Exchange Rate Forecasting: Do Linear Combinations of Exchange Rate Forecasts Outperform?

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ABSTRACT

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In recent years, a limited amount of work has been done on the medium-term linear composite method of forecasting. One common finding in the existing literature is that the consensus forecast measure is a biased predictor of future exchange rates. A widely accepted point of view in exchange rate forecasting research is that no theoretical model should be able to outperform a simple random walk. In this paper, recent exchange rate data and the Granger-Ramanathan linear estimation method are used to test medium-term forecasts. The currencies considered in this study are the most actively traded in the world and include: euros, Japanese yen, Canadian dollars, British pounds and Swiss francs. All currencies are examined relative to the US dollar. The major finding is that the linear composite model does in fact outperform a random walk model and an average forecast for Japanese yen, British pounds and Swiss francs. This evidence suggests that additional research should be conducted on exchange rate forecasting in general and on the linear composite forecast model in particular.

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1. INTRODUCTION

Foreign exchange rate forecasts are of great importance and are widely used in financial research as well as in practice. In recent years during the current period of floating exchange rates, exchange rates have tended to fluctuate to a much larger degree than ever before. This is true in particular of the Japanese yen, the euro, and more recently the Canadian dollar as measured against the US dollar. Fluctuations in exchange rates have important effects on a country's economy and usually increase the risks associated with international trade and investment. These variations in relative currency value are worthy of note and much research has been devoted to predicting exchange rates and to controlling exchange rate risk. Good forecasts generally lead to better decisions. However, there is considerable skepticism about the possibility of obtaining accurate exchange rate forecasts. In fact, many popular exchange rate forecasting models perform poorly and much of the previous research has yielded confusing results.

Economic literature has provided mixed results regarding the forecasting performance of exchange rate models. A seminal paper by Meese and Rogoff (1983) has shown that a simple random walk model is capable of predicting exchange rates better than other competing theoretical models. Since then, a number of researchers have evaluated the forecasting performance of various theoretical models. Several important theoretical models that have been tested in the literature include purchasing power parity, the monetary theory and the portfolio balance theory. Purchasing power parity is the primary theory that pervades exchange rates and has formed the basis for many subsequent theoretical models. It has played an important role in the empirical research dealing with exchange rate determination. Monetary models under the assumption of flexible prices became popular during the post Bretton Woods period of flexible exchange rates. The assumption of flexible prices was relaxed later on and a sticky price monetary model was developed. Portfolio balance models were also developed during the early 1980s with the extension of Tobin's portfolio model which includes the assumption of imperfect substitutability between foreign and domestic assets.

Backus (1984) and Meese and Rogoff (1988) in their analyses also found random walk models to be better predictors than theoretical models of exchange rate determination. On the other hand, Boughton (1984), Woo (1985) and Wolff (1987) found theoretical models to be better predictors of exchange rate movements. Following these studies, many subsequent empirical studies made use of cointegration techniques. The most commonly used cointegration tests are Engel and Granger's (1987) two-step test and Johansen's (1988) maximum likelihood generalization. Cointegration techniques are used to find out the long run relationship between variables and can be employed to describe short run dynamics by using the error correction term. Later on, non linear techniques were introduced by Engel and Hamilton (1990). Recently it has become popular to use survey-based measures of expectations to test a range of hypotheses about the behavior of foreign exchange rates.

When trying to construct or test an exchange rate forecasting model, an important factor which should be considered is the forecasting horizon. It seems reasonable to assume that some techniques should be more suitable for short-run forecasts while others are more effective for longer horizons. Thus, in this paper, the research on exchange rate forecasting is reviewed according to forecasting horizon.

Recently there has been a considerable amount of work on the topic of the medium-term linear composite method. One common finding in the literature is that the consensus forecast measure is a biased predictor of future exchange rates. In this paper, a current database supplied by Corporate Finance[1] (from January 2000 to April 2005) and the Granger-Ramanathan method are used to test medium-term forecasts. The currencies investigated are compared to the US dollar and are the most actively traded in the world. These include the euro (denoted herein as USDEUR), the Japanese yen (denoted herein as USDJPY), the Canadian dollar (denoted herein as USDCAD), the British pound (denoted herein as USDGBP) and the Swiss franc (denoted herein as USDSFR). Whether or not the linear composite model still performs well of late is the primary focus of this study.

Three questions are addressed in this thesis. The first issue is whether all disaggregate forecasts are biased estimates of actual exchange rates or are some forecasts better than others? Second, do mean survey forecasts perform better than individual forecasts and do mean survey forecasts follow the spot exchange rate? Third, is it possible to find a method to combine individual forecasts in an optimal way in order to produce superior exchange rate forecasts? In other words, can a composite forecast extract more relevant exchange rate information from the market than can a series of individual forecasts?

In this paper, test results indicate that most individual forecasters are biased. This result is similar to that found in most previous research. The usual reason offered to

[1] A monthly European journal

explain the bias is that most individual forecasters cannot extract all available market information. In addition, there is no obvious difference in forecasting ability among different individual forecasters. For the average forecast, test results indicate that the performances of average forecasts are related to actual changes in exchange rates, but are not equivalent. In addition, average forecasts do not seem to pick up more information from the market than do individual forecasts. An attempt is then made to see if it is possible to combine individual forecasts to produce superior forecasting performance. The Granger-Ramanathan Method is employed and the results are generally positive. Among five currencies investigated (USDCAD, USDEUR, USDJPY, USDSFR and USDGBP), the composite forecast outperforms well-known comparison benchmarks such as the random walk and average forecast except for USDCAD and USDEUR. The composite model also extracts more information from the market than any individual forecast can with the R-square of the composite model exceeding that of individual forecast regressions. This result was not a total surprise since the composite model has the potential to exhibit superior forecasting ability. However, this empirical result is contrary to that of Meese and Rogoff (1983) who compared the forecasting power of several structural models, and a VAR model. Their empirical evidence suggested that no model could outperform the random walk. It is reasonable to assume that the difference in results is due mainly to the different testing period and is possibly due to the choice of a different group of forecast sources.

The major contributions of this thesis are as follow. First, a description of available exchange rate forecasting data for potential use in academic research is outlined. This type of data is often difficult to find and is generally expensive. This may be helpful for future research in exchange rate forecasting and it is suggested that a test of robustness could be constructed by using the same testing time period but different data sources to test the same forecasting model. Second, although a considerable amount of research has been conducted using non-linear methods, limited work has been done on linear composite forecasting in recent years. Moreover we adopt a novel database and use the Granger-Ramanathan linear method to test whether the composite method has the ability to outperform a random walk or an average forecast. Test results are relatively positive since for USDGBP, USDJPY and USDSFR, the forecasting performances of the composite model outperform the standard benchmarks that are employed. This research result challenges the traditional point of view that no forecasting model can outperform a random walk and also provides an additional incentive to investigate the performance of linear composite models in future research work.

The remainder of this thesis is organized as follows. Section 2 reviews previous research in the exchange rate forecasting area. In section 3, the source of exchange rate data and our test sample and data are described. In section 4, the test methodology and testing results are presented. Section 5 gives the summary and conclusion of this paper. The major contributions and limitations of this study are also discussed in this section.

2. LITERATURE REVIEW

An important factor which should be considered in an exchange rate forecast model is the forecast horizon. Usually for different forecast horizons, different estimation techniques and models are adopted. It seems reasonable to assume that some techniques are more suitable for short-run forecasts while others are more effective when applied to longer horizons. Although some methods and models are widely used in all forecast horizons (the random walk model for example), it makes sense to group forecast methods according to their respective forecast horizon.

2.1 Long-Term Forecasting Methods

For long run projections, forecast horizons in excess of one year are considered. Important theories of long run exchange rate determination include purchasing power parity, the monetary theory and the portfolio balance theory.

Purchasing power parity (PPP) is the oldest theory of exchange rates and has laid the ground work for many theoretical models and empirical research of exchange rate determination. The main point of PPP theory is that exchange rates should tend to equalize relative price levels in different countries. PPP builds on the law of one price by analyzing the behavior of exchange rates and aggregate price indexes in two countries.

Absolute purchasing power parity predicts that these two price measures will be the same after adjusting for the exchange rate. We can express this as:

$$P_a = S_{a,b} \times P_b$$

Where P_a is the price in country a, P_b is the price in country b, and $S_{a,b}$ is the exchange rate between country a and country b. Absolute PPP may not hold for a number of reasons including varying inflation rates, transportation costs, trade restrictions, and costs of non-tradable and imperfect information.

Relative purchasing power parity offers a way to deal with some of the shortcomings of absolute PPP. More generally, relative PPP can be expressed as:

$$P_a = S_{a,b} \times P_b + \alpha$$

Where α captures deviations due to different inflation rates, transportation costs and other shortcomings of absolute PPP.

Mark (1990), Grilli and Kaminsky (1991), Flynn and Boucher (1993), Serletis (1994), and Serletis and Zimonopoulos (1997) in their research show that PPP did not hold during the floating exchange rate period. However, Frankel (1980), Perron and Vogelsang (1992), Phylatis and Kassimatis (1994) and Lothian and Taylor (1996) report evidence that exchange rates exhibit mean reversion tendencies in the long run.

The monetary theory is a direct outgrowth of PPP and the quantity theory of money. This theory is based on the view that since the exchange rate is the relative price of foreign and domestic money it should be determined by the relative supply and demand between currencies. Within monetary theory, there are two well-known models including the flexible price model and the sticky price (overshooting) model.

The flexible price model assumes that prices of goods are fully flexible. It implies that PPP holds continuously and that real exchange rates never change. We can express this as:

$$S_{a,b} = P_a/P_b = (M_a/D_a) \div (M_b / D_b)$$

Where $S_{a,b}$ denotes the exchange rate between country a and country b, P_a (P_b) is the price index in country a (b), M_a (M_b) denotes the money supply in country a (b) and D_a (D_b) denotes the money demand in country a (b). Here, money supply, income and the interest rates of two countries are important variables in explaining the exchange rate.

The sticky price monetary model was introduced by Dornbusch (1976) and assumes that the speed of adjustment of the price of goods is slower compared with the speed of adjustment of asset prices. When the price of goods are sticky, Dornbusch showed that it is necessary for asset prices to move by more than they would need to in the flexible price model in order for markets to reach a temporary equilibrium. The Dornbusch sticky model has been modified and extended by several authors. Frankel (1979) argued that the pure monetarist model was deficient since the nominal interest rate reflects both inflation and the real interest rate. A study by Mark (1990) provides strong evidence that the long-run path of exchange rates can be accurately gauged from knowledge of the level of the rate relative to its equilibrium value in a monetary model.

When considering monetary models, some researchers argue that exchange rates are determined not only by the demand for and supply of money, but also by the demand and supply of all domestic and foreign assets. The portfolio balance model is therefore a dynamic model of exchange rate determination based on the interaction of asset markets, current account balances, prices and rates of asset accumulation. It gives a direction in determining exchange rates by using financial data along with macroeconomic data.

Generally speaking, PPP, and monetary and portfolio theory provide a considerable amount of information regarding the determinants of exchange rates in the long run. Variables include international trade accounts, inflation rates, economic growth, interest rates and money demand and supply to name but a few. Taylor and Allen (1992) show that for a one-year horizon or a longer term forecast, roughly 85 percent of respondents rely primarily on macroeconomic fundamentals including money supply, inflation, national income, trade balance, and the current account.

2.2 Short-Term Forecasting Methods

For short-term forecasts, we usually refer to intra-day, daily or weekly forecasts.

Since short-term exchange rates tend to fluctuate dramatically, and accordingly a random walk (with zero drift) model may be a good choice to develop short-term forecasts. Thus a driftless random walk model, which is in essence a univariate time series model, is widely used in exchange rate forecasting. Meese and Rogoff (1983) compared the forecasting power of several structural models, and a VAR model. According to their empirical evidence, no model could outperform the random walk. Papers by Bilson (1990, 1993) suggest that when a trend is defined in a nonlinear fashion, the future trend is significantly related to past trends. Thus, the failure of traditional econometric models to find a connection between past trends and future trends may be the result of flawed methodology. The underlying relationships between future trends and past trends may in fact be nonlinear.

For intra-day rates, the GARCH model, linear in mean and non-linear in variance, have been adopted by many researchers. Baillie and Bollerslev (1991) adopted a GARCH model in their study of intra-day rates. Subsequently Baillie, Bollerslev and Mikkelson (1996) developed a fractionally integregated GARCH model. Cecen and Erkal (1996) argue that inconsistencies between the persistence of intra-day and daily conditional heteroskedasticity suggest the possibility that intra-day foreign exchange returns are caused by a nonlinear generating process.

For daily exchange rates, the GARCH model has also been widely used to capture the heteroskedasticity of these rates. Examples of research making use of this approach include, Baillie and Bollerslev (1989), Milhoj (1987) and Hsieh (1988, 1989). Fernandez-Rodriguez, Sosvilla-Rivero and Andrada-Felix (1999) analyzed daily exchange rate series within the European Monetary System (EMS). In contrast to the findings of other authors, they found that forecasts based on a multivariate nearest neighbor approach were more accurate than a no change forecast for the majority of the rates considered. An explanation given for this variation is the linkage provided by the EMS exchange rate mechanism, compared to the work of other authors who have analyzed free floating exchange rate data. A different approach was adopted by Gencay (1999) who compared parametric and non-parametric methods applied to moving average based buy-sell signals for daily data. Significant directional predictive performance was found using the non-parametric method.

For the weekly forecast, Meese and Rose (1990), Diebold and Nason (1990) and Lebaron (1992) used a locally weighted regression approach for weekly data. In all these cases, the authors found the applied method was no more accurate than a no-change in rates forecast.

2.3 Medium-Term Forecasting Methods

Medium-term forecasts generally extend from one month to less than one year. There are several problems inherent in medium-term exchange rate forecasting. These horizons may be too short for fundamental factors to take effect, and may be too long for some short-term technical models to offer significant improvements. However, medium-term forecasts are quite important since many financial hedging decisions are made in consideration of these horizons. A composite forecast is often suggested for medium-term forecast horizons since this approach has been shown to be quite efficient in terms of integrating a series of forecasting models in an attempt to outperform any individual forecast. Two fundamental reasons have been given for recommending the composite forecast method. First, each one of the various prediction techniques proposed has its own peculiar set of advantages and they all reflect different types of information. Thus, combining all the different forecasting techniques should yield the kind of diversification benefits often observed in portfolio management. Furthermore, this sort of composition tends to reduce any inherent biases that might arise from the use of just one prediction technique.

In practice, forecasting complex systems often involves seeking expert opinions from more than one person. Each is an expert in his/her own discipline, and it is through the synthesis of these opinions that a final forecast is obtained. This technique may be successful if individual forecasts reflect complementary elements of information. In research, some studies have attempted to combine medium-term exchange rate forecasts in an effort to obtain better results. In this paper, methods of combining forecasts are reviewed and the main focus is to find an optimal way to combine medium-term forecasts in order to produce superior forecasting results.

"Combining Forecasts" by Clemen (1989) is a milestone article on the topic of combining forecasts. This paper summarizes a substantial amount of research from different fields in a concise and readable manner. As noted by Clemen, past research has produced two primary conclusions, one expected and one surprising. The expected conclusion is that combined forecasts reduce error (in comparison with the average error of the component forecasts). The unexpected conclusion is that the simple average performs as well as more sophisticated statistical approaches. These conclusions are summarized succinctly by Clemen when he suggests that the forecasting practitioner should "combine and average." Beyond this conclusion, however, the research has produced few guidelines that are specific enough to be used by forecasters. Rule-based forecasting (Collopy and Armstrong, 1989) incorporates information from experts and from prior research. The procedure calls for the development of empirically validated and fully disclosed rules for the selection and combination of methods. The forecaster can provide information about the situation to the rule-based forecasting system. For example, a forecaster might put more weight on an econometric forecast than an extrapolation forecast in a situation where the firm plans to make substantial changes in its marketing procedures. Much of the research to date has discussed the combination of forecasts from different models. It is often difficult in practice to interpret the results from a combination of models. Inas much as each model contains different elements, it is not always clear why the combinations contribute to increased accuracy.

To set up or adopt a model using the composite forecast method, a specific rule for combining different predictions needs to be considered. Generally speaking, the composite model can be divided into two categories including linear and nonlinear combinations of different forecasts or explanatory variables. Recent research results show that if attention is restricted to mean square forecast errors, the performance of the models, when distinguishable, tends to favor the linear models. However, considering the regime at the forecast origin and the density forecasts, there is some evidence of forecasting gains from nonlinear models (Boero and Marrocu 2002). For linear combinations, one possible approach is to combine different forecast factors such as current spot rates, current forward rates, lagged forward rates and current PPP rates or current professional forecasts. Another way to combine forecasts is to combine some measure of the "consensus" forecast, such as the mean or median. A common procedure is to use a regression that assigns weights to each of the individual techniques (Kwok and Lubecke, 1990). Linear regression is a popular method used to determine the weights in a composite forecast model. With n forecasts ($i = 1....n$), the weight (w_i) on each forecaster can be estimated from the following equation:

$$S^e_{c,t} = w_1 S_{1,t} + w_2 S_{2,t} + ...w_n S_{n,t}$$

Each regression coefficient is interpreted as the marginal value of information from the i^{th} forecast, conditional on the information in the other n -1 forecasts. Thus, an individual forecast might be fairly accurate, but is of little value if it replicates the information in other available forecasts. Alternatively, an individual forecast could be biased or inaccurate, but capture some information that is missing in other forecasts. The weights of each forecast are usually estimated from in-sample data. A simple average that assigns fixed weights (1/n) may produce superior and steady forecasts.

Levich (1982) combined the forecasts of as many as 11 advisory services and the forward rate. His results show that the composite forecast produced a highly significant record of correct forecasts. Macdonald and Marsh (1994) use a disaggregate database to examine various methods of forecast combinations. Their results show that some forecasters are better than others, but most are not as good as naïve no-change predictions. Combining forecasts adds to the accuracy of the predictions, but the gains mainly reflect the removal of systematic and unstable bias.

Papers by Bilson (1990, 1993) argue that most previous studies of exchange rate behavior have used linear regression models to examine whether current exchange rate movements can be used to forecast future exchange rates. When this kind of model is estimated, the regression coefficient is typically insignificantly different from zero.

Hence, these results support the position that future trends appear to be unrelated to past trends. Bilson argues that linear regression analysis assumes the existence of a linear (proportionate) relationship. The failure of traditional econometric models to find a connection between past trends and future trends may be the result of flawed methodology. The underlying relationships may in fact be non linear.

Some researchers argue that composite models attempt to forecast the variability of exchange rates through linear or non linear relationships of explanatory variables such as money supply, real income, interest rates, inflation rates and current-account balances. Despite being based on sound economic principles, all these approaches have rather limited forecasting capability, due to the difficulties experienced in establishing all of the main principles required to successfully model exchange rates. The work done by Takens (1981) and Casdagli (1989), among others, establishes the methodology required for the nonlinear modeling of time series. Later on nonlinear prediction techniques were developed as a functional forecasting approach. Methods include the nearest-neighbor approach, neural networks and genetic programming.

Applied econometrics has recently employed all of these techniques in the prediction of different exchange rates. At first, the most widely employed approaches were those that were based on generalizations of the nearest-neighbor technique. Diebold and Nason (1990), for instance, applied the locally weighted regression method, while Lisi and Medio (1997) used a local regression. Subsequently, neural networks became the focus of much additional research (Kuan and Liu 1995; Tenti 1996; Yao et al. 1997; Zhang and Hu 1998; Hu et al. 1999; Yao and Tan 2000; Walzack 2001). More recently, genetic programming has been used for the prediction of exchange rates (Alvarez-Diaz and Alvarez 2003). Alvarez and Alberto (2005) use a genetic program to combine the predictions obtained by two individual techniques (i.e., a genetic program for the prediction of time-series and a neural network). Their objective is to verify whether employing such techniques, individually or in combination, would make it possible to accurately approximate the function in the specific case of the weekly exchange rate on the Japanese yen and the British pound against the US dollar.

To summarize, from the review for composite medium-term forecasts of exchange rates, it is apparent that in recent years much research has been done with regards to nonlinear composite forecasting methods. However, limited work has been done using linear composite methods. In this paper, an up-to-date database (from January 2000 to April 2005) is used and a linear regression method is adopted to obtain a linear composite model of exchange rates in an effort to outperform a random walk model or a simple average of a series of exchange-rate forecasts.

3. DATA COLLECTION AND DESCRIPTION

In practice, it is difficult to obtain true measures of market expectations of exchange rates. In order to proxy for these expectations, banks and other financial institutions often use surveys of market participants in their analyses. Such surveys may not be perfect since results are often collected over a number of days, the average person filling in the survey may not hold precisely the same views as the average person taking positions in the market, and different people may interpret a survey question in different ways. Therefore, it is important to analyze the information content of these surveys, rather than accept them on face value. Academic studies on exchange rates often make use of data from Consensus Economics. This entity surveys leading financial institutions, forecasting units, and multinationals in G7 countries. It polls more than 250 forecasters monthly and publishes a consensus forecast reflecting the mean value of available forecasts.[2] Periodically, the company also asks forecasters to assess the probability that exchange rates will fall within certain pre-specified ranges. Survey information of this sort helps gauge the chance (as assessed by these forecasters) that an exchange rate might differ from this mean or expected value. In some cases, these results are particularly interesting when they reveal a huge spike of probability for a zero or small change in the rate, and a small jump in probability for larger changes.

In practice, many exchange traders and financial institutions use the Reuters system. Reuters also supplies forecast data on a monthly basis. This survey is of interest since it obtains forecasts from foreign exchange traders and analysts, who might be expected to approximate the views of the market as a whole.[3] In total Reuters supplies forecast data gathered from over 90 institutions in major financial centers around the world. Reuters provides a high quality disaggregate dataset for comparison purposes. Reuters gathers currency forecasts of CAD/USD, CHF/USD, EUR/USD, GBP/USD and JPY/USD for future periods of 1 month, 3 months, 6 months and 1 year. However, Reuters just publishes the historical survey data for a three-month period, which limits the usefulness of the database. For future research, it would be beneficial to gather and retain monthly data. It would take a considerable amount of time to compile a meaningful database but it would greatly facilitate future exchange-rate research.

[2] Further information is available at the company's website www.consensuseconomics.com
[3] The code in Reuters is <Forexpoll01>.

In this study, we use forecasting data from Corporate Finance, which is a monthly journal that has surveyed leading financial institutions concerning their expectations of exchange rates. Five major currencies are considered relative to the US dollar. These include UK pounds, euros, Japanese yen, Swiss francs and Canadian dollars. These will be referred to respectively by the following codes: USDGBP, USDEUR, USDJPY, USDSFR and USDCAD. In this study, for USDGBP, USDEUR, USDJPY and USDSFR, 3-month-ahead forecasts for the period from January 2000 to April 2005 (a total of 64 observations) are considered. However, for USDCAD, Corporate Finance supplies data until October 2002, leaving a total of 34 observations. In total there are 30 financial institutions, which have supplied exchange rate forecast data to the journal. To be included in the sample, financial agencies must supply forecast data for at least six months within one year. Eight financial institutions meet this criterion.[4] When the data for any forecast agency during a particular month is missing, the average forecast during that month is used to represent its forecast for that month. Summary statistics of the data sets used for USDCAD, USDEUR, USDGBP, USDJPY and USDSFR are respectively given in tables 1-5.

It is important to recognize that forecast dispersion is not the same as the market's uncertainty about future exchange rates. This is because the survey collects each respondent's "best guess" of the exchange rate, which does not capture the individual's subjective uncertainty. To emphasize this point, consider a survey where all the respondents forecast the same outcome. For example, suppose that a given forecast is that USDCAD will be 1.30 in three months time. In this situation there is no dispersion. But

[4] The eight financial agencies are: ABN Amro, American Express, Bank of Montreal, Commerzbank, Goldman Sachs, Lloyds TSB, Royal Bank of Scotland and SG.

there may be considerable uncertainty in each forecaster's mind about the likelihood that this forecast is ultimately realized. Each forecaster may believe the USDCAD rate could be anywhere between 1.2 and 1.4 in a three months time, with 1.30 as their best estimate.

In addition to the survey data, actual data on spot exchange rates are collected from Reuters. The average spot rate during the month is assumed to be representative of actual monthly data.

4. THE MODEL, KEY METHODOLOGY AND TEST RESULTS

In this paper, the focus is on testing medium-term forecasts. One common finding is that the consensus forecast measure is a biased predictor of the future exchange rate. Recently, a considerable amount of work has been done using nonlinear forecasting methods. However, there is limited work employing linear analysis in exchange rate forecasting even though studies using linear estimation have shown promise. For example, Levich (1982) combined the forecasts of as many as 11 advisory services and the forward rate. His results indicate that the composite forecast does in fact produce a highly significant number of correct forecasts. In this paper, updated data and linear regression methods are used to determine if a linear combination method is capable of producing superior forecast results. Three primary questions are considered. First, do disaggregated forecasts yield biased estimates or are some better than others? Second, do mean survey forecasts exhibit superior performance in exchange rate forecasting and do the mean survey forecasts follow the actual spot rate? Third, is it possible to combine forecasts in such a way that superior forecasting performance is produced?

4.1 Test Related to Question 1: Are Individual Forecasts Biased?

First, as a preliminary exercise, the question of whether individual forecasts are unbiased is addressed. This test is performed by running the following regression[5]:

$$\Delta S_{t+3} = \alpha + \beta\, \Delta S^{e}_{t+3} \qquad (1)$$

Where S denotes the logarithm of the spot exchange rate, the superscript e denotes an expectation, Δ is the first difference operator and t+3 means the forecast horizon is 3 months ahead. Unbiasedness in the forecasts implies that α should be equal to zero and β should be equal to 1 in equation (1).

As mentioned earlier for USDCAD, Corporate Finance suspended the reporting of exchange-rate forecasts after October 2002. Ten months are then left out for an out-of-sample test yielding 24 observations covering the period from January 2000 to December 2001. For USDGBP, USDEUR, USDJPY and USDSFR, the test period extends from January 2000 to June 2004, for a total of 54 observations. The test results of the OLS estimation of equation (1) are presented in Table 6. From Table 6, it is apparent that for the five currencies under investigation, the hypotheses of α equal to zero fail to be rejected. This means that the change in the forecasts do not diverge from that of the spot exchange rate over time. However, among the 40 forecasts for the 5 currencies, the hypotheses of β equal to 1 are soundly rejected except in the case of the forecast of Commerzbank for USDCAD. This finding suggests that the majority of individual forecasts are biased. In fact, all the β values are quite different from 1. This result raises doubt about the accuracy of individual forecasts.

[5] This approach follows the specification of Macdonald and Marsh (1994).

Among all forecasters, Commerzbank gives superior forecasts for USDCAD compared with the seven remaining forecasters. However, for the other four currencies, it seems that no forecaster's performance stands out. It is noticeable that the R-square of each individual forecaster is quite low. For USDCAD, the highest R-square is 0.1701. For USDEUR, the highest R-square is just 0.0961. For USDJPY, the highest R-square is just 0.0903. For USDSFR, the highest R-square is 0.1364. Finally, for USDGBP, a low maximum R-square of 0.0615 is obtained. It appears that individual forecasters are generally incapable of incorporating the mass of information necessary to produce good exchange-rate forecasts. To summarize, joint tests of unbiasedness of individual forecasters are resoundingly rejected. Individual forecasters can not reliably predict the degree to which actual exchange rates will fluctuate. This test result is consistent with the finding reported in Macdonald and Marsh (1994).

4.2. Test Related to Question 2: Do Mean Survey Forecasts Perform Better than Individual Forecasts?

Since individual forecasts are biased, in this section an attempt is made in this section to determine whether mean survey forecasts perform better than individual forecasts and second, do mean survey forecasts follow the spot rate?

One way to assess the information contained in exchange rate surveys is to examine how "good" the survey mean is at predicting future exchange rates. Although it does not reflect the forecast of any individual respondent, it is likely that the mean forecast will reduce the inherent bias contained in individual forecasts. A frequent criticism of surveys of exchange rate forecasts is that average forecasts appear to simply follow the spot exchange rate. The following regression was run to test this belief:

$$\text{Ln } S_{t+i} - \text{Ln } S_{t+i-1} = \alpha + \beta(\text{Ln } S^e_{t+i} - \text{Ln} S^e_{t+i-1}) + \varepsilon_t \qquad (2)$$

In equation (2), Ln S^e_{t+i} is the log of the mean forecast at time t of the exchange rate for the forecast horizon i months ahead, and Ln S_{t+i} is the log of the actual exchange rate at time t+i. The interpretation of this equation is that revisions to the i month ahead forecast between t + i -1 and t + i are linearly related to the actual change in the exchange rate between t + i -1 and t + i.

The joint hypothesis that $\alpha = 0$ and $\beta = 1$ for the 3-month ahead forecast is examined. This would imply that both the change in the forecast maps one for one with that of the spot rate on average ($\beta = 1$) and that the change in the forecasts does not diverge from that of the spot exchange rate over time ($\alpha = 0$). Of course, it might be entirely rational for the forecast and the spot rate to move together, as the spot rate is forward looking.

The test data used is again obtained from Corporate Finance. The arithmetic mean forecast from the eight selected forecasters is calculated first. For USDCAD, the test period is made up of the 34 observations from January 2000 to October 2002. For USDGBP, USDEUR, USDJPY and USDSFR, the test period spans the 64 months from January 2000 to April 2005. Table 7 displays the regression results for this test. It shows the extent to which mean forecast revisions are related to actual changes in the exchange rate. For the five currencies under investigation, the hypotheses of α equal to zero fail to be rejected. This suggests that the change in the forecasts do not diverge from that of the spot exchange rate over time. However, among all forecasts for the five currencies, the hypothesis of β equal to 1 is soundly rejected. Therefore, we reject the joint hypothesis that $\alpha = 0$ and $\beta = 1$ for all. In fact, all β values are quite different from one. This indicates that a change in the exchange rate does produce a change in the forecast, but not to an equivalent degree.

The R-square values of the average forecast for the five regressions are still quite low. For USDCAD, the R-square is 0.0044. For USDEUR, the R-square is just 0.0167. For USDJPY, the R-square is 0.0520. For USDSFR, the R-square is 0.0584 and for USDGBP, the R-square is 0.0415. The adjusted-R square values are even lower. It seems that simple average forecasts do not pick up more information compared with individual forecasts. Thus, the question remains as to whether it is possible to find a linear combination of the forecasts that can outperform individual and average forecasts.

4.3 Test Related to Question 3: Is It Possible to Combine Forecasts to Produce Superior Forecasting Performance?

To recap, it was determined initially that individual forecasts are not very accurate, are biased, and do not take full account of available information. The subsequent finding was that the average forecast is related to the actual change of exchange rates, but not on a one-to-one basis. In this section an attempt is made to obtain a linear combination of forecasts that exhibits greater forecast accuracy. Put another way, can a composite forecast improve upon the synthesis of available market information. Two basic reasons have been given for recommending the composite forecast method. First, each one of the various prediction techniques proposed has its own particular advantages and they all reflect different sorts of information. Thus, combining all the different forecasting techniques should produce benefits from the advantages of each one thereby improving upon the accuracy of the predictions made. Furthermore, this sort of composite would be expected to reduce the bias that might arise from the use of a single prediction technique.

Granger and Ramanathan (1984) suggest that weights for the combination can be determined via a linear regression of the outcomes on the forecasts. They conclude that the unrestricted combination, with a constant term, is to be preferred since this provides the best fit in the ex post analysis. The weights thus obtained are used for ex ante predictions of the combined forecast. In order to evaluate these composite forecasts, it should be noted that within sample, unconstrained combinations of forecasts must match or outperform the components in terms of accuracy. The only true test of performance however is through an out-of-sample comparison.

Step1: The Granger-Ramanathan method is used to optimally combine the forecasts, whereby the following regression is run to retrieve the optimal weights β_i.[6] The weights are then used to construct a set of out of sample "optimal" forecasts. The regression takes the form:

$$\Delta S_{t+k} = \alpha + \Sigma\, \beta_i \Delta S^e{}_{it+k} \qquad i = 1,\ldots\ldots,n \qquad (3)$$

Where S denotes the logarithm of the spot exchange rate, the superscript e represents an expectation and Δ is the first difference operator. In this model, the actual change in the spot exchange rate is regressed on a constant and a set of n forecast changes. Due to scale biases[7] in the forecasts noted in the test of the first question, no

[6] According to Macdonald and Marsh (1994).

[7] A scale bias occurs when a forecaster systematically under or over estimates ($\beta \neq 1$).

constraints are imposed on equation (3). Running this regression to combine the predictions of a number of forecasters will result in negative weights on some of the components. This is not necessarily a comment on the forecaster's ability but, rather, an indication of the way predictions should be combined given the correlations between forecasts. This procedure is carried out for each exchange-rate prediction for the individual forecasters and then a test is conducted out-of-sample to determine the accuracy of these "combined" forecasts.

The sample periods are the same as in the previous tests. There are 34 observations for USDCAD, extending from January 2000 to October 2002 and 54 observations for the remaining currencies that extend from January 2000 to June 2004. In each case an additional 10 months of data are used to permit out-of-sample tests.

For each currency, there are 8 forecasters. The model is run for each currency and optimal weights are retrieved to obtain a combined forecast for each currency. Details of the regression results are reported in Table 8. From this table, it is clear that the R-square values for the regressions for each currency improve considerably compared with those obtained from regressions for individual forecasters (in Table 6). This result is as expected since a composite model should be capable of capturing more information than can individual forecasts. For USDCAD, the R-square of the composite model is 0.5353, which represents a considerable improvement when compared to the highest R-square for individual forecasts (0.1701). For USDEUR, the R-square of the composite model is 0.1268 (versus the highest R-square for an individual forecast of 0.0961). For USDJPY, the R-square of the composite model is 0.1799 (versus the highest R-square for an individual forecast of 0.0903). For USDSFR, the R-square of the composite model is

0.2306 (versus the highest R-square for an individual forecast of 0.1364). Finally for USDGBP, the R-square of the composite model is 0.1560 (versus the highest R-square for an individual forecast of 0.0615).

According to the R–square measure, it appears that the composite model captures more information than any individual forecast and can explain a greater percentage of exchange-rate variation in sample. However, it can not be concluded that the composite model is capable of making more accurate predictions than can any individual forecaster. As previously stated the only true test of forecasting performance is an out-of-sample comparison.

Step2: Given that the only true test of forecasting performance is an out-of-sample comparison of prediction accuracy, the Granger-Ramanathan method specified earlier is used to obtain the optimal weights to permit the combination of forecasts for each currency. Results appear in Table 8. The initial in-sample weights are held fixed throughout the out-of-sample period. For USDCAD, the out of sample test covers the ten-month period from January 2001 to October 2002. For the remaining currencies the out-of-sample period extends from July 2004 to April 2005.

Reasonable benchmarks to use in the comparison of forecasting accuracy include the average forecast and the random walk model. The simple random walk model predicts that the current spot rate is the best estimate of the future exchange rate and is quite widely accepted as one of the best predictors of future exchange rates. Meese and Rogoff (1983) compared the forecasting power of several structural models, and a VAR model. Their empirical evidence showed that no model could reliably outperform the random walk. The random walk model assumes that foreign exchange rates follow a random pattern, which in turn implies that the forecast for foreign exchange returns is zero. This is also called the no-change forecast. The random walk model can be written as:

$$S^{e}_{t+k} = S_t \tag{4}$$

Where S^{e}_{t+k} denotes the forecast made at time t for forecast horizon k, and S_t denotes the spot exchange rate at time t. It suggests that the exchange rate in the current period is the forecast for the exchange rate in the next period.

A root mean squared error (RMSE) criterion can be used to evaluate the predictive power of the average forecast, the random walk and the composite forecast. The RMSE statistic is:

$$\text{RMSE} = [\Sigma\ (\Delta S_{t+k} - \Delta S^{e}_{t+k})^{2} / n+1]^{1/2}$$

As before, ΔS^{e}_{t+k} gives the first difference of the log of the forecast. Therefore the term ΔS_{t+k} - ΔS^{e}_{t+k} gives the forecast error, and n represents the number of forecasts available. The more accurate the forecast, the smaller will be the RMSE. The results for each of the forecasts appear in Table 9.

From this table, the average forecast for USDCAD appears to be the best one with a relatively low RMSE value of 0.0221. The composite model is second, with a RMSE value of 0.0254, which is in turn lower than the RMSE value (0.0258) of the random walk model. For USDEUR, the situation is similar to that of USDCAD. Among the three forecast methods, the average forecast is the best one with a low RMSE of 0.0287. The performance of the composite forecast model is next, with a RMSE value of 0.0290, which is in turn higher than that of the average forecast but lower than that of the random walk model (0.0303). It is clear that although the composite model performs better than the random walk model, it does not outperform the average forecast for USDCAD and USDEUR.

For the USDJPY, USDGBP and USDSFR, the forecasting performances of the composite forecasts are superior to the other methods with RMSE values of 0.0244, 0.0236 and 0.0293 respectively. They clearly outperform both the random walk (0.0256, 0.0255 and 0.0388), and the average forecast (0.0273, 0.0340 and 0.0369).

These test results are different from a previous study as reported by Meese and Rogoff (1983). Their empirical evidence showed that no model could outperform the random walk. The results of this study are also different from those reported by Macdonald and Marsh (1994). Their research results indicated that composite forecasts are generally not as good as naïve no-change predictions (a random walk). In fact, the current results support the position of Levich. Levich (1982) combined the forecasts of as many as 11 advisory services and the forward rate. His results showed that the composite forecast produced a highly significant record of correct forecasts. Differences in test results can be attributed to different sample periods as well as the choice of different sets of forecasters.

5. SUMMARY AND CONCLUSIONS

In this paper, the research on exchange rate forecasting is reviewed according to the forecast horizon. Academic research seems to be focused of late on nonlinear aspects of exchange rate forecasting. However a limited amount of work has dealt with medium-term forecasting and the linear composite method in particular. One common finding in the literature is that the consensus forecast measure is a biased predictor of the future exchange rate. In this paper, recent exchange rate data are employed and the Granger-Ramanathan linear method is used to test medium-term forecasts. The currencies investigated are the most actively traded in the world and include the euro, the Japanese yen, the Canadian dollar, the British pound and the Swiss franc. All exchange rates are measured relative to the US dollar. The goal is to determine whether the linear composite model can outperform several well-known exchange-rate forecasting benchmarks. Three primary questions are of interest. First, are disaggregate forecasts biased estimates or are some better than others? Second, do mean survey forecasts perform better than individual forecasts and do mean survey forecasts follow the spot rate? Third, is it possible to find a method is to combine the forecasts themselves in an optimal way in order to produce superior forecasts? Expressed differently, is a composite forecast capable of making better use of market information?

In this paper, test results show that most individual forecasts are biased. This conclusion is consistent with that of the majority of previous research. There is no obvious difference among individual forecasters. The only exception among 40 individual forecasts that were investigated is that Commerzbank supplied a better forecast for USDCAD during the sample period.

For the average forecast, test results show that forecasting performance is related to the actual change in exchange rate, but not on a one-to-one basis. In addition, average forecasts do not seem to pick up more information from the market than do individual forecasts.

Finally, an attempt was made to combine individual forecasts in an effort to produce superior forecasting performance. The Granger-Ramanathan method was used and test results were relatively positive. Among the five currencies investigated (USDCAD, USDEUR, USDJPY, USDSFR, USDGBP), composite forecasts outperform the random walk and the average forecast for three currencies (USDJPY, USDSFR and USDGBP). The composite model also makes better use of market information than do any individual forecast since the R-square value of the composite model improves considerably compared with that of individual forecasts. This result is reasonable since a composite model should in theory be capable of using market information efficiently. This test result is contrary to a major paper by Meese and Rogoff (1983), which indicated that a simple random walk model can predict exchange rates better than any theoretical model. Differences are attributed to the different sample period investigated and to the choice of different forecasters.

This thesis makes several important contributions. First, a description of available exchange rate forecasting data is outlined. These types of data are difficult to obtain and are generally quite expensive. This information may to be helpful for future research in exchange rate forecasting. Generally speaking, there are at least three primary data sources that can be used for exchange rate forecasting research. These include databases supplied by Consensus Economics, Reuters and Corporate Finance. In future research it would be interesting to consider the same test period as was used herein but to make use of a different data source to check the robustness of the findings in this paper.

Second, while there is a considerable amount of research devoted to nonlinear methods there has been little work done where a linear composite forecasting method has been employed. Therefore, a recent set of data and the Granger-Ramanathan linear method were used to test whether the composite method has the capability to outperform average forecasts or a random walk model. Test results are relatively positive with the USDGBP, USDJPY and USDSFR exhibiting lower RMSE than either the average forecast or the random walk. This finding is contrary to that of a major paper of Meese and Rogoff (1983) who concluded that no model could outperform a random walk. The test results herein add to the existing body of knowledge on the topic of exchange rate forecasting.

However, there are also some limitations in this thesis that open the door for future work. The current research does not consider precisely the conditions under which combining forecasts is most effective nor does it consider other approaches that could be used to combine forecasts. Finally, future research may help explain why using different test periods or different combination methods may produce substantially different results.

Table 1. Summary Statistics of USDCAD 3 Month Ahead Forecasts

This table reports the summary statistics of USDCAD 3-Month Ahead Forecasts. The data in this table is from Corporate Finance. The sample consists of 34 observations covering the period from January 2000 to October 2002. The mean (median) and other statistics are the arithmetic mean (median) of selected forecasts during the indicated month. CV represents the coefficient of variation, which is the standard deviation scaled by its expected value.

	Forecast Month	Mean	Median	Max	Min	SD	CV
2000	January	1.4633	1.4633	1.4800	1.4500	0.0102	0.0070
	February	1.4488	1.4500	1.4700	1.4200	0.0164	0.0113
	March	1.4375	1.4450	1.4500	1.4000	0.0183	0.0127
	April	1.4425	1.4450	1.4500	1.4300	0.0089	0.0061
	May	1.4483	1.4492	1.4600	1.4400	0.0064	0.0044
	June	1.4550	1.4600	1.4800	1.4000	0.0251	0.0172
	July	1.4688	1.4700	1.4900	1.4500	0.0146	0.0099
	August	1.4700	1.4700	1.4800	1.4500	0.0107	0.0073
	September	1.4663	1.4700	1.4800	1.4400	0.0151	0.0103
	October	1.4675	1.4650	1.4800	1.4500	0.0116	0.0079
	November	1.4843	1.4821	1.5200	1.4600	0.0199	0.0134
	December	1.4929	1.4864	1.5400	1.4500	0.0333	0.0223
2001	January	1.5025	1.5000	1.5400	1.4500	0.0287	0.0191
	February	1.4786	1.4793	1.5000	1.4500	0.0181	0.0122
	March	1.4850	1.4750	1.5500	1.4500	0.0312	0.0210
	April	1.5043	1.5121	1.5400	1.4500	0.0320	0.0213
	May	1.5414	1.5407	1.6400	1.4500	0.0559	0.0363
	June	1.5175	1.5200	1.5600	1.4500	0.0341	0.0225
	July	1.5238	1.5200	1.5600	1.5100	0.0169	0.0111
	August	1.5129	1.5114	1.5600	1.4800	0.0231	0.0153
	September	1.5150	1.5150	1.5300	1.5000	0.0116	0.0077
	October	1.5283	1.5292	1.5600	1.5000	0.0181	0.0118
	November	1.5471	1.5486	1.5700	1.5300	0.0139	0.0090
	December	1.5600	1.5550	1.6200	1.5000	0.0374	0.0240
2002	January	1.5729	1.5650	1.6200	1.5500	0.0342	0.0217
	February	1.5720	1.5710	1.6000	1.5500	0.0151	0.0096
	March	1.5829	1.5800	1.6000	1.5600	0.0141	0.0089
	April	1.5757	1.5750	1.6100	1.5300	0.0243	0.0155
	May	1.5767	1.5733	1.5900	1.5700	0.0147	0.0093
	June	1.5586	1.5600	1.5800	1.5200	0.0181	0.0116
	July	1.5286	1.5300	1.5600	1.4900	0.0245	0.0160
	August	1.5205	1.5200	1.5600	1.4900	0.0213	0.0140
	September	1.5388	1.5294	1.5925	1.4900	0.0367	0.0238
	October	1.5247	1.5274	1.5735	1.4900	0.0252	0.0165

Table 2. Summary Statistics of USDEUR 3 Month Ahead Forecasts

This table reports the summary statistics of USDEUR 3-Month Ahead Forecasts. The data in this table is from Corporate Finance. The sample consists of 64 observations covering the period from January 2000 to April 2005. The mean (median) and other statistics are the arithmetic mean (median) of selected forecasts during the indicated month. CV represents the coefficient of variation, which is the standard deviation scaled by its expected value.

	Forecast Month	Mean	Median	Max	Min	SD	CV
2000	January	1.0650	1.0650	1.1200	1.0200	0.0292	0.0274
	February	1.0538	1.0500	1.1200	0.9900	0.0403	0.0383
	March	1.0213	1.0200	1.0800	0.9800	0.0331	0.0324
	April	1.0188	1.0200	1.0800	0.9100	0.0519	0.0510
	May	0.9917	0.9917	1.0800	0.9200	0.0442	0.0446
	June	0.9363	0.9400	0.9600	0.9100	0.0177	0.0189
	July	0.9200	0.9400	0.9600	0.8200	0.0456	0.0496
	August	0.9560	0.9600	0.9800	0.9100	0.0262	0.0274
	September	0.9567	0.9500	1.0200	0.9200	0.0320	0.0335
	October	0.8933	0.8900	0.9400	0.8300	0.0385	0.0431
	November	0.8775	0.8738	0.9200	0.8400	0.0261	0.0298
	December	0.8800	0.8800	0.9300	0.8400	0.0267	0.0304
2001	January	0.8833	0.8850	0.9300	0.8600	0.0250	0.0283
	February	0.9586	0.9600	0.9800	0.9300	0.0146	0.0152
	March	0.9690	0.9550	1.0000	0.9300	0.0242	0.0249
	April	0.9644	0.9700	0.9800	0.9400	0.0162	0.0168
	May	0.9414	0.9407	0.9800	0.9000	0.0242	0.0257
	June	0.9300	0.9400	0.9800	0.8900	0.0302	0.0325
	July	0.8722	0.8800	0.9200	0.8000	0.0412	0.0472
	August	0.8567	0.8650	0.8900	0.8000	0.0288	0.0336
	September	0.8629	0.8629	0.9000	0.8000	0.0364	0.0422
	October	0.9138	0.9138	0.9600	0.8800	0.0224	0.0245
	November	0.9300	0.9300	0.9600	0.8800	0.0277	0.0298
	December	0.9133	0.9167	0.9400	0.8800	0.0219	0.0239
2002	January	0.8933	0.9000	0.9200	0.8500	0.0213	0.0239
	February	0.8943	0.8943	0.9100	0.8700	0.0138	0.0155
	March	0.8889	0.8850	0.9200	0.8600	0.0193	0.0217
	April	0.8811	0.8850	0.9100	0.8400	0.0223	0.0253
	May	0.8850	0.8875	0.9100	0.8500	0.0205	0.0232
	June	0.9078	0.9100	0.9400	0.8900	0.0152	0.0168
	July	0.9367	0.9450	0.9500	0.9100	0.0155	0.0166
	August	0.9966	0.9913	1.0300	0.9300	0.0354	0.0355
	September	1.0079	1.0039	1.0300	0.9630	0.0218	0.0216
	October	1.0063	1.0063	1.0300	0.9880	0.0117	0.0116

	November	0.9908	0.9904	1.0000	0.9600	0.0150	0.0152
	December	0.9946	0.9946	1.0000	0.9600	0.0133	0.0133
2003	**January**	1.0479	1.0250	1.1200	0.9850	0.0392	0.0374
	February	1.0583	1.0592	1.0800	1.0300	0.0206	0.0195
	March	1.0617	1.0617	1.0800	1.0200	0.0229	0.0216
	April	1.0833	1.0767	1.1300	1.0200	0.0366	0.0338
	May	1.1229	1.1200	1.1300	1.0700	0.0207	0.0184
	June	1.1443	1.1550	1.1700	1.1000	0.0251	0.0219
	July	1.1557	1.1679	1.1800	1.0900	0.0377	0.0327
	August	1.1557	1.1679	1.1800	1.0900	0.0377	0.0327
	September	1.1517	1.1450	1.1600	1.0900	0.0229	0.0199
	October	1.2057	1.1879	1.3300	1.1600	0.0587	0.0487
	November	1.1800	1.1800	1.2200	1.1400	0.0242	0.0205
	December	1.1744	1.1850	1.2200	1.1400	0.0277	0.0236
2004	**January**	1.1744	1.1850	1.2200	1.1400	0.0277	0.0236
	February	1.2825	1.3000	1.3300	1.2600	0.0245	0.0191
	March	1.3014	1.3014	1.3500	1.2600	0.0262	0.0201
	April	1.2675	1.2800	1.3000	1.2000	0.0355	0.0280
	May	1.2313	1.2200	1.2400	1.1800	0.0272	0.0221
	June	1.2500	1.2300	1.2500	1.1900	0.0417	0.0334
	July	1.2257	1.2179	1.2700	1.1700	0.0392	0.0320
	August	1.2257	1.2179	1.2700	1.1700	0.0392	0.0320
	September	1.2400	1.2250	1.2700	1.2100	0.0200	0.0161
	October	1.2522	1.2411	1.3000	1.2000	0.0337	0.0269
	November	1.2744	1.2700	1.3000	1.2300	0.0393	0.0308
	December	1.3025	1.3113	1.3600	1.2600	0.0281	0.0215
2005	**January**	1.3025	1.3113	1.3600	1.2600	0.0281	0.0215
	February	1.3250	1.3250	1.3800	1.2600	0.0375	0.0283
	March	1.3125	1.3263	1.3700	1.2600	0.0406	0.0310
	April	1.3357	1.3279	1.4000	1.2800	0.0395	0.0296

Table 3. Summary Statistics of USDGBP 3 Month Ahead Forecasts

This table reports the summary statistics of USDGBP 3-Month Ahead Forecasts. The data in this table is from Corporate Finance. The sample consists of 64 observations covering the period from January 2000 to April 2005. The mean (median) and other statistics are the arithmetic mean (median) of selected forecasts during the indicated month. CV represents the coefficient of variation, which is the standard deviation scaled by its expected value.

	Forecast Month	Mean	Median	Max	Min	SD	CV
2000	January	1.6367	1.6367	1.6700	1.6100	0.0166	0.0102
	February	1.6425	1.6400	1.6700	1.5900	0.0260	0.0159
	March	1.6250	1.6200	1.6500	1.6100	0.0169	0.0104
	April	1.6138	1.6200	1.6500	1.5600	0.0320	0.0199
	May	1.5950	1.5950	1.6300	1.5700	0.0212	0.0133
	June	1.5700	1.5750	1.6100	1.5200	0.0273	0.0174
	July	1.5025	1.5000	1.5600	1.4300	0.0377	0.0251
	August	1.5138	1.5200	1.5400	1.4800	0.0200	0.0132
	September	1.5163	1.5200	1.5400	1.4900	0.0185	0.0122
	October	1.4325	1.4300	1.5100	1.3600	0.0430	0.0300
	November	1.4471	1.4500	1.5000	1.3600	0.0410	0.0283
	December	1.4233	1.4233	1.4600	1.3600	0.0296	0.0208
2001	January	1.4400	1.4400	1.4700	1.4100	0.0233	0.0162
	February	1.5014	1.5007	1.5600	1.4300	0.0376	0.0250
	March	1.4988	1.4900	1.5600	1.4300	0.0426	0.0284
	April	1.4743	1.4671	1.5100	1.4500	0.0213	0.0144
	May	1.4600	1.4600	1.5000	1.4200	0.0288	0.0197
	June	1.4638	1.4650	1.5100	1.4200	0.0302	0.0206
	July	1.4300	1.4200	1.4700	1.4000	0.0278	0.0194
	August	1.4214	1.4257	1.4500	1.4000	0.0196	0.0138
	September	1.4083	1.4083	1.4800	1.3500	0.0376	0.0267
	October	1.4633	1.4617	1.5000	1.4400	0.0190	0.0130
	November	1.4743	1.4721	1.5000	1.4400	0.0238	0.0162
	December	1.4686	1.4693	1.5000	1.4400	0.0236	0.0160
2002	January	1.4463	1.4350	1.5000	1.4200	0.0292	0.0202
	February	1.4350	1.4350	1.4500	1.4200	0.0089	0.0062
	March	1.4300	1.4250	1.4700	1.4100	0.0200	0.0140
	April	1.4275	1.4350	1.4400	1.4000	0.0158	0.0111
	May	1.4343	1.4321	1.4800	1.4000	0.0226	0.0157
	June	1.4586	1.4593	1.4900	1.4200	0.0210	0.0144
	July	1.4625	1.4650	1.4900	1.4300	0.0198	0.0136
	August	1.5367	1.5369	1.6000	1.4300	0.0520	0.0338
	September	1.5585	1.5600	1.5800	1.5285	0.0140	0.0090
	October	1.5585	1.5593	1.5700	1.5500	0.0064	0.0041
	November	1.5502	1.5502	1.5600	1.5310	0.0090	0.0058

	December	1.5582	1.5582	1.5800	1.5490	0.0100	0.0064
2003	**January**	1.5700	1.5700	1.6000	1.5300	0.0200	0.0127
	February	1.6183	1.6183	1.6500	1.6000	0.0146	0.0090
	March	1.6217	1.6217	1.6600	1.5700	0.0300	0.0185
	April	1.6000	1.6000	1.6500	1.5500	0.0293	0.0183
	May	1.6150	1.6150	1.6300	1.6000	0.0089	0.0055
	June	1.6343	1.6300	1.6700	1.6200	0.0159	0.0097
	July	1.6643	1.6671	1.6900	1.6400	0.0199	0.0120
	August	1.6643	1.6671	1.6900	1.6400	0.0199	0.0120
	September	1.6217	1.6217	1.6500	1.5800	0.0210	0.0129
	October	1.6600	1.6600	1.7000	1.6300	0.0220	0.0133
	November	1.6800	1.6800	1.7200	1.6500	0.0200	0.0119
	December	1.6863	1.6900	1.7200	1.6100	0.0358	0.0212
2004	**January**	1.6863	1.6900	1.7200	1.6100	0.0358	0.0212
	February	1.8486	1.8543	1.9000	1.7500	0.0464	0.0251
	March	1.8583	1.8583	1.9300	1.7500	0.0564	0.0304
	April	1.8500	1.8450	1.9100	1.7600	0.0484	0.0262
	May	1.8129	1.8214	1.8400	1.7600	0.0319	0.0176
	June	1.7880	1.7880	1.8200	1.7400	0.0235	0.0132
	July	1.8057	1.8079	1.8700	1.7500	0.0362	0.0200
	August	1.8057	1.8079	1.8700	1.7500	0.0362	0.0200
	September	1.8233	1.8233	1.8900	1.7700	0.0399	0.0219
	October	1.7757	1.7900	1.8700	1.4900	0.1218	0.0686
	November	1.8250	1.8100	1.9300	1.7900	0.0460	0.0252
	December	1.8600	1.8600	1.9300	1.8000	0.0378	0.0203
2005	**January**	1.8600	1.8600	1.9300	1.8000	0.0378	0.0203
	February	1.8233	1.8600	1.9900	1.4300	0.1681	0.0922
	March	1.8800	1.8750	1.9500	1.8000	0.0513	0.0273
	April	1.8950	1.8950	1.9700	1.8100	0.0520	0.0275

Table 4. Summary Statistics of USDJPY 3 Month Ahead Forecasts

This table reports the summary statistics of USDJPY 3-Month Ahead Forecasts. The data in this table is from Corporate Finance. The sample consists of 64 observations covering the period from January 2000 to April 2005. The mean (median) and other statistics are the arithmetic mean (median) of selected forecasts during the indicated month. CV represents the coefficient of variation, which is the standard deviation scaled by its expected value.

	Forecast Month	Mean	Median	Max	Min	SD	CV
2000	January	103.9750	103.9750	110.0000	97.0000	4.4516	0.0428
	February	103.8488	104.0150	114.0000	96.0000	6.1227	0.0590
	March	107.9250	106.9500	114.0000	103.0000	3.7496	0.0347
	April	108.3438	108.1250	114.0000	103.0000	3.5930	0.0332
	May	107.7833	107.3917	114.0000	104.5000	3.5474	0.0329
	June	108.1750	107.5000	113.0000	103.5000	3.2997	0.0305
	July	107.9375	108.7500	114.0000	102.0000	4.2798	0.0397
	August	106.9250	105.5000	114.0000	103.0000	3.9885	0.0373
	September	107.7250	107.0000	114.0000	101.5000	3.8160	0.0354
	October	106.7063	106.0000	112.0000	105.0000	2.2719	0.0213
	November	106.8571	107.0000	109.0000	104.0000	1.3553	0.0127
	December	107.6000	107.1000	112.0000	104.0000	2.2526	0.0209
2001	January	106.4250	109.0000	112.0000	90.9000	6.5989	0.0620
	February	115.4214	115.2107	118.0000	113.0000	1.5928	0.0138
	March	119.0625	120.0000	124.0000	112.0000	4.1269	0.0347
	April	120.0286	120.0143	124.0000	115.0000	2.7395	0.0228
	May	126.8571	126.9286	130.0000	124.0000	2.4159	0.0190
	June	125.6625	124.5000	130.0000	121.8000	3.0467	0.0242
	July	123.0563	123.0000	128.0000	117.0000	3.3865	0.0275
	August	126.3571	126.7500	130.0000	117.0000	4.0595	0.0321
	September	125.2667	125.6333	128.6000	120.0000	2.9407	0.0235
	October	125.8667	125.8667	130.0000	120.2000	3.0363	0.0241
	November	123.2143	123.1071	129.0000	118.0000	3.1607	0.0257
	December	123.6786	123.3393	129.0000	119.0000	3.5524	0.0287
2002	January	123.9688	124.3750	129.0000	118.0000	3.6264	0.0293
	February	132.6250	132.6875	135.0000	130.0000	1.8981	0.0143
	March	134.7813	135.0000	140.0000	130.0000	3.1888	0.0237
	April	135.2500	136.5000	140.0000	129.0000	4.2003	0.0311
	May	134.2143	133.8571	138.0000	130.0000	2.7756	0.0207
	June	129.9714	129.9857	138.0000	124.0000	4.4599	0.0343
	July	126.2500	125.0000	132.0000	121.0000	3.9188	0.0310
	August	122.2857	121.1429	132.0000	116.0000	5.0346	0.0412
	September	121.4643	120.8571	125.0000	118.0000	2.5927	0.0213
	October	118.9833	118.9833	122.0000	116.0000	1.8597	0.0156
	November	124.1100	124.1100	127.0000	122.0000	1.5626	0.0126

	December	124.3333	124.3333	127.0000	122.0000	1.9760	0.0159
2003	**January**	123.0833	123.0833	131.0000	115.0000	4.9166	0.0399
	February	121.0083	121.0042	125.0000	119.0000	1.9199	0.0159
	March	122.8333	122.4167	128.0000	120.0000	2.5866	0.0211
	April	119.7714	120.3857	123.0000	115.0000	2.7618	0.0231
	May	121.7083	121.3542	126.0000	119.2500	2.2694	0.0186
	June	117.5357	117.7679	121.0000	113.0000	2.6874	0.0229
	July	118.1857	118.2429	121.0000	113.0000	2.3558	0.0199
	August	118.1857	118.2429	121.0000	113.0000	2.3558	0.0199
	September	118.3667	118.3667	120.0000	116.0000	1.1731	0.0099
	October	113.5000	113.5000	122.0000	105.0000	5.5742	0.0491
	November	111.7600	111.7600	117.0000	108.8000	2.7243	0.0244
	December	109.1038	109.2500	111.0000	107.0000	1.3423	0.0123
2004	**January**	109.1038	109.2500	111.0000	107.0000	1.3423	0.0123
	February	104.5357	104.7679	106.0000	102.7500	1.2279	0.0117
	March	104.5000	104.5000	106.0000	103.0000	0.8864	0.0085
	April	106.0625	105.5000	108.0000	105.0000	1.3212	0.0125
	May	103.4286	104.2143	108.0000	98.0000	3.6978	0.0358
	June	107.2000	107.2000	110.0000	104.0000	1.7238	0.0161
	July	108.5000	107.7500	114.0000	106.0000	2.5213	0.0232
	August	108.5000	107.7500	114.0000	106.0000	2.5213	0.0232
	September	109.0000	109.0000	113.0000	107.0000	1.7728	0.0163
	October	107.5714	107.7857	110.0000	105.0000	1.9166	0.0178
	November	104.9750	105.0000	110.0000	100.0000	2.8192	0.0269
	December	103.7917	103.7917	107.0000	101.0000	1.8048	0.0174
2005	**January**	103.7917	103.7917	107.0000	101.0000	1.8048	0.0174
	February	103.7083	103.8542	106.0000	101.0000	1.8536	0.0179
	March	102.7429	102.8714	107.0000	98.0000	2.8278	0.0275
	April	103.1250	103.0625	108.0000	100.0000	2.2825	0.0221

Table 5. Summary Statistics of USDSFR 3 Month Ahead Forecasts

This table reports the summary statistics of USDSFR 3-Month Ahead Forecasts. The data in this table is from Corporate Finance. The sample consists of 64 observations covering the period from January 2000 to April 2005. The mean (median) and other statistics are the arithmetic mean (median) of selected forecasts during the indicated month. CV represents the coefficient of variation, which is the standard deviation scaled by its expected value.

	Forecast Month	Mean	Median	Max	Min	SD	CV
2000	January	1.5050	1.5050	1.5600	1.4300	0.0392	0.0260
	February	1.5263	1.5250	1.6200	1.4300	0.0590	0.0387
	March	1.5800	1.5950	1.6400	1.4700	0.0576	0.0364
	April	1.5950	1.6050	1.7800	1.4700	0.0943	0.0591
	May	1.6417	1.6350	1.7500	1.5800	0.0482	0.0294
	June	1.6650	1.6750	1.7000	1.6200	0.0283	0.0170
	July	1.6963	1.6700	1.8600	1.6300	0.0748	0.0441
	August	1.6475	1.6300	1.7400	1.6100	0.0427	0.0259
	September	1.6325	1.6350	1.7400	1.5300	0.0616	0.0377
	October	1.7350	1.7450	1.8300	1.6300	0.0614	0.0354
	November	1.7450	1.7450	1.8200	1.6700	0.0423	0.0243
	December	1.7717	1.7717	1.8200	1.7400	0.0259	0.0146
2001	January	1.7350	1.7450	1.7700	1.6800	0.0298	0.0172
	February	1.5914	1.5907	1.6300	1.5600	0.0203	0.0128
	March	1.6813	1.6100	2.3900	1.4800	0.2911	0.1731
	April	1.6017	1.6008	1.6400	1.5700	0.0236	0.0147
	May	1.6343	1.6321	1.7000	1.5700	0.0403	0.0247
	June	1.6375	1.6250	1.7300	1.5700	0.0459	0.0280
	July	1.7600	1.7500	1.8800	1.6800	0.0699	0.0397
	August	1.7629	1.7450	1.8800	1.7100	0.0528	0.0300
	September	1.7567	1.7483	1.8800	1.6800	0.0678	0.0386
	October	1.6633	1.6633	1.7400	1.5900	0.0440	0.0264
	November	1.6257	1.6150	1.7400	1.5600	0.0565	0.0348
	December	1.6414	1.6357	1.7400	1.5900	0.0449	0.0273
2002	January	1.6713	1.6550	1.7600	1.6000	0.0541	0.0324
	February	1.6583	1.6583	1.7200	1.6300	0.0290	0.0175
	March	1.6725	1.6850	1.7100	1.6200	0.0354	0.0211
	April	1.6788	1.6950	1.7200	1.6000	0.0398	0.0237
	May	1.6529	1.6564	1.6900	1.6000	0.0328	0.0199
	June	1.6086	1.6000	1.6600	1.5600	0.0323	0.0201
	July	1.5738	1.5650	1.6600	1.5300	0.0378	0.0240
	August	1.4814	1.4827	1.5700	1.4100	0.0512	0.0345
	September	1.4674	1.4737	1.5030	1.4200	0.0273	0.0186
	October	1.4703	1.4760	1.4900	1.4200	0.0213	0.0145
	November	1.4802	1.4802	1.5310	1.4000	0.0376	0.0254

	December	1.4712	1.4712	1.5100	1.4000	0.0327	0.0223
2003	January	1.4452	1.4531	1.5000	1.3600	0.0507	0.0351
	February	1.3850	1.3850	1.4500	1.3300	0.0385	0.0278
	March	1.3867	1.3867	1.4500	1.3400	0.0392	0.0282
	April	1.3629	1.3614	1.4500	1.2900	0.0539	0.0396
	May	1.3667	1.3667	1.4000	1.3400	0.0205	0.0150
	June	1.3100	1.3050	1.3700	1.2800	0.0288	0.0220
	July	1.3414	1.3307	1.4100	1.3000	0.0394	0.0294
	August	1.3414	1.3307	1.4100	1.3000	0.0394	0.0294
	September	1.3717	1.3717	1.4300	1.3300	0.0304	0.0222
	October	1.3350	1.3375	1.3600	1.2800	0.0243	0.0182
	November	1.3200	1.3200	1.3400	1.2800	0.0185	0.0140
	December	1.3175	1.3150	1.3800	1.2600	0.0399	0.0303
2004	January	1.3175	1.3150	1.3800	1.2600	0.0399	0.0303
	February	1.2014	1.1957	1.2500	1.1800	0.0247	0.0206
	March	1.2083	1.2083	1.2500	1.1600	0.0269	0.0223
	April	1.2438	1.2250	1.3300	1.2000	0.0457	0.0367
	May	1.2900	1.2950	1.3400	1.2300	0.0407	0.0316
	June	1.2960	1.2960	1.3500	1.2600	0.0314	0.0243
	July	1.2586	1.2593	1.3100	1.2000	0.0391	0.0310
	August	1.2586	1.2593	1.3100	1.2000	0.0391	0.0310
	September	1.2567	1.2567	1.2800	1.2300	0.0166	0.0132
	October	1.2314	1.2357	1.2800	1.1700	0.0368	0.0299
	November	1.2000	1.2000	1.2500	1.1300	0.0370	0.0309
	December	1.1567	1.1567	1.2100	1.1100	0.0271	0.0234
2005	January	1.1567	1.1567	1.2100	1.1100	0.0271	0.0234
	February	1.1750	1.1750	1.2200	1.1400	0.0260	0.0222
	March	1.1700	1.1650	1.2400	1.1000	0.0424	0.0363
	April	1.1567	1.1583	1.2100	1.1000	0.0341	0.0295

Table 6. Test Results for Question 1: Are Individual Forecasts Unbiased?

This table gives the test results for question1: are individual forecasts unbiased? The joint hypotheses are $\alpha = 0$ and $\beta = 1$. The *, ** and *** indicate significance at 0.10, 0.05 and 0.01 levels.

	CAD		EUR		JPY		SFR		GBP	
	α	β	α	β	α	β	α	β	α	β
ABN Amro	0.0044	-0.0154	0.0047	-0.0792	0.0012	-0.0637	-0.0056	-0.1987	0.0025	-0.1569
T-Statistics	1.3677	-7.6472***	1.1369	-14.8030***	0.2974	-11.3475***	-1.4462	-16.1466***	0.8093	-13.4771***
R-square	0.0006	0.0006	0.0226	0.0226	0.0090	0.0090	0.1232	0.1232	0.0615	0.0615
American Express	0.0039	0.1570	0.0047	-0.0582	0.0010	-0.1118	-0.0059	-0.1962	0.0026	-0.1817
T-Statistics	1.2307	-3.9254***	1.1431	-10.2586***	0.2684	-8.2201***	-1.4694	-11.6974***	0.8335	-10.2184***
R-square	0.0248	0.0248	0.0062	0.0062	0.0132	0.0132	0.0673	0.0673	0.0462	0.0462
Bank of Montreal	0.0039	0.1574	0.0055	-0.2806	0.0011	-0.2036	-0.0062	-0.2858	0.0026	-0.1532
T-Statistics	1.2016	-2.5588**	1.3788	-10.6290***	0.2777	-8.6553***	-1.5661	-9.1821***	0.8276	-7.9081***
R-square	0.0108	0.0108	0.0961	0.0961	0.0403	0.0403	0.0755	0.0755	0.0212	0.0212
Commerzbank	0.0032	0.5922	0.0048	-0.0901	0.0016	-0.2473	-0.0057	-0.1789	0.0026	-0.1271
T-Statistics	1.0636	-1.4283	1.1513	-9.3558***	0.4230	-11.3463***	-1.4171	-10.7180***	0.8129	-9.6605***
R-square	0.1701	0.1701	0.0116	0.0116	0.0903	0.0903	0.0493	0.0493	0.0227	0.0227

Goldman Sachs	0.0046	-0.0571	0.0046	0.0072	0.0013	-0.0647	-0.0052	-0.0130	0.0025	-0.1518
T-Statistics	1.3925	-5.3920***	1.0999	-11.9668***	0.3229	-12.3525***	-1.2611	-10.7987***	0.7997	-9.4387***
R-square	0.0040	0.0040	0.0001	0.0001	0.0109	0.0109	0.0004	0.0004	0.0294	0.0294
Lloyds TSB	0.0048	-0.1569	0.0048	-0.1091	0.0011	-0.1479	-0.0051	0.0074	0.0023	0.0064
T-Statistics	1.5014	-5.7492***	1.1689	-9.8639***	0.3021	-15.0952***	-1.2514	-20.6616***	0.7219	-7.6974***
R-square	0.0281	0.0281	0.0181	0.0181	0.0690	0.0690	0.0005	0.0005	0.0000	0.0000
Royal Bank of Scotland	0.0040	0.1332	0.0048	-0.0800	0.0012	-0.0843	-0.0056	-0.1773	0.0025	-0.0679
T-Statistics	1.2730	-5.7523***	1.1538	-12.0211***	0.3071	-9.3255***	-1.4096	-13.6126***	0.7646	-8.8788***
R-square	0.0359	0.0359	0.0153	0.0153	0.0102	0.0102	0.0761	0.0761	0.0062	0.0062
SG	0.0041	0.0735	0.0046	-0.0122	0.0012	-0.0904	-0.0063	-0.3213	0.0025	-0.0905
T-Statistics	1.2244	-3.4923***	1.1104	-12.2818***	0.3164	-8.4614***	-1.6370	-11.6702***	0.7805	-9.5610***
R-square	0.0036	0.0036	0.0004	0.0004	0.0096	0.0096	0.1364	0.1364	0.0122	0.0122

Table 7: Test Results for Question 2: Do Mean Survey Forecasts Perform Better Than Individual Forec

This table gives the test results for question 2: Do mean survey forecasts perform better than individual forecas survey forecasts follow the spot rate? The joint hypotheses are $\alpha = 0$ and $\beta = 1$. The *, ** and *** indicate si and 0.01 levels.

	CAD		EUR		JPY		SFR	
	α	β	α	β	α	β	α	β
	0.0023	0.1137	0.0043	-0.1310	0.0008	-0.2623	-0.0053	-0.2421
T-Statistics	0.7942	-2.8974***	1.1314	-8.7974***	0.2507	-8.8061***	-1.4219	-9.9770***
R-Square	0.0044		0.0167		0.0520		0.0584	
Adjusted R-Square	-0.0277		0.0006		0.0365		0.0429	

Table 8: Test Results for Question 3: Do Combined Forecasts Exhibit Superior Forecasting Ability?

This table gives detailed regression results of optimal weights used to combine the forecast for USDCAD, USDEUR, USDJPY, USDSFR and USDGBP. The R-Square of the composite model for each currency is also shown in this table.

	CAD	EUR	JPY	SFR	GBP
Intercept	0.0041	0.0054	0.0017	-0.0061	0.0022
ABN Amro	-0.1808	-0.0394	0.1348	-0.1391	-0.2184
American Express	0.1007	0.0685	0.0319	0.1263	-0.1840
Bank of Montreal	-0.1716	-0.3931	-0.0238	-0.0933	0.0264
Commerzbank	1.4366	0.0918	-0.3224	0.0655	-0.0350
Goldman Sachs	-0.1035	0.0712	-0.0849	0.1202	-0.1381
Lloyds TSB	-0.6260	-0.0347	-0.1890	0.0747	0.3854
Royal Bank of Scotland	-0.0391	0.0389	0.1163	-0.0894	-0.0812
SG	0.0406	-0.0062	0.0784	-0.3334	0.1195
R - Square	0.5353	0.1268	0.1799	0.2306	0.1560

Table 9: Forecast Performance of Different Forecasting Methods

This table shows the forecast performance of different forecast methods. The numbers shown in this table are the root mean squared errors (RMSE) of each forecast method.

	USDCAD		USDEUR		USDGBP		USDJPY		USDSFR
Average Forecast	0.0221		0.0287		0.0340		0.0273		0.0369
Random Walk	0.0258		0.0303		0.0255		0.0258		0.0388
Composite Forecast	0.0254		0.0290		0.0236		0.0244		0.0293

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