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Dynamic allocations for currency futures under switching regimes signals

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ABSTRACT

Over the last decades, speculative investors in the FX market have profited in the well known currency carry trade strategy (CT). However, during currencies or global financial crashes, CT produces substantial losses. In this work we present a methodology that enhances CT performance significantly. For our final strategy, constructed backtests show that the mean-semivolatility ratio can be more than doubled with respect to benchmark CT.

To do the latter, we first identify and classify CT returns according to their behavior in different regimes, using a Hidden Markov Model (HMM). The model helps to determine when to open and close positions, depending whether the regime is favorable to CT or not. Finally we employ a mean-semivariance allocation model to improve allocations when positions are opened.

1. Introduction

A currency future (CF) is a popular contract in the FX market. It is an agreement between two parties to exchange one currency for another at some future date at a price fixed on the purchase date. CF allows companies to hedge against currency risk, and it allows speculators to bet on exchange movements with less up-front investments and high leverage.

There are multiple factors that can affect exchange movements. Thus it is hard to derive a model with good prediction powers, especially for the short run. For example, Cheung, Chinn, and Pascual (2005) or Kilian and Taylor (2003) tested several modelsand found that none could consistently beat random walk forecasts. According to them, U.S. exchange traders think that economic fundamentals are more important at longer horizons, while short-run deviations from the fundamentals are attributed to excess speculation and institutional customer/hedge fund manipulation.

A popular CF strategy among financial investors is the carry trade (CT). CT rests on foreign interest rates. It consists of taking short (long) positions in CF from low (high)-yielding currencies. Hence, this strategy expects that a currency will appreciate/depreciate when the interest is high/low in relation to the other currencies. The strategy is net zero, that is, the total value in short positions is equal to the total value in long positions. More about CT strategies performance and details can be found in (Burnside, Eichenbaum, & Rebelo, 2008; Jylha & Suominen, 2009) and (Galati, Heath, & McGuire, 2007).

In this paper we develop CF strategies that can outperform CT. To achieve this, we first see if CT can be classified in regimes, just like many other markets do. The cyclical behavior of markets facilitates the search for regimes that emerge in different periods of time. The aim and success of this classification method is determined by the heterogeneity of the regimes. In the present case, we look for different behavior of CT returns. As explained below, the regime detection is based on a machine learning process, rather than economic fundamentals. Once regimes are identified, we will be able to create a signal for closing and opening positions depending whether the current regime is conducive to CT strategy or not. The idea is to hold onto a CT strategy when the signal is on and stay out when it is off.

One successful model for regime detection is the Hidden Markov Model (HMM). It assumes data behaves as a Markov process, but states are not observed. In this case, CT returns are the observed data, while regimes are the hidden states. Applying HMM in finance is nothing new. Pioneering work in this field was done by Hamilton (1989), who identified U.S. economy cycles with the gross national product series. Guidolin and Timmermann (2007) utilize a four-state HMM for a series of stock returns. Recently, Prajogo (2011) built an HMM for an agribusiness index.

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Bae, Kim, and Mulvey (2014) did HMM regime identification on equity, commodities and bond indexes, also using a four-state model. More applications of HMM in Finance can be found in (Mamon, 2014) and (Bhar & Hamori, 2006).

In a second step, we examine ways to allocate long and short positions during periods when positions open, i.e., during periods when carry trade opportunities work in general. CT strategies are based on simple allocation rules; for example, to take equally-weighted long/short positions in the highest/lowest K interest rates currencies (see Deutsche Bank G10 Currency Harvest Fund).

To improve those simple allocation rules, we therefore allocate with a mean-semivariance approach. We use this approach for several reasons. Semivariance can be considered as a downside risk measure because it belongs to the lower partial moment (LPM) of degree two (Fishburn (1977) for more details about LPM). Markowitz (2010) shows that semivariance can measure investor's utility toward risk, and hence suggests to use the geometric mean-semivariance. We prefer to use this risk measure instead of the alternatives, such as the conditional value at risk (CVaR), because although they are widely used in practice, many of them are not considered risk measures because they are LPM of degree one (CVaR) or zero (VaR). In fact, Markowitz (2010) rejects CVaR and VaR as risk measures. For more mean-semivariance applications see Huang (2008), Ballestero (2005), Vasant, Irgolic, Kruger, and Rajaratnam (2014) and Estrada (2007).

The present work is organized as follows. Section 2 analyzes the performance of standard CT. Section 3 shows HMM fitting results for CT returns. Section 4 implements and tests HMM based strategies. Section 5 tests the same HMM-based strategies, but adding mean-semivariance allocation on openings. Finally, Section 6 concludes and points to possible future research.

2. Carry trade performance

When investing in CF at time t, we buy (or sell) foreign exchange at a rate of F_t^T at some date $T > t$. Then at time T, we can earn a profit of $S_T - F_t^T$ $(F_t^T - S_T)$ if we sell (buy) that amount on the market. F_t^T is priced according to the covered interest parity. If i and i_c denote the interest rate at time t of home and foreign country respectively, and S_t the current spot rate (units of home currency in one unit of foreign currency), then:

$$F_t^T = S_t \exp((i - i_c)(T - t))$$

The return on CF investment $r_t^T := \frac{S_T}{F_t^T} - 1$ is approximated by

$$r_t^T \approx \log \frac{S_T}{S_t} + (i_c - i)(T - t) \quad (1)$$

To include transactions costs, we denote S_t^{bid} and S_t^{ask} as the bid and ask prices respectively. For long CF, returns in (1) can be expressed as

$$r_t^T = \log \frac{S_T^{bid}}{S_t^{ask}} + (i_c - i)(T - t) \quad (2)$$

Analogously, the return for short CF

$$r_t^T = -\log \frac{S_T^{ask}}{S_t^{bid}} - (i_c - i)(T - t) \quad (3)$$

As previously mentioned, CT policy is based on ranking interest rates among the pool of currencies available. As done in (Brunnermeier, Nagel, & Pedersen, 2008), we buy (sell) equal amounts of CF in the K highest (lowest) interest rates. To test this strategy, we take interest rates differentials (relative to the U.S. interest rate) embedded in forward rates from the G10 currencies. The performance of quarterly rebalancing between January 2000 and June 2015 (62 quarters) is presented in Table 1. The period January 1996 to December 1999 was assigned for training performance as explained in next sections.

Table 1
Benchmark carry trade performance for different values of K. Semi-volatility corresponds to the square root of semivariance. MSV is the ratio between geometric mean and semivolatility. Data are taken from Bloomberg database and was available from Jan 96.

K	Geometric mean (percent)	Volatility (percent)	Semi volatility (percent)	MSV (percent)	Skew	Kurtosis
1	1.8	13.9	10.6	17	−2.6	61.2
2	2.3	11.4	8.5	27.3	−0.7	9.7
3	1.4	9.3	6.9	20.1	−0.5	10.0
4	0.4	7.6	5.7	7.0	−0.6	7.9
5	0	6.5	4.9	0	−0.6	7.8

The table shows that CT has been profitable on average. This aligns with the known forward premium puzzle, which basically shows empirically that F_t^T is a poor estimator for S_T . Otherwise, $r \approx 0$ for each currency and hence CT returns would have been close to zero too. The puzzle is analyzed and explained in (Bansal & Dahlquist, 2000; Fama, 1984; Pippenger, 2011) and (Reinert, Rajan, Glass, 2009). If we increase K, we observe diversification effects. The best compromise between profit and downside risk, measured by the mean semivariance ratio (MSV), is when we go long with two currencies and short with another two. The presence of negative skewness means there can be huge losses across periods.

To have some insight of the most active currencies, we look at Fig. 1, which show some metrics about the weights for CT portfolio in time. The New Zealand Dollar (NZD) and the Australian Dollar (AUD) are the main target currencies (where we go long), followed by the Norwegian Krone (NOK). Oppositely, the Swiss Franc (CHF) is always a funding currency. Other funding currencies used are the Japanese Yen (JPY), Swedish Krone (SEK) and Danish Krone (DKK). The rest of the currencies are rarely used and can be either target or funding in time. The best MSV was obtained $K = 2$, meaning that carry trade is mainly constructed with four currencies (NZD, AUD CHF and JPY), followed by three other currencies (SEK, DKK and NOK).

3. Regime construction

The problem with the previous benchmark strategy is that it holds a fixed portfolio for a quarter of a year. No actions are taken when the strategy produces losses. Therefore, we construct an HMM model for CT in order to take early actions. We expect HMM to signal when conditions are unfavorable to CT.

When fitting an HMM, we need to estimate a transition probability matrix P, an initial probability vector and parameters related to the distribution of the data. When the distribution is assumed to follow a normal distribution, the HMM can be calibrated with the Baum Welch Algorithm. For details and explanations about HMM fitting and Baum Welch algorithm see Fraser (2008) and Prajogo (2011).

It's sensible to ask why to fit the HMM with a normal distribution when Table 1 is showing returns distribution is not fitted with such. As emerges below, the strategies proposed in this paper will not depend explicitly on the mean and volatility values of the normal distribution. Rather, they depend on the qualitative characteristic of the regime and the transition probabilities between regimes. The reason to use a normal distribution for the HMM construction is that we have a known algorithm to calibrate the HMM. The assumption for using normal distribution is supported by the discussion in (Mulvey & Zhao, 2011) (pg. 21), about how normal distribution can handle fat-tail distributions properly when applied to HMM on weekly data. Besides, the