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2015

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UNIVERSITY OF CALIFORNIA
SANTA CRUZ

THREE ESSAYS ON INTERNATIONAL FINANCE

A dissertation submitted in partial satisfaction
of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Evan Smith

September 2015

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Abstract

Three Essays on International Finance

Evan Smith

Chapter 1 of this dissertation uses a more flexible modeling methodology in order to test for time varying coefficients in the classic uncovered interest parity regression. By allowing the coefficients to vary over time, but also sharing information across currencies in a random effects type setup, we get clearer picture of the evolution of UIP in financial markets. We find that the once standard failure of the equilibrium condition is no longer as pronounced.

Chapter 2 extends the work done in chapter 1 by forming currency portfolios that exploit the failure of UIP in order to be profitable. We show through the use of dynamic linear models as well as a non parametric random portfolios methodology that excess returns on these strategies are no longer quite so pervasive, adding evidence to the claim that UIP holds better now than in the past.

Chapter 3 switches gears and revisits a classic paper on long swings in the exchange rate. By testing the model on more currencies over a longer time period, and gauging predictive accuracy based on the signals it gives for portfolio formation, we find that the model does not give adequate predictive performance. We conclude that when trends are defined by a markov switching Gaussian model, it is highly unlikely that exchange rates still exhibit long swings.

Acknowledgments

I would first like to thank my wife for her infinite patience when it came to helping me get through this process. The rest of my family and friends also deserve praise for not holding it against me when I failed to keep in touch while trying to stay afloat in graduate school.

None of this would have been possible without the help of all four members of my committee as well as various other members of the staff and faculty at the UC Santa Cruz Economics Department. Of special note are my co-chairs, Professors Dooley and Draper who helped me each step along the way from idea inception to dissertation completion. Professors Hutchison and Kletzer were also extremely understanding and helpful when I came into their offices unannounced with ideas that struck me the night before.

The Graduate Coordinator, Sandra Reebie, also deserves special thanks for keeping me on track with the requisite administrative forms and procedures needed to keep advancing in the program.

Finally, I have to give thanks to my graduate student cohort, all of whom were extremely helpful in matters of economics and life. Jesse Mora and Arsenios Skaperdas were crucial to my finishing this degree.

Chapter 1

Uncovered Interest Parity Through Time

I Introduction

This paper will test the theory of uncovered interest parity (UIP) in a new way using Bayesian hierarchical linear models Lindley and Smith [1972] and the hierarchical dynamic linear model of Gamerman and Migon [1993] to better share information across currencies as well as test for meaningful time variation in the parameters governing the relationship between exchange rates and interest rates.

II Motivation

The failure of uncovered interest parity to hold is one of the longest lasting puzzles in international finance. Hundreds of papers (see Engel [2013] for a recent survey)

have been written estimating regressions of the form:

$$\Delta s_{t+1} = \alpha + \beta(i_t^* - i_t) + \epsilon_{t+1} \quad (1.1)$$

or

$$er_{t+1} = \alpha + \beta(i_t^* - i_t) + \epsilon_{t+1} \quad (1.2)$$

These so called Fama regressions, based on Fama [1984] estimate the response of the exchange rate change or excess return on the previous period interest differential. The literature has also used covered interest parity, an arbitrage condition, to replace the interest differential with the forward premium in the regression to test the equivalent hypothesis

$$er_{t+1} = \alpha + \beta(f_t - s_t) + \epsilon_{t+1} \quad (1.3)$$

where f_t is the log of the forward price at time t for delivery at time t+1. The hypothesis of uncovered interest parity is based on the premise of the existence of a sufficient number of risk neutral speculators who, through competition in financial markets, drive expected excess returns to zero. In the equation 1, this would appear as $\alpha = 0$ and $\beta = 1$, i.e. any interest differential should, on average, be erased by a subsequent exchange rate depreciation which would wipe out any potential excess return from investing in foreign currency. However, as detailed in the literature review below, most research has found that estimates of β in equation 1 is not only significantly less than 1, it is often significantly less than 0 implying that on average high interest rate currencies appreciate instead of depreciate as predicted by theory. This of course implies the existence of excess returns, and manifests itself in estimates of equations 2 and 3 via magnitudes of

β being larger than 0.

There is, however, reason to be skeptical that deviations from UIP continue to be economically significant. First, there is a high degree of sampling variance in the coefficient estimates of above regression due to the high variance of exchange rate movements. For example, below we will try and recreate the evidence presented in Frankel and Poonawala [2010] by running OLS on the GBPUSD currency pair from 1996 until 2004. We can see that our results are similar to theirs in both magnitude and precision. Note that the t-statistics are for a null hypothesis testing $\beta = 0$, which is an even tougher rejection than being statistically significantly different than 1. Both datasets easily reject the null that β is less than 1 (not shown) and my data rejects, at 95 % significance, that β is less than 0. This would suggest, at its surface, that the finding seems to be fairly robust to the specific days of the sampling, sources for data etc.

Table 1.1: OLS Estimates GBP

| | Estimate | Std. Error | t value ($\beta=0$) |
|------------------------------|----------|------------|-----------------------|
| $\beta_{Frankel\text{etal}}$ | -3.99 | 2.87 | -1.39 |
| β_{Smith} | -4.54 | 2.009 | -2.26 |

However, whether nor not we can induct the failure of UIP across time periods is a different question with less promising results (Figure 1). We can see that, in addition to large spikes around times of financial crises, the *rolling* estimates have trended upwards considerably since even before the global financial crisis (even becoming excessively large according to theory). In addition, it is likely that once uncertainty is correctly taken into account (the figure below plots only point estimates) our confidence in rejecting UIP will lessen. Still, why should we

care?

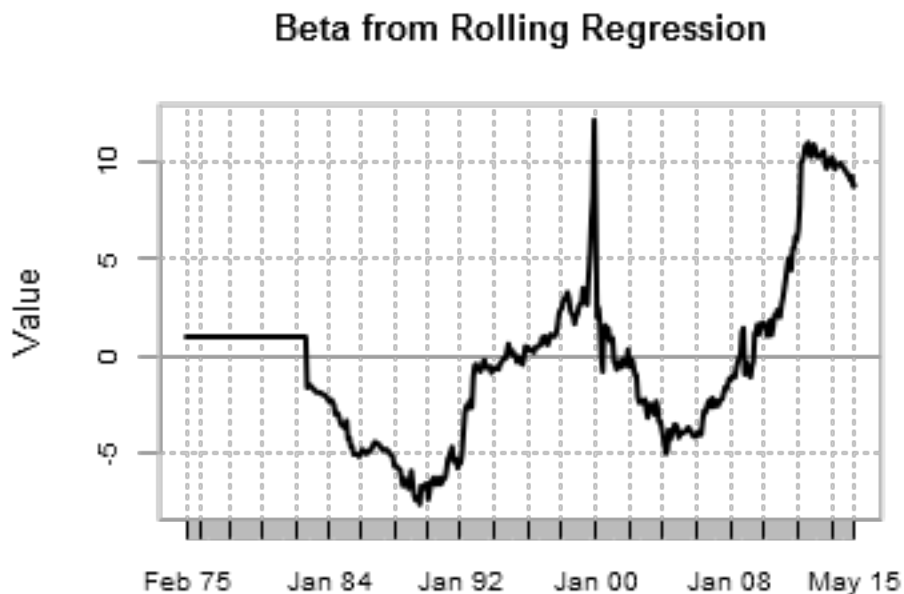


Figure 1.1: Rolling β estimates on an 87 month basis to match Frankel and Poonawala [2010]. UIP implies $\beta = 1$

There are several reasons to continuously test for deviations from uncovered interest parity, as well as bring to bear methods that will better make clear the relationship, if any, between interest rate differentials and exchange rate movements. Most importantly is the presence of UIP as an equilibrium condition present in international macroeconomic models(Obstfeld et al. [1996]). In those models that allow deviations from PPP it is most often the UIP relation that holds continuously and thus transfers shocks across countries via the exchange rate channel. As these models are used in modern central banks and inform policy makers about the proper response of monetary policy to external shocks, their correspondence with the real world is important. In addition, the failure of UIP also has impli-

cations for asset market efficiency as its failure represents the presence of excess returns. Whether or not these deviations continue to exist, as well as their cause has implications for the role of prices and price signals, and thus for the role of government intervention in markets.

As the topic has been widely studied for over 30 years, there are too many papers to cover in detail here. The interested reader is invited to read any number of surveys. For a comprehensive coverage of the literature from the 1970s until present one could read in order Hodrick [2014] (originally written in 1987), Engel [1996], and Engel [2013]

III Data

Data used in this paper consist only of exchange rates, short term interest rates, and forward rates. Spot and forward exchange rates come from Bloomberg and are sampled on the first trading day of each month. Interest rates are the interbank rate from each country and come from Global Financial Data. These are also sampled on the first day of each month. As these interest rates are quoted on an annual basis, they are converted to monthly rates. The primary dataset consists of Australia, Canada, Switzerland, United Kingdom, Japan, Norway, New Zealand, Sweden and a hybrid of the euro and German Deutsch mark for the time period before the introduction of the single currency, however basic OLS regressions are run on various emerging markets which can be found in the appendix.

While data is available for some currencies from 1974, the longest sample containing a meaningful amount of currencies for testing begins in 1989 and thus

we use that as our sample for the primary investigations found in the paper.

Returns used in the paper are log returns, and are calculated as

$$er_{t+1} = s_{t+1} - f_{t,t+1} \tag{1.4}$$

where a lowercase letter denotes that it is a logged variable. s_{t+1} is the spot rate at $t+1$ quoted in foreign currency per dollar and $f_{t,t+1}$ is the forward rate agreed upon at time t for delivery at $t+1$. These returns are quoted using midpoint quotes and thus abstract from transaction costs. While problematic in ways, given the use of FX swaps in modern currency trading, using bid ask spreads can result in overestimating transaction costs by up to 95% ?. In addition, the coverage of bid and ask quotes is much less complete in Bloomberg and would result in a significant decrease in the time span covered.

IV UIP Through Time

The following section will present evidence that the relationship between exchange rate movements and interest differentials is time varying. The first section will attempt to recreate the stylized facts of the UIP literature. We will then formulate a hierarchical model in order to optimally combine information from currency specific coefficients to arrive at an overall average relationship between interest differentials and subsequent exchange rate movements. Finally, we will use Bayesian Dynamic Linear Models in order to investigate the time variation of coefficients for both developed and developing economies.

IV.1 Bilateral Time Series Regressions

In this section, I follow the large literature testing uncovered interest parity by running the following model for each currency:

$$\Delta s_{t+1} = \alpha + \beta(i_t^* - i_t) + \epsilon_{t+1} \quad (1.5)$$

Where s is the log exchange rate. As mentioned, where data on forward exchange rates are available, the forward discount is used:

$$\Delta s_{t+1} = \alpha + \beta(f_t - s_t) + \epsilon_{t+1} \quad (1.6)$$

where f_t is the log of the forward exchange rate for delivery at time $t+1$, observed at time t .

In the parametric Bayesian paradigm, all uncertainty is represented by probability distributions. As such, we are required to specify a sampling distribution, or likelihood, for the exchange rate. We follow a large literature in proposing a normal distribution for the error term, and hence the change in the exchange rate.

IV.2 Hierarchical Model

In order to help with the intuition regarding the hierarchical dynamic linear model, we will first illustrate and fit a hierarchical linear model over the full sample and subsamples. The hierarchical linear model with the individual β as random effects allows us to treat the results of each currency as distinct but related "experiments" in which we tested UIP. This will have the effect of not only shrinking each estimate

of β towards a common mean, but will also allow us to estimate the common mean. This common mean, as shown below, is a compromise between pooling exchange rate data as in Flood and Rose [2001] vs the more common approach of estimating each bilateral regression one at a time, not using information from any other exchange rate. The model to be estimated in this section is:

$$\Delta s_{i,t+1} \sim N(\beta_i FP_t, \sigma_i^2) \quad (1.7)$$

$$\beta_i \sim N(\beta_{global}, \sigma_{global}^2) \quad (1.8)$$

with diffuse priors:

$$\beta_{global} \sim N(0, 1000) \quad (1.9)$$

and

$$\sigma_i^2 \sim IG(.0001, .0001) \quad (1.10)$$

for all i . FP is the forward premium at time t , and the use of the term global is just to distinguish the parameters of random effects distribution. As most studies have found the α in equations 1 and 2 to be economically and statistically insignificantly different from 0, we drop them from estimation here. The estimation is done through simulation methods using the JAGS software Plummer et al..

IV.2.a Results

We first examine developed countries for the whole sample. The estimates for each country and the so called “global β ”.

We see that over the full sample nearly all currencies are centered relatively

Table 1.2: Results from the Hierarchical Linear Model. Quantiles of the posterior distribution for β .

| | 2.5% | 25% | 50% | 75% | 97.5% |
|--------|-------|-------|-------|-------|-------|
| CHF | -1.15 | -0.27 | 0.19 | 0.66 | 1.55 |
| DEMEUR | -0.88 | -0.31 | -0.03 | 0.25 | 0.79 |
| GBP | -0.92 | -0.52 | -0.32 | -0.12 | 0.25 |
| AUD | -0.08 | 0.38 | 0.61 | 0.84 | 1.28 |
| JPY | -0.91 | -0.27 | 0.04 | 0.35 | 0.93 |
| NOK | -0.17 | 0.26 | 0.49 | 0.73 | 1.19 |
| SEK | -0.43 | 0.14 | 0.42 | 0.72 | 1.26 |
| CAD | -1.02 | -0.27 | 0.15 | 0.56 | 1.32 |
| NZD | -0.81 | -0.22 | 0.12 | 0.43 | 1.04 |
| Global | -0.39 | -0.01 | 0.18 | 0.38 | 0.77 |

close to 0. The global β which is a weighted average of each currency specific β as well as the prior is centered at just about 0, suggesting that interest rates are not systematically related to exchange rate movements. Still, this implies a rejection of uncovered interest parity, as the 95 % credible region of the posterior density of the global β does not contain 1, the value hypothesized by UIP. However, this paper was motivated by the large negative values found by papers written earlier. Do we see a significant downward movement in the β coefficients over time? Before moving onto the more flexible HDLM model in the next section, let us first implement a rolling HLM. Rolling regressions have been used in testing exchange rates before (see, for instance Verdelhan [2012] and Baillie and Cho [2014]) but have not attempted to share information across currencies. Thus, the rolling estimation framework will allow a comparison between simple OLS and the HLM framework. We use 5 year periods and plot the time series of the global β below.

IV.2.b Rolling HLM Model

As a bridge between the static hierarchical linear model of this section and the time varying parameter models coming later, we will estimate the HLM model on rolling subsets of data. Using rolling regression type estimation has been used before to measure the time variation in the UIP coefficient, but not with multilevel models to my knowledge. Again, we treat each country specific β as arising from a normal distribution centered at the “true” so called Global β . We start 60 months into our data, and then sequentially update the dataset by moving the 5 year window forward, adding more recent months (from today) and dropping the oldest month. Due to time constraints and the sheer number of models being estimated, we only run the model for 20,000 iterations. However the usual diagnostics and trace plots again suggest that the MCMC has reached its stationary distribution and as such our draws are from the posterior distributions of interest. We report below in graphical form the median of the posterior distribution of the global beta as well as the 95% credible intervals. Also plotted on the graph are lines denoting $\beta = 0$ and $\beta = 1$. The $\beta = 0$ line in green suggests that interest rates play no role in the spot return of the exchange rate, while the blue line at $\beta = 1$ is the hypothesized value for uncovered interest parity. We can see that for a significant portion of the 1980s, 1990s, and 2000s, the median of the posterior distribution of the so called global β was negative, and as such high interest rate currencies appreciated, in direct contradiction of the UIP theory. However, during the Global Financial Crisis and after, the coefficient has moved positive and even, at times, above 1.

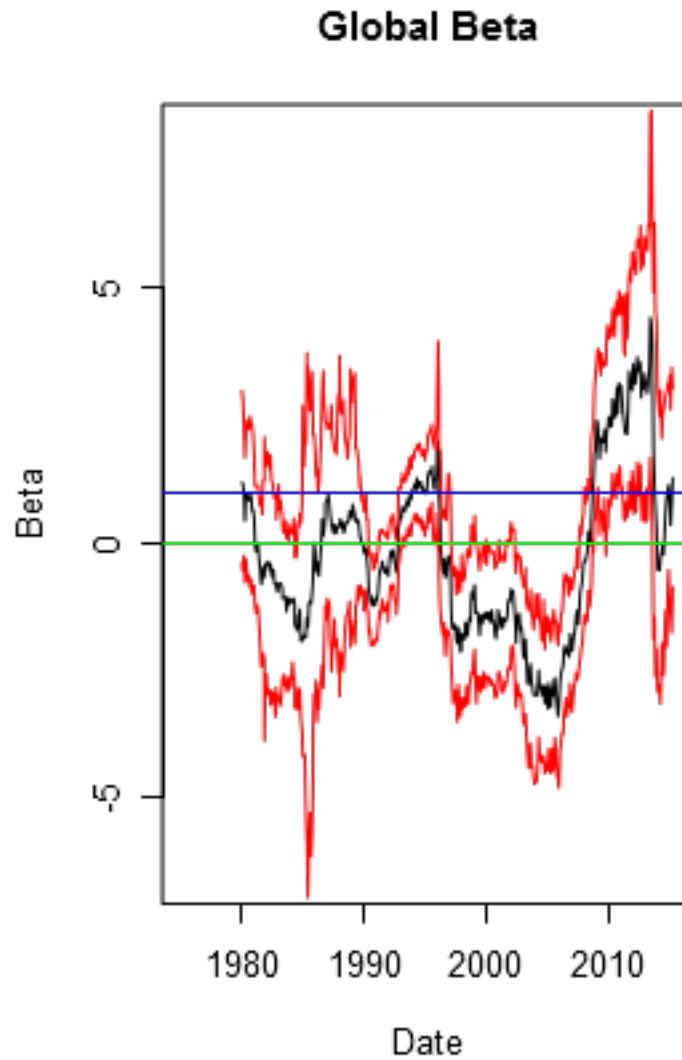


Figure 1.2: Rolling estimates of β_{global}

IV.3 Multivariate Formulation

The previous section treated each exchange rate as conditionally independent once β and the interest rate differential were known. While we shared strength across exchange rates in order to better estimate β , we failed to share strength across the

covariance terms. Recent work by Verdelhan [2012] and Greenaway et al. [2012] have shown that exchange rates are highly correlated with each other. As such, it is highly likely that large shocks to, for example, the USDGBP currency pair are contemporaneous with large shocks in the other USD currency pairs modeled in this paper. As such, to get a better estimate of β we should allow for correlations among error terms in a model similar to that of Seemingly Unrelated Regression (SUR) Zellner [1962]. This model is

$$\Delta S_{t+1} \sim N(\beta FP_t, \Sigma) \quad (1.11)$$

$$\beta_i \sim N(\beta_{global}, \sigma_{global}^2) \quad (1.12)$$

with diffuse priors:

$$\beta_{global} \sim N(0, 1000) \quad (1.13)$$

and

$$\sigma_{global}^2 \sim IG(.0001, .0001) \quad (1.14)$$

and a diffuse inverse Wishart prior on Σ . We have simply replaced the scalar exchange rate change with the time $t+1$ vector of exchange rate changes amongst all J currencies, and consider them a draw from a multivariate normal centered at the vector formulation of βFP_t where each are properly dimensioned vectors and each currency still contains its own specific β . Again, the β 's are considered random effects drawn from the normal distribution as in the last section.

Because our response variable is now a vector, it is assumed that we have a balanced panel. While we could impute missing data as necessary (in the Bayesian paradigm missing data are just another source of uncertainty which we can average

over) we instead choose to shorten the sample. Thus, this sample now runs from March of 1989 until May 2015, still a long enough sample from which to test uncovered interest parity. The estimation was again run in the JAGS software and 1 million samples were taken. Diagnostics (see appendix) and trace plots suggest that the MCMC chains mixed sufficiently and as such our posterior estimates are representative of our uncertainty regarding the parameters conditional on our model being specified correctly. The posterior quantiles estimated from this model are:

Table 1.3: β estimates from Multivariate HLM Model

| Quantiles | 2.5% | 25% | 50% | 75% | 97.5% |
|-----------|-------|------|------|------|-------|
| AUD | 0.03 | 0.30 | 0.43 | 0.55 | 0.89 |
| CAD | -0.11 | 0.24 | 0.38 | 0.50 | 0.81 |
| CHF | -0.12 | 0.24 | 0.38 | 0.50 | 0.76 |
| DEMEUR | -0.28 | 0.13 | 0.29 | 0.42 | 0.65 |
| GBP | 0.01 | 0.29 | 0.42 | 0.56 | 0.96 |
| JPY | -0.28 | 0.18 | 0.34 | 0.46 | 0.71 |
| NOK | 0.09 | 0.31 | 0.41 | 0.52 | 0.71 |
| NZD | -0.14 | 0.22 | 0.36 | 0.48 | 0.75 |
| SEK | 0.06 | 0.31 | 0.43 | 0.56 | 0.86 |
| Global | 0.04 | 0.27 | 0.38 | 0.48 | 0.68 |

We see that even over the full sample, the strong negative coefficients found in earlier work seems to have disappeared. While many of these coefficients have 95% credible intervals that do not contain the hypothesized value of 1, they do suggest that when currencies have higher interest rates, they do tend to depreciate. However, this depreciation is not enough to entirely offset the interest carry gained during the holding period.

IV.4 Hierarchical Dynamic Linear Model

While the rolling HLM models of the previous section shed some light on the presence of time variation in the UIP coefficient, they do so in an ad-hoc way. For instance, it was an entirely subjective choice to assume 5-year rolling periods, and this lack of coherence is unsatisfying. However, state space models provide a coherent method of modeling time varying coefficients and have been used extensively in economics (see Kim and Nelson for a textbook treatment with references). The most common Bayesian formulation of state space models are called dynamic linear models. These models are, obviously, linear, and model uncertainty via Gaussian distributions.

A generic formulation of a multivariate dynamic linear model looks like:

$$Y_t = FX_t + \epsilon_t \quad \epsilon_t \sim N(0, \Sigma) \quad (1.15)$$

$$X_t = GX_{t-1} + \nu_t \quad \nu_t \sim N(0, \Omega) \quad (1.16)$$

Where F and G are known matrices. Both ϵ_t and ν_t are multivariate normal, mean 0 shocks with generic covariance matrices Σ and Ω respectively. Thus, replacing F with our data on interest rates, and X_t with our Fama coefficients β , and G a vector of ones gives us a time varying coefficients model for our UIP regression with the assumption that the coefficients follow a random walk. Models of this type have been used for UIP in papers such as Baillie and Cho [2014] and Wolff [1987] however they show large posterior distributions in the time and currency specific β 's. As such, we will try again to borrow strength across currencies, treating heterogeneity across currencies as arising from a random effects design.

The hierarchical dynamic linear model of Gamerman and Migon [1993] is well suited to our purpose. This model is essentially a combination of the previous DLM with the HLM used earlier. The model is:

$$Y_t = FX_t + \epsilon_t \quad \epsilon_t \sim N(0, \Sigma) \quad (1.17)$$

$$X_t = G\beta_{Global,t} + \nu_t \quad \nu_t \sim N(0, \Omega) \quad (1.18)$$

$$\beta_{Global,t} = \beta_{Global,t-1} + \gamma_t \quad \gamma_t \sim N(0, \sigma_\gamma^2) \quad (1.19)$$

Again, all error terms are normally distributed and the time variation occurs only at the highest level. The structure implied by this model is that there is some unobserved global UIP coefficient that is time varying. Each period, currency specific β 's are treated as random draws centered at this true unobserved global UIP coefficient. Exchange rate returns, then, in each currency-time realization are a product of that currency specific forward discount along with the currency-time specific β . As has been shown in previous papers (Baillie and Cho [2014] for instance) allowing time variation in the regression coefficients leads to estimates with much uncertainty. The goal here is to share strength across currencies and treat $\beta_{Global,t}$ as our estimate of the "True" Fama coefficient in time period t .

This model was simulated in JAGS. The sampler ran for 2.5 million iterations. While trace plots suggested adequate mixing, the diagnostics were less than stellar. \hat{R} statistics were around 1.18 for many of the time specific β 's which is higher than preferred but still acceptable (see appendix). Below is the plot of the individual currency β s as well as $\beta_{Global,t}$ from 1989 until 2015 along with 95 % credible intervals.

Notice the large benefit we get from sharing information across currencies. Looking at each currency in isolation yields estimates that are too uncertain to be useful. The 95 % HPD intervals easily contain not only 0, but also the UIP hypothesized value of 1 as well as the earlier findings of coefficients near -1 and greater (in absolute value). However, examining the plot of β_{global} through time yields conclusions that are much more interesting.

We can see in the graph below that over time the median of the posterior distribution has slowly crawled up. While being below the green line at $\beta_{global} = 0$ for the early 1990s and some of the 2000s, implying the presence of excess returns, the coefficient has slowly crawled above 1 (the blue line) albeit with much more uncertainty given the large exchange rate movements during the global financial crisis. As seen in Chapter 2 of this dissertation, this slow rise in β_{global} coincides with lower risk adjusted returns to popular strategies which exploited the failure of UIP to hold, including the familiar carry trade.

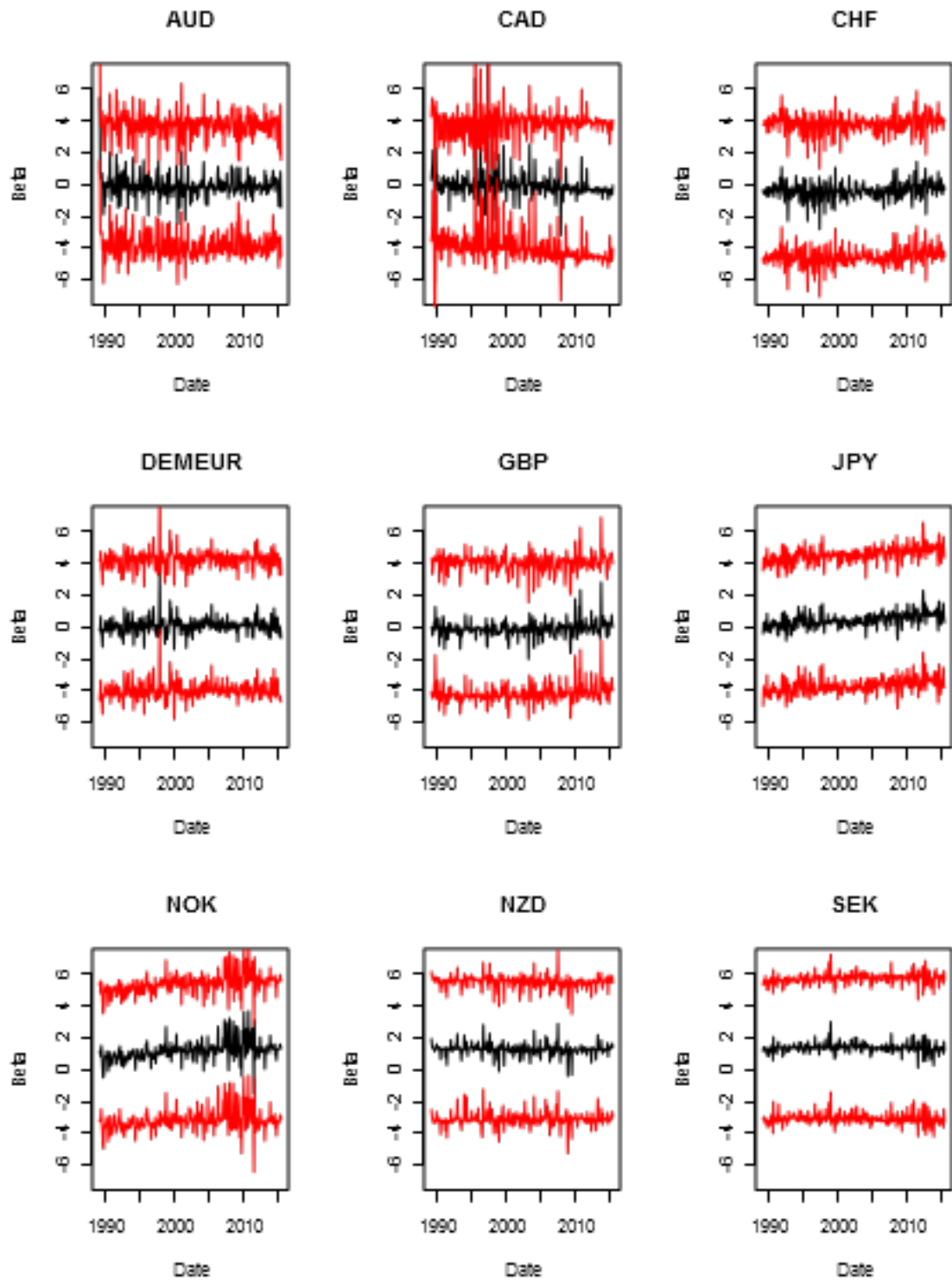


Figure 1.3: Currency specific time varying β s

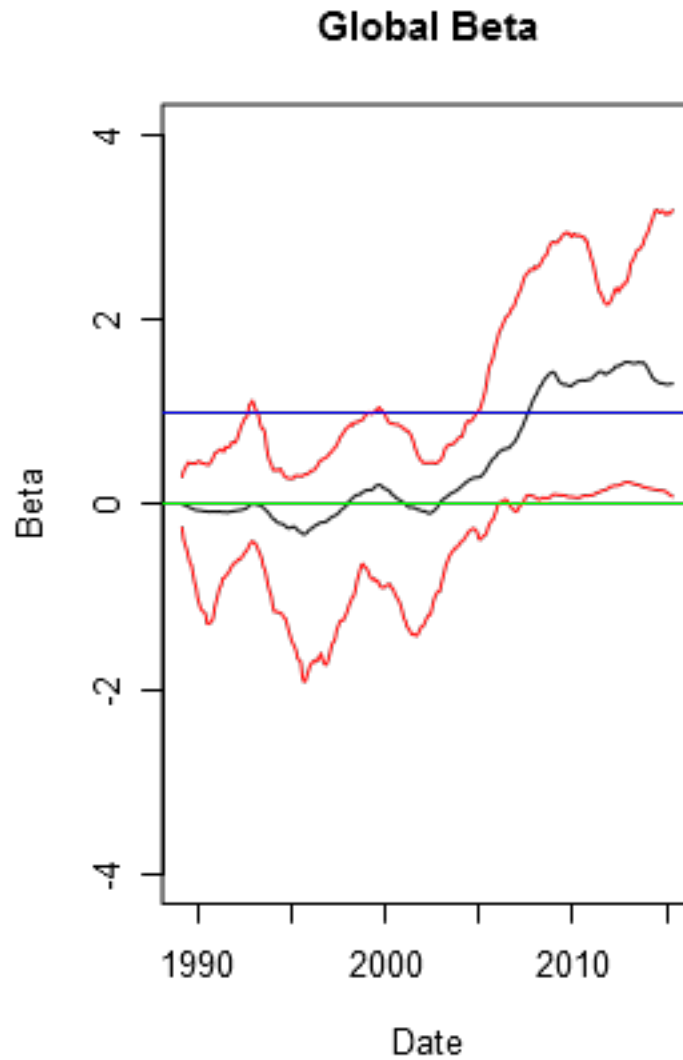


Figure 1.4: Time Varying β_{Global}

V Model Comparison

While our primary concern is with the time variation in the estimates of β_{Global} , it is also important to test model fit. Our measure of model fit is the Deviance Information Criterion Plummer [2008]. The model is in some sense a Bayesian

version of the well known Akaike Information Criterion (AIC) Akaike [1974]. It attempts to proxy for out of sample prediction, given the computational burden and data constraints of true cross validation. The version used here attempts to better penalize complex models, but it should be stated clearly that these types of criteria are not well suited to complex mixture models as it becomes difficult to estimate the number of effective parameters. In addition, there is little theoretical guidance as to "how big is big" when looking at differences in the DIC of non-nested models (differences of 10 are considered important in nested models). Thus, while the results below show that our HDLM model does fit the data considerably better than the various other models tested, we remain cautious in making bold claims about model choice and instead remain focused on the potential for significant time variation in the β coefficients governing the UIP regression.

Table 1.4: DIC Model Comparison

| Model | Mean Deviance | Penalty | Penalized Deviance |
|--------------------------|---------------|---------|--------------------|
| Linear Model | -15879 | 24.35 | -15854 |
| Constrained Linear Model | 15868 | 17.24 | -15851 |
| IID HLM | -15883 | 8.726 | -15874 |
| Multivariate HLM | -19002 | 43.71 | -18958 |
| Multivariate HDLM | -19307 | 264.4 | -19043 |

The models tested above include a simple Linear Regression model of the type shown in equation 1. The Constrained Linear Model puts a uniform prior on β such that it cannot be greater than 0. This is meant to substitute for those estimates found in the earlier literature with negative coefficients. Next is the HLM model discussed earlier in which each exchange rate change was assumed

uncorrelated through time. The multivariate HLM model allows for estimation of a full covariance matrix, allowing information to be shared across exchange rates. Finally, the Multivariate HDLM model, the main focus of this paper, allows for time variation in the β coefficients in addition to estimating a full covariance matrix. The models are ordered by increasing model fit, as can be seen by the decreasing DIC numbers. Even with the large penalty levied on the HDLM model due to the large number of parameters, it still outperforms the multivariate HLM model quite handily, and we can see the large increase in model fit gained by modeling the full covariance matrix.

VI Conclusion

Saving the reader from the famous quote about knowing what isn't so, we have found that the common wisdom regarding the tendency of high interest rate currencies to appreciate on average may require more investigation. Through the use of Bayesian hierarchical linear models and hierarchical dynamic linear models, which allow us to borrow strength across currencies we have shown that failures of UIP are less obvious than was once the case.

Many papers written in earlier decades, and the theoretical literature built upon their empirical findings, concluded that UIP failed to hold and excess returns (in the case of risk neutral investors) were a persistent feature of currency markets. However, bringing more flexible models to newer data sets has allowed us to conclude that UIP holds better now than at any time in the past 25 years.

VII Appendix 1

Table 1.5: OLS Estimates Various Currencies

| Currency | Start Date | End Date | β | 2.5% | 97.5% | R.Squared |
|----------|------------|------------|---------|-------|-------|-----------|
| AUD | 1984-02-01 | 2015-05-01 | 1.30 | 0.17 | 2.43 | 0.01 |
| BRL | 1999-02-03 | 2015-05-04 | 0.23 | -0.92 | 1.38 | 0.00 |
| CAD | 1989-01-03 | 2015-05-01 | -0.04 | -1.83 | 1.76 | 0.00 |
| CHF | 1975-01-02 | 2015-05-01 | -1.23 | -2.38 | -0.08 | 0.01 |
| CLP | 1998-05-04 | 2015-05-04 | 1.01 | -0.60 | 2.61 | 0.01 |
| COP | 1999-02-03 | 2015-05-01 | 1.44 | -0.13 | 3.00 | 0.02 |
| CZK | 1993-07-01 | 2015-05-01 | -0.29 | -2.53 | 1.96 | 0.00 |
| DEM | 1975-01-02 | 1998-12-01 | -0.34 | -1.63 | 0.94 | 0.00 |
| DKK | 1980-01-02 | 2015-05-01 | -0.61 | -1.82 | 0.59 | 0.00 |
| EUR | 1982-11-03 | 2015-05-01 | -0.73 | -2.52 | 1.07 | 0.00 |
| GBP | 1975-01-02 | 2015-05-01 | -1.39 | -2.63 | -0.15 | 0.01 |
| HUF | 1995-09-04 | 2015-05-01 | 0.18 | -1.12 | 1.47 | 0.00 |
| IDR | 1997-04-01 | 2015-05-01 | -0.11 | -1.01 | 0.78 | 0.00 |
| ILS | 1998-08-03 | 2015-05-01 | 0.82 | -1.37 | 3.02 | 0.00 |
| INR | 1998-12-01 | 2015-03-02 | -0.28 | -1.14 | 0.59 | 0.00 |
| JPY | 1986-01-02 | 2015-05-01 | -1.09 | -2.92 | 0.73 | 0.00 |
| KRW | 1999-02-01 | 2015-05-04 | -0.62 | -3.41 | 2.16 | 0.00 |
| MXN | 1997-11-03 | 2015-05-01 | -0.12 | -0.94 | 0.69 | 0.00 |
| MYR | 1993-09-01 | 2015-05-01 | 1.51 | -0.22 | 3.23 | 0.01 |
| NOK | 1986-01-02 | 2015-05-01 | 0.80 | -0.07 | 1.67 | 0.01 |
| NZD | 1989-02-02 | 2015-05-01 | 0.77 | -1.81 | 3.35 | 0.00 |
| PEN | 2000-08-01 | 2015-05-01 | -0.78 | -3.57 | 2.01 | 0.00 |
| PLN | 1993-07-01 | 2015-05-01 | 0.74 | 0.01 | 1.47 | 0.02 |
| RUB | 1998-02-02 | 2015-05-01 | 1.78 | 1.04 | 2.53 | 0.10 |
| SEK | 1987-01-02 | 2015-05-01 | 0.64 | -0.59 | 1.88 | 0.00 |
| SGD | 1986-04-01 | 2015-05-01 | 0.53 | -0.61 | 1.67 | 0.00 |
| THB | 1994-01-04 | 2015-05-01 | 1.33 | 0.55 | 2.10 | 0.04 |
| TRY | 1997-02-03 | 2015-05-01 | 0.95 | 0.22 | 1.68 | 0.03 |
| TWD | 1999-02-01 | 2015-05-04 | 0.13 | -0.57 | 0.82 | 0.00 |
| ZAR | 1989-01-03 | 2015-05-01 | -1.28 | -3.17 | 0.61 | 0.01 |

VIII Appendix 2

In this section we quickly go over convergence diagnostics when using MCMC, and report the diagnostics for our models presented throughout the paper.

VIII.1 \hat{R} Statistic

In Gelman and Rubin [1992] the authors illustrated a way in which to use multiple MCMC chains in order to assess convergence. Were we to run a chain long enough, the variance of the iterations from that chain will converge to variance of the target distribution. However, in finite iterations, the variance of a single chain will underestimate the variance of the target as it has not had sufficient time to explore the entire target distribution. We can, however, use the variance between chains to also estimate the variance of the target distribution. This variance will overestimate the true variance, as MCMC initializations are often over dispersed relative to the target distribution. The \hat{R} is a diagnostic statistic to measure how close the total variance, using both within and between variation, is to the variance of the within variance. A value close to 1 indicates that the chains are mixing well and that the MCMC has converged to the target distribution. In the RJags program, we can use the `gelman.diag()` command to compute the statistic. While hard and fast rules are difficult to find, at least anecdotally values of 1.2 and less are considered acceptable Jackman [2012]. Following the notation of Gelman et al. [2014], the so-called \hat{R} statistic is:

$$\hat{R} = \sqrt{\frac{\hat{var}(\phi|y)}{W}} \quad (1.20)$$

where

$$v\hat{a}r(\phi|y) = \frac{n-1}{n}W + \frac{1}{n}B \tag{1.21}$$

and W is the within chain variance and B the between chain variance. Below presents representative values of the Gelman Rubin statistic for the models tested in this paper, with the exception of the Rolling HLM model of section 5.2.2. Because we have an \hat{R} for each parameter, complete reporting is not feasible but is available on request. Note, as mentioned in the paper, that the HDLM as the least satisfactory mixing even after several million iterations. While currently acceptable, future research should program a more specialized sampler instead of relying on general purpose samplers such as JAGS that are not especially designed for the high levels of autocorrelation in draws from dynamic linear models.

Table 1.6: MCMC Diagnostics

| Model | Coefficient | \hat{R} |
|-------------------|----------------------|-----------|
| LM | AUD β | 1 |
| Constrained LM | AUD β | 1 |
| HLM iid | Global β | 1.01 |
| Multivariate HLM | Global β | 1.05 |
| Multivariate HDLM | Global $\beta_{t=3}$ | 1.18 |

Chapter 2

Portfolio Returns Through Time

I Introduction

The literature examining the determination of exchange rates and the failure of uncovered interest parity (UIP) has proceeded in (at least) two distinct strands. The international macroeconomics method of testing uncovered interest parity was detailed (and expanded) in the last chapter. These tests consisted of running bilateral time series regressions of the form

$$\Delta s_{t+1} = \alpha + \beta(i_t^* - i_t) + \epsilon_{t+1} \quad (2.1)$$

see, for example Fama [1984]. However, a parallel literature has approached and tested exchange rate determination from a different angle. This difference manifests itself in the use of portfolios, Fama-MacBeth regressions and pricing errors instead of the more traditional significance tests and goodness of fit statistics of the OLS regression shown in equation 1.

Much of this literature has focused on the *why* excess returns exist in currency markets. However, as shown in the last chapter it is highly plausible that this was a market inefficiency that has been ironed out. As such, it makes sense to test whether or not there still exist excess returns on strategies that exploit the failure of uncovered interest parity.

These portfolios/strategies have been used in other works, but have thus far not been used to test significant time variation in carry trade returns. This paper will use two different methods in order to test for time variation in returns to these strategies: Bayesian dynamic linear models and random portfolios.

II Data

Data used in this paper consist only of exchange rates, short term interest rates, and forward rates. Spot and forward exchange rates come from Bloomberg and are sampled on the first trading day of each month. Interest rates are the interbank rate from each country and come from Global Financial Data. These are also sampled on the first day of each month. As these interest rates are quoted on an annual basis, they are converted to monthly rates. The developing country dataset consists of Australia, Canada, Switzerland, United Kingdom, Japan, Norway, New Zealand, Sweden and a hybrid of the euro and German Deutsch mark for the time period before the introduction of the single currency. In addition to the countries listed above, the emerging market dataset also contains: Brazil, Chile, Colombia, Czech Republic, Denmark, Hungary, Indonesia, India, Korea, Mexico, Malaysia, Poland, Singapore, Thailand, and South Africa.

While data is available for some currencies from 1974, the longest sample containing a meaningful amount of currencies for testing begins in 1989 for developed countries and 2000 for the full sample including emerging markets.

Returns used in the paper are log returns, and are calculated as

$$er_{t+1} = s_{t+1} - f_{t,t+1} \quad (2.2)$$

where a lowercase letter denotes that it is a logged variable. s_{t+1} is the spot rate at $t+1$ quoted in foreign currency per dollar and $f_{t,t+1}$ is the forward rate agreed upon at time t for delivery at $t+1$. These returns are quoted using midpoint quotes and thus abstract from transaction costs. While problematic in ways, given the use of FX swaps in modern currency trading, using bid ask spreads can result in overestimating transaction costs by up to 95% ?. In addition, the coverage of bid and ask quotes is much less complete in Bloomberg and would result in a significant decrease in the time span covered.

III Portfolios

The three portfolios that will be used are the carry portfolio, the dollar portfolio, and the forward premium portfolio.

III.1 Carry

The carry portfolio is the most widely studied of the three (see, for example Lustig and Verdelhan [2007] and Burnside et al. [2011]). This portfolio is dollar neutral

and does not use information contained in short term US interest rates in order to construct portfolios. Instead, in each period currencies are sorted by their interest differential vis-a-vis the United States (which is equivalent to sorting them by their forward discount vis-a-vis the dollar because of covered interest parity.) One then constructs the carry portfolio by going long the some number of currencies with the highest interest rate and financing that purchase by shorting some number of currencies with the lowest interest rate. The exact implementation of this strategy varies Ilmanen [2011] however we will use the implementation most often used in academic work, and split currencies into 5 portfolios and equally weight currencies in each portfolio.

III.2 Dollar Portfolio

The Dollar Portfolio was first studied by Lustig et al. [2014]. This portfolio is formed by looking at the average forward discount/interest differential among a basket of currencies. When the average interest differential is negative and thus the dollar trades at a forward discount on average to the basket of currencies, we go long the dollar and short the basket. When the average interest differential is positive, and the dollar trades at an average forward premium, we go long the basket of currencies and short the dollar. Thus, unlike the other two strategies we examine this strategy is not dollar neutral.

III.3 The Forward Premium Puzzle Portfolio

This portfolio was first mentioned in Hassan and Mano [2014]. They noticed the disconnect between the use of carry trade strategies as described above, and the

bilateral time series regressions run in equation 1. They noted that a negative coefficient in equation 1 implies that when the interest differential between a currency and the dollar (or whatever base currency is used) is *greater than its average in sample differential* the foreign currency appreciates. This is obviously different than the carry trade as practiced, which goes long high interest rate currencies and short low interest rate currencies regardless of how the current currency specific interest differential relates to the historical interest rate differential for that currency vis-a-vis the dollar.

This portfolio is formed in a manner more closely related to the well known regressions resembling equation 1. To implement the portfolio, we will standardize the interest rate of each currency over the full sample for that currency. Then at each point in time we will go long the currencies with the highest z-score and short the currencies with the lowest z-score. Note that this portfolio cannot be implemented in real time as it standardizes interest rates over the full sample. We use the returns from this portfolio to better understand the UIP relationship as opposed to seriously considering it as a real world trading strategy.

IV Developed Markets Data

IV.1 Summary Statistics

To begin, we document some basic summary statistics regarding the strategies over our sample period. We run each strategy with both a full basket of developed and developing country currencies to choose from, as well as a developed only basket. While the theory of uncovered interest parity applies to currencies that are similar

in risk profile (i.e. using only developed country currencies), we will follow the standard practice in the literature to include emerging market currencies as well. The emerging market analysis follows after the complete analysis of the data with only developed country currencies.

Below in Figure (2.1) is a graph of the three strategies through time followed by return and distributional statistics. We can see from figure BLANK that all three strategies tracked each other closely until about 2002. At that point it looks as though the Dollar Strategy and Carry Strategy remained quite profitable for several years, while the FPP (not implementable) started to have nearly flat performance. All three strategies were deeply affected by the global financial crisis in 2008, however the Dollar and Carry strategies showed a much steeper return to profitability. Finally, in recent periods it seems as though the dollar strategy has performed quite poorly while Carry and the FPP strategies have been slightly more successful. This is no doubt a result of the early 2015 US dollar appreciation. Given that FPP and Carry are dollar neutral they have been able to somewhat sidestep the large depreciation, while given extremely low rates in the US, any sort of interest rate carry in other countries has led to the Dollar Strategy being short USD and long the average basket; not a profitable strategy in 2015.

Table 2.1 shows some full sample summary statistics. We can see that Carry has performed the best, with an annualized return over the period of 5% and a Sharpe ratio of .54. The dollar strategy has a slightly lower return, but also a lower volatility leading to a similar Sharpe ratio. Finally, as is graphically clear from the figure, the FPP strategy has performed least well over the period and has had similar standard deviation leading to a significantly smaller Sharpe ratio. Most notable from the other distributional statistics is the negative skewness of

all three strategies with Carry leading the way. This is a widely known result that has shown up in the data in many papers (see, for example Brunnermeier et al. [2008]). Of note, however, is the more desirable skewness properties of the Dollar strategy, something noticed in Lustig et al. [2014].

Table 2.1: Summary Statistics Developed Markets Data

| | Carry | FPP | Dollar |
|---------------------------|-------|-------|--------|
| Annualized Return | 0.05 | 0.03 | 0.04 |
| Annualized Std Dev | 0.09 | 0.08 | 0.08 |
| Annualized Sharpe (Rf=0%) | 0.54 | 0.34 | 0.53 |
| Monthly Std Dev | 0.02 | 0.02 | 0.02 |
| Skewness | -0.52 | -0.17 | -0.07 |
| Kurtosis | 4.57 | 3.25 | 4.17 |
| Excess kurtosis | 1.57 | 0.25 | 1.17 |
| Sample skewness | -0.52 | -0.17 | -0.07 |
| Sample excess kurtosis | 1.62 | 0.28 | 1.21 |

IV.2 Dynamic Linear Model

Our first test of time varying returns in the three strategies will take a parametric approach. Bayesian Dynamic Linear Models (DLM), and state space models more generally, offer an incredibly flexible framework with which to model the returns to each of our strategies. By allowing the mean of the conditional return distributions to be time varying, we can let the data inform us of whether or not time variation in returns is something to consider. The model is:

$$R_t = \mu_t + \epsilon_t \quad \epsilon_t \sim N(0, \sigma_\epsilon^2) \quad (2.3)$$

$$\mu_t = \mu_{t-1} + \gamma_t \quad \gamma_t \sim N(0, \sigma_\gamma^2) \quad (2.4)$$

Cumulative Returns for all Strategies

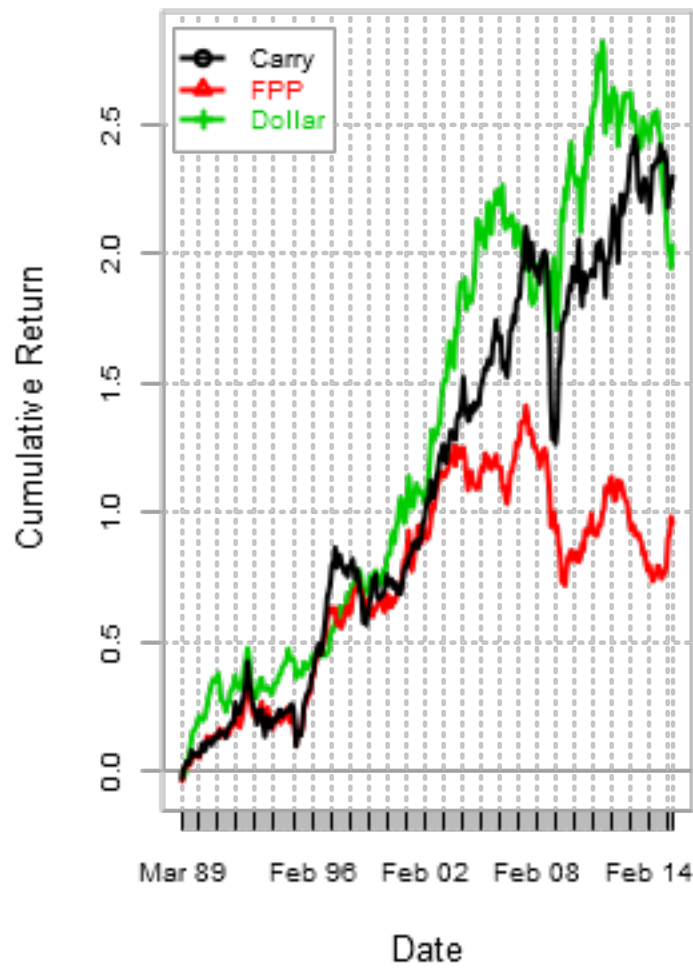


Figure 2.1: Cumulative Returns for Each Strategy

Thus we assume that the return data we observe is a draw from the time specific normal distribution centered at μ_t . However, we assume that μ_t varies through time in a random walk fashion. We can see that this model collapses to the time invariant mean models estimated in the summary statistics section when γ_t is equal to 0. Note that at least part of the identification of this model in its current set up is the assumption of homoscedasticity. This may or may not be a good assumption that will have implications for our estimates for the time varying μ .

The model (see Harrison and West [1999] for a textbook treatment) is a linear state space model with Gaussian errors. As such, the Kalman filter and smoother (kal) could be used for online prediction and ex post estimation respectively. However, in order to be consistent with the more computationally intensive models explored elsewhere in this dissertation we continue to estimate model parameters via MCMC simulation using the software JAGS Plummer et al..

IV.2.a Model Specification

The models specified for each strategy, inclusive of priors, are the same. Rewriting equations 2 and 3 in an equivalent form, the models estimated were:

$$R_t \sim N(\mu_t, \sigma_\epsilon^2) \tag{2.5}$$

$$\mu_t \sim N(\mu_{t-1}, \sigma_\gamma^2) \tag{2.6}$$

with priors

$$\mu_1 \sim N(0, 1000) \tag{2.7}$$

$$\sigma_i^2 \sim InvGamma(.0001, .0001) \tag{2.8}$$

for $i = (\epsilon, \gamma)$

Given the dynamic nature of the model, the prior on μ_1 has little influence on inferences drawn from the majority of the sample. The Inverse Gamma priors put on the variances at both levels of the state space model are meant to be uninformative, allowing the data provide the information used for inference. While other studies have been done on exchange rates and we have some information on the magnitudes of mean returns and variances, the fact that many of these studies used the same data as found in our own sample would lead us to essentially be using the data twice were we to use informative priors.

IV.2.b Results

As the estimation for each strategy results in posterior distribution for μ_t at each point in time (and for each strategy), we find presenting the results graphically to be more reasonable. Of course, the numerical results in table format are available by request.

Figure 2.2 shows the median, and 95% credible intervals of the posterior distribution of μ_t , the mean of the return distribution for the carry strategy. While we do see some time variation in the estimated mean returns, and notably a sustained period of above 0 returns during the 2000s, the amount of uncertainty present in the estimate precludes any serious takeaways. The 95% credible intervals include not only 0, but also economically significant values of both positive and negative monthly returns.

This is continued in the DLM estimates of the Dollar Strategy and the FPP Strategy (Figures 2.3 and 2.4) Again, while we could treat the median value as a

point estimate and draw conclusions from there, taking the substantial uncertainty into account leaves us unable to make concrete conclusions on even the sign of the true unobserved mean of the return distribution. As such, we will be forced to use other methods in order to better answer whether or not these strategies have become less profitable over time, or in other words, if UIP fails less spectacularly in recent years.

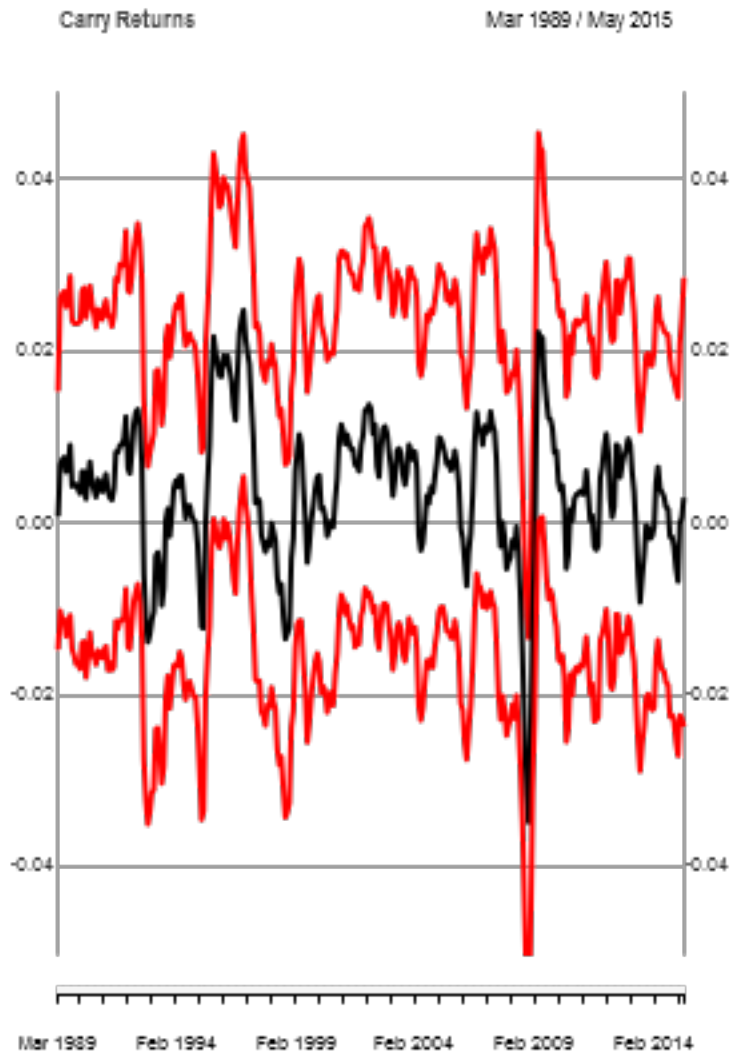


Figure 2.2: Posterior Median and 95 % credible intervals for carry μ_t

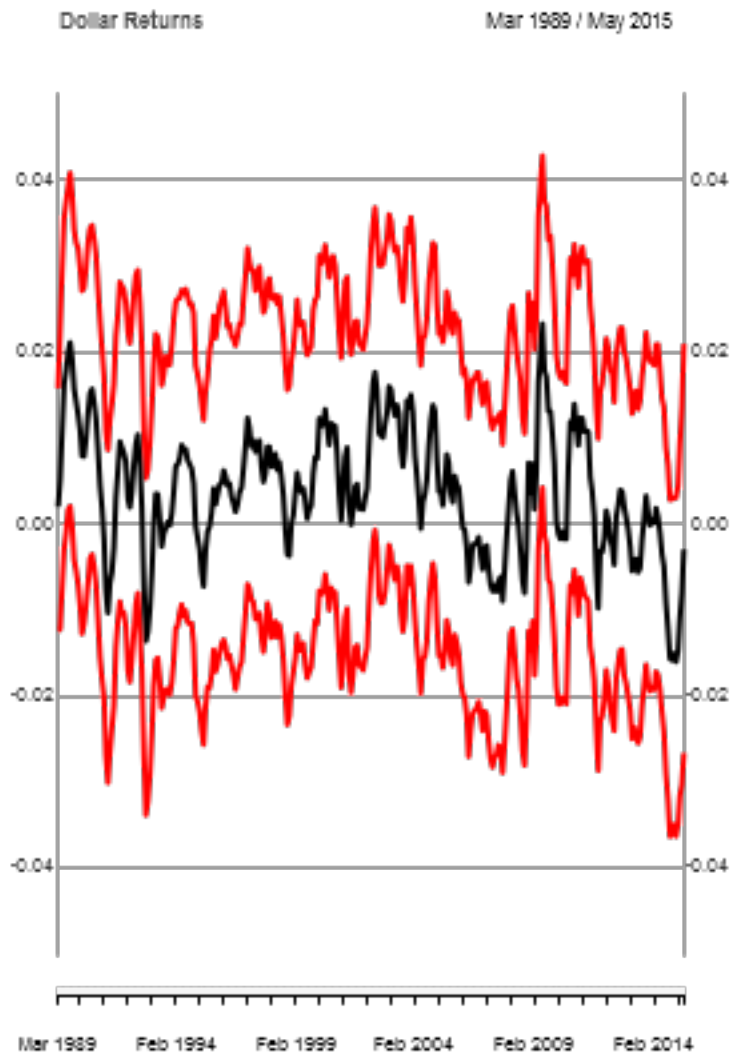


Figure 2.3: Posterior Median and 95 % credible intervals for dollar μ_t

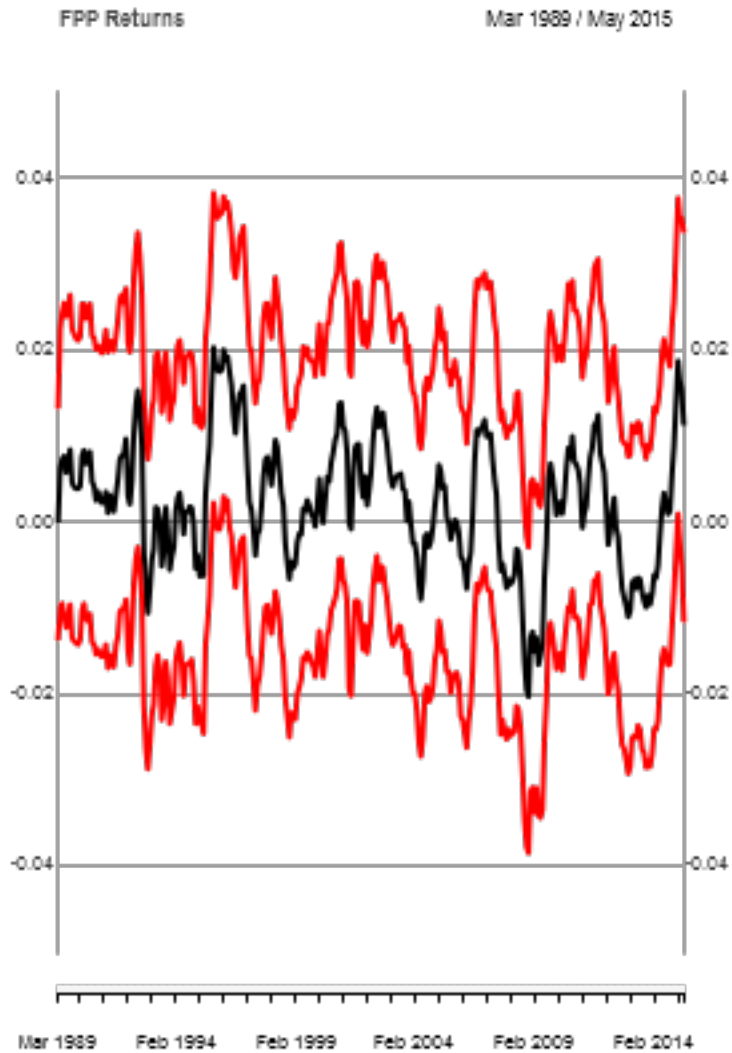


Figure 2.4: Posterior Median and 95 % credible intervals for FPP μ_t

IV.3 Random Portfolios

As the parametric methods used in the previous section were, at the very least, unconvincing, we will attempt to estimate the time varying excess returns to strategies that exploit the failure of UIP using a non parametric method. Random

portfolios are exactly what they sound like: one uses a computer to simulate a distribution of possible returns due to randomly trading currencies. We can then see how likely it is that our portfolios outperform them.

While the use of random portfolios has a long history, see Cohen and Pogue [1968], they have been used sparingly in modern research. However, given the problems inherent in the extremely important issue of measuring active manager skill, there has been a slight resurgence (Kothari and Warner [2001], Burns [2007]). We are essentially going to treat these strategies as active managers, and see how they perform compared to skill-less strategies that are constructed randomly. While many applications of random portfolios allow the weights to be continuous numbers between -1 and 1 subject to some constraints, we will restrict our weights to be the same as with our formed strategies, which again were taken from elsewhere in the literature. Thus, we will randomize over the currencies chosen in the long and short portfolios, but will require the weights to be $\frac{1}{3}$ in each currency in the long portfolio and $-\frac{1}{3}$ for each currency in the short portfolio.

IV.3.a Buy and Hold

For the Buy and Hold strategy, we compare randomizing over portfolios at time $t=0$, then computing the returns from each of those portfolios for the entire sample time period. We then compute the cumulative return and compare to the cumulative return of our strategies. The histogram plotted below (Figure 2.5) best shows how substantial the out performance was of the UIP-exploiting strategies compared to our randomized portfolios. While impressive, our motivation for undertaking this study is to investigate for the possibility of a decrease in excess

Full Sample Buy and Hold Random Portfolios

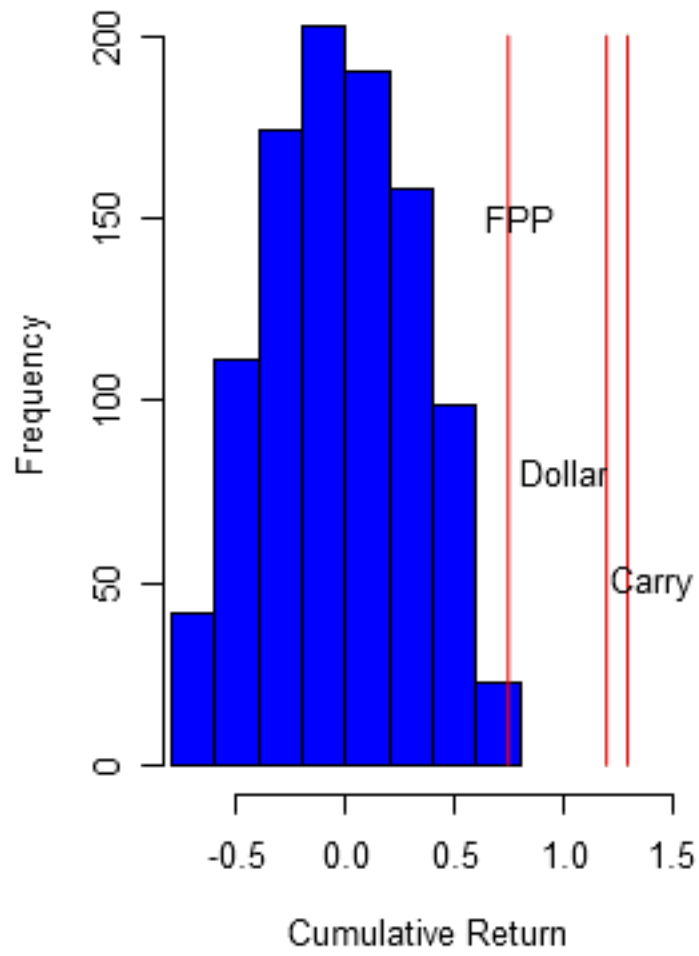


Figure 2.5: Cumulative Returns Full Sample

returns to these strategies, or equivalently, UIP holding more successfully in recent years. As such, we need to measure returns at a more granular time level so that we can hope to uncover time variation if present.

IV.3.b Rolling One Year Holding Period

In this section we investigate the performance of our currency strategies in rolling one year periods against randomly selected portfolios. We also increase the universe of trading strategies in this section because we randomize the portfolio chosen at each time period, not just at $t=0$.

In order to present the relative performance of our strategies against the randomized alternative, we form z-scores at each point in time. Thus, for example, a z-score of 2 means that the strategy performed 2 standard deviations better than the mean return of the randomized portfolios. While it is feasible to perform a time series analysis on the z-scores, due to the overlapping nature of our data and thus the relatively small size of truly independent observations from which to infer any sort of trend, we choose instead to plot the z-scores and let the data speak for itself.

Figures 2.6, 2.7 and 2.8 show the rolling z-scores of the returns through time. While all three are noisy series, we can see that the Dollar strategy and the FPP strategy have seen significantly more of their rolling returns below the mean of the randomized portfolio distribution. Carry has, on the other hand, remained positive most of the time with the exception of a few large drops during periods of financial turbulence.



Figure 2.6: Z-Score of Rolling 1 year returns of carry strategy



Figure 2.7: Z-Score of Rolling 1 year returns of dollar strategy



Figure 2.8: Z-Score of Rolling 1 year returns of FPP strategy

As much of the research on these strategies as stressed, also important is risk adjusted returns. We repeat the analysis above using the Sharpe Ratio Sharpe [1994] below. Here a pattern becomes somewhat clear among all three strategies: Sharpe Ratios z-scores are declining. For Carry and Dollar there looks to be a change point or structural break after the financial crisis, while for FPP we see a steadily declining Sharpe Ratio relative to the randomized portfolios.

V Emerging Market Currencies

Most of the academic literature, as well as practitioners, does not restrict the formation of these portfolios to developed economies. We now expand our sample



Figure 2.9: Z-Score of Rolling 1 year Sharpe Ratios of carry strategy



Figure 2.10: Z-Score of Rolling 1 year Sharpe Ratio of dollar strategy



Figure 2.11: Z-Score of Rolling 1 year Sharpe Ratio of FPP strategy

to include some of the more widely traded emerging market currencies.

V.1 Summary Statistics

Table 2.2: Summary Statistics Emerging Markets Data

| | Carry.EM | FPP.EM | Dollar.EM |
|---------------------------|----------|--------|-----------|
| Annualized Return | 0.09 | 0.09 | 0.03 |
| Annualized Std Dev | 0.11 | 0.08 | 0.08 |
| Annualized Sharpe (Rf=0%) | 0.87 | 1.08 | 0.30 |
| Monthly Std Dev | 0.03 | 0.02 | 0.02 |
| Skewness | -0.55 | 0.22 | -0.73 |
| Kurtosis | 5.30 | 5.22 | 5.81 |
| Excess kurtosis | 2.30 | 2.22 | 2.81 |
| Sample skewness | -0.56 | 0.22 | -0.75 |
| Sample excess kurtosis | 2.40 | 2.32 | 2.93 |

Table 2.2 presents the summary statistics for the full data set. We can see that including emerging market currencies has a substantial effect on both returns and risk adjusted returns (as seen in the Sharpe Ratio). Surprisingly, the Dollar strategy has become much less effective, potentially because we are now averaging over so many more currencies, that it brings the returns closer to a random walk. It is important to note, however, that the sample period is different due to large amounts of missing data pre 2000 in many of the emerging market currencies.

V.2 Dynamic Linear Model

Fitting the Dynamic Linear Model to the expanded dataset gives results that are slightly more informative than with our original developed currency dataset.

V.3 Results

Again we present the results by plotting our posterior estimate, with 95% credible intervals, of μ_t in Figures 2.12 2.13 and 2.14. While the Dollar trade hovers around 0 for the entire sample, there seems to be a clear downward trend in the estimated time varying mean of the return distribution for both carry and for FPP. While again the uncertainty is such that it is hard to make a clear judgment, we do get a clearer picture for the potential that returns to the carry trade are declining through time.

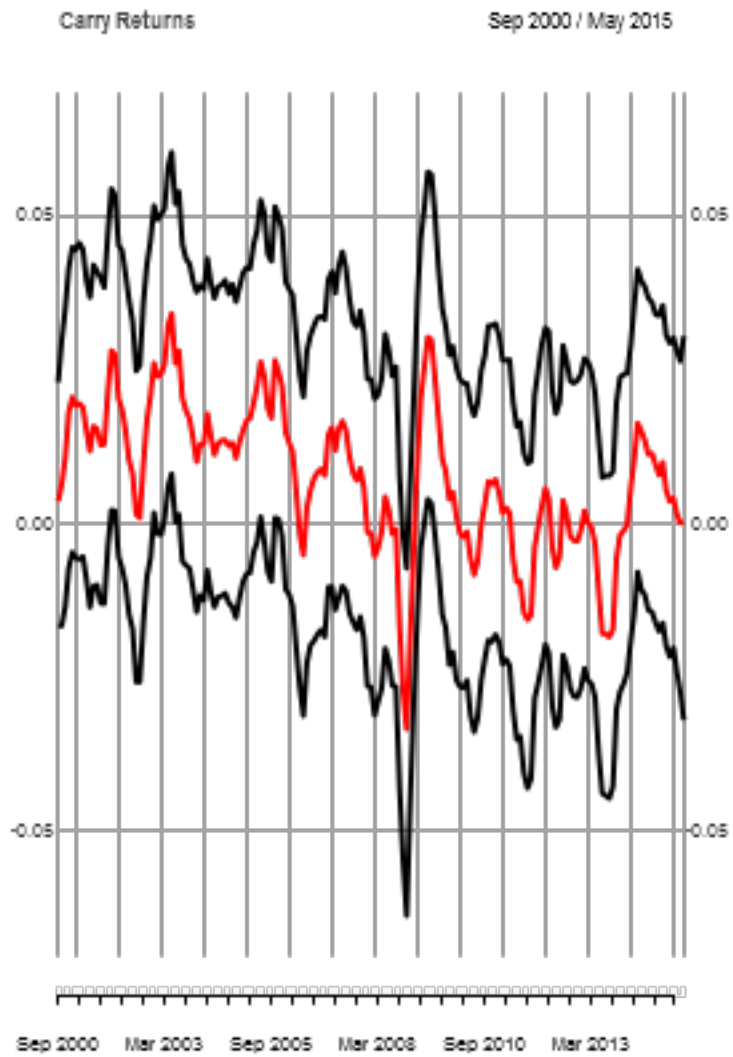


Figure 2.12: Posterior Median and 95 % credible intervals for carry μ_t on EM dataset

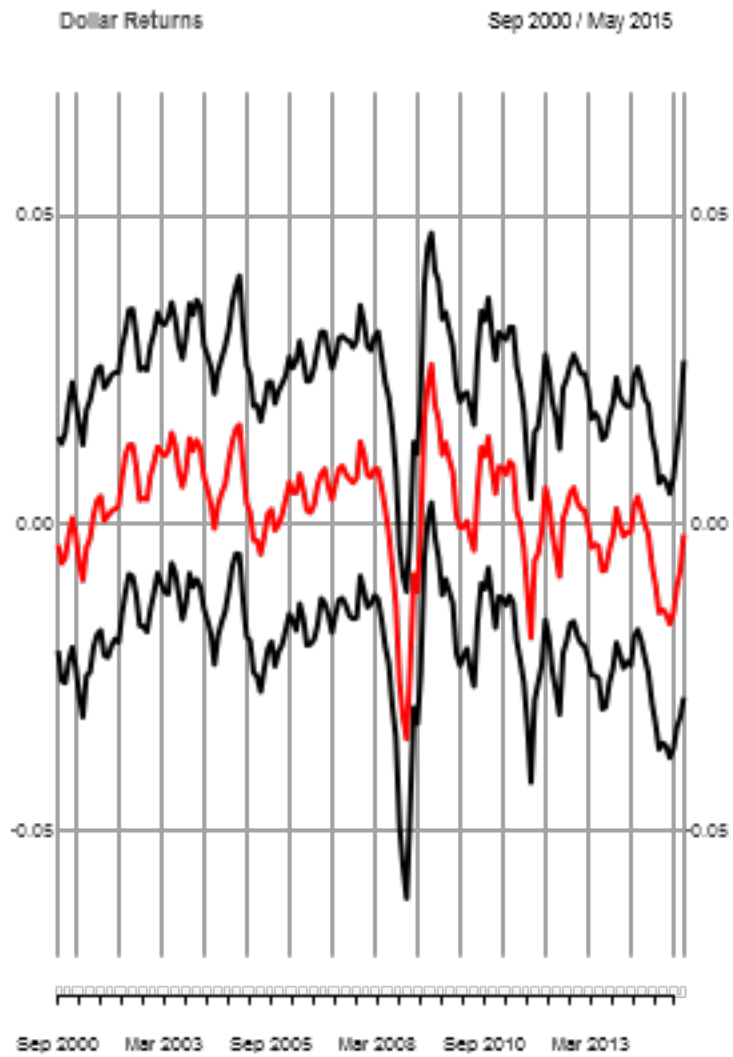


Figure 2.13: Posterior Median and 95 % credible intervals for dollar μ_t on EM dataset

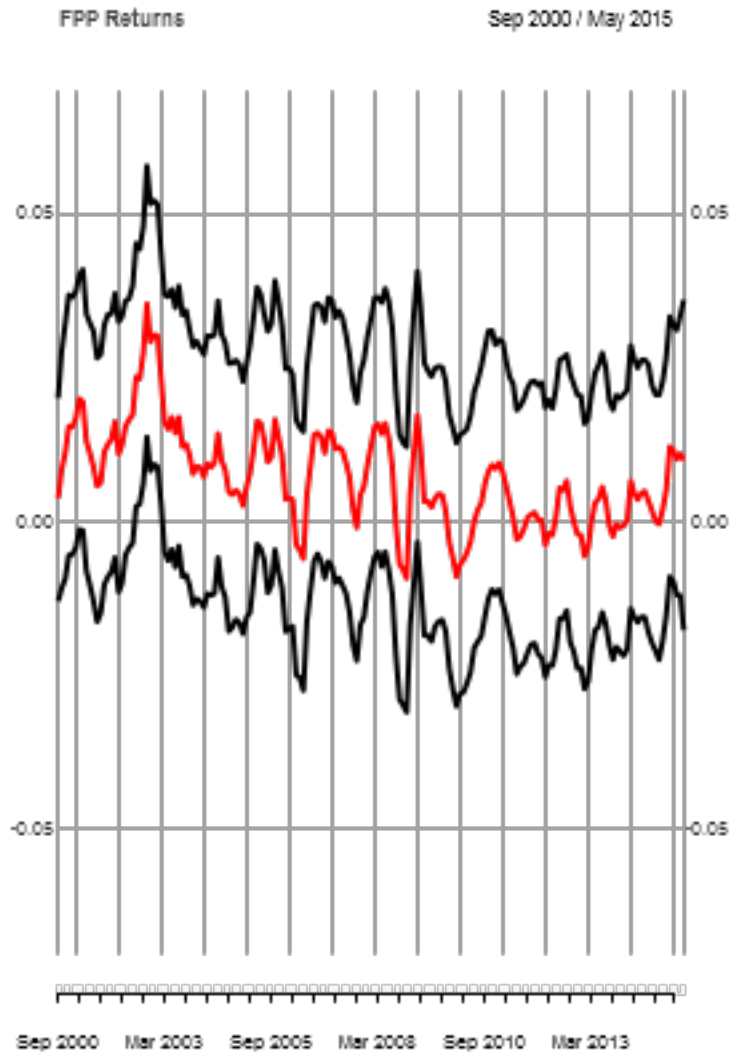


Figure 2.14: Posterior Median and 95 % credible intervals for FPP μ_t on EM dataset

V.4 Random Portfolios

We now repeat the rolling one year randomization exercise from the earlier section. Again, performing the exercise over a larger universe of potential currencies yields

more concrete conclusions about time variation in these currency strategies.

The z-scores formed on rolling 12 month returns are plotted in Figures 2.15, 2.16, and 2.17. We can see that from 2000 until today, there has been a steady decline in the excess returns presented by these strategies relative to the randomized portfolios.



Figure 2.15: Z-Score of Rolling 1 year returns of carry strategy

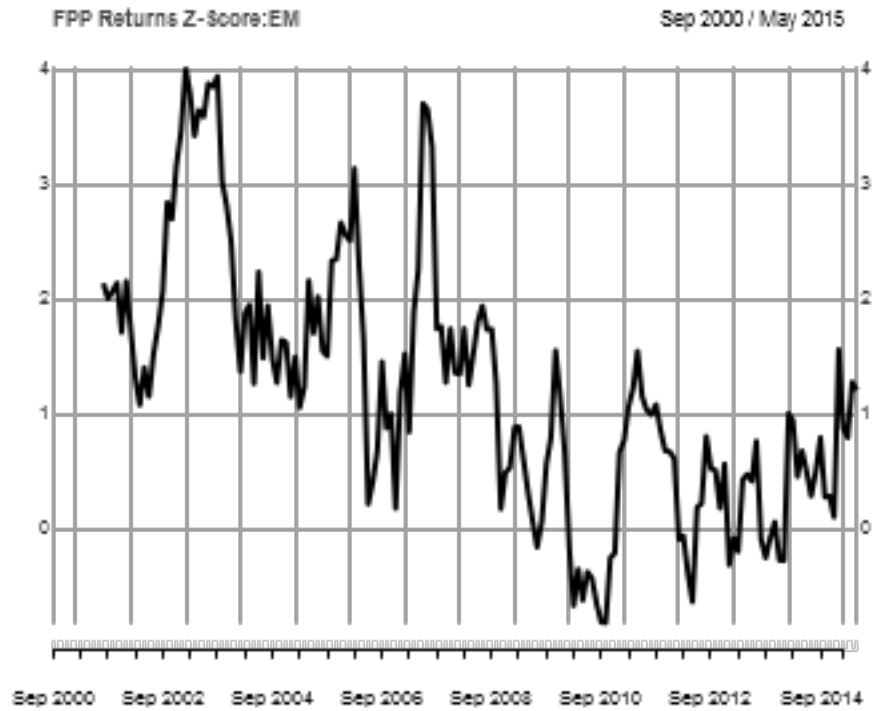


Figure 2.17: Z-Score of Rolling 1 year returns of FPP strategy

We also present below the risk adjusted or Sharpe Ratio rolling z-scores. Again, we see that there is a strong tendency for the risk adjusted returns to become more and more indistinguishable from noise as time moves on.



Figure 2.18: Z-Score of Rolling 1 year Sharpe Ratio of carry strategy



Figure 2.19: Z-Score of Rolling 1 year Sharpe Ratio of dollar strategy

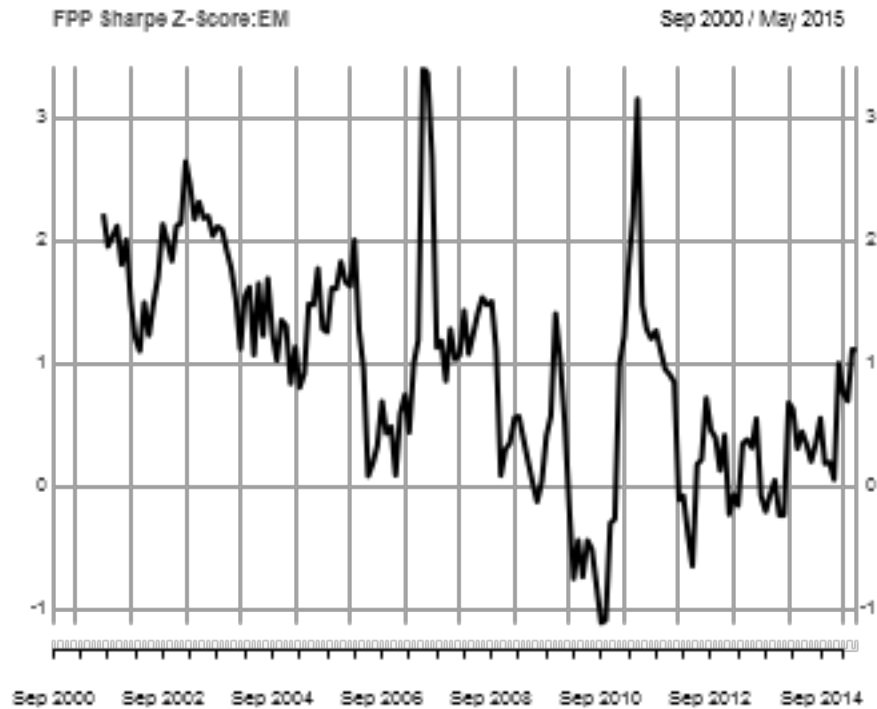


Figure 2.20: Z-Score of Rolling 1 year Sharpe Ratio of FPP strategy

VI Conclusion

We have presented evidence through the use of dynamic linear models as well as the use of random portfolios that it is highly likely that excess returns to the various strategies that exploit the failure of UIP to hold are decreasing through time. This has implications for the theoretical work being done on the determinants of excess returns.

Much of modern asset pricing theory revolved around the use of rational expectations and a stochastic discount factor approach (see Cochrane [2009] for a textbook treatment). This approach explains the presence of excess returns as

the equilibrium response by rational actors to the covariance of these returns to inputs of their utility function. For instance, the carry trade has been explained as the returns required by rational agents due the returns' covariance with domestic consumption (Lustig and Verdelhan [2007]). If the excess returns to these trade remain near 0, and UIP continues to hold more closely than before, we can test whether or not these returns have become less correlated with common formulations of stochastic discount factors. We view this as an interesting path for future research.

Chapter 3

Markov Switching Models and Excess Returns

I Introduction

This paper will extend the seminal Engel and Hamilton [1990] paper in several ways to further examine the presents of trends in exchange rate changes. First, this paper will re-estimate the basic univariate hidden markov/markov switching models. Then the paper will model exchange rates as a multivariate markov switching model to test the benefit to sharing information across exchange rates to estimate whether or not the dollar is in an appreciation or depreciation trend. In addition, this paper will formulate currency baskets in a similar vein to Lustig and Verdelhan [2007] and Verdelhan [2012] and test these baskets for the presence of long swings. A final contribution will be the use of investment strategies based on the forecasts of the hidden markov model as a test of its efficacy, in lieu

of point forecasts and hypothesis tests regarding parameter estimates, following Melvin et al. [2013]

II Motivation

Economic thinking about exchange rate behavior, like scientific progress in any other discipline, has proceeded among many parallel paths that sometimes end, sometimes continue and sometimes intersect to create new ways of looking at the world. This paper will test whether recent improvements in exchange rate modeling can be used to reinvigorate an older method, with the goal that the combination of the two will yield unique insights and a better understanding of exchange rate behavior.

Figure WHAT presents a time series of the Dollar Index (ticker DXY). This is a weighted average of several bilateral exchange rates vis-a-vis the U.S. Dollar. What is clearly present is the *appearance* of trends. However, any time spent with a random number generator on a personal computer will leave no doubt about the possibility that these apparent trends were created by a random walk data generating process.

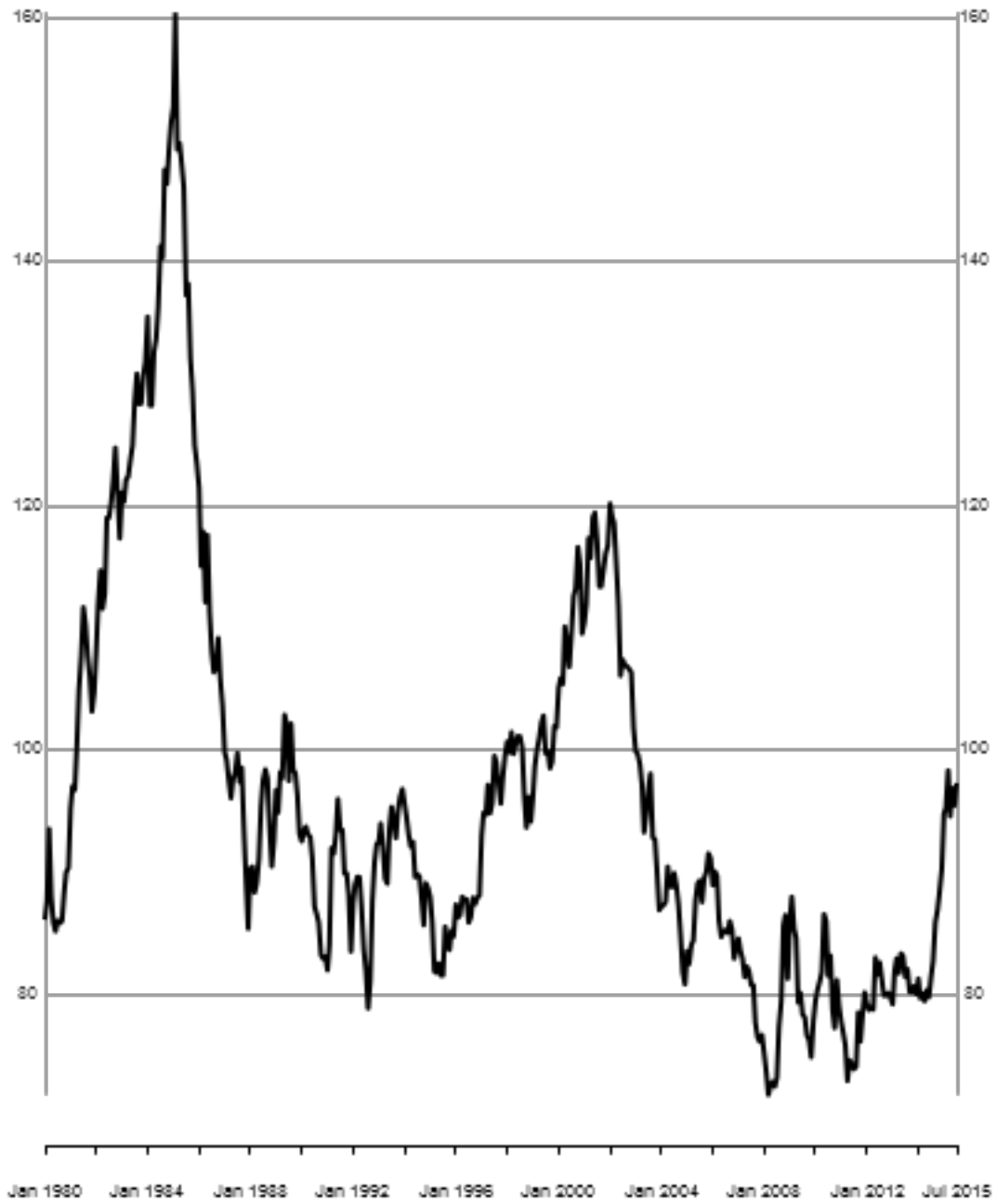


Figure 3.1: Time Series Plot of the Dollar Trade Weighted Index

Understanding whether or not this time series, and the time series of exchange rates more generally, is caused by a process that is somewhat predictable has large implications for both economic theory and economic reality. Our understanding of what exactly drives exchange rates is lacking, with groups still disagreeing whether or not the exchange rate is a random walk or not, much less what drives the behavior Engel and West [2005] Rossi [2006]. In addition, international trade and international financial transactions have exploded over the last century. Exchange rate risk is an economic reality of these transactions, but the way it is handled could and should depend on whether or not we should expect trend behavior, and what that trend behavior depends on e.g.(risk premia or some sort of irrational behavior).

As will be illustrated in the following literature review, the studies to date using markov switching models have typically used univariate specifications as well as have focused on only a few currencies. This paper contributes to the literature both in its currency breadth, its use of a multivariate formulation both explicitly (with a multivariate model) and implicitly (through the use of currency portfolios) and its method of testing the model via portfolio returns.

III Literature Review

This paper is one in a long line of many which seek to statistically explain the behavior of exchange rates. However, we see it as fitting nicely in a reasonably linear strand of the literature that we seek to summarize below.

The parent node of the lineage in which this paper falls is Engel and Hamilton

[1990]. These authors take the markov switching model of Hamilton [1989] to three exchange rates: the French Franc-U.S. Dollar, the German Deutschmark-U.S. Dollar, and the British Pound - U.S. Dollar. They use quarterly data from the late 1970s until late 1980s and find evidence consistent with the dollar showing "long swings".

However, in a 2006 paper, Klaassen [2005] showed using updated data that long swings were no longer present in the data at the quarterly frequency. However, after increasing the sampling frequency to the weekly level, he finds that long swings are still present. At the weekly frequency the assumption of, conditional on the state, the errors being iid from a normal distribution was no longer tenable due to the heteroscedasticity and volatility clustering seen in asset returns. Thus Klaasen modeled the variance as a state-independent GARCH process Bollerslev [1986]. Klaasen, like Engle and Hamilton, focuses on three exchange rates, the DM, GBP, and Yen vs the dollar and models the exchange rates independently of one another. In addition, his focus is on point estimates and more traditional hypothesis tests to distinguish between the model and a random walk.

In addition to these main papers, there have been many others which model exchange rates using a markov switching process Yuan [2011], Bazdresch and Werner [2005], all have modeled the exchange rates independently of each other in a univariate setting as well as testing predictive accuracy via point estimates compared with the random walk.

A separate and more recent strand of the exchange rate literature has examined portfolios of currencies. Two of these are noteworthy (Lustig and Verdelhan [2007] and Verdelhan [2012]) in that they have highlighted the large amount of

systematic variation in exchange rates. These authors have found that in some contexts, averaging out idiosyncratic exchange rate movements via portfolio formation has resulted in exchange rate movements that are more orderly and more economically meaningful. For instance, Lustig et al. are able to plausibly relate excess returns on baskets of currencies to consumption covariance and Verdelhan is able to attain high R^2 statistics in explaining exchange rate movements using a currency portfolio as the explanatory variable.

Lastly, there has been another more recent movement towards measuring the success of investment strategies as a way of testing hypothesis about exchange rate determination. Examples of these include Melvin et al. [2013] who form strategies based on PPP, and Jordà and Taylor [2012] who relate variation in the real exchange rate to subsequent carry trade returns.

IV Univariate Model

In this section we will describe and fit the univariate markov switching model of Engel and Hamilton [1990]. The model is specified as follows. First, let e_t be the exchange rate at time t . Using the common assumption of log normally distributed prices, we find that

$$y_t = \log(e_t) - \log(e_{t-1}) \tag{3.1}$$

is normally distributed. Assuming a markov switching structure we can write the model for y_t as follows:

$$y_t \sim N(\mu_{s_i}, \sigma_{s_i}^2) \tag{3.2}$$

with $i = 1, 2$ and

$$Pr(s_{i,t}|s_{j,t-1}) = p_{j,i} \quad (3.3)$$

To help avoid numerical issues, we multiple y_t by 100, and thus parameter units are on the scale of monthly percentages.

We estimate the model via the **depmixS4** package in R Visser et al. [2010]. This package uses the EM algorithm to estimate the state dependent parameters Baum et al. [1970] and a forward-backward algorithm to compute the ex-post probabilities of being in each state (once all data has been observed).

IV.1 Full Sample

We first fit model to our full data set. Our data contains log exchange rate changes for Australia, Canada, Switzerland, Euro (spliced with Deutschmark pre 1998), United Kingdom, Japan, Norway, New Zealand, and Sweden. The data spans from 1989 until 2015 and the observations are sampled on the first trading day of each month.

Table 3.1: Estimated Parameters Currency Markov Switching Model

| Currency | P(1,1) | P(1,2) | P(2,1) | P(2,2) | Mu(1) | sd(1) | Mu(2) | sd(2) |
|----------|--------|--------|--------|--------|-------|-------|-------|-------|
| AUD | 0.76 | 0.24 | 0.02 | 0.98 | 1.22 | 7.24 | -0.08 | 2.72 |
| CAD | 0.99 | 0.01 | 0.00 | 1.00 | 0.18 | 1.36 | -0.16 | 2.74 |
| CHF | 0.96 | 0.04 | 0.48 | 0.52 | -0.23 | 2.94 | 0.78 | 6.58 |
| DEMEUR | 0.13 | 0.87 | 0.60 | 0.40 | -0.59 | 1.89 | 0.38 | 3.67 |
| GBP | 0.69 | 0.31 | 0.02 | 0.98 | 2.89 | 5.87 | -0.16 | 2.31 |
| JPY | 0.98 | 0.02 | 0.45 | 0.55 | 0.07 | 2.86 | -2.44 | 7.09 |
| NOK | 0.97 | 0.03 | 0.47 | 0.53 | -0.28 | 2.92 | 5.48 | 3.68 |
| NZD | 0.93 | 0.07 | 0.18 | 0.82 | -0.40 | 2.38 | 0.78 | 5.42 |
| SEK | 0.99 | 0.01 | 0.14 | 0.86 | -0.09 | 2.97 | 2.37 | 6.76 |

We can see that for most currencies, the probability of staying in the same state as in the previous period is relatively high. However, many of the state dependent means are quite close to each other, suggesting that the algorithm is determining state allocation by differing variance. However, we hold off judgment of statistical fit until we form portfolios using the model.

Figure 3.2 shows the probability of being in state 1 for each currency over the full sample. We can see obvious warning signs in the Canadian dollar as well as the spliced Deutschmark Euro sample. The Canadian dollar exhibits change point behavior around 2005, while the DEMEUR series oscillates rapidly between the two states. Many of the other series spend considerable time in state 1 according to the estimated probabilities.

IV.2 Portfolio Formation

In this section we test whether or not the simple 2-state Gaussian markov switching model has value for investors and economically significant forecasting power by building portfolios using the expected return forecast from the models as an input.

We build a commonly used high minus low (HML) type portfolio that is dollar neutral, as well as a simple long only portfolio that is not dollar neutral. The steps to producing each portfolio are as follows:

We form the portfolios in the following way:

- At time t , fit the markov switching model to all data for each currency on time t and before.

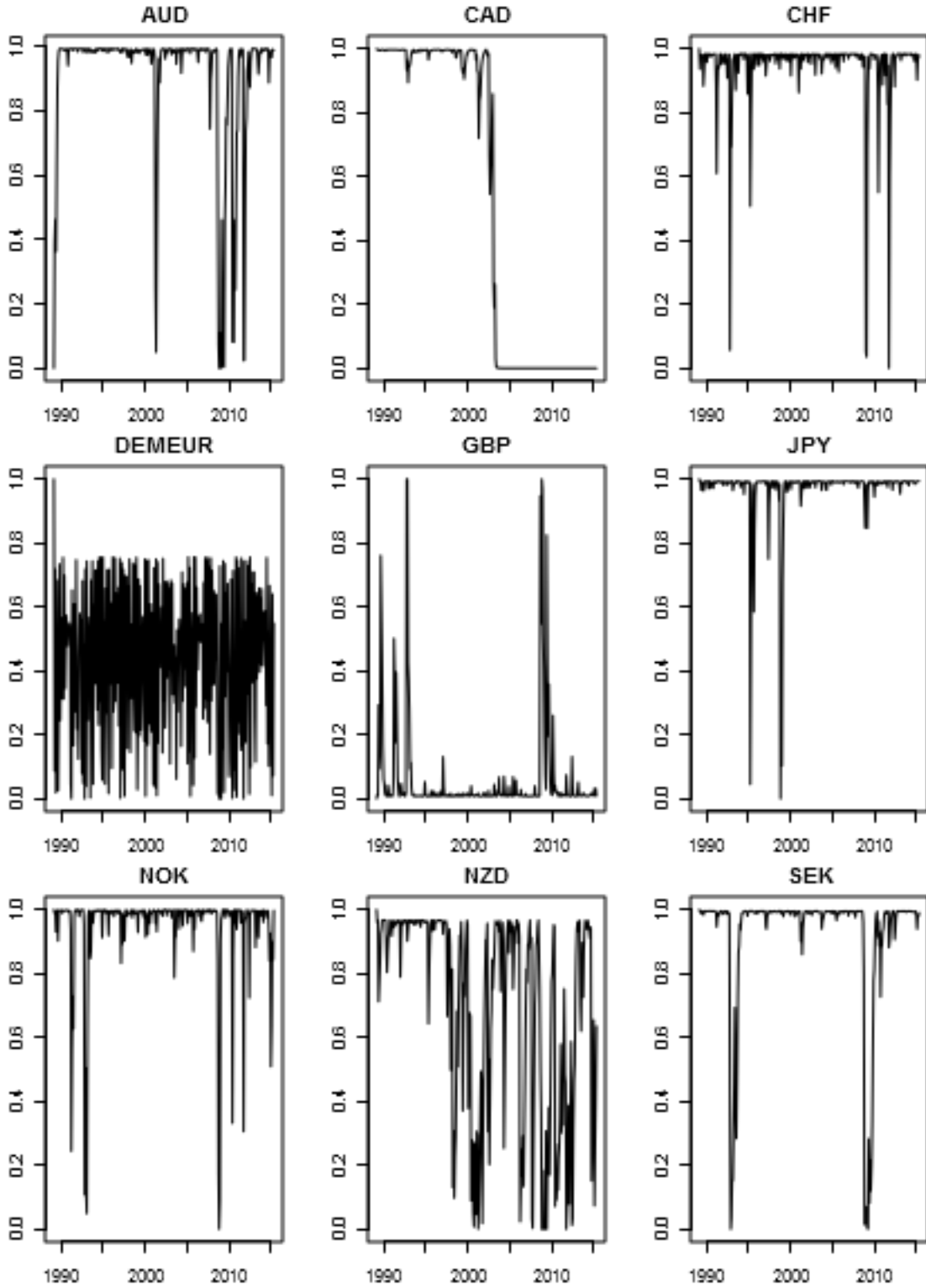


Figure 3.2: Probability of State 1 Currency Markov Switching Model

- Gather the parameters at time t from the estimated model.
- Form a forecast for the expected return next period ($t+1$) using the posterior probability of being in each state at time t , the transition probabilities for staying in the current state or switching, and the state specific means.
- For the HML portfolio, go long the three currencies with the highest expected returns, and short the currencies with the lowest.
- For the long only portfolio, go long the currencies with the highest three expected returns next period.

Currency specific returns are computed as

$$er_{t+1} = s_{t+1} - f_{t,t+1} \quad (3.4)$$

where $f_{t,t+1}$ is the log of the forward exchange rate at time t for deliver at time $t+1$ quoted in foreign currency per dollar and s_{t+1} is the log of the spot exchange rate at time $t+1$ quoted the same way.

IV.2.a Results

Presented below are portfolio statistics and a cumulative wealth chart of the portfolio. We can see that the trading strategies based off of the simple two state Gaussian markov switching model are not impressive. Both have annualized returns of about 0 and extremely small Sharpe Ratios. As the Information Ratio $(\frac{\mu_{er}}{\sigma_{er}})$ is equal to a t-statistic multiplied by the square root of T measuring the statistical significance of the average return, we can easily see that both portfolios

have average returns statistically (and more importantly economically) insignificant from 0. Thus, we find little support in terms of portfolio returns for the markov switching model of Engel and Hamilton [1990] and would have to question whether or not the exchange rates tested here over the sample period used exhibit any meaningful long swings.

Table 3.2: Portfolio Statistics Currency Markov Switching Model

| | High Minus Low | Long Only |
|------------------------|----------------|-----------|
| Annualized Return | -0.01 | -0.00 |
| Annualized Std Dev | 0.07 | 0.09 |
| Information Ratio | -0.16 | -0.03 |
| Monthly Std Dev | 0.02 | 0.03 |
| Skewness | 0.03 | -0.31 |
| Kurtosis | 4.43 | 4.35 |
| Excess kurtosis | 1.43 | 1.35 |
| Sample skewness | 0.03 | -0.32 |
| Sample excess kurtosis | 1.47 | 1.39 |

Cumulative Return of Currency Forecast Strategies

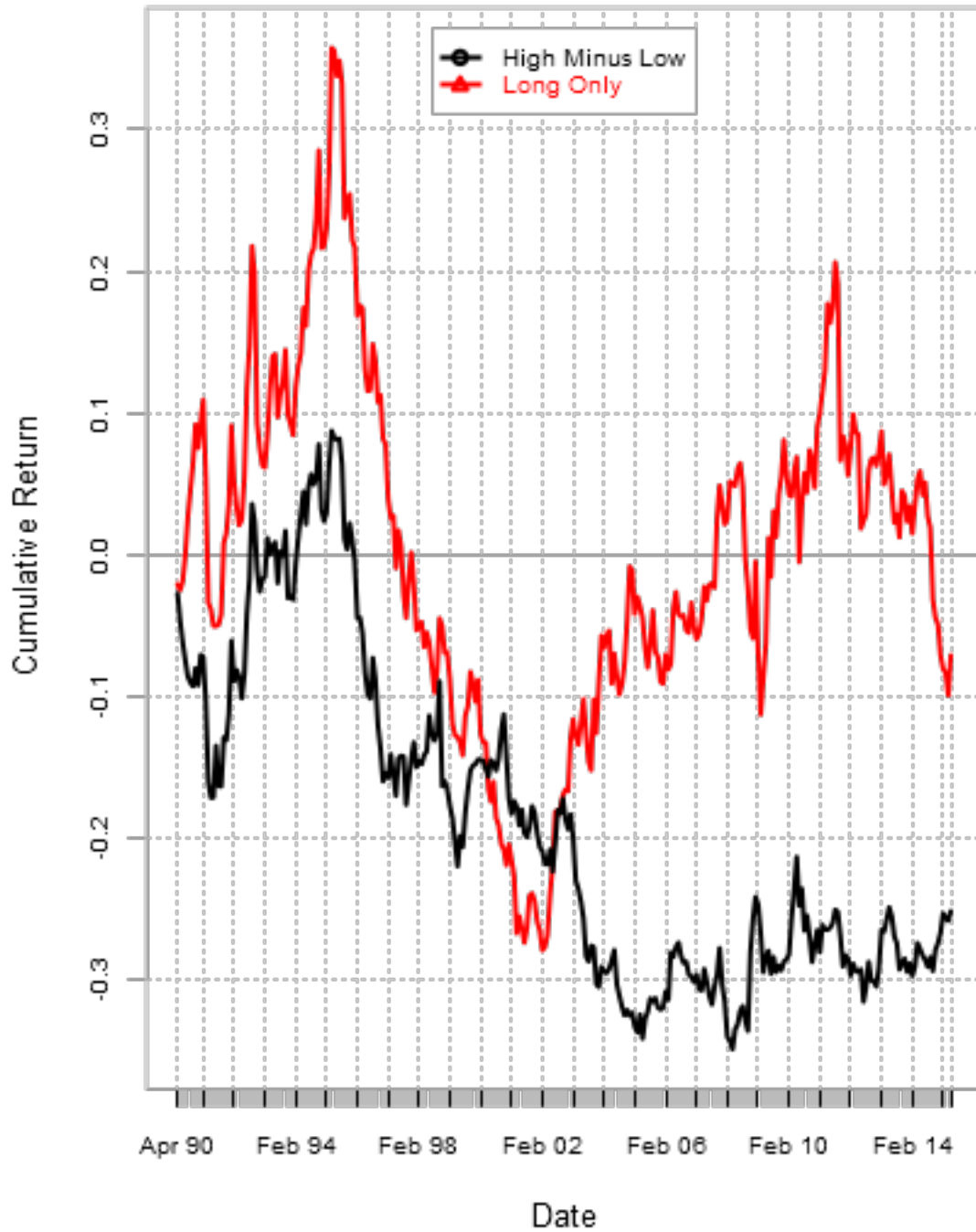


Figure 3.3: Cumulative Returns to Portfolio using Currency Markov Switching Model

V Currency Portfolios and Markov Switching

In this section, following the afore mentioned contributions of Verdelhan [2012] and Lustig and Verdelhan [2007], we form currency portfolios and test whether or not they exhibit long swings. Our justification for doing this is the easily observable volatility in bilateral exchange rates, combined with the insight by Verdelhan that exchange rates exhibit a significant amount of systematic variation.

It seems quite possible that if, for example, the dollar is in a long swing vs the euro, it will be doing so for United States specific reasons and as such it will appreciate against other currencies as well. If idiosyncratic volatility between the euro and dollar make estimating state dependent means difficult, than pooling currencies should make the task of determining trending behavior easier. It is possible, however, that long swings between bilateral exchange rates only emerge when contradictory forces act in each country, one leading to appreciation and one to depreciation. If that is the case then averaging over currencies will more than likely make the regime dependent behavior harder to detect.

V.1 Full Sample

As with the previous section, we first run the model of equations 2 and 3 on our full sample of data. This dataset contains the same currencies and time span of the data used in the basic univariate model of the previous section. In this section, however, we form portfolios for each currency, containing an equally weighted position in every other currency in sample. The returns we model here are the returns to that portfolio, and thus are the average change of each currency against

all other currencies in sample.

We can see from both the table and the figure below, that the model predicts much less

Table 3.3: Estimated Parameters Portfolio Markov Switching Model

| Currency | P(1,1) | P(1,2) | P(2,1) | P(2,2) | Mu(1) | sd(1) | Mu(2) | sd(2) |
|----------|--------|--------|--------|--------|-------|-------|-------|-------|
| AUD | 0.49 | 0.51 | 0.40 | 0.60 | -0.59 | 2.07 | 0.56 | 2.95 |
| CAD | 0.42 | 0.58 | 0.39 | 0.61 | -0.06 | 2.21 | 0.07 | 2.31 |
| CHF | 0.92 | 0.08 | 0.17 | 0.83 | 0.01 | 1.57 | -0.54 | 3.06 |
| DEMEUR | 0.42 | 0.58 | 0.39 | 0.61 | -0.07 | 1.48 | 0.03 | 1.78 |
| GBP | 0.42 | 0.58 | 0.23 | 0.77 | 0.39 | 3.19 | -0.07 | 1.35 |
| JPY | 0.92 | 0.08 | 0.25 | 0.75 | 0.25 | 2.42 | -0.93 | 5.60 |
| NOK | 0.75 | 0.25 | 0.16 | 0.84 | -0.46 | 0.94 | 0.35 | 2.29 |
| NZD | 0.48 | 0.52 | 0.42 | 0.58 | -0.57 | 1.80 | 0.33 | 3.07 |
| SEK | 0.98 | 0.02 | 0.20 | 0.80 | -0.01 | 1.66 | 1.68 | 4.09 |

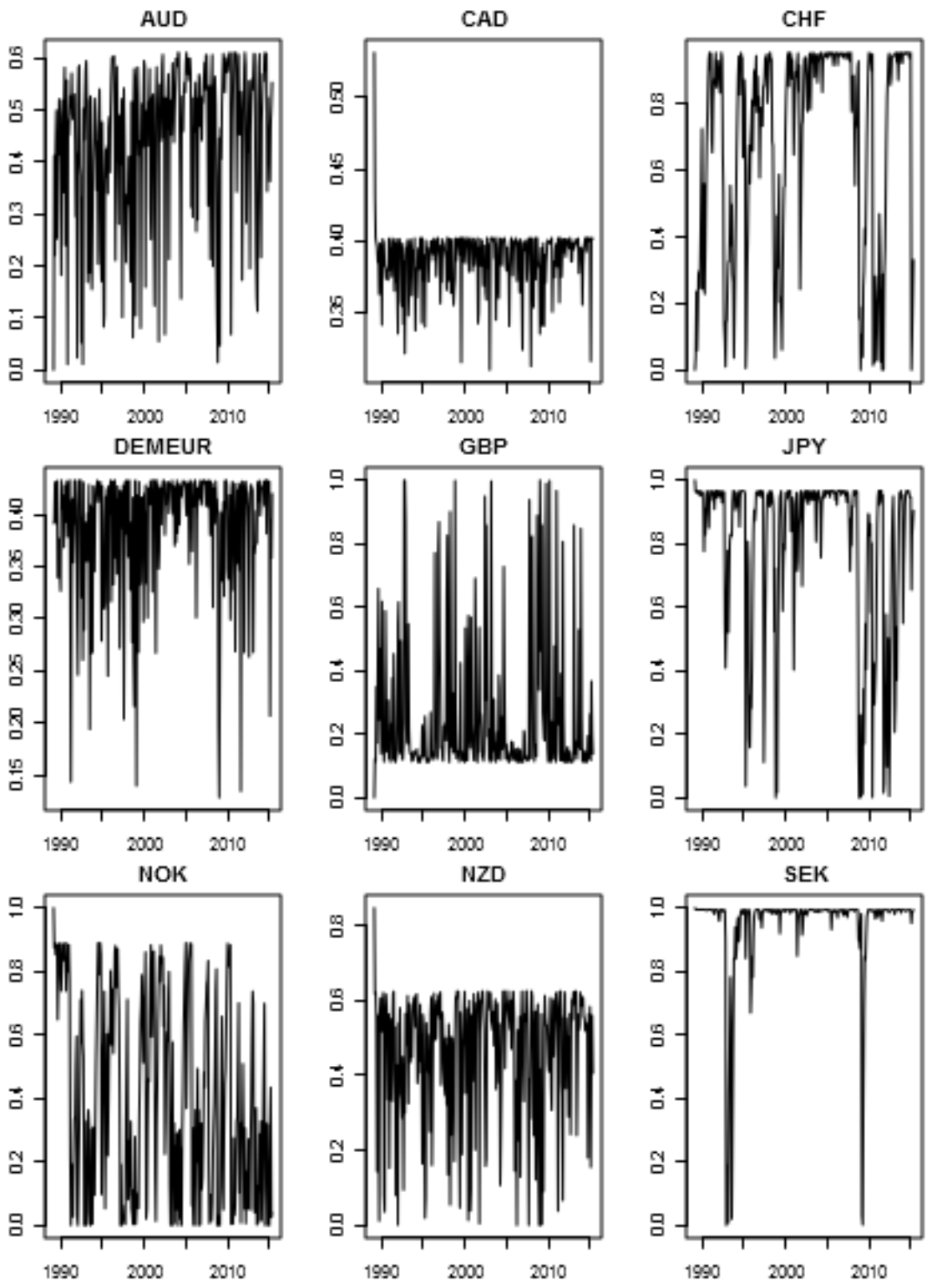


Figure 3.4: Probability of State 1 Portfolio Forecasts

V.2 Portfolio Formation

We follow the same process as in the earlier section to compute portfolios. We form both high minus low (HML) and long only portfolios based on the forecasted *currency portfolio* return, however the positions taken are bilateral vis-a-vis the dollar, and thus the returns used are the same as in the previous section.

Given the highly unstable state transition process estimated in the previous section, it is unsurprising that the portfolio returns are quite poor. Again, transforming the Information Ratio to a standard t-statistic yields a result that is insignificantly different than 0. We again conclude that the markov switching model does not yield economically (or statistically) significant forecasting power for returns.

Table 3.4: Portfolio Statistics Portfolio Markov Switching Model

| | High Minus Low | Long Only |
|------------------------|----------------|-----------|
| Annualized Return | -0.03 | -0.01 |
| Annualized Std Dev | 0.07 | 0.10 |
| Information Ratio | -0.39 | -0.11 |
| Monthly Std Dev | 0.02 | 0.03 |
| Skewness | 0.55 | -0.08 |
| Kurtosis | 5.62 | 3.94 |
| Excess kurtosis | 2.62 | 0.94 |
| Sample skewness | 0.56 | -0.08 |
| Sample excess kurtosis | 2.68 | 0.98 |

Cumulative Return of Portfolio Forecast Strategies

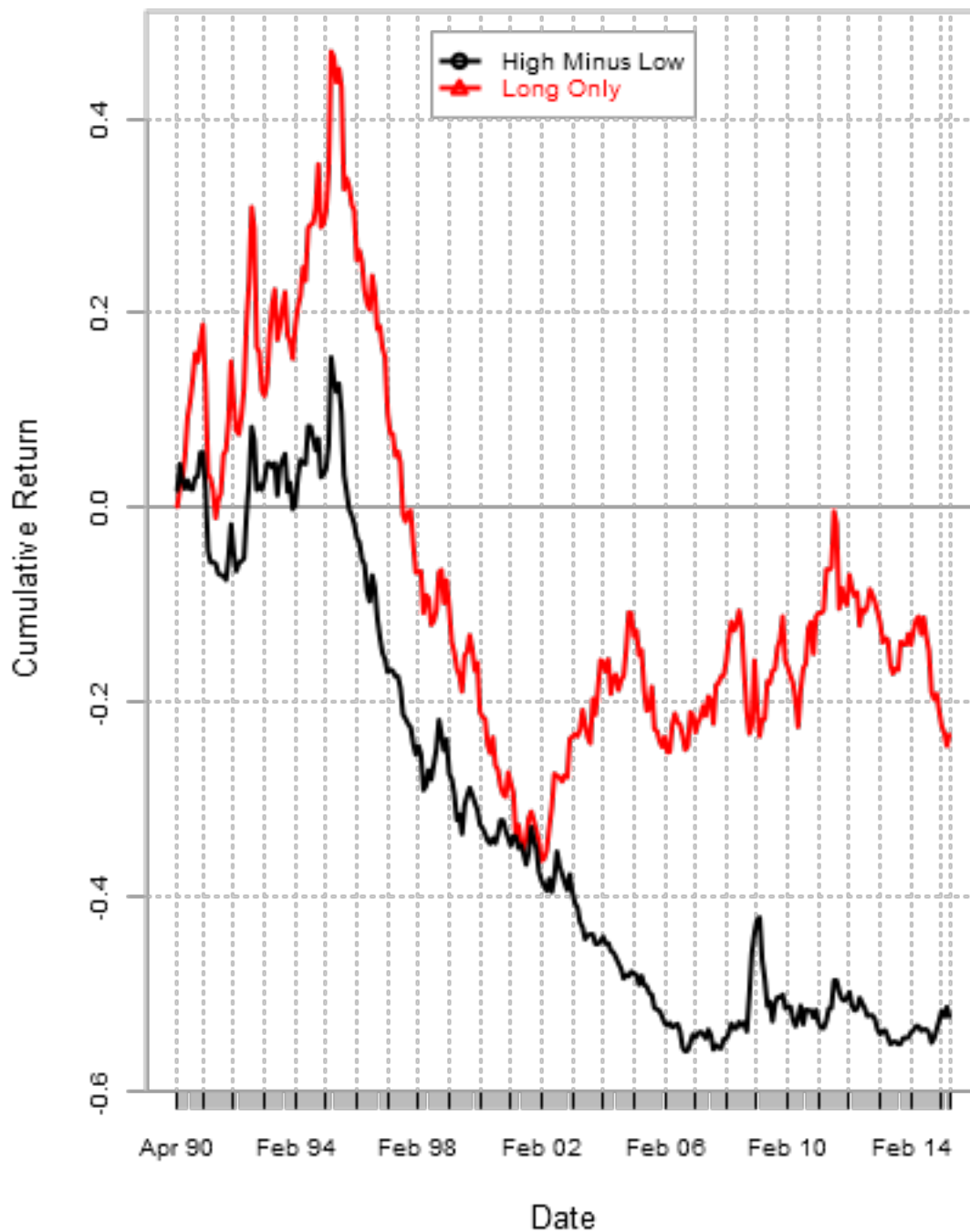


Figure 3.5: Cumulative Returns to Portfolio Strategy using Portfolio Forecasts.

VI Multivariate Formulation

In this final section we estimate a multivariate version of the markov switching model. The work previously cited, and all research done on modeling exchange rates via markov switching models that the author has come across has been in a univariate context. Thus contemporaneous information from other currencies has been ignored. In the previous section we took a pseudo pooling approach by forming portfolios ex-ante before conducting the analysis. Here, we we will explicitly model the markov switching process in a multivariate context, hoping that the added cost in terms of needing to estimate a covariance matrix pays dividends by better identifying shocks and allowing a more efficient estimate of the mean.

The model from equations 2 and 3 can be easily adapted to a multivariate formulation. Thus, we have:

$$Y_t \sim N(\mu_{s_i}, \Sigma_{s_i}) \quad (3.5)$$

with $i = 1, 2$ and

$$Pr(s_{i,t} | s_{j,t-1}) = p_{j,i} \quad (3.6)$$

Where Y_t and μ_{s_i} are $J \times 1$ vectors, and Σ_{s_i} is a $J \times J$ matrix for each $i = 1, 2$.

VI.1 Full Sample

We again estimate the model on our full sample of data and report the state specific means and transition matrix below. While the transition matrix looks

hopeful, we see that many of the state means are quite close together and the estimated means for Australia are positive in both states, suggesting it is only large shocks that lead it to not depreciate perpetually.

The figure below shows that the system is estimated to remain in state 2 for most of the time, with few long lasting periods in state 1.

Table 3.5: State Dependent Means Multivariate Markov Switching Model

| Currency | State 1 | State 2 |
|----------|---------|---------|
| AUD | 0.28 | 0.01 |
| CAD | 0.48 | -0.06 |
| CHF | 0.09 | -0.20 |
| DEMEUR | 0.92 | -0.16 |
| GBP | 1.51 | -0.17 |
| JPY | -0.90 | 0.11 |
| NOK | 1.13 | -0.14 |
| NZD | 0.10 | -0.10 |
| SEK | 1.49 | -0.12 |

Table 3.6: State Transition Probabilities Multivariate Markov Switching Model

| State | State 1 | State 2 |
|---------|---------|---------|
| State 1 | 0.97 | 0.03 |
| State 2 | 0.20 | -0.80 |

Multivariate

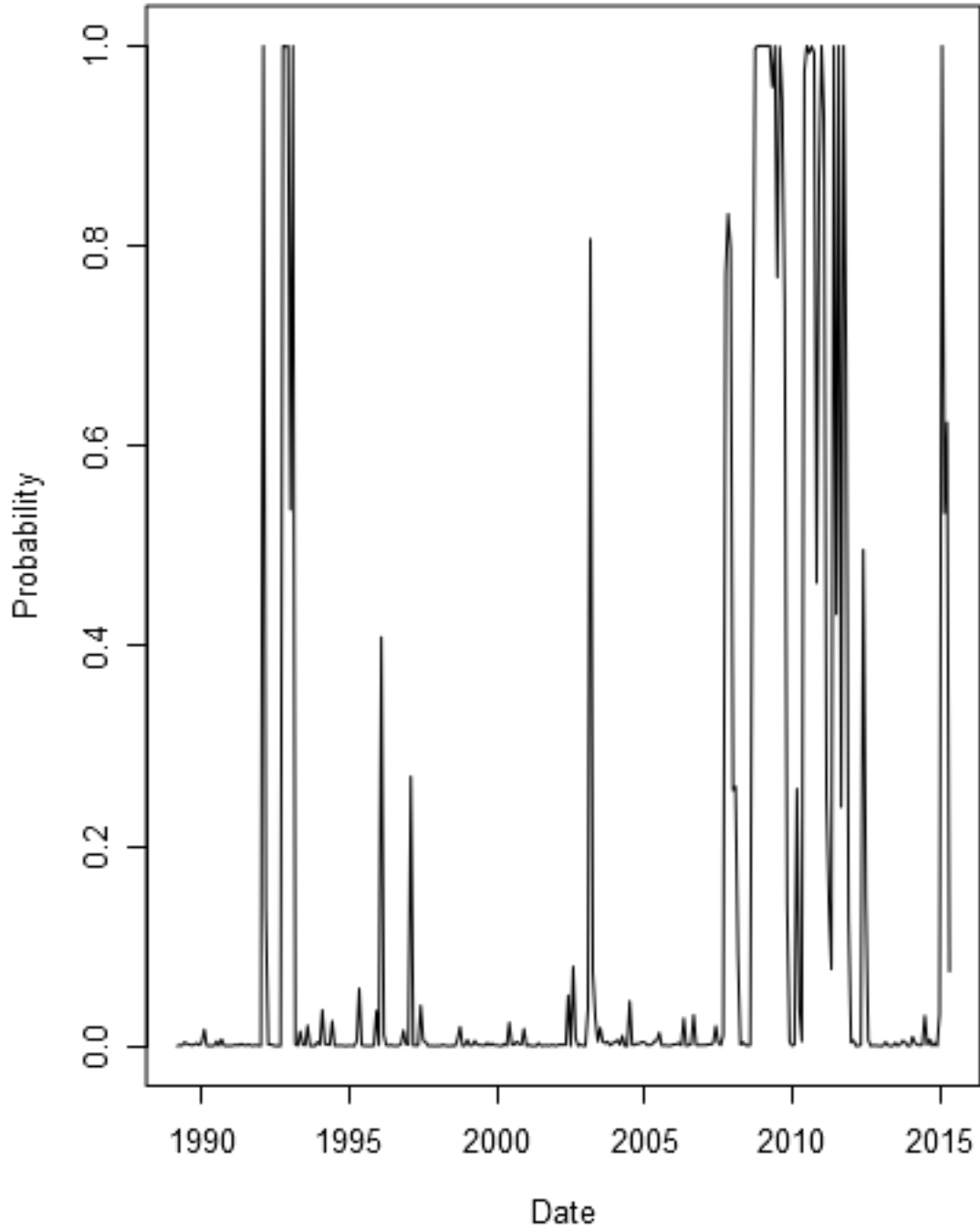


Figure 3.6: Probability of State 1 for the multivariate markov switching model

VI.2 Portfolio Formation

We again form portfolios and again experience less than stellar results. The annualized returns are close to 0 and as such, so are the Information Ratios.

Note that due to the higher computational demands of the model, we needed a longer burn in period before the recursive estimate-forecast-form portfolio algorithm could run.

Table 3.7: Portfolio Statistics Multivariate Markov Switching Model

| | High Minus Low | Long Only |
|------------------------|----------------|-----------|
| Annualized Return | -0.01 | 0.00 |
| Annualized Std Dev | 0.08 | 0.10 |
| Information Ratio | -0.12 | 0.01 |
| Monthly Std Dev | 0.02 | 0.03 |
| Skewness | -0.25 | -0.70 |
| Kurtosis | 4.18 | 5.42 |
| Excess kurtosis | 1.18 | 2.42 |
| Sample skewness | -0.25 | -0.72 |
| Sample excess kurtosis | 1.24 | 2.51 |

Cumulative Return of Multivariate Forecast Strategies

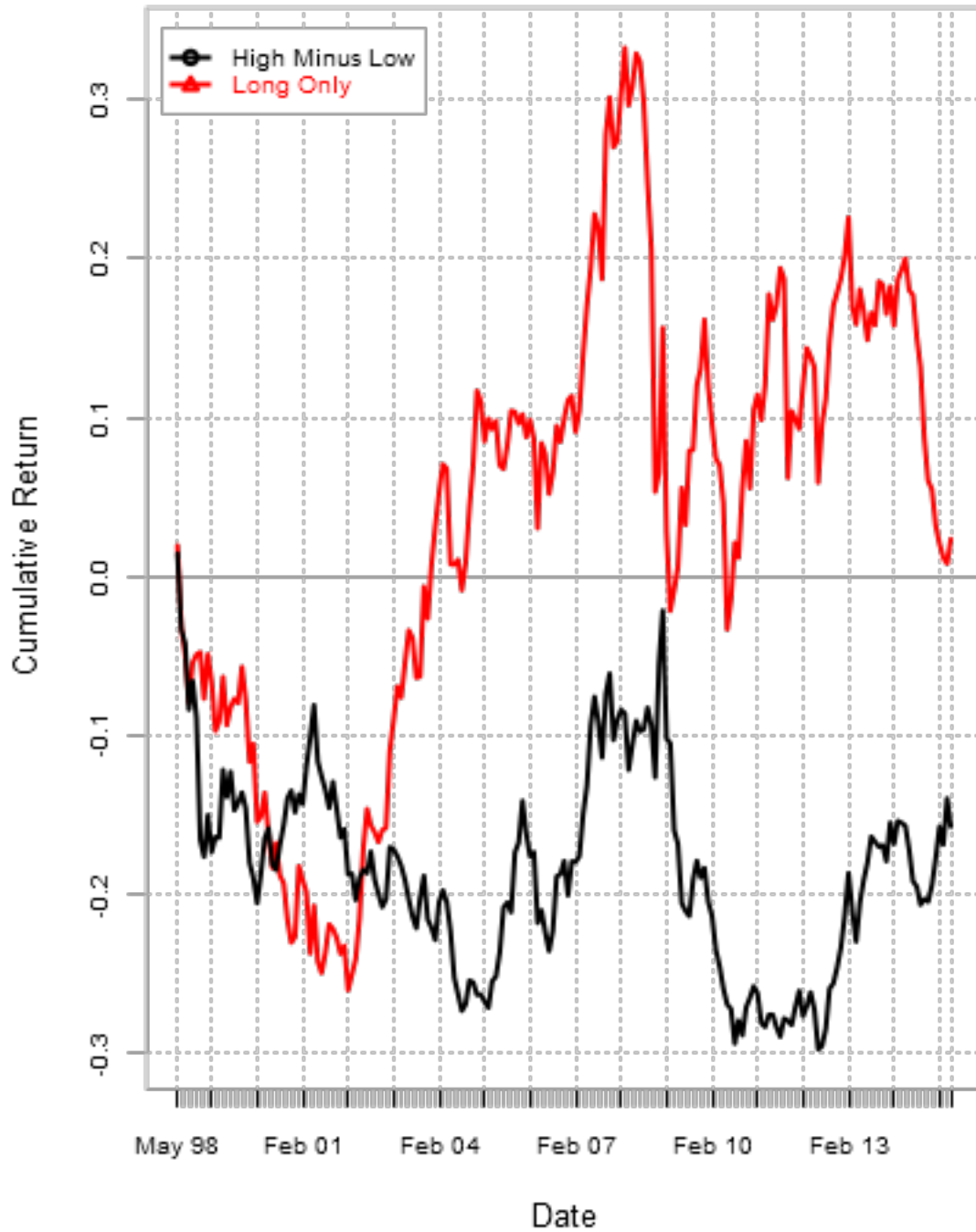


Figure 3.7: Cumulative Returns to Strategy using multivariate markov switching model

VII Conclusion

We have revisited the Engel and Hamilton [1990] model of exchange rate changes. We have foregone familiar statistical tests using point estimates and distance functions to evaluate out of sample fit, and instead of have formed portfolios based on model forecasts, following Melvin et al. [2013]. All portfolios formed were unquestionably unsuccessful against even a benchmark of 0, and without transaction costs. We are left to conclude that the markov switching model does not produce profitable forecasts of exchange rate movements, and we find it unlikely that exchange rates still exhibit long swings. Further research should test the volatility forecasting performance of the model and could form portfolios based on the volatility risk premium as done in Della Corte et al. [2011] given that much of the state identification seemed to come through differences in variance.

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