The Pricing of Unexpected Volatility in the Currency Market

Wenna Lu[a], Laurence Copeland[b], Yongdeng Xu[c]

[a] Cardiff School of Management, Cardiff Metropolitan University, Llandaff Campus, Cardiff, CF5 2YB, United Kingdom. E-mail address: wlu@cardiffmet.com.

[b] Cardiff Business School, Cardiff University, Colum Drive, Cardiff, CF10 3EU, United Kingdom. E-mail address: laurence.copeland@gmail.com.

[c] Cardiff Business School, Cardiff University, Colum Drive, Cardiff, CF10 3EU, United Kingdom. E-mail address: xuy16@cardiff.ac.uk.

Abstract

Many recent papers have investigated the role played by volatility in determining the cross-section of currency returns. This paper employs two time-varying factor models: a threshold model and a Markov-switching model to price the excess returns from the currency carry trade. We show that the importance of volatility depends on whether the currency markets are unexpectedly volatile. Volatility innovations during relatively tranquil periods are largely unrewarded in the market, whereas during the unexpected volatile period, this risk, has a substantial impact on currency returns. The empirical results show that the two time-varying factor models fit the data better and generate a smaller pricing error than the linear model, while the Markov-switching model outperforms the threshold factor models not only by generating lower pricing errors but also distinguishes two regimes endogenously and without any predetermined state variables.

Keywords: carry trade; asset pricing; trading strategies; currency portfolios; Markov-switching model

JEL classification: F3, G12, G15

1. Introduction

The carry trade anomaly that exploits the failure of uncovered interest rate parity (Cumby and Obstfeld 1981, Fama,1984) is a long-established fact among market professionals and has attracted much attention in the academic literature in recent years. Fama (1984) suggested that the cause may be a time-varying risk premium, setting off a hunt for plausible factors. In recent years, attention has centred on the role of volatility as the key variable driving returns. Menkhoff, Sarno, Schmeling, and Schrimpf (2012) demonstrated that two factors accounted for a substantial proportion of carry trade returns: a so-called dollar factor acting as the equivalent of the market return in equity market research, and the volatility of exchange rates in general.

More recently, Copeland and Lu (2016) showed that returns to the carry trade depended on whether the currency markets were in a high- or low-volatility state. This indicates that the volatility risk is priced differently in high- and low-volatility states, suggesting an investigation of currency carry trades through the use of conditional factor models: Ang, Chen, and Xing (2006) and Lettau, Maggiori, and Weber (2014) proposed a model in which the factor loadings in the CAPM are made conditional on the state of the market, specifically whether returns are positive or negative. Atanasov and Nitschka (2014) and Dobrynskaya (2014) use conditional factor models in the currency carry trade context, while all three focus on downside stock market risk.

In this paper, we propose the volatility innovation factor as a new conditional risk factor to model the excess returns from the carry trade portfolios. The approach we take differs insofar as we start from the proposition that volatility innovation, not market return, is the factor that conditions attitudes to risk. In other words, we postulate that markets may well be more sensitive to increases in volatility when the markets are unexpectedly volatile (the volatility innovation is high), whereas when the markets are relatively tranquil, investors are likely to be less concerned about changes in volatility. This proposition is consistent with the extensive literature on asset pricing in crisis and the downside risk factor model (e.g., Brunnermeier, Nagel and Pedersen 2008; Farhi and Gabaix, 2008; Atanasov and Nitschka, 2014; Farago and Tédongap 2018).

Notably, Farago and Tédongap (2018) argue that the volatility downside factor, as one of the three disappointment-related factors, plays an important role in pricing the carry trade and other assets, an approach which is closely related to our models. However, our paper differs in several respects from Farago and Tédongap (2018). First and most importantly, we follow Menkhoff, Sarno, Schmeling, and Schrimpf (2012) and use the dollar factor as the currency market return and calculate the currency market volatility from daily currency returns, whereas Farago and Tédongap (2018) use the stock market return and volatility as a proxy for currency market return and volatility. Second, Farago and Tédongap (2018) define the downside risk when the stock market return is negative (or below a certain threshold), while we define downside risk (or "abnormal" state) when the currency market volatility innovation is above a certain threshold. As a result, we find that only volatility factor in the "abnormal" state (more volatile than expected) has explanatory power with respect to cross-sectional currency asset returns, while Farago and Tédongap (2018) show both volatility and downside volatility factors have explanatory power for currency asset return. Our results imply that investors only require compensation for taking volatility risks when the market is more volatile than expected. Third, in addition to the threshold model[1], we also propose a Markov-switching model, where the two states, "normal" or "abnormal", are determined endogenously by the data. The Markov-switching model allows the probability in the two states to be different for different portfolios, which is more flexible than the threshold model. Indeed, our results show that the threshold and Markov-switching factor models both outperform the linear factor model of Menkhoff, Sarno, Schmeling, and Schrimpf (2012). However, the Markov-switching factor model yields a smaller pricing error than the threshold factor model. Further, we also show that the probability of the "abnormal" state is positively and significantly correlated with high-volatility innovation, which is evidence of the intrinsic link between the threshold and the Markov-switching factor model. Notably, Massacci, Sarno, and Trapani (2021) propose a method to estimate the threshold (rather than imposing it a priori). They find that the point estimates of the thresholds are twice as large in absolute value as the most common value imposed in estimation by the researchers (See, e.g., Lettau, Maggiori and Weber, 2014; Farago and Tédongap, 2018). In this sense, the Markov-switching model is more flexible as it

[1] Ang, Chen and Xing (2006), Lettau, Maggiori and Weber (2014), Atanasov and Nitschka (2014) , Dobrynskaya (2014) and Farago and Tédongap (2018) use threshold model to study the downside risk.

allows the model to switch between the two states endogenously without any pre-determined state variables.

Beyond the aforementioned contributions, our paper relates to the literature on asset pricing with asymmetric pricing of "good" and "bad" volatility associated with positive and negative high-frequency price increments, respectively and priced separately (see, e.g., Barndorff-Nielsen, Kinnebrock, and Shephard, 2010; Bollerslev, Li, and Zhao, 2019). In this literature, the market beta can be decomposed into four semibetas, which depend on the covariation between the high-frequency (positive/negative) return on the market and each individual asset (see Bollerslev, Patton, and Quaedvlieg 2021) where only semibetas stemming from the negative market and negative asset return covariation predict significantly higher future returns. This result is closely related to our finding volatility factor has explanatory power for currency returns only when it is above a threshold level (which we estimate here).

The remainder of this paper is organized as follows. In Section 2, we present the theoretical setup from which we derive the implied cross-sectional model. Section 3 is the data and empirical methods section. Section 4 contains the empirical analysis with several robustness checks. Section 5 includes more robustness checks and comparisons with results provided in the appendix. Section 6 concludes.

2. Theoretical motivation and testable implications

2.1 The ICAPM and the conditional ICAPM

In the setting of the Intertemporal Capital Asset Pricing Model (ICAPM) (Merton1973, Merton 1980 and Chen 2002), apart from market returns, risk-averse investors also want to directly hedge against changes in future market volatility, thus the pricing kernel (m_t) of the ICAPM takes the form of a stochastic discount factor (SDF) with the market excess return and volatility innovations as risk factors:

$$m_t = 1 - \beta_1 r_t^m - \beta_2 \Delta V_t \tag{1}$$

where r_t^m is the log market excess return at time *t* and ΔV_t denotes volatility innovations at time *t*. ICAPM was initially proposed by Merton (1973) in which an asset's expected return depends on its covariance with the market portfolio and with state variables that proxy for changes in the investment opportunity set. In our case, the market portfolio is the dollar factor, and the volatility innovations proxy for changes in the investment opportunity set. In that respect, our definition of the ICAPM is consistent with the stock market literature.

The ICAPM has been found to outperform the traditional CAPM in both stock and exchange rate markets (Ang, Chen and Xing, 2006 and Menkhoff, Sarno, Schmeling and Schrimpf, 2012). Note that in the pricing kernel, rather than the level of volatility, it is the unexpected changes in volatility (volatility innovations) which appear as a pricing factor as volatility is usually highly serially autocorrelated. This is consistent with the empirical applications of this model for both stock and exchange rate markets, i.e., Ang, Chen and Xing (2006) employ changes in the VIX index rather than the level of the VIX to price the cross sectional excess return from the stock market and Menkhoff, Sarno, Schmeling and Schrimpf (2012) use the change in realized volatility to price the cross sectional excess return from the carry trade.

The pricing kernel of the ICAPM takes the form of a two-factor SDF with the market excess return and volatility innovations regardless of all possible different states. This is to assume that the pricing kernel is linear, i.e., the correlations between excess return and risk factors do not change significantly under different states. However, economists have long recognized that investors care differently about downside losses versus upside gains (Ang, Chen and Xing, 2006). In our case, agents who place greater weight on volatility risk during unexpected volatile periods demand additional compensation for holding assets which comove negatively during market turmoil periods. To consider this, we release the assumption and propose an ICAPM model in which we have two different states and we allow the risks to be priced differently under different states. Such a model allows us to measure the changes in correlations between risk and return under different states. We name it the conditional ICAPM to distinguish it from the unconditional ICAPM.

In the conditional ICAPM, we assume that there are two states: a "normal" state and an "abnormal" state and the *SDF* take the form in (1) only in the "normal" state. In the "abnormal" state, we replace (1) with the conditional *SDF*:

$$m_t = 1 - \beta_1^- r_t^m - \beta_2^- \Delta V_t \quad (2)$$

which implies that each factor loading can take either of two possible values, $\beta_1 = \frac{cov(r^i,r^m)}{var\,(r^m)}$ and $\beta_2 = \frac{cov(r^i,\Delta V)}{var\,(r^m)}$ in "normal" times, or $\beta_1^- = \frac{cov(r^i,r^m|abnormal\,state)}{var\,(r^m)}$ and $\beta_2^- = \frac{cov(r^i,V|abnormal\,state)}{var\,(r^m)}$ in "abnormal" times. This allows us to capture the possible changes in correlation in the "abnormal" state. According to Cochrane (2009), the expected return thus is:

$$E[r_t] = \beta_1\lambda_1 + (\beta_1^- - \beta_1)\lambda_1^- + \beta_2\lambda_2 + (\beta_2^- - \beta_2)\lambda_2^- \quad (3)$$

where $\beta_i\ i = 1,2$ are the loadings on the two factors in "normal" times, with associated risk prices $\lambda_i\ i = 1,2$ and $\beta_i^-\ i = 1,2$ are the loadings in "abnormal" times where $\lambda_i^-\ i = 1,2$ are the risk prices.

An "abnormal" state is defined as a state when the correlation between risks and returns are significantly different from that in a "normal" state. The intuition is that in such states, investors care differently about risks and hence price them differently. This is inspired by the conditional-CAPM of Ang, Chen and Xing (2006), and in their model the market return is the only risk factor and thus the "abnormal" state is defined as when the market return is negative. In our conditional-ICAPM, although both market return and market volatility innovation are risk factors, we emphasize the role of volatility innovation and thus the "abnormal" state is defined as when the volatility innovation is higher than a threshold[2]. By doing so, we build a threshold conditional ICAPM. We then release this restriction and construct a Markov-switching ICAPM, where the "abnormal state" is determined endogenously by the dataset without any pre-determined state variables and threshold. Within a Markov-switching framework, we can also test if the "abnormal state" is determined by market return, volatility innovation, or any other state variables.

In the empirical analysis, $\beta_i\ i = 1,2$ are estimates for the full sample rather than for the normal period only. It is constructed in this way when the estimated $\beta_i^-\ i = 1,2$ are not significantly different from $\beta_i\ i = 1,2$, the conditional ICAPM in (3) reduces to the unconditional ICAPM $E[r_t] = \beta_1\lambda_1 + \beta_2\lambda_2$. This construction is also consistent with Lettau, Maggiori and Weber (2014).

[2] The correlations between return and market return risk factor do not change significantly when the "abnormal state" is defined in this way.

2.2 *The threshold regime-switching conditional ICAPM implication*

In the threshold conditional ICAPM, we assume that the volatility innovation is the state variable. In the event, we cannot reject the hypothesis $\beta_1^- = \beta_1$, in other words that the loadings of the dollar factor are insignificantly[3] affected by the level of volatility innovations, so imposing this restriction $\beta_1^- = \beta_1$ in equation (3), we work with the equation:

$$E[r_t^i] = \beta_1\lambda_1 + \beta_2\lambda_2 + (\beta_2^- - \beta_2)\lambda_2^- \quad (4)$$

Our econometric approach follows the standard Fama-Macbeth 2-stage procedure[4], starting from time-series estimation of the factor loadings, which are then used as explanatory variables in cross-sectional regressions. The currency market return is considered as the dollar risk factor (DOL_t) as it is measuring the risk of borrowing one dollar and investing equally weighted in the other currencies.

In the first stage, we estimate the time series:

$$r_t^i = a_i + b_{1i}DOL_t + b_{2i}\Delta V_t + \epsilon_{it} \quad (5)$$

on each portfolio $i = 1 \ldots 6$ [5], for the whole sample $t = 1,2,\ldots,T$ and for $t = 1,2,\ldots,T^-$ that is whenever volatility innovation is above a certain threshold[6]:

$$r_t^i = a_i^- + b_{1i}^-DOL_t + b_{2i}^-\Delta V_t + \epsilon_{it} \quad (6)$$

In the second stage, we estimate the cross-section:

$$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + \left(\hat{b}_{2i}^- - \hat{b}_{2i}\right)\lambda_2^- + \epsilon_i \quad (7)$$

where $\bar{r}^i$ is the average return for portfolio i. $\hat{b}_{1i}$, $\hat{b}_{1i}^-$, $\hat{b}_{2i}$ and $\hat{b}_{2i}^-$ are the point estimates from the first stage. The market risk price λ_1 is restricted to be equal to the

[3] See appendix A1 for a simple t statistics test result.

[4] GMM could be used as an alternative estimator to the Fama-Macbeth 2-stage procedure, and the two estimators lead to consistent results as shown in Copeland and Lu (2016). Note that GMM could be used in the threshold model, but not in the Markov-switching model.

[5] The portfolios are defined in the following data section.

[6] The threshold is defined in the empirical results section.

sample average of the market excess return as the market has a unit loading of market risk and therefore the risk price is equal to the average of the market return. From the second stage estimation, we can get the volatility risk price λ_2 and the additional volatility risk price λ_2^- for the high unexpected volatility state.

2.3 The Markov regime-switching conditional ICAPM implication

The threshold model assumes the volatility innovation to be a state variable, which determines if the state is "abnormal" or not. However, the probability of being in an "abnormal state" at any time can either be indicated by market return (Ang, Chen and Xing 2006, Farago and Tédongap 2018), or volatility innovation (Copeland and Lu 2016), or other state variables. The choice of the state variable, volatility innovation, and the threshold is arbitrary in this model. Although a lot of literature has been arguing that there is a nonlinear relationship between carry trade returns and volatility innovation, that "carry trades go up by the stairs and down by the elevator", it is still not clear which variable(s) is (are) driving the process. To solve this problem, we go on to fit a Markov-switching model to price the returns of the carry trade, which has the advantage that it allows us to estimate the regression with data-determined unobservable state variables. We can also investigate the determinants of the regime probabilities on a selection of related variables that potentially influence the carry trade returns nonlinearly.

The first stage estimation of a Markov-switching model of the ICAPM is shown in eq. 8 below on each portfolio $i = 1 \ldots 6$ and for $t = 1,2, \ldots, T$.

$$r_t^i = a_i(s_t) + b_{1i}(s_t)DOL_t + b_{2i}(s_t)\Delta V_t + \epsilon_{it} \qquad \epsilon_{it} \sim iidN(0, \sigma_i^2(s_t)) \tag{8}$$

where s_t is the states (or regimes, s_t=1 or $s_t = 2$) and each state will have distinct values for each of the three parameters, where the first state (s_t=1) is the "abnormal" state and the second (s_t=2) the "normal" state. We expect the loading of volatility innovation b_{2i} to be noticeably greater in absolute terms in the first regime ($s_t = 1$) and relatively smaller in absolute terms, in the second regime ($s_t = 2$). As for the constant term a_i and the loadings of market risk b_{1i} we expect them not to be significantly different between the first regime and the second regime.

The Markov-switching model is then estimated by maximizing the likelihood function as discussed in Hamilton and Susmel (1994). From the model estimations, we generate the ex-ante probability $p_{1,t|t-1} = \Pr(s_t = 1|I_{t-1})$, i.e., the probability of being in the first regime at the time t given the information at time *t-1*.

Note that the two states are identically defined in the model specification. The only way to distinguish the two states is the inputs of the initial parameters in the maximum likelihood estimation. By doing so, we expect the first state to be the "abnormal" (high unexpected volatility) state and the second state to be the "normal" (low unexpected volatility) state [7].

The Markov-switching ICAPM shares the same second stage estimation with the threshold ICAPM model. Similarly, we make use of the high unexpected volatility state estimates in the second-stage estimation.

3. Data

The data covers the period from November 1983 to January 2017, at a monthly frequency. As in Copeland and Lu (2016), our sample consists of the 29 OECD countries: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Euro Zone, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, South Korea, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, United Kingdom and the United States.

Following Menkhoff, Sarno, Schmeling and Schrimpf (2012), we take the US dollar as domestic currency and other currencies as foreign currencies. We compute excess returns from the carry trade using the forward premium, on the assumption that covered interest rate parity holds at all times. Hence, we define the (excess) return to the carry trade, rx_{t+1} for the currency (other than the US dollar) as follows:

$$rx_{t+1} = (i_t^* - i_t) - (s_{t+1} - s_t) = (f_t - s_t) - (s_{t+1} - s_t) = f_t - s_{t+1} \tag{9}$$

[7] Specifically, the first-state initial parameters $\{b_1(s_t = 1), b_2(s_t = 1), \sigma^2(s_t = 1)\}$ are taken from the conditional SDF estimates from the periods where volatilities are above the threshold. The second-state initial parameters $\{b_1(s_t = 2), b_2(s_t = 2), \sigma^2(s_t = 2)\}$ are likewise taken from the unconditional SDF estimates for the periods where volatilities are below the threshold.

where i_t is the one-period risk-free interest rate for US dollar and i_t^* is the one-period risk-free interest rate for foreign currency, and s_t and f_t are logs of the spot and forward exchange rates in foreign currency per unit of the US dollar.

The spot and forward exchange rates are end of month mid-rates obtained from BBI and Reuters (via DataStream). Our spot and forward exchange rates against the US dollar are closing mid-rates. The excess return is calculated by taking the difference between the 1-month forward rate at *t* and the spot rate at *t+1*.

We sort currencies into 6 portfolios[8] according to their risk-free interest rates differentials with US risk-free interest rate, which are equivalent to 1-month forward discounts, providing covered interest rate parity holds. After the sorting, portfolio 1 contains currencies with the lowest interest rate while Portfolio 6 contains currencies with the highest interest rate. For each portfolio, currencies are equally weighted. Portfolios are rebalanced at the beginning of each month. The monthly rebalancing ensures that the portfolios resemble carry trade portfolios, the composition of which changes over time as the forward discounts change.

Descriptive statistics are given in Table 1. As can be seen from Table 1, the excess return on a long position in the highest-carry currencies combined with a short position in the lowest yielded an excess return of 6.65% and a Sharpe Ratio of 0.72, albeit with negative skewness.

Monthly FX market return ($\mathrm{DOL_t}$) is defined as the average return of all portfolios. It is also considered as the dollar risk factor as it is measuring the risk of borrowing one dollar and investing equally weighted in the other 29 currencies.

Monthly exchange rate volatility is defined as in Menkhoff, Sarno, Schmeling and Schrimpf (2012):

$$V_t = \frac{1}{T} \sum_{\tau \in T_t} \left[\sum_{k \in K_\tau} \frac{|\Delta s_\tau^k|}{K_\tau} \right]$$

where K_τ is the number of currencies for which data are available on day τ and there are T_t days in month t. We concentrate on the unexpected volatility ΔV_t, as Chen (2002) argues that it is the unexpected change in future market volatility rather than the level of volatility itself that risk-averse investors want to hedge and this idea

[8] This is standard in the carry trade study, as the currency number is small (e.g., 29 currencies in our case). In the literature, Ang, Chen and Xing (2006) and Menkhoff, Sarno, Schmeling and Schrimpf (2012) sort the currencies into 5 portfolios, Lettau, Maggiori, and Weber (2014) and Farago and Tédongap (2018) sort the currencies into 6 portfolios.

is empirically supported by Ang, Chen and Xing (2006) in the stock market and by Menkhoff, Sarno, Schmeling and Schrimpf (2012) in the currency market. There are two ways to measure the unexpected volatility. The simplest way is to take first differences of the volatility level (see for example, Ang, Chen and Xing 2006). Another approach is to estimate a simple AR(1) for the volatility level and take the residuals as the proxy for volatility innovations (see for example, Menkhoff, Sarno, Schmeling and Schrimpf 2012). We take the latter as our measure of unexpected volatility, since we find that the AR (1) residuals are uncorrelated with their own lags while the first differences are significantly autocorrelated with their first order lags. More sophisticated time series models may be used to obtain the unexpected volatility, see for example, Horvath, Lyócsa and Baumöhl (2018) and Lyócsa and Horvath (2018).

We also consider another sample: a bigger 48-country sample, which was used in Menkhoff, Sarno, Schmeling and Schrimpf (2012), as a robustness check. The details are reported in appendix A5.

4. Empirical Results

4.1 The threshold ICAPM Results

In the setting of the threshold conditional ICAPM, we assume that the volatility innovation is the state variable and in periods when the volatility innovation exceeds the threshold of one standard deviation above the mean (zero) $\Delta V_t > \sigma_{\Delta V}$[9].

Table 2 shows the results of the 1st-stage regressions for the full sample of 399 months (Panel A) and for the 49 high-volatility innovation months (Panel B). All the estimates in both panels are significantly different from zero. The first thing to note is that, in both panels, while the loadings for the dollar (market) factor are all very close to 1.0, the loadings on volatility innovation are diminishing from lowest- (#1) to highest-carry portfolios (#6).

Secondly and most importantly, if we compare the two panels, we can see that the betas for volatility innovation are noticeably greater in absolute terms in the high unexpected volatility state, providing support for the superiority of the conditional

[9] Copeland and Lu (2016) used 75th percentile of volatility innovation as the threshold, which is very close to the threshold we defined here.

over the unconditional model. Indeed, the difference is most marked at the two extremes - portfolios #1 and #6, hinting at a possible nonlinearity which we do not investigate here. In Figure 1, we plot the volatility risk loading β_2 against the realized mean excess returns of 6 portfolios for the unconditional and conditional model in Panel A and B respectively. Clearly, the conditional model in Panel B fits the data better.

The results for the second-stage cross-section regressions are given in Table 3, which provides the risk price for each risk factor. We present the results from the unconditional-ICAPM model in Panel A as a benchmark. Comparing the results in Panel A and Panel B, it is clear that the incremental volatility pricing makes an important contribution to explaining the return. Its coefficient is negative and significantly different from zero, and its inclusion makes the volatility factor price λ_2 insignificant. Note also that the equation adjusted R^2 raises from 0.83 to 0.93, very high in the context of monthly currency returns. Figure 2 illustrates graphically the superior fit of the conditional over the unconditional ICAPM for our portfolios.

We also reduce our model to contain only the market risk factor and the extra volatility risk factor (Panel C) and we find that the model provides an even better fit. This suggests that it is the volatility risk during the unexpected volatile period that requires compensation. The excess return of the currency carry trade is mainly compensation for bearing volatility risk during the most unexpected volatile periods.

4.2 Markov Switching ICAPM Results

In the previous section, the conditional ICAPM setting can price the carry trade returns better than the unconditional ICAPM. However, the choice of the state variable, volatility innovation, and the threshold is arbitrary. In this session, we employ a Markov-switching model to price the returns of the carry trade, which has the advantage that it allows us to estimate the regression with data-determined unobservable state variables. We can then investigate the determinants of the regime probabilities on a selection of related variables that potentially influence the carry trade returns nonlinearly.

Table 4 shows the results of the 1st-stage regressions for the full sample of 399 months (Panel A) and for the Markov-switching model as in equation (8) (Panel B). Again, all the estimates in both panels are significantly different from zero and the loadings for the market factor are all very close to 1.0, the loadings on volatility innovation are diminishing from lowest- (#1) to highest-carry portfolios (#6).

If we compare the two panels, we can see that the betas for volatility innovation are noticeably greater in absolute terms in the "abnormal" regime, providing support for the superiority of the conditional over the unconditional model. Indeed, the difference is most marked at the two extremes - portfolios #1 and #6.

In Figure 2 Panels A and B, we plot the fitted mean excess returns from 6 portfolios against the realized mean excess returns of the 6 portfolios for all three models. The distance from the points to the 45-degree line shows absolute pricing errors of the model. The conditional models (Threshold ICAPM and Markov-switch ICAPM) outperform the unconditional benchmark model by providing smaller pricing errors. In Panels C and D, we compare the conditional models with different factors – the full three-factor (estimated DOL, VOL and extra VOL) model and the significant two-factor (DOL, and extra VOL) model. The latter is found to outperform the former and again this finding is consistent with the argument that it is the volatility risk during the unexpected volatile period that requires compensating. Again, we see that the excess return of the currency carry trade is for the most part compensation for bearing volatility risk during the "abnormal" periods.

The results for the second-stage cross-section regressions are given in Table 5, which provides the risk price for each risk factor. Comparing the results in Table 2 Panel A and Panel B, it is clear that the incremental volatility pricing makes an important contribution to explaining the return. Its coefficient is negative and significantly different from zero, and its inclusion makes the volatility factor price λ_2 insignificant. Note also that the equation adjusted R^2 raises from 0.83 to 0.93 in Panel A and even 0.94, when we drop the insignificant factor in Panel B, which is again very high in the context of monthly currency returns. The Markov-switching model provides a better fit and smaller pricing error, confirming the existence of the nonlinear relationship between unexpected volatility and the carry trade returns.

4.3 Determinants of "abnormal" regime probabilities

How is the "abnormal" regime probability determined? What is the relationship between the "abnormal" regime and the state variable that has been chosen in the threshold model? To answer these questions, we regress the ex-ante probability $p_{1,t}$ on its lag and a set of possible state variables which were in the threshold models: the volatility innovation, currency market return (DOL), high-minus-low carry return (*HML)*, stock market return and FX-market skewness.

The state variables are defined as the following:

HML_t: is the high minus low currency portfolio return from Lustig et al. (2011) - a proxy for the slope factor from the second principal component.

$Skew_t$: is the skewness of currency market return. We use the same measure as Rafferty (2012) to proxy the global FX skewness. As argued by Rafferty (2012), differences in exposure to the global currency skewness risk factor can explain the systematic variation in average excess currency returns within the carry trade portfolios, the momentum portfolios and portfolios sorted based on the deviation from the PPP implied exchange rates. The high-interest rate currency portfolio and the carry trade portfolio are more negatively skewed indicating crash risk as argued by Brunnermeier, Nagel and Pedersen (2008).

SMR_t: is the global stock market return which is computed using the S&P500 index. We also use this factor from the stock market as a robustness check as the two markets are highly correlated and factors in the stock market are used in pricing the excess return from the currency market. (Dobrynskaya, 2014; Farago and Tédongap, 2018).

The ex-ante probability $p_{1,t|t-1} = \Pr(s_t = 1|I_{t-1})$, i.e., the probability of being in the first regime (the "abnormal" regime) at the time *t* given the information at time *t-1*, can be obtained after Markov-switching estimation[10].

Figure 3 plots the regime probabilities of being in the first regime (the "abnormal" regime) at time *t* given the information at time *t-1* for each portfolio. The regime probabilities are found to be highly persistent and different across different portfolios. This is, as we mentioned earlier, another advantage of using the Markov-switching model as it allows heterogeneity among different portfolios so we have fewer restrictions to our conditional model compared with the threshold model.

[10] See the derivation of the ex-ante probabilities $p_{1,t|t-1}$ in Appendix A2.

Then we regress the ex-ante probability $p_{1,t|t-1}$ on its lag and a set of possible state variables:

$$p_{1,t|t-1} = \beta_0 + \beta_1 p_{1,t-1|t-2} + \beta_2 X_t + \epsilon_t \tag{10}$$

where $p_{1,t-1|t-2}$ is the lag of the ex-ante probability, and X_t is the possible state variable.

Table 6 provides estimation results for the determinants of the regime probabilities. We report the results for portfolios 1 and 6. The coefficient for the lagged dependent variable is positive and close to one which is not surprising considering the regime probabilities are highly persistent.

As per expectation, the volatility innovation coefficient is positive and significant, suggesting that a high unexpected volatility period is associated with a high probability of being in the "abnormal" regime in this period. This is consistent with the findings of Kim (2015) where a low unexpected volatility regime is more conducive to UIP, and Cenedese, Sarno and Tsiakas (2014) who report that larger future losses for carry trade positions are associated with high foreign exchange volatility innovation. The results from this regression also link the threshold- and Markov-switching factor model we used, showing that the time-varying property of the ICAPM is driven by the nonlinearity of market volatility innovation.

Notably, Dobrynskaya (2014) and Farago & Tédongap (2018) used global stock market return as a state variable in their threshold models for carry trade returns. From table 6, we can see the stock market return coefficients are insignificant, which suggests that the probabilities of being in an "abnormal" state for portfolios 1 and 6 are not explained by the global stock market return. Other state variables, HML and FX market skewness, are also found insignificant for probabilities of being in "abnormal" states.

Overall, the probabilities of being in an "abnormal" state for portfolios 1 and 6 are more likely to be explained by the carry trade volatility innovation, but not by global stock market return.

Further insight can be gained from the descriptive statistics of $p_{1,t|t-1}$ for the different portfolios. In Table 7, we report the number of months that the portfolios are in regime 1. We select the different threshold c and report number of months where

$p_{1,t|t-1} > c$. When c=0.5, there are 199 months that portfolio 1 is in regime 1, where only 42 months that portfolio 6 is in regime 1. When c=0.75, there are 138 months that portfolio 1 is in regime 1, and only 14 months that portfolio 6 is in regime 1. When c=0.90, there are 81 months that portfolio 1 is in regime 1, and 0 months that portfolio 6 is in regime 1. Therefore, it seems portfolio 1 is more likely to be in the "abnormal" regime at any point in time and portfolio 6 is more likely to be in the "normal" regime.

4.4 Robustness Check

As robustness checks, we re-estimate our two models using different thresholds and a wider sample of currencies. We also compare our results with existent literature. Our results are found to be consistent.

Different thresholds

We run a robustness check by choosing different thresholds, defining the 75-percentile point and the 90-percentile point as the boundaries for the high unexpected -volatility period and run the 2-stage Fama-Macbeth regression as in Section 4. The results are reported in Appendix A3 and A4, and they are found to be consistent with the threshold we use in the body of the paper.

Different samples

We run another robustness check by choosing a larger sample of 48 countries. We use the same 48 countries as in Menkhoff, Sarno, Schmeling and Schrimpf (2012) from November 1983 to January 2017. Six currency portfolios are sorted and the portfolios are adjusted every month. The threshold and Markov-switching ICAPM are estimated. The results are reported in Appendix A5 and are found to be consistent with our 29 countries sample.

We also run another robustness check by sorting the 48 currencies into 10 portfolios, where the portfolios are adjusted every month. The sample begins from Feb 1985 as there are only 9 currencies before this period in our sample. The sample size is 384 and the degrees of freedom in the second stage estimation are 7. The threshold and Markov-switching ICAPM are estimated accordingly. The results are reported in Appendix A6. We can see that the excess return of the 10 portfolios does not have a monotonic increasing pattern as in the 6-portfolio case. The threshold ICAPM does not show a better fit of data than the unconditional ICAPM. However, the Markov-switching ICAPM still outperforms the unconditional ICAPM.

5. Conclusion

As far as currency market behaviour is concerned, the evidence presented in this paper suggests that investors are more concerned with volatility risk in states when it is unexpectedly high than when it is low, and that these concerns are reflected in the difference in risk premia in the two states. In modelling terms, the implication is that the conditional ICAPM which takes account of this effect fits the facts better than the unconditional ICAPM and that ignoring this conditioning gives misleading results. The most likely behavioural explanation is that our results are a consequence of the sort of patterns observed in the large empirical literature documenting nonlinear adjustment in the exchange rate process (see for example Michael, Nobay and Peel, 1997 and Taylor, Peel and Sarno, 2001). If there is a band of low-amplitude fluctuations around the long-run equilibrium exchange rate, investors may well be quite relaxed about changes in the level of volatility ("noise") within this zone, especially if in this region transaction costs are relatively high compared to the returns to currency trading (Dumas, 1992). It should be noted in this regard that Copeland and Lu (2016) showed that results of estimating the threshold model were largely unaffected by the introduction of bid-ask spreads.

Overall, our contribution can be seen as a partial resolution of the uncovered interest rate puzzle. Knowledge gained from this investigation is useful for all types of participants in the carry trade, including those traders who rely on estimates of day-to-day crash risk probabilities to implement an appropriate currency hedge.

For further research, we suggest using the Markov-Switching ICAPM model in the equity market and comparing it with Farago and Tedongap (2018)'s five-factor model. Notably, it is not possible to use the five-factor model in our paper, as the portfolio size is limited. For example, if all five factors are used, the degree of freedom will be zero in the second stage estimation. The portfolio size in the equity market is large. A Markov-switching type of factor model can be developed. And it will be interesting to compare it with Farago and Tedongap (2018)'s five-factor model. We leave this direction for further research.

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Table 1: Annualized Excess Returns from Currency Portfolios

Portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*DOL*	*HML*
Mean	-1.49	0.30	1.58	1.69	2.75	5.16	1.665	6.65
Std. Dev.	9.56	10.07	9.70	9.56	10.07	10.30	8.89	9.19
Skewness	0.08	-0.14	-0.08	-0.37	-0.78	-0.63	-0.33	-1.08
SR	-0.16	0.03	0.16	0.18	0.27	0.50	0.19	0.72

In this table, 29 currencies have been allocated into 6 portfolios according to the size of the forward discount against the dollar. Portfolios are adjusted monthly.

Table 2: The 1st Stage of FMB Regression for the Threshold Model

Panel A. For all observations (399-month)					Panel B. For observations when $\Delta V_t >$ **mean+1sd** (49-month)				
$r_t^i = a_i + b_{1i}DOL_t + b_{2i}\Delta V_t + \epsilon_{it}$					$r_t^i = a_i^- + b_{1i}^- DOL_t + b_{2i}^- \Delta V_t + \epsilon_{it}$				
PF	*Alpha*	*DOL*	ΔV	R^2	*PF*	*Alpha*	*DOL*	ΔV	R^2
1	-0.003	0.968	3.982	0.794	1	-0.017	1.062	11.873	0.894
	[0.001]	[0.044]	[1.052]			[0.004]	[0.065]	[2.099]	
2	-0.001	1.047	1.711	0.844	2	-0.006	1.078	3.953	0.912
	[0.001]	[0.041]	[0.638]			[0.004]	[0.064]	[2.099]	
3	-0.000	1.038	1.706	0.893	3	-0.001	1.020	1.987	0.928
	[0.001]	[0.024]	[0.559]			[0.003]	[0.054]	[1.940]	
4	0.000	0.999	-1.337	0.876	4	-0.005	1.035	0.851	0.944
	[0.000]	[0.028]	[0.608]			[0.003]	[0.050]	[2.165]	
5	0.001	1.016	-2.726	0.835	5	0.010	0.948	-8.022	0.889
	[0.001]	[0.045]	[0.920]			[0.005]	[0.060]	[3.109]	
6	0.003	0.932	-3.336	0.682	6	0.022	0.874	-12.22	0.787
	[0.001]	[0.047]	[1.035]			[0.005]	[0.075]	[2.710]	

This table reports the results from the 1st stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (*Δ V*) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations are beyond the threshold. Newey-West standard errors are reported in the brackets.

Table 3: The 2nd Stage of FMB Regression for the Threshold Model

Panel A. Unconditional ICAPM model

$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + \epsilon_i$

	Market Return	Market Volatility risk		R^2	MAE
λ	0.138***	-0.060***		0.825	3.07e-6
S.E.	[0.036]	[0.014]			

Panel B. Conditional ICAPM model (1)

$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + (\hat{b}_{2i}^{-} - \hat{b}_{2i})\lambda_2^{-} + \epsilon_i$

	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.138	-0.018	-0.023***	0.930	1.1e-6
S.E.		[0.017]	[0.008]		

Panel C. Conditional ICAPM model (2)

$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}^{-}\lambda_2^{-} + \epsilon_i$

		Market Return	Extra Market Volatility risk	R^2	MAE
λ		0.132***	-0.021***	0.938	1.09e-6
S.E.		[0.021]	[0.006]		

This table reports the results from the 2nd stage time series FMB regression[11]. The test assets are excess returns to the six carry trade portfolios. Factors are the market return factor, market volatility risk factor and the extra market volatility risk factor. Newey-West standard errors are reported in the brackets. R^2 and mean absolute errors (MAE) are provided. *** denotes significant at 1% level.

[11] Note that intercept is not included in Tables 3 and 5. λ_1 in Tables 3 and 5 served as an intercept as $\hat{b}_{1i}$ is closed to 1 for *i=1,2,…,6*.

Table 4: The 1st Stage of FMB Regression for the Markov-switching Model

Panel A. For all observations (399-month)					Panel B. Markov-switch high regime				
$r_t^i = a_i + b_{1i}DOL_t + b_{2i}\Delta V_t + \epsilon_{it}$					$r_t^i = a_i^H + b_{1i}^H DOL_t + b_{2i}^H \Delta V_t + \epsilon_{it}$				
PF	*Alpha*	*DOL*	*ΔV*	R^2	*PF*	*Alpha*	*DOL*	*ΔV*	*LL*
1	-0.003	0.968	3.982	0.794	1	-0.003	1.006	5.267	-1208.76
	[0.001]	[0.044]	[1.052]			[0.001]	[0.025]	[1.148]	
2	-0.001	1.047	1.711	0.844	2	0.000	1.096	1.787	-1265.78
	[0.001]	[0.041]	[0.638]			[0.002]	[0.019]	[1.237]	
3	-0.000	1.038	1.706	0.893	3	0.005	1.033	0.682	-1325.41
	[0.001]	[0.024]	[0.559]			[0.003]	[0.019]	[1.708]	
4	0.000	0.999	-1.337	0.876	4	0.001	0.980	-0.494	-1295.50
	[0.000]	[0.028]	[0.608]			[0.000]	[0.018]	[0.510]	
5	0.001	1.016	-2.726	0.835	5	-0.001	0.996	-4.079	-1227.80
	[0.001]	[0.045]	[0.920]			[0.001]	[0.024]	[1.060]	
6	0.003	0.932	-3.336	0.682	6	-0.002	0.924	-5.908	-1116.87
	[0.001]	[0.047]	[1.035]			[0.005]	[0.031]	[2.793]	

This table reports the results from the 1st stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (*ΔV*) factor. Panel A provides estimation for the full sample while Panel B provides estimation for the Markov-switching high regime. Newey-West standard errors are reported in the brackets. LL denotes log-likelihood.

Table 5: The 2nd Stage of FMB Regression for the Markov-switching Model

Panel A. Markov-switching Conditional ICAPM model (1)					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + (\hat{b}_{2i}^- - \hat{b}_{2i})\lambda_2^- + \epsilon_i$					
	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.138	-0.041	-0.052**	0.930	1.26e-6
S.E.		[0.026]	[0.018]		

Panel B. Markov-switching Conditional ICAPM model (2)				
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}^-\lambda_2^- + \epsilon_i$				
	Market Return	Extra Market Volatility risk	R^2	MAE
λ	0.117***	-0.045***	0.941	1.04e-6
S.E.	[0.023]	[0.006]		

This table reports the results from the 2nd stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (ΔV) factor. Newey-West standard errors are reported in the brackets. Adjusted R^2 and mean absolute errors (MAE) are provided. *** denotes significant at 5% level.

Table 6: The relationship between regime probabilities and market volatility innovation

	$p_{1,t\|t-1} = \beta_0 + \beta_1 p_{1,t-1\|t-2} + \beta_2 X_t + \epsilon_t$						
	β_0	$p_{1,t-1\|t-2}$	ΔV_t	HML_t	DOL_t	SMR_t	$Skew_t$
P1	0.040***	0.919***	13.792***				
	[0.012]	[0.020]	[7.004]				
P6	0.060***	0.719***	19.249***				
	[0.010]	[0.034]	[6.978]				
P1	0.042***	0.918***		-0.140			
	[0.013]	[0.020]		[0.257]			
P6	0.060***	0.721***		-0.751***			
	[0.010]	[0.035]		[0.255]			
P1	0.041***	0.918***			-0.086		
	[0.012]	[0.020]			[0.264]		
P6	0.060***	0.720***			0.174		
	[0.010]	[0.035]			[0.264]		
P1	0.041***	0.918***				0.022	
	[0.012]	[0.020]				[0.158]	
P6	0.061***	0.723***				-0.201	
	[0.010]	[0.035]				[0.158]	
P1	0.040***	0.919***					0.008
	[0.012]	[0.020]					[0.036]
P6	0.059***	0.721***					0.020
	[0.010]	[0.035]					[0.036]

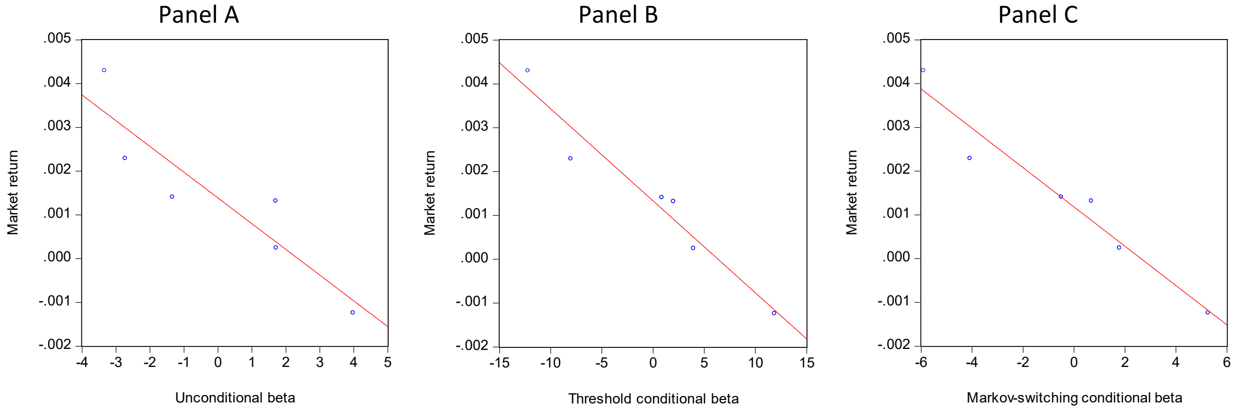
This table provides estimation results for the determinants of the regime probabilities. $p_{1,t|t-1} = \Pr(s_t = 1|I_{t-1})$ is the probability of the observation lies in regime 1 (high volatility regime) at time *t*. Only the results for portfolio 1 and 6 are reported. P1 denotes the portfolio 1. P6 denotes portfolio 2. *** denotes significant at 5% level.

Table 7: Number of months that portfolios are in regime 1

	P1	P2	P3	P4	P5	P6
$p_{1,t\|t-1} > 0.50$	199	125	26	54	246	42
$p_{1,t\|t-1} > 0.75$	138	94	9	24	0	14
$p_{1,t\|t-1} > 0.90$	81	55	0	0	0	0

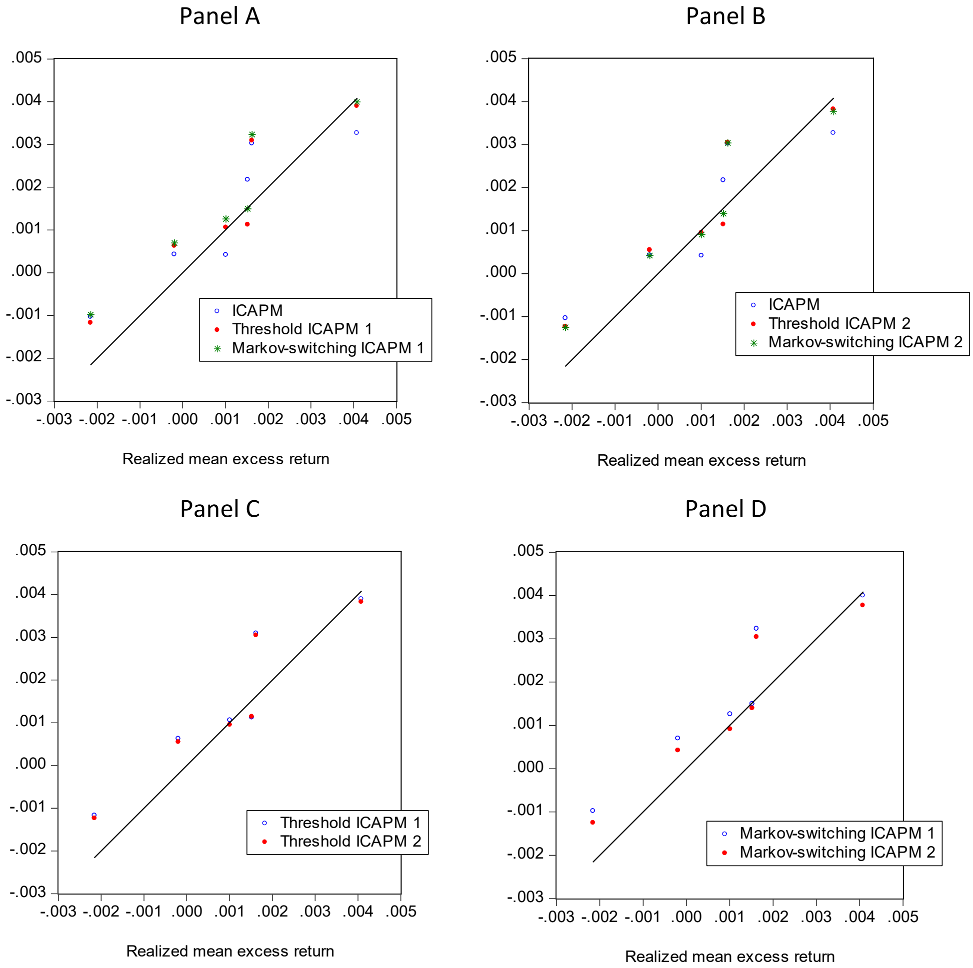
This table reports report the number of months that the portfolios are in regime 1, when different threshold c is used, where $c = 0.50, 0.75, 0.90$ respectively.

Figure 1: Risk-return relations for Unconditional and Conditional ICAPM Models



Plotted are risk-return relations for six currency portfolios monthly re-sampled based on the interest rate differential with the US. Panel A plots the realized mean excess return versus the ICAPM betas. Panel B plots the realized mean excess return versus the threshold conditional relative betas. Panel C plots the realized mean excess return versus the Markov-switching conditional relative betas.

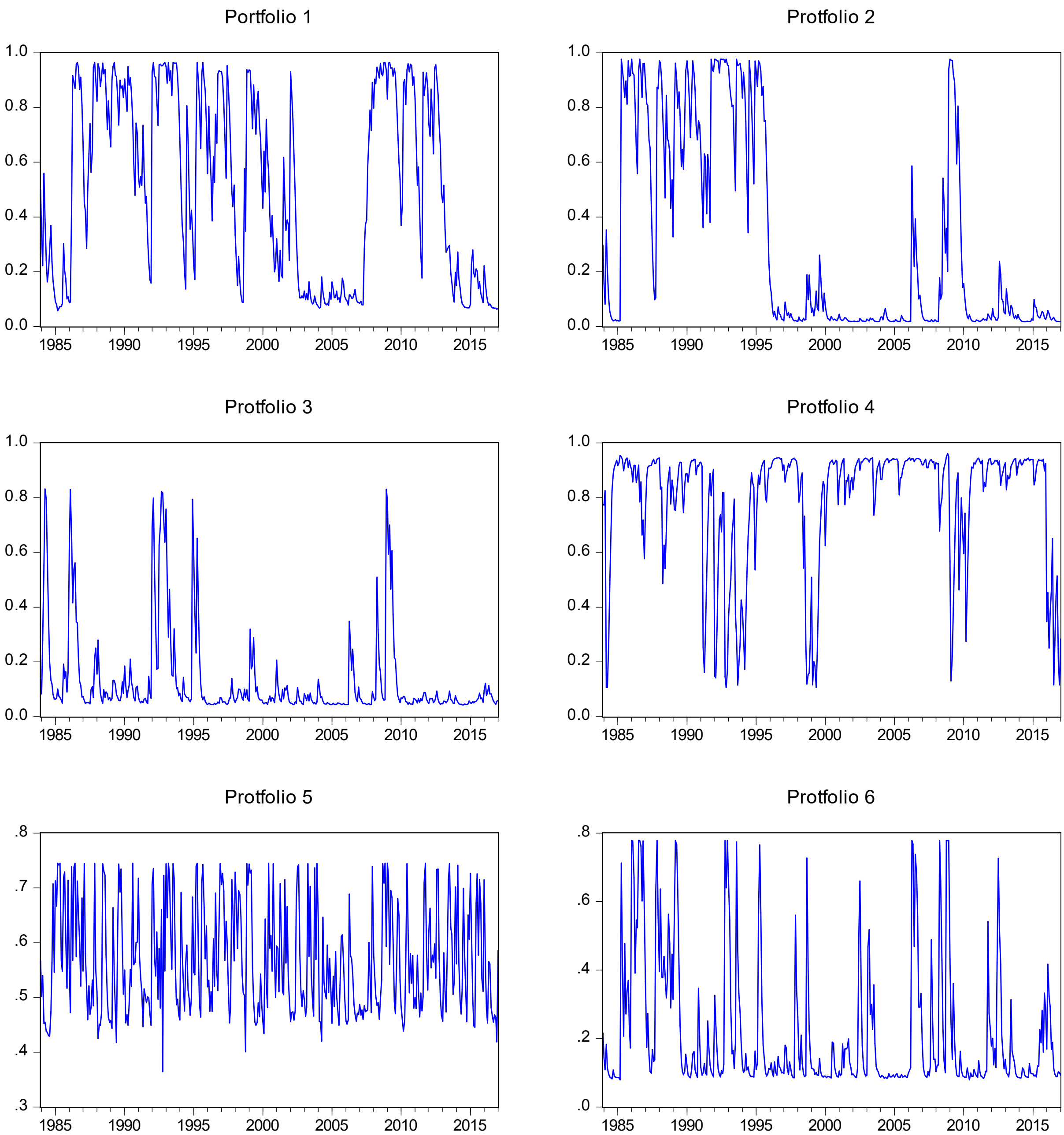
Figure 2: Pricing Error Plots for Unconditional and Conditional ICAPM Models



This figure plots the fitted mean excess returns from 6 portfolios against the realized mean excess returns of the 6 portfolios for both the unconditional ICAPM model and conditional ICAPM model (both threshold and Markov-switch). The distance from the points to the 45-degree line shows absolute pricing errors of the model. The sample period is 12/1983 to 01/2017.

ICAPM 1 denotes the full three-factor (DOL, VOL and extra VOL) model, which is from the estimates of Penal A in table 4 and 5. ICAPM 2 denotes the two-factor (DOL and extra VOL) model, which is from the estimates of Penal B in table 4 and 5.

Figure 3: Regime probabilities



This figure plots the regime probabilities of being in the first regime (the "abnormal" regime) at time *t* given the information at time *t-1* for each portfolio.

Appendix

Appendix A1: Testing for the restriction $b_{1i} - b_{1i}^{-} = 0$

Table A1: The time series Regression for the portfolio return

$r_t^i = a_i + b_{1i}DOL_t + (b_{1i} - b_{1i}^{-})DOL_t * D_t + b_{2i}\Delta V_t + \epsilon_{it}$				
PF	$\hat{a}$	$\widehat{b_1}$	$\widehat{b_1} - \widehat{b_1^-}$	$\widehat{b_2}$
1	-0.003	0.955***	0.038	4.070***
	[0.001]	[0.044]	[0.095]	[0.948]
2	-0.001	1.040***	0.020	1.758***
	[0.001]	[0.051]	[0.075]	[0.722]
3	-0.000	1.063***	-0.077	1.529***
	[0.000]	[0.026]	[0.057]	[0.583]
4	0.000	0.988***	0.033	-1.261***
	[0.001]	[0.033]	[0.048]	[0.639]
5	0.001	1.027***	-0.030	-2.795***
	[0.001]	[0.034]	[0.068]	[0.892]
6	0.003	0.927***	0.015	-3.301***
	[0.001]	[0.052]	[0.089]	[1.044]

This table reports the t-statistics of the test H_0: $b_{1i} - b_{1i}^{-} = 0$. D_t is a dummy variable which takes the value 1 if $\Delta V_t > 0.00091$(mean + 1sd) and takes the value 0 otherwise. Newey-West standard errors are reported in the brackets. *** denotes significant at 5% level. ** denotes significant at 10% level. The null hypothesis $\widehat{b_1} - \widehat{b_1^-}$ cannot be rejected for all the six portfolios, which implied that the dollar factor does not change across the states.

Appendix A2: The ex-ante probability and Log-likelihood function of the Markov switching model

The unobservable state variable s_t is assumed to evolve according to the following time-varying transition probabilities. The first-order Markov Chain, with transition probability

$$\Pr(s_t = j | s_{t-1} = i) = P_{ij} \tag{10}$$

That indicates the probability of switching from state *i* at time *t−1* into state *j* at *t*. These probabilities are grouped into the transition matrix

$$\mathrm{P} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} = \begin{bmatrix} p & (1-q) \\ 1-p & q \end{bmatrix} \tag{11}$$

where P_{ij} are the probabilities of moving from state i in period $t-1$ to state j in period t.

An essential ingredient is an ex-ante probability $p_{1,t|t-1} = \Pr(s_t = 1|I_{t-1})$, i.e., the probability of being in the first regime at the time t given the information at time *t*, whose specification is

$$p_{1,t|t-1} = \Pr(s_t = 1|I_{t-1}) = (1-q)\left[\frac{f(y_{t-1}|s_{t-1}=2)(1-p_{1,t-1|t-2})}{f(y_{t-1}|s_{t-1}=1)p_{1,t-1|t-2}+f(y_{t-1}|s_{t-1}=2)(1-p_{1.t-1|t-2})}\right] + p\left[\frac{f(y_{t-1}|s_{t-1}=1)p_{1,t-1}}{f(y_{t-1}|s_{t-1}=1)p_{1,t-1|t-2}+f(y_{t-1}|s_{t-1}=2)(1-p_{1.t-1|t-2})}\right] \quad (12)$$

where the ergodic probability (that is the unconditional probability (Hamilton, 1994) of being in the state $s_t = 1$ is given by $\pi_1 = (1-q)/(2-p-q)$. So ex-ante probability $p_{1,t|t-1}$ can be calculated recursively. Thus, the log-likelihood function can be written as

$$l = \sum_{t=1}^{T} \log\left[p_{1,t|t-1} f(y_t|s_t = 1, I_{t-1}) + \left(1 - p_{1,t|t-1}\right) f(y_t|s_t = 2, I_{t-1})\right] \quad (13)$$

where $f(.|s_t = i)$ is the conditional distribution given that regime *i* occurs at time *t*.

Appendix A3: Robustness check with 75 percentile as the boundary

Table A3.1: The 1st Stage of FMB Regression for the Threshold Model

	Panel B. For observations when $\Delta V_t >$ 75 percentile				Panel C. Markov-switch high regime			
	$r_t^i = a_i + b_{1i}DOL_t + b_{2i}\Delta V_t + \epsilon_{it}$				$r_t^i = a_i^- + b_{1i}^-DOL_t + b_{2i}^-\Delta V_t + \epsilon_{it}$			
PF	*Alpha*	*DOL*	*Δ V*	R^2	*Alpha*	*DOL*	*Δ V*	*LL*
1	-0.008	0.967	7.414	0.848	-0.003	1.006	5.267	-1208
	[0.003]	[0.042]	[1.669]		[0.001]	[0.025]	[1.148]	
2	0.000	1.073	1.752	0.913	0.000	1.096	1.787	-1265
	[0.002]	[0.035]	[1.385]		[0.002]	[0.019]	[1.237]	
3	0.001	1.000	1.742	0.929	0.005	1.033	0.682	-1325
	[0.002]	[0.029]	[1.160]		[0.003]	[0.019]	[1.708]	
4	-0.001	1.016	-1.271	0.907	0.001	0.980	-0.494	-1295
	[0.002]	[0.035]	[1.395]		[0.000]	[0.018]	[0.510]	
5	0.002	0.991	-3.901	0.875	-0.001	0.996	-4.079	-1227
	[0.002]	[0.041]	[1.640]		[0.001]	[0.024]	[1.060]	
6	0.007	0.952	-5.737	0.769	-0.002	0.924	-5.908	-1116
	[0.004]	[0.059]	[2.335]		[0.005]	[0.031]	[2.793]	

Table A3.2: The 2nd Stage of FMB Regression for the Threshold Model

Panel A. Unconditional ICAPM model					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + \epsilon_i$					
	Market Return	Market Volatility risk		R^2	MAE
λ	0.138***	-0.060***		0.825	3.07e-6
S.E.	[0.036]	[0.014]			
Panel B. Threshold ICAPM model (1)					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + (\hat{b}_{2i}^- - \hat{b}_{2i})\lambda_2^- + \epsilon_i$					
	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.138	0.029	-0.053**	0.880	1.52e-6
S.E.		[0.047]	[0.028]		
Panel C. Markov-switching ICAPM model (2)					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + (\hat{b}_{2i}^- - \hat{b}_{2i})\lambda_2^- + \epsilon_i$					
	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.138	0.024	-0.060***	0.944	1.01e-6
S.E.		[0.025]	[0.017]		

This table reports the results from the 2nd stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) fact or, and the volatility risk (*ΔV*) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations exceed the threshold. Newey-West standard errors are reported in the brackets. R^2 and mean absolute errors (MAE) are provided. *** denotes significant at 5% level.

Appendix A4: Robustness check with 90 percentile as the boundary

Table A4.1: The 1st Stage of FMB Regression for the Threshold Model

	Panel B. For observations when ΔV_t> 90 percentile				Panel C. Markov-switch high regime			
	$r_t^i = a_i + b_{1i}DOL_t + b_{2i}\Delta V_t + \epsilon_{it}$				$r_t^i = a_i^- + b_{1i}^- DOL_t + b_{2i}^- \Delta V_t + \epsilon_{it}$			
PF	Alpha	DOL	ΔV	R^2	Alpha	DOL	ΔV	LL
1	-0.017	1.053	11.334	0.873	-0.003	1.006	5.267	-1208
	[0.006]	[0.066]	[2.780]		[0.001]	[0.025]	[1.148]	
2	-0.002	1.057	2.601	0.900	0.000	1.096	1.787	-1265
	[0.006]	[0.061]	[2.557]		[0.002]	[0.019]	[1.237]	
3	-0.003	1.032	3.675	0.939	0.005	1.033	0.682	-1325
	[0.004]	[0.045]	[1.899]		[0.003]	[0.019]	[1.708]	
4	-0.004	1.053	0.319	0.933	0.001	0.980	-0.494	-1295
	[0.005]	[0.050]	[2.083]		[0.000]	[0.018]	[0.510]	
5	0.010	0.937	-7.235	0.885	-0.001	0.996	-4.079	-1227
	[0.006]	[0.064]	[2.698]		[0.001]	[0.024]	[1.060]	
6	0.017	0.868	-10.694	0.774	-0.002	0.924	-5.908	-1116
	[0.009]	[0.094]	[3.958]		[0.005]	[0.031]	[2.793]	

Table A4.2: The 2nd Stage of FMB Regression for the Threshold Model

Panel A. Unconditional ICAPM model

$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + \epsilon_i$

	Market Return	Market Volatility risk		R^2	MAE
λ	0.138***	-0.060***		0.825	3.07e-6
S.E.	[0.036]	[0.014]			

Panel B. Threshold ICAPM model (1)

$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + (\hat{b}_{2i}^- - \hat{b}_{2i})\lambda_2^- + \epsilon_i$

	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.138	-0.010	-0.026***	0.894	1.31e-6
S.E.		[0.035]	[0.013]		

Panel C. Markov-switching ICAPM model (2)

$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + (\hat{b}_{2i}^- - \hat{b}_{2i})\lambda_2^- + \epsilon_i$

	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.138	0.021	-0.058***	0.937	1.12e-6
S.E.		[0.026]	[0.018]		

This table reports the results from the 2nd stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, or and the volatility risk (ΔV) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations exceed the threshold. Newey-West standard errors are reported in the brackets. R^2 and mean absolute errors (MAE) are provided. *** denotes significant at 5% level.

Appendix A5: Robustness check with 48-country sample

Table A5.1: Excess Returns from 48-country Currency Portfolios

Portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*DOL*	*HML*
Mean	-1.45	0.35	1.63	1.51	2.56	5.15	1.63	6.60
Std. Dev.	9.12	10.08	9.79	9.21	9.87	10.11	8.97	9.01
Skewness	0.07	-0.12	-0.15	-0.46	-0.19	-0.71	-0.31	-1.02
SR	-0.16	0.03	0.17	0.16	0.26	0.51	0.18	0.73

In this table, 48 currencies have been allocated into 6 portfolios according to the size of the forward discount. Portfolios are adjusted monthly.

Table A5.2: The 1st Stage of FMB Regression for the Threshold Model

Panel A. For all observations [399-month]					Panel B. For observations when $\Delta V_t >$ **mean+1sd** [49-month)				
$r_t^i = a_i + b_{1i} DOL_t + b_{2i} \Delta V_t + \epsilon_{it}$					$r_t^i = a_i^- + b_{1i}^- DOL_t + b_{2i}^- \Delta V_t + \epsilon_{it}$				
PF	*Alpha*	*DOL*	*Δ V*	R^2	*PF*	*Alpha*	*DOL*	*Δ V*	R^2
1	-0.003	0.975	3.666	0.799	1	-0.016	1.061	11.137	0.890
	[0.001]	[0.024]	[0.655]			[0.005]	[0.055]	[2.367]	
2	-0.001	1.040	1.776	0.843	2	-0.004	1.069	3.148	0.911
	[0.001]	[0.023]	[0.601]			[0.004]	[0.052]	[2.204]	
3	-0.000	1.030	1.810	0.895	3	-0.003	0.997	3.344	0.936
	[0.000]	[0.018]	[0.473]			[0.003]	[0.040]	[1.714]	
4	-0.000	1.003	-1.555	0.872	4	-0.005	1.047	0.503	0.944
	[0.001]	[0.020]	[0.524]			[0.004]	[0.042]	[1.802]	
5	0.001	1.006	-2.461	0.840	5	0.010	0.929	-6.854	0.890
	[0.001]	[0.023]	[0.603]			[0.005]	[0.056]	[2.378]	
6	0.003	0.944	-3.236	0.690	6	0.020	0.898	-11.28	0.798
	[0.001]	[0.033]	[0.878]			[0.007]	[0.082]	[3.491]	

This table reports the results from the 1st stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (*Δ V*) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations are beyond the threshold. Newey-West standard errors are reported in the brackets.

Table A5.3: The 2nd Stage of FMB Regression for the Threshold Model

Panel A. Unconditional ICAPM model					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + \epsilon_i$					
	Market Return	Market Volatility risk		R^2	MAE
λ	0.135***	-0.059***		0.769	3.92e-6
S.E.	[0.040]	[0.016]			

Panel B. Conditional ICAPM model [1]					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + (\hat{b}_{2i}^- - \hat{b}_{2i})\lambda_2^- + \epsilon_i$					
	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.135	-0.013	-0.027**	0.917	1.43e-6
S.E.		[0.020]	[0.010]		

Panel C. Conditional ICAPM model [2]					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}^-\lambda_2^- + \epsilon_i$					
		Market Return	Extra Market Volatility risk	R^2	MAE
λ		0.135***	-0.022***	0.911	1.51e-6
S.E.		[0.025]	[0.006]		

This table reports the results from the 2nd stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (ΔV) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations exceed the threshold. Newey-West standard errors are reported in the brackets. R^2 and mean absolute errors (MAE) are provided. *** denotes significant at 5% level.

Table A5.4: The 1st Stage of FMB Regression for the Markov-switching Model

Panel A. For all observations					Panel B. Markov-switch high regime				
$r_t^i = a_i + b_{1i}DOL_t + b_{2i}\Delta V_t + \epsilon_{it}$					$r_t^i = a_i^H + b_{1i}^H DOL_t + b_{2i}^H \Delta V_t + \epsilon_{it}$				
PF	*Alpha*	*DOL*	*Δ V*	R^2	*PF*	*Alpha*	*DOL*	*Δ V*	*LL*
1	-0.003	0.975	3.666	0.799	1	-0.003	1.006	5.317	624.61
	[0.001]	[0.024]	[0.655]			[0.001]	[0.024]	[1.153]	
2	-0.001	1.040	1.776	0.843	2	-0.000	1.095	1.769	567.16
	[0.001]	[0.023]	[0.601]			[0.002]	[0.019]	[1.237]	
3	-0.000	1.030	1.810	0.895	3	0.005	1.030	0.804	508.17
	[0.000]	[0.018]	[0.473]			[0.003]	[0.019]	[1.769]	
4	-0.000	1.003	-1.555	0.872	4	0.001	0.980	-0.534	537.22
	[0.001]	[0.020]	[0.524]			[0.000]	[0.018]	[0.511]	
5	0.001	1.006	-2.461	0.840	5	-0.001	0.996	-3.998	605.37
	[0.001]	[0.023]	[0.603]			[0.001]	[0.024]	[1.075]	
6	0.003	0.944	-3.236	0.690	6	-0.003	0.925	-6.041	716.36
	[0.001]	[0.033]	[0.878]			[0.005]	[0.031]	[3.082]	

This table reports the results from the 1st stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (*Δ V*) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations are beyond the threshold. Newey-West standard errors are reported in the brackets.

Table A5.5: The 2nd Stage of FMB Regression for the Markov-switching Model

Panel A. Markov-switching Conditional ICAPM model [1]					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + [\hat{b}_{2i}^H - \hat{b}_{2i})\lambda_2^H + \epsilon_i$					
	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.135	-0.038***	-0.054**	0.922	1.36e-6
S.E.		[0.012]	[0.020]		

Panel B. Markov-switching Conditional ICAPM model [2]					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}^H\lambda_2^H + \epsilon_i$					
		Market Return	Extra Market Volatility risk	R^2	MAE
λ		0.115***	-0.044***	0.928	1.23e-6
S.E.		[0.023]	[0.006]		

This table reports the results from the 2nd stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (*Δ V*) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations exceed the threshold. Newey-West standard errors are reported in the brackets. Adjusted R^2 and mean absolute errors (MAE) are provided. *** denotes significant at 5% level.

Appendix A6: Robustness check with 48-country and 10 Portfolios

Table A6.1: Excess Returns from 48-country and 10 Portfolios

Portfolio	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*8*	*10*
Mean	-7.8	-0.23	-1.48	0.91	3.35	3.19	3.1	3.27	2.53	12.46
Std. Dev.	10.65	8.36	8.68	8.77	7.95	7.95	8.52	9.4	10.56	11.65
Skewness	-0.37	-0.11	-0.29	-0.17	0.06	-0.02	-0.46	-1.1	-1.63	-0.6
SR	-0.73	-0.03	-0.17	0.1	0.42	0.4	0.36	0.35	0.24	1.07

In this table, 48 currencies have been allocated into 10 portfolios according to the size of the forward discount. Portfolios are adjusted monthly.

Table A6.2: The 1st Stage of FMB Regression for the Threshold Model

Panel A. For all observations [385-month)					Panel B. For observations when $\Delta V_t >$ **mean+1sd** [45-month)				
$r_t^i = a_i + b_{1i}DOL_t + b_{2i}\Delta V_t + \epsilon_{it}$					$r_t^i = a_i^- + b_{1i}^- DOL_t + b_{2i}^- \Delta V_t + \epsilon_{it}$				
PF	*Alpha*	*DOL*	*Δ V*	R^2	*PF*	*Alpha*	*DOL*	*Δ V*	R^2
1	-0.820	1.054	6.704	0.536	1	-1.215	1.026	9.746	0.664
	[0.106]	[0.050]	[1.126]			[0.369]	[0.074]	[2.455]	
2	-0.175	0.971	1.994	0.726	2	0.081	0.969	0.519	0.778
	[0.064]	[0.030]	[0.680]			[0.272]	[0.055]	[1.810]	
3	-0.274	0.937	-0.232	0.642	3	-0.014	0.847	-2.109	0.656
	[0.076]	[0.036]	[0.806]			[0.331]	[0.067]	[2.203]	
4	-0.090	1.035	1.788	0.750	4	-0.197	1.023	2.944	0.803
	[0.064]	[0.030]	[0.681]			[0.262]	[0.053]	[1.741]	
5	0.127	0.947	2.024	0.764	5	-0.056	0.933	3.237	0.797
	[0.057]	[0.027]	[0.600]			[0.242]	[0.049]	[1.613]	
6	0.111	0.960	0.290	0.797	6	0.188	0.948	-0.125	0.835
	[0.052]	[0.025]	[0.555]			[0.222]	[0.045]	[1.480]	
7	0.096	1.009	-1.349	0.784	7	0.391	1.042	-3.313	0.846
	[0.058]	[0.027]	[0.614]			[0.242]	[0.049]	[1.611]	
8	0.105	1.039	-1.824	0.690	8	0.223	1.025	-2.742	0.731
	[0.077]	[0.036]	[0.813]			[0.337]	[0.068]	[2.241]	
9	0.036	1.087	-4.038	0.624	9	0.032	1.080	-4.333	0.623
	[0.095]	[0.045]	[1.005]			[0.462]	[0.093]	[3.072]	
10	0.884	0.961	-5.357	0.423	10	0.566	1.106	-3.824	0.559
	[0.129]	[0.061]	[1.373]			[0.536]	[0.108]	[3.567]	

This table reports the results from the 1st stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (*Δ V*) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations are beyond the threshold. Newey-West standard errors are reported in the brackets.

Table A6.3: The 2nd Stage of FMB Regression for the Threshold Model

Panel A. Unconditional ICAPM model

$$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + \epsilon_i$$

	Market Return	Market Volatility risk		R^2	MAE
λ	0.155***	-0.102***		0.690	4.73e-6
S.E.	[0.079]	[0.028]			

Panel B. Conditional ICAPM model [1)

$$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + (\hat{b}_{2i}^- - \hat{b}_{2i})\lambda_2^- + \epsilon_i$$

	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.155	-0.113***	0.062	0.703	3.42e-6
S.E.		[0.028]	[0.044]		

Panel C. Conditional ICAPM model [2)

$$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}^-\lambda_2^- + \epsilon_i$$

		Market Return	Extra Market Volatility risk	R^2	MAE
λ		0.168	-0.067***	0.514	5.52e-6
S.E.		[0.101]	[0.022]		

This table reports the results from the 2nd stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (ΔV) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations exceed the threshold. Newey-West standard errors are reported in the brackets. R^2 and mean absolute errors (MAE) are provided. *** denotes significant at 5% level.

Table A6.4: The 1st Stage of FMB Regression for the Markov-switching Model

Panel A. For all observations					Panel B. Markov-switch high regime				
$r_t^i = a_i + b_{1i}DOL_t + b_{2i}\Delta V_t + \epsilon_{it}$					$r_t^i = a_i^H + b_{1i}^H DOL_t + b_{2i}^H \Delta V_t + \epsilon_{it}$				
PF	*Alpha*	*DOL*	*ΔV*	R^2	*PF*	*Alpha*	*DOL*	*ΔV*	*LL*
1	-0.820	1.054	6.704	0.536	1	-5.243	0.968	1.287	756.461
	[0.106]	[0.050]	[1.126]			[0.459]	[0.031]	[3.631]	
2	-0.175	0.971	1.994	0.726	2	-0.259	0.986	1.152	634.486
	[0.064]	[0.030]	[0.680]			[0.194]	[0.028]	[1.393]	
3	-0.274	0.937	-0.232	0.642	3	-0.415	1.056	-2.296	688.04
	[0.076]	[0.036]	[0.806]			[0.218]	[0.031]	[1.961]	
4	-0.090	1.035	1.788	0.750	4	-0.017	1.112	1.371	624.120
	[0.064]	[0.030]	[0.681]			[0.063]	[0.026]	[0.706]	
5	0.127	0.947	2.024	0.764	5	0.274	0.929	2.757	586.688
	[0.057]	[0.027]	[0.600]			[0.136]	[0.021]	[0.928]	
6	0.111	0.960	0.290	0.797	6	0.055	0.966	0.706	555.546
	[0.052]	[0.025]	[0.555]			[0.139]	[0.020]	[1.002]	
7	0.096	1.009	-1.349	0.784	7	0.179	0.974	-0.479	578.791
	[0.058]	[0.027]	[0.614]			[0.253]	[0.021]	[2.017]	
8	0.105	1.039	-1.824	0.690	8	-0.266	0.987	-7.285	674.83
	[0.077]	[0.036]	[0.813]			[0.447]	[0.027]	[3.562]	
9	0.036	1.087	-4.038	0.624	9	0.132	1.022	-11.006	736.20
	[0.095]	[0.045]	[1.005]			[1.663]	[0.028]	[16.519]	
10	0.884	0.961	-5.357	0.423	10	1.436	0.920	-8.525	870.844
	[0.129]	[0.061]	[1.373]			[0.270]	[0.041]	[2.072]	

This table reports the results from the 1st stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (*ΔV*) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations are beyond the threshold. Newey-West standard errors are reported in the brackets.

Table A6.5: The 2nd Stage of FMB Regression for the Markov-switching Model

Panel A. Markov-switching Conditional ICAPM model [1]					
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}\lambda_2 + [\hat{b}_{2i}^H - \hat{b}_{2i})\lambda_2^H + \epsilon_i$					
	Market Return	Market Volatility risk	Extra Market Volatility risk	R^2	MAE
λ	0.155	-0.097***	-0.078***	0.732	3.31e-6
S.E.		[0.025]	[0.036]		

Panel B. Markov-switching Conditional ICAPM model [2]				
$\bar{r}^i = \hat{b}_{1i}\lambda_1 + \hat{b}_{2i}^H\lambda_2^H + \epsilon_i$				
	Market Return	Extra Market Volatility risk	R^2	MAE
λ	0.184***	-0.094***	0.771	3.10e-6
S.E.	[0.066]	[0.018]		

This table reports the results from the 2nd stage time series FMB regression. The test assets are excess returns to the six carry trade portfolios. Factors are the dollar risk (*DOL*) factor, and the volatility risk (ΔV) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations exceed the threshold. Newey-West standard errors are reported in the brackets. Adjusted R^2 and mean absolute errors (MAE) are provided. *** denotes significant at 5% level.