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PITFALLS IN ECONOMETRIC FORECASTING WITH ILLUSTRATIONS FROM EXCHANGE RATE ECONOMICS*

ABSTRACT

Pitfalls in econometric forecasting are illustrated with reference to the ability of economists to forecast exchange rates, which is bound to bring about the Meese-Rogoff puzzle that exchange rate forecasting models cannot outperform the random walk in out-of-sample forecasting. Loopholes in forecasting include the use of dynamic models to generate forecasts, taking the forward rate to be a forecaster, and invoking the concept of cointegration to resolve the Meese-Rogoff puzzle. It is concluded that the flaws that can be detected easily in the forecasting literature provide a good enough reason for handling forecasts with care and that the way forward is to abandon the practice of producing allegedly precise point forecasts.

Keywords: Forecasting; Meese-Rogoff Puzzle; Forward Rate; Dynamic Models; Cointegration
JEL Classification: C10; C18; F31

RIASSUNTO

Difficoltà delle previsioni econometriche con spiegazioni dall'economia dei tassi di cambio

Le difficoltà delle previsioni econometriche vengono illustrate con riferimento all'abilità degli economisti di prevedere i tassi di cambio. Ciò rinvia al puzzle di Meese-Rogoff secondo il quale i modelli di previsione dei tassi di cambio non possono dare migliori risultati delle previsioni fuori campioni con modelli *random walk*. Gli artifici usati nelle previsioni includono l'uso di modelli dinamici per generare le previsioni, considerando il tasso a termine come previsore e ricorrendo al concetto di cointegrazione per risolvere il puzzle di Meese-Rogoff. Si conclude che le lacune in genere evidenziate nella letteratura sulle previsioni rappresentano una ragione

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sufficientemente valida per considerare le previsioni ottenute con attenzione e per abbandonare la pratica di fornire previsioni presumibilmente poco precise.

1. Introduction

Forecasting is a formal method of generating expectations. In econometric forecasting, "formality" takes the shape of estimating and testing models of various degrees of complexity that are ultimately used to generate forecasts. Some econometricians suggest that out of the two functions of econometrics, hypothesis testing and forecasting, the latter is the main function (for example, Brown 2010)[1]. Economists use forecasting for policy analysis (for example, forecasting inflation under various policy scenarios) or for forecasting-based trading. Examples of the latter are financial operations involving the exchange rate as a decision variable, which require exchange rate forecasting because the outcome of these operations (in terms of profit and loss) depends on the spot exchange rate prevailing at a future point in time[2].

Forecasting is important and it is needed because we live, operate and make decisions in an uncertain world. Although forecasting as a professional activity has flourished at an accelerating rate, it is often looked upon with scepticism, both from within and outside the profession. The sceptics assert that forecasts have little value because they are invariably inaccurate, which means that decision makers perform just as well or as badly by acting on the basis of tossing a coin. J.K. Galbraith, an eminent economist, put this view quite vividly when he once said:

"We have two forecasters, those who don't know and those who don't know that they don't know"[3].

In its issue of 1 August 1998, *The Economist* published an article entitled "The Perils of Prediction", which concluded that

"it seems near impossible to create models that neither miss too many crises that have occurred nor predict too many that never happen".

In a comment posted as a letters to the editor published in the 15 August 1998 issue, a reader described forecasting models as

[1] Sometimes the functions of econometrics are listed as estimation, hypothesis testing and forecasting. The estimation of a model is an integral part of the forecasting process, and it is a step that precedes the generation of forecasts.
[2] Examples are short-term investment and financing operations, hedging and capital budgeting.
[3] https://www.goodreads.com/quotes/476607-there-are-two-kinds-of-forecasters-those-who-don-t-know.

"financial tools which the world is better off without" because they can "attract enough believers to become self-fulfilling".

In the issue of 26 November 2015, *The Economist* highlights the

"perils of planning on the basis of economic forecasts", arguing that "governments plan years ahead on the basis of economic forecasts that must be wrong".

The objective of this paper is to highlight pitfalls in econometric forecasting by using illustrations involving exchange rate forecasting, explain why forecasting is looked at with scepticism, both from within the profession and by outsiders, and to identify flaws in the econometric forecasting literature. A research gap is represented by the need to challenge the dominant views expressed by economists on the issues discussed in this paper. The literature predominantly reflects the view that the Meese-Rogoff puzzle is indeed a puzzle when it can be resolved easily. Forecasting with dynamic models is quite common when any dynamic model is no more than a glorified random walk where the lagged dependent variable dominates other explanatory variables. Failure of the forward rate to forecast the spot rate is also considered to be a puzzle when the forward rate has nothing to do with forecasting[4]. The view that cointegration, or lack thereof, can be used to explain poor forecasting power is widely accepted when cointegration is no more than "glorified correlation"[5]. These views will be challenged for the purpose of filling a research gap represented by the absence of alternative views and non-standard interpretation of the empirical results found in the literature.

The structure of this paper is as follows. Following the introduction, some views on the dismal state of econometric forecasting are presented. With reference to exchange rate forecasting, the Meese-Rogoff puzzle is considered to see why economists feel that their models are worse than what they actually are. The discussion leads to related issues that demonstrate some loopholes in forecasting, including the use of dynamic models to generate forecasts, the use of the forward rate for the same purpose, and invoking the concept of cointegration to resolve the Meese-Rogoff puzzle. The last section contains some concluding remarks. For the purpose of the

[4] Moosa (2020) shows how the Meese-Rogoff puzzle, the forward premium puzzle, and other puzzles in international finance can be solved easily, arguing that they are not puzzles at all.
[5] Moosa (2017) explains why cointegration conveys no more information than correlation and that it cannot be used to detect spurious correlation.

following discussion, the terms "econometric forecasting" and "economic forecasting" may be used interchangeably.

2. THE DISMAL STATE OF ECONOMETRIC FORECASTING

Econometric (or economic) forecasting is criticised by insiders and outsiders. Observers note that forecasters tend to over-estimate cyclical upturns and under-estimate cyclical downturns. When the forecasts turn out to be way off the mark, forecasters put the blame on extraneous variables or unreliable data. Evidence against the reliability of economic forecasting is provided by economists themselves. For example, Frankel (2011) examines the forecasts of real growth rates and budget balances generated by official government agencies in 33 countries to find that these forecasts have positive average bias, that they are more biased in booms, and that they are even more biased at the three-year horizon than at shorter horizons. He suggests that over-optimism in official forecasts explains excessive budget deficits and the failure to run surpluses during periods of high output. Frankel concludes as follows:

"evidently official forecasters … over-estimate the permanence of the booms and the transitoriness of the busts".

Practitioners criticise econometric forecasting. For example, Oliver (2017) makes the sarcastic comments that

"if forecasting was easy I wouldn't be writing this… and you wouldn't be reading it" and that "we would be very rich and sipping champagne in the south of France". He refers to "numerous examples of gurus using grand economic, demographic or financial theories – usually resulting in forecasts of 'new eras' or 'great depressions' – who may get their time in the sun but who also usually spend years either before, or after, losing money".

Oliver warns that forecasts of economic and investment indicators should be treated with care, arguing that quantitative point forecasts convey no information on the risks surrounding the forecasts when in fact they are conditional upon the information available when the forecast was made. In their *Machine, Platform, Crowd: Harnessing Our Digital Future*, McAfee and Brynjolfsson (2017) say the following about forecasting:

Our world is increasingly complex, often chaotic, and always fast-flowing. This makes forecasting something between tremendously difficult and actually impossible, with a strong shift toward the latter as timescales get longer.

Academic economists also criticise econometric forecasting. While accepting the Nobel Prize, Friedrich Hayek made the comment that economists were unsure about their predictions and that the tendency to present their findings with the certainty of the language of science was misleading and "may have deplorable effects" (Shaw, 2017)[6]. Weber (2011) surveyed the opinions of academic economists participating in the 2011 Davos meeting, which witnessed a session on the perils of economic prediction. Carmen Reinhart wishes good luck to anyone trying to get the timing of a crisis right. Looking back at his days as director of research at the International Monetary Fund, Raghuram Rajan admits that they were "always wrong on Africa" (as if they were good at forecasting Europe or anywhere else). Robert Shiller argues that the models used by economists are based on what used to happen although the ingredients of the economy change over time. Simon Johnson, a former IMF chief economist, warns economists as follows:

> "If you step outside the comfort band of the consensus forecast, you get beaten up, you can risk your career"[7].

Loungani (2001) demonstrates that the European Central Bank consistently underestimates inflation and overestimates growth[8].

Economists are sceptical of the usefulness of forecasting for specific applications. Smith and Aaronson (2003) criticise forecasting in health economics by referring to a 1996 widely circulated forecast for the Philadelphia Metropolitan Area. Likewise, Smil (2000) warns of the perils of long-range energy forecasting and recommends the abandonment of detailed quantitative point forecasts in favour of decision analysis or contingency planning under a range of alternative scenarios. Whitmore (2008) highlights the perils and pitfalls of oil price forecasting, where faulty forecasts of oil prices are blamed on a

[6] On the hazard of thinking that economics or econometrics is a science, see Moosa (2017) who refers to the "forecasting fiasco".
[7] This statement is not only valid for forecasting. It is equally applicable to any challenge of the *status quo*. For example, neoliberal thinking has acquired what seems to be widespread acceptance because any dissenting voice is muted by several means, including denial of publication in top journals (see, for example, Moreira, 2018).
[8] Underestimating inflation may be deliberate because governments have the means and incentives to do that (see, for example, Moosa, 2020).

"whole host of unknown factors that are independent of classic supply-and-demand calculations – from the weather, to unexpected fluctuations on the financial markets, to civil wars and major geopolitical crises".

Forecasters are notorious for claiming credit when (or if) they get it right and blame it on factors beyond their control when they get it wrong.

The Covid-19 pandemic has made it more difficult for economic forecasters to indulge in business as usual. Pohlman and Reynolds (2020) suggest that the pandemic has introduced pervasive uncertainty manifested in a sudden and massive divergence in macroeconomic projections. To illustrate their proposition, they present the following facts and figures. In early February 2020, the spread among U.S. economic growth forecasts for the second quarter was 3.5 percentage points, but by 29 April, the most optimistic forecast among the 28 institutions surveyed saw the U.S. economy contracting 8.2%. The most pessimistic projected a huge 65.0% contraction, which gives a spread of 56.8 percentage points. They add that the current forecast spread among analysts is far larger than at any point during the past 20 years, and significantly above that seen during the height of the global financial crisis.

3. The Meese-Rogoff puzzle

Generally speaking, economists see their models as being good, while outsiders think that the models are bad. It is ironic therefore that some economists believe that exchange rate forecasting models are extremely bad because these models cannot outperform the random walk in out-of-sample forecasting. On this occasion, these economists are wrong as their models are actually better than the random walk, but this does not make the models good. This belief has arisen out of flaws in research on exchange rate forecasting, flaws that are not difficult to detect.

In what has become a highly cited paper, Meese and Rogoff (1983) demonstrate the inability of macroeconomic and time series models to outperform the random walk in out-of-sample forecasting, a finding that has become to be known as the "Meese-Rogoff puzzle". Engel *et al.* (2007) summarise the current state of affairs by stating that the

"explanatory power of these [exchange rate] models is essentially zero".

Numerous attempts have been made to overturn the results by using a variety of data, sample periods, methodologies and model specifications. Most of these attempts have been "unsuccessful" in the sense that they could not produce lower forecasting errors than the random walk. As a result, belief in the Meese-Rogoff puzzle has persisted.

Economists working in the areas of international finance and open economy macroeconomics express views indicating the presence of a puzzle. For example, Abhyankar *et al.* (2005) describe the Meese-Rogoff findings as a "major puzzle in international finance". Evans and Lyons (2005) contend that the Meese-Rogoff finding

"has proven robust over the decades" despite it being "the most researched puzzle in international macroeconomics".

Fair (2008) describes exchange rate models as

"not the pride of open economy macroeconomics" and suggests that the "general view still seems pessimistic".

Frankel and Rose (1995) argue that the puzzle has a "pessimistic effect" on the field of exchange rate modelling in particular and international finance in general. Bacchetta and van Wincoop (2006) describe the puzzle as most likely the major weakness of international macroeconomics. Neely and Sarno (2002) consider the Meese-Rogoff conclusion to be a

"devastating critique" of the monetary approach to exchange rate determination and to have "marked a watershed in exchange rate economics".

Flood and Rose (2008) emphasise the point that the Meese-Rogoff results are

"devastating for the field of international finance", going as far as claiming that "the area [international finance] has fell into disrepute".

And there is more where these came from, even though this puzzle is not a puzzle[9].

[9] Not all studies of exchange rate forecasting refer to the Meese-Rogoff puzzle. For example, Moosa and Vaz (2018) compare direct and indirect forecasting of exchange rates. Dritaski (2019) examines the volatility of the EUR/USD exchange rate and derives implications for static and dynamic forecasting. Moosa and Ma (2018) focus on the nature of the attractor in purchasing power parity.

Economists have put forward several explanations to demystify the puzzle. Meese and Rogoff themselves explained the puzzle in terms of some econometric problems, including simultaneous equations bias, sampling errors, stochastic movements in the true underlying parameters, model misspecification, failure to account for nonlinearities, and the proxies for inflationary expectations. However, the main reason underpinning, and the root cause of, the Meese-Rogoff puzzle has been overlooked in the literature. Assessing forecasting accuracy exclusively by the magnitude of the forecasting error (which is what Meese and Rogoff did) may explain why the random walk cannot be outperformed. Moosa and Burns (2015) demonstrate that all of the explanations put forward to resolve the puzzle cannot be used to overturn the Meese-Rogoff findings, with the exception of the use of measures of forecasting accuracy other than those that depend on the magnitude of the forecasting error. Moosa (2020) suggests that the puzzle has survived the test of time because economists exhibit an incredible lack of resolve in challenging dubious but established ideas. It is simply the tyranny of the *status quo*.

To illustrate the difficulty of outperforming the random walk in terms of the magnitude of forecasting errors, consider the simple PPP model

$$s_t = a_0 + a_1 r_t + \varepsilon_t \tag{1}$$

where s is the log of the exchange rate (measured as the domestic currency price of one unit of the foreign currency) and r is the log of the ratio of domestic to foreign price level. Equation (1) can be used to generate one-period-ahead out-of-sample forecasts over the period December 2009-September 2015 from a total sample covering the period January 2000-September 2015. Six exchange rates involving four currencies are used: US dollar (USD), British pound (GBP), Japanese yen (JPY) and Canadian dollar (CAD). The time series observations were obtained from the IMF's *International Financial Statistics*.

The actual and forecast values of the six exchange rates are presented in Figure 1. As we can see, the magnitude of the forecasting error (the deviation of the forecast from actual values) are non-trivial. Compare these forecasts with those obtained by using the lagged spot rate as a forecaster (random walk without drift) as displayed in Figure 2. In this case the forecast values are very close to the actual values, meaning that the forecasting errors produced by the random walk are much smaller. Table 1 reports the mean square errors of the PPP model (equation 1) and the random walk for the six exchange rates. The statistical significance of the difference between the MSEs of the model and random walk is indicated by the t statistic for the null hypothesis that they are equal. We can see that the random walk produces smaller MSEs than the model and that the difference is statistically significant in all cases. While these results are consistent with the findings of Meese and Rogoff, they should come as no surprise, as the error of the random walk is the month-to-month change in the exchange rate, which tends to be small.

Meese and Rogoff seem to have overlooked the proposition that the ability of the forecaster to predict the direction of change is more important, at least in terms of profit generation by trading on the forecasts, than the magnitude of the forecasting error (see, for example, Moosa, 2014). The random walk without drift predicts no change at a time when exchange rates are highly volatile, making the direction accuracy (DA) of the random walk zero (it fails to capture the direction of change on any occasion). By contrast, the results presented in Table 1 show that the direction accuracy of the model (which takes values between 0 and 1) ranges between 0.39 and 0.59 and that DA is significantly different from zero in all cases. The model outperforms the random walk for all currency pairs.

Although the forecasts generated by the random walk look great (as in Figure 2), the random walk is a dumb forecasting tool. If we enlarge the graphs for the GBP/USD exchange rate, as displayed in Figure 3, we can see that while the actual and forecast rates move together, the actual rate turns before the forecast rate, which means that the actual rate forecasts the forecast rate, when it should be the other way round. This sounds rather dumb, which means that any model should be better than the random walk because no model is that dumb. It is not clear, therefore, why the Meese-Rogoff puzzle is a puzzle and why eminent economists believe that it is a puzzle. This of course does not mean that the forecasts generated from the PPP model are great – it just means that the model is better (or less bad) than a dumb forecaster like the random walk without drift. The PPP model is bad but not ugly, and one can only wonder why economists who are supposedly proud of their forecasting models undermine the credibility of those models.

4. Forecasting with dynamic models

Some economists have attempted to boost the forecasting power of exchange rate models by introducing dynamics, including the use of error correction mechanisms. For example, Taylor

(1995) suggests that

"researchers have found that one key to improving forecast performance based on economic fundamentals lies in the introduction of equation dynamics".

However, the use of dynamics, including error correction models, implicitly and effectively introduces a lagged dependent variable, which makes the underlying model some sort of an "augmented" random walk. The random walk component, which is represented by the lagged dependent variable, typically dominates the effect of the explanatory variables suggested by theory to be important determinants of the exchange rate. It may be disingenuous, therefore, to claim that a model outperforms the random walk just because it has been augmented by a random walk component.

Four dynamic versions of the static PPP model represented by equation (1) are used for illustrative purposes. The first of these is an error correction model (ECM) with an autoregressive structure of order 1. The equation (Model A) is written as follows:

$$\Delta s_t = \alpha_0 + \beta_1 \Delta s_{t-1} + \gamma_0 \Delta r_t + \gamma_1 \Delta r_{t-1} + \phi \varepsilon_{t-1} + \xi_t \quad (2)$$

where $\varepsilon_t = s_t - a_0 - a_1 r_t$ is the residual of the cointegrating regression. By imposing the restrictions $\beta_1 = \gamma_1 = 0$, we arrive at Model B, which is written as

$$\Delta s_t = \alpha_0 + \gamma_0 \Delta r_t + \phi \varepsilon_{t-1} + \xi_t \quad (3)$$

Model C is a first difference model, which can be obtained by imposing the restriction $\phi = 0$ on equation (2). Hence

$$\Delta s_t = \alpha_0 + \beta_1 \Delta s_{t-1} + \gamma_0 \Delta r_t + \gamma_1 \Delta r_{t-1} + \xi_t \quad (4)$$

Model D is an ARDL in levels, which is written as

$$s_t = \alpha_0 + \beta_1 s_{t-1} + \gamma_0 r_t + \gamma_1 r_{t-1} + \xi_t \quad (5)$$

It can be demonstrated that any form of dynamics leads to the introduction of a random walk component represented by a lagged dependent variable, which appears explicitly in equation (5). For example, equation (3) can be re-written as

$$s_t - s_{t-1} = \alpha_0 + \gamma_0(r_t - r_{t-1}) + \phi(s_{t-1} - a_0 - a_1 r_{t-1}) + \xi_t \tag{6}$$

which gives

$$s_t = (\alpha_0 - \phi a_0) + \gamma_0 r_t - (\gamma_0 + \phi a_0) r_{t-1} + (1+\phi) s_{t-1} + \xi_t \tag{7}$$

The introduction of dynamics, which boosts forecasting accuracy, results from the fact that this process boils down to the introduction of a random walk component. Schinasi and Swamy (1989) make this point quite explicit with respect to exchange rate models, suggesting that

"the random walk model and the structural models with lagged dependent variables are nested". This is why they uncover the "striking observation" that "adding a lagged dependent variable makes a substantial difference in the forecasting ability of all three structural models".

Schinasi and Swamy (1989) view a structural model with a lagged dependent variable as a model in which the lagged variable (representing a random walk process) and the explanatory variables "are allowed to explain the spot exchange rate". However, experience shows that the random walk component invariably prevails (Kling, 2010, 2011), in which case a random walk with explanatory variables is unlikely to perform better (in terms of the RMSE) than a pure random walk.

Let us look at some results, using one exchange rate only for illustrative purposes. In Figure 4 we can see the actual values of the GBP/USD rate, together with the forecast values generated from models A, B, C and D. Two observations can be readily made. The first is that the forecasts produced by dynamic models share a property with the random walk – the property of being dumb, because the forecast values follow the actual values, and not vice versa (albeit not on all occasions as in the case of the random walk). The second observation is that the patterns of the forecast values are similar, irrespective of model specification. In Table 2 we can see that the mean square errors of the four models are very close. Like the random walk, the dynamic models produce smaller errors than the static PPP model (1). In all cases the null of the equality of the

MSEs of the dynamic and static models is rejected as indicated by the t statistics. However the t statistics for the null of the equality of the MSEs of models B, C and D and that of model A cannot be rejected.

5. The forward rate as a forecaster

Following Meese and Rogoff (1983), it has become customary in any exchange rate forecasting exercise to use the random walk (the lagged spot rate) as a benchmark for measuring forecasting accuracy. In terms of the level (not the log) of the exchange rate, the general random walk (with drift) model is specified as

$$S_t = \alpha_0 + \alpha_1 S_{t-1} + \varepsilon_t \tag{8}$$

If the coefficient restriction $(\alpha_0, \alpha_1) = (0,1)$ is imposed, the forecaster becomes the lagged spot rate – that is, $\hat{S}_t = S_{t-1}$

The use of the forward rate as a forecaster is based on the unbiased efficiency hypothesis (UEH) that the forward rate is an unbiased and efficient predictor of the future spot rate (the spot rate observed on the maturity date of the forward contract). The UEH is written as

$$S_t = \beta_0 + \beta_1 F_{t-1} + \varepsilon_t \tag{9}$$

Again, if the coefficient restriction $(\beta_0, \beta_1) = (0,1)$ is imposed, the forecaster becomes the lagged forward rate – that is, $\hat{S}_t = F_{t-1}$. According to covered interest parity, which necessarily holds as a deterministic equation representing the means whereby bankers determine and quote the forward rate for a given maturity, the lagged spot and forward rates are related as follows:

$$S_{t-1} = \theta F_{t-1} \tag{10}$$

where

$$\theta = \frac{1+i}{1+i^*} \tag{11}$$

which is the ratio of 1 plus the domestic interest rate to 1 plus the foreign interest rate (a measure of the interest rate differential). This is why Lavoie (2000) argues that the forward exchange rate is not an expectation variable but rather the result of a "simple arithmetic operation". Since the forward rate is related contemporaneously to the spot rate, it follows that it is erroneous to use the forward rate as a forecaster and the spot rate as a benchmark, because the forecaster and the benchmark should be independent. It also follows that the forward and spot rates should produce forecasts that are equally good or equally bad, which is why it is preposterous to suggest that the forward rate can outperform the random walk in terms of forecasting power. As a matter of fact, the mere notion of the forward rate as a forecaster is ludicrous because the forward rate has nothing to do with forecasting. Aggarwal and Zong (2008) wonder why the forward-spot relation "remains a theoretical and empirical puzzle" whereas Aggarwal *et al.* (2009) suggest that

> "an important puzzle in international finance is the failure of the forward exchange rate to be a rational forecast of the future spot rate".

The only puzzle here is why these economists think that this is a puzzle.

Let us see some results by using the GBP/USD exchange rate for illustrative purposes. In Figure 5 we can see the actual and forecast values of the exchange rate using the forward rate as a forecaster. By comparing Figure 5 with Figure 3, we can hardly see any difference. The forecasts generated by using the lagged forward rate and the lagged spot rate as forecasters are identical, which is to be expected because the spot and forward rates are related contemporaneously. Figure 6 is a scatter plot of the forecasts of the random walk on the forecasts of the forward rate. It is obvious that correlation is perfect but this is only because the forecasts are identical. In Table 3 we can see that the null of equality between the mean square errors of the forward rate and random walk cannot be rejected in any case. This makes one wonder how some economists managed to outperform the random walk by using the forward rate as a forecaster when the forward rate has nothing to do with forecasting.

6. Forecasting and cointegration

Studies of the effect of cointegration on forecasting accuracy involve a comparison of the forecasting power of an ECM with a straight first difference model (or VAR in levels and first differences). The general finding of this strand of literature is that taking account of coitegration does not pay off, in the sense that it does not boost forecasting accuracy. More specifically, it has been found that a cointegration-based error correction model does not forecast better than the corresponding first difference model. This finding has been explained in terms of many factors such as measurement errors in the long-run relation, measures of forecasting accuracy, structural breaks, the length of forecasting horizon, and inadequacy of the basic ECM. Moosa and Vaz (2016) take this matter further by comparing the forecasting power of dynamic models that exhibit no cointegration with models that exhibit cointegration with and without the error correction term. They argue against the prevailing explanation of measurement errors and put forward another explanation for what seems to be yet another puzzle.

If cointegration counts, equation (2), or Model A, should produce better forecasts than equation (4), or model C. For cointegration to make a difference (if it makes a difference), it must be present, something that we can never make sure of, given that different cointegration tests produce different results. Table 4 reports the results of three coitegration tests. The first is based on the significance or otherwise of the coefficient on the error correction term, in which case the null of no cointegration is rejected if the coefficient is significantly negative as indicated by its t statistic, $t(\phi)$. The second and third are the F and W statistics used in conjunction with the bounds test (for example, Pesaran and Pesaran, 2009). In this case, cointegration is established if the test statistic is greater than the upper bound. The results presented in Table 4 tell us, based on the $t(\phi)$ statistic, that cointegration is present in three cases.

If cointegration does matter, Model A should produce better forecasts than Model C for the three cases in which cointegration is present. But this is not the case, as the results in Table 2 show. Models A and C are just as good or as bad, irrespective of the presence or absence of cointegration. This can be explained easily: there is no value added in the error correction term over and above what is offered by the distributed lag structure of the dependent and explanatory variables. The assumption made in the literature is that the forecasting power of ECMs lies in the error correction mechanism because deviations from the long-run relation determine in which direction the dependent variable should move and by how much. While this proposition is intuitively plausible, an ECM and the corresponding first difference model have similar dynamic structures, meaning that which model outperforms the other is an empirical issue. This is a simple but more logical explanation for the underlying issue.

7. Concluding remarks

Economics is a social science where the behaviour of decision makers is not governed only by economic considerations but also by social and psychological factors, which are not amenable to econometric testing and forecasting. This is why no economic theory holds everywhere all the time. And this is why the results of empirical testing of economic theories can be a mixed bag and why the forecasts generated from these models are typically way off the mark.

Econometric forecasting is not really forecasting. In-sample forecasting is simply a curve-fitting exercise that invariably produces huge residual sum of squares. Out-of-sample *ex post* forecasting cannot be used for decision making although it is good for writing academic papers. Forecasts are generated out of sample by using the actual realised values of the explanatory variables, yet these forecasts turn out to be dreadful. *Ex ante* forecasting, which is useful for decision making, requires the forecasting of the explanatory variables, which augments the forecasting error. This is why simple trend extrapolation produces less bad forecasts than those produced by "structural" econometric models.

The flaws that can be detected easily in the forecasting literature provide a good enough reason for handling forecasts with care. The way forward is to abandon the practice of producing allegedly precise point forecasts showing, for example, that the exchange rate between the Australian dollar and US dollar will be 0.7863 on 23 December 2022. We should abandon attempts to derive forecasts from "stir-fry regressions", empirical equations that contain 20+ explanatory variables without any theoretical or intuitive explanation. We should make extensive use of judgment and write narratives explaining logically where things are likely to be. We should utilise input from other social sciences and consider the effect of non-quantifiable factors. By doing that, we will move some way towards the restoration of the credibility of our discipline, hopefully making the dismal science less dismal.

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TABLE 1 - *The Forecasting Power of the Static PPP Model (MSE)*

Exchange Rate	Model	Random Walk	t-statistic	DA
GBP/USD	39.00	4.93	6.61	0.41
JPY/USD	163.99	6.91	10.53	0.42
CAD/USD	39.89	3.51	7.54	0.39
JPY/GBP	206.14	15.59	12.15	0.42
CAD/GBP	61.32	6.34	7.38	0.51
JPY/CAD	78.79	13.24	6.65	0.41

TABLE 2 - *The Forecasting Power of Dynamic Models (GBP/USD)*

Model	MSE	t-Statistic (Static)	t-Statistic (A)
A	5.696	-6.40	--
B	5.404	-6.47	0.24
C	5.603	-6.42	0.08
D	5.464	-6.45	0.19

TABLE 3 - *The Forecasting Power of the Forward Rate Relative to Random Walk (MSE)*

Exchange Rate	Forward Rate	Random Walk	t-statistic
GBP/USD	4.929	4.934	-0.004
JPY/USD	6.907	3.513	0.0006
CAD/USD	3.489	6.906	-0.023
JPY/GBP	15.577	15.597	-0.005
CAD/GBP	6.321	6.345	-0.012
JPY/CAD	13.328	13.248	-0.001

TABLE 4 - *Cointegration Test Statistics (Equation 1)*

Exchange Rate	$t(\phi)$	F	W
GBP/USD	-2.11*	2.31	4.62
JPY/USD	-0.90	3.34	5.12
CAD/USD	-1.39	1.66	3.33
JPY/GBP	-1.53	1.17	2.35
CAD/GBP	-2.27*	2.27	4.53
JPY/CAD	-2.42*	2.98	5.96

The lower and upper bounds are 4.98-5.82 for F and 9.95-11.63 for W.

FIGURE 1 - *Actual and Forecast Values (Static PPP Model)*

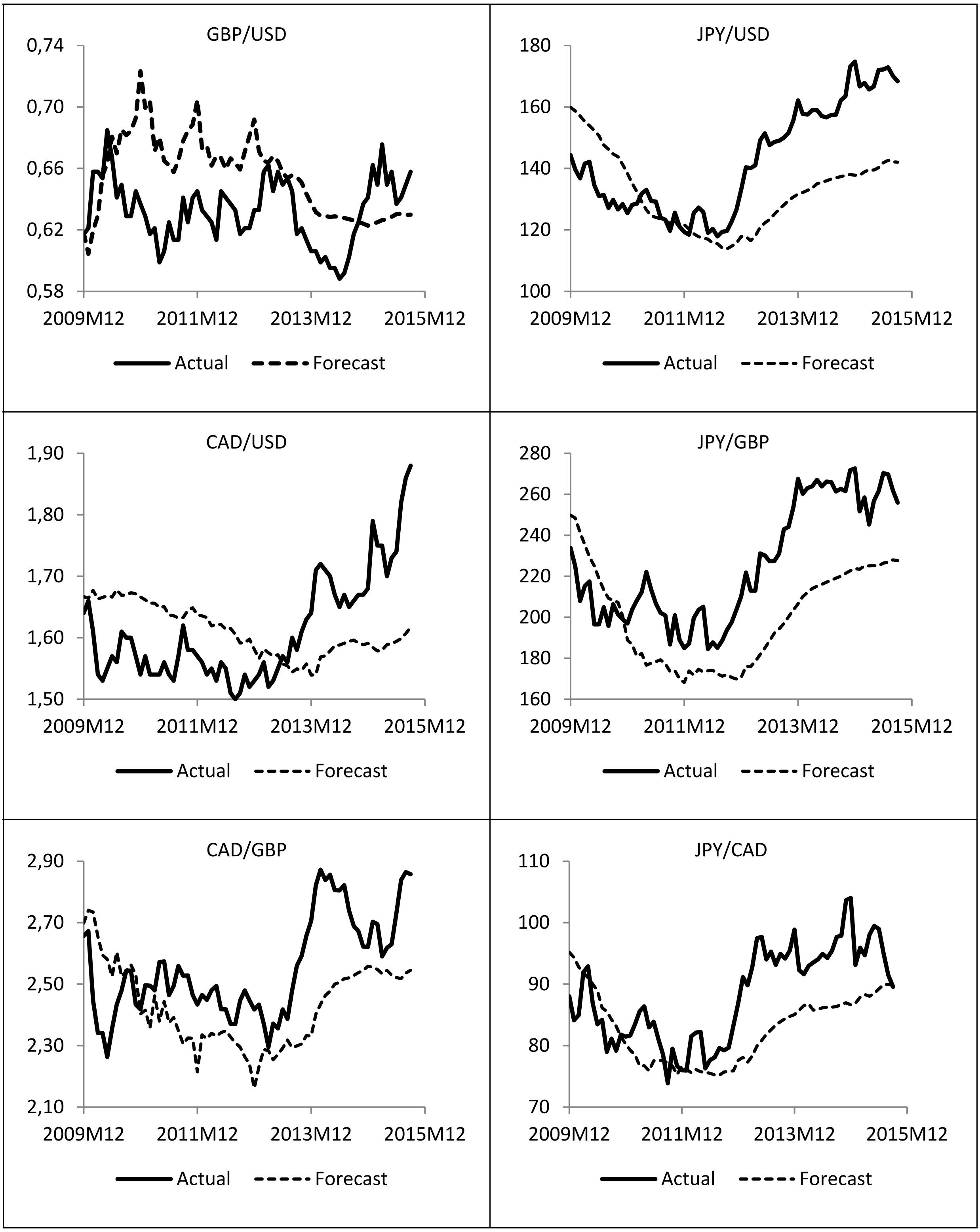

FIGURE 2 - *Actual and Forecast Values (Random Walk)*

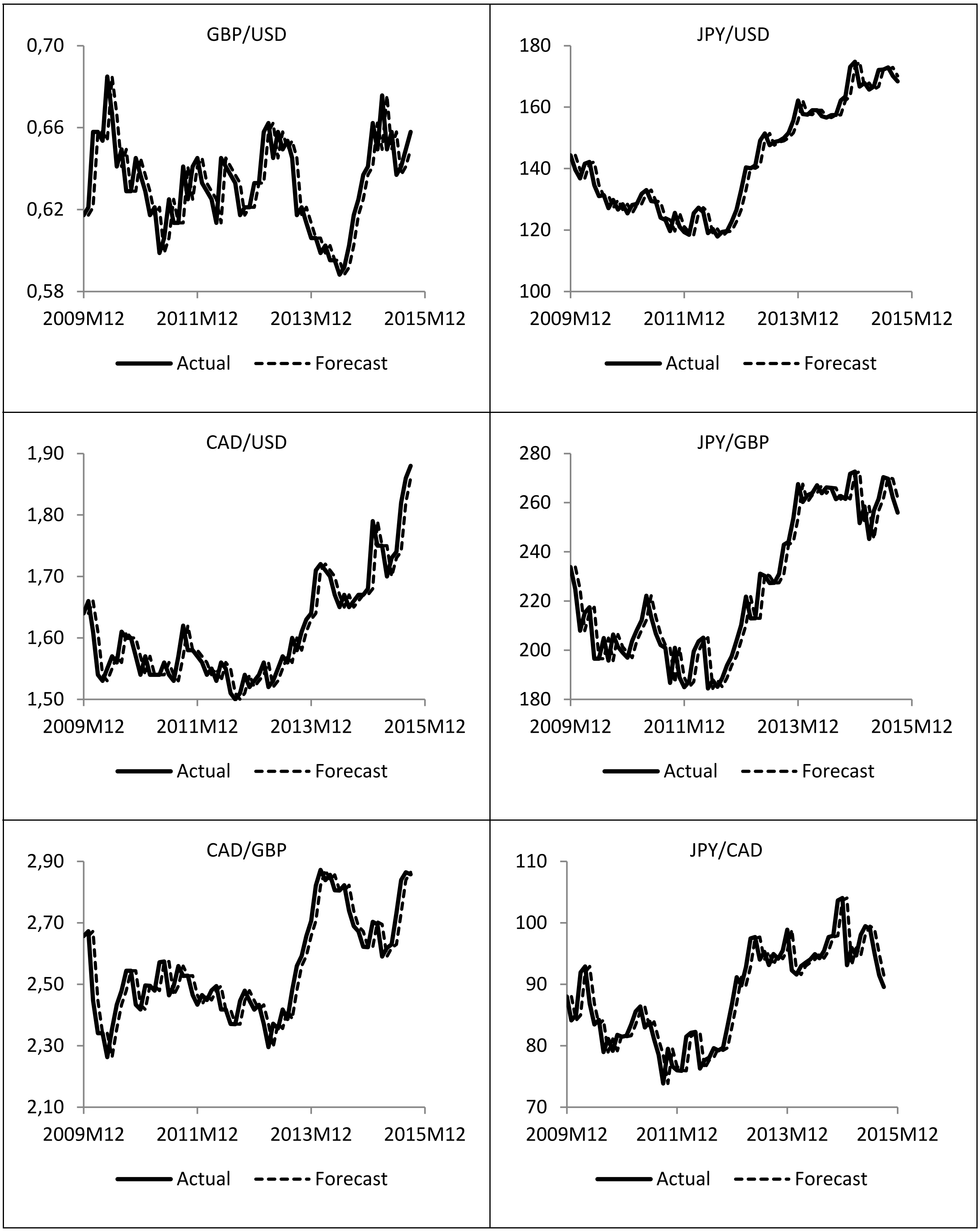

FIGURE 3 - *Actual and Forecast Values (Random Walk, GBP/USD)*

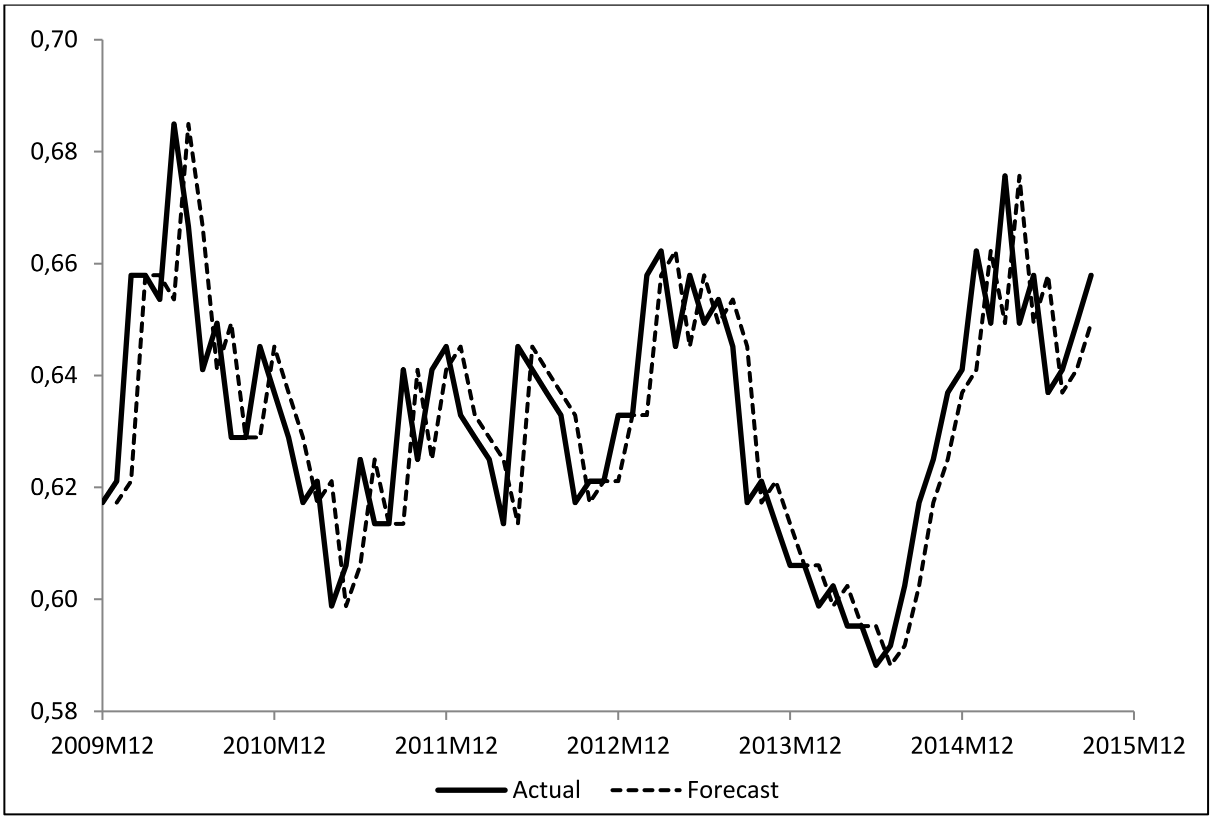

FIGURE 4 - *Actual and Forecast Values of GBP/USD (Dynamic Models A, B, C and D)*

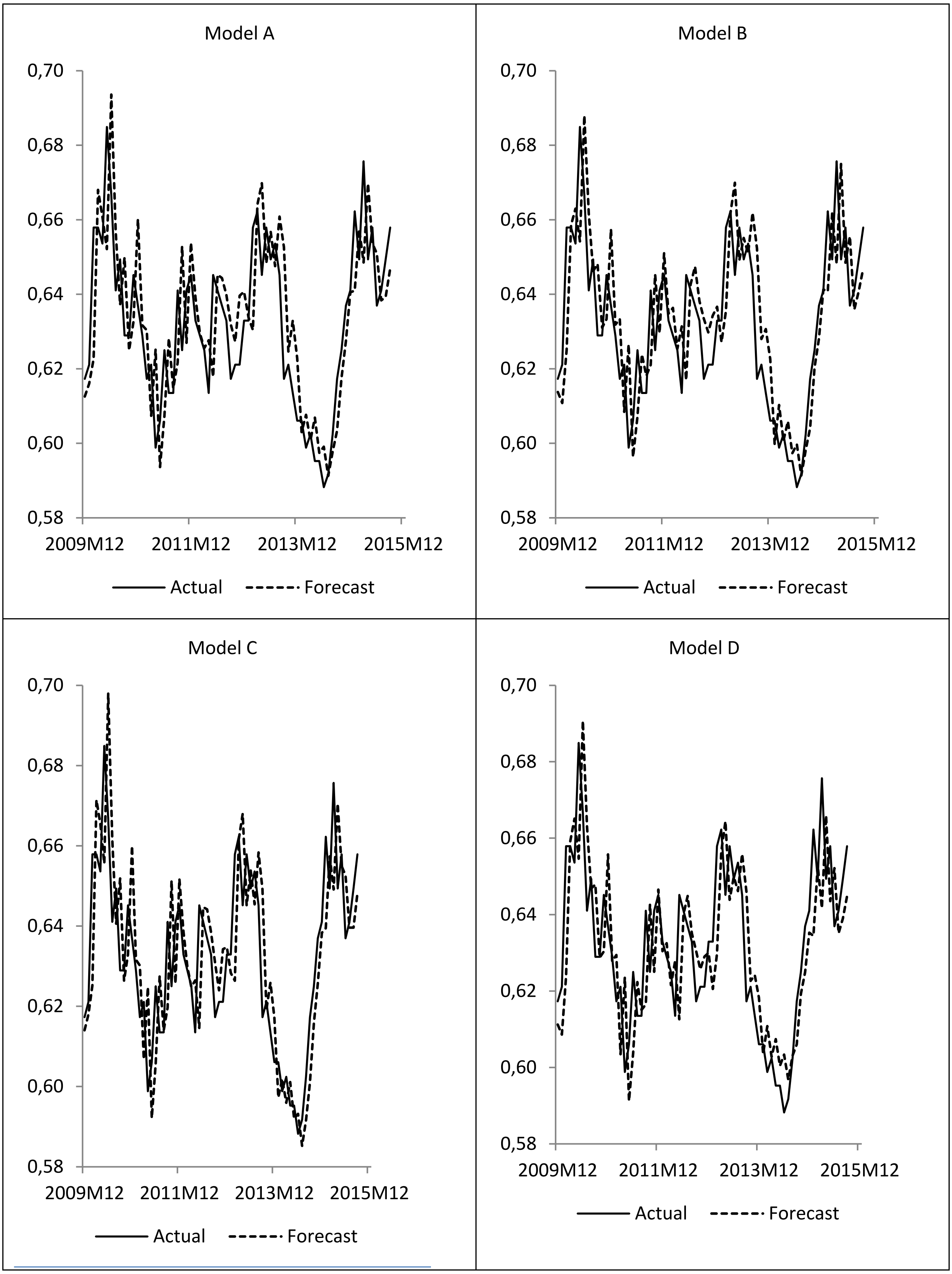

FIGURE 5 - *The Forecasting Power of the Forward Rate (GBP/USD)*

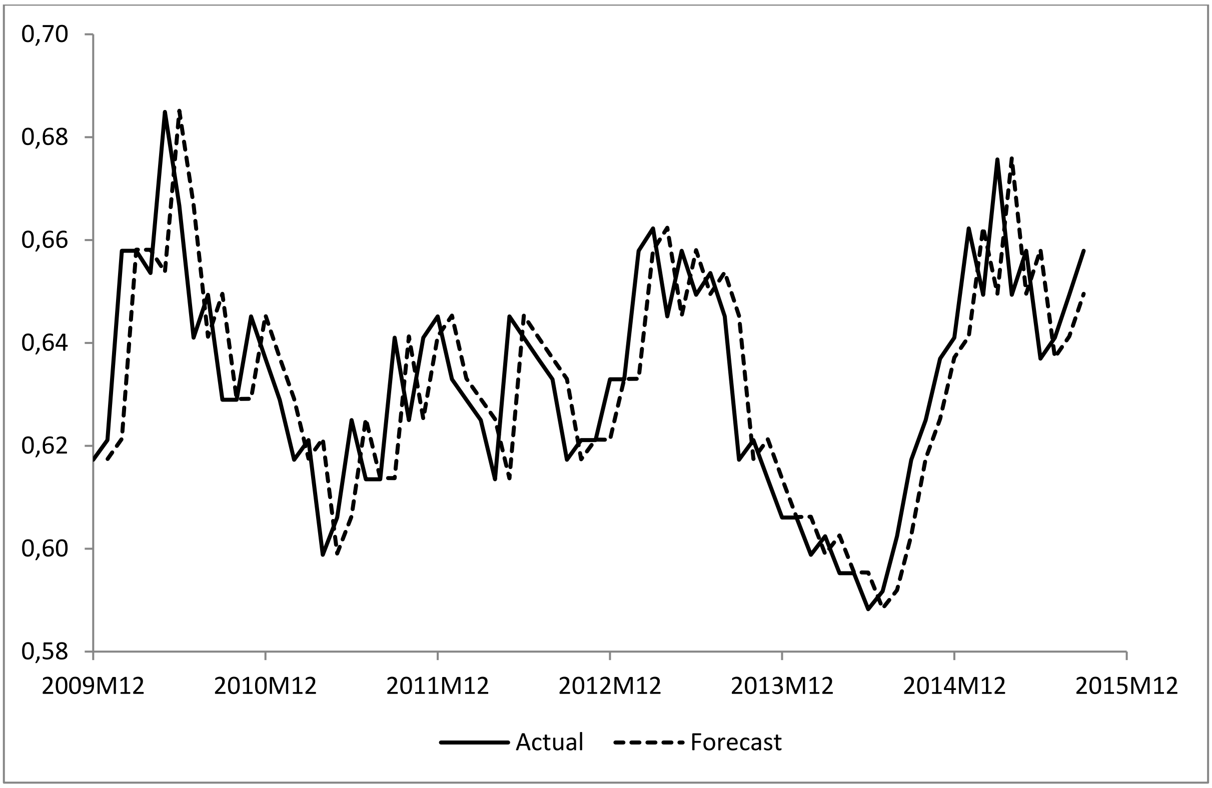

FIGURE 6 - *A Scatter Plot of Forecasts (Random Walk on Forward Rate)*