Exchange Rates and Fundamentals: Evidence on the Economic Value of Predictability*

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Abstract

A major puzzle in international finance is the inability of models based on monetary fundamentals to produce better out-of-sample forecasts of the nominal exchange rate than a naive random walk. While prior research has generally evaluated exchange rate forecasts using conventional statistical measures of forecast accuracy, in this paper we investigate whether there is any economic value to the predictive power of monetary fundamentals for the exchange rate. We estimate, using a framework that allows for parameter uncertainty, the economic and utility gains to an investor who manages her portfolio based on exchange rate forecasts from a monetary fundamentals model. In contrast to much previous research, we find that the economic value of the exchange rate forecasts implied by monetary fundamentals can be substantially greater than the economic value of forecasts obtained using a random walk across a range of horizons.

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1 Introduction

In an influential series of papers, Meese and Rogoff (1983a,b, 1988) noted that the out-of-sample forecasts of exchange rates produced by structural models based on fundamentals are no better than those obtained using a naive random walk or no-change model of the nominal exchange rate. These results, seen as devastating at the time, spurred a large literature that has re-examined the conclusions of the Meese-Rogoff studies. Some recent research, using techniques that account for several cumbersome econometric problems, including small sample bias and near-integrated regressors in the predictive regressions, suggests that models based on monetary fundamentals can explain a small amount of the variation in exchange rates (e.g., Mark, 1995; Mark and Sul, 2001). However, others remain skeptical (e.g., Berkowitz and Giorgianni, 2001; Faust, Rogers and Wright, 2003). Thus, even with the benefit of almost twenty years of hindsight, the Meese-Rogoff results have not been convincingly overturned: evidence that exchange rate forecasts obtained using fundamentals models are better than forecasts from a naive random walk is still elusive (e.g., Cheung, Chinn and Pascual, 2002; Neely and Sarno, 2002).

Prior research on the ability of monetary-fundamentals models to forecast exchange rates relies on *statistical* measures of forecast accuracy, like mean squared errors. Surprisingly little attention has been directed, however, to assessing whether there is any *economic* value to exchange rate predictability (i.e., to using a model where the exchange rate is forecast using economic fundamentals)[1]. The present paper fills this gap. We investigate the ability of a monetary-fundamentals model to predict exchange rates by measuring the economic or utility-based value to an investor who relies on this model to allocate her wealth between two assets that are identical in all respects except the currency of denomination. We focus on two key questions. First, as a preliminary to the forecasting exercise, we ask how exchange rate predictability and parameter uncertainty affect optimal portfolio choice for investors with a range of horizons up to ten years. Second, and more importantly, we ask whether there is any additional economic value to a utility-maximizing investor who uses exchange rate forecasts from a monetary-fundamentals model relative to an investor who uses forecasts from a naive random walk model. We quantify the economic value of predictability in a Bayesian framework that allows us to account for uncertainty surrounding parameter estimates in the forecasting model. Indeed, parameter uncertainty or 'estimation risk' is likely to be of importance, especially over long horizons.

[1] An exception is West, Edison and Cho (1993), who compare the utility gains from competing models for forecasting the volatility of exchange rates.

Our results with regard to the two questions addressed in this paper, obtained using three major US dollar exchange rates during the recent float and considering forecast horizons from 1 to 10 years, are as follows. First, we find that each of exchange rate predictability and parameter uncertainty substantially affect, both quantitatively and qualitatively, the choice between domestic and foreign assets for all currencies and across different levels of risk aversion. Specifically, exchange rate predictability can generate optimal weights to the foreign asset that are substantially different (in magnitude and, sometimes, in sign) from the optimal weights generated under a random walk model. Further, we find that taking into account parameter uncertainty causes the allocation to the foreign asset to fall (in absolute value) relative to the case when parameter uncertainty is not taken into account, effectively making the foreign asset look more risky. Second, our main result is that we find evidence of economic value to exchange rate predictability across all exchange rates examined and for a wide range of plausible levels of risk aversion. In particular, the realized end-of-period wealth, utility and certainty equivalent return achieved by a US investor over a ten-year horizon using a monetary fundamentals-exchange rate model for forecasting the exchange rate are higher than the corresponding end-of-period wealth, utility and certainty equivalent return obtained by an investor who acts as if the exchange rate were a random walk. Our results show that the economic value of predictability can be substantial also over relatively short horizons and across different levels of risk aversion, regardless of whether the investment strategy is static or dynamic and whether parameter uncertainty is taken into account. We view our findings as suggesting that the case against the predictive power of monetary fundamentals may be overstated.

Our work is related to and builds on earlier research by Kandel and Stambaugh (1996) and Barberis (2000), who use a Bayesian framework to study asset allocation[2] between a riskless asset and risky equities. Our work differs from theirs in three important ways. First, since we consider the economic gains (losses) to an investor whose problem is allocating her wealth between two assets that are identical in all respects except the currency of denomination, our focus is on exchange rate prediction. Put differently, in our framework risk only enters the investor's problem through the nominal exchange rate[3]. Second, we allow the investor to hold short positions in the assets, which is an important feature in real-world foreign exchange markets (e.g., Lyons, 2001). Third, while we analyze the impact of predictability and parameter uncertainty on optimal allocation decisions, our primary goal is to evaluate the out-of-sample economic value of exchange rate predictability. We do this by

[2] This decision-theoretic approach has also been used recently by Avramov (2001), Bauer (2000), Cremers (2002), Shanken and Tamayo (2001) and Tamayo (2002).

[3] See Karolyi and Stulz (2002) for an elegant survey of asset allocation in an international context.

comparing the end-of-period wealth, end-of-period utility and certainty equivalent return obtained using a standard monetary fundamentals model of the exchange rate with the corresponding measures of economic value obtained using a naive random walk, which remains the standard benchmark in the exchange rate forecasting literature.

Another related paper is Campbell, Viceira and White (2002), who study long-horizon currency allocation using a vector autoregressive framework where the predictive variables are the real interest rate and the real exchange rate. Our study differs from theirs in at least two ways. First, our basic forecasting instrument is the conventional set of monetary fundamentals proposed by exchange rate determination theory and used in the exchange rate forecasting literature since the Meese-Rogoff studies. Second, our framework allows for parameter uncertainty, which may be relevant over long investment horizons.

The rest of the paper is organized as follows. Section 2 provides a brief outline of the theoretical background, while in Section 3 we describe the framework used to analyze the economic value of exchange rate predictability both with and without parameter uncertainty. Next, in Section 4, we discuss our empirical results relating to the asset allocation choice of our investor over various horizons. In Section 5 we report the results from an out-of-sample forecasting exercise, where we compare the realized end-of-period wealth, utility gains and certainty equivalent return for an investor who relies on the monetary fundamentals model and one who uses a random walk model. Section 6 concludes. Details of the estimation procedure and the numerical methods used are provided in a Technical Appendix.

2 Exchange Rates and Monetary Fundamentals

A large literature in international finance has investigated the relationship between the nominal exchange rate and monetary fundamentals. This research focuses on the deviation, say u, of the nominal exchange rate from its fundamental value:

$$u_t = s_t - f_t, \tag{1}$$

where s denotes the log-level of the nominal bilateral exchange rate (the domestic price of the foreign currency); f is the long-run equilibrium of the nominal exchange rate determined by the monetary fundamentals; and t is a time subscript.

The fundamentals term is, most commonly, given by

$$f_t = (m_t - m_t^*) - \phi(y_t - y_t^*), \tag{2}$$

where m and y denote the log-levels of the money supply and income respectively; ϕ is a constant; and asterisks denote foreign variables. Here f may be thought of 'as a generic representation of the long-run equilibrium exchange rate implied by modern theories of exchange rate determination' (Mark and Sul, 2001, p. 32). For example, equation (2) is implied by the monetary approach to exchange rate determination (Frenkel, 1976; Mussa, 1976, 1979; Frenkel and Johnson, 1978) as well as by Lucas' (1982) equilibrium model and by several 'new open economy macroeconomic' models (Obstfeld and Rogoff, 1995, 2000; Lane, 2001). Hence, the link between monetary fundamentals and the nominal exchange rate is consistent with both traditional models of exchange rate determination based on aggregate functions as well as with more recent microfounded open economy models.

While it has been difficult to establish the empirical significance of the link between monetary fundamentals and the exchange rate due to a number of cumbersome econometric problems[4], some recent research suggests that the monetary fundamentals described by equation (2) co-move in the long run with the nominal exchange rate and therefore determine its equilibrium level (Groen, 2000; Mark and Sul, 2001; Rapach and Wohar, 2002). This result implies that current deviations of the exchange rate from the equilibrium level determined by the monetary fundamentals induce future changes in the nominal exchange rate which tend to correct the deviations from long-run equilibrium, so that estimation of a regression of the form

$$\Delta_k s_{t+k} = \alpha + \beta u_t + \varepsilon_{t+k} \tag{3}$$

(where Δ_k denotes the k-difference operator) often produces statistically significant estimates of β (e.g., Mark, 1995; Mark and Sul, 2001). Indeed, equation (3) is the equation analyzed by a vast literature investigating the ability of monetary fundamentals to forecast the nominal exchange rate out of sample at least since Mark (1995)[5]. In this paper, we follow this literature and use equation (3) in our empirical analysis, imposing the conventional restriction that $\phi = 1$ in the definition of f_t given by equation (2) (e.g., Mark, 1995; Taylor and Peel, 2000; Mark and Sul, 2001)[6].

[4] E.g., see Mark (1995), Berben and van Dijk (1998), Kilian (1999), Berkowitz and Giorgianni (2001).

[5] See Mark (2001, Ch. 4) for a recent review of the relevant studies. Also, note that equation (3) implicitly assumes that deviations from long-run equilibrium are restored via movements in the exchange rate; however, it seems possible that they may be restored also via movements in the fundamentals. Notably, Engel and West (2002) show analytically that, in a stylized rational expectations present value model, the exchange rate follows a near random walk if fundamentals are nonstationary and the discount factor is close to unity. Under these conditions, therefore, the exchange rate is exogenous but an exchange rate-monetary fundamentals relationship may still exist where fundamentals bear the burden of adjustment towards long-run equilibrium. See also the papers in the special issue on "Empirical Exchange Rate Models" forthcoming in the *Journal of International Economics*.

[6] We also tested the validity of the unity restriction as a preliminary to the forecasting exercise and we could not reject the hypothesis that the unity restriction is valid for each exchange rate examined in this paper. In the interest of brevity, these results are not reported.

3 International Asset Allocation, Predictability and Parameter Uncertainty: Methodology

In this section we describe our framework for measuring the economic value of predictability of exchange rates, both with and without parameter uncertainty. Our work is related to and builds on the empirical finance literature that analyzes asset allocation in a Bayesian framework, including the work of Kandel and Stambaugh (1996) and Barberis (2000)[7]. We consider a utility-maximizing US investor who faces the problem of choosing how to invest in two assets that are identical in all respects except the currency of denomination. As a result we can focus on evaluating the economic and utility gains to an investor who relies on the monetary-fundamentals model to forecast exchange rates. Our benchmark is an investor who does not believe in predictability or, in other words, believes that the exchange rate follows a random walk - the benchmark used in the exchange rate literature since Meese and Rogoff (1983a,b). In our framework, the investor uses the forecasts from the model (either the fundamentals model or the random walk model) to construct strategies designed to decide how much of her wealth to invest in the domestic and foreign assets respectively.

We consider the following two cases. First, we study the problem of an investor who has to decide at time T how much of her wealth to invest in a nominally safe (or riskless) domestic bond and a foreign bond which is nominally safe in local currency over a time period $\widetilde{T}$ using a simple buy-and-hold strategy. Second, we allow our investor to optimally re-balance her portfolio at the end of every year over her investment horizon. Finally, for each of these two cases - buy-and-hold and dynamic rebalancing strategies - we consider both cases with and without parameter uncertainty in estimating the monetary-fundamentals model.

3.1 Buy-and-Hold Strategy

Consider first the problem of an investor who has to decide at time T how much of her wealth to invest in nominally safe domestic and foreign bonds respectively. These two bonds yield the continuously compounded returns r and r^* respectively, each expressed in local currency. The investor wishes to hold the portfolio for $\widetilde{T}$ periods.

The exchange rate may be modelled using a vector autoregression (VAR) of the following form (Campbell, 1991; Bekaert and Hodrick, 1992; Hodrick, 1992; Barberis, 2000; Campbell, Viceira and

[7] Lewis (1989) is an example of an early application of Bayesian techniques to the foreign exchange market. See also Lewis (1995).

White, 2002):

$$z_t = a + Bx_{t-1} + \eta_t, \tag{4}$$

where $z_t' = (\Delta s_t, x_t')$, $x_t = (x_{1,t}, x_{2,t}, \ldots, x_{n,t})'$, and $\eta_t \sim iid(0, \Sigma)$.[8] The first component of z_t, namely Δs_t, is the change in the nominal exchange rate between period t and $t-1$. The remaining components of z_t consist of variables useful for predicting the change in the exchange rate, such as the deviation from the long-run equilibrium level of the exchange rate as measured by the monetary fundamentals (u_t as defined by equations (1)-(2)). Thus, the VAR (4) comprises a first equation which specifies the exchange rate change as a function of the predictor variables, while the other equations govern the stochastic evolution of the predictor or state variables.

In our empirical work, we implement the VAR (4) assuming a monetary fundamentals equation of the form (3) as the predictive regression and a first-order autoregressive process for the deviations from the fundamentals, u_t. This amounts to estimating a bivariate VAR with $z_t' = (\Delta s_t, u_t)$; a is a 2×1 vector of intercept terms; B is a 2×1 vector of parameters; the predictor variables vector comprises only one variable, namely the deviation from the fundamental exchange rate equilibrium level, i.e., $x_t = u_t$; and $\eta_t' = (\eta_{1t}, \eta_{2t})$ where η_{jt} is the error term of the jth equation in the VAR, for $j = 1, 2$. In the case of no predictability of the exchange rate, Δs_t equals a drift term plus a random error term.

Given initial wealth $W_T = 1$ and defining ω the allocation to the foreign bond, the end-of-horizon or end-of-period wealth is

$$W_{T+\widetilde{T}} = (1-\omega) \exp\left(r\widetilde{T}\right) + \omega \exp\left(r^*\widetilde{T} + \Delta_{\widetilde{T}} s_{T+\widetilde{T}}\right). \tag{5}$$

The investor's preferences over end-of-period wealth are governed by a constant relative risk-aversion (CRRA) power utility function of the form

$$v(W) = \frac{W^{1-A}}{1-A}, \tag{6}$$

where A is the coefficient of risk aversion.

The investor's problem may then be written as follows:

$$\max_{\omega} E_T \left\{ \frac{\left[(1-\omega) \exp\left(r\widetilde{T}\right) + \omega \exp\left(r^*\widetilde{T} + \Delta_{\widetilde{T}} s_{T+\widetilde{T}}\right)\right]^{1-A}}{1-A} \right\}, \tag{7}$$

[8] We term the model in equation (4) a VAR to adhere to the standard terminology used in this literature (e.g., Kandel and Stambaugh, 1996; Barberis, 2000).

where the expectation operator $E_T(\cdot)$ reflects the fact that the investor calculates the expectation conditional on her information set at time T. A key issue in solving this problem relates to the distribution the investor uses in calculating this expectation, which depends both upon whether the exchange rate is predictable and on whether parameter uncertainty is taken into account.

To shed light on the impact of the predictability of exchange rates on portfolio decisions, we compare the allocation of an investor who ignores predictability to the allocation of an investor who takes it into account. This can easily be done by estimating the VAR model (4), with and without the deviations from fundamentals u_t, to obtain estimates of the parameters vector, say θ.[9] The model can be iterated forward with the parameters fixed at their estimated values. This gives a distribution of future exchange rates conditional on the estimated parameters vector, $p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} \mid \widehat{\theta}, z\right)$, where $z_t = (z_1, z_2, \ldots, z_T)'$ is the observed data up to the date when the investment begins. Thus, the investor's problem is

$$\max_{\omega} \int \upsilon\left(W_{T+\widetilde{T}}\right) p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} \mid \widehat{\theta}, z\right) d\Delta_{\widetilde{T}} s_{T+\widetilde{T}}. \tag{8}$$

In order to take into account parameter uncertainty, however, one can use the posterior distribution $p(\theta \mid z)$, which summarizes the uncertainty about the parameters given the data observed so far. Integrating over the posterior distribution, we obtain the predictive distribution of exchange rate movements conditioned only on the data observed, not on the estimated parameters vector, $\widehat{\theta}$. Then the predictive distribution is

$$p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} \mid z\right) = \int p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} \mid \theta, z\right) p(\theta \mid z)\, d\theta, \tag{9}$$

which implies that the investor's problem under parameter uncertainty is

$$\begin{aligned} & \max_{\omega} \int \upsilon\left(W_{T+\widetilde{T}}\right) p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} \mid z\right) d\Delta_{\widetilde{T}} s_{T+\widetilde{T}} && (10) \\ = \; & \max_{\omega} \int \upsilon\left(W_{T+\widetilde{T}}\right) p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}}, \theta \mid z\right) d\Delta_{\widetilde{T}} s_{T+\widetilde{T}} d\theta \\ = \; & \max_{\omega} \int \upsilon\left(W_{T+\widetilde{T}}\right) p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} \mid \theta, z\right) p(\theta \mid z)\, d\Delta_{\widetilde{T}} s_{T+\widetilde{T}} d\theta. && (11) \end{aligned}$$

Finally, given the optimal weights derived by the maximization problems (8) and (10), we can calculate the realized end-of-period wealth using the wealth function (5) for an investor who ignores parameter uncertainty - equation (8) - and an investor who recognizes it and takes it into account - equation (10). Given end-of-period wealth, we can then calculate also end-of-period utility of wealth using

[9] θ comprises a, B and the variance-covariance matrix of the error terms, say Σ.

equation (6) and the certainty equivalent return[10] to measure the economic value of predictability.[11]

The maximization problems (8) and (10) are solved by calculating the integrals in these equations for values of $\omega = -100, -99, \ldots, 199, 200$ (in percentage terms), which essentially allows for short selling.[12] In our empirical analysis below, we report the value of ω that maximizes expected utility. The integrals are calculated by numerical methods, using $1,000,000$ simulations in each experiment. In our case, the conditional distribution $p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} \mid \widehat{\theta}, z\right)$ is normal, so that the integral in (8) is approximated by generating $1,000,000$ independent draws from this normal distribution and averaging $v\left(W_{T+\widetilde{T}}\right)$ over all draws. For the maximization problem under parameter uncertainty, it is convenient to evaluate it in its reparameterized form (11) by sampling from the joint distribution $p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}}, \theta \mid z\right)$ - i.e., by first sampling from the posterior $p(\theta \mid z)$ and then from the conditional distribution $p\left(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} \mid \theta, z\right)$ - and averaging $v\left(W_{T+\widetilde{T}}\right)$ over all draws[13].

3.2 Dynamic Rebalancing Strategy

We next consider an investor who optimally re-balances her portfolio at the end of every period using exchange rate forecasts based on the monetary-fundamentals model. We again analyze the optimal allocation both with and without parameter uncertainty. In this multi-period asset allocation problem, the optimal weights are now the solution to a dynamic programming problem that can be solved by discretizing the state space and using backward induction. We divide the investor's horizon starting at T and ending at $\widetilde{T}$ into K subperiods denoted by $[t_0, t_1], \ldots [t_{K-1}, t_K]$, where $t_0 = T$ and $t_K = T + \widetilde{T}$. Thus the investor now adjusts her portfolio K times over the investment horizon by changing ω, the allocation to the foreign bond, at the end of each sub-period. To simplify the notation we denote by W_k the quantity W_{t_k}, the investor's wealth at time t_k. The investor's problem now is

$$\max_{t_0} E_{t_0}\left(\frac{W_K^{1-A}}{1-A}\right), \tag{12}$$

[10] The certainty equivalent return (CER) can be defined as the return that, if earned with certainty, would provide the investor with the utility equal to the end-of-period utility calculated for a given allocation, $\overline{v}_{T+\widetilde{T}}$. In general, the CER can be obtained by solving the equation:

$$v\left[W_T\left(1+CER\right)\right] = \overline{v}_{T+\widetilde{T}}$$

where W_T denotes wealth at time T and $v[\cdot]$ is the utility function in (6).

[11] See Section 6 for more details on these measures of economic value of predictability.

[12] Obviously no allowance for short selling would involve a weight ω between 0 and 100. Given the wide use of short selling in the foreign exchange market (e.g., Lyons, 2001) we allow ω to be defined between -100 and 200, which essentially allows for full proceeds of short sales and assumes no transactions costs.

[13] For further details on the estimation procedure and the numerical methods used see the Technical Appendix.

where the investor maximizes over all remaining decisions from t_0 onwards. The law of motion of her wealth is given by

$$W_{k+1} = W_k \left\{ (1-\omega_k) \exp\left(r \frac{\widetilde{T}}{K} \right) + \omega_k \exp\left(r^* \frac{\widetilde{T}}{K} + \Delta_{k+1} s_{k+1} \right) \right\}. \tag{13}$$

We can then define the indirect utility of wealth as

$$J\left(W_k, x_k, t_k\right) = \max_{t_k} E_{t_k} \left(\frac{W_K^{1-A}}{1-A} \right), \tag{14}$$

where the maximization is over all remaining decisions from t_k on. This can be written, using an induction argument, as

$$J\left(W_k, x_k, t_k\right) = \frac{W_k^{1-A}}{1-A} Q\left(x_k, t_k\right) \tag{15}$$

when $A \neq 1$. Accordingly, the Bellman equation is

$$Q\left(x_k, t_k\right) = \max_{\omega_k} E_{t_k} \left\{ \left[(1-\omega_k) \exp\left(r \frac{\widetilde{T}}{K} \right) + \omega_k \exp\left(r^* \frac{\widetilde{T}}{K} + \Delta_{k+1} s_{k+1} \right) \right]^{1-A} \times Q\left(x_{k+1}, t_{k+1}\right) \right\}. \tag{16}$$

We first consider the case without parameter uncertainty. Here the expectation in equation (16) is evaluated conditional on fixed parameter values based on the posterior mean. When we allow for parameter uncertainty there are two main differences compared to the case with no parameter uncertainty. The first is that the expectation in the value function is now taken over the predictive distribution which incorporates parameter uncertainty. The second is that, in this multi-period case, parameter uncertainty may change over time and the investor updates her posterior distribution for the parameters. Thus, in addition to the hedging demand arising from the stochastic investment opportunity set (see Merton, 1973; Karolyi and Stulz, 2002), there may be an additional source of hedging demand arising from changes in the investor's beliefs about the model parameters over time.

Evaluating the joint dynamics of the state variables as well as the parameters in the model is a non-trivial dynamic programming problem. It is useful therefore to make some reasonable simplifying assumptions so that this task is numerically tractable. The dimensionality of the problem is reduced by assuming that the investor's beliefs about the parameters of the model do not change from what they are at the beginning of the investment horizon (e.g., Barberis, 2000). In other words, these beliefs are summarized by the posterior distribution calculated conditional only on the data observed at the beginning of the investment horizon. We can thus still use equation (16) to calculate the value function, but the expectation is now evaluated over $p\left(\Delta_{k+1} s_{k+1}, x_{k+1} \mid x_k\right)$ rather than over

$p(\Delta_{k+1}s_{k+1}, x_{k+1} \mid \theta, x_k)$. The investor constructs a sample from the predictive distribution by taking a large number of draws from the posterior $p(\theta \mid z_1, \ldots, z_T)$ - conditional only on data until the horizon start date - and then, for each set of parameters values drawn, makes a draw from $p(\Delta_{k+1}s_{k+1}, x_{k+1} \mid \theta, x_k)$.

We now turn to a description of our data set, to which we apply the procedure outlined above.

4 Data

Our data set comprises monthly observations on money supply and income (industrial production) for the US, Canada, Japan and the UK, and spot exchange rates for the Canadian dollar, Japanese yen and UK sterling *vis-à-vis* the US dollar. The sample period covers most of the recent floating exchange rate regime, from 1977M01 to 2000M12, and the start date of the sample was dictated by data availability. The data are taken from the International Monetary Fund's *International Financial Statistics* data base. We use the monthly industrial production index (line code 66) as a proxy for national income since gross domestic product (GDP) is available only at the quarterly frequency.[14] Our measure of money is defined as the sum of money (line code 34) and quasi-money (line code 35) for the US, Canada, Japan, while for the UK we use M0. We deseasonalize the money and industrial production indices, following Mark and Sul (2001). The exchange rate is the end-of-month nominal bilateral exchange rate (line code AE). Our choice of countries reflects our intention to examine exchange rate data for major industrialized economies belonging to the G7 that have been governed by a pure float over the sample[15]. As a proxy for the nominally safe (riskfree) domestic and foreign bonds, we use end-of-month Euro-market bid rates with one month maturity for each of the US, Canada, Japan and the UK, provided by the Bank for International Settlements (BIS).

The data were transformed in natural logarithms prior to beginning the empirical analysis to yield time series for s_t, m_t, m_t^*, y_t and y_t^*. The monetary fundamentals series, f_t, was constructed with these data in logarithmic form according to equation (2) with $\phi = 1$; and s_t is taken as the logarithm of the domestic price of the foreign currency, with the US denoting the domestic country. In our

[14] Note that a preliminary analysis of the statistical properties of the (quarterly) industrial production indices and GDP time series over the sample period and across the countries examined in this paper produced a coefficient of correlation higher than 0.95.

[15] Note that, while Canada and Japan have experienced a free float since the collapse of the Bretton Woods system in the early 1970s, the UK was in the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS) for about two years in the early 1990s. However, given the short length of this period, we consider sterling as a freely floating exchange rate in this paper. The remaining three G7 countries not investigated here, namely Germany, France and Italy, have all been part of the ERM for most of the sample period under investigation and in fact joined the European Monetary Union on 1 January 1999, when the euro replaced the national currencies of these three countries.

empirical work, we use the data over the period January 1977-December 1990 for estimation, and reserve the remaining data for the out-of-sample forecasting exercise.[16] In addition, the domestic and foreign interest rates are treated as constant and set equal to their historical mean.

5 International Asset Allocation, Predictability and Parameter Uncertainty: Empirical Results

We now report our empirical results based on solving the maximization problems (8) and (10), which allow us to study the implications for portfolio weights when the exchange rate is either a random walk or predictable respectively. In each case our investor uses two different investment strategies. The first is a simple static buy-and-hold strategy, where the investor chooses the optimal weight to the foreign asset and does not change it until the end of the investment (forecast) horizon. The second is a dynamic strategy where the investor optimally rebalances her portfolio at the end of each rebalancing period. We report results for four cases: random walk exchange rate and predictable exchange rate, and in each case both with and without parameter uncertainty. We begin by describing the case of a buy-and-hold investor in the next sub-section.[17]

5.1 Buy-and-Hold Strategy

As described in Section 3.1, a buy-and-hold investor with an horizon $\widetilde{T} = 1, ..., 10$ solves the problem in equation (8). Using a recursive Monte Carlo sampling procedure, we obtain an accurate representation of the posterior distributions of the estimated vector of parameters θ.[18] Using data till December 1990, we estimate the posterior distribution of the parameters for all countries by drawing samples of size $1,000,000$. From these estimated distributions, we obtain out-of-sample forecasts for the investment horizon $\widetilde{T} = 1, ..., 10$ years when the investor takes into account parameter uncertainty and when she ignores it.

[16] It should be noted that the original Meese-Rogoff studies considered forecast horizons of up to 12 quarters ahead, while Mark (1995), for example, uses a maximum horizon of 16 quarters. In general, most studies in this literature have focused on horizons of up to 4 years ahead and therefore the forecast horizon considered in this paper is - to the best of our knowledge - the longest horizon considered in the relevant exchange rate literature to date.

[17] Preliminary estimation of the VAR model in equation (4) produced results consistent with a vast literature in this context (see Mark, 1995). Specifically, we find significant estimates of all parameters, with the parameter associated with the deviations from the fundamentals u_t being negative and very small in magnitude, suggesting slow adjustment of the exchange rate towards its equilibrium level. Also, the estimated AR(1) parameter on u_t is positive and quite large in magnitude, albeit clearly lower than unity, suggesting that u_t is stationary but persistent. (These preliminary results are not reported to conserve space but are available upon request.)

[18] See footnote 9.

Figures 1-3 (which refer to the Canadian dollar, the Japanese yen and the UK sterling respectively) show the optimal weight ω (in percentage terms) allocated by a US investor to the foreign asset on the vertical axis, and the investment horizon (in years) on the horizontal axis. For each exchange rate, we show optimal weights for four different values of the coefficient of risk aversion, A, ranging from 2 to 20. The dotted and solid lines correspond to the case where the investor relies on the fundamentals model (predictability) with and without parameter uncertainty respectively. The dot-dash and dash lines refer to the cases where the investor uses a random walk model (no predictability) with and without parameter uncertainty respectively.[19]

It is important to note one point about the variability that would be attached to the estimate of ω obtained using this procedure. Barberis (2000) provides a detailed discussion of this issue and shows that, given the sample size used in the simulated draws $(1,000,000)$, there is no significant variation in the estimate of ω. In other words, for this number of draws, the law of large numbers holds, resulting in a vanishing small variance of ω. As a result, we assume that we have converged to the optimal portfolio weight ω that would have been obtained if we could perform the integrations exactly (see Barberis, 2000, Appendix, for further details). Hence, in our empirical results, we do not report confidence intervals for ω given that its variability is 'virtually' zero for our number of draws.

The graphs show several interesting features that are common to all three exchange rates examined. We begin with an analysis of the case where the investor uses a random walk model (dash and dot-dash lines in Figures 1-3), which suggests the following results. First, if the investor does not account for parameter uncertainty (dash line in each of Figures 1 to 3), the optimal asset allocation does not vary with the investment horizon. This is consistent with studies on stock market data (Barberis, 2000) and may be seen as simply validating Samuelson's (1969) result that, under power utility, if asset prices follow a random walk then the optimal investment in the risky asset is constant regardless of the investment horizon.[20] Second, regardless of whether parameter uncertainty is accounted for, the optimal weight to the foreign bond, ω is lower (in absolute value) for higher levels of risk aversion, A (dash and dot-dash lines in Figures 1-3). Third, if the investor takes into account parameter uncertainty, we find that for low values of the coefficient of risk aversion (say $A = 2$), the optimal weight is virtually identical to the optimal weight obtained when parameter uncertainty is not accounted for (i.e., dot-dash and dash lines are virtually identical). This suggests that, for low levels of risk aversion, parameter uncertainty does not influence asset allocation for our data and sample

[19] Note that, within each figure, the graphs use different scales for clarity.

[20] Note, however, that Samuelson's result was obtained for an investor applying a rebalancing strategy, rather than a buy-and-hold strategy.

period. Fourth, for moderate to high values of the coefficient of risk aversion (say $A = 5, 10, 20$), if the investor takes into account parameter uncertainty (dot-dash line), we find a different optimal allocation across horizons: specifically, the absolute value of the initial optimal allocation to the foreign asset generally decreases with the length of the investment horizon. These results suggest that, under no predictability, parameter uncertainty matters more for optimal asset allocation the higher the coefficient of risk aversion and the longer the investment horizon.

We now turn to the case where the investor relies on the monetary-fundamentals model (solid and dotted lines in Figures 1-3), where we present our results on the impact of parameter uncertainty in an order similar to that in the preceding paragraph for the case of no predictability. First, in the case without parameter uncertainty (solid line in each of Figures 1 to 3), the absolute value of the initial optimal allocation to the foreign asset increases with the investment horizon. This result suggests that, if the investor believes in predictability of the exchange rate, she will be more prone to invest in the foreign asset the longer the investment horizon. This result contrasts with the invariance of the optimal weight over the investment horizon under no predictability and may be explained as follows. Under no predictability, the mean and the variance of the exchange rate increase linearly over time and, as shown by Samuelson (1969) for stock prices, this implies identical optimal weights for all investment horizons. However, as noted by Barberis (2000, p. 243-5), under predictability the variance of the exchange rate *may* grow less than linearly over time, making the foreign asset look less risky at longer investment horizons, leading to a higher optimal weight at longer horizons[21]. Second, regardless of whether parameter uncertainty is accounted for, the optimal allocation to the foreign bond, ω is lower (in absolute value) for higher levels of risk aversion, A (solid and dotted lines in Figures 1-3), essentially replicating the result discussed above for the case of no predictability. Third, if the investor takes into account parameter uncertainty, we find that, for low values of the coefficient of risk aversion (say $A = 2$), the optimal allocation line across horizons is virtually identical to the optimal allocation line obtained when parameter uncertainty is not accounted for (i.e., solid and dotted lines are identical). Again, this is similar to the case of no predictability and suggests that, for low levels of risk aversion, parameter uncertainty does not matter for asset allocation, for the exchange rates and sample period examined. Fourth, for moderate to high values of the coefficient of risk aversion (say $A = 5, 10, 20$), if the investor takes into account parameter uncertainty (dotted line), this implies a different optimal allocation across horizons where the absolute value of the initial optimal allocation to the foreign asset is generally non-decreasing with the length of the investment

[21] However, note that this result may not hold if learning is taken into account (Xia, 2001).

horizon. This result replicates the finding under no parameter uncertainty in a qualitative, but not quantitative, way.

In addition, with regard to the effects of predictability versus no predictability in determining the optimal weights to the foreign asset, our results clearly indicate that the optimal weights may differ significantly in these two cases. Indeed, the difference can be so large as to imply optimal weights with different signs, as reported, for example, in the cases of Canada and Japan (Figures 1-2). For the UK, however, the sign of the optimal weight is the same under predictability and no predictability, but the difference in the two corresponding weights is still sizable for higher levels of risk aversion (Figure 3). In addition, it is instructive to note that this result holds, in a qualitative sense, regardless of whether parameter uncertainty is taken into account.

A final observation, based on these results, is that the absolute value of the initial optimal allocation to the foreign asset for short investment horizons (say one or two years) is very similar for all cases examined here as the coefficient of risk aversion increases - regardless of whether the investor recognizes predictability and/or takes into account parameter uncertainty. Intuitively this suggests that for very high levels of risk aversion neither predictability nor parameter uncertainty matter particularly for asset allocation at short investment horizons.

Overall, our results show that both predictability and parameter uncertainty play an important role in the investor's choices for all countries and for different values of the coefficient of risk aversion. Specifically, predictability implies different optimal weights to the foreign asset compared to no predictability. The difference can be as large as to generate weights with a different sign - effectively meaning that when a fundamentals model implies a long (short) position in the foreign asset the random walk model may imply a short (long) position in the foreign asset. Parameter uncertainty induces the foreign asset allocation to fall (rise) as the horizon increases when the models predict positive (negative) weights assigned to the foreign asset.[22] Intuitively, this means that parameter uncertainty makes the allocation to the foreign asset look more risky than without parameter uncertainty. Across different countries (on average), parameter uncertainty changes the optimal weight to the foreign asset, relative to the case without parameter uncertainty, by 33% in the case of no predictability (14% in the case of predictability) for a coefficient of risk aversion $A = 5$, and 44% in the case of no predictability (41% in the case of predictability) for a coefficient of risk aversion $A = 20$.

[22] Put differently, when the models would suggest buying the foreign asset, parameter uncertainty (by increasing the variance associated with the out-of-sample prediction) reduces the percentage of wealth invested in the foreign asset. This reduction is generally larger the longer is the investment horizon. If the models predict that the foreign asset be short sold, parameter uncertainty works in the opposite direction, by reducing the percentage of foreign asset to be sold short.

5.2 Dynamic Rebalancing Strategy

We now examine the case where the investor optimally rebalances over her investment horizon, assuming a rebalancing period of one year. Again, we analyze the cases with and without parameter uncertainty. The problem faced by the investor is as detailed in Section 3.2. To solve the Bellman equation (16), we discretize the state space by taking intervals ranging from three standard deviations below to three standard deviations above the historical mean of the deviation from the monetary fundamentals, u and dividing it into 25 equally spaced grid points. We draw a sample of size $1,000,000$ from the distributions of exchange rate changes as in the static buy-and-hold strategy. The number of grid points selected and the large number of replications used should guarantee satisfactory accuracy of the results.

We depict graphically, in Figures 4-6, changes over different horizons and for varying coefficients of risk aversion in the patterns of holding of a US investor who optimizes her portfolio annually. Our results, reported in the left-hand panels of Figures 4-6, show optimal allocations for the investor when parameter uncertainty is ignored. The graphs in the right-hand panels show the optimal allocation when parameter uncertainty is taken into account. Each graph refers to a different level of risk aversion and, in each graph, the lines plotted correspond to a different initial value of the predictor variable. In particular, each graph reports asset allocations relative to an initial value equal to three and one standard deviations below the historical mean, three and one standard deviations above the historical mean, and the historical mean itself.

Our results show that, even if different initial values of the predictor variable (i.e., the deviation from the fundamental exchange rate equilibrium value) influence the magnitude of the allocation to the foreign asset, the optimal allocation under dynamic rebalancing is qualitatively similar to the allocation implied by the static buy-and-hold strategy. The differences, for different initial values, in the foreign asset allocation under dynamic rebalancing are more pronounced for lower levels of risk aversion. Further, as in the static buy-and-hold case, parameter uncertainty affects asset allocation in the same way; that is, it causes the foreign asset allocation to fall (rise) as the horizon increases when the models predict positive (negative) weights assigned to the foreign asset.[23]

It is interesting to note that the higher the initial value of the predictor variable, the lower (higher) is the proportion of wealth invested in the foreign asset when the underlying model predicts a positive (negative) weight to the foreign asset. Intuitively, for example, a high initial value of the predictor

[23] However, although the results are qualitatively similar, the effect driving them is not the same in that the increase in allocation across horizons in the case of a rebalancing strategy is due to hedging demand effects, as first described by Merton (1973) and reported, for example, by Barberis (2000). See also Karolyi and Stulz (2002).

variable means that there is a large positive departure of the nominal exchange rate from its fundamental value. This in turn implies that, in order to restore equilibrium, the nominal exchange rate will decrease in the future - in other words, it will appreciate. A future appreciation of the nominal exchange rate will of course induce the US investor to invest less in the foreign asset and more in the domestic asset.

We now turn to the core of our empirical work, a quantitative analysis of the economic value of exchange rate predictability.

6 The Out-of-Sample Economic Value of Predictability

This section reports estimates of the economic value of predictability. We begin by calculating end-of-period wealth, as defined in equation (5) and normalizing its initial value $W_T = 1$. In these calculations ω is obtained from the utility maximization problems (10) and (16) for the static and dynamic rebalancing cases respectively. In our context, the random walk model and the fundamentals model may be seen as reflecting two polar approaches to exchange rate forecasting. Specifically, an investor who assumes predictability (believes in the fundamentals model) considers the fundamentals approach as a perfect description of reality. An investor who believes in the random walk approach assumes, on the other hand, that there is no variable able to predict the exchange rate. The wealth calculations on the basis of which we compare the two models are obtained using realized or *ex post* data in equation (5).[24] We also calculate the realized end-of-period utilities, using equation (6), and the realized certainty equivalent returns in order to compare the out-of-sample performance of the two competing models on the basis of various measures of economic and utility gains.

A related question involves the *ex ante* performance of each of the random walk model and the fundamentals model. In this case, the evaluation of the performance of the models would be based on an *ex ante* or expected end-of-period wealth calculation, where the change in the exchange rate $\Delta s_{T+\widetilde{T}}$ is the forecast of the exchange rate implied by the model being considered rather than its realized value. This calculation would provide information on the returns and on the economic value that the investor would expect given the data and investment horizon and given her belief in a particular model. Clearly, while this exercise can be implemented out-of-sample, it implicitly assumes that the model which provides the forecasts is the true data generating process - that is, no *ex post* realized data are used. However, this is helpful as it provides an estimate of expected returns or

[24] Thus, given equation (5), the forecasts produced by each of the two models considered affect the end-of-period wealth only through the choice of the optimal weight ω.

economic value, which the investor may use in deciding whether, given her belief in the model, the investment in foreign exchange is worthwhile *ex ante*. It should be clear, on the other hand, that such *ex ante* calculation does not address the key question in this paper, which is about the out-of-sample forecasting ability of the fundamentals model relative to a random walk model. A pure out-of-sample comparison designed to evaluate the ability of a model to match the realized data can only be done by comparing the outcome from the model-based forecasts to the *ex post* data, which is the approach we follow in this paper, in line with the literature on exchange rate forecasting.

We now turn to the core of the results in this section, which relates to the calculation of the *ex post* end-of-period wealth in each of our four cases (predictability and no predictability under each of parameter uncertainty and no parameter uncertainty) for both buy-and-hold and dynamic rebalancing strategies. We define the following measures of economic gain (loss): (i) the wealth ratio as the ratio of the end-of-period wealth from using the fundamentals model to the end-of-period wealth from using a random walk; (ii) the utility ratio as the ratio of the end-of-period utility from the fundamentals model to the end-of-period utility from using a random walk; (iii) the differences in certainty equivalent returns (CERs) as the annualized differences between the CER calculated from the utility from the fundamentals model and the CER corresponding to the utility using a random walk. It is important to emphasize that none of these measures of economic value has a standard error since they are based on a pure ex post out-of-sample evaluation which relies on the calculation of the end-of-period wealth given in equation (5) at time $\widetilde{T}$.[25]

Note that the end-of-period wealth is calculated on the basis of interest rates which are known (r and r^*), a realized value of the change in the exchange rate at time $\widetilde{T}$, and the value of ω implied by a particular investment strategy, risk aversion parameter and model. Hence, given that ω has a variance that may be regarded as 'virtually' zero for our number of draws (see our discussion at p.

[25] Although, as explained above, this is not directly relevant to the question addressed in this paper, as a preliminary exercise we also carry out the analysis on an *ex ante* basis. In particular, for each of static and dynamic strategies, we calculate the *ex ante* end-of-period wealth to verify that it is consistent with an *ex ante* economic value which would validate the belief of the investor (either in the random walk or the fundamentals model). In each case, the *ex ante* calculations indicate sizable increases in the end-of-period wealth up to ten years ahead. Indeed, the *ex ante* returns and measures of economic value are larger than their *ex post* corresponding measures we report later in the paper, especially for longer investment horizons. One advantage of the *ex ante* calculations is that it is possible to obtain a measure of the uncertainty surrounding the expected end-of-period wealth because the calculation is based on forecasts for exchange rates, obtained by drawing 1,000,000 times from the predictive distribution of exchange rates. This allows us to recover the distribution of the end-of-period wealth and hence to assign confidence intervals. Our general result is that, for each of the random walk model and the fundamentals model and for each of the two strategies employed here, the expected end-of-period wealth is not only large but also strongly statistically significant, which implies that any investor believing in either the random walk model or the fundamentals model would carry out the investment. The results from this preliminary *ex ante* analysis are not reported but are available upon request.

13), the end-of-period wealth obtained using equation (5) does not have an associated variance. As a result, our empirical results allow us to compare the ex post economic value across different models and investment strategies without having to test for statistical significance of the difference between different end-of-period wealths. Put differently, this means that in our framework if the results suggest that one strategy/model yields higher ex post returns than an alternative strategy/model, this implies the first strategy/model has greater economic value than the competing one, given the investment (forecast) horizon and sample period utilized.

In our discussion of the empirical results in this section, we focus mainly on end-of-period wealth and wealth ratios, since, as briefly reviewed below, the results from using the other measures of economic value of predictability (utility ratios and differences in certainty equivalent returns) are qualitatively identical. In Tables 1-2 we report our results from calculating the measures of economic gain (loss) defined above.

6.1 Buy-and-Hold Strategy

We first analyze the case of a buy-and-hold US investor and compute the end-of-period wealth for our investor over the period January 1991-December 2000 for each of the Canadian dollar, Japanese yen and UK sterling. The results for this case, reported in Table 1, show the economic values and gains for different investment horizons $\widetilde{T} = 1, \ldots, 10$ and for different coefficients of risk aversion ($A = 2, 5, 10, 20$). For a given coefficient of risk aversion, Table 1 reports the end-of-period wealth both without and with parameter uncertainty (p.u.). The figures in parentheses, brackets and braces denote the wealth ratios, utility ratios and differences in CERs respectively, as defined above. Our results show that predictability using monetary fundamentals is, in general, of incremental economic value above that for a random walk specification. For example, for a less risk averse investor ($A = 2$), in the case of Canada, the wealth ratio is greater than unity at all horizons longer than one year, indicating that at all horizons longer than one year the end-of-period wealth achieved from using the fundamentals model is higher than the end-of-period wealth attained from using a random walk. Even allowing for parameter uncertainty, this still remains the case. For $A = 5, 10, 20$, the fundamentals model outperforms the random walk for all horizons except for 1 year. In the case of Japan, for $A = 2$ the end-of-period wealth under predictability is much higher than that for a naive no-change investor: the wealth ratio ranges from a low of 1.08 at the one-year horizon to a high of 1.60 at the ten-year horizon. The effects of predictability are dramatically reduced for a very risk averse investor ($A = 20$), with a wealth ratio ranging from 1.01 at the one-year horizon to a high of 1.05 at the ten-year horizon.

For the UK, however, the use of predictability does not seem to be economically important for $A = 2$, although for more risk averse investors there is some gain from using the monetary fundamentals model compared with using a naive random walk model at medium to long horizons.

It is interesting to note that, in general, our results are not very sensitive to the length of the investment horizon for a low level of risk aversion. The results in Table 1 also show that it is mainly at horizons longer than one year that monetary fundamentals predict future nominal exchange rates better than a naive random walk. However, we find that the wealth ratio is often greater than unity even for relatively short horizons such as $\widetilde{T} = 2$ and occasionally even for $\widetilde{T} = 1$. This is in sharp contrast with the conventional wisdom that monetary fundamentals can forecast the exchange rate only at horizons as long as 4 or 5 years ahead.[26] In the case of investors with greater risk aversion ($A = 20$), the results are qualitatively similar. We also find that allowing for parameter uncertainty at higher levels of risk aversion results in a lower relative wealth ratio. This indicates that the effect of parameter uncertainty at higher levels of risk aversion (in terms of reducing the absolute value of the optimal weight relative to the case without parameter uncertainty) is generally greater for the case of predictability than for the case of the random walk model.

However, note that, while wealth increases monotonically with the investment horizon both under predictability and no predictability, the wealth ratio measuring the gain from using the fundamentals model does not increase monotonically over the investment horizon. For example, for each of Canada and Japan, the wealth ratio drops at $\widetilde{T}$ equal to 5 or 6, while increasing again afterwards. Hence, while the wealth ratio always increases in period 10 as compared with period 1, its increase over the investment horizon is not monotonic. Nevertheless, it is notable that the return at the end of the 10-year investment horizon from employing a fundamentals model is relatively large, at least 120, 102 and 137 percent for Canada, Japan and the UK respectively.

Overall, these results provide evidence of economic value to exchange rate predictability across countries and for a range of values of the coefficient of risk aversion. This is clear from the fact that the end-of-period wealth achieved by the investor who assumes that the exchange rate is predictable is higher than that obtained by the investor who assumes that the exchange rate follows a random walk. The order of magnitude varies across countries and with the coefficient of risk aversion. In particular, we find that the difference between end-of-period wealth under predictable and unpredictable exchange rate changes is lower for higher levels of risk aversion. However, taken together, the results that the

[26] As pointed out by Lyons (2002) : "The [...] puzzle [that macro variables cannot account for exchange rates empirically] does indeed remain unresolved. (Read 'exchange rates' as referring to major floating rates against the U.S. dollar and 'account for' as referring to horizons less than two years)." Note that the sentence in parentheses is in the original text.

wealth ratio increases non-monotonically and that the return from employing a fundamentals model is large imply that the return from a random walk is also large in terms of economic value. This confirms the stylized fact that a random walk model is a very difficult benchmark to beat, even when the assessment of its predictive power is based on economic criteria.[27]

6.2 Dynamic Rebalancing Strategy

We now turn to the forecasting results for an investor who uses a dynamic rebalancing strategy. Table 2 reports the end-of-period wealth (and the relevant wealth ratio, the utility ratio and the difference in CERs) for a US investor who dynamically rebalances her portfolio annually over an investment horizon of ten years. These results are obtained from solving the Bellman equation (16) by discretizing the state space and using backward induction. We take intervals ranging from three standard deviations ($\pm 3\sigma_u$) above and below the historical mean ($\mu(u)$) of the predictor variable, the deviation from the monetary fundamentals u. Intuitively, larger intervals for u imply the possibility of larger misalignments of the nominal exchange rate from its fundamental value. We report the expected end-of-period wealth calculated for five initial values of the predictor variable ranging from $-3\sigma_u$ to $+3\sigma_u$ at the end of the 10th year for different values of A. In the last column of Table 2, we report for comparison the end-of-period wealth obtained under a static buy-and-hold strategy as well as the relevant wealth ratio.

The results in Table 2 confirm, in general, the predictive ability of the monetary fundamentals model, as measured in terms of economic value. Except for Japan, where the random walk outperforms the monetary fundamentals framework for large negative initial values of u, the wealth and utility ratios recorded are almost always larger than unity, which is corroborated by the generally positive differences in the CERs, suggesting a higher CER for the fundamentals model. The results for the UK display virtually no change in end-of-period wealth and relative ratios for all values of A other than 20. This is not surprising given that the optimal weights from which these wealth calculations are derived do not show much variability over investment horizons and across lower levels of risk aversion (see Figure 6). The results in the last column of Table 2 clearly show that a static buy-and-hold strategy that recognizes predictability leads to the largest end-of-period wealth relative to all other strategies

[27] Indeed, an extreme case is the UK for $A = 2$ (Panel C of Table 1), where we report a wealth ratio of unity over the whole investment horizon. This is of course due to the fact that the optimal weights are the same under each of predictability and no predictability in this case (see top-left graph in Figure 3). Generally, although for the UK we record high returns in absolute terms from assuming predictability, these returns are not much larger than the returns obtained using a random walk specification. This result seems consistent with the difficulty to forecast the UK sterling during the 1990s often recorded in the literature even in studies where time-series models are found to beat a random walk (see, for example, Clarida, Sarno, Taylor and Valente, 2001).

considered here for a forecast horizon equal to 10 years. Also, in general, a dynamic rebalancing strategy leads to worse outcomes relative to a static buy-and-hold strategy for a forecast horizon of 10 years.

At first glance, one might argue that this result is puzzling since it is always possible for the dynamic strategy to mimic the static strategy. In essence, the two strategies have the same weight at the end of the investment horizon $T+\widetilde{T}$. However, while the static strategy results in the same weight throughout the investment horizon, the dynamic strategy chooses weights by backward induction from time $T+\widetilde{T}$ to time $T+1$; the weight is adjusted depending on the predicted path of the exchange rate between time T and $T+\widetilde{T}$ according to the Bellman equation (16). Therefore, in the dynamic strategy, maximization of expected utility occurs on the basis of the period-by-period predictive distributions of the exchange rate, whereas the static strategy maximizes expected utility on the basis of the $\widetilde{T}$-period predictive distribution of the exchange rate. This implies that, *ex ante*, when one knows or assumes the true data generating process of the exchange rate (and hence its distribution is known), the investor would always prefer the dynamic strategy to the static one[28]. However, this is not necessarily true *ex post* in finite sample. In our *ex post* evaluation over the sample period and exchange rates examined, the dynamic strategy performs worse than the static one. This suggests that, while the exchange rate forecasts at long horizons are accurate, as indicated by the evidence that the fundamentals model beats a random walk model *for both dynamic and static strategies*, the predicted dynamic adjustment path of the exchange rate towards its forecast at the end of the horizon $T+\widetilde{T}$ may be poor. This is not suprising since the model used for forecasting exchange rates with fundamentals is a classic long-horizon regression which does not attempt to model the short run dynamics. Clearly, a richer specification of the short-run exchange rate dynamics in our empirical model might well yield the result that the dynamic strategy makes the investor better off relative to a static strategy. To sum up, what we take from the result that *ex post* the dynamic strategy performs worse than the static strategy on our data set is that if one uses a long-horizon regression out of sample the gain from using a dynamic strategy rather than a static one is not obvious.[29]

[28] As a special case, note that dynamic and static strategies will imply identical weights ω only if the investor assumes a random walk for the exchange rate *and* does not take into account parameter uncertainty. In this case the weights do not change with the investment horizon (Samuelson, 1969).

[29] Also, our result might be due to our choice of the rebalancing period, which is assumed to be one year. This may be suboptimal in light of the evidence that fundamentals are *most* powerful at predicting the exchange rate in the medium to long run, say 3 or 4 years (e.g., Mark, 1995). In principle, one would expect that the optimal rebalancing period is a function of the speed at which the exchange rate change adjusts to restore deviations of the exchange rate from its fundamental value in a way that the rebalancing is carried out over the horizon where the predictive power of the deviations from fundamentals is at its peak. Given the large amount of evidence in the literature (e.g., Mark, 1995; Mark and Sul, 2001) and in this paper that the predictive power of monetary fundamentals is higher at medium

It is important to note that the results discussed above for end-of-period wealth and wealth ratios do not change qualitatively when looking at utility ratios and differences in CERs. In general, the utility ratios, reported in brackets in Tables 1-2, confirm that the investor using the fundamentals model enjoys higher utility than the investor using a random walk model. The gains increase, albeit non-monotonically, with the investment horizon, with a pattern that resembles the pattern of the wealth ratios. Finally, the differences in the CERs, reported in braces in Tables 1-2, indicate the certain return that would equate the end-of-period utility of the two investors. Our results show that the differences in CERs are almost always positive, suggesting that the end-of-period utility of the investor using a fundamentals model is generally higher than the end-of-period utility for the random-walk investor. Indeed, the positive differences in CERs can also be quite large in magnitude, suggesting that the difference in the utilities obtained under no predictability and predictability can be quite substantial.

6.3 Summing up the Forecasting Results

In general, our results provide evidence that there is economic value to predictability at various forecast horizons - which also include relatively short horizons - for a range of coefficients of risk aversion, regardless of whether the investment strategy is static or dynamic and whether parameter uncertainty is taken into account. However, the gain from assuming predictability appears to vary somewhat across currencies and increases non-monotonically over the 10-year investment horizon considered here. We find that the gain from using a fundamentals model is positively related to the investment horizon, negatively related to the level of risk aversion, and negatively related to parameter uncertainty. Of course, the results are based on a particular sample period for estimation and for out-of-sample prediction, so that our claims are subject to the caveat that they are sample specific. Nevertheless, for the sample period investigated, the evidence we present suggests that an investor using a fundamentals model in 1990 to take positions in domestic and foreign bonds would have been better off than an investor using a random walk model. Overall, these results may be viewed as suggesting that the case against the predictive power of monetary-fundamentals models may be overstated.

to longer horizons (albeit still being potentially substantial at shorter horizons) one would expect the optimal dynamic rebalancing period to be somewhat longer than one year. Rules of selection of the optimal rebalancing period are not investigated in this paper, but we consider this issue as an immediate avenue for future research.

7 Conclusion

Meese and Rogoff (1983a,b, 1988) first noted that standard structural exchange rate models are unable to outperform a naive random walk model in out-of-sample exchange rate forecasting, even with the aid of *ex post* data. Despite the increasing sophistication of econometric techniques employed and quality of the data sets utilized, the original results highlighted by Meese and Rogoff continue to present a challenge and constitute a component of what Obstfeld and Rogoff (2000) have recently termed as the 'exchange rate disconnect puzzle'.

Prior research in this area has largely relied on statistical measures of forecast accuracy. Our study departs from this in that we focus instead on the metric of economic value to an investor in order to assess the performance of fundamentals models. This is particularly important given the several cumbersome econometric issues that plague statistical inference in this literature. Our paper provides the first evidence on the economic value of the exchange rate forecasts provided by an exchange rate-monetary fundamentals framework. Specifically, we compare the economic value, to a utility maximizing investor, of out-of-sample exchange rate forecasts using a monetary-fundamentals model with the economic value under a naive random walk model. We assume that our investor faces the problem of choosing how much she will invest in two assets that are identical in all respects except the currency of denomination. This problem is studied in a Bayesian framework that explicitly allows for parameter uncertainty.

Our main findings are as follows. First, each of predictability and parameter uncertainty substantially affect, both quantitatively and qualitatively, the choice between domestic and foreign assets for all currencies and across different levels of risk aversion. Specifically, exchange rate predictability (characterized using the monetary-fundamentals model) can yield optimal weights to the foreign asset that may be very different (in magnitude and, sometimes, in sign) from the optimal weights obtained under a random walk model. Parameter uncertainty causes the foreign asset allocation to fall (rise) as the horizon increases when the models predict positive (negative) weights assigned to the foreign asset, effectively making the foreign asset look more risky. Second, and more importantly, our results lend some support for the predictive ability of the exchange rate-monetary fundamentals model. This finding holds for the three major exchange rates examined in this paper using data for the modern floating exchange rate regime. The gain from using the information in fundamentals in order to predict the exchange rate out of sample (as opposed to assuming that the exchange rate follows a random walk) is often substantial, although it varies somewhat across countries. We find that the gain from using a fundamentals model is, in general, positively related to the investment horizon, negatively related to the level of risk aversion, and negatively related to parameter uncertainty. In turn, these findings suggest that the case against the predictive power of monetary-fundamentals models may be overstated.

There are a number of ways in which this study could be extended. First, one obvious concern is that our results may be sample specific. Our choice of exchange rates and sample period reflects our intention to focus on freely floating exchange rates over the post-Bretton Woods period and follows much previous research in the literature on exchange rate forecasting. Testing the robustness of our findings using other exchange rate data and/or sample periods is a logical extension. Second, we consider here a simple case where the investor allocates wealth between two assets; a more realistic scenario would be to allow for multiple assets. However, while this will require more complex estimation techniques, it would also take us away from the main point of this paper, which is to draw attention to the economic value of forecasting fundamentals models rather than only on the use of statistical metrics for forecast comparison. Third, we use a simple power utility set up to illustrate our main point. However, in the context of an international investor, the use of other utility functions, such as those that allow for ambiguity aversion or habit formation, may also be of great interest.

A Technical Appendix

This appendix provides details of the Bayesian econometric approach used in our paper. We begin by describing the computations used in the static buy-and-hold case described in Section 3.1.

First, we assume that the exchange rate is a random walk with drift: $\Delta s_t = \mu + \varepsilon_t$, where Δs_t is the log-difference of the end-of-period nominal exchange rate, and Δ is the first-difference operator; and $\varepsilon_t \sim iidN(0, \sigma^2)$. We incorporate parameter uncertainty by using the predictive distribution of the nominal exchange rate, $p(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} | \Delta s)$, where Δs is the vector of observed nominal exchange rate changes over the sample period. In the case without parameter uncertainty, on the other hand, we compute the expected value over the distribution of the future nominal exchange rate conditional on fixed parameters values, $p(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} | \Delta s, \widehat{\mu}, \widehat{\sigma}^2)$. In both of these cases, the conditional distribution of the nominal exchange rate is a normal distribution. Under no parameter uncertainty, $p(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} | \Delta s, \widehat{\mu}, \widehat{\sigma}^2)$ is a normal distribution, $N\left(\widetilde{T}\widehat{\mu}, \widetilde{T}\widehat{\sigma}^2\right)$, where $\widehat{\mu}$ and $\widehat{\sigma}^2$ denote the estimates of the mean and variance calculated over the sample period. When parameter uncertainty is accounted for, $p(\Delta_{\widetilde{T}} s_{T+\widetilde{T}} | \Delta s)$ is obtained using the value of the parameters μ and σ^2 obtained by iterative sampling from the marginal posterior distributions under a noninformative prior (that is, $p\left(\mu, \sigma^2\right) \propto \frac{1}{\sigma^2}$).[30] In other words, in order to get a sample $\left\{\Delta_{\widetilde{T}}^{(i)} s_{T+\widetilde{T}}\right\}_{i=1}^{M}$ from the two possible distributions, we draw M times from the normal distribution $N\left(\widetilde{T}\widehat{\mu}, \widetilde{T}\widehat{\sigma}^2\right)$ in the case of no parameter uncertainty; in the case of parameter uncertainty we draw M times from the normal distribution $N\left(\widetilde{T}\widehat{\mu}^{(i)}, \widetilde{T}\widehat{\sigma}^{2\,(i)}\right)$, where $\widehat{\mu}^{(i)}, \widehat{\sigma}^{2\,(i)}$ are values from the ith draw from $p\left(\sigma^2 | \Delta s\right)$ and $p\left(\mu | \sigma^2, \Delta s\right)$.

Second, we consider the case when the exchange rate is predictable, that is $z_t = a + Bx_{t-1} + \eta_t$, where $z_t' = (\Delta s_t, x_t')$, $x_t = (x_{1,t}, x_{2,t}, \ldots, x_{n,t})'$, and $\eta_t \sim iidN(0, \Sigma)$. The vector of explanatory variables x_t are used for predicting the exchange rate; these include the deviation from the long-run equilibrium level of the exchange rate as measured by the monetary fundamentals. Here too we consider the effects of accounting for parameter uncertainty. In particular, under no parameter uncertainty, $p(z_{T+\widetilde{T}} | z, \widehat{a}, \widehat{B}, \widehat{\Sigma})$ is a bivariate normal distribution, $N_2\left(\widehat{\widehat{\mu}}, \widehat{\widehat{\Sigma}}\right)$, where

$$\begin{aligned}
\widehat{\widehat{\mu}} &= \widetilde{T}\widehat{a} + \left(\widetilde{T} - 1\right)\widehat{B}_0\widehat{a} + \left(\widetilde{T} - 2\right)\widehat{B}_0^2\widehat{a} + \ldots + \widehat{B}_0^{\widetilde{T}-1}\widehat{a} + \left(\widehat{B}_0 + \ldots + \widehat{B}_0^{\widetilde{T}}\right) z_T \\
\widehat{\widehat{\Sigma}} &= \widehat{\Sigma} + \left(I + \widehat{B}_0\right)\widehat{\Sigma}\left(I + \widehat{B}_0\right)' + \ldots + \\
&\quad \left(I + \widehat{B}_0 + \ldots + \widehat{B}_0^{\widetilde{T}-1}\right)\widehat{\Sigma}\left(I + \widehat{B}_0 + \ldots + \widehat{B}_0^{\widetilde{T}-1}\right)' \qquad \text{(A1)}
\end{aligned}$$

[30] The posterior distribution of the parameters conditional upon the data $p(\mu, \sigma^2 | \Delta s)$ can be obtained by first sampling from the marginal distribution, $p(\sigma^2 | \Delta s)$, an inverse gamma distribution, and then, given the draw for the variance, from the conditional distribution $p(\mu | \sigma^2, \Delta s)$, which is a normal distribution. See Zellner (1971).

and $\widehat{a}$, $\widehat{B}$, $\widehat{\Sigma}$ are estimates of the parameters in the VAR $z_t = a + Bx_{t-1} + \eta_t$, obtained over the sample period used; $\widehat{B}_0$ is a matrix obtained by adding an initial vector of zeros to $\widehat{B}$; and I is the identity matrix. If parameter uncertainty is taken into account, $p(z_{T+\widetilde{T}}|z)$ is computed using the value of the estimated parameters $\widehat{a}$, $\widehat{B}$, $\widehat{\Sigma}$ obtained by iterative sampling from the marginal posterior distributions under a noninformative prior (that is, $p\,(a, B, \Sigma) \propto |\Sigma|^{-(n+2)/2}$):[31]

$$
\begin{aligned}
\widehat{\widehat{\mu}} &= \widetilde{T}\widehat{a}^{(i)} + \left(\widetilde{T}-1\right)\widehat{B}_0^{(i)}\widehat{a}^{(i)} + \left(\widetilde{T}-2\right)\widehat{B}_0^{2(i)}\widehat{a}^{(i)} + \ldots + \widehat{B}_0^{\widetilde{T}-1(i)}\widehat{a}^{(i)} + \left(\widehat{B}_0^{(i)} + \ldots + \widehat{B}_0^{\widetilde{T}(i)}\right) z_T \\
\widehat{\widehat{\Sigma}} &= \widehat{\Sigma}^{(i)} + \left(I + \widehat{B}_0^{(i)}\right)\widehat{\Sigma}^{(i)}\left(I + \widehat{B}_0^{(i)}\right)' + \ldots + \\
&\quad + \left(I + \widehat{B}_0^{(i)} + \ldots + \widehat{B}_0^{\widetilde{T}-1(i)}\right)\widehat{\Sigma}^{(i)}\left(I + \widehat{B}_0^{(i)} + \ldots + \widehat{B}_0^{\widetilde{T}-1(i)}\right)'
\end{aligned}
\tag{A2}
$$

for $i = 1, \ldots, M$, where $\widehat{a}^{(i)}, \widehat{B}_0^{(i)}, \widehat{\Sigma}^{(i)}$ are values from the ith draw from $p(\Sigma^{-1}|z)$ and $p(vec\,(a, B)\,|\Sigma, \Delta s)$. By computing $p(z_{T+\widetilde{T}}|z, a, B, \Sigma)$ and $p(z_{T+\widetilde{T}}|z)$, we are able to extract a sample $\left\{\Delta_{\widetilde{T}}^{(i)} s_{T+\widetilde{T}}\right\}_{i=1}^{M}$ which represents the future expected nominal exchange rate for the horizon $\widetilde{T}$ under predictability, without and with parameter uncertainty respectively.

Finally, we approximate the integrals for expected utility (8) and (11) by using the sample $\left\{\Delta_{\widetilde{T}}^{(i)} s_{T+\widetilde{T}}\right\}_{i=1}^{M}$ from the two cases of no predictability and predictability and then computing

$$
\frac{1}{M}\sum_{i=1}^{M} \frac{\left[(1-\omega)\exp\left(r\widetilde{T}\right) + \omega\exp\left(r^{*}\widetilde{T} + \Delta_{\widetilde{T}}^{(i)} s_{T+\widetilde{T}}\right)\right]^{1-A}}{1-A}. \tag{A3}
$$

To obtain an accurate representation of the posterior distributions, the data have been used to generate different sample sizes M. The results reported in the paper refer to a sample size of $M = 1,000,000$ and were produced using an initial value of the predictor variables vector (in our case simply u_t as defined in equations (1)-(2)) equal to its historical mean.

Next, we provide details of the computations related to the dynamic allocation problem described in Section 3.2. We solve this by discretizing the state space and then using backward induction to solve the Bellman equation. In particular, in the case of predictability, we take an interval ranging from three standard deviations below the historical mean of the predictor variables in x_t (simply u_t as defined in equations (1)-(2)), to three standard deviations above and discretize this range using j equally spaced grid points. The maximization problem (16) in the main text can be solved as follows:

[31] The posterior distribution of the parameters conditional upon the data is obtained in this case by first sampling from the marginal distribution $p(\Sigma^{-1}|z)$, a Wishart distribution, and then, given the draws for the variance-covariance matrix, from the conditional distribution $p(vec\,(a, B)\,|\Sigma, \Delta s)$, which is a multivariate normal distribution. See Zellner (1971).

$$Q\left(x_k^j, t_k\right) = \max_{\omega} \frac{1}{M} \sum_{i=1}^{M} \left\{ \left[(1-\omega_k) \exp\left(r \frac{\widetilde{T}}{K} \right) + \omega_k \exp\left(r^* \frac{\widetilde{T}}{K} + \Delta_{k+1} s_{k+1}^{(i)} \right) \right]^{1-A} \times Q\left(x_{k+1}^j, t_{k+1}\right) \right\}, \tag{A4}$$

where $Q\left(x_k^j, t_k\right)$ is the value function calculated for x_k^j for all j.[32] In order to carry out the backward induction we assume that $Q\left(x_{T+\widetilde{T}}, t_{T+\widetilde{T}}\right) = 1$ for all $x_{T+\widetilde{T}}$ and we use equation (A4) to approximate $Q\left(x_k^j, t_k\right)$. $\Delta_{k+1} s_{k+1}^{(i)}$ can then be computed as explained above in this appendix in the case of predictable exchange rates under the cases of both parameter uncertainty and no parameter uncertainty and for different values of the explanatory variable x^j. This calculation gives $Q\left(x_k^j, t_k\right)$ for all j. Solving through all of the rebalancing points allows us to obtain $Q\left(x_0^j, t_0\right)$ and hence the optimal allocation at time T. As in the static optimization problem the sample size used is $M = 1,000,000$. We performed additional robustness checks to investigate the effect of the number of grid points selected. We produced our results for $j = 15, 25, 35$ grid points and we selected $j = 25$ since the accuracy of our results was better than in the case of $j = 15$ but not qualitatively different from the case where $j = 35$.

[32] An alternative procedure would involve allowing for learning over the investment horizon. We did not explore the implications of learning for our results in this paper, although this is a logical exercise for future research (e.g., see Lewis, 1995; Xia, 2001).

Table 1. The economic value of predictability: Static buy-and-hold strategy

Panel A) - Canada

$\widetilde{T} =$	1	2	3	4	5	6	7	8	9	10
					$A = 2$					
without p.u.	1.0844	1.2167	1.3241	1.4497	1.5320	1.6441	1.8010	1.9798	2.0628	2.2501
	(0.96)	(1.04)	(1.05)	(1.09)	(1.02)	(1.01)	(1.06)	(1.14)	(1.05)	(1.10)
	[0.96]	[1.03]	[1.04]	[1.08]	[1.01]	[1.00]	[1.05]	[1.12]	[1.04]	[1.09]
	{-0.047}	{0.022}	{0.021}	{0.031}	{0.005}	{0.001}	{0.015}	{0.031}	{0.011}	{0.020}
with p.u.	1.0844	1.2167	1.3241	1.4497	1.5320	1.6441	1.8010	1.9798	2.0628	2.2501
	(0.96)	(1.04)	(1.05)	(1.09)	(1.02)	(1.01)	(1.06)	(1.14)	(1.05)	(1.10)
	[0.95]	[1.03]	[1.04]	[1.08]	[1.01]	[1.00]	[1.05]	[1.12]	[1.04]	[1.09]
	{-0.047}	{0.022}	{0.021}	{0.031}	{0.005}	{0.001}	{0.015}	{0.031}	{0.011}	{0.020}
					$A = 5$					
without p.u.	1.0875	1.2167	1.3241	1.4497	1.5320	1.6441	1.8010	1.9798	2.0628	2.2501
	(0.96)	(1.04)	(1.05)	(1.09)	(1.02)	(1.01)	(1.06)	(1.14)	(1.05)	(1.10)
	[0.82]	[1.13]	[1.18]	[1.30]	[1.07]	[1.02]	[1.21]	[1.42]	[1.18]	[1.31]
	{-0.044}	{0.022}	{0.021}	{0.031}	{0.005}	{0.001}	{0.015}	{0.031}	{0.011}	{0.020}
with p.u.	1.0973	1.2092	1.3163	1.4377	1.5307	1.6437	1.7981	1.9738	2.0598	2.2432
	(0.97)	(1.03)	(1.04)	(1.08)	(1.02)	(1.01)	(1.06)	(1.14)	(1.05)	(1.10)
	[0.86]	[1.11]	[1.16]	[1.27]	[1.06]	[1.02]	[1.21]	[1.41]	[1.17]	[1.31]
	{-0.035}	{0.018}	{0.018}	{0.028}	{0.005}	{0.001}	{0.014}	{0.030}	{0.010}	{0.019}
					$A = 10$					
without p.u.	1.0941	1.2145	1.3241	1.4497	1.5320	1.6441	1.8010	1.9798	2.0628	2.2501
	(0.97)	(1.04)	(1.05)	(1.09)	(1.02)	(1.01)	(1.06)	(1.14)	(1.05)	(1.10)
	[0.63]	[1.27]	[1.36]	[1.55]	[1.15]	[1.05]	[1.42]	[1.70]	[1.36]	[1.57]
	{-0.038}	{0.021}	{0.021}	{0.031}	{0.005}	{0.001}	{0.015}	{0.031}	{0.011}	{0.020}
with p.u.	1.0961	1.2065	1.3116	1.4260	1.5270	1.6423	1.7834	1.9416	2.0488	2.2225
	(0.97)	(1.03)	(1.04)	(1.08)	(1.02)	(1.01)	(1.05)	(1.12)	(1.04)	(1.09)
	[0.66]	[1.23]	[1.30]	[1.48]	[1.12]	[1.04]	[1.37]	[1.65]	[1.31]	[1.52]
	{-0.036}	{0.017}	{0.017}	{0.025}	{0.004}	{0.001}	{0.012}	{0.026}	{0.009}	{0.017}
					$A = 20$					
without p.u.	1.0965	1.2091	1.3183	1.4481	1.5320	1.6441	1.8010	1.9798	2.0628	2.2501
	(0.98)	(1.02)	(1.03)	(1.07)	(1.01)	(1.00)	(1.05)	(1.11)	(1.04)	(1.07)
	[0.50]	[1.33]	[1.45]	[1.70]	[1.22]	[1.08]	[1.57]	[1.85]	[1.50]	[1.73]
	{-0.023}	{0.012}	{0.013}	{0.022}	{0.004}	{0.001}	{0.011}	{0.023}	{0.008}	{0.015}
with p.u.	1.0981	1.2035	1.3058	1.4148	1.5247	1.6415	1.7744	1.9187	2.0391	2.2018
	(0.98)	(1.02)	(1.02)	(1.03)	(1.01)	(1.00)	(1.02)	(1.03)	(1.01)	(1.02)
	[0.59]	[1.24]	[1.30]	[1.45]	[1.10]	[1.03]	[1.24]	[1.42]	[1.16]	[1.24]
	{-0.019}	{0.008}	{0.008}	{0.011}	{0.001}	{0.001}	{0.003}	{0.006}	{0.002}	{0.003}

(continued ...)

(... Table 1 continued)

Panel B) - Japan

$\widetilde{T} =$	1	2	3	4	5	6	7	8	9	10
					$A = 2$					
without p.u.	1.1079	1.2094	1.3846	1.6306	1.7437	1.7784	1.8217	2.1529	2.5325	2.5762
	(1.08)	(1.12)	(1.28)	(1.52)	(1.52)	(1.36)	(1.24)	(1.48)	(1.79)	(1.60)
	[1.07]	[1.10]	[1.21]	[1.34]	[1.34]	[1.26]	[1.19]	[1.32]	[1.44]	[1.37]
	{0.081}	{0.062}	{0.100}	{0.140}	{0.118}	{0.078}	{0.050}	{0.087}	{0.124}	{0.096}
with p.u.	1.1043	1.1949	1.3425	1.4922	1.6266	1.6755	1.7465	1.9814	2.2261	2.3038
	(1.08)	(1.10)	(1.24)	(1.39)	(1.41)	(1.28)	(1.19)	(1.36)	(1.58)	(1.43)
	[1.07]	[1.09]	[1.19]	[1.28]	[1.29]	[1.22]	[1.15]	[1.26]	[1.36]	[1.30]
	{0.078}	{0.055}	{0.086}	{0.105}	{0.095}	{0.061}	{0.039}	{0.066}	{0.090}	{0.069}
					$A = 5$					
without p.u.	1.0857	1.1690	1.2859	1.4181	1.5407	1.6180	1.7014	1.8999	2.1150	2.2168
	(1.06)	(1.08)	(1.19)	(1.32)	(1.34)	(1.24)	(1.16)	(1.31)	(1.50)	(1.38)
	[1.20]	[1.25]	[1.49]	[1.67]	[1.68]	[1.57]	[1.44]	[1.65]	[1.80]	[1.72]
	{0.059}	{0.042}	{0.067}	{0.086}	{0.078}	{0.052}	{0.033}	{0.055}	{0.077}	{0.060}
with p.u.	1.0844	1.1639	1.2742	1.3860	1.4808	1.5645	1.6608	1.8155	1.9774	2.0919
	(1.05)	(1.06)	(1.14)	(1.22)	(1.22)	(1.16)	(1.10)	(1.17)	(1.27)	(1.19)
	[1.17]	[1.22]	[1.41]	[1.54]	[1.55]	[1.44]	[1.32]	[1.47]	[1.61]	[1.50]
	{0.052}	{0.035}	{0.053}	{0.062}	{0.053}	{0.035}	{0.022}	{0.033}	{0.046}	{0.033}
					$A = 10$					
without p.u.	1.0807	1.1620	1.2641	1.3786	1.4782	1.5645	1.6593	1.8099	1.9818	2.1032
	(1.03)	(1.04)	(1.10)	(1.16)	(1.16)	(1.11)	(1.08)	(1.14)	(1.22)	(1.17)
	[1.24]	[1.31]	[1.56]	[1.73]	[1.73]	[1.61]	[1.48]	[1.69]	[1.83]	[1.75]
	{0.032}	{0.024}	{0.036}	{0.047}	{0.040}	{0.026}	{0.016}	{0.028}	{0.039}	{0.030}
with p.u.	1.0762	1.1551	1.2481	1.3514	1.4470	1.5398	1.6397	1.7733	1.9241	2.0503
	(1.03)	(1.03)	(1.07)	(1.11)	(1.10)	(1.07)	(1.04)	(1.08)	(1.12)	(1.09)
	[1.20]	[1.24]	[1.43]	[1.59]	[1.56]	[1.44]	[1.32]	[1.49]	[1.64]	[1.55]
	{0.026}	{0.017}	{0.025}	{0.032}	{0.025}	{0.016}	{0.009}	{0.016}	{0.023}	{0.017}
					$A = 20$					
without p.u.	1.0758	1.1545	1.2467	1.3464	1.4444	1.5378	1.6397	1.7761	1.9285	2.0541
	(1.01)	(1.02)	(1.05)	(1.07)	(1.08)	(1.05)	(1.04)	(1.07)	(1.11)	(1.08)
	[1.23]	[1.32]	[1.56]	[1.73]	[1.74]	[1.62]	[1.49]	[1.71]	[1.85]	[1.78]
	{0.015}	{0.011}	{0.017}	{0.022}	{0.020}	{0.013}	{0.008}	{0.014}	{0.020}	{0.015}
with p.u.	1.0735	1.1513	1.2380	1.3341	1.4288	1.5254	1.6292	1.7536	1.8885	2.0200
	(1.01)	(1.01)	(1.03)	(1.05)	(1.05)	(1.03)	(1.02)	(1.04)	(1.06)	(1.05)
	[1.20]	[1.24]	[1.43]	[1.59]	[1.58]	[1.47]	[1.34]	[1.52]	[1.66]	[1.59]
	{0.013}	{0.008}	{0.012}	{0.015}	{0.013}	{0.008}	{0.005}	{0.008}	{0.011}	{0.009}

(continued ...)

(... Table 1 continued)

Panel C) - UK

$\widetilde{T}=$	1	2	3	4	5	6	7	8	9	10
					$A=2$					
without p.u.	1.1241	1.0773	1.2109	1.4343	1.6020	1.9264	2.1020	2.3551	2.5288	2.6014
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
	-	-	-	-	-	-	-	-	-	-
with p.u.	1.1241	1.0773	1.2109	1.4343	1.6020	1.9264	2.1020	2.3551	2.5288	2.6014
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]
	-	-	-	-	-	-	-	-	-	-
					$A=5$					
without p.u.	1.1241	1.0773	1.2109	1.4343	1.6020	1.9264	2.1020	2.3551	2.5288	2.6014
	(1.01)	(0.96)	(0.97)	(1.01)	(1.02)	(1.06)	(1.08)	(1.09)	(1.09)	(1.07)
	[1.03]	[0.79]	[0.87]	[1.02]	[1.07]	[1.21]	[1.22]	[1.27]	[1.28]	[1.23]
	{0.009}	{-0.025}	{-0.011}	{0.002}	{0.006}	{0.018}	{0.018}	{0.023}	{0.022}	{0.016}
with p.u.	1.1241	1.0773	1.2109	1.4343	1.6020	1.9264	2.1020	2.3551	2.5288	2.6014
	(1.01)	(0.94)	(0.96)	(1.01)	(1.03)	(1.11)	(1.12)	(1.15)	(1.16)	(1.13)
	[1.03]	[0.73]	[0.81]	[1.04]	[1.11]	[1.33]	[1.36]	[1.43]	[1.44]	[1.38]
	{0.009}	{-0.033}	{-0.017}	{0.003}	{0.009}	{0.030}	{0.032}	{0.038}	{0.037}	{0.029}
					$A=10$					
without p.u.	1.1199	1.0854	1.2114	1.4343	1.6020	1.9264	2.1020	2.3551	2.5288	2.6014
	(1.01)	(0.95)	(0.96)	(1.01)	(1.03)	(1.09)	(1.09)	(1.11)	(1.11)	(1.09)
	[1.06]	[0.36]	[0.57]	[1.08]	[1.20]	[1.52]	[1.54]	[1.61]	[1.60]	[1.54]
	{0.008}	{-0.030}	{-0.016}	{0.003}	{0.008}	{0.025}	{0.024}	{0.029}	{0.027}	{0.021}
with p.u.	1.1179	1.1004	1.2271	1.4301	1.5896	1.8804	2.0529	2.2950	2.4610	2.5465
	(1.01)	(0.95)	(0.97)	(1.01)	(1.03)	(1.08)	(1.09)	(1.13)	(1.13)	(1.10)
	[1.05]	[0.47]	[0.65]	[1.07]	[1.20]	[1.51]	[1.55]	[1.65]	[1.67]	[1.59]
	{0.007}	{-0.026}	{-0.013}	{0.003}	{0.007}	{0.024}	{0.025}	{0.032}	{0.031}	{0.024}
					$A=20$					
without p.u.	1.1102	1.1429	1.2556	1.4226	1.5693	1.8129	1.9767	2.1909	2.3657	2.4657
	(1.00)	(0.97)	(0.98)	(1.01)	(1.02)	(1.06)	(1.07)	(1.09)	(1.10)	(1.08)
	[1.07]	[0.34]	[0.51]	[1.10][	[1.29]	[1.68]	[1.73]	[1.82]	[1.84]	[1.78]
	{0.004}	{-0.015}	{-0.008}	{0.002}	{0.005}	{0.017}	{0.018}	{0.023}	{0.024}	{0.019}
with p.u.	1.1089	1.1529	1.2657	1.4187	1.5554	1.7655	1.9141	2.1007	2.2628	2.3775
	(1.00)	(0.98)	(0.99)	(1.00)	(1.01)	(1.05)	(1.05)	(1.07)	(1.08)	(1.06)
	[1.05]	[0.52]	[0.65]	[1.07]	[1.20]	[1.58]	[1.61]	[1.72]	[1.76]	[1.69]
	{0.003}	{-0.011}	{-0.006}	{0.001}	{0.003}	{0.013}	{0.013}	{0.017}	{0.018}	{0.014}

Notes: These figures refer to the end-of-period (equal to 10 years) economic value, as measured by wealth levels, wealth ratios, utility ratios and certainty equivalent returns for the case of an investor acting on the basis of the static buy-and-hold strategy. Initial wealth is assumed to be equal to unity. A is the coefficient of risk aversion in the CRRA utility function defined by equation (6). $\widetilde{T}$ is the investment horizon in years. 'With p.u.' and 'without p.u.' denote the case where the investor takes into account parameter uncertainty (p.u.) and the case where she ignores it respectively. Under each of these cases, the first row reports the end-of-period wealth calculated using the definition given by equation (5). Values in parentheses in the second row, for each of the two cases with and without p.u., are ratios of the end-of-period wealth levels obtained in the case of predictability to the end-of-period wealth levels obtained under a random walk exchange rate. Values in brackets in the third row are ratios of the end-of-period utility levels obtained in the case of predictability (with and without p.u.) to the end-of-period utility levels obtained under a random walk exchange rate model (with and without p.u.). Values in braces in the fourth row are differences of the end-of-period certainty equivalent return (CER) obtained in the case of predictability (with and without p.u.) and the end-of-period CER obtained under a random walk exchange rate model (with and without p.u.). The differences in CERs are annualized.

Table 2. The economic value of predictability: Dynamic rebalancing strategy

Panel A) - Canada

	$-3\sigma_u$	$-1\sigma_u$	$\mu(u)$	$+1\sigma_u$	$+3\sigma_u$	Static
			$A = 2$			
without p.u.	2.2269	2.2269	2.2269	2.2269	2.2269	2.2501
	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.10)
	[1.08]	[1.08]	[1.08]	[1.08]	[1.08]	[1.09]
	{0.018}	{0.018}	{0.018}	{0.018}	{0.018}	{0.020}
with p.u.	2.2269	2.2269	2.2269	2.2269	2.2269	2.2501
	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.10)
	[1.08]	[1.08]	[1.08]	[1.08]	[1.08]	[1.09]
	{0.018}	{0.018}	{0.018}	{0.018}	{0.018}	{0.020}
			$A = 5$			
without p.u.	2.2269	2.2269	2.2269	2.2269	2.2269	2.2501
	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.10)
	[1.29]	[1.29]	[1.29]	[1.29]	[1.29]	[1.31]
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.020)
with p.u.	2.1739	2.2102	2.2211	2.2269	2.2269	2.2432
	(1.06)	(1.08)	(1.09)	(1.09)	(1.09)	(1.10)
	[1.21]	[1.26]	[1.28]	[1.29]	[1.29]	[1.31]
	{0.012}	{0.016}	{0.017}	{0.018}	{0.018}	{0.019}
			$A = 10$			
without p.u.	2.2269	2.2269	2.2269	2.2269	2.2269	2.2501
	(1.09)	(1.09)	(1.09)	(1.09)	(1.09)	(1.10)
	[1.53]	[1.53]	[1.53]	[1.53]	[1.53]	[1.57]
	{0.018}	{0.018}	{0.018}	{0.018}	{0.018}	{0.020}
with p.u.	2.1900	2.2084	2.2136	2.2165	2.2165	2.2225
	(1.07)	(1.08)	(1.08)	(1.08)	(1.08)	(1.09)
	[1.46]	[1.50]	[1.51]	[1.51]	[1.51]	[1.52]
	(0.014)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
			$A = 20$			
without p.u.	2.2269	2.2269	2.2269	2.2269	2.2269	2.2501
	(1.06)	(1.06)	(1.06)	(1.06)	(1.06)	(1.07)
	[1.67]	[1.67]	[1.67]	[1.67]	[1.67]	[1.73]
	{0.012}	{0.012}	{0.012}	{0.012}	{0.012}	{0.015}
with p.u.	2.1854	2.1912	2.1917	2.1935	2.1969	2.2018
	(1.01)	(1.01)	(1.01)	(1.01)	(1.01)	(1.02)
	[1.13]	[1.17]	[1.17]	[1.18]	[1.21]	[1.24]
	{0.001}	{0.002}	{0.002}	{0.002}	{0.002}	{0.003}

(continued ...)

(... Table 2 continued)

Panel B) - Japan

	$-3\sigma_u$	$-1\sigma_u$	$\mu(u)$	$+1\sigma_u$	$+3\sigma_u$	Static
			$A = 2$			
without p.u.	1.1399	1.1450	1.3715	1.5516	1.7627	2.5762
	(0.71)	(0.71)	(0.85)	(0.96)	(1.09)	(1.60)
	[0.58]	[0.59]	[0.82]	[0.96]	[1.08]	[1.37]
	{-0.047}	{-0.046}	{-0.023}	{-0.005}	{0.015}	{0.096}
with p.u.	1.3355	1.5413	1.7421	1.8038	1.9377	2.3038
	(0.83)	(0.96)	(1.08)	(1.12)	(1.20)	(1.43)
	[0.79]	[0.95]	[1.07]	[1.10]	[1.16]	[1.30]
	{-0.027}	{-0.007}	{0.013}	{0.019}	{0.032}	{0.069}
			$A = 5$			
without p.u.	1.5928	1.6546	1.8605	2.0200	2.1693	2.2168
	(0.99)	(1.03)	(1.15)	(1.25)	(1.35)	(1.38)
	[0.95]	[1.10]	[1.43]	[1.59]	[1.69]	[1.72]
	{-0.001}	{0.004}	{0.024}	{0.040}	{0.055}	{0.060}
with p.u.	1.6185	1.7833	1.9891	2.0921	2.1641	2.0919
	(0.92)	(1.01)	(1.13)	(1.19)	(1.23)	(1.19)
	[0.60]	[1.05]	[1.38]	[1.50]	[1.56]	[1.50]
	{-0.014}	{0.002}	{0.023}	{0.033}	{0.040}	{0.033}
			$A = 10$			
without p.u.	1.8656	1.9531	2.0149	2.0612	2.0509	2.1032
	(1.03)	(1.09)	(1.12)	(1.15)	(1.14)	(1.17)
	[1.28]	[1.52]	[1.64]	[1.70]	[1.69]	[1.75]
	{0.006}	{0.015}	{0.021}	{0.026}	{0.025}	{0.030}
with p.u.	1.9788	2.0406	2.0869	2.1230	2.1693	2.0503
	(1.05)	(1.09)	(1.11)	(1.13)	(1.16)	(1.09)
	[1.38]	[1.53]	[1.61]	[1.67]	[1.72]	[1.55]
	{0.010}	{0.016}	{0.021}	{0.024}	{0.029}	{0.017}
			$A = 20$			
without p.u.	2.0200	2.0406	2.0818	2.1024	2.1127	2.0541
	(1.07)	(1.08)	(1.10)	(1.11)	(1.11)	(1.08)
	[1.70]	[1.75]	[1.83]	[1.86]	[1.87]	[1.78]
	{0.012}	{0.014}	{0.018}	{0.020}	{0.021}	{0.015}
with p.u.	2.0766	2.0921	2.1281	2.1744	2.2104	2.0200
	(1.08)	(1.09)	(1.11)	(1.13)	(1.15)	(1.05)
	[1.76]	[1.79]	[1.85]	[1.90]	[1.92]	[1.59]
	{0.015}	{0.016}	{0.020}	{0.024}	{0.028}	{0.009}

(continued ...)

(... Table 2 continued)

Panel C) - UK

	$-3\sigma_u$	$-1\sigma_u$	$\mu(u)$	$+1\sigma_u$	$+3\sigma_u$	Static
			$A = 2$			
without p.u.	2.6163	2.6163	2.6163	2.6163	2.6163	2.6014
	(1.01)	(1.01)	(1.01)	(1.01)	(1.01)	(1.00)
	[1.01]	[1.01]	[1.01]	[1.01]	[1.01]	[1.00]
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	-
with p.u.	2.6163	2.6163	2.6163	2.6163	2.6163	2.6014
	(1.01)	(1.01)	(1.01)	(1.01)	(1.01)	(1.00)
	[1.01]	[1.01]	[1.01]	[1.01]	[1.01]	[1.00]
	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}	-
			$A = 5$			
without p.u.	2.6163	2.6163	2.6163	2.6163	2.6163	2.6014
	(1.07)	(1.07)	(1.07)	(1.07)	(1.07)	(1.07)
	[1.25]	[1.25]	[1.25]	[1.25]	[1.25]	[1.23]
	{0.018}	{0.018}	{0.018}	{0.018}	{0.018}	{0.016}
with p.u.	2.6163	2.6163	2.6163	2.6163	2.6163	2.6014
	(1.13)	(1.13)	(1.13)	(1.13)	(1.13)	(1.13)
	[1.39]	[1.39]	[1.39]	[1.39]	[1.39]	[1.38]
	{0.031}	{0.031}	{0.031}	{0.031}	{0.031}	{0.029}
			$A = 10$			
without p.u.	2.6163	2.6163	2.6163	2.6163	2.4613	2.6014
	(1.10)	(1.10)	(1.10)	(1.10)	(1.03)	(1.09)
	[1.56]	[1.56]	[1.56]	[1.56]	[1.25]	[1.54]
	{0.023}	{0.023}	{0.023}	{0.023}	{0.007}	{0.021}
with p.u.	2.6163	2.6163	2.5624	2.5017	2.4186	2.5465
	(1.14)	(1.14)	(1.11)	(1.09)	(1.05)	(1.10)
	[1.68]	[1.68]	[1.61]	[1.52]	[1.36]	[1.59]
	{0.031}	{0.031}	{0.026}	{0.020}	{0.011}	{0.024}
			$A = 20$			
without p.u.	2.5736	2.5736	2.5557	2.5332	2.5197	2.4657
	(1.13)	(1.13)	(1.12)	(1.11)	(1.11)	(1.08)
	[1.90]	[1.90]	[1.88]	[1.86]	[1.85]	[1.78]
	{0.029}	{0.029}	{0.027}	{0.025}	{0.024}	{0.019}
with p.u.	2.4546	2.4231	2.3580	2.2726	2.1760	2.3775
	(1.10)	(1.08)	(1.06)	(1.02)	(0.97)	(1.06)
	[1.83]	[1.78]	[1.64]	[1.27]	[0.35]	[1.69]
	{0.022}	{0.018}	{0.012}	{0.003}	{-0.005}	{0.014}

Notes: These figures refer to the end-of-period (equal to 10 years) economic value, as measured by wealth levels, wealth ratios, utility ratios and certainty equivalent returns for the case of an investor acting on the basis of the dynamic buy-and-hold strategy with a rebalancing period of 1 year. Initial wealth is assumed to be equal to unity. A is the coefficient of risk aversion in the CRRA utility function defined by equation (6). $\mu(u)$ denotes the historical mean of the predictor variable, u_t, calculated over the sample period September 1977 - December 1990. $\pm 3\sigma_u$ and $\pm 1\sigma_u$ denote three and one standard deviations above (below) the historical sample mean of the predictor variable. "Static" denotes the 10-year wealth obtained with a static buy-and-hold strategy under predictable exchange rates (as reported in Table 1). 'With p.u.' and 'without p.u.' denote the case where the investor takes into account parameter uncertainty (p.u.) and the case where she ignores it respectively. Under each of these cases, the first row reports the end-of-period wealth calculated using the definition given by equation (5). Values in parentheses in the second row, for each of the two cases with and without p.u., are ratios of the end-of-period wealth levels obtained in the case of predictability to the end-of-period wealth levels obtained under a random walk exchange rate. Values in brackets in the third row are ratios of the end-of-period utility levels obtained in the case of predictability (with and without p.u.) to the end-of-period utility levels obtained under a random walk exchange rate (with and without p.u.). Values in braces in the fourth row are differences of the end-of-period certainty equivalent return (CER) obtained in the case of predictability (with and without p.u.) and the end-of-period CER obtained under a random walk exchange rate (with and without p.u.). The differences in CERs are annualized.

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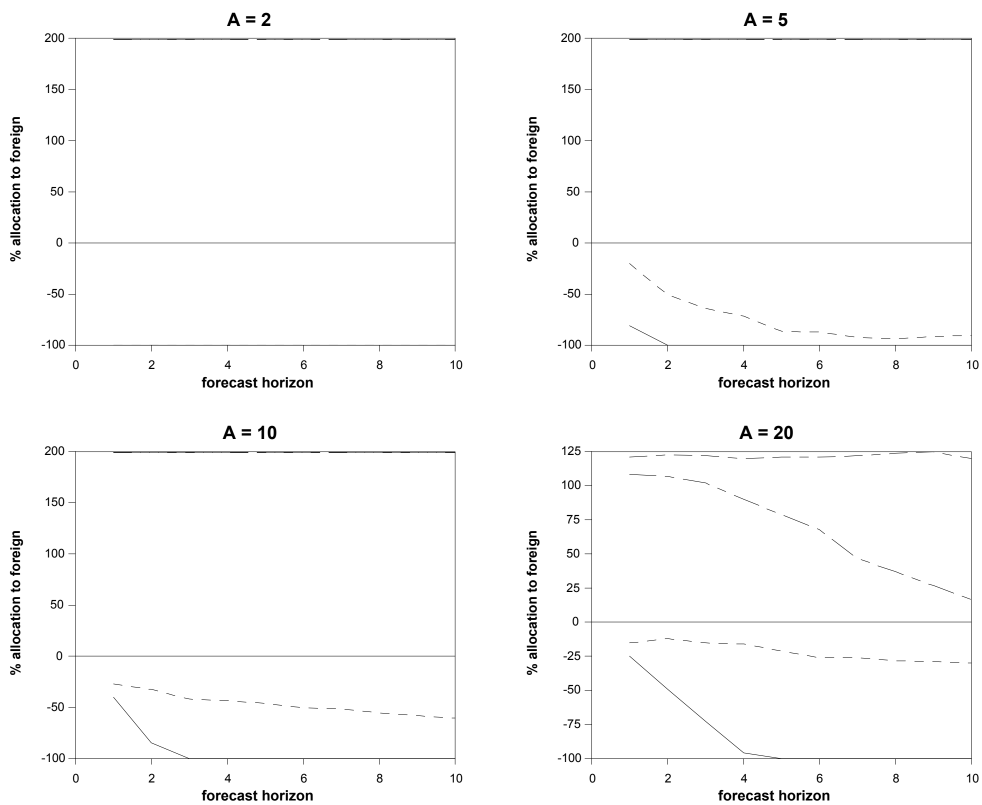

Figure 1: **US/Canada, static buy-and-hold strategy.** The figure shows the optimal weight ω to the foreign asset plotted against the investment horizon in years. The dotted and solid lines correspond to the cases where the investor assumes predictability with and without parameter uncertainty respectively. The dot-dash and dash lines correspond to the cases where the investor assumes that the exchange rate follows a random walk with and without parameter uncertainty respectively.

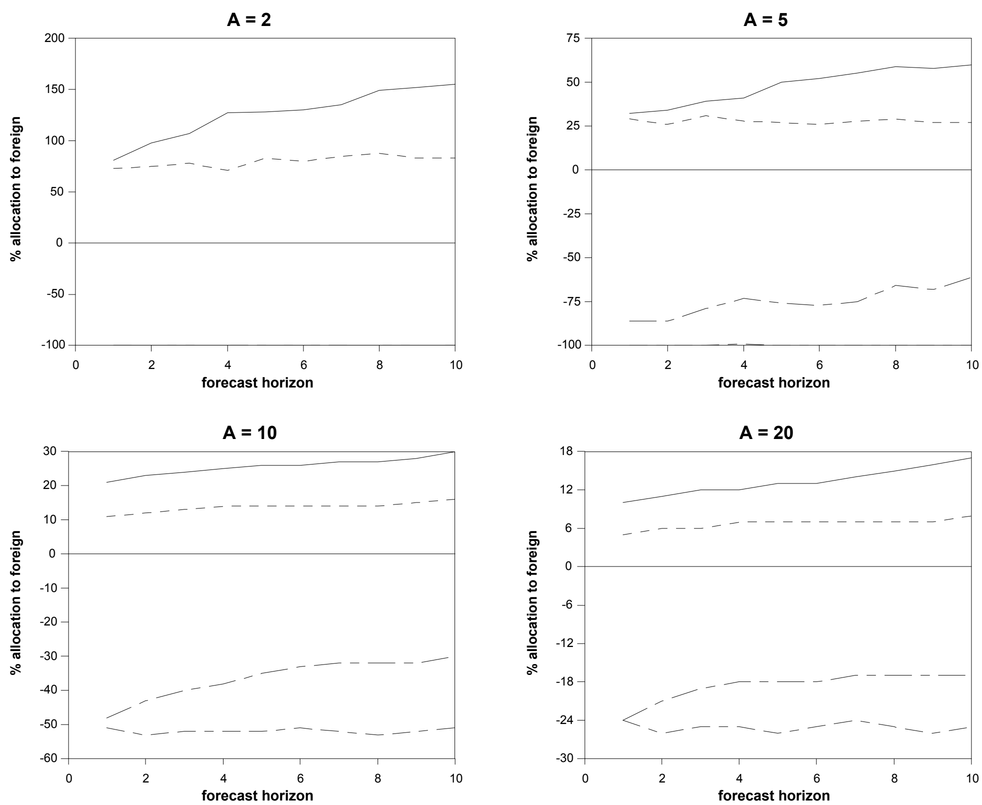

Figure 2: **US/Japan, static buy-and-hold strategy.** The figure shows the optimal weight ω to the foreign asset plotted against the investment horizon in years. The dotted and solid lines correspond to the cases where the investor assumes predictability with and without parameter uncertainty respectively. The dot-dash and dash lines correspond to the cases where the investor assumes that the exchange rate follows a random walk with and without parameter uncertainty respectively.

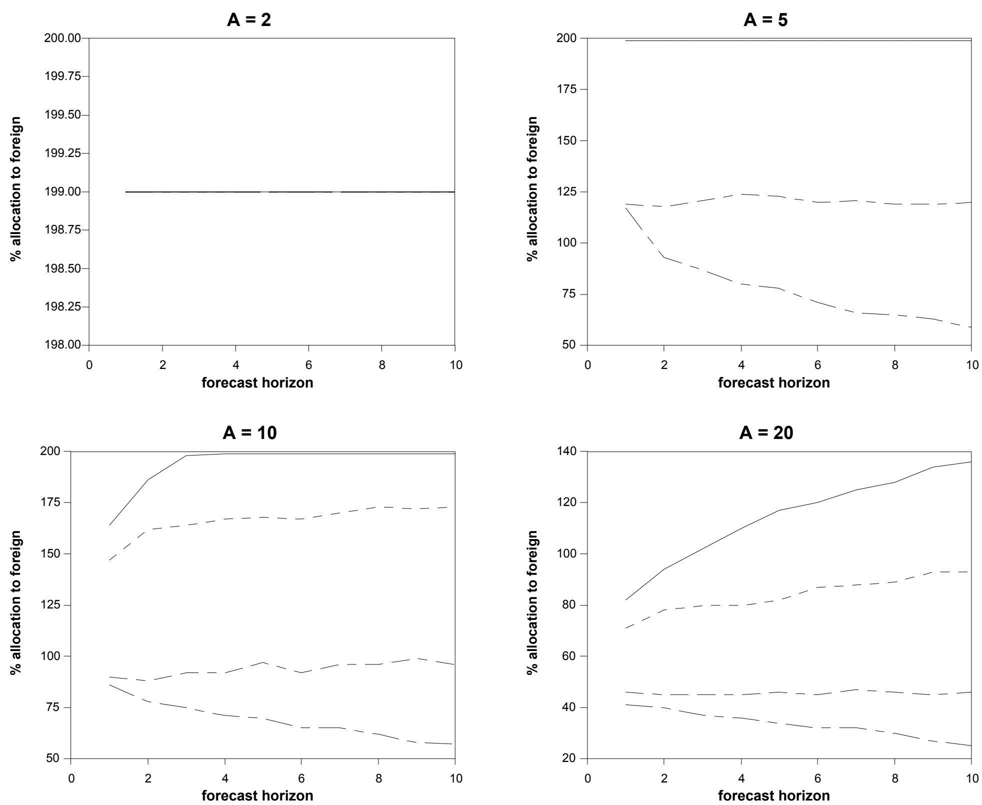

Figure 3: **US/UK, static buy-and-hold strategy.** The figure shows the optimal weight ω to the foreign asset plotted against the investment horizon in years. The dotted and solid lines correspond to the cases where the investor assumes predictability with and without parameter uncertainty respectively. The dot-dash and dash lines correspond to the cases where the investor assumes that the exchange rate follows a random walk with and without parameter uncertainty respectively.

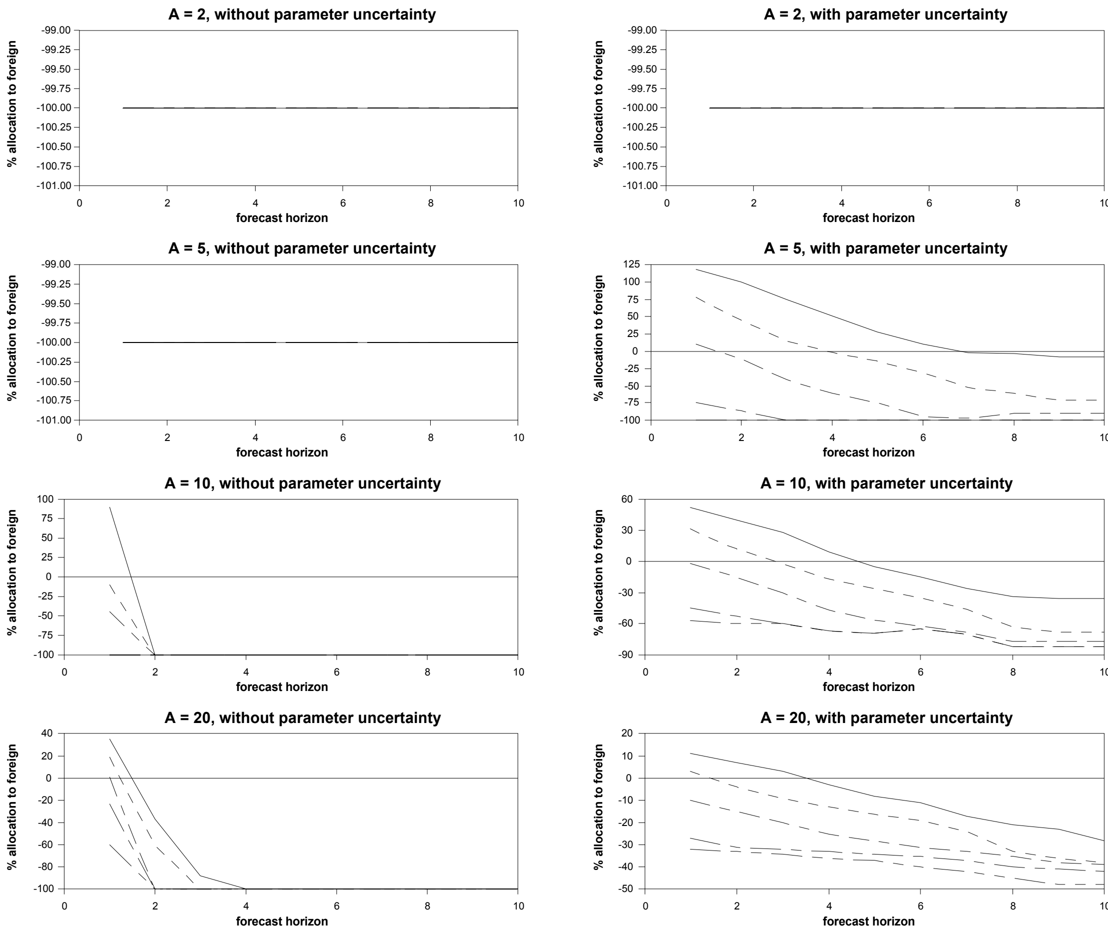

Figure 4: **US/Canada, optimal dynamic rebalancing strategy.** The figure shows the optimal weight ω to the foreign asset plotted against the investment horizon in years. The four graphs on the left refer to the case without parameter uncertainty, those on the right refer to the case with parameter uncertainty. The five lines within each graph correspond to different intial values of the predictor variable: $+3\sigma_u$ (solid), $+1\sigma_u$ (dotted), $\mu(u)$ (dash), $-1\sigma_u$ (dot/dash single), $-3\sigma_u$ (dot/dash double).

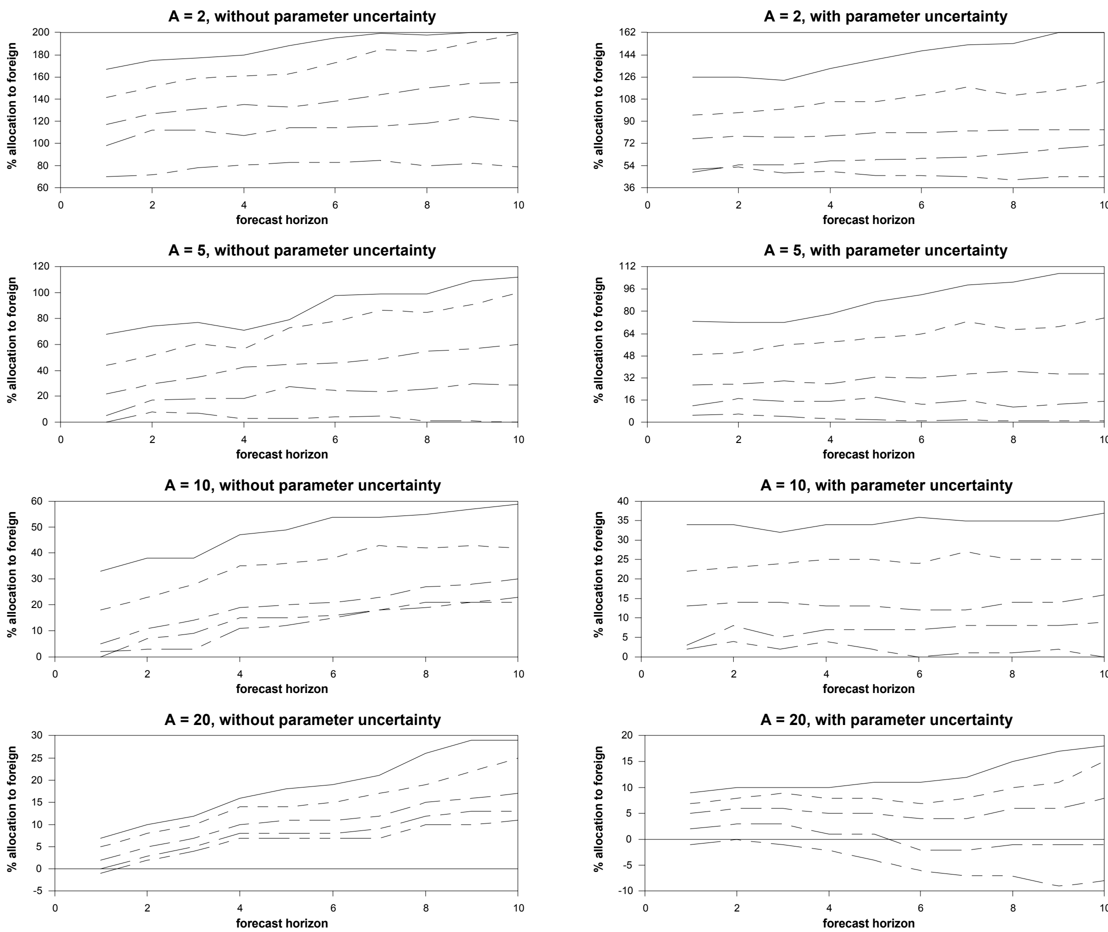

Figure 5: **US/Japan, optimal dynamic rebalancing strategy.** The figure shows the optimal weight ω to the foreign asset plotted against the investment horizon in years. The four graphs on the left refer to the case without parameter uncertainty, those on the right refer to the case with parameter uncertainty. The five lines within each graph correspond to different intial values of the predictor variable: $+3\sigma_u$ (solid), $+1\sigma_u$ (dotted), $\mu(u)$ (dash), $-1\sigma_u$ (dot/dash single), $-3\sigma_u$ (dot/dash double).

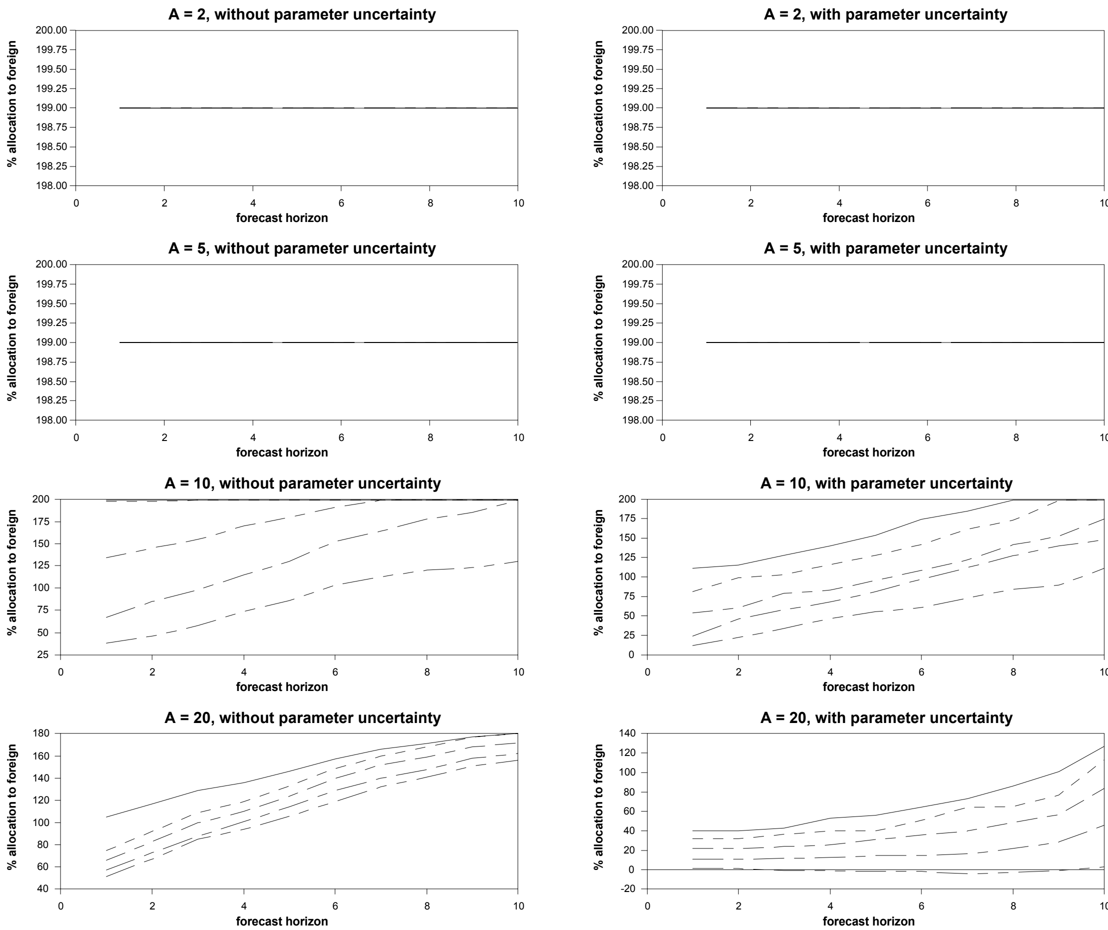

Figure 6: **US/UK, optimal dynamic rebalancing strategy.** The figure shows the optimal weight ω to the foreign asset plotted against the investment horizon in years. The four graphs on the left refer to the case without parameter uncertainty, those on the right refer to the case with parameter uncertainty. The five lines within each graph correspond to different intial values of the predictor variable: $+3\sigma_u$ (solid), $+1\sigma_u$ (dotted), $\mu(u)$ (dash), $-1\sigma_u$ (dot/dash single), $-3\sigma_u$ (dot/dash double).