Global Risks in the Currency Market[1]

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Abstract

This paper uses a numeraire-invariant cross section of currency carry trades to identify global risk factors in the currency market. First, we examine whether the US dollar can play the role of a global risk factor, and demonstrate that it can explain the returns of the invariant cross section only when the US interest rate is relatively low. Second, we reconcile this data feature in a modified version of the model of Lustig, Roussanov and Verdelhan (2014), where the sensitivities to one of its global factors depend on the US interest rate. Third, we design an asset pricing test that is consistent with the implications of the modified model, and evaluate with it a large set of candidate global risk factors, among those suggested in prior studies. We find that only a few combinations of these factors are supported by the test, even marginally, and conclude that global risks still present a challenge to the empirical research of the currency market. Our results, however, highlight the role of the global equity market and the global financial cycle (Rey (2015)) for understanding currency risks.

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1. Introduction

Recent empirical work has strived to identify and rationalize risk factors that can explain return cross sections reflecting currency market risks, as for example in Christiansen, Ranaldo, and Söderlind (2011), Lustig, Roussanov, and Verdelhan (2011), Lettau, Maggiori, and Weber (2014), Della Corte, Ramadorai, and Sarno (2016), Colacito, Croce, Gavazzoni, and Ready (2018), among others. Given the inherently global nature of the currency market, such factors are often viewed as global risk factors, i.e., representing risks to which *all* economies are exposed.[1] The global risk interpretations also agree with the use in asset pricing tests of currency portfolios where country-specific risks are presumably diversified.

Yet, demonstrating empirically the global nature of a risk factor in the currency market is not straightforward. In particular, if a factor explains well the returns of certain test assets or portfolios when these are expressed in some numeraire currency, but not in others, it may not be a global risk factor; the analysis of risk pricing from multiple currency perspectives is not trivial, and prior studies have often focused only on the US perspective. Addressing the impact of the choice of numeraire currency, Verdelhan (2017, Section 4.1) reports results obtained with returns in several currency denominations to demonstrate broad consistency; still, this approach involves burdensome replications of tests and leaves open the question of how to compare statistically the results obtained in different base currencies. Hassan and Mano (2017, Section 3.3) suggest an answer to this question in one specific situation, illustrating the relevance of the issue. Aloosh and Bekaert (2017, Section V.1) discuss some statistical pitfalls in tests with currency returns in different denominations, and propose currency market factors that aggregate several currency perspectives.

This paper offers a new approach for identifying global risk factors in the currency market. First, we construct a novel cross section of test assets which have largely the *same* returns from the perspective of *any* currency; such numeraire-invariant test assets represent all perspectives, circumventing the need to consider in turn returns in all possible denominations. While such test assets can be constructed in many

[1] Global risks require compensation from the perspective of *all* investors, regardless of their home currency, as, for example, the global equity volatility risk in Lustig et al. (2011). Other examples are the global currency volatility risk in Menkhoff, Sarno, Schmeling, and Schrimpf (2012); global imbalance risk in Della Corte, Riddiough, and Sarno (2016); global macro risk in Filippou and Taylor (2017); global growth news risk in Colacito et al. (2018).

ways, we focus specifically on a cross section of carry trades, which have been extensively studied in the currency literature. The carry cross section is described in Section 2, and the robustness of our findings to the carry return patterns studied in Maurer, Tô, and Tran (2018) is established in the Appendix.

Second, we rely on a version of the model of Lustig et al. (2014) (the LRV model) to impose discipline on the search for global risk factors and provide guidance for their economic interpretation. We design an asset pricing test that reflects the predictions of this model version; the test accepts candidate factors if they meet standard statistical criteria *and* are consistent with the key model implications.

The LRV model incorporates global risk factors and offers in a parameterized form a currency cross section, facilitating the construction of realistic carry trades. Besides, being of reduced form, it does not pre-specify the risk factors, and we exploit this flexibility in our search. However, the model does not reproduce certain observed features of the invariant cross section; to reconcile it with the data, we modify the model, while preserving consistency with its original calibration.

The suggested model modification is motivated by our inquiry into the role of the US dollar (the USD) for understanding carry trade returns, which is still a debated topic. We find that the average returns of our carry trades are highly correlated with the betas of these trades with respect to the dollar factor (DOL) of Lustig et al. (2011), indicating that dollar risk is priced in our carry trade cross section; this data feature stems *only* from the subsample where the US interest rate is relatively low, which is a new insight. Section 3 shows, heuristically and with simulations, that the LRV model can generate this trait if the dispersion in the sensitivities of different economies to one of its global risk factors depends on the US interest rate. Confirming such a model modification from a different angle, we show that it also allows to reproduce the sharp difference between the static and dynamic components of the carry trade, as studied in Hassan and Mano (2017), which is observed in the data, but only when the US interest rate is relatively low.

We search for factors that are consistent with the modified LRV model among a large set of variables that have been used in prior studies, and represent equity and bond market risks and real activity, as well as different dimensions of uncertainty. While our pricing tests identify several that could be viable global risk factors in the currency market, these variables still can meet all the requirements imposed by the model, which leads us to conclude that the global risks in the currency market still pose a challenge for the empirical research. The modified LRV model, combined with the invariant cross section, raises the bar for risk factors, and prior empirical results on global risks in the currency market may need to be re-visited.

At the same time, our tests reveal a unique role of the global equity market variable, which alone qualifies to have sensitivities with time-varying dispersion, implying that standard systematic risks may be more relevant for the currency market that typically assumed. We also link the findings from our tests to the Global financial cycle, as in Passari and Rey (2015) and Miranda-Agrippino and Rey (2017); the "boom" regime of this cycle coincides with the periods of relatively high US interest rate, which indicates that the currency market reflects a specific counter-cyclical dispersion in global risk sensitivities.

This paper builds on Lustig et al. (2014), similar to Brusa, Ramadorai, and Verdelhan (2015), Mueller, Stathopoulos, and Vedolin (2017), Verdelhan (2017) and Lustig, Stathopoulos, and Verdelhan (2018), who have explored various extensions of the LRV model. Our version of the model asserts further the link between asymmetric exposure to global risk and carry trade profitability, which has been emphasized in Lustig et al. (2011). Besides, we examine, as done in Verdelhan (2017), the pricing ability of a dollar factor, and use the average forward differential (AFD) of the USD as a key conditioning variable.

On the other hand, we depart from the above studies in several ways. First, instead of long-only currency portfolios, we employ an alternative set of numeraire-invariant long-short trades that are better suited for detecting global risks (Section 2.1 offers a comparison). Second, we demonstrate the dollar's pricing ability in a cross section of carry trades, instead of dollar beta-sorted portfolios, which implies that the separation between dollar and carry risks is not as sharp as previously assumed. Third, we show that the dollar's pricing ability is built mechanically into the modified LRV model, hence the dollar factor (DOL) may not represent a separate source of global risk, in this framework; we search for non-currency market variables that can explain currency market risks. Fourth, we treat the AFD of the USD as a key conditioning variable affecting all economies, and not as an indicator of the differences between the economic conditions of the US and the remaining economies, which allows the modified LRV model to capture better the profitability of the Dollar carry trade of Lustig et al. (2014).[2] Fifth, while the global risk factors in the LRV model are only broadly characterized in Lustig et al. (2014), we aim to identify specific variables that can play the role of such factors; furthermore, our estimations imply that economies exhibit persistent (and possibly counter-cyclical) differences in their exposure to standard systematic risks like the global equity market risk, whereas their exposure to uncertainty-related variables tends to be similar on average.

2. Carry trade cross section

Though the returns of any currency trade must ultimately be expressed in some specific currency, the analysis of currency market risks, and of global risks in particular, does *not* have to be restrained by the choice of such a (numeraire) currency, as one can easily construct currency trades with largely the same returns when these are expressed in any currency. This section first points briefly to some issues related to the use of numeraire *non*-invariant test assets in asset pricing tests. Then it describes the particular cross section of invariant trades employed in this paper.

2.1. Non-invariant test assets

We consider here the interest rate sorted currency portfolios as in Lustig et al. (2011), with monthly data available at Verdelhan's website ("All countries" version, without transaction costs), which we extend till 11/2016. The six portfolios correspond to long positions in all other currencies against the USD; when expressed in different currencies, the returns of these long-only portfolios are not highly correlated, because when re-denominating such a return, one adds, approximately, the change in the exchange rate between the two base currencies, which can be of similar magnitude as the return itself.

Table 1 shows results from replicating the test of a two-factor model with the DOL (average of the six portfolio returns) and HML (return difference between the portfolios with highest and lowest forward

[2]Note that this profitability cannot be explained with the differences between the marginal utilities of US and non-US investors, as previously argued, because Dollar carry is numeraire-invariant and, therefore gives US and non-US investors, at each point in time, largely the same returns, in their *own* currencies.

differentials) factors on the original six portfolios, and on the same portfolios re-denominated in each of the remaining G-10 currencies. Each column in the table refers to the base currency displayed in the first row, and P1 to P6 denote the six portfolios.[3] The table shows the average returns, intercepts (alphas) and slopes (betas) from time-series regressions of the portfolio returns on the two factors, and the corresponding R^2's. The differences between the columns of the table are very notable, with respect *both* to the signs and magnitudes of the estimates, and their statistical significance. The reported R^2 also vary widely, averaging above 80% for the USD perspective, but below 10% for the GBP perspective. These disparities pose a non-trivial challenge for the study of the global nature of the risks reflected in the two factors.

We recognize that some patterns in the table can be rationalized. For example, the β_{DOL} estimates are typically negative for the non-USD perspectives, as the respective portfolios are long the USD, unlike the DOL factor; similarly, the β_{HML} estimates are negative (positive) for the high (low)-yield currency perspectives, as the respective currencies are typically held long (short) in the HML factor. Further, the differences among the numbers on each row in the first four panels of the table are fairly stable across the six rows in a panel, because at each point in time re-denomination amounts, approximately, to adding the same number to the return of each portfolio, as mentioned above. Another example is the large R^2 for the USD perspective, which can be naturally attributed to the DOL factor representing the same perspective. While potentially informative, however, the search for such patterns would complicate significantly the analysis, and this motivates our alternative approach based on numeraire-invariant test assets.

Given our main focus on global risks, the last two rows in Table 1 are of particular interest. They show the prices of risk (lambdas) for the two factors, with standard errors estimated via GMM (see also Appendix D), and again for each currency perspective. The estimates of λ_{HML} are typically statistically significant and thus consistent with the claim that HML can be seen as a global risk factor in the currency market, although the two exceptions (the AUD and JPY perspectives) may pose a statistical challenge to

[3]The G-10 currencies are the New Zealand dollar (NZD), Australian dollar (AUD), British pound (GBP), Norwegian krone (NOK), Swedish krona (SEK), Canadian dollar (CAD), Euro (EUR), Swiss franc (CHF) and Japanese yen (JPY), whereby the German mark is used (DEM) prior to 1999 instead of the Euro, and our sample period is 12/1984 to 11/2016. The data source is Barclays Bank, via Datastream.

this claim. On the other hand, the estimates of λ_{DOL} vary widely, being large and statistically significant for the AUD, CAD and JPY perspectives, and do not warrant an unambiguous conclusion.

For a further clarification, we repeat the same tests using the average forward differential (AFD) of the USD as a conditioning variable, following Lustig et al. (2014) and Verdelhan (2017). We report separately the prices of risk (lambdas) for the subsamples where the AFD is negative (first two lines in the table insert below) or positive (the next two lines):

	NZD	AUD	GBP	NOK	SEK	CAD	USD	EUR	CHF	JPY
λ_{DOL}	-4.93	2.96	-1.27	-0.09	-3.71	-0.49	-1.69	-0.16	0.42	-2.56
λ_{HML}	8.91**	4.89	10.40**	10.19**	11.02**	10.08**	10.23**	10.27**	10.04**	11.10**
λ_{DOL}	13.86**	14.01**	0.76	1.16	-0.78	9.07**	4.35**	1.85	4.54*	10.49**
λ_{HML}	6.57*	3.34	4.47**	5.26**	5.23**	5.33**	5.71**	6.07**	6.24**	1.89

Whereas the estimates of λ_{HML} remain mostly significant in each of the two AFD regimes, there is a clear distinction with respect to the λ_{DOL} estimates: they are small and *never* significant when $AFD < 0$, but are typically much larger in magnitude and more often significant when $AFD > 0$ (including that for the USD perspective). This distinction highlights a possible link between carry trades, dollar risk and the AFD regimes, which is explored further in this paper.

Overall, non-invariant test assets, as the above six portfolios, may not be suitable for the study of global risks in the currency market. The invariant test assets considered next present an alternative which, among other features, avoids the analysis of a host of different currency perspectives, which may raise non-trivial statistical issues.

2.2. Cross section of invariant carry trades

Unlike the interest rate sorted portfolios which represent long-only positions against certain currency, the numeraire-invariant test assets that we consider are long-short trades, further discussed in Appendix A. The invariance follows from the fact that, roughly speaking, when re-denominating the return of such an asset, the change due to the long side of the trade is offset by the change due to its short side. While, in principle, such test assets can be constructed in many ways, we focus on a cross section of carry trades, which have been extensively studied in the currency literature and offer modeling advantages.

The carry trades in our invariant cross section are constructed from the G-10 currencies. While bid and ask quotes are also available, it has been argued that they likely overestimate actual transaction costs (e.g., Lyons (2001)); we ignore these costs, which helps maintain the invariance. Otherwise, the trade construction is standard, following prior carry research and practice.[4]

To ensure numeraire invariance, the trades *can* include the USD, so when the USD is among the three highest- or lowest-yielding currencies, the position in it has a guaranteed zero return from the USD perspective. However, the return of the USD position is non-zero from all other perspectives. Identically zero returns in the numeraire currency are an inherent feature of trades with numeraire-invariant returns, and investable indexes like those offered, for example, by Deutsche Bank share this invariance feature.

Specifically, we consider the cross section of all trades that use all possible combinations of *eight* out of the ten G-10 currencies; the total number of these trades is 45 and further details are provided in Appendix B. While one can similarly construct smaller or larger invariant cross sections, we have verified that if nine currencies are used for each trade (hence the cross section has a total of 10 trades), the returns of these trades are highly correlated. On the other hand, if seven or fewer currencies are used in each trade, then the number of trades in the cross section grows quickly, while the length of our return time-series remains fixed. Nevertheless, all three cross sections can reproduce the relation between carry returns and the dollar factor that plays a key role in this paper, as shown in the next section.

2.3. Average returns and DOL betas in the carry cross section

In a first application of the invariant carry trades, we revisit the ability of the DOL factor to explain the returns in this cross section, and hence its ability to serve as a global risk factor; recall that no clear

[4]At the end of each month we sort the currencies in each trade according to their forward differentials. Then we go long (short) the top (bottom) three currencies in the ranking, with equal weights, and drop from the trade the currencies in the middle, as in the HML factor of Lustig et al. (2011) and various investable currency indexes. As in Burnside et al. (2011) we assume that at the beginning of the trade the three long positions sum to half a dollar in value, as do the three short positions, which implies that the payoff in each period is generated with the same investment of one dollar. All trades are re-balanced at the end of each month.

conclusion in this respect could be made when using the interest rate sorted portfolios in Section 2.1. For simplicity and easier mapping into the LRV model in the next section, we examine the DOL factor alone, and not together with HML - since the correlation between DOL and HML is relatively low, this simplification does not affect much the conclusions. Besides, we define from now on DOL to be the return of an equally weighted portfolio of long positions in all G-10 currencies against the USD, but verify that using the original DOL factor yields very similar results. As previously, we consider both the full sample and the two subsamples where the AFD of the USD is positive or negative, respectively, with one clarification:

[Figure 1 about here.]

Figure 1 plots the time series of the AFD in two versions - actual and a three-month moving average, which removes several sharp spikes and reveals clearly that the relatively high US interest rates, and hence negative AFD are concentrated in two episodes during 1995-2001 and then 2005-2007 (in total about 30% of the sample). Throughout the paper, we use the smoothed version, which highlights the persistent, regime-like nature of the AFD, but check that our main results are robust to this choice (see Appendix E).[5]

We also show robustness results for a smaller cross section of ten trades, each using nine of the G-10 currencies, and a larger cross section of 120 trades, each using only seven of these currencies. The results are from univariate regressions (with a constant) of carry trade returns on DOL, which provide useful intuition; results from formal asset pricing tests are presented in Section 4.

The table insert below first shows, for each set of carry trades, the correlation between average returns and betas, then the 5-th and 95-th percentiles of the respective beta distribution, and, in parentheses, the number of betas that are significant at the 5% confidence level, all obtained in estimations in our full data sample (1985-2016). The remaining columns show the same statistics, estimated solely over the subsamples when the AFD is negative or positive (i.e., the US interest rate is relatively high or low).

[5]Prior studies have pointed out that the standard currency data sets may contain a few questionable forward quotes, and Hassan and Mano (2017) and Koijen, Moskowitz, Pedersen, and Vrugt (2018) have suggested cleaning procedures to address possible data issues. Using a moving average can be seen as an alternative partial remedy which emphasizes the regime feature.

	full				$AFD < 0$ (high US int. rate)				$AFD > 0$ (low US int. rate)			
trades	corr.	β_{5-th}	β_{95-th}	sign.	corr.	β_{5-th}	β_{95-th}	sign.	corr.	β_{5-th}	β_{95-th}	sign.
45	0.75	0.07	0.24	(45)	0.05	-0.28	-0.11	(38)	0.73	0.15	0.33	(45)
10	0.80	0.10	0.22	(10)	0.12	-0.27	-0.13	(10)	0.75	0.17	0.33	(10)
120	0.66	0.03	0.25	(105)	-0.07	-0.30	-0.06	(90)	0.69	0.10	0.35	(120)

Over the full sample period, the correlation between betas and average returns is between 66 and 80%, and the betas are all positive and mostly statistically significant. The pattern is almost identical in the subsample when the AFD is positive, with a somewhat smaller variation in the betas. In contrast, when the AFD is negative the correlation is close to zero, and all betas are negative, and some are not significant, confirming our result obtained with the interest rate sorted portfolios. Therefore, DOL has explanatory power for our return cross section, stemming entirely from the longer subsample with positive AFD.[6]

3. Global risks and carry trades in the LRV model

Any asset pricing test on an invariant cross section can be informative about global risks in the currency market, which is the main subject of this paper, and one approach would be to simply test a large number of candidate factors and then seek possible interpretations. On the other hand, one could develop a model that explicitly postulates the global factor or factors, and then demonstrate consistency with an invariant cross section. This paper takes a middle road and searches among a number of factors, guided by the implications of a model that reflects the pricing ability of DOL for the invariant carry cross section.

We adopt the model of Lustig et al. (2014), which is suitable for our study for several reasons. First, the LRV model provides in a parameterized form a currency cross section, allowing to build realistic carry trades. Second, it features two global risk factors, consistent with the specific time-varying relation between dollar and carry risks that we find in the data, which hints that different factors determine carry returns over

[6]The dominant role of the subsample with low US interest rates can also be seen if instead of DOL one uses Dollar carry, which trades again all currencies against the USD with equal weights, but when the AFD is negative (i.e., the US interest rate is relatively high), takes *short*, not long position in these currencies. In this case we obtain almost identical results for the full sample (with respective correlations of 63, 65 and 59%) and beta percentiles of about 0.15 and 0.30 in each of the three cases.

the two AFD regimes. Third, its reduced form offers the flexibility to search among a large set of candidate global risk factors, while the inherent distinction among its factors can inform the economic interpretation of the test results. Fourth, the relation between DOL and carry returns can be conveniently formalized within the LRV model; we exploit this feature to suggest a modification that better reconciles the model with the data, and then design an asset pricing test that reflects the implications of the modified model.

Explicitly targeting data features related to the USD as discussed in Section 2.3 is also justified by the prior evidence on the global role of the USD, as presented, from different angles, in Adrian, Etula, and Shin (2015), Rey (2015) and Passari and Rey (2015) among others; Shin (2016) argues that in the recent years the USD has replaced the VIX as a global measure of risk appetite. Linking our tests to the USD is desirable, but also presents an additional requirement, thus raising the bar for alternative models or factors.

3.1. The LRV model

The LRV model adapts the affine framework of term structure models of interest rates to the currency market, in the spirit of Backus, Foresi, and Telmer (2001). In the model, markets are complete, currency returns are driven by real variables, and inflation risk is not priced. The model equations, following exactly the notation in Lustig et al. (2014) are reproduced below. Superscripts denote variables for different currencies/economies, except for the respective US variables which have no superscript. The log pricing kernel m^i of economy i (and similar for the US) is:

$$\begin{aligned} -m^i_{t+1} &= \alpha + \chi z^i_t + \sqrt{\gamma z^i_t}u^i_{t+1} + \tau z^w_t + \sqrt{\delta^i z^w_t}u^w_{t+1} + \sqrt{\kappa z^i_t}u^g_{t+1}, \qquad \text{with} \qquad (1) \\ z^i_{t+1} &= (1-\phi)\theta + \phi z^i_t - \sigma\sqrt{z^i_t}u^i_{t+1} \qquad \text{and} \qquad z^w_{t+1} = (1-\phi^w)\theta^w + \phi^w z^w_t - \sigma^w\sqrt{z^w_t}u^w_{t+1}, \end{aligned}$$

where u^i, u^w and u^g are all independent standard normal variables. The interest rates r^i_t and currency excess returns rx^i_{t+1} are:

$$\begin{aligned} r^i_t &= -E_t[m^i_{t+1}] - \frac{1}{2}Var_t[m^i_{t+1}] = \alpha + \left(\chi - \frac{1}{2}(\gamma+\kappa)\right)z^i_t + \left(\tau - \frac{1}{2}\delta^i\right)z^w_t \qquad (2) \\ rx^i_{t+1} &= r^i_t - r_t - \Delta s^i_{t+1} = r^i_t - r_t - m_{t+1} + m^i_{t+1} = \frac{1}{2}(\gamma+\kappa)(z_t - z^i_t) + \frac{1}{2}(\delta - \delta^i)z^w_t \\ &\quad + \left(\sqrt{\delta} - \sqrt{\delta^i}\right)\sqrt{z^w_t}u^w_{t+1} + \sqrt{\gamma}\left(\sqrt{z_t}u_{t+1} - \sqrt{z^i_t}u^i_{t+1}\right) + \sqrt{\kappa}\left(\sqrt{z_t} - \sqrt{z^i_t}\right)u^g_{t+1}, \qquad (3) \end{aligned}$$

where spot exchange rate changes are denoted Δs^i_{t+1}, and exchange rates are expressed as foreign currency units per one USD. All constant parameters are positive and $\chi < \frac{1}{2}(\gamma+\kappa)$. It is also assumed that the parameter δ for the US takes the average value of the δ^i's in the sample. If an over-bar denotes averages across all currencies except for the USD, $AFD_t = \overline{r_t} - r_t = (\chi - \frac{1}{2}(\gamma+\kappa))(\overline{z_t} - z_t)$; if N is large enough, $\overline{z_t} \approx \theta$ and the sign of the AFD depends mostly on z_t. While the above relations refer to real variables, because inflation risk is not priced and all economies share the same expected inflation rates we follow Brusa et al. (2015) and treat them throughout as applying to nominal variables (see also Mueller et al. (2017, Section 5.1)).

Can the LRV model reproduce the patterns in the betas of our carry trades with respect to DOL and their correlation with the average returns of these trades, as observed in the data? Some heuristic arguments pointing to a negative answer to this question are provided in Appendix C. Here we note that the model gives no special role to the AFD, and hence is unlikely to generate a sharp difference in the correlations between DOL betas and average carry returns in the two AFD regimes.

To verify this intuition, we simulate the model using the parameters in Table 5 in Lustig et al. (2014), as also reproduced in the note to our Table 2. We do not, however, include inflation in the simulation, and we set the parameter α to match a nominal average interest rate, as in Brusa et al. (2015) (this parameter is cancelled in all expressions involving carry trade returns and DOL, and does not impact our conclusions).

We simulate 1000 sets of 11 interest rate and 11 exchange rate series, as per equations (2) and (3), assuming that the USD has the middle value of the δ^i's. The first 200 simulated values in each series are discarded to reduce the impact of initial values, and the next 400 are retained, matching the length of our actual series. From each set we construct a cross section of 55 carry trades, with all possible combinations of nine out of the 11 simulated currencies, as well as a DOL factor and the corresponding AFD series. The carry trades go long (short) the three currencies with the highest (lowest) interest rate.

The table insert below reports averages from the 1000 simulations, showing that the model does not reproduce well the correlations between DOL betas and average carry returns, as observed in the data. In fact, while only 1% of the simulated correlations in the full sample exceed 0.72, this correlation is 0.75 in the data; similarly, when $AFD > 0$ the first percentile of the simulated correlations is 0.69, in contrast to a correlation of 0.73 in the data. This model feature remains intact if we keep the same parameters, and assume that not the middle value, but some of the higher possible values of the δ^i's is given to the US, thereby deviating from the assumptions of the original model calibration.

full				$AFD < 0$				$AFD > 0$			
corr	β_{5-th}	β_{95-th}	sign.	corr	β_{5-th}	β_{95-th}	sign.	corr	β_{5-th}	β_{95-th}	sign.
0.091	-0.02	0.05	(24.5)	0.042	-0.27	-0.14	(53.1)	0.073	0.14	0.28	(53.7)

Further departure from the data can be seen with respect to the model-based DOL betas in the full sample, which are now close to zero and significant only in half of the cases (on average 24.5 out of 55).

3.2. Modifying the LRV model

To accommodate the findings from the carry cross section, we seek a model which delivers: (i) high positive correlation between average carry returns and DOL betas over the full sample and when $AFD > 0$, (ii) positive DOL betas over the full sample and when $AFD > 0$, (iii) correlation close to zero and negative DOL betas when $AFD < 0$. It would be also desirable for the model to generate a relatively high Sharpe ratio of the Dollar carry trade, which remained an issue for the original LRV model.[7]

We suggest that these features can be reconciled with the model if we introduce ***time-varying dispersion*** in the parameters δ^i (deltas) that define the sensitivity of different pricing kernels to one of the global factors in the LRV model. We posit that the dispersion is high (low) when the AFD of the USD is positive (negative), and denote by LRV^d the model version with this feature; "d" stands for delta dispersion.

The suggested modification is prompted by the asymmetric results for the pricing ability of the DOL factor, obtained *both* with the interest rate sorted portfolios and the invariant carry cross section: in both

[7] Section 5.5. of Lustig et al. (2014) points out that in their data sample this trade is highly profitable, with a Sharpe ratio close to twice that of the Standard carry trade, whereas simulations from their calibrated model generate a much lower Sharpe ratio for Dollar carry, about half of that for the simulated Standard carry. See also Mueller et al. (2017, Section 5.5) for a similar finding in the context of their own model.

cases the correlation between DOL betas and average returns is much weaker in one of the AFD regimes, i.e., a risk reflected in DOL tends to get a much smaller compensation in average returns in this regime. As per equation (3), expected currency returns have two components: $\frac{1}{2}(\gamma+\kappa)(z_t - z_t^i)$ and $\frac{1}{2}(\delta - \delta^i)z_t^w$, each corresponding to one of the global risk factors, and hence the desired asymmetry could be generated if one of these components is reduced in magnitude in one of the AFD regimes. A regime-dependent dispersion in the δ^i parameters presents one possible way to achieve this effect, while further emphasizing the heterogeneity across economies reflected in the δ^i's, which is a feature of the LRV model.

Recall also that Lustig et al. (2014, Section 6) argue that the AFD of the USD is counter-cyclical, and so the suggested model change can be seen as introducing counter-cyclical dispersion in deltas. Since the deltas are also components of factor loadings of the currency returns in equation (3), their dispersion can be mapped to dispersion among the betas with respect to one of the global factors; if confirmed in the data, the modified model LRV^d can then be linked to a body of literature which has conjectured that the cross-sectional dispersion of market betas and/or other key variables is counter-cyclical.

To demonstrate intuitively the relevance of the suggested model change, we first write down the expressions for DOL and carry returns in the LRV^d model, giving a time subscript to the deltas (except for the middle one) and setting the parameter γ equal to zero, to emphasize the global factors and main effects:

$$DOL_{t+1} = \frac{\kappa}{2}(z_t - \overline{z_t^i}) + \left(\sqrt{\delta} - \overline{\sqrt{\delta_t^i}}\right)\sqrt{z_t^w}u_{t+1}^w + \sqrt{\kappa}\left(\sqrt{z_t} - \overline{\sqrt{z_t^i}}\right)u_{t+1}^g \quad (4)$$

$$rx_{t+1}^{carry} = -\frac{\widetilde{\delta_t^i}}{2}z_t^w - \frac{\kappa}{2}\widetilde{z_t^i} - \widetilde{\sqrt{\delta_t^i}}\sqrt{z_t^w}u_{t+1}^w - \sqrt{\kappa}\widetilde{\sqrt{z_t^i}}u_{t+1}^g, \quad (5)$$

where tilde $(\widetilde{\ })$ denotes weighted average across all currencies in the sample, possibly including the USD, where the weights are those given to individual currencies in a carry trade. All carry trades are symmetric, with three long and three short positions with equal weights, hence the sum of the weights denoted by a tilde equals zero (whereas the sum of the weights denoted by an over-bar equals one).[8]

[8] Note that the expression for a carry trade return does not have explicitly US variables (i.e., without superscript), since these cancel out due to the equal weights of the long and short positions. At the same time, our cross section includes symmetric trades constructed from various subsets of the G-10 currencies. many of these subsets include the USD and in the respective carry trades the weight of the USD, like the weight of any other currency, is determined by its relative interest rate or forward differential.

The covariance between DOL and carry returns is:

$$
\begin{aligned}
COV^{rx^{carry},DOL} &= -\frac{\kappa^2}{4}E[(z_t-\overline{z_t^i})\widetilde{z_t^i}] - E\left[\left(\sqrt{\delta}-\overline{\sqrt{\delta_t^i}}\right)\widetilde{\sqrt{\delta_t^i}z_t^w}\right] - \kappa E\left[\left(\sqrt{z_t}-\overline{\sqrt{z_t^i}}\right)\widetilde{\sqrt{z_t^i}}\right] \\
&\approx -\frac{\kappa^2 N}{4(N-1)}E[z_t\widetilde{z_t^i}] - E\left[\left(\sqrt{\delta}-\overline{\sqrt{\delta_t^i}}\right)\widetilde{\sqrt{\delta_t^i}}\right]\theta^w - \frac{\kappa N}{N-1}E\left[\sqrt{z_t}\widetilde{\sqrt{z_t^i}}\right], \qquad (6)
\end{aligned}
$$

where $E[.]$ denotes *un*conditional expectation, for proper comparison with our findings in the data. To obtain the second (approximate) equality, we rewrite:

$$
z_t-\overline{z_t^i} = \frac{N}{N-1}z_t - \overline{\overline{z_t^i}}, \qquad \text{where} \qquad \overline{\overline{z_t^i}} = \left(\sum z_t^i + z_t\right)/(N-1), \qquad (7)
$$

and note that $\overline{\overline{z_t^i}}$ includes z_t and the z_t^i's all with positive sign, while $\widetilde{z_t^i}$ has an equal number of them with positive and negative signs. Given the assumption $\delta = \overline{\delta_t^i}$, we also have $\sqrt{\delta}-\overline{\sqrt{\delta_t^i}} > 0$.

When delta dispersion is high, the difference in the deltas is the dominant component of the interest rate differentials; the high-delta currencies then tend to have low interest rates and are shorted in the carry trade, while the low-delta currencies have high interest rates and are held long. Due to this effect, $\widetilde{\sqrt{\delta_t^i}}$ is negative and large in magnitude when $AFD > 0$; hence, the second term in (6) contributes to a positive covariance between DOL and the carry return, and, so, to a positive DOL beta. A positive correlation between these betas and the average carry returns now follows, due to the $-\frac{\widetilde{\delta_t^i}}{2}z_t^w$ term in (5), reconciling the model and the data when $AFD > 0$. Note that the first and third terms in (6) will have small impact in this AFD regime, because z_t is uncorrelated with the z_t^i's and will more rarely enter $\widetilde{z_t^i}$ and $\widetilde{\sqrt{z_t^i}}$, which will be dominated by the currencies corresponding to the highest and lowest deltas.

When $AFD < 0$, the deltas are compressed and interest rate differentials are dominated by the terms with z_t and z_t^i. When the USD enters the carry trades, it is held long, as the US interest rate is relatively high in this AFD regime. Therefore, z_t will tend to have positive weight in $\widetilde{z_t^i}$, and the first and third terms in (6) will generate negative covariance and negative DOL beta, as observed in the data for this regime. With small delta dispersion, $\sqrt{\delta}-\overline{\sqrt{\delta_t^i}}$ is small, and so is the relative importance of the second term in (6).

Note however, that in this case DOL beta will be negative due to z_t, but not the remaining z_t^i's in $\widetilde{z_t^i}$.

At the same time, the average carry return depends on the entire $\widetilde{\sqrt{z_t^i}}$ term, as seen in (5). Therefore, the LRV^d model does not predict a strong link between DOL betas and average returns, consistent with the small correlation between betas and average returns observed in the data when $AFD < 0$. The suggested model change can thus generate realistic patterns in correlations and betas in each of the two AFD regimes.

The conjectured time-varying cross-sectional dispersion of deltas, combined with a counter-cyclical AFD point to links with a different body of literature that can be explored. For example, Baele and Londono (2013) show that the cross-sectional dispersion on industry betas is larger during recessions, consistent with the model predictions in Gomes, Kogan, and Zhang (2003) and earlier observations by Chan and Chen (1988). The model in Frazzini and Pedersen (2013) predicts compression of market betas during times of high funding liquidity risk, or when credit is more likely to be rationed. In a similar vein, evidence for counter-cyclical cross-sectional dispersion has been presented in Bloom (2009) for various firm-level variables, Kehrig (2011) for total factor productivity, Christiano and Ikeda (2013) for banks' equity returns, and Dou (2016) for sales and investment. Unlike these studies which refer to the US context, our analysis based on invariant carry trades and the LRV model with global factors suggests that a similar pattern characterizes the global currency market as well, adding to the evidence in Mueller et al. (2017) on the counter-cyclical dispersion in currency correlations.

3.3. Simulating the LRV^d model

Table 2 reports results from simulations of the modified model LRV^d, in three different versions V_1, V_2 and V_3, together with the original LRV model. Time-varying delta dispersion is introduced by defining:

$$\delta_t^i = \delta + \nu_t(\delta^i - \delta), \qquad \text{with } \nu_t \leq 1 \text{ when } AFD < 0, \text{ and } \nu_t > 1 \text{ otherwise} \tag{8}$$

When $AFD > 0$, we set in all versions $\nu_t = 2.5$, which is close to the upper bound on ν_t that ensures that all deltas stay positive in the high-dispersion regime. When $AFD < 0$, the three versions have ν_t equal to 0, 0.5, and 1, respectively. A value of 1 implies no change in the deltas compared to the original model, while a value of zero results in all deltas being the same in this AFD regime (extreme delta compression).

To highlight qualitative effects, we illustrate the performance of the LRV^d with a small set of parameter values; we do not aim for a full calibration of the model, but use it to provide guidance in our search for global risk factors. We also consider different values for the γ and κ parameters. In equations (4) and (5) γ was set to zero, allowing to focus on the global factors. Now it takes the values of zero (for V_1 and V_2) and 0.01 (for V_3), both smaller than the original value of 0.04. We also reduce κ by 5% when $AFD < 0$ and increase it by 5% otherwise for V_2 and V_3.

The top panel in Table 2 reports the averages across 1000 simulations of the annualized means and standard deviations of interest rates and exchange rates, as well as the respective average correlations, for each of the four model versions (original and three modified). As previously, each simulation generates 11 series of interest rates and exchange rates, with which we construct the long-only DOL factor, as well as a Dollar carry (DC) and Standard carry (SC) trades, the latter using the currencies with three highest and three lowest interest rates. The top panel of the table also reports average Sharpe ratios for the DC and SC trades. The bottom panel shows average DOL beta percentiles and correlations between betas and average carry returns, using simulated cross sections of all carry trades constructed from nine out of 11 currencies (a total of 55 trades). As done before, results are shown both for the full sample and the two AFD subsamples. For completeness, the corresponding quantities from the 45 carry trades in our sample are shown in the "data" row.

First, V_1, which only introduces (extreme) delta dispersion, reproduces well some of the interest rate and currency statistics, but fails with respect to the correlation between interest rates. It does, however, generate higher Sharpe ratio for Dollar carry than for Standard carry (0.43 versus 0.36). While still below the one observed in Lustig et al. (2014), this difference is closer to that in our data sample, where both Sharpe ratios are close to 0.50. Importantly, the V_1 version matches well all three correlations between betas and average returns, as well as all beta signs and the magnitude of betas in the full sample, even though the betas in the two simulated AFD regimes are higher in absolute terms than in the data.

To improve the match with the original calibration, the V_2 version increases the delta dispersion in the regime with negative AFD (ν_t equals 0.5). A mild variation in κ brings the correlation between interest rates exactly to its value under the original model (0.11), leaving largely intact the rest of the statistics in the top panel of Table 2. In this version the betas in the two AFD regimes remain large in magnitude.

Finally, the V_3 version increases ν_t to 1, and also includes a small γ, which allows for country-specific risk factors. This version comes closer to the original model with respect to the average standard deviations $\overline{\sigma_r}$ and $\overline{\sigma_r}$, and also matches the beta magnitudes when $AFD < 0$. The betas, however, remain large when $AFD > 0$, and the two Sharpe ratios are now equal.[9]

Overall, these simulations support the LRV^d model, showing that it can largely preserve the main calibrated quantities from the original model, and at the same time match several stylized facts coming from the cross section of invariant carry trades. While the model remains in reduced form, leaving open the question about the identity of the global risks, it imposes certain economic structure by linking delta dispersion to the AFD regimes. It also points to a possible relation with a growing literature that documents similar dispersions beyond the context of the currency market, and seeks risk-based interpretations.

3.4. Static and dynamic carry components and the LRV^d model

The modified model can be further supported independently of DOL and its relation to carry returns. For this purpose we consider the static and dynamic components of the carry trade, as emphasized in Hassan and Mano (2017), which for simplicity are defined here unconditionally, based on the full data sample, where the NZD, AUD and NOK have the highest forward differentials (4.3, 3.1, and 2.1% annualized average), while CHF and JPY have the lowest (-1.5 and -2.4%). The other average forward differentials are 1.8% for GBP, 1.5% for SEK, 0.8% for CAD and -0.4% for EUR.

We examine two cases (denoted I and II) of the static and dynamic components of the Standard carry trade (SC). In case I, the static component employs the five currencies with highest and lowest forward differentials, leaving the remaining five to represent the dynamic component of the trade. In case II, the

[9] Note that all three versions have lower parameter γ than in the original model, giving zero or lower weight to the country-specific risk factors u_t^i, which would presumably induce stronger co-movements, due to the common factors u^w and u^g. Yet, the correlations between the interest rates can remain the same, while those between the exchange rates in fact decrease, indicating that the variable delta dispersion can generate significant heterogeneity among economies or currencies.

static component uses only the three currencies with extreme forward differentials (NZD, AUD and JPY), and the remaining seven account for the dynamic component.

The first three columns in the top panel of Table 3 show the average return of the SC trade and the contribution of its two components (all annualized and in percent). The contribution of a static component is found by setting to zero the return of each "dynamic" currency in the SC return, and similarly for the contribution of a dynamic component. Note that in the full sample the contribution of the static component is about twice bigger than that of the dynamic component, consistent with Hassan and Mano (2017), and this holds even for version II with only three "static" currencies.

The main observation from Table 3, however, is that in the data the two components contribute differently to the SC return over the two AFD regimes. When $AFD < 0$, these contributions are equal (0.44 and 0.45) for case I, where the number of currencies in the two components are also equal (five in each); the contribution of the static component is twice smaller for case II (0.31 vs. 0.59), but then also the number of static currencies is also about twice smaller. In contrast, when $AFD > 0$, the static component is three times bigger than the dynamic one in case I (1.13 vs. 0.36), and 6.8 times bigger in case II with only three static currencies (1.29 vs. 0.19!). The contribution of each component is thus proportional to the number of its currencies in one regime, while the static component strongly dominates in the other regime.

To check the statistical significance of the above differences, consider the statistics:

$$\Omega^{+} = \widehat{STA}_{AFD>0}/\widehat{SC}_{AFD>0} - N_{STA}/N_{SC} \qquad \text{and} \qquad \Omega^{-} = \widehat{STA}_{AFD<0}/\widehat{SC}_{AFD<0} - N_{STA}/N_{SC}, \quad (9)$$

where STA denotes the static component of SC, hats denote time-series averages, and N_{STA}/N_{SC} is the proportion of static currencies. These statistics allow comparisons across situations with different total numbers of currencies and numbers of static currencies, such as we encounter in this paper.

When $AFD < 0$, Ω^{-} is close to zero in the data. When $AFD > 0$, $\Omega^{+} = 1.13/1.49 - 5/10 = 0.26$ in case I, and $\Omega^{+} = 1.29/1.49 - 3/10 = 0.57$ in case II. Calculating Ω^{+} in 1000 random samples from STA and SC, where observations corresponding to negative AFD are set to zero, we find less than 11% of these to be negative in case I, and only 4.6% to be negative in case II, confirming the distinction between the two AFD regimes from the perspective of static and dynamic carry components. These results also imply that the regression-based decomposition of carry trade returns in Hassan and Mano (2017) depends on the AFD of the USD; in particular, the dominant role of the static component in carry trade returns appears to stem entirely from the regime where $AFD > 0$.

Now consider the last three columns in the top panel of Table 3, which show analogous averages obtained in 1000 simulations of the LRV model with 11 currencies. As per equation (2), the currencies with the three highest and three lowest δ^i's are designated as "static", and the ones with middle δ^i's as "dynamic", in case I. Similarly, the currencies with the two highest and two lowest δ^i's are "static", and those remaining are "dynamic" in case II. Of note, in the model, no difference is discernable between the two regimes: both Ω^+ and Ω^- are close to 0.19 for each case, in contrast with what is observed in the data, implying that the model has a built-in permanent dominance of static currencies.

Can the LRV^d model reproduce the higher share of the dynamic component of the carry trade when $AFD < 0$, as observed in the data? Intuitively, if deltas are compressed when $AFD < 0$, the first term in (5) will have little contribution to average carry returns, which will be mostly driven by the second term (with κ and $\widetilde{z_t^i}$). Since the z_t^i's share the same parameters, all currencies, static or dynamic, have about equal chance to enter the carry trade, and hence the per-currency contribution of each component should be about the same, exactly as was observed in the data when $AFD < 0$. On the other hand, when $AFD > 0$ the carry trades in the model are dominated by the currencies with high and low deltas, i.e., the "static" currencies, consistent with the observed higher share of the static component in carry returns in this AFD regime.

The bottom panel of Table 3 shows simulated results for the static and dynamic carry components in the three versions of the LRV^d model. The Ω^- and Ω^+ statistics are about 0.08 and 0.32 for versions V_1 and V_2, and 0.16 and 0.20 for V_3. Recall that in the data Ω^- is close to zero (when $AFD < 0$) and Ω^+ equals 0.26 or 0.57 (when $AFD > 0$), while in the original LRV model $\Omega^+ \approx \Omega^- \approx 0.19$ in each case. Therefore, versions V_1 and V_2 reproduce much better the pattern in the data.

The static and dynamic components thus provide a separate confirmation for the LRV^d model, unrelated to DOL betas. A link between the original LRV model and the decomposition of carry returns is conjectured in Hassan and Mano (2017, page 26), who emphasize the need for modeling certain asymmetry between the USD and other currencies. They also suggest (their Section 3.2) that an additional state variable is needed to reflect the special role of the USD, and our use of the AFD is in line with this suggestion.

4. Searching for global risk factors in the currency market

This section examines in a standard linear asset pricing framework (see Appendix D) a number of variables as possible global risk factors, which are required both to explain the carry return cross section *and* to be consistent with the predictions of the LRV^d model. The approach is promising, since the model reflects a number of data features and can impose realistic restrictions on our search.

4.1. Factor models to be estimated

Among a number of candidate global risk factors in the currency market, we look for pairs f^1 and f^2 that can accommodate a time-varying delta dispersion, as in the LRV^d model. In practice, we estimate three-factor linear models with factors f^1 and f^2, and a third factor that interacts f^1 with an indicator for the sign of the AFD. For each carry trade i, the first-pass regression is of the form:

$$rx_{t+1}^{carry,i} = \alpha^i + \xi_1^i f_{t+1}^1 + \beta_2^i f_{t+1}^2 + \xi_2^i f_{t+1}^1 \mathbb{1}_{AFD_t>0} + \varepsilon_{t+1}^i. \quad (10)$$

The slope coefficient on f^1 is $\beta_1^i = \xi_1^i$ when $AFD_t < 0$, and $\beta_1^i = \xi_1^i + \xi_2^i$ when $AFD_t > 0$.[10]

Two model predictions guide our search: First, ξ_2 should be statistically significant, to reflect the observed differences in risk pricing across the two AFD regimes. Second, β_1 should be larger in magnitude when $AFD > 0$, which can be seen as follows: if f^1 stands for the global factor u_{t+1}^w in equation (5), the

[10] In principle, the indicator $\mathbb{1}_{AFD_t>0}$ should also be included as a separate regressor, allowing to capture shifts in the regression intercept over the two AFD regimes; however, we find that its slope coefficient is negligible in magnitude (about 100 times smaller than the average carry return), almost never statistically significant (either when used together with the other three regressors in our numerous specifications, or alone), and with no impact on the remaining coefficient estimates. We omit this term from our regressions and tests.

beta on this factor should be close to the time-series average of $-\widetilde{\sqrt{\delta_t^i}\sqrt{z^w}}$, which, from (8), is:

$$-\widetilde{\sqrt{\delta_t^i}}\sqrt{\theta^w} = -\sqrt{\widetilde{\delta + \nu_t(\delta^i - \delta)}}\sqrt{\theta^w} \approx -\widetilde{\sqrt{\delta^i}}\sqrt{\nu_t\theta^w}, \tag{11}$$

given the equal weights of the long and short positions in a trade. When $AFD > 0$, the interest rates are dominated by the term with z_t^w in equation (2) and currencies with low (high) deltas tend to have positive (negative) weights in $\widetilde{\sqrt{\delta^i}}$, yielding high beta even before multiplying by $\nu_t > 1$. On the other hand, when $AFD < 0$ not only is $\nu_t \leq 1$, but also interest rates are dominated by the term with κ, and hence low (high) delta currencies can be short (long), further reducing the magnitude of the beta.

Importantly, we do *not* require that the ξ_1 or β_2 estimates be statistically significant, for two reasons. First, unlike in the model, where the two global risk factors are orthogonal, the actual variables that we use are typically correlated; we discuss below factor orthogonalization. Second, because the test assets are long-short trades, they may not detect certain priced risks, if all individual assets that enter these trades have similar betas with respect to the respective factors. Such a knife-edge situation is not ruled out, even though it is not likely to occur in small samples, as has also been pointed out with respect to international asset pricing models with ex-ante symmetric economies (e.g., Colacito et al. (2018), Section 4). The model's explicit prediction on the ξ_2 estimate, however, is the centerpiece of our empirical approach.

4.2. Global financial and economic variables as candidate pricing factors

Finding standard systematic risk factors that can explain carry returns has been a somewhat elusive goal, even though such factors were shown to have some explanatory power, especially in crisis times. We continue this search, with a focus on global variables representing global equity and bond market risk, real activity and various measures of financial and macro-economic uncertainty, and having a sufficiently long history of monthly observations.

The full list of variables (18 in total) is shown in Table 4, and most of them have been used in prior carry research. For example, Christiansen et al. (2011) and Daniel et al. (2017) show that equity and/or bond market risks are priced in carry returns, and Melvin and Taylor (2009) study these effects in a regimeswitching setup; Lettau et al. (2014) find significant role for a downside equity market risk; Ready et al. (2016) show that the commodity and shipping cost indexes CRB and BDI impact carry returns; Lustig et al. (2011) and Menkhoff et al. (2012) find that carry returns reflect global equity volatility and currency volatility risk, respectively; Londono and Zhou (2017) examine the link between the variance risk premium and the forward premium puzzle; Berg and Mark (2017) study the relation between carry trade returns and a number of uncertainty indexes; the VIX index is considered in a carry context in Koijen et al. (2018).

Note that the boundary between global and US-based variables is sometimes unclear. For example, the financial and macro-uncertainty variables of Jurado, Ludvigson, and Ng (2015) are constructed from the conditional volatilities of a large number of financial or macroeconomic series, both global and US-based, the VIX is nominally tied to the US equity market, and the "MPU" variables reflect the uncertainty in the US monetary policy. Still, we include these variables in our set of candidate factors, as their importance for the world economy is documented in prior studies. All variables are in percentage changes, except for the three volatility (EQV, FXV, VIX) and three variance (CV, VP, VRP) variables, which are in first differences of the respective monthly values, the latter three scaled by 100.

We explore all possible *ordered* pairs among the 18 variables. For each pair we interact the first variable with the AFD sign indicator and estimate the respective three-factor model on the carry cross section. We accept a pair if (i) at least half of the 45 estimates ξ_2 are significant at the 5% confidence level, and (ii) $|\xi_1 + \xi_2| > |\xi_1|$ for at least half of the 45 carry trades. In addition, no more than half of the 45 time-series intercepts (alphas) can be significant at the 5% level when both factors are returns.[11]

4.3. Test results

Our empirical findings are quite unexpected: First, only 12 (out of 306!) pairs meet the above requirements. Second, only the global equity market index qualifies for the role of the f^1 factor; in this aspect our results deviate from previous studies, which have often emphasized the role of variables capturing the risk

[11]The average annualized raw carry returns in our sample are on average equal to 2.2%, all of them are statistically significant at the 5% confidence level, and more than half are significant even at the 1% level. Such a significance is desirable in pricing tests which aim to explain average asset returns, but is not always observed, for example, for interest rate sorted portfolios.

in volatility or other uncertainty measures for explaining carry returns and heterogeneity among currencies. Third, even the pairs which meet the requirements do not perform uniformly well, and hence it remains a challenge for the empirical work to find global risk factors in the currency market.

Table 5 shows results for the six pairs with the highest cross sectional R^2 (out of the 12 accepted pairs). The top panel in the table summarizes the output from time series regressions and shows average coefficient estimates and, in parentheses, the number of respective estimates (out of 45) which are significant at the 5% confidence level. It also shows the p-values p_1 to p_4 for the tests evaluating the relevance of adding the interacted term which distinguishes the two AFD regimes. The bottom panel reports results from cross-sectional tests, including p-values for the GRS test statistic when both factors are returns.

First, the slope coefficients ξ_1 are small and rarely significant, which can be consistent with high compression of the deltas in the LRV^d model when $AFD < 0$. In contrast, the slope coefficients ξ_2 are positive and much larger in magnitude, even if not always significant. The average time-series R^2's are relatively low (10 to 17%). Second, the factor price of risk (λ) is highly significant for the equity index and the interacted term. The cross-sectional R^2's are between 43 and 70%, and all three joint tests support the model, with p-values above 0.20. Third, the p-values p_1 to p_4 are rarely below 10%, showing at best marginal statistical advantage of adding the interacted term predicted by the LRV^d model. Fourth, the estimates for β_2 are more often significant; we reiterate that our search procedure focuses on the interacted term involving f^1, and does not depend on estimates related to f^2.

Table 5 also shows results for a three-factor model with DOL as f^1, Standard carry (SC) as f^2, and a term interacting DOL with the AFD sign indicator. Recall that in our context DOL itself should not be viewed as a valid candidate for a global risk factor, as its explanatory power for the invariant carry cross section is obtained mechanically in the LRV^d model, for any factors u^w and u^g; hence, it is more informative about the factor structure in the data. We report on this model to highlight the distinctions with the remaining factor models, and note that no model with SC in the role of f^1 meets our requirements.

In the model with DOL and SC, the alphas are not significant, the time-series R^2 is above 83% on average (due to SC), and the factor risk prices are all significant. Yet, the GRS test statistic rejects the model (the high R^2's make even small intercepts distinguishable from zero in the joint test), the cross-sectional R^2 is not too high (51%), and none of the tests of the nested models supports clearly the need for an interacted term. These findings can be tentatively taken as evidence for the limitations of our three-factor setup, but also highlight the similarity between the pricing ability of DOL for this cross section, which is built in the LRV^d model, and that of the global equity market risk factor.

The main message from Table 5 is that the global equity market factor is the only variable in our set which can play the key role of the f^1 factor, and can be combined with variables (f^2's) of a different economic nature, including a bond index, a proxy for real economic activity (BDI), and measures of macro- and policy uncertainty. While the success of the equity factor, is not unambiguous, given the marginal significance or lack thereof in some aspects, the fact that it stands out among all variables considered indicates that interpretations of carry trade returns based on established systemic risks are feasible.

For completeness, Table Appendix-1 shows results for the remaining six of the 12 factor models which satisfy our model selection requirements. These models deliver lower cross-sectional R^2's, less significant prices of risk, and never come close to supporting statistically the relevance of an interacted term, given the high p-values p_1 to p_4. In fact, these models marginally outperform the model which omits the f^2 factor (also shown in the table) only with respect to the time-series R^2's, implying that a stricter selection procedure may allow even fewer candidate variables to be consistent with the LRV^d model.

At this point we note that our results are robust to three aspects of the empirical strategy followed. First, we have used throughout a carry cross section with returns denominated in USD, which are presumably invariant to the choice of numeraire currency. Second, we have used a smoothed version of the AFD as a key conditioning variable, as explained in Section 2.3. Third, the factors used in the tests are correlated, with correlation coefficients sometimes exceeding 0.50 in magnitude, and not orthogonal, as postulated in the model. Appendix E discusses additional results, which confirm that our conclusions are little affected by these choices.

4.4. AFD regimes

While the identity of the "true" global factors in the currency market remains an open question, we have nevertheless found candidate variables that can explain differently carry returns over the two AFD regimes, which is a major prediction of the LRV^d model. Seeking economic intuition for our results, next we examine in more detail the two regimes.

What variables take significantly different values over these regimes? We consider here some of the key variables from Table 4, together with: (i) total GDP growth, industrial production growth (denoted "IP") and changes in unemployment ("UNEMP") of the OECD economies, (ii) a measure of dealer leverage ("DLEV"), and (iii) measures of global liquidity and cross-border loans ("GLIQ" and "CB"), related to bank lending in foreign currencies in the global economy.[12] We also consider the Global financial cycle factor of Miranda-Agrippino and Rey (2017) (denoted "GFC", with data from the authors' website), which summarizes the common price variation in a large set of risky assets traded around the world, and reflects the US monetary policy (see also Rey (2015) and Passari and Rey (2015)). We use the shorter version of the factor (covering 1990-2012), spliced with the longer one over 1985-1989, with matched values at the first overlapping point. Because the initial value of the factor is undetermined, we consider differences and not percentage changes.

Table 6 shows results from categorical regressions of the above variables on a constant and the indicator function $\mathbb{1}_{AFD_t>0}$. The intercept in such a regression equals the average value of the dependent variable in the regime $AFD < 0$. The sum of the intercept and slope estimate equals the average value when $AFD > 0$, and the p-value for the slope allows us to test whether the two averages are equal. The table shows statistically significant (at the 10% confidence level) differences over the two AFD regimes for two

[12] Bruno and Shin (2015) argue that changes in the leverage of international banks are closely related to other risk measures (like the VIX); these changes impact cross-border bank capital flows and hence the demand for foreign assets, as well as their risk premia, and can generate a feedback loop of changes in leverage, flows, and risk premia, which eventually affects exchange rates. Such a mechanism was first proposed in Borio and Zhu (2012) as a "risk taking channel" of transmission of monetary policy, in a domestic context (see also Shin (2015)). Koijen et al. (2018) examine explicitly the relation between carry trades and global liquidity risk. DLEV is calculated as in Bruno and Shin (2015), with data for US security brokers and dealers' liabilities and equity from the Federal Reserve. GLIQ is from www.bis.org/statistics/gli.htm and CB from www.bis.org/statistics/bankstats.htm, all representing loans from banks in all countries and all types of instruments. About half of the cross-border loans (CB) are in USD and about a quarter in Euro.

global real activity variables, the financial and macro-uncertainty variables of Jurado et al. (2015), and the bank loan variables, in particular when they are expressed as a percentage of the global GDP. Different signs and large differences between the averages (even if not statistically significant) are observed for the dealer leverage, GFC, and most of the volatility/variance variables.

Therefore, the $AFD > 0$ regime is characterized by (i) lower global output growth and growing unemployment, (ii) *de*creasing uncertainty, (iii) stagnant or slowly growing cross-border bank loans in foreign currency, and (iv) depreciating USD. This regime covers about 70% of the sample period, and can be viewed as a "normal" regime. In the remaining 30% of the sample these features are reversed, with stronger real economy and higher liquidity, but also *in*creasing uncertainty, higher US interest rates and appreciating USD, and this can be seen as a "boom" regime.

Figure 2 indicates the periods when $AFD < 0$, the NBER recessions, and also plots the GFC.

[Figure 2 about here.]

It is seen that few years of negative AFD precede the two most recent US recessions, but not the one in 1991; there is also a brief recent period of negative AFD which does not lead into a recession. The graph also shows that the two peaks of the GFC are well aligned with the regime of negative AFD (the available data does not extend to 2015), and indicates that the AFD regimes reflect some global cycle.[13]

Probing further the role of the GFC factor, we include it in asset pricing tests, applying the same criteria as before, and report the results in Table 7. First, the GFC indeed has some pricing ability for the carry cross section, and is included in four models that meet our requirements. Second, while we have used it in all possible ordered pairs, it qualifies only for the role of the f^1 factor. Third, the cross-sectional R^2's, with one exception, are much lower than previously. While the shorter period over which GFC is available (ending in 2012) may impact the results, these findings point to a potentially important link between the GFC and currency market risks, consistent with the LRV^d model, and provide additional justification for

[13] Unlike the global real activity variables (output and unemployment growth) in Table 6, the corresponding US variables do not show even marginally significant differences over the two AFD regimes, with p-values above 0.20.

our treatment of the AFD of the USD as a global (conditioning) variable.

4.5. The challenge of counter-cyclical dispersion

We have argued that the sensitivity of different currencies towards certain global risk exhibits counter-cyclical dispersion: higher in a "normal" regime of the global economy, and lower in a "boom" regime. While counter-cyclical cross-sectional dispersion in various variables has been previously found in a single-economy context (see Section 3.2), the currency market offers new perspectives. For example, it appears to be exposed to a different type of a cyclical dynamics, related to the GFC, which in turn requires new interpretations of the underlying economic mechanisms. The following three examples illustrate such need.

Bloom (2014, page 155) has forcefully argued that counter-cyclical dispersion reflects the behavior of uncertainty over time, stating: "In fact, almost every macroeconomic indicator of uncertainty I know of - from disagreement amongst professional forecasters to the frequency of the word "uncertain" in the *New York Times* - appears to be counter-cyclical." He adds that uncertainty endogenously increases during recessions, as lower economic growth induces greater micro- and macro-uncertainty. Our Table 6, however, has shown that in the AFD regimes higher uncertainty goes together with *higher* economic growth, and vice versa, reflecting different economic dynamics, or possibly a distinction between good and bad uncertainty, in the spirit of Bekaert and Engstrom (2017) or, similarly, Segal, Shaliastovich, and Yaron (2015).

Frazzini and Pedersen (2013, Proposition 4) develop a model predicting that the cross-sectional dispersion in (market) betas should be lower when individual credit constraints are more likely to be binding, and demonstrate that in their sample this dispersion shrinks when credit is more likely to be rationed. However, Table 6 shows that when $AFD < 0$ (and dispersion is arguably lower), most measures of global liquidity growth *exceed* those in the alternative regime, with differences that are typically statistically significant. A liquidity-based interpretation of dispersion in the currency market context may need to be refined.

Bruno and Shin (2015, page 119) find that "... a contractionary shock to US monetary policy leads to a decrease in cross-border banking capital flows and a decline in the leverage of international banks ... associated with an appreciation of the US dollar." Table 6, however, reveals a different angle and in particular associates dollar appreciation with *in*creased bank flows, indicating that the cycle reflected in the AFD regimes requires careful further analysis.

5. Conclusion

A number of recent studies have advanced the understanding of the risks that are priced in the currency market, and have proposed variables that reflect such risks and can play the role of currency risk factors. Given the global nature of the currency market, such variables are typically seen as global risk factors.

This paper contributes by introducing a novel cross section of currency carry trades, which is well-suited for studying the global risks in the currency market, and can provide new insights on the carry trade itself. We use this cross section, first, to derive some stylized facts related to the pricing ability of the USD for carry trades, which have not been previously reported. Second, we turn to the model in Lustig et al. (2014), verify whether it can explain these facts, and then introduce time-varying cross-sectional dispersion in one of the model's parameters and demonstrate the empirical advantages of the modified model LRV^d.

Next, we exploit the insights of the modified model in a search for global risk factors among a range of variables considered in prior carry studies; the role of the model to impose discipline in the search for such factors and their economic interpretation. Our tests show that only a few combinations of previously used factors can meet our requirements, and at the same time highlight the role of a global equity market factor in this context, and possibly of a variable capturing the Global financial cycle proposed in Rey (2015).

Our main insight is that global risks in the currency market are likely related to time variation in the dispersion of sensitivities (of currencies or economies) to global equity risk, whereby high dispersion is associated with "normal" economic environment and low dispersion characterizes "boom" periods. While similar counter-cyclical dispersion has been observed in single economies with respect to a number of economic and financial variables, and has prompted various economic interpretations in the literature, our evidence indicates that the global currency market may require alternatives interpretations, which are left for future research.

Appendix

A. Numeraire-invariant currency trades

Suppose, first, that the USD is the numeraire currency and define the weight of currency i at time t in a trade as w_t^i. With spot and forward exchange rates denoted as S_t^i and F_t^i, and quoted as USD per one unit of foreign currency, the return of a USD-based currency trading strategy over the interval t to $t+1$ is: $r_{t+1}^{USD} = \sum_{i=1}^{N} w_t^i \left(S_{t+1}^i / F_t^i - 1\right)$. Now consider the same strategy, say, from the perspective of a Japanese investor, and express its return in Japanese yen (JPY). If we denote the JPY exchange rates by $\overline{S}_t^i$ and $\overline{F}_t^i$ (quoted as JPY per one unit of currency i), then the strategy's return (in JPY) is:

$$r_{t+1}^{JPY} = \sum_{i=1}^{N} w_i \left(\overline{S}_{t+1}^i / \overline{F}_t^i - 1\right) = \sum_{i=1}^{N} w_t^i \, \overline{S}_{t+1}^i / \overline{F}_t^i - \sum_{i=1}^{N} w_t^i. \tag{12}$$

We assume as key features for the trades under consideration that the short and long legs of the trade have equal weight, and that the positions in the trade are the same for all currency perspectives. These are standard features of carry and other currency trades, both in academic studies and practical implementations. For any such trade, the term $\sum_{i=1}^{N} w_t^i$ at the end of (12) cancels, for any t, and we are left with $r_{t+1}^{JPY} = \sum_{i=1}^{N} w_t^i \overline{S}_{t+1}^i / \overline{F}_t^i$. By triangular arbitrage, we can also derive:

$$r_{t+1}^{JPY} = \left(r_{t+1}^{USD} + \sum_{i=1}^{N} w_i\right) \overline{S}_{t+1}^{USD} / \overline{F}_t^{USD} = r_{t+1}^{USD} \, F_t^{JPY} / S_{t+1}^{JPY}. \tag{13}$$

As the forward to spot ratio in (13) multiplies a return and is close to one, the difference in the returns from the perspectives of the USD and JPY is of a second order. This conclusion can be clarified if we repeat the previous calculation for *log* returns:

$$\begin{aligned} r_{t+1}^{JPY} &= \sum_{i=1}^{N} w_t^i \, \log\left(\overline{S}_{t+1}^i / \overline{F}_t^i\right) = \sum_{i=1}^{N} w_t^i \, \log\left(S_{t+1}^i / F_t^i \;\; \overline{S}_{t+1}^{USD} / \overline{F}_t^{USD}\right) \\ &= \sum_{i=1}^{N} w_t^i \, \log\left(S_{t+1}^i / F_t^i\right) + \sum_{i=1}^{N} w_t^i \, \log\left(\overline{S}_{t+1}^{USD} / \overline{F}_t^{USD}\right) \\ &= \sum_{i=1}^{N} w_t^i \, \log\left(S_{t+1}^i / F_t^i\right) + \log\left(\overline{S}_{t+1}^{USD} / \overline{F}_t^{USD}\right) \sum_{i=1}^{N} w_t^i = \sum_{i=1}^{N} w_t^i \, \log\left(S_{t+1}^i / F_t^i\right) + 0 = r_{t+1}^{USD}, \end{aligned} \tag{14}$$

which verifies that the log returns of our trades, as seen from all perspectives, are *identical*. It follows that the differences between the percentage returns of such trades from different perspectives are due to a convexity correction (see also Bekaert and Panayotov (2017, Appendix I)).

The above derivations do not rely on equality between individual currency positions (i.e., equal weights), but only on equal total long and short sides of the trade. Therefore, various trades can achieve invariance of returns if their implementation respects this equality. Note that the notion of numeraire invariance is not confined to carry trades: momentum, value and other currency trades considered in the literature often are or can be made invariant. However, since the conditioning variable (i.e., trading signal) for carry trades is the interest rate differential, their returns can be easily formalized within the framework of international asset pricing models, and hence carry trades offer a unique advantage from a modeling perspective.

B. Additional details about the cross section of invariant carry trades

If S_t^i denotes the spot exchange rate of currency i at the end of month t, quoted as USD per one unit of foreign currency, and F_t^i is the forward exchange rate at the same time and quoted in the same way, then the percentage return at the end of month $t+1$ of one USD invested at the end of month t in a long or short forward foreign currency contract is $rx_{t+1}^{i,long} = S_{t+1}^i/F_t^i - 1$ or $rx_{t+1}^{j,short} = 1 - S_{t+1}^j/F_t^j$, respectively. The return of a carry trade from t to $t+1$ is then $rx_{t+1} = \sum_{i=1}^3 rx_{t+1}^{i,long}/6 + \sum_{j=1}^3 rx_{t+1}^{j,short}/6$, where i and j index the three currencies at the top and at the bottom of the forward differential ranking.

We consider the cross section of all trades that use all possible combination of eight out of the ten G-10 currencies. The total number of these trades is 45, and the length of the return time-series used is 383 months (12/1984 till 11/2016). The table insert below presents summary statistics:

	avg.ret.	st.dev.	SR	skew
SC	2.38	4.58	0.52	-0.84
max	2.86	4.67	0.71	-0.01
median	2.28	4.13	0.53	-0.61
min	1.21	3.41	0.30	-0.82
prop. below	0.62	0.84	0.49	0.00

The first row shows average returns and return standard deviation (in percent and annualized) for the Standard carry trade (SC) constructed using all G-10 currencies, together with its Sharpe ratio (annualized) and return skewness. The next three rows show the maximum, median and minimum value of the respective statistic across the 45 trades from eight currencies. The last row shows the proportion of the 45 values of each statistic that are below the corresponding one for the SC trade.

The numbers in the table insert illustrate the variation in average returns in the cross section that are to be explained. The highest average return is more than twice larger than the lowest ones, but this spread is somewhat lower than that observed, for example, for the 25 size and book-to-market sorted US equity portfolios over the same sample period (maximum return of 15.9% and minimum of 4.5%). On the other hand, the return correlations within the currency trade cross sections are comparable with those for these equity portfolios: the maximum, median and minimum correlations are 0.96, 0.85 and 0.57 for the carry cross section, and 0.96, 0.80 and 0.44 for the equity cross section.

Note also that the carry trades from eight currencies in many cases exhibit better return profiles than the Standard carry trade (SC) from all G-10 currencies: about 40% of these have higher average return than SC, about half have higher Sharpe ratio, and *all* without exception have less negative skewness.

C. Dollar betas and carry returns in the LRV model

In the LRV model, DOL and the return of an invariant carry trade can be expressed as:

$$\begin{aligned} DOL_{t+1} &= \overline{rx^i_{t+1}} = \frac{1}{2}(\gamma+\kappa)(z_t - \overline{z^i_t}) + \frac{1}{2}(\delta - \overline{\delta^i})z^w_t \\ &\quad + \sqrt{\gamma z_t}u_{t+1} - \overline{\sqrt{\gamma z^i_t}u^i_{t+1}} + \left(\sqrt{\delta} - \overline{\sqrt{\delta^i}}\right)\sqrt{z^w_t}u^w_{t+1} + \sqrt{\kappa}\left(\sqrt{z_t} - \overline{\sqrt{z^i_t}}\right)u^g_{t+1} \qquad (15) \\ rx^{carry}_{t+1} &= -\frac{1}{2}(\gamma+\kappa)\widetilde{z^i_t} - \frac{1}{2}\widetilde{\delta^i}z^w_t - \widetilde{\sqrt{\gamma z^i_t}u^i_{t+1}} - \widetilde{\sqrt{\delta^i}}\sqrt{z^w_t}u^w_{t+1} - \sqrt{\kappa}\widetilde{\sqrt{z^i_t}}u^g_{t+1}, \qquad (16) \end{aligned}$$

where tilde ($\widetilde{\ }$) denotes weighted average across all currencies in the sample, possibly including the USD, where the weights are those given to individual currencies in a carry trade. All carry trades considered are symmetric, with three long and three short positions with equal weights, hence the sum of the weights denoted by a tilde equals zero (whereas the sum of the weights denoted with an over-bar equals one). Furthermore, the second term in (15) cancels, as by assumption $(\delta - \overline{\delta^i}) = 0$.

From equations (15) and (16), note that the shocks in the model are uncorrelated, so the contributions to the *un*conditional covariance between DOL and carry trade returns, if any, should come from products of terms with the same shocks in the two equations, and more precisely from the time-series averages of such products. The first terms in (15) and (16), containing $(z_t - \overline{z_t^i})$ and $\widetilde{z_t^i}$, should not contribute to covariance: from equation (7) in Section 3.2, $\overline{\overline{z_t^i}}$ includes z_t and the z_t^i's all with positive signs, while $\widetilde{z_t^i}$ has an equal number of them with positive and negative signs, so these two terms should not induce covariance between DOL and carry returns. Furthermore, z_t is not correlated with the z_t^i's in $\widetilde{z_t^i}$. Finally, z_t enters $\widetilde{z_t^i}$ with positive or negative signs with equal probability, as $\delta = \overline{\delta^i}$, whereas the z_t in (7) has always a positive sign, and hence these terms also do not generate covariance.

A similar argument can be applied to the terms with u_{t+1} and u_{t+1}^i, as well as to those with u_{t+1}^g in (15) and (16), where again the positive and negative contributions to covariance resulting from z_t and the z_t^i's cancel overall, due to the symmetry of the long and short sides in the carry trade. Crucial for this argument is describing the dynamics of z_t and all z_t^i's with the same parameters, as shown in equation (1).

On the other hand, the terms with u_{t+1}^w could have a non-negligible effect, reflecting three facts: (i) $\widetilde{\delta^i}$ is on average a negative number, because currencies with high δ^i tend to have low interest rate, from equation (2), and will be more likely shorted in the carry trade, and vice versa for currencies with low δ^i; (ii) z_t^w is always positive; and (iii) $\sqrt{\delta} > \overline{\sqrt{\delta^i}}$ due to the convexity of the square root and the assumption $\delta = \overline{\delta^i}$. Importantly, such non-zero covariances will generate some cross sectional correlation between average carry returns (containing $\widetilde{\delta^i} z_t^w$) and DOL betas (containing $\widetilde{\sqrt{\delta^i}} z_t^w$), as observed in the data.

Nevertheless, the actual impact of the terms with u_{t+1}^w is likely to be small, as (i) the convexity correction is of second order, and (ii) the terms with δ^i may not always dominate the interest rates in (2), and hence determine their ranking; deviations of this ranking from that of the δ^i's reduces the magnitude of $\widetilde{\delta^i}$.

D. Design of cross-sectional pricing tests

The pricing kernel (or stochastic discount factor, SDF) is $m_{t+1} = 1 - b'(f_{t+1} - \mu_f)$, where $E(m_{t+1}) = 1$, b is a constant vector of SDF coefficients, f_{t+1} is a vector of risk factors, and $E(f_{t+1}) = \mu_f$. The kernel is normalized when excess returns are used and hence the expectation of the SDF is not identified. The excess percentage returns of the test assets, indexed by i, are denoted by rx^i_{t+1}. The pricing model and its beta representation are:

$$E[rx^i_{t+1} m_{t+1}] = 0 \qquad \text{and} \qquad E[rx^i_{t+1}] = \lambda' \beta^i, \tag{17}$$

with systematic risk exposures for asset i given by the vector β^i, and factor risk prices denoted by λ. The β's are estimated from time-series regressions of returns on the factors, and we then run a cross-sectional regression (without a constant) of average returns on the β's to estimate the λ's.

Standard errors for the coefficient estimates are obtained via GMM, accounting for heteroskedasticity, as in Cochrane (2005, Chapters 12 and 13). We also include one Newey-West lag, as in Lustig et al. (2011). To establish robustness, we also follow Shanken and Zhou (2007) who develop testing techniques which do not impose the null hypothesis that a model is correctly specified, but instead estimate statistics that are valid for potentially mis-specified models as well. Such a conservative estimation approach is justified when different criteria for model validity show sometimes marginal or no significance, and/or do not always agree, and when non-return variables are used as factors, as we do in many of our tests.

We report p-values for the χ^2 statistic, which tests whether the pricing errors are jointly equal to zero (Cochrane (2005, pp. 241-243)), as well as cross-sectional R^2's and approximate finite sample p-values of Shanken's CSRT statistic (mis-specification robust) as in Kan, Robotti, and Shanken (2013). Where appropriate, we also show the p-value for the GRS statistic of Gibbons, Ross, and Shanken (1989). Finally, we show p-values for four tests comparing models that include a term reflecting time-varying delta dispersion with the nested models without such a term. These are the tests that compare cross-sectional R^2's for correctly specified and mis-specified models, as in Kan et al. (2013), the test based on the Hansen-Jagannathan distance as in Li, Xu, and Zhang (2010), and the weighted χ^2 test of Gospodinov, Kan, and Robotti (2013).

E. Three robustness checks

This appendix discusses the robustness of our results in three aspects, related to the construction of the test assets, the AFD variable used in the paper, and the orthogonality of the factors in the LRV model.

As mentioned in the introduction, our carry trade return cross section is only approximately numeraire-invariant. While this invariance holds exactly for log-returns, the percentage returns which are used throughout the paper deviate from this exact feature, due to a convexity correction term. Maurer et al. (2018) have identified a specific (monotonic) pattern in this deviation, whereby the returns (and Sharpe ratios) of carry trades constructed from the perspective of the currencies with the highest interest rates are consistently lower than those taking the perspective of the lowest interest rate currencies. This pattern is confirmed in our sample, where the returns obtained in JPY (the lowest-yielding currency) exceed those in NZD (the highest-yielding currency) by 17% on average (1.99% vs 2.33%). Because the pattern is monotonic, this is the maximum discrepancy among all pairs of currency perspectives in our sample.

We do not expect this deviation from exact invariance to affect our main conclusions, and in particular those from the asset pricing tests; but, because the returns constructed from different currency perspectives exhibit almost perfect correlation (above 0.995 on average, as pointed out in the introduction), for completeness we replicate some results using the carry cross sections constructed from the (extreme) perspectives of the NZD and JPY. Table Appendix-2 corresponds to Table 5 and shows the results for the two currency perspectives one above the other (separated by a line), to facilitate comparison.

Despite minor differences, the two perspectives lead, notably, to practically identical conclusions, which in turn fully agree with those in Section 4.2, obtained from the perspective of the USD. Except for the alphas in the time-series regressions, the magnitudes and significance of the various estimates match closely. The ξ_2 coefficients obtained from the JPY perspective are somewhat smaller, and lose significance in some cases, but all previous conclusions remain intact. This comparison strongly confirms our main premise that the carry cross section used in this paper exhibits an important invariance feature, making it particularly suitable for the study of global risks in the currency market.

The second robustness exercise relates to the AFD of the USD. As clarified in Section 2.3, we use a three-month moving average of the AFD, which effectively ignores the sign changes due to a few extreme moves in the AFD series that revert within one month, and highlights the strong regime-like pattern in the sign of the AFD. It is important to verify that this choice does not materially affect the results.

In Table Appendix-3 we repeat the tests for the models reported in Table 5, using the raw, and not smoothed AFD series. While the results are again consistent with those in Table 5, now the estimate of ξ_2 is smaller in magnitude and less often significant. At the same time, the p-values p_1 to p_4 are below 10%, with just few exceptions (many are even below 5%), in support of the importance of a time-varying dispersion in the loadings on one of the global risk factors. Furthermore, the results from the cross-sectional tests are essentially identical, with or without smoothing the AFD.

Finally, we address the impact of the fact that the factors used in our tests are often correlated, thus deviating from the model assumptions. We repeat the tests from Table 5 (except for DOL and SC), but now using instead of the original f^2 factor its component orthogonal to f^1, defined as: $f^{2,orth} = f^2 - bf^1$, where b is the slope coefficient from regressing f^2 on f^1 and a constant. Table Appendix-4 shows, first, that the ξ_1 estimates are now the same in all six models; they are in fact equal to the regression slopes in univariate regressions with only the f^1 factor, which is also shown in the table (for a proof of this fact see, e.g., Liu, Sercu, and Vandebroek (2015, page 262)); the number of significant estimates is sometimes slightly higher, due to the effect of estimated regressors. (Note that the number of significant estimates differs in some of the six specifications due to the different number of available observations for f^2, as per Table 4.) Second, the λ_2 estimates are somewhat larger in magnitude, and marginally significant in two cases. What is important for our study, however, is that the estimates related to the interacted term and the identity of the factors that meet our requirements remain intact, and so do the various measures of model fit. Therefore, orthogonalizing the two global factors has little effect on our main conclusions.

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Table 1

A two-factor model from different currency perspectives

This table presents results from tests of a two-factor model with the DOL and HML factors of Lustig et al. (2011) on six interest rate sorted currency portfolios (denoted P1 to P6), with data from Verdelhan's website ("All countries" version, without transaction costs), extended till 11/2016. Each column shows results for the test assets re-denominated in the currency displayed in the first row. The five panels show the mean return of each portfolio and intercepts (alphas), both annualized and in %, as well as slopes (betas) from time-series OLS regressions of the monthly portfolio returns on the two factors, and the corresponding R^2's, in %. Statistical significance of an estimate at the 5 (10)% confidence level is denoted by two (one) stars. The last two rows show prices of risk (lambdas, annualized and in %) for the two factors, with standard errors estimated via GMM (see also Appendix D), again for each currency perspective. The sample period is 12/1984-11/2016.

		NZD	AUD	GBP	NOK	SEK	CAD	USD	EUR	CHF	JPY
mean	P1	-6.25**	-3.49	-3.04*	-3.34**	-2.44	-1.74	-1.12	-2.42**	-2.59**	-1.21
	P2	-4.96**	-2.28	-1.81	-2.07	-1.16	-0.52	0.14	-1.09	-1.17	0.30
	P3	-3.62*	-0.93	-0.44	-0.69	0.21	0.86	1.55	0.28	0.19	1.68
	P4	-1.98	0.69	1.22	0.94	1.82	2.53*	3.27**	1.93*	1.86	3.47*
	P5	-0.93	1.79	2.33	2.03	2.92**	3.67**	4.39**	3.03**	2.94**	4.54**
	P6	0.71	3.40*	4.14**	3.86**	4.75**	5.41**	6.21**	4.93**	4.88**	6.45**
α	P1	-0.85	2.36	0.38	0.43	1.48	1.18	-0.71	0.14	-1.10	-2.24
	P2	-1.13	1.99	0.04	0.12	1.20	0.82	-1.02*	-0.08	-1.23	-2.27
	P3	0.04	3.18*	1.24	1.34	2.40*	2.05	0.22	1.11	-0.05	-1.07
	P4	0.52	3.62**	1.74	1.81	2.85**	2.56**	0.79	1.61*	0.47	-0.43
	P5	1.09	4.25**	2.38	2.42**	3.47**	3.21**	1.43**	2.24**	1.06	0.16
	P6	-1.27	1.83	0.21	0.28	1.32	0.96	-0.71	0.16	-0.95	-1.85
β_{DOL}	P1	-0.09	0.08	-0.04	-0.36**	-0.37**	0.53**	1.03**	-0.46**	-0.48**	0.05
	P2	-0.24**	-0.08	-0.20**	-0.51**	-0.53**	0.37**	0.87**	-0.61**	-0.63**	-0.11
	P3	-0.17**	-0.01	-0.13**	-0.45**	-0.46**	0.44**	0.94**	-0.54**	-0.56**	-0.04
	P4	-0.10	0.06	-0.05	-0.37**	-0.38**	0.51**	1.02**	-0.47**	-0.49**	0.03
	P5	-0.02	0.14*	0.02	-0.29**	-0.31**	0.59**	1.10**	-0.39**	-0.41**	0.11
	P6	-0.08	0.08	-0.04	-0.35**	-0.37**	0.53**	1.03**	-0.45**	-0.47**	0.04
β_{HML}	P1	-0.71**	-0.83**	-0.45**	-0.40**	-0.41**	-0.57**	-0.39**	-0.20**	-0.05	0.12**
	P2	-0.44**	-0.56**	-0.19**	-0.13**	-0.15**	-0.31**	-0.13**	0.06**	0.22**	0.39**
	P3	-0.44**	-0.56**	-0.19**	-0.13**	-0.15**	-0.31**	-0.13**	0.07**	0.22**	0.39**
	P4	-0.31**	-0.42**	-0.05	0.00	-0.02	-0.17**	0.00	0.20**	0.35**	0.52**
	P5	-0.27**	-0.38**	-0.01	0.04	0.03	-0.13**	0.04**	0.24**	0.39**	0.56**
	P6	0.30**	0.19**	0.55**	0.61**	0.59**	0.43**	0.61**	0.80**	0.95**	1.12**
R^2	P1	31.4	36.6	19.6	30.8	30.2	39.9	90.4	32.8	22.9	1.7
	P2	16.0	21.0	7.8	26.9	24.5	19.2	75.6	38.4	30.5	11.3
	P3	15.5	21.3	5.7	20.4	19.6	22.3	78.6	31.4	26.6	11.3
	P4	7.2	12.9	0.2	13.3	13.2	21.4	79.1	30.8	29.8	17.5
	P5	5.0	10.1	-0.5	7.6	7.2	21.6	79.7	22.9	27.8	21.6
	P6	6.8	3.1	25.9	40.5	37.0	38.3	93.8	65.3	67.5	61.1
λ_{DOL}		7.98	17.62*	-1.05	-0.04	-2.55	5.98**	2.44	0.92	3.29	10.98**
λ_{HML}		6.31**	3.46	6.96**	7.35**	7.47**	6.97**	7.36**	7.62**	7.60**	5.31

Table 2
Simulations of the LRV model and modified versions
The LRV model parameters are as in Lustig et al. (2014), Table 5, except for α, which we choose to fit the average nominal interest rate, following Brusa et al. (2015):

α (%)	χ	γ	κ	τ	δ_M	δ_L	δ_U	ϕ	θ (%)	σ (%)	ϕ^w	θ^w (%)	σ^w (%)
1	0.89	0.04	2.78	0.06	0.36	0.22	0.49	0.91	0.77	0.68	0.99	2.09	0.28

The δ^i's in equation (1) are uniformly distributed between δ_L and δ_U, with a middle value δ_M, which is assumed to correspond to the US pricing kernel. The versions of the modified model LRV^d, denoted V_1, V_2 and V_3, have time-varying deltas given by $\delta_t^i = \delta_M + \nu_t(\delta^i - \delta_M)$. The modified versions also have different values for γ and time-varying $\kappa_t = \xi_t\kappa$, with different ξ_t when $AFD < 0$ and $AFD > 0$:

	ν_t		ξ_t		γ
	$AFD < 0$	$AFD > 0$	$AFD < 0$	$AFD > 0$	
LRV	1	1	1	1	0.04
V_1	0	2.5	1	1	0.00
V_2	0.5	2.5	0.95	1.05	0.00
V_3	1	2.5	0.95	1.05	0.01

We simulate 11 sets of interest rates (r) and currency excess returns (rx), with exchange rates quoted against the USD. The top panel in the table shows, for each model version, averages across 1000 simulations of average interest rates and their standard deviations ($\overline{r}$ and $\overline{\sigma_r}$, annualized and in percent), as well as the average correlation between them ($\overline{\rho_r}$), and similar for the currency returns. Also shown are average Sharpe ratios for the Dollar carry (DC) and Standard carry (SC) trades. The bottom panel of the table shows, as in Sections 2.3 and 3.1, correlations between model-based DOL betas of carry trades and average carry returns, together with 5-th and 95-th beta percentiles, for the full sample and for each of the two AFD regimes. We construct all possible carry trades from nine out of 11 simulated currencies (55 trades). The "data" row reproduces the quantities from the 45 trades in our sample.

							Sharpe ratio	
	$\overline{r}$	$\overline{\sigma_r}$	$\overline{rx}$	$\overline{\sigma_{rx}}$	$\overline{\rho_r}$	$\overline{\rho_{rx}}$	DC	SC
LRV	4.24	0.29	0.63	10.4	0.11	0.41	0.24	0.48
V_1	4.44	0.44	0.54	9.0	-0.001	0.23	0.43	0.36
V_2	4.46	0.43	0.64	9.1	0.11	0.22	0.43	0.37
V_3	4.41	0.39	0.71	10.1	0.17	0.25	0.37	0.36

				$AFD < 0$			$AFD > 0$		
	corr	β_{5-th}	β_{95-th}	corr	β_{5-th}	β_{95-th}	corr	β_{5-th}	β_{95-th}
data	0.75	0.07	0.24	0.05	-0.28	-0.11	0.73	0.15	0.33
LRV	0.09	-0.02	0.05	0.04	-0.27	-0.14	0.07	0.14	0.28
V_1	0.64	0.09	0.25	-0.02	-0.75	-0.64	0.65	0.75	1.03
V_2	0.59	0.17	0.36	-0.01	-0.61	-0.44	0.64	0.75	1.01
V_3	0.57	0.18	0.34	0.16	-0.30	-0.12	0.55	0.54	0.74

Table 3

Static and dynamic components of the carry trade

The table shows returns of the Standard carry trade (SC) or its static and dynamic components, annualized and in %. "full" refers to the full sample period, and the table also shows results for the subperiods of negative and positive AFD, respectively. The numbers for the two subperiods sum to the corresponding one for the full period, and the numbers for the two components sum to that for the SC trade. In the columns denoted "data" in the top panel, SC is the carry trade constructed from all G-10 currencies (three highest- and three lowest-yielding currencies, with equal weights), the static component is defined as the contribution of NZD, AUD, NOK, CHF and JPY in case I, and only of NZD, AUD and JPY in case II. The dynamic component complements the static component to the return of the SC trade. The columns denoted "LRV model" show averages of analogous numbers obtained in 1000 simulations of the LRV model with 11 currencies. Here SC refers to the carry trade using all 11 simulated currencies (three highest- and three lowest-yielding ones, with equal weights). The currencies with three (two) highest and three (two) lowest values of the δ^i are designated as static in case I (II), and the complementing currencies are dynamic. The bottom panel of the table shows, similar to the "LRV model" columns in the top panel, the corresponding results from simulations of the three versions of the modified LRV model (V_1 to V_3), as defined in Section 3.2 and Table 2.

	data			LRV model		
	full	$AFD < 0$	$AFD > 0$	full	$AFD < 0$	$AFD > 0$
SC	2.38	0.90	1.49	2.70	1.30	1.40
Static I	1.80	0.44	1.13	1.87	0.89	0.97
Dyna. I	0.58	0.45	0.36	0.83	0.41	0.42
Static II	1.60	0.31	1.29	1.32	0.63	0.69
Dyna. II	0.78	0.59	0.19	1.38	0.67	0.71

	V_1			V_2			V_3		
	full	$AFD < 0$	$AFD > 0$	full	$AFD < 0$	$AFD > 0$	full	$AFD < 0$	$AFD > 0$
SC	3.46	1.33	2.14	3.41	1.23	2.18	3.50	1.30	2.20
Static I	2.72	0.85	1.87	2.69	0.81	1.88	2.87	0.96	1.91
Dyna. I	0.74	0.48	0.27	0.72	0.41	0.30	0.63	0.34	0.29
Static II	2.04	0.59	1.45	2.02	0.57	1.45	2.17	0.69	1.48
Dyna. II	1.43	0.74	0.69	1.39	0.66	0.73	1.33	0.60	0.73

Table 4

Global variables: definitions and sources

This table shows the variables used as candidate global risk factors in our asset pricing tests, including the abbreviations used in subsequent tables, periods of availability and data sources.

	abbrev.	availability	data source
MSCI-World	MSCI	12/1984 to 11/2016	Datastream
Barclay's Global Aggregate Bond index	BGAB	12/1989 to 11/2016	Bloomberg
Barclay's Global Treasury Bond index	BGT	12/1986 to 11/2016	— " —
Barclay's Global High Yield Bond index	BGHY	12/1989 to 11/2016	— " —
CRB commodity price index	CRB	12/1984 to 11/2016	Datastream
Baltic Dry index	BDI	05/1985 to 11/2016	— " —
Global equity volatility	GEV	12/1984 to 06/2015	Lustig et al. (2011), author's website
Global currency volatility	FXV	12/1984 to 11/2016	as in Menkhoff et al. (2012)
VIX	VIX	01/1986 to 11/2016	www.cboe.com
Conditional variance	CV	01/1990 to 11/2016	Bekaert and Hoerova (2014), authors' data
Variance premium	VP	01/1990 to 11/2016	— " —
Variance risk premium	VRP	01/1990 to 11/2016	Bollerslev et al. (2009), author's website
Financial uncertainty measure (1 month)	FINU	12/1984 to 11/2016	Jurado et al. (2015), author's website
Macroeconomic uncertainty measure (1 month)	MCRU	— " —	— " —
Global uncertainty index	GU	11/1989 to 07/2014	Ozturk and Sheng (2016), author's website
Global political risk index	GPR	01/1985 to 11/2016	Caldara and Iacoviello (2016), author's website
Baker-Bloom-Davis MPU index (Access World News)	MPU1	— " —	www.policyuncertainty.com
Husted-Rogers-Sun MPU index	MPU2	— " —	— " —

Table 5

Three-factor models with global variables

This table presents result from tests of three-factor models, as described in Section 4.2, on the 45 invariant carry trades. The f^1 and f^2 factors for each model are shown in the first two columns. The top panel refers to time-series regressions as per equation (10):

$$rx_{t+1}^{carry,i} = \alpha^i + \xi_1^i f_{t+1}^1 + \beta_2^i f_{t+1}^2 + \xi_2^i f_{t+1}^1 \mathbb{1}_{AFD_t>0} + \varepsilon_{t+1}^i$$

The numbers in parentheses show how many of the respective estimates (out of 45) of slope coefficients are significant at the 5% confidence level. The intercepts α are annualized and in percent, adjusted R^2's are in percent. The last four columns in the top panel show p-values for tests comparing the respective three-factor model to the two-factor model only with f^1 and f^2 (i.e., excluding the interacted term). "p_1" and "p_2" refer to testing the null hypothesis that the cross-sectional R^2's from the two compared models are equal, under a correctly specified and misspecified model, respectively, as in Kan et al. (2013). "p_3" refers to the weighted χ^2 test of Gospodinov et al. (2013) and "p_4" is based on the Hansen-Jagannathan distance as in Li et al. (2010). The bottom panel refers to cross-sectional regressions, λ_1 to λ_3 are the risk prices for the three factors in each model, "*p-val*" denotes p-values obtained with GMM standard errors, and "*p-rob*" are mis-specification robust p-values, as in Kan et al. (2013). R^2_{CS} is the cross-sectional R^2, "*GRS*" denotes the p-values of the Gibbons et al. (1989) test statistic, "χ^2" denotes the p-values for the test of the null hypothesis of pricing errors being jointly equal to zero, and "*CSRT*" denotes the approximate finite sample p-values of Shanken's CSRT statistic (mis-specification robust).

f^1	f^2	α	sig.	ξ_1	sig.	β_2	sig.	ξ_2	sig.	R^2	p_1	p_2	p_3	p_4
MSCI	BGHY	1.32	(16)	-0.02	(1)	0.09	(37)	0.09	(38)	17.3	0.19	0.26	0.33	0.34
MSCI	BDI	1.68	(30)	0.02	(4)	0.02	(0)	0.08	(25)	10.0	0.10	0.18	0.12	0.11
MSCI	VIX	2.00	(43)	-0.01	(1)	-0.21	(44)	0.08	(28)	13.8	0.11	0.18	0.22	0.21
MSCI	MPU1	2.07	(42)	0.01	(3)	-0.02	(32)	0.08	(28)	11.1	0.06	0.12	0.11	0.09
MSCI	MPU2	2.04	(42)	0.02	(4)	-0.02	(30)	0.08	(25)	11.2	0.09	0.17	0.17	0.15
MSCI	MCRU	1.69	(33)	0.02	(4)	-0.05	(5)	0.08	(25)	10.5	0.09	0.18	0.16	0.14
DOL	SC	0.12	(3)	-0.03	(21)	0.80	(45)	0.08	(33)	83.9	0.28	0.29	0.13	0.12

		λ_1	p-val	p-rob	λ_2	p-val	p-rob	λ_3	p-val	p-rob	R^2_{CS}	GRS	χ^2	CSRT
MSCI	BGHY	33.5	0.01	0.00	1.9	0.75	0.77	26.1	0.01	0.00	66.9	0.23	0.45	0.88
MSCI	BDI	27.6	0.01	0.02	-12.6	0.10	0.11	24.7	0.01	0.01	70.1		0.73	0.90
MSCI	VIX	35.7	0.00	0.01	-2.5	0.41	0.39	28.9	0.00	0.00	58.3		0.80	0.95
MSCI	MPU1	32.2	0.01	0.02	20.5	0.58	0.54	26.9	0.00	0.00	44.6		0.19	0.82
MSCI	MPU2	30.9	0.00	0.01	27.8	0.35	0.29	27.1	0.00	0.00	57.3		0.33	0.86
MSCI	MCRU	32.3	0.02	0.12	8.3	0.40	0.64	26.1	0.01	0.02	42.8		0.37	0.73
DOL	SC	6.2	0.02	0.03	2.4	0.00	0.01	5.8	0.00	0.00	51.3	0.00	1.00	0.89

Table 6
AFD regimes
A number of variables are regressed on a constant and an indicator function $\mathbb{1}_{AFD_t>0}$. The intercept in such a regression equals the average of the respective variable in the regime $AFD < 0$, and these intercepts are shown in the columns denoted "$AFD < 0$" (in percent). The sum of the intercept and slope coefficient estimate in such a regression equals the respective average when $AFD > 0$, as shown in the columns "$AFD > 0$". "p-val" denotes p-values for the slope, estimated with Newey-West standard errors with automatically selected lag length. The top panel shows results for variables from Table 4, and few additional variables as defined in Section 4.4: GDP, industrial production and unemployment growth in the OECD economies (GDP, IP and UNEMP), and changes in dealer leverage and the Global financial cycle factor (DLEV and GFC). The bottom panel refers to bank loans *in foreign currency* from the BIS Locational Banking Statistics (quarterly data). Subscripts "A", "B" and "NB" denote loans to all, bank and non-bank borrowers (from all countries, all types of instruments), respectively. The columns on the left (right) of the panel refer to percentage change in such loans (ratios of such loans to the total GDP of the OECD). The "GLIQ" (global liquidity) variables include cross-border and local loans, in all currencies. The "CB" (cross-border) variables include only cross-border loans, in all currencies, USD, or Euro, as shown in parentheses, and are adjusted for exchange rate changes and breaks in the series.

	AFD<0	AFD>0	p-val		AFD<0	AFD>0	p-val
GDP	0.72	0.53	0.10	EQV	0.08	-0.02	0.53
IP	0.24	0.11	0.12	FXV	0.01	0.05	0.67
UNEMP	-0.26	0.11	0.09	VIX	0.04	-0.02	0.42
MSCI	0.92	0.85	0.88	CV	0.50	-0.36	0.30
BGB	0.40	0.54	0.48	VP	-0.09	-0.06	0.96
BGT	0.37	0.56	0.37	VRP	0.40	-0.42	0.49
BGHY	0.69	0.89	0.57				
				FINU	0.70	-0.22	0.05
GFC	0.49	-0.10	0.69	MCRU	0.29	-0.13	0.10
DLEV	0.58	-0.23	0.43	DOL	-0.22	0.33	0.01

$GLIQ_A$	2.25	1.90	0.69		1.13	0.27	0.14
$GLIQ_B$	2.05	1.69	0.71		0.93	0.07	0.18
$GLIQ_{NB}$	2.60	2.17	0.58		1.48	0.54	0.07
CB_A (All)	2.89	1.50	0.06		1.82	-0.12	0.00
CB_A (USD)	2.48	1.21	0.06		1.33	-0.36	0.00
CB_A (Euro)	3.42	2.33	0.25		2.38	0.69	0.04
CB_B (All)	2.74	1.29	0.08		1.64	-0.32	0.00
CB_B (USD)	2.43	0.92	0.03		1.23	-0.64	0.00
CB_B (Euro)	3.13	2.40	0.49		2.00	0.78	0.18
CB_{NB} (All)	3.17	1.85	0.05		2.13	0.22	0.00
CB_{NB} (USD)	2.59	1.72	0.28		1.55	0.08	0.02
CB_{NB} (Euro)	3.98	2.23	0.05		3.02	0.57	0.01

Table 7

Models with the Global financial cycle factor

Exactly in the format of Table 5, this table presents results from tests of three-factor models that include the change in the Global financial cycle factor of Miranda-Agrippino and Rey (2017) (denoted "GFC") and meet the same requirements.

f^1	f^2	α	sig.	ξ_1	sig.	β_2	sig.	ξ_2	sig.	R^2	p_1	p_2	p_3	p_4
GFC	MSCI	2.92	(45)	0.02	(17)	-0.05	(25)	0.03	(40)	17.6	0.07	0.14	0.46	0.45
GFC	BGB	2.62	(45)	0.01	(5)	0.00	(3)	0.03	(31)	16.8	0.37	0.46	0.59	0.60
GFC	BGT	3.06	(45)	0.01	(7)	-0.05	(16)	0.03	(39)	18.4	0.27	0.36	0.32	0.34
GFC	CRB	2.51	(45)	0.01	(3)	0.04	(12)	0.03	(33)	16.9	0.04	0.08	0.38	0.38
		λ_1	p-val	p-rob	λ_2	p-val	p-rob	λ_3	p-val	p-rob	R^2_{CS}	GRS	χ^2	CSRT
GFC	MSCI	78.9	0.01	0.01	39.5	0.00	0.00	78.4	0.00	0.00	63.7		0.53	0.89
GFC	BGB	85.2	0.01	0.01	10.0	0.02	0.02	57.4	0.02	0.02	5.0		0.74	0.80
GFC	BGT	100	0.00	0.01	10.3	0.04	0.06	70.6	0.00	0.00	7.7		0.60	0.89
GFC	CRB	51.1	0.21	0.19	-20.2	0.12	0.34	92.0	0.01	0.01	10.3		0.52	0.98

Table Appendix-1

Additional three-factor models

Exactly in the format of Table 5, this table presents results from tests of the remaining three-factors models which meet our search criteria, as well as from a model with the DOL and Standard carry (SC) factor. Also shown are the results for a two-factor model that does not include an f^2 factor.

f^1	f^2	α	sig.	ξ_1	sig.	β_2	sig.	ξ_2	sig.	R^2	p_1	p_2	p_3	p_4
MSCI	EQV	1.81	(37)	0.00	(2)	-0.03	(18)	0.09	(29)	10.4	0.08	0.16	0.63	0.63
MSCI	CV	1.82	(38)	0.01	(4)	-0.01	(13)	0.10	(39)	15.5	0.30	0.38	0.34	0.33
MSCI	VP	1.76	(34)	0.02	(4)	-0.00	(0)	0.10	(37)	14.4	0.32	0.39	0.43	0.43
MSCI	VRP	1.85	(38)	0.00	(2)	-0.01	(10)	0.09	(37)	15.6	0.30	0.39	0.37	0.37
MSCI	OS	2.06	(41)	0.02	(4)	-0.00	(0)	0.10	(35)	13.4	0.13	0.20	0.37	0.38
MSCI	GPR	1.57	(25)	0.02	(4)	-0.00	(1)	0.08	(26)	10.4	0.10	0.17	0.19	0.18
MSCI		1.67	(32)	0.02	(5)			0.08	(25)	10.2	0.09	0.17	0.16	0.10

f^1	f^2	λ_1	p-val	p-rob	λ_2	p-val	p-rob	λ_3	p-val	p-rob	R^2_{CS}	GRS	χ^2	CSRT
MSCI	EQV	23.6	0.05	0.08	-1.6	0.91	0.94	23.9	0.02	0.02	31.9		0.09	0.69
MSCI	CV	23.8	0.01	0.04	2.4	0.95	0.97	20.1	0.01	0.01	27.0		0.14	0.54
MSCI	VP	20.5	0.04	0.06	32.4	0.52	0.80	17.7	0.03	0.04	16.3		0.00	0.83
MSCI	VRP	25.1	0.01	0.02	-13.5	0.76	0.81	20.7	0.01	0.01	33.1		0.48	0.69
MSCI	OS	20.6	0.13	0.12	-68.7	0.33	0.46	18.7	0.09	0.08	31.0		0.47	0.80
MSCI	GPR	21.6	0.05	0.05	150	0.54	0.64	19.4	0.04	0.05	37.1		0.10	0.66
MSCI		22.2	0.04	0.05				22.0	0.01	0.01	32.5	0.10	0.99	0.74

Table Appendix-2

Replications with carry trades constructed from different currency perspectives

This table replicates the results in Table 5, exactly in the same format, but using as test assets the 45 carry trades now constructed from the perspectives of the NZD and JPY, as shown in the first column.

persp.	f^1	f^2	α	sig.	ξ_1	sig.	β_2	sig.	ξ_2	sig.	R^2	p_1	p_2	p_3	p_4
NZD	MSCI	BGHY	1.12	(11)	-0.02	(1)	0.09	(36)	0.10	(40)	18.0	0.21	0.27	0.37	0.38
	MSCI	BDI	1.44	(22)	0.02	(5)	0.02	(0)	0.08	(26)	10.7	0.13	0.23	0.15	0.14
	MSCI	VIX	1.78	(39)	-0.02	(1)	-0.21	(45)	0.08	(29)	14.8	0.17	0.24	0.28	0.27
	MSCI	MPU1	1.84	(39)	0.01	(3)	-0.02	(33)	0.08	(30)	11.8	0.08	0.16	0.12	0.11
	MSCI	MPU2	1.81	(38)	0.02	(5)	-0.02	(30)	0.08	(28)	11.8	0.13	0.23	0.17	0.16
	MSCI	MCRU	1.45	(22)	0.02	(4)	-0.05	(4)	0.08	(25)	11.1	0.13	0.23	0.18	0.17
JPY	MSCI	BGHY	1.45	(20)	-0.01	(1)	0.09	(37)	0.09	(38)	16.8	0.22	0.29	0.31	0.32
	MSCI	BDI	1.83	(37)	0.03	(7)	0.02	(0)	0.07	(24)	9.8	0.14	0.24	0.10	0.09
	MSCI	VIX	2.14	(44)	-0.01	(1)	-0.20	(45)	0.07	(24)	13.6	0.13	0.20	0.19	0.18
	MSCI	MPU1	2.21	(43)	0.02	(4)	-0.02	(32)	0.07	(26)	10.9	0.08	0.15	0.09	0.08
	MSCI	MPU2	2.19	(44)	0.02	(5)	-0.02	(31)	0.07	(22)	10.9	0.12	0.21	0.12	0.10
	MSCI	MCRU	1.84	(40)	0.02	(5)	-0.05	(3)	0.07	(21)	10.2	0.12	0.22	0.12	0.11

persp.	f^1	f^2	λ_1	p-val	p-rob	λ_2	p-val	p-rob	λ_3	p-val	p-rob	R^2_{CS}	GRS	χ^2	CSRT
NZD	MSCI	BGHY	31.4	0.01	0.01	0.7	0.90	0.91	24.0	0.01	0.01	71.2	0.23	0.52	0.82
	MSCI	BDI	24.5	0.03	0.04	-12.8	0.08	0.07	22.2	0.01	0.01	67.1	0.12	0.77	0.85
	MSCI	VIX	34.6	0.00	0.01	-1.7	0.58	0.56	27.3	0.00	0.00	55.0	0.16	0.69	0.93
	MSCI	MPU1	28.4	0.02	0.06	19.7	0.57	0.55	23.7	0.00	0.01	29.0	0.12	0.03	0.80
	MSCI	MPU2	27.6	0.01	0.01	28.3	0.34	0.28	24.2	0.00	0.00	46.8	0.12	0.45	0.83
	MSCI	MCRU	31.5	0.02	0.10	11.3	0.25	0.48	24.0	0.01	0.02	38.8	0.12	0.26	0.76
JPY	MSCI	BGHY	32.5	0.01	0.01	3.4	0.57	0.59	25.6	0.01	0.00	69.6	0.23	0.53	0.81
	MSCI	BDI	29.6	0.01	0.01	-11.0	0.18	0.17	26.3	0.00	0.00	77.9	0.09	0.74	0.92
	MSCI	VIX	34.4	0.00	0.01	-3.5	0.26	0.24	28.6	0.00	0.00	63.0	0.12	0.61	0.94
	MSCI	MPU1	30.6	0.01	0.02	7.7	0.83	0.81	26.7	0.00	0.00	49.0	0.10	0.75	0.80
	MSCI	MPU2	30.8	0.00	0.00	17.4	0.55	0.51	27.3	0.00	0.00	57.2	0.10	0.65	0.82
	MSCI	MCRU	32.9	0.01	0.06	6.6	0.50	0.66	27.0	0.00	0.01	52.7	0.10	0.17	0.75

Table Appendix-3

Replications without smoothing the AFD

This table replicates the results in Tables 5, exactly in the same format, but without smoothing the AFD of the USD, used to construct the third factor in each model.

f^1	f^2	α	sig.	ξ_1	sig.	β_2	sig.	ξ_2	sig.	R^2	p_1	p_2	p_3	p_4
MSCI	BGHY	1.16	(8)	0.00	(0)	0.10	(41)	0.08	(31)	16.8	0.09	0.12	0.18	0.17
MSCI	BDI	1.60	(26)	0.05	(15)	0.03	(0)	0.04	(23)	9.3	0.02	0.03	0.07	0.06
MSCI	VIX	1.92	(41)	0.01	(0)	-0.21	(45)	0.05	(19)	13.1	0.02	0.04	0.08	0.07
MSCI	MPU1	1.97	(42)	0.05	(7)	-0.02	(28)	0.04	(9)	10.2	0.02	0.03	0.03	0.03
MSCI	MPU2	1.97	(42)	0.05	(12)	-0.02	(29)	0.04	(9)	10.3	0.03	0.06	0.04	0.04
MSCI	MCRU	1.63	(29)	0.05	(13)	-0.05	(5)	0.04	(21)	9.8	0.03	0.05	0.04	0.03
		λ_1	p-val	p-rob	λ_2	p-val	p-rob	λ_3	p-val	p-rob	R^2_{CS}	GRS	χ^2	CSRT
MSCI	BGHY	32.4	0.01	0.01	2.4	0.68	0.70	25.1	0.00	0.00	67.4	0.21	0.65	0.86
MSCI	BDI	27.6	0.01	0.02	-10.2	0.13	0.18	25.1	0.00	0.00	72.9	0.08	0.80	0.90
MSCI	VIX	30.9	0.00	0.04	-3.1	0.30	0.28	26.0	0.00	0.00	62.4	0.11	0.91	0.95
MSCI	MPU1	27.0	0.01	0.09	5.7	0.85	0.89	25.0	0.00	0.00	54.5	0.09	0.30	0.86
MSCI	MPU2	29.4	0.00	0.01	20.7	0.45	0.42	26.1	0.00	0.00	65.0	0.09	0.62	0.89
MSCI	MCRU	24.3	0.05	0.24	0.3	0.98	0.99	24.1	0.00	0.01	51.4	0.09	1.00	0.84

Table Appendix-4

Three-factor models with an orthogonal factor

Exactly in the format of Table 5, this table presents results from tests of the same three-factors models. However, instead of the original f^2 factor, the models include the orthogonal component $f^{2,orth}$ of f^2 with respect to f^1: $f^{2,orth} = f^2 - bf^1$, where b is the slope coefficient from regressing f^2 on f^1 and a constant. Shown are also results for a one-factor model only with the global equity factor.

f^1	$f^{2,orth}$	α	sig.	ξ_1	sig.	β_2	sig.	ξ_2	sig.	R^2	p_1	p_2	p_3	p_4
MSCI	BGHY	1.32	(16)	0.02	(7)	0.09	(37)	0.09	(38)	17.3	0.19	0.26	0.33	0.34
MSCI	BDI	1.68	(30)	0.02	(5)	0.02	(0)	0.08	(25)	10.0	0.10	0.18	0.12	0.11
MSCI	VIX	2.00	(43)	0.02	(5)	-0.21	(44)	0.08	(28)	13.8	0.11	0.18	0.22	0.21
MSCI	MPU1	2.07	(42)	0.02	(4)	-0.02	(32)	0.08	(28)	11.1	0.06	0.12	0.11	0.09
MSCI	MPU2	2.04	(42)	0.02	(5)	-0.02	(30)	0.08	(25)	11.2	0.09	0.17	0.17	0.15
MSCI	MCRU	1.69	(33)	0.02	(5)	-0.05	(5)	0.08	(25)	10.5	0.09	0.18	0.16	0.14
MSCI		1.65	(31)	0.08	(45)					8.9				

f^1	$f^{2,orth}$	λ_1	p-val	p-rob	λ_2	p-val	p-rob	λ_3	p-val	p-rob	R^2_{CS}	GRS	χ^2	CSRT
MSCI	BGHY	33.5	0.01	0.00	-13.1	0.06	0.09	26.1	0.01	0.00	66.9	0.23	0.77	0.88
MSCI	BDI	27.6	0.01	0.02	-13.7	0.07	0.08	24.7	0.01	0.01	70.1		0.63	0.90
MSCI	VIX	35.7	0.00	0.01	4.0	0.28	0.28	28.9	0.00	0.00	58.3		0.78	0.95
MSCI	MPU1	32.2	0.01	0.02	34.3	0.38	0.35	26.9	0.00	0.00	44.6		0.74	0.82
MSCI	MPU2	30.9	0.00	0.01	33.5	0.26	0.21	27.1	0.00	0.00	57.3		0.42	0.86
MSCI	MCRU	32.3	0.02	0.12	10.7	0.30	0.57	26.1	0.01	0.02	42.8		0.32	0.73
MSCI		26.2	0.01	0.01							21.4	0.14	1.00	0.76

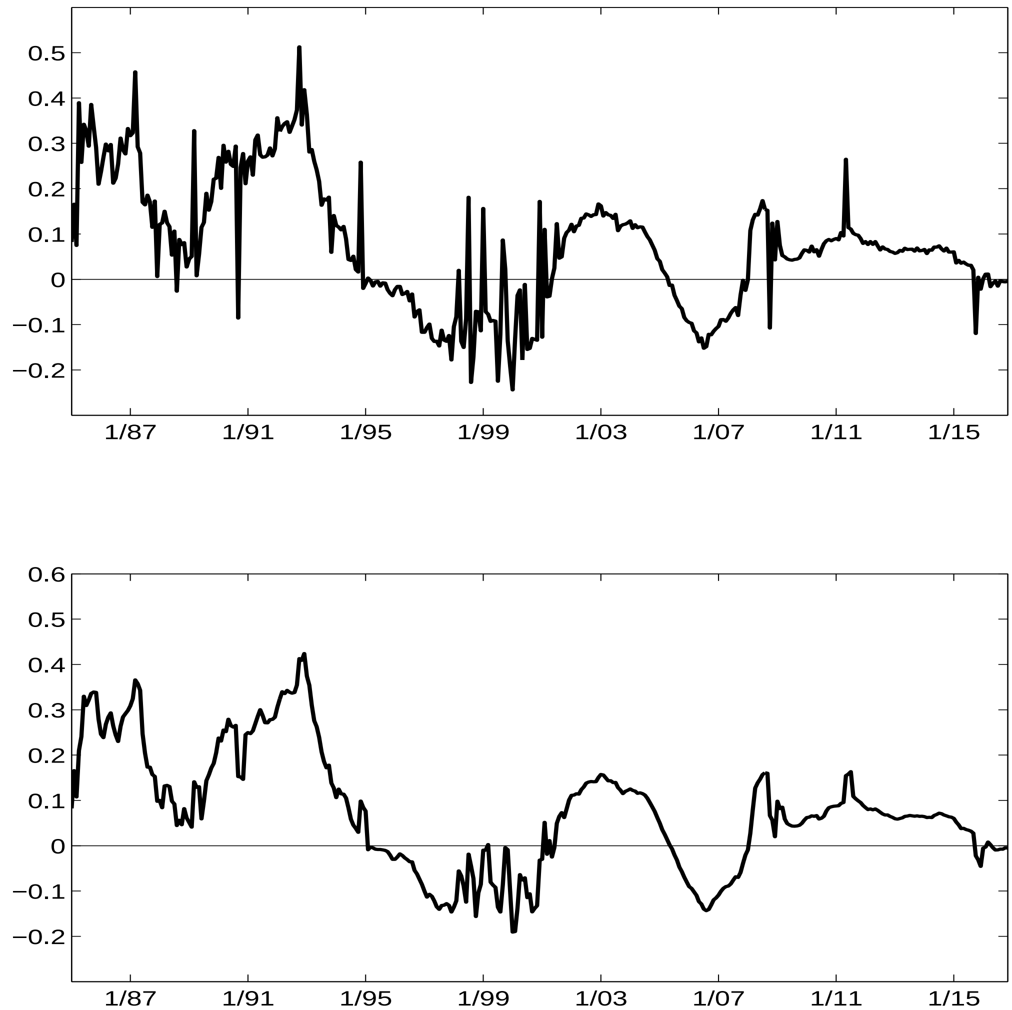

Figure 1. **Actual and smoothed average forward differential (AFD)**

The top panel in the figure plots the average forward differential (AFD) of the USD against the remaining G-10 currencies, at the end of each month in the sample period 12/1984 to 11/2016 (multiplied by 100), while the bottom panel plots the three-month moving average of the same series.

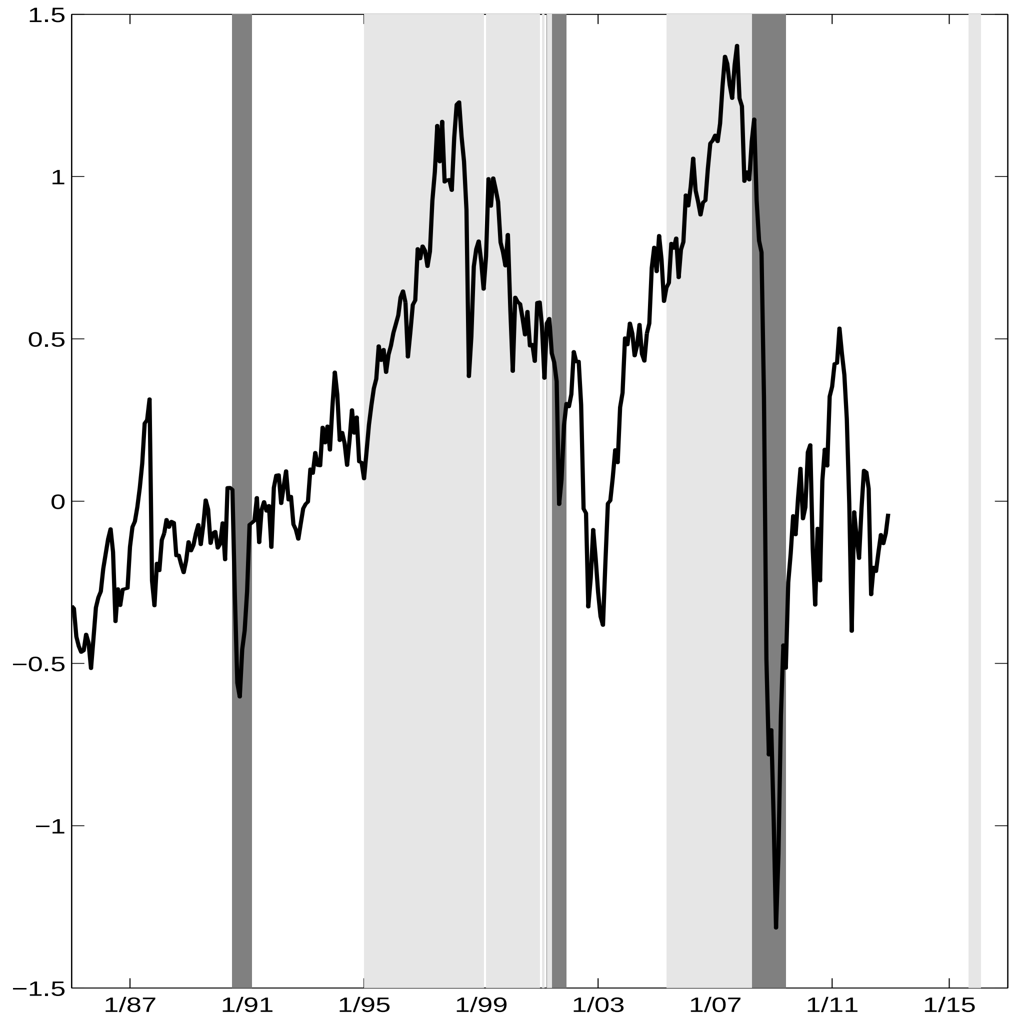

Figure 2. **AFD regimes, recessions and the Global financial cycle**

The figure shows in light grey the periods when the AFD of the USD against the remaining G-10 currencies is positive. In dark grey are shown the NBER recessions. Also plotted is the monthly time series of the Global financial cycle factor as in Miranda-Agrippino and Rey (2017). We use the shorter version of the factor, available over 1990-2012, spliced with the longer version over 1985-1989 and matching the values at the first point of overlapping.