Unexploited Currency Carry Trade Profit Opportunity*

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Abstract

In this paper, we find a significant amount of profit opportunities unexploited by conventional currency carry trade strategies. This finding implies that the uncovered interest parity fails to a greater extent than the conventional carry trade suggests. To find the unexploited profit opportunities, we propose a new currency carry trade strategy to exploit differential predictive capacity of forward discounts on future currency excess returns. We also find that emerging market currencies provide relatively large profit opportunities. While both strategies show decreasing carry trade profits as FX markets get volatile, the relative outperformance of the new carry trade strategy tends to be found in stable periods but disappears in volatile periods. The superiority of the new method relative to the conventional one is robust to various specification changes.

Keywords: Uncovered interest parity. Currency carry trade. Profit opportunity. Sorting. Filtered sorting.

JEL classification: F31, G11.

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1 Introduction

The uncovered interest parity (UIP) postulates that risk neutral and rational investors try to earn more by holding bonds in currencies with interest rates that are higher than usual, which subsequently leads to an appreciation of those currencies, eliminating trade profits. A similar equilibrium argument can be applied to the cross-section of currencies. That is, exchange rate changes tend to offset gains arising from interest rate differentials across countries. However, previous studies have documented the failure of UIP in reality (see, for example, Hansen and Hodrick (1980) and Fama (1984)). Empirical literature on the UIP shows that exchange rate changes do not offset the interest rate differential. In contrast to theory, we empirically observe that currencies with high interest rates tend to appreciate, while currencies with low interest rates tend to depreciate. In exploiting this empirical regularity, we form a profitable investment strategy used as a popular trading strategy, referred to as "carry trade": borrowing in currencies with low interest rates and investing in currencies with high interest rates. The approach gives rise to the "forward premium puzzle" developed by Fama (1984) from which betting on the violation of UIP determines the profitability of the carry trade strategy. Lustig and Verdelhan (2007) and Lustig, Roussanov and Verdelhan (2011) sort currencies by interest rate differentials (or forward discounts), build currency portfolios, and show that UIP fails for the cross-section of currencies. Investors can earn large excess returns by simply holding bonds from currencies with interest rates that are currently higher than those of other currencies.

Lustig and Verdelhan (2007) show that aggregate consumption growth risk explains why low (high) interest rate currencies do not appreciate (depreciate) as much as the interest rate differential. Lustig et al. (2011) identify a "slope" factor (i.e., carry trade profits) to account for the cross-sectional variation in average excess returns between high and low interest rate currencies. In this paper, we depart from explaining the UIP failure and try to find profit opportunities unexploited by conventional currency carry trade strategies. While it has been well documented that this FX market anomaly exists as a whole, finding unexploited currency carry trade profit opportunities would imply that UIP fails to a greater extent than conventional currency carry trade strategies suggest. To search for unexploited

profit opportunities, we present a new method of improving currency carry trade strategies to exploit differential predictive capacity of forward discounts on future currency excess returns. The new carry trade strategy provides implementable profits, and the relative profit gains from the new strategy can be regarded as an economic value of the carry trade profit opportunities which are not captured by the conventional carry trade strategy.

Lustig and Verdelhan (2007) sort currencies based on interest rate differentials and then form a long-short currency portfolio by going long for currencies with high interest rates and short for currencies with low interest rates. This sorting-based carry trade strategy has become a standard method and has been employed in other studies, including Lustig et al. (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), and Della Corte, Ramadorai, and Sarno (2016). The conventional sorting-based strategies frequently use forward discounts as a predictive variable for future currency returns, and thus its profitability relies on the predictive capacities of forward discounts. This predictive capacity may not be uniform across currencies. Rather, it may greatly differ across currencies depending on the selection of sample currencies. Our new method is to select currencies with high predictive capacity first and then to employ the conventional sorting method to form carry trade portfolios using only those currencies selected in the first stage. We expect to find that applying this new two-staged *filtered* sorting method to a set of sample currencies sufficiently differentiated by their predictability levels could improve the profitability of the carry trade strategy as a result of superior predictive capacities of the information variable. To apply the filtered sorting method to carry trade, we devise a measure to denote the predictive capacities of forward discounts. The measure is used to select currencies in the first stage, and we refer to it as the "signal ratio." We dynamically select currencies in an optimal and ex ante manner using historical information available at each trade time.

We apply our new filtered sorting method to a broad set of currencies and compare its carry trade performance with that of the conventional carry trade. Our main empirical findings are as follows. First, carry trade with the new filtered sorting significantly outperforms conventional carry trade. It implies that UIP fails more significantly than the conventional carry trade suggests. It also indicates that the new carry trade strategy uncovers profit opportunities that are not exploited by the conventional carry trade strategy. Second, cur-

rencies are found to be sufficiently differentiated in terms of the predictive capacities of forward discounts, suggesting that carry trade profit opportunities differ across currencies. In particular, emerging market currencies provide relatively large profit opportunities. Third, both strategies exhibit time-varying patterns of carry trade profits. Specifically, while both strategies show decreasing carry trade profits as FX markets get volatile, the relative outperformance of the new carry trade strategy over the conventional one tends to be found in stable periods but disappears in volatile periods.

In addition, our result not only deepens the UIP puzzle related to currency carry trade but also serves as an effective way for investors to enhance currency carry trade profits. Our new strategy is a profitable trade strategy that is implementable to actual cases of currency trade. Therefore, improving the profitability of carry trade should be of much interest in the realm of currency trading. The relative outperformance of the new carry trade strategy over the conventional one is robust to various specification changes. We obtain similar results for various currency subgroups, sample periods, and base currencies. The new carry trade portfolio is also better than the conventional one for investors who are exposed to various background risks.

The rest of this paper is organized as follows. Section 2 reviews the literature related to this paper. Section 3 explains not only conventional carry trade but also the new carry trade approach via filtered sorting. Section 4 describes the data to be used in the analysis, provides empirical results on portfolio performance, explains the mechanism through which the filtered sorting method affects portfolio performance, and characterizes the profit opportunities uncovered by the new carry trade strategy. Section 5 provides the results of various robustness checks and additional analyses. Section 6 concludes the paper.

2 Related literature

Our paper is directly related to the literature on the currency carry trade strategy, including Lustig and Verdelhan (2007), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Christiansen, Ranaldo, and Soderlind (2011), Lustig et al. (2011), Menkhoff et al. (2012a), Barroso and Santa-Clara (2015), and Orlov (2016). Although we apply the filtered sorting

method to currency carry trade, the method is quite generalized and can be used for other applications as a substitute for conventional sorting. Our paper is thus indirectly related to the literature on currency trade strategies, which the filtered sorting method may be applicable to. For example, Della Corte, Ramadorai, and Sarno (2016) build currency portfolios using the conventional sorting based on currency volatility premiums. Della Corte, Riddiough, and Sarno (2016) construct currency portfolios based on external imbalances and debts. Menkhoff, Sarno, Schmeling, and Schrimpf (2017) sort currencies by real exchange rates to form currency portfolios. Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) and Orlov (2016) apply the momentum strategy to currency portfolios and show its profitability. As all of these currency trade strategies with conventional sorting are known to be profitable, it is worthwhile exploring whether the filtered sorting method also works well with currency trade strategies other than the carry trade strategy. Empirical results from combinations of currency trade strategies with the filtered sorting method help us to judge whether suggested strategies sufficiently capture currency trade profit opportunities or not and to identify unexploited currency trade profit opportunities in FX markets.

The filtered sorting method is applicable not only for currency trade but also for other asset trade. For example, as the momentum strategy has proven its profitability not only for currency but also for equity, commodity and other asset classes, the momentum strategy with filtered sorting can also be examined.[1]

3 Currency portfolios

3.1 Currency carry trade portfolios

We form currency carry trade portfolios following Lustig and Verdelhan (2007), Lustig et al. (2011), and Menkhoff et al. (2012a). We apply the perspective of U.S. investors and use spot and forward foreign exchange contracts to form currency portfolios. Using s and f as

[1] The literature on the momentum strategy includes Jegadeesh and Titman (1993, 2001), Asness (1994), Asness, Liew, and Stevens (1997), Rouwenhorst (1998, 1999), Moskowitz and Grinblatt (1999), Okunev and White (2003), Erb and Harvey (2006), Moskowitz, Ooi, and Pedersen (2012), Asness, Moskowitz, and Pedersen (2013), Israel and Moskowitz (2013), Daniel and Moskowitz (2016), among others.

the log of the spot and forward exchange rates in units of foreign currency per U.S. dollar (USD), respectively, the log excess return rx on buying a foreign currency via a forward contract and then selling it in the spot market after one month is

$$rx_{t+1} = f_t - s_{t+1} = (f_t - s_t) - (s_{t+1} - s_t) \equiv fd_t - \Delta s_{t+1}. \tag{1}$$

Note that the excess return rx_{t+1} is decomposed into the currency forward discount (FD) fd_t and the negative of exchange rate changes Δs_{t+1}.

We use the currency forward discount fd_t to allocate currencies to five portfolios at the end of each period t. As the covered interest parity condition holds at daily and lower frequencies, sorting on forward discounts is equivalent to sorting on interest rate differentials (see, for example, Akram, Rime, and Sarno (2008)). We rebalance portfolios at the end of each month. Currencies are ranked from low to high FD. Portfolio 1 (P1) contains currencies belonging to the lowest 20% of the empirical FD distribution while portfolio 5 (P5) contains currencies belonging to the highest 20%. We compute the log currency excess return for a portfolio by taking the (equally weighted) average of log currency excess returns in the portfolio.

By using bid (denoted by superscript b) and ask (denoted by superscript a) quotes for spot and forward contracts, we compute *net* log excess returns for currency positions. Consistent with Menkhoff et al. (2012b), we compute net log excess returns for the following six cases: if a currency enters a portfolio at time t and exits the portfolio at the end of the month, the net return for the currency is (i) $rx^l_{t+1} = f^b_t - s^a_{t+1}$ for a long position and is (ii) $rx^s_{t+1} = -f^a_t + s^b_{t+1}$ for a short position. If a currency enters a portfolio but stays in the portfolio by the end of the month, the net return for the currency is (iii) $rx^l_{t+1} = f^b_t - s_{t+1}$ for a long position and is (iv) $rx^s_{t+1} = -f^a_t + s_{t+1}$ for a short position. If a currency exits a portfolio at the end of month t but entered in the portfolio before $(t-1)$, the net return is (v) $rx^l_{t+1} = f^b_t - s^a_{t+1}$ for a long position and is (vi) $rx^s_{t+1} = -f^a_t + s^b_{t+1}$ for a short position.

Returns for P1 (i.e., funding currencies in carry trade) are adjusted for transaction costs in short positions whereas portfolios 2-5 (investment currencies) are adjusted for transaction costs in long positions. The long-short carry trade portfolio (CAR) is built by borrowing

low interest rate currencies and by simultaneously investing in high interest rate currencies, and the portfolio return is computed as the return difference between P5 and P1. Following Lustig et al. (2011), we also form the zero-cost "dollar risk factor" portfolio (DOL), which is the average of all five currency portfolios (i.e., the average return of a strategy that involves borrowing money from the U.S. and investing in global money markets outside of the U.S.).

3.2 New currency carry trade portfolios

We propose a new two-stage method for forming currency carry trade portfolios. In a first stage, we assess the predictive capacities of interest rate differential (or FD) on the currency return and then remove currencies with low levels of return predictability from the set of funding or investment currencies. In a second stage, we employ the typical method of forming carry trade portfolios using currencies selected in the first stage.

To assess the extent to which the FD predicts the next period's currency return, we propose an indicator that is defined as the ratio of the difference between the number of correct predictions and the number of incorrect predictions to the total number of periods assessed. We refer to the indicator as the *signal ratio*. By construction, the signal ratio varies from -1 to 1, and the higher the signal ratio the greater the level of currency return predictability. A prediction is regarded as "correct" when the current FD and the next period's currency return have the same sign, as the carry trade strategy is based on the notion that the positive interest rate differential (or FD) should generate positive currency returns. More formally, the signal ratio $\omega_{k,t}$ at time t for currency k is computed as

$$\omega_{k,t} = \frac{1}{M} \sum_{m=1}^{M} \left[I_{rx_{k,t-m} \times fd_{k,t-m-1} > 0} - I_{rx_{k,t-m} \times fd_{k,t-m-1} \leq 0} \right], \tag{2}$$

where I_A is an indicator function valued at one when condition A holds and valued at zero otherwise. $fd_{k,t}$ denotes currency k's forward discount $f_{k,t} - s_{k,t}$, and M is the number of assessment periods. The signal ratio is computed with a moving window to capture the potential time-varying nature of the predictive capacities of forward discounts.

We select currencies with high signal ratios of higher than a threshold level $\overline{\omega}_t$ for each

month t. We use historical long-short portfolio returns to determine the threshold level for currency selection. Formally, the threshold level $\overline{\omega}_t$ for each month t is determined as a level to maximize historical long-short portfolio returns:

$$\overline{\omega}_t \in \arg\max_{\overline{\omega}} \frac{1}{t-1} \sum_{\tau=1}^{t-1} \left[P5_\tau \left(C\left(\overline{\omega}\right)\right) - P1_\tau \left(C\left(\overline{\omega}\right)\right)\right], \tag{3}$$

where $C\left(\overline{\omega}\right)$ denotes the set of currencies available for funding and investment when the threshold level $\overline{\omega}$ is applied for currency selection. $P1_\tau \left(C\left(\overline{\omega}\right)\right)$ and $P5_\tau \left(C\left(\overline{\omega}\right)\right)$ denote the returns of P1 and P5 with the set of currencies $C\left(\overline{\omega}\right)$ for month τ, respectively. When signal ratios change over time, the threshold level $\overline{\omega}_t$ changes over time. The threshold level can be found through a grid search, which is easily applied because the signal ratio is bounded between -1 and 1.

We refer to the new long-short carry trade portfolio as the *filtered* carry trade portfolio (FCAR) to differentiate it from the conventional long-short carry trade portfolio (CAR). The return of the FCAR at month t is $P5_t \left(C\left(\overline{\omega}_t\right)\right) - P1_t \left(C\left(\overline{\omega}_t\right)\right)$.

4 Empirical analyses

In this section we first describe the data to be used in our analysis. We then present the portfolio performance of the conventional and new carry trade portfolios. We also analyze the mechanism through which the filtered sorting procedure affects carry trade portfolio performance and characterize the profit opportunities uncovered by the new carry trade strategy.

4.1 Data

We obtain spot and one-month forward exchange rates vis-à-vis USD from Barclays and Reuters via Datastream. Our analysis uses monthly data obtained by sampling end-of-month rates for October 1983 to December 2016. The sample data cover fifty-five countries, and we refer to this sample as "all countries." The countries examined are listed in the

Internet Appendix, which also provides further information on the FX data used (see Table A1 and Figure A1).

4.2 Portfolio performance

As a preliminary analysis, we investigate whether currency carry trade profits differ according to the level of the signal ratio. We form carry trade currency portfolios for high, middle, and low signal-ratio currencies belonging to top 30%, middle 40%, and bottom 30% signal ratio, respectively.[2] Table 1 shows the net excess returns for the conventional carry trade portfolios using currency sets with different levels of signal ratio. While the high signal-ratio currencies offer the highest CAR average return of 8.65%, the middle and low signal-ratio currencies yield the returns of 4.58% and 6.92%, respectively. This result suggests that selecting currencies with high predictive capabilities of forward discounts could improve carry trade profits. Moreover, as the CAR return is not monotonically decreasing as the level of signal ratio decreases, a simple double-sort (based on both forward discount and the signal ratio) currency portfolios may not appropriately find unexploited profit opportunities.

Table 2 shows the net excess returns for the conventional carry trade portfolios and the new filtered carry trade portfolios and presents summary statistics of the five portfolios and of the long-short portfolios for both strategies. Table 2 shows some remarkable observations. First, the conventional carry trade portfolio return monotonically increases from P1 to P5. The CAR average return is 6.11%, and it is statistically significantly different from zero (at 5% or higher). These results are largely consistent with those of Lustig et al. (2011). Second, the new long-short carry trade portfolio FCAR exhibits an average return of 9.03% and thus it is more profitable than the CAR. Although the FCAR return is more volatile than the CAR return, it is not only statistically significantly different from zero but it also shows higher Sharpe and Sortino ratios and a similar maximum draw down. In sum, the FCAR performs better than the CAR. The new carry trade portfolio return also tends to increase from P1 to P5, although this increase is not monotonic.

[2] We restrict each currency portfolio to contain at least two currencies (i.e., ten currencies in total). Due to this restriction and the limited number of available currencies in early sample periods, different currency portfolios belonging to different currency groups may contain some common currencies.

We also analyze the stability of carry trade returns, as many institutional investors have short investment horizons and are concerned with variations in carry trade profits over time. Figure 1 shows not only cumulative net returns from the beginning of the sample period for the CAR and FCAR (Panel A) but also rolling cumulative net returns with a moving window of 36 months (Panel C). Compared to the CAR, the FCAR not only consistently shows a higher cumulative return for the sample period but also exhibits a higher cumulative return for a three-year investment horizon for most periods.

To investigate the role of transaction costs in currency portfolio performance, we present gross excess returns (without transaction cost adjustments) for both strategies by showing summary statistics in Table 3 and by demonstrating cumulative gross returns in Figure 1 (Panels B and D). The CAR return drops by nearly 3%p (p.a.) after transaction costs are adjusted, and the FCAR return also drops by 3.5%p. Without the adjustment of transaction costs, the outperformance of the FCAR over the CAR becomes more pronounced. As the bid-ask spread is known to be too large relative to actual effective spread (Lyons (2001)), the FCAR outperforms the CAR by a greater margin than is shown in Table 2.

4.3 Filtered sorting

In this subsection we analyze the mechanism through which the filtered sorting approach affects the performance of the FCAR. The filtered sorting method is based on the notion that return predictability is sufficiently differentiated across currencies and it attempts to select currencies with high predictability. Figure 2 shows averages of the signal ratio of the sample currencies for the sample period. Table A2 of the Internet Appendix reports not only currency belonging ratios for CAR and FCAR but also summary statistics of the signal ratios for individual currencies. Most currencies in our sample exhibit positive signal ratios, which implies that the currency return predictability of FD contributes to the profitability of the CAR. However, the sample currencies are sufficiently differentiated in terms of the predictive capacities of FD. The average signal ratio roughly ranges from -0.1 to 0.5, and several currencies present low signal ratios (e.g., less than 0.1). This suggests that as our sample includes many currencies of low return predictability, sorting out such currencies

could help boost portfolio performance.

The threshold of the signal ratio for currency selection is optimally determined based on the historical portfolio performance of each month and it thus is time-varying. We use an initial 36-month period to compute the signal ratio. To avoid data losses, we include currencies with observations of less than 36 as available currencies for the FCAR strategy for each month t. Further, for the first 36-month sample period, the FCAR portfolio is formed to be the same as that of the CAR. For currencies entering our sample after October 1983, we require at least twelve observations (i.e., one year) to compute the signal ratio and we include the currencies in the new portfolios for the first year after sample inclusion. To maintain a minimum level of diversification, we include at least ten currencies (i.e., two currencies in each portfolio) in forming the new portfolios. Figure 3 illustrates the time trend of the signal ratio threshold, which is contrasted from its percentile of the signal ratio distribution for each time. As is shown in Figure 3, the signal ratio threshold is time-varying. Interestingly, the threshold was determined to a low percentile level for the initial period, but it shifted to a high percentile level later on, implying that this filtering becomes more selective as levels of return predictability decrease. On an absolute level, the threshold tends to be more persistent than percentiles of the signal ratio distribution. Panel A of Figure A2 in the Internet Appendix contrasts the number of currency belongings for the conventional and new currency portfolio strategies. While the number of sample currencies grows over time, the number of currencies used for the new currency portfolio strategy does not. Figure A3 of the Internet Appendix also contrasts individual currency belonging ratios of the two strategies. Intuitively, the currency belonging ratio of the new strategy is lower than that of the conventional strategy due to currency selection; however, the difference between the two ratios greatly differs across currencies, as return predictability is sufficiently differentiated across individual currencies.

To better understand the mechanism through which the filtered sorting approach affects the performance of the FCAR, we devise a measure to denote how accurately currencies are allocated to portfolios and we refer to this as the *accuracy ratio*. The accuracy of currency allocation is determined in an ex-post sense. That is, the lowest 20% of currencies based on *realized* currency returns should be accurately allocated to portfolio 1, whereas currencies

belonging to the top 20% of realized returns should be included in portfolio 5. Thus, these accurate portfolios are ex-post optimal but are unreal. The accuracy ratio denotes the ratio of the number of currencies belonging to their accurate portfolios to the total number of available currencies. Figure 4 shows the rolling cumulative excess returns (Panel A), the ex-post optimal returns (Panel B), the accuracy ratios for both strategies (Panel C), and the number of currency belongings (Panel D). Noteworthily, both strategies differed little early on in the sample period and largely due to the small number of currencies sampled. While the number of sample currencies grows over time, the filtered sorting method becomes more selective and the number of currencies in the FCAR does not grow proportionately. Furthermore, the accuracy ratio of the filtered sorting approach is higher than that of the conventional sorting approach for most periods. On the other hand, ex-post optimal returns of the two strategies were not found to greatly differ over time. This implies that currencies excluded by the filtered sorting approach tend to spread across the realized currency return distribution. The outperformance of the FCAR relative to the CAR is mainly driven by more accurate currency allocation achieved via the filtered sorting method.

We next analyze the degree to which the "rolling" signal ratio improves portfolio performance. For our comparisons, we compute the signal ratio in a recursive manner by using all historical information available for each time and we refer to this as the "recursive" signal ratio. We also compute the signal ratio in an ex-post manner by using all of the sample information and we apply the same signal ratio for all of the periods, which we refer to as the "full" signal ratio. Figure 5 shows FCAR returns for the rolling signal ratio and the full signal ratio (Panels A and B) and for the rolling signal ratio and the recursive signal ratio (Panels C and D). Table 4 also reports summary statistics of the returns of five portfolios and the FCAR for the full and the recursive signal ratios. The FCAR with the static signal ratio shows an average return of 13.45%, which is 4.42%p higher than that of the FCAR with a rolling signal ratio. This suggests that using full information for the estimation of the signal ratio could greatly contribute to the profitability of the FCAR. On the other hand, the FCAR with the recursive signal ratio shows a 7.11% average return, which is 1.92%p lower than the return of the FCAR with the rolling signal ratio. This implies that to improve the performance of the FCAR, it is necessary to appropriately capture the time-varying nature

of the predictive capabilities of FDs. In particular, the rolling signal ratio works better than not only the recursive one but also the full one when the volatile financial crisis period running from 2007 to 2010, consistent with our intuition.

4.4 Currency subgroup and FX market volatility

Subsection 4.2 shows that the new carry trade strategy identifies a significant amount of carry trade profit opportunities unexploited by the conventional carry trade strategy. In this subsection, we use currency subgroups and FX market volatilities to characterize the relative profit gains uncovered by the new strategy.

Currency subgroup: We investigate whether the relative profit gains of the new strategy mainly come from a particular subset of currencies. We consider several currency groupings. We consider advanced countries (AD) and emerging market countries (EM) according to the classification in Della Corte et al. (2016). The ADs include fifteen countries and the EMs include forty countries. We also use the IMF's classification of advanced / emerging market countries, which we refer to as AD2 and EM2, respectively.[3] The AD2 and the EM2 include 30 and 25 countries, respectively. Another currency grouping that we consider is based on currency regimes. We take the classification of free-floating currencies (FFL) and other currencies (nonFFL) developed by the IMF.[4] In total, 25 FFL and 30 nonFFL currencies are considered. Finally, we consider a classification based on capital account openness levels. In particular, we limit the sample to currencies with a positive score on the capital account openness index developed by Chinn and Ito (2006), which we denote as CI. We also consider a smaller sample with a restriction that the Chinn-Ito index must exceed a value of one (instead of zero). Table A3 of the Internet Appendix lists the countries of each subgroups that we consider.

Table 5 shows summary statistics of net excess returns for the long-short portfolios for both strategies (the CAR and the FCAR) and for various popular currency subgroups. We also show not only cumulative net returns from the beginning of the sample period for both

[3]It is based on the classification by the IMF's International Financial Statistics.

[4]This classification is based on the Annual Report on Exchange Arrangements and Exchange Restrictions 2014 by the IMF. Although the classification changes over time, we use the classification at a fixed time.

the CAR and FCAR in Figure 6 but also rolling cumulative net returns with a moving window of 36 months in Figure 7 for each currency subgroup. The empirical results reveal some remarkable facts. First, employing popular currency grouping can improve the CAR return in some cases. In particular, we observe higher CAR net excess returns from the EM2, CI, or nonFFL than the return with all sample currencies. This implies that the profitability of the currency carry trade strategy largely stems from emerging market currencies rather than from advanced currencies, consistent with Lustig et al. (2011). Second, the filtered sorting still applies well to emerging market currencies such as the EM2, nonFFL, and EM whereas it does not apply to advanced currencies (the AD, AD2, and FFL). Both the first and second observations imply that UIP is more likely to fail for emerging market currencies than for advanced currencies. Third, the relative outperformance of the filtered sorting method is related with the signal ratio distribution. Figure A4 of the Internet Appendix shows the distribution of average signal ratios for each currency subgroup. Intuitively, a signal-based currency selection method should apply to heterogenous currencies better than homogenous currencies. As is shown in Figure A4, the signal ratio of emerging currencies shows a more disperse distribution than that of advanced currencies, which explains why the filtered sorting method works better for emerging currencies than for advanced ones. In sum, profit opportunities uncovered by the new carry trade strategy are largely found from emerging market currencies.

FX market volatility: To examine a potential relation between the relative profit gains of the new strategy and FX market volatility, we first construct FX market volatility index following Lustig et al. (2011). Then, we calculate both the CAR and the FCAR returns over sub-periods with four different levels of FX market volatility or its innovation level whose results are shown in Table 6. Both the CAR and the FCAR returns decrease as FX market volatility (or its innovation) increases. Furthermore, while the relative profit gains of the new strategy significantly exist in stable periods, they disappear in volatile periods. Next, we observe that this profit pattern is related with portfolio allocation accuracy. Specifically, portfolio allocation accuracy deteriorates as FX markets become volatile. While the new strategy consistently offers more accurate allocation than the conventional one, the relative accuracy gain also tends to decrease as FX market volatility increases.

5 Robustness and additional analyses

In this section we investigate whether the outperformance of the FCAR over the CAR is robust to various specification changes or not. We also conduct additional analyses that complement the main results.

Exchange rate changes: As is shown in (1), the currency excess return is decomposed into the forward discount (FD) and the negative of exchange rate changes. We report average exchange rate changes and the forward discount for the two long-short portfolios in Table 7. Some remarks are in order. First, the CAR profit is mostly driven by the interest rate differential while exchange rate movements insufficiently offset the FD, consistent with Lustig et al. (2011). Second, the FCAR outperforms the CAR for emerging currencies due to interest rate differentials that become higher than corresponding exchange rate changes.

Correlation: As a simple way to characterize portfolios, we provide correlation coefficients between the CAR and FCAR net excess returns for several currency groups in Table A4 of the Internet Appendix. Consistent with our intuition, we observe a strong correlation between portfolios belonging to advanced or emerging currency groups but a much lower correlation between an advanced currency portfolio and an emerging currency portfolio. Moreover, while the CAR and FCAR tend to be closely correlated for advanced currencies, they tend to be less correlated for emerging currencies. This suggests that advanced currencies are homogeneous relative to emerging currencies. Indeed, Figure A4 shows that signal ratios of advanced currencies are distributed more closely than emerging currencies.

Hypothesis testing: To statistically confirm our judgment on the relative outperformance of the filtered sorting approach over the conventional sorting approach, we conduct formal hypothesis tests and provide corresponding results in Table 8. To determine whether the portfolios significantly differ from one another, we follow DeMiguel, Garlappi, and Uppal (2009) and use two measures for our performance evaluation: the certainty-equivalent return (CEQ) and the Sharpe ratio (SR). Table 8 shows p-values for the null hypothesis that the two portfolios perform equally and the alternative hypothesis that one portfolio outperforms the other.[5] Panel A of Table 8 statistically confirms that the filtered sorting method out-

[5] We follow DeMiguel, Garlappi, and Uppal (2009) to calculate p-values.

performs the conventional sorting method not only for all of the sample currencies but also for emerging currencies at least from the CEQ-based evaluations.

Risk-adjusted alpha: To supplement statistical judgments on whether the filtered sorting outperforms the conventional sorting, we run a time-series regression (TSR) of FCAR returns on relevant currency risk factors and we then estimate risk-adjusted alphas of currency portfolios via filtered sorting. As a high return of currency portfolios formed through the filtered sorting method may simply reflect high levels of risk-taking, it is useful to determine whether portfolios still yield positive excess returns after risk adjustments are made. Specifically, we apply two risk factors for our TSR (the DOL and the CAR) proposed by Lustig et al. (2011). We believe that our selection of risk factors is natural because our currency portfolio is simply an adjustment of the CAR portfolio. We provide the corresponding estimation results in Table 9. The risk-adjusted alpha of the FCAR is significantly positive not only for all of the sample currencies but also for emerging currencies (EM2). In addition, the FCARs using currencies of open capital accounts also yield significantly positive risk-adjusted alphas. This risk-adjusted alpha-based result roughly confirms our previous cross-sectional characterization of the profit opportunities uncovered by the new currency carry trade strategy.

Diversification benefits: We assume that investors already hold diversified portfolios of major asset classes and we investigate whether adding currencies to existing portfolios could further contribute to diversification benefits. As investable portfolios, we consider the market portfolio minus the risk-free asset (RMRF), the Fama-French (1992) three portfolios (FF3) (RMRF, small minus big (SMB) portfolio, and high minus low (HML) portfolio), and the Carhart (1997) portfolios (the FF3 and the momentum (MOM) portfolio). We form minimum variance (MV) portfolios from the investable assets plus the CAR or FCAR portfolio and assess whether the FCAR portfolio still outperforms the CAR with background risks. The MV portfolios are formed each month in an ex ante manner from information available at a given time. Table 10 shows summary statistics for the MV portfolios. Table 10 (Panel D) also presents hypothesis test results for the null hypothesis that both the MV portfolio with the FCAR and the MV portfolio with the CAR perform equally and for the alternative hypothesis that the MV portfolio with the FCAR is superior to the other. The

results for the MV portfolios without the CAR or FCAR are also presented. Figure A5 of the Internet Appendix shows (rolling) cumulative returns of the three MV portfolios. Adding currencies to the diversified portfolios improves portfolio performances in all cases. Moreover, the addition of the FCAR to the MV portfolios improves portfolio performances more than the addition of the CAR in all cases. Formal hypothesis tests statistically confirm this relative superiority of the FCAR relative to the CAR in the presence of background risks.

Sub-period analysis: We also conduct a sub-period analysis by equally dividing the sample period into two sub-periods. Table A5 of the Internet Appendix shows summary statistics of net and gross excess returns of the CAR and the FCAR portfolios for both sub-periods. The currency portfolio strategies are consistently profitable for both periods, and their average returns for the sub-periods are also similar. Consistent with the case of whole sample period, the FCAR portfolio also outperforms the CAR portfolio for both sub-periods. As the first sub-period includes fewer currencies than the second one, we observe a less return gain of the FCAR (relative to the CAR) in the first sub-period than in the second one.

Different base currency: We have taken the perspective of U.S. investors until now. For a robustness check, we also present analysis results from the viewpoint of British (GBP), Swiss (CHF), Canadian (CAD), and Swedish (SEK) investors. By converting spot and forward exchange rates such that they are quoted against one of these four alternative base currencies, we lose the base currency but gain the USD as a new currency. Table A6 of the Internet Appendix shows summary statistics of CAR and FCAR portfolio returns for each alternative base currency, and Figures A6 and A7 of the Internet Appendix show the cumulative and rolling cumulative portfolio returns, respectively. The empirical results show that we can also use the new carry trade strategy to find significant amounts of profit opportunities unexploited by the conventional strategy for different base currencies, although the uncovered profit opportunities differ according to the choice of base currency.

6 Conclusion

In this paper, we find a significant amount of profit opportunities unexploited by the conventional currency carry trade strategy. It implies that UIP fails more significantly than the conventional carry trade suggests. We also find that emerging market currencies provide relatively large profit opportunities. While both strategies show decreasing carry trade profits as FX markets get volatile, the relative outperformance of the new carry trade strategy over the conventional one tends to be found in stable periods but disappears in volatile periods. We propose a new currency carry trade strategy to find the unexploited currency carry trade profit opportunities. To implement the new strategy, we first filter out currencies exhibiting a low predictability of forward discounts, and we then apply the conventional sorting method to the selected currencies in building carry trade portfolios. The new method involves a two-stage approach and is an adjustment of the conventional sorting method. A dynamic selection of currencies in the first stage helps improve portfolio performance. We apply the new method to a broad set of currencies and find that the new carry trade portfolio significantly outperforms the conventional portfolio. The superiority of the new method over the conventional one is robust to various specification changes, and we conduct additional analyses to supplement our main results.

The proposed two-stage method is quite generalized and can be used for other applications that include other trade strategies not only for currencies but also for other asset classes. This line of research is worth exploring in the future.

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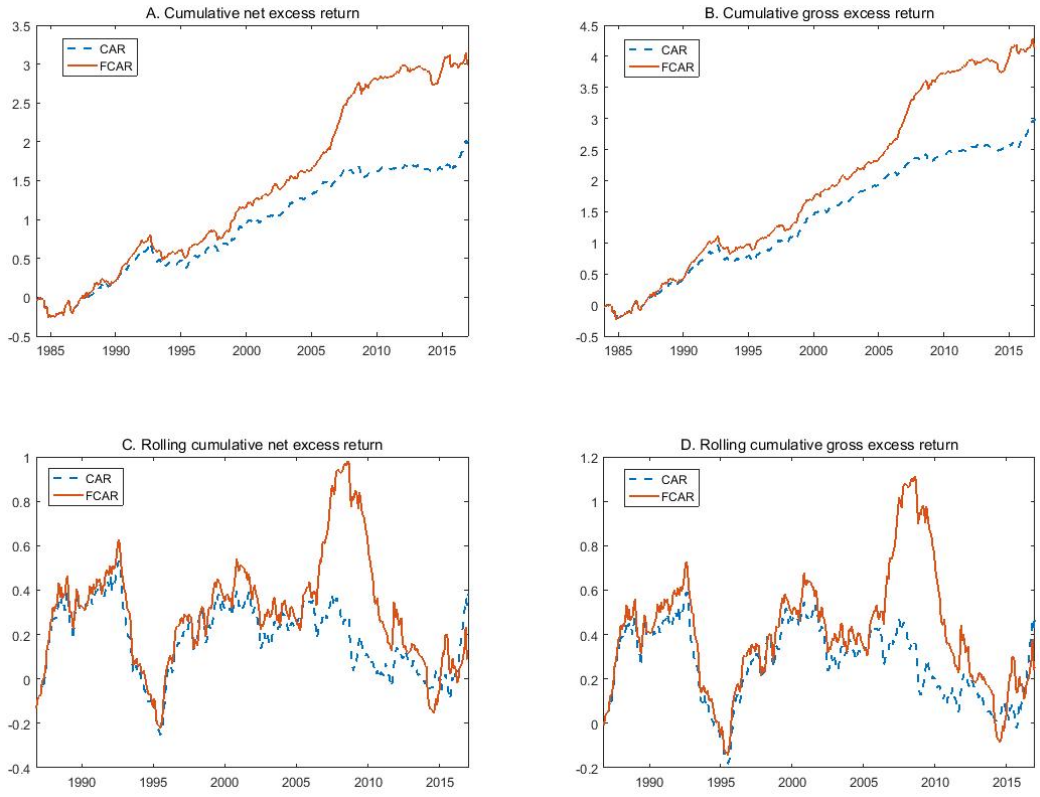

Figure 1. Excess returns. This figure shows the cumulative excess returns of CAR and FCAR net of transaction costs (Panel A) and including transaction costs (Panel B). Rolling cumulative excess returns with a moving window of 36 months are also presented for adjusting (Panel C) and including transaction costs (Panel D).

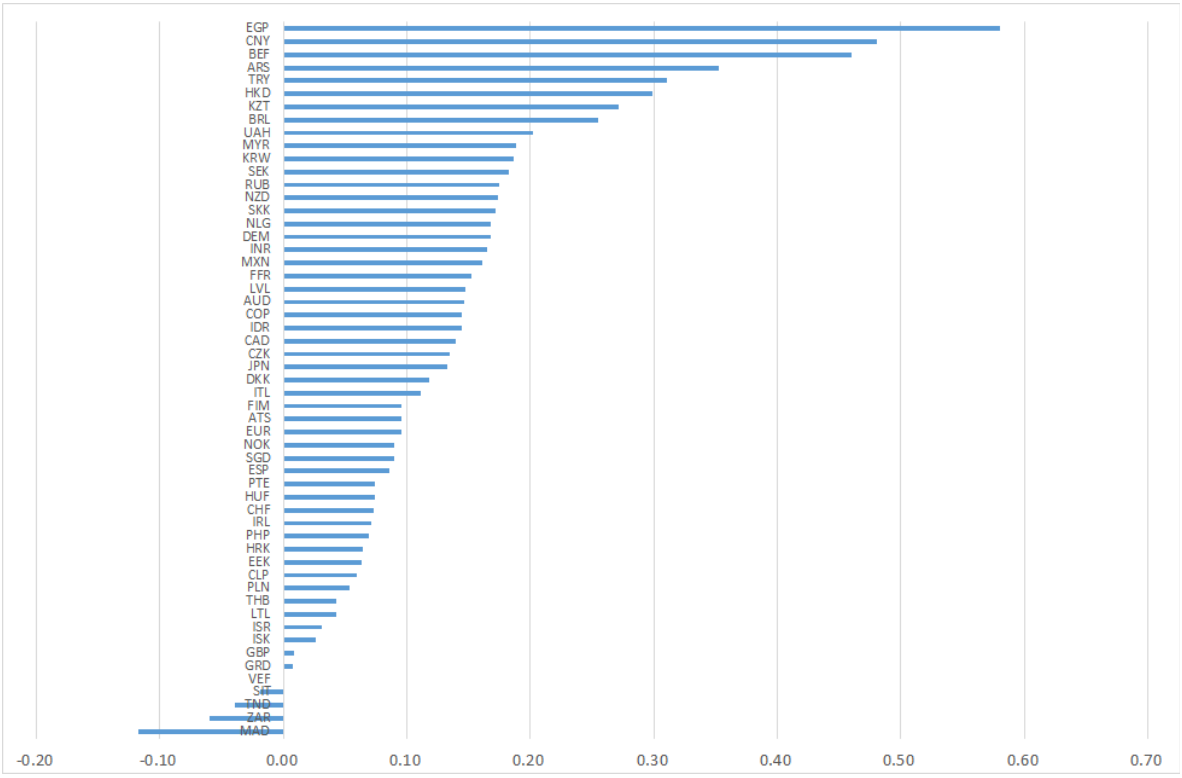

Figure 2. Average signal ratio. This figure shows averages of the signal ratio for the sample currencies during the sample period. The signal ratio is defined as (2).

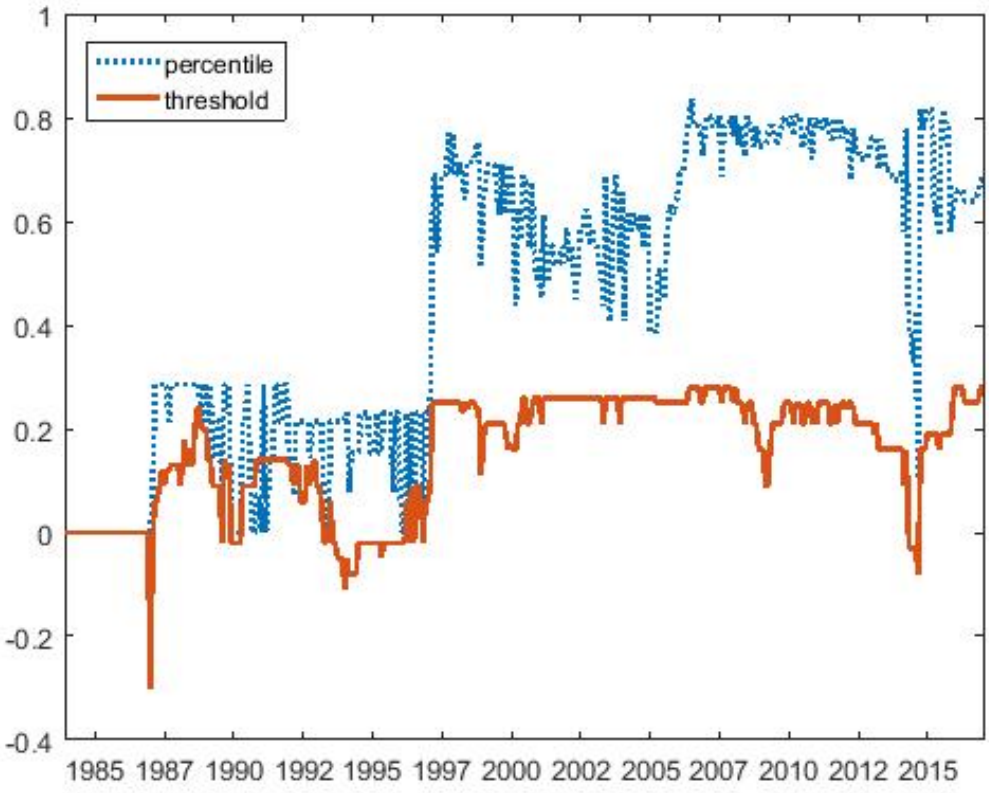

Figure 3. Signal ratio threshold for currency selection. This figure shows the signal ratio threshold (solid line) over time along with its percentile (dotted line) in the signal ratio distribution for each time.

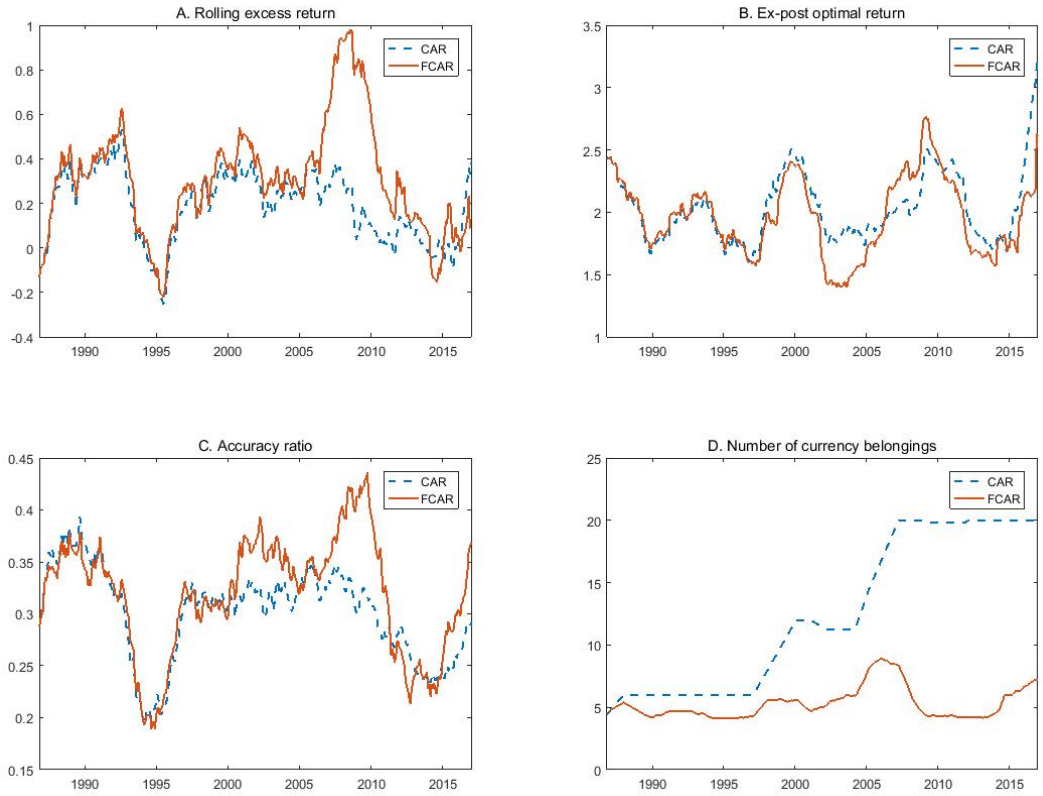

Figure 4. Accuracy ratio and ex-post optimal return. This figure shows the rolling cumulative excess returns (Panel A), ex-post optimal returns (Panel B), accuracy ratios for both strategies (Panel C), and the number of currency belongings (Panel D).

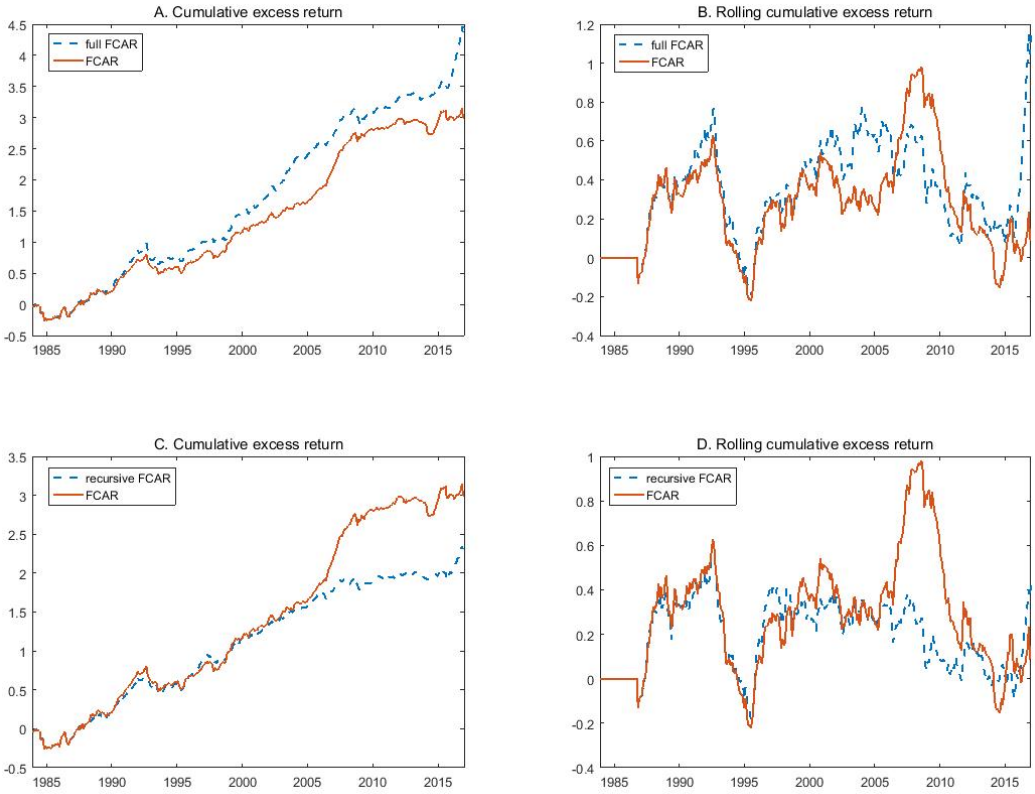

Figure 5. FCAR returns with full and recursive signal ratios. This figure shows (rolling) cumulative returns of the FCAR with a full signal ratio computed in an ex-post manner using all of the sample information and applying the same signal ratio for all periods (Panels A and B) and of that with the recursive signal ratio computed in a recursive manner from historical information available for each time (Panels C and D).

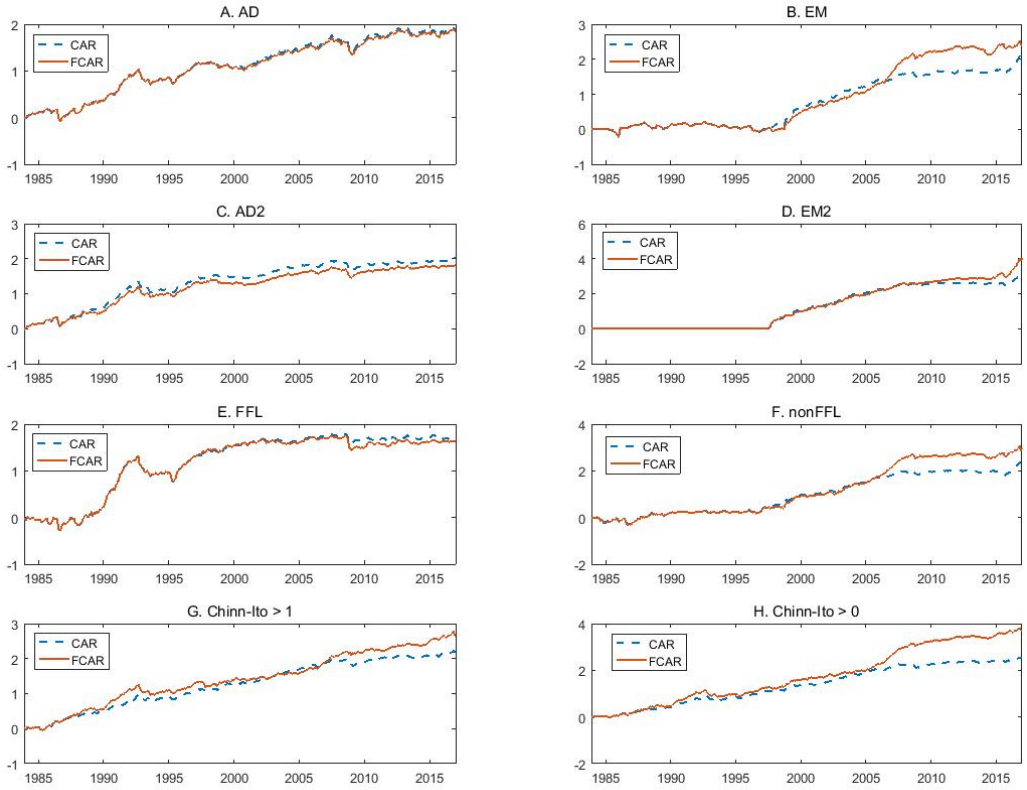

Figure 6. Country subgroups: Cumulative net excess returns. This figure shows cumulative excess returns of CAR and FCAR net of transaction costs for several country subgroups. Refer to the text for the explanations about country subgroups.

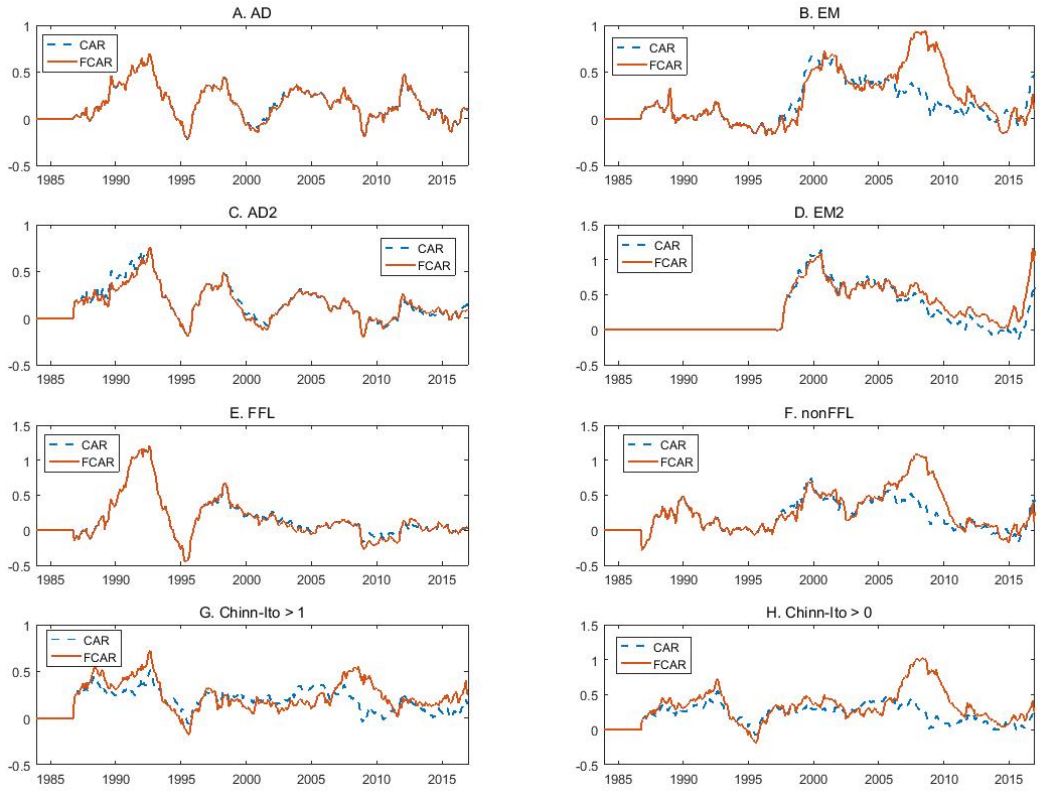

Figure 7. Country subgroups: Rolling cumulative net excess returns. This figure shows rolling cumulative excess returns (with a 36-month moving window) of CAR and FCAR net of transaction costs for several country subgroups. Refer to the text for the explanations about country subgroups.

Table 1. Signal ratio and currency portfolio return.

The table presents mean excess returns of currency carry trade portfolios sorted on the one-month forward discount or interest rate differential relative to the Unites States (FD). The first portfolio (P1) contains the bottom 20% of all currencies with low FD (low-yielding currencies), whereas the last portfolio (P5) contains the top 20% of all currencies with high fd (high-yielding currencies). The CAR is a long-short strategy that buys P5 and sells P1 (P5-P1). The currency portfolios are constructed for high, middle, and low signal-ratio currencies belonging to top 30%, middle 40%, and bottom 30% signal ratio, respectively. Each currency portfolio contains at least two currencies. t-statistics based on Newey and West (1987) standard errors are reported. Excess returns are expressed in percentage per annum and adjusted for transaction costs. The portfolios are rebalanced monthly, and the sample runs from October 1983 to December 2016.

Signal ratio		P1	P2	P3	P4	P5	P5-P1
High	Mean	-1.19	-1.17	2.65	0.99	7.46	8.65
	[t-val]	-0.83	-0.80	1.56	0.55	3.01	4.03
Middle	Mean	-3.46	-0.01	0.17	2.63	1.11	4.58
	[t-val]	-1.93	-0.01	0.09	1.57	0.47	2.16
Low	Mean	-3.56	-0.37	-0.09	1.55	3.36	6.92
	[t-val]	-1.97	-0.22	-0.05	0.90	1.50	3.41

Table 2. Net excess return.

The table presents descriptive statistics of currency carry trade portfolios sorted on the one-month forward discount or interest rate differential relative to the Unites States (FD). The first portfolio (P1) contains the bottom 20% of all currencies with low FD (low-yielding currencies), whereas the last portfolio (P5) contains the top 20% of all currencies with high fd (high-yielding currencies). The CAR is a long-short strategy that buys P5 and sells P1. The FCAR is also a long-short strategy that buys P5 and sells P1 after selecting currencies with high currency return predictability based on the signal ratio. The table also reports the first-order autocorrelation coefficient (AC(1)), the annualized Sharpe ratio (SR), the annualized Sortino ratio (SO), the maximum drawdown (mdd), and the frequency of portfolio switches (Freq). t-statistics based on Newey and West (1987) standard errors are reported. Excess returns are expressed in percentage per annum and adjusted for transaction costs. The portfolios are rebalanced monthly, and the sample runs from October 1983 to December 2016.

	P1	P2	P3	P4	P5	P5-P1
			A. CAR			
Mean	-2.62	-1.10	1.02	1.95	3.49	6.11
(t-val)	-1.71	-0.68	0.67	1.23	1.62	3.55
Median	-2.28	-0.96	0.23	3.36	5.53	8.41
SD	7.56	8.50	7.77	8.45	9.95	8.66
Skew	-0.04	-0.06	-0.16	-0.51	-1.16	-1.12
Kurt	3.36	4.31	4.01	4.99	8.37	6.92
AC(1)	0.07	-0.01	0.05	0.06	0.16	0.11
SR	-0.35	-0.13	0.13	0.23	0.35	0.71
SO	-0.45	-0.18	0.19	0.33	0.48	1.02
mdd	0.63	0.55	0.28	0.33	0.43	0.29
Freq	0.27	0.36	0.34	0.27	0.13	0.20
			B. FCAR			
Mean	-1.31	-1.27	1.50	0.70	7.72	9.03
(t-val)	-0.94	-0.84	0.90	0.40	2.98	4.02
Median	-0.08	-0.49	1.98	2.50	9.54	11.10
SD	7.29	7.89	8.71	9.06	11.60	10.95
Skew	0.04	-0.15	-0.68	-0.46	-1.06	-1.18
Kurt	5.80	4.78	7.56	4.44	10.64	7.07
AC(1)	0.01	0.04	0.08	0.13	0.18	0.11
SR	-0.18	-0.16	0.17	0.08	0.67	0.82
SO	-0.24	-0.22	0.24	0.10	0.95	1.20
mdd	0.49	0.63	0.32	0.41	0.43	0.28
Freq	0.27	0.43	0.43	0.37	0.17	0.22

Table 3. Gross excess return.

This table presents descriptive statistics of gross excess returns of currency carry trade portfolios without adjustment of transaction costs. Refer to Table 2 for other explanations.

	P1	P2	P3	P4	P5	P5-P1
			A. CAR			
Mean	-3.43	-0.33	2.05	3.25	5.61	9.03
(t-val)	-2.24	-0.20	1.33	2.06	2.62	5.21
Median	-2.97	-0.08	0.99	4.30	7.35	11.49
SD	7.55	8.51	7.80	8.43	9.99	8.71
Skew	-0.05	-0.06	-0.13	-0.49	-1.08	-1.02
Kurt	3.34	4.31	4.00	4.95	8.18	6.65
AC(1)	0.07	0.00	0.05	0.06	0.15	0.11
SR	-0.45	-0.04	0.26	0.39	0.56	1.04
SO	-0.58	-0.05	0.39	0.56	0.80	1.60
mdd	0.70	0.51	0.24	0.27	0.42	0.26
Freq	0.27	0.36	0.34	0.27	0.13	0.20
			B. FCAR			
Mean	-2.27	-0.47	2.56	2.03	10.27	12.54
(t-val)	-1.62	-0.31	1.55	1.18	3.92	5.46
Median	-0.71	0.44	3.05	3.52	11.95	13.94
SD	7.30	7.90	8.69	9.03	11.70	11.06
Skew	-0.01	-0.12	-0.64	-0.42	-0.83	-1.02
Kurt	5.69	4.76	7.44	4.38	10.84	6.69
AC(1)	0.02	0.04	0.08	0.13	0.18	0.11
SR	-0.31	-0.06	0.30	0.23	0.88	1.13
SO	-0.41	-0.08	0.42	0.32	1.31	1.78
mdd	0.58	0.60	0.27	0.37	0.42	0.26
Freq	0.27	0.43	0.43	0.37	0.17	0.22

Table 4. Full and recursive signal ratios.

This table shows summary statistics of the returns of the FCAR with the full signal ratio computed in an ex-post manner using all of the sample information and applying the same signal ratio for all periods (Panel A) and of that with the recursive signal ratio computed in a recursive manner from historical information available for each time (Panel B).

	P1	P2	P3	P4	P5	P5-P1
	A. FCAR with full signal ratio					
Mean	-6.02	0.19	1.23	1.43	7.43	13.45
(t-val)	-2.88	0.13	0.83	0.74	2.92	5.11
Median	-2.41	0.12	1.28	2.58	10.22	14.87
SD	8.54	7.36	7.55	9.80	11.61	11.78
Skew	-0.29	0.17	-0.61	-0.56	-1.43	-0.49
Kurt	5.86	4.15	6.32	6.25	8.95	5.77
AC(1)	0.17	0.02	0.05	0.09	0.17	0.17
SR	-0.70	0.03	0.16	0.15	0.64	1.14
SO	-0.83	0.04	0.23	0.20	0.89	1.89
mdd	0.88	0.50	0.29	0.51	0.43	0.30
Freq	0.24	0.41	0.35	0.32	0.18	0.21
	B. FCAR with recursive signal ratio					
Mean	-3.37	-0.64	0.79	2.18	3.74	7.11
(t-val)	-2.12	-0.41	0.51	1.43	1.65	3.93
Median	-3.04	-0.40	0.41	2.94	7.39	9.24
SD	7.79	8.28	7.88	8.27	10.51	9.45
Skew	-0.14	-0.03	-0.13	-0.58	-1.14	-1.12
Kurt	3.80	4.54	4.11	5.65	7.46	6.42
AC(1)	0.06	-0.02	0.04	0.05	0.15	0.08
SR	-0.43	-0.08	0.10	0.26	0.36	0.75
SO	-0.55	-0.11	0.14	0.37	0.48	1.09
mdd	0.70	0.49	0.37	0.27	0.43	0.30
Freq	0.29	0.38	0.34	0.27	0.14	0.22
	C. Hypothesis tests					
FCAR	CEQ			SR		
	γ =1	γ =3	γ =5			
Full vs rolling	0.00	0.00	0.00	0.01		
Rolling vs. recursive	0.09	0.13	0.19	0.29		

Table 5. Currency subgroups.

This table shows summary statistics of net excess returns for the long-short portfolios for CAR and FCAR with various currency subgroups. Refer to the text for the explanations about currency subgroups.

	AD	EM	AD2	EM2	FFL	nonFFL	CI	CI1
					A. CAR			
Mean	5.67	6.35	6.05	9.45	5.20	7.22	7.62	6.62
(t-val)	2.86	3.43	3.45	4.28	2.20	3.39	5.67	5.19
Median	8.34	5.05	6.98	0.00	6.04	7.79	8.84	7.70
SD	10.48	9.38	8.72	9.35	10.89	11.01	7.33	6.91
Skew	-1.01	0.64	-1.32	1.55	-0.92	-0.69	-0.55	-0.45
Kurt	6.30	8.14	8.30	10.77	8.11	5.86	4.21	4.32
AC(1)	0.09	0.13	0.22	0.26	0.22	0.06	0.15	0.16
SR	0.54	0.68	0.69	1.01	0.48	0.66	1.04	0.96
SO	0.76	1.16	0.98	2.30	0.68	0.98	1.68	1.55
mdd	0.33	0.26	0.28	0.18	0.45	0.31	0.23	0.19
Freq	0.22	0.21	0.23	0.17	0.27	0.17	0.17	0.16
					B. FCAR			
Mean	5.57	7.22	5.47	12.11	4.90	8.98	11.10	7.98
(t-val)	2.82	3.39	3.18	4.52	2.00	3.77	5.88	4.82
Median	8.73	6.65	6.76	0.00	4.80	9.73	11.69	9.98
SD	10.42	10.86	8.63	10.81	11.17	13.34	9.73	9.24
Skew	-1.02	0.20	-1.14	1.29	-1.10	-0.98	-0.78	-1.02
Kurt	6.40	9.67	6.95	13.89	9.05	9.68	6.01	7.22
AC(1)	0.09	0.11	0.22	0.24	0.22	-0.03	0.11	0.04
SR	0.53	0.66	0.63	1.12	0.44	0.67	1.14	0.86
SO	0.75	1.08	0.90	2.51	0.62	0.99	1.87	1.31
mdd	0.33	0.27	0.28	0.19	0.45	0.31	0.29	0.28
Freq	0.22	0.20	0.24	0.19	0.29	0.20	0.24	0.24

Table 6. FX market volatility.

This table shows net excess returns for the long-short portfolios for CAR and FCAR over sub-periods with four different levels of FX market volatility or its innovation level. The FX market volatilities and their innovations are constructed by following Lustig et al. (2011). The differences between the FCAR and CAR returns ("Diff") and its t-values based on Newey and West (1987) standard errors are reported. Portfolio allocation accuracies are measured based on ex post optimal portfolios and are reported not only for all five currency portfolios but also for the first and the fifth portfolios.

FX volatility					FX volatility				
	CAR	FCAR	Diff	t-val	innovation	CAR	FCAR	Diff	t-val
	A. Excess Return					D. Excess Return			
Low	12.804	19.011	6.207	2.406	Low	12.368	15.554	3.186	1.087
2	9.983	12.570	2.587	1.140	2	9.583	13.074	3.490	1.343
3	5.654	8.392	2.738	1.130	3	8.479	14.942	6.463	2.139
High	-3.534	-3.306	0.228	0.052	High	-5.472	-6.785	-1.314	-0.375
	B. Accuracy: All five portfolios					E. Accuracy: All five portfolios			
Low	0.602	0.622	0.020	1.144	Low	0.594	0.637	0.043	2.587
2	0.587	0.613	0.026	1.617	2	0.565	0.595	0.030	1.792
3	0.556	0.586	0.030	1.959	3	0.571	0.602	0.031	2.143
High	0.517	0.527	0.010	0.645	High	0.534	0.514	-0.019	-1.200
	C. Accuracy: P1 & P5 portfolios					F. Accuracy: P1 & P5 portfolios			
Low	0.619	0.643	0.024	1.267	Low	0.597	0.648	0.052	2.624
2	0.607	0.644	0.038	2.020	2	0.625	0.653	0.028	1.321
3	0.581	0.624	0.042	2.530	3	0.591	0.632	0.041	2.203
High	0.535	0.566	0.031	1.499	High	0.533	0.545	0.012	0.587

Table 7. Exchange rate changes and forward discounts.

This table shows average of exchange rate changes (Δs) and the forward discount (FD) for CAR and FCAR with all sample currencies (All) and currency subgroups. Refer to the text for the explanations about currency subgroups.

Subgroup	CAR		FCAR	
	FD	Δs	FD	Δs
All	14.59	5.56	18.94	6.47
AD	8.69	1.22	8.68	1.31
EM	15.56	5.66	18.01	6.76
AD2	8.86	0.66	8.68	1.03
EM2	25.34	5.17	32.11	7.37
FFL	10.44	3.63	10.39	3.89
nonFFL	18.54	7.46	22.07	8.82
CI	10.38	0.99	17.42	3.19
CI1	7.43	-0.47	13.41	2.49

Table 8. Hypothesis tests of currency portfolios.

This table shows p-values for the null hypothesis that two portfolios perform equally and the alternative hypothesis that the first portfolio outperforms the second one. Portfolio performance is measured by the certainty-equivalent return (CEQ) (with risk-aversion coefficient γ) or the Sharpe ratio (SR). Refer to the text for the explanations about the portfolios and the currency subgroups.

	CEQ			SR
Group	γ =1	γ=3	γ=5	
	A. FCAR(Group) vs. CAR(Group)			
All	0.015	0.036	0.076	0.167
AD	0.719	0.693	0.667	0.665
EM	0.267	0.358	0.458	0.541
AD2	0.886	0.879	0.871	0.859
EM2	0.011	0.022	0.041	0.161
FFL	0.776	0.816	0.849	0.837
nonFFL	0.119	0.235	0.395	0.432
CI	0.004	0.010	0.024	0.239
CI1	0.181	0.269	0.374	0.730
	B. FCAR(All) vs. CAR(Group)			
All	0.015	0.036	0.076	0.167
AD	0.041	0.046	0.053	0.058
EM	0.085	0.116	0.155	0.209
AD2	0.054	0.089	0.138	0.227
EM2	0.609	0.668	0.721	0.814
FFL	0.020	0.021	0.022	0.023
nonFFL	0.139	0.138	0.138	0.139
CI	0.236	0.390	0.562	0.913
CI1	0.101	0.205	0.354	0.785

Table 9. Time-series regressions of FCAR returns.

This table shows the results of the time-series regressions of FCAR returns on currency risk factors (the DOL and the CAR.) Refer to the text for the explanations about the risk factors. The alpha is expressed in annualized percentage. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

FCAR	coefficient			R^2
	alpha	DOL	CAR	
All	3.22**	0.08	0.94***	0.57
AD	1.34	0.01	0.69***	0.33
EM	2.12	0.14**	0.73***	0.29
AD2	1.72	0.08*	0.61***	0.39
EM2	13.56***	-0.02	0.95***	0.26
FFL	0.09	-0.15***	0.80***	0.38
nonFFL	2.55	-0.02	1.05***	0.47
CI	6.74***	0.01	0.71***	0.40
CI1	3.95***	-0.06	0.66***	0.38

Table 10. Currencies in diversified portfolios.

This table shows summary statistics of minimum variance (MV) portfolios which are formed using (i) the market portfolio minus the risk-free asset (RMRF) in Panel A, (ii) the Fama-French (1992) three portfolios (FF3) in Panel B, or (iii) the Carhart (1997) portfolios (the FF3 and the momentum (MOM) portfolio) in Panel C. The MV portfolios are formed solely with the investable assets or including the CAR or FCAR portfolio. The MV portfolios are formed each month in an ex ante manner using historical information available at a given time. Panel D also presents hypothesis test results for the null hypothesis that both the MV portfolio with the FCAR and the MV portfolio with or without the CAR perform equally and the alternative hypothesis that the MV portfolio with the FCAR outperforms the other.

	A. RMRF with			B. FF3 with			C. FF3+MOM with		
	none	CAR	FCAR	none	CAR	FCAR	none	CAR	FCAR
Mean	7.61	9.29	11.85	3.24	4.02	4.51	3.68	4.35	4.78
(t-val)	2.62	5.81	6.26	2.49	3.45	3.92	3.61	4.71	5.23
Median	13.98	11.22	13.01	2.72	3.82	5.66	3.56	4.83	4.94
SD	15.32	7.92	9.31	5.86	5.11	5.09	5.01	4.50	4.52
Skew	-0.91	-1.14	-1.25	-0.18	-0.30	-0.43	-0.34	-0.48	-0.54
Kurt	5.88	8.92	8.00	5.08	4.91	4.96	5.40	5.98	5.94
AC(1)	0.09	0.17	0.14	0.18	0.23	0.22	0.07	0.10	0.10
SR	0.50	1.17	1.27	0.55	0.79	0.89	0.73	0.97	1.06
SO	0.70	1.88	2.00	0.86	1.28	1.44	1.17	1.59	1.77
mdd	0.54	0.17	0.17	0.17	0.16	0.15	0.10	0.09	0.09

	D. Hypothesis tests				
	FCAR	CEQ			SR
	vs.	γ =1	γ =3	γ =5	
RMRF with	none	0.01	0.00	0.00	0.00
	CAR	0.01	0.01	0.02	0.20
FF3 with	none	0.00	0.00	0.00	0.00
	CAR	0.03	0.03	0.03	0.03
FF3+MOM with	none	0.00	0.00	0.00	0.00
	CAR	0.02	0.02	0.02	0.03

Internet Appendix to "Unexploited Currency Carry Trade Profit Opportunity"

January 2018

Abstract

This appendix presents supplementary results not included in the main body of the paper.

1 Data

Our data set is similar to that used in Della Corte, Riddiough, and Sarno (2016). We obtain spot and one-month forward exchange rates vis-à-vis USD from Barclays and Reuters via Datastream. Our analysis uses monthly data obtained by sampling end-of-month rates from October 1983 to December 2016. Our sample comprises 55 countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Estonia, Euro Area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, Ukraine, United Kingdom, and Venezuela. We call this sample "all countries". Following Della Corte, Riddiough, and Sarno (2016), we remove data when we observe large deviations from the covered interest rate parity (CIP) condition: Argentina from September 2008 to April 2009, and from May 2012 to June 2014; Egypt from November 2011 to August 2013; Indonesia from December 1997 to July 1998, and from February 2001 to May 2005; Malaysia from May 1998 to June 2005; Turkey from November 2000 to November 2001; South Africa for August 1985, and from January 2002 to May 2005; Russia from December 2008 to January 2009; Kazakhstan from November 2008 to February 2009; Venezuela from March 2008 to the end of the sample. Table A1 shows descriptive statistics of individual currencies. Figure A1 shows time trend of average bid-ask spreads for all and advanced countries.

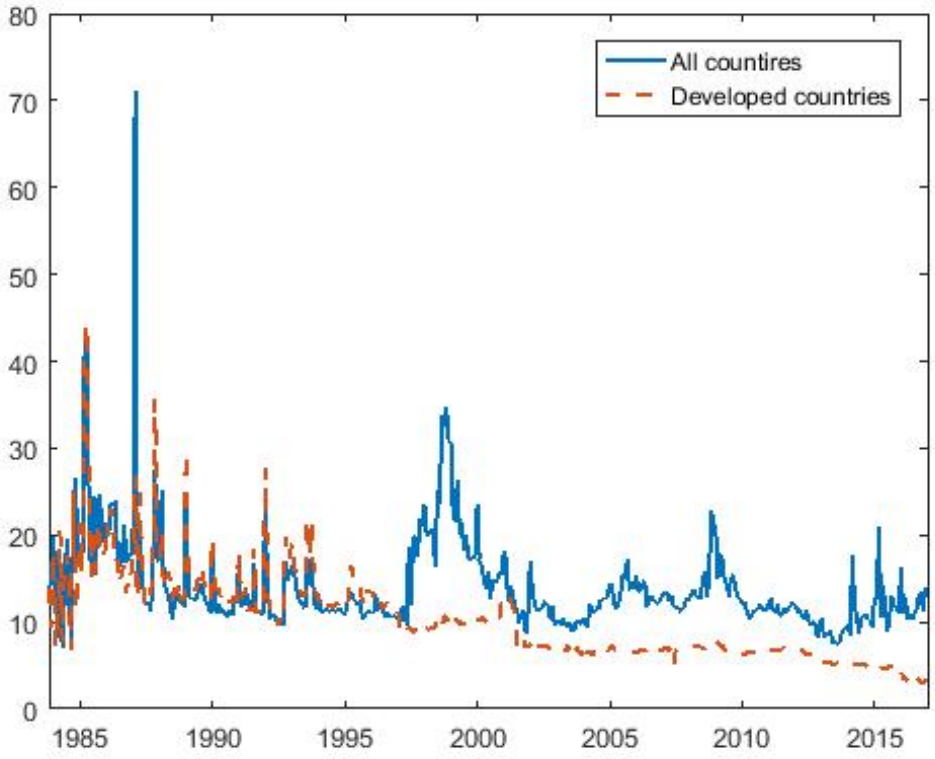

Figure A1. Bid-ask spreads. This figure shows percentage bid-ask spreads in basis points for the sample period from 1983:1 to 2016:12. The solid line shows average spreads for all countries whereas the dashed line shows spreads for a subset of 15 developed countries (according to Della Corte, Riddiough, and Sarno (2016)). Average bid-ask spread across countries in a given month are shown. We include both bid-ask spreads between spot rates as well as 1-month forward rates.

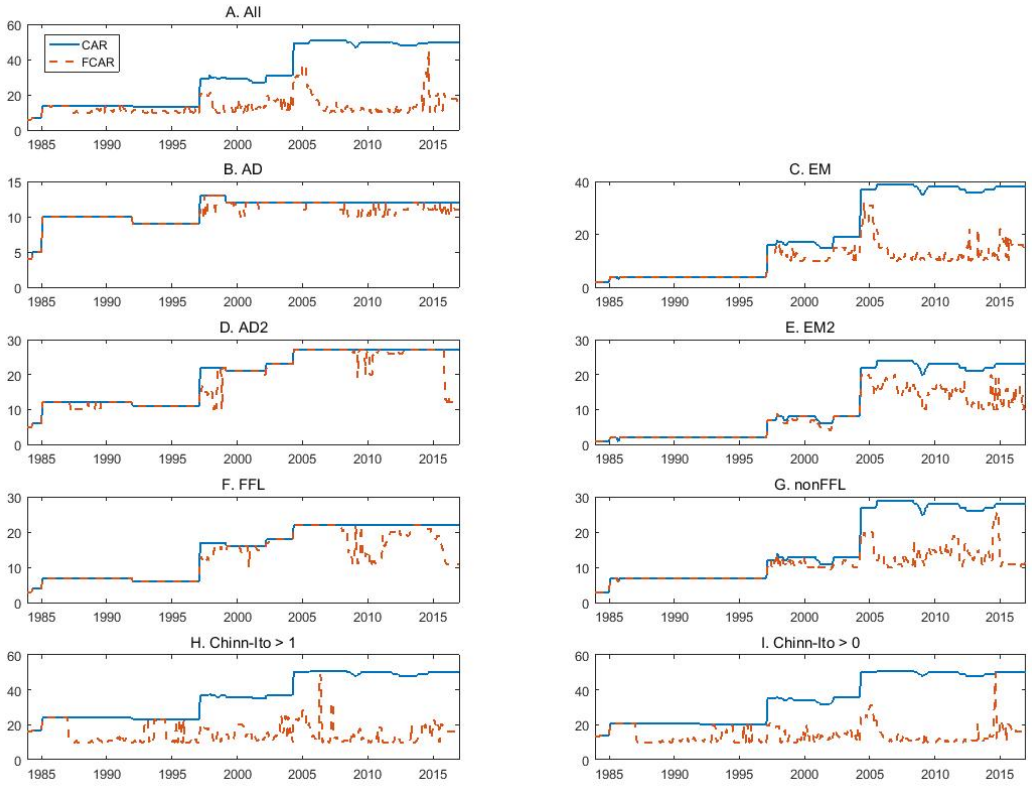

Figure A2. Number of currency belongings. This figure shows the number of currency belongings with the conventional (CAR) and the filtered (FCAR) sorting method not only for all sample countries (All) but also for country subgroups. Refer to Table A4 for the explanations about country subgroups.

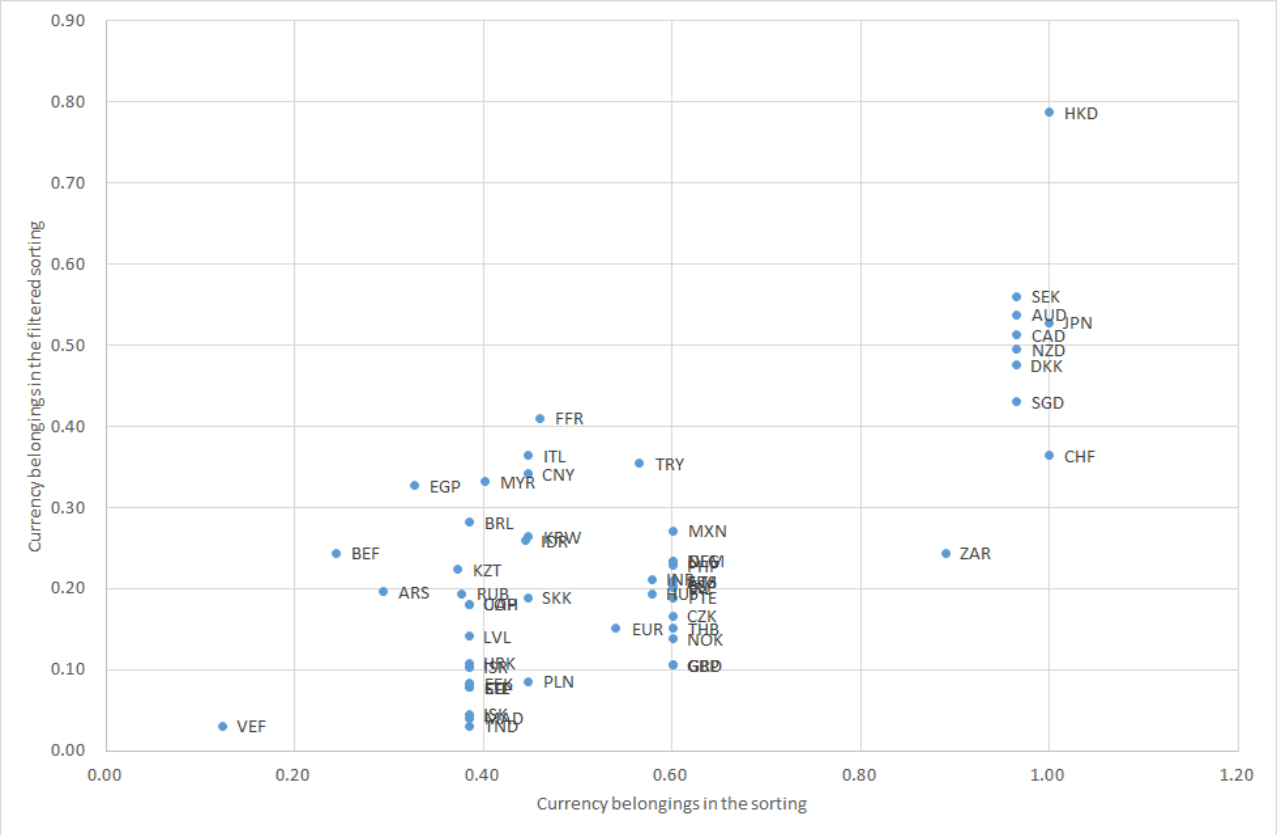

Figure A3. Average currency belonging ratios of individual currencies. This figure contrasts average currency belonging ratios for CAR (x-axis) with those for FCAR (y-axis).

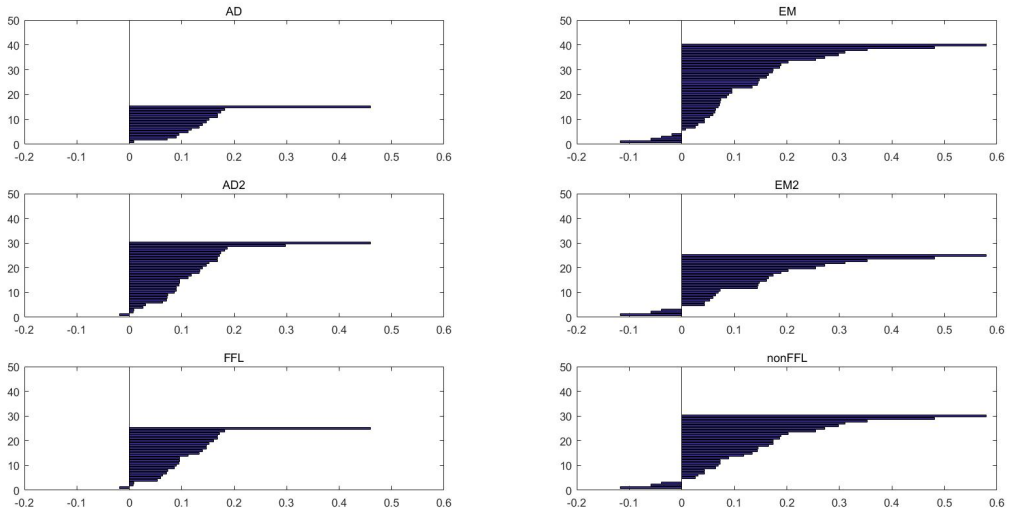

Figure A4. Average signal ratios for currency subgroups. This figure shows the averages of the signal ratio over the sample period for several currency subgroups. The signal ratio is defined by (2). Refer to the text for the explanations of the currency subgroups.

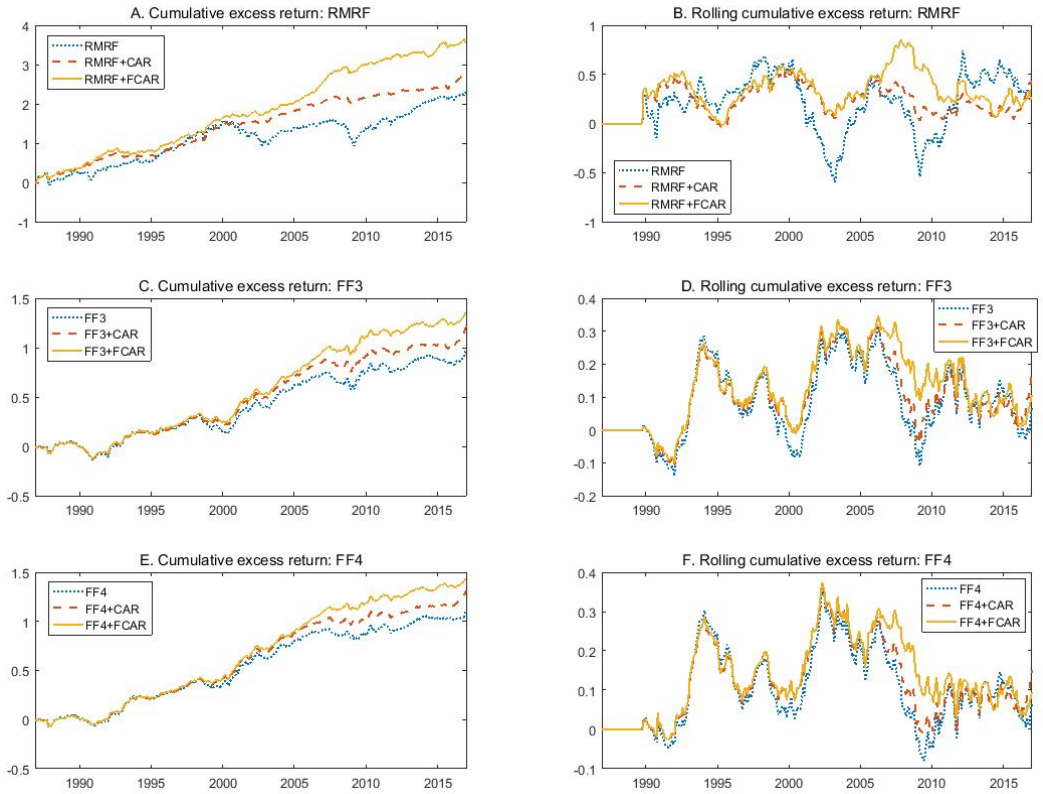

Figure A5. Currencies in diversified portfolios: cumulative and rolling cumulative net excess returns. This figure shows cumulative and rolling cumulative net excess returns of minimum variance (MV) portfolios which are formed using (i) the market portfolio minus the risk-free asset (RMRF) in Panels A and B, (ii) the Fama-French (1992) three portfolios (FF3) in Panels C and D, or (iii) the Carhart (1997) portfolios (the FF3 and the momentum (MOM) portfolio) in Panels E and F. The MV portfolios are formed solely with the investable assets or including CAR or FCAR portfolio. The MV portfolios are formed each month in an ex ante manner using only historical information available at a given time.

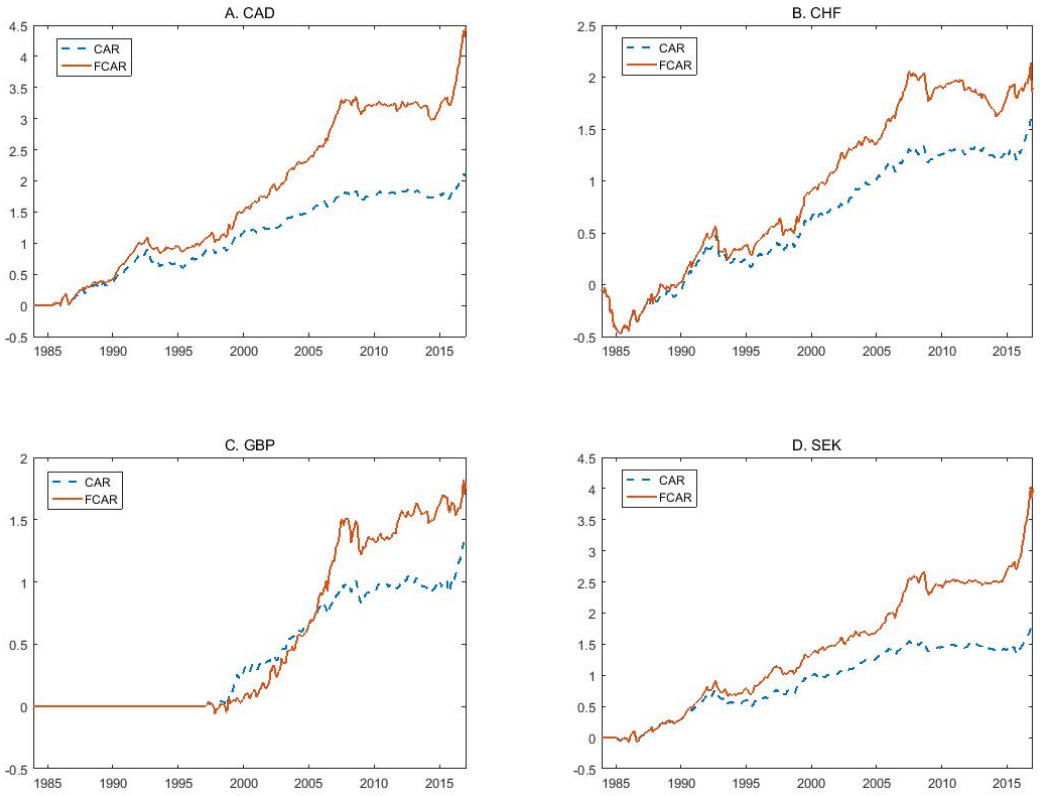

Figure A6. Alternative base currencies: cumulative net excess returns. This figure shows cumulative net excess returns of CAR and FCAR net excess returns for each alternative base currency.

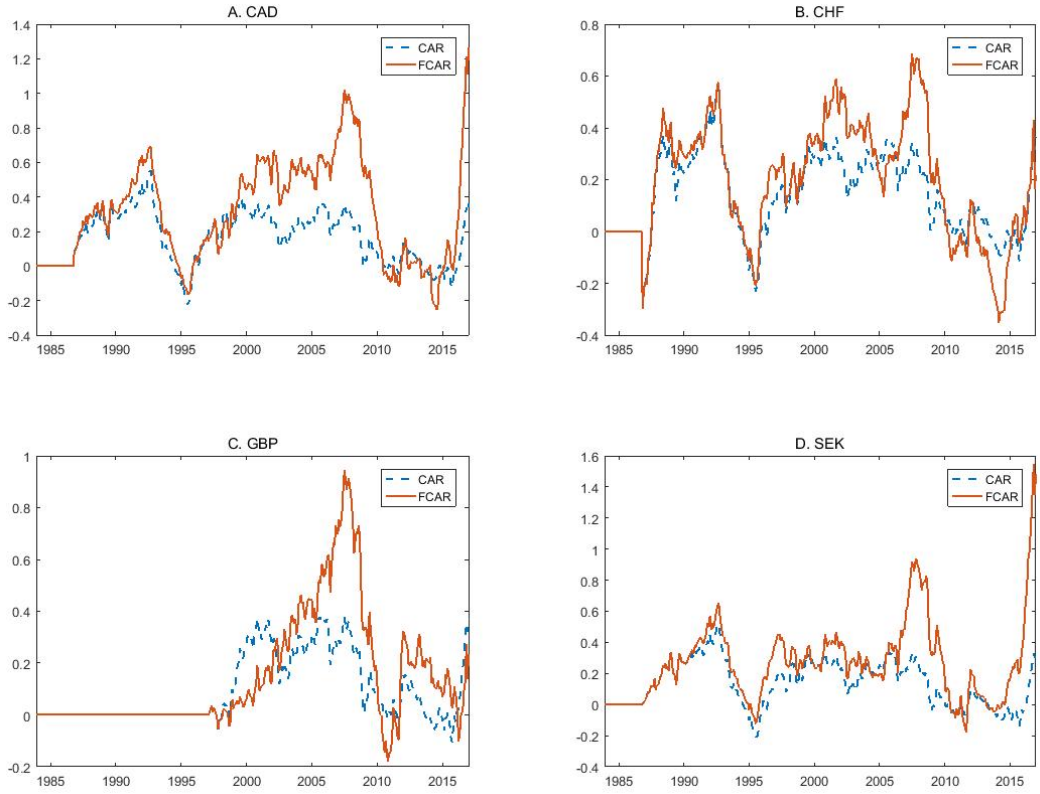

Figure A7. Alternative base currencies: rolling cumulative net excess returns. This figure shows rolling cumulative net excess returns of CAR and FCAR net excess returns for each alternative base currency.

Table A1. Descriptive statistics - Individual currencies.

This table shows descriptive statistics for individual currencies. Means and standard deviations for excess returns and the forward discounts are annualized and in percent. Bid-ask spreads are in basis points. The sample period runs from January 1983 to December 2016.

	Sample		Excess returns		Forward discounts				Spreads (spot)		Spreads (forward)	
	Start	End	mean	std	mean	std	max	min	mean	std	mean	std
Argentina	1994.01	2016.12	4.87	6.70	15.99	11.64	428.00	-2.33	10.39	23.09	27.19	68.02
Australia	1984.12	2016.12	1.26	11.75	3.06	0.80	14.06	-8.12	9.78	5.98	13.01	24.88
Austria	1994.01	2016.12	-1.53	10.25	-0.53	0.38	1.98	-4.01	3.28	1.30	3.37	4.75
Belgium	1983.1	1991.11	15.84	12.62	14.08	7.16	68.76	-13.96	22.90	27.01	28.31	38.58
Brazil	1994.06	2016.12	7.20	16.12	9.30	0.98	17.49	0.00	8.65	8.92	13.67	28.98
Canada	1984.12	2016.12	-0.16	7.33	0.75	0.47	5.84	-5.46	6.00	2.13	8.32	9.17
Chile	1994.01	2016.12	0.70	12.18	2.36	0.70	9.34	-4.24	8.59	6.80	10.92	13.60
China	1994.01	2016.12	0.42	2.03	-0.54	1.04	7.87	-14.59	0.36	4.23	3.66	12.67
Colombia	1994.01	2016.12	0.62	13.90	3.19	0.88	8.54	-12.56	9.73	7.34	18.68	31.67
Croatia	1997.05	2016.12	-1.40	10.81	1.57	0.80	15.75	-2.40	24.78	25.79	18.20	26.91
Czech Republic	1994.12	2016.12	-0.37	12.85	0.93	1.15	40.04	-5.33	12.65	5.06	15.19	38.49
Denmark	1984.12	2016.12	0.89	10.68	0.78	0.91	22.92	-10.13	6.94	4.31	15.63	37.67
Egypt	1994.12	2016.12	3.10	18.21	17.64	8.83	218.11	1.16	28.06	23.66	79.92	286.67
Estonia	1997.05	2016.12	-1.63	10.58	0.18	0.52	7.12	-2.57	3.74	1.58	7.84	29.84
Euro Area	1999.01	2016.12	-1.27	10.31	-0.31	0.40	1.89	-8.00	3.85	1.59	5.21	5.74
Finland	1994.01	2016.12	-1.73	10.27	-0.55	0.39	1.99	-4.00	5.13	4.78	3.90	9.31
France	1983.1	2016.12	2.24	10.86	1.53	0.93	12.99	-11.05	5.52	7.04	13.08	26.91
Germany	1983.1	2016.12	-1.45	10.20	-0.54	0.76	9.99	-7.02	3.78	5.42	3.21	4.11
Greece	1994.01	2016.12	-0.78	10.44	0.90	0.75	14.25	-4.01	4.81	4.61	5.09	20.77
Hong Kong	1983.1	2016.12	-0.57	0.66	-0.18	0.40	10.36	-7.21	1.64	2.11	5.26	41.34
Hungary	1994.01	2016.12	1.45	13.96	5.48	1.05	16.52	-1.14	12.58	6.42	17.72	27.07
Iceland	1997.05	2016.12	-0.58	15.12	5.97	0.64	13.76	1.16	19.59	15.30	28.80	68.17
India	1994.01	2016.12	0.51	7.25	4.71	0.82	12.24	-2.13	9.53	19.03	9.47	28.13
Indonesia	1994.01	2016.12	4.72	18.50	13.70	7.50	123.43	-83.82	27.29	50.29	53.92	235.87
Ireland	1994.01	2016.12	-1.67	10.25	-0.28	0.36	1.98	-4.03	5.13	5.15	4.41	15.42
Israel	1994.01	2016.12	0.36	8.44	0.53	0.30	3.25	-1.72	18.41	20.55	13.43	30.08
Italy	1983.1	2016.12	1.58	11.19	4.06	1.07	23.52	-11.40	7.73	11.53	20.23	41.43
Japan	1983.1	2016.12	-1.32	10.95	-2.42	0.85	26.80	-14.26	6.65	2.26	9.51	8.58
Kazakhstan	1998.12	2016.12	-0.89	10.68	6.88	4.24	103.78	-8.40	6.01	6.24	36.46	129.84
Latvia	1997.05	2016.12	-2.89	10.45	0.63	0.66	12.93	-2.85	11.02	6.24	18.23	40.32
Lithuania	1997.05	2016.12	-1.75	10.54	0.05	0.45	6.06	-2.56	4.25	2.48	7.80	14.92
Malaysia	1984.12	2016.12	-5.47	9.02	-0.13	1.83	21.96	-57.70	31.61	30.13	23.61	109.36
Mexico	1994.01	2016.12	1.30	10.26	7.02	1.71	33.69	1.62	9.53	22.16	8.69	30.76
Morocco	1994.12	2016.12	-2.92	8.49	3.30	0.67	10.16	-2.37	31.34	17.87	52.51	68.50

Table A1. Continued.

	Sample		Excess returns		Forward discounts				Spreads (spot)		Spreads (forward)	
	Start	End	mean	std	mean	std	max	min	mean	std	mean	std
Netherlands	1983.1	2016.12	-1.49	10.21	-0.56	0.78	10.27	-6.99	4.17	6.46	3.28	4.52
New Zealand	1984.12	2016.12	3.10	12.34	4.23	1.28	36.81	-4.20	15.66	11.05	22.73	68.82
Norway	1994.01	2016.12	-1.30	11.42	1.04	0.57	5.89	-2.77	7.18	2.23	8.19	7.04
Philippines	1994.01	2016.12	-2.17	8.78	4.03	1.08	23.69	-2.13	27.35	34.04	28.70	102.33
Poland	1995.01	2016.12	1.31	14.70	2.59	0.61	8.68	-1.41	12.58	8.10	11.97	17.11
Portugal	1994.01	2016.12	-1.52	10.24	-0.38	0.36	1.98	-4.01	3.93	2.70	3.52	5.89
Russia	1996.03	2016.12	-0.16	14.91	5.81	1.92	53.09	-3.20	15.23	58.41	15.35	54.47
Singapore	1984.12	2016.12	-1.71	5.65	-1.13	0.62	12.28	-21.57	8.57	8.39	22.22	101.55
Slovakia	1997.02	2016.12	3.11	11.39	0.66	0.64	6.95	-2.23	10.95	8.36	9.74	27.14
Slovenia	1997.05	2016.12	-1.75	10.56	-0.10	0.34	4.22	-4.01	14.65	19.09	4.56	12.84
South Africa	1983.1	2016.12	-7.24	14.48	6.60	1.09	22.89	-22.58	30.18	36.78	39.07	193.84
South Korea	1994.01	2016.12	-0.28	11.65	1.12	0.54	4.05	-10.67	7.17	9.71	28.77	100.26
Spain	1994.01	2016.12	-1.43	10.26	-0.39	0.36	1.98	-4.01	3.57	2.16	3.34	5.00
Sweden	1984.12	2016.12	-0.04	11.21	1.47	0.94	23.19	-13.41	9.56	4.17	14.99	16.72
Switzerland	1983.1	2016.12	-0.46	11.54	-1.64	0.75	10.63	-10.53	6.93	6.48	10.38	28.79
Thailand	1994.01	2016.12	-1.39	11.02	2.32	1.47	54.14	-2.42	12.89	11.80	20.94	78.71
Tunisia	1997.05	2016.12	-3.69	7.78	4.70	1.31	26.96	-0.45	27.11	14.88	38.48	53.36
Turkey	1994.01	2016.12	6.91	13.36	24.05	6.69	85.88	3.94	23.43	50.89	31.48	90.16
Ukraine	1998.12	2016.12	-31.20	27.53	-11.37	18.70	57.66	-289.56	38.58	68.45	76.98	270.55
United Kingdom	1983.1	2016.12	-0.92	8.61	0.80	0.32	3.48	-3.19	4.41	3.93	3.28	4.67
Venezuela	1994.01	2008.04	8.19	32.48	0.00	0.00	0.00	0.00	14.84	11.42	6.04	37.21

Table A2. Signal ratio and currency belongings.

This table shows not only currency belonging ratios for both CAR and FCAR but also summary statistics of the signal ratios for individual currencies.

	CAR	FCAR	Signal ratio					
			Mean	S.D.	Median	Min	Max	AC(1)
Argentina	0.29	0.20	0.35	0.28	0.47	-0.23	1.00	0.97
Australia	0.96	0.54	0.15	0.17	0.17	-0.19	0.44	0.97
Austria	0.60	0.21	0.10	0.19	0.11	-0.33	0.39	0.97
Belgium	0.24	0.24	0.46	0.30	0.33	0.00	1.00	0.96
Brazil	0.38	0.28	0.26	0.22	0.33	-0.17	0.67	0.97
Canada	0.96	0.51	0.14	0.19	0.14	-0.28	0.47	0.98
Chile	0.38	0.08	0.06	0.12	0.06	-0.17	0.33	0.93
China	0.45	0.34	0.48	0.29	0.44	0.00	0.94	0.99
Colombia	0.38	0.18	0.14	0.29	0.08	-0.28	0.70	0.98
Croatia	0.38	0.11	0.06	0.18	0.11	-0.39	0.33	0.95
Czech Republic	0.60	0.17	0.13	0.13	0.17	-0.28	0.39	0.94
Denmark	0.96	0.47	0.12	0.17	0.11	-0.28	0.57	0.96
Egypt	0.33	0.33	0.58	0.16	0.59	0.22	0.91	0.95
Estonia	0.38	0.08	0.06	0.13	0.06	-0.22	0.39	0.94
Euro Area	0.54	0.15	0.10	0.20	0.08	-0.33	0.60	0.97
Finland	0.60	0.21	0.10	0.19	0.11	-0.33	0.39	0.97
France	0.46	0.41	0.15	0.12	0.19	-0.33	0.33	0.90
Germany	0.60	0.23	0.17	0.10	0.17	-0.17	0.33	0.92
Greece	0.60	0.11	0.01	0.18	0.06	-0.39	0.39	0.97
Hong Kong	1.00	0.79	0.30	0.15	0.31	0.00	0.58	0.97
Hungary	0.58	0.19	0.07	0.21	0.11	-0.33	0.50	0.97
Iceland	0.38	0.05	0.03	0.10	0.00	-0.17	0.28	0.92
India	0.58	0.21	0.17	0.18	0.17	-0.23	0.61	0.97
Indonesia	0.44	0.26	0.14	0.38	0.08	-0.54	0.92	0.96
Ireland	0.60	0.20	0.07	0.22	0.09	-0.43	0.50	0.97
Israel	0.38	0.10	0.03	0.12	0.00	-0.28	0.28	0.94
Italy	0.45	0.36	0.11	0.18	0.11	-0.47	0.44	0.96
Japan	1.00	0.53	0.13	0.21	0.17	-0.44	0.56	0.98
Kazakhstan	0.37	0.22	0.27	0.17	0.25	-0.03	0.68	0.95
Latvia	0.38	0.14	0.15	0.18	0.14	-0.22	0.56	0.97

Table A2. Continued.

	CAR	FCAR	Signal ratio					
			Mean	S.D.	Median	Min	Max	AC(1)
Lithuania	0.38	0.08	0.04	0.15	0.03	-0.22	0.44	0.94
Malaysia	0.40	0.33	0.19	0.15	0.14	-0.23	0.56	0.94
Mexico	0.60	0.27	0.16	0.19	0.17	-0.22	0.60	0.96
Morocco	0.38	0.04	-0.12	0.12	-0.11	-0.39	0.11	0.93
Netherlands	0.60	0.23	0.17	0.10	0.17	-0.17	0.33	0.92
New Zealand	0.96	0.49	0.17	0.18	0.17	-0.22	0.61	0.98
Norway	0.60	0.14	0.09	0.16	0.11	-0.33	0.43	0.95
Philippines	0.60	0.23	0.07	0.20	0.11	-0.33	0.39	0.98
Poland	0.45	0.09	0.05	0.17	0.06	-0.33	0.33	0.94
Portugal	0.60	0.19	0.07	0.20	0.06	-0.33	0.39	0.97
Russia	0.38	0.19	0.17	0.18	0.17	-0.22	0.57	0.97
Singapore	0.96	0.43	0.09	0.18	0.11	-0.28	0.50	0.97
Slovakia	0.45	0.19	0.17	0.26	0.11	-0.22	0.87	0.97
Slovenia	0.38	0.08	-0.02	0.18	0.00	-0.33	0.39	0.96
South Africa	0.89	0.24	-0.06	0.20	-0.06	-0.58	0.39	0.96
South Korea	0.45	0.26	0.19	0.16	0.25	-0.17	0.44	0.95
Spain	0.60	0.20	0.09	0.19	0.11	-0.33	0.39	0.97
Sweden	0.96	0.56	0.18	0.19	0.22	-0.22	0.56	0.98
Switzerland	1.00	0.36	0.07	0.13	0.06	-0.17	0.53	0.96
Thailand	0.60	0.15	0.04	0.23	0.11	-0.67	0.42	0.96
Tunisia	0.38	0.03	-0.04	0.10	-0.06	-0.28	0.23	0.91
Turkey	0.57	0.35	0.31	0.26	0.39	-0.22	0.70	0.98
Ukraine	0.38	0.18	0.20	0.27	0.17	-0.17	0.72	0.98
United Kingdom	0.60	0.11	0.01	0.15	-0.04	-0.22	0.39	0.96
Venezuela	0.12	0.03	0.00	0.00	0.00	0.00	0.00	n.a.

Table A3. Country subgroups.

This table shows country subgroup belongings for our sample countries. AD and EM indicates the advanced / emerging market country according to Della Corte, Riddiough, and Sarno (2016). AD2 and EM2 are also the classification of the advanced and emerging market countries by the IMF. FFL denotes countries with free-floating currency regime while nonFFL indicates the rest countries based on the IMF classification. CI indicates the proportion of the Chinn-Ito (2006) capital account openness index being positive to the sample period when the corresponding currency is available for portfolio formation. Similarly, CI1 indicates the proportion that the Chinn-Ito exceeds one (instead of zero).

	AD	EM	AD2	EM2	FFL	nonFFL	CI	CI1
Argentina	0	1	0	1	0	1	0.000	0.000
Australia	1	0	1	0	1	0	1.000	0.997
Austria	0	1	1	0	1	0	1.000	1.000
Belgium	1	0	1	0	1	0	1.000	0.237
Brazil	0	1	0	1	0	1	0.468	0.000
Canada	1	0	1	0	1	0	1.000	1.000
Chile	0	1	0	1	1	0	1.000	1.000
China	0	1	0	1	0	1	0.000	0.000
Colombia	0	1	0	1	0	1	0.078	0.078
Croatia	0	1	0	1	0	1	1.000	1.000
Czech Republic	0	1	1	0	0	1	0.850	0.800
Denmark	1	0	1	0	0	1	0.904	0.904
Egypt	0	1	0	1	0	1	0.697	0.697
Estonia	0	1	1	0	1	0	1.000	1.000
Euro Area	1	0	1	0	1	0	1.000	1.000
Finland	0	1	1	0	1	0	1.000	1.000
France	1	0	1	0	1	0	0.593	0.396
Germany	1	0	1	0	1	0	1.000	1.000
Greece	0	1	1	0	1	0	1.000	0.900
Hong Kong	0	1	1	0	0	1	1.000	1.000
Hungary	0	1	0	1	0	1	0.831	0.831
Iceland	0	1	1	0	0	1	0.299	0.299
India	0	1	0	1	0	1	0.000	0.000
Indonesia	0	1	0	1	0	1	0.600	0.572
Ireland	0	1	1	0	1	0	1.000	1.000
Israel	0	1	1	0	0	1	1.000	1.000
Italy	1	0	1	0	1	0	0.607	0.404
Japan	1	0	1	0	1	0	1.000	1.000
Kazakhstan	0	1	0	1	0	1	0.000	0.000

Table A3. Continued.

	AD	EM	AD2	EM2	FFL	nonFFL	CI	CI1
Latvia	0	1	0	1	1	0	1.000	1.000
Lithuania	0	1	0	1	0	1	1.000	1.000
Malaysia	0	1	0	1	0	1	1.000	0.826
Mexico	0	1	0	1	1	0	1.000	0.900
Morocco	0	1	0	1	0	1	0.000	0.000
Netherlands	1	0	1	0	1	0	1.000	1.000
New Zealand	1	0	1	0	0	1	1.000	1.000
Norway	1	0	1	0	1	0	1.000	1.000
Philippines	0	1	0	1	0	1	0.800	0.000
Poland	0	1	0	1	1	0	1.000	0.000
Portugal	0	1	1	0	1	0	1.000	1.000
Russia	0	1	0	1	0	1	0.625	0.316
Singapore	0	1	1	0	0	1	1.000	1.000
Slovakia	0	1	1	0	1	0	0.939	0.603
Slovenia	0	1	1	0	1	0	1.000	1.000
South Africa	0	1	0	1	0	1	0.000	0.000
South Korea	0	1	1	0	0	1	0.603	0.335
Spain	0	1	1	0	1	0	1.000	1.000
Sweden	1	0	1	0	1	0	1.000	1.000
Switzerland	1	0	1	0	0	1	0.633	0.633
Thailand	0	1	0	1	0	1	0.000	0.000
Tunisia	0	1	0	1	0	1	0.000	0.000
Turkey	0	1	0	1	0	1	0.476	0.000
Ukraine	0	1	0	1	0	1	0.000	0.000
United Kingdom	1	0	1	0	1	0	1.000	1.000
Venezuela	0	1	0	1	0	1	0.000	0.000

Table A4. Correlations between currency portfolios.

This table shows correlation coefficients between currency portfolio excess returns net of transaction costs. The currency portfolios comprise both long-short strategies (CAR and FCAR) for all of the sample currencies (All) and other currency subgroups. Refer to the text for the explanations about the currency subgroups.

		CAR								
		All	AD	EM	AD2	EM2	FFL	nonFFL	CI	CI1
CAR	All	1.00	0.57	0.62	0.66	0.38	0.62	0.78	0.75	0.66
	AD		1.00	0.16	0.87	0.10	0.73	0.43	0.65	0.57
	EM			1.00	0.22	0.52	0.28	0.57	0.50	0.44
	AD2				1.00	0.10	0.76	0.49	0.72	0.65
	EM2					1.00	0.13	0.47	0.32	0.22
	FFL						1.00	0.32	0.62	0.54
	nonFFL							1.00	0.54	0.45
	CI								1.00	0.95
	CI1									1.00
		FCAR								
		All	AD	EM	AD2	EM2	FFL	nonFFL	CI	CI1
CAR	All	0.75	0.57	0.49	0.62	0.33	0.61	0.68	0.63	0.62
	AD	0.47	0.99	0.15	0.83	0.09	0.73	0.33	0.53	0.49
	EM	0.46	0.16	0.79	0.22	0.42	0.28	0.51	0.45	0.41
	AD2	0.51	0.87	0.18	0.95	0.06	0.75	0.37	0.56	0.54
	EM2	0.31	0.10	0.38	0.07	0.81	0.12	0.45	0.31	0.19
	FFL	0.51	0.72	0.23	0.71	0.12	0.97	0.27	0.56	0.51
	nonFFL	0.61	0.43	0.46	0.46	0.40	0.31	0.84	0.49	0.42
	CI	0.61	0.64	0.44	0.69	0.25	0.59	0.50	0.69	0.64
	CI1	0.54	0.57	0.40	0.64	0.18	0.51	0.42	0.61	0.62
FCAR	All	1.00	0.48	0.69	0.52	0.36	0.51	0.74	0.83	0.71
	AD		1.00	0.15	0.84	0.10	0.73	0.34	0.54	0.50
	EM			1.00	0.18	0.39	0.23	0.62	0.62	0.50
	AD2				1.00	0.06	0.72	0.35	0.58	0.56
	EM2					1.00	0.09	0.51	0.33	0.20
	FFL						1.00	0.27	0.57	0.53
	nonFFL							1.00	0.62	0.51
	CI								1.00	0.87
	CI1									1.00

Table A5. Sub-period analysis

This table shows summary statistics of net and gross excess returns of CAR and FCAR portfolios for two equally-divided sub-periods. The results for exchange rate changes are also presented. Panel C shows hypothesis test results for the null hypothesis that FCAR and CAR portfolios equally perform and for the alternative hypothesis that FCAR portfolio outperforms CAR portfolio for each sub-period.

	Net excess return		Gross excess return		Exchange rate changes	
	CAR	FCAR	CAR	FCAR	CAR	FCAR
			A. First half subperiod (H1)			
Mean	5.84	7.25	8.96	10.66	8.22	8.16
(t-val)	2.10	2.38	3.20	3.44	1.71	1.62
Median	11.05	11.79	13.86	17.07	3.04	3.61
SD	10.03	10.86	10.08	11.00	15.94	17.00
Skew	-1.30	-1.10	-1.21	-0.94	0.55	-0.09
Kurt	6.70	5.84	6.45	5.65	5.74	8.15
AC(1)	0.07	0.09	0.06	0.09	0.10	0.08
SR	0.58	0.67	0.89	0.97	0.52	0.48
SO	0.79	0.94	1.28	1.46	0.87	0.76
mdd	0.29	0.28	0.26	0.26	0.53	0.60
Freq	0.19	0.20	0.19	0.20	0.19	0.20
			B. Second half subperiod (H2)			
Mean	6.37	10.88	9.11	14.34	4.64	4.75
(t-val)	3.12	3.60	4.41	4.44	1.14	1.18
Median	5.91	8.52	8.20	12.24	2.15	2.28
SD	7.03	10.50	7.09	10.89	14.59	14.15
Skew	-0.36	-1.21	-0.31	-1.13	0.60	0.84
Kurt	3.98	8.99	3.93	8.26	4.48	6.88
AC(1)	0.19	0.10	0.20	0.12	0.11	0.14
SR	0.91	1.04	1.29	1.32	0.32	0.34
SO	1.51	1.62	2.36	2.14	0.53	0.56
mdd	0.15	0.17	0.14	0.19	0.48	0.57
Freq	0.20	0.22	0.20	0.22	0.20	0.22
	C. Hypothesis tests: FCAR vs. CAR					
	CEQ			SR		
	γ =1	γ =3	γ =5			
H1	0.11	0.15	0.19	0.29		
H2	0.02	0.04	0.08	0.28		

Table A6. Alternative base currencies

This table shows summary statistics of CAR and FCAR net excess returns for each alternative base currency.

	A. CAD		B. CHF		C. GBP		D. SEK	
	CAR	FCAR	CAR	FCAR	CAR	FCAR	CAR	FCAR
Mean	6.40	13.48	4.84	5.72	4.00	5.42	5.32	12.06
(t-val)	4.09	4.32	2.68	2.49	3.30	3.07	3.51	3.91
Median	6.91	12.22	7.32	10.32	0.00	0.00	6.08	10.14
SD	7.98	12.95	8.81	11.97	5.76	9.37	7.83	13.12
Skew	-0.58	0.26	-1.16	-2.01	0.03	-0.50	-0.49	0.07
Kurt	4.31	6.17	7.83	14.87	5.88	10.43	4.17	7.85
AC(1)	0.18	0.24	0.12	0.06	0.19	0.11	0.17	0.22
SR	0.80	1.04	0.55	0.48	0.69	0.58	0.68	0.92
SO	1.24	1.89	0.77	0.63	1.19	0.89	1.04	1.58
mdd	0.27	0.33	0.38	0.38	0.17	0.28	0.26	0.33
Freq	0.20	0.21	0.20	0.23	0.20	0.26	0.20	0.22

	E. Hypothesis tests: FCAR vs. CAR			
	CEQ			SR
	γ =1	γ =3	γ =5	
CAD	0.00	0.00	0.00	0.03
CHF	0.34	0.53	0.72	0.73
GBP	0.16	0.30	0.48	0.81
SEK	0.00	0.00	0.00	0.02