

# Currency Betas and Interest Rate Spreads

Andrew Lilley and Gianluca Rinaldi\*

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## Abstract

We document that the relationship between currencies and risk premia has changed dramatically since the financial crisis: the covariance of equity returns and exchange rates sharply increased after the crisis. Since 2008, 21 per cent of the variation in monthly currency appreciations can be explained by the interaction of the currency's conditional equity beta with the contemporaneous return on the US stock market, compared to less than 1 per cent beforehand. We provide evidence that, prior to the crisis, interest rate spreads responded to risk premia changes in a way that decreased the sensitivity of exchange rates to risk premia.

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\*PhD Candidates, Harvard University: [andrewlilley@g.harvard.edu](mailto:andrewlilley@g.harvard.edu), [rinaldi@g.harvard.edu](mailto:rinaldi@g.harvard.edu).

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# 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 the prices of other risky assets: Lustig and Verdelhan (2007) find that the return of the stock market can only explain 4 percent of the monthly variation in currency portfolio returns from 1971-2002. 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 dollar are -0.24 and 0.35 respectively since 2008, but were indistinguishable from zero before.

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 (1983) puzzle: that exchange rate moves are unexplainable by both macro and financial variables.<sup>1</sup> 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 21% after the crisis, but only 1% before.

A broad literature, following Meese and Rogoff (1983) and summarized in Rossi (2013),

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<sup>1</sup>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 worse than a forecast of no change.

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.<sup>2</sup>

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 in a period when interest rate spreads, often taken as a proxy of risk, have become substantially smaller and less volatile. 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 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

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<sup>2</sup>At decade-long horizons, purchasing power parity differentials, and differential inflation can explain exchange rates between advanced countries. ([Rogoff, 1996](#)).

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. 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.<sup>3</sup>

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. 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.<sup>4</sup>

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 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, as evidenced by the muted move in the spread in the fall of 2008, central banks were not expected to respond differently to this risk premium shock and the Australian dollar suffered a dramatic depreciation of around 20% in this two month period, mirroring the return on the S&P 500.

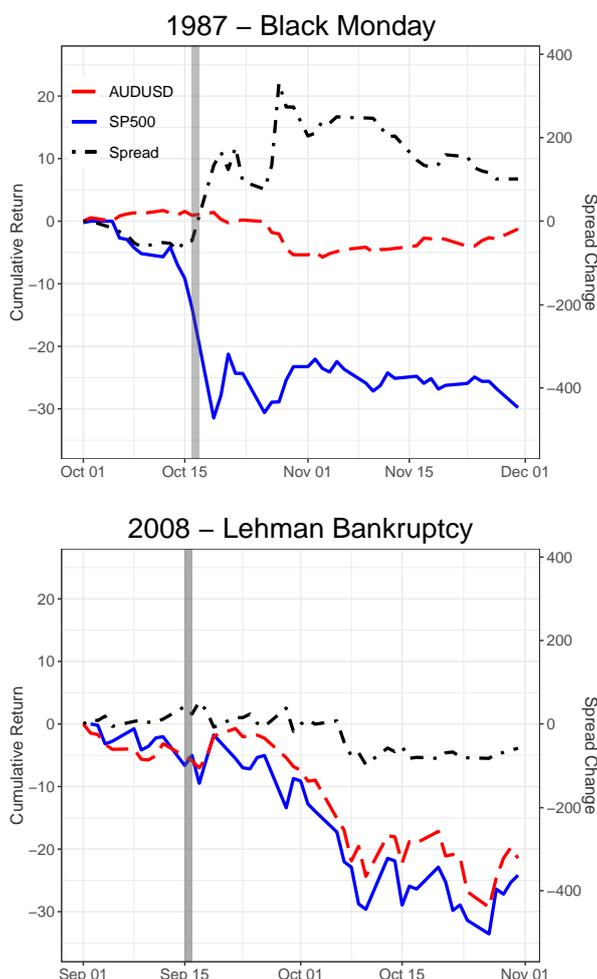
This example is representative of interest rate spreads behavior before the financial crisis. We regress changes in the 2 year government bond yield spread on movements in the S&P 500, and show that in the two decades prior to the 2008 crisis, central banks

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<sup>3</sup>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 market prices decrease.

<sup>4</sup>The fact that the price of risk increased in those two periods is confirmed empirically by standard valuation measures (Campbell and Shiller (1988), Lettau and Ludvigson (2001)) and by more recent predictors based on option prices (Martin, 2017).

**Figure 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.

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 decom-

position 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 with traditional 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.<sup>5</sup>

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<sup>5</sup>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

Two 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. Our paper in turn shows that realized covariances with the S&P 500 were a poor measure of risk premia before 2007, but can explain currency movements afterwards. [Jiang et al. \(2018\)](#) 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. We use a similar approach to decompose currency returns, but focus instead on the risk premia component, rather than convenience yields. Another strand of literature following [Lustig et al. \(2011\)](#) 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 [Ilzetzi et al. \(2019\)](#). In particular, we focus on the impact of central bank behavior on traditional 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 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.<sup>6</sup> Our work complements a growing literature on the specialness

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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](#)); future carry trade returns are higher versus the US dollar when the VIX is high ([Kalemli-Özcan and Varela, 2019](#)).

<sup>6</sup>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 \(2019\)](#) show that the major foreign central banks can use their

of the US dollar, to which our contribution is in documenting foreign central banks' preference for currency stability against the US dollar specifically.<sup>7</sup> We also add to a nascent literature on the impact of the effective lower bound on asset prices.<sup>8</sup>

## 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 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 year of 2009.

The well-known exchange rate disconnect with macroeconomic variables is mirrored here for risk premia: all G10 exchange rates showed little co-variation with changes in risk premia 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

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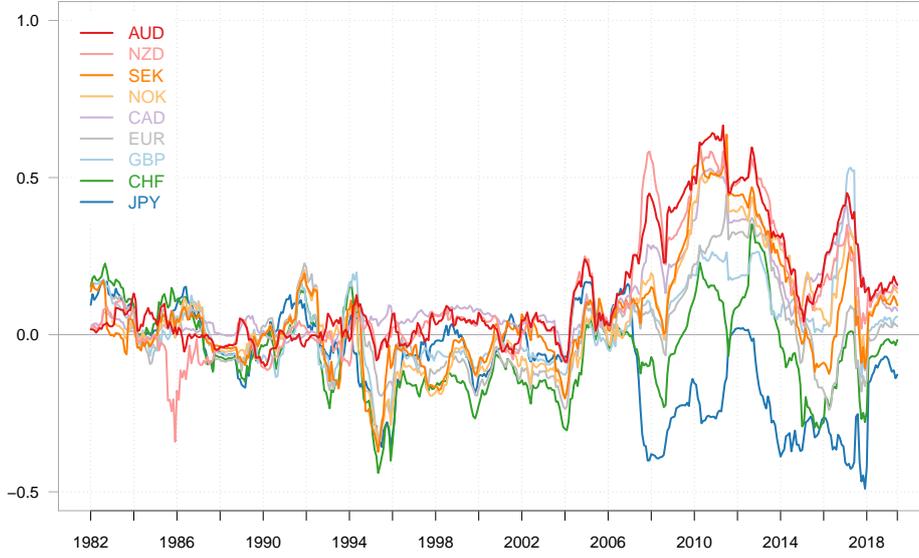
language to affect the price of their currencies vis-à-vis to the US dollar.

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

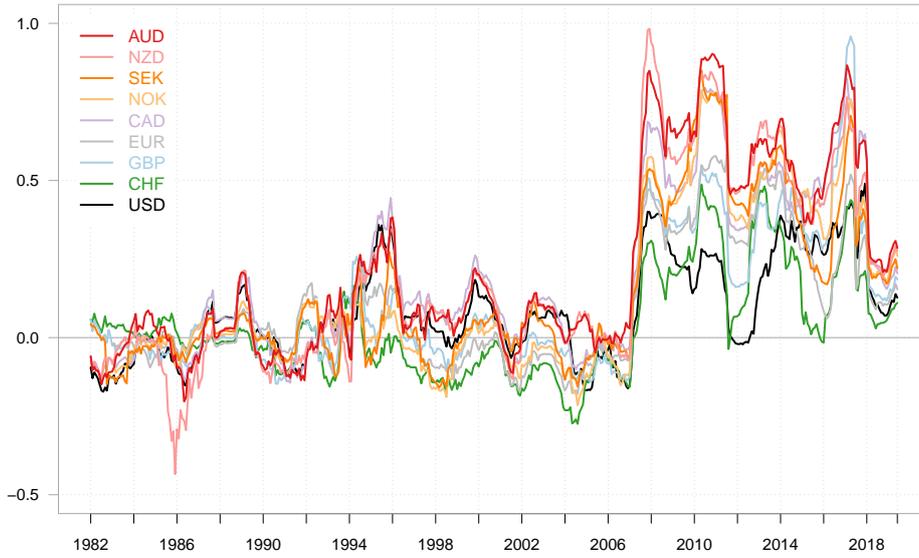
<sup>8</sup>[Ferrari et al. \(2017\)](#) document that monetary policy shocks have had larger impacts on currencies in the era of low rates. In other asset classes, recent work by [Datta et al. \(2018\)](#) links the constraint of the effective lower bound to a significant change in the correlation of 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.

**Figure 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:

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

A positive  $\Delta e_t^i$  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.

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., 2018, 2019). 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 2.<sup>9</sup> 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 graph, reported in Appendix Figure A.2.

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, 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 2, we also define each exchange rate relative to an equally weighted basket of its log appreciation against all other G10 exchange rates.<sup>10</sup> 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  $\beta$  of 0.21) to the most safe (Japanese yen, with a  $\beta$  of -0.38). Since we use log appreciations, the  $\beta$  between the Australian dollar and Japanese yen exchange rate and the return on the market must be equal to the difference in their baskets'  $\beta$  with the return on the market, i.e. the  $\beta$  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

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<sup>9</sup>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.4, 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.

<sup>10</sup>See Figure A.1 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.

when measured against the Australian dollar, or the Japanese yen, are -0.21 and 0.38 respectively.

**Table 1:** Average conditional betas before and after the effective lower bound

(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	
<b>G10 Basket</b>	0.05	0.03	0.05	-0.02	-0.01	-0.02	-0.02	0.01	-0.06	-0.01

(b) Jan 2008-Jun 2019.										
	AUD	NZD	CAD	NOK	SEK	GBP	EUR	USD	CHF	JPY
AUD										
NZD	0.03									
CAD	0.08	0.04								
NOK	0.11	0.07	0.03							
SEK	0.13	0.10	0.06	0.03						
GBP	0.21	0.18	0.13	0.10	0.08					
EUR	0.25	0.21	0.17	0.14	0.11	0.04				
USD	0.35	0.31	0.27	0.24	0.21	0.14	0.10			
CHF	0.37	0.33	0.29	0.26	0.23	0.16	0.12	0.02		
JPY	0.59	0.55	0.51	0.48	0.45	0.38	0.34	0.24	0.22	
<b>G10 Basket</b>	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 row  $i$  in terms of the currency in column  $j$ , 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.

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

A positive value for  $\beta^{i,j}$  signifies that the currency in row  $i$  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.

Whilst the rank ordering of conditional betas remains largely fixed throughout the post-2008 sample, two exceptions to this rule are worth accounting for. 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 in themselves.

## 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 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 2, 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 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

**Table 2:** Tests of informativeness of conditional betas

		Pre-financial crisis			Post-financial crisis
Test		1983-1993	1990-2000	1997-2007	2008-2018
$R^2$	In-sample	0.01	0.00	0.00	0.21
pseudo- $R^2$	Meese-Rogoff	0.01	0.00	0.00	0.19
True Positive t-stat	Meese-Rogoff	0.53 (1.44)	0.52 (0.77)	0.54** (2.11)	0.59*** (5.02)
True Negative t-stat	Meese-Rogoff	0.52 (0.97)	0.53 (1.36)	0.52 (0.90)	0.67*** (7.43)
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 1993, Jan 1990-Dec 2000, Jan 1997-Dec 2007, and Jan 2008-Dec 2018.

**In-sample.  $R^2$ :** We run pooled regressions of the following form:

$$\Delta e_{t+1}^i = \alpha + \gamma(\hat{\beta}_t^i \cdot r_{t+1}^m) + \epsilon_{t+1}^i$$

for each of the samples listed in the first row of the table.  $\Delta e_{t+1}^i$  is the log appreciation of each currency versus the US dollar, and  $\hat{\beta}_t^i$  are the estimates of conditional beta for each currency in Figure 2.  $\alpha$  and  $\gamma$  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:

$$\widehat{\Delta e_{t+1}^i} = \hat{\alpha}_t^i + \hat{\beta}_t^i r_{t+1}^m$$

*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:

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

*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.

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. As in a traditional in-sample regression, we allow the model to estimate parameters over the full sample, as a benchmark. In the regime prior to the

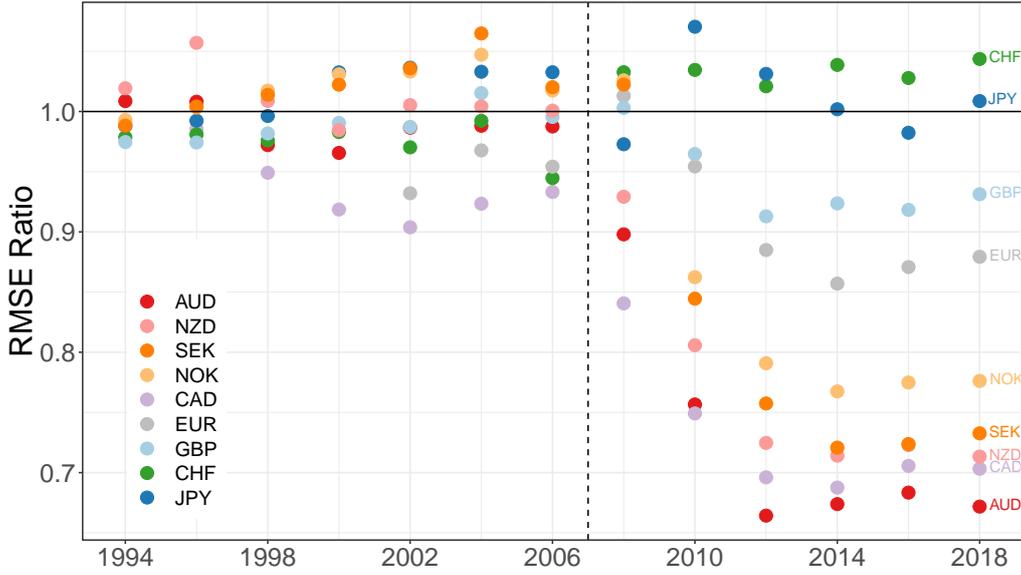
effective lower bound, this specification has little explanatory power, with an  $R^2$  of at most 1 percent. In post-crisis sample, we find an  $R^2$  of 21 percent.

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 Figure 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, and the intercept, 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 exercise, and construct three more forecast metrics. Following [Jordà 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.

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 3. For example, the data point for 2018 corresponds to the forecast window of January 2009 to December

**Figure 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:

$$\widehat{\Delta e_{t+1}^i} = \widehat{\alpha}_t^i + \widehat{\beta}_t^i r_{t+1}^m$$

Using each forecast, we calculate the ratio of root mean squared error for the above forecasts versus a random walk model over the prior 11 years. We find the average root mean squared error of our prediction was 75% as large as that of the random walk model.

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

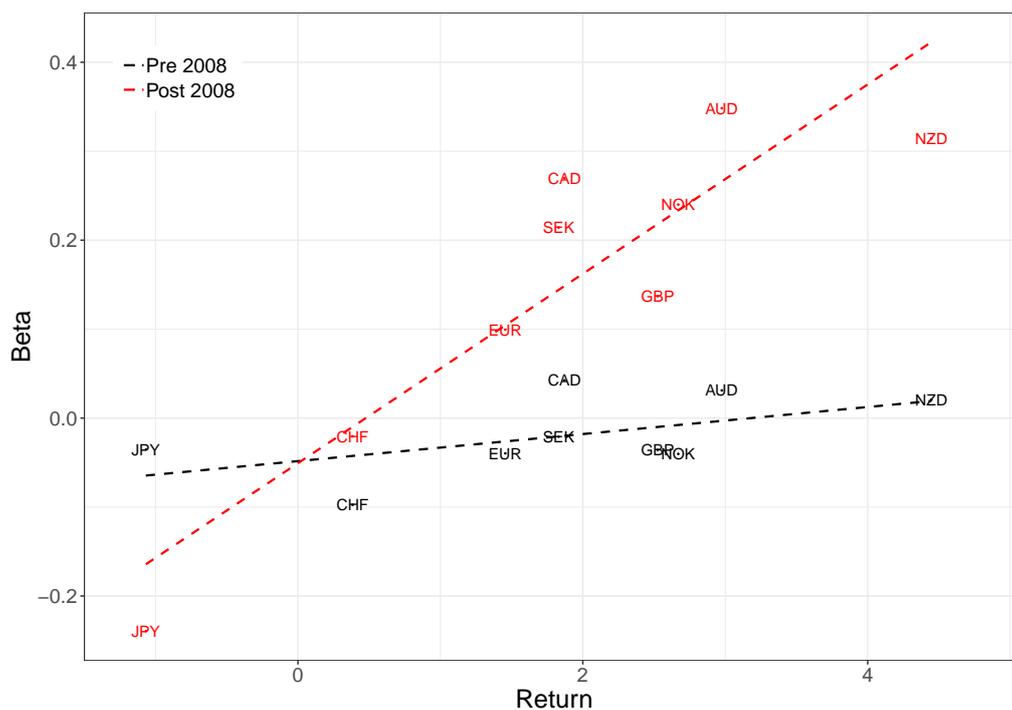
2018. For this window, the riskiest currencies (with respect to the US dollar) have the best forecasting performance, e.g. the Australian dollar exchange rate has a RMSE ratio of 0.68. Two patterns emerge - the first is that forecasts over a 10 year window begin to beat that of a random walk once the 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.3 we report the results of a Diebold-Mariano test of forecast accuracy for each window, and find that for the sample from January 2009 to December 2018, the forecasts of the Norwegian and Swedish kronas, and

the New Zealand, Canadian and Australian dollars outperform those of a random walk with a p-value below 0.05.

## 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 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.

**Figure 4:** Carry trade returns and average conditional betas

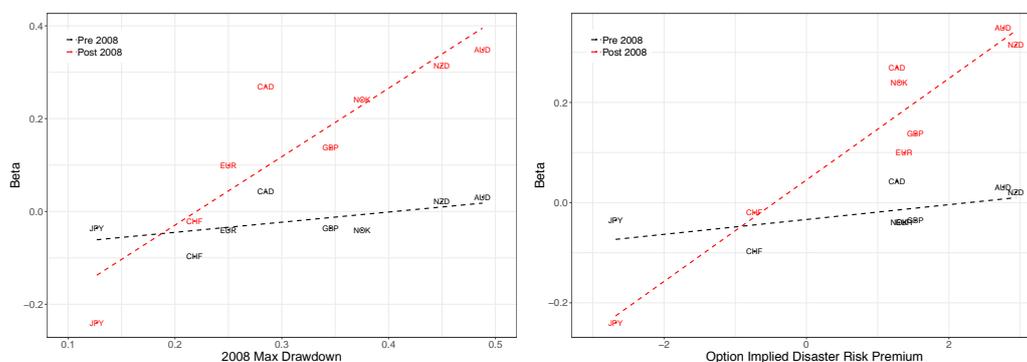


This graph shows that post-crisis average currency betas are explained by pre-crisis average carry trade returns, while the relationship with pre-crisis average betas is much weaker. The horizontal axis shows the average annual return to the carry trade versus the US dollar in the pre-crisis sample (Jan 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.

Riskier assets 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 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 3.

**Figure 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 5 we show a pattern analogous to the one displayed in Figure 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.

### 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 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 3.1.

The observed structural break in equity betas then 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 below zero. We show this increase in equity betas is only apparent for developed economy currencies whose central bank policies were constrained, which fits with this narrative.<sup>11</sup> We report

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<sup>11</sup>Of these ten central banks, 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.

the time series of two year interest rate spreads in Appendix Figure A.4, which shows a decline in both absolute spreads, and in the volatility of spreads, after the crisis.<sup>12</sup>

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

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

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

$$e_t = \sum_{i=0}^{\infty} \mathbb{E}_t [d_{t+i} - r_{t+i+1}] + \mathbb{E}_t \left[ \lim_{j \rightarrow \infty} e_j \right] \quad (2)$$

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  $\mathbb{E}_t [\lim_{j \rightarrow \infty} e_j] = \bar{e}$ .<sup>13</sup>

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

$$r_{t+1} - \mathbb{E}_t[r_{t+1}] = v_{IR,t+1} - v_{FR,t+1}, \quad (3)$$

$v_{IR,t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{i=1}^{\infty} d_{t+i}$  captures changes in expected future short interest rate

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Their two year bonds showed similar price volatility to those central banks with policy rates at or below zero.

<sup>12</sup>On the other hand, emerging market economies' monetary policies were not constrained by the effective lower bound, as they have higher natural nominal interest rates. In the Appendix Figure A.5, 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.

<sup>13</sup>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 ( $Cov_t(\mathbb{E}_{t+1} [\lim_{j \rightarrow \infty} e_j], r_{S\&P,t+1}) = 0$ ). 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., 2018).

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 3, we can similarly decompose the conditional stock market betas for each currency  $i$  reported in Figure 2:

$$\beta_t^i = \frac{Cov_t(v_{IR,t+1}, r_{t+1}^m)}{Var_t(r_{t+1}^m)} - \frac{Cov_t(v_{FR,t+1}, r_{t+1}^m)}{Var_t(r_{t+1}^m)} = \beta_{IR,t}^i - \beta_{FR,t}^i. \quad (4)$$

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 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 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.

### 3.1 Test of the stability of $\beta_{FR}^i$

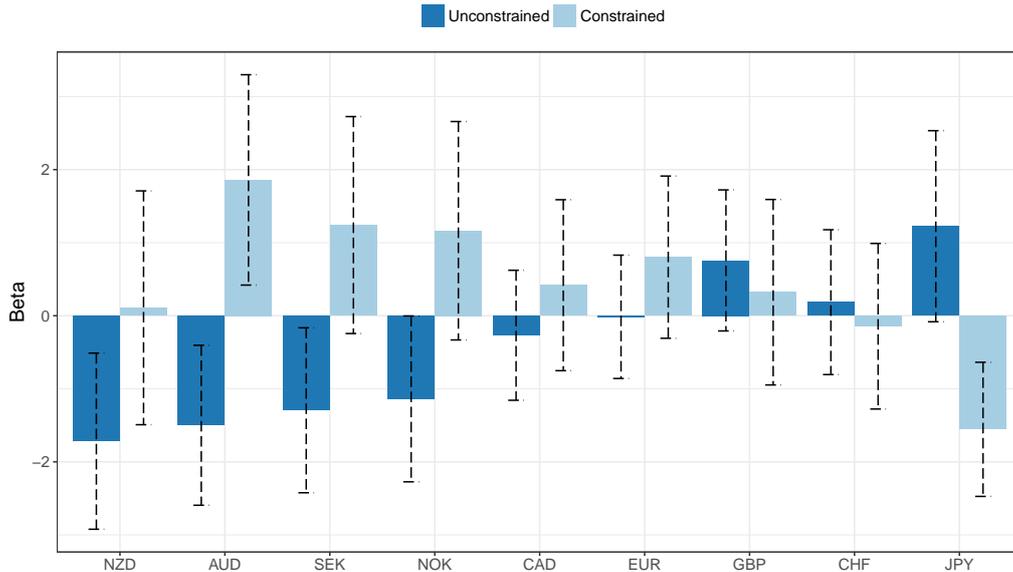
We measure investor expectations of non-US central bank intentions by the yields on 2 year government bonds for each currency in order to proxy for news about current and future policy rates, and construct spreads to the corresponding US Treasury yield. For each currency, we regress changes in the 2 year spread on changes in the risk factor, measured by S&P 500 returns.<sup>14</sup> 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.

<sup>14</sup>We use changes in 2 year bond nominal yields as our measure of changes in the path of central bank rates for two reasons. A 2 year nominal bond allows us to estimate a path of central bank intentions, and estimate the persistence of a change in expected spread. Since local currency term premia offset currency risk premia, taking a longer bond would mix term premia with central bank intentions. Lustig et al. (2019) show that the term premia in foreign currency 10 year bonds is opposite to foreign currency risk premia, and large enough to entirely cancel it.

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.<sup>15</sup>

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 6: the dark bars correspond to the unconstrained period and the light bars to the constrained.

**Figure 6:** Regression coefficients of 2 year risk-free yield spreads versus 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&P 500, split by pre- and post-crisis periods:

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

in which  $i_t^j$  is the yield on the 2 year government bond of country  $j$ ,  $i_t^{\$}$  is the yield on the US 2 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  $\beta^{j,con}$ . The sample is from Apr 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 declines

<sup>15</sup>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.

in the value of equities, we see yields rise on Australian government bonds by more than US government bonds at the 2 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.

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 ( $\beta_{FR,t}^i$ ) has stayed unchanged. A rearrangement of equation 4 yields:

$$\beta_t^i - \beta_{IR,t}^i = -\beta_{FR,t}^i \quad (5)$$

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 ( $\beta_t^i$ ), without a corresponding change in the riskiness of the currency ( $\beta_{FR,t}^i$ ), then we could estimate equation 5 for each currency, pre- and post-crisis. We now conduct this exercise.

In Figure 6, we showed that prior to the crisis, interest rate spreads moved with the price of risk, as measured by 2 year yield spreads. The relationship between these estimates and a long-run estimate of  $\beta_{IR,pre}^i$  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.

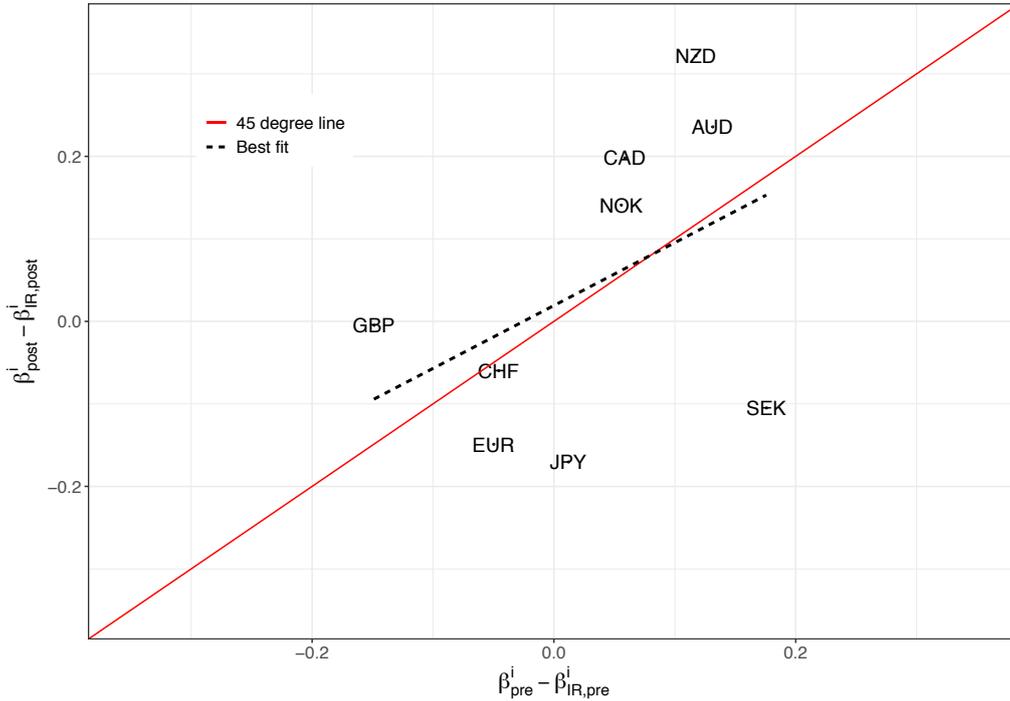
We estimate the persistence of interest rate changes for each country as follows. We model interest rates as an AR(1) process, estimating the persistence of 2 year bond yields between two year lags:  $i_t^j = \alpha + \rho i_{t-24}^j$ , and then estimate the long-run impact of an interest rate shock from a 2 year yield as  $2 \times \frac{1}{1-\rho}$ .<sup>16</sup> We multiply the coefficients in Figure 6 by these estimates of persistence to obtain a proxy of  $\beta_{IR,pre}^i$ . Our estimates of the responsiveness of exchange rates (with respect to the US dollar) to risk premia ( $\beta^i$ ) are taken directly from table 1. We then compare the estimates of  $\beta_{post}^i - \beta_{IR,post}^i$  to those of  $\beta_{pre}^i - \beta_{IR,pre}^i$ .

We show the results of this exercise in Figure 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  $\alpha_0$  and  $\alpha_1$  of the following regression are equal to zero and one:  $\beta_{post}^i - \beta_{IR,post}^i = \alpha_0 + \alpha_1(\beta_{pre}^i - \beta_{IR,pre}^i)$ . 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.

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

**Figure 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 5.  $\beta^i$  refers to the covariance of the currency with the S&P500 and  $\beta_{IR}$  refers to the covariance of the current and future free rate with the S&P500. The line of best fit plots the following regression:  $\beta_{post}^i - \beta_{IR,post}^i = \alpha_0 + \alpha_1(\beta_{pre}^i - \beta_{IR,pre}^i)$ . 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.5. 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.

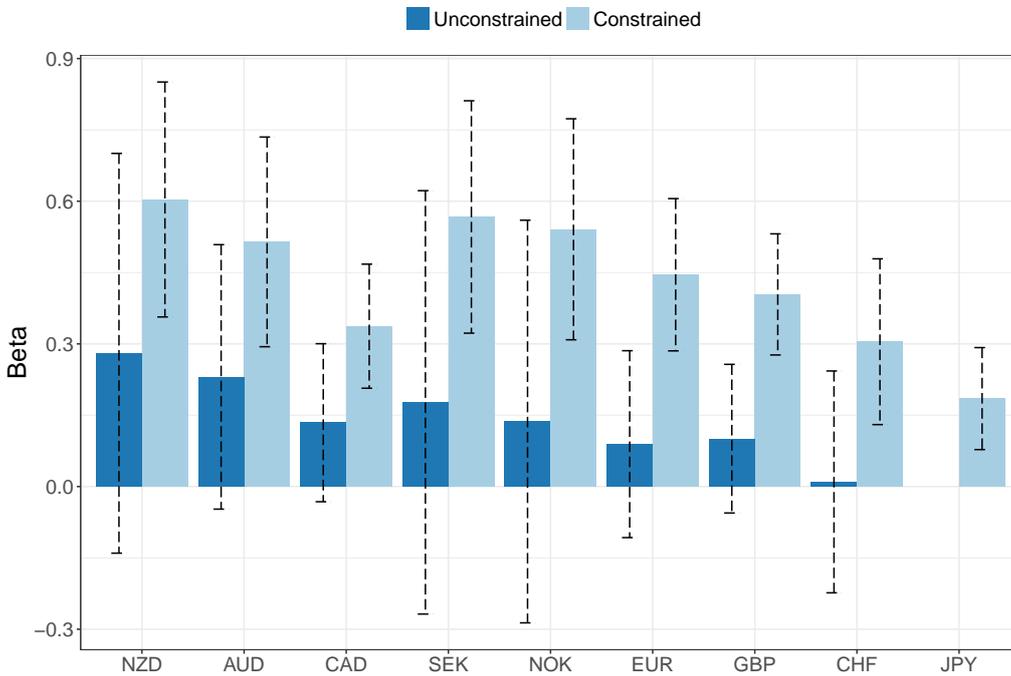
### 3.2 High frequency test: FOMC shocks

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 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 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 8:** Regression coefficients of currency appreciations versus the S&P 500, high frequency sample



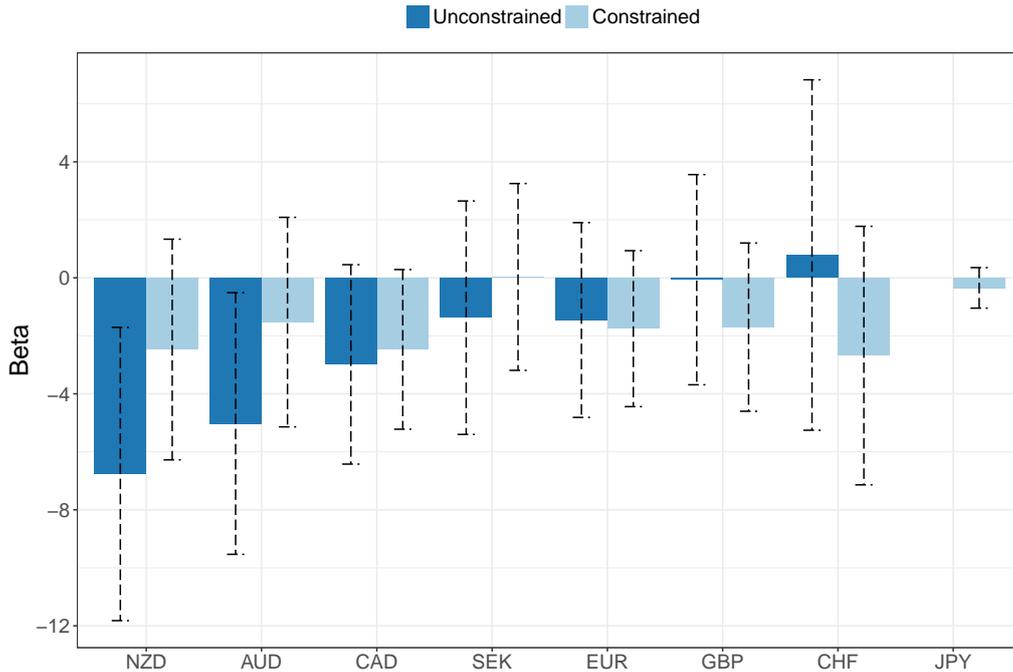
Regression coefficients of currency appreciations against the US dollar on the return on the S&P 500 over 30 minute windows around FOMC announcements. The return on the S&P 500 is interacted with a variable indicating whether this meeting occurred after January 2009, resulting in pre-crisis and post-crisis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

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

in which  $\Delta e_t^j$  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 9, we use the change in the 2 year bond yield for each currency as the dependent variable.<sup>17</sup> Consistent with the evidence in Figure 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 premia increased.

**Figure 9:** Regression coefficients of 2 year risk-free yield spreads versus the S&P 500, high frequency sample



Regression coefficients of changes in the 2 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:

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

in which  $\Delta i_t^j$  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.

<sup>17</sup>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.

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.2](#).

## 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.

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# APPENDIX FOR “CURRENCY BETAS, RISK, AND CENTRAL BANKS”

Andrew Lilley and Gianluca Rinaldi

## A.1 Data

The three core pieces of data for this analysis 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.1.1](#).

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<sup>1</sup>, 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 2 year government bond yields from Global Financial Data, from April 1987 to June 2019.<sup>2</sup>

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.

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<sup>1</sup>Prior to the introduction of the Euro in 1999, we use the Deutsche mark in its place.

<sup>2</sup>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.

### A.1.1 High frequency sample

We focus on FOMC announcement dates from June 2000 to October 2015, which is the sample for which we have been provided 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. The below Table summarizes our data sources and windows.

**Table A.1:** Sources of dependent variable 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 8 and 9.

	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

*Yield data:* We collect daily 2-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 14:00EST on a Wednesday, the change in Australian yields is measured from 02:00EST on Wednesday, to 02:00EST on Friday, while the change in Canadian Treasury yields is measured from 17:00EST on Tuesday to 17:00EST on Thursday.

We make the following sample adjustments. We exclude Norway 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 2 year government bond

yield with a predicted yield from a regression of the 2 year government bond yield on the 5 year government bond yield during months in which no New Zealand 2 year government bond was on issue.

**Table A.2:** Sources of currency and 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 6 and 9.

	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.2 Data descriptive statistics

In Table A.3 we report 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.

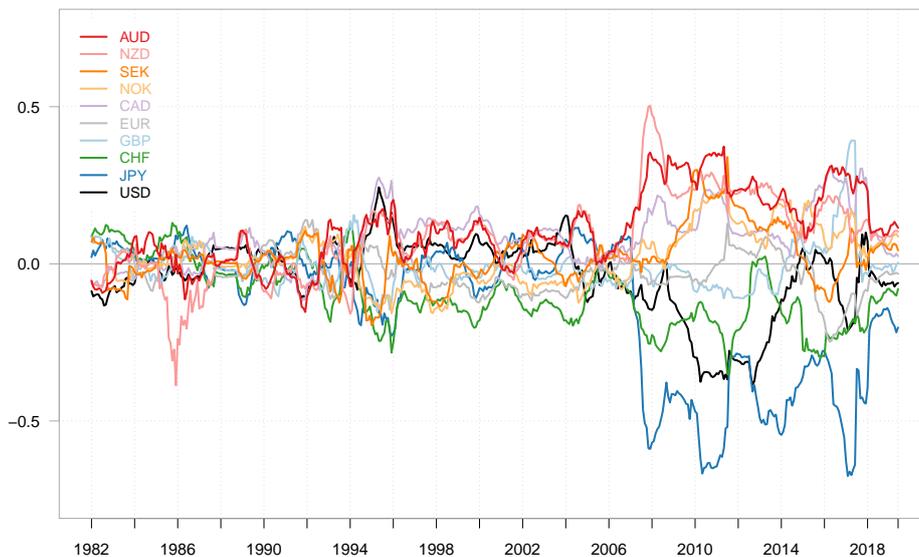
**Table A.3:** Summary statistics for (annualized) currency movements and 2 year interest rates spreads

		AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK	Mean
<b>87-07</b>											
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
<b>08-19</b>											
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
<b>87-19</b>											
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.3 Additional Figures

**Figure A.1:** Conditional betas with equity returns of exchange rates with an equally weighted G10 basket

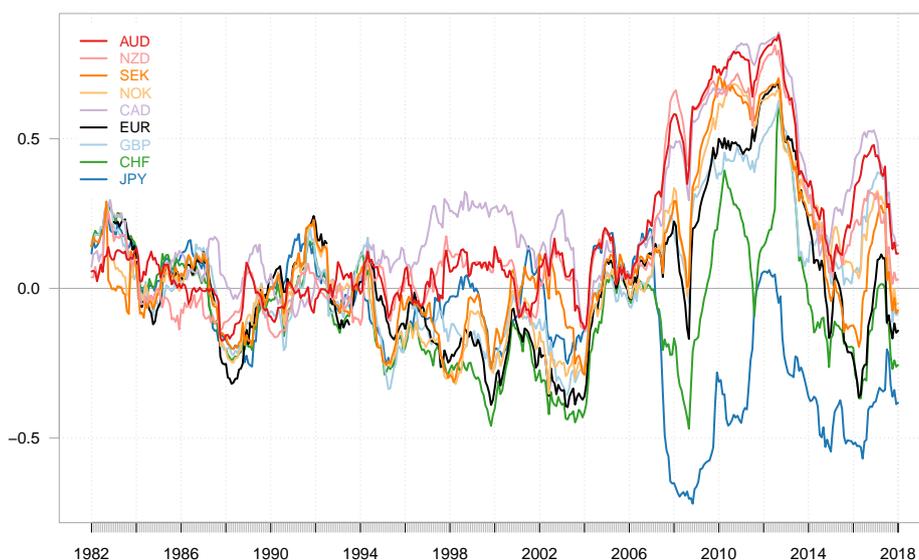


Conditional betas of every exchange rate measured with respect to an equally weighted G10 basket against the log return on the S&P 500. Conditional betas are estimated by the following regression:

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

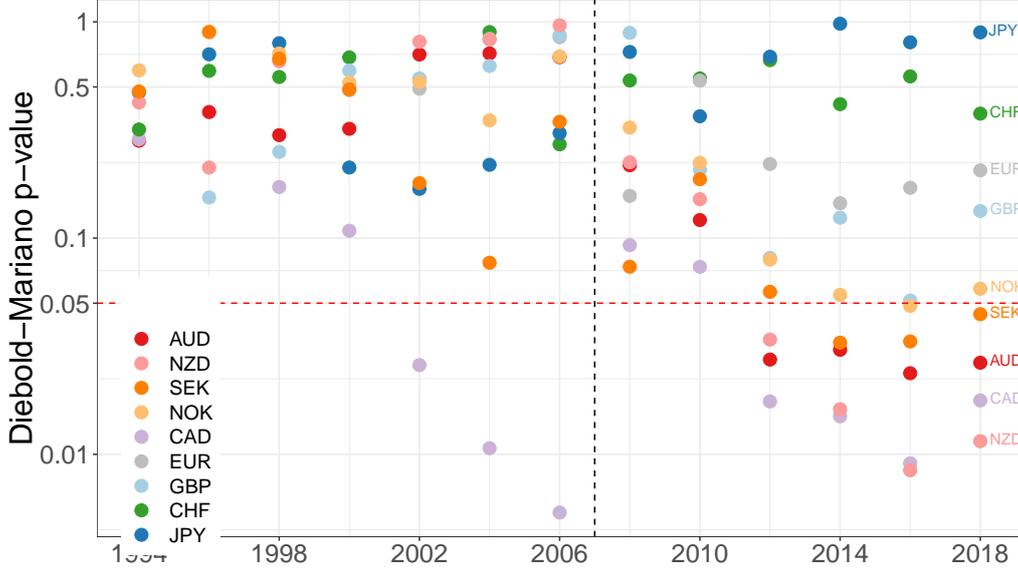
A positive value for  $\Delta e_t^i$  reflects an appreciation of the currency against the G10 basket. Each beta is estimated using one year (252 trading days) of historical data, with one coefficient estimated per currency per month. Data are from Jan 1981 to June 2019, from Bloomberg.

**Figure A.2:** 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:  $corr(\Delta e_t^i, r_t^m)$ . A positive value for  $\Delta e_t^i$  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.3:** Out of sample Meese-Rogoff tests by currency



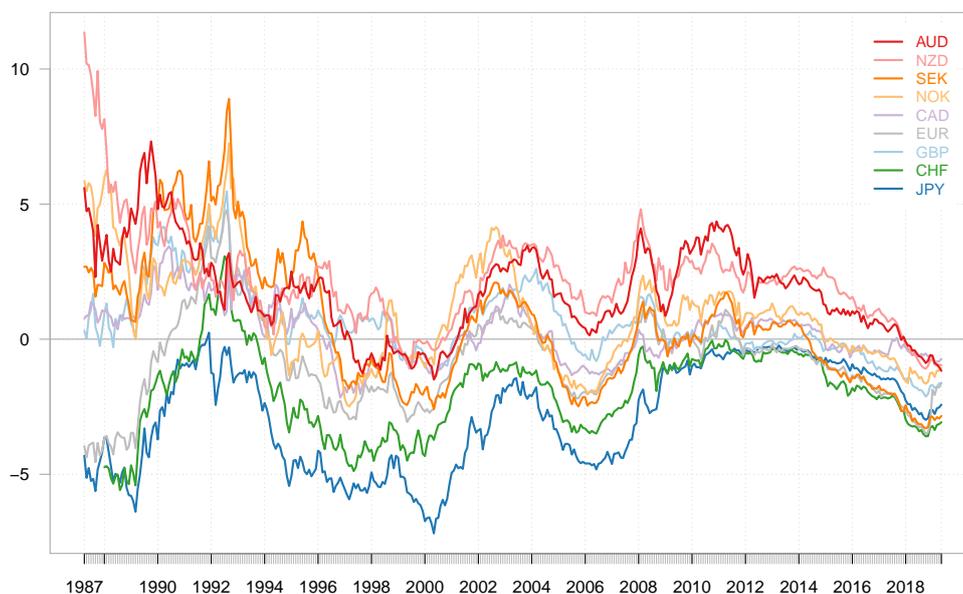
This Figure displays the statistical significance analog of Figure 3. We make out of sample predictions of each exchange rate for the next out of sample period using the conditional beta, and compare the forecast accuracy to that of a random walk. We predict every exchange rate's monthly appreciation 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:

$$\widehat{\Delta e_{t+1}^i} = \widehat{\alpha}_t^i + \widehat{\beta}_t^i r_{t+1}^m$$

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.

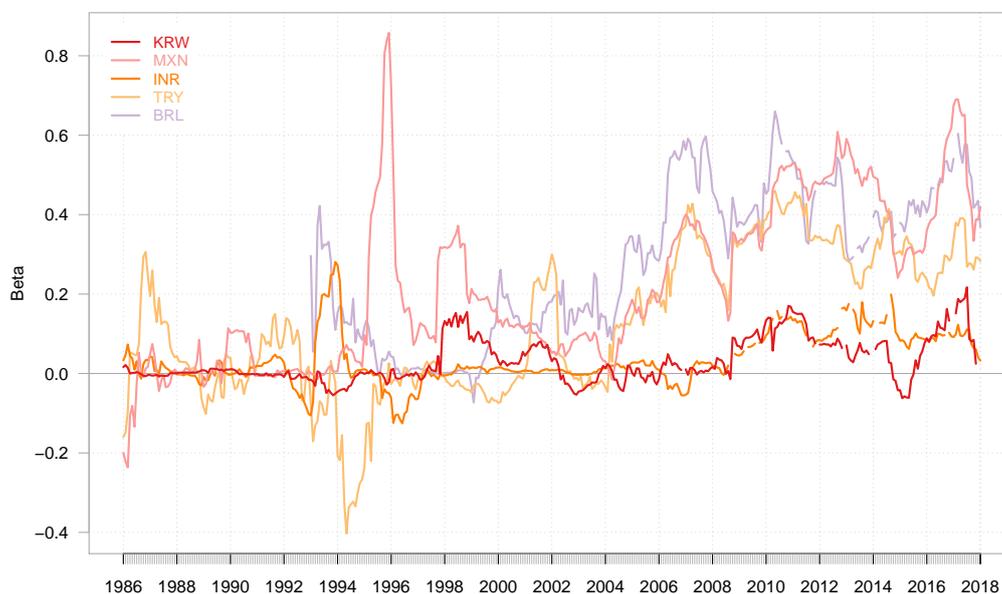
$$RMSE \text{ Ratio} : \sqrt{\sum_{i \in G10} \sum_{t=T-132}^T \frac{(\widehat{\Delta e_{t+1}^i} - \Delta e_{t+1}^i)^2}{(\Delta e_{t+1}^i)^2}}$$

**Figure A.4:** 2 Year spread over US Treasuries for each of the G10 government bonds



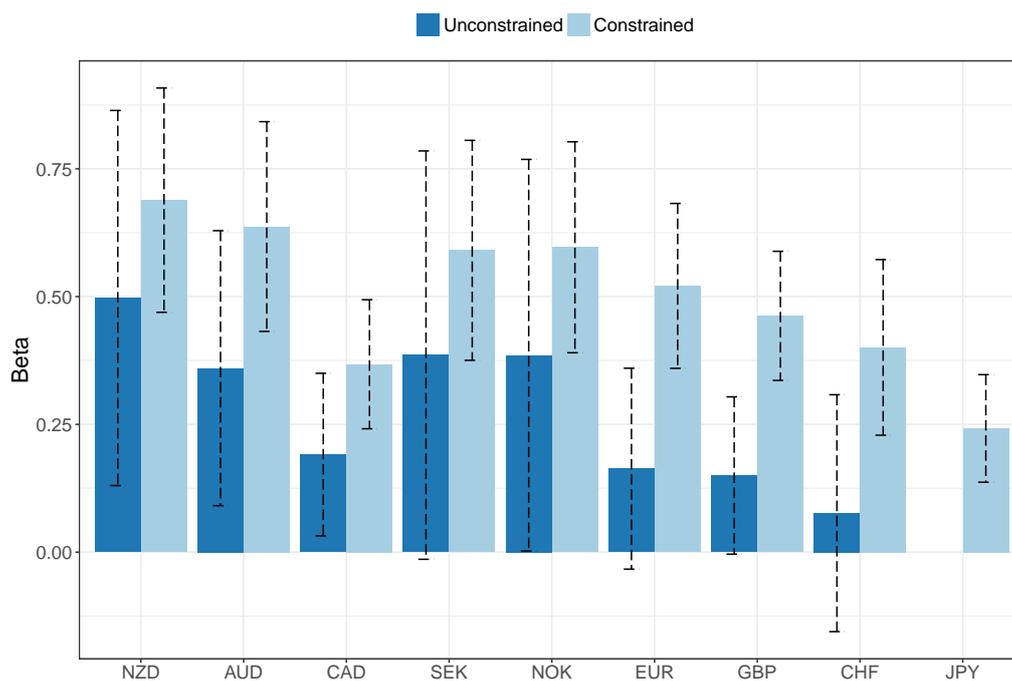
Spreads of 2 year G10 government nominal bonds over the 2 year US Treasury bond. Data are from Apr-1987 to June-2019, from Global Financial Data.

**Figure A.5:** 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 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.

**Figure A.6:** Regression coefficients of currency appreciations versus the S&P 500, high frequency sample

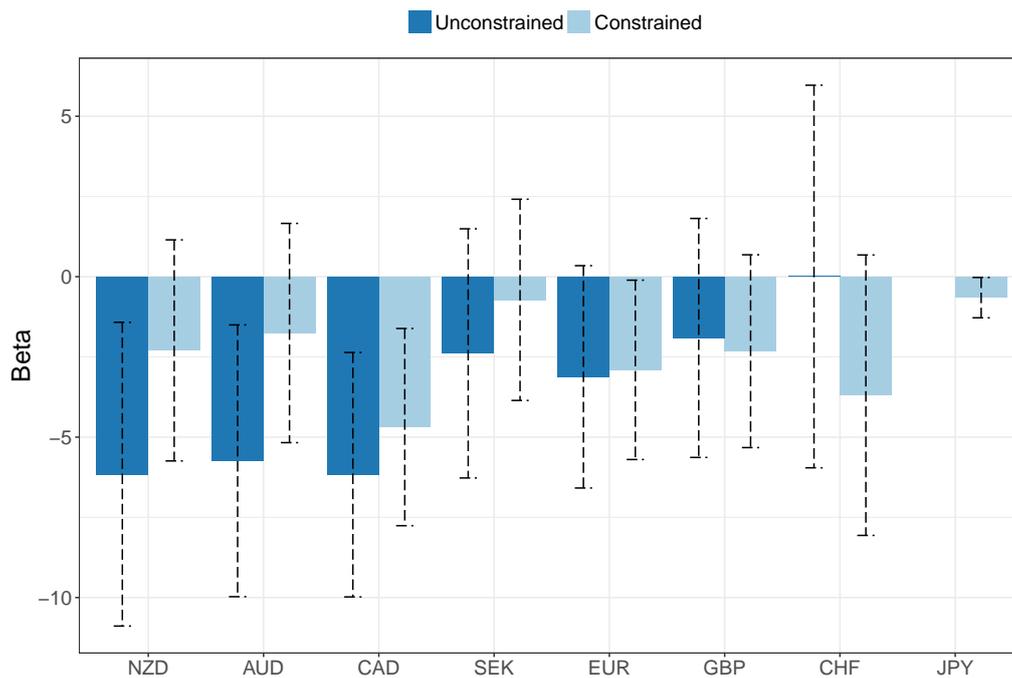


Regression coefficients of currency appreciations against the US dollar on the return on the S&P 500 over 30 minute windows around FOMC announcements. The return on the S&P 500 is interacted with a variable indicating whether this meeting occurred after January 2009, resulting in pre-crisis and post-crisis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

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

in which  $\Delta e_t^j$  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.7:** Regression coefficients of 2 year risk-free yield spreads versus the S&P 500, high frequency sample



Regression coefficients of changes in the 2 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:

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

in which  $\Delta i_t^j$  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.

## A.4 Additional Tables

**Table A.4:** 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 2:

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

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.5:** 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 (0.62)	-0.04 (0.64)	-0.05 (0.43)	0.21 (0.37)	0.99 (0.53)	-0.17 (0.32)	-0.91 (0.47)	-1.49 (0.61)	-1.07 (0.56)	0.23 (0.51)
(B) Post-2008 $Cov(i_t, r_m)$	3.11 (0.47)	1.71 (0.34)	1.30 (0.27)	2.08 (0.34)	1.59 (0.37)	0.21 (0.10)	2.29 (0.41)	1.42 (0.47)	2.50 (0.35)	1.31 (0.37)
$\rho$	0.69 (0.03)	0.79 (0.03)	0.80 (0.03)	0.88 (0.03)	0.86 (0.03)	0.77 (0.03)	0.75 (0.02)	0.65 (0.02)	0.88 (0.02)	0.70 (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	
$\beta_{pre}^i$ (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	
$\beta_{post}^i$ (Table 1)	0.35	0.27	-0.02	0.10	0.14	-0.24	0.24	0.31	0.21	
$\beta_{FR,pre}^i$	0.13	0.06	-0.05	-0.05	-0.15	0.01	0.06	0.12	0.18	
$\beta_{FR,post}^i$	0.24	0.20	-0.06	-0.15	0.00	-0.17	0.14	0.32	-0.11	