008 as a measure of currency risk.

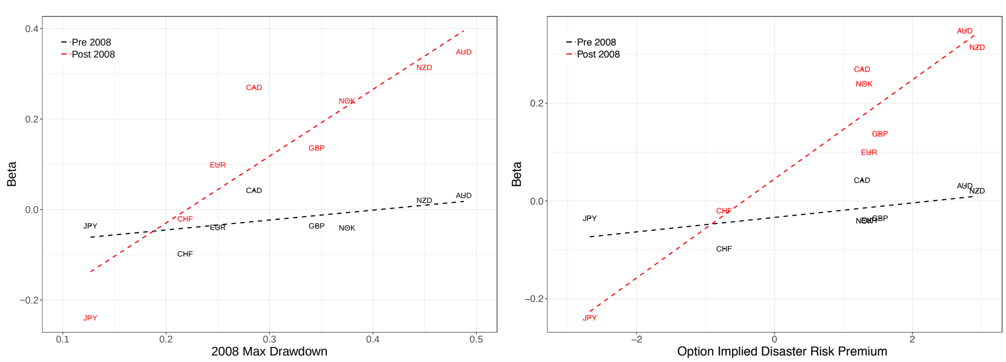
Riskier assets should have higher returns, so a validation of the post-currency betas as a measure of risk is to relate the average return on each carry trade to the average equity beta of the corresponding currency. We use pre-crisis average returns on each carry trade as a measure of its riskiness to show that the post-crisis betas capture a characteristic of currencies which was already present before the crisis. In Figure 1.4, we show that the pre-crisis average yearly return on each currency carry trade is strongly related to the currency's average post-crisis equity beta, but not to its average pre-crisis equity betas. If this is the case, then why were currency betas so small before the crisis? We answer this question and further investigate the implications of the relationship between post-crisis betas and riskiness proxies in section 1.3.

Figure 1.4: *Carry trade returns and average conditional betas*



This graph shows that post-crisis average currency betas are explained by pre-crisis average carry trade returns, while the relationship with pre-crisis average betas is much weaker. The horizontal axis shows the average annual return to the carry trade versus the US dollar in the pre-crisis sample (Jan 1986 to Dec 2007). The vertical axis shows the average estimated beta for each currency, in the pre-crisis and post-crisis (Jan 2008 to June 2019) samples.

Figure 1.5: *Disaster risk proxies and average conditional betas*



The vertical axis shows the average estimated beta for each currency, in the pre-crisis and post-crisis (Jan 2008 to June 2019) samples.
Left panel: The horizontal axis shows the maximum drawdown to the carry trade during 2008.
Right panel: The horizontal axis shows the disaster risk premium, the premium from selling out of the money puts on risky currencies, or out of the money calls on safe currencies, from Farhi *et al.* (2015).

Other measures of currency risk, aside from realized returns, also suggest that post-crisis betas captured a characteristic of currency risk which was already important before the crisis. In Figure 1.5 we show a pattern analogous to the one displayed in Figure 1.4 for two alternative measures of currency risk. In the left panel, we show that the drawdown each currency experienced against the dollar during 2008 can explain the cross-section of average betas in the post-crisis period. In the right panel, we compare the betas to a measure of disaster risk premium in currency forwards proposed by Farhi *et al.* (2015) - the pre-crisis return to selling deep out of the money puts on risky currencies and buying calls on safe currencies.

1.3 Beta Decomposition and Interest Rate Spreads

In this section, we propose an explanation for the increase in equity betas of currencies documented above. If a central bank responds to an increase in the risk premium of its currency by increasing short term interest rates, investors are compensated for holding the currency through its spread, and will accept a relatively higher exchange rate. If instead the interest rate spread is unresponsive to the increase in risk premia, then the spot exchange rate falls to compensate investors through expected appreciation. In this case, if risk premia change with the value of the equity market portfolio, a regression of exchange rates on market returns will deliver non zero betas. Hence, the pattern in Figure 1.2 can be explained by a change in the responsiveness of expected interest rate spreads to changes in risk premia from before to after the crisis.

The low betas observed prior to the crisis require the market to expect interest rate spreads on risky (safe) currencies to increase (decrease) when risk premia rose. These expectations would have been well founded if they were consistent with our understanding of how central banks used to operate. This was indeed the case - using policy rates for exchange rate stabilization was a standard policy recommendation of the early literature on central banking (Girton and Henderson (1976), Henderson (1982), Fischer (1998).) We directly document this property of pre-crisis interest rate spreads in section 1.3.1.

This explanation for the observed structural break in equity betas of currencies therefore requires that central banks simultaneously abandoned this objective, or became unable to use policy rates to achieve it, in 2008. Reaching the effective lower bound on interest rates is a possible reason for this: for all of these countries, the optimal interest rate to stabilize output was plausibly below zero in the aftermath of the financial crisis (Holston *et al.*, 2017). We report the time series of two year interest rate spreads in Appendix Figure A.9, which shows a decline in both absolute spreads, and in the volatility of spreads, after the crisis.[11]

We show the change in equity betas of currencies is only apparent for developed economy currencies whose central bank policies were constrained, which is consistent with this explanation. Emerging market economies' monetary policies were not constrained by the effective lower bound, as they have higher nominal natural interest rates. In Appendix Figure A.10, we show that the betas of currencies of Brazil, India, Mexico, Turkey and South Korea have either increased gradually or stayed flat over the last two decades, but do not display a similar structural break in 2008.

To quantitatively evaluate the importance of the dynamics of interest rate spreads in explaining changes in currency equity betas, we decompose currency excess returns as in Froot and Ramadorai (2005). By definition, the log excess return on a carry trade buying foreign currency i by funding the trade with US dollars is given by

$$r_{t+1} = (e_{t+1} - e_t) + (i_t^* - i_t^\$) \tag{1.1}$$

in which e_t is the log nominal exchange rate and i_t^*, $i_t^\$$ are the log foreign and domestic interest rates, respectively. Iterating this equation forward and taking expectations we obtain an expression for the nominal exchange rate

$$e_t = \sum_{i=0}^{\infty} \mathbb{E}_t \left[d_{t+i} - r_{t+i+1}\right] + \mathbb{E}_t \left[\lim_{j\to\infty} e_j\right] \tag{1.2}$$

in which $d_t = i_t^* - i_t^\$$ is the interest rate differential at time t. For simplicity, we assume that the nominal exchange rate is stationary, so that $\mathbb{E}_t \left[\lim_{j\to\infty} e_j\right] = \bar{e}$.[12]

[11] Australia and New Zealand held rates above zero but consistently asserted they were at an effective lower bound as further cuts would have hampered macro-financial stability. Their two year bonds showed similar price volatility to those central banks with policy rates at or below zero.

[12] This assumption is not needed for the following argument but simplifies the notation: what is actually needed is that the expected long-run value of currencies does not change with risk premia ($Cov_t\left(\mathbb{E}_{t+1}\left[\lim_{j\to\infty} e_j\right], r_{S\&P,t+1}\right) = 0$). Real exchange rates are stationary under the assumption that Purchase Power Parity holds in the long run. Assuming the nominal exchange rates are stationary is equivalent to assuming inflation rate differentials are stationary, which is not implausible for developed markets since the 1980s (Jiang *et al.*, 2018b).

This implies that unexpected carry trade returns can be decomposed into two terms:

$$r_{t+1} - \mathbb{E}_t[r_{t+1}] = v_{IR,t+1} - v_{FR,t+1}, \tag{1.3}$$

$v_{IR,t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t)\sum_{i=1}^{\infty} d_{t+i}$ captures changes in expected future short interest rate differentials and $v_{FR,t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t)\sum_{i=1}^{\infty} r_{t+i+1}$ is the change in future expected log returns on the carry trade.

Given the decomposition in equation 1.3, we can similarly decompose the conditional stock market betas for each currency i reported in Figure 1.2:

$$\beta_t^i = \frac{Cov_t(v_{IR,t+1}, r_{t+1}^m)}{Var_t(r_{t+1}^m)} - \frac{Cov_t(v_{FR,t+1}, r_{t+1}^m)}{Var_t(r_{t+1}^m)} = \beta_{IR,t}^i - \beta_{FR,t}^i. \tag{1.4}$$

If the US dollar funded carry trade investing in currency i is risky, one would expect $\beta_{FR,t}^i$ to be negative: as the stock market declines, risk premia rise and therefore future log expected returns on the carry trade rise: $v_{FR,t+1}$ is positive. Conversely, for currencies which are safer than the US dollar such as the Japanese yen, one would expect a positive $\beta_{FR,t}^i$. Given our results relating pre-crisis measures of currency risk and post-crisis betas in section 1.2.2, we hypothesize that the sensitivity of expected carry trade returns to risk premia ($\beta_{FR,t}^i$) is maintained across currencies from the period before to the period after the financial crisis. In section 1.3.1 we test this formally by estimating proxies for $\beta_{IR,t}^i$ before and after the financial crisis and comparing the average $\beta_t^i - \beta_{IR,t}^i$ in the two periods.

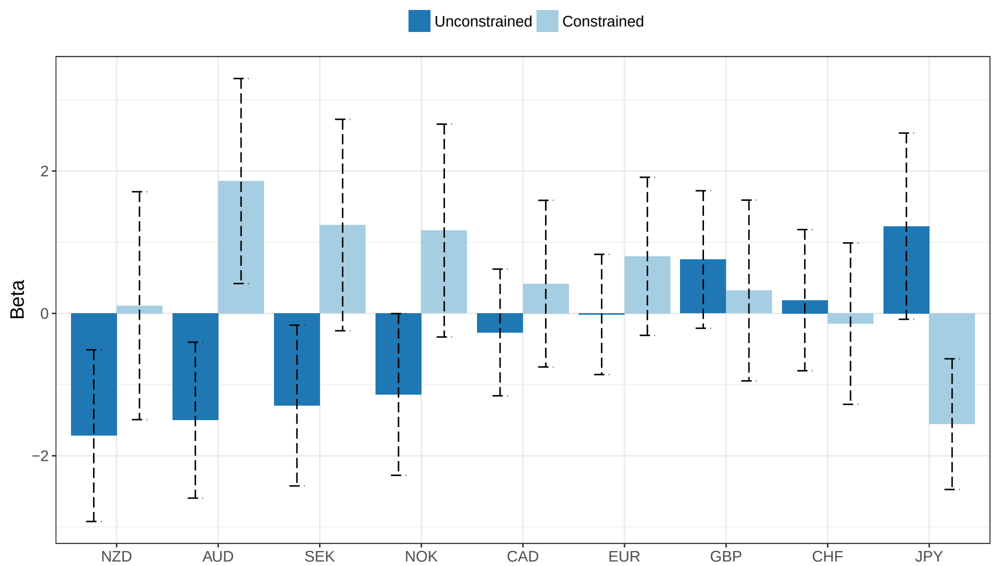
1.3.1 Equity betas of expected carry trade returns: stability test

We begin by constructing empirical estimates of $\beta_{IR,t}^i$ for each currency. As equation 1.4 shows, an empirical test of our theory requires measuring the relationship of expected future short term interest rate spreads and risk premia. For each currency, we regress changes in the two year spread on changes in the risk factor, measured by S&P 500 returns. We use monthly changes in bond yields for two reasons. Firstly, daily data are not available for most of these currencies prior to the early 1990s. Secondly, we cannot observe these prices at the same cutoff time, since the yields on the bonds are measured with respect to local market closing times.[13]

[13]Using monthly changes in spreads, the difference in cut-times, of up to 16 hours, is minimized. Currency forward data, which does not suffer a cut-time problem, cannot be used for our sample, due to the limited length in which these time series are available.

We estimate separate regressions for the period in which central banks were constrained and for the one in which they were not, reporting the results in Figure 1.6: the dark bars correspond to the unconstrained period and the light bars to the constrained.

Figure 1.6: *Regression coefficients of two year risk-free yield spreads on the S&P 500*



Regression coefficients of monthly changes of two year government bond spreads versus the US dollar, on the monthly log return on the S& 500, split by constrained and unconstrained periods:

$$\Delta(i_t^j - i_t^{\$}) = \alpha_j + \beta^{j,unc} r_t^m + \beta^{j,con} r_t^m + \varepsilon_{j,t}$$

in which i_t^j is the yield on the two year government bond of country j, $i_t^{\$}$ is the yield on the US two year treasury yield, r_t^m is the log return of the S&P 500 over the month. We define a month to be constrained if it is either after 2008, or if the central bank was operating at the effective lower bound before 2008, as has been the case for Japan (from 1998) and Switzerland (from 2003 to 2004). The dark bars correspond to estimates of $\beta^{j,unc}$ and the light to $\beta^{j,con}$. Currencies are ordered along the horizontal axis by decreasing risk, as measured by their average pre-crisis carry trade return. The sample is from April 1987 to June 2019.

During the period in which central banks were unconstrained, we observe opposing behavior between central banks whose currencies are bought on the long side of the carry trade (such as the Reserve Banks of Australia and New Zealand), and those on the short side (such as the Bank of Japan and the Swiss National Bank). In months with equity prices declines, we see yields rise on Australian government bonds by more than US government bonds at the two year tenor, while bonds in Japanese yen decline by the most.

This result is particularly surprising considering the confounding effect of changes in global growth.

Whilst changes in the price of equities convey information about global growth alongside changes in the risk factor, the component relating to growth prospects works against the result - we would anticipate the central banks of the commodity currencies, Australia and New Zealand, to ease monetary conditions the most when equity prices are falling. Rather, we find the goal of exchange rate smoothing takes precedence, and they do the opposite.

We use two year yields in order to strike a balance between capturing expectations of future changes without incorporating significant term premia. To verify that the term premium component of two year yields cannot be driving this result, we conduct additional analyses in Appendix section A.2. We fit a term structure model to the estimated zero coupon yield curve of each country constructed by Wright (2011) and decompose yields into short term rate expectations and term premia.[14] For all countries, the monthly change in expected future short term rates accounts for at least 97% of the change in two year yields. In Appendix Figure A.1, we show the reaction of spreads to equity price movements is driven by the estimated risk-free rate expectations component of two year yields, rather than by term premia.[15]

To provide an assessment of the quantitative importance of our results, we test whether the change in interest rate behavior is large enough to explain the change in the covariance between exchange rates and the equity market, assuming that the sensitivity of expected carry trade returns to risk premia (β_{FR_t}) has stayed unchanged. A rearrangement of equation 1.4 yields:

$$\beta_t^i - \beta_{IR,t}^i = -\beta_{FR,t}^i \tag{1.5}$$

For the change in interest rate behavior for currency i ($\beta_{IR,t}^i$) to be large enough to explain the change in equity market covariances of currencies (β_t^i), without a corresponding change in the riskiness of the currency ($\beta_{FR,t}^i$), then we could estimate equation 1.5 for each currency, pre- and post-crisis. We now conduct this exercise.

In Figure 1.6, we showed that prior to the crisis, two year interest rate spreads moved with the

[14]Due to insufficient bond data for Norway, we cannot estimate a term structure model for the full sample.

[15]As a robustness check, we repeat the regression using six month yields in Appendix Figure A.2, with the caveat that for some countries, we must use interbank rates rather than government bonds. The same pattern holds, though effect sizes are smaller for the shorter bonds.

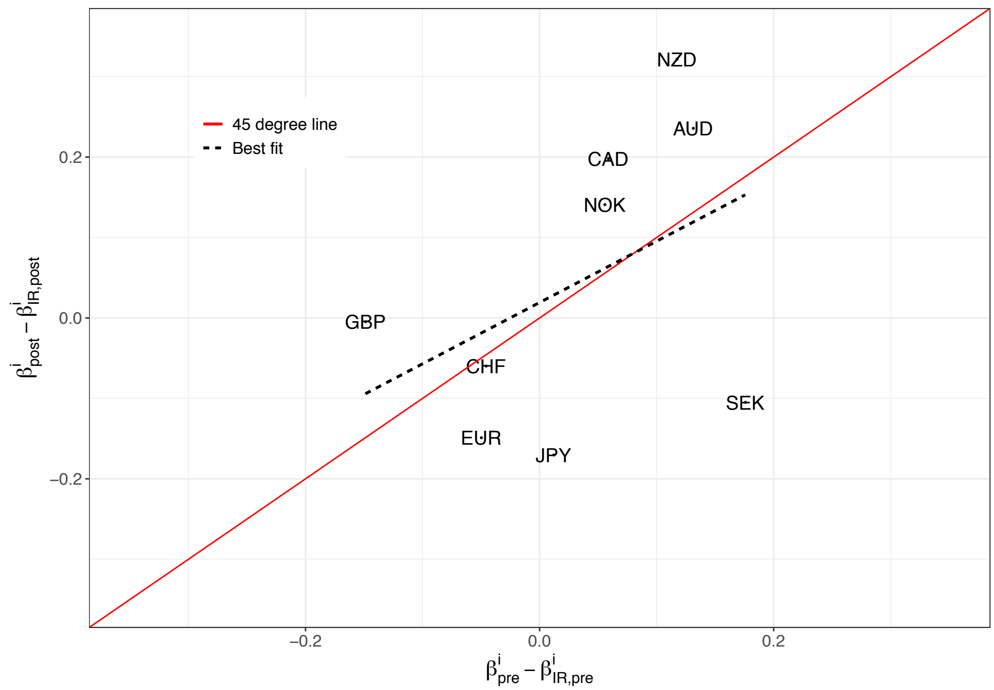
price of risk. The relationship between these estimates and a long-run estimate of $\beta^i_{IR,pre}$ depends on the expected persistence of these changes. For example, during the post-crisis era, we estimate that the New Zealand dollar depreciated by around 30 basis points in response to a 1% decline in the S&P 500. If the central bank wanted to offset the impact on the currency entirely, it would need to increase their policy rate by 30bps for one year. If the policy rate change were expected to persist for four years, they would need to increase the path by 7.5bps.

We estimate the persistence of interest rate changes for each country as follows. We model interest rates as an AR(1) process, estimating the persistence of two year bond yields between two year lags: $i^j_t = \alpha + \rho\ i^j_{t-24}$, and then estimate the long-run impact of an interest rate shock from a two year yield as $2 \times \frac{1}{1-\rho}$.[16] We multiply the coefficients in Figure 1.6 by these estimates of persistence to obtain a proxy of $\beta^i_{IR,pre}$. Our estimates of the responsiveness of exchange rates (with respect to the US dollar) to risk premia (β^i) are taken directly from table 1.1. We then compare the estimates of $\beta^i_{post} - \beta^i_{IR,post}$ to those of $\beta^i_{pre} - \beta^i_{IR,pre}$.

We show the results of this exercise in Figure 1.7. The comparison of overall betas, pre- and post-the crisis lie close to the 45 degree line, indicating that the sensitivity of expected carry trade returns to risk premia remained unchanged between regimes. We cannot statistically reject that the coefficients α_0 and α_1 of the following regression are equal to zero and one: $\beta^i_{post} - \beta^i_{IR,post} = \alpha_0 + \alpha_1(\beta^i_{pre} - \beta^i_{IR,pre})$. Thus, we cannot reject that the change in interest rate spread behavior can fully account for the increases in covariance between exchange rates and risk premia.

[16]The constant multiplier of 2 is necessary as a two year yield change pays interest rates (which are annualized) for two years. E.g. even if ρ were 0, a 2 yield change of x basis points still pays off $2 \cdot x$.

Figure 1.7: *Pre- and post-crisis period currency and interest rate betas with the S&P 500*



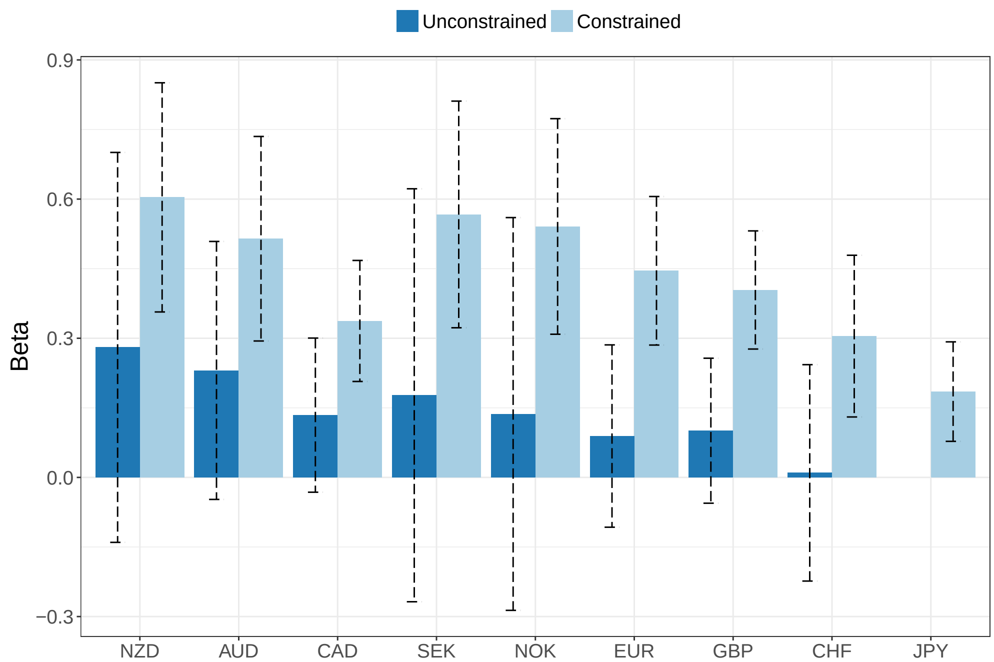
Decomposition of currency and interest rate betas as outlined in equation 1.5. β^i refers to the covariance of the currency with the S&P 500 and β_{IR} refers to the covariance of the current and future free rate with the S&P 500. The line of best fit plots the following regression: $\beta^i_{post} - \beta^i_{IR,post} = \alpha_0 + \alpha_1(\beta^i_{pre} - \beta^i_{IR,pre})$. The estimates of $\hat{\alpha}_0$ and $\hat{\alpha}_1$ are 0.02 and 0.76 respectively, and their standard errors are 0.06 and 0.60. An F-test fails to reject a null hypothesis that the coefficients describe a 45 degree line with a p-value of 0.7. We provide the underlying values for calculation in Appendix Table A.7. The data sample for the pre period is from January 1982 to December 2007, and for the post period is from January 2008 to June 2019.

1.3.2 High frequency test: FOMC shocks

For the empirical test in the previous section, we used monthly changes in spreads and in the risk factor. One drawback of this approach is that currencies, interest rate spreads, and the risk factor are all reacting to other news at a monthly frequency. While we cannot account for all such news, we can instead use changes in these variables around FOMC announcements, as these windows have been shown to be associated to large changes in risk premia, at a time when the impact of other macroeconomic news is small (Bernanke and Kuttner, 2005).

We confirm our results for the reaction of currencies and interest rate spreads to the risk factor in those windows. In Figure 1.8, we report the estimates from regressing the log appreciation of foreign currencies, measured in dollars, against the log appreciation of the S&P 500, over the 30 minute window around FOMC announcements, separately for each of the 9 currencies. Those results confirm the finding reported in Figure 1.2: the covariance of currency and equity returns has increased substantially in the period in which central banks were unable to dampen currency movements.

Figure 1.8: *Regression coefficients of currency appreciations on the S&P 500, high frequency sample*



Regression coefficients of currency appreciations against the US dollar on the return on the S&P 500 over 30 minute windows around FOMC announcements. The return on the S&P 500 is interacted with a variable indicating whether this meeting occurred after January 2009, resulting in pre-crisis and post-crisis coefficients. The regression specification is:

$$\Delta e_t^j = \alpha_j + \beta^{j,unc} r_t^m + \beta^{j,con} r_t^m + \tilde{\gamma}^j \tilde{X}_t + \varepsilon_{j,t}$$

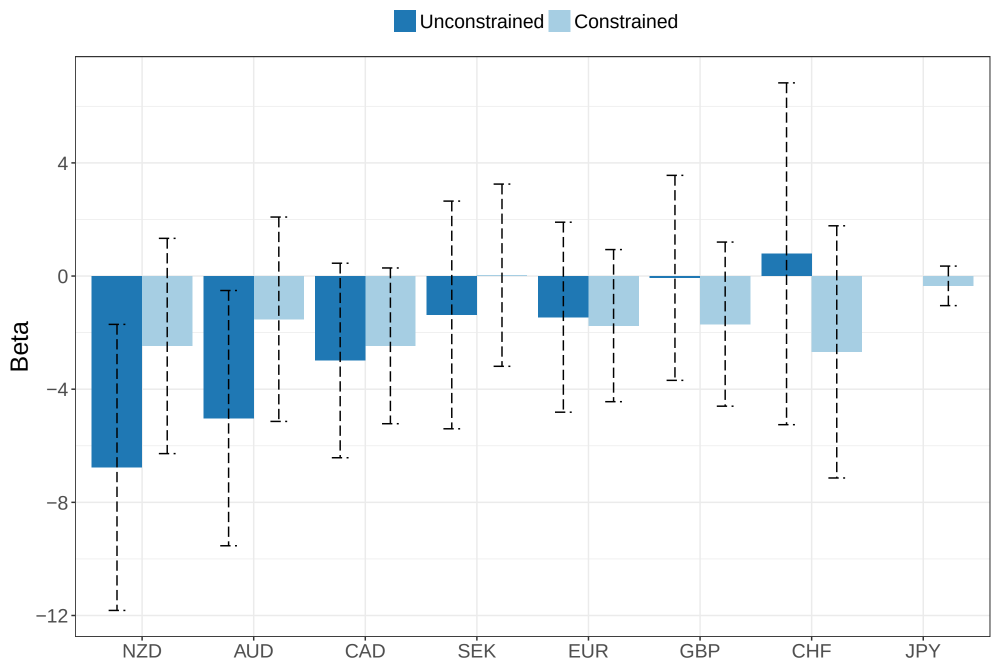
in which Δe_t^j is the log appreciation of currency j in US dollars, r_t^m refers to the log appreciation of the S&P 500 equity index in the hour surrounding the FOMC announcement, and $\tilde{X}_t$ are controls for the direct change in Fed monetary policy expectations (changes to the implied effective federal funds rate in the current and the next three FOMC meetings, derived from federal funds rate futures changes over these window). Currencies are ordered along the horizontal axis by decreasing risk, as measured by their average pre-crisis carry trade return. Further details on data construction and sample coverage are provided in appendix A.1.

In Figure 1.9, we use the change in the two year bond yield for each currency as the dependent variable.[17] Consistent with the evidence in Figure 1.6, we find that in the period prior to the crisis, central banks of the riskiest currencies were expected to hike policy rates most aggressively when risk

[17] As many of these bond markets are not open during the FOMC announcement window, we use the 2 day change in bond yields as the dependent variable, while using the 30 minute change in the S&P 500 to ensure we are using a high frequency shock free of other macroeconomic news as our source of variation.

premia increased.

Figure 1.9: *Regression coefficients of two year risk-free yield spreads on the S&P 500, high frequency sample*



Regression coefficients of changes in the two year yields of each bond in a FOMC announcement day on the return on the S&P 500 over an hour window around the FOMC announcement. The return on the S&P 500 is interacted with a variable indicating whether this meeting occurred after January 2009, resulting in pre-crisis (unconstrained) and post-crisis (constrained) coefficients. The regression specification is:

$$\Delta i_t^j = \alpha_j + \beta^{j,unc} r_t^m + \beta^{j,con} r_t^m + \tilde{\gamma}^j \tilde{X}_t + \varepsilon_{j,t}$$

in which Δi_t^j is the yield change of the government bond in currency j, r_t^m refers to the log return of the S&P 500 equity index in the hourly window surrounding the FOMC announcement, and $\tilde{X}_t$ are controls for the direct change in Fed monetary policy expectations (proxied by changes to the implied effective federal funds rate in the current and the next three FOMC meetings, derived from federal funds rate futures changes over these windows). Currencies are ordered along the horizontal axis by decreasing risk, as measured by their average pre-crisis carry trade return. Further details on data construction and sample coverage are provided in appendix A.1.

For both specifications, we control for the direct effect on foreign currencies and yields stemming from changes in the expected path of monetary policy in the US. These controls are the implied basis points change to the effective federal funds rate in the current and the next three FOMC meetings, derived from federal funds rate futures changes over these windows. We describe the FOMC meeting coverage and show that the results are similar when we do not control for changes in the expected path of the federal funds rate in Appendix section A.3.

1.4 Conclusion

In this paper, we documented a large shift in the relationship between currency movements and risk premia after the recent financial crisis and proposed an explanation based on interest rate spreads behavior. Correlations between risky assets and exchange rates are larger when interest rate spreads do not adjust in response to changes in risk premia. We documented a structural break in the betas of major currencies with the S&P 500 at the onset of the crisis - the period in which interest rates have been constrained by the effective lower bound.

Moreover, we highlighted that while currency appreciations are unexplained by contemporaneous equity market returns before the financial crisis, this is not the case in the recent post-crisis period in which interest rate spreads across currencies have not reacted to changes in the risk factor.

Interest rate spreads tended to move with risk premia in the period before the financial crisis: interest rate spreads of risky (safe) currencies increased (decreased) when the S&P 500 fell. We also show that these responses can account for low measured exchange rate betas with the stock market before the crisis.

This development is particularly important given the role of the nominal exchange rate in determining international purchasing power and relative wealth. As such, understanding what makes certain currencies risky and others safe, and in turn what makes one country benefit from a rise in the global risk factor at the loss of another, is the next step in this line of work.

Chapter 2

The Transactional Cost of Quantitative Easing[1]

2.1 Introduction

Quantitative easing is emerging as the de facto primary tool of monetary policy for the United States. Since the start of 2009, interest rate policy in the United States has been constrained at the zero lower bound in 8 out of the last 12 years, and the Federal Reserve has conducted Large Scale Asset Purchases (LSAPs) of Treasuries in 7 out of 8 of these years. In this paper, we provide the first measure of the transaction costs of these purchases. We find a total transaction cost (defined as the price paid over market value) of approximately 6.4 billion for purchases over 4.4 trillion of Treasury purchases, or 0.15% of the fair value.

The cost of implementing central bank policy with quantitative easing (QE) is more direct than conventional interest rate policy announcements, which are effectively costless to implement for a credible central bank - policy rates quickly move to the announced target without requiring a transaction. Balance sheet expansions involve transacting with a select set of market participants with market power on a large scale. Since the bonds are purchased in the secondary market, transacting at prices

[1] Co-authored with Gianluca Rinaldi

higher than fair value are equivalent to to wealth transfers from from the consolidated balance sheet of the government to intermediaries and end investors. We find that the transaction prices do not persist, and so the transfer is entirely to intermediaries, rather than to end investors.

The preponderance of these costs were paid in during the months of March through May of 2020, where transaction costs were much higher than average during the preceding years. We decompose the transaction costs and total purchase costs by year in Table 2.1. We calculate that 75% of transaction costs were incurred during the first three months of LSAPs in the response to the COVID-19 induced recession, which make up only 42% of the all term debt purchases.

Table 2.1: *Transaction Costs of Treasury Notes and Bonds Purchased, by Year*

	Transaction Cost (USD billions)	Total Purchase Cost (USD billions)	Transaction Cost as % of Total
2010	0.1	182	0.03%
2011	0.0	823	0.00%
2012	1.1	605	0.18%
2013	0.4	562	0.07%
2014	0.2	250	0.07%
2019	0.0	79	0.06%
2020	5.2	1800	0.29%
Total	6.9	4300	0.16%

Notes: Purchases of US Treasuries for the System Open Market Account (SOMA), including Treasury Coupon Bonds and Treasury Inflation Protected Securities. Transaction costs are estimated by estimating the markup between the market mid price at 4pm before the SOMA transaction (P_{t-1}^{market}) and the SOMA weighted average purchase price the following day (P_t^{SOMA}) using the following regression:

$$\log\left(\frac{P_t^{SOMA}}{P_{t-1}^{market}}\right) = \alpha_{2010} + ...\alpha_{2020} + \varepsilon_t$$

to take an estimate of the average markup for each year, $\hat{\alpha}_T$, equally weighting each transaction within-year. This estimate is multiplied by the volume weighted average price of each transaction and quantity of each transaction, i.e. Transaction $\text{Cost}_T = \hat{\alpha}_T \sum_{i,t\in T} Price_{i,t} \cdot Quantity_{i,t}$ where i is at the security level and T is annual. The period of analysis spans January 2010 through May 2020. Years with fewer than 1 billion of purchases are excluded.

Transaction costs are substantially affected by operational decisions. First, the rate of purchasing is the most important determinant of cost. We find transaction costs do not scale linearly with the size of the daily operation - a one standard deviation increase in the total size of purchases that day increases the average transaction cost by 0.16 cents per dollar of purchase. Second, the cost is increasing in the share of the security which is already owned by the Federal Reserve.

Risk compensation and liquidity also drive some of the variation, both in the time-series and at the security level. At the aggregate level, we find that the transaction cost increases as market risk premia increases (as proxied by the daily level of the VIX) - a one standard deviation increase in the level of the VIX increases the transaction cost by 0.06 cents per dollar. At the security level, we find that an increase of Macaulay Duration of one year increases the transaction cost by 0.03 cents per dollar.

Related literature:

Our paper is most closely related to the literature on the costs of financing government debt, and the behavior of primary dealers.

Lou *et al.* (2013) find that the prices of Treasury securities in the secondary market decrease in the days in advance of auctions and recover quickly thereafter, which increases the cost of financing government debt by around 0.14 cents per $100 issued. They argue the price pressure is due to risk compensation, as the discount increases in the closeness of broker-dealers to their leverage constraint.

The surplus from participating in auction transactions also reflects the risk aversion of agents who have less information than the largest bidders. Hortaçsu *et al.* (2018) document that primary dealers strategically use their private information to bid-shade, and use this information to extract surplus from participating in multiple price auctions.

Song and Zhu (2018) use proprietary data on the full bidding book of POMO auctions during QE2 to show that the decision function of which bonds the SOMA will purchase is predictable, and this predictability assists primary dealers in extracting surplus from the auctions.

Our findings of increased transaction costs in 2020 relate to those of He *et al.* (2020), who document the accumulation of Treasury and reverse repo positions on dealer balance sheets during the COVID-19 crisis, which temporarily cheapened the market value of Treasury bonds.

A broad literature has measured the reaction of the broad yield curve to LSAP announcements (Gagnon *et al.*, 2011; Krishnamurthy and Vissing-Jorgensen, 2011; Bauer *et al.*, 2014; Chodorow-Reich, 2014). This literature measures the high frequency impact of balance sheet expansions on the broad yield curve, and finds that announcements prior to 2014 increased the price of long term bonds. Another literature measures the effect of supply on yields (Krishnamurthy and Vissing-Jorgensen, 2012). This literature focuses on the permanent effects of the announcements of large changes in the quantity of Treasuries, measuring the effect on the aggregate yield curve, while we measure the transaction costs of of implementing the policy.

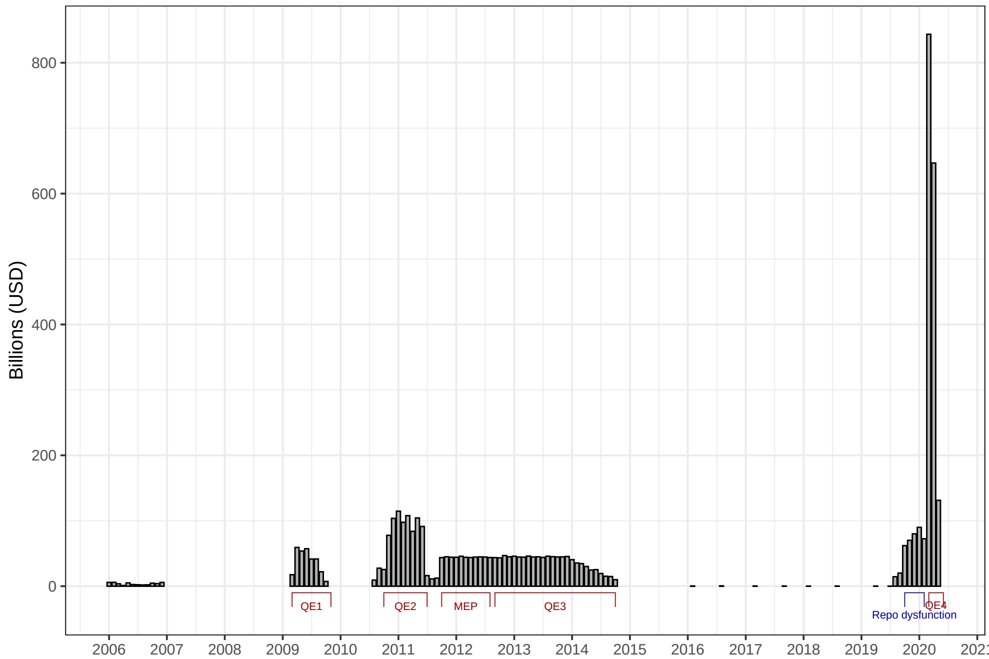
2.2 Institutional context

The Federal Reserve (Fed) periodically purchases and sells Treasury securities - an operation formally known as permanent open market operations (POMOs) - to change the quantity of reserves in the financial system. When the primary tool of monetary policy was interest rate management, these transactions were small in size, and temporary open market operations (known as repurchase agreements, or repo) were primarily used for reserve management. All transactions are conducted between the trading desk arm of the New York Fed and their primary dealers- a group of 24 banks who are authorized to make competitive bids at Treasury auctions.

Starting in December of 2008, the Fed introduced the use of Large Scale Asset Purchases (LSAPs), which vastly increased the size and frequency of POMOs, and then expanded the programme to include Treasuries by March of 2009, ending this operation by October that year. In August of 2010, the FOMC decided to use the proceeds of maturing agency debt to reinvest in purchasing Treasury securities. These purchases were complemented by future rounds of quantitative easing in the years 2011 through 2014, and a maturity extension programme in 2011 and 2012 which saw the Fed sell shorter term

Treasuries to purchase longer term Treasuries.

Figure 2.1: *Monthly Purchases of Treasuries by the Federal Reserve*



Notes: Purchases of US Treasuries for the System Open Market Account (SOMA), including Treasury Coupon Bonds, Treasury Inflation Protected Securities, Floating Rate Notes and Treasury Bills. The monthly total gross number of purchases is shown on the vertical axis. Data spans December 2005 through May 2020.

The need for reinvestment of Treasuries via POMOs dropped substantially after 2015, and daily operations were below 1 billion per year. In August 2019, the reinvestment of maturing Treasury securities was replaced with non-competitive bids at primary auctions rather than transactions in the secondary market.

POMO operations became more significant after the overnight funds market began to experience disruptions in 2019. At this time, the Fed directed the SOMA to purchase Treasury securities to increase the quantity of reserves in the system. This was the first time since the LSAPs that POMOs were used to ensure the overnight lending rate would trade within the target band.

The POMOs are scheduled up to two weeks in advance, with flexible guidance given on upcoming operation dates, times, security types and maturities, and maximum purchase amounts. Any primary dealer is then allowed to bid on each tender with under a multiple-price, multiple-unit competitive auction with variable supply. Approved counterparties can submit up to nine increasing bids of multiple quantities for each unique CUSIP on offer. The SOMA trading desk then evaluates which offers to accept based on a proprietary model of relative value, and the proximity of bids to prevailing market prices. In the following month, the average price of each transaction is reported publicly.

2.3 Measuring the transactional cost of POMOs

Our analysis merges four datasets - transaction data from the New York Fed, Treasury security characteristics from Wharton Research Data Services, Treasury daily price data from Bloomberg, and equity market pricing data from the CBOE.

To obtain the weighted average price that bonds are purchased at, we web scrape the daily operations of the New York Fed's Treasury Securities Operational Details announcements from December 2006 to May 2020. We select only purchases of Coupon Bonds and Treasury Inflation Protected securities, excluding bills and floating rate notes from our analysis due to the short tenor. At the CUSIP level, this covers 17267 completed and 17552 rejected tenders across 943 CUSIPs. The announcements include the date of operation, the CUSIP of the security, the number of bids, the amount of bids accepted, and the weighted average accepted price.

We include bond characteristics from the CRSP dataset provided by WRDS. We match all 943 CUSIPs which are Coupon Bonds and Treasury Inflation Protected securities. The CRSP database includes data on the duration of the bond, the amount of each CUSIP on issue, and the amount available for sale not held in the SOMA account. We construct the proportion held by the Fed as the complement of the share that is available for sale.

Finally, we merge data on the prices of these Treasury securities from Bloomberg, from 1 January 2010 to 30 May 2020. We collect the market mid price at the time of the New York trading close for each trading day. While prices at the market open are closer to the timing of SOMA purchases, we find they are unreliable.

Table 2.2: *Summary of Permanent Open Monetary Operations, by Year*

	2010	2011	2012	2013	2014	2016	2017	2018	2019	2020
Number of Auction Days	53	166	172	212	147	2	2	1	41	79
Unique Securities Purchased, Per Operation	27	24	17	19	19	14	21	35	34	133
Unique Securities Rejected, Per Operation	4	1	3	3	4	5	8	1	4	8
Total Par Amount Purchased, Per Security Per Auction (million)	168	193	181	133	90	23	10	3	55	156
Securities Purchased, Average Years to Maturity	7.0	9.0	18.0	17.2	16.9	8.8	20.0	11.2	5.9	7.8

Notes: Purchases of US Treasuries for the System Open Market Account (SOMA). The period of analysis spans January 2010 through May 2020. The table summarizes the number of operations per year, the number of unique securities purchased and rejected at each operation, and the average purchase sizes.

We exclude the years that have very fewer than 5 purchase dates from the analysis for parsimony, in order to have a consistently usable sample for both the pooled and the year-specific analysis.[2]

2.3.1 Estimating the transactional costs of purchases

We estimate the dynamic impact of the Fed's purchase operations on bond prices around the timing of the auction. For each auction, we collect the price of the bond over seven periods - the average weighted price paid by the Fed at the 11am auction, and three days of market closes both before and after the auction. We denote each CUSIP by the index i, each purchase operation by t, and the bond price as P. We define the log price change over a period as follows:

$$\Delta p_{i,t+s,t+r} = \log\left(\frac{P_{i,t+s}}{P_{\mathrm{i,t+r}}}\right)$$

[2] The excluded years are 2016, 2017, and 2018. All other years have between 400 and 6000 purchase operations. Their inclusion has no impact on the pooled results, but provide imprecise estimates for the yearly regressions. The year 2015 has no purchase operations.

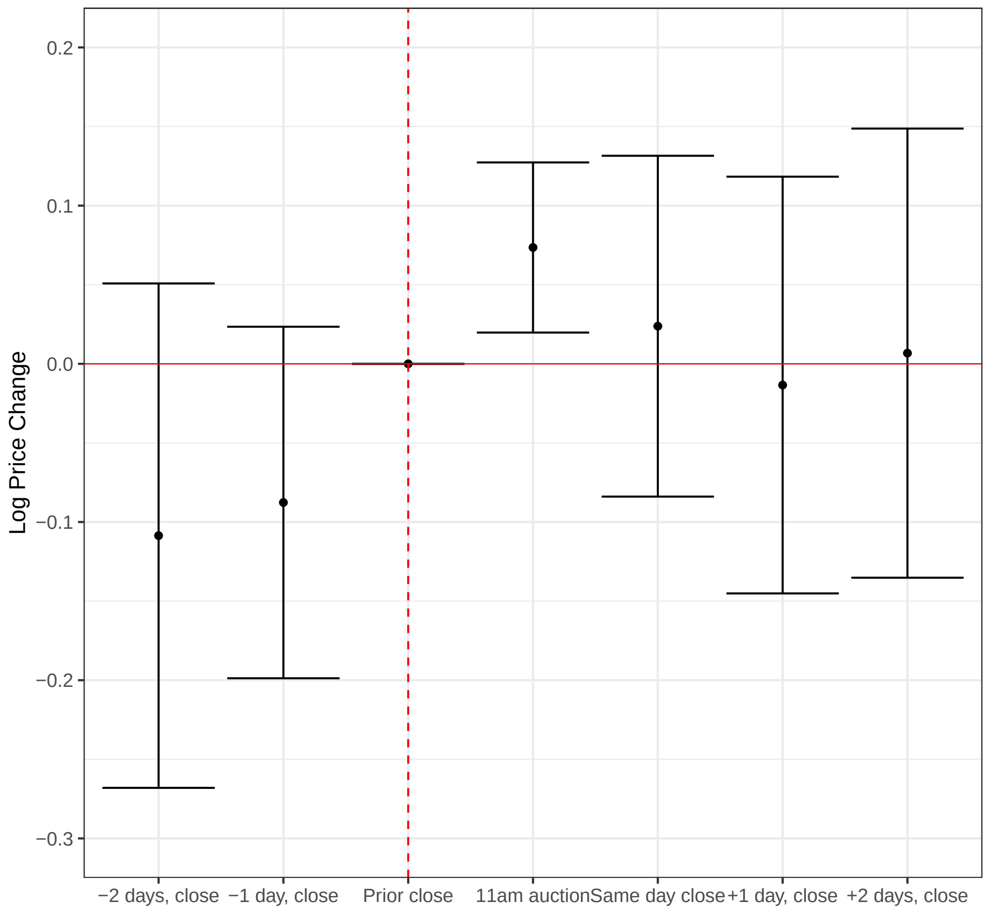
For example, we define the log price difference $\Delta p_{i,t,t-1}$ to be the difference in price between the 4pm close before the purchase (i.e. -1 period relative to the purchase), and the 11am auction purchase (+0 periods relative to the auction), as follows:

$$\Delta p_{i,t,t-1} = \log\left(\frac{P_{i,t}}{P_{\text{i,t-1}}}\right)$$

where i is the security-level identifier (i.e. the CUSIP), t is the date of the open market operation, s and r are indices of time relative to the time of the purchase operation.

We then regress each of these variables against a constant to estimate the average log difference in price versus the price at the 4pm close before the auction, and plot the outcomes in Figure 2.2. The average purchase price transacted at the POMO auction is 0.08% higher than the prior market closing price, with a 95% confidence interval of 0.03% to 0.13%. No other difference is statistically significant. As such, while the Fed pays more for the security at the 11am auction than the close on other days, the price does not stay elevated after the purchase but rather reverts back to its prior close. Since the price completely reverts, we can think of the difference between the 4pm market close and the 11am price, $\Delta p_{i,t,t-1}$, as the markup paid by the Fed - the transactional cost of their purchases. The estimates in Figure 2.2 weight each transaction equally at the CUSIP-transaction level, regardless of the transaction size.

Figure 2.2: *Price Impact of Purchases by Year*



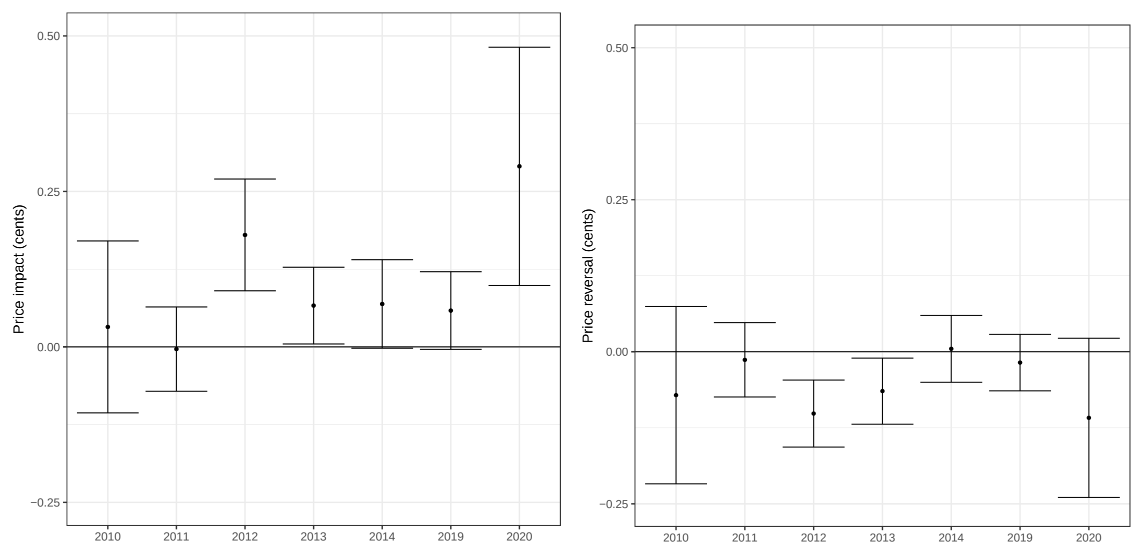
Notes: Coefficients of a regression of the price change from the 4pm close the day before the POMO operation to days around the POMO. We plot the estimated constants $\hat{\alpha}_s$ of the following regression specifications:

$$\Delta p_{i,t+s,t-1} = \alpha_{s,-1} + \varepsilon_t$$

for each s in the set of days $\{-3,-2,-1,0,1,2,3\}$ where $\hat{\alpha}_{s,-1}$ is estimated from a separate regression for each reference period s. We show the 95% confidence intervals as error bars. Standard errors are clustered at the daily level using the leave-one-cluster-out jackknife variance estimator (Bell and McCaffrey, 2002) to allow for correlated price moves across the yield curve in the same time period.

We then turn to deconstructing the estimate of the average price transaction cost paid into annual estimates by splitting the regression into annual calendar samples and estimating a parameter for each calendar year. We show the results in the left panel of Figure 2.3. These parameters underlie the calculations in Table 2.1. Two years stand out in particular - 2012 and 2020, where the premium paid was an average 0.18% and 0.29% respectively - as where the transaction cost paid was much higher than the average of 0.08%. We then measure the subsequent price move between the 11am auction and the *subsequent* market close later that day, and show these estimates in the right panel of Figure 2.3. Again, we see the same pattern in the price reversals across years - the same years that saw the largest increases in price between the market close prior to the auction also saw the largest reversal the same day the auction.

Figure 2.3: *Log price Changes of Bonds Purchased at Auction by Year*



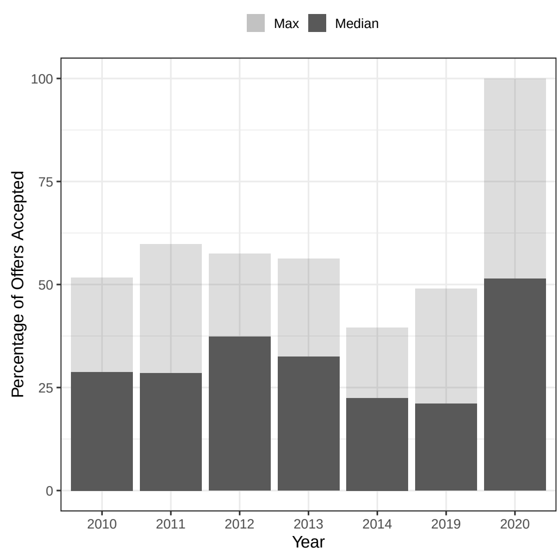
Notes: The left panel plots the average price change from the prior 4pm close to the 11am auction, splitting the sample into each calendar year. The right panel plots the average price change from the 11am auction to the 4pm close, splitting the sample the same way. Standard errors are clustered at the daily level using the leave-one-cluster-out jackknife variance estimator (Bell and McCaffrey, 2002) to allow for correlated price moves across the yield curve in the same time period.

The pattern of markups across years closely mirrors the pattern of competition amongst offers, as measured by the percentage of offers which were accepted at tender.

The auction process involves a reverse tender made by the SOMA with all primary dealers as a reverse tender. The auctions operate as as a multiple unit auction with variable supply. Since each seller can submit staggered quantities and prices, the dominant strategy for each eligible participant is to offer at least 100% of the quantity of each security they hold, hence the proportion of offers accepted is a lower bound on the percentage of securities held by bond desks which were purchased by the Fed.[3]

The percentage of offers which are accepted summarizes how far along the schedule of offers the SOMA was forced to go in order to complete its preannounced tender size. In figure 2.4 below, we show both the average percentage of offers accepted at each auction date, as well as the maximum percentage of offers accepted, within each year. During 2020, the year in which the required purchase programme was the largest, more than half of offers made were accepted by the SOMA on the average day; in some days all 100% of offers were accepted. This suggests a key reason for the higher markup in 2020 was due to the fact that competitive forces in offers were hampered on the days with the largest purchases.

Figure 2.4: *Share of Bond Offers Accepted at Tender*



Notes: Figure summarizes the outcomes of purchase operations, at the security level. The dark (light) gray bars show the median (maximum) percentage of offers which are accepted for each security which was included in the purchase operation, by year.

[3]It is a lower bound as some counter-parties may make offers for quantities of securities which they do not own, expecting they could borrow them via repurchase agreements.

2.3.2 Determinants of the transactional cost of purchases

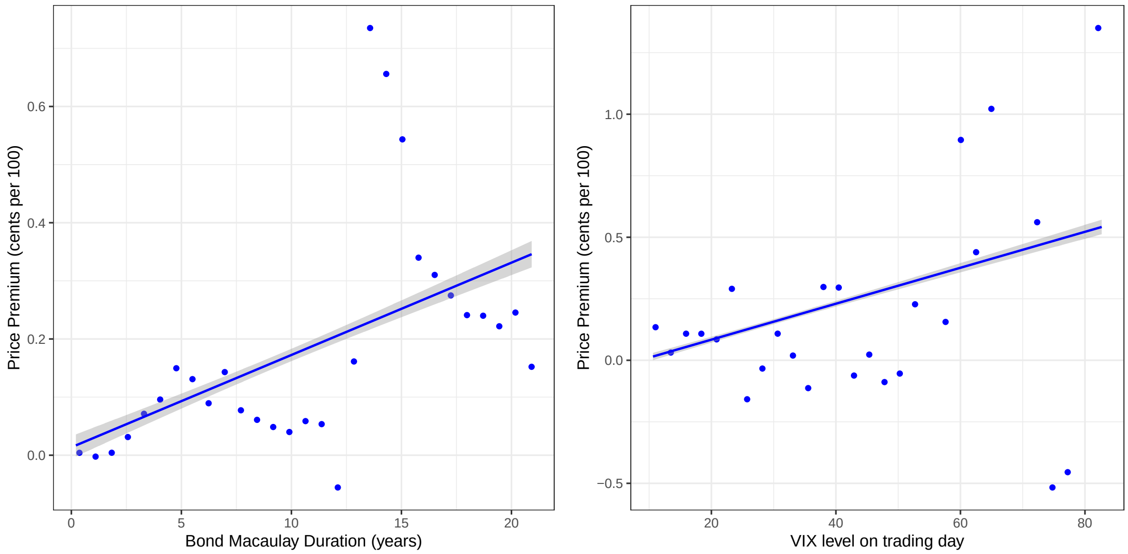
We now turn to deconstructing this premium paid for bond purchases into its explanatory factors. First, we measure the markup on bond purchases which can be explained by compensation for risk. Second, we measure how the choice of security determines the markup, using characteristics that are unrelated to risk (such as the share of each CUSIP that is already owned by the Fed). Third, we use details on the total purchases on the day, independent of the choice of security.

The markups paid for bond purchases are consistent with compensation for risk. Intermediating bond purchases requires a dealer to hold these securities on their balance sheet for a period of time, which requires them to be exposed to interest rate risk. Even thought the securities will be held with offsetting positions in bond futures, since the securities are purchased outright by the Fed. As such, dealers will be left exposed to a rise in interest rates until they can exit their offsetting positions in bond futures.

The premium paid for purchases is influenced both by the security level exposure to interest rate risk (the quantity of risk that each security is exposed to), and the aggregate level of risk premia on the day (the price of risk). We show the influence of these factors in figure 2.5. In the left panel we show a binned scatterplot of the premium paid at the security level against the Macaulay duration of each bond security, which measures the price impact of each bond for a change in yield. The expected premium is strongly related to the duration of the bond, averaging 0.01 cents (per $100) for a bond with duration of less than one year, and 0.35 cents for a bond with macaulay duration of 21 years. In the right panel we show this relationship with an aggregate measure of risk premia as proxied by the VIX. The expected premium 0 cents on days where the aggregate level of the VIX is at 15, the lowest in the sample, but rises to 0.52 cents on days where the VIX is at 81, the highest in the sample.

Purchases of securities have largely been focused on longer run bonds, particularly during the Maturity Extension Programme in 2011 and the second round of Quantitative Easing in 2012. The tenure of these programmes has resulted in the Fed being the majority owner of securities in certain

Figure 2.5: *Price Impact on Markups by Risk Determinants*



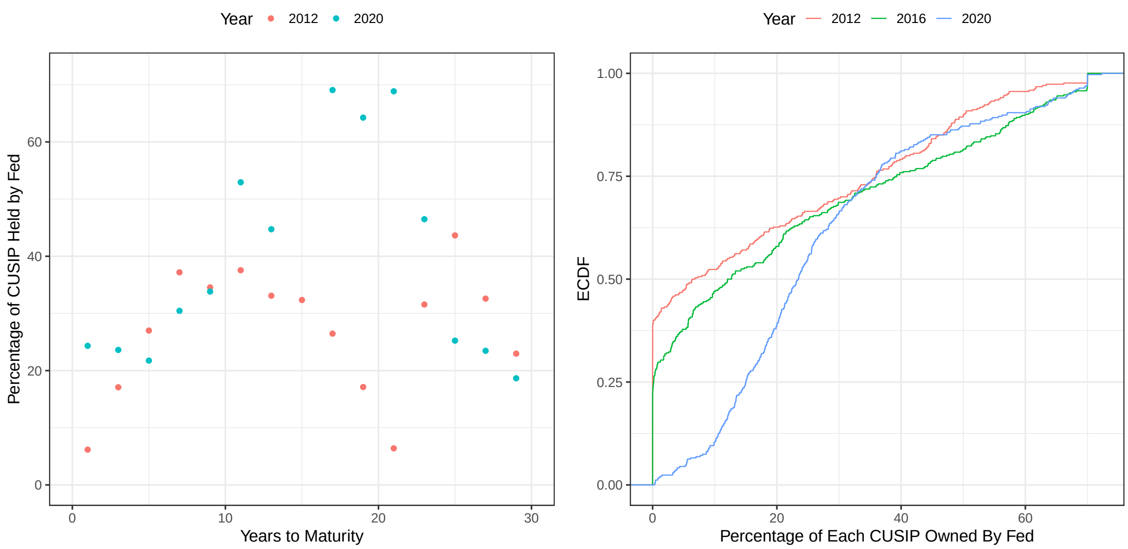
Notes: The above figures show a binned scatterplot of the average log price premium paid at auction against a measure of risk for the transaction. The markup is measured as the log price difference from the market mid price at 4pm before the SOMA transaction (P_{t-1}^{market}) and the SOMA weighted average purchase price the following day (P_t^{SOMA}). In the left panel, the risk indicator is the Macaulay duration of the security at the date of purchase. In the right panel, the risk indicator is the level of the VIX. The analysis is at the security by purchase operation level. The period of analysis spans January 2010 through May 2020.

maturities of outstanding debt. All newly established bond lines are issued consecutively for several months, until a new bond line is established and they move to be "off-the-run". After this point, these lines are not issued again, but replaced with new securities. The Fed then begins to purchase these older lines as part of its POMOs. The size of allowable purchases declines as it owns a larger share of the security, until it owns 70% of each particular security, at which point its purchases are capped permanently.

In figure 2.6 we show the evolution of ownership trends. In the left panel, we show the average share of each two year maturity bucket which is owned by the Fed. When the third round of quantitative easing began, the Fed owned around 30% of each bond line, spread evenly across the bond curve. Today, the Fed is the majority owner of the belly of the bond curve, owning between 45% and 70% of bonds which mature in 10 to 20 years. In the right panel, we show the empirical cumulative distribution function for the share of each CUSIP with maturity greater than 1 year which is owned by the Fed.

One eighth of all bond lines are now majority owned by the Fed, and around 4% are now at the 70% ownership cap, making them ineligible for purchase.

Figure 2.6: *Price Impact on Markups by Security Characteristics*



Notes: The above figures plot the average share of each Treasury bond (at the CUSIP-level) with maturity over one year which was held by the Federal Reserve during the years 2012, 2016 and 2020. The left panel shows the percentage held by the Federal Reserve against the years to maturity remaining, binned for each year. The right panel shows the empirical cumulative density function of the share of each CUSIP which was owned by the Federal Reserve at the end of the year. The discrete increase at 70% is due to a policy which bars the consideration of CUSIPs for auctions after the Federal Reserve holds 70% of the outstanding value.

We use the share owned by the Fed as a measure of the relative scarcity of each security, and find that for every additional 10% of a security line that is owned by the Fed, the price premium paid increases by 2.2 cents (Table 2.3). The marginal effect of Fed ownership shares remains significant after controlling for the duration of the bond, but it halves in size to 1.0 cents per every additional 10% held by the Fed. Another relevant security characteristic is the type of instrument - inflation protected securities command a markup which is 0.14 cents higher than for nominal bonds - again an indicator of their relative scarcity compared to nominal bonds.

Lastly we find that the speed of purchases are a significant determinant. An additional 100bn of POMOs on the day increases the average premium paid per security by 0.7 cents. (We do not use the quantity of purchases of the CUSIP itself since the Fed has discretion over which securities to purchase, and it is endogenous to the prices of offers.)

Table 2.3: *Determinants of Markups on Purchase Price Paid*

	Price Premium (cents per \$100 notional)					
Nominal						-0.327^{***}
						(0.018)
TIPS	0.142					-0.207^{***}
	(0.117)					(0.027)
Share Held		0.222^{***}				0.098^{***}
		(0.073)				(0.030)
Duration			0.027^{***}			0.026^{***}
			(0.010)			(0.001)
VIX Level				0.011^{*}		0.003^{***}
				(0.006)		(0.001)
Amount Bought (bn)					0.007^{***}	0.006^{***}
					(0.003)	(0.0004)
Year Fixed Effect	*Y*	*Y*	*Y*	*Y*	*Y*	*N*
Observations	16,628	16,297	16,628	16,628	16,628	16,297
R^2	0.078	0.079	0.114	0.099	0.103	0.144

Notes: Each column shows the output of a regression of the price markup against an indicator pertaining to the auction. The markup is measured as the log price change between the market mid price at 4pm before the SOMA transaction (P_{t-1}^{market}) and the SOMA weighted average purchase price the following day (P_t^{SOMA}) using the following regression:

$$\log\left(\frac{P_t^{SOMA}}{P_{t-1}^{market}}\right) = \tilde{X}_T + \beta X_{i,t} + \varepsilon_{i,t}$$

, where $\tilde{X}_T$ are yearly fixed effects, and $X_{i,t}$ varies by column. The analysis is at the security by purchase operation level. The period of analysis spans January 2010 through May 2020. Years with fewer than 1 billion of purchases are excluded. Standard errors are clustered at the daily level using the leave-one-cluster-out jackknife variance estimator (Bell and McCaffrey, 2002) to allow for correlated price moves across the yield curve in the same time period. *p<0.1; **p<0.05; ***p<0.01.

In table 2.4 below we contextualize these factors in terms of the standard deviation of each component. The most significant determinants are the total size of the daily purchase operations, and the interest rate risk of the security itself. A one standard deviation increase in either of these factors increases the expected markup paid by 0.16 cents per \$100.

Table 2.4: *Relative Marginal Effect Sizes of Determinants of Markups*

	Share of CUSIP Owned by Fed	VIX Level	TIPS (v. Nominal)	Amount Purchased on Day	Bond Macaulay Duration
Δ Price (cents)	0.02	0.06	0.12	0.16	0.16
ΔX	1 s.d.	1 s.d.	Binary	1 s.d.	1 s.d.

Notes: Each column shows the marginal effect on the log markup paid at auction from a one standard deviation increase in each explanatory factor used in the analysis. The marginal effect is equal to the estimated beta from the rightmost column of Table 2.3 scaled by one standard deviation of each variable. For the marginal effect of a purchase of TIPS rather than coupon bonds, we use the discrete change as the scaling factor.

2.4 Conclusion

In this paper, we provided the first measures of the direct costs of permanent open monetary operations. We estimate the transactional costs paid for open monetary operations thus far have totalled 7 billion USD, of which 75% was incurred during the response to the 2020 pandemic-induced recession.

Since the bonds are purchased in the secondary market, transacting at prices higher than fair value are equivalent to to wealth transfers from from the consolidated balance sheet of the government to intermediaries and end investors. We find that the transaction prices do not persist, and so the transfer is entirely to intermediaries, rather than to end investors.

We deconstruct the markup paid into three components: compensation for risk, the relative scarcity of the bond, and the daily aggregate size of purchase operations. Many of these factors are in the Fed's control. Our results suggest that transaction costs of implementing these programmes can be reduced along four dimensions - by focusing larger purchases to days with lower market risk premia, spreading purchases over additional days, reducing purchases of TIPS, and weighting purchases towards lines of securities for which the Fed is a minority holder.

Chapter 3

Exchange Rate Reconnect[1]

3.1 Introduction

Starting with the influential contribution by Meese and Rogoff (1983b), a long literature has demonstrated the difficulty in finding economic variables that co-move with exchange rates, a phenomenon known as "exchange rate disconnect." The paucity of robust empirical relationships between exchange rates and other aggregates offers little guidance for researchers and policymakers on which macroeconomic models to use. While progress has certainly been made, the proverbial glass remains – at the very most – half full.

It is against this backdrop that we uncover a surprising pattern that emerged with the global financial crisis: exchange rates, and in particular the broad US dollar, have co-moved closely with global risk appetite and with U.S. foreign bond purchases. Since 2007, during months when proxies for global risk appetite decrease, the dollar contemporaneously appreciates. When risk appetite increases, the dollar depreciates. Whereas risk measures had little or no explanatory power for exchange rates prior to the crisis, the risk measures statistically explain a meaningful share of all subsequent exchange rate variation. Furthermore, during 2007-2012, U.S. purchases of foreign bonds rose and fell with these measures of global risk appetite, and so these capital flows also co-moved with the broad US dollar. In quarters when U.S. residents increased their holdings of external debt, the dollar contemporaneously

[1]Co-authored with Matteo Maggiori, Brent Neiman, and Jesse Schreger

depreciated. When U.S. residents decreased these foreign bond holdings, the dollar appreciated.

We dub the emergence of the relationships of global risk proxies and U.S. foreign bond purchases with the exchange rate as "exchange rate reconnect." It is difficult to reach definitive conclusions from such short time series as the 2013-2018 period, but it appears that the risk measures remain reconnected with exchange rates even at the end of our sample. U.S. foreign bond purchases, however, appear to have again disconnected with the broad US dollar.

We start our analysis by examining the connection between exchange rates and common proxies of global risk appetite, including credit spreads, financial intermediary returns, the S&P 500 returns and their implied volatility in option markets, and the premium on U.S. Treasuries. Consistent with Lilley and Rinaldi (2018), who first showed that the S&P 500 and exchange rates began to co-move since the crisis, we demonstrate that all six risk proxies exhibit a structural break around 2007. We run rolling regressions of exchange rates on our risk proxies using monthly data spanning 10- and 5-years. We find negligible explanatory power before the crisis and large R^2s – in some cases, surpassing 50 percent – since then. Even at the end of our sample, the estimated coefficients in these regressions generally remained significantly different from zero and above their pre-crisis values.

We decompose the explanatory power of these risk measures for the broad dollar into its bilateral exchange rate components. Intuitively, the co-movement of these risk measures and bilateral exchange rates between the dollar and other safe-haven currencies such as the Swiss franc and Japanese yen remains fairly muted, even after the crisis. Instead, the reconnect of global risk measures and the broad dollar is largely driven by the bilateral exchange rates between the US dollar and currencies conventionally thought of as riskier, such as the Australian dollar.

Next, we turn to publicly available data from the IMF Balance of Payments (BoP) and International Investment Positions (IIP) to construct quarterly measures of U.S. capital flows. In rolling 10-year and 5-year regressions using these data, quarterly changes in U.S. gross foreign bond flows (as a share of the stock of U.S. foreign bond positions) had near-zero explanatory power for changes in the broad US dollar exchange rate prior to 2007. At the time of the crisis, the correlation between these objects increased and the R^2 on the regressions climbed sharply. The R^2 of the 5-year regressions, after peaking above 50 percent for the period corresponding to 2007-2012, returns to a near-zero level for

2013-2018. We conclude that the connection of U.S. gross foreign bond flows to exchange rates lasted for a number of years when markets were in a heightened state of turmoil.

When we repeat the identical exercise for other countries and for other flow measures (including outflows, inflows, and net flows of bonds, equity, and direct investment), we do not find similarly compelling evidence of reconnect. Since other flows likely interact similarly to U.S. foreign bond flows in terms of the pressure they exert on currency markets and their interaction with various market frictions, and given the continued reconnect of risk measures and exchange rates, we do not view the relationship between U.S. foreign bond flows and the dollar as causal. Rather, we believe fluctuations in global risk appetite simultaneously influenced both exchange rates and U.S. foreign bond flows during the crisis and several years of its aftermath. In this sense, the reconnect carries something of a special role for the United States.

Having demonstrated the strong in-sample explanatory power of U.S. purchases of foreign bonds for the broad US dollar, at least during 2007-2012, we turn to a novel micro dataset capable of elaborating on the mechanics of this reconnect. We use data assembled by Maggiori, Neiman and Schreger (2019a) on mutual fund and exchange traded fund (ETF) holdings from Morningstar that covers $32 trillion of assets from individual security-level positions. These data do not extend backward enough in time to capture the change that occurs around 2007, but they do offer a number of benefits relative to BoP and IIP data.

First, the mutual fund holdings decompose the market value of positions into prices and quantities. As such, we can use them to isolate changes in foreign bond positions that come from purchases of additional securities and not from movements in prices or exchange rates. This ensures that reconnect does not reflect the mechanical influence of the exchange rate on the value of foreign bond purchases. Indeed, even with this conservative notion of flows, U.S. foreign bond flows in the Morningstar data do have a similarly high explanatory power for the broad dollar as we found in the public macro data from 2007 onward.

Second, U.S. purchases of foreign bonds in the Maggiori *et al.* (2019a) dataset can be separated by issuing country, sector (corporate or government), and currency of denomination. Further, the data can be used to explore these purchases across different kinds of investors, including large versus small mutual funds or those that specialize in international investment versus those that do not. In doing so, we find that the explanatory power of U.S. portfolio flows is driven as much by U.S. net purchases of dollar-denominated bonds as by U.S. purchases of foreign-currency-denominated bonds. This further corroborates that the explanatory power is indeed coming from the relationship between these flows and changes in a global risk factor, rather than from the direct effect of a sale of US dollars and purchase of foreign currencies. In addition, in contrast to BoP data, the Morningstar data allow us to see which securities investors are buying domestically. Consistent with the idea that flows are picking up changes in investors' risk appetite, we see that when U.S. investors buy less U.S. Treasuries or more domestic corporate debt, the dollar depreciates.

Third, we sort the open-end and exchange-traded funds in Maggiori *et al.* (2019a) according to their size, the degree to which they specialize in foreign investment or foreign currency investment, and the degree to which they follow a passive investment strategy. We find that the aggregate results are driven by large actively-managed funds that are not specialists in foreign currency or foreign issuers. The fund-level analysis therefore also supports the view that U.S. foreign bond flows largely pick up the risk appetite of sizable dollar-centric discretionary U.S. investors.

In summary, we identify the emergence of a close relationship between various global risk measures and the broad US dollar that emerged with the global financial crisis. Further, we identify a particular quantity, U.S. foreign bond purchases, that has strongly comoved with these risk measures and the broad US dollar during the crisis and several years of its aftermath, even though this relationship no longer appears to hold at the end of our data. In the context of the voluminous literature on exchange rate disconnect which offers few comparably successful covariates, we consider this progress even if the post-crisis time series is short and we do not establish a causal mechanism.

Our results are consistent with the narrative that when U.S. residents have a greater risk appetite, they use it to purchase foreign bonds in all currencies and at the same time require a lower risk premium, which causes the world's primary safe-haven currency to depreciate, particularly against riskier currencies. Most theoretical models do not contain all the elements required to study, let alone to fully explain, the phenomena we document and their stark emergence after 2007. An emerging literature has incorporated time variation in the global risk appetite, asymmetries between the United

States and other countries, and financial frictions into dynamic models with well-defined nominal exchange rates and cross-border investment flows. We hope our findings serve as motivation for further development of these types of approaches.

Related Literature Our documentation that exchange rate reconnect started around 2007 relates to the finding in Du, Tepper and Verdelhan (2017) of large covered interest rate parity deviations (CIP) over this same period, which Avdjiev, Du, Koch and Shin (2019b) show are systematically related to the dollar exchange rate. More generally, a number of papers have made progress on the exchange rate disconnect puzzle. Gourinchas and Rey (2007) show predictability over medium term horizons using the cyclical component of net external balances, and Kremens and Martin (2018) have success forecasting exchange rates with S&P 500 options-implied risk premia. Measures of the convenience yield on treasuries have been shown to covary with the broad dollar exchange rate in Jiang *et al.* (2018a) and Engel and Wu (2018). Adrian *et al.* (2010) find that growth in the dollar-denominated liabilities of the banking sector forecasts appreciations of the U.S. dollar, and Adrian and Xie (2019) find that a higher share of US dollar loans in the portfolio of non-U.S. banks forecasts a dollar depreciation. Lustig, Roussanov and Verdelhan (2011b) highlight the importance of common factors in explaining the cross-section of exchange rate movements.

Further, the crisis seems to have further cemented the role of the US dollar as the primary global safe asset. Maggiori *et al.* (2019a,b) document a broad and persistent portfolio shift into dollar-denominated bonds (and away from euro-denominated bonds) since the financial crisis. These latter two developments suggest an increase in the role of risk premia in driving the broad dollar. Our results support an emerging narrative that the US dollar's role as an international and safe-haven currency has surged since the global financial crisis (Bruno and Shin (2015); Jiang *et al.* (2019a); Kekre and Lenel (2020); Cerutti *et al.* (2019)).

3.2 Exchange Rate Disconnect and Reconnect

A large literature documents the disconnect between the exchange rate and macroeconomic fundamentals. For example, uncovered interest parity implies a strong relationship between the nominal exchange rate for two countries and the difference in their interest rates. As we demonstrate in Appendix Figure B.1a, however, during 1977-2006, less than 5 percent of the variation in quarterly log-changes in the broad dollar, defined as an equally-weighted basket of nine currencies (the G10, excluding the United States) against the US dollar, is explained by the quarterly interest differential between the United States and those nine other countries. Appendix Figure B.1b similarly demonstrates that changes in observed inflation differentials and the exchange rate over that same period exhibit an even weaker realtionship, at odds with many standard models. Given this much-studied exchange rate disconnect holds in-sample for realized outcomes, it is not surprising that interest rates and inflation differentials, as well as many other economic aggregates, also offer no out-of-sample forecasting power.

3.2.1 Reconnect with Global Risk Appetite

The reconnect of exchange rates to global risk appetite can be clearly seen in Figure 3.1, which plots the R^2 values of rolling univariate regressions run in monthly data of the broad dollar exchange rate on a constant and the contemporaneous change in six global risk proxies. These proxies include (i) the "GZ Spread", an index of aggregated U.S. corporate bond spreads constructed by Gilchrist and Zakrajšek (2012) (ii) the "VXO", calculated as the monthly change in the log implied volatility on the S&P100 stock index, (iii) the log total return on the "S&P500", (iv) the "Treasury Premium" constructed as the average one-year covered interest parity deviation between developed country government bonds and U.S. Treasuries taken from Du *et al.* (2018), (v) the "Global Factor" in world asset prices constructed by Miranda-Agrippino and Rey (2018), and (vi) the "Intermediary Returns" from a value-weighted portfolio of holding companies of New York Federal Reserve primary dealers taken from He *et al.* (2017). Figure 3.1a shows regressions estimated on 10-year rolling windows, and Figure 3.1b considers 5-year windows, starting in January of 1977 and ending in December of 2018.

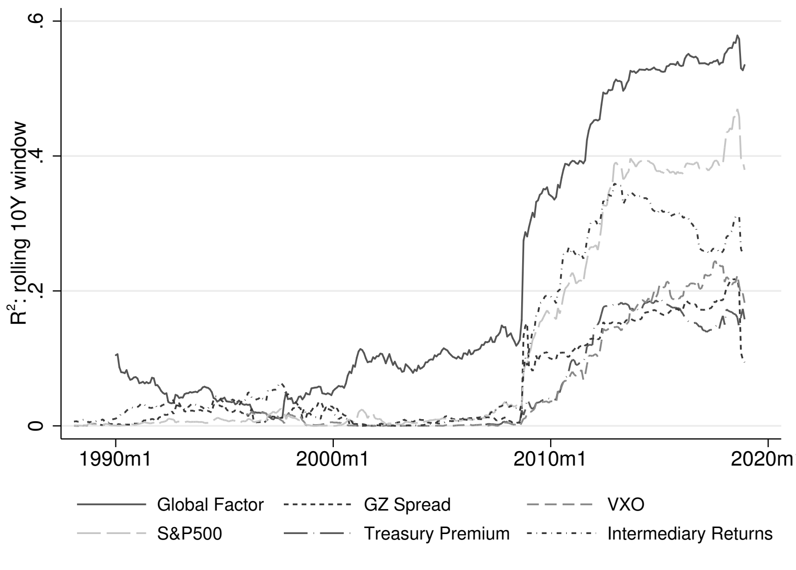
During 1977-2006, most of the rolling regressions in Figure 3.1a have R^2s that average only a few percentage points and peak at about 5-10 percent. Around 2007, however, there is an abrupt but sustained increase in the explanatory power of most of these risk proxies for the broad dollar. The measures subsequently have R^2 values ranging from 10 to 60 percent, with most finishing the sample with R^2 values above 20 percent, large values that stand out in the exchange rate disconnect literature.

Even after the steep one-quarter declines in the R^2s at the very end of the sample, which arise from dropping the second quarter of 2009 from the rolling regressions, all of the 10-year regressions in Figure 3.1a have R^2s well above their pre-crisis peak values. The 5-year regressions in Figure 3.1b similarly have R^2 values that peak between 30-70 percent, though these R^2s also sharply decline toward the end of our sample, suggesting that the explanatory power of global risk measures for the exchange rate was greater during 2007-2012 than during 2013-2018. Nonetheless, four of the six measures, even in this final five-year period of our sample, offer more explanatory power than they did at any point prior to the crisis.

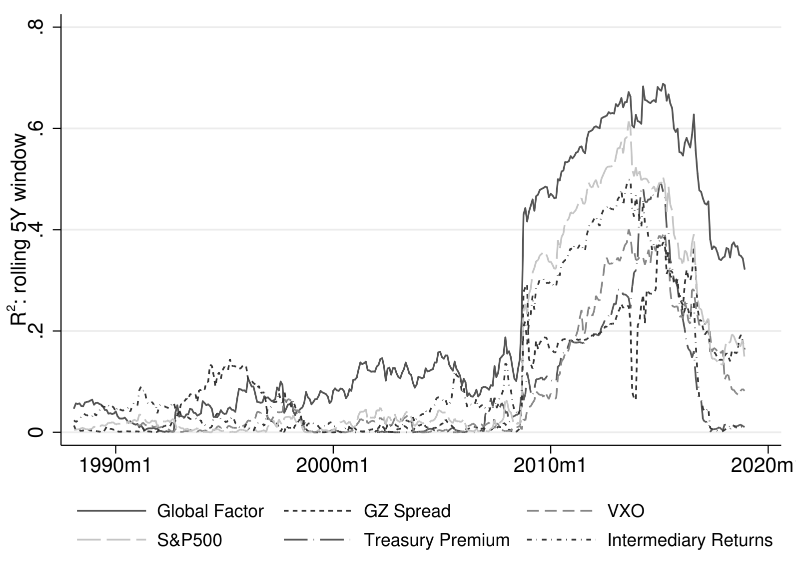
The break from historical experience in the relationship between these risk measures and the broad dollar can be additionally seen by examining the regression coefficients underlying the R^2 values shown in Figure 3.1b. For each of the six risk proxies, we plot in Figure 3.2 the point estimates from the rolling regressions along with their 95 percent confidence intervals. In the regressions, a positive coefficient indicates that a depreciation of the broad dollar is associated with a decline in the risk premium (or an increase in risk appetite) captured by our proxies. We plot the estimates after normalizing them as z-scores, so they give the percent depreciation of the broad dollar in response to a one-standard-deviation increase in each measure of risk appetite. For example, the value in Figure 3.2b corresponding to the GZ Spread ends our sample at 0.0125, implying that when corporate credit spreads drop by one standard deviation, the dollar depreciates by 1.25 percent. In all six cases, the coefficients rise dramatically from their typical pre-crisis values to their post-crisis peaks near 2012, all of which are statistically greater than zero. In four of the six cases, the estimates remain statistically greater than zero, even by the last quarter of 2018, the last observation for these risk measures in our data.

Figure 3.1: *Reconnect of The Broad Dollar and Risk Measures: R^2s*

(a) *10-Year Rolling Window*



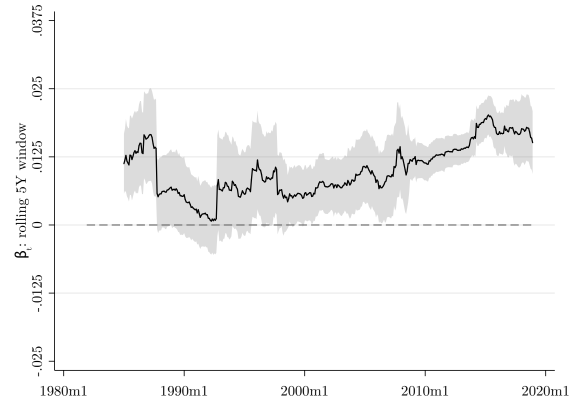
(b) *5-Year Rolling Window*



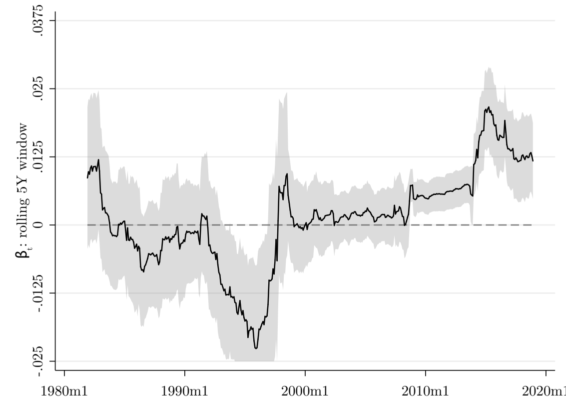
Notes: The figures show the 120- and 60- month rolling R^2 for regressions of the average log change in the US dollar versus the other G10 currencies against various indicators of risk. The regression specification is $\Delta e^B_{USD,t} = \alpha + \beta X_t + \varepsilon_t$, where X_t corresponds to different variables depending on the model in question. For "VXO," X_t is the monthly change in the log transformation of an index of implied volatility on the stocks in the S&P100, from the CBOE. For "S&P500," X_t is the log total return on the S&P500 index. For "Treasury Premium," X_t is the change in the one-year Treasury Premium, the average one-year tenor CIP deviation between developed country government bonds and U.S. Treasuries from Du *et al.* (2018). For "GZ Spread," X_t is the U.S. corporate bond credit spread, taken from Gilchrist and Zakrajšek (2012). For "Intermediaries," X_t is the value-weighted return on a portfolio of NY Fed primary dealers' holding companies and is taken from He *et al.* (2017). For "Global Return Factor," X_t is the global factor in world asset prices constructed by Miranda-Agrippino and Rey (2018).

Figure 3.2: *Reconnect of The Broad Dollar and Risk Measures: βs*

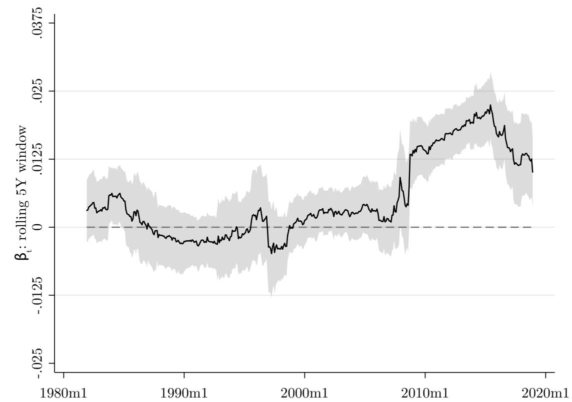
(a) *Global Return Factor*



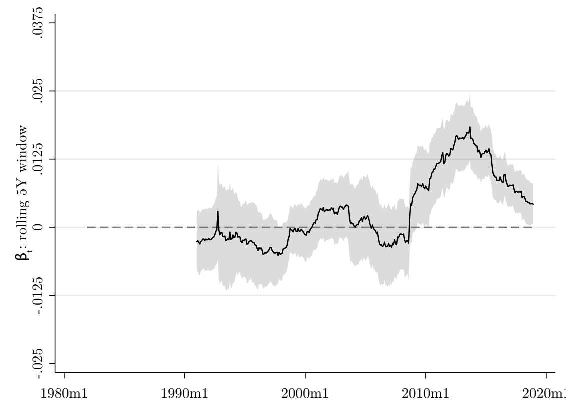
(b) *GZ Spread*



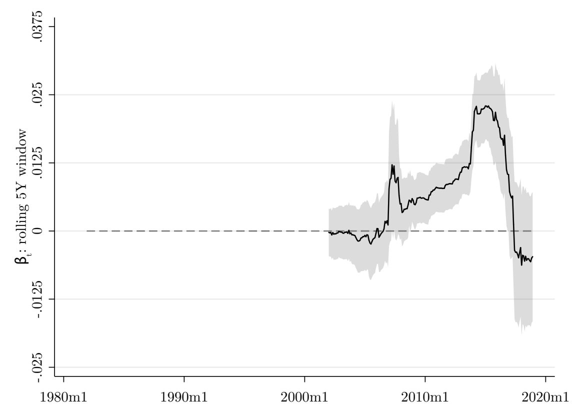
(c) *S&P500 Log Return*



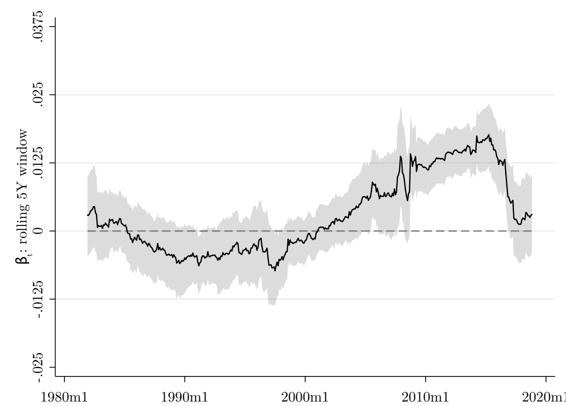
(d) *Log VXO*



(e) *Treasury Premium*



(f) *Intermediary Returns*



Notes: The figure shows the 60 month rolling β for regressions of the average log change in the US dollar versus the other G10 currencies against various indicators of risk, normalized as z-scores. The regression specification is $\Delta e^{B}_{USD,t} = \alpha + \beta X_t + \varepsilon_t$, where X_t corresponds to different variables depending on the model in question. The shaded errors correspond to 95% confidence intervals, calculated using heteroskedasticity robust standard errors.

Bilateral Exchange Rates

We can further unpack the exchange rate reconnect of global risk appetite by studying how the risk proxies correlate differently with different bilateral exchange rates. We find that when our measures of the risk premium decrease, the dollar depreciates most strongly against currencies conventionally described as "riskier" and less strongly or not at all against currencies conventionally considered to be "safe havens". Appendix Figure B.2 reports the coefficients from regressions of changes in each bilateral exchange rate against the dollar on changes in the GZ Spread using monthly data from 2007 to 2018. While safe-haven currencies such as the Yen and Swiss Franc hold steady or even depreciate vis-a-vis the US dollar when credit spreads are low (i.e. when risk appetite is high), the emerging market currencies and the New Zealand and Australian dollars appreciate. In fact, as shown in Appendix Table B.1, the different degrees of comovement across bilateral pairs with the US dollar implies that in the post-crisis period, fluctuations in global risk appetite explain significant shares of variation in all bilateral exchange rates. Appendix Table B.2 demonstrates that this was not at all the case before the crisis. Appendix Tables B.6-B.7 and Figures B.7-B.8 examine the loadings and R^2 of each currency to these various measures of risk appetite.

Out-of-Sample Forecasting

As detailed in Appendix B.1, we evaluate the forecasting capabilities of our risk proxies. We follow the tradition established by Meese and Rogoff (1983b) in evaluating the "out-of-sample" fit of a model while giving the model the realized values of the regressors. Appendix Figure B.4 and Table B.5 shows our results. Prior to 2007, we find the standard result: all model forecasts based on the risk proxies perform worse, or on par at best, with a random walk. Yet for the last decade, we find that all of these models outperform the "no-change" benchmark.

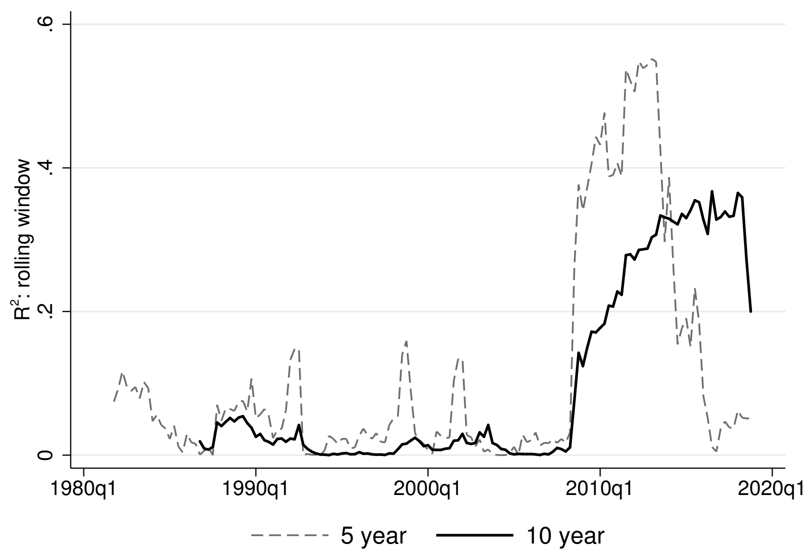
x

3.2.2 Reconnect with U.S. Foreign Bond Purchases

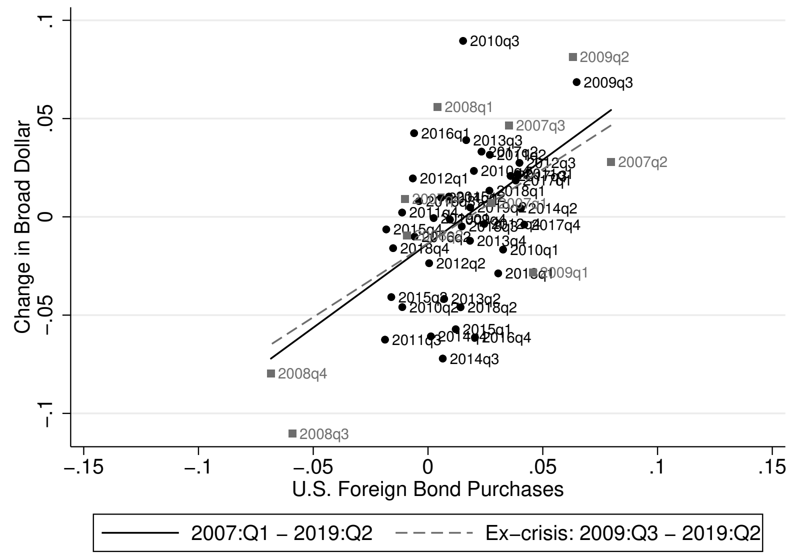
The post-crisis reconnect between global risk measures and exchange rates is strong, appears long-lived, and complements a small number of recent successes in the exchange rate forecasting literature that

Figure 3.3: *Reconnect of The Broad Dollar and U.S. Foreign Bond Purchases*

(a) *Rolling R^2s*



(b) *2007:Q1-2019:Q2*



Notes: In the top panel, the y-axis corresponds to the R^2 of a 20- and 40-quarter rolling regression of the following specification: $\Delta e^B_{USD,t} = \alpha + \beta X_t + \varepsilon_t$, where $\Delta e^B_{USD,t}$ is the average log appreciation of the US dollar against all other G10 currencies and X_t is the U.S. net purchases of foreign bonds, normalized as a percentage of the U.S. value of foreign bond investment at the end of the prior quarter. In the bottom panel, the y-axis corresponds to the quarterly average change in the US dollar against all other G10 currencies, defined such that a positive value corresponds to a depreciation. The x-axis shows the purchases of foreign bonds by the United States in the contemporaneous quarter. Regression lines are estimated using the full sample (2007:Q1 to 2019:Q2) and excluding the crisis (2009:Q3 to 2019:Q2).

use other price-based variables. The finding of reconnect between quantity-based macroeconomic aggregates and exchange rates, however, has been even more elusive. In this section we demonstrate that U.S. purchases of foreign bonds, a type of U.S. capital flow, strongly comoved with these risk measures and, therefore, strongly moved with the broad dollar during 2007-2012.

We start by constructing U.S. purchases of foreign bonds as the quarterly flow of U.S. funds into foreign debt securities (from BoP) divided by the value of U.S. foreign debt holdings at the start of the quarter (from IIP). During 2007-2012, in a clear break from the pre-crisis relationship, these U.S. purchases of foreign bonds moved closely together with each of the six risk measures.[2] Further, we find that the comovement of this U.S. capital flow and our risk measures led to the reconnection of U.S. foreign bond purchases and the broad dollar over this period.

Figure 3.3a shows the R^2 of 10- and 5-year rolling regressions of the broad US dollar and U.S. foreign bond purchases and demonstrates that the answer is yes. The series estimated with rolling 10-year windows, plotted in a solid black line, shows that the explanatory power of changes in these bond flows for changes in the broad dollar jumps from near-zero to about 15 percent with the onset of the crisis and peaks near 40 percent shortly thereafter. The removal of the first post-crisis quarter from the estimation window causes a steep decline for the last plotted value, but the level even at the end of our series remains clearly elevated relative to pre-crisis values. The 5-year series, plotted with a red dashed line, shows an even greater surge in the explanatory power of these bond flows for the broad dollar during the period from 2007-2012, though the R^2 values return by the end of the sample to negligible levels. We do not wish to draw definitive conclusions based on 5-year windows, but the results do suggest that the reconnect of U.S. foreign bond purchases and the broad dollar did not persist through the end of our sample.

Much of the stark change in Figure 3.3a is driven by the particularly large appreciation of the US dollar and particularly large reduction in U.S. foreign bond holdings during the third and fourth quarters of 2008. The confluence of reconnect of this capital flow and the global financial crisis is important and intriguing. We emphasize, however, that the large movements during 2007-2009 are not

[2] Appendix Figures B.5a and B.5b report the R^2 of rolling 10-year and 5-year univariate regressions of quarterly changes in U.S. holdings of foreign bonds on the six risk measures. All series jump starting in 2007, though the R^2s from the 5-year regressions all also sharply decline after 2013.

wholly responsible for reconnect. To give a better sense for how evenly distributed reconnect is across the post-crisis period, Figure 3.3b plots the change in flows against the change in the broad dollar for each quarter of 2007:Q1-2019:Q2 in a scatterplot. The solid black best-fit line has a positive slope of 0.85 that indicates that greater U.S. purchases of foreign bonds are associated with larger depreciations of the US dollar and the R^2 on this relationship between the broad dollar and U.S. purchases of foreign bonds equals 32 percent. The red dashed line in Figure 3.3b demonstrates that the best-fit slope relating these two variables is nearly identical whether including or excluding 2007:Q1 to 2009:Q2, the key quarters of the global crisis.[3]

Other U.S. Capital Flows?

Interestingly, other types of U.S. capital flows have not exhibited a post-crisis reconnect with global risk measures nor with the broad dollar.[4] Appendix Table B.3 reports regression estimates for gross foreign purchases, gross foreign sales, and net foreign purchases by the United States of bonds and of equities. Of these six types of U.S. capital flows, only U.S. gross foreign purchases of debt securities and U.S. gross sales of equities exhibit a meaningful post-crisis change in their explanatory power for the broad dollar, with the change for U.S. foreign bond purchases being the largest by far.[5]

Other Macroeconomic Fundamentals

In Appendix Figure B.6 and Appendix Table B.4, we analyze whether there has been a reconnect of other macroeconomic fundamentals to exchange rates. We run 40-quarter and 20-quarter rolling-window regressions using the fundamentals that are related to exchange rates in several standard models in international economics, analogous to what we did with global risk measures in Figure

[3] Appendix Figure B.1d offers an equivalent plot of pre-crisis quarters and has an R^2 of less than one percent.

[4] We do not offer a theory of why some flows have reconnected while others have not. We hope our empirical results might offer further guidance on the source of these shocks. For example, recent models such as Farhi and Werning (2014) and Itskhoki and Mukhin (2017) have introduced financial shocks in the Euler equations for foreign currency bonds.

[5] The importance of the distinction between gross and net capital flows has been documented empirically by Forbes and Warnock (2012), Broner *et al.* (2013), and Avdjiev *et al.* (2018). An interesting literature studies the relationship between bank credit and exchange rates, including Avdjiev *et al.* (2019b,a), Miranda-Agrippino and Rey (2018), and Niepmann and Schmidt-Eisenlohr (2019)).

3.1. Guided by the excellent review of exchange rate predictability in Rossi (2013b), the models that we test include the UIP model, the monetary model, the Taylor-rule model, and the Backus-Smith model.[6] While most models perform relatively poorly, it is not unusual to find short spans of data over which a particular model works well. Relative to these other macro fundamentals, the relationship between U.S. foreign bond purchases and the broad dollar during 2007-2012 is clearly sharper and more persistent. Nonetheless, these appendix analyses remind us of the need for caution in reaching too strong conclusions from short time series.

In sum, before the global financial crisis of 2007-2008, exchange rates rarely comoved with other economic aggregates. We demonstrate, however, that several common proxies for global risk appetite, and even more surprisingly, U.S. purchases of foreign bonds, strongly reconnected with the broad dollar starting around 2007. Reconnect remains even after excluding the quarters of the global financial crisis, though it has significantly attenuated in recent years. The short time series cautions against definitive conclusions, but at the end of our sample, risk-based reconnect appears to continue while we no longer see evidence for capital-flow-based reconnect.[7]

3.3 Elaborating Reconnect with Micro Data

One key benefit of our finding that a type of U.S. capital flow began to co-move with the broad dollar is that it offers a natural pathway to explore reconnect further. In particular, we can disagregate those capital flows using the security-level holdings details assembled by Maggiori *et al.* (2019a) using Morningstar data on open-end mutual fund positions.[8] These data cover $32 trillion of assets and allow us to make two distinct contributions. First, our micro data allow us to directly disentangle

[6]Appendix B.2 provides details about the implementation of each model. Recent contributions of this literature include Engel and West (2005), Chen *et al.* (2010), Eichenbaum *et al.* (2017), Schmitt-Grohé and Uribe (2018), and Calomiris and Mamaysky (2019b).

[7]All results presented in this section can be easily replicated using the code and datasets posted to `http://www.globalcapitalallocation.com`.

[8]We refer the reader to Maggiori *et al.* (2019a) and its Online Appendix for an extensive study of the representativeness of this type of flows for the BoP. Here, we only note that the measured changes in U.S. holdings of foreign bonds in the two sources have a correlation of 0.64. Appendix Figure B.3 plots the two time series from 2005:Q1 to 2017:Q4, the maximum span we can study in the micro data.

security purchases from changes in security prices, whereas BoP or IIP data necessarily conflate the two to some degree when calculating changes in positions. This means that we can confirm that our finding that flows correlate with exchange rates is not a mechanical effect from using exchange rates to measure these flows. Second, the micro data allow us to study reconnect using various subsets of the data, distinguishing flows by currency, asset class, and investor type, for example.[9] In this final section of the paper, therefore, we use these micro data to unpack the reconnect of exchange rates with U.S. foreign bond purchases.

3.3.1 Reconnect after Separating Purchases from Price Changes

Our previous analyses defined flows as quarterly purchases of foreign securities during a quarter divided by the stock of holdings of such securities at the start of the quarter. Aggregated data on these purchases, however, do not allow us to completely separate the quantity of securities purchased and the price at which they were purchased. The flow measures might therefore contain information about the exchange rate, since it may be an important driver of the security's price (particularly if the security is not dollar-denominated). For claims such as ours, that a macroeconomic variable co-moves with the exchange rate, this limitation is critical.

We circumvent this issue in this section by building a measure of flows that keeps all prices and exchange rates constant at their beginning-of-quarter levels, which we are able to do using the dataset assembled by Maggiori *et al.* (2019a). These data capture the detailed holdings of all U.S. mutual funds and ETFs and allow us to separately track for each position s at the end of each quarter t the number of securities $N_t(s)$ and the price per security $P_t(s)$. The total start-of-quarter value of the position is then simply the product of the two at the end of the prior quarter: $Q_{t-1}(s) = P_{t-1}(s) \times N_{t-1}(s)$, while the flow is the change in the number of securities during the current quarter times the start-of-quarter price: $F_t(s) = (N_t(s) - N_{t-1}(s)) \times P_{t-1}(s)$. We can then aggregate the flows across all positions s within some category S (such as corporate or government bonds, denominated in dollars or otherwise), $F_{t,S} = \sum_{s \in S} F_t(s)$, and divide the total by the aggregated start-of-quarter positions,

[9] We follow the procedure in Coppola *et al.* (2019) to classify positions based on nationality of the ultimate parent and not residency of the immediate issuer. The BoP and IIP are instead based on residency.

$Q_{t-1,S} = \sum_{s \in S} Q_{t-1}(s)$, to construct a measure equivalent to what we studied using aggregated data above, $F_{t,S}/Q_{t-1,S}$.

In Appendix Table B.8, we confirm that U.S. foreign bond purchases constructed from these micro data connect with the broad US dollar to a similar extent as did these purchases when taken from the macro data. While the coefficients are slightly different, the R^2 are quite close: 33 percent for the BoP and 39 percent for the Morningstar data.

3.3.2 Which Flows Matter?

As discussed above, we believe the post-crisis era has been characterized by a reconnect between the exchange rate and proxies for global risk appetite. Unique among the set of flows we examined, U.S. purchases of foreign bonds appear to have themselves started to comove with these risk proxies, which brought about our capital-flow-based reconnect.

One might find it natural that bonds are more connected to exchange rates than equities since bonds are promises to pay units of a particular currency and equities are claims on real assets. Therefore, one might conjecture that the connection between U.S. foreign bond flows and the broad dollar occurs because U.S. residents are changing their positions in foreign-currency bonds, thus directly and causally affecting the exchange rate as in portfolio balance models of exchange rate determination.[10] Panel A of Table 3.1 shows that this is not the case. Much of the information about the exchange rate contained in U.S. purchases of foreign bonds is contained in U.S. purchases of foreign, but US dollar-denominated, bonds. The table separately investigates the explanatory power for the broad dollar of flows by U.S. residents in corporates and sovereigns and dollar- and non-dollar-denominated bonds. Flows to corporate bonds denominated in US dollars has the most explanatory power for the US dollar, while flows to sovereigns in foreign currency are statistically significant, though weaker.[11]

These empirical findings suggest that when U.S. residents have a higher risk appetite, they purchase

[10]Models of portfolio balance such as Kouri (1976) and Gabaix and Maggiori (2015) connect foreign currency risk taking to exchange rates via imperfect substitutability of the assets. A growing empirical literature has focused on portfolio rebalancing of foreign currency exposures and its connection to exchange rates, including Hau and Rey (2006), Camanho *et al.* (2017), and Bergant and Schmitz (2018).

[11]In the Appendix Table B.10, we show bilateral exchange rates co-move with multilateral flows, rather than only flows to the related country, thus further corroborating our interpretation of flows as a proxy of global risk appetite.

foreign bonds and require a lower risk premium, leading safe-haven currencies to depreciate and risky currencies to appreciate. This logic suggests a similar relationship in domestic portfolio allocations, which unlike the BoP data, are included in our micro dataset. We explore this in Panel B of Table 3.1, which examine the co-movement between the broad dollar and changes in U.S. fund investment in overall domestic bonds, corporate bonds, and domestic sovereign bonds (Treasuries), the safest asset class. The first column of Panel B shows that overall flows into domestic bonds by U.S. residents covaries negatively with the broad dollar. This means that during times when U.S. mutual funds are increasing their flows into domestic debt, the broad dollar tends to appreciate. This is the opposite of what we saw for U.S. foreign bond flows. Interestingly, we find strong effects with opposite signs for domestic investment in corporate versus sovereign bonds. When U.S. funds purchase the riskier corporate bonds or sell the safer sovereign bonds, the dollar contemporaneously depreciates.[12]

Purchases of foreign bonds by U.S. mutual funds must be financed either by selling other securities or from net flows into the mutual fund sector. In appendix Table B.9 we show that it is flows into and out of the mutual fund sector, rather than purchases and sales of domestic securities by the funds themselves, that coincide with these foreign bond flows.

This duality between domestic risk-bearing capacity and foreign bond investments can be further confirmed by focusing on which type of funds drive the aggregate results. We sort U.S.-domiciled funds on four characteristics: total size of the fund, fraction of the fund that is invested in foreign assets, fraction of the fund that is invested in foreign currency, and how close a fund is to being a passive investor. We split funds into quintiles for each characteristic and report coefficient estimates and R^2 from univariate regressions of changes in the broad dollar on foreign bond flows for each of these subgroups in Figure 3.4.

The key driver of the aggregate results are the large active funds that are not specialized in foreign investment. Indeed, the upper left panels of Figures 3.4a and 3.4b show that the degree to which a fund specializes in foreign currency investments does not have a strong effect on the results. The upper right hand panels show that funds that have the least percentage of asset under management invested

[12] This pattern is consistent with investor retrenchment in bad times as shown empirically in Forbes and Warnock (2012) and modeled theoretically in Caballero and Simsek (2020).

abroad have the strongest covariation and explanatory power for the exchange rate. The lower left panels show that it is the largest funds that drive the overall results. Finally, the bottom right panels show that the most passive funds have no explanatory power for the exchange rate. Therefore, we see that the aggregate explanatory power is driven by active funds who do not specialize in foreign investment. The fact that the results are driven by the purchases or sales of non-specialists supports the idea that the key driver of the aggregate results is the risk-bearing capacity of large U.S.-based investors, rather than the flows themselves causing exchange rate changes.

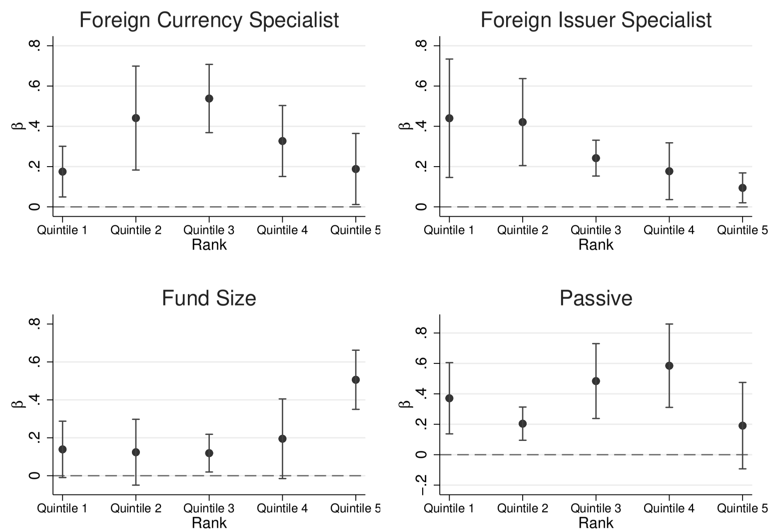
Table 3.1: *US Dollar and Subcomponents of U.S. Outflows*

		Panel A: Cross-Border Flows					*Panel B:* Within U.S. Flows			
		Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}
Corporates	USD	0.43				0.36				
		(0.069)				(0.072)				
	NonUSD		0.085			-0.034				
			(0.065)			(0.068)				
Sovereigns	USD			0.15		-0.0024				
				(0.12)		(0.12)				
	NonUSD				0.24	0.16				
					(0.066)	(0.069)				
All U.S. Bonds							-0.51			
							(0.24)			
U.S. Sovereigns								-0.27		-0.18
								(0.082)		(0.088)
U.S. Corporates									0.76	0.51
									(0.25)	(0.28)
Observations		44	44	44	44	44	44	44	44	44
R2		0.35	0.03	0.04	0.22	0.42	0.10	0.20	0.21	0.27

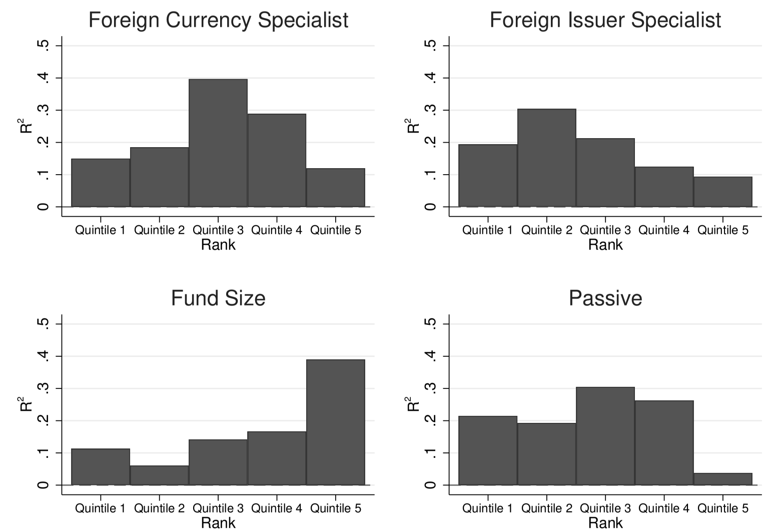
Notes: This table reports regressions results of the form $\Delta e^B_{USD} = \alpha + \beta f_t + \varepsilon_t$, where $\Delta e^B_{USD,t}$ is the quarterly change in the broad dollar and f_t is a particular measure of capital flows. All variables are defined as U.S. purchases of foreign securities belonging to a particular category, scaled by U.S. holdings of bonds belonging to that category at the end of the previous quarter. "Corporates" refers to corporate debt, "Sovereigns" refers to sovereign debt, "USD" indicates that the bond is denominated in US dollars, and "NonUSD" indicates that the bond is denominated in a currency other than the US dollar. Each row refers to a bond in the relevant category, a bond included in Corporates, USD indicates U.S. purchases of corporate debt issued by a non-US firm denominated in a currency other than the US dollar. "All United States Bonds" refers to U.S. domiciled mutual fund purchases of U.S. debt, scaled by the value all holdings of U.S. bonds by U.S. mutual funds at the end of the previous quarter. "U.S. Sovereigns" and "U.S. Corporates" are defined equivalently, restricting the sample to the universe of debt issued by the U.S. Federal Government and U.S. corporations, respectively. Exchange rate data are from Thomson Reuters Datastream and bond position data are from Morningstar. All other variables are defined equivalently. The sample period for all regressions is from 2007:Q1 to 2017:Q4. Standard errors are calculated allowing for heteroskedasticity. Exchange rate data are from Thomson Reuters Datastream and bond position data are from Morningstar.

Figure 3.4: *Broad US Dollar and U.S. Foreign Bond Purchases by Subsets of Mutual Funds*

(a) *Coefficients by Fund Characteristics*



(b) *R^2s by Fund Characteristics*



Notes: This figure reports the coefficient estimate (Panel A), and R^2 (Panel B) of the following regression specification: $\Delta e^{\$}_{i,t} = \alpha_i + \beta_q f^q_t + \varepsilon_t$, where $\Delta e^{\$}_{i,t}$ is the change in average log change in the US dollar versus the other G10 currencies against f^q_t which is U.S. mutual funds' foreign bond purchases, normalized as a percentage of the same mutual funds' value of foreign bond investment at the end of the prior quarter, subsetted into fund quantiles q. In each panel, we separately construct the flow measure for some quintile of the mutual fund universe. We first explain this process for fund size (the AUM in US dollar). For each quarter from 2007:Q1 to 2019:Q2, we sort each fund i by AUM separately within 10 fund categories (e.g. Fixed Income, Equity, Money Market) as defined by Morningstar and measure their percentile ranking within each category for that quarter, $R_{i,t}$. We then average that percentile ranking for each fund over all t, to yield an average ranking $\bar{R}_i$. We then sort each category by $\bar{R}_i$ into 5 quintiles of an equal number of funds. Then we aggregate the positions of each quintile and construct the flow in the usual way. The characteristic "foreign currency specialist" is defined by the percentage of bonds the fund holds in currencies other than the US dollar. The characteristic "foreign issuer specialist" is defined by the percentage of bonds the fund holds which were issued by a foreign parent, using the parent match procedure described in (Coppola *et al.*, 2019). The characteristic "passive" is defined by the R^2 of the fund's monthly returns with the monthly returns of any bond or equity index (we compare their returns with the returns of the 500 most popular indices and take the maximum). Quintile 5 corresponds to largest AUM, highest proportion of foreign currency bonds (by AUM), highest proportion of foreign country issuers (by AUM), highest R^2 with a published index for fund size, foreign issuer specialist, foreign currency specialist, and passive respectively.

3.4 Conclusion

This paper documents a correlation between global risk proxies, U.S. foreign bond purchases, and exchange rates that emerged starting with the global financial crisis. The US dollar, a safe-haven currency, depreciates when risk-appetite is high and when these flows out of the United States increase. And since currencies load heterogeneously on this global risk factor, these relationships explain more than just the broad US dollar, they also explain variation in bilateral currency pairs where one currency is considered "safe" and the other is considered "risky". The reconnect of the global risk proxies has clearly weakened relative to the 2007-2012 period, but appears to remain intact at the end of our sample. The reconnect of the U.S. capital flows, however, appears to have ended by 2018.

While we do not offer a theory of the reconnect nor do we establish a causal link between global risk proxies and U.S. foreign bond purchases, we offer here one possible view of the facts uncovered in this paper. Perhaps currencies began to strongly covary with measures of global risk at the time of the global crisis because of a drastic reduction in global financial intermediation capacity compared to global flows and a repricing of currency risk. This is consistent with the evidence in Du et al. (2017) that persistent CIP deviations have emerged after the crisis. Perhaps U.S. foreign bond purchases became connected with measures of global risk around the same time because that is the unique component of global capital flows whose direction alone reveals whether investors are shifting their portfolio towards riskier foreign securities compared to the ultimate safety of domestic government bonds. This is consistent with the idea that the US dollar's role as a safe asset and international currency has sharply increased since the financial crisis.[13] Seeing whether or not the reconnect continues or vanishes during a period of strong bank balance sheets and low uncertainty will help shed further light on the drivers of this episode.

[13] The literature on the international monetary system focuses on the dollar as a safe asset (Caballero *et al.* (2008b); Gourinchas *et al.* (2011); Maggiori (2017b); Farhi and Maggiori (2018b)).

References

ADRIAN, T., ETULA, E. and SHIN, H. S. (2010). Risk appetite and exchange rates. *FRB of New York Staff Report*, (361).

— and XIE, P. (2019). The non-u.s. bank demand for u.s. dollar assets. *Working Paper*.

ANDREWS, D. W. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica: Journal of the Econometric Society*, pp. 821–856.

AVDJIEV, S., BRUNO, V., KOCH, C. and SHIN, H. S. (2019a). The dollar exchange rate as a global risk factor: evidence from investment. *IMF Economic Review*, pp. 1–23.

—, DU, W., KOCH, C. and SHIN, H. S. (2019b). The dollar, bank leverage and the deviation from covered interest parity. *Forthcoming in American Economic Review: Insights*.

—, HARDY, B., KALEMLI-ÖZCAN, S. and SERVÉN, L. (2018). *Gross capital flows by banks, corporates, and sovereigns*. The World Bank.

BACKUS, D. K. and SMITH, G. W. (1993). Consumption and real exchange rates in dynamic economies with non-traded goods. *Journal of International Economics*, **35** (3-4), 297–316.

BARRO, R. J. (2006). Rare Disasters and Asset Markets in the Twentieth Century*. *Quarterly Journal of Economics*, **121** (3), 823–866.

BAUER, M. D., RUDEBUSCH, G. D. and WU, J. C. (2014). Term Premia and Inflation Uncertainty: Empirical Evidence from an International Panel Dataset: Comment. *American Economic Review*, **104** (1), 323–337.

BELL, R. M. and MCCAFFREY, D. (2002). Bias reduction in standard errors for linear regression with multi-stage samples. *Survey Methodology*, **28**, 169–181.

BERGANT, K. and SCHMITZ, M. (2018). Valuation effects and capital flows - security level evidence from euro area investors.

BERNANKE, B. S. and KUTTNER, K. N. (2005). What Explains the Stock Market's Reaction to Federal Reserve Policy? *The Journal of Finance*, **60** (3), 1221–1257.

BILAL, M. (2017). Zeroing In: Asset Pricing Near the Zero Lower Bound.

BRONER, F., DIDIER, T., ERCE, A. and SCHMUKLER, S. L. (2013). Gross capital flows: Dynamics and crises. *Journal of Monetary Economics*, **60** (1), 113–133.

BRUNNERMEIER, M. K., NAGEL, S. and PEDERSEN, L. H. (2008). Carry trades and currency crashes. *NBER macroeconomics annual*, **23** (1), 313–348.

BRUNO, V. and SHIN, H. S. (2015). Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics*, **71**, 119–132.

CABALLERO, R. J., FARHI, E. and GOURINCHAS, P.-O. (2008a). An Equilibrium Model of "Global Imbalances" and Low Interest Rates. *American Economic Review*, **98** (1), 358–393.

—, — and — (2008b). An equilibrium model of "global imbalances" and low interest rates. *American Economic Review*, **98** (1), 358–393.

— and SIMSEK, A. (2020). A model of fickle capital flows and retrenchment. *Journal of Political Economy*, **128** (6), 2288–2328.

CALOMIRIS, C. W. and MAMAYSKY, H. (2019a). Monetary Policy and Exchange Rate Returns: Time-Varying Risk Regimes. *SSRN Electronic Journal*.

— and — (2019b). Monetary policy and exchange rate returns: Time-varying risk regimes. *National Bureau of Economic Research Working Paper*.

CAMANHO, N., HAU, H. and REY, H. (2017). Global portfolio rebalancing under the microscope.

CAMPBELL, J. and COCHRANE, J. (1999). By Force of Habit: A Consumption-Based of Aggregate Stock Market Behavior. *Journal of Political Economy*, **107** (2), 205–251.

— and SHILLER, R. (1988). The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *The Review of Financial Studies*, **1** (3,), 195–228.

CERUTTI, E. M., OBSTFELD, M. and ZHOU, H. (2019). Covered interest parity deviations: Macrofinancial determinants.

CHAHROUR, R. and VALCHEV, R. (2018). *International Medium of Exchange: Privilege and Duty*. Tech. Rep. 317, Society for Economic Dynamics.

CHEN, Y.-C., ROGOFF, K. S. and ROSSI, B. (2010). Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics*, **125** (3), 1145–1194.

CHODOROW-REICH, G. (2014). Effects of Unconventional Monetary Policy on Financial Institutions. *Brookings Papers on Economic Activity*, pp. 155–204, publisher: Brookings Institution Press.

COCHRANE, J. H. and PIAZZESI, M. (2005). Bond risk premia. *The American economic review*, **95** (1), 138–160.

COLACITO, R. and CROCE, M. M. (2011). Risks for the Long Run and the Real Exchange Rate. *Journal of Political Economy*, **119** (1), 153–181.

COPPOLA, A., MAGGIORI, M., NEIMAN, B. and SCHREGER, J. (2019). Redrawing the map of global capital flows: The role of cross-border financing and tax havens.

DATTA, D., JOHANNSEN, B. K., KWON, H. and VIGFUSSON, R. J. (2018). Oil, Equities, and the Zero Lower Bound. *Finance and Economics Discussion Series*, **2018** (058).

DORNBUSCH, R. (1976). Expectations and exchange rate dynamics. *Journal of Political Economy*, **84** (6), 1161.

DU, W., IM, J. and SCHREGER, J. (2018). The u.s. treasury premium. *Journal of International Economics*, **112**, 167–181.

—, TEPPER, A. and VERDELHAN, A. (2017). Deviations from covered interest rate parity. *Forthcoming at the Journal of Finance*.

EICHENBAUM, M., JOHANNSEN, B. K. and REBELO, S. (2017). Monetary policy and the predictability of nominal exchange rates. *National Bureau of Economic Research Working Paper*.

ENGEL, C. and WEST, K. D. (2005). Exchange rates and fundamentals. *Journal of political Economy*, **113** (3), 485–517.

— and WU, S. P. Y. (2018). Liquidity and exchange rates: An empirical investigation. *National Bureau of Economic Research Working Paper*.

FAMA, E. F. (1984). Forward and spot exchange rates. *Journal of Monetary Economics*, **14** (3), 319–338.

FAN, Z., LONDONO, J. M. and XIAO, X. (2019). *US Equity Tail Risk and Currency Risk Premia*. SSRN Scholarly Paper ID 3399980, Social Science Research Network, Rochester, NY.

FARHI, E., FRAIBERGER, S., GABAIX, X., RANCIERE, R. and VERDELHAN, A. (2015). Crash Risk in Currency Markets.

— and MAGGIORI, M. (2018a). A Model of the International Monetary System. *The Quarterly Journal of Economics*, **133** (1), 295–355.

— and — (2018b). A model of the international monetary system. *The Quarterly Journal of Economics*, **133** (1), 295–355.

— and WERNING, I. (2014). Dilemma not trilemma? capital controls and exchange rates with volatile capital flows. *IMF Economic Review*, **62** (4), 569–605.

FERRARI, M., KEARNS, J. and SCHRIMPF, A. (2017). Monetary policy's rising FX impact in the era of ultra-low rates.

FISCHER, S. (1998). The IMF and the Asian Crisis - Address.

FORBES, K. J. and WARNOCK, F. E. (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics*, **88** (2), 235–251.

FRANKEL, J. (1979). On the mark: A theory of floating exchange rates based on real interest differentials. *American Economic Review*, **69** (4), 610–22.

FRATZSCHER, M., MENKHOFF, L., SARNO, L., SCHMELING, M. and STOEHR, T. (2018). *Systematic Intervention and Currency Risk Premia*. SSRN Scholarly Paper ID 3119907, Social Science Research Network, Rochester, NY.

FROOT, K. A. and RAMADORAI, T. (2005). Currency Returns, Intrinsic Value, and Institutional-Investor Flows. *The Journal of Finance*, **60** (3), 1535–1566.

GABAIX, X. (2012). Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance. *The Quarterly Journal of Economics*, **127** (2), 645–700.

— and MAGGIORI, M. (2015). International liquidity and exchange rate dynamics. *Quarterly Journal of Economics*, **3**, 1369–1420.

GAGNON, J. E., RASKIN, M., REMACHE, J. and SACK, B. P. (2011). Large-scale asset purchases by the Federal Reserve: did they work? *Economic Policy Review*, **17** (May), 41–59.

GILCHRIST, S. and ZAKRAJŠEK, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, **102** (4), 1692–1720.

GIRTON, L. and HENDERSON, D. W. (1976). Financial capital movements and central bank behavior in a two-country, short-run portfolio balance model. *Journal of Monetary Economics*, **2** (1), 33–61.

GOPINATH, G. and STEIN, J. C. (2018). *Banking, Trade, and the making of a Dominant Currency*. Working Paper 24485, National Bureau of Economic Research.

GOURINCHAS, P.-O., GOVILLOT, N. and REY, H. (2011). Exorbitant privilege and exorbitant duty. *Working Paper UC Berkeley and LBS*.

— and REY, H. (2007). International financial adjustment. *Journal of Political Economy*, **115** (4), 665–703.

—, — and GOVILLOT, N. (2010). *Exorbitant Privilege and Exorbitant Duty*. Tech. Rep. 10-E-20, Institute for Monetary and Economic Studies, Bank of Japan.

HASSAN, T. A. and MANO, R. C. (2019). Forward and Spot Exchange Rates in a Multi-Currency World*. *The Quarterly Journal of Economics*, **134** (1), 397–450.

HAU, H. and REY, H. (2006). Exchange rates, equity prices, and capital flows. *Review of Financial Studies*, **19** (1), 273–317.

HE, Z., KELLY, B. and MANELA, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, **126** (1), 1–35.

—, NAGEL, S. and SONG, Z. (2020). *Treasury Inconvenience Yields during the COVID-19 Crisis*. Working Paper 27416, National Bureau of Economic Research, series: Working Paper Series.

HENDERSON, D. W. (1982). *The role of intervention policy in open economy financial policy: a macroeconomic perspective*. Tech. Rep. 202, Board of Governors of the Federal Reserve System (U.S.).

HOLSTON, K., LAUBACH, T. and WILLIAMS, J. C. (2017). Measuring the natural rate of interest: International trends and determinants. *Journal of International Economics*, **108**, S59 – S75.

HORTAÇSU, A., KASTL, J. and ZHANG, A. (2018). Bid Shading and Bidder Surplus in the US Treasury Auction System. *American Economic Review*, **108** (1), 147–169.

ILZETZKI, E., REINHART, C. M. and ROGOFF, K. S. (2019). Exchange Arrangements Entering the Twenty-First Century: Which Anchor will Hold? *The Quarterly Journal of Economics*, **134** (2), 599–646.

INOUE, A. and ROSSI, B. (2018). *The Effects of Conventional and Unconventional Monetary Policy on Exchange Rates*. Working Paper 25021, National Bureau of Economic Research.

ITSKHOKI, O. and MUKHIN, D. (2017). Exchange rate disconnect in general equilibrium. *National Bureau of Economic Research Working Paper*.

JIANG, Z. (2019). *Fiscal Cyclicality and Currency Risk Premia*. SSRN Scholarly Paper ID 3059245, Social Science Research Network, Rochester, NY.

—, KRISHNAMURTHY, A. and LUSTIG, H. (2018a). Foreign safe asset demand and the dollar exchange rate. *National Bureau of Economic Research Working Paper*.

—, — and — (2019a). Dollar safety and the global financial cycle. *Available at SSRN 3328808*.

—, — and LUSTIG, H. N. (2018b). *Foreign Safe Asset Demand and the Dollar Exchange Rate*. SSRN Scholarly Paper ID 3142280, Social Science Research Network, Rochester, NY.

—, — and — (2019b). *Dollar Safety and the Global Financial Cycle*. SSRN Scholarly Paper ID 3328808, Social Science Research Network, Rochester, NY.

JORDA, O. and TAYLOR, A. M. (2012). The carry trade and fundamentals: Nothing to fear but FEER itself. *Journal of International Economics*, **88** (1), 74–90.

KALEMLI-OZCAN, S. and VARELA, L. (2019). Exchange rate and interest rate disconnect: The role of capital flows, currency risk and default risk. *Working Paper*.

KEKRE, R. and LENEL, M. (2020). The dollar and the global price of risk. *Working Paper*.

KOURI, P. J. K. (1976). The exchange rate and the balance of payments in the short run and in the long run: A monetary approach. *Scandinavian Journal of Economics*, **78** (2), 280–304.

KREMENS, L. and MARTIN, I. (2018). The Quanto Theory of Exchange Rates. *American Economic Review*.

KRISHNAMURTHY, A. and VISSING-JORGENSEN, A. (2011). *The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy*. NBER Working Papers 17555, National Bureau of Economic Research, Inc.

— and — (2012). The Aggregate Demand for Treasury Debt. *Journal of Political Economy*, **120** (2), 233–267.

LETTAU, M. and LUDVIGSON, S. (2001). Consumption, aggregate wealth, and expected stock returns. *The Journal of Finance*, **56** (3), 815–849.

—, MAGGIORI, M. and WEBER, M. (2014). Conditional risk premia in currency markets and other asset classes. *Journal of Financial Economics*, **114** (2), 197–225.

LILLEY, A., MAGGIORI, M., NEIMAN, B. and SCHREGER, J. (2019). *Exchange Rate Reconnect*. Working Paper 26046, National Bureau of Economic Research.

— and RINALDI, G. (2018). Currency risk and central banks. *Available at SSRN 3262313*.

LOU, D., YAN, H. and ZHANG, J. (2013). Anticipated and Repeated Shocks in Liquid Markets. *Review of Financial Studies*, **26** (8), 1891–1912.

LUCCA, D. O. and MOENCH, E. (2015). The Pre-FOMC Announcement Drift. *The Journal of Finance*, **70** (1), 329–371.

LUSTIG, H., ROUSSANOV, N. and VERDELHAN, A. (2011a). Common Risk Factors in Currency Markets. *Review of Financial Studies*, **24** (11), 3731–3777.

—, — and — (2011b). Common risk factors in currency markets. *Review of Financial Studies*, **24** (11), 3731–3777.

—, — and — (2014). Countercyclical currency risk premia. *Journal of Financial Economics*, **111** (3), 527–553.

— and VERDELHAN, A. (2007). The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk. *The American Economic Review*, **97** (1), 37.

MAGGIORI, M. (2017a). Financial Intermediation, International Risk Sharing, and Reserve Currencies. *American Economic Review*, **107** (10), 3038–3071.

— (2017b). Financial intermediation, international risk sharing, and reserve currencies. *American Economic Review*, **107** (10), 3038–3071.

—, NEIMAN, B. and SCHREGER, J. (2019a). International currencies and capital allocation. *Forthcoming in Journal of Political Economy*.

—, — and — (2019b). The rise of the dollar and fall of the euro as international currencies. In *AEA Papers and Proceedings*, vol. 109, pp. 521–26.

MARTIN, I. (2017). What is the Expected Return on the Market? *The Quarterly Journal of Economics*, pp. 367–433.

MEESE, R. A. and ROGOFF, K. (1983a). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of international economics*, **14** (1-2), 3–24.

— and — (1983b). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of international economics*, **14** (1-2), 3–24.

MENDOZA, E., QUADRINI, V. and RÍOS-RULL, J. (2009). Financial Integration, Financial Development, and Global Imbalances. *Journal of Political Economy*, **117** (3), 371–416.

MERTENS, T., HASSAN, T. and ZHANG, T. (2017). *Currency Manipulation*. Tech. Rep. 175, Society for Economic Dynamics.

MIRANDA-AGRIPPINO, S. and REY, H. (2018). Us monetary policy and the global financial cycle. *National Bureau of Economic Research Working Paper*.

MOLODTSOVA, T. and PAPELL, D. H. (2009). Out-of-sample exchange rate predictability with taylor rule fundamentals. *Journal of International Economics*, **77** (2), 167 – 180.

MUELLER, P., STATHOPOULOS, A. and VEDOLIN, A. (2017). International correlation risk. *Journal of Financial Economics*, **126** (2), 270–299.

NGO, P. and GOURIO, F. (2016). *Risk Premia at the ZLB: a macroeconomic interpretation*. Tech. Rep. 1585, Society for Economic Dynamics.

NIEPMANN, F. and SCHMIDT-EISENLOHR, T. (2019). Institutional investors, the dollar, and us credit conditions. *FRB International Finance Discussion Paper*, (1246).

ROGOFF, K. (1996). The Purchasing Power Parity Puzzle. *Journal of Economic Literature*, **34**.

ROSSI, B. (2013a). Exchange Rate Predictability. *Journal of Economic Literature*, **51** (4), 1063–1119.

— (2013b). Exchange rate predictability. *Journal of economic literature*, **51** (4), 1063–1119.

SCHMITT-GROHÉ, S. and URIBE, M. (2018). Exchange rates and uncovered interest differentials: The role of permanent monetary shocks. *National Bureau of Economic Research Working Paper*.

SONG, Z. and ZHU, H. (2018). Quantitative easing auctions of Treasury bonds. *Journal of Financial Economics*, **128** (1), 103–124.

TAYLOR, J. B. (2001). The Role of the Exchange Rate in Monetary-Policy Rules. *American Economic Review*, **91** (2), 263–267.

VALCHEV, R. (2019). Bond Convenience Yields and Exchange Rate Dynamics. *American Economic Journal: Macroeconomics*, (Forthcoming).

VERDELHAN, A. (2010). A habit-based explanation of the exchange rate risk premium. *The Journal of Finance*, **65** (1), 123–146.

WACHTER, J. A. (2013). Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility?: Time-Varying Risk of Rare Disasters. *The Journal of Finance*, **68** (3), 987–1035.

WRIGHT, J. H. (2011). Term premia and inflation uncertainty: Empirical evidence from an international panel dataset. *American Economic Review*, **101** (4), 1514–34.

Appendix A

Appendix to Chapter 1

A.1 Data

The three core pieces of data for the analysis in the paper are exchange rates, short term interest rates, and the S&P 500 index. S&P 500 and currency data are collected at daily frequencies, while the data on interest rates is collected at a monthly frequency. For the section on high frequency FOMC shocks, we also collect intra-day exchange rate data as detailed in Appendix A.3.

We focus on the most traded currencies, according to the Bank of International Settlements Triennial Surveys, commonly referred to as the G10. From 1995 to 2016, the US dollar, Euro[1], Japanese yen, British pound, Swiss franc, Australian dollar, Canadian dollar, Norwegian krona, Swedish krona, and New Zealand dollar represented an outsized share of global foreign exchange turnover, accounting for 95 percent of annual foreign exchange turnover, whereas every other currency occupied less than an average 1 percent of turnover over this horizon. Our analysis focuses on these currencies since they should most reliably respond to changes in risk premia at high frequencies.

For each of the aforementioned currencies, we collect daily exchange rate data from Bloomberg, measured at the foreign exchange market closing time of 5pm EST. We collect data on the S&P 500 from Yahoo Finance, measured at the market close of 4pm EST. We collect two year government bond

[1] Prior to the introduction of the Euro in 1999, we use the Deutsche mark in its place.

yields from Global Financial Data (GFD), from April 1987 to June 2019.[2]

For the section on high frequency FOMC announcement shocks, we use data on changes in currencies and the S&P 500 collected from the 30 minute period following Federal Reserve Open Market Committee announcements. Since government bond data are not available at such a high frequency, we use 2 day changes in government bond yields collected from Bloomberg. We compile high frequency exchange rate data using tick data sourced from HistData.com, and minute level exchange rate data sourced from Forexite.com, as explained in Appendix A.3.

Table A.1 reports the mean and standard deviation of monthly currency appreciations and spreads, for the entire sample as well as splitting before and after 2008. While currency standard deviation slightly increased in the post sample, once we remove 2008 and the first half of 2009 from the sample, the difference in the average standard deviations is negligible. On the other hand, the standard deviation of spreads is much lower in the post period.

[2]No other source provides data on bond or swap yields for the majority of these currencies earlier than 1993, and currency forwards data for most of these currencies begins between 1993 and 1995.

Table A.1: *Currency movements and two year interest rates spreads summary statistics*

		AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	Mean
87-07											
Currency	Mean	1.04	1.29	1.37	1.77	1.02	1.28	1.09	1.46	-0.11	1.13
	SD	9.83	5.99	10.88	9.53	9.75	11.35	9.84	10.16	10.78	9.79
Spread	Mean	1.79	0.34	-2.29	-0.86	1.08	-3.80	1.14	2.45	1.13	0.11
	SD	1.85	1.28	1.74	1.92	1.33	1.69	2.25	2.04	2.60	1.86
08-19											
Currency	Mean	-1.93	-2.36	1.30	-2.17	-3.88	0.31	-3.91	-1.15	-3.15	-1.88
	SD	13.66	9.93	10.99	10.54	9.32	10.01	11.87	14.10	12.00	11.38
Spread	Mean	1.77	0.05	-1.33	-0.81	-0.31	-1.16	0.41	1.74	-0.55	-0.02
	SD	1.45	0.53	0.98	1.12	0.79	0.79	1.04	1.31	1.37	1.04
87-19											
Currency	Mean	-0.02	-0.01	1.34	0.32	-0.73	0.93	-0.70	0.53	-1.19	0.05
	SD	11.34	7.64	10.90	9.91	9.61	10.87	10.62	11.70	11.22	10.42
Spread	Mean	1.78	0.24	-1.95	-0.84	0.59	-2.86	0.88	2.22	0.54	0.07
	SD	1.72	1.08	1.58	1.68	1.34	1.91	1.94	1.86	2.38	1.72

Average and standard deviations of (annualized) currency appreciations and spreads against the US dollar at a monthly frequency. The first panel provides a summary for the pre-financial crisis period. The second panel provides a summary for the post-crisis period, and the final panel uses the full sample. Data are from April 1987 to June 2019, currency data are from Bloomberg, and yield data are from Global Financial Data.

A.2 Spreads, term premia, and equity returns

In this appendix section, we provide further evidence on interpreting Figure 1.6 as a change in the covariance of expected future risk free rates and equity returns. We first show that term premia in two year rates do not seem to be driving our findings using a standard term premia model, and then show that our findings are robust to using shorter term rates.

We use the method of Cochrane and Piazzesi (2005) to estimate an affine three factor term structure model for each G10 country to decompose their yield curves into rates expectations and term premia. To do so requires monthly estimates of the yield curve, which is not always available for all G10 countries. For this purpose, we take estimates of zero coupon yields from Wright (2011), who uses the Nelson-Siegel approximation to fit a yield curve over available bonds. These estimates are available from 1987 through 2008 for all countries except Norway.

The monthly change in two year yields is well summarized by the monthly change in the risk-free rate expectations component, as shown in the below table A.2.

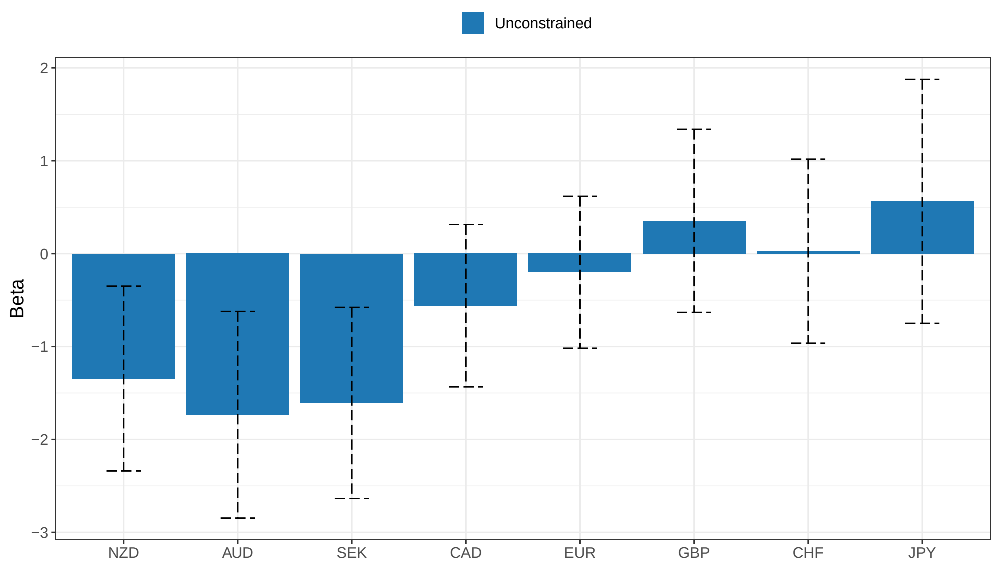
Table A.2: *Expectations component of two year bond yield changes*

	AUD	NZD	SEK	NOK	CAD	EUR	GBP	CHF	JPY	USA
R^2	.99	.99	.97	.97	.99	.99	.99	.98	.98	.99

This Table shows the R^2 of a regression of the monthly change in the risk-neutral expectation component of yields against the total monthly change in yields, using the Cochrane and Piazzesi (2005) decomposition with a three factor model. Zero coupon data are from Wright (2011).

We then take the expectations component of two year yields and repeat the regression of spreads on equity returns in Figure A.1. We can only do so for the unconstrained period since the data ends in early 2009. The results mimic Figure 1.6 closely, and are more statistically significant for the risky currencies (the New Zealand Dollar, Australian Dollar, and Swiss Krona), but less for the safe currencies (the Swiss Franc and Japanese Yen). The primary difference is due to the discrepancies in the data source. If we instead subtracted the estimate of term premia from the actual bond yields, rather than from the Nelson-Siegel yield curve estimates, there would be no discernible difference from Figure 1.6.

Figure A.1: *Regression coefficients of the expectations component of two year yield spreads on the S&P 500*



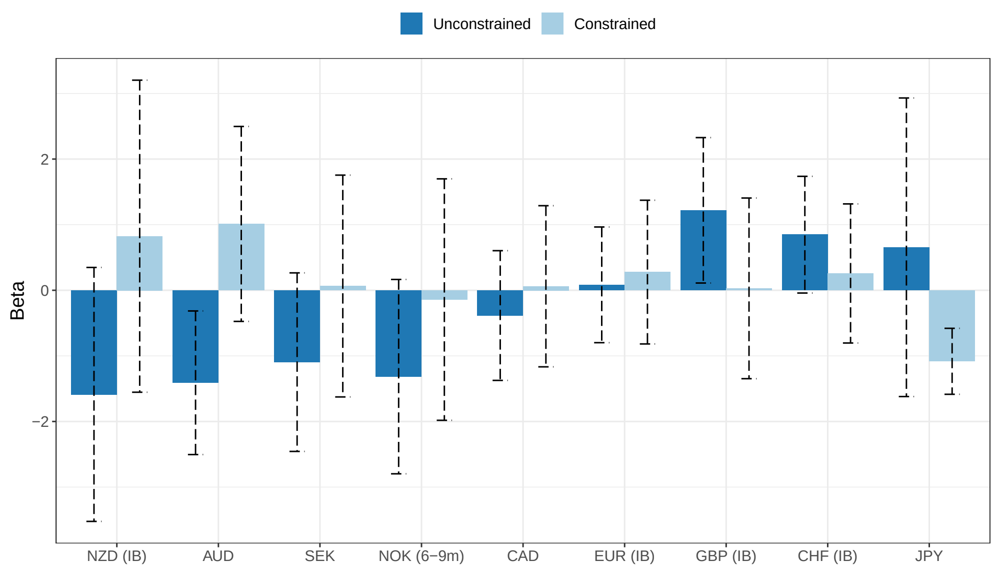
Regression coefficients of monthly changes of the spread between risk-free interest rate expectations in country i versus the risk-free interest rate expectations in US dollars, on the monthly log return on the S& 500:

$$\Delta(i_t^j - i_t^\$) = \alpha_j + \beta r_t^m + \varepsilon_{j,t}$$

in which i_t^j is the expectations component of two year yields for country j, $i_t^\$$ is the corresponding US yield, and r_t^m is the log return of the S&P 500 over the month. The expectations component is constructed using the method of Cochrane and Piazzesi (2005) with estimates of zero coupon yields from Wright (2011). We estimate these coefficients for the unconstrained period in which each central bank was not operating at the zero lower bound as the data is only available through Q1 2009. We exclude Norway from this analysis, as estimates of its yield curve are only available from 1998.

Additionally, we repeat the exercise for shorter term yields in figure A.2. GFD provides six month government bond interest rates starting from 1986 for AUD, SEK, CAD and JPY. For NZD, EUR, GBP, and CHF, only interbank lending rates are available for the six month tenor. While this is not a concern for the unconstrained period in which spreads between government bonds and interbank rates were low and stable, it complicates the analysis for the post-crisis period in which these differences have been much more volatile. The magnitude of betas are slightly smaller for the shorter yield horizon, but the same upward sloping pattern from risky to safe currencies is observable for the unconstrained period coefficient estimates.

Figure A.2: *Regression coefficients of six month yield spreads on the S&P 500*



Regression coefficients of monthly changes of two year government bond spreads versus the US dollar, on the monthly log return on the S& 500, split by constrained and unconstrained periods:

$$\Delta(i_t^j - i_t^\$) = \alpha_j + \beta^{j,unc} r_t^m + \beta^{j,con} r_t^m + \varepsilon_{j,t}$$

in which i_t^j is the yield on the six month yield of country j, $i_t^\$$ is the corresponding US six month yield, and r_t^m is the log return of the S&P 500 over the month. We define a month to be constrained if it is either after 2008, or if the central bank was operating at the effective lower bound before 2008, as has been the case for Japan (from 1998) and Switzerland (from 2003 to 2004). The dark bars correspond to estimates of $\beta^{j,unc}$ and the light to $\beta^{j,con}$. Six month interest rate spreads from April 1987 to June 2019 are constructed from Global Financial Data (GFD). For AUD, SEK, CAD, and JPY, six month government bond rates are available and so we use the difference between those and the US 6 month Treasury Bill rate. For NOK, a more generic six to nine month government bond rate is available from GFD, we take the difference between this measure and the US 6 month Treasury Bill rate. For NZD, EUR, GBP, and CHF, there is no data on government bond yields with maturities shorter than two years for our sample period, but GFD provides data on six month interbank rates, so we use the difference between those and the corresponding six month LIBOR USD rate.

A.3 High frequency FOMC analysis

We focus on FOMC announcement dates from June 2000 to October 2015, which is the sample for which we were able to obtain high frequency data on movements in the S&P 500. We use the meeting dates recorded by Lucca and Moench (2015) until 2011, and collect the remainder from Bloomberg thereafter.

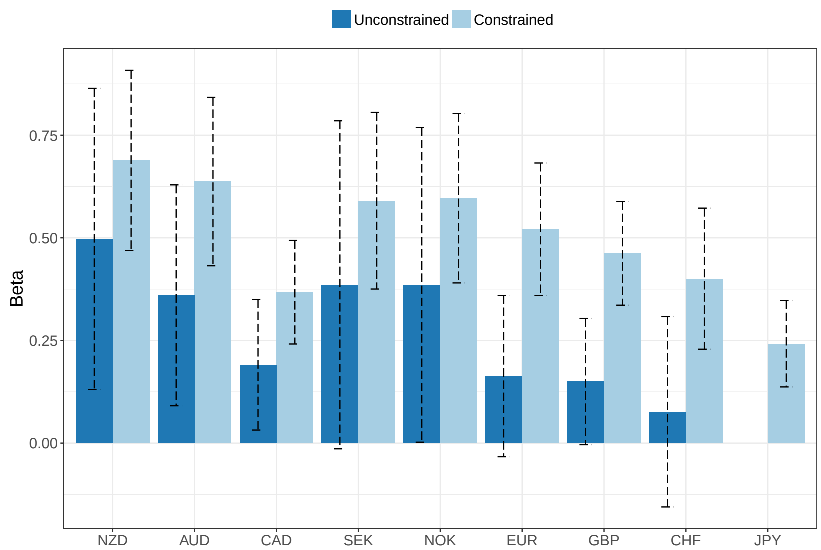
Currency data: We collect tick-level exchange rate data from HistData.com when available, and use minute-level data from Forexite.com for the remainder. Table A.3 below summarizes our data sources and windows.

Yield data: We collect daily two year government bond yield data from Bloomberg. Data are not available with a constant cut time, as they are measured with respect to each market's own bond closing time. For the euro, we use German government bonds. In order to take measurements over similarly timed windows, we take two day yield changes, aligning the measurement windows such that we take the change in the yield from the local market close prior to the FOMC announcement, to the second market close after the FOMC announcement. For example, for an FOMC announcement which occurs at 14:00 EST on a Wednesday, the change in Australian yields is measured from 02:00 EST on Wednesday, to 02:00 EST on Friday, while the change in Canadian Treasury yields is measured from 17:00EST on Tuesday to 17:00 EST on Thursday.

We make the following sample adjustments. We exclude Norwegian Government Bonds due to a paucity of available data - all yield curve points are recorded only intermittently, and for less than half the sample. We replace the New Zealand two year government bond yield with a predicted yield from a regression of the two year government bond yield on the five year government bond yield during months in which no New Zealand two year government bond existed. More detail on the data sources are reported in Table A.4 below.

We reported the baseline specification results of the high frequency analysis for the relationship of currencies and yields with equity returns in Figures 1.8 and 1.9, respectively. Here we repeat the analysis removing the controls for the direct effect of monetary policy changes: Figures A.3 and A.4 show that these results are not sensitive to the addition of the short term rate changes controls.

Figure A.3: *Regression coefficients of currency appreciations on the S&P 500, high frequency sample*

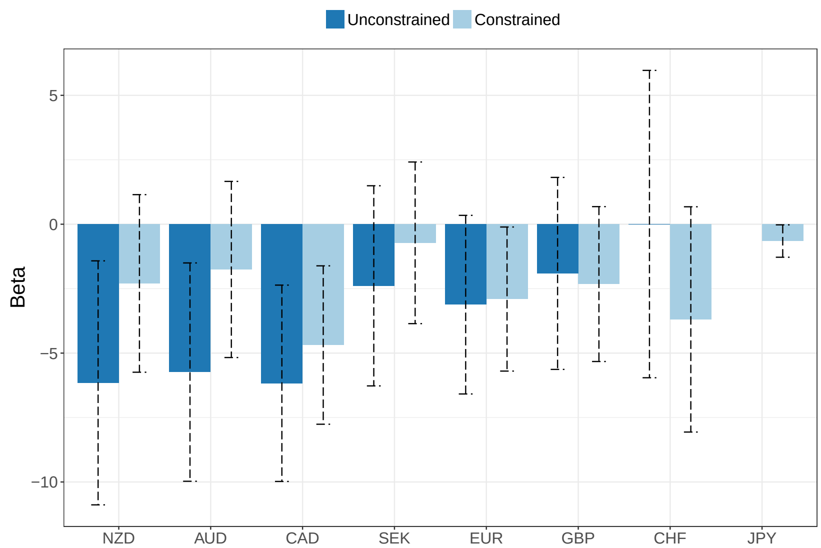


Regression coefficients of currency appreciations against the US dollar on the return on the S&P 500 over 30 minute windows around FOMC announcements. The return on the S&P 500 is interacted with a variable indicating whether this meeting occurred after January 2009, resulting in pre-crisis and post-crisis coefficients. The regression specification is:

$$\Delta e_t^j = \alpha_j + \beta^{j,unc} r_t^m + \beta^{j,con} r_t^m + \varepsilon_{j,t}$$

in which Δe_t^j is the log appreciation of currency j in US dollars, r_t^m refers to the log appreciation of the S&P 500 equity index in the hour surrounding the FOMC announcement. Currencies are ordered along the horizontal axis by decreasing risk, as measured by their average pre-crisis carry trade return. Further details on data construction and sample coverage are provided in appendix A.1.

Figure A.4: *Regression coefficients of two year risk-free yield spreads on the S&P 500, high frequency sample*



Regression coefficients of changes in the two year yields of each bond in a FOMC announcement day on the return on the S&P 500 over an hour window around the FOMC announcement. The return on the S&P 500 is interacted with a variable indicating whether this meeting occurred after January 2009, resulting in pre-crisis (unconstrained) and post-crisis (constrained) coefficients. The regression specification is:

$$\Delta i_t^j = \alpha_j + \beta^{j,unc} r_t^m + \beta^{j,con} r_t^m + \varepsilon_{j,t}$$

in which Δi_t^j is the yield change of the government bond in currency j, r_t^m refers to the log return of the S&P 500 equity index in the hourly window surrounding the FOMC announcement. Currencies are ordered along the horizontal axis by decreasing risk, as measured by their average pre-crisis carry trade return. Further details on data construction and sample coverage are provided in appendix A.1.

Table A.3: *Sources of high frequency currency data, and sample sizes for regressions of currency reactions to S&P 500 movements during FOMC announcement windows. The following data are used to produce the results reported in Figures 1.8 and A.3.*

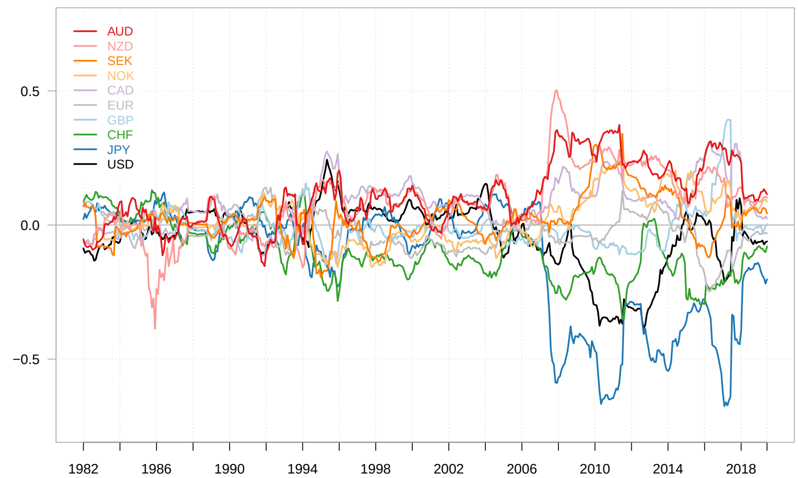
	AUDUSD	EURUSD	GBPUSD
Source	HistData	HistData	HistData
Window	2001-06/2015-12	2000-06/2015-12	2000-06/2015-12
N obs	112	123	121
	NZDUSD	USDCAD	USDCHF
Source	Forexite	HistData	HistData
Window	2003/01-2015	2001-01/2015-12	2000-06/2015-12
N obs	102	116	120
	USDJPY	USDNOK	USDSEK
Source	HistData	Forexite	Forexite
Window	2000-06/2015-12	2005-02/2015-12	2005-02/2015-12
N obs	121	85	85

Table A.4: *Sources of interest rate data, and sample sizes for regressions of currency reactions to S&P 500 movements during FOMC announcement windows. The following data are applicable to the regressions underlying Figures 1.9 and A.4.*

	AUD	EUR	GBP
Bloomberg code	GTAUD2Y	GTDEM2Y	GTGBP2Y
Window	2000-06/2015-12	2000-06/2015-12	2000-06/2015-12
N obs	123	123	123
	NZD	CAD	CHF
Bloomberg code	GTNZD2Y	GTCAN2Y	GTCHF2Y
Window	2000-06/2015-12	2000-06/2015-12	2000-06/2015-12
N obs	109	123	120
	JPY	NOK	SEK
Bloomberg code	GTJGB2Y	-	GTSEK2Y
Window	2000-06/2015-12	-	2000-06/2015-12
N obs	120	0	121

A.4 Additional Figures

Figure A.5: *Conditional betas with equity returns of exchange rates with an equally weighted G10 basket*

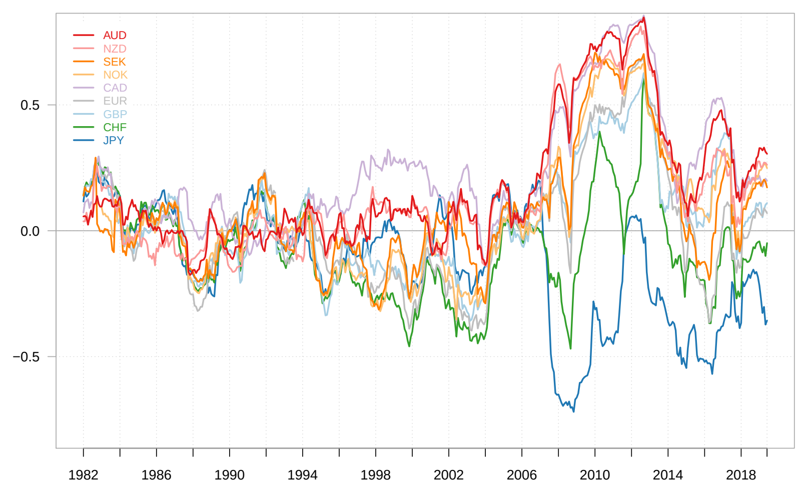


Conditional betas of every exchange rate measured with respect to an equally weighted G10 basket against the log return on the S&P 500. Conditional betas are estimated by the following regression:

$$\Delta e_t^i = \alpha_{i,t} + \beta^i r_t^m + \varepsilon_{i,t}$$

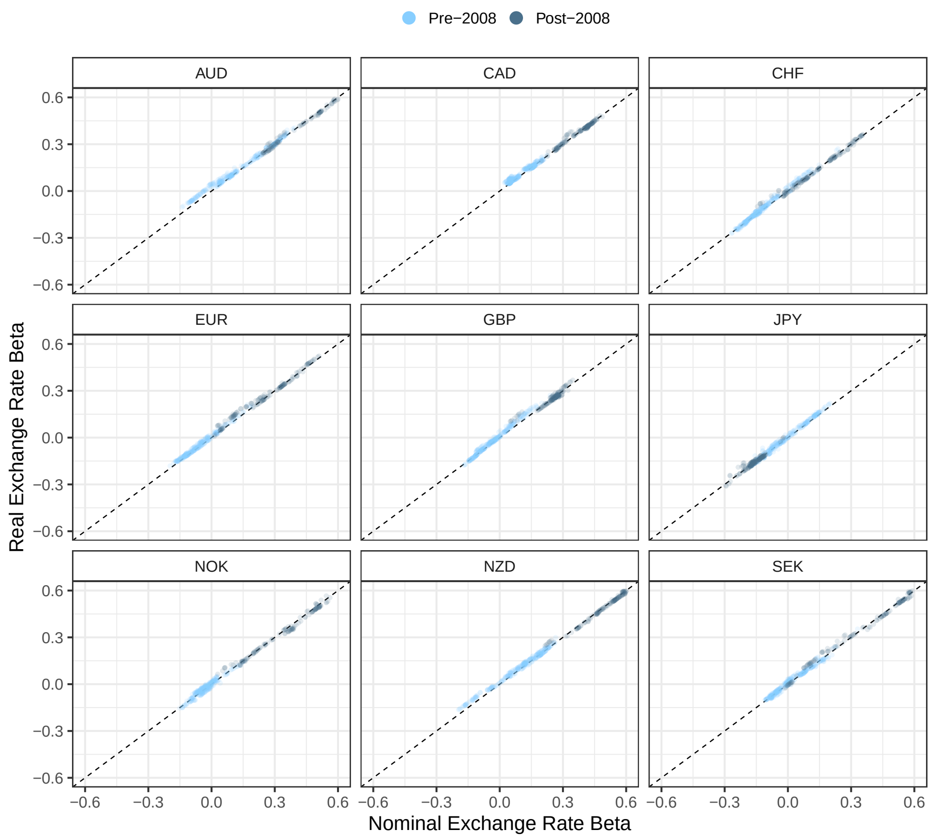
A positive value for Δe_t^i reflects an appreciation of the currency against the G10 basket. Each beta is estimated using one year (252 trading days) of historical data, with one coefficient estimated per currency per month. Data are from Jan 1981 to June 2019, from Bloomberg.

Figure A.6: *Conditional correlation with equity returns of each exchange rate against the USD*



Conditional correlations of every exchange rate with respect to the US dollar against the log return on the S&P 500: $corr\left(\Delta e_t^i, r_t^m\right)$. A positive value for Δe_t^i reflects an appreciation of the non-US dollar currency. Each correlation is estimated using one year (252 trading days) of historical data, with one coefficient estimated per currency per month. Data are from Jan 1981 to June 2019, from Bloomberg.

Figure A.7: *Real and nominal exchange rate betas*

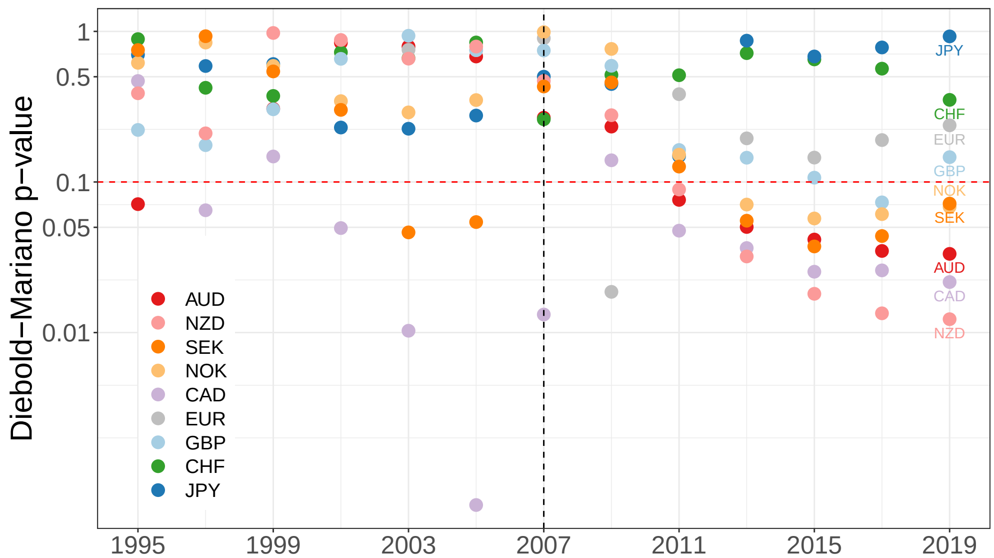


The Figures above show the conditional betas of the real and nominal exchange rate measured with respect to the US dollar against the log return on the S&P 500. Conditional betas are estimated by the following regression:

$$\Delta e_t^i = \alpha_{i,t} + \beta^i r_t^m + \varepsilon_{i,t}$$

A positive value for Δe_t^i reflects an appreciation of the currency in real or nominal terms against the US dollar. Each beta is estimated using five years (60 monthly observations) of historical data, with one coefficient estimated per currency per month. The conditional betas which are estimated using data ending before (after) 2008 are shown in light (dark) blue. Currency data are from Jan 1981 to June 2019, from Bloomberg. Real exchange rates are constructed using the consumer price index of each country, from the OECD main economic indicator database. Monthly CPIs for Australia and New Zealand are interpolated linearly from the quarterly data.

Figure A.8: *Out of sample Meese-Rogoff tests by currency*



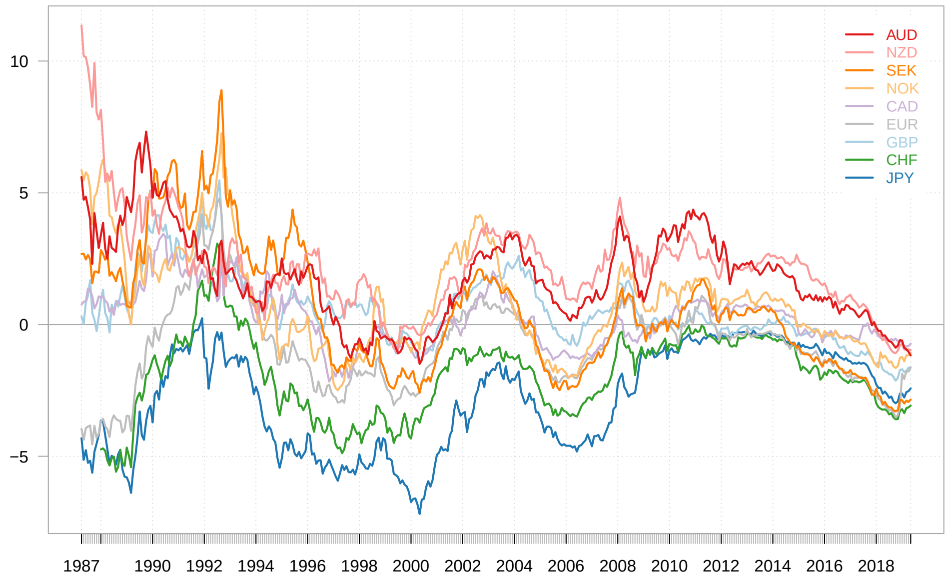
This Figure displays the statistical significance analog of Figure 1.3. We make out of sample predictions of each exchange rate for the next out of sample period using the conditional beta, and compare the forecast accuracy to that of a random walk. We predict every exchange rate's monthly appreciation versus the US dollar (i.e. we make 9 predictions per month) by taking the betas for each currency appreciation against the S&P 500 in rolling samples, and then taking these parameters out of sample, and including the next period's actual return of the S&P 500:

$$\widehat{\Delta e^i_{t+1}} = \widehat{\beta}^i_t r^m_{t+1}$$

Using each forecast, we then calculate the ratio of root mean squared error for the above forecasts versus a random walk model (a forecast of no change) over the prior 11 years, and use the Diebold-Mariano forecast test for significance. For example, the forecast accuracy recorded for the data point for the Australian dollar 2011 was measured using the predictions for January 2001 to December 2011. The Diebold-Mariano test of equal forecast accuracy would reject the null with a p-value of 0.025.

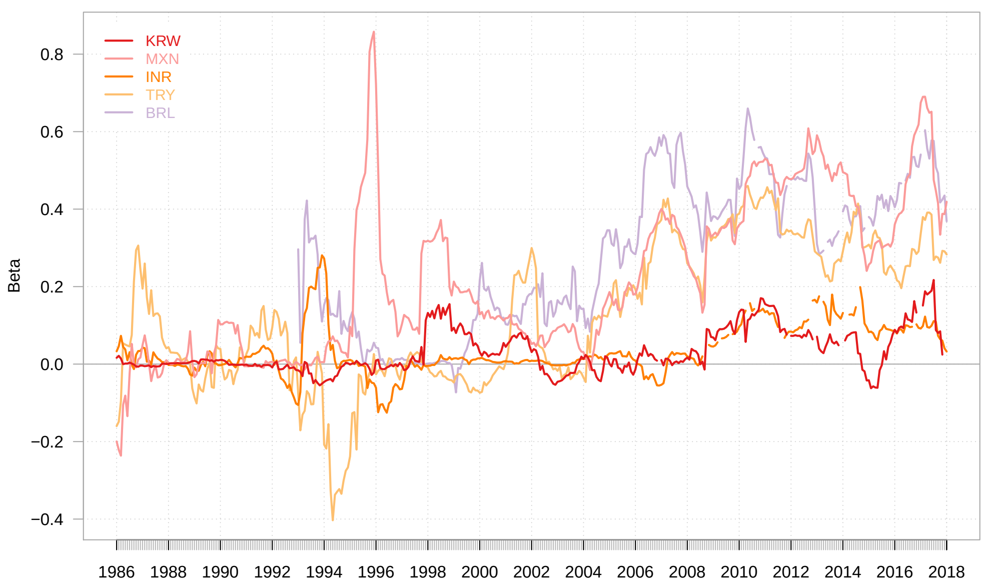
$$RMSE\ Ratio : \sqrt{\sum_{i \in G10} \sum_{t=T-132}^{T} \frac{(\widehat{\Delta e^i_{t+1}} - \Delta e^i_{t+1})^2}{(\Delta e^i_{t+1})^2}}$$

Figure A.9: *Two year spread over US Treasuries for each of the G10 government bonds*



Spreads of two year G10 government nominal bonds over the two year US Treasury bond. Data are from April-1987 to June-2019, from Global Financial Data.

Figure A.10: *Conditional betas for emerging market economies*



Betas estimated from a regression of the daily log appreciation of the currencies of the Korean Won, Mexican Peso, Indonesian Rupiah, Turkish Lira and Brazilian Real against the US dollar on the daily log return on the S&P 500 in US dollars, as in figure 1.2. Each beta is estimated using one year (252 trading days) of historical data, with one coefficient estimated per currency per month. Data are from Jan-1986 to June 2019, collected from Bloomberg.

A.5 Additional Tables

Table A.5: *Other Equity Market Specifications*

Model Specification	$\bar{R^2}$: Pre-Crisis	$\bar{R^2}$: Post-Crisis	Change
S&P 500 Equity Return	1.5%	17.5%	16.1%
Common Equity Factor	3.8%	15.7%	12.8%
Local Equity Return	4.4%	15.1%	10.6%
Relative Equity Return	2.7%	9.5%	6.9%
S&P 500 & Common Equity Factor	8.1%	23.9%	15.7%
S&P 500 & Local Equity Return	5.5%	24.4%	18.8%

We run rolling annual regressions of the following form, as in Figure 1.2:

$$\Delta e_t^i = \alpha_{i,t} + \beta^i r_t^m + \varepsilon_{i,t}$$

in which e_t^i is the log appreciation of currency i against the USD, and r_t^m is the log return on a stock market, at the weekly frequency. We use weekly frequencies to minimize the issue that some stock markets have close data separated by up to 12 hours from the currency market closes. In the first four rows, we use a single regressor for the specification. In the first row, S&P 500 equity return, we use the S&P 500 as the stock market for all currency pairs. In the second row, local equity market return, we use the log return on stock market for the country of currency i instead of the S&P 500. For the third row, we use the first principal component of all G10 local equity market returns. For the fourth regression, we use the relative log return of the local equity market minus the log return of the S&P 500. or the last two rows, we use two regressors in each specification. In the fifth row, we use both the log return on stock market for the country of currency i and the log return of the S&P 500. In the sixth row, we use both the log return on stock market for the country of currency i and the first principal component of all G10 local equity market returns. We report the average R^2 of each currency pair regression, for the pre-crisis period (1987-2008) and post-crisis period (2009-2018).

Table A.6: *High Minus Low Carry Factor Versus S&P 500*

	HML (All)		HML (Developed)	
	1983-2006	2007-2020	1983-2006	2007-2020
Constant	0.004*	0.000	0.005***	0.000
	(0.002)	(0.002)	(0.001)	(0.002)
Market Return	0.139***	0.249***	0.094**	0.381***
	(0.0355)	(0.0332)	(0.0337)	(0.0471)
R^2	0.05	0.26	0.03	0.29
N	283	163	283	163

Table shows regressions of the high minus low carry factors developed and described Lustig *et al.* (2011a) against the log return on the S&P 500:

$$HML_t = \alpha_{i,t} + \beta^i r_t^m + \varepsilon_{i,t}$$

in which HML_t is the monthly log return of the high minus low carry factor, and r_t^m is the log return on a stock market, at the monthly frequency. The high minus low carry factor titled HML (all) uses a set of sixty countries, while the high minus low carry factor titled HML (developed) considers a restricted subsample of 15 developed countries.

Table A.7: *Decomposition of total expected future returns pre- and post-crisis*

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	USA
(A) Pre-2008 $Cov(i_t, r_m)$	-1.27	-0.04	-0.05	0.21	0.99	-0.17	-0.91	-1.49	-1.07	0.23
	(0.62)	(0.64)	(0.43)	(0.37)	(0.53)	(0.32)	(0.47)	(0.61)	(0.56)	(0.51)
(B) Post-2008 $Cov(i_t, r_m)$	3.11	1.71	1.30	2.08	1.59	0.21	2.29	1.42	2.50	1.31
	(0.47)	(0.34)	(0.27)	(0.34)	(0.37)	(0.10)	(0.41)	(0.47)	(0.35)	(0.37
ρ	0.69	0.79	0.80	0.88	0.86	0.77	0.75	0.65	0.88	0.70
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
$\beta_{IR,pre} = (A_i \cdot \rho) - (A_{US} * \rho)$	0.10	0.02	0.02	-0.02	-0.13	0.03	0.09	0.10	0.19	
β^i_{pre} (Table 1)	0.03	0.04	-0.07	-0.03	-0.02	-0.02	-0.03	0.02	-0.01	
$\beta_{IR,post} = (B_i \cdot \rho) - (B_{US} * \rho)$	-0.11	-0.07	-0.04	-0.25	-0.14	0.07	-0.10	0.01	-0.32	
β^i_{post} (Table 1)	0.35	0.27	-0.02	0.10	0.14	-0.24	0.24	0.31	0.21	
$\beta^i_{FR,pre}$	0.13	0.06	-0.05	-0.05	-0.15	0.01	0.06	0.12	0.18	
$\beta^i_{FR,post}$	0.24	0.20	-0.06	-0.15	0.00	-0.17	0.14	0.32	-0.11	

Appendix B

Appendix to Chapter 3

B.1 Details on Meese-Rogoff Forecasting Regressions

We follow the tradition established by Meese and Rogoff (1983) in evaluating the "out-of-sample" fit of a model while giving the model the realized values of the regressors. The logic of this approach is this if a model were to fail at a true out-of-sample forecast exercise (predicting changes of the exchange rate in period $t+1$ only using information available at time t) then it would be unclear whether the failure was to due to the inability to forecast the model-relevant macroeconomic variables, or whether the implied relationship between macroeconomic variables and exchange rates does not hold in the data. By using the realized value of the regressors, we can be sure that if the model fails to predict exchange rates, it is because of the latter concern. Therefore, the sense in which this is an “out-of-sample” forecasting exercise is that we restrict the coefficients to be estimated using data available prior to the period in which the exchange rate is being forecast.

We consider an out-of-sample forecasting exercise with period K quarters to estimate model coefficients and P quarters to evaluate the model’s performance. We denote the end of the model evaluation period as time period T. To estimate model parameters, we regress the quarterly change on the broad dollar on US portfolio flows to provide an in-sample estimate of the model parameters:

$$\Delta e^{B}_{USD,t} = \alpha_t + \beta_t f_t + \varepsilon_t. \tag{B.1}$$

In our baseline specifications, we will have an estimation window K of 40 quarters and an evaluation period P of 40 quarters. If we consider our latest evaluation window, where T is 2019Q2, then we begin our exercise by running the regression in Equation B.1 from 1997Q4 to 2007Q4. We then use the estimated coefficients $\hat{\alpha}_t$ and $\hat{\beta}_t$ and the realized observation of the capital flow in period $T-P+1$ (2008Q1) to forecast the exchange rate change in this period. We calculate our forecast of next period's exchange rate as

$$\widehat{\Delta e^B_{USD,t+1}} = \hat{\alpha}_t + \hat{\beta}_t f_{t+1} \tag{B.2}$$

The model's forecast error is the difference between the realized exchange rate change and the model-implied forecast

$$\varepsilon_{t+1} = \Delta e^B_{USD,t+1} - \widehat{\Delta e^B_{USD,t+1}} \tag{B.3}$$

We then repeat the procedure for the next sample period, running the regression in equation B.1 from $t \in [T-P-K+1, T-P+1]$, and using the newly estimated coefficients and the realization of capital flows in period $T-P+2$ to forecast the exchange rate change in period $T-P+2$. We repeat this exercise until we have an out-of-sample forecast for all quarters from period $T-P$ to T.[1]

We can then evaluate the out-of-sample forecasting performance of the model by calculating two loss functions, the root mean squared error (RMSE) and the mean absolute error (MAE) for the evaluation period ending in period T.

$$RMSE_T = \left(\frac{1}{P} \sum_{t=T-P}^{T} \varepsilon_t^2 \right)^{1/2} \tag{B.4}$$

$$MAE_T = \left(\frac{1}{P} \sum_{t=T-P}^{T} |\varepsilon_t| \right) \tag{B.5}$$

[1]This is a rolling window estimation scheme, meaning that we keep the number of observations used to estimate Equation B.1 fixed.

B.2 Macroeconomic Model Descriptions

To select alternative models, we follow the literature review on fundamentals-based models is surveyed in Rossi (2013b). In particular, we consider four alternative sets of explanatory variables. The first, which we label "UIP" for uncovered interest rate parity, uses the lagged interest rate differential between the US and the average of the other G10 currencies.

$$\Delta e^{B}_{USD,t} = \alpha + \beta \left(i^{USD}_{t-1} - \overline{i^{G10}_{t-1}} \right) + \varepsilon_t \tag{B.6}$$

This arises from models assuming that the expected excess return on currency investment is zero. Data on interest rates are from the IMF's database of International Financial Statistics. For market interest rates, we use the deposit rate for all countries except the Euro Area, for which we use the 3 month interbank rate, and the UK and US for which we use the 3 month treasury bill rate.

The second, which we label the "Monetary" model includes the inflation differential between the US and the other G10 countries, as well as the growth rate difference:

$$\Delta e^{B}_{USD,t} = \alpha + \beta \left(\pi^{USD}_{t} - \overline{\pi^{G10}_{t}} \right) + \gamma \left(\Delta y^{USD}_{t} - \overline{\Delta y^{G10}_{t}} \right) + \varepsilon_t \tag{B.7}$$

This is motivated by the classical monetary models of Dornbusch (1976) and Frankel (1979), where we replace money stock differentials with inflation differentials.

The third set of fundamentals, which we label "Taylor Rule" includes in the inflation differential between the US and the other G10 countries, alongside the output gap differential:

$$\Delta e^{B}_{USD,t} = \alpha + \beta \left(\pi^{USD}_{t} - \overline{\pi^{G10}_{t}} \right) + \gamma \left(\tilde{y}^{USD}_{t} - \overline{\tilde{y}^{G10}_{t}} \right) + \varepsilon_t \tag{B.8}$$

This is motivated by the empirical framework introduced in Molodtsova and Papell (2009), wherein a strict adherence to the UIP condition combined with adherence to a Taylor rule would make changes in the inflation and output gap differentials sufficient statistics for exchange rate depreciations. The fourth set of fundamentals we consider, which we label "Backus-Smith" uses the mean inflation and consumption growth differential between the US and the other G10 countries.

$$\Delta e^B_{USD,t} = \alpha + \beta\left(\pi_t^{USD} - \overline{\pi_t^{G10}}\right) + \gamma\left(\Delta c_t^{USD} - \overline{\Delta c_t^{G10}}\right) + +\varepsilon_t \tag{B.9}$$

The condition that the (real) exchange rate change is pinned down by the ratio of relative consumption growth is an equilibrium condition of open economy models with complete asset markets and CRRA preferences as in Backus and Smith (1993). We adopt a more flexible empirical implementation of this model, by not restricting the impact of relative prices on exchange rates to be one, and then estimate the nominal exchange rate appreciation.

B.3 Measuring Capital Flows

B.3.1 Balance of Payments

The primary measure of a capital flow we consider in this paper is the quarterly flow as a percentage of the lagged stock. We define this flow as $f_{a,i,d,t}$ where:

$$f_{a,i,d,t} \equiv \frac{F_{a,i,d,t}}{Q_{a,i,d,t-1}}$$

where a denotes the asset class and refers to the various BoP categories considered, i denotes the country investing or receiving the invest, t denotes the quarter, and d denotes the direction of the flow. The direction of the flow d can either be purchases of foreign securities (assets) or foreign purchases of domestic securities (liabilities). F denotes net purchases of securities during quarter. Q denotes the outstanding stock of securities at end of quarter. If the stock Q is reported annually in the IIP, we linearly interpolate the series to approximate the quarterly values. The U.S. IIP series for the stock of foreign bond positions is reported quarterly beginning in the fourth quarter of 2005, and therefore all observations after 2006 do not use any interpolation.

B.3.2 Morningstar

To study capital flows at the micro-level, we use data from Morningstar covering position-level data collected from mutual funds domiciled in over 50 countries. These data are collected from open-end funds (including exchange traded funds) that invest in a range of securities and derivatives. Reporting is typically monthly and, when not, is almost always quarterly. The dataset contains millions of individual positions, and by December 2017 we observe 11.5 million unique positions (6 million equity and 5.5 million bond positions) held by approximately 40,000 mutual funds worldwide. For more details on this data, see Maggiori *et al.* (2019a).

Each reported position contains information on the domicile of the mutual fund, the currency denomination of the security, the country in which the issuer is domiciled, the local currency price of the security, and the number of securities held since the last report. We use the procedure introduced in Coppola *et al.* (2019) to map the issuer of each security to the nationality of its ultimate parent. As such, we know the market values of every invested position of each fund in each reporting month. The change in the market value of each position (in US dollars) between two points in time is made up of three components - the foreign currency appreciation (if the asset is denominated in foreign currency), the local currency price appreciation of the asset, and the purchase or sale of the security at the US dollar price at the time of the transaction. We focus on the third component - the capital flow.

We measure the capital flow at the security level by taking each recorded sale or purchase of an individual security held by a fund, and multiplying this change in quantity by the price of the security (converted to US dollars) in the prior month, before the transaction occurred. While this method is the only way to ensure we exclude the two other aforementioned components, we note that we necessarily will measure the capital flow with error, since we do not observe the local currency price of the security at the time of the transaction, nor do we observe the exchange rate at the time of the transaction.

$$
\begin{aligned}
P_{s,t} &= \text{Price of security s, in US dollars, at time t} \\
N_{s,z,t} &= \text{Number of shares of security s, held by fund } z \text{ at time t} \\
\Delta N_{s,z,t} &= N_{s,z,t} - N_{s,z,t-1} \\
F_{s,z,t} &= P_{s,t-1} \cdot \Delta N_{s,z,t} \\
Q_{s,z,t} &= P_{s,t} \cdot N_{s,z,t}
\end{aligned}
$$

We are able to use this method to construct the capital flow for approximately 97% of positions, though we lack the information to do so in some cases (e.g. the first time a fund purchases a security) since we do not observe the reported price for a prior month. This means that in the remaining 3% of cases, we must include the local currency price appreciation in our measure of capital flows, though we never include the foreign currency appreciation.

After constructing this capital flow for each position, we then aggregate these flows to various levels of analysis. The most detailed level is broken down to flows within each asset class (bond or equity), by the currency of the security, the source country (the domicile of the investing fund), and the destination country (the domicile of the ultimate parent issuer of the security). For example, for our benchmark regression using capital flows presented in Figure 3.3a, the set $\mathscr{Z}_i$ includes all securities which are bonds, bought or sold by funds domiciled in the United States, and issued by destination countries which are not the United States.

$$F_{\mathscr{Z},t} \equiv \sum_{z \in \mathscr{Z}_i} F_{s,z,t}$$

$$Q_{\mathscr{Z},t} = \sum_{z \in \mathscr{Z}_i} Q_{s,z,t}$$

For all analysis except where noted, we measure these capital flows in percentage growth terms, compared to the market value of investment in the prior quarter. When we refer to a 1% capital flow, we will be referring to a value of 0.01 for the following measure:

$$f_{\mathscr{Z},t} \equiv \frac{F_{\mathscr{Z},t}}{Q_{\mathscr{Z},t-1}} = \frac{\sum_{z \in \mathscr{Z}_i} P_{s,t-1} \cdot \Delta N_{s,z,t}}{\sum_{z \in \mathscr{Z}_i} P_{s,t-1} \cdot N_{s,z,t-1}}$$

B.4 Funding the purchases of foreign bonds

Purchases of foreign bonds by U.S. mutual funds must be financed either by selling other securities or from net flows into the mutual fund sector. In Appendix Table B.9, we show that it is flows into and out of the mutual fund sector, rather than purchases and sales of domestic securities by the funds themselves, that coincide with these foreign bond flows. To demonstrate this, we run regressions of the following form:

$$F_t = \alpha + \beta F^B_{USA,foreign,t} + \varepsilon_t$$

where $F^B_{USA,foreign,t}$ is the quarterly purchase of foreign issued bonds by the U.S. investor and F_t is a particular measure of flows from U.S. mutual funds. All variables are measured in US dollars.

The first column, labeled “Flows into Funds," measures the total dollar value of flows into and out of the US-domiciled mutual fund sector. The regression coefficient of 1.38 on U.S. Foreign Bond Purchases means that for every $1 of foreign bond purchases by U.S. mutual funds, an average of $1.38 flows into the U.S. mutual fund sector.

The next four columns look within the U.S. mutual fund sector and ask whether fund holdings of all U.S. bonds, U.S. Sovereign Bonds, U.S. Corporate Bonds, U.S. Other Bonds (i.e. ABS, MBS), and equities change with purchases or sales of foreign bonds. When U.S. mutual funds purchase $1 of foreign bonds, they also buy 40 cents worth of corporate bonds. We also find statistically insignificant sales of sovereign and other bonds, as well as purchases of equities. We therefore conclude the bulk of U.S. flows into and out of foreign bonds is largely financed with flows into and out of the mutual fund sector, rather than sales or purchases of other asset classes by the mutual funds themselves.

B.5 Supplementary Tables

Table B.1: *G10 Bilateral Exchange Rates and Change in GZ Spreads, 2007-2018*

R^2	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	USD
AUD		2	24	17	5	34	1	4	7	23
CAD	2		14	9	2	36	0	0	2	30
CHF	24	14		4	7	12	20	11	10	1
EUR	17	9	4		2	19	17	5	6	7
GBP	5	2	7	2		25	3	1	0	20
JPY	34	36	12	19	25		35	22	26	9
NOK	1	0	20	17	3	35		1	5	24
NZD	4	0	11	5	1	22	1		1	12
SEK	7	2	10	6	0	26	5	1		13
USD	23	30	1	7	20	9	24	12	13	
Mean	13	10	11	10	7	24	12	6	8	16

Notes: This table reports the R^2 of regressions of the form $\Delta e_{i,j,t} = \alpha + \beta f_t + \varepsilon_t$, where $\Delta e_{i,j,t}$ is the monthly change in the bilateral exchange rate of the currency in row i and column j, and f_t is the change in U.S. corporate bond spreads, taken from Gilchrist and Zakrajšek (2012). Exchange rate data are from Thomson Reuters Datastream and bond position data are from the IMF Balance of Payments database. Data is measured monthly from 2007-2018.

Table B.2: *G10 Bilateral Exchange Rates and Change in U.S. Corporate Bond Spreads, 1977-2006*

R^2	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	USD
AUD		2	6	5	7	5	5	0	3	5
CAD	2		3	2	3	2	2	1	1	4
CHF	6	3		1	0	0	1	6	2	1
EUR	5	2	1		0	0	0	5	1	0
GBP	7	3	0	0		0	1	6	1	1
JPY	5	2	0	0	0		0	4	0	0
NOK	5	2	1	0	1	0		4	0	0
NZD	0	1	6	5	6	4	4		3	3
SEK	3	1	2	1	1	0	0	3		0
USD	5	4	1	0	1	0	0	3	0	
Mean	4	2	2	2	2	1	1	4	1	2

Notes: This table reports the R^2 of regressions of the form $\Delta e_{i,j,t} = \alpha + \beta f_t + \varepsilon_t$, where $\Delta e_{i,j,t}$ is the quarterly change in the bilateral exchange rate of the currency in row i and column j, and f_t is the change in U.S. corporate bond spreads, taken from Gilchrist and Zakrajšek (2012). Exchange rate data are from Thomson Reuters Datastream and bond position data are from the IMF Balance of Payments database. Data is measured monthly from 2007-2018.

Table B.3: *US Dollar and Gross and Net Capital Flows*

Panel A: 1977-2006								
Purchaser	Issuer	Asset Class	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}
Net IIP (US - RoW)	Net IIP (US - RoW)	Bond	0.21					
			(0.11)					
		Equity		-0.11				
				(0.16)				
U.S.	RoW	Bond			0.091			
					(0.13)			
		Equity				-0.23		
						(0.17)		
RoW	U.S.	Bond					0.30	
							(0.16)	
		Equity						-0.48
								(0.28)
Observations			120	120	120	120	120	120
R^2			0.03	0.01	0.00	0.01	0.02	0.03
Panel B: 2007-2019								
Purchaser	Issuer	Asset Class	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}
Net IIP (US - RoW)	Net IIP (US - RoW)	Bond	-0.12					
			(0.36)					
		Equity		0.62				
				(0.28)				
U.S.	RoW	Bond			0.85			
					(0.16)			
		Equity				0.30		
						(0.70)		
RoW	U.S.	Bond					0.91	
							(0.43)	
		Equity						1.05
								(0.35)
Observations			50	50	50	50	50	50
R^2			0.00	0.05	0.32	0.01	0.08	0.14

Notes: This table reports regressions results of the form $\Delta e^B_{USD,t} = \alpha + \beta f_t + \varepsilon_t$, where $\Delta e^B_{USD,t}$ is the quarterly change in the broad US dollar and f_t is a particular measure of capital flows described in the first three columns of the table. Purchases of bonds and equities are normalized by the stock of holdings of that asset at the end of the previous quarter. Net positions are normalized by the sum of the stock of the U.S. position in foreign assets and the foreign position in U.S. assets for each type of security. Panel (A) reports regression results from 1977Q1-2006Q4 and Panel (B) reports regression results from 2007Q1-2019Q2. Exchange rate data are from Thomson Reuters Datastream and international investment position data are from the IMF Balance of Payments.

Table B.4: *Broad Dollar, Capital Flows, and Macro Fundamentals*

	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}
Model		UIP	Backus-Smith	Monetary	Taylor Rule
			Panel A: 1977-2006		
U.S. Flows	0.086				
	(0.14)				
$i^{US}_{t-1} - \bar{i}_{t-1}$		-0.53			
		(0.22)			
$\pi^{US}_t - \bar{\pi}_t$			-2.5	-0.32	-0.48
			(1.3)	(0.80)	(0.71)
$\Delta c^{US}_t - \overline{\Delta c_t}$			1.1		
			(1.3)		
$\Delta y^{US}_t - \overline{\Delta y_t}$				0.25	
				(0.47)	
$\tilde{y}^{US}_t - \bar{\tilde{y}}_t$					0.83
					(0.33)
Obs.	108	108	47	108	108
R^2	0.00	0.07	0.10	0.00	0.08
			Panel B: 2007Q1-2019Q2		
U.S. Flows	0.85				
	(0.16)				
$i^{US}_{t-1} - \bar{i}_{t-1}$		1.3			
		(0.61)			
$\pi^{US}_t - \bar{\pi}_t$			2.5	2.8	2.9
			(0.65)	(0.57)	(0.54)
$\Delta c^{US}_t - \overline{\Delta c_t}$			-0.75		
			(1.28)		
$\Delta y^{US}_t - \overline{\Delta y_t}$				0.50	
				(1.17)	
$\tilde{y}^{US}_t - \bar{\tilde{y}}_t$					0.0063
					(0.099)
Obs.	50	50	50	50	50
R^2	0.32	0.08	0.15	0.15	0.15

Notes: This table reports regressions results of the form $\Delta e^B_{USD,t} = \alpha + \beta X_t + \varepsilon_t$, where $\Delta e^B_{USD,t}$ is the quarterly change in the broad US dollar and X_t captures various macroeconomic variables. For our baseline regressions, X_t is "U.S. Flows," net purchases of foreign bonds by the United States, normalized as a percentage of the value of the United States' foreign bond investment at the end of the prior quarter. For the "UIP" model, X_t is the lagged interest rate spread between the United States and the average of the other G10 countries. For the "Monetary" model, X_t contains two variables, the mean inflation difference between the United States and the other G10 countries and the mean growth difference between the United States and the other G10 countries. For "Taylor Rule", X_t contains the (relative value of) the two variables in a Taylor Rule, the mean inflation difference between the United States and the other G10 countries and the mean output gap differential between the United States and the other G10 countries. All macroeconomic variables are computed as the difference between the quarterly observation for the United States versus the average of all other G10 countries. Panel (A) reports regression results from 1977:Q1-2006:Q4 and Panel (B) reports regression results from 2007:Q1-2019:Q2. Exchange rate data are from Thomson Reuters Datastream, international investment data are from the IMF Balance of Payments, and macroeconomic data are from the IMF International Financial Statistics Database.

Table B.5: *Meese-Rogoff Out Of Sample Model Performance*

		Monthly				Quarterly			
		All Periods		Without Crisis		All Periods		Without Crisis	
Model		MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Global Return Factor	Ratio	0.75	0.71	0.78	0.73	0.78	0.74	0.86	0.82
	p-value	0.00	0.00	0.00	0.00	0.08	0.06	0.14	0.05
GZ Spread	Ratio	0.94	0.97	0.93	0.94	0.96	0.93	0.99	0.96
	p-value	0.03	0.37	0.01	0.00	0.42	0.20	0.78	0.33
S&P500 Log Return	Ratio	0.88	0.86	0.90	0.88	1.05	0.99	1.08	1.02
	p-value	0.05	0.02	0.12	0.05	0.66	0.89	0.44	0.84
Log VXO	Ratio	0.97	0.95	0.97	0.95	1.07	1.01	1.08	1.02
	p-value	0.54	0.21	0.61	0.30	0.61	0.92	0.58	0.87
Treasury Premium	Ratio	0.96	0.96	0.95	0.95	1.01	0.95	1.02	0.96
	p-value	0.25	0.24	0.26	0.26	0.95	0.61	0.85	0.71
Intermediary Returns	Ratio	0.91	0.88	0.94	0.92	0.98	0.99	0.98	1.00
	p-value	0.19	0.13	0.40	0.29	0.55	0.68	0.50	0.83
US Foreign Bond Purchases	Ratio					0.94	0.93	0.97	0.96
	p-value					0.35	0.22	0.54	0.37
Uncovered Interest Parity	Ratio					1.03	1.04	1.04	1.05
	p-value					0.38	0.18	0.30	0.08
Backus-Smith	Ratio					0.98	0.99	0.99	1.00
	p-value					0.65	0.60	0.81	0.85
Monetary	Ratio					0.98	1.00	0.99	1.01
	p-value					0.60	0.94	0.72	0.80
Taylor	Ratio					1.02	1.03	1.03	1.05
	p-value					0.81	0.62	0.69	0.39

Notes: This table reports the performance of exchange rate forecast models for the broad US dollar over the most recent 10 year sample for which data is available, using the standard Meese-Rogoff forecasting benchmark. We report the ratio of the model's root mean squared forecast error relative to a random walk, and the p-value of a Diebold-Mariano test for the performance of the model. We measure performance according to two penalty criteria - the mean absolute error (MAE) and the root mean squared error (RMSE). Each observation represents a 10 year model evaluation period (120 periods for the monthly model, 40 periods for the quarterly model), using 10 year estimation windows for the parameters, as described in Appendix Section B.1. The columns labelled “Without Crisis" exclude 2008:Q1 - 2009:Q2 from the evaluation period.

Table B.6: *Bilateral Exchange Rates and Risk Factors*

Panel A: Pre-2007		AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
	β	-0.065	-0.035	-0.012	-0.021	-0.034	-0.028	-0.032	-0.064	-0.040
Global Return Factor	SE	0.008	0.006	0.015	0.013	0.014	0.014	0.010	0.009	0.013
	R^2	17	17	0	2	4	2	4	13	5
	β	0.045	0.020	-0.025	-0.013	-0.020	-0.013	-0.007	0.041	-0.001
GZ Spread	SE	0.011	0.006	0.012	0.011	0.010	0.011	0.013	0.012	0.012
	R^2	5	4	1	0	1	0	0	3	0
	β	-0.112	-0.099	0.085	0.045	0.027	-0.002	0.009	-0.068	-0.015
S&P 500	SE	0.036	0.019	0.046	0.041	0.039	0.047	0.038	0.046	0.046
	R^2	3	8	1	0	0	0	0	1	0
	β	0.039	0.017	-0.045	-0.027	-0.025	-0.024	-0.020	0.029	-0.013
Log VXO	SE	0.010	0.006	0.010	0.009	0.009	0.015	0.009	0.013	0.010
	R^2	6	4	5	2	2	1	1	3	1
	β	0.018	0.018	-0.004	-0.005	-0.003	0.037	0.011	0.021	-0.006
Treasury Premium	SE	0.034	0.016	0.027	0.025	0.023	0.037	0.024	0.033	0.023
	R^2	0	1	0	0	0	1	0	0	0
	β	-0.064	-0.053	0.086	0.061	0.042	0.023	0.035	-0.032	0.044
Intermediary Returns	SE	0.025	0.012	0.029	0.025	0.025	0.033	0.025	0.031	0.038
	R^2	2	5	2	2	1	0	1	0	1
	β	0.065	-0.046	-0.192	-0.102	-0.333	0.095	-0.084	-0.194	-0.024
U.S. Foreign Bond Purchases	SE	0.174	0.127	0.248	0.197	0.170	0.251	0.176	0.209	0.207
	R^2	0	0	0	0	2	0	0	1	0
Panel B: Post-2007		AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
	β	-0.101	-0.075	-0.043	-0.057	-0.053	0.019	-0.082	-0.094	-0.079
Global Return Factor	SE	0.008	0.006	0.010	0.008	0.005	0.009	0.008	0.013	0.009
	R^2	55	56	16	31	34	4	49	42	46
	β	0.060	0.050	0.010	0.025	0.037	-0.027	0.053	0.045	0.039
GZ Spread	SE	0.016	0.009	0.011	0.013	0.006	0.007	0.008	0.019	0.011
	R^2	23	30	1	7	20	9	24	12	13
	β	-0.574	-0.435	-0.215	-0.333	-0.276	0.159	-0.454	-0.584	-0.470
S&P 500	SE	0.084	0.055	0.067	0.063	0.052	0.070	0.067	0.075	0.064
	R^2	38	41	9	23	20	6	32	35	35
	β	0.077	0.052	0.028	0.045	0.028	-0.027	0.061	0.076	0.056
Log VXO	SE	0.015	0.010	0.013	0.012	0.010	0.009	0.012	0.014	0.013
	R^2	21	18	5	13	6	5	18	18	15
	β	0.119	0.056	0.096	0.100	0.051	-0.020	0.102	0.107	0.098
Treasury Premium	SE	0.028	0.020	0.033	0.029	0.028	0.025	0.025	0.023	0.026
	R^2	12	5	12	15	5	1	11	9	11
	β	-0.277	-0.227	-0.099	-0.173	-0.179	0.123	-0.225	-0.295	-0.256
Intermediary Returns	SE	0.056	0.038	0.046	0.045	0.034	0.040	0.045	0.064	0.041
	R^2	25	31	5	17	23	10	22	25	29
	β	-1.36	-1.23	-.356	-0.660	-1.12	0.481	-1.36	-1.07	-1.11
U.S. Foreign Bond Purchases	SE	0.287	0.193	0.276	0.221	0.336	0.354	0.238	0.254	0.228
	R^2	35	45	5	14	36	5	37	26	29

Notes: This table reports regressions results of the form $\Delta e^{\$}_{i,t} = \alpha + \beta X_t + \varepsilon_t$, where $\Delta e^{\$}_{i,t}$ is the change in a bilateral exchange rate with the US dollar and X_t corresponds to the row label. "Global Return Factor," X_t is the global factor in world asset prices constructed by Miranda-Agrippino and Rey (2018). "GZ Spread," X_t is the U.S. corporate bond credit spread, taken from Gilchrist and Zakrajšek (2012). "S&P500," X_t is the log total return on the S&P500 index. "VXO," X_t is the change in the log transformation of an index of implied volatility on the stocks in the S&P100, from the CBOE. "Treasury Premium," X_t is the change in the one-year Treasury Premium, the average one-year tenor CIP deviation between developed country government bonds and U.S. Treasuries from Du *et al.* (2018). "Intermediary Returns," X_t is the value-weighted return on a portfolio of NY Fed primary dealers' holding companies and is taken from He *et al.* (2017). "U.S. Foreign Bond Purchases" is U.S. net purchases of foreign bonds, normalized as a percentage of the U.S. value of foreign bond investment at the end of the prior quarter.

Table B.7: *Broad Exchange Rates and Risk Factors*

Panel A: Pre-2007		AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	USD
	β	-0.035	-0.002	0.023	0.014	0.000	0.005	0.001	-0.035	-0.008	0.037
Global Return Factor	SE	0.010	0.006	0.009	0.007	0.009	0.010	0.005	0.011	0.008	0.009
	R^2	5	0	4	2	0	0	0	5	1	9
	β	0.047	0.020	-0.030	-0.018	-0.025	-0.018	-0.011	0.042	-0.004	-0.003
GZ Spread	SE	0.010	0.008	0.009	0.007	0.007	0.009	0.009	0.010	0.007	0.008
	R^2	6	2	3	2	3	1	1	5	0	0
	β	-0.110	-0.095	0.109	0.064	0.044	0.012	0.024	-0.061	-0.002	0.015
S&P 500	SE	0.040	0.025	0.032	0.024	0.028	0.038	0.023	0.049	0.033	0.028
	R^2	3	3	4	3	1	0	0	1	0	0
	β	0.051	0.027	-0.043	-0.022	-0.020	-0.019	-0.015	0.039	-0.007	0.008
Log VXO	SE	0.009	0.007	0.006	0.005	0.008	0.013	0.006	0.013	0.007	0.007
	R^2	9	4	11	5	3	1	2	7	0	0
	β	0.010	0.010	-0.014	-0.016	-0.013	0.031	0.003	0.014	-0.016	-0.010
Treasury Premium	SE	0.027	0.017	0.024	0.017	0.021	0.034	0.018	0.027	0.015	0.018
	R^2	0	0	1	1	0	1	0	0	1	0
	β	-0.087	-0.075	0.080	0.052	0.030	0.010	0.023	-0.051	0.033	-0.016
Intermediary Returns	SE	0.025	0.018	0.021	0.015	0.020	0.028	0.015	0.030	0.030	0.018
	R^2	4	5	4	4	1	0	1	1	1	0
	β	0.163	0.040	-0.123	-0.023	-0.279	0.196	-0.003	-0.125	0.064	0.091
U.S. Foreign Bond Purchases	SE	0.174	0.164	0.190	0.121	0.113	0.220	0.133	0.198	0.161	0.13
	R^2	0	0	0	0	3	1	0	0	0	0
Panel B: Post-2007		AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	USD
	β	-0.049	-0.020	0.015	-0.001	0.004	0.084	-0.029	-0.042	-0.025	0.063
Global Return Factor	SE	0.006	0.007	0.007	0.005	0.006	0.011	0.005	0.009	0.005	0.006
	R^2	36	8	4	0	0	46	17	18	15	52
	β	0.034	0.023	-0.021	-0.005	0.009	-0.063	0.026	0.018	0.011	-0.032
GZ Spread	SE	0.010	0.006	0.005	0.006	0.006	0.014	0.005	0.013	0.004	0.009
	R^2	20	13	9	1	2	31	17	4	3	17
	β	-0.285	-0.130	0.115	-0.017	0.047	0.530	-0.151	-0.295	-0.169	0.354
S&P 500	SE	0.059	0.050	0.050	0.034	0.038	0.095	0.045	0.057	0.042	0.045
	R^2	26	7	5	0	1	40	10	20	15	35
	β	0.041	0.014	-0.013	0.006	-0.013	-0.074	0.024	0.041	0.018	-0.044
Log VXO	SE	0.008	0.007	0.009	0.006	0.008	0.012	0.007	0.009	0.007	0.010
	R^2	16	3	2	1	2	23	8	11	5	17
	β	0.053	-0.017	0.028	0.032	-0.023	-0.101	0.035	0.041	0.030	-0.079
Treasury Premium	SE	0.020	0.021	0.030	0.021	0.030	0.025	0.020	0.014	0.017	0.017
	R^2	6	1	2	5	1	10	4	3	3	12
	β	-0.129	-0.074	0.069	-0.014	-0.020	0.316	-0.071	-0.149	-0.106	0.179
Intermediary Returns	SE	0.034	0.030	0.035	0.024	0.031	0.057	0.029	0.046	0.021	0.034
	R^2	15	7	5	0	0	39	6	14	17	25
	β	-0.654	-0.394	0.457	0.120	-0.394	1.388	-0.661	-0.334	-0.381	0.850
U.S. Foreign Bond Purchases	SE	0.187	0.237	0.243	0.173	0.347	0.374	0.187	0.193	0.134	0.160
	R^2	22	11	14	1	7	34	25	5	13	32

Notes: This table reports regressions results of the form $\Delta e^B_{i,t} = \alpha + \beta X_t + \varepsilon_t$, where $\Delta e^B_{i,t}$ is the change in a broad exchange rate versus all other G10 currencies equally weighted and X_t corresponds to the row label. "Global Return Factor," X_t is the global factor in world asset prices constructed by Miranda-Agrippino and Rey (2018). "GZ Spread," X_t is the U.S. corporate bond credit spread, taken from Gilchrist and Zakrajšek (2012). "S&P500," X_t is the log total return on the S&P500 index. "VXO," X_t is the change in the log transformation of an index of implied volatility on the stocks in the S&P100, from the CBOE. "Treasury Premium," X_t is the change in the one-year Treasury Premium, the average one-year tenor CIP deviation between developed country government bonds and U.S. Treasuries from Du *et al.* (2018). "Intermediary Returns," X_t is the value-weighted return on a portfolio of NY Fed primary dealers' holding companies and is taken from He *et al.* (2017). "U.S. Foreign Bond Purchases" is U.S. net purchases of foreign bonds, normalized as a percentage of the U.S. value of foreign bond investment at the end of the prior quarter.

Table B.8: *Broad US Dollar and U.S. Purchases of Foreign Bonds*

	Δe^B_{USD}	Δe^B_{USD}	Δe^B_{USD}
	1977-2006	2007-2017	2007-2017
	BoP	BoP	Morningstar
U.S. Purchases of Foreign Bonds	0.091	0.86	0.50
	(0.13)	(0.16)	(0.08)
Constant	-0.0016	-0.013	-0.014
	(0.0045)	(0.0060)	(0.0055)
Observations	120	44	44
R^2	0.00	0.33	0.39

Notes: This table reports regressions results of the form $\Delta e^B_{USD,t} = \alpha + \beta f_t + \varepsilon_t$, where $\Delta e^B_{USD,t}$ is the quarterly change in the broad US dollar and f_t is a particular measure of capital flows listed in the first column of the table. Purchases of bonds are normalized by the stock of holdings of that asset at the end of the previous quarter. The BoP measure is defined as net purchases of foreign bonds by the United States, where transactions are recorded at their current value during the quarter, normalized as a percentage of the United States' value of foreign bond investment at the end of the prior quarter. The Morningstar measure defines net purchases of foreign bonds as the change in the quantity of each foreign bond held multiplied by the prior quarter's end of period price, normalized as a percentage of the value of mutual fund foreign bond investment at the end of the prior quarter.

Table B.9: *U.S. Purchases of Foreign Bonds and Coincident Flows*

	External Allocations	Internal Allocations				
	Flows into Funds	All U.S. Bonds	U.S. Sov Bonds	U.S. Corp Bonds	U.S. Other Bonds	Equities
U.S. Foreign Bond Purchases	1.38	-0.16	-0.20	0.40	-0.29	0.81
	(0.31)	(0.65)	(0.45)	(0.094)	(0.32)	(0.45)
Constant	26.5	50.3	25.3	9.18	16.8	34.1
	(6.98)	(10.5)	(6.42)	(1.96)	(6.18)	(8.41)
Observations	44	44	44	44	44	44
R^2	0.28	0.00	0.11	0.33	0.01	0.10

Notes: This table reports regression results of the form $F_t = \alpha + \beta F^B_{USA,foreign,t} + \varepsilon_t$, where $F^B_{USA,foreign}$ is the quarterly purchases of foreign issued bonds by the U.S. investor, and F_t is a particular measure of U.S. flows. All variables are in the units of U.S. dollars in levels. External allocations refer to flows at the outside investor level - injections and withdrawals from U.S. domiciled mutual funds. Internal allocations refer to flows at the fund level. "Flows into Funds" refers to end investor injections into U.S. domiciled mutual funds. "U.S. Sovereign Bonds" and "U.S. Corporate Bonds" are bond purchases, restricting the sample to the universe of debt issued by the U.S. Federal Government and U.S. corporations, respectively. "U.S. Other Bonds" refers to all other bonds issued domestically and "Equities" refers to flows into stocks. All position data are from Morningstar.

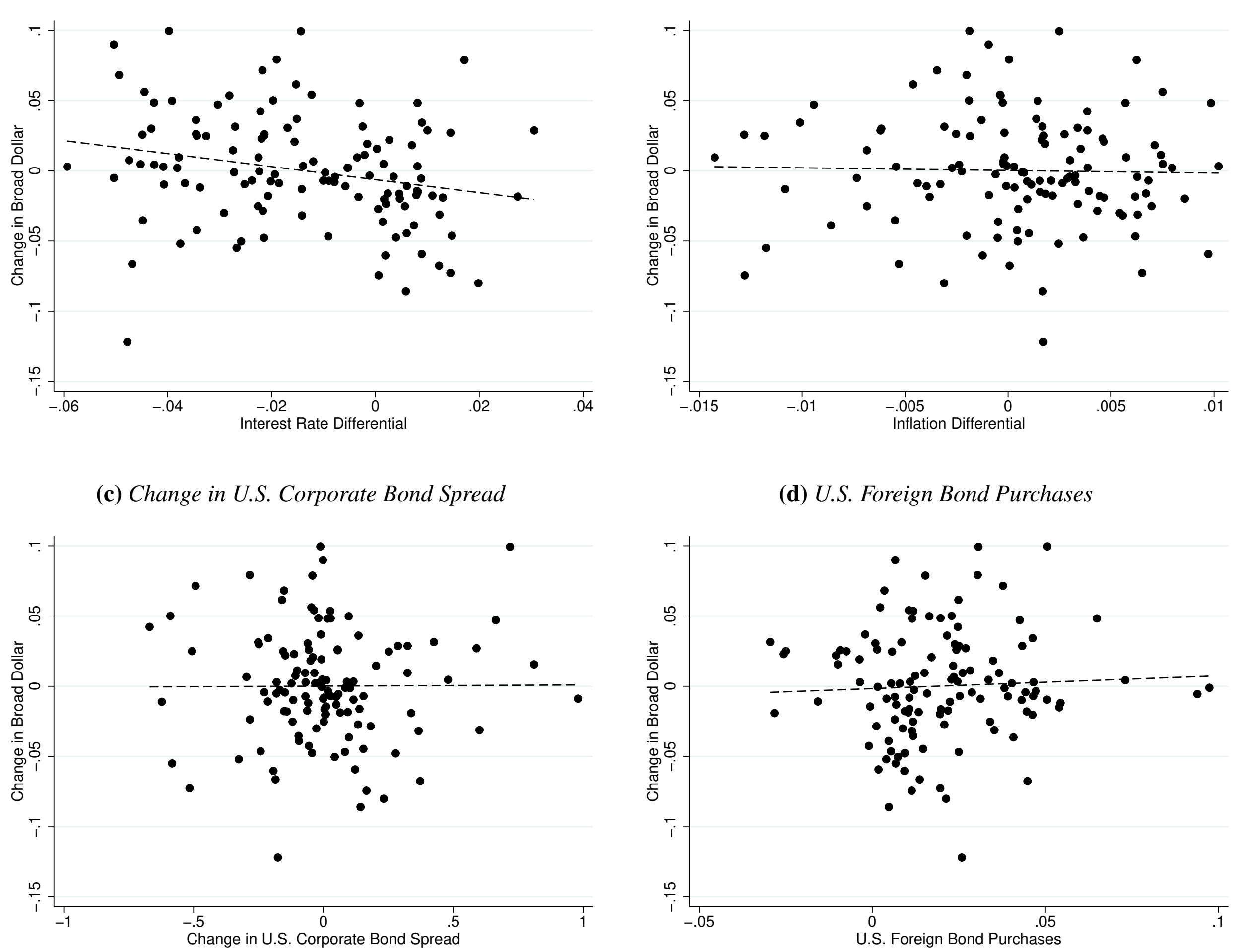
Table B.10: *Bilateral Exchange Rates with the US Dollar, Global and Idiosyncratic Factors*

Currencies	Restricted Regression			Unrestricted Regression					Partial-R^2
	US to all ex. country i			US to all ex. country i		US to country i			
	β	s.e.	R^2	β	s.e.	β	s.e.	R^2	
AUD	-0.82	(0.14)	0.44	-0.55	(0.16)	-0.31	(0.12)	0.53	0.09
BRL	-0.85	(0.16)	0.29	-0.88	(0.16)	0.081	(0.17)	0.30	0.01
CAD	-0.47	(0.14)	0.31	-0.46	(0.14)	-0.03	(0.13)	0.31	0.00
CHF	-0.26	(0.13)	0.09	-0.28	(0.13)	0.12	(0.050)	0.17	0.08
COP	-0.71	(0.17)	0.29	-0.55	(0.17)	-0.26	(0.11)	0.34	0.05
CZK	-0.57	(0.14)	0.20	-0.58	(0.13)	-0.0068	(0.0012)	0.29	0.09
DKK	-0.38	(0.11)	0.16	-0.37	(0.13)	-0.0036	(0.027)	0.16	0.00
EUR	-0.32	(0.17)	0.09	-0.062	(0.21)	-0.22	(0.11)	0.19	0.10
GBP	-0.58	(0.16)	0.36	-0.44	(0.20)	-0.08	(0.091)	0.37	0.01
IDR	-0.35	(0.16)	0.16	-0.34	(0.18)	-0.1	(0.13)	0.18	0.02
ILS	-0.31	(0.10)	0.13	-0.31	(0.11)	0.0037	(0.025)	0.13	0.00
INR	-0.42	(0.067)	0.31	-0.42	(0.069)	-0.017	(0.024)	0.32	0.01
JPY	0.042	(0.17)	0.00	0.039	(0.17)	0.0098	(0.061)	0.00	0.00
KRW	-0.60	(0.081)	0.40	-0.61	(0.081)	0.021	(0.027)	0.41	0.01
MXN	-0.54	(0.19)	0.24	-0.55	(0.20)	0.01	(0.17)	0.24	0.00
MYR	-0.27	(0.084)	0.12	-0.26	(0.074)	-0.0066	(0.024)	0.12	0.00
NOK	-0.69	(0.13)	0.34	-0.58	(0.10)	-0.11	(0.029)	0.41	0.07
NZD	-0.66	(0.11)	0.36	-0.64	(0.13)	-0.015	(0.037)	0.36	0.00
PLN	-0.81	(0.18)	0.28	-0.69	(0.19)	-0.046	(0.023)	0.30	0.02
RUB	-0.70	(0.20)	0.17	-0.68	(0.20)	-0.076	(0.14)	0.18	0.01
SEK	-0.63	(0.12)	0.33	-0.46	(0.14)	-0.12	(0.058)	0.38	0.05
SGD	-0.24	(0.056)	0.20	-0.25	(0.058)	0.0044	(0.020)	0.20	0.00
TRY	-0.44	(0.21)	0.19	-0.48	(0.18)	-0.17	(0.071)	0.24	0.05
ZAR	-0.54	(0.19)	0.18	-0.28	(0.18)	-0.20	(0.048)	0.37	0.19
Average			0.23					0.26	0.04

Notes: The dependent variable of each regression in the left panel is the log change in each foreign currency against the US dollar, defined such that a negative value corresponds to an appreciation of the non-US dollar currency. The average R^2 is the mean R^2 from separate regressions for each currency. The regressor titled “U.S. to All ex. Country i" is the percentage increase in foreign bond investment in all countries which are not the natural issuer of the currency, while the regressor titled “US to Country i" is the percentage increase in foreign bond investment in all countries which are the natural issuer of the currency. A negative coefficient for “U.S. to All ex. Country i" indicates that the listed currency appreciates against the US dollar when the United States is purchasing foreign bonds. A negative coefficient for “U.S. to Country i" indicates that the listed currency appreciates against the US dollar when the United States is purchasing that country’s bonds. Units are defined as percentage changes, as described in section B.3.2. All regressions are conducted at a quarterly frequency. The sample period for all regressions is from 2007:Q1 to 2017:Q4. Standard errors are calculated allowing for heteroskedasticity. Exchange rate data are from Thomson Reuters Datastream and bond position data are from Morningstar.

B.6 Supplementary Figures

Figure B.1: *Exchange Rate Disconnect, 1977-2006*

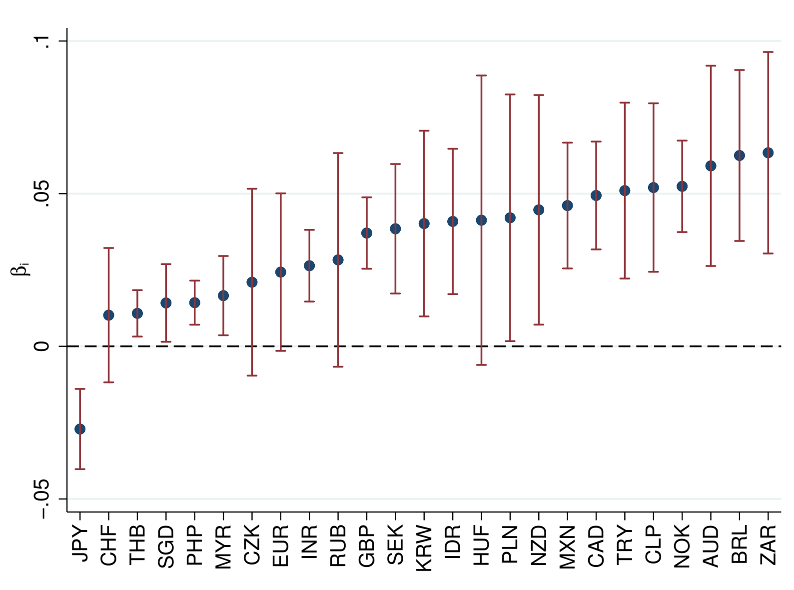


(a) *Interest Rate Differential* **(b)** *Inflation Differential*

(c) *Change in U.S. Corporate Bond Spread* **(d)** *U.S. Foreign Bond Purchases*

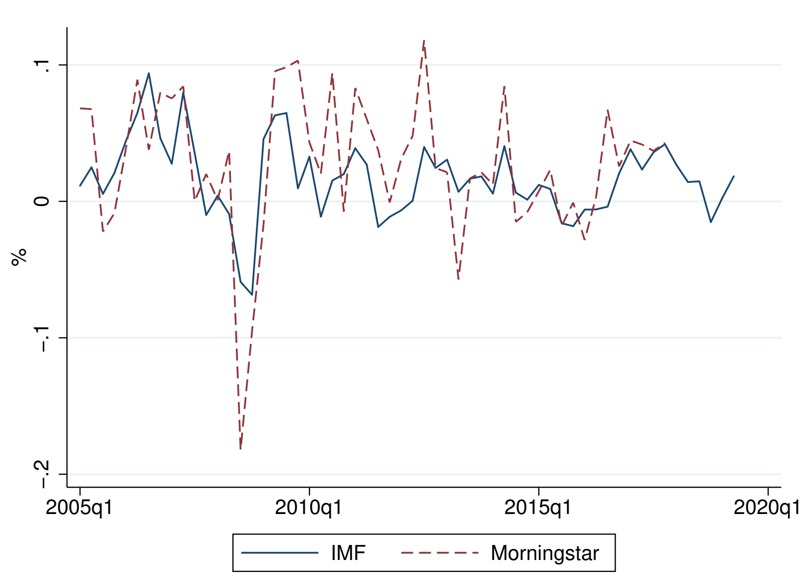
Notes: This figure plots the relationship between various macroeconomic variables and quarterly changes in the broad dollar exchange rate from 1977-2006. Changes in the broad dollar are reported on the y-axis and the relevant macroeconomic quantity is reported on the x-axis. A positive change in the broad dollar indicates dollar depreciation, and a rightward move in the x-axis corresponds to a higher level for the United States minus the G10 countries. Panel A tests the UIP model, using the average lagged interest rate differential in the United States relative to the mean of the other G10 economies. Panel B looks at the equivalent in the U.S. inflation rate relative to the inflation rate of the other G10 economies. Panel C uses the change in U.S. corporate bond spreads, taken from Gilchrist and Zakrajšek (2012). Panel D looks at U.S. purchases of foreign bonds by the United States, normalized as a percentage of the United States' value of foreign bond investment at the end of the prior quarters. The R^2s of these regressions are 0.06, 0.00, 0.00 and 0.00 respectively. Exchange rate data are from Thomson Reuters Datastream and macroeconomic data are from the IMF International Financial Statistics Database.

Figure B.2: *Reconnect of Bilateral Exchange Rates and GZ Spread, β's for 2007-2018*



Notes: This figure reports the coefficient estimate of the following regression specification: $\Delta e^{\$}_{i,t} = \alpha_i + \beta_i f_t + \varepsilon_t$, where $\Delta e^{\$}_{i,t}$ is the monthly change in the log bilateral exchange rate against the US dollar and f_t is the change in U.S. corporate bond spreads, as measured by the "GZ Spread" taken from Gilchrist and Zakrajšek (2012). The blue dots indicate the coefficient point estimates, β_i, and the red bars indicate two standard error bands. A positive coefficient indicates that the listed currency depreciates bilaterally against the US dollar when U.S. corporate bond spreads rise.

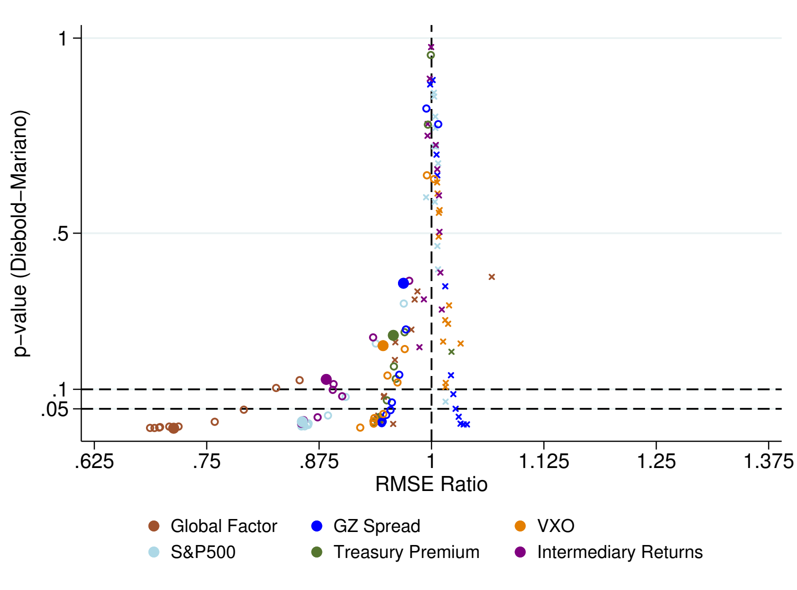
Figure B.3: *U.S. Foreign Bond Flows: BoP and Morningstar*



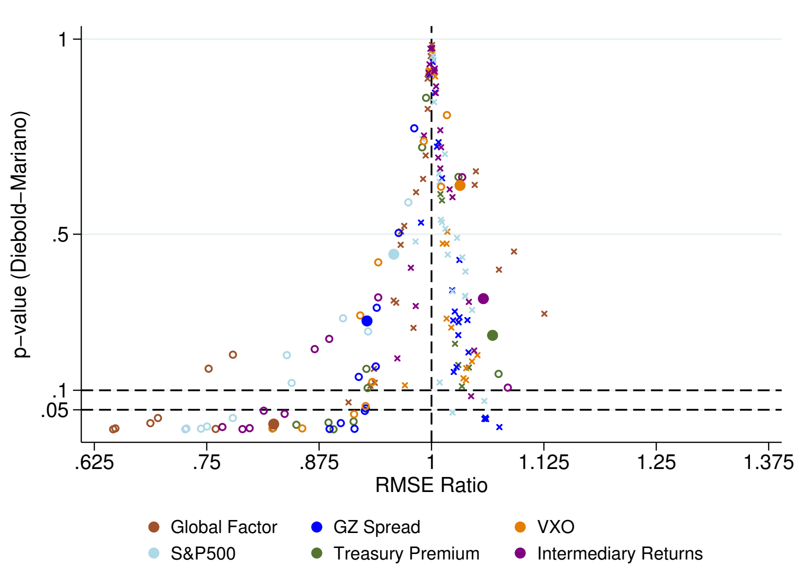
Notes: A comparison of two measures of U.S. purchases of foreign assets using the IMF Balance of Payments and Morningstar's database of U.S. mutual fund positions. The IMF measure is defined as net purchases of foreign bonds by the United States, where transactions are recorded at their current value during the quarter, normalized as a percentage of the United States' value of foreign bond investment at the end of the prior quarter. The Morningstar measure defines net purchases of foreign bonds by the change in the quantity of each foreign bond held multiplied by the prior quarter's end of period price, normalized as a percentage of the mutual funds' value of foreign bond investment at the end of the prior quarter. The correlation coefficient between the two series is 0.66.

Figure B.4: *Reconnect of Risk Measures: Out-Of-Sample Forecasting*

(a) *10-Year Evaluation Periods*



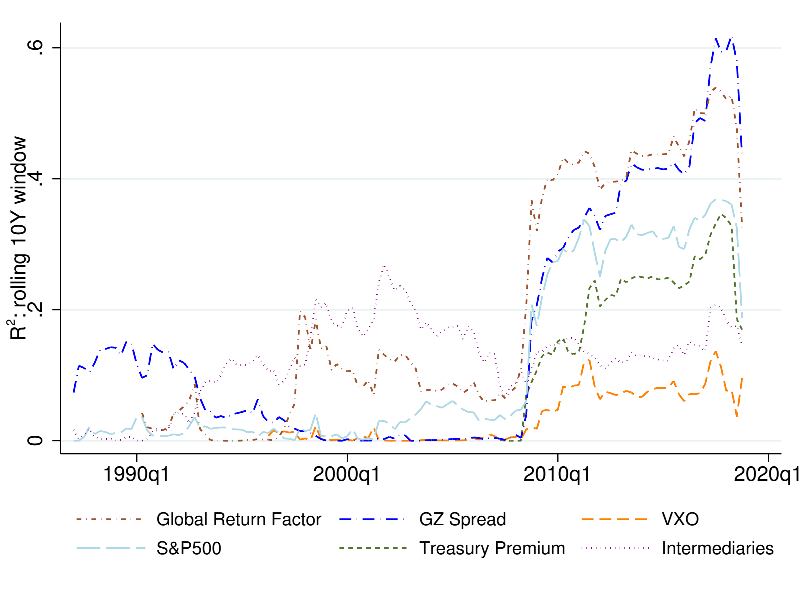
(b) *5-Year Evaluation Periods*



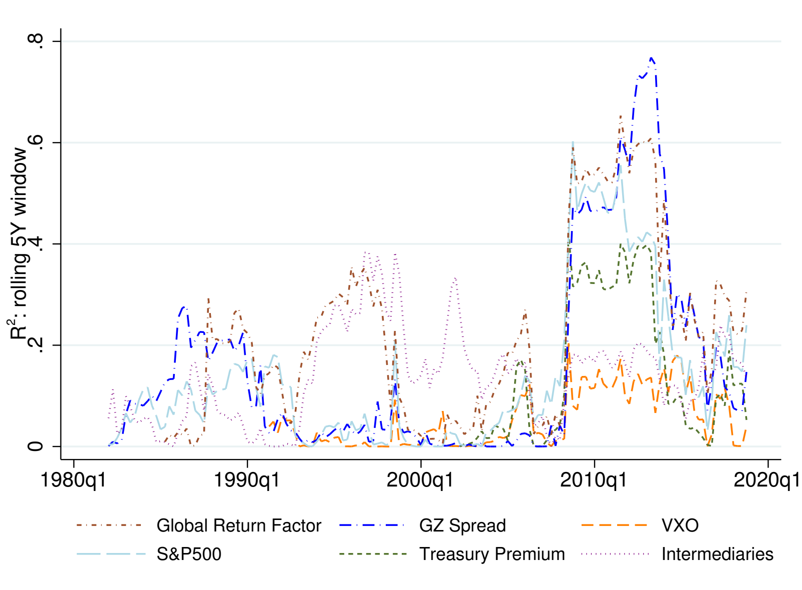
Notes: This figure reports the performance of exchange rate forecasts using each of our six risk proxies relative to a random walk over different sample periods. Each marker reports the p-value of a Diebold-Mariano test for the performance of the model relative to a random walk (y-axis) and the ratio of the model's root mean squared forecast error relative to a random walk. Each observation represents a 120- or 60-month model evaluation period, using a 120- or 60-month rolling estimation windows, as described in Appendix Section B.1. The "x" markers represent windows where all forecasts are for periods prior to 2007, the hollow dots represent windows where the forecasts mix periods before and after 2007, and the solid dots represent windows where all forecast periods occur after 2007.

Figure B.5: *Comovement of U.S. Foreign Bond Purchases and Risk Measures*

(a) *10-Year Rolling Window*



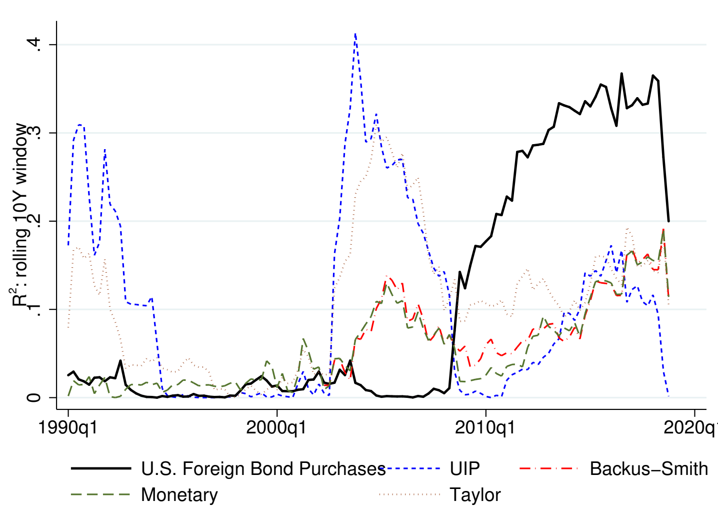
(b) *5-Year Rolling Window*



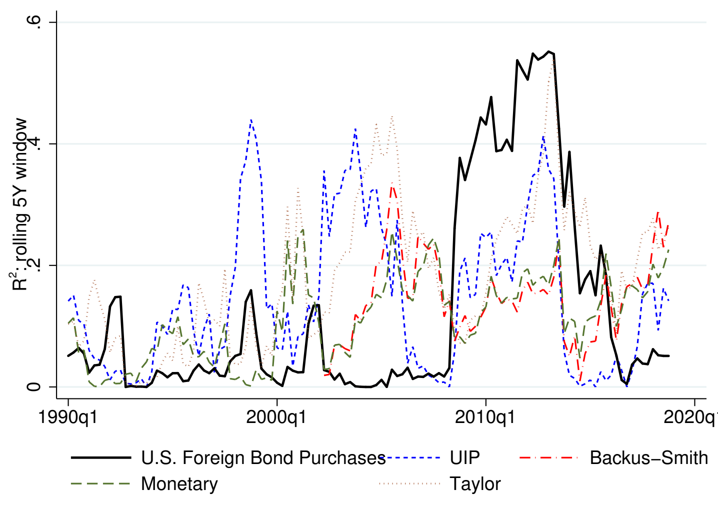
Notes: The figures show the R^2 from 40-quarter and 20-quarter rolling regressions of U.S. Foreign Bond Purchases against various indicators of risk. The regression specification is $f_t = \alpha + \beta X_t + \varepsilon_t$, where f_t refers to the net purchases of foreign bonds by the United States, normalized as a percentage of the value of U.S. foreign bond holdings at the end of the prior quarter. X_t corresponds to different variables depending on the model in question.For "VXO," X_t is the quarterly change in the log transformation of an index of implied volatility on the stocks in the S&P100, from the CBOE. For "S&P500," X_t is the log total return on the S&P500 index. For "Treasury Premium," X_t is the change in the one-year Treasury Premium, the average one-year tenor CIP deviation between developed country government bonds and U.S. Treasuries from Du *et al.* (2018). For "GZ Spread," X_t is the U.S. corporate bond credit spread, taken from Gilchrist and Zakrajšek (2012). For "Intermediaries," X_t is the value-weighted return on a portfolio of NY Fed primary dealers' holding companies and is taken from He *et al.* (2017). For "Global Return Factor," X_t is the global factor in world asset prices constructed by Miranda-Agrippino and Rey (2018).

Figure B.6: *In-Sample Explanatory Power of Capital Flows and Other Fundamentals*

(a) *10-Year Rolling Window*



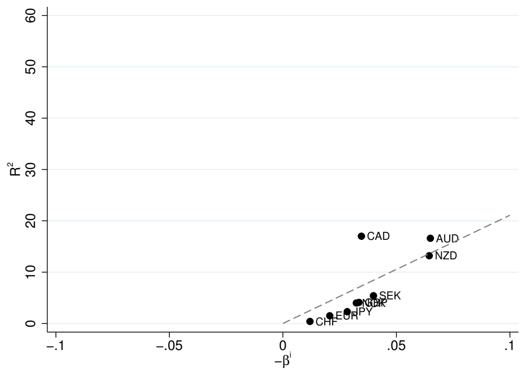
(b) *5-Year Rolling Window*



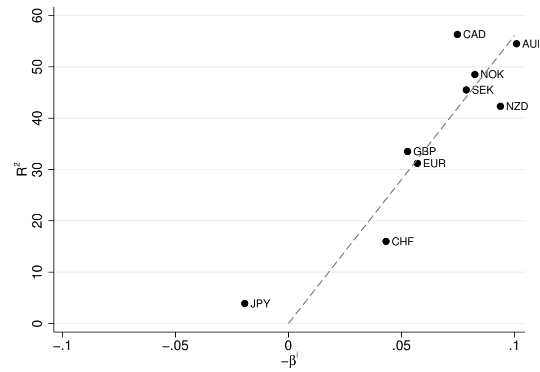
Notes: The figure shows the rolling R^2 for regressions of the form $\Delta e^B_{USD,t} = \alpha + \beta X_t + \varepsilon_t$ where $\Delta e_{USD,t^B}$ is the quarterly average log change in the US dollar versus the other G10 currencies against various models. X_t corresponds to different variables depending on the model in question. For "U.S. Foreign Bond Purchases," X_t is net purchases of foreign bonds by the United States, normalized as a percentage of the United States' value of foreign bond investment at the end of the prior quarter. For the "UIP" model, X_t is the lagged interest rate spread between the United States and the average of the other G10 countries. For the "Monetary" model, X_t contains two variables, the mean inflation difference between the United States and the other G10 countries and the mean growth difference between the United States and the other G10 countries. For "Taylor", X_t contains the (relative value of) the two variables in a Taylor Rule, the mean inflation difference between the United States and the other G10 countries and the mean output gap differential between the United States and the other G10 countries. All macroeconomic variables are computed as the difference between the quarterly observation for the United States versus the average of all other G10 countries. Interest rate differentials are computed from the series "Deposit Rates" from the IFS where available, and from "Treasury Bills, 3 month" otherwise. Growth is measured as the log change in real Gross Domestic Product and the output gap is calculated using the cyclical component of the same logarithmic series from a detrended HP filter with l = 1600.

Figure B.7: *Regression β and R^2, Bilateral Exchange Rates*

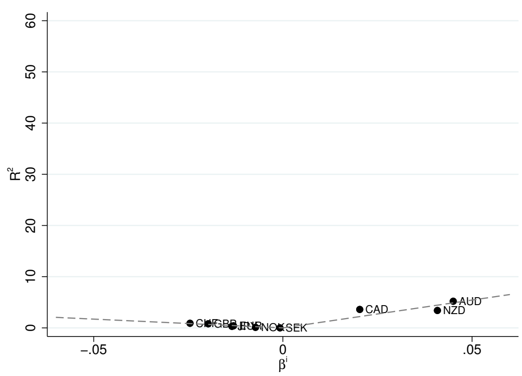
(a) *Global Return Factor, Pre-2007*



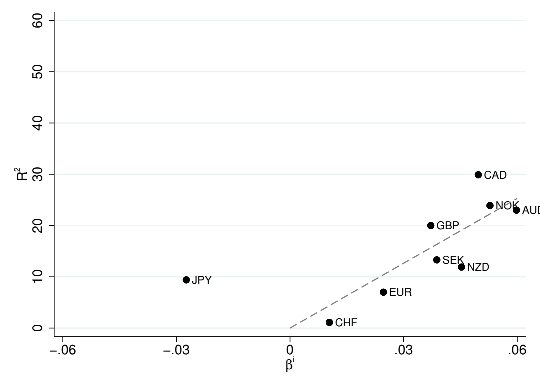
(b) *Global Return Factor, Post-2007*



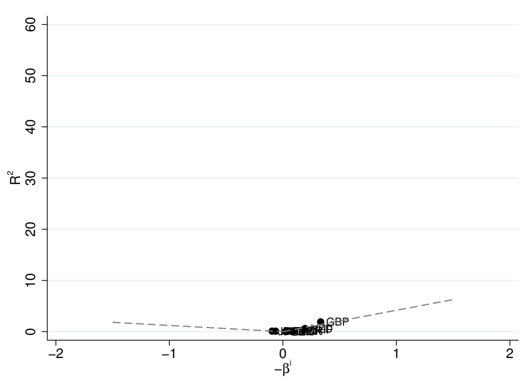
(c) *GZ Spread, Pre-2007*



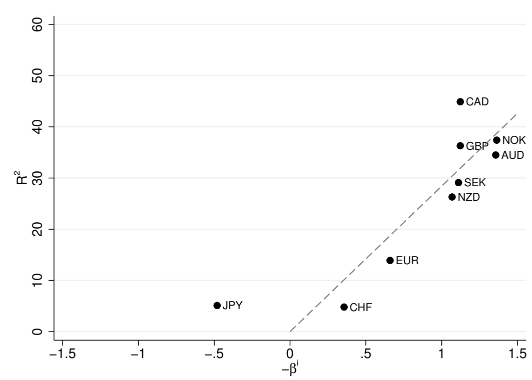
(d) *GZ Spread, Post-2007*



(e) *Foreign Bond Purchases, Pre-2007*

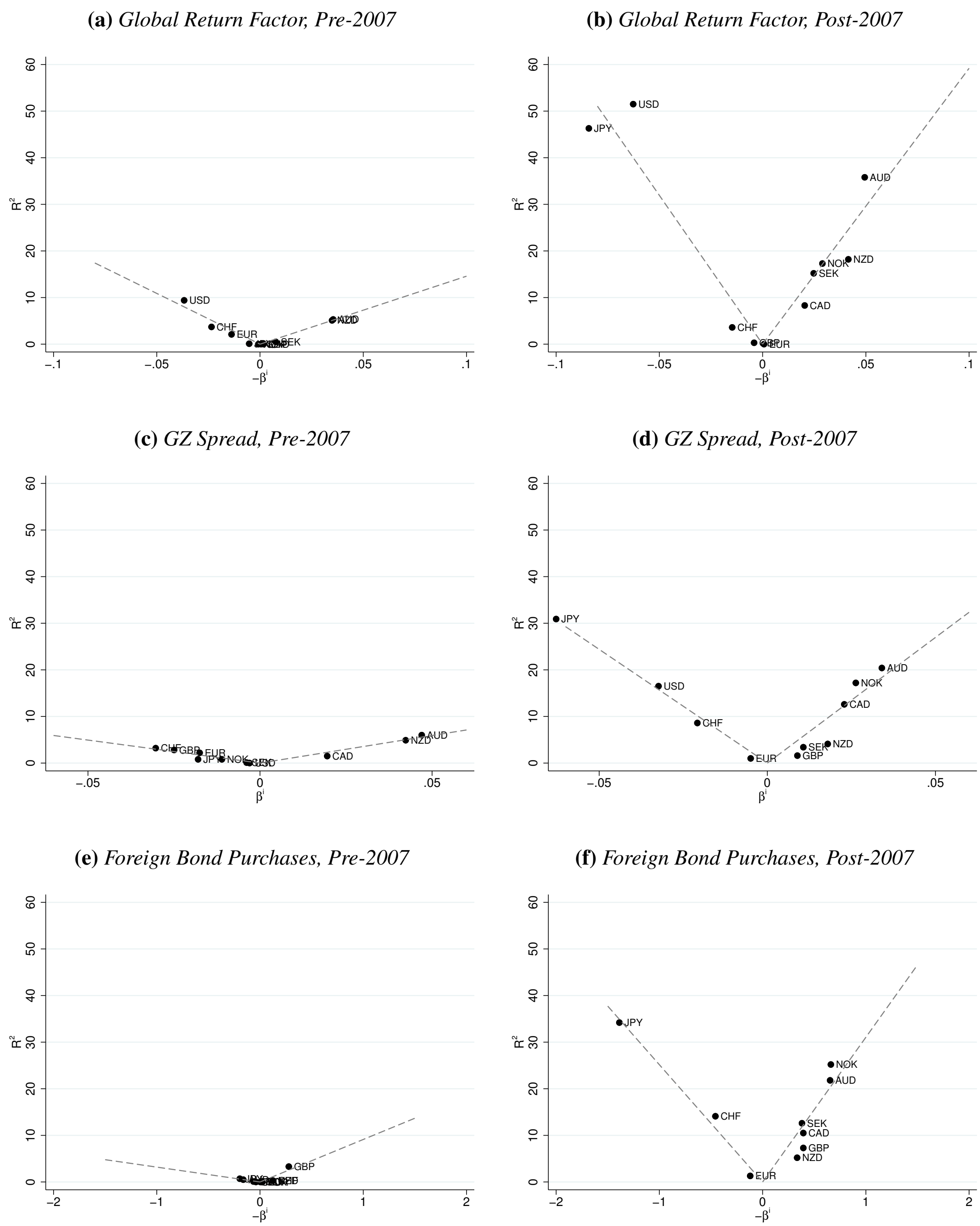


(f) *Foreign Bond Purchases, Post-2007*



Notes: These graphs report the β and R^2 of regressions of $\Delta e^{\$}_{i,t} = \alpha + \beta X_t + \varepsilon_t$, where $\Delta e^{\$}_{i,t}$ is the change in a bilateral exchange rate versus the US dollar and X_t corresponds to an indicator of risk. The left panels show the results for the sample prior to 2007, while the right panels use the sample of 2007 onwards. The top panel uses "Global Return Factor" as X_t - the the global factor in world asset prices constructed by Miranda-Agrippino and Rey (2018). The middle panel uses "GZ Spread" as X_t - the U.S. corporate bond credit spread, taken from Gilchrist and Zakrajšek (2012). The bottom panel “Foreign Bond Purchases" is U.S. net purchases of foreign bonds, normalized as a percentage of the U.S. value of foreign bond investment at the end of the prior quarter. Dashed lines indicate the best fit between the R^2 and β of each currency sample, constrained such that the line passes through (0,0).

Figure B.8: *Regression β and R^2, Broad Exchange Rates*



(a) *Global Return Factor, Pre-2007*

(b) *Global Return Factor, Post-2007*

(c) *GZ Spread, Pre-2007*

(d) *GZ Spread, Post-2007*

(e) *Foreign Bond Purchases, Pre-2007*

(f) *Foreign Bond Purchases, Post-2007*

Notes: These graphs report the β and R^2 of regressions of the form $\Delta e^B_{i,t} = \alpha + \beta X_t + \varepsilon_t$, where $\Delta e^B_{i,t}$ is the change in a broad exchange rate versus all other G10 currencies and X_t corresponds to an indicator of risk. The left panels show the results for the sample prior to 2007, while the right panels use the sample of 2007 onwards. The top panel uses "Global Return Factor" as X_t - the the global factor in world asset prices constructed by Miranda-Agrippino and Rey (2018). The middle panel uses "GZ Spread" as X_t - the U.S. corporate bond credit spread, taken from Gilchrist and Zakrajšek (2012). The bottom panel “Foreign Bond Purchases" is U.S. net purchases of foreign bonds, normalized as a percentage of the U.S. value of foreign bond investment at the end of the prior quarter. Dashed lines indicate the best fit between the R^2 and β of each currency sample, constrained such that the line passes through (0,0).