Time-varying Transitional Dynamics of Macroeconomic Determinants on the Carry Trade

Chien-Hsiu Lin and Chih-Nan Chen*

Abstract

This research examines the effects of the macroeconomic determinants on the returns of a carry trade portfolio to be channeled through the transition probabilities in a Markovian process. We investigate the impacts of macroeconomic factors on carry trade performance via the time-varying transition probabilities (TVTP) model. Our results indicate that funding liquidity risk measured by TED spreads can explain the carry reversal. The unwinding trading strategy based on the prediction probabilities of TVTP is shown to outperform a purely carry trade strategy.

Keywords: Exchange Rate, Carry Trade, Macroeconomic Determinants, Time-varying Transition Probabilities

JEL Classification: F31, G11, G12

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1. Introduction

Uncovered interest-rate parity (UIP) is a key international relation that is used repeatedly in the fields of international finance and open-economy macroeconomics in both model construction and other analytical work. However, one of the most puzzling features of exchange rate behavior since the advent of floating exchange rates in the early 1970s, is the tendency for countries with high interest rates to see their currencies appreciate rather than depreciate as UIP would suggest. This UIP puzzle, known in its other name as "the forward-premium puzzle," is now so well documented that it has taken on the aura of a stylized fact and as a result, has spawned a second generation of papers attempting to account for its existence, such as Fama (1984), Hodrick (1987), Bekaert and Hodrick (1993), Bekaert (1995), Dumas and Solnik (1995), Engel (1996), Flood and Rose (1996), Bansal (1997), Bakshi and Naka (1997), Backus et al. (2001), Chinn and Meredith (2005), Brennan and Xia (2006), and Bekaert et al. (2007).

The violation of the UIP relation has been the motivation for the carry trade, where speculators borrow in the low interest rate currency and invest in that with the high interest rate. Consequently, in historical data, the profits gained from differential in interest rates across countries will not be wiped out by the losses due to the appreciation of the funding currencies. On the other hand, Brunnermeier and Pedersen (2009) argue that sharp appreciation of funding currencies may be the underlying cause of the failure of UIP. Carry trade is risky, because the UIP infers that the low-interest-rate funding currencies appreciate. Hence, carry traders may require risk premiums for taking short positions in low-interest-rate funding currencies, with which speculators would face losses when the low-interest-rate currencies sharply appreciated. Therefore, the time-varying premiums stem from carry trade may be a source of the failure of UIP.

In this study, we form a carry trade strategy following Lustig et al. (2011), by shorting baskets of low interest rate currencies and going long in baskets of high interest rate currencies. We attempt to find the macroeconomic determinants with the explanatory power of transition from profitable carry trade state to non-profitable carry reversal state, and vice versa. The high profitability of carry trades has been proved to be dependent upon market states, such as the FX market volatility (Christiansen et al., 2011; Copeland and Lu, 2016). Based on the evidence, we would like to adopt the Markov regime switching model to capture the state changes of carry trade returns. Moreover, past literature show that a number of macroeconomic factors can influence the risk perceptions of carry traders, such as Anzuini and Fornari (2012); Hutchison and Sushko (2013). In addition, Lustig et al. (2011) pointed out that heterogeneity in exposure to country-specific risk cannot explain the cross-section of carry trade returns. As carry traders invest in large baskets of currencies by shorting baskets of low interest rate currencies and going long in baskets of high interest rate currencies, they are not exposed to any country-specific risk. Hence, we add to the literature by adopting a Markov regime switching model with time-varying transition probabilities (TVTP) to capture the time-varying effects of macro shocks rather than country-specific risk on carry trade performance. In effect, allowing macroeconomic fundamentals to affect the transition probabilities in the Markovian process is intuitively attractive: the market responds to the updated news in the macro variables and in turn, alters the belief in the chance of the process staying in certain regime next period. Therefore, through examining the effects of the macroeconomic determinants on the returns of carry trade portfolio to be channeled through the transition probabilities in a Markovian process, we are able to find which macroeconomic variables has influences on carry reversal.

Our results show that through the Markov regime switching model, two economic regimes can capture important time-variations in mean returns and volatilities of the excess returns of the above carry trade strategy. One state captures periods of low volatility and high returns of the carry trade strategy. The other regime captures the periods of high exchange rate volatility and negative return of the carry trade. The result is consistent with Ichiue and Koyama (2011) and Copeland and Lu

(2016). Carry trade is mostly executed in times of global financial and exchange rate stability. Due to carry trade execution, low-interest-rate currencies tend to depreciate, resulting in higher returns for the carry trade. However, during liquidity shortages, such as the recent global financial meltdown, many investors turn away from commonly practiced carry-trade strategies, causing low-interest-rate currencies to appreciate rapidly, thus offsetting the profits gained from the differential in interest rates from the carry trade.

Next, we investigate the impacts of macroeconomic factors on carry trade performance. We run stepwise regression to input the selected macroeconomic variables into the regime-switching model, with time-varying transition probabilities, to uncover the impacts of macro shocks. Our results indicate that funding liquidity risk measured by the TED spread can significantly influence the transition probabilities from bull state to bear state. The results also show that the unwinding strategy based on the prediction probabilities of the TVTP model outperforms either the strategy based on the Markov regime switching model with the constant transition probabilities or the purely carry trade strategy.

The paper is structured as follows. Section 2 describes the data and portfolio construction as well as the macroeconomic variables used in the paper. Section 3 presents the Markov regime switching model with time-varying transition probabilities. We display the empirical results in section 4. Section 5 presents investment strategy performances based on different models and section 6 concludes the paper.

2. Data Description

We collect the monthly spot and 1-month forward exchange rates against the US dollar (USD) from Datastream. The empirical analysis involves using monthly data obtained by sampling end-of-month prices from January 1986 to August 2017. Our main data set contains 37 different currencies pertaining to: Australia, Austria, Belgium, Canada, Hong Kong, Czech Republic, Denmark, the Euro area, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand and the United Kingdom.

Some of these currencies have had their exchange rate partly or completely pegged to the US dollar over the course of the sample. We keep them in our sample because forward contracts were easily accessible to investors. The Euro series started in January 1999 and so, we exclude the Euro area countries after this date, keeping only the Euro series. Moreover, we have eliminated the following data due to the failures of covered interest parity: Malaysia from the end of August 1998 to the end of June 2005; Indonesia from the end of December 2000 to the end of May 2007; and the Belgium from the end of June 1990 to the end of August 1992.

2.1 Currency Excess Returns

We denote time *t* log spot and forward exchange rates as s_t and f_t, respectively. Exchange rates are defined in units of foreign currency per US dollar. Therefore, an increase in s_t means depreciation of the foreign currency. The excess return of investing a foreign currency on buying a foreign currency *i* in the forward market at time *t* and then selling it in the spot market at time $t+1$ can be computed as:

$$rx_{t+1}^i = f_t^i - s_{t+1}^i, \tag{1}$$

which is equivalent to the foreign currency's forward discount minus the spot exchange rate return:

$$rx_{t+1}^i = f_t^i - s_t^i - \Delta s_{t+1}^i, \tag{2}$$

According to the covered interest rate parity (CIP) condition, the forward discount is approximately equal to the interest rate differential between home and foreign countries, $f_t - s_t \approx i_t^* - i_t$, where i_t and i_t^* represent the domestic and foreign risk free rates, respectively. Hence, the currency excess return is approximately equal to the interest rate differential net of the rate of depreciation:

$$rx_{t+1}^{i} = \left(i_t^{*} - i_t\right) - \Delta s_{t+1}. \tag{3}$$

To adjust for transaction costs, currency excess returns are thus computed by bid-ask quotes on the spot and forward rates. The net excess return for holding foreign currency (selling USD) for a month is computed as $rx_{t+1}^{l} = f_t^{b} - s_{t+1}^{a}$, where a indicates the ask price, b the bid price and l a long position on a foreign currency. In contrast, the net excess return for shorting foreign currency (buying USD) for a month is computed as $rx_{t+1}^{s} = -\left(f_t^{a} - s_{t+1}^{b}\right)$, where s denotes a short position on a foreign currency.

2.2 Currency Portfolios

We sort currencies into six portfolios and rebalance them at the end of each month, according to their forward discount, as in Lustig and Verdelhan (2007) and Lustig et al. (2011). The top 1/6 forward discount currencies form portfolio C1 and the lowest 1/6 form portfolio C6. Sorting of forward discount is equivalent to using the interest differential relative to the US dollar, $i^{*} - i$, to rank foreign currencies. Portfolio C6 contains the funding currencies of a carry trade strategy (lowest forward discount or interest rate differential), while C1 contains the investment currencies in a carry trade strategy (highest forward discount or interest rate differential). Next, we compute the excess return for each portfolio as an equally weighted average of the currency excess return within that portfolio. Following Lustig et al. (2011), we assume that investors go short on foreign currencies in C6 and long on foreign currencies in the rest of the portfolios with adjustment of transaction costs.

2.3 Descriptive Statistics

Table 1 presents summary statistics for the six currency portfolios net of transaction costs. We report currency annualized mean excess returns and *t*-statistics. We construct HML_{FX} as a long short strategy, which is long in C1 and short in C6. This is equivalent to a carry trade strategy that borrows in the money markets of low yielding currencies and invests in the money markets of high yielding ones. All figures in table 1 are annualized and reported in US dollars. Average excess returns display a monotonically decreasing pattern when moving from C1 to C6 except for C3. We find that carry trade strategies yield substantial (and statistically significant) excess returns of about 3.575%. The Sharpe ratio is equal to the average excess return of a portfolio divided by the standard deviation of the portfolio returns. From the table, we observe the annualized Sharpe ratio ranges from -0.043 (portfolio 5) to 0.113 (HML).

Table 1 Descriptive Statistics

	1	2	3	4	5	6	HML_{FX}
Mean	3.320%	0.931%	1.585%	0.948%	-0.997%	0.255%	3.575%**
t-statistics	1.627	0.550	1.010	0.652	-0.765	0.188	1.976
Standard Deviation	34.435%	29.608%	28.100%	26.999%	23.223%	25.730%	31.648%
Sharpe ratio	0.096	0.031	0.056	0.035	-0.043	0.010	0.113

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels or below.

This table presents the descriptive statistics of currency excess returns by sorting currencies into six groups using their one-month forward discount. The first portfolio contains currencies with the highest forward discount (high interest rate), while the last has the lowest (low interest). HML_{FX} is a long-short portfolio that is long in portfolio 1 and short in portfolio 6. The table reports discrete excess returns adjusted for transaction costs for the 1-month holding periods. The mean and Sharpe ratios are annualized. Numbers in *t*-statistics are HAC based on Newey and West (1987). The sample period is February 1986 to August 2017 and we employ monthly returns.

2.4 Macroeconomic Variables

We attempt to investigate the impacts of different macroeconomic variables on carry trade returns to be channeled through the transition probabilities in a Markovian process. Below, we list ten variables and the motivation for including them in the research.

Innovations in Equity Volatility (ΔVOL_t^{equity})

Ang et al. (2006), Lustig et al. (2011) and Menkhoff et al. (2012) argue that investors require compensation for holding those assets that pay poorly in periods with positive innovations in equity volatility. The intuition is that positive changes in equity volatility are perceived to be bad states where the marginal utility is high. Given the carry factor performs poorly in the bear state, but well during a bull market, we consider ΔVOL_t^{equity} as an economic risk variable for the currency strategies. Following Menkhoff et al. (2012) and Bakshi et al. (2019), ΔVOL_t^{equity} is thus defined as the cross-sectional equity return volatility across the G20 countries.

Liquidity Risk (*Funding Liq. risk*; *Market Liq. risk*)

According to Plantin and Shin (2018), the carry trade returns can be the compensation for exposure to illiquidity spirals. We thus investigate the linkage between the carry trade returns and liquidity risk. To measure the liquidity risk, we use a proxy for funding liquidity risk (*Funding Liq. risk*), the TED spread, as suggested by Brunnermeier and Pedersen (2009) and Asness et al. (2013), as well as the proxy for market liquidity risk (*Market Liq. risk*), as constructed by Pastor and Stambaugh (2003).

Innovations in Currency Volatility ($\Delta VOL_t^{currency}$)

We follow Menkhoff et al. (2012) to construct a measure of global currency volatility and take first differences of it, which we denote by $\Delta VOL_t^{currency}$. To proceed, we take the monthly sum of absolute daily log returns for each currency and the cross-sectional volatility is the average across them.

The Short Rate (*SR*)

Lustig et al. (2014) linked carry trade returns to macroeconomic business cycle risk. Therefore, we want to investigate whether the variation in carry trade returns can be influenced by macroeconomic variables that relate to the business cycle. Since the three-month T-bill rate or short rate is known to be negatively related to future stock market returns, it serves as a proxy for expectations of future economic activity.

Dividend Yield (*DY*)

The dividend yield (*DY*) has been shown to be related with slow mean reversion in stock returns across several economic cycles. We denote it as the total dividend payments accruing to the CRSP value-weighted index over the previous twelve months divided by the current level of the index.

Term Spread (*TERM*)

Rudebusch and Williams (2009) showed that a negative term spread (*TERM*), reliably predicts low future output growth and indicates a high probability of recession. The term spread is measured as the difference between the average yields of 10-year Treasury bonds and three-month T-bills.

Default Spread (*DEF*)

According to Fama and French (1988), the default spread (*DEF*) tracks long term business cycles. It is found to be higher in recessions and lower during expansions, thus capturing the unobservable default risk premium embedded in corporate debts. Specifically, the DEF is calculated as the average yield of bonds rated BAA minus bonds rated AAA by Moody's.

Innovations in G7 Industrial Production (ΔIP)

Following Fama (1990) and Bakshi et al. (2019), we consider the variable of innovations (the first difference) in the log of G7 industrial production to explain the factor returns.

Innovations in G7 Inflation Rate (ΔINF)

Guided by the connection between inflation and exchange rates in Bakshi et al. (2019), we consider innovations (the first difference) in G7 inflation as the explaining variable.

2.5 Stepwise Regression

To incorporate appropriate variables into the TVTP model, we use stepwise regression to select variables from the above ten macroeconomic variables. Stepwise regression is a method of fitting regression models in which the choice of explanatory variables is carried out by an automatic procedure, whereby a variable is considered for addition to or subtraction from the set of explanatory variables, based on F-tests or t-tests. In our studies, the selection criterion α is set to be 0.05. From the procedure of stepwise regression, we choose the market liquidity risk ($Market\ Liq.\ risk$), funding liquidity risk (*Funding Liq. risk*) and the short rate (*SR*) from the above macroeconomics variables to input to the TVTP model. Figure 1 plots these three variables and the cumulative returns of carry trade strategy. From the figure, we observe that during the financial crisis events, funding liquidity risk measured by the TED spread is negatively correlated with carry trade returns, implying that illiquidity in the funding market would lead to the unwind of carry trade position. On the other hand, the market liquidity index constructed by Pastor and Stambaugh (2003) show the positive association with carry trade returns, meaning that carry trade performs poorly when market liquidity is low. Furthermore, the decrease of the short rate is observed to be related to the decrease of carry trade returns, meaning that the market recession capturing by the low short rate would lead to the carry reversal.

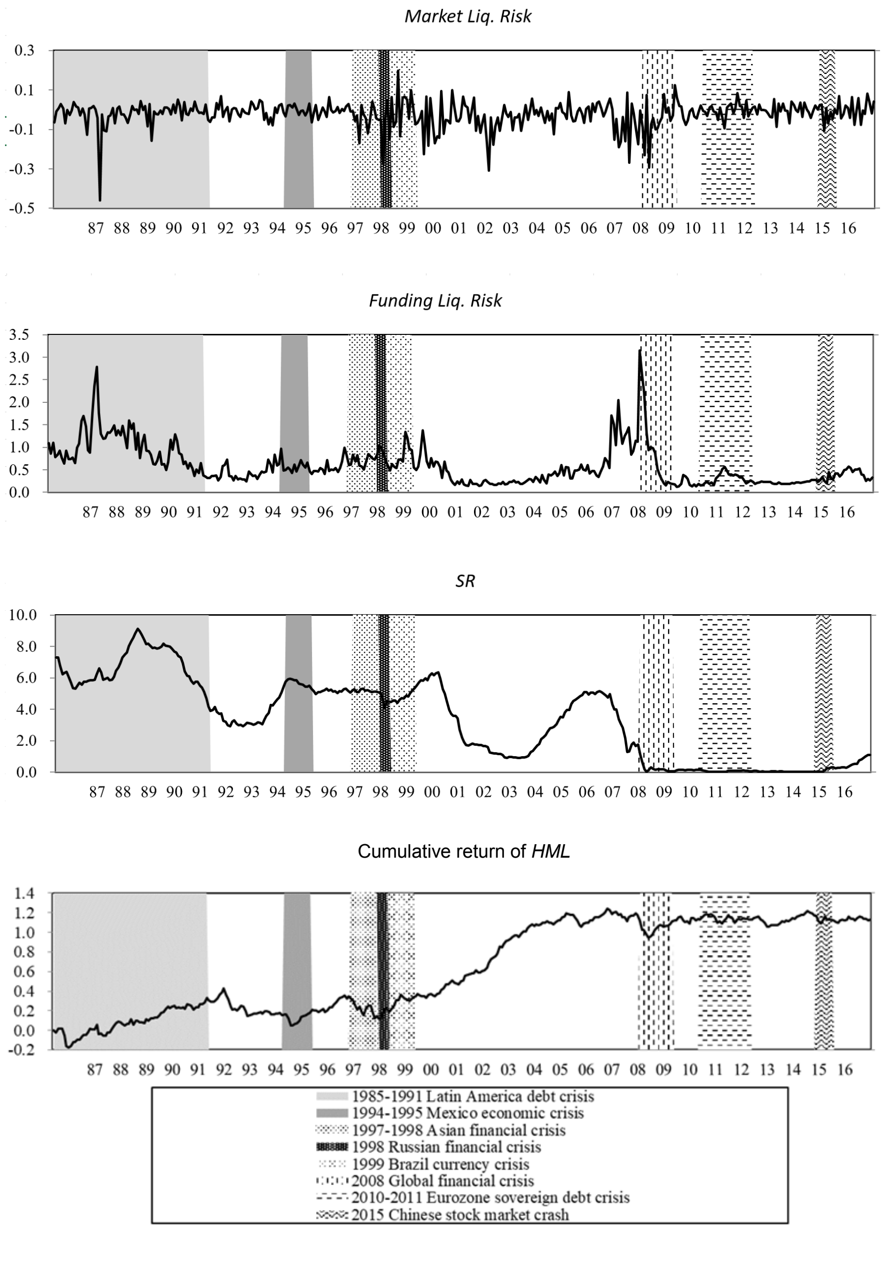


Figure 1 The Selected Variables by Stepwise Regression and the Cumulative Returns of Carry Trade Strategy

3. Methodology

In this section, we present the framework of the regime switching model with time-varying transition probabilities. Since 1989, when Hamilton (1989) adopted the regime-switching model (RSM) to describe the business cycles in the U.S., there has been a surge of empirical research and extension of the model. Because the RSM can match the cyclical movements of financial assets returns, it becomes an important class of financial time series models. A key feature of the RSM is that the model parameters are functions of a hidden Markov chain whose states represent hidden states of an economy, or different stages of business cycles. Past literatures that have employed the RSM in relation to exchange rates include Engel and Hamilton (1990), Engel (1994), Kirikos (2000), Caporale and Spagnolo (2004), Bergman and Hansson (2005), Ismail and Isa (2007) and Ichiue and Koyama (2011). Particularly, Ichiue and Koyama (2011) confirm that the RSM can explain the most popular theme in the currency markets, carry-trade. In a low exchange rate volatility state, low-interest-rate currencies tend to depreciate and enable speculators to take more carry trade positions. While in a high exchange rate volatility state consistent with the recent global financial meltdown, low-interest-rate currencies appreciate rapidly, causing investors to liquidate their carry trade positions.

The basic idea of the RSM is that the model assigns probabilities to the occurrence of different regimes and the probabilities have to be inferred from the data. The nonlinearity feature of the financial time series that can be in two or more regimes has motivated the used of RSMs. We model the distribution of carry trade returns, r_t, as a regime-switching process driven by a common discrete state variable s_t that takes integer values between 1 and k:

$$r_t = \mu_{s_t} + \varepsilon_t, \tag{4}$$

where μ_{s_t} is mean return in state s_t and $\varepsilon_t = N(0, \sigma_{s_t}^2)$ is the vector of return innovations that are assumed to be normally distributed with zero mean and state-specific variance $\sigma_{s_t}^2$. Our assumption about the innovations to returns is, thus, capable of capturing time-varying volatilities in the distribution of asset returns as Timmermann (2000), Manganelli (2004) and Patton (2004). Each state is the realization of a first order Markov chain governed by the $k \times k$ transition probability matrix P, with element p_{ij}, defined as:

$$\Pr\left(s_t = j \mid s_{t-1} = i\right) = p_{ij}, \quad i, j = 1,...,k. \tag{5}$$

The model (1) and model (2) nests several popular models from the finance literature as special cases. In the case of two states, i.e. $k = 2$, the model can describe a variety of processes depending on the values taken by the six parameters: μ_1, μ_2, σ_1, σ_2, p_{11} and p_{22}. State 1 and state 2 represent the different currency states. When in the state 1, the mean value is μ_1, and the volatility is σ_1. On the other hand, in state 2, the mean value is μ_2 and the volatility is σ_2. The transition probability can be defined by P. The exchange rate is expected to remain in the state 1 for $1/\left(1 - p_{11}\right)$ periods. Once the state switches to state 2, the exchange rate is expected to remain there for $1/\left(1 - p_{22}\right)$ periods.

To model the time-varying transition probabilities, we assume the transition probabilities $\Pr\left(s_t = j \mid s_{t-1} = i\right)$ are governed by a function of several macroeconomic variables.

$$\Pr\left(s_t = j \mid s_{t-1} = i\right) = p_t^{ij}\left(z_{t-1}\right), \tag{6}$$

where $P_t^{ij}\left(\bullet\right)$ is a function of a ($k \times 1$) vector of the observed exogenous or predetermined variables z_{t-1} and $\sum_j P_t^{ij}\left(\bullet\right) = 1 \ \forall i, j \in \{1, \ldots, \mathrm{k}\}$. In the present analysis, the observed information vector z_{t-1} contains a constant and the three macroeconomic variables selected by the stepwise regression described in the previous section.

The transition probabilities are further assumed to be evolving as a probit function of z_{t-1}. Specifically, in the case of two states, the transition probability matrix is given as:

$$P_t = \begin{bmatrix} p_t^{11} & p_t^{12} \\ p_t^{21} & p_t^{22} \end{bmatrix}, \tag{7}$$

with

$$p_t^{11} = \Phi(a \cdot z'_{t-1}),\ p_t^{12} = 1 - \Phi(a \cdot z'_{t-1}),$$
$$p_t^{21} = \Phi(b \cdot z'_{t-1}),\ p_t^{22} = 1 - \Phi(b \cdot z'_{t-1}),$$

where Φ is the cumulative standard normal density function as illustrated in Ding (2012).

Diebold et al. (1994) provide a tractable methodology to derive the maximum likelihood estimation based on an EM algorithm. They demonstrate that their extension to Hamilton's Markov switching model by allowing for time-varying transition probabilities not only nests the framework with fixed transition probabilities, but also better describes the true data generating process through simulation.

4. Empirical Results

4.1 Evidence from the Regime Switching Model with Constant Transition Probabilities

Table 2 presents the parameter estimates of excess returns of a carry trade strategy when using the RSM with constant transition probabilities. Figure 2 plots the associated state probabilities. Regime 2 is a highly volatile bear state, with the mean returns on the carry trade strategy significantly negative at -0.208 per annum and the annualized volatility as high as 0.439. The expected duration in this regime is about 3 months. During this regime, as the carry trade incurs large loss, many investors would liquidate the positions from commonly practiced carry-trade strategies and thus causing low-interest-rate currencies to appreciate rapidly. Figure 2 shows that this regime captures major currency crashes and periods with sustained decline in currency values, such as the 1982 Latin American debt crisis, which lasted until 1991, the 1994 economic crisis in Mexico, the 1997 Asian financial crisis, the 1998 Russian financial crisis, the 1999 Brazil currency crisis, the 2008 global financial crisis, the 2010-2011 Eurozone sovereign debt crisis, as well as the 2015 and 2016 Chinese stock market crash.

Regime 1 is a highly persistent low-volatility bull state, with the mean returns significantly positive at 0.107 per annum and the annualized volatilities as low as 0.226. The average duration in this regime is about 12 months and captures long periods with relatively stable currency values before the 2008 global financial crisis and the period between the European sovereign debt crisis and the 2015 Chinese stock market crash. Carry trade is observed to earn high profit in this regime. Furthermore, the transition probabilities indicate that the market more easily transits to regime 1 from regime 2 (0.299) than vice versa (0.085).

Table 2 Parameter Estimates of the Regime-switching Model with Constant Transition Probabilities for Carry trade Returns

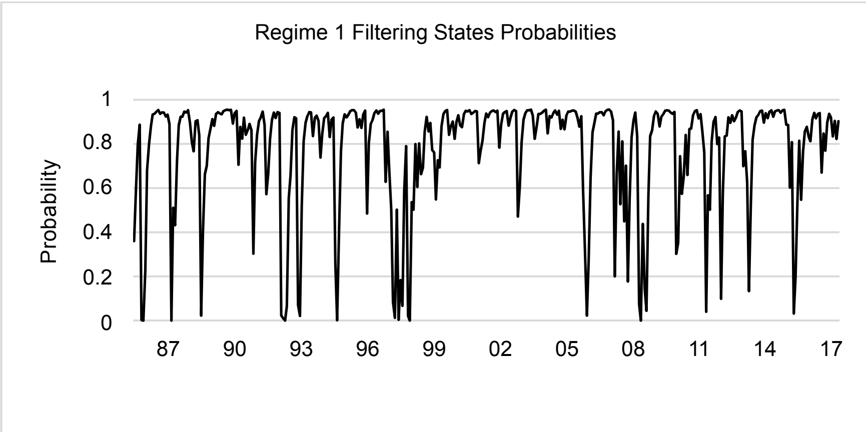
	Coefficient	Std	*Z*-statistics	P-value
Mean excess return				
Regime 1	0.107^{***}	0.017	6.149	0.000
Regime 2	-0.208^{*}	0.106	-1.959	0.051
Volatilities				
Regime 1	0.226^{***}	0.088	2.583	0.000
Regime 2	0.439^{***}	0.194	2.262	0.000
Transition probabilities				
	Regime 1	Regime 2		
Regime 1	0.915	0.299		
Regime 2	0.085	0.701		
Expected durations	Regime 1	Regime 2		
	11.811	3.342		

Note: 1. The sample period is February1986 to August 2017.

2. Values reported on the coefficients of mean excess return and volatilities are annualized.

3. ***, ** and * refers to significant at the 1%, 5% and 10% level.

This table reports parameter estimates for the regime-switching model $r_t = \mu_{s_t} + \varepsilon_t$, where μ_{s_t} is mean return in state s_t, and $\varepsilon_t = N(0, \sigma^2_{s_t})$ is the vector of return innovations that are assumed to be normally distributed with zero mean and state-specific variance $\sigma^2_{s_t}$. The unobserved state variable, s_t, is governed by a first order Markov chain that can assume k=2 values.



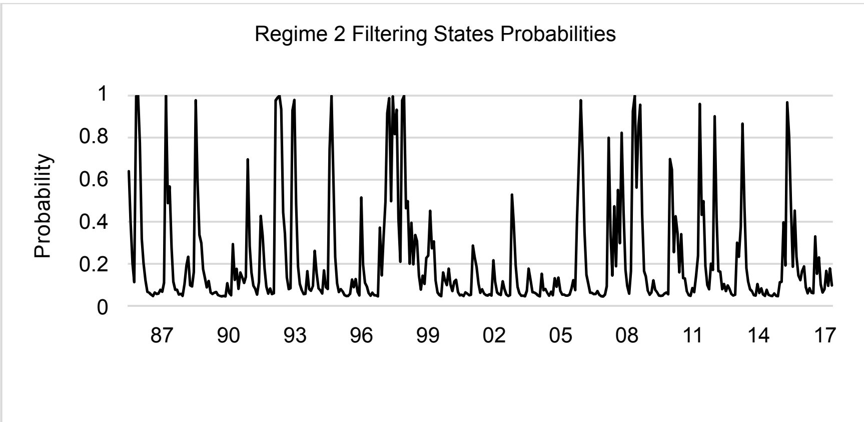


Figure 2 Filtering Regime Probabilities with Constant Transition Probabilities for Carry Trade Returns

4.2 Evidence from the Regime Switching Model with Time-varying Transition Probabilities

When we implemented stepwise regression in section 2, the market liquidity risk (*Market Liq. Risk*), the funding liquidity risk (*Funding Liq. Risk*) and the short rate (*SR*) were selected to input in the regime switching model with time-varying transition probabilities. Table 3 presents the parameter estimates of excess returns of a carry trade strategy with the TVTP of "*Market Liq. Risk*", "*Funding Liq. Risk*" and "*SR*". Figure 3 plots the associated state probabilities. Similar to the results of constant transition probabilities, we still find two regimes. Regime 2 is a highly volatile bear state of average duration about 2 months and the mean returns on the carry trade strategy is significantly negative at -0.445 per annum. Moreover, the annualized volatility is as high as 0.340. Regime 2 is a low-volatility bull sate with an average duration about 12 months and mean returns on the carry trade strategy is significantly positive at 0.109 per annum. The annualized volatilities of returns for this regime is as low as 0.239. The time-varying transition probabilities results show that the coefficient of "*Funding Liq. Risk*" on P^{11} is -0.976, which is statistically significant at the 5% confidence interval. The results indicate that increases in funding liquidity risk (the wider of TED spreads) would decrease the transition probabilities staying at regime 1, thus increasing the transition probabilities to regime 2 from regime 1. The evidence shows that the TED spreads can explain the carry reversal through the transition probabilities. Investors should unwind their carry trade position if they observe the abrupt increase of TED spreads. The average P^{21} increases from 0.299 in table 2 to 0.487 in table 3. Consequently, from figure 3, we can also observe more chances of transiting from state 2 to state 1 compared with the results of figure 2.

Table 3 Parameter Estimates of the Regime-switching Model with Time-varying Transition Probabilities (TVTP)

	Coefficient	Std	*Z*-statistics	P-value
Mean excess return				
Regime 1	0.109***	0.020	5.530	0.000
Regime 2	-0.445***	0.151	-2.939	0.004
Volatilities				
Regime 1	0.239***	0.080	3.001	0.000
Regime 2	0.340***	0.209	1.626	0.009
Transition matrix parameters				
P11-constant	1.833***	0.338	5.430	0.000
P11-*Market liq. risk*	-4.725	3.292	-1.435	0.152
P11-*Funding liq. risk*	-0.976**	0.404	-2.417	0.016
P11-*SR*	0.044	0.067	0.664	0.507
P21-constant	-0.317	0.584	-0.543	0.588
P21- *Market liq. risk*	-4.509	4.135	-1.090	0.276
P21- *Funding liq. risk*	-0.150	0.495	-0.303	0.762
P21-*SR*	0.081	0.107	0.761	0.447
Mean transition probabilities				
	Regime 1	Regime 2		
Regime 1	0.919	0.487		
Regime 2	0.081	0.513		
Mean expected durations				
	Regime 1	Regime 2		
	12.312	2.054		

Note: 1. The sample period is from February 1986 to August 2017.
2. Values reported on the coefficients of mean excess return and volatilities are annualized.
3. ***, ** and * refers to significant at the 1%, 5% and 10% level.

This table reports parameter estimates for the regime-switching model $r_t = \mu_{s_t} + \varepsilon_t$, where μ_{s_t} is mean return in state s_t, and $\varepsilon_t = N(0, \sigma_{s_t}^2)$ is the vector of return innovations that are assumed to be normally distributed with zero mean and state-specific variance $\sigma_{s_t}^2$. The transition probabilities $\Pr\left(s_t = j \mid s_{t-1} = i\right) = p_t^{ij}\left(z_{t-1}\right)$, where $P_t^{ij}\left(\bullet\right)$ is a function of a ($k \times 1$) vector of observed exogenous or predetermined variables z_{t-1} and $\sum_j P_t^{ij}\left(\bullet\right) = 1 \ \forall i, j \in \{1, \ldots, \mathrm{k}\}$.

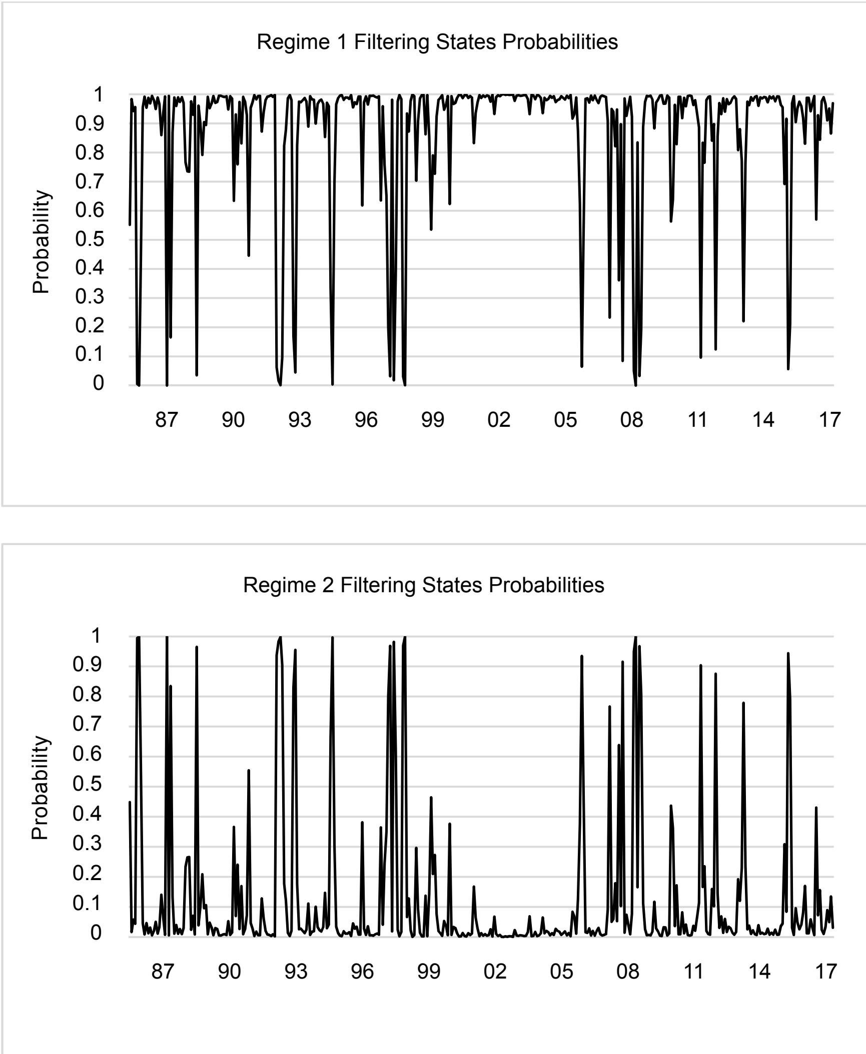


Figure 3 Filtering Regime Probabilities with Time-varying Transition Probabilities

5. Investment Strategy Performances

In this section, we want to investigate if the investment strategy based on our TVTP model can generate the better performance than either the carry trade strategy or the strategy based on the RSM with constant transition probabilities. To proceed, we employ an out of sample test for the period January 2002 to August 2017. We build a set of investment strategies based on the prediction probabilities of the TVTP and the RSM with constant transition probabilities, respectively. According to the Bayes theorem, the prediction probabilities, $\mathrm{P}\left(s_{t+1}=i \mid \mathrm{Z}^t;\theta\right)$, are calculated as following:

$$\begin{aligned}\mathrm{P}\left(s_{t+1}=i \mid \mathrm{Z}^t;\theta\right) &= \mathrm{P}\left(s_t=0, s_{t+1}=i \mid \mathrm{Z}^t;\theta\right)+\mathrm{P}\left(s_t=1, s_{t+1}=i \mid \mathrm{Z}^t;\theta\right)\\ &= p_t^{0i}\mathrm{P}\left(s_t=0 \mid \mathrm{Z}^t;\theta\right)+p_t^{1i}\mathrm{P}\left(s_t=1 \mid \mathrm{Z}^t;\theta\right),\end{aligned} \tag{8}$$

where $\mathrm{P}\left(s_t=i \mid \mathrm{Z}^t;\theta\right)$ is the filtering probabilities of s_t, and p_t^{0i} and p_t^{1i} are transition probabilities at time t. The trading strategy is set to buy and hold a HML_{FX} portfolio when the prediction probabilities for regime 2 is less than 0.5, while unwind or even short a HML_{FX} portfolio when the prediction probabilities for regime 2 is greater than or equal to 0.5. We then compare the out-of-sample portfolio performance across different investment strategies based on the prediction probabilities of the TVTP, the RSM with constant transition probabilities, respectively, and the purely carry trade portfolio.

Table 4 reports the mean returns, standard deviations, Sharpe ratios and maximum drawdown for the different investment strategies. We define the maximum drawdown of a strategy as:

$$\text{Max } DD = \max_{0\le t_1 \le t_2 \le T}\left(Y_{t_1}-Y_{t_2}\right), \tag{9}$$

where Y_t is the cumulative log return from date 0 through t. From the table, we observe that the unwinding strategy based on the prediction probabilities of the TVTP performs the best among all strategies with the highest monthly mean returns and the lowest standard deviation, thus generating the highest Sharpe ratio.

Table 4 Out-of-sample Investment Strategy Performances

	The Unwinding Strategy		The Reversal Strategy		Purely Carry Trade Strategy
	RSM	TVTP	RSM	TVTP	HML_{FX}
Monthly Mean returns	3.502%	3.981%	2.601%	3.320%	3.676%
Standard deviations	25.030%	24.172%	27.896%	27.637%	27.847%
Sharpe ratio	0.140	0.165	0.093	0.120	0.132
Max *DD*	18.306%	19.126%	29.990%	29.059%	29.318%

Note: The sample period is from February 1986 to August 2017.

This table presents investment strategy performances across the five different strategies. The unwinding strategy based on the prediction probabilities of the Markov regime-switching model with constant transition probabilities (RSM) and the Markov regime-switching model with time-varying transition probabilities, respectively: the investors would unwind the carry trade position when the prediction probabilities of regime 2 is greater than or equal to 0.5. The reversal strategy based on the prediction probabilities of the RSM and the TVTP, respectively: the investors would short the HML_{FX} portfolio when the prediction probabilities of regime 2 is greater than or equal to 0.5. The out-of-sample periods is from January 2002 to August 2017.

6. Conclusion

In this paper, we have examined the effects of the macroeconomic determinants on the returns of a carry trade portfolio to be channeled through the transition probabilities in a Markovian process. From the Markov regime switching model, we have found two economic regimes can capture important time-variations in mean returns and volatilities of the excess returns of the carry trade strategy. One state captures periods of low exchange rate volatility and high returns of this strategy. The other regime captures the periods of high exchange rate volatility and non-significant negative return of the carry trade. During this regime, as the carry trade incurs large loss, many investors would liquidate the positions from commonly practiced carry-trade strategies and thus causing low-interest-rate currencies to appreciate rapidly.

Next, we investigated the impacts of macroeconomic factors on carry trade performance through TVTP. Our results show that funding liquidity risk (the TED spreads) can explain the carry reversal through the transition probabilities. Investors should unwind their carry trade position if they observe the abrupt increase of funding liquidity risk (the TED spreads). Furthermore, the out-of-sample analysis shows that the unwinding strategy based on the prediction probabilities of the TVTP model outperform either the purely carry trade strategy or the strategy based on prediction probabilities of the RSM.

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利差交易報酬轉換動態的總體決定因素

林建秀、程智男*

摘　要

本研究檢視利差交易組合報酬的馬可夫轉換模型，是否受到總體變數的影響。我們使用時序變異特性（time-varying transition probabilities, TVTP）的馬可夫轉換模型，探索總體變數與狀態轉換機率的聯繫。本篇論文發現使用 TED 利差代表的資金流動性風險，可以預測狀態切換的轉換機率，因此可以用於探討利差交易策略報酬反轉的時機。利用狀態轉換機率的預測，我們建構了適時贖回所有部位以避險的投資策略，並發現此策略樣本外績效優於利差交易組合報酬。

關鍵詞：匯率、利差交易、總體決定因素、狀態轉換機率
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