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MSc in Economics: Applied Economics and Finance

Thesis: Speculative Bubbles in the Foreign Exchange Markets

Kontra Ioanna-Kleopatra

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Supervisor: Pantelidis Theologos

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Abstract

The study examines the existence, duration and size of speculative bubbles in the exchange rate markets. More in detail, we use various two-state regime-switching models to describe the dynamics in three different exchange rates, namely the British pound/US dollar exchange rate, the Canadian dollar/US dollar exchange rate and the Swiss franc/US dollar exchange rate. We also test the predictive ability of our models to detect "extreme" positive or negative movements in the aforementioned exchange rates. Our findings provide evidence supporting the existence of bubbles in the exchange rate markets. In some cases, our regime-switching models seem to predict extreme market movements.

1. Introduction

Speculative bubbles have a long history in world markets. As a bubble, we define the deviation of an asset from its fundamental value and it is a situation in which prices appear to be based on inconsistent views about the future. While it is accepted that each speculative bubble has its own driving factors and variables, most of them were caused from a combination of fundamental and psychological factors, such as exaggerated expectations of future growth, price appreciation or other events that could cause an increase in asset values.

This paper addresses the problem of testing for the presence of speculative bubbles in the foreign exchange markets, a problem that has been attracting admirable attention in the recent years. Forex markets have faced a lot of periods of high volatility in the last years. We focus on three different foreign exchange markets. Specifically, we examine three currencies, the Canadian dollar, the Swiss franc and the Great Britain pound, with respect to the American dollar. In our approach, we estimate a regime switching model employed by van Norden and Schaller (1993), van Norden (1996), Schaller and van Norden (1997, 1999, 2002) and van Norden and Vigfusson (1998). Our objective is to detect the presence of such bubbles, their duration and their magnitude, using the regime switching approach, as well as to test the predictive ability of the model. The model we chose is the two state regime-switching model, where the bubble can be in two different states. The first state is when the bubble appears and begins to grow, while the second one is when the bubble collapses. We used a sample of 483 observations of the last forty years (December 1972 to March 2013).

Our results show the existence of bubbles in some of the cases under scrutiny. Using graphs that show the probability of a boom, i.e., the probability of an “extreme” positive return in the market and the probability of a crash, i.e., the probability of an “extreme” negative return in the market, we conclude that our regime switching models do not lack predictive power for extreme movements in the exchange rates under examination. However, our estimated models do not detect all extreme events in forex markets.

The layout of this paper is the following: Section 2 presents the literature review, Section 3 provides the definition of the bubble used in our two regime-switching models and briefly describes the econometric methodology that we use. Section 4 describes our dataset, Section 5 presents the model selection procedure, while Section 6 contains the empirical results. Finally, Section 7 concludes with a summary of the main findings of the paper.

2. Literature Review

A large number of papers has been written trying to find evidence of bubbles in financial markets, such as equity markets or foreign exchange markets (FX markets). All these papers report contradicting results regarding the existence of bubbles. In others words, some papers claim that there is no significant evidence that a bubble occurred or that a bubble caused deviations of an asset from its equilibrium level, while others argue that bubbles did exist and caused appreciations or depreciations of an asset's value.

Flood and Garber (1980) conduct the first econometric test for price-level bubbles of the German hyperinflation. They find no significant evidence of a bubble. However, they only test for deterministic bubbles. Blanchard and Watson (1982) examine the probability of a rational bubble in a financial market, i.e., the deviation of the price of an asset from its fundamental value when the behavior and the expectations of the market participants are rational. Their results show that their test lacks power to explain whether the bubble appeared or not. Meese (1986) supports the view that speculative bubbles do occur and they caused the dramatic increase in the value of the US dollar during the early 1980s and its sudden drop from late 1985 to 1988. West (1987) uses Hausman's (1978) test to detect bubbles in stock markets and finds the presence of bubbles in the dollar/German mark and dollar/British pound exchange rates. Woo (1987) proposes a portfolio-balance model and examines the importance of speculative bubbles in the exchange rate of the US dollar with the currencies of Germany, France and Japan, maintaining the assumption of rational expectations among the market participants. The sample period is determined by availability of monthly data: Germany, April 1973 to April 1980; France, April 1973 to September 1982 and Japan, April 1973 to April 1980. Woo finds two bubbles over a decade of floating exchange rates. The first bubble is a long one that lasted for five months (June- October 1978) and affected German and French bilateral exchange rates with the US dollar while the second one is the 1979-1980 bubble. Both bubbles were caused by uncertain conditions in the US economy, mainly due to economic and political reasons.

Frankel and Froot (1990) test the rationality of foreign exchange rates and try to explain the appreciation of dollar from June 1984 to February 1985 even though the real interest rates and all the other macroeconomics factors (that could justify such an increase in dollar value) were floating in that specific period. They suggest two main reasons for this appreciation: the shifts in "tastes and technologies" and the existence of speculative bubbles, i.e., bubbles which are not characterized by rational expectations. Investors are heterogeneous and their expectations in FX markets are widely dispersed. Wu (1995) uses an alternative test to investigate

rational stochastic bubbles in the post-Bretton Woods period. He finds no strong evidence of bubbles. His results are in contrast with previous papers, such as Meese's paper, and claims that huge dollar appreciation in that period was not the consequence of the appearance of a speculative bubble. He uses monthly observations for the US dollar/British pound exchange rate, the US dollar/Japanese yen exchange rate and the US dollar/German mark exchange rate, from January 1974 to December 1988. He reports two set of results: in the first one he uses the whole sample (January 1974-December 1988) and claims that all major US dollar exchange rates floated in late 1973/ early 1974, so January 1974 is a possible time for a bubble to appear. In the second set of results he uses a sub-sample (January 1981-February 1985) and shows that the US dollar appreciated in a persistent way against the pound, the yen and the mark. So, a bubble is likely to initiate in this period more than in any other period. Van Norden (1996) develops a new test for speculative bubbles using data for the Japanese Yen, the German mark and the Canadian dollar exchange rates against the U.S. dollar over the 1977-1991 period, following the assumption that bubbles display a particular kind of regime-switching behavior. Van Norden describes a two-regime model of speculative bubbles. It focuses on stochastic bubbles that are expected either to continue growing or to collapse -partially or completely. The results for the Canada/U.S., Germany/U.S. and Japan/U.S. currencies appear to be sensitive to changes in the definition of the fundamental exchange rate or the measurement of exchange rate innovations. In many cases there is no evidence of a bubble, maybe because the bubble did not exist or the test was not powerful enough to detect it. Evidence that support the bubble model is stronger when using excess returns data and an overshooting model of fundamentals for the Canada/U.S. exchange rate or a PPP model for the Japan/U.S. exchange rate. Van Norden and Schaller (1996) use regime-switching models to explain stock market crashes and present two different explanations to account for historical crashes. The first model, which is a model of speculative behavior, is based on historical accounts of "manias and panics." The stylized pattern is an accelerating increase in asset prices which is followed by an abrupt decrease. They use monthly stock market data. Their first model is consistent with the fact that there is a non-linear predictability of returns based on the degree of apparent market overvaluation. It also proves that there is a huge difference in expected returns between the regime that corresponds to the survival of a speculative component and the regime that corresponds to a speculative collapse. In the first case, the typical return is positive while in the second case the typical return is negative. The difference in expected returns between the two regimes increases the size of the apparent overvaluation. The second model is based on switches in fundamentals which can lead markets to mime speculative behaviors. Van Norden and Schaller use a Markov-switching model of dividend growth to U.S. data for 1926-1989, simulate

the resulting asset-pricing model and estimate the switching regression using the artificial data from the simulations. Results show that there is evidence of regime-switching in the simulated returns and the degree of apparent overvaluation influences expected returns, in spite of the fact that the degree and variability of the apparent market overvaluations are much smaller in the simulations than in the real data. When they examine specific stock market crashes, they find out that the probability of a crash calculated from the model of switching fundamentals fail to rise before the 1929 and 1987 crashes. In conclusion, findings suggest that the two models are complements rather than substitutes. Some crashes (1929 and 1987) fit well to the speculative model, while others are more closely related to the model of switching fundamentals. Van Norden and Vigfusson (1998) try to examine the size and the power of regime-switching tests for bubbles, using simulation methods. These tests appear to be powerful enough to detect bubbles despite the fact that they are conservative because of the size distortion that they show. Hall, Psaradakis and Hola (1999) present the problem of testing for the existence of periodically collapsing rational bubbles in time series. Their paper propose a methodology based on a generalization of the Augmented Dickey Fuller (ADF) unit root test which makes use of the class of dynamic Markov regime-switching models. The methodology is explained with an empirical example: the analysis of the integration properties of three time series, namely monetary base, consumer prices and exchange rate (in terms of US dollar) in Argentina. The data sample consists of 82 monthly observations from January 1983 to November 1989. Using the Markov-switching model they get the following results: an obvious switch to the explosive regime in 1984, which is common in all three series that they study. Thus the 1989 hyperinflation in Argentina can be explained by the rapid growth in money supply. Furthermore, the period June 1988-August 1988 is associated with explosive behavior only in consumer prices which suggests the presence of a rational bubble in consumer prices during that period. Finally, another bubble is present in the exchange rate series in 1984-1985. This bubble collapses with the implementation of a stabilization plan from the ruling party which introduces a price ceiling, a massive one-off increase in the money supply and a fixed parity of the currency relative to the US dollar.

In the last decade, many papers focus on the regime-switching approach. Brooks and Katsaris (2003) make an empirical investigation on rational speculative bubbles. They study the London Stock Exchange and use cointegration techniques that show that the long-run relationship between prices and dividends did not hold in the late 90s. This could be attributed to the appearance of a speculative bubble or it is likely that some non-observable fundamental variables have caused this deviation. Results are not so clear. Brooks and Katsaris (2005) examine whether a three-regime switching model can explain the dynamics of the S&P 500 index. They include a third regime in

which the bubble grows at the fundamental rate of return and they propose that abnormally high volume can be used to measure the probability of a bubble collapse in a more effective way. The sample period covers January 1988 to January 2003. Results show that the speculative behavior model has significant explanatory power for the next month's returns, i.e. if the bubble grows in size, the probability of being in the explosive regime in the next period increases. Additionally, they examine the predictive ability of the bubble models by evaluating the ability of alternative trading strategies to generate excess return over the benchmark strategy based on simulations. The results reveal that the three-regime model can lead to higher Sharpe ratios than the van Norden and Schaller model, the randomly generated trading rules and the buy-and-hold strategy. Their model is very useful to protect investors from downside risk if they are willing to pay the associated transaction costs. In addition, Anderson, Brooks and Katsaris (2005) examine the existence of a periodically collapsing speculative bubble in the S&P index and its constituent sectors, using a regime-switching approach. Their paper employs data on 10 S&P 500 Global Industry Classification Standard (GICS) sector indices. These indices represent the ten major economic sectors of the member firms (Cyclical Services, Financials, Basic Industries, General Industrials, Cyclical Consumer Goods, Information Technology (IT), Non-Cyclical Consumer Goods, Non-Cyclical Services, Resources and Utilities). The sample period covers January 1973 to June 2004. They estimate two speculative behavior models: the model of van Norden and Schaller (1997), the augmented model of Brooks and Katsaris (2005) and five alternative models as well. The results show that IT is not the only bubbly sector. There is a bubble-like behavior in three other sectors, namely Financials, General Industrials and Non-Cyclical Services. Finally, the paper tests the presence of bubble spillovers among sectors and concludes that there is bubble transmission not only from the IT sector but also from other sectors such as Cyclical Consumer Goods and Basic Industries. Thus, there is a bubble-like behavior to more than 70% of the stock market and not only to a small segment of it. Shi and Arora (2011) refer to the existence of a speculative bubble in oil prices using the three-regime model of Brook and Katsaris (2005,BK hereafter), the two-regime model of van Norden and Schaller (2002) and the three-regime variant of van Norden and Schaller (2002,VNS hereafter). VNS and BK can be extended beyond stock markets to include commodity prices and they are also both suitable for oil prices data. The article examines data from January 1985 to December 2010. Test statistics show that VNS and BK do not differ statistically. According to the analysis, the likelihood of being in a bubble collapsing regime rises at the same period that the oil prices decrease (late 2008/early 2009). In addition, the results show that the probability of being in a bubble surviving regime spikes just before or at the same time as the probability of being in a collapsing regime increases. Thus, the bubble did exist for a short time and then it quickly collapsed.

3. a) Calculation of the bubble measure

In this study, we use the term bubble to describe the deviations of the exchange rate from its fundamental value. We can express a speculative bubble by the following equation:

$$\mathbf{b_t = s_t - f_t}$$

where b_t is the speculative bubble, s_t is the spot exchange rate and f_t is the fundamental value. To measure the bubble, we use the Purchasing Power Parity Theory (PPP), which states that the nominal exchange rate and the relative price differential are moving one-to-one, causing the real exchange rate to become stationary. The fundamental price in the PPP theory is defined as $f_t = p_t - p_t^*$, where p_t is the domestic price level, p_t^* is the foreign price level and f_t is measured in units of domestic currency per unit of the foreign currency. In order to test whether the PPP is valid or not, we use the cointegration relation between the log of the nominal exchange rate and the log of the relative prices. We use the residual of this cointegrating relationship, b_t, as a measure of the deviation from fundamental values, i.e., as a measure of the bubble.

b) Estimation methodology

In this section of the paper, we present the econometric model used to identify the presence and the size of a speculative bubble in the foreign exchange markets. We use a two-state regime-switching model. In other words, we assume that the foreign exchange market in each country can be in two different states. The first state is when the bubble appears and begins to grow, while the second one is when the bubble collapses. We estimate eight alternative regime switching models.

1st model: This is the simplest one and assumes that the gross return of the FX market (R_t) can be in two different states. The mean is the same in both states, while the variance differs. The probability of being in the first regime is constant and does not depend on the size of the bubble (b_t). More specifically, the first model can be described by the following equations:

- First regime: $R_{t+1} = c_1 + e_t$, $e_t \sim N(0, \sigma_1^2)$
- Second regime: $R_{t+1} = c_1 + e_t$, $e_t \sim N(0, \sigma_2^2)$
- The probability of being in the first regime: $P = \Phi(q_0)$

where R_{t+1} is the returns from period t to period t+1 and Φ is the cumulative density function of the standard normal distribution.

2nd model: The mean is the same in both states, while the variance changes. The probability of being in the first regime depends on the size of the bubble.

- First regime: $R_{t+1} = c_1 + e_t$, $e_t \sim N(0, \sigma_1^2)$
- Second regime: $R_{t+1} = c_1 + e_t$, $e_t \sim N(0, \sigma_2^2)$
- Probability of being in the first regime: $P_{t+1}=\Phi(q_0 + q_1|bt|)$

3rd model: This is a generalization of the first model. The only thing that changes is that in this model both the mean and the variance of the process differ across regimes. The probability of being in the first regime is constant like in the first model.

- First regime: $R_{t+1} = c_1 + e_t$, $e_t \sim N(0, \sigma_1^2)$
- Second regime: $R_{t+1} = c_2 + e_t$, $e_t \sim N(0, \sigma_2^2)$
- Probability of being in the first regime: $P=\Phi(q_0)$

where $c_1 \neq c_2$.

4th model: It is a generalization of the second model. We have different variance and different mean in the two regimes, while the probability of being in the first regime depends on the size of the bubble.

- First regime: $R_{t+1} = c_1 + e_t$, $e_t \sim N(0, \sigma_1^2)$
- Second regime: $R_{t+1} = c_2 + e_t$, $e_t \sim N(0, \sigma_2^2)$
- Probability of being in the first regime: $P_{t+1}=\Phi(q_0 + q_1|bt|)$

where $c_1 \neq c_2$.

In models 5-8 we include the bubble size to the conditional mean equations as well. So, the bubble does not appear only in the probability function.

5th model: We assume that the conditional mean equations are the same in both regimes. The probability of being in the first regime is constant as in models 1 and 3.

- First regime: $R_{t+1}= c_1 + c_2b_t + e_t$, $e_t \sim N(0,\sigma_1^2)$
- Second regime: $R_{t+1}= c_1 + c_2b_t + e_t$, $e_t \sim N(0,\sigma_2^2)$
- Probability of being in the first regime: $P=\Phi(q_0)$

6th model: We make the assumption that the conditional mean equations are the same in both regimes. The probability of being in the first regime depends on the size of the bubble.

- First regime: $R_{t+1}= c_1 + c_2b_t + e_t$, $e_t\sim N(0,\sigma_1^2)$
- Second regime: $R_{t+1}= c_1 + c_2b_t + e_t$, $e_t\sim N(0,\sigma_2^2)$
- Probability of being in the first regime: $P_{t+1}=\Phi(q_0 + q_1|bt|)$

7th model: In this model we have a different conditional mean specification in the two regimes. The probability of being in the first regime is constant.

- First regime: $R_{t+1}= c_1 + c_2b_t + e_t$, $e_t\sim N(0,\sigma_1^2)$
- Second regime: $R_{t+1}= c_1' + c_2'bt + e_t$, $e_t\sim N(0,\sigma_2^2)$
- Probability of being in the first regime: $P=\Phi(q_0)$

where $c_1\neq c_1'$ and $c_2\neq c_2'$.

8th model: We have a different conditional mean specification in the two regimes. The probability of being in the first regime depends on the size of the bubble.

- First regime: $R_{t+1}= c_1 + c_2b_t + e_t$, $e_t\sim N(0,\sigma_1^2)$
- Second regime: $R_{t+1}= c_1' + c_2'bt + e_t$, $e_t\sim N(0,\sigma_2^2)$
- Probability of being in the first regime: $P_{t+1}=\Phi(q_0 + q_1|bt|)$

where $c_1\neq c_1'$ and $c_2\neq c_2'$.

It is obvious that the 8th model is the most general model among all, while models 1-7 are restricted versions of model 8, i.e., models in which the more complex one can be transformed into the simpler model by imposing a set of constraints on the parameters.

The ex-post probability of each regime for the 8th model is given by the following equations:

- $p_t^{x,1}=\{p_t\phi[(R_{t+1}-c_1-c_2b_t)/\sigma_1]\sigma_1^{-1}\}/A$
- $p_t^{x,2}=\{(1-p_t)\phi[(R_{t+1}-c_1'-c_2'b_t)/\sigma_2]\sigma_2^{-1}\}/A$

where $A=\prod_t\left\{p_t\varphi\left[(R_{t+1}-c_1-c_2b_t)/\sigma_1\right]\sigma_1^{-1}+(1-p_t)\varphi[(R_{t+1}-c_1'-c_2'b_t)/\sigma_2]\sigma_2^{-1}\right\}$ and ϕ is the standard normal probability density function.

4. Data

The data we use for our estimation are taken from the FRED (Federal Reserve Economic Data) database. We examine monthly observations for the CPI (consumer price index) and exchange rates for the following countries: USA, United Kingdom,

Switzerland and Canada. For all the aforementioned countries, we use data from 01-12-1972 to 01-03-2013.

5. Model selection

In this section, we describe the methodology used to select which of the eight alternative models is more suitable for each case that we examine. To choose between two nested models, we use the likelihood-ratio test. Likelihood ratio (or its logarithm) can be used to compute a p-value and decide whether to reject the model under the null hypothesis in favor of the model under the alternative hypothesis. When the logarithm of the likelihood ratio is used, the statistic is known as a log-likelihood ratio statistic. Each of the two competing models, the null model and the alternative model, is separately fitted to the data and the log-likelihood is recorded. The test statistic is defined as:

D = -2ln(likelihood of the null model/likelihood for alternative model)

= -2ln(likelihood for null model) + 2ln(likelihood for alternative model)

The probability distribution of the test statistic is approximately a chi-squared distribution with degrees of freedom equal to df2-df1, where df1 is the number of free parameters of the null model while df2 is the number of free parameters of the alternative model.

We first estimate the eight different models described before for the three different exchange rates we examine. For each case, we need to select the model that fits our data best. We can use the LR-test to choose between model 8 and each one of the seven remaining models since models 1 to 7 are all restricted versions of model 8 but we cannot apply it to models that are not nested.

Tables 1-3 report the log likelihood ratio tests and each one refers to a specific exchange rate. We implement the LR-test to compare 19 different pairs of models to decide which one fits better our data for each case we examine. Tables 4-6 present the estimates of the model we chose after the implementation of the LR-test in each case.

[TABLES 1-3 ABOUT HERE]

Firstly, we compare the general model 8 to each one of the remaining seven models. If LR-test shows that model 8 fits better than all the other models, we choose this model to perform our analysis. Unless model 8 is the most preferable, we implement

the LR-test to choose among the models that appear to be more appropriate for our data.

For example, in the case of Switzerland, LR-test shows that models 2,4,6,7 are better than model 8. Furthermore, LR-test indicates that model 2 is superior to models 4 and 6. We are not able to compare models 2 and 7 because they are not nested models (model 2 is not a restricted version of model 7). Thus, we conclude that both models 2 and 7 are optimal.

[TABLES 4-6 ABOUT HERE]

After the application of LR-test to each exchange rate under scrutiny, we conclude that models 2 and 7 fit best our data for Switzerland, model 4 is the best fitting model for the United Kingdom, while model 1 is the most suitable one in the case of Canada. Tables 4-6 report the estimates of the chosen model for each exchange rate under scrutiny.

6. Empirical Results

We now present the main empirical results of our study. We already know that the most appropriate model for the UK pound/American dollar exchange rate is model 4, for the Canadian dollar/American dollar exchange rate the most suitable model is model 1 and for the Swiss franc/American dollar exchange rate both models 2 and 7 seem appropriate.

- UK pound/US dollar

We apply the log-likelihood ratio test for the GBP/USD currency and we conclude that the best model for our data is the forth one. In order to examine the predictive ability of our model, we use two graphs with the probability of a boom and the probability of a crash. Figure 1, shows the probability of having high positive gross returns, while Figure 2 plots the probability of having a high negative return. The vertical lines highlight the periods with the highest actual positive (Figure 1) and negative (Figure 2) monthly return in the exchange rate.

Figure 1 clearly shows the ability of our model to capture periods of high positive returns in the exchange rate under scrutiny. In all four cases, the estimated probability of a boom increases substantially before the occurrence of an “extreme”

positive movement in the exchange rate. For example, the probability of a boom increases from less than 2% to about 13% just before February 1985 when we observe a significant positive return in the UK pound to US dollar exchange rate. However, we should note that the probability of a boom plotted in Figure 1 has been calculated based on the full-sample estimates of our model. If we want to test whether the estimated probability of a boom has any real predictive power for large movements in the market, we should estimate it in a recursive way using only the available to the investor information in each period.

Figure 2 presents the predictive ability of our model to predict periods when the returns in the exchange rates under scrutiny are highly negative. In most cases, the probability of a crush that we estimated increases before an extreme movement in the exchange rates. As a matter of fact, just before October 1980, when we notice a crucial negative return in the GBP/US dollar exchange rate, the probability of a crash rose from about 1,5% to about 5,5%.

- Canadian dollar/US dollar

According to the log-likelihood ratio test, in the case of the Canadian dollar/ US dollar currency the most appropriate model for our data is the simplest one, i.e. the first model. In model 1, we have two regimes, a low-variance regime and a high-variance regime. We note that model 1 has a constant probability of being in each regime. Therefore, the probability of a boom or a crash is constant as illustrated in Figures 3 and 4.

- Swiss franc/US dollar

Applying the log-likelihood test for the Swiss franc/USD currency, we find that both models two and seven are optimal according to our data. In order to simplify our analysis, we select model seven to perform our analysis. As before, Figure 5 shows the probability of having high positive gross return and Figure 6 highlights the probability of having a high negative return. The vertical lines represent the periods with the maximum positive returns (Figure 5) and the maximum negative returns (Figure 6) in the exchange rates.

Figure 5 clearly shows that in just one case, in the period around 1985, the estimated probability of a boom began to increase just before a significant positive movement in the exchange rates.

Figure 6 presents the estimated probability of a crash. In general, the results indicate that our model could not predict the presence of any negative movement, so its predictive ability is relatively weak.

7. Conclusions

In this paper, we examine three different exchange rate markets, the British pound/ US dollar exchange rate, the Canadian dollar/US dollar exchange rate and the Swiss franc/US dollar exchange rate. Our aim is to examine whether a speculative bubble did occur in these markets, its durance and size, as well as to check if our regime-switching approach has any ability to predict negative or positive episodes of extreme market movement before they really occur. First of all, we provided a definition for the bubble in the two regime-switching model and then we described the eight models used in our study. Afterwards, we applied the log likelihood ratio test in order to find out which of the eight alternative models is more suitable for each case. Our results indicate that in some episodes there was evidence that a bubble appeared, began to grow and then collapsed. Each one had its own size and duration. Finally, in some cases our model managed to capture points of extreme market movements before they happen, so we can assume that our approach has some predictive power over the data examined.

References

Anderson, K., C. Brooks and A. Katsaris, (2010). Speculative bubbles in the S&P 500: Was the tech bubble confined to the tech sector?, *Journal of Empirical Finance* 17 (2010), pp. 345-361

Blanchard, O.J. and M.W. Watson, (1982). Bubbles, Rational Expectations and Financial Markets, *NBER Working Paper Series No. 945*, pp. 1-30

Brooks, C. and A. Katsaris, (2003). Rational Speculative Bubbles: an empirical investigation of the London stock exchange, *Bulletin of Economic Research* 55:4, 0307-3378

Brooks, C. and A. Katsaris, (2005). A three regime model of speculative behavior: modeling the evolution of the S&P 500 composite index*, The economic journal*, 115, pp. 767-797

Evans, G.W., (1991). Pitfalls in testing for explosive bubbles in asset prices, *American Economic Review* 81, pp. 922-930

Flood, R.P. and P.M. Garber, (1980). Market Fundamentals Versus Price-levels Bubbles: the first tests, *Journal of Political Economy* 88, pp. 745-770.

Frankel, A.J. and K.A. Froot, (1990). Chartists, Fundamentalists and Trading in the Foreign Exchange Market, *The American Economic Review, vol.80, No.2, Papers and Proceedings of the Hundred and Second Annual Meeting of the American Economic Association*, pp. 181-185

Hall, S.G., Z. Psaradakis and M. Sola, (1999). Detecting Periodically Collapsing Bubbles: a Markov- Switching unit root test, *Journal of Applied Econometrics* 14, pp. 143-154

Meese, R.A., (1986). Testing for Bubbles in Exchange Markets: A case of Sparkling Rates?, *Journal of Political Economy* 94, pp. 345-373

Schaller, H. and S. van Norden, (1997). Regime switching in stock market returns, *Applied Financial Economics*, 7, pp.177-191

Schaller, H. and S. van Norden, (2002). Fads or bubbles?, *Empirical Economics* 27 (2), pp.335-362

Shi, S. and V. Arora, (2011). An application of models of speculative behavior to oil prices, *Economics Letters* 115 (2012), pp. 469-472

van Norden, S. and H. Schaller, (1993). The predictability of stock markets regime: Evidence from Toronto stock exchange, *Review of Economics and Statistics* 75(3), pp.505-510

van Norden, S., (1996). Regime Switching as a test for Exchange Rate Bubbles, *Journal of Applied Econometrics*, 11, pp. 219-251

van Norden S, and H. Schaller, (1999). Speculative Behavior, Regime-Switching and Stock Market Crashes, *Nonlinear Time Series Analysis of Economic and Financial Data*, pp. 321-56

van Norden, S. and R. Vigfusson, (1998). Avoiding the Pitfalls: Can Regime-Switching Test Reliably Detect Bubbles, *Studies in Nonlinear Dynamics and Econometrics* 3(1), pp. 1-22

West, K.W., (1987). A specification test for speculative bubbles, *Quarterly Journal of Economics*, vol. 102, pp. 553-80

Woo, W.T., (1987). Some Evidence of Speculative Bubbles in the Foreign Exchange Markets*, Journal of Money, Credit and Banking,* vol.19, pp. 499-514

Wu, Y., (1995). Are there rational bubbles in foreign exchange markets? Evidence from an alternative test, *Journal of International Money and Finance*, vol.14, No.1, pp.27-46

Tables and Figures

Table 1: Log likelihood-ratio test for Switzerland

	LR-stat	p-value
{8} vs {1}	20.551	0.000
{8} vs {2}	5.730	0.126
{8} vs {3}	19.716	0.000
{8} vs {4}	5.690	0.058
{8} vs {5}	19.362	0.000
{8} vs {6}	4.526	0.104
{8} vs {7}	1.212	0.271
{7} vs {1}	19.339	0.000
{7} vs {3}	18.504	9.59E-05
{7} vs {5}	18.150	0.000
{6} vs {1}	16.025	0.000
{6} vs {2}	1.204	0.273
{6} vs {5}	14.837	0.000
{5} vs {1}	1.189	0.276
{4} vs {1}	14.861	0.001
{4} vs {2}	0.040	0.842
{4} vs {3}	14.025	0.000
{3} vs {1}	0.835	0.361
{2} vs {1}	14.821	0.000

Table 2: Log likelihood-ratio test for the United Kingdom

	LR-stat	p-value
{8} vs {1}	19.742	0.001
{8} vs {2}	8.054	0.045
{8} vs {3}	16.986	0.001
{8} vs {4}	3.755	0.153
{8} vs {5}	17.576	0.001
{8} vs {6}	5.490	0.064
{8} vs {7}	5.572	0.018
{7} vs {1}	14.170	0.003
{7} vs {3}	11.414	0.003
{7} vs {5}	12.004	0.003
{6} vs {1}	14.252	0.001
{6} vs {2}	2.565	0.109
{6} vs {5}	12.086	0.001
{5} vs {1}	2.166	0.141
{4} vs {1}	15.987	0.000
{4} vs {2}	4.300	0.038
{4} vs {3}	13.231	0.000
{3} vs {1}	2.756	0.097
{2} vs {1}	11.687	0.001

Table 3: Log likelihood-ratio test for Canada

	LR-stat	p-value
{8} vs {1}	3.288	0.511
{8} vs {2}	3.066	0.382
{8} vs {3}	3.146	0.370
{8} vs {4}	2.874	0.238
{8} vs {5}	1.913	0.591
{8} vs {6}	1.677	0.432
{8} vs {7}	0.638	0.424
{7} vs {1}	2.649	0.449
{7} vs {3}	2.508	0.285
{7} vs {5}	1.275	0.529
{6} vs {1}	1.610	0.447
{6} vs {2}	1.388	0.239
{6} vs {5}	0.236	0.627
{5} vs {1}	1.374	0.241
{4} vs {1}	0.414	0.813
{4} vs {2}	0.192	0.662
{4} vs {3}	0.272	0.602
{3} vs {1}	0.142	0.707
{2} vs {1}	0.222	0.638

Table 4: Estimates for model 7 for Switzerland

	Coefficient	**Std. Error**
c_1	0.998	0.002
c_2	0.028	0.014
c_1'	0.998	0.006
c_2'	-0.169	0.055
σ_1	0.025	0.002
σ_2	0.030	0.006
q_0	0.810	0.343

Log likelihood	1034.205

Table 5: Estimates for model 4 for the United Kingdom

	Coefficient	**Std. Error**
c_1	0.999	0.001
c_2	1.010	0.007
σ_1	0.019	0.001
σ_2	0.037	0.004
q_0	1.513	0.441
q_1	-6.984	2.411

Log likelihood	1127.629

Table 6: of Estimates for model 1 for Canada

	Coefficient	**Std. Error**
c_1	1.000	0.001
σ_1	0.012	0.001
σ_2	0.046	0.010
q_0	1.937	0.246

Log likelihood	1408.628

Figure 1: Probability of a boom (full-sample estimation) based on model 4 for the GBP/USD exchange rate

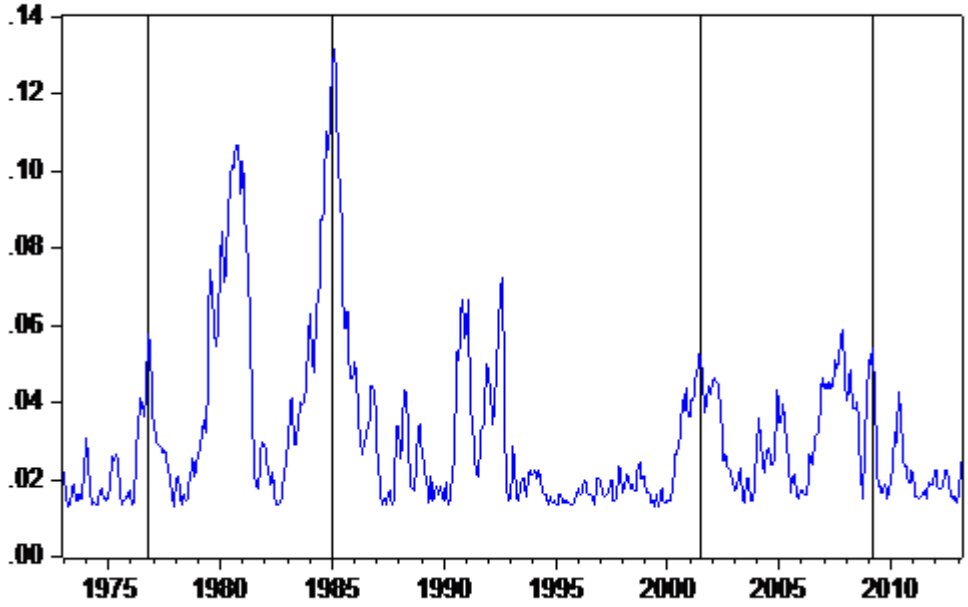

Figure 2: Probability of a crash (full-sample estimation) based on model 4 for the GBP/USD exchange rate

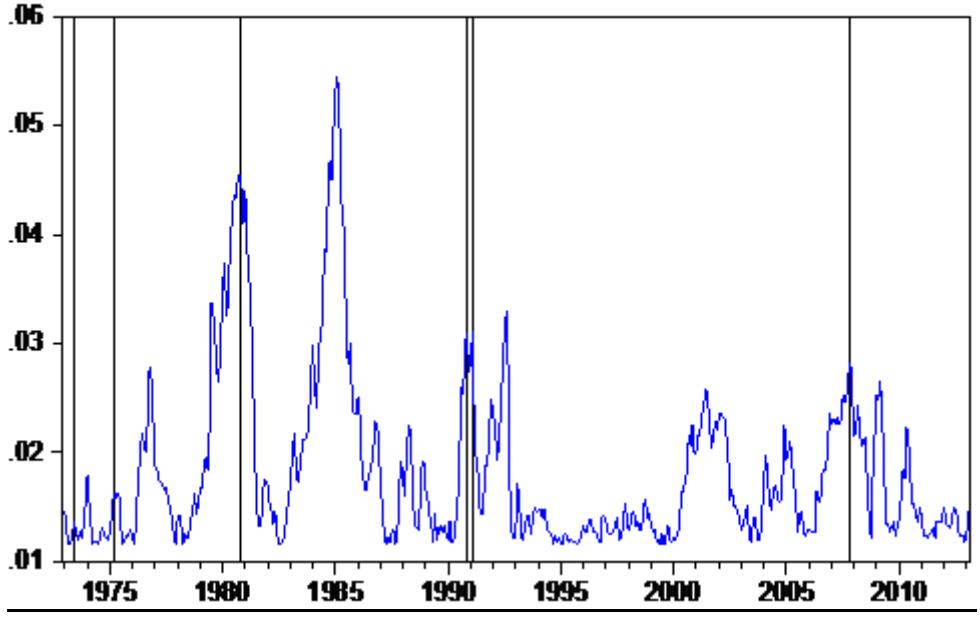

Figure 3: Probability of a boom (full-sample estimation) based on model 1 for the Canadian dollar/USD exchange rate

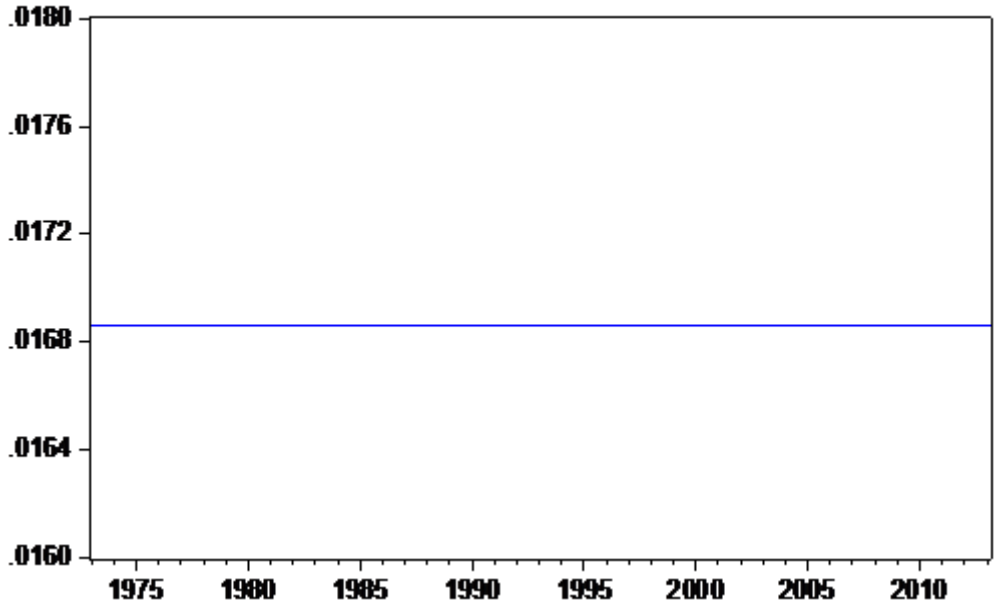

Figure 4: Probability of a crash (full-sample estimation) based on model 1 for the Canadian dollar/USD exchange rate

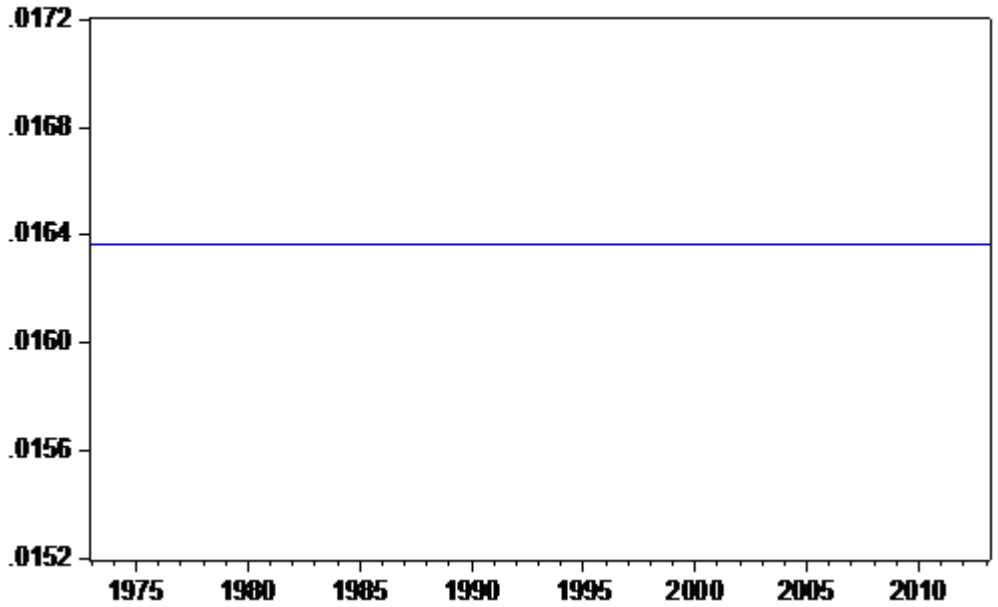

Figure 5: Probability of a boom (full-sample estimation) based on model 7 for the Swiss franc/USD exchange rate

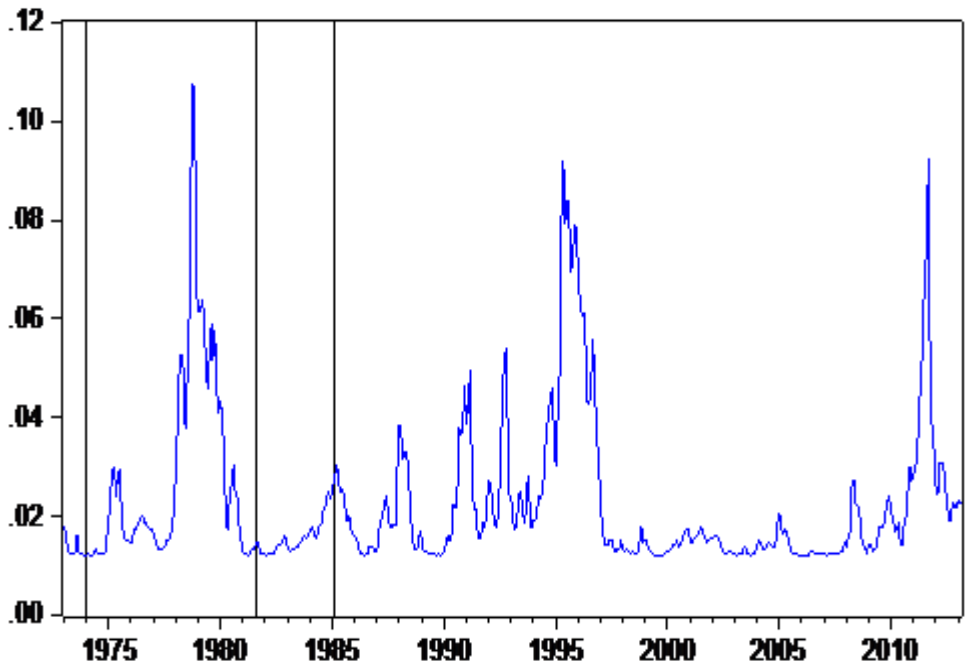

Figure 6: Probability of a crash (full-sample estimation) based on model 7 for the Swiss franc/USD exchange rate