NBER WORKING PAPER SERIES

FORWARD AND SPOT EXCHANGE RATES IN A MULTI-CURRENCY WORLD

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Working Paper 20294
http://www.nber.org/papers/w20294

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2014

We are grateful to Craig Burnside, John Cochrane, Jeremy Graveline, Ralph Koijen, Matteo Maggiori, Lukas Menkhoff, Toby Moskowitz, Ralph Ossa, Andreas Schrimpf, and Adrien Verdelhan. We also thank seminar participants at the University of Chicago, CITE Chicago, the Chicago Junior Finance Conference, KU Leuven, University of Sydney, New York Federal Reserve, University of Zurich, SED annual meetings , and the NBER Summer Institute for useful comments. All mistakes remain our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. F31,G12,G15

ABSTRACT

We decompose violations of uncovered interest parity into a cross-currency, a between-time-and-currency, and a cross-time component. We show that most of the systematic violations are in the cross-currency dimension. By contrast, we find no statistically reliable evidence that currency risk premia respond to deviations of forward premia from their time- and currency-specific mean. These results imply that the forward premium puzzle (FPP) and the carry-trade anomaly are separate phenomena that may require separate explanations. The carry trade is driven by static differences in interest rates across currencies, whereas the FPP appears to be driven primarily by cross-time variation in all currency risk premia against the US dollar. Models that feature two symmetric countries thus cannot explain either of the two phenomena. Once we make the appropriate econometric adjustments we also cannot reject the hypothesis that the elasticity of risk premia with respect to forward premia in all three dimensions is smaller than one. As a result, currency risk premia need not be correlated with expected changes in exchange rates.

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1 Introduction

The forward premium puzzle and the carry-trade anomaly are two major stylized facts in international economics. In this paper, we introduce a decomposition that allows us to show analytically how the two anomalies relate to each other and to estimate the joint restrictions they place on models of currency risk premia and exchange rate determination.

The forward premium puzzle is usually documented using a bilateral regression of currency returns on forward premia (Fama, 1984):

$$rx_{i,t+1} = \alpha_i + \beta_i^{fpp}(f_{it} - s_{it}) + \varepsilon_{i,t+1}, \tag{1}$$

where f_{it} is the log one-period forward rate of currency i, s_{it} is the log spot rate, and $rx_{i,t+1} = f_{it} - s_{i,t+1}$ is the log excess return on currency i between time t and $t+1$. Although estimates of β_i^{fpp} tend to be noisy, we tend to find $\beta_i^{fpp} > 0$ for most currencies. A pooled specification that constrains all β_i^{fpp} to be identical across currencies yields point estimates significantly larger than zero and often larger than one.[1] This fact, the forward premium puzzle (FPP), has drawn a lot of interest from theorists because it seems to suggest profitable trades in currency markets: currencies that have unusually high interest rates also tend to appreciate.[2] The FPP is usually interpreted to (i) motivate the carry trade, a trading strategy that is long high-interest-rate currencies and short low-interest-rate currencies; (ii) show that bilateral currency risk premia are highly elastic with respect to time-series variation in forward premia; and (iii) show that these elasticities tend to be larger than one, such that risk premia must play a role in determining expected changes in bilateral exchange rates. In this paper, we show that this interpretation is misleading on all three counts.

We generalize the regression-based approach in (1) to study the covariance of expected currency returns ("risk premia") with forward premia without conditioning on a specific currency pair i. We decompose the unconditional covariance into a cross-currency, a between-time-and-currency, and a cross-time component. Each of the three components can be written either as the expected return to a trading strategy or as a function of a slope coefficient from a regression that relates variation in currency returns to variation in forward premia in the corresponding dimension.

Our decomposition shows that the expected return on the carry trade is the sum of the

[1] The same relationship is often estimated using the change in the spot exchange rate as the dependent variable, in which case, the coefficient estimate is $1 - \beta_i^{fpp}$. An equivalent way of stating the FPP is thus that $1 - \beta_i^{fpp} < 1$.

[2] Throughout the paper, we follow the convention in the literature and refer to conditional expected returns as "risk premia." However, this terminology need not be taken literally. Our analysis is silent on whether currency returns are driven by risk premia, institutional frictions, or other limits to arbitrage. See Burnside et al. (2011) and Lustig et al. (2011) for a discussion.

cross-currency and the between-time-and-currency component of the unconditional covariance, whereas the FPP consists of the sum of the between-time-and-currency and the cross-time components.

We estimate the elasticity of risk premia with respect to forward premia in each of the three dimensions. Our results show that most of the systematic variation in currency returns is in the cross-section (the cross-currency variation in α_i in (1)) rather than the time series. Currencies that have persistently higher forward premia pay significantly higher expected returns than currencies with persistently lower forward premia. Some of our specifications also show statistically significant variation in the cross-time dimension: expected returns on the US dollar appear to fluctuate with its average forward premium against all other currencies in the sample. This cross-time variation is particular to the US dollar and, potentially, a small number of other currencies. It explains the vast majority of the variation that generates the FPP. By contrast, we cannot reject the null that currency risk premia are inelastic with respect to variation in forward premia in the between-time-and-currency dimension.

These results imply that the traditional interpretation of the FPP is misleading: (i) the carry trade and the FPP are not significantly related in the data and may thus require distinct theoretical explanations. Explaining the carry trade primarily requires explaining persistent differences in interest rates across currencies that are partially, but not fully, reversed by predictable movements in exchange rates. (High-interest-rate currencies depreciate, but not enough to reverse the higher returns resulting from the interest rate differential.) By contrast, explaining the FPP may require explaining time-series variation in the risk premium of the US dollar against all other currencies. The US dollar may be one of a small number of currencies that pays higher expected returns when its interest rate is high relative to its own currency-specific average and to the world average interest rate at the time. However, this relationship is only marginally statistically significant in the data.

Counter to the traditional interpretation of the FPP (ii) we cannot reject the hypothesis that currency risk premia are inelastic with respect to variation of forward premia in the between-time-and-currency dimension. Once we control for the cross-time variation of the average forward premium of all currencies against the US dollar, we find little additional evidence of a covariance of risk premia with forward premia in the time-series dimension.

In addition, none of the three elasticities we estimate is significantly larger than one such that (iii) we cannot reject the hypothesis that risk premia and expected changes in exchange rates are uncorrelated in the data.

Part of the reason for our failure to find evidence of a covariance of risk premia with forward premia in the between-time-and-currency dimension is that the FPP itself is greatly diminished once we stop conditioning on a specific currency pair i.

We show that, when using data for more than one currency, an unbiased estimate of the elasticity of risk premia with respect to forward premia requires using out-of-sample regressions, such that the right-hand-side variables that predict returns between t and $t+1$ are known at time t. Because each of our regressions maps into a trading strategy, this result appears only natural: when we estimate the expected returns on a given trading strategy, we typically require that all information used in the formation of the portfolio is available ex ante. For example, an investor who plans to go long a currency when its forward premium is higher than its unconditional mean needs to estimate this unconditional mean using data available at t. Similarly, when we estimate the elasticity of behavior (demanding a risk premium) with respect to some right-hand-side variable, this variable needs to be measurable at time t.

By contrast, measures that do not correct for the fact that the sample mean of each currency's forward premium is unknown ex-ante may not produce unbiased estimates of the true elasticity of risk premia with respect to forward premia. In particular, the pooled version of (1) that constrains all β_i^{fpp} to be equal across currencies produces an upwardly biased measure of the elasticity of risk-premia with respect to forward premia in the time-series dimension. In other words, skimming across a table that lists β_i^{fpp} for each currency and mentally averaging across these estimates is not innocuous and makes the FPP appear more severe than it actually is. For example, in our standard specification, the weighted average of β_i^{fpp} is 1.81 (s.e.=0.53), whereas our unbiased point estimate for the elasticity of risk premia with respect to forward premia in the time-series dimension is only half that number (0.86, s.e.=0.34).

We view our results as both good and bad news. The good news is that currency risk premia may be much simpler objects than previously thought. First, the majority of the violations of uncovered interest parity is static (or highly persistent) across currencies. Second, we find no statistically reliable evidence supporting the idea that currency risk premia respond to deviations of forward premia from their time- and currency-specific mean. Third, we can never reject the hypothesis that the elasticity of risk premia with respect to forward premia in any of the three dimensions is larger than one. As a result, currency risk premia need not be correlated with expected changes in exchange rates, neither for the US dollar nor for any of the other currencies in our sample.

The bad news is that the persistent differences in interest rates that drive the carry trade are not well understood. Most existing models of currency risk premia focus on two symmetric countries and are thus calibrated to explain the relatively small and statistically insignificant between-time-and-currency dimension of the covariance of risk premia with forward premia.[3]

[3] It may be worthwhile revisiting the predictions of these models in the light of our findings. Examples include Farhi and Gabaix (2008), Verdelhan (2010), Burnside et al. (2009), Heyerdahl-Larsen (2012), Yu (2011), Bacchetta et al. (2010), and Ilut (2012).

We make three caveats to our interpretation. First, our methodology does not allow us to distinguish between permanent and highly persistent differences in expected returns across currencies. Second, the fact that we do not find statistically reliable evidence of a non-zero elasticity of risk premia with respect to forward premia in the between-time-and-currency dimension does not mean that it does not exist. Third, there may be non-linearities in the functional form linking risk premia to forward premia or other variables that predict currency returns.[4] Our purpose is simply to use linear regressions to place restrictions on affine models linking currency returns to forward premia.

Papers that offer explicit models of either permanent or highly persistent asymmetries in currency risk premia include Hassan (2013), Martin (2012), and Govillot, Rey, and Gourinchas (2010) who focus on differences in country size, Maggiori (2013) and Caballero, Farhi, and Gourinchas (2008) who focus on differences in financial development, Ready, Roussanov, and Ward (2013) who focus on production specialization, and Mark and Berg (2013) who focus on asymmetries in the conduct of monetary policy. Another strand of the literature has connected persistent currency risk premia with shocks that are themselves persistent, as in Engel and West (2005) and Colacito and Croce (2011).

Our work builds heavily on a series of papers that apply factor analysis to study the cross section of multilateral currency returns. Most closely related are Menkhoff, Sarno, Schmeling, and Schrimpf (2012) and Lustig, Roussanov, and Verdelhan (2010, 2011) who identify a risk factor that explains the cross section of currency returns and a "dollar factor" that explains the time-series variation in the returns on the US dollar.[5] Our contribution is to recast these findings in terms of regression coefficients, relate them to established puzzles in the literature, and translate them into restrictions on linear models of currency risk premia.

Many authors have described and theorized about the carry trade and the FPP.[6] We contribute to this literature in three ways. First, we show that the carry trade and the FPP are distinct, quantitatively unrelated, anomalies in the data. Second, we generalize the empirical approach that has framed the debate on the FPP to a multi-currency framework. Third, we use this framework to derive restrictions on linear models of multilateral currency risk premia.

The remainder of this paper is structured as follows: Section 2 describes the data. Section

[4] See fore example Jordà and Taylor (2012).

[5] Also see Koijen et al. (2013) who decompose carry trades in different asset classes into static and dynamic components.

[6] See, for example, Hansen and Hodrick (1980), Bilson (1981), Meese and Rogoff (1983), Fama (1984), Backus et al. (1993), Evans and Lewis (1995), Bekaert (1996), Bansal (1997), Bansal and Dahlquist (2000), Backus et al. (2001), Chinn (2006) Evans and Lyons (2006), Graveline (2006), Burnside et al. (2006), Lustig and Verdelhan (2007), Brunnermeier et al. (2009), Alvarez et al. (2008), Jurek (2009), Bansal and Shaliastovich (2010), Burnside et al. (2011), and , Sarno et al. (2012). Hodrick (2014), Froot and Thaler (1990), Engel (1996), Lewis (2011), and Engel (2013) provide surveys.

3 establishes the FPP and the carry trade as separate anomalies. Section 4 discusses the restrictions that our empirical results impose on linear models of currency risk premia. Section 5 discusses implications for models of exchange rate determination. Section 6 concludes.

2 Data

Throughout the main text, we use monthly observations of US dollar-based spot and forward exchange rates at the 1-, 6- and 12-month horizon. All rates are from Thomson Reuters Financial Datastream. The data range from October 1983 to June 2010. For robustness checks, we also use all UK pound-based data from the same source as well as forward premia calculated using covered interest parity from interbank interest rate data, which are available for longer time horizons for some currencies. Our dataset nests the data used in recent studies on the cross section of currency returns, including Lustig et al. (2011) and Burnside et al. (2011). In additional robustness checks, we replicate our findings using only the subset of data used in these studies.

Many of the decompositions we perform require balanced samples. However, currencies enter and exit the sample frequently, the most important example of which is the euro and the currencies it replaced. We deal with this issue in two ways. In our baseline sample ("1 Rebalance"), we use the largest fully balanced sample we can construct from our data by selecting the 15 currencies with the longest coverage (the currencies of Australia, Canada, Denmark, Hong Kong, Japan, Kuwait, Malaysia, New Zealand, Norway, Saudi Arabia, Singapore, South Africa, Sweden, Switzerland, and the UK from December 1990 to June 2010). In addition, we construct three alternative samples that allow for entry of currencies at 3, 6, and 12 dates during the sample period, where we chose the entry dates to maximize coverage. The "3 Rebalance" sample allows entry in December of 1989, 1997, and 2004 and covers 30 currencies. The "6 Rebalance" sample allows entry in December of 1989, 1993, 1997, 2001, 2004, and 2007 and covers 36 currencies. Our largest sample, "12 Rebalance," allows entry in June 1986, and in June of every second year thereafter through June 2008, and covers 39 currencies. In between each of these dates, all samples are balanced except for a small number of observations removed by our data-cleaning procedure (see Appendix A for details). Currencies enter each of the samples if their forward and spot exchange rate data are available for at least four years prior to the rebalancing date (the reason for this prior data requirement will become apparent below).[7]

Throughout the main text, we take the perspective of a US investor and calculate all

[7] The only exception we make to this rule is for the first set of currencies entering the 12 Rebalance sample, which become available in October 1983.

returns in US dollars. In section 4.5, we discuss how our results change when we use different base currencies.

Appendix A lists the coverage of individual currencies and describes our data-selection and -cleaning process in detail.

3 FPP & Carry Trade as Separate Anomalies

Consider a version of the carry trade in which, at the beginning of each month, $t = 1, ...T$, we form a portfolio of all available foreign currencies, $i = 1, ..N$, weighted by the difference of their forward premia ($fp_{it} \equiv f_{it} - s_{it}$) to the average forward premium of all currencies at the time ($fp_t \equiv \sum_i \frac{1}{N} fp_{it}$). This portfolio is long currencies that have a higher forward premium than the average of all currencies at time t and short currencies that have a lower than average forward premium. We can write the expected return on this portfolio as

$$E\left[rx_{i,t+1}\left(fp_{it} - fp_t\right)\right], \tag{2}$$

where

$$E\left[\cdot\right] \equiv \sum_{t=1}^{T} \sum_{i=1}^{N} \frac{1}{NT} \int \left(\cdot\right) dF_{it}\left(rx_{it+1}, fp_{it}, fp_{jt}, ...\right) \tag{3}$$

is the unconditional expectations operator defined over a finite number of currencies and time periods, and $F_{it}\left(rx_{it+1}, fp_{it}, fp_{jt}, ...\right)$ is some joint cumulative distribution function of the returns on currency i at time t and the vector of forward premia of all currencies around the world.[8]

We use linear portfolio weights ($fp_{it} - fp_t$), because they allow us to relate portfolio returns directly to coefficients in linear regressions. Our results would be similar if we sorted currencies into bins and then analyzed the returns on a long-short strategy as in Lustig et al. (2011).[9] As with this alternative formulation, the return on the carry trade portfolio is neutral with respect to the dollar, that is, it is independent of the bilateral exchange rate of the US dollar against any other currencies.[10]

Table 1 shows the annualized mean return on the carry trade portfolio in our 1 Rebalance sample. Consistent with earlier research, we find the carry trade is highly profitable and yields a mean annualized net return of 4.95% with a Sharpe ratio of 0.54. However, the table also shows that currencies which the carry trade is long (i.e., currencies with high interest rates)

[8] See Appendix B.1 for some properties of this expectations operator.

[9] See Appendix Table 1 for a detailed comparison between linear weights (2), the long-short strategy of Lustig et al. (2011), and the equally weighted strategy in Burnside et al. (2011).

[10] See Appendix B.2 for a formal proof of this statement.

on average *depreciate* relative to currencies with low interest rates. Our carry trade portfolio loses 2.15 percentage points of annualized returns due to this depreciation.

[Table 1 about here]

As we show below, this pattern holds across a wide range of plausible variations: currencies with high interest rates thus tend to depreciate. An obvious question is then why the FPP appears to suggest the opposite. The answer is in the currency-specific intercepts in (1), α_i. We tend to find that $\beta_i^{fpp} > 1$ in regressions in which currency fixed effects absorb the currency-specific mean forward premium ($fp_i \equiv \sum_{t=1}^{T} \frac{1}{T} fp_{it}$). If we wanted to trade on the correlation in the data that drives the FPP, we would thus have to buy currencies that have a higher forward premium than they usually do (Cochrane, 2001; Bekaert and Hodrick, 2008). Such a strategy, we call it the "forward premium trade", weights each currency with the deviation of its current forward premium from its currency-specific average. We can write the expected return on the forward premium trade as $E\left[rx_{i,t+1}\left(fp_{it} - fp_i\right)\right]$.

[Figure 1 about here.]

The carry trade (2) thus exploits a correlation between currency returns and forward premia conditional on time fixed effects, whereas the FPP describes a correlation conditional on currency fixed effects. Figure 1 illustrates the difference between the carry trade and the forward premium trade for the case in which a US investor considers investing in two foreign currencies. The left panel plots the forward premium of the New Zealand dollar and the Japanese yen over time. Throughout the sample period, the forward premium of the former is always higher than the forward premium of the latter, reflecting the fact that New Zealand has consistently higher interest rates than Japan. The carry trade is always long New Zealand dollars and always short Japanese yen. By contrast, the forward premium trade evaluates the forward premium of each currency in isolation and goes long if the forward premium is higher than its sample mean. As a result, the forward premium trade is not "dollar neutral" in the sense that it may be long or short both foreign currencies at any given point in time.

It is immediately apparent that implementing the forward premium trade may be more difficult in practice than implementing the carry trade, because it requires an estimate of the mean forward premium of each country (fp_i), which is not known at time t. In what follows, we denote the expectation of the country-specific and the unconditional mean forward premium as

$$\widehat{fp}_i \equiv E_i\left[fp_i\right], \quad \widehat{fp} \equiv E\left[fp\right],$$

where $E_i[\cdot] = \sum_{t=1}^{T} \frac{1}{T} \int (\cdot)\, dF_{it}\left(rx_{it+1}, fp_{it}, fp_{jt}, ...\right)$, and we continue the convention of denoting sample means by omitting the corresponding subscripts,

$$x_i \equiv \frac{1}{T}\sum_{t=1}^{T} x_{it} \quad x_t \equiv \frac{1}{N}\sum_{i=1}^{N} x_{it} \quad x \equiv \frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N} x_{it}, \quad x = fp, rx \ . \tag{4}$$

The ex-ante implementable version of the forward premium trade (which we show below is the version that is relevant for estimating covariances of risk premia and forward premia) has an expected return of

$$E\left[rx_{i,t+1}\left(fp_{it} - \widehat{fp}_i\right)\right], \tag{5}$$

where $\widehat{fp}_i \neq fp_i$ and $\widehat{fp} \neq fp$ in a finite sample ($T < \infty$).

How do the carry trade and the forward premium trade relate to each other? The expected returns on both portfolios load on different components of the unconditional (population) covariance between currency returns and forward premia. To show this result, we can decompose the unconditional covariance into the sum of the expected returns on three trading strategies plus a constant term. Re-writing the covariance in expectation form, adding and subtracting fp_t, $\widehat{fp}_i$, and $\widehat{fp}$ and re-arranging yields

$$\begin{gathered} cov\left(rx_{i,t+1}, fp_{it}\right) = E\left[\left(rx_{i,t+1} - rx\right)\left(fp_{it} - fp\right)\right] \\ = \underbrace{E\left[rx_{i,t+1}\left(\widehat{fp}_i - \widehat{fp}\right)\right]}_{\text{Static Trade}} + \underbrace{E\left[rx_{i,t+1}\left(fp_{it} - fp_t - \left(\widehat{fp}_i - \widehat{fp}\right)\right)\right]}_{\text{Dynamic Trade}} + \underbrace{E\left[rx_{i,t+1}\left(fp_t - \widehat{fp}\right)\right]}_{\text{Dollar Trade}} \\ + \underbrace{E\left[rx_{i,t+1}(\widehat{fp} - fp)\right]}_{\text{Constant}}, \end{gathered} \tag{6}$$

where rx again refers to the sample mean currency return across currencies and time periods.

The "Static Trade" trades on the cross-currency variation in forward premia. It is long currencies that have an unconditionally high forward premium and short currencies that have an unconditionally low forward premium. We may think of it as a version of the carry trade in which we never update our portfolio. We weight currencies once, based on our expectation of the currencies' future mean level of interest rates, and never change the portfolio thereafter. The "Dynamic Trade" trades on the between-time-and-currency variation in forward premia. It is long currencies that have high forward premia relative to the time average forward premium of all currencies and relative to their currency-specific mean forward premium. We may think of the expected return on the Dynamic Trade as the incremental benefit of re-weighing the carry trade portfolio every period. Finally, the "Dollar Trade" trades on the cross-time variation in the average forward premium of all currencies against the US dollar. It goes long all foreign currencies when the average forward premium of all currencies against the US dollar is high relative to its unconditional mean and goes short all foreign currencies when it is low.[11]

Upon inspection, the carry trade (2) is simply the sum of the Static and Dynamic trades,

$$\underbrace{E\left[rx_{i,t+1}\left(fp_{it}-fp_t\right)\right]}_{\text{Carry Trade}}=\underbrace{E\left[rx_{i,t+1}\left(\widehat{fp}_i-\widehat{fp}\right)\right]}_{\text{Static Trade}}+\underbrace{E\left[rx_{i,t+1}\left(fp_{it}-fp_t-\left(\widehat{fp}_i-\widehat{fp}\right)\right)\right]}_{\text{Dynamic Trade}},$$

whereas the forward premium trade (5) is the sum of the Dynamic and the Dollar Trades:

$$\underbrace{E\left[rx_{i,t+1}\left(fp_{it}-\widehat{fp}_i\right)\right]}_{\text{FP Trade}}=\underbrace{E\left[rx_{i,t+1}\left(fp_{it}-fp_t-\left(\widehat{fp}_i-\widehat{fp}\right)\right)\right]}_{\text{Dynamic Trade}}+\underbrace{E\left[rx_{i,t+1}\left(fp_t-\widehat{fp}\right)\right]}_{\text{Dollar Trade}}.$$

The common element between the Carry Trade and the forward premium trade is the Dynamic Trade, that is, the between-time-and-currency part of the unconditional covariance between currency returns and forward premia. By contrast, the cross-currency component is unique to the carry trade and the cross-time component is unique to the forward premium trade. The question of whether the two anomalies, the carry trade and the forward premium trade, are related in the data thus reduces to estimating the relative contribution of the Dynamic Trade.

[Table 2 about here]

Table 2 lists the mean returns and Sharpe ratios of the three strategies, as well as the mean returns and Sharpe ratios of the carry trade and the forward premium trade. All returns are again annualized and normalized by dividing with fp to facilitate comparison. Columns 1-4 on the top left give the results for our 1 Rebalance sample, where we use all available data prior to December 1994 to estimate $\widehat{fp}_i$ and $\widehat{fp}$. Column 1 shows the results for one-month forwards, without taking into account bid-ask spreads. The mean annualized return on the static trade is 3.46% with a Sharpe ratio of .39. It thus contributes 70% of carry trade returns. By contrast, the Dynamic Trade contributes 30%, with an annualized return of 1.50% and a Sharpe ratio of .24.

Although the forward premium trade is not commonly known as a trading strategy in foreign exchange markets, it yields similar returns to the carry trade, with a mean annualized return of 4.04% and a Sharpe ratio of .27. The Dollar Trade contributes 63% to this overall return and has a Sharpe ratio of .25, with the Dynamic Trade contributing the remaining 37%.

Columns 2-4 replicate the same decomposition but take into account bid-ask spreads in forward and spot exchange markets.[12] Column 2 again uses one-month forward contracts,

[11] The Dollar Trade was first described by Lustig et al. (2010). We follow their naming convention here.

[12] We calculate returns net of transaction costs as $rx^{net}_{i,t+1} = I[w_{it} \geq 0](f^{bid}_{it} - s^{ask}_{i,t+1}) + (1 - I[w_{it} \geq 0])(f^{ask}_{it} -$

column 3 uses 6-month contracts, and column 4 uses 12-month contracts. Once we take into account bid-ask spreads, the mean returns on all trading strategies fall.[13] In the case of the Dynamic Trade, the mean return in column 2 actually turns negative. However, the same basic pattern persists across all columns: the Static Trade accounts for 70%-121% of the mean returns on the carry trade, and the Dollar Trade accounts for 63%-124% of the mean returns on the forward premium trade.[14] [15]

The only potentially sensitive assumption we make in performing this decomposition is that investors use data prior to 1995 to estimate $\widehat{fp_i}$ and $\widehat{fp}$. To show that our results do not depend on this particular cutoff date (and the resulting selection of currencies in our 1 Rebalance sample), the remaining panels and columns repeat the same exercise using the 3, 6, and 12 Rebalance samples. In each case, we use all available data before each cutoff date to update the estimates of $\widehat{fp_i}$ and $\widehat{fp}$. In the 3 Rebalance sample, investors thus update their expectation at three dates, and so forth.

The results remain broadly the same across the different samples, where the Static Trade on average contributes 85.7% of the mean returns to the carry trade, and the Dollar Trade on average contributes 81.3% of the mean returns on the forward premium trade. In addition, the Sharpe ratio on the Dynamic Trade appears economically small or even negative in all calculations that take into account the bid-ask spread (they range from -0.14 to 0.19). Whereas the carry trade delivers an economically significant Sharpe ratio in all samples (ranging from 0.12 to 0.44 net of transaction costs), the forward premium trade tends to deliver somewhat lower Sharpe ratios (ranging from 0.00 to 0.27), particularly in the samples that allow more rebalances. Appendix Table 3 shows that these patterns also hold when we exclude pegged exchange rates, use an extended sample of interest rate data, or use a wide of alternative samples of exchange rate data used in other studies.

Our main conclusion from Table 2 is that the Dynamic Trade, the common element between

$s^{bid}_{i,t+1}$), where w_{it} is the portfolio weight of currency i at time t, and I is an indicator function that is one if $w_{it} \geq 0$ and zero otherwise.

[13] Transaction costs in currency markets are thus of the same order of magnitude as the mean returns on the Dynamic Trade. See Burnside et al. (2006) for a discussion. However, bid-ask spreads reported on Datastream may be larger than the effective inter-dealer market spreads; see Lyons (2001) and Gilmore and Hayashi (2008).

[14] The mean returns on the three underlying trades no longer add up to the mean returns on the carry trade and the forward premium trade when we take into account bid-ask spreads. We thus calculate the percentage contribution of Static (Dollar) Trade by dividing its mean return with the maximum of zero and the sum of the mean returns on the Static (Dollar) and Dynamic Trades.

[15] In a similar comparison, Lustig et al. (2011) attribute a somewhat smaller share of the static (unconditional) component in carry trade returns (53% in their standard specification). The reason for this apparent discrepancy is that in their exercise, they allow the carry trade to use up to 36 currencies, whereas the unconditional carry trade uses only 18 currencies. By contrast, our decomposition requires that we restrict all five trading strategies to use the same set of currencies. These differences in implementation arise because their decomposition views portfolios as the primitive (regardless of the number of their constituents), whereas our decomposition focuses on currencies $i, 1, ..N$ as the object of interest. See Appendix Table 2 for a detailed comparison between the two approaches.

the carry trade and the forward premium trade, contributes an economically small share to the expected returns on the two strategies. The majority of the returns on the carry trade are driven by static differences in expected returns across currencies and the majority of the returns on the forward premium trade are driven by time-series variation in the expected returns on the US dollar relative to all other currencies in the sample.

4 Restrictions on Models of Currency Risk Premia

Currency risk premia may vary across currencies, between-time-and-currency, and across time. Each of these dimensions corresponds to one of the three basic trading strategies outlined above. To test whether the variation of risk premia in each of these dimensions is statistically significant, it is useful to rewrite (6) in terms of regression coefficients. Manipulating the expected return on the static trade (the first term on the right-hand side of (6)) yields

$$\begin{aligned} E\left[rx_{i,t+1}\left(\widehat{fp}_i-\widehat{fp}\right)\right] &= E\left[(rx_{i,t+1}-rx_{t+1})\left(\widehat{fp}_i-\widehat{fp}\right)\right]+\underbrace{E\left[rx_{t+1}\left(\widehat{fp}_i-\widehat{fp}\right)\right]}_{=0} \\ &= cov\left(rx_{i,t+1}-rx_{t+1},\widehat{fp}_i-\widehat{fp}\right)=\beta^{stat}var\left(\widehat{fp}_i-\widehat{fp}\right). \end{aligned}$$

We get the first equality from adding and subtracting rx_{t+1} to the first term in the expectations operator. The second equality follows from the fact that $\left(\widehat{fp}_i-\widehat{fp}\right)$ is zero in unconditional expectation and does not vary across t. The third equality follows from rewriting the covariance as an OLS regression coefficient where $\beta^{stat}=cov\left(rx_{i,t+1}-rx_{t+1},\widehat{fp}_i-\widehat{fp}\right)/var\left(\widehat{fp}_i-\widehat{fp}\right)$ is the slope coefficient from the pooled regression

$$rx_{i,t+1}-rx_{t+1}=\beta^{stat}\left(\widehat{fp}_i-\widehat{fp}\right)+\epsilon^{stat}_{i,t+1}. \tag{7}$$

Appendix C.1 shows that similarly rewriting the second and third terms in (6) yields

$$\begin{gathered} cov\left(rx_{i,t+1},fp_{it}\right) \\ = \\ \underbrace{\beta^{stat}var\left(\widehat{fp}_i-\widehat{fp}\right)}_{\text{Static Trade}}+\underbrace{\beta^{dyn}var\left(fp_{i,t}-fp_t-\left(\widehat{fp}_i-\widehat{fp}\right)\right)+\alpha^{dyn}}_{\text{Dynamic Trade}}+\underbrace{\beta^{dol}var\left(fp_t-\widehat{fp}\right)+\alpha^{dol}}_{\text{Dollar Trade}}-\alpha^{dol}, \end{gathered} \tag{8}$$

where β^{dyn} and β^{dol} are again slope coefficients from pooled regressions of currency returns on the variation in forward premia in the relevant dimension:

$$rx_{i,t+1}-rx_{t+1}-(rx_i-rx)=\beta^{dyn}\left[(fp_{it}-fp_t)-\left(\widehat{fp}_i-\widehat{fp}\right)\right]+\epsilon^{dyn}_{i,t+1}, \tag{9}$$

$$rx_{i,t+1} - rx = \gamma + \beta^{dol}\left(fp_t - \widehat{fp}\right) + \epsilon^{dol}_{i,t+1}, \tag{10}$$

rx_{t+1} is the mean return across all currencies at time $t+1$, and $\gamma = \beta^{dol}\left(\widehat{fp} - fp\right)$.

The two constants, $\alpha^{dyn} = E\left[rx_i\left(fp_i - fp - (\widehat{fp}_i - \widehat{fp})\right)\right]$ and $\alpha^{dol} = E\left[rx_i(fp_t - \widehat{fp})\right]$, measure the covariance of currency returns with expectational errors (the deviation of the sample means fp_i and fp from their expected values). Both terms may be non-zero if $T < \infty$, because sample and population means do not coincide in a finite sample, $\widehat{fp}_i \neq fp_i$ and $\widehat{fp} \neq fp$. By contrast, the three slope coefficients determine the systematic part of the mean returns calculated in Table 2. Apart from enabling us to test the statistical significance of the systematic returns on each of our three trading strategies, the three coefficients also have a clear economic interpretation.

Definition 1 *The risk premium on currency i at time t is the expected log return on the currency given that all currencies' forward premia at time t, $\{fp_{it}\}_{i=1}^{N}$, are known:*

$$\pi_{it} \equiv E_{it}\left[rx_{i,t+1}\right],$$

where

$$E_{it}\left[\cdot\right] = \int (\cdot)\, dF_{it}\left(rx_{it+1}, fp_{it}, fp_{jt}, ...|fp_{it}, fp_{jt}, ...\right).$$

Collapsing (7) and (10) into a single cross section and single time series, respectively, adding the right- and left- hand sides of the two resulting equations to (9), and taking conditional expectations yields a generic affine model of currency risk premia:

$$\pi_{it} - \pi = \gamma + \beta^{stat}\left(\widehat{fp}_i - \widehat{fp}\right) + \beta^{dyn}\left[(fp_{it} - fp_t) - \left(\widehat{fp}_i - \widehat{fp}\right)\right] + \beta^{dol}\left(fp_t - \widehat{fp}\right). \tag{11}$$

Proposition 1 *The slope coefficients β^{stat}, β^{dyn}, and β^{dol} measure the elasticity of currency risk premia with respect to forward premia in the cross-currency, between-time-and-currency, and the cross-time dimension, respectively:*

$$\beta^{stat} = \frac{cov\left(\pi_i, \widehat{fp}_i\right)}{var\left(\widehat{fp}_i\right)}, \quad \beta^{dyn} = \frac{cov\left(\pi_{it}, (fp_{it} - fp_t) - \left(\widehat{fp}_i - \widehat{fp}\right)\right)}{var\left((fp_{it} - fp_t) - \left(\widehat{fp}_i - \widehat{fp}\right)\right)}, \quad \beta^{dol} = \frac{cov(\pi_{it}, fp_t)}{var(fp_t)}.$$

Proof. By the properties of linear regression, we can write β^{stat} as

$$\begin{aligned} \beta^{stat} &= E\left[(rx_{i,t+1} - rx_{t+1})\left(\widehat{fp}_i - \widehat{fp}\right)\right] var\left(\widehat{fp}_i\right)^{-1} = E\left[E_{it}\left\{(rx_{i,t+1} - rx_{t+1})\left(\widehat{fp}_i - \widehat{fp}\right)\right\}\right] var\left(\widehat{fp}_i\right)^{-1} \\ &= E\left[E_{it}\left\{(rx_{i,t+1} - rx_{t+1})\right\}\left(\widehat{fp}_i - \widehat{fp}\right)\right] var\left(\widehat{fp}_i\right)^{-1} = cov\left(\pi_{it}, \widehat{fp}_i\right) var\left(\widehat{fp}_i\right)^{-1}. \end{aligned}$$

The second equality applies the law of iterated expectations. The third equality uses the fact that the population means $\widehat{fp}_i$ and $\widehat{fp}$ are known at time t. The proofs for β^{dyn} and β^{dol} are analogous. ■

The crucial feature of the coefficients β^{stat}, β^{dyn}, and β^{dol} is that they link behavior at time t (demanding a risk premium between t and some future time period) to information investors can condition on at time t. In this sense, the three elasticities are behavioral parameters in any model of currency risk premia, regardless of whether we think of (11) as a generic affine model of currency risk premia or as a first-order approximation to a non-linear model of currency risk premia.

Which of these elasticities is statistically distinguishable from zero? Columns 1-4 of Table 3 estimate the specifications (7), (9), and (10) using our 1 Rebalance sample. As in Section 3, we use all available data prior to December 1994 to estimate $\widehat{fp}_i$ and $\widehat{fp}$. The standard errors for β^{stat} and β^{dol} are clustered by currency and time, respectively, whereas the standard errors for β^{dyn} are Newey-West with 12, 18, and 24 lags for the 1-, 6-, and 12-month horizons, respectively. Where appropriate, we use the Murphy and Topel (1985) procedure to adjust all standard errors for the estimated regressors $\widehat{fp}_i$ and $\widehat{fp}$ (see Appendix C.2 for details). An asterisk indicates we can reject the null hypothesis that the coefficient is equal to zero at the 5% level.

The specifications in column 1 use monthly forward contracts and show a highly statistically significant estimate for β^{stat} of 0.47 (s.e.=0.08). The estimate of β^{dyn} is about the same size 0.44 (s.e.=0.25) but statistically indistinguishable from zero, as is the much larger estimate for β^{dol} (3.11, s.e.=1.60).

[Table 3 about here.]

The same column also reports estimates of the slope coefficients of equivalent specifications for the returns on the carry trade (β^{ct}) and the forward premium trade (β^{fpp}), where in each case, we regress currency returns in the relevant dimension on the portfolio weights used to implement the trading strategy:

$$rx_{i,t+1} - rx_{t+1} = \beta^{ct}\left(fp_{it} - fp_t\right) + \epsilon^{ct}_{i,t+1}, \tag{12}$$

$$rx_{i,t+1} - rx_i = \beta^{fpp}\left(fp_{it} - \widehat{fp}_i\right) + \epsilon^{fpp}_{i,t+1}. \tag{13}$$

As expected, the coefficients in both regressions are positive and statistically significant. The coefficient in the carry trade regression is 0.68 (s.e.=0.27), whereas the one in the forward premium trade regression is 0.86 (s.e.=0.34). In both regressions, we use Newey-West standard errors with the appropriate number of lags, following the convention outlined above. In addition, we also adjust standard errors for β^{fpp} for estimated regressors $\widehat{fp}_i$ as above.

As with the portfolio-based decomposition in Table 2, the coefficients β^{ct} and β^{fpp} are linear functions of $\beta^{stat}, \beta^{dyn}$ and β^{dol}, β^{dyn} respectively.[16] Column 1 of Table 3 thus also reports the partial R^2 of the static trade in the carry trade regression (62%) and the partial R^2 of the dollar trade in the forward premium trade regression (90%).[17]

The remaining columns report variations of the same estimates, showing that our results are robust to adjusting for transaction costs, using forward contracts of longer maturity, including different countries in the sample, and using different time horizons for estimating $\widehat{fp}_i$ and $\widehat{fp}$. The structure of the table is identical to Table 2. Columns 2-4 use returns adjusted for the bid-ask spread and forward contracts at the 1-, 6-, and 12-month horizon. The remaining columns and panels repeat the same estimations using our 3, 6, and 12 Rebalance samples, where in each case, we again use all available data before each cutoff date to update the estimates of $\widehat{fp}_i$ and $\widehat{fp}$.

The pattern that emerges from the range of variations in Table 3 is similar to the results in column 1. In all samples, the coefficient on the static trade is a precisely estimated number between zero and one (point estimates range from 0.15 to 0.6), and this coefficient usually explains about two thirds of the systematic variation driving the identification of β^{ct}. We thus always reject the null that currency risk premia do not vary with unconditional differences in forward premia across currencies. The coefficient on the dollar trade is imprecisely estimated and statistically distinguishable from zero in one out of 16 specifications. Point estimates range from -0.23 to 3.72. We thus rarely reject the null that no covariance exists between risk premia and forward premia in the cross-time dimension. However, the dollar trade always explains more than half, often more than 90%, of the variation driving the identification of β^{fpp}. By contrast, the Dynamic Trade often explains less than 10% of the variation identifying β^{fpp}. Finally, we reject the null that $\beta^{dyn} = 0$ in only one of our 16 specifications. Appendix Table 4 shows that these conclusions also hold across a wide range of alternative samples used in other studies.

As an additional robustness check, we use our 12 Rebalance sample to block-bootstrap standard errors. In this procedure, we treat each of the 12 two-year periods in between rebalancing dates as one block and draw 100,000 random samples with replacement from this set of histories. Table 4 shows that this procedure produces somewhat wider standard errors for some of our estimates. However, the basic pattern is identical to the one in Table 3: β^{stat} and β^{ct} are statistically significant in three out of four specifications, whereas the remaining parameters are not.

[16] See Appendix C.5 for the analytical expressions.

[17] We calculate the partial R^2 as $\frac{ESS^d}{ESS^d+ESS^{dyn}}$, $d \in \{stat, dol\}$, where ESS^{dyn} refers to the explained sum of squares in specification (9) and ESS^{stat}, ESS^{dol} refer to the explained sum of squares in specifications (7) and (10), respectively.

[Table 4 about here.]

These results have two surprising implications. First, the fact that we cannot reject the hypothesis that currency risk premia do not vary in the between-time-and-currency dimension means the FPP and the carry trade are not significantly related phenomena in the data. The FPP does not appear to "drive" or "motivate" the carry trade, contrary to what most textbooks and many papers on the subject suggest. Models that are designed to fit the FPP thus do not automatically explain the carry trade and vice versa. The two phenomena may thus require separate theoretical explanations.

Second, throughout the table, the evidence that currency risk premia co-vary with forward premia over time is quite weak. Whereas both the Dynamic and the Dollar trade appear to yield positive expected returns in Table 2, the systematic part of the returns on these strategies are not statistically distinguishable from zero in most specifications. (Recall that in (8), the terms α^{dyn} and α^{dol} result from expectational errors, such that risk premia on both the Dynamic and the Dollar trade are positive if and only if β^{dyn} and β^{dol}, respectively, are strictly greater than zero.) By contrast, the most robust feature of the data appears to be the feature that has received the least attention in the literature – a significantly positive risk premium on the Static Trade, that is, a significant covariance between currency risk premia and unconditional differences in forward premia across countries.

4.1 In-sample Estimates Are Biased

The estimation in the previous section is based on "out-of-sample" regressions in the sense that $\widehat{fp}_i$, $\widehat{fp}$ are estimated in the pre-period. This approach came naturally, because we used these regressions to analyze the statistical properties of the portfolios from Section 3, where investors also needed to estimate $\widehat{fp}_i$, $\widehat{fp}$ to be able to form their portfolios. The following proposition shows that this correspondence between portfolio formation and out-of-sample regressions is not an accident: in-sample regressions that use currency fixed effects such that $\widehat{fp}_i = fp_i$ and $\widehat{fp} = fp$ in (7), (9), and (13) yield biased estimates of the elasticity of risk premia with respect to forward premia in a finite sample. In the discussion below, we denote the slope coefficients from the in-sample regressions corresponding to (7), (9), and (13) as $\beta^{stat}_{in-sample}$, $\beta^{dyn}_{in-sample}$, and $\beta^{fpp}_{in-sample}$, respectively.

Proposition 2 *If $T < \infty$, the slope coefficients $\beta^{dyn}_{in-sample}$ and $\beta^{fpp}_{in-sample}$ are upwardly biased measures of the elasticity of risk premia with respect to forward premia in the between-time-*

and-currency and the time-series dimensions:

$$\beta^{dyn} = \beta^{dyn}_{in-sample}\left(1 + \frac{var\left(fp_i - \widehat{fp}_i\right)}{var\left(fp_{it} - fp_t - (fp_i - fp)\right)}\right)^{-1} < \beta^{dyn}_{in-sample}, \tag{14}$$

and

$$\beta^{fpp} = \beta^{fpp}_{in-sample}\left(1 + \frac{var\left(fp_i - \widehat{fp}_i\right)}{var\left(fp_{it} - fp_i\right)}\right)^{-1} < \beta^{fpp}_{in-sample}. \tag{15}$$

In addition, the slope coefficient $\beta^{stat}_{in-sample}$ may be an upwardly or downwardly biased measure of the elasticity of risk premia with respect to forward premia in the cross-currency dimension,

$$\beta^{stat} = \beta^{stat}_{in-sample}\frac{var\left(fp_i\right)}{var\left(\widehat{fp}_i\right)} + \frac{E\left[(rx_i - rx)\left(\widehat{fp}_i - \widehat{fp} - (fp_i - fp)\right)\right]}{var\left(\widehat{fp}_i\right)}. \tag{16}$$

Proof. See Appendix C.3. ■

In-sample estimates $\beta^{dyn}_{in-sample}$ and $\beta^{fpp}_{in-sample}$ thus over-estimate the true elasticity of risk-premia with respect to forward premia in proportion to the variance of the deviation of the sample mean fp_i from its population equivalent $\widehat{fp}_i$. For any finite sample, this variance is positive, and so the resulting bias of the in-sample estimates is larger than one. The reason for the bias is that when we run (7), (9), and (13) using currency fixed effects, we use information about sample means, fp_i and fp, that is available to the econometrician ex post, but that is unknown to investors ex ante. Although some part of the variation in the data must be due to errors, $fp_i - \widehat{fp}_i$, the in-sample versions of (7) and (9) assign all of the variation to behavior, resulting in an upwardly biased measure of the true elasticity of risk premia with respect to forward premia.

By contrast, no distinction exists between in-sample and out-of-sample coefficients in the cross-time dimension. In that dimension, the fact that investors need to estimate fp ex ante has no bearing on the estimate of the covariance of risk premia with forward premia, because $cov\left(\pi_{it}, fp_t\right) = cov(\pi_{it}, fp_t - \widehat{fp}) = cov(\pi_{it}, fp_t - fp)$, such that $\beta^{dol} = \beta^{dol}_{in-sample}$. This is why equation (10) has a constant $\left(\gamma = \beta^{dol}\left(\widehat{fp} - fp\right)\right)$ that absorbs any errors in predicting fp.

[Table 5 about here]

Table 5 compares estimates of the biased in-sample measures $\beta^{stat}_{in-sample}$, $\beta^{dyn}_{in-sample}$, and $\beta^{fpp}_{in-sample}$ with their unbiased counterparts from columns 1 and 5 in Table 3. All specifications use one-month forwards and exclude bid-ask spreads. The table shows that the bias in the in-sample measures is considerable. For example, in our 1 Rebalance sample, the estimate of

$\beta^{dyn}_{in-sample}$ is 1.13 (s.e.=0.45) and highly statistically significant, whereas our estimate of β^{dyn} is 60% smaller and statistically insignificant (0.44, s.e.=0.25). Similarly, $\beta^{fpp}_{in-sample}$ is 1.81 (s.e.=0.53), whereas β^{fpp} is less than half the size and smaller than one (0.86, s.e.=0.34).

In-sample regressions thus return inflated estimates of the elasticity of risk premia with respect to forward premia in the between-time-and-currency and time-series dimensions. This finding is particularly important because it qualifies the interpretation of the FPP. Many papers on international currency returns feature a table showing a list of estimates of β^{fpp}_i from Fama's bilateral regression (1). Table 6 replicates this list for our 1, 3, 6, and 12 Rebalance samples.

[Table 6 about here]

The coefficients β^{fpp}_i exhibit wide variation. Some are significantly positive, others are significantly negative, but most are statistically indistinguishable from zero. Because (1) includes a currency-specific intercept that absorbs any expectational errors $fp_i - \widehat{fp}_i$, in-sample and out-of-sample estimates of β^{fpp}_i are identical, such that we can rewrite (1) as

$$rx_{i,t+1} - rx_i = \alpha_i + \beta^{fpp}_i \left(fp_{it} - \widehat{fp}_i \right) + \epsilon^{fpp}_{i,t+1}, \tag{17}$$

where $\alpha_i = \beta^{fpp}_i \left(\widehat{fp}_i - fp_i \right)$. Consequently, we may interpret the coefficients β^{fpp}_i as unbiased estimates of the *currency-specific* elasticity of risk premia with respect to forward premia corresponding to the model:

$$\pi_{it} - \pi = \beta^{stat} \left(\widehat{fp}_i - \widehat{fp} \right) + \sum_i D_i \left(\alpha_i + \beta^{fpp}_i \left(fp_{it} - \widehat{fp}_i \right) \right). \tag{18}$$

However, this interpretation seems somewhat unappealing due to its sheer complexity. For example, such a model would have to explain why the elasticities of Kuwait and South Africa have opposing signs and why Canada has a significantly larger elasticity than Japan, but about the same elasticity as Denmark.

Instead, this table is usually taken as evidence that the average country's elasticity of currency risk premia with respect to forward premia is positive and statistically significant because most currencies have a $\beta^{fpp}_i > 1$ such that the pooled version of the regression (a convex combination of the β^{fpp}_i) typically yields a positive and statistically significant coefficient. However, in Appendix C.4, we show

$$\sum_i \frac{1}{N} \frac{var_i \left(fp_{it} \right)}{\sum_i \frac{1}{N} var_i \left(fp_{it} \right)} \beta^{fpp}_i = \beta^{fpp}_{in-sample} > \beta^{fpp}. \tag{19}$$

The weighted average of β_i^{fpp} thus yields an upwardly biased estimate of the elasticity of risk premia with respect to forward premia in the time-series dimension. Because the α_i in (17) vary across countries, the distinction between in-sample and out-of-sample regressions is no longer innocuous once we constrain all β_i^{fpp} to be identical in (18). Mentally averaging across currency-specific estimates in Table 6 thus results in the same upwardly biased estimate of the elasticity of risk premia with respect to forward premia as the in-sample version of (13). In this sense, tables like our Table 6 make the FPP look a lot worse than it actually is.

Rather than averaging across the estimates in Table 6, the correct procedure for estimating the constrained model uses out-of-sample regressions (7) and (13). Collapsing (7) into a single cross section, adding (13) and taking conditional expectations, yields

$$\pi_{it} - \pi = \beta^{stat}\left(\widehat{fp}_i - \widehat{fp}\right) + \beta^{fpp}\left(fp_{it} - \widehat{fp}_i\right), \tag{20}$$

where $\beta^{fpp} = \omega\beta^{dyn} + (1-\omega)\,\beta^{dol} < \beta^{fpp}_{in-sample}$ (see equation (19) and Appendix C.5 for a formal proof).

4.2 Alternative Corrections of In-sample Estimates

A difficulty in directly estimating (7), (9), and (13) is that all three specifications require explicit estimates of $\widehat{fp}_i$ and $\widehat{fp}$ as inputs. Although we have performed a number of variations in estimating these inputs by allowing a varying number of re-balances during the sample and by bootstrapping across periods, we may still worry that these estimates of population means are noisy. An alternative approach is to instead depart from in-sample estimates and to correct these estimates to make them unbiased in a finite sample.

In particular, the bias in (14) and (15) is simply a function of the variance of the forecast error $var\left(fp_i - \widehat{fp}_i\right)$. Figure 2 plots estimates of β^{dyn} and β^{fpp} in our 1 Rebalance sample as a function of this variance. To the left of the two graphs, when $var\left(fp_i - \widehat{fp}_i\right) = 0$, we get the in-sample estimates from column 1 of Table 5 (marked with a square). The larger the variance of the error relative to the variance of the right-hand-side variable in the in-sample regression, the larger the resulting bias in the two coefficients. A diamond marks our out-of-sample estimates from column 1 of Table 3.

An alternative way of calculating these two numbers would have been to simply estimate the variance $var\left(fp_i - \widehat{fp}_i\right)$ by comparing our pre-1995 estimates of $\widehat{fp}_i$ directly to the sample means fp_i. The horizontal axis shows that the estimated $var\left(fp_i - \widehat{fp}_i\right)$ is about twice the size of the estimated $var\left(fp_{it} - fp_i - (fp_t - fp)\right)$ (left panel) and about the same size as the estimated $var\left(fp_{it} - fp_i\right)$. The variance of the forecast error is thus large relative to the time-series variation in forward premia, resulting in a large bias in the in-sample estimates.

[Figure 2 about here]

The remaining estimates in the figure show two alternative adjustments of the in-sample estimates that use the entire sample to estimate a process for the evolution of forward premia over time and use this process to calculate a structural estimate of $var\left(fp_i - \widehat{fp_i}\right)$. The circles in the two graphs mark the point estimates we obtain from estimating the AR(1),

$$fp_{it} = \rho_i fp_{i,t-1} + \epsilon^f_{it}, \tag{21}$$

over the full sample and then calculating the implied variance of the forecast error in a sample with length $T = 186$, months under the assumption that the estimated autocorrelation coefficients ρ_i and standard deviations of ϵ^f_{it} characterize the true process governing the evolution of fp_{it} and are known to investors. In both cases, this calculation results in a slightly smaller adjustment, returning an estimate of 0.56 (s.e.=0.32) for β^{dyn} and an estimate of 1.18 (s.e.=0.42) for β^{fpp}. However, the standard errors on both estimates are now also considerably wider. When we repeat our calculation while imposing the same autocorrelation coefficient ρ for all currencies in (2), we obtain tighter standard errors but also a larger adjustment to both coefficients (marked with a triangle).

Regardless of the method we choose for correcting the in-sample bias of our estimates, our conclusions from Table 3 continue to hold: β^{dyn} is never statistically distinguishable from zero, whereas β^{fpp} is statistically significant in some specifications.

4.3 Model Selection

The generic affine model of currency risk premia (11) has three parameters. A theorist wishing to focus her energy on the most salient features of the data may want to begin with the null hypothesis that each of these parameters is equal to zero and include them if and only if they significantly improve the model's fit to the data. Based on the results from Table 3, she might thus start with the simplest model the data do not clearly reject $\{\beta^{stat} > 0, \beta^{dyn} = 0, \beta^{dol} = 0\}$. This model explains returns on the carry trade as the result of static, unconditional, differences in risk premia across currencies.

Although this model explains most of the significant correlations shown in Table 3, discarding the mean returns to the forward premium trade and thus the FPP itself as a statistical fluke may not be satisfactory. Columns 1-5, 7, and 8 of the 1 Rebalance and 3 Rebalances samples, show significantly positive returns to the forward premium trade. Although neither β^{dyn} nor β^{dol} are by themselves usually statistically distinguishable from zero, their convex combination (β^{fpp}) is statistically significant in these seven specifications. We might thus want to relax our model by adding an additional parameter that can explain this pattern.

The three simplest options to extend the model are $\{\beta^{dyn} > 0, \beta^{dol} = 0\}$, $\{\beta^{dyn} = 0, \beta^{dol} > 0\}$, and $\{\beta^{dyn} = \beta^{dol} = \beta^{fpp} > 0\}$.

Table 7 performs χ^2 difference tests, asking which of the three extensions is best able to explain the mean returns on the forward premium trade observed in the data under the assumption that the coefficients estimates of β^{fpp}, β^{dyn}, and β^{dol} are normally distributed (see Appendix C.7 for details). The two columns in the table use the coefficient estimates and standard errors from columns 1 and 5 of the 1 Rebalance and the 3 Rebalances samples in Table 3, respectively. (Because the linear relationship between the three coefficients holds only in the absence of transaction costs, these specifications are the only two of relevance.) In both cases, we cannot reject $\beta^{dyn} = 0$ or $\beta^{dyn} = \beta^{dol}$, whereas we can reject $\beta^{dol} = 0$ at the 5% level. The two simplest models that can explain all the statistically significant correlations in Table 3 are thus $\{\beta^{stat} > 0, \beta^{dyn} = 0, \beta^{dol} > 0\}$ and $\{\beta^{stat} > 0, \beta^{dyn} = \beta^{dol} = \beta^{fpp} > 0\}$.

[Table 7 about here.]

The conclusion from this section is that the data strongly reject models in which $\beta^{stat} = 0$ and, to the extent that the FPP is a robust fact in the data, also reject models in which $\beta^{dol} = 0$. A parsimonious affine model of currency risk premia thus need only allow for variation in currency risk premia in the cross-currency and cross-time dimensions. Any assumptions about β^{dyn} do not significantly affect the model's ability to fit the data.

4.4 Dynamics of Bilateral Currency Risk Premia

Given the large literature that analyzes the dynamics of bilateral currency risk-premia using currency by currency regressions (1), a natural question is whether our three-parameter model is too restrictive by imposing the same between-time-and-currency dynamics for all foreign currencies. In this section, we relax this assumption by generalizing (9) to allow for heterogeneous elasticities of risk premia with respect to forward premia across currencies:

$$rx_{i,t+1} - rx_{t+1} - (rx_i - rx) = \alpha_i^{dyn} + \sum_i D_i \beta_i^{dyn} \left[(fp_{it} - fp_t) - \left(\widehat{fp}_i - \widehat{fp} \right) \right] + \epsilon_{i,t+1}^{dyn}, \quad (22)$$

where D_i is a currency fixed effect:

$$\alpha_i^{dyn} = \beta_i^{dyn} \left(\widehat{fp}_i - \widehat{fp} - (fp_i - fp) \right).$$

Again collapsing (7) and (10) into a single cross section and single time series, respectively, adding the right- and left- hand sides of the two resulting equations to (22), and taking conditional expectations yields

$$\pi_{it} - \pi = \gamma + \beta^{stat}\left(\widehat{fp}_i - \widehat{fp}\right) + \sum_i D_i \beta_i^{dyn}\left[(fp_{it} - fp_t) - \left(\widehat{fp}_i - \widehat{fp}\right)\right] + \beta^{dol}\left(fp_t - \widehat{fp}\right). \tag{23}$$

This is our most flexible affine model, nesting the models (11) and (20). Following the same steps as the proof of proposition 1 we can again show that currency-specific coefficients β_i^{dyn} are unbiased measures of the elasticity of the risk premium on currency i with respect to deviations of currency i's forward premium from its currency- and time-specific mean. In addition, Appendix C.6 shows we can re-write the decomposition in (8) as

$$cov\left(rx_{i,t+1}, fp_{it}\right)$$
$$=$$
$$\underbrace{\beta^{stat} var\left(\widehat{fp}_i - \widehat{fp}\right)}_{\text{Static Trade}} + \underbrace{\frac{1}{N}\sum_i \beta_i^{dyn} var_i\left(fp_{i,t} - fp_t\right) + \alpha^{dyn}}_{\text{Dynamic Trade}} + \underbrace{\beta^{dol} var\left(fp_t - \widehat{fp}\right) + \alpha^{dol}}_{\text{Dollar Trade}} - \alpha^{dol}. \tag{24}$$

Corollary 1 *Allowing for heterogeneous elasticities of risk premia with respect to forward premia across currencies does not change the model's ability to match the expected returns to the carry trade and the forward premium trade as defined in (2) and (5).*

Proof. From comparing equations (8) and (24), it follows immediately that

$$\beta^{dyn} var\left(fp_{i,t} - fp_t - \left(\widehat{fp}_i - \widehat{fp}\right)\right) = \frac{1}{N}\sum_i \beta_i^{dyn} var_i\left(fp_{i,t} - fp_t\right), \tag{25}$$

such that models (11) and (23) predict identical expected returns on the static, dynamic, dollar, carry, and forward premium trade. ■

The purpose of allowing for heterogeneous elasticities across countries is thus not to improve the model's ability to account for the two anomalies, but rather to detect whether specific currencies appear to behave significantly different than others. Table 8 shows the coefficients from this regression for our 1, 3, 6, and 12 Rebalance samples. To save space, we show only the coefficients using one-month forwards, without taking into account bid-ask spreads. An asterisk again denotes significance at the 5% level, where standard errors are Newey-West, correcting for heteroskedasticity and auto-correlation at the 12-month horizon.

The table shows that we cannot reject the null that $\beta_i^{dyn} = 0$ for most currencies. In fact, looking across columns, we do not appear to robustly reject this null for any currency, with the possible exception of the Indian rupee, the Austrian schilling, and the Belgian franc. Although we remain open to the possibility that risk premia of these, and potentially a few other, currencies may co-move with deviations of forward premia from their time- and currency specific mean, the evidence does not appear overwhelming.

In particular, comparing these results with the results of Table 6 shows substantially fewer significant coefficients. Including β^{dol} in the model (23) thus accounts for most of the variation in currency risk premia that drives the FPP, consistent with our results in Section 4.3.

[Table 8 about here.]

4.5 Is the Dollar Special?

Throughout the paper, we account for returns in terms of US dollars. Although this convention is standard practice in the literature, it is also somewhat arbitrary. How would our results change if we had chosen a different base currency? Given a large enough sample of currencies, our estimates of the returns on the Dynamic and the Static trades as well as our estimates of β^{stat} and β^{dyn} would not change at all, as both strategies are neutral with respect to the base currency (i.e., their returns are not affected by the returns on the base currency). However, our estimates β^{dol} might be different, because the Dollar Trade is not neutral with respect to the returns on the dollar.[18]

In what follows, we generalize our analysis to allow for an arbitrary choice of base currency. To this end, denote the elasticity of risk premia with respect to forward premia in the cross-time dimension from the perspective of an investor using currency j as base currency as β^{j}, $j = 1, ...N$.

Proposition 3 *In a large sample of convertible currencies, the elasticity of the risk premium on any base currency j with respect to the average forward premium on all other foreign currencies equals the elasticity of currency j's risk premium against the US dollar with respect to deviations of its forward premium against the US dollar from its time- and currency-specific mean,*

$$\beta^{j} = \beta^{dyn}_{j}.$$

Proof. See Appendix C.8 ■

Given a large sample of currencies, the coefficients in Table 8 are thus identical to the coefficients we would estimate on the "Base Currency Trade" (i.e., the equivalent of the Dollar Trade but using currency j as the base currency) of the other currencies in the sample. For example, had we chosen to account for all returns in terms of Japanese yen, our estimates of β^{stat} and β^{dyn} would (in a large sample of currencies) be identical to those in Table 3, but our estimate of β^{yen} would be equal to $\beta^{dyn}_{Japan} = 0.55$ in column 1 of Table 8.

[18] See Appendix D for a formal proof of these statements.

From (25), it is apparent that β^{dyn} is a linear combination of the β_i^{dyn} multiplied with a variance ratio that is smaller than one.[19] Thus, the null hypothesis that $\beta^{dol}=\frac{var(fp_{i,t}-fp_t-(fp_i-fp))}{var\left(fp_{i,t}-fp_t-\left(\widehat{fp}_i-\widehat{fp}\right)\right)}\beta^{dyn}$ is a formal test of whether the elasticity of the risk premium on the US dollar is significantly different from elasticity of the average currency in the sample. Table 9 shows we cannot reject this hypothesis in any of our samples. However, given that we can reject the hypothesis that $\beta^{dol}=0$ but cannot reject the hypothesis that $\beta^{dyn}=0$ in Table 7, our overall results are at least consistent with the notion that the risk-premium on the US dollar might have dynamics that are systematically different from those of other countries.[20] Indeed, Table 8 suggests that this property may be shared with a small number of other currencies, including the Indian rupee.

[Table 9 about here.]

5 Implications for Models of Exchange Rate Determination

Part of the enduring legacy of the analysis of bilateral currency risk premia has been a debate about whether time variation in currency risk premia might be partially responsible for the observed volatility of exchange rates, which is one implication of the $\beta_i^{fpp}>1$ in (1).

Following the argument in Fama (1984), we can write[21]

$$\beta^{stat}=\frac{cov\left(\pi_i,\widehat{fp}_i\right)}{var\left(\widehat{fp}_i\right)}=\frac{cov\left(\pi_i,\pi_i+E_{it}\Delta s_i\right)}{var\left(\pi_i+E_{it}\Delta s_i\right)}=\frac{var\left(\pi_i\right)+cov\left(\pi_i,E_{it}\Delta s_i\right)}{var\left(\pi_i\right)+var\left(E_{it}\Delta s_i\right)+2cov\left(\pi_i,E_{it}\Delta s_i\right)}. \tag{26}$$

The fraction on the right-hand side can be larger than one only if a negative covariance exists between risk premia and expected depreciations in the cross-currency dimension. However, as long as β^{stat} is between zero and one Fama's analysis has no implications for the covariance between currency risk premia and expected changes in exchange rates. Any number between zero and one may simply result from the fact that both risk premia and expected changes in exchange rates vary in the cross-currency dimension. ($var(\pi_i)>0$, $var\left(E_{it}\Delta s_i\right)>0$).

Similarly, estimates between zero and one for β^{dyn} and β^{dol} have no implications for the covariance of currency risk premia and expected changes in exchange rates in the relevant

[19]To see this, divide on both sides of the above equation by $var\left(fp_{i,t}-fp_t-(fp_i-fp)\right)$ and note that $\sum_i var_i\left(fp_{i,t}-fp_t\right)/N=var\left(fp_{i,t}-fp_t-(fp_i-fp)\right)$.

[20]For other evidence on the special role of the US dollar, see, for example, Gourinchas and Rey (2007), Lustig et al. (2010), and Maggiori (2013).

[21]See Appendix E for details.

dimension. Figure 3 summarizes the implications of our estimates in Table 3 for the covariance of currency risk premia with expected appreciations. The figure shows all point estimates and standard errors from the table and highlights the median estimate for each of the three coefficients.

None of our point estimates for β^{stat} and β^{dyn} are larger than one. In fact, we can reject the hypothesis that either of the two coefficients is larger than one in all but one specification. The data thus provide no evidence that risk premia and expected appreciations are correlated in the cross-currency and the between-time-and-currency dimensions.

In fact, the only potential evidence in favor of a positive covariance between currency risk premia and expected appreciations comes from the cross-time dimension. There, a number of point estimates are above one. However, the standard errors in this estimation are so large that we reject the hypothesis that $\beta^{dol} > 0$ in only one specification and *never* reject the hypothesis that $\beta^{dol} < 1$. Our multilateral regressions of currency returns on forward premia thus offer little evidence of a non-zero covariance of currency risk premia with expected changes in exchange rates.

[Figure 3 about here.]

6 Conclusion

In this paper, we generalize the regression-based approach that identified the forward premium puzzle to analyze the covariance of currency risk premia with forward premia in a multi-currency world. The first main insight from our multilateral analysis is that the carry trade and the forward premium puzzle are two distinct anomalies that are not significantly related in the data. The carry trade results mainly from permanent differences in forward premia across currencies that are partially, but not fully, reversed by predictable movements in exchange rates. By contrast, the forward premium puzzle appears to mainly arise from time-series variation in the risk premium of the US dollar against all other currencies. The between-time-and-currency variation in risk premia is not statistically distinguishable from zero and thus does not contribute significantly to either of the two anomalies.

The second main insight from our analysis is that the vast majority of the theoretical literature on the forward premium puzzle that features two, symmetric currencies focuses on a relatively small, mostly statistically insignificant part of the covariance between risk premia and forward premia. Moreover, we cannot reject the hypothesis that the covariance between currency risk premia and expected changes in exchange rates is zero in any of the samples we analyze.

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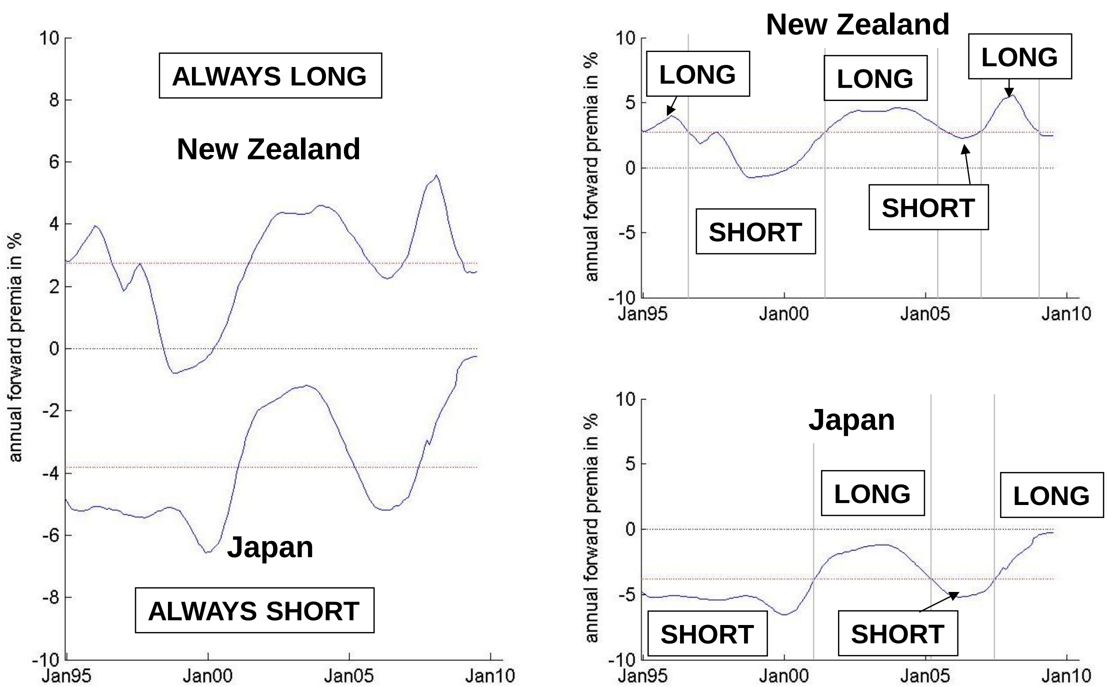

Figure 1: **Carry Trade vs. Forward Premium Trade**

Forward premia of the New Zealand dollar and Japanese yen against the US dollar 1995-2010. Left panel: Carry Trade uses $fp_{it} - fp_t$ as portfolio weights, always long the New Zealand dollar, always short the Japanese yen; Right panel: Forward Premium Trade uses $fp_{it} - fp_i$ as portfolio weights, goes long when a currency's forward premium exceeds its currency-specific mean. The plot cumulates monthly forward premia to the annual frequency according to $fp_{i,t} = \sum_{m=1}^{12} fp_{i,t+m}$.

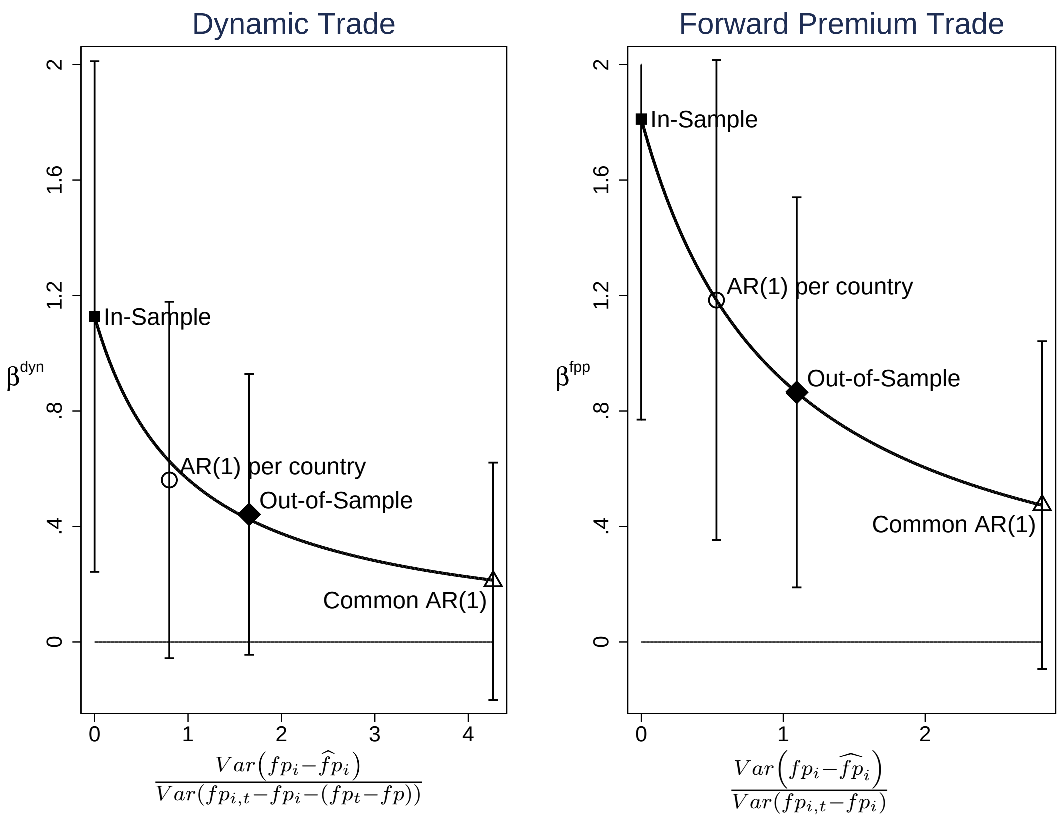

Figure 2: **Alternative Corrections of In-sample Estimates**
Estimates of β^{dyn} and β^{dol} as a function of the estimate of $\beta^{dyn}_{in-sample}$ and $\beta^{dol}_{in-sample}$ from column 1 of Table 5 and the variance of the forecast error $var(fp_i - \widehat{fp}_i)$ as given in equations (14) and (15). Rhomboids mark the estimates from our standard specification in column 1 of Table 3. Circles mark the point estimates we obtain from estimating the AR(1), $fp_{it} = \rho_i fp_{i,t-1} + \epsilon^f_{it}$, over the full sample and then calculating the implied variance of the forecast error in a sample with length $T = 186$, months under the assumption that the estimated autocorrelation coefficients ρ_i and standard deviations of ϵ^f_{it} characterize the true process governing the evolution of fp_{it} . Triangles mark results of the same calculation while imposing the same autocorrelation coefficient for all currencies. Discrepancies between the actual estimate and the one implied by the function are due to small departures from a fully balanced sample due to our data-cleaning algorithm.

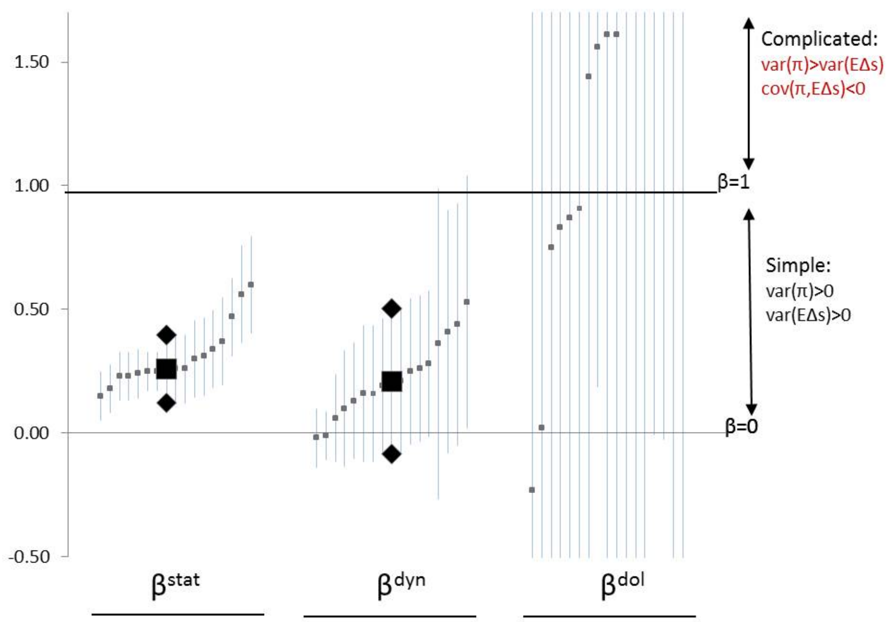

Figure 3: **Summary of Estimates of the Elasticity of Risk Premia with Respect to Forward Premia across Samples and Horizons**
The figure plots all coefficient estimates and respective standard errors from Table 3. Small squares show point estimates, and large squares identify the median estimate for each elasticity across samples/horizons. The shaded lines give the standard errors corresponding to each specification. The right-hand-side axis summarizes the implications of the estimates for linear models of currency risk premia.

Table 1: Mean Annualized Return to the Carry Trade

$E\left[rx_{i,t+1}\left(fp_{it} - fp_t\right)\right]$	4.95
Forward Premium	7.11
Appreciation	-2.15
Sharpe Ratio	0.54

Note: Annualized returns to the carry trade calculated by standardizing the expression in (2) with the unconditional mean forward premium in the sample, fp. One-month forward and spot exchange rates from the 1 Rebalance sample ranging from12/1994 to 6/2010.

Table 2: Mean Returns on Five Trading Strategies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample		**1 Rebalance**				**3 Rebalance**		
Horizon (months)	1	1	6	12	1	1	6	12
Static Trade								
$E[rx_{i,t+1}(\widehat{fp}_i - \widehat{fp})]$	3.46	1.36	3.58	3.82	3.09	0.33	2.55	2.53
Sharpe Ratio	0.39	0.15	0.32	0.32	0.37	0.04	0.24	0.22
Dynamic Trade								
$E[rx_{i,t+1}(fp_{i,t} - fp_t - (\widehat{fp}_i - \widehat{fp}))]$	1.50	-0.24	0.33	1.20	1.42	-0.85	-0.12	0.45
Sharpe Ratio	0.24	-0.04	0.05	0.19	0.20	-0.12	-0.02	0.07
Dollar Trade								
$E[rx_{i,t+1}(fp_t - \widehat{fp})]$	2.55	1.24	2.52	3.18	1.90	0.26	2.20	2.36
Sharpe Ratio	0.25	0.12	0.26	0.27	0.15	0.02	0.17	0.18
Carry Trade								
$E[rx_{i,t+1}(fp_{i,t} - fp_t)]$	4.95	2.81	4.25	5.24	4.50	1.99	2.95	3.35
Sharpe Ratio	0.54	0.31	0.34	0.44	0.54	0.23	0.26	0.29
% Static Trade	**70%**	**121%**	**92%**	**76%**	**69%**	**.**	**105%**	**85%**
Forward Premium Trade								
$E[rx_{i,t+1}(fp_{i,t} - \widehat{fp}_i)]$	4.04	1.77	3.03	4.51	3.31	0.28	2.26	2.94
Sharpe Ratio	0.27	0.12	0.20	0.27	0.18	0.02	0.12	0.16
% Dollar Trade	**63%**	**124%**	**88%**	**73%**	**57%**	**.**	**106%**	**84%**
Sample		**6 Rebalance**				**12 Rebalance**		
Static Trade								
$E[rx_{i,t+1}(\widehat{fp}_i - \widehat{fp})]$	2.42	-0.38	1.96	1.96	3.81	0.22	2.92	2.87
Sharpe Ratio	0.29	-0.05	0.20	0.21	0.46	0.03	0.30	0.29
Dynamic Trade								
$E[rx_{i,t+1}(fp_{i,t} - fp_t - (\widehat{fp}_i - \widehat{fp}))]$	1.85	-0.48	0.34	-0.08	1.65	-0.89	0.41	0.19
Sharpe Ratio	0.26	-0.05	0.04	-0.00	0.26	-0.14	0.06	0.01
Dollar Trade								
$E[rx_{i,t+1}(fp_t - \widehat{fp})]$	2.09	0.23	2.39	3.64	1.88	-0.18	1.15	2.13
Sharpe Ratio	0.16	0.02	0.18	0.19	0.14	-0.01	0.09	0.13
Carry Trade								
$E[rx_{i,t+1}(fp_{i,t} - fp_t)]$	4.28	1.66	2.81	2.23	5.45	2.19	3.95	3.45
Sharpe Ratio	0.50	0.19	0.25	0.12	0.69	0.28	0.40	0.22
% Static Trade	**57%**	**.**	**85%**	**104%**	**70%**	**.**	**88%**	**94%**
FP Trade								
$E[rx_{i,t+1}(fp_{i,t} - \widehat{fp}_i)]$	3.95	0.74	2.92	3.71	3.53	-0.01	1.78	2.44
Sharpe Ratio	0.21	0.04	0.15	0.17	0.20	-0.00	0.10	0.12
% Dollar Trade	**53%**	**.**	**88%**	**102%**	**53%**	**.**	**74%**	**92%**
Bid-Ask Spreads	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Note: Mean returns and Sharpe ratios on the Static, Dynamic, Dollar, Carry, and Forward Premium Trades defined in equations (2), (5), and (6) calculated using 1-, 6-, and 12-month currency forward contracts against the US dollar. All returns are annualized and divided by fp estimated in the 1 Rebalance sample post 12/1994 to facilitate comparison. The table also reports the percentage contribution of Static (Dollar) Trade to the mean returns on the Carry (Forward Premium) Trade, calculated by dividing its mean return by the maximum of zero and the sum of the mean returns on the Static (Dollar) and Dynamic Trades. See Appendix A for details.

Table 3: Estimates of the Elasticity of Risk Premia with respect to Forward Premia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample		**1 Rebalance**				**3 Rebalance**		
Horizon (months)	1	1	6	12	1	1	6	12
Static T: β^{stat}	0.47*	0.37*	0.56*	0.60*	0.26*	0.18*	0.26*	0.25*
	(0.08)	(0.09)	(0.10)	(0.10)	(0.05)	(0.05)	(0.04)	(0.06)
Dynamic T: β^{dyn}	0.44	0.41	0.36	0.53*	0.28	0.24	0.21	0.26
	(0.25)	(0.25)	(0.32)	(0.26)	(0.15)	(0.15)	(0.15)	(0.15)
Dollar T: β^{dol}	3.11	3.09	3.21	3.72	0.91	0.83	1.44	1.78
	(1.60)	(1.58)	(1.96)	(2.16)	(1.18)	(1.18)	(1.22)	(1.20)
Carry Trade: β^{ct}	0.68*	0.55*	0.62*	0.71*	0.57*	0.45*	0.42*	0.43*
	(0.27)	(0.26)	(0.29)	(0.26)	(0.19)	(0.18)	(0.21)	(0.19)
% ESS Static T	62	54	79	66	56	44	72	62
Forward Premium T: β^{fpp}	0.86*	0.83*	0.85*	1.09*	0.41*	0.37	0.48*	0.60*
	(0.34)	(0.34)	(0.42)	(0.40)	(0.20)	(0.20)	(0.21)	(0.21)
% ESS Dollar T	90	91	94	91	75	76	93	93
N	2706	2706	2631	2541	4494	4494	4374	4230
Sample		**6 Rebalance**				**12 Rebalance**		
Static T: β^{stat}	0.23*	0.15*	0.25*	0.24*	0.34*	0.23*	0.31*	0.30*
	(0.05)	(0.05)	(0.04)	(0.05)	(0.08)	(0.09)	(0.08)	(0.08)
Dynamic T: β^{dyn}	0.19	0.16	0.10	-0.02	0.16	0.13	0.06	-0.01
	(0.14)	(0.14)	(0.12)	(0.06)	(0.11)	(0.12)	(0.09)	(0.05)
Dollar T: β^{dol}	0.87	0.75	1.83	1.56*	1.71	1.61	0.02	-0.23
	(2.59)	(2.60)	(2.14)	(0.70)	(2.26)	(2.27)	(2.04)	(1.35)
Carry Trade: β^{ct}	0.56*	0.45*	0.45*	0.11	0.67*	0.52*	0.57*	0.22
	(0.18)	(0.17)	(0.19)	(0.14)	(0.16)	(0.16)	(0.16)	(0.17)
% ESS Static T	70	58	92	99	90	86	99	100
Forward Premium T: β^{fpp}	0.24	0.20	0.22	0.08	0.30	0.26	0.05	-0.03
	(0.19)	(0.19)	(0.17)	(0.08)	(0.16)	(0.16)	(0.14)	(0.05)
% ESS Dollar T	62	64	96	100	92	94	1	95
N	4842	4842	4712	4556	6019	6019	5874	5626
Bid-Ask Spreads	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Note: Estimates of the elasticity of currency risk premia with respect to forward premia in the cross-currency (β^{stat}), between-time-and-currency (β^{dyn}), and cross-time dimension (β^{dol}) using specifications (7), (9), and (10), respectively. The table also shows the slope coefficients from specifications (12) and (13) and the partial R^2, calculated as $\frac{ESS^d}{ESS^d+ESS^{dyn}}$, $d \in \{stat, dyn\}$, where ESS^{dyn} refers to the explained sum of squares in specification (9) and ESS^{stat}, ESS^{dyn} refer to the explained sum of squares in specifications (7) and (10), respectively. Standard errors are in parentheses. An asterisk denotes statistical significance at the 5% level. Standard errors for β^{stat} and β^{dol} are clustered by currency and time, respectively, whereas the standard errors for β^{dyn}, β^{ct}, and β^{fpp} are Newey-West with 12, 18, and 24 lags for the 1-, 6-, and 12-month horizons, respectively. Where appropriate, we use the Murphy and Topel (1985) procedure to adjust all standard errors for the estimated regressors $\widehat{fp}_i$ and $\widehat{fp}$ (see Appendix C.2 for details).

Table 4: Bootstrapped Standard Errors for 12 Rebalance Sample

	(1)	(2)	(3)	(4)
Horizon (months)	1	1	6	12
Static T: β^{stat}	0.34*	0.23	0.31*	0.30*
	(0.15)	(0.15)	(0.12)	(0.11)
Dynamic T: β^{dyn}	0.16	0.13	0.06	-0.01
	(0.11)	(0.12)	(0.14)	(0.11)
Dollar T: β^{dol}	1.71	1.61	0.02	-0.23
	(2.36)	(2.40)	(2.88)	(1.76)
Carry Trade: β^{ct}	0.67*	0.52*	0.57*	0.22
	(0.24)	(0.25)	(0.23)	(0.26)
Forward Premium T: β^{fpp}	0.30	0.26	0.05	-0.03
	(0.27)	(0.28)	(0.37)	(0.24)
Bid-Ask Spreads	No	Yes	Yes	Yes

Note: This tables uses our 12 Rebalance sample to block-bootstrap standard errors corresponding to columns 5-8 of Table 3. In this procedure, we treat each of the 12 two-year periods in between re-balancing dates as one block and draw 100,000 random samples with replacement from this set of histories. An asterisk denotes statistical significance at the 5% level.

Table 5: Slope Coefficients from In-sample vs. Out-of-sample Regressions

Sample	**1 Rebalance**		**3 Rebalance**		**6 Rebalance**		**12 Rebalance**	
	$\beta^{stat}_{in-sample}$	β^{stat}	$\beta^{stat}_{in-sample}$	β^{stat}	$\beta^{stat}_{in-sample}$	β^{stat}	$\beta^{stat}_{in-sample}$	β^{stat}
Static Trade	0.53*	0.47*	0.43*	0.26*	0.50*	0.23*	0.65*	0.34*
	(0.13)	(0.08)	(0.09)	(0.05)	(0.11)	(0.05)	(0.12)	(0.08)
	$\beta^{dyn}_{in-sample}$	β^{dyn}	$\beta^{dyn}_{in-sample}$	β^{dyn}	$\beta^{dyn}_{in-sample}$	β^{dyn}	$\beta^{dyn}_{in-sample}$	β^{dyn}
Dynamic Trade	1.13*	0.44	0.83*	0.28	0.71*	0.19	0.74*	0.16
	(0.45)	(0.25)	(0.32)	(0.15)	(0.34)	(0.14)	(0.33)	(0.11)
	$\beta^{fpp}_{in-sample}$	β^{fpp}	$\beta^{fpp}_{in-sample}$	β^{fpp}	$\beta^{fpp}_{in-sample}$	β^{fpp}	$\beta^{fpp}_{in-sample}$	β^{fpp}
F.P. Trade	1.81*	0.86*	0.89*	0.41*	0.77	0.24	1.04*	0.30
	(0.53)	(0.34)	(0.32)	(0.20)	(0.41)	(0.19)	(0.37)	(0.16)

Note: This table compares estimates of the biased in-sample measures $\beta^{stat}_{in-sample}$, $\beta^{dyn}_{in-sample}$, and $\beta^{fpp}_{in-sample}$ (the slope coefficients from the in-sample regressions with currency fixed effects corresponding to (7), (9), and (13)) with estimates of the unbiased measures of the elasticity of risk premia with respect to forward premia from columns 1 and 5 in Table 3. All specifications use one-month forwards and exclude bid-ask spreads. An asterisk denotes statistical significance at the 5% level.

Table 6: Traditional Bilateral Forward Premium Puzzle Regressions

	(1)	(2)	(3)	(4)
Sample	**1 Rebalance**	**3 Rebalance**	**6 Rebalance**	**12 Rebalance**
Australia	3.25	2.15	2.06	1.86
Austria			6.27*	0.09
Belgium			3.03	3.99
Canada	4.36*	2.31*	4.47*	4.73*
Czech Rep.		-3.60	-5.50	5.28*
Denmark	4.43*	1.13	0.96	1.45
ECU			1.49	-4.10*
Euro			3.63	4.38
France			0.73	0.34
Germany			1.90	3.33
Hong Kong	1.05*	1.03*	1.06*	1.14*
Hungary		2.34	8.04	7.40*
Iceland				0.42
India		2.68*	3.63*	2.83*
Indonesia				3.97*
Ireland			4.26	1.86*
Italy			-2.09	-2.59
Japan	2.55*	2.88*	3.32	2.03
Korea			-2.45	-2.52
Kuwait	-1.94*	-2.08*	-2.00*	-1.78*
Malaysia	-1.96*	-1.72	-2.61	-1.10
Mexico		-0.73	-0.37	2.01
Netherlands			2.00	1.84
New Zealand	1.10	1.26	-2.06	-1.58
Norway	1.89	-0.12	-1.07	-0.88
Philippines		0.85	3.51	2.77
Poland		-5.99*	-5.80	3.40
Saudi Arabia	1.36*	1.46*	1.47*	1.58*
Sweden	3.37*	0.02	-0.75	-1.25
Singapore	0.74	1.31	1.13	2.66*
Slovak Rep.				11.47*
Spain			5.42*	-3.42
Switzerland	3.59*	2.37*	3.57	4.58*
Taiwan		-0.05	-0.05	0.55
Thailand		0.96	1.07	2.26*
Turkey			-0.99	-0.82
UAE		1.15*	1.15*	1.19*
United Kingdom	2.66	0.63	0.88	0.06
South Africa	2.43*	2.44	2.65*	1.33
$\beta^{fpp}_{in-sample}$	1.81*	0.89*	0.77	1.04*
β^{fpp}	0.86*	0.41*	0.24	0.30

Note: Estimates of the currency-specific elasticity of risk premia with forward premia β_i^{fpp} using the specification $rx_{i,t+1} = \alpha_i + \beta_i^{fpp} fp_{it} + \epsilon_{it}$. An asterisk denotes statistical significance at the 5% level, standard errors (not shown) are Newey-West using 12 lags. 1-month forward contracts used throughout.

Table 7: χ^2 Difference Tests

	(1)	(2)
Sample	**1 Rebalance**	**3 Rebalance**
Null Hypothesis	*p-values*	
$\beta^{dyn} = 0$	0.14	0.30
$\beta^{dol} = 0$	0.02*	0.04*
$\beta^{dol} = \beta^{dyn}$	0.10	0.15

Note: χ^2 difference tests of the ability of restricted linear models of currency risk premia to explain the returns on the forward premium trade documented in columns 1 and 5 of the 1 Rebalance and 3 Rebalance samples in Table 2, under the assumption that the coefficients estimates in column 1 of Table 3 of β^{fpp}, β^{dyn}, and β^{dol} are normally distributed.

Table 8: Currency-specific Elasticities of Risk Premia with Respect to Forward Premia

	(1)	(2)	(3)	(4)
Sample	**1 Rebalance**	**3 Rebalance**	**6 Rebalance**	**12 Rebalance**
Australia	1.03	0.23	-0.26	-0.33
Austria			4.29*	4.40*
Belgium			2.95*	3.79*
Canada	1.20	1.45	1.31	2.84
Czech Rep.		-0.76	2.68	7.30*
Denmark	1.91	0.69	0.56	0.33
ECU			-0.50	-1.25*
Euro			4.29	2.04
France			0.82	0.15
Germany			2.16	3.64
Hong Kong	1.66	1.12	0.20	0.62
Hungary		6.06*	8.69	6.27*
Iceland				-5.93*
India		3.66*	3.44*	3.59*
Indonesia				2.67*
Ireland			1.24	1.18*
Italy			-1.43	-0.27
Japan	0.55	0.80	-0.72	-0.27
Korea			-1.76	-1.05
Kuwait	1.33	1.59	0.44	0.96
Malaysia	-1.64	-2.44	-2.17	-2.46*
Mexico		0.91	0.76	1.96
Netherlands			2.50	3.88
New Zealand	-0.84	-0.19	-1.77	-2.09
Norway	0.55	-0.69	-0.84	-0.95
Philippines		1.03	0.25	1.00
Poland		-3.08	-1.61	5.43*
Saudi Arabia	2.72	2.40	1.40	3.43*
Sweden	3.08*	-0.09	0.16	0.18
Singapore	1.25	0.09	0.27	0.11
Slovak Rep.				21.76*
Spain			1.61	-2.22*
Switzerland	1.59	2.90	3.03	4.50
Taiwan		0.70	1.00	0.07
Thailand		1.55	1.63	1.75
Turkey			-0.27	2.18
UAE		1.21	3.77*	3.21*
United Kingdom	2.86	2.52*	2.83*	-0.58
South Africa	2.34*	2.27*	2.95*	0.92

Note: Currency-specific covariance of risk premia with forward premia β_i^{dyn} are estimated by running equation (22). When we allow multiple entry of currencies (columns 2-3), α_i are specific to each balanced sub-period. An asterisk denotes statistical significance at the 5% level. Standard errors (not shown) are Newey-West using 12 lags. 1-month forward contracts used throughout.

Table 9: Is the US Dollar Special?

	(1)	(2)	(3)	(4)
Sample	**1 Rebalance**	**3 Rebalance**	**6 Rebalance**	**12 Rebalance**
β^{dol}	3.11	0.91	0.87	1.71
	(1.60)	(1.18)	(2.59)	(2.26)
$\sum_i \omega_i \beta_i^{dyn}$	1.13*	0.83*	0.71*	0.74*
	(0.45)	(0.32)	(0.34)	(0.33)
p-val($\beta^{dol} = \sum_i \omega_i \beta_i^{dyn}$)	0.17	0.96	0.95	0.65

Note: This table compares point estimates of β^{dol} from columns 1 and 5 of Table 3 with the weighted average of estimates of β_i^{dyn} from columns 1-4 of Table 8, where $\omega_i = \frac{var_i(fp_{it}-fp_t)}{var(fp_{it}-fp_t-(fp_i-fp))}$. To obtain the p-value of the test $\beta^{dol} = \sum_i \omega_i \beta_i^{dyn}$, we run a bivariate panel regression of $rx_{it} - rx_i$ on both $fp_t - fp$ and $fp_{it} - fp_t - (fp_i - fp))$, and test if the two resulting coefficients are equal. The standard errors in that regression are clustered by time. There is a small discrepancy between β^{dol} estimated from the multivariate regression and the one presented in the first row of this table due to few data exclusions resulting from the data-filtering procedure. See Appendix A for details.

Online Appendix

A Appendix to Section 2

We use two different types of data: foreign exchange data, which comprises spot and forward rates for maturities of 1, 6, and 12 months, and interbank interest rate data, for maturities of 1 and 12 months. All data are monthly, retrieved at the last trading day of the month.

We use an algorithm to clean the foreign exchange data based on departures from Covered Interest Parity (CIP) and discrepancies between different sources of data. The algorithm is described below.

A.1 Interest Rate Data

We use two different sources for interbank interest rate data. The first is sourced from Global Financial Data (GFD). This source comprises interbank rates (mostly local LIBOR rates) for maturities 1 and 12 months. The second source is Datatastream (DS) Eurocurrency rates for the 1- and 12-month maturity, which comprise a smaller cross section of currencies. Generally, these series are virtually equal to each other.

- GFD Interbank rates: mnemonics for these series are IB*ccg*1D and IB*ccg*12D for 1- and 12-month maturities, respectively. *ccg* is the country code for each country in GFD, which are not the official ISO currency codes.
- DS Interbank Eurocurrency rates: mnemonics for 1 and 12 months are EC*iso*1M and EC*iso*1Y, respectively. As mentioned above, DS uses ISO codes. Check in the FX Data subsection for details.

In both cases, we did not use the series for 2, 3, and 6 months because their coverage tends to be less extensive, both in the cross-section and time-series dimension. See the data provider's websites for details on respective detailed methodology.

A.2 Spot and Forward Rates

We use data on dollar-based spot and forward exchange rates from Datastream (DS) to construct currency returns. Datastream contains four sources of these data: World Markets PLC/Reuters (WM/R), Thomson/Reuters (T/R), HSBC, and Barclays Bank PLC (BB). The most comprehensive in terms of currencies is WM/R. However, this series only begins in December 1996. T/R goes back to May 1990. Both HSBC and BB are not available for recent years but have data back to October 1983 (BB) and October 1986 (HSBC) for some currencies. All providers also offer spot exchange rates corresponding to their forward rates. The mnemonics for these series are: *dsiso*SP for spot and *dsiso*1F, -3F, -6F, and -1Y or -YF for 1-, 3-, 6-, and 12-month-maturity forwards. *ds* corresponds to the dataset mnemonic: *TD* for Thomson/Reuters, *BB* for Barclays Bank, and *MB* for HSBC. WM/R has a different structure for spot and forward rates. The mnemonics for spot rates do not have a clear pattern other than some abbreviation of the currency name and the dollar sign in the end (e.g., *AUSTDO$* for the Australian Dollar quote). The forward rates follow the pattern given above for the other sources with mnemonic *US*. Datastream uses the *iso* codes as country codes. To check ISO codes specified by the International Organization for Standardization (ISO), go to *http://www.oanda.com/help/currency-iso-code-country.*

The general rules for mnemonics (e.g., departures from ISO codes) have some exceptions. In addition to mid rates, bid and offer quotes are also available. To distinguish between these three, DS codes have a suffix -Ex where x is B, R, or O, respectively, for bid, mid, and offer quotes. See the data provider's website for details on respective detailed methodology.

In addition to dollar-based data, we complement our spot and forward data with pound-based data from another provider also available through DS listed as BMI. These data include one-month forward and spot rates for 14 European currencies, the US dollar, and Japanese yen from January 1976 onward. These are same as those in Burnside et al. (2006).

In time periods in which they overlap, the data from the different providers are very similar. We assemble a comprehensive panel of dollar-based forward premia and currency returns in three steps. First, we use forward and spot rates from the same source to construct a panel of forward premia and currency returns from each provider. (The data providers vary on the fixing time. Using a forward rate from one source with a spot from another could therefore lead to inaccuracies.) Second, we combine the panels in the following order: When available we use WM/R data, which appears to be the most recent and most accurate source. We fill in missing observations using the Thomson/Reuters, HSBC and Barclays Bank datasets in that order. In a final step, we check the consistency of the data using the following algorithm.

For observations for which we have information on a single dollar-based forward premium, we compare the forward premia to differentials in the interbank rates at the one-month horizon. If the interest rate differential in the Global Financial Data (GFD) data is within 20bps of the interest differential sourced from DS, we exclude the observation if the one-month forward premium deviates from the one-month GFD interest differential by more than 50bps (a dramatic violation of covered interest parity). By this criterion, we exclude Italy 1/1985 and 2/1985; Switzerland 2/1985; Germany 2/1985; United Kingdom 3/1985; Belgium 7/1990;

and Indonesia 12/1997, 3/1998, 5/1998-7/1998, 2/2001-11/2002.

For observations for which we have information on a single forward premium, a forward premium from the pound-based data and information on interest rate differentials from one source, we again check if the one-month forward premium deviates from the interest differential by more than 50bps. If it does, we check the forward premium from the pound-based dataset. If the pound-based forward premium deviates from the interest differential by less than 50bps, we exclude this observation. By this criterion, we exclude Austria 1/1990-2/1990; Spain 9/1987, 5/1988; Ireland 11/1986, 11/1987, 1/1989, 1/1991, 9/1992-11/1992, 1/1993; Belgium 2/1985; and Norway 2/1985.

For observations for which we have information on the forward premium from multiple dollar-based sources and information on interest differentials from one source, we again check if the 1-month forward premium deviates from the interest differential by more than 50bps. If it does we check the forward premium from the alternative sources. If the forward premia from one other source deviates from the interest differential by less than 50bps we substitute this observation. By this criterion we replace Norway 5/1988, Sweden 5/1988, Malaysia 12/1993, and Belgium 10/1987 and 5/1988 with data from BB; and Iceland 2/2009 and Thailand 12/2006, 11/2008 with data from TD.

For observations for which we have information on the forward premium from multiple dollar-based sources and information on interest differentials from both GFD and DS, we check if the interest rate differential in the GFD data is within 20bps of the interest differential sourced from DS. If so, we check if the one-month forward premium deviates from one of the interest differentials by more than 50bps. If it does, we check the forward premium from the alternative sources. If the forward premium from one other source deviates from the interest differential by less than 50bps we substitute this observation. By this criterion, we replace Switzerland 1/1989, Germany 5/1988, France 1/1989, Italy 5/1988, Netherlands 5/1988, United Kingdom 1/1989 with data from BB; and Singapore 10/1997 and Thailand 10/2003 with data from TD.

Following Lustig et al. (2011), we drop South Africa 8/1985 and Turkey before 11/2001 due to large covered interest parity departures we could not verify. Finally, we drop Malaysia 8/1998-6/2005 and Indonesia 1/2003-5/2007 because forward rates are zero.

Our "1 Rebalance," "3 Rebalance," "6 Rebalance," and "12 Rebalance" samples are built with the dollar-based data after applying the above algorithm and exclusions.

In addition, we look at four alternative samples: "1 Rebalance (no fixed)," "LRV," "4 Rebalances (CIP)," and "BER." "1 Rebalance (no fixed)" is the same as "1 Rebalance," excluding Saudi Arabia riyal and Hong Kong dollar. "LRV" is the same as "1 Rebalance" but instead of using our data cleaning algorithm, we use the notes provided in p.8 of Lustig et al.

(2011) to approximate as best as we can the dataset used there. “4 Rebalance (CIP)” is a sample with four rebalances at 6/1983, 12/1989, 12/1997, and 12/2004 where we extended our dollar-based data with both pound-based data and interest rate differentials. Finally, “BER” uses the same pound-based data as Burnside et al. (2006) with the same rebalacing periods as “4 Rebalance (CIP).”

B Appendix to Section 3

B.1 Detailed proofs in Section 3

Lemma 1 *The following identities hold for all* $x_{it}, y_{it} = fp_{it}, rx_{i,t+1}$

$$E[x_t y_{it}] = E[x_t y_t],$$

$$E[x y_{it}] = E[x y_i] = E[x y_t] = E[xy],$$

and

$$E[x_i y_{it}] = E[x_i y_i].$$

Proof. Using the expectations operator (3) and the definition (4) we can write

$$E[x_t y_{it}] = \sum_{t=1}^{T} \sum_{i=1}^{N} \frac{1}{NT} \int (x_t (y_{it} - y_t) + x_t y_t)\, dF_{it}(rx_{it+1}, fp_{it}, fp_{jt}, ...).$$

Now note that $(y_{it} - y_t)$ does not vary across t, such that

$$\sum_{t=1}^{T} \sum_{i=1}^{N} \frac{1}{NT} \int (x_t (y_{it} - y_t))\, dF_{it}(rx_{it+1}, fp_{it}, fp_{jt}, ...) = 0,$$

and thus $E[x_t y_{it}] = E[x_t y_t]$. The proof for the remaining identities follows analogously. ■

B.2 The Carry Trade is neutral with respect to the US dollar

To see this formally, note that the return on an equally weighted portfolio of all foreign currencies relative to the US dollar is $rx_{t+1} = \sum_i \frac{1}{N} rx_{i,t+1}$. In addition, we have that

$$E[rx_{t+1}(fp_{it} - fp_t)] = 0,$$

such that

$$E[(rx_{i,t+1} - rx_{t+1})(fp_{it} - fp_t)] = E[rx_{i,t+1}(fp_{it} - fp_t)]. \tag{27}$$

The returns to the carry trade are thus uncorrelated with the returns on the US dollar.

C Appendix to Section 4

C.1 Detailed derivation of (8)

Re-writing the second term on the right-hand side of (6) yields

$$\begin{aligned}
E\left[rx_{i,t+1}\left(fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)\right)\right] &= E\left[\left(rx_{i,t+1}-rx_{t+1}-(rx_i-rx)\right)\left(fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)\right)\right] \\
&\quad +E\left[\left(rx_{t+1}+(rx_i-rx)\right)\left(fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)\right)\right] \\
&= cov\left(rx_{i,t+1}-rx_{t+1}-(rx_i-rx),fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)\right) \\
&\quad +E\left[rx_i\left(fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)\right)\right] \\
&= \beta^{dyn}var\left((fp_{i,t}-fp_t)-\left(\widehat{fp_i}-\widehat{fp}\right)\right)+ \\
&\quad E\left[rx_i\left(fp_{it}-fp_t-(fp_i-fp)+(fp_i-fp)-\left(\hat{fp}_i-\hat{fp}\right)\right)\right].
\end{aligned}$$

We again get the first equality from adding and subtracting $rx_{t+1}+(rx_i-rx)$. The second equality again follows from the fact that $\left(fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)\right)$ is zero in expectation and does not vary across t. The third equality then follows from re-writing the covariance as an OLS regression coefficient where

$$\beta^{dyn}=cov\left(rx_{i,t+1}-rx_{t+1}-(rx_i-rx),fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)\right)/var\left((fp_{i,t}-fp_t)-\left(\widehat{fp_i}-\widehat{fp}\right)\right)$$

is the slope coefficient from regression (9).

Similarly, we can rewrite the third term on the right-hand side of (6) as

$$\begin{aligned}
E\left[rx_{i,t+1}\left(fp_t-\hat{fp}\right)\right] &= E\left[(rx_{it}-rx_i)\left(fp_t-\hat{fp}\right)\right]+E\left[rx_i\left(fp_t-\hat{fp}\right)\right] \\
&= cov\left(rx_{it}-rx_i,fp_t-\hat{fp}\right)+E\left[rx_i\left(fp_t-\hat{fp}\right)\right] \\
&= \beta^{dol}var\left(fp_t-\widehat{fp}\right)+\alpha^{dol},
\end{aligned}$$

where β^{dol} is again the slope coefficient of the regression (10).

C.2 Choice of Standard Errors

Standard errors for estimates of β^{stat} clustered by country because the panel is composed of repeated values in the time-series dimension. Similarly, standard errors for estimates of β^{dol} are clustered by time.

Standard errors for estimates of β^{dyn} are corrected for both heteroskedasticity and serial correlation using a Newey-West adjustment (Bartlett kernel) with a 12-month lag. Such an adjustment is typically smaller than that implied by robust estimation of the standard errors. For horizons larger than one month, we must additionally take into account the fact that returns overlap. Therefore, for 6- and 12-month horizons, the standard errors of estimates of β^{dyn} are clustered by time and additionally corrected for serial correlation at 12- and 24-month lags. Throughout we calculate standard errors for β_i^{dyn}, β_i^{fpp}, and β^{fpp} in the same way as those for β^{dyn}.

Finally, an additional adjustment to the standard errors for estimates of β^{stat}, β^{dyn}, and β^{fpp} is made following Murphy and Topel (1985) to account for the fact that we estimate the average forward premium in a pre-sample.

We also computed an adjustment based on GMM. This method generated very large standard errors, a feature that is documented in the literature (e.g., Hayashi (2000) states that GMM generally leads to imprecise estimates of the variance of an estimator if the time-series span is not long, which is indeed the case in our application). An additional problem in using GMM to estimate jointly both the static and dynamic regressors standard errors is that one cannot use different corrections for each of the regressions, which we argue is important to do. In the end, average forward premia are very precisely estimated given a sample, and thus pre-estimating the average forward premia should not lead to large corrections in the standard errors of the different regression coefficients presented in Table 3. The Murphy Topel two-step correction confirms this and does not lead to large adjustments in any of the standard errors. However, if one is concerned about robustness in the estimation of average forward premia due to sample variance, the Murphy Topel procedure indeed will not address how large the corrections would be. For that purpose, we bootstrap standard errors across blocks of rebalances in Table 4. We choose the 12 Rebalance sample as our population and run our regressions on boostrapped draws with replacement from those original 12 blocks of data. Standard errors presented are for 100,000 draws.

C.3 Detailed proof of Proposition 2

By the properties of an OLS estimate of (9),

$$\beta^{dyn} = \frac{E\left[E_{it}\left(rx_{i,t+1} - rx_{t+1} - (rx_i - rx)\right)\left\{fp_{it} - fp_t - \left(\hat{f}p_i - \hat{f}p\right)\right\}\right]}{var\left(fp_{it} - fp_t - \left(\hat{f}p_i - \hat{f}p\right)\right)}.$$

Taking iterated expectations, adding and subtracting $(fp_i - fp)$ in the curly brackets, and multiplying and dividing with $var\left(fp_{it} - fp_t - (fp_i - fp)\right)$ yields

$$\beta^{dyn} = \left(\beta^{dyn}_{in-sample} + \frac{E\left((rx_{i,t+1} - rx_{t+1} - (rx_i - rx)) \left[(fp_i - fp) - \left(\hat{fp}_i - \hat{fp} \right) \right] \right)}{var\left(fp_{it} - fp_t - (fp_i - fp)\right)} \right) \frac{var\left(fp_{it} - fp_t - (fp_i - fp)\right)}{var\left(fp_{it} - fp_t - \left(\hat{fp}_i - \hat{fp}\right)\right)},$$

where $\beta^{dyn}_{in-sample} = \frac{E((rx_{i,t+1} - rx_{t+1} - (rx_i - rx))[fp_{it} - fp_t - (fp_i - fp)])}{var(fp_{it} - fp_t - (fp_i - fp))}$ is the in-sample estimate from the specification $rx_{i,t+1} - rx_{t+1} - (rx_i - rx) = \beta^{dyn}_{in-sample}\left((fp_{it} - fp_t) - (fp_i - fp)\right) + \epsilon_{i,t+1}$. Now note that the second term in the round brackets is equal to zero and write

$$\beta^{dyn} = \beta^{dyn}_{in-sample} \frac{var\left(fp_{it} - fp_t - (fp_i - fp)\right)}{var\left(fp_{it} - fp_t - \left(\hat{fp}_i - \hat{fp}\right)\right)}.$$

Finally, replace

$$\begin{aligned} var\left(fp_{it} - fp_t - \left(\hat{fp}_i - \hat{fp}\right)\right) &= var\left(fp_{it} - fp_t - (fp_i - fp) + (fp_i - fp) - \left(\hat{fp}_i - \hat{fp}\right)\right) \\ &= var\left(fp_{it} - fp_t - (fp_i - fp)\right) + var\left(fp_i - \hat{fp}_i\right) \end{aligned}$$

and cancel terms to get (14).

By the properties of an OLS estimate of (13),

$$\beta^{fpp} = E\left[E_{it}\left(rx_{i,t+1} - rx_{t+1} - (rx_i - rx)\right) \left\{ fp_{it} - \hat{fp}_i \right\} \right] var\left(fp_{it} - \hat{fp}_i\right)^{-1}.$$

Taking iterated expectations, adding and subtracting fp_i in the curly brackets, and multiplying and dividing with $var\left(fp_{it} - fp_i\right)$ yields

$$\beta^{fpp} = \left(\beta^{fpp}_{in-sample} + \frac{E\left((rx_{i,t+1} - rx_{t+1} - (rx_i - rx)) \left[fp_i - \hat{fp}_i \right] \right)}{var\left(fp_{it} - fp_i\right)} \right) \frac{var\left(fp_{it} - fp_i\right)}{var\left(fp_{it} - \hat{fp}_i\right)},$$

where $\beta^{fpp}_{in-sample} = E\left((rx_{i,t+1} - rx_{t+1} - (rx_i - rx))\left[fp_{it} - fp_i\right]\right) var\left(fp_{it} - fp_i\right)^{-1}$ is the in-sample estimate from $rx_{i,t+1} - rx_i = \beta^{fpp}_{in-sample}\left(fp_{it} - fp_i\right) + \epsilon^{fpp}_{i,t+1}$. The second term in the round brackets is equal to zero and so

$$\beta^{fpp} = \beta^{fpp}_{in-sample} \frac{var\left(fp_{it} - fp_i\right)}{var\left(fp_{it} - \hat{fp}_i\right)},$$

which leads to equation (15). Take the definition of β^{stat} from equation (7),

$$\beta^{stat} = E\left[E_{it}\left((rx_i - rx)\right)\left\{\hat{fp_i} - \hat{fp}\right\}\right] var\left(\hat{fp}_i - \hat{fp}\right)^{-1}$$

Taking iterated expectations, adding and subtracting $(fp_i - fp)$ in the curly brackets, and multiplying and dividing with $var\,(fp_i - fp)$ yields:

$$\beta^{stat} = \left(\beta^{stat}_{in-sample} + \frac{E\left((rx_i - rx)\left[\left(\hat{fp}_i - \hat{fp}\right) - (fp_i - fp)\right]\right)}{var\,(fp_i - fp)}\right)\frac{var\,(fp_i - fp)}{var\left(\hat{fp}_i - \hat{fp}\right)},$$

where $\beta^{stat}_{in-sample} = E\left[(rx_i - rx)\{fp_i - fp\}\right] var\,(fp_i - fp)^{-1}$. Because fp and $\hat{fp}$ are constants, one can disregard them when measuring $var\,(.)$. Doing so, leads to equation (16):

$$\beta^{stat} = \beta^{stat}_{in-sample}\frac{var\,(fp_i)}{var\left(\hat{fp}_i\right)} + \frac{E\left((rx_i - rx)\left[\left(\hat{fp}_i - \hat{fp}\right) - (fp_i - fp)\right]\right)}{var\left(\hat{fp}_i\right)}$$

C.4 Derivation of (19)

When proving equation (15), we defined $\beta^{fpp}_{in-sample}$ as $\frac{cov(rx_{it} - rx_i, fp_{it} - fp_i)}{var(fp_{it} - fp_i)}$. Equation (1) introduced β_i, where β_i can be written as $\beta_i = cov_i\left(rx_{i,t+1} - rx_i, fp_{i,t}\right)\left[var\left(fp_{i,t}\right)\right]^{-1}$, because a currency-specific constant is in the regression.

Using the definition of $\beta^{fpp}_{in-sample}$,

$$\beta^{fpp}_{in-sample} = cov\left(rx_{it} - rx_i, fp_{it} - fp_i\right)\left[var\left(fp_{it} - fp_i\right)\right]^{-1}.$$

One can rewrite the above $cov\,(.)$ into an expectation $E\left[(rx_{it} - rx_i)(fp_{it} - fp_i)\right]$. Using the law of iterated expectations and our definition of $E\,[.]$,

$$\begin{aligned}\beta^{fpp}_{in-sample} &= E\left[E_i\left[(rx_{it} - rx_i)(fp_{it} - fp_i)\right]\right]\left[var\left(fp_{it} - fp_i\right)\right]^{-1} \\ &= \sum_i \frac{1}{N} E_i\left[(rx_{it} - rx_i)(fp_{it} - fp_i)\right]\left[var\left(fp_{it} - fp_i\right)\right]^{-1}\end{aligned}$$

After dividing and multiplying each term inside the summation by the currency-level variance of forward premium, $var_i\,(fp_{it})$, one gets

$$\beta^{fpp}_{in-sample} = \sum_i \frac{1}{N} E_i\left[(rx_{it} - rx_i)(fp_{it} - fp_i)\right]\frac{var_i\,(fp_{it})}{var_i\,(fp_{it})}\left[var\left(fp_{it} - fp_i\right)\right]^{-1}.$$

Replace into the above equation the definition of β_i:

$$\beta^{fpp}_{in-sample} = \frac{\frac{1}{N}\sum_i var_i\left(fp_{it}\right)\beta_i}{var\left(fp_{it} - fp_i\right)}.$$

Finally, note that $var\left(fp_{it} - fp_i\right) = E\left[\left(fp_{it} - fp_i\right)^2\right] = E\left[E_i\left[\left(fp_{it} - fp_i\right)^2\right]\right] = \frac{1}{N}\sum_i var_i\left(fp_{i,t}\right)$, which leads to equation (19).

C.5 Details on the coefficients β^{ct} and β^{fpp}

Equation (13) defines $\beta^{fpp} = \frac{E\left[\left(rx_{i,t+1} - rx_i\right)\left(fp_{it} - \hat{fp}_i\right)\right]}{var\left(fp_{it} - \hat{fp}_i\right)}$. Multiply through by $var\left(fp_{it} - \hat{fp}_i\right)$, add and subtract $\left(fp_t - \hat{fp}\right)$ from the term that multiplies $\left(rx_{i,t+1} - rx_i\right)$ inside the expectation, and reorganize to get

$$\beta^{fpp} var\left(fp_{it} - \hat{fp}_i\right) = E\left[\left(rx_{i,t+1} - rx_i\right)\left(fp_{it} - \hat{fp}_i - \left(fp_t - \hat{fp}\right)\right)\right] + E\left[\left(rx_{i,t+1} - rx_i\right)\left(fp_t - \hat{fp}\right)\right].$$

Adding and subtracting $rx_{t+1} - rx$ to the returns term in the first expectation above,

$$\begin{aligned}\beta^{fpp} var\left(fp_{it} - \hat{fp}_i\right) &= E\left[\left(rx_{i,t+1} - rx_i - \left(rx_{t+1} - rx\right)\right)\left(fp_{it} - \hat{fp}_i - \left(fp_t - \hat{fp}\right)\right)\right] + \\ &\quad + E\left[\left(rx_{t+1} - rx\right)\left(fp_{it} - \hat{fp}_i - \left(fp_t - \hat{fp}\right)\right)\right] + E\left[\left(rx_{i,t+1} - rx_i\right)\left(fp_t - \hat{fp}\right)\right].\end{aligned}$$

Note that the first term equals $\beta^{dyn} var\left(fp_{it} - \hat{fp}_i - \left(fp_t - \hat{fp}\right)\right)$, as defined in equation (9). Gathering terms yields

$$\begin{aligned}\beta^{fpp} var\left(fp_{it} - \hat{fp}_i\right) &= \beta^{dyn} var\left(fp_{it} - \hat{fp}_i - \left(fp_t - \hat{fp}\right)\right) + \\ &\quad E\left[\left(rx_{t+1} - rx\right)\left(fp_{it} - \hat{fp}_i\right)\right] + E\left[\left(rx_{i,t+1} - rx_i - \left(rx_{t+1} - rx\right)\right)\left(fp_t - \hat{fp}\right)\right].\end{aligned}$$

The last term is equal to zero since $\left(fp_t - \hat{fp}\right)$ do not vary across i, and $\sum_i \left(rx_{i,t+1} - rx_i\right)/N = rx_{t+1} - rx$. Additionally, the second term simplifies to $E\left[\left(rx_{t+1} - rx\right)\left(fp_t - \hat{fp}\right)\right]$, because $\left(rx_{t+1} - rx\right)$ do not vary across i. Using the definition of β^{dol} from equation (10),

$$\beta^{fpp} var\left(fp_{it} - \hat{fp}_i\right) = \beta^{dyn} var\left(fp_{it} - \hat{fp}_i - \left(fp_t - \hat{fp}\right)\right) + \beta^{dol} var\left(fp_t - \hat{fp}\right).$$

Finally, because

$$\begin{aligned} var\left(fp_{it}-\hat{fp}_i\right) &= var\left(fp_{it}-fp_t+\hat{fp}-\hat{fp_i}+fp_t-\hat{fp}\right) \\ &= var\left(fp_{it}-fp_t+\hat{fp}-\hat{fp}_i\right)+var\left(fp_t-\hat{fp}\right) \\ &\quad \underbrace{+2cov\left(fp_{it}-fp_t+\hat{fp}-\hat{fp}_i, fp_t-\hat{fp}\right)}_{=0}, \end{aligned}$$

one arrives at

$$\begin{aligned} \beta^{fpp} &= \frac{var\left(fp_{it}-\hat{fp}_i-\left(fp_t-\hat{fp}\right)\right)}{var\left(fp_{it}-fp_t+\hat{fp}-\hat{fp}_i\right)+var\left(fp_t-\hat{fp}\right)}\beta^{dyn} \\ &\quad +\frac{var\left(fp_t-\hat{fp}\right)}{var\left(fp_{it}-fp_t+\hat{fp}-\hat{fp}_i\right)+var\left(fp_t-\hat{fp}\right)}\beta^{dol}. \end{aligned}$$

Take the definition of β^{ct} as in equation (12):

$$\beta^{ct}=E\left[\left(rx_{i,t+1}-rx_{t+1}\right)\left(fp_{it}-fp_t\right)\right]\left[var\left(fp_{it}-fp_t\right)\right]^{-1}.$$

Take the expectation term, and add and subtract (rx_i-rx):

$$E\left[\left(rx_{i,t+1}-rx_{t+1}\right)\left(fp_{it}-fp_t\right)\right]=E\left[\left(rx_{i,t+1}-rx_{t+1}-\left(rx_i-rx\right)\right)\left(fp_{it}-fp_t\right)+\left(rx_i-rx\right)\left(fp_{it}-fp_t\right)\right].$$

Note that $E\left[\left(rx_i-rx\right)\left(fp_{it}-fp_t\right)\right]=\beta^{stat}_{in-sample}var\left(fp_i-fp\right)$ as defined in C.3. Moreover, by (16), we have that $\beta^{stat}_{in-sample}var\left(fp_i-fp\right)=\beta^{stat}var\left(\hat{fp_i}-\hat{fp}\right)$, which means

$$E\left[\left(rx_{i,t+1}-rx_{t+1}\right)\left(fp_{it}-fp_t\right)\right]=E\left[\left(rx_{i,t+1}-rx_{t+1}-\left(rx_i-rx\right)\right)\left(fp_{it}-fp_t\right)\right]+\beta^{stat}var\left(\hat{fp}_i-\hat{fp}\right).$$

Add and subtract $\left(\hat{fp}_i-\hat{fp}\right)$ from the forward premia to get

$$\begin{aligned} E\left[\left(rx_{i,t+1}-rx_{t+1}\right)\left(fp_{it}-fp_t\right)\right] &= E\left[\left(rx_{i,t+1}-rx_{t+1}-\left(rx_i-rx\right)\right)\left(fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)+\left(\hat{fp}_i-\hat{fp}\right)\right)\right] \\ &\quad +\beta^{stat}var\left(\hat{fp}_i-\hat{fp}\right). \end{aligned}$$

From equation (9) we know that β^{dyn} is such that

$$E\left[\left(rx_{i,t+1}-rx_{t+1}-\left(rx_i-rx\right)\right)\left(fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)\right)\right]=\beta^{dyn}var\left(fp_{it}-fp_t-\left(\hat{fp}_i-\hat{fp}\right)\right),$$

which means

$$E\left[\left(rx_{i,t+1}-rx_{t+1}\right)\left(fp_{it}-fp_{t}\right)\right] = E\left[\left(rx_{i,t+1}-rx_{t+1}-\left(rx_{i}-rx\right)\right)\left(f\hat{p}_{i}-\hat{fp}\right)\right] +\beta^{dyn}var\left(fp_{it}-fp_{t}-\left(\hat{fp}_{i}-\hat{fp}\right)\right)+\beta^{stat}var\left(\hat{fp}_{i}-\hat{fp}\right).$$

Let $\alpha^{dyn}=E\left[\left(rx_{i,t+1}-rx_{t+1}-\left(rx_{i}-rx\right)\right)\left(\hat{fp}_{i}-\hat{fp}\right)\right]$, and collect terms to get

$$\beta^{ct}=\frac{\alpha^{dyn}}{var\left(fp_{it}-fp_{t}\right)}+\beta^{dyn}\frac{var\left(fp_{it}-fp_{t}-\left(\hat{fp}_{i}-\hat{fp}\right)\right)}{var\left(fp_{it}-fp_{t}\right)}+\beta^{stat}\frac{var\left(f\hat{p}_{i}-\hat{fp}\right)}{var\left(fp_{it}-fp_{t}\right)}.$$

C.6 Derivation of (24)

In Section C.1, we derived equation (8):

$$cov\left(rx_{i,t+1},fp_{it}\right) = \underbrace{\beta^{stat}var\left(\hat{fp}_{i}-\hat{fp}\right)}_{\text{Static Trade}}+\underbrace{\beta^{dyn}var\left(fp_{i,t}-fp_{t}-\left(\hat{fp}_{i}-\hat{fp}\right)\right)+\alpha^{dyn}}_{\text{Dynamic Trade}}+\underbrace{\beta^{dol}var\left(fp_{t}-\hat{fp}\right)+\alpha^{dol}}_{\text{Dollar Trade}}-\alpha^{dol}. \tag{28}$$

Use $\beta^{dyn}var\left(fp_{i,t}-fp_{t}-\left(\hat{fp}_{i}-\hat{fp}\right)\right) = \beta^{dyn}_{in-sample}var\left(fp_{i,t}-fp_{t}-\left(fp_{i}-fp\right)\right)$(equation (14)), together with the definition of $\beta^{dyn}_{in-sample}$,

$$\beta^{dyn}_{in-sample}var\left(fp_{i,t}-fp_{t}-\left(fp_{i}-fp\right)\right)=E\left[\left(rx_{it}-rx_{t+1}-\left(rx_{i}-rx\right)\right)\left(fp_{it}-fp_{t}-\left(fp_{i}-fp\right)\right)\right].$$

Using law of iterated expectations and our definition of $E\left[.\right]$,

$$\begin{aligned}\beta^{dyn}var\left(fp_{i,t}-fp_{t}-\left(\hat{fp}_{i}-\hat{fp}\right)\right) &= \frac{1}{N}\sum_{i}E_{i}\left[\left(rx_{it}-rx_{t+1}-\left(rx_{i}-rx\right)\right)\left(fp_{it}-fp_{t}-\left(fp_{i}-fp\right)\right)\right]\\ &= \frac{1}{N}\sum_{i}var_{i}\left(fp_{it}-fp_{t}-\left(fp_{i}-fp\right)\right)\beta_{i}^{dyn}\\ &= \frac{1}{N}\sum_{i}var_{i}\left(fp_{it}-fp_{t}\right)\beta_{i}^{dyn}.\end{aligned}$$

Replacing into equation (8) leads to (24).

C.7 Details on χ^2 difference tests

This section gives analytical details for the construction of the χ^2 difference test statistics used to calculate the p-values in Table 7. For the hypothesis that $\beta^{dyn} = 0$, we calculate

$$X^r = \frac{\left(\frac{\sum_{it} rx_{it}\left(fp_{it} - \hat{fp}_i\right)}{NT} - \alpha_{dyn} - \alpha_{dol}) - \beta^{dol} \frac{\sum_{it}\left[\left(fp_t - \hat{fp}\right) - \left(fp - \hat{fp}\right)\right]^2}{NT} \right)^2}{Var\left(\beta^{dol} \frac{\sum_{it}\left[\left(fp_t - \hat{fp}\right) - \left(fp - \hat{fp}\right)\right]^2}{NT}\right)}.$$

Similarly, for $\beta^{dol} = 0$,

$$X^r = \frac{\left(\frac{\sum_{it} rx_{it}\left(fp_{it} - \hat{fp}_i\right)}{NT} - \alpha_{dyn} - \alpha_{dol} - \beta^{dyn} \frac{\sum_{it}\left[\left(fp_{it} - fp_t\right) - \left(\hat{fp}_i - \hat{fp}\right)\right]^2}{NT} \right)^2}{Var\left(\beta^{dyn} \frac{\sum_{it}\left[\left(fp_{it} - fp_t\right) - \left(\hat{fp}_i - \hat{fp}\right)\right]^2}{NT}\right)},$$

and for $\beta^{dol} = \beta^{dyn}$,

$$X^u = \frac{\left(\frac{\sum_{it} rx_{it}\left(fp_{it} - \hat{fp}_i\right)}{NT} - \alpha_{dyn} - E\left(rx\left(fp - \hat{fp}\right)\right) - \beta_r^{dyn} \frac{\sum_{it}\left[\left(fp_{it} - fp_t\right) - \left(\hat{fp}_i - \hat{fp}\right)\right]^2}{NT} - \beta_r^{dol} \frac{\sum_{it}\left[\left(fp_t - \hat{fp}\right) - \left(fp - \hat{fp}\right)\right]^2}{NT} \right)^2}{Var\left(\beta_r^{dyn} \frac{\sum_{it}\left[\left(fp_{it} - fp_t\right) - \left(\hat{fp}_i - \hat{fp}\right)\right]^2}{NT} + \beta_r^{dol} \frac{\sum_{it}\left[\left(fp_t - \hat{fp}\right) - \left(fp - \hat{fp}\right)\right]^2}{NT}\right)},$$

where in each case,

$$X^r - X^u \sim \chi_1.$$

C.8 Proof of Proposition 3

First, we generalize our notation to account for returns in units of different currencies. Denote by $fp^j_{i,t}$ the forward premium of currency i against currency j at time t, where for the US dollar, we maintain $fp^{dol}_{i,t} = fp_{i,t}$. By convertibility, we have

$$fp^j_{i,t} = fp_{i,t} - fp_{j,t}, \quad \Delta s^j_{i,t+1} = \Delta s_{i,t+1} - \Delta s_{j,t+1}, \text{ and thus } rx^j_{i,t+1} = rx_{i,t+1} - rx_{j,t+1},$$

where we again use the convention that $\Delta s^j_{i,t+1}$ and $rx^j_{i,t+1}$ refer to values in terms of currency j. If the number of currencies is large, we can also write $fp^j_t = fp_t - fp_{j,t}$ and consequently, $\widehat{fp}^j = \widehat{fp} - \widehat{fp}_j$.

Using these identities, we can show that

$$\begin{aligned} E\left[\left(rx^j_{t+1} - rx^j\right)\left(fp^j_t - \widehat{fp}^j\right)\right] &= E_j\left[\left(rx^j_{t+1} - rx^j\right)\left(fp^j_t - \widehat{fp}^j\right)\right] \\ &= E_j\left[\left(rx_{j,t+1} - rx_j - (rx_{t+1} - rx)\right)\left(fp_{j,t} - \widehat{fp}_j - \left(fp_t - \widehat{fp}\right)\right)\right]. \end{aligned}$$

By definition, the left-hand side of this equation is equal to $cov\left(fp^j_t - \widehat{fp}^j, rx^j_{t+1} - rx^j\right) = \beta^j var\left(fp^j_t\right)$. Similarly, the right-hand side can be replaced with $cov_j\left(fp_{j,t} - fp_t, rx_{j,t+1} - rx_{t+1}\right) = \beta^{dyn}_j var_j\left(fp_{j,t} - fp_t\right) = \beta^{dyn}_j var\left(fp^j_t\right)$, where the last equality again uses the identities above. It follows that $\beta^j = \beta^{dyn}_j$.

D Appendix to Section 4.5

Denote by $fp^j_{i,t}$ the forward premium of currency i against currency j at time t. If $j = USD$, we simply write $fp_{i,t}$ as before. For any two currencies, i and j, it must be true by convertibility (existence of triangular trades) that:

$$\begin{aligned} fp^j_{i,t} &= fp_{i,t} - fp_{j,t} \\ rx^j_{i,t+1} &= rx_{i,t+1} - rx_{j,t+1}. \end{aligned} \tag{29}$$

Taking means over time of the equations in (29) one gets:

$$\begin{aligned} fp^j_i &= fp_i - fp_j \\ rx^j_i &= rx_i - rx_j \end{aligned} \tag{30}$$

Take the mean over currencies of equation (29) to get

$$\begin{aligned} \frac{\sum_{i\neq j} fp^j_{i,t}}{N} &= \frac{\sum_{i\neq j} fp_{i,t}}{N} - fp_{j,t} \\ fp^j_t &= \frac{\sum_i fp_{i,t}}{N} - fp_{j,t}\left(1 + \frac{1}{N}\right) \\ fp^j_t &= fp_t - fp_{j,t}\left(\frac{N+1}{N}\right). \end{aligned}$$

If N is large,

$$\begin{aligned} fp^j_t &= fp_t - fp_{j,t} \\ rx^j_{t+1} &= rx_{t+1} - rx_{j,t+1}, \end{aligned} \tag{31}$$

where we followed the same steps for excess returns.

Finally, take means over currencies j in equation (30):

$$\begin{aligned}\frac{\sum_{i\neq j} fp_i^j}{N} &= \frac{\sum_{i\neq j} fp_i}{N} - fp_j \\ fp^j &= \frac{\sum_i fp_i}{N} - fp_j\left(1+\frac{1}{N}\right) \\ fp^j &= fp - fp_j\left(1+\frac{1}{N}\right).\end{aligned}$$

Using large N,

$$\begin{aligned}fp^j &= fp - fp_j \\ rx^j &= rx - rx_j,\end{aligned} \tag{32}$$

where we used the same steps for excess returns as for forward premia.

Claim 2 *Both β^{stat} and β^{dyn} are independent of the base currency.*
Proof. *By the definition of β^{stat} in equation (7), where the US dollar is the base currency,*

$$\beta^{stat} = cov\left(rx_i - rx, \hat{fp}_i - \hat{fp}\right)\left[var\left(\hat{fp}_i - \hat{fp}\right)\right]^{-1}.$$

Note that $rx_i^j - rx^j = rx_i - rx_j - (rx - rx_j) = rx_i - rx$ and similarly $\hat{fp}_i^j - \hat{fp}^j = \hat{fp}_i - \hat{fp}$ by taking the conditional expectations operator defined in equation (3) through equation (30) and (32). Thus,

$$\beta^{stat} = cov\left(rx_i^j - rx^j, \hat{fp}_i^j - \hat{fp}^j\right)\left[var\left(\hat{fp}_i^j - \hat{fp}^j\right)\right]^{-1}$$

for any base currency j other than the US dollar as well.

By the definition of β^{dyn} in equation (9), where the US dollar is the base currency,

$$\beta^{dyn} = cov\left(rx_{i,t+1} - rx_{t+1} - (rx_i - rx), fp_{i,t} - fp_t - \left(\hat{fp}_i - \hat{fp}\right)\right)\left[var\left(fp_{i,t} - fp_t - \left(\hat{fp}_i - \hat{fp}\right)\right)\right]^{-1}.$$

Note that

$$\begin{aligned}rx_{i,t+1}^j - rx_{t+1}^j - \left(rx_i^j - rx^j\right) &= (rx_{i,t+1} - rx_{j,t+1}) - (rx_{t+1} - rx_{j,t+1}) - (rx_i - rx_j - (rx - rx_j)) = \\ &= rx_{i,t+1} - rx_{t+1} - (rx_i - rx),\end{aligned}$$

and similarly for forward premia by taking the conditional expectations operator defined in *equation (3) through equations (30), (31), and (32). Thus,*

$$\beta^{dyn} = cov\left(rx^j_{i,t+1} - rx^j_{t+1} - \left(rx^j_i - rx^j\right), fp^j_{i,t} - fp^j_t - \left(\hat{fp}^j_i - \hat{fp}^j\right)\right)\left[var\left(fp^j_{i,t} - fp^j_t - \left(\hat{fp}^j_i - \hat{fp}^j\right)\right)\right]^{-1}$$

for any base currency j other than the US dollar as well. ■

E Appendix to Section 5

Replace $\pi_i = E_{it}[rx_i] = E_{it}[fp_i] - E_{it}\Delta s_i = \hat{fp}_i - E_{it}\Delta s_i$ into the definition of β^{stat} (given in Proposition 1) to get equation (26).

Appendix Table 1: Implementing the Carry Trade Using Alternative Weighting Schemes

	1 Rebalance			**3 Rebalance**			**6 Rebalance**			**12 Rebalance**		
Expected Return	4.95	6.43	2.73	4.50	4.60	3.11	4.28	4.60	2.97	5.45	5.29	2.88
Sharpe Ratio	0.54	0.66	0.80	0.54	0.53	0.69	0.50	0.55	0.67	0.69	0.66	0.63
max $ short	0	0	-0.60	0	0	-0.42	0	0	-0.23	0	0	-0.17
max $ long	0	0	0.71	0	0	0.75	0	0	0.69	0	0	0.72
Linear weights	Yes			Yes			Yes			Yes		
HML		Yes			Yes			Yes			Yes	
Equally weighted			Yes			Yes			Yes			Yes

Note: Mean returns and Sharpe ratios achieved by three different implementations of the carry trade across our four main samples. (1) "Linear weights": weight each currency by the difference between its forward premium and the average forward premium across currencies at the time as in equation (2); (2) "HML": separate currencies into five portfolios and go long the currencies in the last portfolio (highest forward premia) and short the currencies on the first portfolio (lowest forward premia) as described in Lustig et al. (2011); (3) "Equally weighted": go long all currencies whose forward premium is larger than zero and short currencies otherwise, normalizing total investment to $1 as described in Burnside et al. (2011).

Appendix Table 2: Comparing Carry Trade and Static Trade

	(1)	(2)	(3)	(4)	(5)	(6)
Panel I: All Countries						
Static Trade						
Returns	4.90	4.90	4.90	5.36	4.51	3.46
SR	0.46	0.46	0.46	0.47	0.43	0.39
Carry Trade						
Returns	10.15	7.18	7.05	6.94	6.43	4.95
SR	1.13	0.64	0.63	0.64	0.66	0.54
Ratio Static/Carry	48%	68%	70%	77%	70%	70%
Max total curr.	36	18	18	13	15	15
Max curr. short	6	3	3	2	3	n.a.
Max curr. long	6	3	3	3	3	n.a.
Currencies added and substracted relative to 1 Rebalance sample	- kwd sar + bef dem frf frf itl nlg	- kwd sar + bef dem frf frf itl nlg	- kwd sar + bef dem frf frf itl nlg	- kwd sar	=	=
Same # curr. in Static & Carry T.	No	Yes	Yes	Yes	Yes	Yes
Prtf. Construction	HML	HML	HML	HML	HML	linear weights
Time Period	1/95-12/09	1/95-12/09	1/95-12/09	1/95-12/09	1/95-6/10	1/95-6/10
Data Source	LRV	LRV	LRV	LRV	Hassan-Mano	Hassan-Mano

Continuing Appendix Table 2: Comparing Carry Trade and Static Trade

	(1)	(2)	(3)	(4)	(5)	(6)
Panel II: Developed						
Static Trade						
Returns	4.23	4.23	4.83	5.60	4.51	3.46
SR	0.46	0.46	0.47	0.41	0.43	0.39
Carry Trade						
Returns	6.75	5.33	6.72	6.06	6.43	4.95
SR	0.64	0.45	0.50	0.43	0.66	0.54
Ratio Static/Carry	63%	79%	72%	92%	70%	70%
Max total curr.	14	14	14	9	15	15
Max curr. short	2	2	2	1	3	n.a.
Max curr. long	6	6	3	2	3	n.a.
Currencies added and substracted relative to 1 Rebalance sample	- hkd kwd myr sar sgd zar + bef dem frf itl nlg	- hkd kwd myr sar sgd zar + bef dem frf itl nlg	- hkd kwd myr sar sgd zar + bef dem frf itl nlg	- hkd kwd myr sar sgd zar	=	=
Same # curr. in Static & Carry T.	No	Yes	Yes	Yes	Yes	Yes
Prtf. Construction	HML	HML	HML	HML	HML	linear weights
Time Period	1/95-12/09	1/95-12/09	1/95-12/09	1/95-12/09	1/95-6/10	1/95-6/10
Data Source	LRV	LRV	LRV	LRV	Hassan-Mano	Hassan-Mano

Note: This table compares our decomposition of carry trade from Table 2 to a similar exercize in Lustig et al. (2011) (LRV). It shows that the procedure in LRV attributes a lower percentage to the static trade predominantly due to the inculsion of additional currencies in the carry trade relative to the static trade. Column (6) of Panel I replicates our results from Table 2. Column (1) replicates closely the results from Table 2 in LRV. The remaining columns show step by step the differences in the two procedures. Panel I uses the full sample of currencies. Panel II uses only 15 developed coutries' currencies: Australia, Belgium, Canada, Denmark, Germany, Euro, France, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the UK as in LRV. Data come from two sources: "LRV" was downloaded on 6/12/2014 from http://web.mit.edu/adrienv/www/Data.html; "Hassan-Mano" denotes the data used throughout this paper. The Static Trade uses only currencies that were available prior to December 1994 in all columns. The Carry Trade is either not constrained to use the same currencies as the Static Trade (1) or constrained to do so (2)-(6). (3) uses the same data as (2) but assigns currencies to portfolios to minimize the difference in the number of countries in all portfolios. (4) uses the same data and portfolio allocation as (3) but excludes euro-zone currencies, which we excluded to get a balanced sample. Column (5) uses our 1 Rebalance sample with 15 currencies, which differs slightly from the sample used in LRV on three dimensions: (1) it goes beyond Dec09 to Jun10; (2) it extends the time coverage for some currencies; and (3) uses a different filtering algorithm for cleaning the data. Column (6) uses the same data as (5), but weights all currencies linearly by their forward premia to construct the static and carry trades, rather than building the HML portfolio. This is Table 1 in this paper.

Appendix Table 3: Currency Portfolios Using Alternative Samples

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	**1 Rebalance (no fixed)**				**LRV**	
Horizon (months)	1	1	6	12	1	1
Static Trade						
$E[rx_{i,t+1}(\widehat{fp}_i - \widehat{fp})]$	3.36	1.38	3.64	3.97	4.10	1.96
Sharpe Ratio	0.44	0.18	0.37	0.38	0.47	0.22
Dynamic Trade						
$E[rx_{i,t+1}(fp_{i,t} - fp_t - (\widehat{fp}_i - \widehat{fp}))]$	1.05	-0.62	-0.25	0.50	1.02	-0.76
Sharpe Ratio	0.18	-0.11	-0.04	0.09	0.16	-0.12
Dollar Trade						
$E[rx_{i,t+1}(fp_t - \widehat{fp})]$	2.86	1.37	3.01	3.82	2.42	1.09
Sharpe Ratio	0.24	0.12	0.26	0.27	0.24	0.11
Carry Trade						
$E[rx_{i,t+1}(fp_{i,t} - fp_t)]$	4.41	2.31	3.70	4.68	5.12	2.93
Sharpe Ratio	0.50	0.26	0.32	0.41	0.55	0.32
% Static Trade	**76%**	**182%**	**107%**	**89%**	**80%**	**163%**
Forward Premium Trade						
$E[rx_{i,t+1}(fp_{i,t} - \widehat{fp}_i)]$	3.90	1.65	2.97	4.48	3.44	1.10
Sharpe Ratio	0.27	0.11	0.20	0.26	0.23	0.07
% Dollar Trade	**73%**	**183%**	**109%**	**88%**	**70%**	**330%**
Sample	**4 Rebalance (CIP)**				**BER**	
Static Trade						
$E[rx_{i,t+1}(\widehat{fp}_i - \widehat{fp})]$	4.87	0.19		2.97	5.11	-6.78
Sharpe Ratio	0.53	0.02		0.21	0.49	-0.63
Dynamic Trade						
$E[rx_{i,t+1}(fp_{i,t} - fp_t - (\widehat{fp}_i - \widehat{fp}))]$	0.93	-2.34		0.11	1.12	-5.94
Sharpe Ratio	0.12	-0.31		0.01	0.21	-1.09
Dollar Trade						
$E[rx_{i,t+1}(fp_t - \widehat{fp})$	4.51	2.55		4.26	6.30	1.54
Sharpe Ratio	0.31	0.17		0.26	0.26	0.06
Carry Trade						
$E[rx_{i,t+1}(fp_{i,t} - fp_t)]$	5.80	2.08		3.62	6.23	-2.78
Sharpe Ratio	0.71	0.25		0.24	0.63	-0.28
% Static Trade	**84%**	**.**		**99%**	**82%**	**.**
Forward Premium Trade						
$E[rx_{i,t+1}(fp_{i,t} - \widehat{fp}_i)]$	5.44	1.57		4.54	7.42	-1.36
Sharpe Ratio	0.27	0.08		0.22	0.30	-0.05
% Dollar Trade	**83%**	**747%**		**99%**	**85%**	**.**
Bid-Ask Spreads	No	Yes	Yes	Yes	No	Yes

Note: This table replicates all calculations in Table 2 using alternative data samples. Columns 1-4 of the top panel uses the 1 Rebalance sample but drops currencies that have a fixed official exchange rate with respect to the US dollar. Columns 5 and 6 of the top and bottom panels use samples that are as close as possible to the samples used in Lustig et al. (2011) and Burnside et al. (2006). Columns 1-4 of the bottom panel use an extended sample using all available US dollar- and UK pound-based forward data as well as forward rates imputed using interest rate data. See Appendix A for details.

Appendix Table 4: Estimates of the Elasticity of Risk Premia with respect to Forward Premia Using Alternative Samples

	1 Rebalance (no fixed)				**LRV**	
	(1)	(2)	(3)	(4)	(5)	(6)
Horizon (months)	1	1	6	12	1	1
Static CT: β^{stat}	0.52*	0.44*	0.63*	0.66*	0.57*	0.45*
	(0.08)	(0.08)	(0.10)	(0.10)	(0.09)	(0.10)
Dynamic T: β^{dyn}	0.41	0.38	0.28	0.46	0.43	0.40
	(0.28)	(0.28)	(0.36)	(0.29)	(0.25)	(0.25)
Dollar T: β^{dol}	3.12	3.11*	3.28	3.80	3.32*	3.23
	(1.61)	(1.57)	(2.25)	(2.24)	(1.59)	(1.82)
Carry Trade: β^{ct}	0.63*	0.50	0.56*	0.65*	0.69*	0.56*
	(0.26)	(0.26)	(0.28)	(0.25)	(0.27)	(0.26)
% ESS Static T	71	68	90	78	73	65
Forward Premium T: β^{fpp}	0.96*	0.92*	0.95	1.22*	0.88*	0.84*
	(0.40)	(0.40)	(0.50)	(0.47)	(0.35)	(0.35)
% ESS Dollar T	94	95	98	95	92	93
N	2334	2334	2269	2191	2616	2616
	4 Rebalance (CIP)				**BER**	
Static CT: β^{stat}	0.21*	0.13*		0.24*	0.26*	0.19
	(0.06)	(0.03)		(0.06)	(0.03)	(0.14)
Dynamic T: β^{dyn}	0.18	0.15		0.21	0.38*	0.19
	(0.11)	(0.11)		(0.12)	(0.15)	(0.11)
Dollar T: β^{dol}	1.83	1.72		2.06	1.31	1.46
	(1.19)	(1.20)		(1.10)	(1.32)	(1.25)
Carry Trade: β^{ct}	0.57*	0.39*		0.35*	0.67*	0.38*
	(0.16)	(0.17)		(0.17)	(0.18)	(0.18)
% ESS Static T	69	55		73	53	68
Forward Premium T: β^{fpp}	0.42*	0.38*		0.64*	0.74*	0.60*
	(0.15)	(0.15)		(0.18)	(0.25)	(0.20)
% ESS Dollar T	94	95		96	88	96
N	5533	5533		5179	3997	3997
Bid-Ask Spreads	No	Yes	Yes	Yes	No	Yes

Note: This table replicates all calculations in Table 3 using alternative data samples. Columns 1-4 of the top panel uses the 1 Rebalance sample but drops currencies that have a fixed official exchange rate with respect to the US dollar. Columns 5 and 6 of the top and bottom panels use samples that are as close as possible to the samples used in Lustig et al. (2010) and Burnside et al. (2006). Columns 1-4 of the bottom panel use an extended sample using all available US dollar- and UK pound-based forward data as well as forward rates imputed using interest rate data. See Appendix A for details.