Global Risks in the Currency Market[1]

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Abstract

Using a new cross section of test assets and a new asset pricing test, this paper evaluates empirically a large set of variables that have been proposed in recent studies as global risk factors in the currency market. The test assets are numeraire-invariant carry trades, which, as we show, are better suited than the typically used interest rate sorted portfolios for studying global risks. The global risk factors accepted by our test (i) can price the cross section of numeraire-invariant carry trades, and (ii) are consistent with a version of the model of Lustig, Roussanov and Verdelhan (2014); in this model version, the exposures to one of the global risk factors depend on the US interest rate, reflecting observed data features. We find that only a few combinations of previously suggested variables are (marginally) accepted by our test, indicating that global risks still present a challenge to empirical research in the currency market.

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1. Introduction

Global risks, that require compensation from the perspective of *all* investors, regardless of their home currency, play a central role in extant risk-based interpretations of currency returns. Examples of such risks are the global equity volatility risk in Lustig, Roussanov, and Verdelhan (2011), global currency volatility risk in Menkhoff, Sarno, Schmeling, and Schrimpf (2012), global imbalance risk in Della Corte, Riddiough, and Sarno (2016), global economic risk in Ready, Roussanov, and Ward (2017), global dollar risk in Verdelhan (2018).[1] Yet, prior empirical work has typically considered currency returns only from the perspective of the US investor and has avoided the analysis of risk from multiple currency perspectives, even though the ability of a risk factor or factors to explain the returns of given test assets may significantly depend on the currency in which these returns are expressed.

To address the impact of the choice of numeraire currency when studying global risk, one could replicate tests using returns in different currency denominations, as done, for example in Verdelhan (2018, Section 4.1); this approach, however, leaves open the question of how to compare statistically the test results obtained in different 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 global currency factors that aggregate several currency perspectives.

This paper offers a new approach for evaluating global risk factors in the currency market, based on a novel cross section of test assets that have largely the *same* returns from the perspective of *any* currency. Such numeraire-invariant test assets allow to circumvent the analysis of returns in various denominations and the related statistical issues, and are thus well-suited for the study of global risks, as we demonstrate in Section 2 of the paper. While invariant test assets can be constructed in different ways, we focus on a cross section of carry trades, which have been investigated extensively in the currency literature and present

[1] Related recent empirical studies that strive to rationalize risk factors that can explain return cross sections reflecting currency market risks are Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Christiansen, Ranaldo, and Söderlind (2011), Lettau, Maggiori, and Weber (2014), Della Corte, Ramadorai, and Sarno (2016), Daniel, Hodrick, and Lu (2017), Mueller, Stathopoulos, and Vedolin (2017), Filippou and Taylor (2017), Colacito, Croce, Gavazzoni, and Ready (2018), among others.

modeling advantages in our context.

To impose discipline on the candidate global risk factors, our approach combines the invariant cross section with a version of the model of Lustig, Roussanov, and Verdelhan (2014) (denoted here "the LRV model"), which enforces consistency with key stylized facts in the currency market and involves two global factors, while at the same time affords flexibility with respect to the identity of these factors. Importantly, while the original LRV model does not reproduce certain observed features of the invariant carry cross section, we show in Section 3 that a simple, yet consequential, modification can reconcile the model with this data dimension as well. The modified model, that we denote "the LRV^d model", introduces time-varying global risk exposures of different economies, driven by the (relative) US interest rate.

We design a new asset pricing test that reflects the predictions of the LRV^d model for the invariant cross section, and use it in Section 4 of the paper to evaluate a large set of candidate global risk factors that have been considered in prior studies, and represent equity and bond market risks, real activity, and different aspects of uncertainty. Surprisingly, we find that very few of the examined factors are accepted by our test, and even they fall short in some dimensions, which indicates that the invariant cross section, combined with the LRV^d model, raises the bar for global risk factors, and hints that prior empirical results on global risks in the currency market may need to be re-visited. On the positive side, our test results single out the global equity market factor as the only factor in our set which can account for time-varying risk exposures, as predicted by the LRV^d model, and thus highlight the relevance of standard risks in the currency market. In Section 5 we also link the findings from our tests to the Global financial cycle (e.g., Rey (2015)).

This paper builds on Lustig et al. (2014), and is thus similar to Brusa, Ramadorai, and Verdelhan (2015), Mueller, Stathopoulos, and Vedolin (2017), Verdelhan (2018) and Lustig, Stathopoulos, and Verdelhan (2018), who have explored various extensions of the LRV model. Furthermore, our version (the LRV^d model) reinforces the link between asymmetric exposure to global risk and carry trade profitability, which has been emphasized in Lustig et al. (2011). On the other hand, we depart from their work and treat the (relative) US interest rate 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.[2] Offering further distinction, (i) we provide a method for evaluating empirically candidate global risk factors, whereas such factors are only broadly characterized in Lustig et al. (2014), and (ii) our test results imply that economies tend to exhibit persistent (possibly counter-cyclical) differences in their exposure to global equity market risk, but not to volatility risk or other uncertainty-related variables, as argued in Lustig et al. (2011, 2014).

This paper is also close to Verdelhan (2018), and like him we examine the role of a dollar factor (DOL) in the currency market. However, our approach to dollar risk differs from his. First, we use only the DOL factor and carry trades, and not a separate global version of DOL and dollar beta sorted portfolios. Second, we demonstrate the high correlation between the average carry returns and the respective DOL betas, which implies that the distinction between dollar and carry risks is not as sharp as previously assumed. Third, we view this (time-varying) correlation as a new stylized fact that underlines the global role of the US interest rate, and also motivates our modification of the LRV model. Importantly, we do *not* emphasize the role of DOL as a global risk factor and elaborate on this point in Section 2.3; our tests examine instead non-currency global risk factors.

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. This section discusses numeraire-invariant trades which have largely the same returns when expressed in any currency. It also provides an example that involves numeraire *non*-invariant test assets, as used in prior studies, which helps to clarify the advantages of the invariant cross section, and highlights the distinction between the regimes where the US interest rate is relatively low or

[2] Such differences, together with differences between the marginal utilities of US and non-US investors have been previously employed for explaining the profitability of the Dollar carry trade of Lustig et al. (2014), which goes long (short) all currencies against the US dollar (USD) when the relative US interest rate, or, more precisely, the average forward differential (AFD) of the USD, is positive (negative). However, our treatment, as reflected in the LRV^d model, agrees with the observation that Dollar carry is numeraire-invariant, and hence gives US and non-US investors, at each point in time, largely the *same* returns, in their *own* currencies. Therefore, these returns are likely compensation for common risks, rather than reflection of differences among investors in different countries. In Section 3.3 we also show that the LRV^d model comes closer than the original LRV model to reproducing the high Sharpe ratio of Dollar carry, as observed in the data.

high, which has a major role in this paper.

2.1. Non-invariant test assets

We consider here interest rate sorted currency portfolios, as in Lustig et al. (2011). Together with the original portfolios from their study, which represent long positions in other currencies against the US dollar (USD) and have returns in USD, we use similarly sorted portfolios, but constructed from the perspective of each of the remaining G-10 currencies.[3] Note that the difference between the returns of a portfolio when expressed in two different currencies is approximately equal to the (percentage) change in the exchange rate between the two currencies, which is of similar magnitude as the returns themselves. Therefore, these returns are not highly correlated, and the portfolios are *not* numeraire invariant.

With these portfolios denominated in different currencies, we replicate the test of a model with the DOL and HML factors (DOL is the average return in USD of all portfolios, and HML is the return difference between the portfolios with the highest and lowest yield currencies). We focus here on the cross-sectional risk pricing results, while Table A-1 reports detailed results from the respective time-series regressions, and shows that these results vary widely across different currency denominations (for example, the adjusted R^2's average above 80% for the USD perspective, but below 10% for the GBP perspective).

The table insert below shows the prices of risk λ (annualized and in %) for the two factors, which are obtained by first estimating, from time-series regressions of returns on the factors, the vector of factor risk exposures β^i for each asset i, and then running a cross-sectional regression (without a constant) of average returns on these betas to estimate the vector of λ's: $E[rx^i_{t+1}] = \lambda' \beta^i + \varepsilon^i$. The standard errors are estimated via GMM (see Appendix A for details of the estimation procedure). Each column refers to the test assets denominated in the currency shown at the top of the column. The first two lines show risk prices obtained in the full sample period, and the remaining lines refer to the subsamples where the average

[3]The use of the G-10 currencies in carry trade research is standard (see also Daniel et al. (2017, Section 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 (DEM) is used 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. Return data for the original six portfolios is available at Verdelhan's website. We use the "All countries" version, without transaction costs, and extend it till 11/2016.

forward differential (AFD) of the G-10 currencies against the USD is negative (third and fourth line) or positive (last two lines). The AFD of the USD (which we will denote simply as AFD, for brevity) has strong predictive power for currency returns and is a key conditioning variable for the Dollar carry trade, as shown in Lustig et al. (2014), which prompts our interest in the AFD-based subsamples. Statistical significance at the 10 and 5% level is denoted by one and two stars:

		NZD	AUD	GBP	NOK	SEK	CAD	USD	EUR	CHF	JPY
full	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
$AFD < 0$	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**
$AFD > 0$	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

In the full sample, the λ_{HML} estimates are statistically significant, except those for the AUD and JPY perspectives, while the estimates of λ_{DOL} are insignificant, except for the AUD, CAD and JPY perspectives. These findings broadly confirm that HML can be a global risk factor in the currency market, while DOL can not (although the two exceptions in the case of HML may provide statistical challenge to this claim).

The results from the two subsamples, however, bring an important distinction, with the λ_{DOL} estimates being small and *never* significant when $AFD < 0$, but typically much larger and significant (in six out of ten cases) when $AFD > 0$. This distinction has two implications that underlie our approach to the study of global risks in the currency market: (i) the pricing of currency risks appears to be strongly impacted by the relative US interest rate, and (ii) results obtained with test assets in different currency denominations can differ significantly and thus may not allow for unambiguous conclusions regarding global risks.

2.2. *Cross section of invariant carry trades*

Next, we consider numeraire-invariant test assets, which, unlike the above portfolios, allow to avoid the analysis of different currency perspectives and the related statistical issues. In contrast to the interest rate sorted portfolios, which represent long-only positions against certain currency, the invariant test assets are long-short trades. They have largely the same returns from each perspective, and 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 (see Appendix B for further discussion).

In particular, we consider numeraire-invariant *carry* trades, constructed from the G-10 currencies in a standard way, following prior carry research and practice.[4] While other currency trades can also be made invariant, carry trades offer modeling advantages that we exploit below. To ensure numeraire invariance, the trades *can* include the USD. If they do, the position in the USD has a guaranteed zero return from the USD perspective, while this return is non-zero from all other perspectives. Identically zero returns in a numeraire currency are an inherent feature of numeraire-invariant trades, and investable indexes like those offered, for example, by Deutsche Bank share this invariance feature (see also Bekaert and Panayotov (2017)).

To obtain a cross section, we construct carry trades from each of the 45 possible combinations of *eight* out of the ten G-10 currencies (further details are in Appendix C). While one can similarly construct smaller or larger invariant cross sections, we find that if nine currencies are used for each trade (for a total of 10 trades in the cross section), 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 the return time series remains fixed. Nevertheless, various cross sections can reproduce the relation between carry returns and the dollar factor, which plays a key role in our approach to evaluating global risks.

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

In a first application of the invariant carry trades, we examine the ability of the dollar factor DOL to explain the returns in this cross section (recall that no clear conclusion with respect to DOL's pricing

[4] At the end of each month we sort the currencies in each trade according to their forward differentials. Then we go long (short) against the USD the top (bottom) three currencies in the ranking, with equal weights, as in the HML factor of Lustig et al. (2011) and various investable currency indexes. As in Burnside et al. (2011), we assume that initially 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. 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 numeraire invariance.

ability could be made when using the interest rate sorted portfolios in Section 2.1). This empirical exercise complements tests in Verdelhan (2018), who also studies the pricing of dollar risk, but uses as test assets specifically constructed dollar beta sorted portfolios.

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 affects little 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 is positive or negative, respectively.

At this point one clarification should be made regarding the AFD. For this purpose, we plot in Figure 1 the time series of the AFD in two versions - actual (top panel) and a three-month moving average (bottom panel). The smoothed version removes several sharp spikes, that indicate large moves reverting within a month, 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 (which together account for about a third of our 30-year sample). Throughout the paper, we use the smoothed version, which highlights the persistent, regime-like nature of the AFD, but also check that our main results are robust to this choice (see Appendix E).[5]

The table insert below shows results for our baseline cross section of 45 carry trades, and, for robustness, analogous 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 seven of these currencies. We first display, for each set of carry trades, the correlation between their average returns and DOL betas (obtained from univariate regressions of carry returns on DOL), 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

[5] Prior studies have pointed out that the standard currency data sets may contain a few questionable forward quotes, and Della Corte et al. (2016), Hassan and Mano (2017), 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.

in estimations in our full data sample (1985-2016). The remaining columns show the same statistics, but estimated over the subsamples when the AFD is negative or positive (i.e., the US interest rate is relatively high or low).

	full				$AFD < 0$ (high US int. rate)				$AFD > 0$ (low US int. rate)			
no. trades	corr.	β_{5-th}	β_{95-th}	sgnf.	corr.	β_{5-th}	β_{95-th}	sgnf.	corr.	β_{5-th}	β_{95-th}	sgnf.
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)

These results reveal a sharp contrast: Over the full sample period and when the AFD is positive, the correlation between betas and average returns is large and positive, and the DOL betas are positive and mostly statistically significant. When the AFD is negative, however, all DOL betas are negative and some are not significant, while the correlation with average carry returns is close to zero. Therefore, DOL can indeed explain the returns of the carry trade cross sections, but this explanatory power stems *entirely* from the longer subsample with relatively low US interest rate and thus positive AFD.

Concluding this section, we elaborate on the treatment of *dollar risk* in this paper. On one hand, our results so far do show that DOL is able to price the invariant carry cross section(s), and hence can play the (possibly time-varying) role of a global risk factor. Such a conclusion broadly agrees with our evidence from the interest rate sorted portfolios denominated in different currencies, and would be consistent with studies that invoke the global role of the USD, as for example Rey (2015), Passari and Rey (2015) and Verdelhan (2018), or Shin (2016), who argues that in the recent years the dollar has replaced the VIX as a global measure of risk appetite. On the other hand, the economic mechanisms that would give rise to a priced global dollar risk are not yet well-understood and have not been rigorously modeled, with a few notable exceptions (e.g., Adrian, Etula, and Shin (2015)). Furthermore, the modified LRV model that we use to inform our empirical work, can reproduce this pricing ability of DOL for *any* pair of global risk factors, indicating that DOL may be reflecting the factor structure in the data instead of being itself a global factor. Recognizing this ambiguity with respect to DOL's nature, we rather view the time-varying relation between DOL betas and carry trade returns as a new stylized fact, that emphasizes the global role of the AFD, but also hints that the practice of using separate dollar and carry risk factors in asset pricing tests in the currency market may need to be refined. We focus on non-currency variables as candidate global risk factors in our empirical tests, which incorporate the predictions of a model as discussed next.

3. Global risks and carry trades in the LRV model

The model of Lustig et al. (2014) is particularly well-suited for the purpose of this study. 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, and thus can be consistent with the time-varying relation between DOL betas and carry returns that we find in the data, which hints that different factors determine carry returns over the two AFD regimes. Third, it does not specify the factors, and hence offers the flexibility to consider various candidate global risk factors. Fourth, it allows to conveniently formalize the relation between DOL betas and carry returns, and, as we show, can be easily modified and reconciled with additional data features.

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. Following exactly the notation in Lustig et al. (2014), the log pricing kernel m^i of economy i 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. Superscripts i denote variables for different currencies/economies, except for the respective US variables which have no superscript. It follows that the interest rates r_t^i and currency excess returns rx_{t+1}^i in this model are:

$$r_t^i = -E_t[m_{t+1}^i] - \frac{1}{2}Var_t[m_{t+1}^i] = \alpha + \left(\chi - \frac{1}{2}(\gamma+\kappa)\right) z_t^i + \left(\tau - \frac{1}{2}\delta^i\right) z_t^w \quad (2)$$

$$\begin{aligned} rx_{t+1}^i &= r_t^i - r_t - \Delta s_{t+1}^i = r_t^i - r_t - m_{t+1} + m_{t+1}^i = \frac{1}{2}(\gamma+\kappa)(z_t - z_t^i) + \frac{1}{2}(\delta - \delta^i) z_t^w \\ &+ \left(\sqrt{\delta} - \sqrt{\delta^i}\right)\sqrt{z_t^w} u_{t+1}^w + \sqrt{\gamma}\left(\sqrt{z_t} u_{t+1} - \sqrt{z_t^i} u_{t+1}^i\right) + \sqrt{\kappa}\left(\sqrt{z_t} - \sqrt{z_t^i}\right) u_{t+1}^g, \quad (3) \end{aligned}$$

where Δs_{t+1}^i are spot exchange rate changes, and exchange rates are expressed as foreign currency units per one USD. All constant parameters are positive, $\chi < \frac{1}{2}(\gamma+\kappa)$, and 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.[6] 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 DOL betas of our carry trades 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 D. Here we note only 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), which are also reproduced in the note to our Table 1. We do not, however, include inflation in the simulation, and set the parameter α to match a nominal average interest rate, as in Brusa et al. (2015) (α is cancelled in all expressions involving carry trade returns and DOL, and does not impact any 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

[6]This observation implies that even though the AFD represents the *relative* US interest rate, its sign can be derived from the US interest rate *alone*, which offers modeling advantage when using the sign of the AFD as a conditioning variable for all economies/pricing kernels, as done in this paper.

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, which are 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, while the correlation is 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.

full				$AFD < 0$				$AFD > 0$			
corr	β_{5-th}	β_{95-th}	sgnf.	corr	β_{5-th}	β_{95-th}	sgnf.	corr	β_{5-th}	β_{95-th}	sgnf.
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 statistically significant only in half of the cases (on average 24.5 out of 55). Regardless of these discrepancies between the LRV model and the data, however, we demonstrate next that the model is sufficiently flexible and can be reconciled with the evidence from our carry trades, after a simple modification.

3.2. Modifying the LRV model

To accommodate the findings from the carry cross section, we seek a model modification 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 is 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]

[7] Lustig et al. (2014) point out that 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 (Section 5.5). Mueller et al. (2017, Section 5.5) report a similar finding in the context of their model.

We suggest that these features can be attained by introducing a ***time-varying dispersion*** in the parameters δ^i (deltas) that define the exposure 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 is positive (negative), and denote by LRV^d the model version with this feature, where "d" stands for "delta dispersion".

The suggested modification is prompted by the asymmetric pricing ability of the DOL factor, which was observed in Section 2, *both* with the interest rate sorted portfolios and the invariant carry cross section. In both cases the correlation between DOL betas and average returns is much weaker when $AFD < 0$, which can be rationalized by a risk that is reflected in DOL and tends to be similarly compensated in all currency returns (or not compensated at all) in one AFD regime, and differently compensated in the other regime. As per equation (3), expected currency returns in the LRV model 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 global risk factor, and hence a regime-dependent dispersion in the δ^i's would be one natural way to vary the exposure to one global factor (z^w), aiming to generate the desired asymmetry. Note that our modeling choice further emphasizes the heterogeneity across economies reflected in the δ^i's, which is an essential feature of the LRV model (see also Lustig et al. (2011)).

Recall also that Lustig et al. (2014, Section 6) argue that the AFD is counter-cyclical, and therefore, the suggested model change can be seen as introducing counter-cyclical dispersion in the deltas. As we discuss below, this feature can link the LRV^d model to a body of literature which has conjectured that the cross-sectional dispersion of market betas and/or other key variables is counter-cyclical. Furthermore, the explicit impact of the US interest rate on *all* economies (via the AFD-dependent deltas) can link the LRV^d model to studies of the international transmission or spillover effects of the US monetary policy (see, e.g., Bernanke (2017) for a recent contribution).

To justify more formally 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, that corresponds to the US economy) and setting the parameter γ equal to zero, to emphasize the global factors and main effects:

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

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

where $\widetilde{x^j}$ denotes the weighted sum of a variable or expression x across all currencies used in a carry trade, *possibly* including the USD, and the weights are those given to the currencies in the 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]

The covariance between DOL and carry trade returns is:

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

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

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

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

When $AFD > 0$ and the 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, $\widetilde{\sqrt{\delta_t^j}}$ is negative and large in magnitude in this case. Hence, the second term in (6) contributes to a positive covariance between DOL and the carry return, and, hence, to a positive DOL beta. A positive

[8] Note that unlike the expression in (4), the one in (5) 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 in the trade. At the same time, our cross section includes symmetric trades constructed from various subsets of the G-10 currencies. Many of these subsets do 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.

correlation between these betas and the average carry returns now follows, due to the $-\frac{\widetilde{\delta_t^j}}{2} z_t^w$ 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 (if at all) enter $\widetilde{z_t^j}$ and $\widetilde{\sqrt{z_t^i}}$, which will be dominated by the currencies corresponding to the highest and lowest deltas.

When $AFD < 0$ and the deltas are compressed, interest rate differentials are dominated by the terms with z_t and z_t^i, and the relative importance of the second term in (6) is small. When the USD does not enter the carry trade, the first and third terms are also small, and hence DOL beta is small or statistically insignificant, as seen sometimes in the data. When the USD enters the carry trade, it is held long, z_t has positive weight in $\widetilde{z_t^j}$, and the first and third terms in (6) generate negative DOL beta. Note however, that in this case DOL beta will be negative due to z_t, but not the remaining z_t^i's in $\widetilde{z_t^j}$, whereas the average carry return depends on the entire $\widetilde{\sqrt{z_t^j}}$ term, as per (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 $AFD < 0$.

A time-varying cross-sectional dispersion of deltas, combined with a counter-cyclical AFD, also points 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. While these studies refer to the US context, our analysis suggests that a similar pattern characterizes the global currency market, adding to the evidence in Mueller et al. (2017) on the counter-cyclical dispersion in currency correlations.

3.3. *Simulating the LRV^d model*

To provide empirical support for the modified model LRV^d, Table 1 reports results from simulations of the model, in three different parametric versions (V_1, V_2 and V_3), which offer comparison with the original LRV model. Time-varying delta dispersion is introduced by defining, for any currency j:

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

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 do not aim for a full calibration of the LRV^d model, but illustrate its performance with a small set of parameter values.

We also consider different values for the γ and κ parameters. While in equations (4) and (5) γ was set to zero, allowing to focus on the global factors, here 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 1 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 the LRV model, and three versions of the LRV^d model. 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. The "data" row shows the corresponding quantities from our 45 carry trades.

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.

Improving 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 1. 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. The model imposes certain economic structure by linking delta dispersion to the AFD regimes, and points to possible linkages 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*

To provide further support for the LRV^d model, *independent* of DOL and its relation to carry trade returns, we consider the static and dynamic components of the carry trade, similar to Hassan and Mano

[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.

(2017). For simplicity, we define these components unconditionally, based on the full data sample, where the NZD, AUD and NOK have the highest forward differentials against the USD (4.3, 3.1, and 2.1% annualized average, respectively), while CHF and JPY have the lowest (-1.5 and -2.4%). The other forward differential averages 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 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 2 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 2, however, is that in the data the two components contribute quite 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, with equal number of currencies in the two components (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 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 seven (!) times bigger in case II, which features 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. 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 2, which show analogous averages obtained in 1000 simulations of the original 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, no difference is discernable between the two regimes in the model: both Ω^+ and Ω^- are close to 0.19 for each case, implying that the LRV model exhibits a built-in permanent dominance of the static currencies in the carry trade.

Next we turn to the the LRV^d model. Intuitively, if the 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 $\widetilde{z_t^j}$). Since all z_t'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.

The bottom panel of Table 2 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 of the carry trade 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 has been 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. Evaluating global risk factors in the currency market

This section examines in a standard linear asset pricing framework (see Appendix A) a number of candidate global risk factors. These factors are required both to explain the carry return cross section *and* to be consistent with the predictions of the LRV^d model. Incorporating the LRV^d model in asset pricing tests is a distinctive feature of this paper's approach to evaluating global risk factors.

4.1. Factor models to be estimated

We look for pairs f^1 and f^2 of factors that can accommodate a time-varying delta dispersion, as postulated 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:

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

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]

[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 have verified 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.

We exploit two predictions of the LRV^d model: First, ξ_2 should be statistically significant, to reflect 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^w_{t+1} in equation (5), the slope coefficient on this factor should be close to the time-series average of $-\widetilde{\sqrt{\delta_t^j}\sqrt{z^w}}$, which, from (8), is:

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

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 the carry trade; $\widetilde{\sqrt{\delta^j}}$ is then large in magnitude, and is further multiplied by $\nu_t > 1$. On the other hand, when $AFD < 0$, not only $\nu_t \leq 1$, but also interest rates are dominated by the term with κ, and hence low (high) delta currencies can be held short (long), further reducing the magnitude of β_1.

4.2. Global financial and economic variables as candidate risk factors

The test based on the three-factor model above is implemented using variables that represent global equity and bond market risk, real activity and various dimensions of financial and macro-economic uncertainty, and have a sufficiently long history of monthly observations. The full list of variables (18 in total) is shown in Table 3, and most of them have been used in prior carry research. For example, Christiansen, Ranaldo, and Soderlind (2011), Filippou and Taylor (2017) 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 regime-switching setup; Lettau et al. (2014) find significant role for a downside equity market risk; Ready et al. (2017) 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.

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] We recognize that more stringent requirements for statistical significance of estimates and/or consistency with additional quantitative predictions of the LRV^d model can be imposed, and that would set an even higher hurdle for factors and will likely strengthen our overall conclusion that global risks remain a challenge to empirical research in the currency market.

4.3. Test results

Our empirical findings are quite surprising: 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 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.

Table 4 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

[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.

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 in the cases when both factors are returns (and hence the alphas are informative).

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, but we reiterate that our approach focuses on the interacted term involving f^1, and does not depend explicitly on estimates related to f^2.

Table 4 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 DOL has explanatory power for the invariant carry cross section in the LRV^d model for *any* factors u^w and u^g, and therefore, we do not emphasize its role as a global risk factor. 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 (with three exceptions), 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.

An important observation from Table 4 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 various variables (f^2's), 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.

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 LRV^d model. Appendix E discusses additional results, which confirm that our conclusions are little affected by these choices.

For completeness, Table A-2 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 do not support 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 only with respect to the time-series R^2's, implying that under a more stringent selection procedure even fewer candidate variables may be able to price the carry cross section in a manner consistent with the LRV^d model.

In sum, many of the variables in our set may not qualify, within our testing framework, to be considered as global risk factors. A likely exception to this conclusion is the global equity market variable, which adds new evidence on the role of standard risk factors in the currency market.

5. Economic insights

While the identity of the "true" global factors in the currency market remains an open question, our tests have nevertheless identified candidate variables that, to some extent, 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, we examine next the two regimes in more detail, and then draw some parallels with possibly related results from prior studies.

5.1. AFD regimes

In what aspects do the two AFD regimes differ most clearly? What variables take significantly different values over these regimes? We consider here some of the key variables from Table 3, 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]

Table 5 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 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 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 thus be

[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.

tentatively denoted 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. This clear distinction between the two AFD regimes can be seen as justification for our treatment of the AFD as a global (conditioning) variable, and for its role as a key element of an international asset pricing model as the LRV^d model.

5.2. Link with the Global financial cycle

The Global financial cycle, as suggested in Rey (2015), summarizes the common price variation in a large set of risky assets traded around the world (see also Passari and Rey (2015)). It offers a dimension worth pursuing in our context, because of its global nature and essential link with the US monetary policy (Miranda-Agrippino and Rey (2017)), which is a key driver of the AFD. Our interest in a global cycle is also prompted by the fact that, while we have referred above to "counter-cyclical dispersion in deltas" and have found statistically significant differences in several economic and financial variables over the two AFD regimes, we have not yet clarified which cycle is involved. For example, this does not appear to be the US business cycle, because the US analogues of the global real activity variables (output and unemployment growth) in Table 5 do not show even marginally significant differences over the two AFD regimes, with p-values above 0.20.

We employ data for the Global financial cycle factor (GFC) from Miranda-Agrippino's website. In particular, we use the shorter version of the GFC, covering 1990-2012, and splice it with the longer version of the factor for the 1985-1989 period, matching their values at the first overlapping point. Because the initial value of the factor is undetermined, we consider differences and not percentage changes.

For an illustration of the possible relations, Figure 2 indicates the periods when $AFD < 0$ and the NBER recessions, and plots the GFC factor. It is seen that a 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 GFC are well aligned with the periods of negative AFD.

Next, we include the GFC factor (more precisely, its first differences) in asset pricing tests, applying the same criteria as before, and report the results in Table 6. 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 (the cross-sectional R^2's, however, are often lower than previously). While the shorter period over which the 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, which can be explored further in the context of the LRV^d model.

5.3. Counter-cyclical dispersion in deltas: a new challenge?

While counter-cyclical cross-sectional dispersion in various variables has been previously found in a single-economy context (see Section 3.2), our findings from the currency market and the LRV^d model offer new perspectives, and imply that new interpretations of the underlying economic mechanisms may be required. 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: "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 5, 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 5 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.

Finally, 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 5, 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.

6. Conclusion

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 this model version (the LRV^d model).

Next, we design a test for evaluating candidate global risk factors which incorporates the predictions of the LRV^d model. We find that only few combinations of previously used factors can be accepted by the test. At the same time, our test results highlight the role of a global equity market factor, and possibly of a variable capturing the Global financial cycle proposed in Rey (2015), for understanding currency risks.

Our main economic insight is that the exposures of various currencies to certain global risks exhibit high dispersion in a "normal" economic environment and low dispersion in "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 currency market may require alternative interpretations, which are left for future research.

Appendix

A. Design of cross-sectional asset 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:

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

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 employ in Section 4.3 standard errors that are valid for potentially mis-specified models (e.g., Kan, Robotti, and Shanken (2013)): such a conservative estimation approach is justified 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). Where appropriate, we also show the p-value for the GRS statistic of Gibbons, Ross and Shanken. 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).

B. 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:

$$r_{t+1}^{JPY} = \sum_{i=1}^{N} w_i \left(\overline{S}_{t+1}^i / \overline{F}_t^i - 1\right) = \sum_{i=1}^{N} w_t^i \, \overline{S}_{t+1}^i / \overline{F}_t^i - \sum_{i=1}^{N} w_t^i. \tag{A-2}$$

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 (A-2) 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:

$$r_{t+1}^{JPY} = \left(r_{t+1}^{USD} + \sum_{i=1}^{N} w_i\right) \overline{S}_{t+1}^{USD} / \overline{F}_t^{USD} = r_{t+1}^{USD} \, F_t^{JPY} / S_{t+1}^{JPY}. \tag{A-3}$$

As the forward to spot ratio in (A-3) 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:

$$\begin{aligned} r_{t+1}^{JPY} &= \sum_{i=1}^{N} w_t^i \, \log\left(\overline{S}_{t+1}^i / \overline{F}_t^i\right) = \sum_{i=1}^{N} w_t^i \, \log\left(S_{t+1}^i / F_t^i \;\; \overline{S}_{t+1}^{USD} / \overline{F}_t^{USD}\right) \\ &= \sum_{i=1}^{N} w_t^i \, \log\left(S_{t+1}^i / F_t^i\right) + \sum_{i=1}^{N} w_t^i \, \log\left(\overline{S}_{t+1}^{USD} / \overline{F}_t^{USD}\right) \\ &= \sum_{i=1}^{N} w_t^i \, \log\left(S_{t+1}^i / F_t^i\right) + \log\left(\overline{S}_{t+1}^{USD} / \overline{F}_t^{USD}\right) \sum_{i=1}^{N} w_t^i = \sum_{i=1}^{N} w_t^i \, \log\left(S_{t+1}^i / F_t^i\right) + 0 = r_{t+1}^{USD}, \end{aligned} \tag{A-4}$$

which verifies that the log returns of our trades, as seen from all perspectives, are *identical*.

The above derivations rely only on equality between the total long and short sides of the trade, and hence various trades can be made invariant by enforcing this equality. For example, 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 in this paper.

C. 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 (assuming a full collateralization). 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.

Our baseline cross section includes 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 in our tests. The highest average return is more than twice larger than the lowest ones, but this spread is 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 trade 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.

D. 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:

$$\begin{aligned} DOL_{t+1} &= \overline{rx^i_{t+1}} = \frac{1}{2}(\gamma+\kappa)(z_t - \overline{z^i_t}) + \frac{1}{2}(\delta - \overline{\delta^i})z^w_t \\ &\quad + \sqrt{\gamma z_t}u_{t+1} - \overline{\sqrt{\gamma z^i_t}u^i_{t+1}} + \left(\sqrt{\delta} - \overline{\sqrt{\delta^i}}\right)\sqrt{z^w_t}u^w_{t+1} + \sqrt{\kappa}\left(\sqrt{z_t} - \overline{\sqrt{z^i_t}}\right)u^g_{t+1} \qquad \text{(A-5)} \\ rx^{carry}_{t+1} &= -\frac{1}{2}(\gamma+\kappa)\widetilde{z^j_t} - \frac{1}{2}\widetilde{\delta^j}z^w_t - \widetilde{\sqrt{\gamma z^j_t}u^j_{t+1}} - \widetilde{\sqrt{\delta^j}}\sqrt{z^w_t}u^w_{t+1} - \sqrt{\kappa}\widetilde{\sqrt{z^j_t}}u^g_{t+1}, \qquad \text{(A-6)} \end{aligned}$$

where $\widetilde{x^j}$ denotes the weighted sum of a variable or expression x across all currencies, *including* the USD, and the weights are those given to these 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). Furthermore, the second term in (A-5) cancels, as by assumption $(\delta - \overline{\delta^i}) = 0$.

From equations (A-5) and (A-6), 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 (A-5) and (A-6), containing $(z_t - \overline{z_t^i})$ and $\widetilde{z_t^j}$, 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 weights, while $\widetilde{z_t^j}$ has an equal number of them with positive and negative weights, 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 $\widetilde{z_t^j}$. Finally, z_t enters $\widetilde{z_t^j}$ with positive or negative weight with equal probability, as $\delta = \overline{\delta^i}$, whereas the z_t in (7) has always a positive weight, 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 (A-5) and (A-6), 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) $\widetilde{\delta^j}$ is on average negative, 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 $\widetilde{\delta^j} z_t^w$) and DOL betas (containing $\widetilde{\sqrt{\delta^j}} z_t^w$), 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 $\widetilde{\delta^j}$.

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, Tô, and Tran (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, because the returns constructed from different currency perspectives exhibit almost perfect correlation (above 0.995 on average). Still, for completeness, we replicate some results using the carry cross sections constructed from the (extreme) perspectives of the NZD and JPY. Table A-3 corresponds to Table 4 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 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 suitable for the study of global risks in the currency market.

The second robustness exercise relates to the AFD. 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 A-4 we repeat the tests for the models reported in Table 4, using the raw, and not smoothed AFD series. While the results are again consistent with those in Table 4, 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 a 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, with or without smoothing the AFD, are practically identical.

Finally, we address the fact that the factors used in our tests are often correlated, thus deviating from the model assumptions. We repeat the tests from Table 4 (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 A-5 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 regressions which omit the f^2 factor, as shown in Table A-2 (see also Liu, Sercu, and Vandebroek (2015, page 262)).[13] Second, the λ_1 and λ_3 estimates in Table A-5 are exactly the same as those in Table 4 (and so are their p-values), which can be seen as a special case of the invariance result in Giglio and Xiu (2018, Section 3.2). Importantly, the identity of the factors that meet our requirements and the various measures of model fit remain intact, and, therefore, orthogonalizing the two global factors does not affect our main conclusions.

[13]Slight differences in the number of significant estimates are due to the different number of available observations for f^2, as per Table 3.

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Table 1
Simulations of the LRV and LRV^d models
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	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^j's (as in equation (5), where j indexes all economies, including the US), are uniformly distributed between δ_L and δ_U, with a middle value δ (corresponding to the US). The versions of the LRV^d model, denoted V_1, V_2 and V_3, have time-varying deltas given by $\delta_t^j = \delta + \nu_t(\delta^j - \delta)$. The three model versions also have different values for γ and time-varying $\kappa_t = \xi_t \kappa$:

	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, each with length 400, similar to our monthly data series. 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 across the 1000 simulations. The bottom panel of the table shows average correlations between model-based DOL betas of carry trades and average carry returns, together with the average 5-th and 95-th beta percentiles, for the full sample and for each of the two AFD regimes, as in Sections 2.3 and 3.1. We construct all possible carry trades from nine out of 11 simulated currencies (55 trades). The "data" row reproduces the respective quantities from the 45 trades in our sample.

	$\overline{r}$	$\overline{\sigma_r}$	$\overline{rx}$	$\overline{\sigma_{rx}}$	$\overline{\rho_r}$	$\overline{\rho_{rx}}$	Sharpe ratio DC	Sharpe ratio 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

	full			$AFD<0$			$AFD>0$		
	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 2

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 percent, for the full sample period (denoted "full"), and 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 the three highest- and three lowest-yielding of the G-10 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, with equal weights, the three highest- and three lowest-yielding of the 11 simulated currencies. 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. In an analogous way, the bottom panel of the table shows the corresponding results from simulations of the three versions of the LRV^d model (V_1 to V_3), as defined in Section 3.2 and Table 1.

	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 3

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. All variables used in our tests are in percentage changes, except for the three volatility (GEV, 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.

	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 4

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-Ross-Shanken 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	sgnf.	ξ_1	sgnf.	β_2	sgnf.	ξ_2	sgnf.	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

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	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 5

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 "$AFD < 0$". 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 3, and few additional variables as defined in Section 5.1: GDP, industrial production and unemployment growth in the OECD economies (GDP, IP and UNEMP), and changes in dealer leverage (DLEV). 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	GEV	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
				CV	0.50	-0.36	0.30
MSCI	0.92	0.85	0.88	VP	-0.09	-0.06	0.96
BGB	0.40	0.54	0.48	VRP	0.40	-0.42	0.49
BGT	0.37	0.56	0.37				
BGHY	0.69	0.89	0.57	FINU	0.70	-0.22	0.05
				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 6

Models with the Global financial cycle factor

Exactly in the format of Table 4, this table presents results from tests of three-factor models that combine the changes (first differences) in the Global financial cycle factor of Miranda-Agrippino and Rey (2017) (denoted "GFC") with the variables in Table 3, and meet the same requirements.

f^1	f^2	α	sgnf.	ξ_1	sgnf.	β_2	sgnf.	ξ_2	sgnf.	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 A-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 precent, 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 percent). Statistical significance of an estimate at the 5 (10)% confidence level is denoted by two (one) stars. 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

Table A-2

Additional three-factor models

Exactly in the format of Table 4, this table presents results from tests of the remaining three-factors models which meet our criteria. Also shown are the results for a two-factor model that does not include an f^2 factor.

f^1	f^2	α	sgnf.	ξ_1	sgnf.	β_2	sgnf.	ξ_2	sgnf.	R^2	p_1	p_2	p_3	p_4
MSCI	GEV	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	GEV	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 A-3

Replications with carry trades constructed from different currency perspectives

This table replicates the results in Table 4, exactly in the same format, but using as test assets the 45 carry trades now constructed from the perspectives of the NZD or JPY, as shown in the first column.

persp.	f^1	f^2	α	sgnf.	ξ_1	sgnf.	β_2	sgnf.	ξ_2	sgnf.	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 A-4

Replications without smoothing the AFD

This table replicates the results in Tables 4, exactly in the same format, but without smoothing the AFD, used to construct the third factor in each model.

f^1	f^2	α	sgnf.	ξ_1	sgnf.	β_2	sgnf.	ξ_2	sgnf.	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 A-5

Three-factor models with an orthogonal factor

Exactly in the format of Table 4, 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.

f^1	$f^{2,orth}$	α	sgnf.	ξ_1	sgnf.	β_2	sgnf.	ξ_2	sgnf.	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
		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

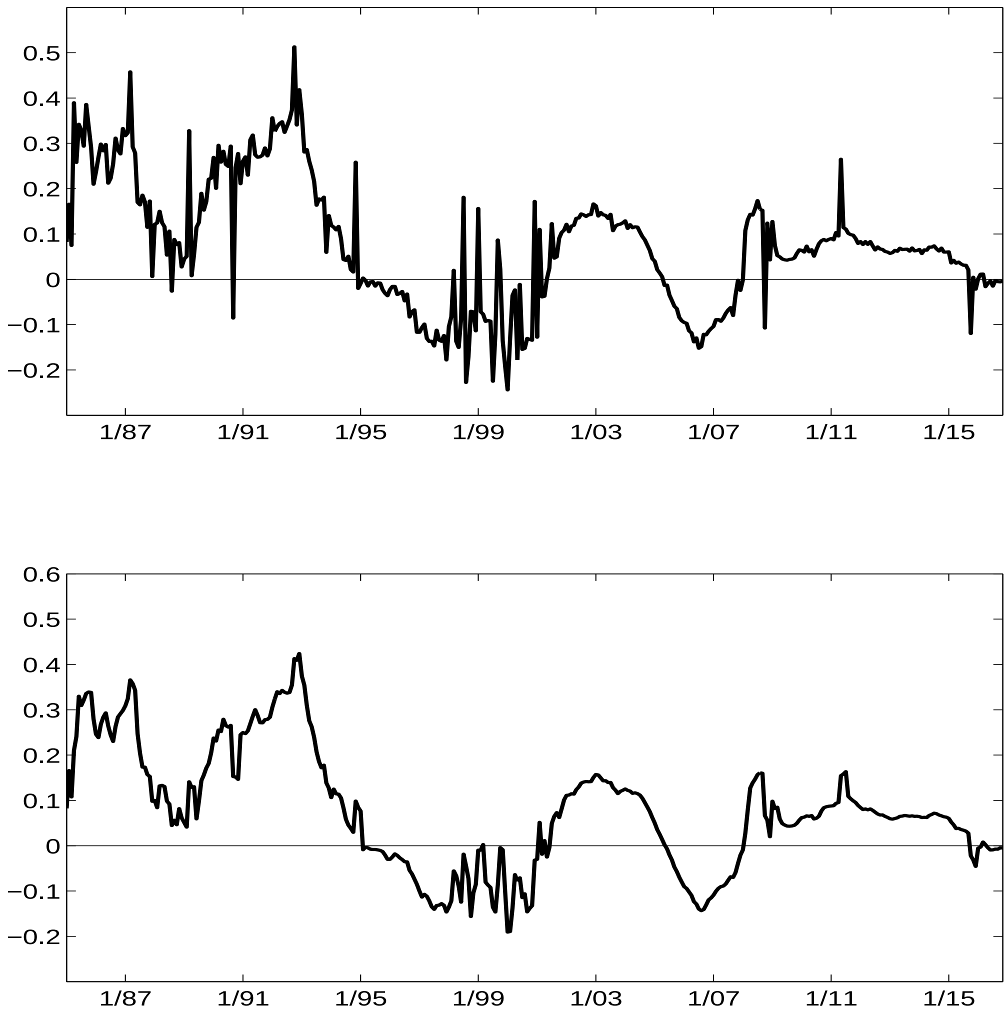

Figure 1. **Actual and smoothed average forward differential (AFD)**

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.

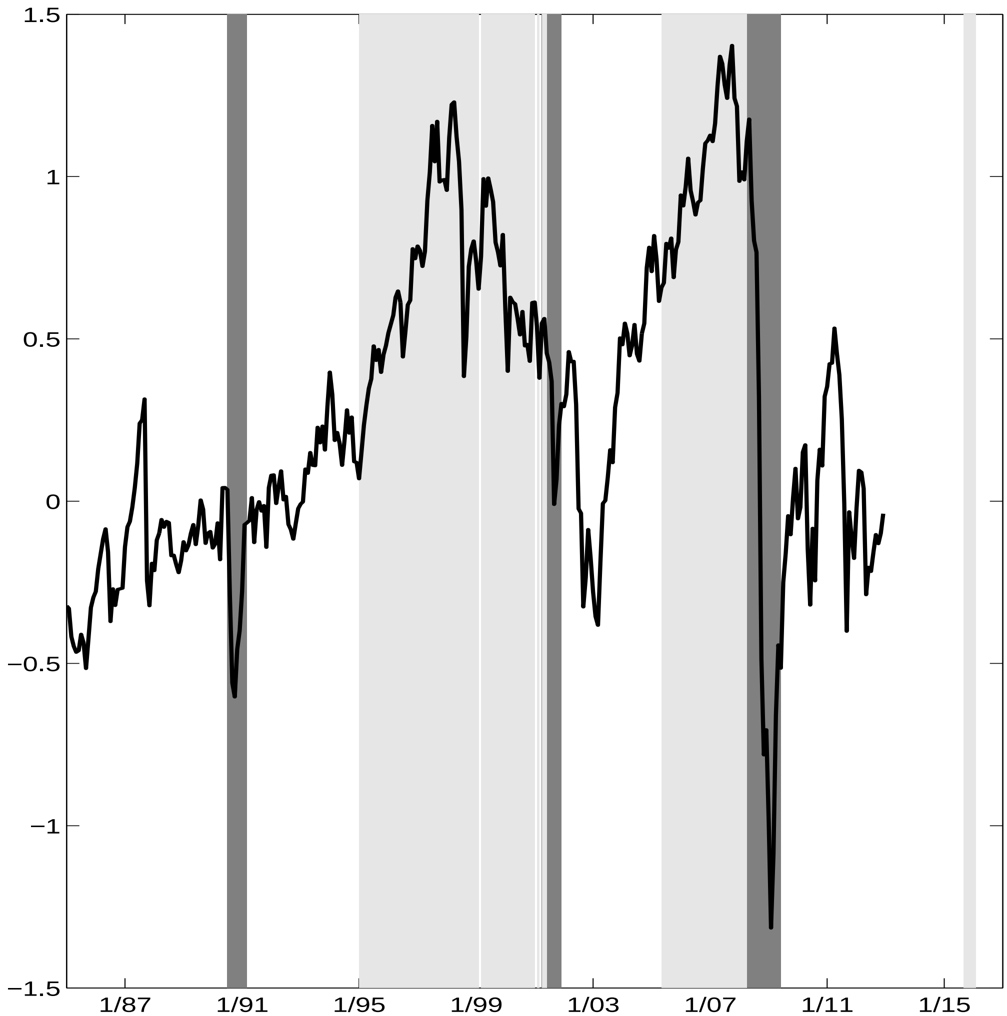

Figure 2. **AFD regimes, recessions and the Global financial cycle**

The figure shows in light grey the periods when the AFD 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.