ABSTRACT

ZERO LOWER BOUND AND UNCOVERED INTEREST PARITY – A FORECASTING PERSPECTIVE

by Yifei Zhang

Abstract: In recent years, close to zero nominal interest rate becomes a norm in several developed economies. This paper is concerned with how extremely low interest rates or Zero Lower Bound (ZLB) affects the Uncovered Interest Rate Parity (UIP). Using exchange rate data and interest rates with different terms for U.S. Dollar, British Pound, Euro, Japanese Yen, and Swiss Franc, I am able to statistically reject UIP in all cases based on in-sample fitting. Besides, I find the estimated coefficient of the one-month interest differential becomes much more volatile as the interest rate gets closer to ZLB, while this change in volatility is less obvious when longer term interest rates are used in the regression. Finally, I consider for methods related to UIP in order to forecast the future exchange rate, and for each method, I compute the out-of-sample mean squared prediction errors. I find that using the interest rate differential generally does not improve the forecast, meaning that UIP can be viewed unfavorably from the forecasting perspective.

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1. Introduction

As one of the most important theories in international finance, Uncovered Interest Rate Parity (UIP) builds upon the idea that any investor in the foreign exchange market has options to choose to hold their assets in two forms: either to hold domestic currency asset with the return of current domestic interest rate (i), or foreign currency asset with return of the foreign interest rate (i^*). The goal of rational and risk-neutral investors is to pursue the highest return, but they also take into account the expected change in the exchange rate (denoted by $S_{t+k} - S_t$). If it turns out that the return of one asset is higher than the other after transaction cost and the change in exchange rate has been accounted for, then the investor can make risk-free profits, and so the market is not in equilibrium. Thus, when the market equilibrates, the foreign and domestic investments must offer the same returns. More explicitly, the so-called no arbitrage condition must hold as follows: $1 + i_{t,k} = \frac{S_{t+k}}{S_t}(1 + i^*_{t,k})$, where S_t is the spot exchange rate of time t, $i_{t,k}$ is the domestic interest rate, $i^*_{t,k}$ is the foreign interest rate, and k is the duration of the investment (e.g., the maturity of a bond). After taking the log and algebra rearrangement, we get $\log S_{t+k} - \log S_t = i_t - i^*_t$, which is the famous uncovered interest parity (UIP). It is referred to as "uncovered" since no forward contract is involved in the transaction.

The theory of UIP implies that the difference between two countries' interest rates is roughly equal to the expected change in spot exchange rates between these two countries, under the condition that all arbitrage opportunities have been exhausted. In theory, the country with the higher interest rate is expected to experience depreciation in its currency equal to the interest differential. Therefore, the UIP implies that interest rate differential can be used as a predictor for the future exchange rate.

In addition to provide forecasting guidance for the exchange rate, the UIP typically is an important component for a dynamic multi-period open-macroeconomic model. Based on those models a government can decide how to intervene in the foreign exchange market or implement certain policy to manage the open economy. Because of these reasons, UIP is the focus of many empirical studies.

Most empirical researches test UIP using an in-sample fitting approach. However, not much research has been done to reflect the fact that short-term interest rates in some developed economies have hit the zero lower bound (ZLB) in recent years. This paper distinguishes itself by making two contributions to the literature---first, I consider how the zero lower bound in interest rate affects UIP, using the interest rate of U.S. dollar, Japanese yen, British pound, European euro and Swiss franc. Traditionally, the UIP makes an implicit assumption of non-zero interest rate. According to the UIP, the exchange rate would remain fixed in the presence of zero interest rate differential. This paper attempts to examine how UIP fares in the latest ZLB setting.

Second, we focus on out-of-sample forecasting to verify the validity of UIP, from an alternative perspective that matters more for practitioners. In some sense, a theory can be deemed as less useful if the predictor implied by the theory in fact does not own much forecasting power. Thus, we want to subject the UIP to the ultimate forecasting test and see, in particular, whether using the interest rate differential can lead to superior forecast for the exchange rate.

The rest of the paper orders as the following: section 2 provides a series of relevant literature; section 3 explains the methodology used also presents the results and the last section concludes.

2. Literature Review

The empirical literature on testing UIP is vast, with the majority of studies rejecting the UIP. A standard test is based on a regression of change in exchange rate onto the interest rate differential and tests whether the slope coefficient of the interest rate differential is equal to unity. Most often a puzzling result is found that the estimated slope coefficient is significantly different from one, in some cases even being negative.

Also, the empirical findings can be sensitive to the methodologies used. Fama (1984) is one of the early studies that reject UIP. Using the spot exchange rate and thirty-day forward rate from nine currencies, Fama shows that the interest differentials and future spot exchange rate are negatively correlated, which is the exact opposite of what the theory would suggest. Since Fama, a lot of studies have been done to test UIP from various angles and try to build theoretical models to explain the “UIP Puzzle”.

Huisman, Koedijk, Kool, and Nissen (1998) found that the rejection of UIP is not as severe as other studies indicate by taking a panel-data approach, with the inclusion of random time effect accounting for unobserved confounding factors. This approach resolves issues such as small sample, market inefficiencies, etc. This panel-data approach yields a slope coefficient around 0.5 which is significantly different from one, but at least the positive sign is consistent with UIP. They then categorized observations into normal and abnormal ones using the average size of the forward premium over exchange rates. They found more support for UIP if only using the observations with substantial forward premium.

Baillie and Bollerslev (2000) stated that the anomaly in forwarding premium could be viewed as a statistical phenomenon which occurs because of the highly persistent autocorrelation in forwarding premium. They designed a modified UIP model to be consistent with the stylized time series properties of spot and forward exchange rates. In their model, the exchange rate is approximated by a martingale difference process with highly persistent volatility. The results of their simulations are consistent with what had been reported in other literature. To summarize their findings, the forward premium has very strong positive autocorrelation, resulting in extremely large variance of the slope coefficient and an imprecise estimate. The combination of small sample sizes and protracted memory of forwarding premium makes the rejection of hypothesis (the forward rate being an unbiased predictor of the future spot rate) in conventional "anomalous” regression very unlikely.

Chabound and Wright (2003) ran UIP regression over very short time intervals (e.g., from 16:30 – 21:00) and found that UIP hypothesis only holds over very short windows. In particular, they focused on special overnight periods during when interest rates did accrue and argue that intraday UIP regression over a short time span is more suitable for identifying the effect of the interest differential since the premium risk presumably varies little in such short period. In other words, exanimating UIP regression over short time intervals helps to isolate the changes in exchanges rate that were purely caused by change in interest differentials. They found that the slope coefficient of UIP regression is close to unity over the daily horizon. However, they found when the time span increases over the daily horizon, and they are able to reject UIP. This rejection may be due to the presence of a risk premium.

Baillie and Kilic (2006) attempted to explain the forward premium anomaly by accounting for asymmetries and nonlinearities in the time series data. They estimated Logistic Smooth Transition Dynamic Regression models and found the existence of two major regimes (defined in terms of closeness to the theoretical boundaries of one and zero), where the inner regime is consistent with the forward premium anomaly while the outer regimen is consistent with Uncovered Interest Parity. However, the estimated transition function is not statistically significant due to some estimation issues, which leads to imprecise definitions of the regime. Their work does not resolve the anomaly yet places a critical forwarding step in the path of unraveling this anomaly.

Bacchetta and Wincoop (2010) attempted to explain the UIP puzzle by constructing a two-country model where agents make infrequent portfolio decisions. Their model can explain not just UIP, but some related empirical findings such as delayed overshooting. With the assumption of infrequent portfolio decisions, agents will continue to purchase currency with rising interest rate, which leads to an appreciation of the currency. This explains why increases in excess return are normally associated with high interest rates. Infrequent portfolio decisions can also explain the phenomenon of delayed overshooting which states that interest rate shocks have a delayed impact on exchange rates. They found the large magnitude of excess return can lead to predictability for delayed overshooting, yet this magnitude declines over time.

2.1 UIP and ZLB

Extremely low interest rate started to catch people's attention since the Great Recession started in 2008. The U.S. Federal Reserve has conducted an unusual expansionary monetary policy called quantitative easing, which brings down the short-term interest rate close to zero. This phenomenon is often referred to as the Zero Lower Bound (ZLB). Although it might seem obvious that the Theory of UIP implicitly rules out the case of ZLB, it is still interesting to investigate how zero lower bound statistically affects UIP. Moreover, it would also be interesting to differentiate between different terms of interest rates since empirical data often suggests less rejection when the term gets large (Chinn & Zhang, 2018).

Chinn and Zhang (2018) investigated the behavior of the UIP near and far from the ZLB by proposing a standard New Keynesian DSGE model, and find that monetary policy rule can induce the positive correlation between depreciation and interest differentials at long horizons. Their results explain two empirical findings in international finance. First, interest differentials for longer term interest rates tend to positively correlate with exchange rate depreciation, and the opposite result is found for shorter term interest rates. Second, as a currency experiences an extended period of low interest rates, the rejection rate for UIP tends to increase, even for longer term interest rates.

3. Methodology

3.1 Data

London Interbank Offered Rate (LIBOR), the average interest rate applied to banks when borrowing sizable amounts from each other in the London market, is used here as the reference rate for interest rates for U.S. dollar, European euro, British pound, Japanese yen, and Swiss franc. All of the data is downloaded from the website of Federal Reserve Bank of St. Louis.

In order to compare various time horizons, one-month, three-month, six-month, and 12-month interest rates are obtained for each currency. For dollar, pound, and yen, the dataset contains monthly data from January 1986 to April 2018, a total of 388 observations. Monthly data for euro is available starting January 1989 to April 2018, and data for Swiss franc is available starting January 1999 to April 2018. Therefore, a total of 232 and 352 observations are contained for pound and Swiss franc, respectively. Table 1 presents the descriptive statistics for interest rates across four-time horizons for each of the currencies, along with the monthly spot exchange rates for each currency against US dollar.

From Table 1 we can see that all five countries have experienced close to zero or even negative nominal interest rates, and surprisingly, there is no big difference between the means of one-month and 12-month interest rates. Before fitting any regressions, it would be interesting to plot the raw time series of the interest rates and exchange rates over time, which is shown in Figure 1. We can see that exchange rates series are much more volatile relative to the interest rate differentials[1]. According to UIP, we would see almost close to perfect co-movement between exchange rate and interest rate differential, yet instead, the finding from Figure 1 somehow gives us the idea that the real world does not function as the UIP theory suggests.

3.2 In Sample Fitting—Whole Sample & Subsample

UIP implies that the interest rate differential is a predictor for the future change in exchange rate, with the coefficient of being one under the no-arbitrage condition. To test for that implication, I first regress the difference in the spot exchange rates on the interest differential as shown below,

$$s_{t+k} - s_t = \alpha + \beta(i_t - i_t^*) + \varepsilon_{t+k} \tag{1}$$

where i_t is the LIBOR for dollar, i_t^* is LIBOR for pound, euro, yen and Swiss franc, s_t is the log spot exchange rate denominated as foreign currency per one US dollar, s_{t+k} is the future k-period (k=one-month, three-month, six-month and twelve-month) exchange rate, and ε_{t+k} is assumed to be the random error term capturing unobserved factors such as risk premium, home-country premium, etc. If the realized change of the spot rate is just the interest differential plus a random error term, β is supposed to be unity. The OLS regression results based on the whole sample are reported in Table 2.

Noting that most of the estimated βs in Table 2 are negative, which is consistent with existing literature. There is not a single case that matches with the theory of UIP. As the time horizon increases, the coefficient estimates on the interest differentials become statistically more significant, except for the case of pound. Furthermore, compared to euro and pound, the rejection of the null hypothesis $H_0{:}\,\beta = 0$ is more evident given the t-statistic. This may be due to the fact that Japanese yen and Swiss franc are the two currencies experiencing a much more extended period of extremely low interest rate than the other two currencies. This finding confirms the empirical phenomenon mentioned by Chinn and Zhang (2018) that the rejection rate of UIP tends to rise for currencies experiencing longer periods of low interest rates.

[1] Figure 1. only plots one-month interest rate against the exchange rate. The plots for 3, 6, and 12-month interest rate look very similar to what is shown in Figure 1. Since the plot for 1-month is enough to demonstrate the author's point, the rest of the plots are not included in Appendix.

Next, I test the UIP implication $H_0: \beta = 1$ for the entire sample, and I am able to strongly reject[2] the null hypothesis for all four foreign currencies and for all four time-horizons. This step may seem somewhat redundant, but it further confirms that the theory of UIP is far from being supported by the real data. I extend the test further by restricting my sample purely to the "low nominal interest rate era", which is from January 2009 to April 2018. The subsample contains a total of 112 observations. During this period, all the selected currencies experienced very low nominal interest rates. The same regression has been applied to the subsample, and the results are presented in Table 3. It is interesting to note that most of the estimated β become positive, and the negative ones are statistically indifferent from zero. Moreover, the only βs that are statistically significant are the ones on euro. Once again, I can strongly reject the null that $\beta = 1$. Compare to the entire sample, these subsample results suggest that when interest rate becomes closer and closer to zero, it plays a less significant role in determining the future exchange rate, much less than what the UIP theory suggests. To sum up, I am able to duplicate the UIP puzzle in the literature – empirical data often suggests β be statistically significantly different from unity, many times even be negative.

3.3 Rolling Regression – How β changes

We have shown that using the whole sample, the estimated β is statistically significantly different from 1. Nevertheless, we do not know how stable β is throughout the period. Therefore, in order to examine the potential structural changes in estimated βs overtime, I run rolling regression for each currency across four time-horizons. The rolling regressions are fitted over partially overlapping windows of 60 observations, each time the windows moving one month forward. Figure 2A plots the time-evolving estimated β for each currency at given time horizon.

At first glance, it is obvious that βs using one-month interest rate have experienced substantial volatility since 2008, while the variation was mostly close to zero prior to that. Even though changes for euro is more modest, β still is more volatile after 2008 compared to before 2008. Except the change in variation, there is no other pattern observed for the directions of the change. With that being said, if the major difference pre and post 2008 is ZLB, it is puzzling that βs for

[2] P-values are all extremely close to zero.

yen and Swiss franc only has started to become more volatile since 2008, given the fact that these two currencies have experienced close to zero interest rate as early as 2002.

As we increase the time horizon, the year 2008 becomes less of a clear threshold for changes in β. We can still tell the difference pre and post 2008 for pound and yen, yet it becomes hard to conclude that β is volatile only after 2008 for euro and Swiss franc. This result is interesting because euro and Swiss franc are the two currencies that experience negative interest rates for the 12-month horizon. Although we cannot conclude the correlation between negative interest rate and movements in β based on this result, negative interest rate may become something to pay attention to for research in the future.

To see how statistically significant these βs are, Figure 2B plots the t-statistics of estimated β. All of the βs are extremely significant. Overall, we can draw the conclusion that the use of short-term interest rates worsens the effectiveness of UIP, especially for short-term interest rates like one-month and three-month. As the interest rate term gets longer, the effect of low interest rate mitigates. Although UIP is still puzzling, the movements of β of longer term interest rates are less likely to be caused by close to zero interest rates.

3.4 Out-of-sample Forecasting: Mean Squared Prediction Errors

To our best knowledge, most of the empirical literature on testing UIP center on in-sample fitting. For practitioners, however, what matters more may be forecasting the exchange rates based on theories such as UIP, with forecasts being used for purposes including speculation and hedging. Thus, in this section, I compare the forecasting errors for several different methods and see if the UIP outperforms other methods.

The ranking criterion used here is the mean squared prediction error (MSPE), computed in the pseudo out-of-sample sense. More specifically, I select a subsample of data containing 60 observations, estimate the statistical model using the 60 observations if necessary, and compute the forecasting value for the (out-of-sample) k-step ahead observation. This process is repeated as I ran the rolling regression before---each time I move one month forward and redo all steps. In the end, I am able to obtain a series of forecasting errors (the differences between the forecasts and actual values), and the average of the squared forecasting error is computed as MSPE.

The first method is naïve by simply using the current exchange rate as the forecast for future exchange rate:

$$\hat{s}_{t+k} = s_t \tag{2}$$

$k = 1, 3, 6, 12$. Therefore, the MSPE for this method is $E[(s_{t+k} - \hat{s}_{t+k})^2] = E[(s_{t+k} - s_t)^2]$. This method is commonly used as the comparing benchmark thanks to its simplicity. Actually, this method is the optimal one if the exchange rate follows a random walk process.

The second way to forecast future exchange rate is to use current exchange rate plus the interest rate differential:

$$\hat{s}_{t+k} = s_t + \left(i_{t,k} - i^*_{t,k}\right) \tag{3}$$

This method is the direct application of UIP imposing the restriction that $\beta = 1$. If UIP holds, we expect superior forecasts generated by this method.

The third method entails running the UIP regression (1). That means I am not restricting the value of β to be 1, instead, I let it be determined by data. Mathematically,

$$\hat{s}_{t+k} = s_t + \hat{\beta}\left(i_{t,k} - i^*_{t,k}\right) \tag{4}$$

Lastly, I add the estimated intercept term to the forecasting value:

$$\hat{s}_{t+k} = s_t + \hat{\alpha} + \hat{\beta}\left(i_{t,k} - i^*_{t,k}\right) \tag{5}$$

With the inclusion of the intercept term, change in exchange rates can be nonzero even if the interest differential is zero. Figure 3 provides the comparison of forecasting errors using method

1, 3, and 4. Method 2, the direct application of the UIP, is excluded from the comparison because this method produces a much bigger forecasting error than the other three methods[3].

Figure 3 is the comparison between forecasting errors using method 1, 3, and 4 for each currency and for four time horizons. Method 1 is shown in green, method 3 is in red and method 4 is in black. As expected, the forecasting errors become larger as the time horizons increases since there are more uncertainties futher out in the future. Looking at the comparison using one-month interest rate, it is hard to tell which method outperforms the others, since all three line is overlapping each other. As the time horizon increases, however, it becomes more obvious that the forecasting errors from method 1 stay relatively close to zero, while the forecasting errors for the other two methods become more noticeable.

To confirm the fact that method 1 produces the lowest forecast, I implement the paired two sample t-test for methods 1&3, methods 1&4, and methods 3&4. Testing results for other pairs are similar, so unreported here. The null hypothesis is that the average squared forecasting errors from two methods are equal. Table 3 presents the t-statistics.

All of the t-stats are negative, indicating that method 1 gives the smallest forecasting error and method 4 gives the largest forecasting error. In addition, even though all of the t-statistics are statistically significant at 1% level, its magnitude increases as the time horizon k increases. This makes sense since it is always harder to predict farther into the future. By just looking at this result, method 1 may seem to be the best way to forecast future exchange rates while method 3 is slightly better than method 4. But is this really the case? Something to pay attention to here is the fact that all of these forecasts are performed on currencies that have experienced a long period of close to zero interest rates. Therefore, method 1 provides the lowest forecasting errors may not be due to the fact that this method is superior to any other method, but because of the low level of the interest rates.

[3] With the inclusion of Method 2, the plots for forecasting errors from method 1, 3, and 4 become straight lines, making it impossible to distinguish between the three methods.

To review these forecasting errors in the statistical sense, I perform a simple t-test with the null hypothesis is that all of the average forecasting errors are equal to zero. It is obvious that forecasting errors are nowhere near to zero, but we use the result to see if one method outperforms the others with forecasting errors statistically closer to zero. The results are presented in Table 4. We can see from the results, although method 1 gives the smallest forecasting error, it is not necessarily the one that is statistically the closest to zero. For example, for Japanese yen, method 4 provides a forecast that is much closest to zero statistically than method 1. In general, method 2 has the largest t-statistics for all currencies except for pound, and the forecasts become less accurate as the time horizon increases.

Next, I apply the same test to the subgroup, which the data is removed from the analysis from January 2008 to April 2018, and the results are very similar. The only difference between the subgroup and the whole sample is that the t-statistics are generally lower than t-statistics from the entire sample, although the forecasting errors are still significantly different from zero for the subgroup. This t-test might not be able to provide any significant results, but at least, we know that it is hard to conclude one method is better than another. Each method performs differently for different currencies. Overall, the forecasting errors are pretty large, including the forecasts made using UIP.

4. Extensions

4.1 Plotting α

In some researches, the intercept term, or α, is often seen as the term that captures the omitted variable bias caused by the risk premium. A statistically significant α indicates risk premium is an important confounding factor that can affect the test of UIP. According to my previous findings, β becomes more volatile in the presence of the zero lower bound, meaning less support for UIP when interest rate becomes close to zero (at least for short term rates). This decreases in effectiveness in UIP may be due to the changes in risk premium, that is, risk premium may become more relevant when interest rates are close to zero. To see how risk premium changes over time, I run the same rolling regression and plot α. I also plot the t-statistics for each of the α. The results are presented in Figure 4A & 4B.

From the plots, we can see that α stays relatively close to zero for one-month interest rates for all four currencies, and it becomes more and more volatile as the time horizon increases. This is expected because risk premium is more critical for long-term investments. Compared to the β plots, we see a very drastic change in β after 2008 only for the short term interest rates. This gives us a hint that interest rates becoming close to zero does affect the effectiveness of UIP. This influence becomes less visible for longer term rates due to the unneglected risk premium.

4.2 Using Window of 72

Rolling regression is quite useful in terms of giving an overview of changes in certain variables, yet the results can be sensitive to the window size. To ensure the robustness of my results, I run rolling regression on the same data, but change the window size from 60 to 72. The results for the new rolling regression are presented in Figure 5. Compared to Figure 2 (the window size is 60), we don't see a big difference between the plots. Regardless of the window size, β becomes more volatile since 2008 for the one-month interest rates. Again, 2008 becomes a less obvious threshold as the time horizon increases.

4.3 Using Weekly Data

One may argue that for forecasting, the low-frequency monthly data are not useful. Thus, I compare across four forecasting methods using the relative higher-frequency weekly data. Figure 6. plots the forecasting errors produced by method 1, 3, & 4. Method 1 is in green, method 3 is in red, and method 4 is in black. Again, method 2 is omitted in this plot because of the large forecasting error it produced. From the plot, forecasting errors produced by each method are very similar for shorter terms. As the time horizon increases, the difference between the methods becomes more obvious. Again, similar to the monthly data, method 4 produces the largest forecasting error, and method 1 produces the smallest. This is consistent with the result when monthly data are used. One thing worth to point out is that for weekly data, the forecasting errors are the biggest during the zero lower bond period, which is the opposite of the result when using the monthly data. In addition to the plot, I preform a t-test for all of the currencies across all periods, with the null hypothesis being average squared forecasting errors are zero. The t-statistics are presented in Table 6. Compare to Table 5., which shows the t-statistics for the same null using monthly data, we can see that most of the t-statistics have increased a lot, and some even doubled in magnitude. This indicates that all four methods are rejected more strongly as the frequency of the data increases. Again, no particular method dominates, and one method may work best for one currency but not for the others. In general, when the frequency of data increases, UIP is rejected more strongly.

4.4 Using Euro as the Base Currency

The last robustness check I did is to change my base currency from dollar to euro, and see if the forecast improves. To compare to the original forecasting results, I did this using the original dataset, for which the frequency is month. The plot for the forecasting errors are shown in Figure 7. Again, plot for method 2 is omitted due to extremely large forecasting errors. Compare Figure 7. to Figure 3., there is not much difference between the two. The takeaways are quite similar: forecasting errors overlap each other for one-month interest rates; method 3 & 4 produces larger forecasting errors as the time horizon increases; and the forecasting errors produced by method 1 stay close to zero graphically. Again, I test how far away these forecasting errors are from zero, and the t-statistics are presented in Table 7. Compared to Table 5, the t-statistics are mostly smaller, although all of them are still significantly different from zero at the one percent level. In addition, as we find previously, there is no dominating forecasting method.

5. Conclusion

There are many empirical studies testing the validity of UIP and often find rejections. One limitation is that those studies fail to account for the recent phenomenon of zero lower bound. In contrast, this paper examines the performance of UIP under the condition of close to zero nominal interest rates. The results show that the UIP puzzle becomes more puzzling in the setting of low or negative interest rates. As shown by the rolling regression, variation in the estimated β coefficient of interest differentials becomes much more substantial starting the year 2008, when close to zero interest rates become wide-spread among some developed economies.

After showing the theory of UIP does not align with the in-sample fitting, I redirect focus to out-of-sample forecasting and compute the mean squared prediction error using four different methods, in order to see if UIP can lead to superior forecasts relative to other methods. I find that no method can dominate – one method can provide best forecasts for one currency, but not all the currencies. Moreover, all of the forecasted results are quite far from the actual values. Most importantly, the forecasts obtained from UIP tend to perform worst. Therefore, at least from an out-of-sample forecasting perspective, uncovered interest parity is once again rejected by the data.

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Appendix

Table 1: Descriptive Statistics (in percentage except exchange rates)

	Symbol	Term	Statistics			
			Mean	Std. Dev.	Minimum	Maximum
U.S. Dollar	USD	1-month	3.69	2.79	0.15	10.09
		3-month	3.80	2.76	0.23	10.30
		6-month	3.92	2.71	0.32	10.59
		12-month	4.15	2.69	0.54	10.90
British Pound	GBP	1-month	5.36	4.08	0.25	15.13
		3-month	5.46	4.05	0.28	15.32
		6-month	5.53	3.96	0.41	15.51
		12-month	5.68	3.82	0.60	15.73
European Euro	EUR	1-month	1.79	1.71	-0.41	4.94
		3-month	1.91	1.72	-0.38	5.11
		6-month	2.01	1.69	-0.33	5.21
		12-month	2.17	1.67	-0.26	5.39
Japanese Yen	JPY	1-month	1.56	2.31	-0.08	8.53
		3-month	1.60	2.29	-0.06	8.40
		6-month	1.63	2.25	-0.03	8.61
		12-month	1.71	2.21	0.06	8.78
Swiss Franc	CHF	1-month	2.14	2.77	-0.91	9.73
		3-month	2.21	2.76	-0.89	9.60
		6-month	2.26	2.71	-0.77	9.60
		12-month	2.38	2.61	-0.67	9.53
Dollar/Pound	EXUSUK		1.62	0.17	1.23	2.07
Dollar/Euro	EXUSEU		1.21	0.17	0.85	1.58
Dollar/Yen	EXUSJP		0.00895	0.00153	0.005	0.0135
Dollar/Franc	EXUSSZ		0.811	0.170	0.484	1.282

Table 2. Estimated Beta Coefficient Using Whole Sample (January 1986 – April 2018)

	1-month	3-month	6-month	12-month
GBP	-.0001064	.000011	.0009128	-.0000809
	(.0005992)	(.001240)	(.001901)	(.002729)
EUR	-.001165	-.001979	-.002813	-.009223*
	(.001231)	(.002495)	(.003746)	(.005559)
JPY	-.0009483	-.002738**	-.006111***	-.01245***
	(.0006253)	(.001323)	(.001936)	(.002672)
CHF	-.001141*	-.002704**	-.004358**	-.008187***
	(.000687)	(.001366)	(.001985)	(.002900)

Notes: numbers in parentheses are standard errors. *** p-value < 1%, ** p-value < 5%, and * p-value < 10 %.

Table 3. Estimated Beta Coefficient Using Subsample (January 2009 – April 2018)

	1-month	3-month	6-month	12-month
GBP	.004080 (.004278)	.006563 (.008189)	.01160 (.01241)	.02471 (.01657)
EUR	.003969 (.002672)	.01069** (.005363)	.02383*** (.007913)	.04326*** (0.1071)
JPY	.006831 (.005173)	.014553 (.011235)	.01713 (.01673)	.03630 (.02663)
CHF	-.001454 (.003272)	.0001147 (.005127)	-.0006373 (.009179)	-.0007491 (.01312)

Notes: numbers in parentheses are standard errors. *** p-value < 1%, ** p-value < 5%, and * p-value < 10 %.

Table 4: Two-Sample T-test – Null Hypothesis: Average Squared Forecasting Errors are the Same for the Given Two Methods (Base Currency: Dollar)

	Time Horizon	t-statistics		
		Methods 1=3	Methods 1=4	Methods 3=4
British Pound	1-month	-2.49	-2.97	-2.89
	3-month	-4.74	-6.89	-8.40
	6-month	-6.65	-10.23	-12.38
	12-month	-8.19	-11.87	-16.14
European Euro	1-month	-3.05	-2.71	-1.38
	3-month	-4.40	-4.85	-4.25
	6-month	-6.37	-7.35	-6.52
	12-month	-5.91	-7.12	-7.28
Japanese Yen	1-month	-3.03	-3.10	-3.08
	3-month	-5.68	-5.44	-5.17
	6-month	-9.08	-9.57	-9.31
	12-month	-10.79	-11.15	-10.94
Swiss Franc	1-month	-2.99	-3.89	-4.18
	3-month	-4.92	-5.84	-6.04
	6-month	-7.72	-8.29	-7.85
	12-month	-9.08	-9.54	-9.07

Table 5: One-Sample T-test – Null Hypothesis: Average Squared Forecasting Errors are Zero (Monthly data: Dollar is the base currency)

	Time Horizon	t-statistics			
		Method 1	Method 2	Method 3	Method 4
British Pound	1-month	11.05	8.47	10.16	10.11
	3-month	9.34	8.57	8.65	9.57
	6-month	7.95	8.66	8.83	11.78
	12-month	9.41	8.89	9.50	12.75
European Euro	1-month	7.96	10.25	8.48	8.84
	3-month	9.17	10.52	8.86	8.98
	6-month	8.57	10.85	9.16	10.03
	12-month	8.83	10.46	7.60	8.23
Japanese Yen	1-month	12.01	14.15	7.59	5.03
	3-month	11.81	14.51	8.19	6.41
	6-month	10.99	14.65	10.62	10.21
	12-month	11.63	14.87	11.37	11.35
Swiss Franc	1-month	8.18	14.16	8.72	9.54
	3-month	10.18	14.37	10.88	9.26
	6-month	9.74	14.69	10.60	9.31
	12-month	9.59	14.85	10.73	9.98

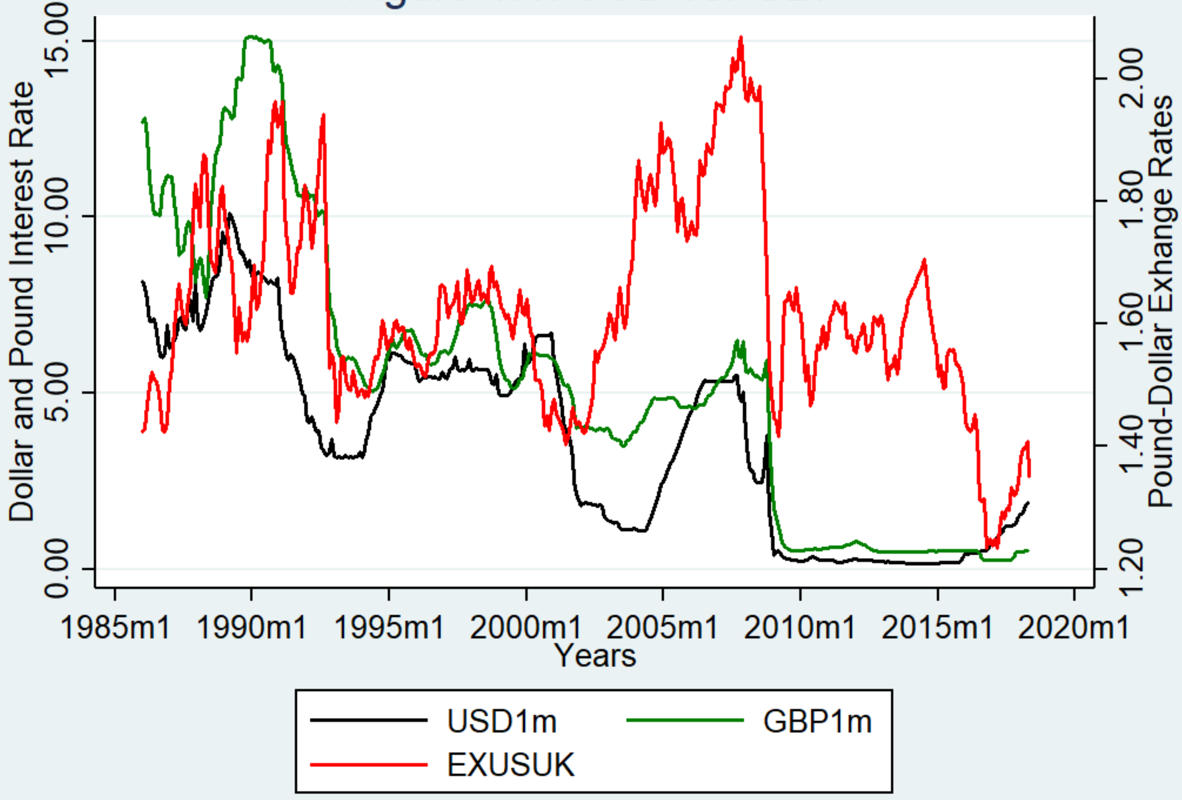
Table 6: One-Sample T-test – Null Hypothesis: Average Squared Forecasting Errors are Zero (Weekly data, Dollar is the base currency)

	Time Horizon	t-statistics			
		Method 1	Method 2	Method 3	Method 4
British Pound	1-month	10.31	20.18	14.16	12.03
	3-month	18.83	20.29	15.83	12.66
	6-month	15.05	20.44	14.67	12.34
	12-month	13.61	20.74	13.99	13.10
European Euro	1-month	19.31	27.28	20.58	19.65
	3-month	18.56	27.44	18.34	15.00
	6-month	18.14	27.81	15.26	14.18
	12-month	19.06	27.04	11.15	11.06
Japanese Yen	1-month	12.75	18.99	14.43	16.60
	3-month	15.71	19.28	16.24	15.37
	6-month	18.92	19.69	13.95	14.61
	12-month	17.13	20.29	10.90	10.98
Swiss Franc	1-month	7.38	21.03	4.27	5.37
	3-month	9.16	21.71	8.89	10.06
	6-month	8.28	22.78	12.76	12.99
	12-month	8.00	24.05	14.32	13.79

Table 7: One-Sample T-test – Null Hypothesis: Average Squared Forecasting Errors are Zero (Monthly data, Euro is the base currency)

	Time Horizon	t-statistics			
		Method 1	Method 2	Method 3	Method 4
British Pound	1-month	7.60	9.28	7.59	7.41
	3-month	7.83	9.02	8.39	7.63
	6-month	5.87	8.90	7.22	7.59
	12-month	7.11	9.09	6.92	7.88
US Dollar	1-month	7.47	10.19	7.82	8.12
	3-month	9.01	10.45	8.89	9.18
	6-month	8.51	10.75	9.21	10.35
	12-month	9.01	10.36	8.61	9.18
Japanese Yen	1-month	8.37	8.89	7.26	6.39
	3-month	8.17	8.95	5.20	5.03
	6-month	6.21	9.11	3.91	4.46
	12-month	6.52	9.50	4.59	4.96
Swiss Franc	1-month	3.67	11.32	4.19	5.23
	3-month	4.24	12.35	5.35	5.95
	6-month	4.30	13.47	5.05	6.68
	12-month	3.82	14.19	7.70	11.15

Figure 1.1. USD vs. GBP



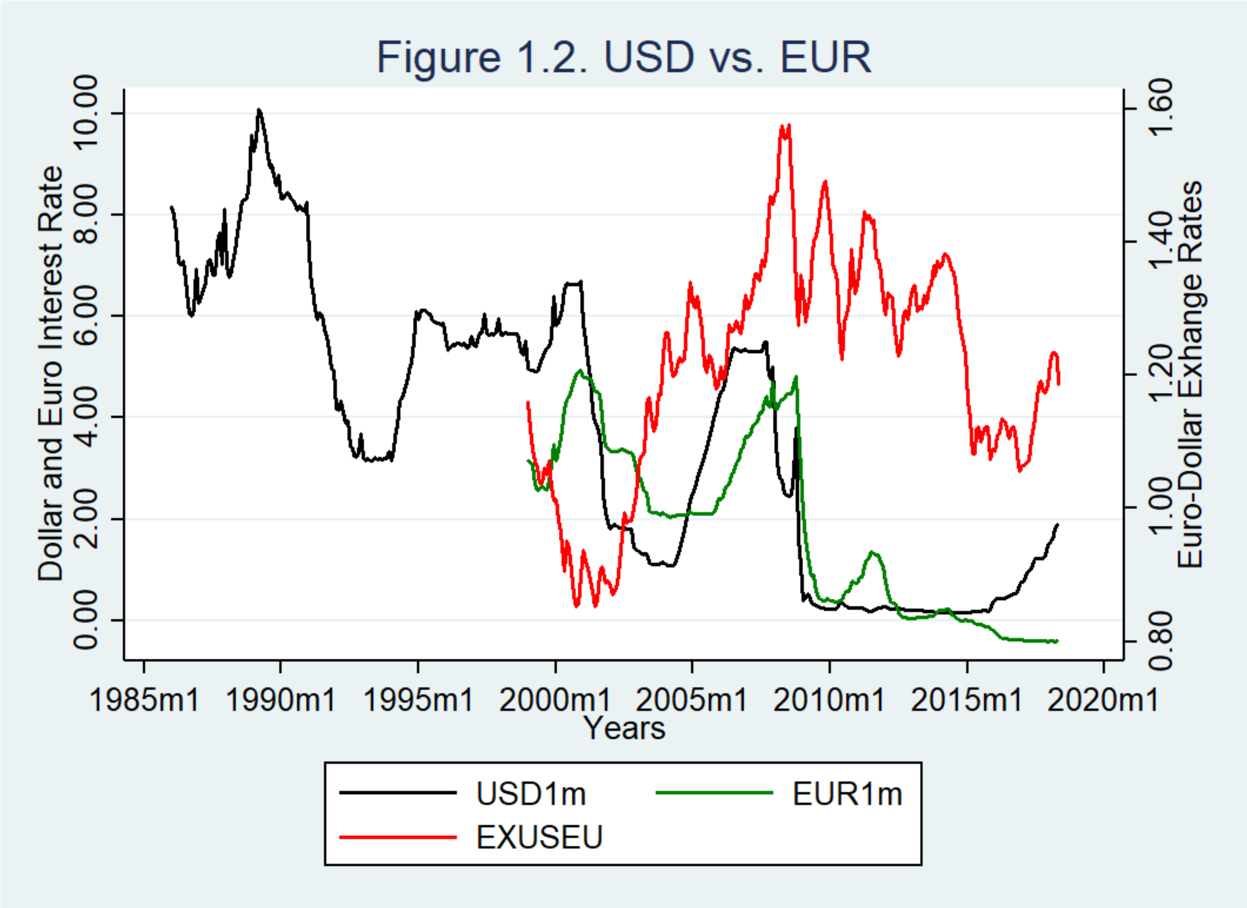


Figure 1.2. USD vs. EUR
Dollar and Euro Interest Rate
0.00
2.00
4.00
6.00
8.00
10.00
Euro-Dollar Exhange Rates
0.80
1.00
1.20
1.40
1.60
1985m1
1990m1
1995m1
2000m1
2005m1
2010m1
2015m1
2020m1
Years
USD1m
EUR1m
EXUSEU

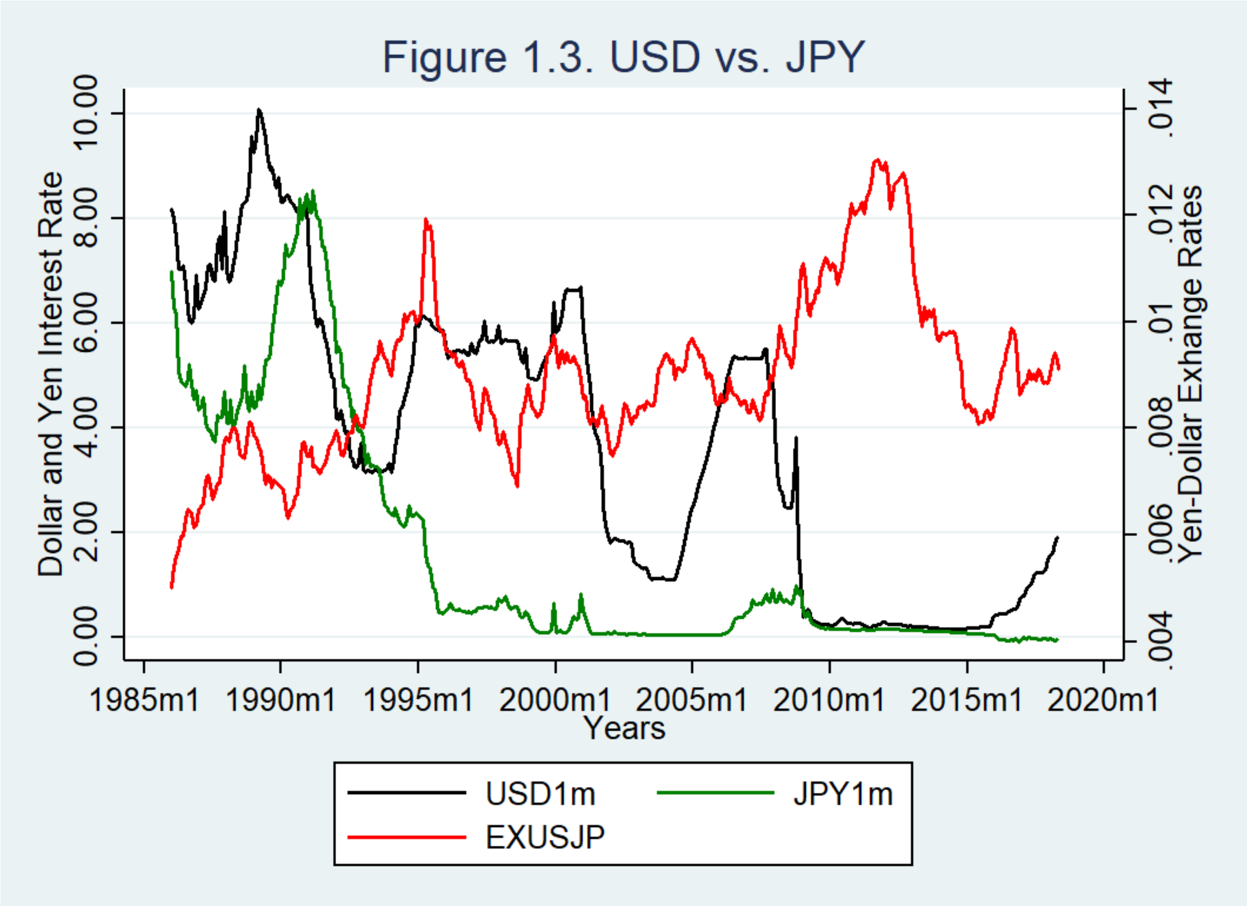


Figure 1.3. USD vs. JPY
Dollar and Yen Interest Rate
0.00
2.00
4.00
6.00
8.00
10.00
Yen-Dollar Exhange Rates
.004
.006
.008
.01
.012
.014
1985m1
1990m1
1995m1
2000m1
2005m1
2010m1
2015m1
2020m1
Years
USD1m
JPY1m
EXUSJP

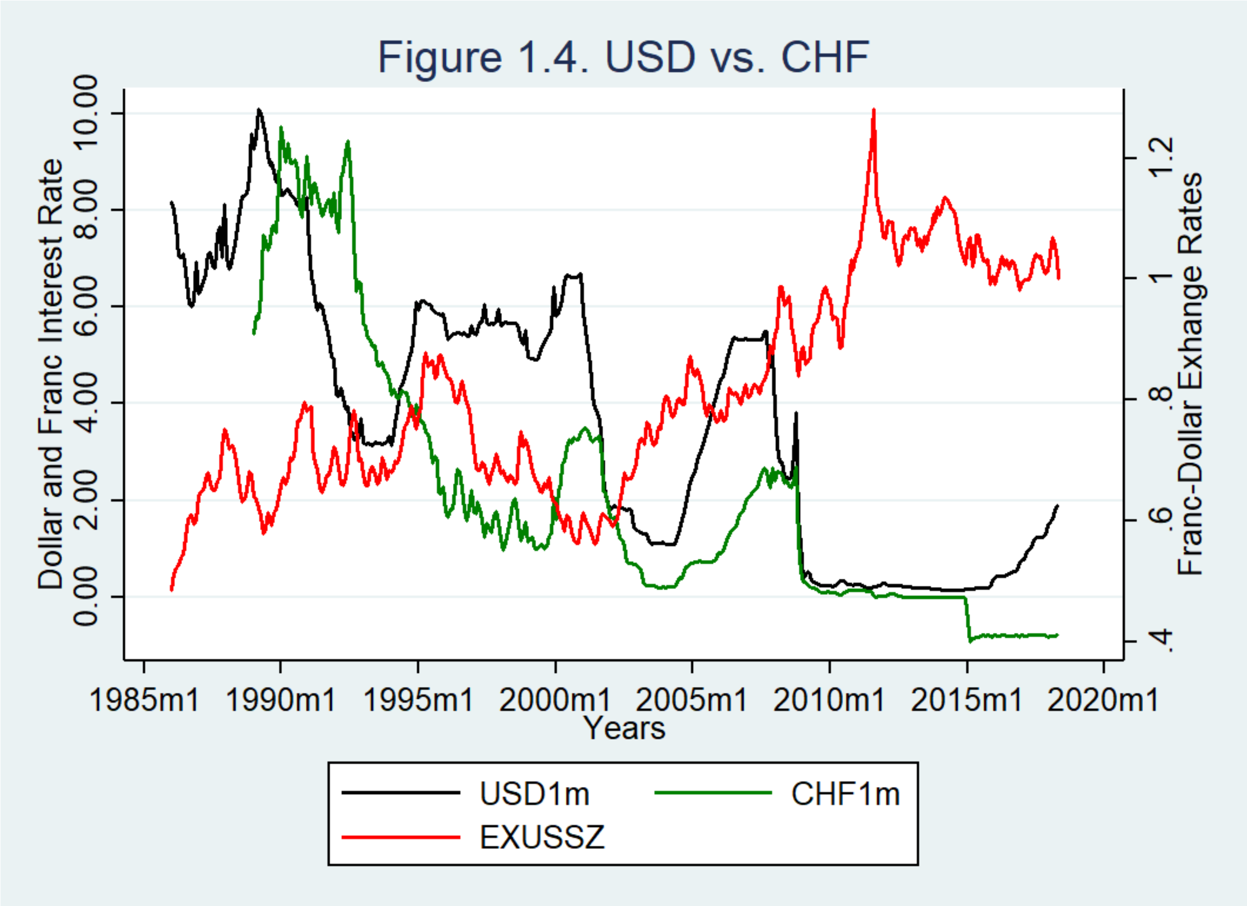


Figure 1.4. USD vs. CHF
Dollar and Franc Interest Rate
0.00
2.00
4.00
6.00
8.00
10.00
Franc-Dollar Exhange Rates
.4
.6
.8
1
1.2
1985m1
1990m1
1995m1
2000m1
2005m1
2010m1
2015m1
2020m1
Years
USD1m
CHF1m
EXUSSZ

Figure 2A.1. British Pound

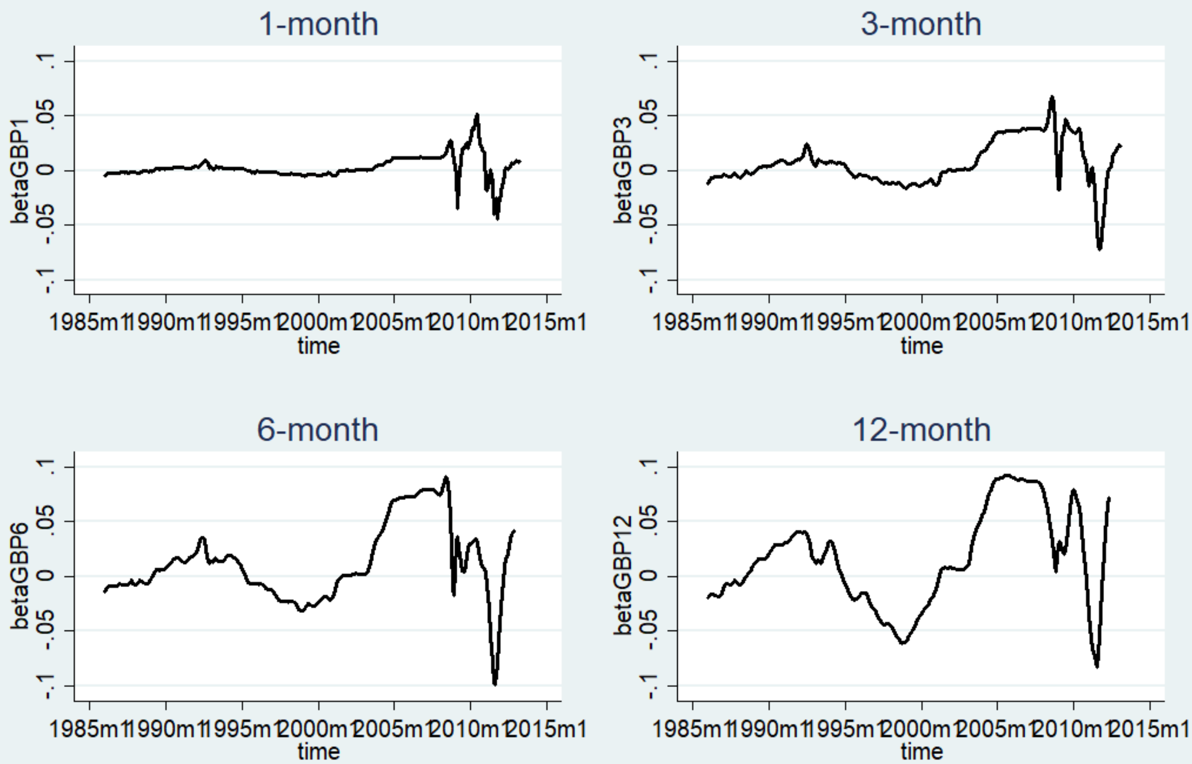


Figure 2B.1. t-stat: British Pound

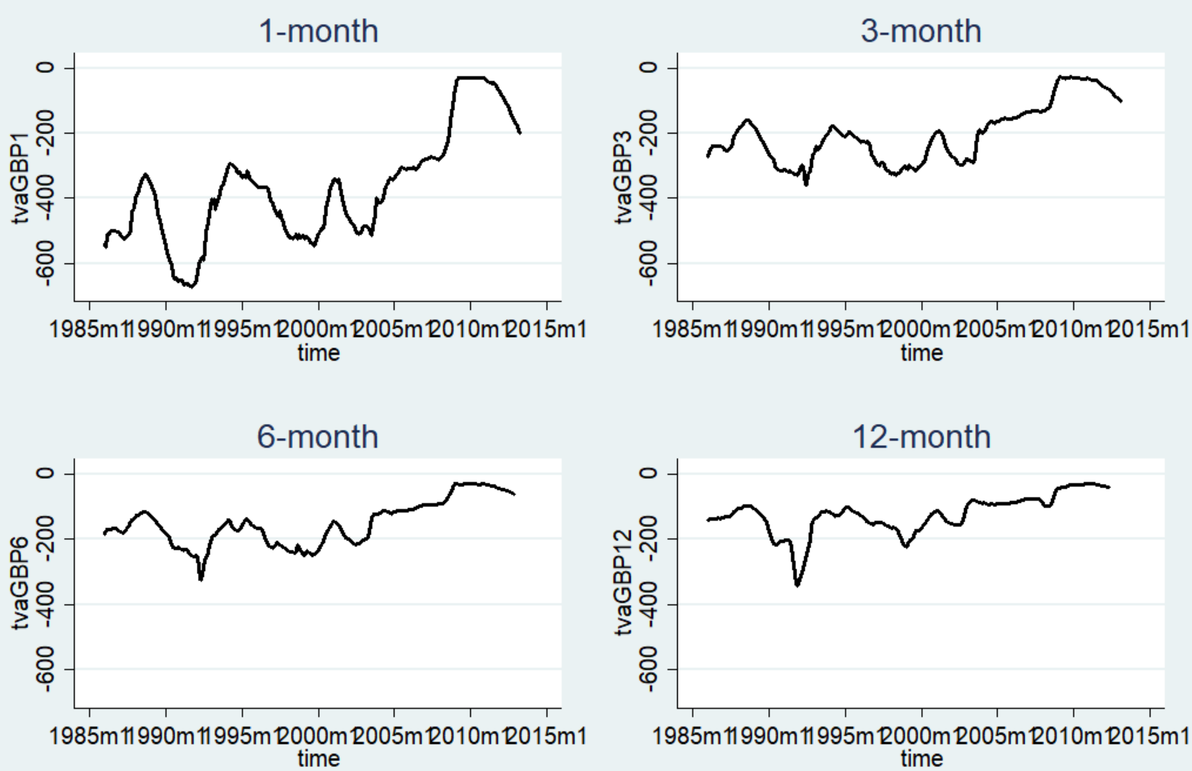


Figure 2A.2. European Euro

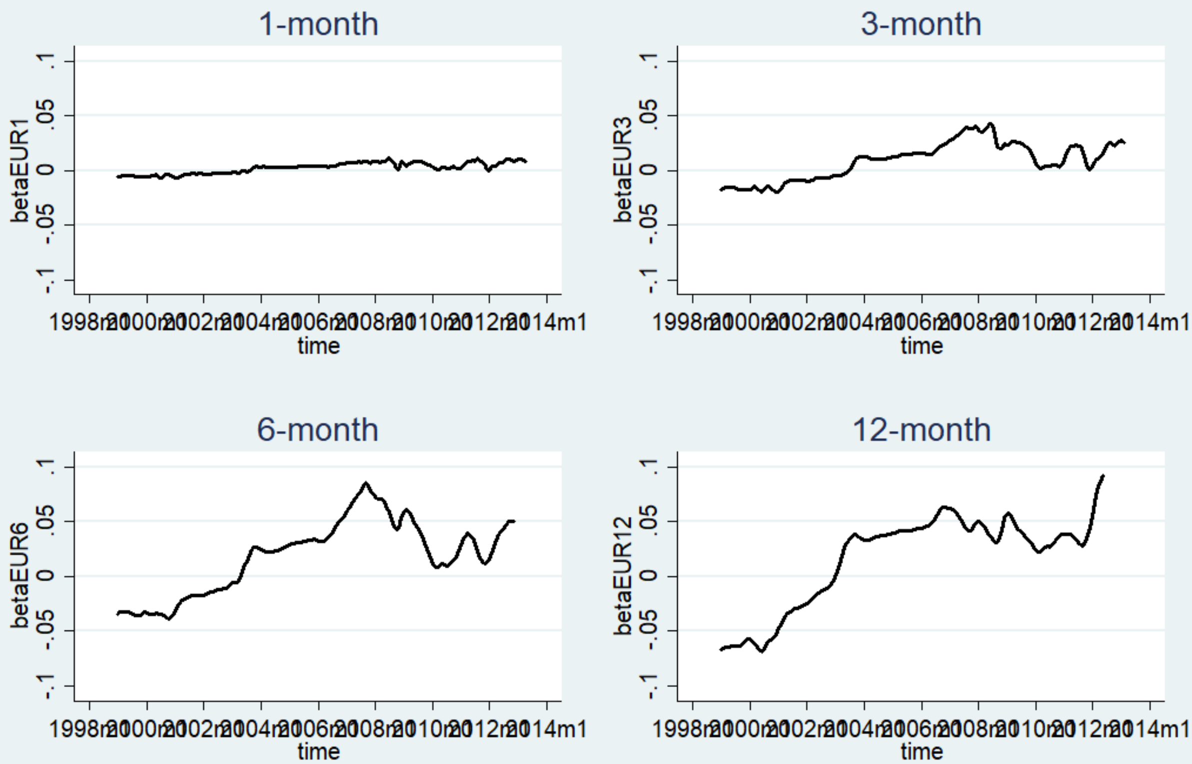


Figure 2B.2. t-stat: European Euro

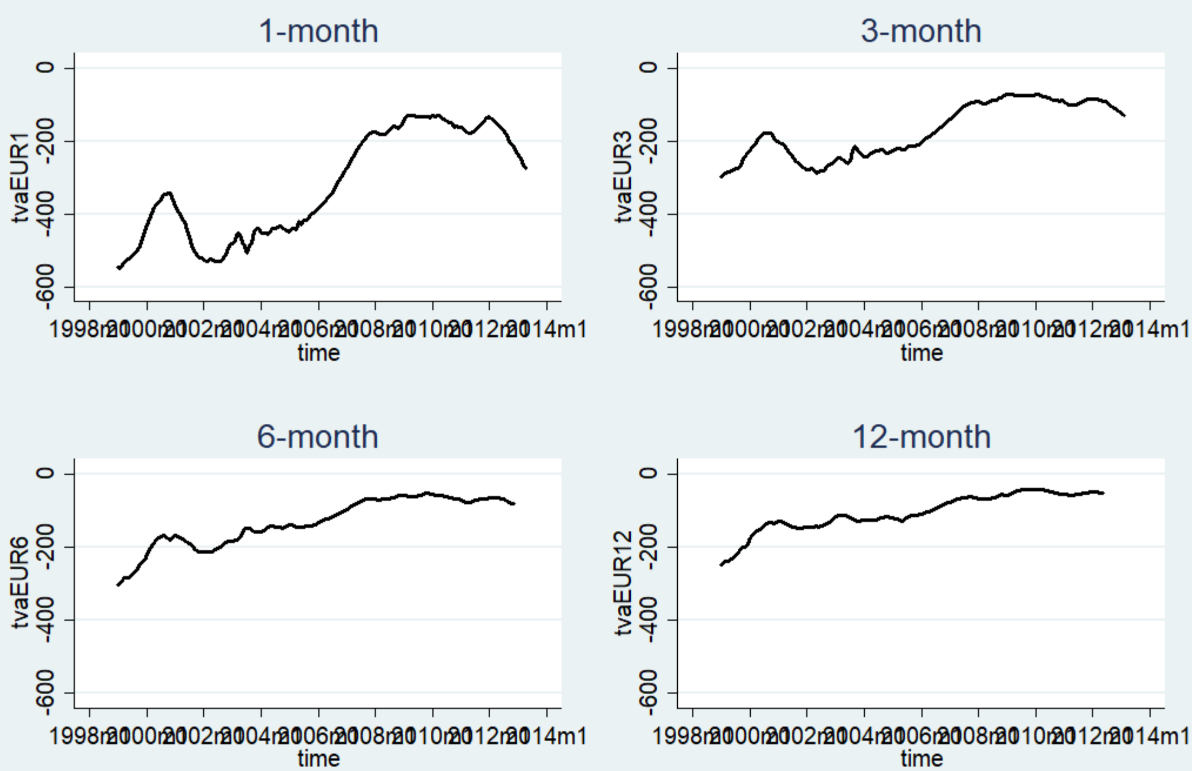


Figure 2A.3. Japanese Yen

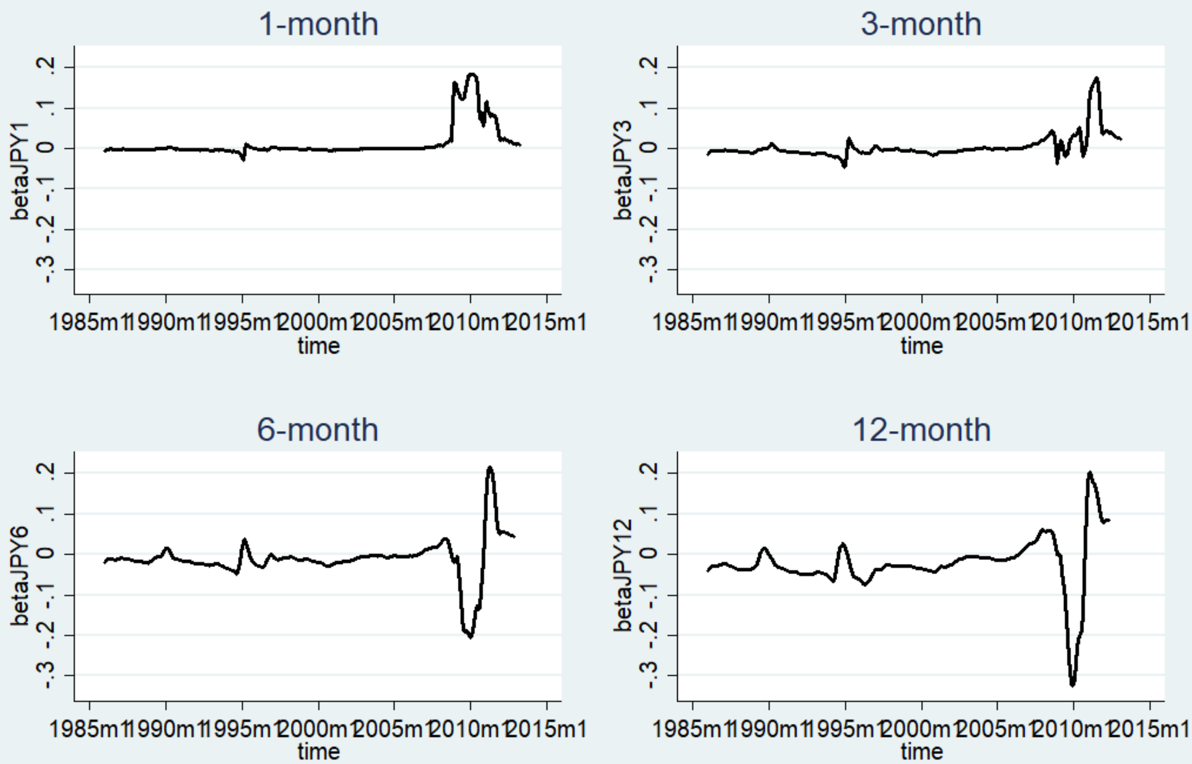


Figure 2B.3. t-stat: Japanese Yen

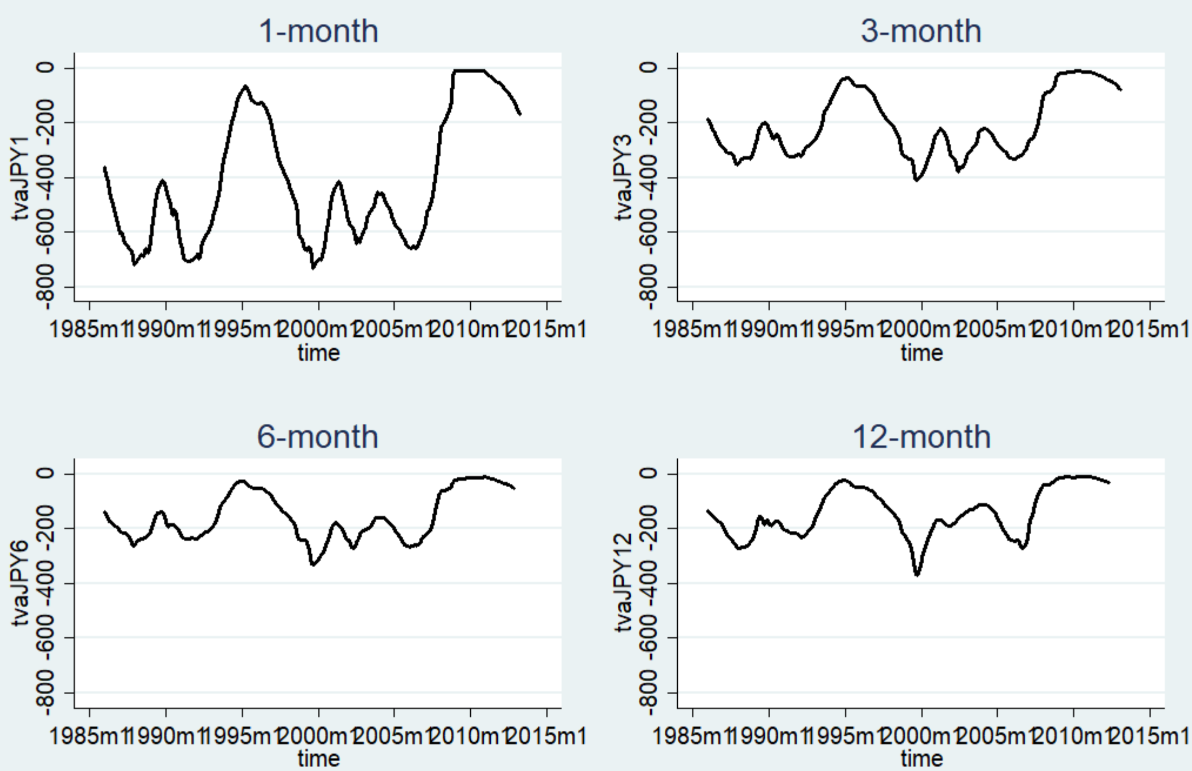


Figure 2A.4. Swiss Franc

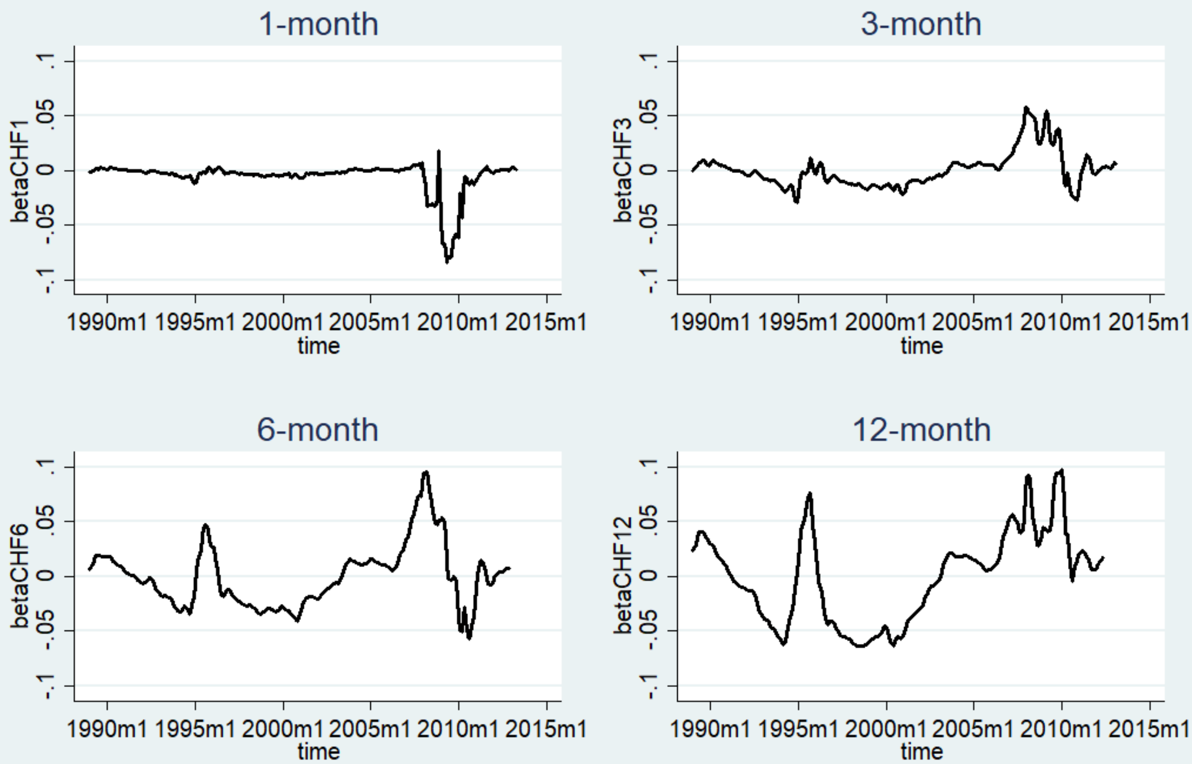


Figure 2B.4. t-stat: Swiss Franc

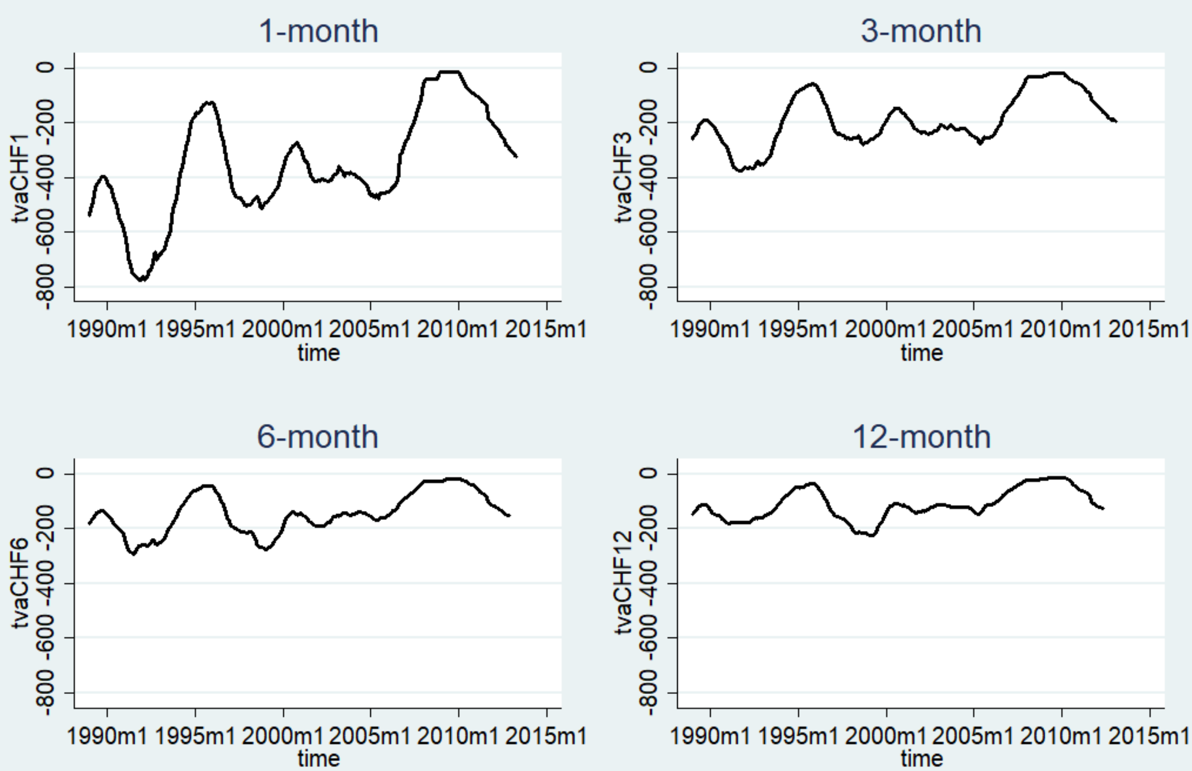


Figure 3: Plotting forecasting error using monthly data, base currency: euro.

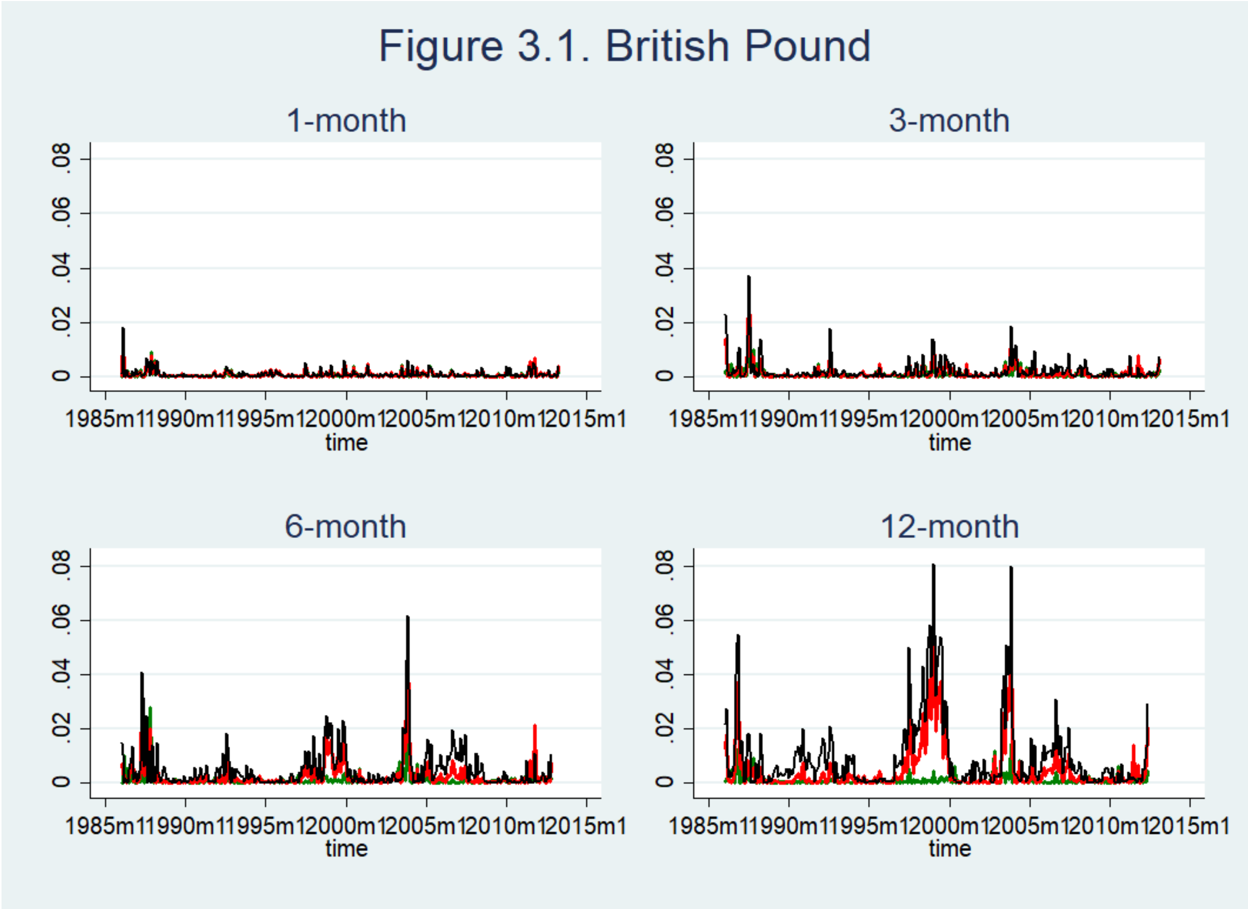
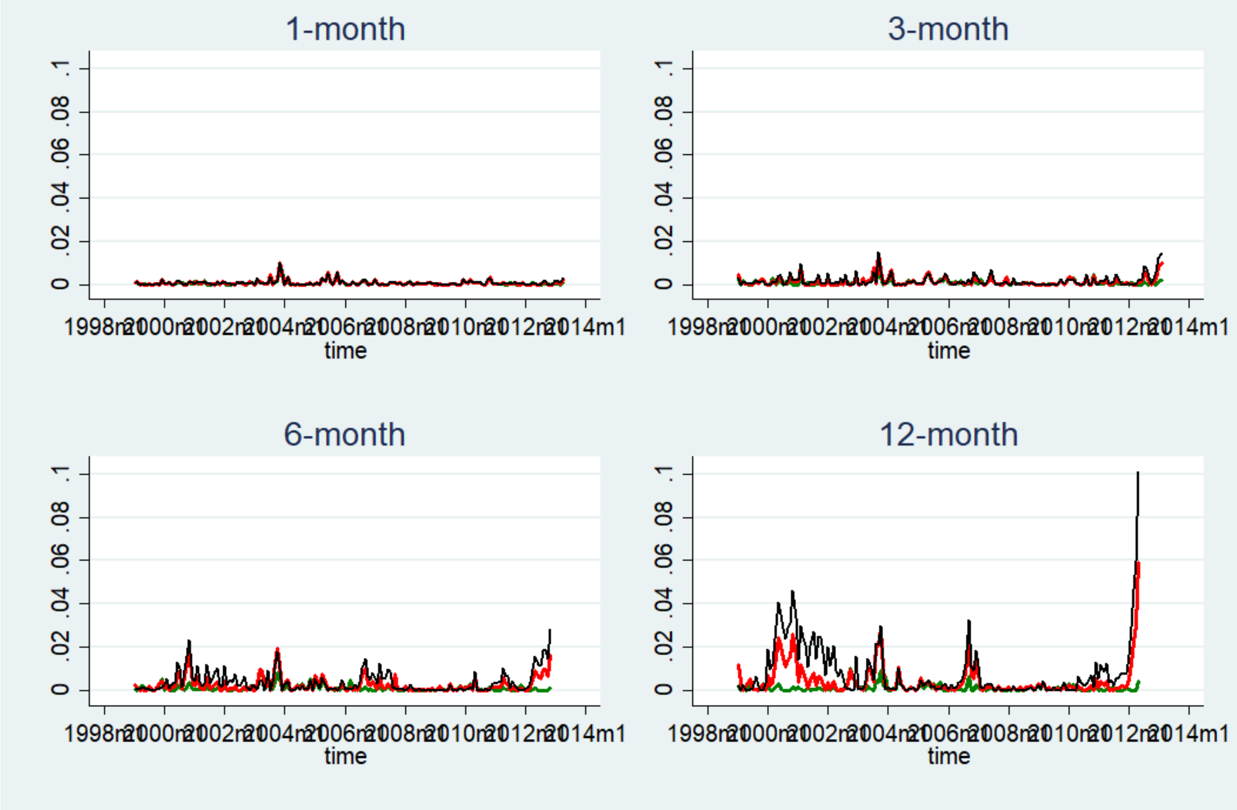


Figure 3.2. European Euro



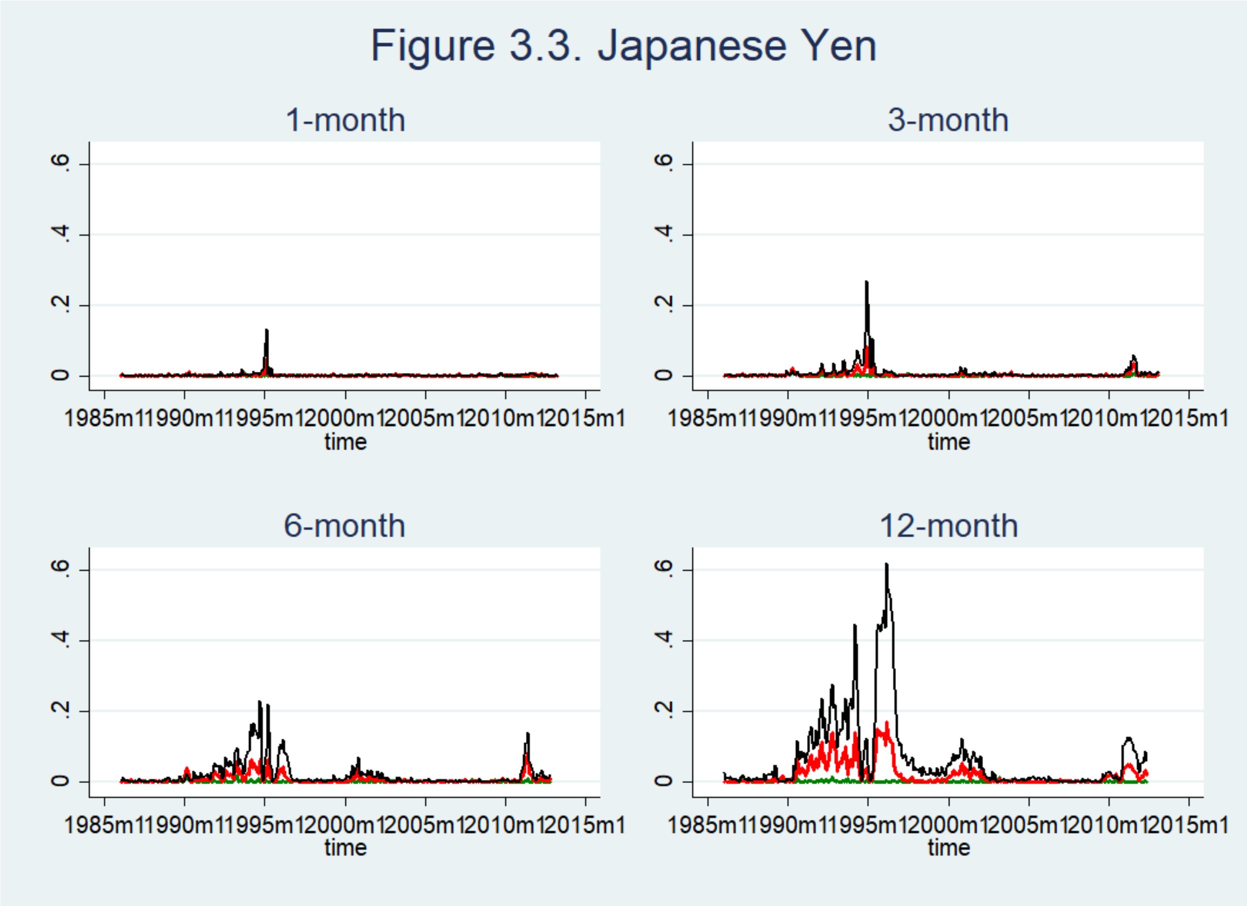


Figure 3.3. Japanese Yen
1-month
3-month
6-month
12-month
0
.2
.4
.6
1985m1
1990m1
1995m1
2000m1
2005m1
2010m1
2015m1
time

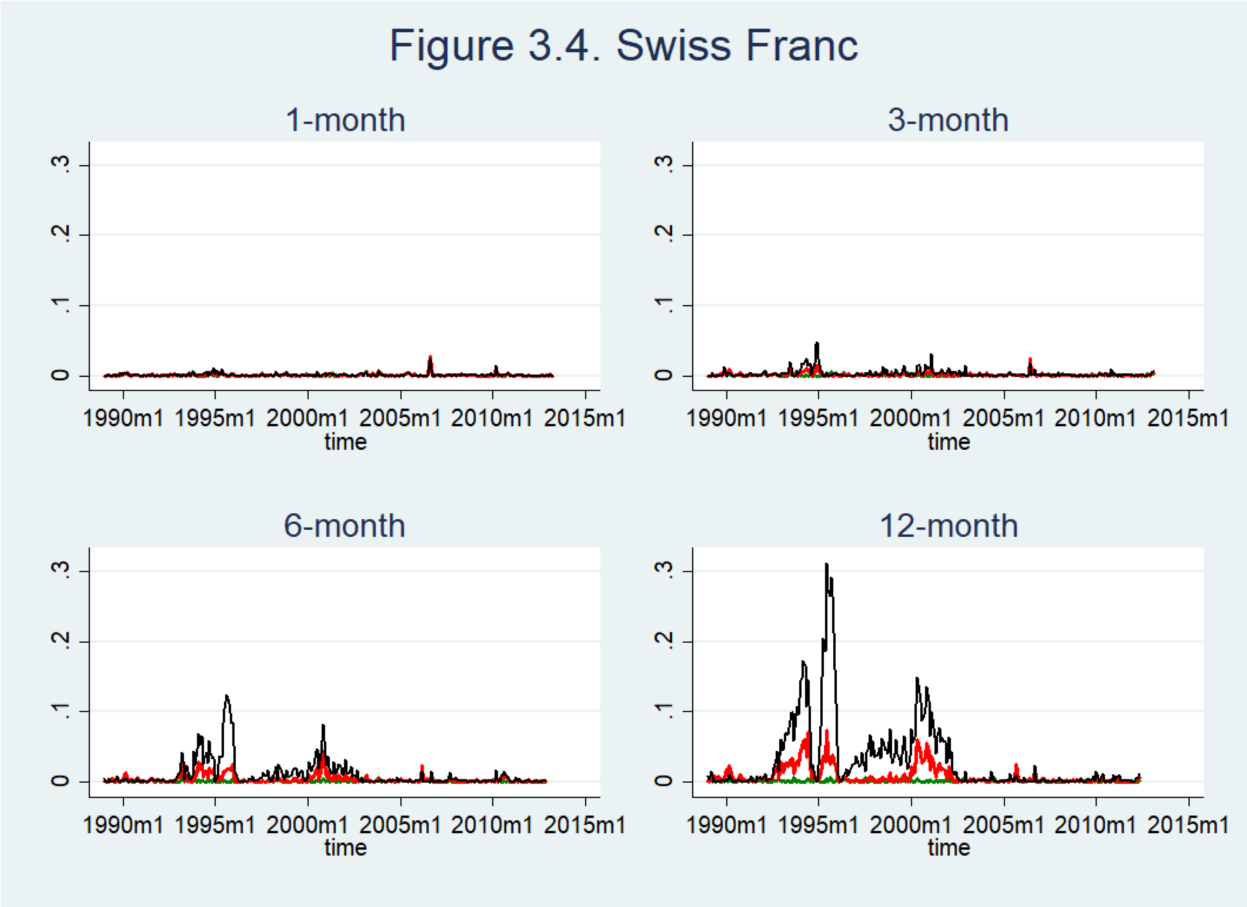


Figure 3.4. Swiss Franc
1-month
3-month
6-month
12-month
0
.1
.2
.3
1990m1
1995m1
2000m1
2005m1
2010m1
2015m1
time

Figure 4A.1. British Pound

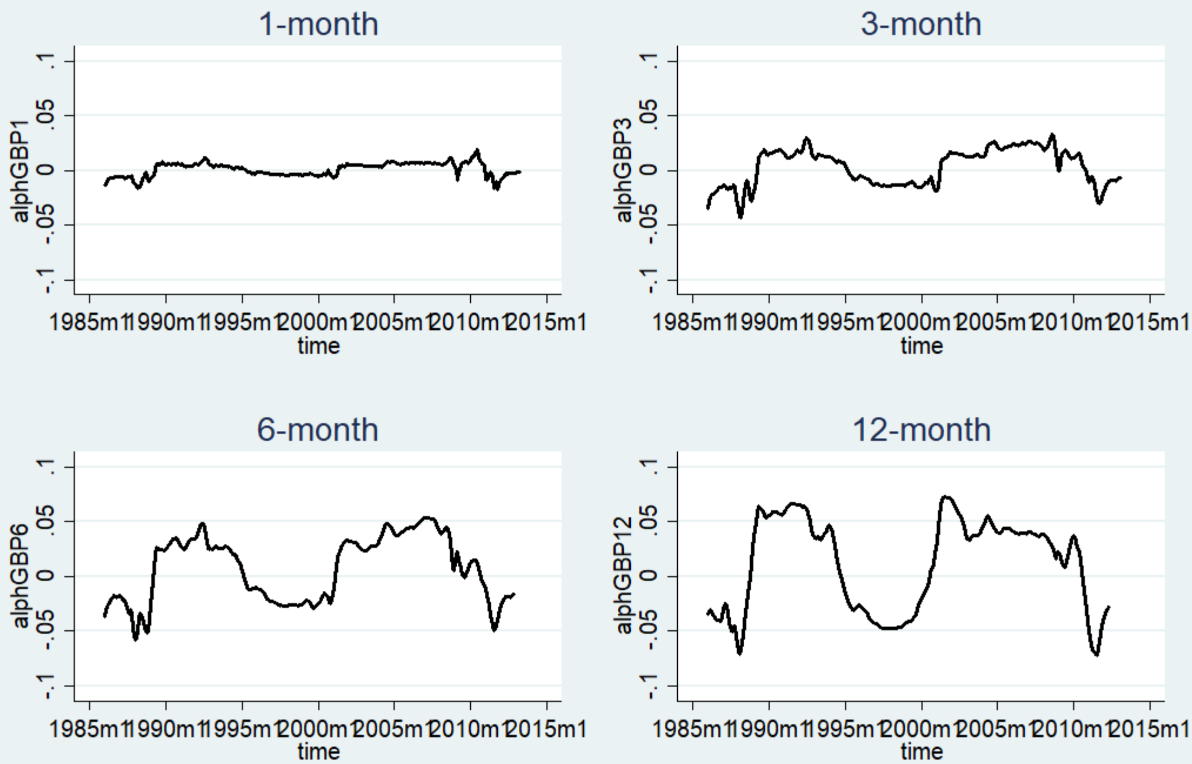


Figure 4B.1. t-stat: British Pound

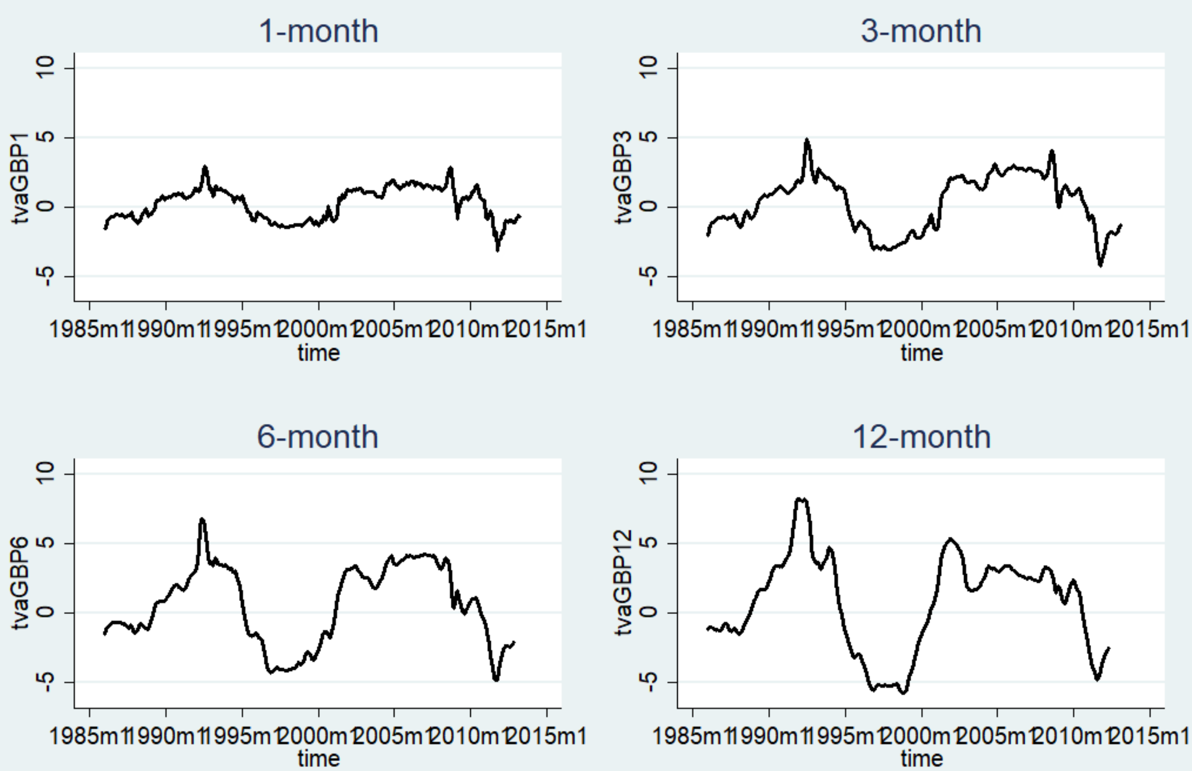


Figure 4A.2. European Euro

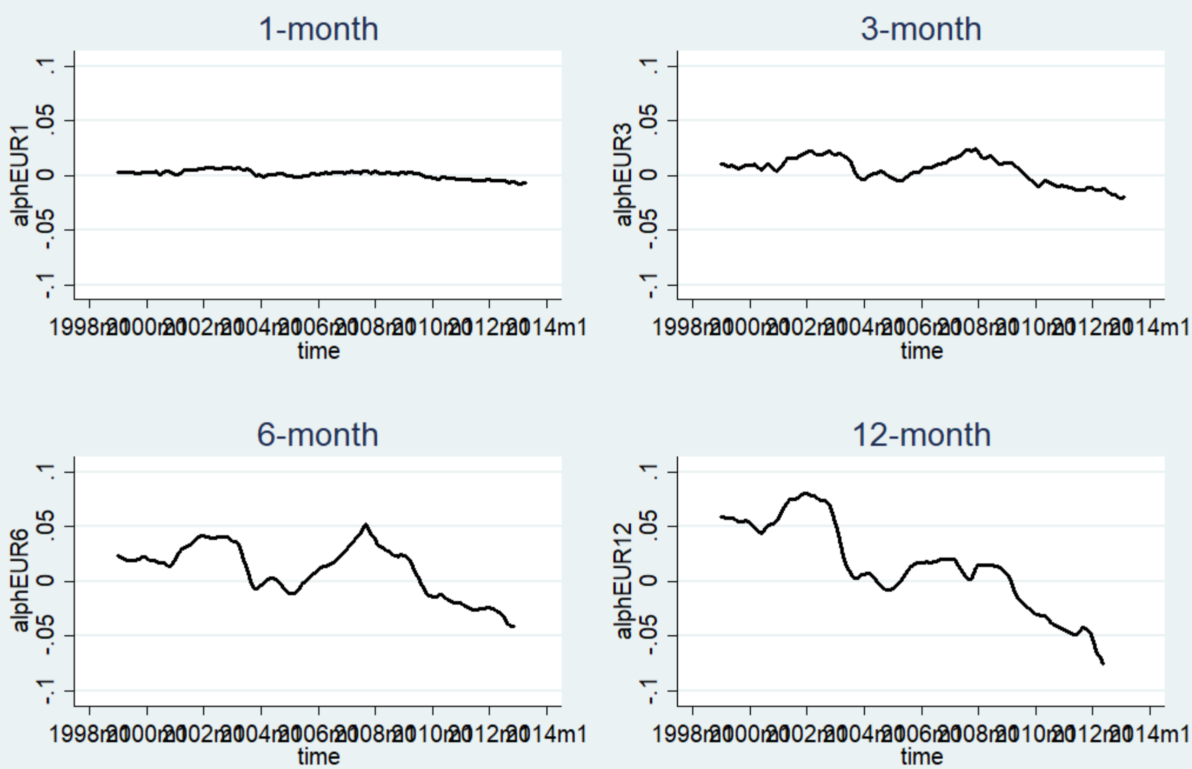


Figure 4B.2. t-stat: European Euro

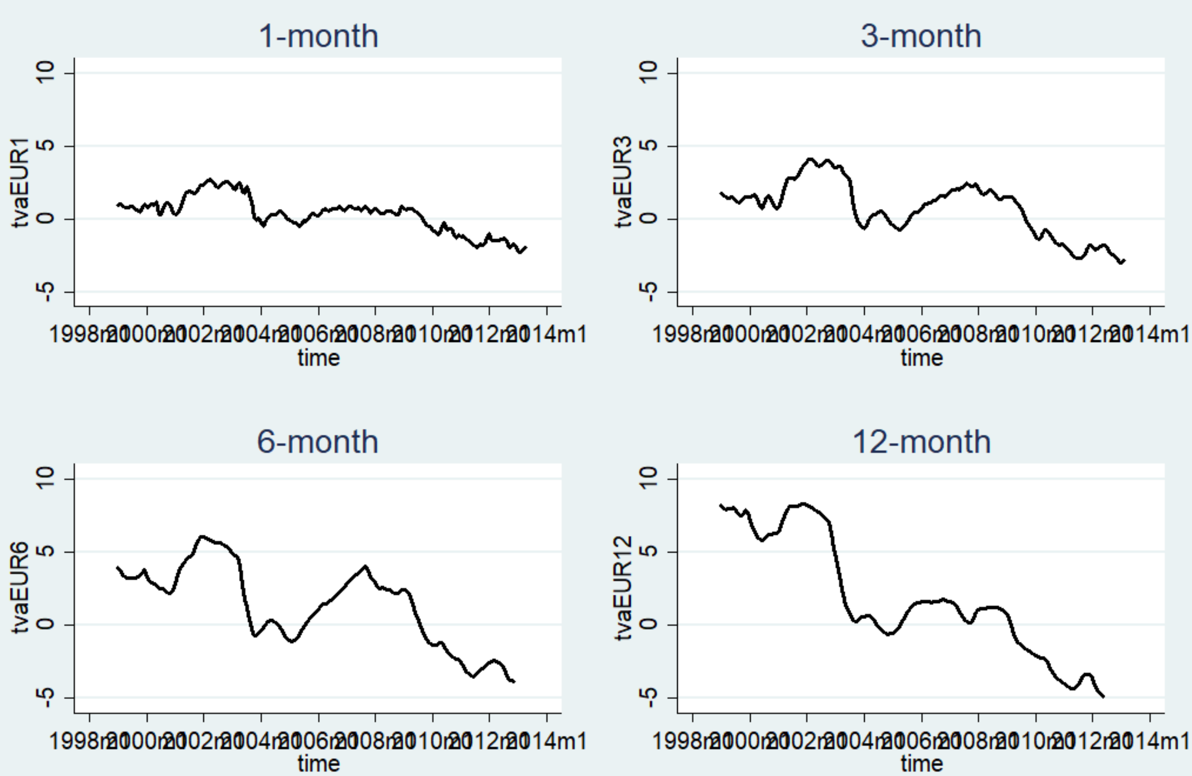


Figure 4A.3. Japanese Yen

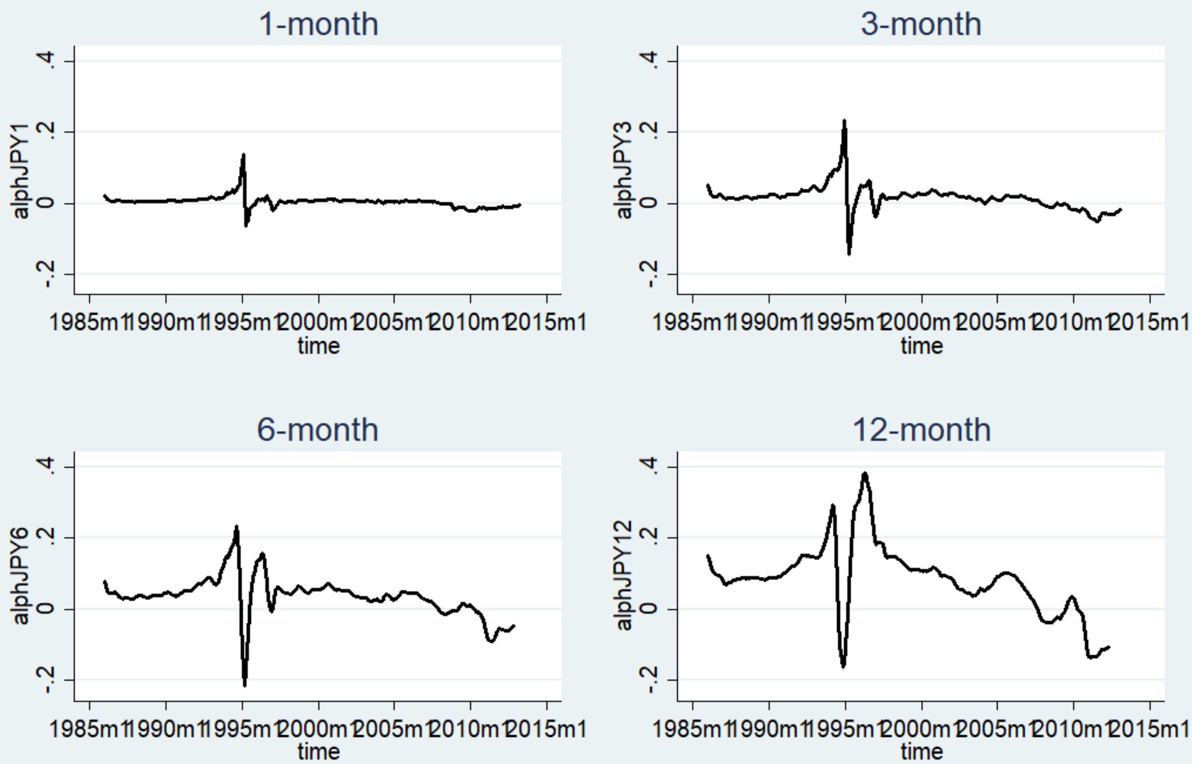


Figure 4B.3. t-stat: Japanese Yen

Figure 4A.4. Swiss Franc

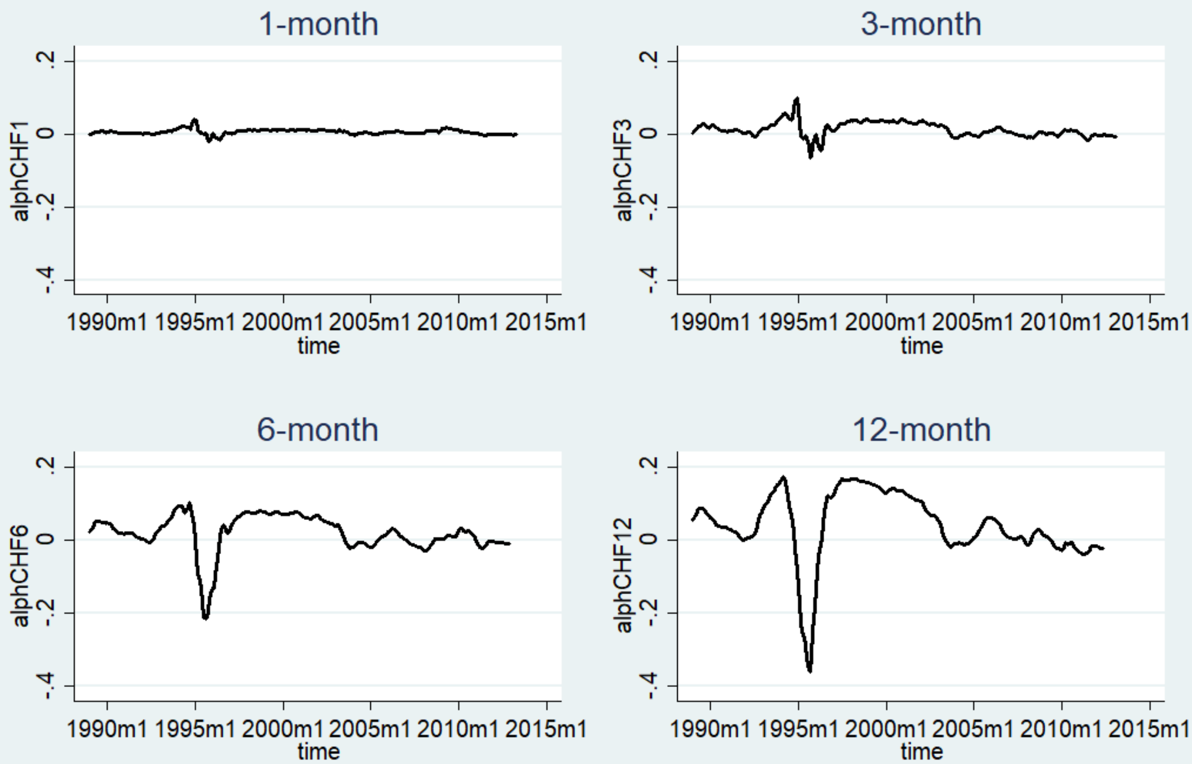


Figure 4B.4. t-stat: Swiss Franc

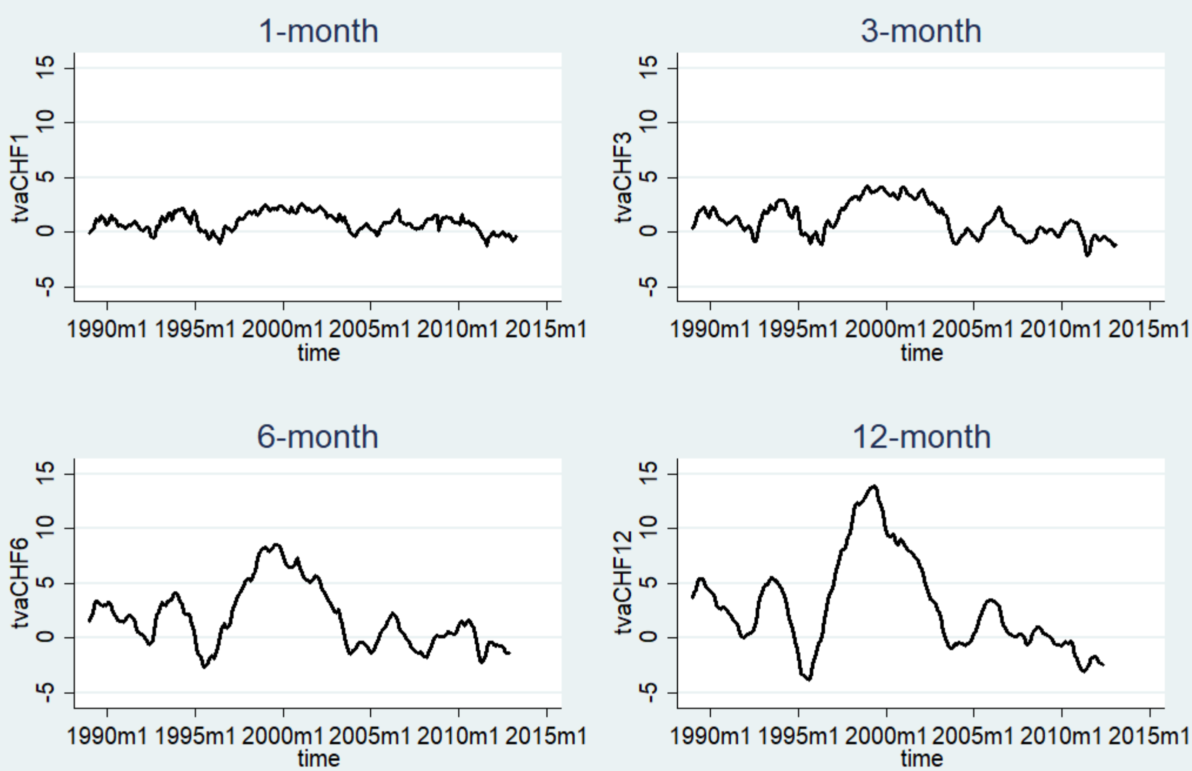


Figure 5A.1. British Pound (Window=72)

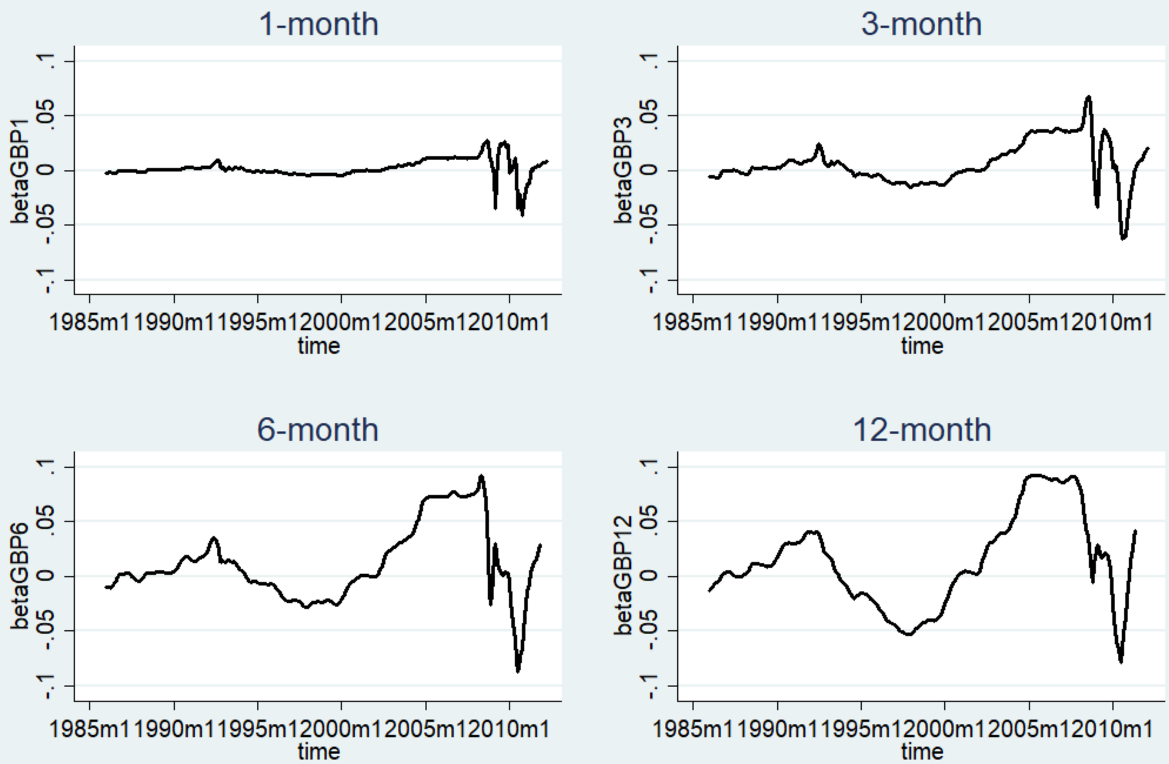


Figure 5B.1. t-stat: British Pound (Window=72)

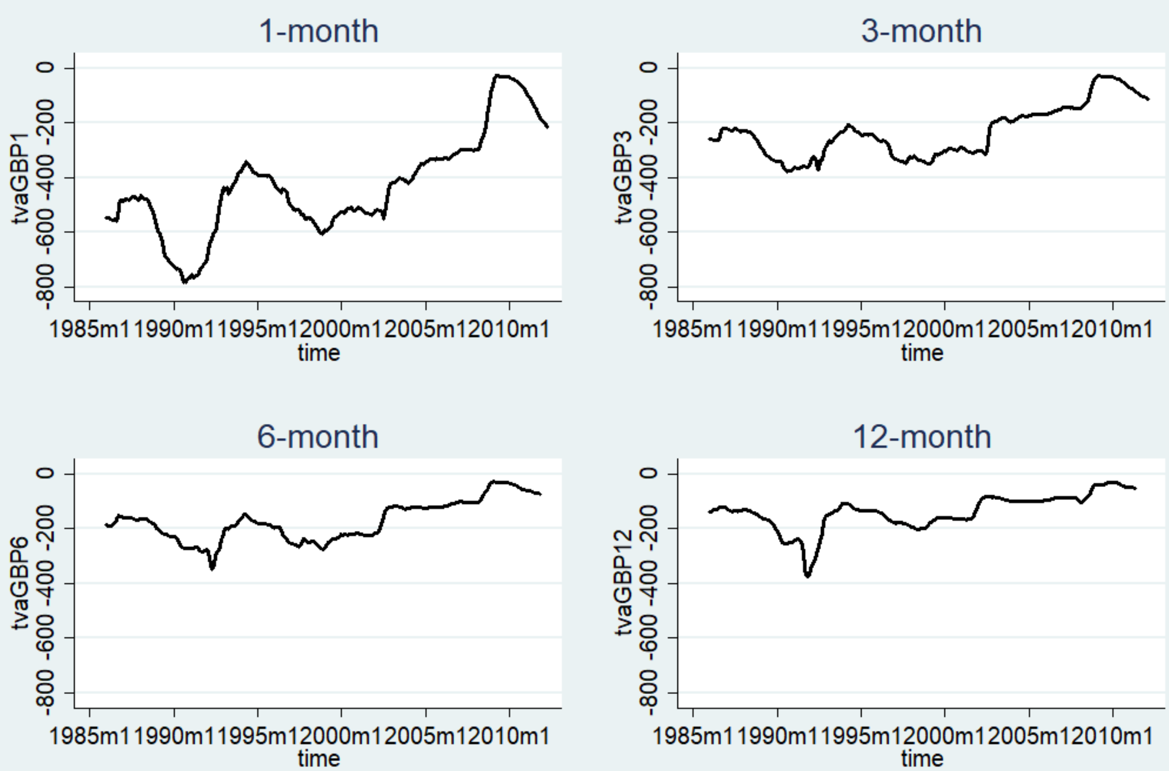


Figure 5A.2. European Euro (Window=72)

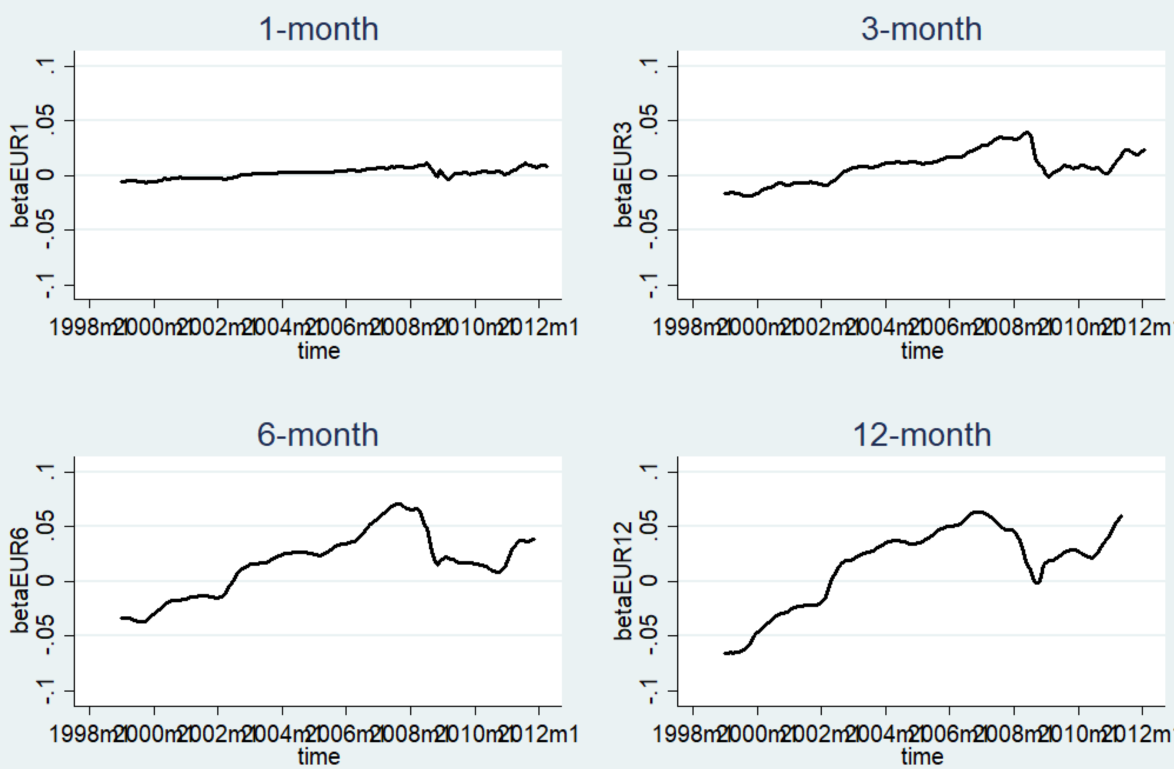


Figure 5B.2. t-stat: European Euro (Window=72)

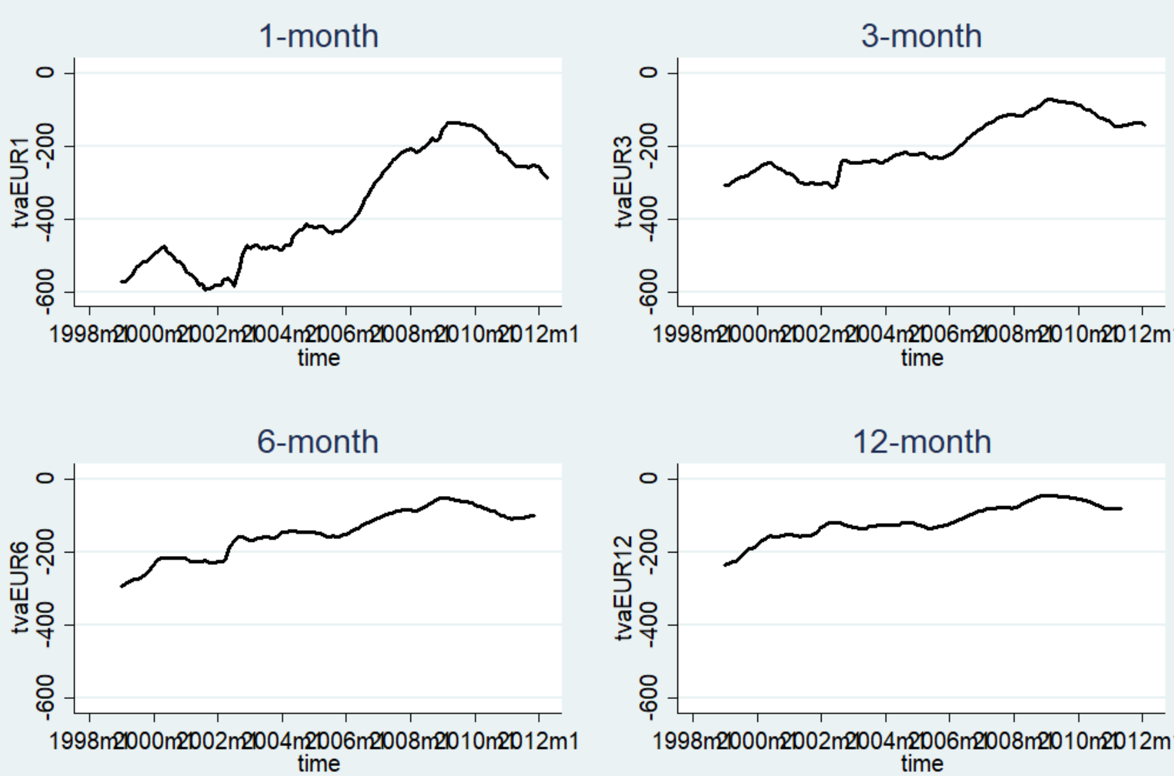


Figure 5A.3. Japanese Yen (Window=72)

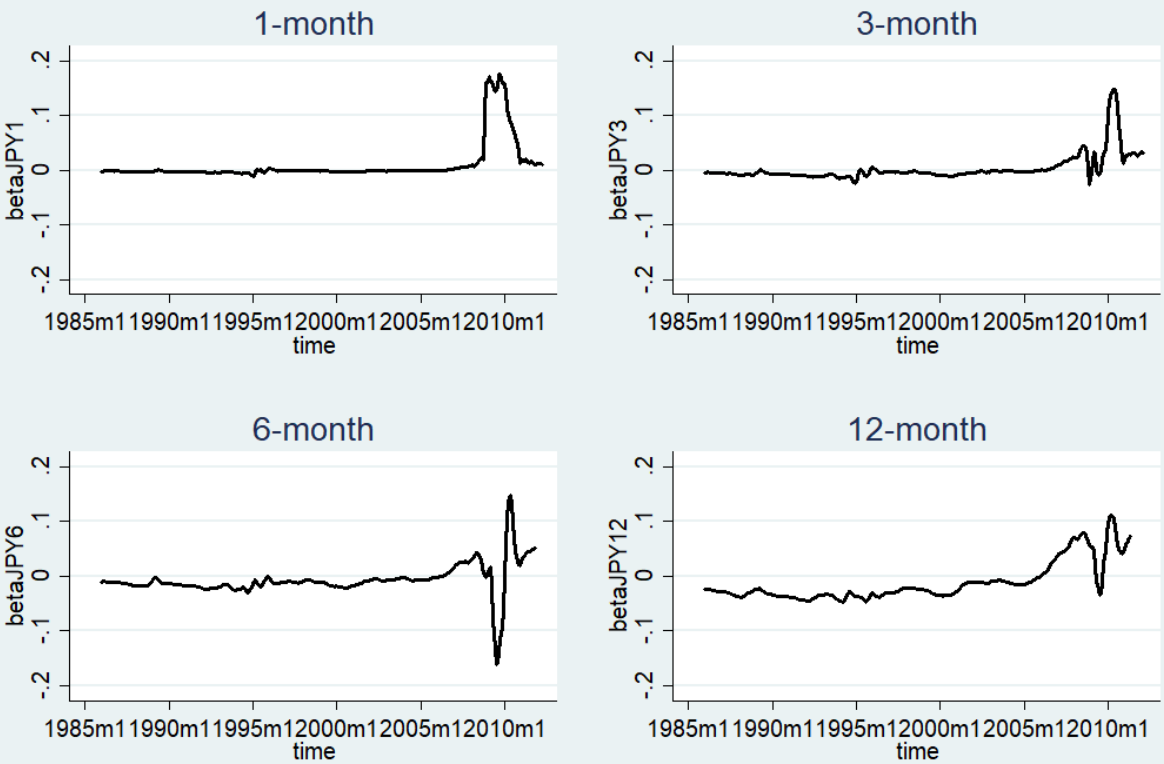


Figure 5B.3. t-stat: Japanese Yen (Window=72)

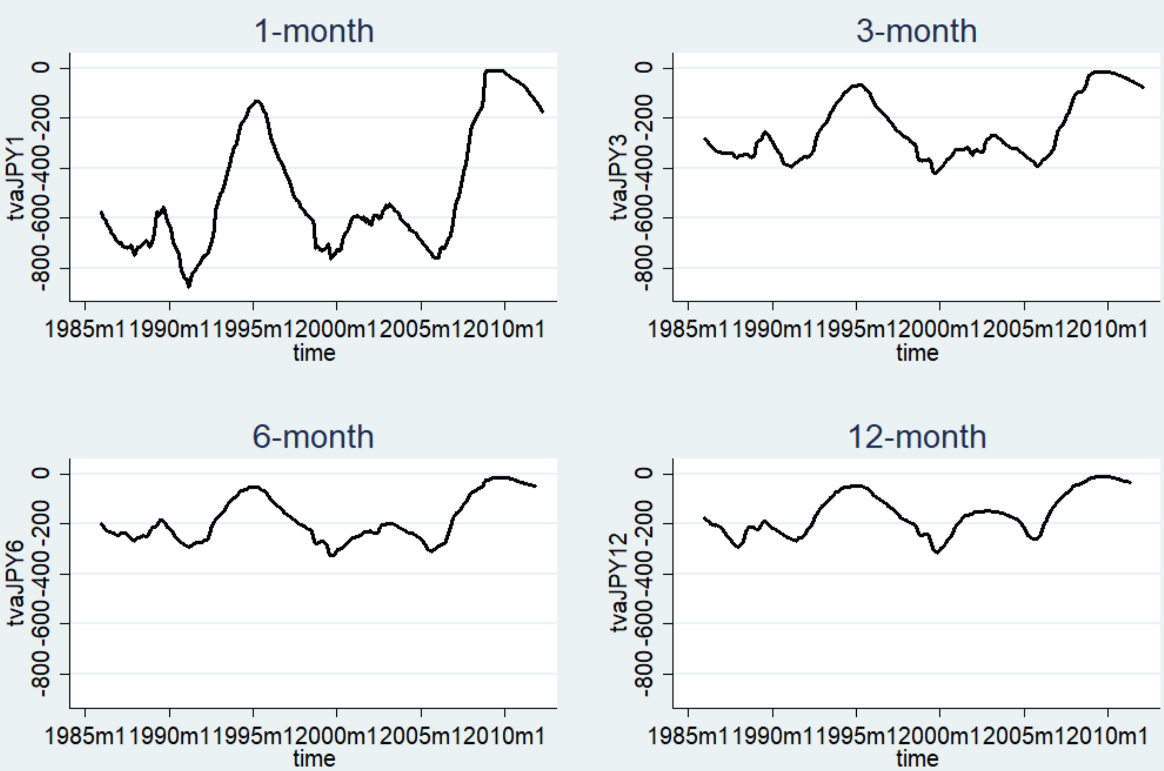


Figure 5A.4. Swiss Franc (Window=72)

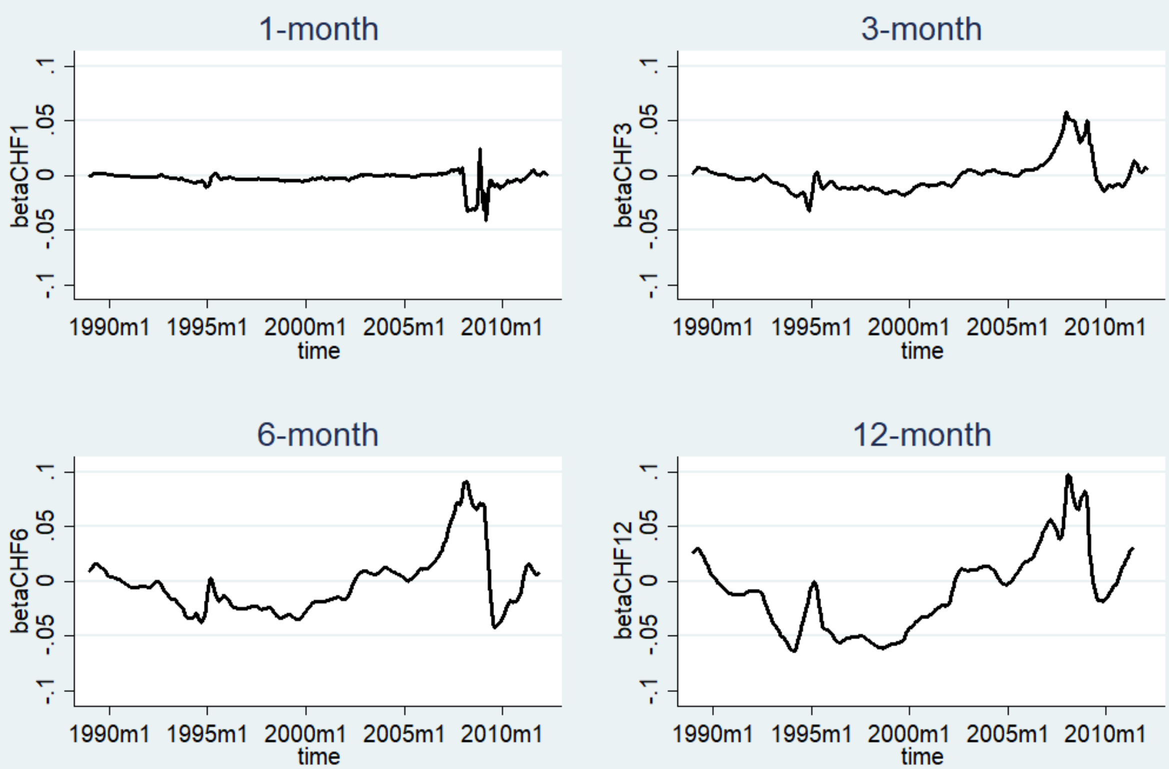


Figure 5B.4. t-stat: Swiss Franc (Window=72)

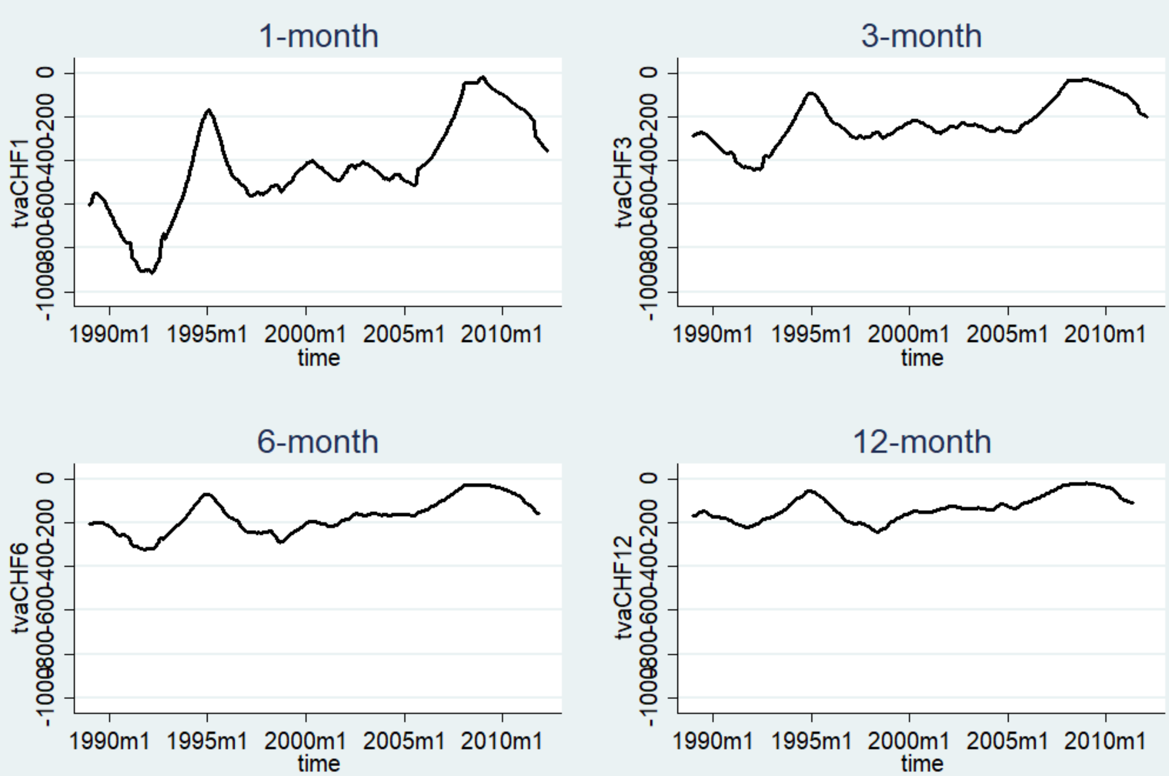
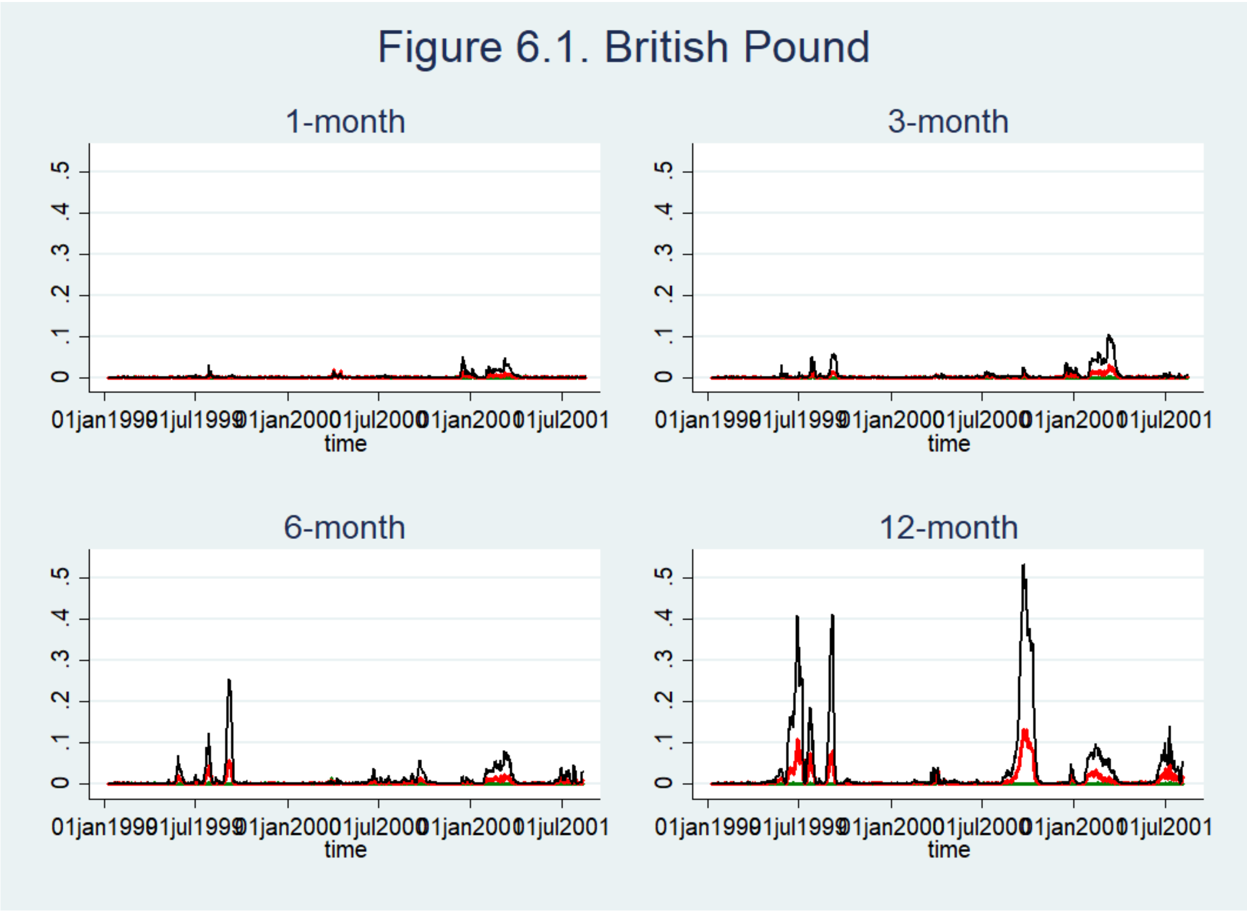


Figure 6: Plot of forecasting error using weekly data, base currency: dollar.



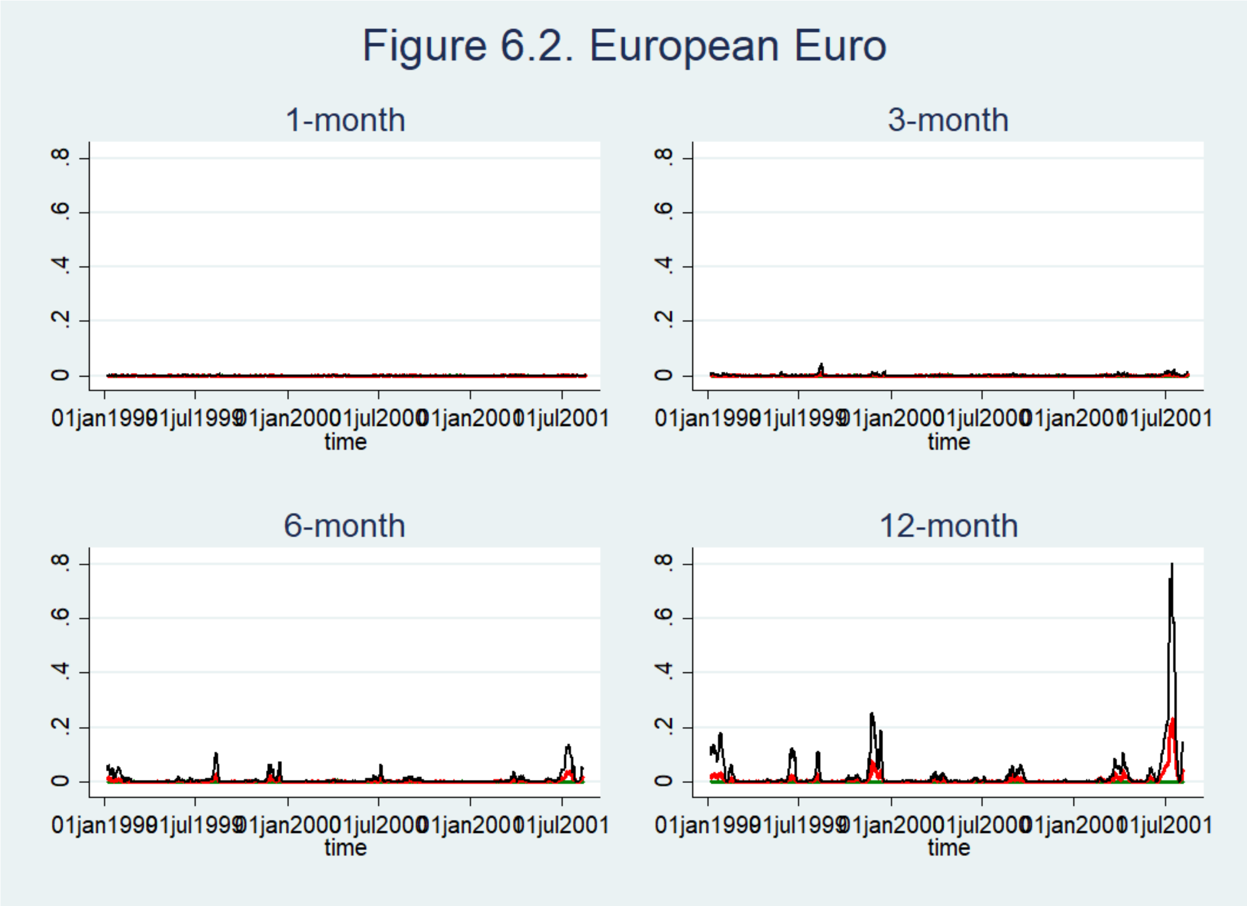


Figure 6.2. European Euro
1-month
3-month
6-month
12-month
0
.2
.4
.6
.8
01jan1999
01jul1999
01jan2000
01jul2000
01jan2001
01jul2001
time

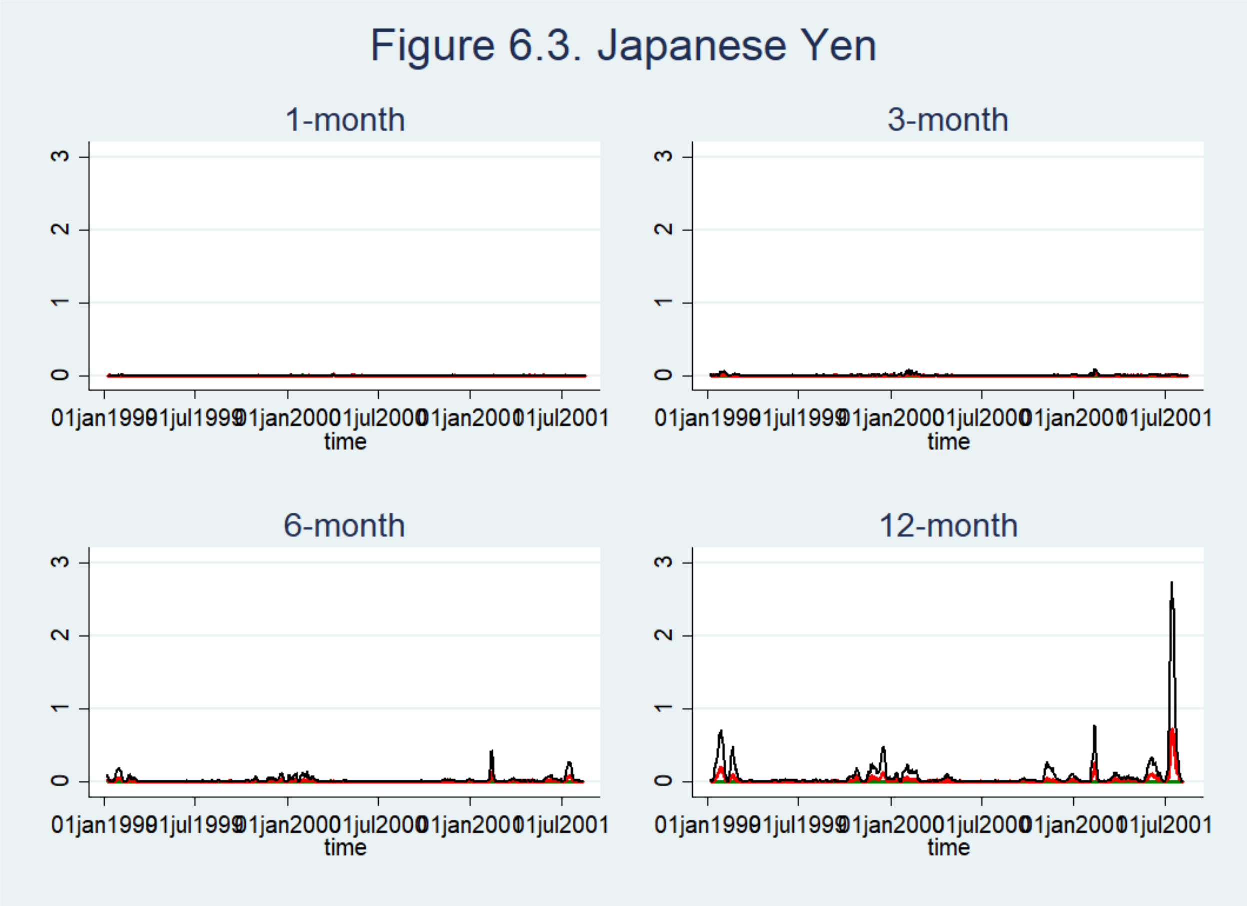


Figure 6.3. Japanese Yen
1-month
3-month
6-month
12-month
0
1
2
3
01jan1999
01jul1999
01jan2000
01jul2000
01jan2001
01jul2001
time

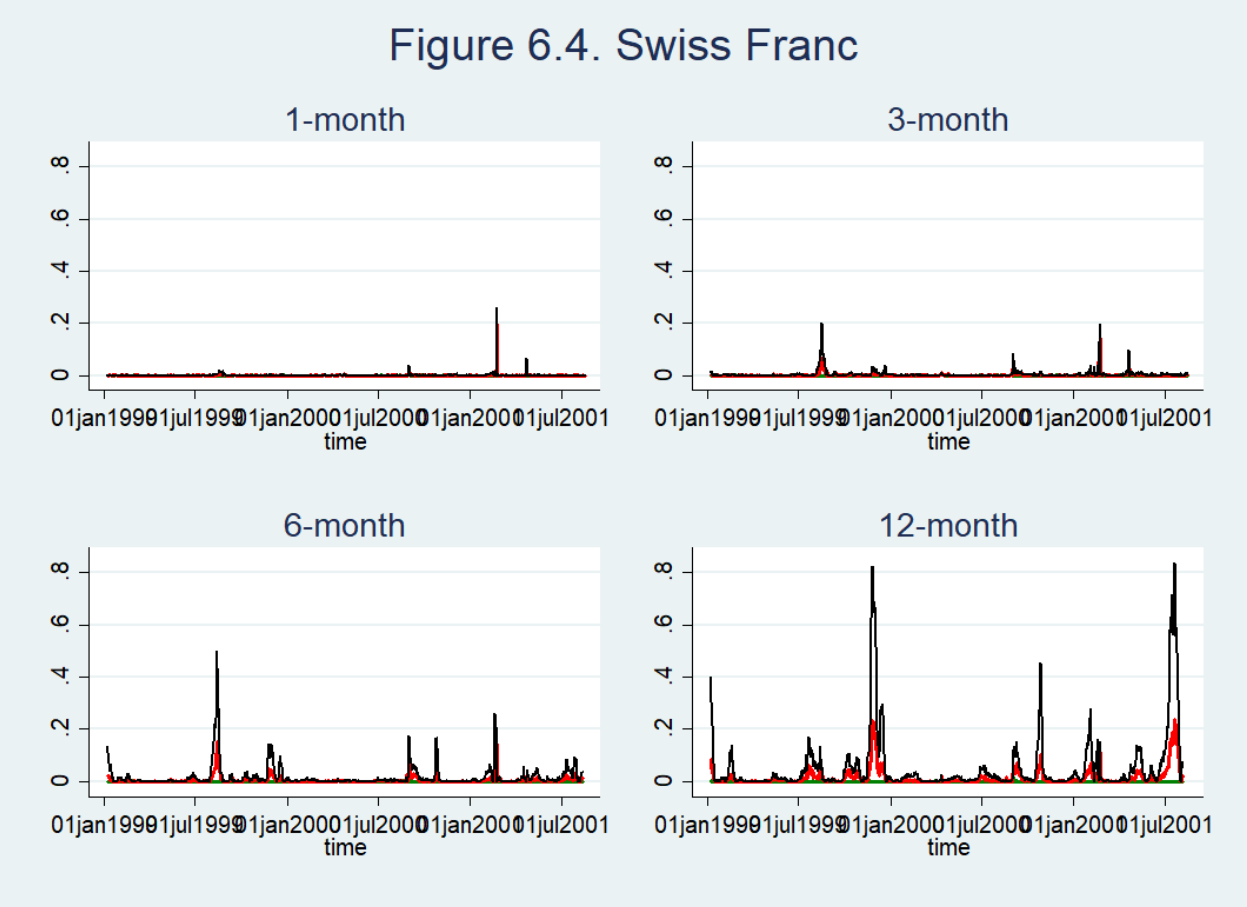


Figure 6.4. Swiss Franc
1-month
3-month
6-month
12-month
0
.2
.4
.6
.8
01jan1999
01jul1999
01jan2000
01jul2000
01jan2001
01jul2001
time

Figure 7: Plot of forecasting error using Euro as the base currency, data frequency: monthly

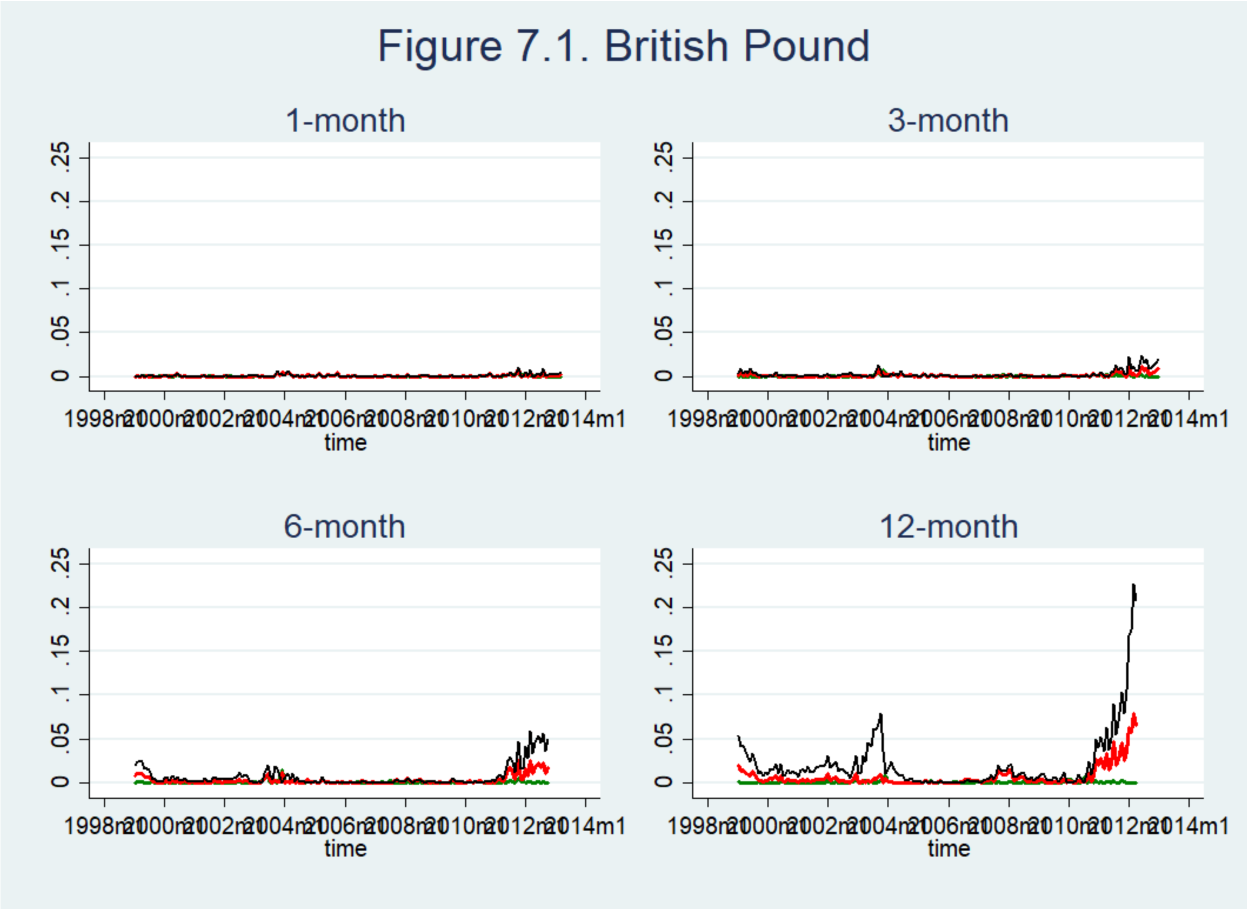
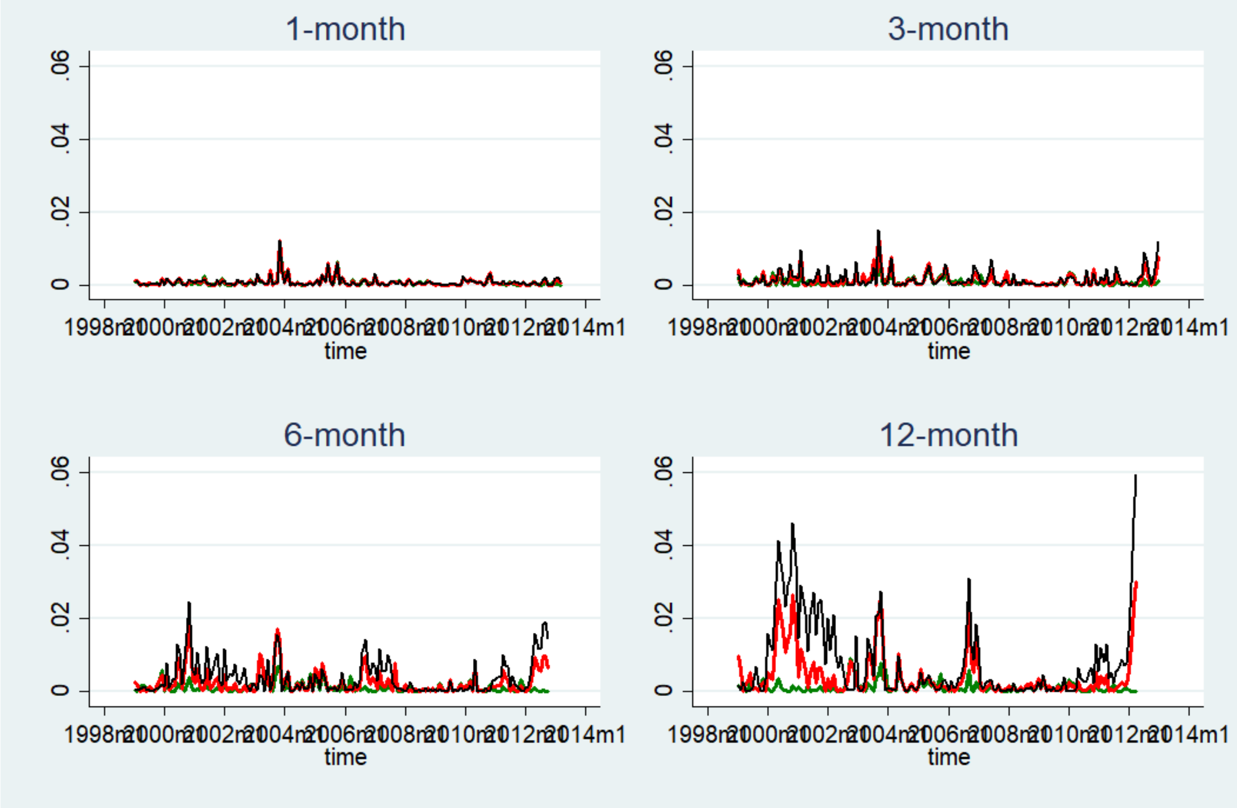


Figure 7.2. US Dollar



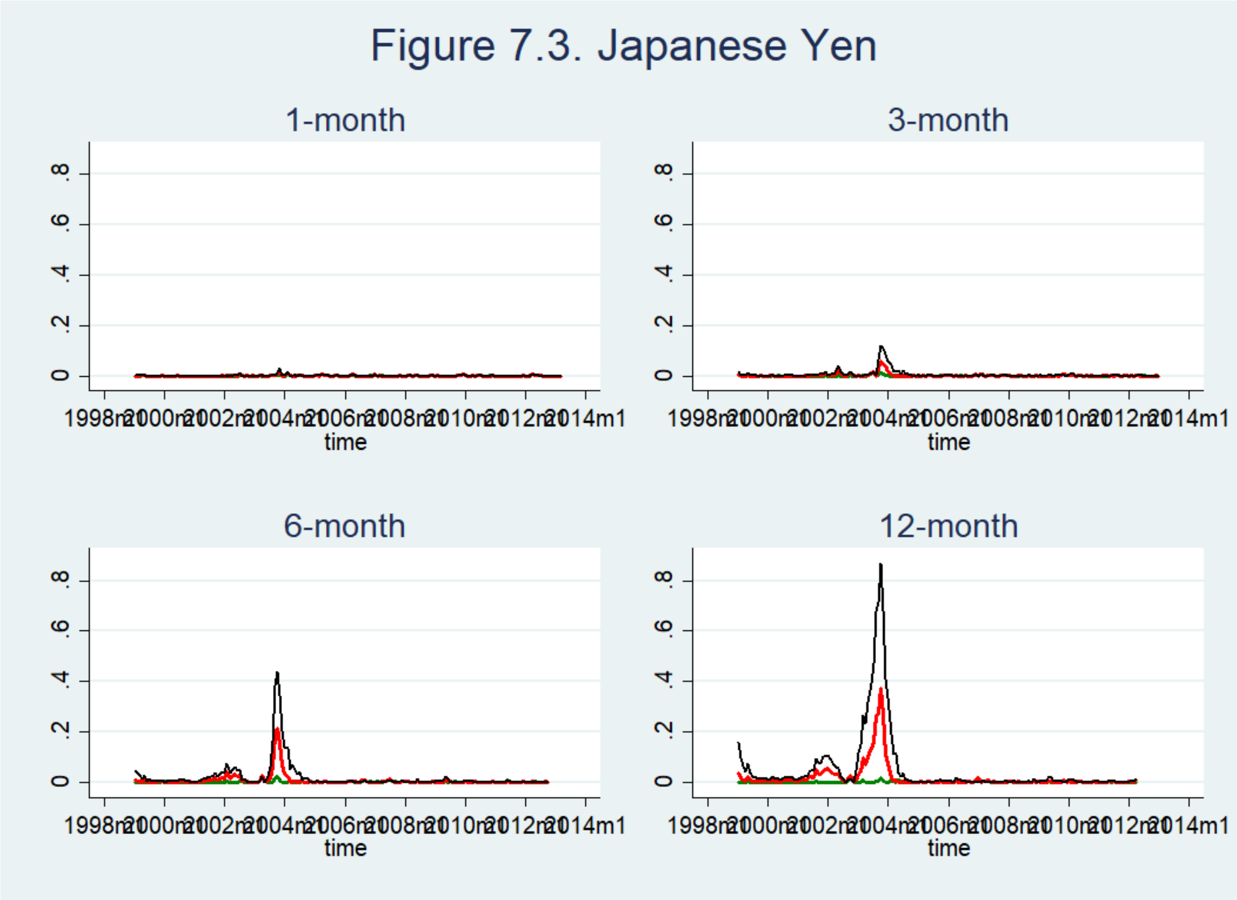


Figure 7.3. Japanese Yen
1-month
3-month
6-month
12-month
0
.2
.4
.6
.8
1998m1
2000m1
2002m1
2004m1
2006m1
2008m1
2010m1
2012m1
2014m1
time

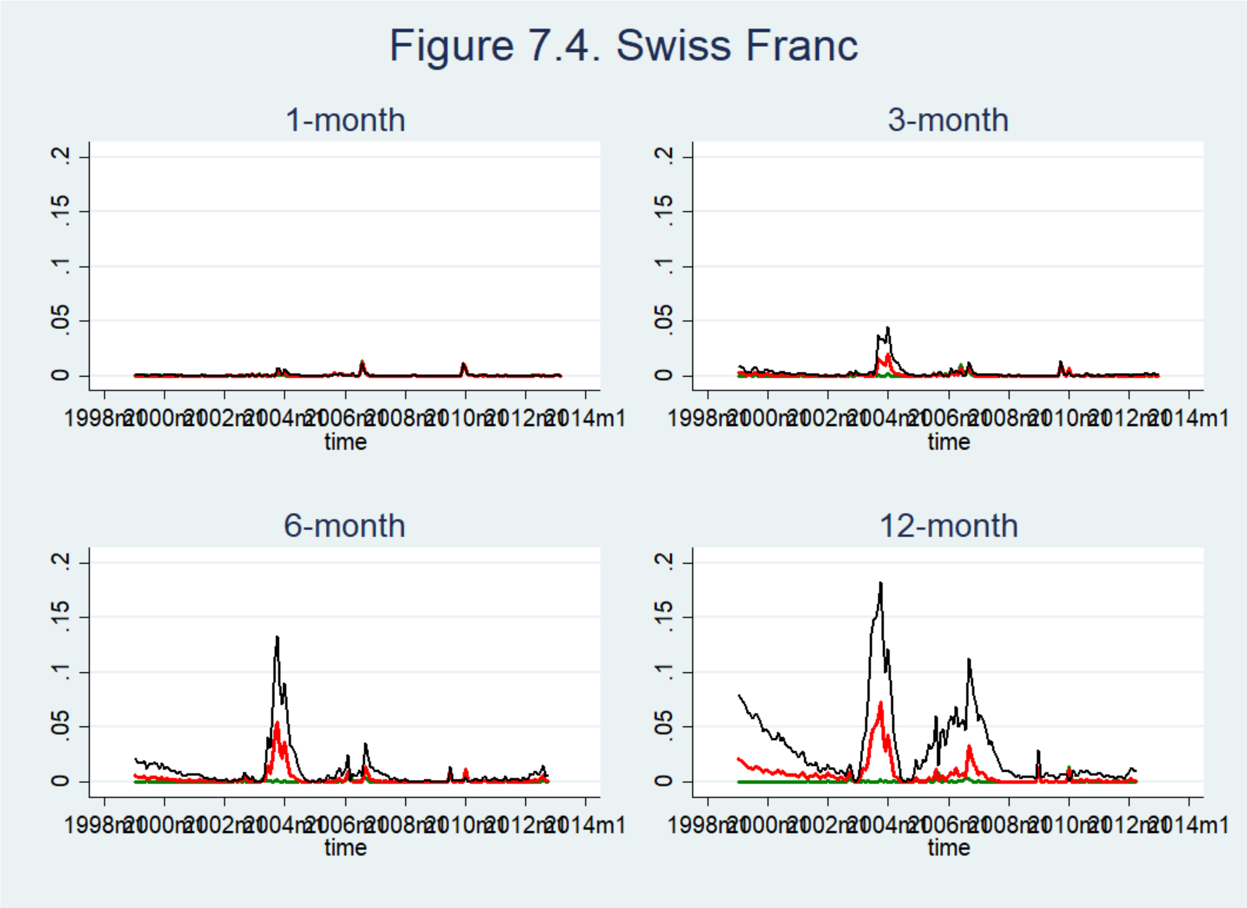


Figure 7.4. Swiss Franc
1-month
3-month
6-month
12-month
0
.05
.1
.15
.2
1998m1
2000m1
2002m1
2004m1
2006m1
2008m1
2010m1
2012m1
2014m1
time