Weekly foreign exchange forecasting using higher frequency data

by

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I. Introduction

The focus of this paper is on the behavior of weekly foreign exchange rates. I investigate whether daily closing prices of spot exchange rate data is more useful in forecasting a week ahead than weekly closing prices are. I chose this time horizon because the literature is sparse at this forecasting horizon. Weekly data may be somewhat overlooked in the literature. Since the advent of fast computing power, there has been a growing interest in short term forecasting and trading. In the very short term, the object of interest is in exploiting inefficiencies in market microstructure. Rather than using the typical vector autoregressive methodology, Danielsson and Love (2006) develop contemporaneous feedback trading to explain the behavior of 1 minute and 5 minute prices in the foreign exchange market. They examine the behavior of the EUR/USD between December 1999 and July 2000. This period covers the busting of the technology bubble and coincides with the initial period of my own sample for this paper. The first period I forecast uses data from July 1999 to March 2000.

At a slightly longer intraday horizon, Jordà et al (2003) use 30-minute data to explore the dynamics of the bid-ask spread. They develop a model that highlights the variation in information content associated with changes in the intensity of activity levels. More recently, Berger et al. (2007) confirm the association between order flow and exchange rate returns, but explain that the effect is substantially lower at longer horizons. Since I am using daily data, most high frequency issues with market microstructure can be avoided. High frequency data typically refers to intraday observations. When we extend the horizon to short term price movements, this typically refers to observations from one month to three months in duration. For example, Sartore et al. (2002) use a vector error correction model (VECM) to develop a monthly forecast of the EUR/USD pair between 1990 and 1999. This horizon is useful for monthly accounting and risk management. The medium term period beginning at the three month horizon captures the quarterly period of corporate and government reporting. According to Benassay-Quéré et al (1999), this is the point where destabilizing prices evolve into relationships that more closely follow theoretically economic relationships. They study the 3 to 12 month horizon. At a minimum, the long term period begins at more than 12 months.

In an effort to fill the gap between high frequency (intraday) and short term (1-3 mos.), I begin with daily and weekly data. The direction of inquiry for this paper is to test for any benefit of using daily data to forecast weekly foreign exchange rates. Specifically, my question of interest is whether the fifth trading day of a daily forecast may be an improvement over the one period ahead forecast using weekly data. One limitation of this approach is that the further out a prediction is cast, the broader the accompanying forecast must be. For this reason, I do not expect great predictive accuracy five periods into the future. My question is just whether it is a worthwhile improvement over the weekly forecast. Obviously, the daily forecast is more informative, since we get a value for each day of the week.

The methodology I use in this paper is the familiar ARMA model to forecast the often overlooked weekly horizon. To narrow the scope into a more useful focus, my contribution is to test for predictive power at significant turning points in the foreign exchange market since 1999. These include the end of the technology bubble in early 2000. More recently, a massive unwinding of the carry trade began in August of 2007. Of course, we are still experiencing the end of the real estate bubble of 2008. Studying market movements at these junctures is important because any improvements in predictability will increase our ability to control risk by making use of better lead time. The magnitude of any crisis is by nature unpredictable; but the better we can model it, the more successfully we can plan for it.

To provide some background for my topic, Section 2 will cover the underlying formal theory of foreign exchange rate determination. Some of it may not seem realistic; but then this is the point of empirical testing. Section 3 provides a brief review of the literature related to forecasting exchange rates. The method and data will be explained in section 4, followed by the tests and results of section 5. I will conclude section 6 with policy implications and some remarks on further research into other uses of higher frequency data to predict weekly prices. Tables, charts and empirical results follow the references.

II. Theory

Foreign exchange transactions become necessary to carry out any trading across political borders. Trading partners around the world operate different exchange rate regimes. The time horizon of this study was partly chosen so as to include the value of a recently formed common currency regime, the Euro. The spot price of foreign exchange rates is handled through international banks in an over the counter (OTC) market. Currencies also trade on futures exchanges, but the bulk of trading is through bank dealers. Each currency is quoted relative to another currency; or in some cases relative to a basket of currencies. The dollar index is one such instrument. The factors that drive exchange rate movements are many. The main four drives that are discussed in the literature are consumer prices, the money supply, GDP growth and interest rates. I will discuss each one of these briefly and then drill down into theories of short term exchange rate determination which relates directly to our weekly forecasting horizon.

In the long run, price theories such as Purchasing Power Parity (PPP) may help determine exchange rate movements. The absolute version of this theory is also the Law of One Price.

When adjusting for exchange rates, the prices of goods in two countries should be roughly equal. For example, if the price of domestic goods rises relative to foreign goods, then the domestic currency will fall to offset the relative price difference according to PPP. Mathematically, the exchange rate between two countries is equal to the ratio of their price indexes as follows:

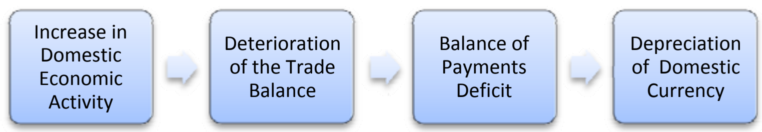
$$\frac{Pd}{Pf} = S$$

where P is the price of a basket of goods in the domestic and foreign markets. The Spot exchange rate, S, in the domestic currency is given per unit of foreign currency. As Pd increases, S also increases; but this represents a lower exchange rate because one unit of foreign currency buys more domestic currency. So S can be represented by $\frac{Sd}{1f}$. When S increases, the domestic currency falls.

Less restrictive is the relative purchasing power parity. In this case, the exchange rate will change over time to offset differences in the national inflation rates. For example, if domestic inflation is higher than foreign inflation, then the domestic currency will fall to offset the gap in relative inflation rates. In the following equation, $\dot{P}$ is the percent change in the price level of a basket of goods. We interpret this change as the inflation rate. So, we see in the equation that the percent change in the spot rate is equal to the inflation differential between the domestic and foreign country. In the long run, inflation differentials may dominate exchange rate movements.

$$\dot{S} = \dot{P}d - \dot{P}f$$

Changes in consumer prices help to develop a solid theoretical background, but are not very useful for determining the movements of exchange rates in a practical time horizon. More closely watched are Gross Domestic Product (GDP) numbers which give some sense of a country's economic growth in income and output. In the short run, domestic economic growth should increase the exchange rate for domestic currency because this may attract inflows of capital from abroad which are converted into domestic currency, thus pushing up the price of that currency. In the long run, an increase in GDP growth may give rise to an increase in import demand from domestic consumers. According to the Mundell-Flemming model, the long run exchange rate may fall due to balance of payment constraints. Assuming perfect capital mobility, the transmission mechanism is illustrated by this flow chart which is partially reproduced from Rosenberg (1996):



In addition to prices and economic growth, exchange rates are largely determined by Central Banks and their respective monetary policy. In this study, we only consider how monetary policy affects floating exchange rates. With a fixed exchange rate, a central bank gives up its monetary policy in acceptance of the policy from the country to which its currency is pegged. For the small open economy with floating rates, the monetary approach to the exchange rates for any two countries is determined by relative money demand and supply between the two countries. Of course, money demand depends on our previous two discussions of prices and income. A monetary expansion increases the money supply relative to a foreign trading partner which will lower the relative value of the domestic currency. From Mankiw (2007), we find that an increase in the money supply will put downward pressure on domestic interest rates causing capital to flow out of the country. These outflows prevent the domestic interest rate from falling below the world interest rate. Capital outflows into higher earning foreign investments require domestic currency to be converted into some foreign currency. This increases the supply of domestic currency in the foreign exchange market causing the domestic currency to depreciate in value. In the medium term, domestic monetary policy may help determine changes in exchange rates.

Prior to our recent market collapse, the primary driver of new Millennium exchange rate movements has been the interest rate differential. Relative interest rates are an invaluable component of exchange rate determination in medium term and short term planning horizons. In the non-theoretical world, interest rates and exchange rates are simultaneously determined. Both are jointly affected by new information and events as well as expectations about inflation. Holding other factors constant, an increase in domestic interest rates will theoretically cause the domestic exchange rate to fall. Intuitively, higher rates and the accompanying inflation will erode the value of the currency over time. In the short term, this may not be the case. We can show this with a representation of the covered interest rate parity condition:

$$rd = rf + \frac{F - S}{S}$$

where r is the interest rate, F is the forward rate and S is still the Spot rate of the domestic currency per unit of foreign currency. The forward premium $\frac{F-S}{S}$ ensures that an investment in foreign bonds does not generate excess returns after accounting for the exchange rate. Mathematically, if the domestic interest rates increases, holding other things constant, the spot exchange rate must come down in order for the right hand side of the equation to maintain the equality. Since S is still represented by $\frac{Sd}{1f}$, the domestic currency appreciates in this scenario. One unit of foreign currency buys fewer domestic units as S decreases. One mechanism for this is that as the domestic interest rate increases, the domestic currency will attract foreign money which will raise the relative value of the domestic currency. While higher rates may cause a currency to fall over the medium term, in the short term weekly horizon that I study, traders chase higher interest rates. This is confirmed in Dornbusch (2001) who concedes that a rising interest rate may give rise to capital inflows that appreciate the exchange rate in the short run. In the long run, PPP may dominate exchange rate movements. In the short run, interest rate differentials are the main drivers of exchange rate movements.

III. Literature review

We took a look at the four most common variables used to determine and forecast future exchange rate levels. Most of the literature discusses prices, money supply, economic growth and interest rates. These economic phenomena are considered fundamental variables. In the monetary approach to exchange rate determination, Neely and Sarno (2002) show the specified model as: $m_t = p_t + ky_t - \lambda i_t$ where m_t, p_t, y_t and i_t denote the log-levels of the money supply, the price level, income and the level of the interest rate respectively at time t, while k and λ are just positive constants. As I mentioned in the discussion of interest rates, one problem with this specification is a simultaneity bias. At least some of the variables are simultaneously determined. Meese and Rogoff (1983) used instrumental variables to correct for this problem. Overall, forecasting was not improved. Their results established that fundamental variables were not very useful in predicting future changes in exchange rates. The Granger-causality tests of Engel and West (2005) actually find that exchange rates may be useful in forecasting these economic variables into the future. Whatever the direction or accuracy, the link between fundamentals and exchange rates tends to be played out at horizons of three months or more. As Douch (1989) informed us, “Economic fundamentals tell us about medium to long term equilibrium positions.”[1]

[1] Douch, Nick. The Economics of Foreign Exchange: A practical market approach. Quorum Books. New York. 1989, pg. 114

A practical problem with Fundamental Analysis is that prices may stray from some underlying economic fundamentals for very long periods. Former Federal Reserve chief, Alan Greenspan, called this irrational exuberance in explaining extreme stock market valuation. Statistically, these prices may be distributed with what we call "fat tails." The natural question that comes to mind is, if economic variables cannot help us predict future exchange rates, what can? For shorter term analysis, many market participants use technical analysis. This was popularized by Charles Dow which became known as the Dow Theory. This approach essentially breaks the pattern of prices into three groups of long, medium and short term trends. The basic assumption is that prices trend. His phases of the trend included accumulation, public participation and distribution. These trends are observed to exist until definitive signals prove that they have ended. Following Technical Analysis, Dow Theory uses the historical evolution of an exchange rate in order to predict future movements as opposed to using fundamental economic variables to predict future movements of the exchange rate.

Often moving averages and chart patterns are used to identify and exploit trends in a market. From Charles Dow at the beginning of the 20th century to Harris and Yilmaz (2009), western markets have used trends to forecast future prices. Harris and Yilmaz use the Hodrick and Prescott filter and Nadaraya-Watson kernel regression to decompose the spot exchange rate. They use the low frequency trend component to generate directional forecasts of the spot exchange rate. They found greater directional accuracy than typical moving average strategies by exploiting the short term momentum in the non-linear trend component of the exchange rate rather than in the exchange rate itself. Combining economic fundamentals and recent extrapolation, Pilbeam (1995) found a significant increase in the probability of successfully forecasting exchange rates. He mentions that expectations may be extrapolative in the short run with attention increasingly switching to underlying economic fundamentals in the long run.

In a discussion of a regressive model, Benassy-Quere et al. (1999) note that regression to a moving average is a technical (chartist) approach whereas regression to an economic variable (e.g. PPP) is a fundamental approach. In a survey conducted by these authors, the extrapolative model seemed to be the most widely used specification based on 80% of survey respondents. This is also a method that I use to examine forecasting predictions at turning points. In the daily and weekly data that I use, high frequency issues of order flow, news announcements, etc. become of negligible concern. I chose to use simple econometric techniques since they are found to often work as well as more complicated approaches. For the weekly horizon that I study, my chosen econometric method is more similar to technical analysis than fundamental. I will not use economic variables. I will only extrapolate from past values of each variable of interest.

While simple methods are competitive in the forecasting area of study, some methods have shown an ability to out predict basic econometric techniques. Since the advent of greatly increased computer power, Kamruzzaman and Sarker show that Artificial Neural Networks (ANN) have better predicting power than simple models such as autoregressive integrated moving average (ARIMA) models. The authors cite better effectiveness in describing the dynamics of non-stationary time series. The ANN approach is non-parametric, noise tolerant and adaptive. Lin et al. (2002) take this analysis even further and combine fuzzy logic with neural network algorithms in a neuro-fuzzy model. The authors find this approach to outperform the predictability of linear methods when tested on 30 major stock indexes. While this is quite impressive, it represents overkill for the one to five period ahead forecast that I am testing.

IV. Method

The direction of my chosen econometric method was partly motivated by Nijman and Palm (1990) as they studied the predictive accuracy gain of using higher frequency data in ARIMA models. In this study the authors disaggregate annual data to predict one quarter in advance. They found this to reduce the variance of forecast errors considerably. Further disaggregation from quarterly to monthly data is not found to improve the accuracy of monthly forecasts. For the purposes of my study, I will not disaggregate weekly data. Rather I simply use daily data to forecast five days ahead in comparison to using weekly data to forecast one period ahead. Ultimately, the goal is to predict better than a random walk forecast.

Stock prices and foreign exchange prices may actually follow a random walk with drift pattern which is mathematically described as:

$$X_t = \mu + X_{t-1} + \varepsilon_t$$

where X_t is the price at time t, μ is a drift parameter, X_{t-1} is the value of X with one lag and ε_t is the random disturbance term. If μ is zero, then this model is a random walk without a drift. From Malkiel (1973) we learn that past values of an exchange rate price should not be able to predict its future movement. Malkiel suggested that since prices take a random, unpredictable path, one cannot out-perform the market without assuming additional risk. He may have inferred that technical analysis and fundamental analysis were both a waste of time. Theory holds that price changes have the same distribution and are independent of each other, so that past movements or trends cannot be used to predict future movements. The efficiency of the markets causes the prices to behave randomly, especially in the short run. In this case, there is a lack of correlation between past and present.

What I am modeling, according to the theory, is a sequence of random variables indexed by time which is called a time series process or a stochastic process. We find that stock prices and foreign exchange prices tend to be non-stationary. A time series is considered weakly stationary if its mean and covariance are time invariant. If there is, in fact, any linear dependence between an exchange price and its past values, then there is autocorrelation that will allow past values to be used to predict future values. We can do this using an autoregressive (AR) model. The random walk model is essentially an AR(1) model. With this model we predict that this period's value will equal last period's value plus some constant that represents the average change between periods. This is commonly known to be a good predictor of future prices and so I use this one as a base model. When there is a clear trend or drift in a series, we can take the first difference of the series to predict the change between periods rather than the level. The quantity $X_t - X_{t-1}$ is the first difference. This process de-trends the data to make it stationary. For testing autoregressive models, the data needs to be stationary.

In an effort to allow the model to be slightly more rigorous, we will test for the need to add a moving average term. In this case we get an autoregressive moving average (ARMA) model. If the series has a unit root, then it is non-stationary and considered integrated. The integrated ARMA model is described as an ARIMA model. For my specific forecasts, I am using this Box-Jenkins methodology to model a univariate time series of foreign exchange prices. Box Jenkins methodology applies ARMA or ARIMA models to find the fit of a time series to past values of that series. Changing from the notation of the random walk, the common specification for an autoregressive model of order p, AR(p) is:

$$S_t = \phi_0 + \phi_1 S_{t-1} + \phi_2 S_{t-2} + \cdots + \phi_p S_{t-p} + \epsilon_t$$

Where S is the spot price of the exchange rate, ϵ is the error term and the ϕ are coefficients. The moving average model of order q is written as:

$$S_t = \theta_0 + \epsilon_1 - \theta_1\epsilon_{t-1} - \theta_2\epsilon_{t-2} - \cdots - \theta_q\epsilon_{t-q}$$

This model specifies the spot price of the exchange rate in terms of the lagged values of the error term. In this paper, I have used a few mixed ARMA models. Combining the equations above give us the specification for the ARMA (p,q) model.

$$S_t = \mu + \phi_1 S_{t-1} + \phi_2 S_{t-2} + \cdots + \phi_p S_{t-p} + \epsilon_t - \theta_1\epsilon_{t-1} - \theta_2\epsilon_{t-2} - \cdots - \theta_q\epsilon_{t-q}$$

The Box-Jenkins methodology is known to be one of the most efficient forecasting techniques. It is particularly useful for univariate time series. The autoregressive models I use forecast the exchange rate variable based on a linear function of its past value (The data have been first differenced for stationarity). When the moving average term is added, the prediction includes a linear combination of past errors. The criterion used for the fitted models is the Schwarz-Bayes information criterion (SBIC), although I will also note the Akaike Information Criterion (AIC) and the Final Prediction Error (FPE). I will use daily data to predict five periods into the future. Using weekly data, this will be compared to a one period prediction into the future. The question is whether there is improved predictive accuracy using higher frequency data.

Data

Following this data description are summaries of the daily and weekly data used in this paper. Datastream is the source for all data. The yen pairs are typically quoted to two decimal places while non-yen pairs are typically quoted to four decimal places. I have kept this convention. The data begins at the second half of 1999, specifically 7/1/1999. The observations are brought forward until the last shock to the markets is tested in October of 2008. This time period captures the advent of the Euro as a common currency and allows for a few data points before the bursting of the technology bubble in early 2000. I use this period for the first set of forecasts which predict 3/2/00. The next period predicted is 12/18/03. This is just a random check to make sure that the behavior of the results are similar to the other tests. The next major shock to the exchange markets is 8/16/07. This date is also used to compare predictive accuracy. The most recent shock to the markets was last year's real estate crisis. The date tested is 10/02/08. The GBP/JPY (labeled uk_yen) is clearly the most volatile currency pair. It is also one that has been extensively used as a carry trade perhaps adding to the volatility. In Table 1, we see its variance is much greater than the other pairs and it almost has fat tails if we define fat tails as having a kurtosis of more than 3. The GBP/USD is the most normally distributed with the smallest skewness statistic. We will see if any of these characteristics affect our ability to predict a point forecast one week ahead.

The weekly Chart 1 that follows Table 2 shows the path of the four foreign exchange rates chosen for this study. It makes for an easy visual analysis of some of the key turning points in relative prices. A scalar of 100 has been multiplied to the EUR/USD and GBP/USD in order to show them on the same graph. The level of the rate is actually irrelevant, since I am only interested in forecasting the path. There were no devaluations in these major pairs during the time of the study which would necessitate making adjustments for the level. I use the conventional backslash in discussion and underscore in the tables. Please note the following relationships in the tables: GBP/JPY—uk_yen, USD/JPY—us_yen, EUR/USD—eur_us and GBP/USD—uk_us.

V. Tests and Results

One of the first things to be concerned with in forecasting foreign exchange rates is that they tend to be non-stationary. There are several tests such as the Dickey-Fuller test for unit roots that help us identify a trending series. In order to work with a linear relationship, the data need to be stationary or mean reverting as opposed to trending. Continuing with our visual analysis, in Chart 2 I have included an example of the partial autocorrelation of the GBP/USD pair with twenty lags and a 95% confidence band.

The spike at the first lag suggests that taking the first difference may help make this data stationary. There are two higher order lags outside of the 95% confidence band which we also find in our selection order criteria for our first subset of data. In Appendix A, we can see the Akaike information criterion chooses lag 17 for the GBP/USD pair with the lowest final prediction errors. If we use the Schwartz-Bayesian criterion for our decision rule, we find that each pair just needs to be first differenced to become stationary. So, I begin the tests with a simple autoregressive model of order 1, abbreviated as AR(1). The weekly data behave similarly to the daily data. For this reason, I test the same AR(1) model on daily and weekly rates except that the daily forecast is five periods (days) into the future whereas the weekly forecast is only one period (week) into the future. Typically, the further out the prediction is forecast, the less accurate it becomes. This is a disadvantage for the five period daily forecast. However, we may still get some predictive gain from using higher frequency data. This is the reason for the tests. The benchmark is the common AR(1) model for the weekly forecast, which also represents a random walk forecast. The question is whether we can improve on the weekly forecast using higher frequency (daily) data. Appendix A shows all of the first period selection criteria. The

Table 3 output shows the daily out of sample (OOS) results from the simple AR(1) model on forecast day five.

These results are not very respectable. So, we will see if we can improve on our model. Upon inspecting autocorrelations in the residuals, we find that the EUR/USD and GBP/USD may benefit from the addition of a moving average term, changing our autoregressive model into an ARMA model. The inclusion of a moving average improves the model slightly for EUR/USD using an ARMA (1, 16) model. This model uses one autoregressive lag with a moving average lag of 16. The new point forecast is 0.9961. For the GBP/USD, I used an ARMA ar(1) ma(16, 17) since there were two spikes in the autocorrelation function of the residuals from the AR(1) model. After running the new model, all of the residuals fit within the 95% confidence band. The results of the coefficients and significance are shown in Appendix B. The GBP/USD prediction with the new fitted model is 1.6015. The benefit from the fitted models is 36 pips and 16 pips respectively. Foreign exchange pricing is enumerated in pips to reduce confusion about how many decimal places a point change is. Given that 3/2/00 was a turning point in these currencies, a total of 52 pips in improvement is not something to get very excited about. The benefit, however from the better specified models can be substantial if leverage is very high. At any rate, it seems to be an improvement over the random walk.

The weekly out of sample forecasts were almost the same as the daily forecasts. Table 4 shows the results from predictions. In order to analyze whether there is any improvement using higher frequency data, I calculate the sum of squared errors for the daily and weekly results. The sum of squared errors for the daily AR(1) model is 434.67. For the weekly AR(1) model, the sum of squared errors is 435.03. Using these criteria, it would seem that the daily data may yield slightly better predictive accuracy than the weekly data. The idea is to minimize the sum of squared errors in order to determine which process is closest to the actual outcome. The daily sum is smaller. Over the entire period studied, daily data may not improve predictive accuracy. I have shown, however, that at turning points there is a slight advantage of using higher frequency data. Although the difference is not of great magnitude, keep in mind that the daily prediction is cast five periods into the future. So, the daily prediction starts out with a disadvantage and still manages to outperform the one period ahead forecast of the weekly data.

I also ran tests on the fitted ARMA models to see if we could improve on our accuracy. The coefficients are listed for each time period in Coefficient Tables A through D. To the AR(1) model, a moving average term or two was added when there were spikes in the autocorrelation of the residuals. The fitted models were rechecked to make sure all autocorrelations were within the 95% confidence bands. While these models may have been a better fit for the data overall, they did not help to reduce risk at turning points by providing an improved prediction. I use the same criteria to determine predictive accuracy. The result is a bit surprising. With the fitted models, the weekly predictions outperformed the daily predictions. The weekly sum of squared errors is 438.61. The daily sum of squared errors is 441.26. Again, we take the one with the lower sum of squared errors to be the best predictor. In this case, it was the weekly fitted model. The fitted models actually perform worse at turning points than the random walk, AR(1) models. Both sums of squared errors are lower for the AR(1) models than for the fitted models which incorporate a moving average term. The two things my test results demonstrate are first, the use of daily data offers slight predictive improvement over weekly data and second, the random walk models are better predictors at turning points.

VI. Conclusion

The recent bursting of the real estate bubble has caused many of us to reassess our risk. One way to do that is to look at how our asset holdings have responded to past shocks in the market. This may give us an idea of what to expect in the future. It may be wise to assume future shocks will be of greater magnitude than previous ones. Whatever forecasting method we are using may work well during the good times. Unfortunately, we could end up giving much or all of our gains back as a result of an unexpected shock. This line of thinking has led me to investigate whether we might find a predictive accuracy gain from using higher frequency data. Using the popular Box-Jenkins methodology, I was not able to improve weekly forecasting using daily data. The basic AR(1) model was tested along with better fitting ARMA models. The AR(1) model was found to out-predict when daily data was used. For the fitted ARMA models, the result was the opposite. The weekly fitted model outperformed.

In this study of turning points in the foreign exchange market, I was not able to find enough predictive accuracy to warrant changes in policy. The policy implications of this study simply confirm the notion that simple is better. The AR(1) model works better than the fitted model at turning points and daily data predicts slightly better forecasts than weekly data. In order to have enough information for policy implications, this study would need to be combined with the results of predictive accuracy over the entire period studied. The dates covered were 7/1/1999 to 10/02/2008. It was certainly an eventful period. Further research could fill in the gap of the normal market movements during this time. Also, turning points could be investigated in other markets using a similar approach.

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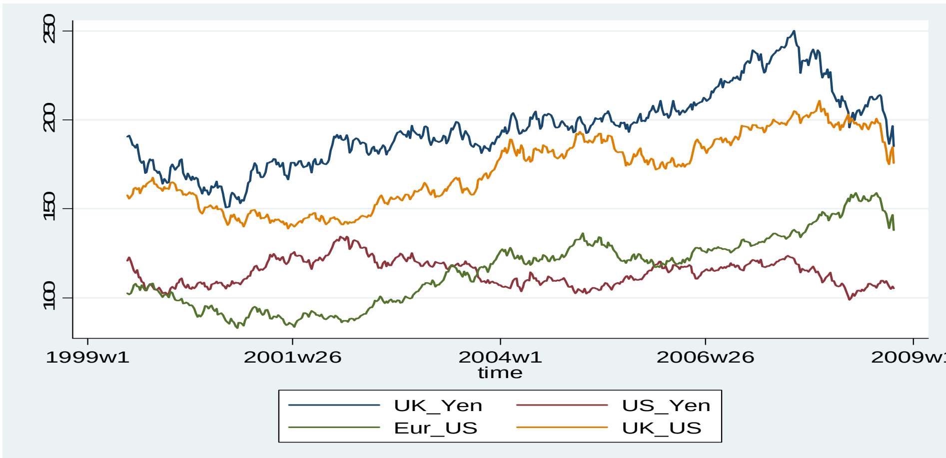
Appendix A
Lag Order Selection March 2, 2000

Selection-order criteria			Sample: 21 – 171			Number of obs	= 151	
	LL	LR	df	p	FPE	AIC	HQIC	SBIC
lag								
uk_yen	-476.308				32.5925	6.32196	6.33008	6.34194
1	-265.317	421.98	1	0	2.0193	3.54063	3.55686	3.58059*
2	-263.598	3.4394	1	0.064	2.00015*	3.5311*	3.55545*	3.59104
lag								
us_yen	-411.376				13.7916	5.46194	5.47005	5.48192
1	-178.539	465.67	1	0	.639778*	2.39124*	2.40748*	2.4312*
lag								
eur_us	316.697				0.000894	-4.18141	-4.1733	-4.16143
1	557.821	482.25	1	0	0.000037	-7.36187	-7.34563*	-7.3219*
2	558.864	2.0851	1	0.149	.000037*	-7.36243*	-7.33808	-7.30249
lag								
uk_us	371.664				0.000432	-4.90946	-4.90134	-4.88948
1	528.993	314.66	1	0	0.000054	-6.98004	-6.96381*	-6.94008*
2	530.412	2.8382	1	0.092	0.000054	-6.98559	-6.96124	-6.92565
3	530.495	0.16452	1	0.685	0.000055	-6.97344	-6.94097	-6.89351
4	530.732	0.47493	1	0.491	0.000055	-6.96334	-6.92275	-6.86343
5	530.74	0.01475	1	0.903	0.000056	-6.95019	-6.90149	-6.8303
6	531.186	0.89251	1	0.345	0.000057	-6.94286	-6.88603	-6.80298
7	531.266	0.16097	1	0.688	0.000057	-6.93068	-6.86574	-6.77082
8	531.283	0.03251	1	0.857	0.000058	-6.91765	-6.84459	-6.73781
9	531.403	0.24196	1	0.623	0.000059	-6.90601	-6.82483	-6.70619
10	531.749	0.69079	1	0.406	0.000059	-6.89734	-6.80804	-6.67753
11	533.118	2.7391	1	0.098	0.000059	-6.90223	-6.80482	-6.66245
12	533.317	0.39659	1	0.529	0.00006	-6.89161	-6.78608	-6.63185
13	533.367	0.10045	1	0.751	0.00006	-6.87903	-6.76538	-6.59928
14	536.073	5.4126	1	0.02	0.000059	-6.90163	-6.77987	-6.6019
15	536.095	0.04393	1	0.834	0.00006	-6.88868	-6.75879	-6.56897
16	541.301	10.412	1	0.001	0.000056	-6.94439	-6.80639	-6.60469
17	547.401	12.199*	1	0	0.000053*	-7.01193*	-6.86581	-6.65225

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.

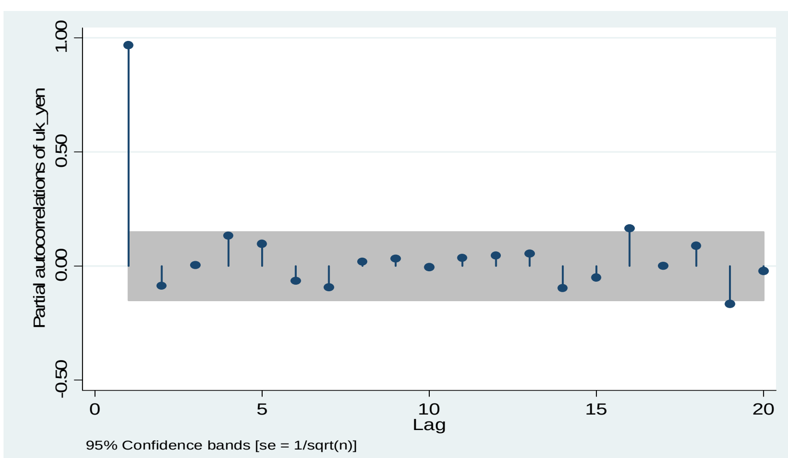
* Represents the best fitting order based on the criterion of the corresponding column

Chart 1
Last 10 Years Major Foreign Exchange Rates



Note: EUR/USD and GBP/USD have been rescaled to fit on the same graph as GBP/JPY and USD/YEN. The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.

Chart 2
Example of Unit Root



Note: The example is of the GBP/JPY pair in the chart as uk_yen

Table 1
Daily descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Variance	Skewness	Kurtosis
uk_yen	2411	195.23	21.1629	149.77	250.09	447.8694	0.3663	2.7657
us_yen	2411	114.22	7.3197	96.89	134.83	53.5791	0.3537	2.5459
eur_us	2411	1.1537	0.1983	0.8287	1.5978	0.0393	0.1731	2.1035
uk_us	2411	1.7143	0.1980	1.3727	2.1082	0.0392	-0.0007	1.6837

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.

Table 2
Weekly descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Variance	Skewness	Kurtosis
uk_yen	484	195.22	21.1864	150.72	250.09	448.8617	0.3613	2.7738
us_yen	484	114.18	7.2912	98.78	134.40	53.1617	0.3623	2.5517
eur_us	484	1.1544	0.1988	0.8290	1.5904	0.0395	0.1639	2.0934
uk_us	484	1.7148	0.1979	1.3888	2.1082	0.0392	-0.0069	1.6956

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.

Table 3
Fifth Day Forecast

OOS daily AR(1) forecasts						Actuals			
Date	obs	uk_yen	us_yen	eur_us	uk_us	uk_yen	us_yen	eur_us	uk_us
Mar-00	176	177.91	111.11	0.9997	1.6031	170.12	107.70	0.9663	1.5796
Dec-03	1166	188.39	108.43	1.2134	1.7402	190.84	108.00	1.2374	1.7672
Aug-07	2121	240.63	118.59	1.3698	2.0286	226.31	114.23	1.3402	1.9813
Oct-08	2416	196.53	106.58	1.4662	1.8463	185.11	105.29	1.3803	1.7582

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.

Table 4
Weekly Random Walk

OOS weekly AR (1) forecasts						Actuals			
Date	obs	uk_yen	us_yen	eur_us	uk_us	uk_yen	us_yen	eur_us	uk_us
Mar-00	36	177.92	111.11	1.0003	1.6040	170.12	107.70	0.9663	1.5796
Dec-03	234	188.40	108.42	1.2134	1.7402	190.84	108.00	1.2374	1.7672
Aug-07	425	240.64	118.59	1.3699	2.0287	226.31	114.23	1.3402	1.9813
Oct-08	484	196.53	106.57	1.4662	1.8463	185.11	105.29	1.3803	1.7582

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.

Coefficient Tables A
AR(1) Models 2000

AR(1) Daily 3/2/2000	(1) uk_yen	(2) us_yen	(3) eur_us	(4) uk_us
L.ar	0.985***	0.993***	0.975***	0.962***
	(0.0124)	(0.00874)	(0.0161)	(0.0235)
Constant	179.2***	113.0***	1.026***	1.611***
	(4.580)	(4.706)	(0.0226)	(0.0124)
sigma	1.407***	0.793***	0.00623***	0.00725***
	(0.0568)	(0.0346)	(0.000293)	(0.000396)
Observations	171	171	171	171

Note: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

AR(1) Weekly 3/2/2000	(1) uk_yen	(2) us_yen	(3) eur_us	(4) uk_us
L.ar	0.931***	0.963***	0.867***	0.790***
	(0.0569)	(0.0462)	(0.0934)	(0.0978)
Constant	179.4***	112.9***	1.028***	1.614***
	(4.621)	(4.565)	(0.0217)	(0.0109)
sigma	2.961***	1.770***	0.0144***	0.0161***
	(0.336)	(0.244)	(0.00228)	(0.00217)
Observations	35	35	35	35

Note: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

ARMA Models 2000

ARMA Daily 3/2/2000	(3) eur_us	(4) uk_us
L.ar	0.984***	0.975***
	(0.0140)	(0.0202)
L16.ma	-0.235**	-0.257***
	(0.109)	(0.0880)
L17.ma		-0.0710
		(0.0869)
Constant	1.025***	1.611***
	(0.0262)	(0.0117)
sigma	0.00606***	0.00699***
	(0.000321)	(0.000400)
Observations	171	171

Notes: The currency pairs have been renamed as follows.
EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order, "L.ma" is the moving average lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

There is no ARMA model for the weekly values of this period because the AR(1) model was the best fit.

Coefficient Tables B
AR(1) Models 2003

AR(1) Daily 12/18/2003	(1) uk_yen	(2) us_yen	(3) eur_us	(4) uk_us
L.ar	0.994***	0.996***	0.999***	0.998***
	(0.00316)	(0.00255)	(0.00141)	(0.00223)
Constant	181.0***	116.1***	1.058***	1.585***
	(5.988)	(4.704)	(0.140)	(0.0971)
sigma	1.205***	0.720***	0.00621***	0.00723***
	(0.0186)	(0.0115)	(0.000110)	(0.000125)
Observations	1161	1161	1161	1161

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

AR(1) Weekly 12/18/2003	(1) uk_yen	(2) us_yen	(3) eur_us	(4) uk_us
L.ar	0.973***	0.980***	0.993***	0.988***
	(0.0151)	(0.0122)	(0.00722)	(0.0108)
Constant	181.0***	116.0***	1.057***	1.585***
	(6.069)	(4.833)	(0.137)	(0.0956)
sigma	2.647***	1.561***	0.0141***	0.0162***
	(0.110)	(0.0689)	(0.000762)	(0.000778)
Observations	233	233	233	233

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

ARMA Models 2003

ARMA Daily 12/18/2003	(1) uk_yen	(2) us_yen
L.ar	0.994***	0.996***
	(0.00323)	(0.00253)
L5.ma	0.0817***	0.0602*
	(0.0300)	(0.0318)
L15.ma	-0.0638**	-0.0717**
	(0.0311)	(0.0291)
Constant	180.9***	116.0***
	(5.865)	(4.724)
sigma	1.199***	0.717***
	(0.0185)	(0.0115)
Observations	1161	1161

Notes: The currency pairs have been renamed as follows.
GBP/JPY as uk_yen. USD/JPY as us_yen.
"L.ar" is the autoregressive lag order, "L.ma" is the moving average lag order
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$

ARMA Weekly 12/18/2003	(1) uk_yen
L.ar	0.981***
	(0.0134)
L3.ma	-0.178**
	(0.0809)
Constant	181.6***
	(7.077)
sigma	2.615***
	(0.106)
Observations	233

Notes: The GBP/JPY currency pair has been renamed uk_yen
"L.ar" is the autoregressive lag order, "L.ma" is the moving average lag order
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$

Coefficient Tables C
AR(1) Models 2007

AR(1) Daily 8/16/2007	(1) uk_yen	(2) us_yen	(3) eur_us	(4) uk_us
L.ar	0.999***	0.995***	0.999***	0.999***
	(0.00101)	(0.00195)	(0.000843)	(0.00105)
Constant	203.2***	115.8***	1.160***	1.745***
	(21.65)	(3.151)	(0.151)	(0.171)
sigma	1.164***	0.672***	0.00639***	0.00842***
	(0.0135)	(0.00780)	(8.41e-05)	(0.000109)
Observations	2116	2116	2116	2116

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

AR(1) Weekly 8/16/2007	(1) uk_yen	(2) us_yen	(3) eur_us	(4) uk_us
L.ar	0.995***	0.979***	0.997***	0.996***
	(0.00490)	(0.00902)	(0.00409)	(0.00522)
Constant	203.5***	115.8***	1.160***	1.747***
	(22.14)	(3.209)	(0.152)	(0.173)
sigma	2.542***	1.447***	0.0141***	0.0184***
	(0.0789)	(0.0443)	(0.000525)	(0.000586)
Observations	424	424	424	424

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

ARMA Models 2007

ARMA Daily 8/16/2007	(2) us_yen	(4) uk_us
L.ar	0.996***	0.999***
	(0.00195)	(0.00109)
L5.ma	0.0435*	
	(0.0225)	
L15.ma	-0.0485**	
	(0.0213)	
L4.ma		0.0394*
		(0.0204)
Constant	115.8***	1.743***
	(3.156)	(0.167)
sigma	0.670***	0.00842***
	(0.00783)	(0.000109)
Observations	2116	2116

Notes: The currency pairs have been renamed as follows.
USD/JPY as us_yen. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order, "L.ma" is the moving average lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

ARMA Weekly 8/16/2007	(3) eur_us
L.ar	0.997***
	(0.00373)
L13.ma	-0.0940**
	(0.0455)
Constant	1.165***
	(0.156)
sigma	0.0141***
	(0.000524)
Observations	424

Notes: The EUR/USD currency pair has been renamed eur_us.
"L.ar" is the autoregressive lag order, "L.ma" is the moving average lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

Coefficient Tables D
AR(1) Models 2008

AR(1) Daily 10/2/2008	(1) uk_yen	(2) us_yen	(3) eur_us	(4) uk_us
L.ar	0.998***	0.996***	1.000***	0.999***
	(0.00117)	(0.00183)	(0.000645)	(0.000987)
Constant	194.8***	114.1***	1.212***	1.713***
	(12.08)	(2.976)	(0.186)	(0.140)
sigma	1.304***	0.692***	0.00669***	0.00880***
	(0.0122)	(0.00759)	(7.85e-05)	(0.000106)
Observations	2411	2411	2411	2411

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

AR(1) Weekly 10/2/2008	(1) uk_yen	(2) us_yen	(3) eur_us	(4) uk_us
L.ar	0.989***	0.980***	0.998***	0.994***
	(0.00553)	(0.00854)	(0.00324)	(0.00497)
Constant	194.8***	114.1***	1.212***	1.714***
	(12.63)	(3.123)	(0.185)	(0.140)
sigma	2.829***	1.464***	0.0150***	0.0199***
	(0.0734)	(0.0427)	(0.000488)	(0.000566)
Observations	483	483	483	483

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

ARMA Models 2008

ARMA Daily 10/2/2008	(1) uk_yen	(2) us_yen	(4) uk_us
L.ar	0.998***	0.996***	0.999***
	(0.00111)	(0.00174)	(0.00103)
L15.ma	-0.0499***	-0.0555***	
	(0.0180)	(0.0199)	
L4.ma			0.0482***
			(0.0187)
Constant	194.7***	114.1***	1.714***
	(12.54)	(3.098)	(0.137)
sigma	1.303***	0.691***	0.00879***
	(0.0122)	(0.00757)	(0.000106)
Observations	2411	2411	2411

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. USD/JPY as us_yen. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order, "L.ma" is the moving average lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05

ARMA Weekly 10/2/2008	(1) uk_yen	(3) eur_us	(4) uk_us
L.ar	0.992***	0.997***	0.993***
	(0.00486)	(0.00366)	(0.00545)
L6.ma	-0.0907**		
	(0.0439)		
L19.ma	-0.0892*		
	(0.0497)		
L18.ma		0.112**	0.104**
		(0.0477)	(0.0458)
Constant	194.5***	1.202***	1.710***
	(14.34)	(0.176)	(0.135)
sigma	2.802***	0.0149***	0.0197***
	(0.0749)	(0.000484)	(0.000559)
Observations	483	483	483

Notes: The currency pairs have been renamed as follows. GBP/JPY as uk_yen. EUR/USD as eur_us. GBP/USD as uk_us.
"L.ar" is the autoregressive lag order, "L.ma" is the moving average lag order
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1