Predictability and 'Good Deals' in Currency Markets

Richard M. Levich[a] Valerio Potì[b]

Initial Draft: 21 October 2006

This version: 29 September 2013

Forthcoming in the International Journal of Forecasting

In this paper, we study predictability of currency returns over the period 1972-2012. To assess the economic significance of currency predictability, we construct an upper bound on the explanatory power of predictive regressions. The upper bound is motivated by "no good-deal" restrictions that rule out unduly attractive investment opportunities. We find that predictability exceeds this bound during recurring albeit short-lived episodes. Excess-predictability is highest in the 1970s and tends to decrease over time, but it is still present in the final part of the sample period. Moreover, periods of high and low predictability tend to alternate. These stylized facts pose a challenge to Fama's (1970) Efficient Market Hypothesis but are consistent with Lo's (2004) Adaptive Market Hypothesis, coupled with slow convergence towards efficient markets. Transaction costs can explain much of the daily excess-predictability but not monthly excess-predictability.

Key words: Foreign Exchange, Predictability, Filter Rules, Market Efficiency

JEL Classification: F31

Contact details:

[a] Richard M. Levich, New York University Stern School of Business, 44 West 4th Street, New York, NY 10012-1126, USA. Tel: 212-998-0422, Fax: 212-995-4256; E-mail: rlevich@stern.nyu.edu.

[b] Valerio Potì, Room Q233, University College Dublin and Università Cattolica S.C. at Piacenza, UCD Michael Smurfit School of Business, Carysfort Avenue, Blackrock, Co. Dublin, Ireland; Tel: 3531-7005823, Fax: 3531- 7005446; Email: valerio.poti@ucd.ie.

The authors wish to thank Chris Neely (Federal Reserve Bank of St. Louis), Ming-Yuan Leon Li (National Cheng Kung University, Taiwan), Stephen Taylor (Lancaster University), Devraj Basu (EDHEC), and discussants and participants to the INFINITI 2007 conference, the EFM 2008 Symposium on Risk and Asset Management, the EFA 2008 meeting and seminars at Lancaster University and Reading University ICMA Centre for helpful comments and suggestions. Any remaining errors are the authors' sole responsibility.

Predictability and ‘Good Deals’ in Currency Markets

In this paper, we study predictability of currency returns over the period 1972-2012. To assess the economic significance of currency predictability, we construct an upper bound on the explanatory power of predictive regressions. The upper bound is motivated by “no good-deal” restrictions that rule out unduly attractive investment opportunities. We find that predictability exceeds this bound during recurring albeit short-lived episodes. Excess-predictability is highest in the 1970s and tends to decrease over time, but it is still present in the final part of the sample period. Moreover, periods of high and low predictability tend to alternate. These stylized facts pose a challenge to Fama’s (1970) Efficient Market Hypothesis but are consistent with Lo’s (2004) Adaptive Market Hypothesis, coupled with slow convergence towards efficient markets. Transaction costs can explain much of the daily excess-predictability but not monthly excess-predictability.

1. Introduction

In a literature that spans more than thirty years, various studies have reported that filter rules, moving average crossover rules, and other technical trading rules often result in statistically significant trading profits in currency markets. Beginning with Dooley and Shafer (1976, 1984) and continuing with Sweeney (1986), Levich and Thomas (1993), Neely, Weller and Dittmar (1997), Chang and Osler (1999), Gencay (1999), LeBaron (1999), and Schulmeister (2006), among others, this evidence casts doubts on the simple efficient market hypothesis, even though it is not incompatible with efficient markets under time-varying risk premia and predictability induced by time-varying expected returns. More recently, however, and contrary to the bulk of these earlier findings, a number of authors, including Olson (2004) and Pukthuanthong, Levich and Thomas (2007), find evidence of diminishing profitability of currency trading rules over time. In a comprehensive re-evaluation of the evidence, Neely, Weller and Ulrich (2009), also conclude in favour of declining profitability of technical trading rules. Menkhoff et al. (2012) report significant profitability of momentum strategies but find that, in foreign exchange markets, successful momentum portfolios are significantly skewed towards minor currencies, with relatively high transactions costs and high idiosyncratic and country risk.

Based on these more recent studies, it is tempting to conclude that the foreign exchange market, or at least the more liquid portion thereof where the main currencies are traded, has become increasingly efficient. This conclusion, however, rests on an implicit assumption that the set of trading rules examined by the studies span all the strategies that currency market participants could have deployed to earn excess-profits. Because the econometrician, as also noted by Griffin (2010), necessarily works with only a subset of information available to traders, and hence can identify at best only a subset of possible trading strategies, findings in support of efficiency based on this methodology may be suspect. The econometrician might end up formulating inferences on market efficiency by evaluating the performance of the wrong strategies, thereby losing power against the null of market efficiency, as demonstrated more formally in Appendix A.[1] This danger is compounded by the possibility that, at different points in time, the market misprices different aspects of the multi-period distribution of asset returns, with the consequence that different

[1] The very success of a particular strategy may cause its eventual demise, when the mispricing it exploits is wiped out because the strategy becomes popular, without necessarily implying that all mispricing has been eliminated. This leaves open the possibility that other strategies might be equally profitable. Neely, Weller and Ulrich (2009) offer evidence this might be the case in the currency domain in that relatively less known trading rules appear to be profitable even as the profitability of the more traditional ones fades away. That is, there might be changing sources of predictability and the econometrician might simply not be aware of the full set of strategies that rational currency traders may deploy over time to exploit predictability.

strategies might be required at different times to exploit predictability, making it difficult for an imperfectly rational (i.e., not endowed with RE) econometrician to identify the set of appropriate strategies.

In this paper, we overcome this inherent shortcoming of prior studies by focussing on the predictability picked up by predictive models chosen to provide a flexible yet parsimonious reduced form representation of the data generating process (henceforth, DGP) of currency returns, so as to capture as much of their predictability as possible, rather than on the profitability of specific trading strategies. Importantly, we estimate the predictive models by Maximum Likelihood (ML), thereby imposing the null of rational expectations (RE), as defined by Muth (1961). We then make inferences on currency market efficiency by imposing an economically motivated restriction directly on a natural measure of predictability, namely the coefficient of determination of the estimated predictive models. The advantage of this approach is that it is based on estimates of the DGP of currency returns that, because of the well-known link between ML and RE, e.g. Sargent (1979), mimic those that would be generated by currency traders endowed with RE, rather than on specific trading strategies selected from sets of trading rules that might not contain the ones that rational currency traders would deploy.

The restriction we test is derived by ruling out "good deals" from the point of view of an investor endowed with RE. Following the terminology introduced by Cochrane and Saà Requeio (2000), Cerný and Hodges (2001) and Cochrane (2005), "good deals" are defined as investment opportunities that offer unduly high Sharpe ratios.

As shown by Potì and Siddique (2013), the Sharpe ratio (henceforth, SR) is a popular measure of investment performance in foreign exchange markets because currency traders, due to imperfect access to risk capital and economies of scale in currency trading, seek reward for total risk rather than for systematic risk only. In this context, ruling out good deals, and therefore high SRs, is consistent with the implications of the efficient market hypothesis (henceforth, EMH).

We base our inferences mainly, though not exclusively, on in-sample predictability. This is not, however, a limitation of our analysis. To the contrary, as long as in-sample moments provide consistent estimates of 'population' moments, it allows checking specific implications of RE, in our case the no good-deal restriction, and therefore of the EMH.[2] As demonstrated by Inoue and Kilian (2004), in-sample tests have greater power against the null of no-predictability compared with out-of-sample ones, for a given size of the test, especially in the presence of un-modelled changing collinearity between predictive variables. Moreover, in-sample tests lend themselves more naturally to the use, as predictive models, of reduced form representations of the DGP, thereby helping the researcher circumvent the noted limitation of many market efficiency tests, namely the fact that the econometrician typically observes

[2] A short-cut to understanding our approach can be had by drawing an analogy to studies of excess volatility in equity markets, where researchers compare the volatility of share returns (in-sample) to the volatility of dividends, earnings, and discount factors (also in-sample). Along the same lines, but in the context of currency markets, Brennan and Xia (2006) relate the volatility of exchange rates to the volatility of the economy pricing kernel and, ultimately, to the volatility of discount factors. As noted by Cochrane (2005, p. 396), "'excess volatility' is exactly the same thing as return predictability" (quotes and italics in the original text). In the same vein, our study of foreign exchange markets examines whether in-sample predictability is too high relative to the admissible variability of discount factors. In this respect, our approach can be seen as building upon the intuition developed in Kirby's (1998) seminal article on rational asset pricing and predictability. Kirby (1998) offers a formal analysis of the restrictions that rational asset pricing models place on the coefficient of determination of predictive regressions as well as on the intercept and slope coefficients of such regressions, and uses in-sample moments to make inferences about whether specific asset pricing models can account for observed in-sample predictability of CRSP stock deciles.

(even ex post) only a subset of the information set available to a professional market participant. Also, as we shall demonstrate later and perhaps against widespread belief, there is empirically a tight link between in-sample and out-of-sample predictability and therefore the former is a good instrument for the latter.

The empirical results in our study offer evidence of violations of the predictability upper bound. While such violations are especially severe in the initial and middle part of our sample period, excess-predictability of currency returns has not disappeared from the mid-1990s onwards. Our results thus contrast with the vanishing profitability of many popular technical trading rules reported in several recent studies referenced earlier. Importantly, we find that predictability varies over time in a roughly cyclical manner, with recurring albeit relatively short-lived episodes during which it exceeds the no good-deal bound. While our evidence is in contrast with the EMH, it is consistent with implications of Lo's (2004) Adaptive Market Hypothesis (AMH), in that bursts of predictability would appear to occur when shifts in market conditions require market participants to re-learn how to make efficient forecasts. Realistic levels of transaction costs can account for daily predictability, but monthly predictability cannot be explained away on this basis, thus rationalizing market participants' enduring tendency to engage in technical analysis and other active currency management practices.

In the next section, we outline the relation between predictability and time-varying expected returns, and introduce the predictability upper bound. In Section 3, we describe our dataset. In Section 4, we present preliminary empirical results on the predictability of the currencies in our sample. In Section 5, we consider strategies that exploit predictability and evaluate the impact of transaction costs on their profitability. In Section 6, we assess the impact of sampling error on our inferences. In Section 7, we compare out-of-sample and in-sample predictability. In the final Section, we summarize our main findings and offer conclusions.

2. Predictability, Time-Varying Expected Returns and Pricing Kernel Volatility

Consider the following general model of the data-generating process (DGP) of currency excess-returns:

$$r_{i,t+1} = \mu_{i,t+1} + u_{i,t+1} \tag{1}$$

where

$$\mu_{i,t+1} \equiv E(r_{i,t+1} \mid I_t) \equiv \mu_i(I_t) \tag{2}$$

Here, $r_{i,t+1}$ is the excess-return on the ith currency (i.e., the currency appreciation net of the difference between the interest rate on deposits denominated in the currency and deposits denominated in US Dollars, our numeraire currency), I_t is the information set available at time t and $u_{i,t}$ is a conditionally zero-mean innovation, a (non-degenerate) random variable unpredictable with respect to the information set I_t, i.e. $E_t(u_{i,t+1}) = 0$. We let I_t include not only the sigma-field generated by the past of $u_{i,t+1}$, which belongs to the information set J_t available to the econometrician, but also other available public and private information which might not be in J_t, so that it is possible that $J_t \subset I_t$. We can write the unconditional variance of both sides of (1) as follows:

$$\sigma^2(r_{i,t+1}) = \sigma_\mu^2 + \sigma^2(u_{i,t+1}) \tag{3}$$

Here, $\sigma_\mu^2 = \sigma^2[\mu_i(I_t)]$. Dividing both sides by $\sigma^2(r_{i,t+1})$ and rearranging, we see that predictability[3] is related to variation σ_μ^2 in mean excess returns,

$$R^2 = 1 - \frac{\sigma^2(u_{i,t+1})}{\sigma^2(r_{i,t+1})} = \frac{\sigma_\mu^2}{\sigma^2(r_{i,t+1})} \tag{4}$$

Variation in mean returns (conditional expected returns), in turn, can either come from variation in discount rates, consistent with the EMH, or from variation in abnormal mean returns that has not been exploited by the posited rational investor and thus is at odds with the EMH. To discriminate between these two possibilities, one must identify the component of σ_μ^2 arising from variability of discount rates. To do so, we exploit the fact that, as shown by Lo and MacKinlay (1997) and Cochrane (1999), there is a close relation between the SR of any trading strategy and the coefficient of determination of the predictive regression on which (explicitly or otherwise) the strategy is based. Following Cochrane (1999) and as shown in the online Appendix of Potì and Siddique (2013), we can write

$$SR\left(r_{i,t+1}^*\right)^2 = \frac{R^2 + SR^2\left(r_{i,t+1}\right)}{1 - R^2} \tag{5}$$

Here, $r_{i,t+1}^*$ is the excess-return on the strategy that exploits the predictability (of the *i*th currency) implied by the predictive regression with coefficient of determination R^2 defined by (1) and (2). To generate this SR, one needs to enter a strategy consisting of a time-varying position in the currency. Using a result derived by Ferson and Siegel (2001, 2009), the allocations to the currency in each period are

[3] See Equation (13) in Kirby (1998).

$$w_{i,t} = \lambda \frac{\mu_{i,t+1}}{\mu_{i,t+1}^2 + \sigma_t^2(u_{i,t+1})} \qquad (6)$$

Here, $\sigma_t^2(u_{i,t+1})$ is the conditional variance of the predictive regression error, namely the error in (1), and λ is a coefficient of proportionality which plays the role of a scaling constant and, as such, has no direct impact[4] on the performance of the strategy in terms of SR (it can be set, for convenience, equal to 1). The strategy defined by the inter-temporal allocation rule in (6) has excess-return $r_{i,t+1}^* = w_{i,t} r_{i,t+1}$ and we refer to it as a rational trading rule, in that it rationally exploits the predictability of the ith currency to attain the squared unconditional SR on the left hand-side of (5). Intuitively, it amounts to using a directional signal, the conditional mean $\mu_{i,t+1}$, combined with a volatility filter, i.e. $\sigma_t^2(u_{i,t+1})$. Because $0 \leq R^2 \leq 1$, (5) implies that the squared SR of such a strategy represents an upper bound to the R^2 of the predictive regression on which it is based,[5]

$$R^2 \leq SR\left(r_{i,t+1}^*\right)^2 \qquad (7)$$

In turn, the right hand-side of (7) is bounded from above by the variance of the minimum variance kernel m_{t+1} that prices all assets in the economy (including the trading strategies), i.e.

$$SR\left(r_{i,t+1}^*\right)^2 \leq \sigma(m_{t+1})^2 \qquad (8)$$

Potì and Siddique (2013), who use results put forth by Ross (2005) and elaborated upon by Potì and Wang (2010), place the following upper bound on the right hand-side of (8):

---

[4] Though it determines the size of the dynamic allocation under the strategy and, therefore, it may influence the SR if, due to microstructure issues, transaction costs are a function of transaction size

[5] It may be worth noting that $SR^2(r_{i,t+1})$, in the case of currencies, is typically very small, empirically close to zero. That is, a simple buy and hold in a currency is typically a very poor investment, though trading the currency, exploiting its predictability over time, may be a better one.

$$\sigma^2(m_{t+1}) \leq RRA_V^2\sigma^2(r_{m,t+1}) \tag{9}$$

Here, RRA_V is a relative risk aversion upper bound, which restricts the curvature of the marginal trader's utility function, and $\sigma(r_{m,t+1})$ is the volatility of the market portfolio excess-return $r_{m,t+1}$. Combined with (7) and (8), the bound in (9) implies the following restriction on the explanatory power of any excess-return predictive regression:

$$R^2 \leq RRA_V^2\sigma^2(r_{m,t+1}) \equiv \phi \tag{10}$$

From the point of view of (4), violations of this predictability bound amount to excessive volatility of the (conditional) mean return, as picked up by a high predictive regression R^2, relative to the admissible volatility of discount rates and, as such, violations of the EMH. In the language of Cochrane and Saà Requeio (2000) and Cochrane (2005), they represent unexploited "good deal" opportunities in that, because of (7), they result in unduly large SRs of the predictability-based strategy defined by (6). This implies mispricing of the latter and hence of the underlying currency. Because the RE assumption implies the law of iterated expectations, such mispricing is to be deemed to occur at the beginning of every period over which the bound in (10) is violated. Notably, the restrictions in (7) through (10) hold unconditionally and thus, if the data generating processes of the asset returns and the kernel are sufficiently ergodic, they hold for the *in-sample* coefficient of determination of any consistently estimated predictive regression. To operationalize the predictability bound in (10), we need to specify the RRA upper bound RRA_V. Ross (2005) suggests imposing an upper bound of 5 on the relative risk aversion of the marginal investor, i.e. $RRA_V \leq 5$. Based on the comprehensive re-evaluation of the empirical evidence on investors' risk aversion offered by Meyer and Meyer (2005), who show that risk aversion estimates reported by the extant literature are less heterogeneous and extreme if one takes into account measurement issues and the outcome variable with respect to which each study defines risk aversion, Potì and Wang (2010) consider a tighter upper bound, namely $RRA_V \leq 2.5$, alongside the bound advocated by Ross (2005). This is the approach we adopt also in this study.

3. Data

In this study, we take the perspective of the US marginal investor. The numeraire currency is thus the US Dollar (USD). Our dataset includes the spot exchange rates against the USD, from the beginning of 1971 till the end of 2012 (extended to August 2013 in the final part of the paper), of the 6 major currencies (except those that were replaced by the Euro). The latter include the Australian and Canadian Dollar (AUD and CAD, respectively), the Japanese Yen (JPY), the British Pound (GPB), the Swiss Franc (CHF) and the Euro (denoted as ECU/EUR because we combine data on the ECU before the introduction of the Euro in 1999 and on the latter after its launch) provided by Bloomberg at the close of business in London at 6:00 p.m. GMT. The exchange rate is expressed in terms of units of USD for a unit of the currency under consideration. We construct daily and monthly currency return series by calculating the daily and monthly rate of change of the corresponding exchange rates. To remain consistent with the perspective of the American marginal investor, we use daily and monthly returns on the S&P500 index, constructed from last traded price and dividend data provided by Datastream, to proxy for the return on the market portfolio of risky assets. Though the dataset includes series that start in March 1971 and end in August 2013, we treat the sample period 1972-2012 as the benchmark in many of the analyses that follow.

4. Preliminary Results on Currency Predictability

As shown by Taylor (1994), among others, relatively parsimonious ARIMA models of exchange rates, and thus ARMA models of currency returns, capture substantial predictability. Our estimated predictive models are thus specifications of the general ARMA(p,q) model, where p denotes the autoregressive (AR) lag order and q denotes the order of the moving average (MA) term:

$$y_t = const. + b_1 y_{t-1} + ... + b_p y_{t-p} + c_1 u_{t-1} + ... + c_q u_{t-q} + u_t \tag{11}$$

For $y_t = r_{i,t}$, the above predictive regressions are intended as reduced-form representations of the DGP of the (excess-)return on the ith currency over the estimation window from t_0 to t_1, with $t_0 \leq t \leq t_1$, where t_0 and $t_1 \in \{1, 2, \ldots, T\}$ and T denotes the end of our overall sample period. Consistent with the RE null, they are estimated by ML. The p and q parameters are selected using the Akaike Information Criterion (AIC), which is consistent with ML and therefore with the null of RE. It is also the model selection criterion recommended, in a predictive setting, by Pesaran and Timmermann (1995).[6] In conducting the AIC-based model selection,

[6] Unlike the Bayesian Information Criterion (BIC), the Akaike Information Criterion (AIC) is not consistent (just like the popular R^2 criterion), in the sense of selecting the 'true' model as the sample size increases without bounds. Pesaran and Timmermann (1995), however, note that, in the context of forecasting asset returns, where the 'true' model or the 'correct' list of regressors is clearly unknown and may be changing over time, the consistency property is not as important as it may appear at first. In such a context, they suggest that the ability to select a forecasting equation that could be viewed at the time as being a reasonable approximation to the DGP is of greater importance. The AIC, although statistically inconsistent, displays such ability, in that it has the property of yielding an approximate

we allow for AR and MA terms p and q of up to the fifth order. We fit versions of (11) to both raw returns and returns adjusted by the interest rate differential (i.e., the differential between the interest rate on deposit denominated in the currency and the US Dollars funding cost). While data on a suitable risk-free asset proxy is not available throughout the sample period, we find that adjusting returns for the interest differential has virtually no impact on estimated predictability. This is because the volatility of the interest differential is negligible relative to currency returns volatility. Thus, to avoid problems that arise from the incomplete availability of data and unless otherwise specified, we report results for currency return data only.[7]

The in-sample coefficient of determination $\hat{R}^2_{i,t_0\to t_1}$ of the predictive regression in (11) represents our measure of predictability over the estimation window for the ith currency and therefore an estimate of the left-hand side of (10). To compute an estimate $\hat{\phi}_{t_0\to,t_1}$ of the predictability bound, i.e. the quantity in the right-hand side of (10), we use the square of an estimate of the unconditional volatility $\hat{\sigma}_{m,t_0\to t_1}(r_{m,t_0+s})$ of the market portfolio proxy from t_0 to t_1 and for $s = 1,2,\dots,(t_1 - t_0)$, and multiply by the square of RRA_V. The latter is set to either 2.5 or

model and, as shown by Shibata (1976), strikes a good balance between giving biased estimates when the order of the model is too low and the risk of increasing the variance when too many regressors are included.

[7] As a proxy for the risk-free rate on assets denominated in the currencies included in our dataset, we use daily middle rate data on Australian Dollar and German Mark inter-bank ‘call money’ deposits, on Canadian Dollar and Swiss Franc Euro-market short-term deposits (provided by the Financial Times/ICAP), on inter-bank overnight deposits in GBP and the middle rate implied by Japan’s Gensaki T-Bill overnight contracts (a sort of repo contract used by arbitrageurs in Japan to finance forward positions). The rate on German Mark deposits is used as a proxy for the rate at which it is possible to invest funds denominated in ECU, while the overnight Euribor is used as a proxy for the rate at which it is possible to invest Euro denominated funds. As a proxy for the US risk-free rate, we use daily data on 1 month T-Bills (yields implied by the mid-price at the close of the secondary market). The interest rate data are taken from Datastream.

5. We refer to the difference between our measure of predictability and the predictability bound as the '*boundary violation index*' (henceforth *BVI*), defined as

$$BVI_{i,t_0\to t_1} \equiv \hat{R}^2_{i,t_0\to t_1} - \hat{\phi}_{t_0\to t_1} \tag{12}$$

The inequality in (10) implies that, under RE/EMH, this quantity should be non-positive. Given the ML estimate of the DGP between t_0 and t_1 and the predictability bound, it is a measure of excess-predictability over the period from t_0 to t_1 and of the mispricing that occurs at time t_0 and is corrected by time t_1, $\forall\, t_0$ and $t_1 \in \{1, 2, \dots, T\}$. In presenting our results, to facilitate their interpretation, we express excess-predictability as follows:

$$\gamma_{i,t_0\to t_1} \equiv \sqrt{BVI_{i,t_0\to t_1}\frac{l}{years}} \tag{13}$$

Based on (5) and (12), the quantity $\gamma_{i,t_0\to t_1}$ can be seen as the annualized excess-SR that can be earned by a RE investor by exploiting observed predictability. As such, it provides an intuitively appealing measure of "good deal" availability, and hence currency mispricing relative to the estimated RE benchmark, at t_0. Clearly, $\gamma_{i,t_0\to t_1}$ is defined only when $BVI_{i,t_0\to t_1} \geq 0$. For each currency, we also define a quantity to which we refer as *implied* RRA. This is the level of RRA_V such that $BVI = 0$ and therefore the RRA that explains the estimated currency predictability, given the estimated volatility of the market portfolio of risky assets, that is

$$RRA_{i,t_0\to t_1} = \sqrt{\hat{R}^2_{i,t_0\to t_1}/\hat{\sigma}^2_{t_0\to t_1}(r_{m,t_0+s})} \tag{14}$$

Unlike the BVI, this quantity does not require us to take a stance on the level of RRA but translates the estimate of predictability in terms of RRA itself. This way, we give the reader the possibility to form her own judgement as to whether the predictability we observe is excessive, given the reader's belief concerning what constitutes a reasonable upper bound on the marginal currency trader RRA.

Daily and monthly predictability and excess-predictability estimates are reported in Table 1 and Table 2, respectively. In the daily case, we simply set $p = 5$ and $q = 0$ in the predictive ARMA(p,q) because, for most sample periods and currencies, these are the parameter values selected by the AIC procedure and this seems a natural choice at the daily frequency.[8] In Table 1, we report the coefficients of determination, the corresponding values of $\gamma_{i,t_0 \to t_1}$ of the AR(5) models of daily returns, estimated over the full sample period and seven consecutive non-overlapping 5-year windows, as well as the predictability bound used for computing $\gamma_{i,t_0 \to t_1}$, based on the sample volatility of the market portfolio proxy and the two different RRA_V values. Table 2 reports the AR and MA orders as well as the coefficients of determination and related excess-predictability measures of the selected ARMA(p,q) models of monthly returns, estimated over the full sample period and four sub-sample periods of roughly equal length (except the last one, 2007-2012, which is shorter and coincides with the recent financial crisis) and chosen using the AIC. The excess-predictability measures are calculated based on the bounds on monthly predictability reported in Table 3. The reported excess-predictability measures are in many cases sizable, suggesting the attainability of excess-SRs even larger than 100 per annum, especially for daily returns in the initial part of the sample period. Differences between the initial and

[8] The results of these tests are not tabulated to save space, but they are available from the authors upon request. Also, This model captures reasonably well the daily predictability of currencies in our sample, as suggested by Ljung-Box (1978) tests of the null of residual serial correlation, rejected for lags of up to the 36th order.

subsequent part of the sample period appear less pronounced in the monthly than in the daily case.

To gain visual perspective on how predictability and possible currency mispricing have evolved over time, we also estimate specifications of (11) over rolling windows of daily and monthly data and record their coefficients of determination. For each currency i, this yields series of coefficients of determination $\hat{R}^2_{i,t\to t+l}$ estimated over rolling estimation windows, each running from t to $t+l$, with $t = 1, 2, \dots, T-l$, where l denotes the (fixed) length of each estimation window. The predictive models are ARMA(p,q) with p and q selected, within each rolling estimation window, by the AIC. To estimate the predictability bound $\phi_{t\to t+l}$, we proxy for the variance of the market return between t and $t+l$, i.e. $\sigma^2_{t\to t+l}(r_{S\&P,t+s})$ with $s \in [1, 2 \dots . l]$, as the average, over rolling windows of l periods, of GARCH(1,1) estimates of the variance of S&P500 returns $r_{S\&P,t+s}$ (with the return frequency of the S&P500 returns that matches the currency return frequency, daily or monthly). To compute $\phi_{t\to t+l}$, we then multiply the $\hat{\sigma}^2_{t\to t+l}(r_{S\&P,t+s})$ thus obtained by the square of the chosen RRA upper bound, i.e. by the square of RRA_V. For each currency, we then construct both a *BVI* series, as the difference between $\hat{R}^2_{i,t\to t+l}$ and $\varphi_{t\to t+l}$, and an implied *RRA* series, computed as $RRA_{i,t\to t+l} = \sqrt{\hat{R}^2_{i,t\to t+l}/\hat{\sigma}_{t\to t+l}(r_{m,t+s})}$.

In Figure 1, we plot the simple equally-weighted average across currencies of the daily series of the rolling coefficients of determination (in Panel A) thus obtained, namely $R^2_{avg,t\to t+l} = \frac{1}{6}\sum_{i=1}^{6} R^2_{i,t\to t+l}$, together with the corresponding average BVI series (in Panel B), i.e. $BVI_{avg,t\to t+l} = \frac{1}{6}\sum_{i=1}^{6} BVI_{i,t\to t+l}$. While the latter is always positive throughout the sample period, suggesting excess-predictability for the average currency, it appears to be considerably higher at the beginning of the 40-year period under consideration, especially in the 70s, and subsequently decreasing over time, in agreement with Table 1 and the diminishing abnormal profitability of technical trading rules reported by Olson (2004) and Neely, Weller and Ulrich (2009).[9]

The monthly time-series of the rolling coefficients of determination $R^2_{i,t\to t+l}$ for each currency are plotted in Figure 2 against the time series of the rolling predictability bound $\varphi_{t\to t+l}$, computed by setting $RRA_V = 5$. Instead of plotting the monthly BVI series or, as in the daily case, the average thereof, we plot the series of implied RRA coefficients as the latter coveys all information conveyed by BVI but not vice versa. The series of monthly implied RRA series for each currency is shown in Figure 3, with superimposed a smoothed version obtained using a HP filter. The level of implied RRA inherits the considerable time-variation of predictability and many of its salient traits. For each currency, it exceeds even the tighter RRA bound, namely $RRA_V = 5$, for extended periods of time. Visual inspection suggests the occurrence of bursts of predictability at various points, implying RRA in excess of the upper bounds, especially in the 1970s, around times of market turmoil and shifting

[9] Olson (2004) applies double moving-average rules to GBP, CHF, JPY and the German Mark exchange rate against the US dollar and finds evidence that they would have generated abnormal profitability over the periods 1976-1980 and 1986-1990 but also that excess-profitability disappeared after 1991. Neely, Weller and Ulrich (2009) examine a more comprehensive set of trading rules and report similar findings.

economic and institutional/geopolitical circumstances, such as the so-called Asian crisis and the events surrounding the European monetary integration process in the second part of the 1990s. Predictability appears to decline after a peak in the late 1980s until about 1997 and to increase again afterwards, with the partial exception of the Swiss Franc. Overall, the Figure suggests that excess-predictability displays a roughly cyclical pattern, i.e. periods of high and low predictability alternate over time, rather than the prevalence of deterministic trends. [10]

On balance, these findings offer *prima facie* evidence of excess-predictability in currency markets and that such excess-predictability has not disappeared, though in the daily case excess-predictability appears much more sizeable in the early part of the sample period. There is the possibility, however, that high transaction costs might have to be incurred to rationally exploit the estimated predictability and that our estimates of the coefficient of determination R^2 may be inflated by sampling error. We now investigate these possibilities in turn.

5. The Impact of Transaction Costs

We construct predictability-based strategies using the time-varying allocation rule in (6) and calculate the returns on such strategies after transaction costs. The conditional mean in (6) is given by the conditional mean of (11), i.e. $\mu_{i,t+1}(I_t) = r_{i,t+1} - u_{i,t+1}$, while, as an estimate of $\sigma_t^2(u_{i,t+1})$, we use the squared standard error of the

[10] As confirmed by the results of the regression of the implied RRA series on a deterministic time trend and other control variables, which we do not report to save space, there is no upwards or downwards trend over time, thought the series do appear to display a sort of mean-reverting behaviour, hovering with ample swings around what appears to be a lung-run value of around 10.

regression, thus neglecting possible heteroskedasticity. Much of the extant literature considers transaction costs of about 0.05 percent, or 5 basis points, realistic for a typical round trip trade between professional counterparts, see Levich and Thomas (1993) and Neely, Weller and Dittmar (1997). This corresponds to about 2-3 basis points on each one way, i.e. buy or sell, transaction. In calculating the return to these strategies, therefore, we allow for transaction costs of up to 5 basis points. For comparison, we also experiment with transaction costs of 25 basis points.

In Table 4, we report the SRs offered by the predictability-based trading rules for each currency for these different levels of transaction costs. As before, the predictive model for daily returns is ARMA(5,0) and, for monthly returns, ARMA(p,q) with an AIC-based selection of *p* and *q*. Transaction costs of 3 basis points are enough to lower the SRs of the daily strategies below the level that corresponds to the tightest predictability bound for all the currencies under consideration except CHF, to the point that the SRs of the strategies based on the daily predictability of AUD, JPY and ECU/Euro become negative. With transaction costs of 5 basis points, the SRs of daily strategies are negative for all currencies. The strategies that exploit monthly predictability are much less sensitive to transaction costs. In all sub-sample periods, the SRs for the monthly strategies are positive even with transaction costs of 5 basis points.[11] To save space, we tabulate the SRs only for the full sample period. Results

[11] A word of caution is in order, however, with respect to the likely magnitude of any available "good deal." There is substantial evidence that transaction costs depend on the size of the transaction and, more specifically, on "price pressure." For example, Evans and Lyons (2002) estimate that a buy order of 1 million US dollars increases the execution exchange rate against the Deutsche Mark and the Japanese Yen by as much as 0.54 percent, or 54 basis points. Similar figures are provided by Berger et al. (2008), at least for trades executed over a daily horizon. As shown in Table 4, transaction costs of 25 basis points are enough, with few exceptions, to lower SRs below the threshold that corresponds to the wider predictability bound, i.e. the bound corresponding to , and often below the level implied by

for other sub-sample periods are, however, available from the authors upon request as well as in previously circulated versions of the paper.

The much heavier impact of transaction costs on the profitability of the daily strategies is due to the greater variability of the allocation rule prescribed by (6), resulting in much frequent and heavy rebalancing. In Figure 4, to illustrate, we plot the time-varying currency allocation, calculated using (6) and normalized to add up to unity, under the strategies that exploit the daily and monthly predictability of the Canadian Dollar.[12] There is much less variation in the currency allocation under the (monthly) monthly strategy. Like in classic filter and moving-average strategies, which also typically exploit predictability at low frequency, trading positions change relatively infrequently.[13] Taking fully into account transaction costs at the daily frequency requires careful modelling of microstructure mechanisms that are outside the scope of this study. We therefore drop the daily series from further analysis and leave the investigation of daily predictability for future research.

6. The Impact of Sampling Error: Asymptotic and Bootstrap Distribution

To make inferences on the statistical significance of our (monthly) predictability estimates, we first use a test based on Hosking's (1979) asymptotic distribution of the

---

the tighter predictability bound, i.e. the bound corresponding to . Similar or even higher levels of transaction costs, as implied by the evidence provided by the literature on "price pressure," are to be expected for large transactions.

[12] They are based on AR(5) and ARMA(5,2) specifications, respectively, over the 1996-2006 sample period. We pick this currency and sample period simply for illustrative purposes and, to save space, omit to report the corresponding plots for other currencies and sample periods, as similar considerations apply for any other choice of both currency and period.

[13] For example, Levich and Thomas (1993) report that over their 15 year sample period of major currencies, the 5 day / 20 day moving average rule traded 13 times per year.

coefficient of determination of estimated ARMA models which is described in Appendix B. The results for the period 1972-2012 are reported in Panel A of Table 5. The Table, after giving details on the estimated ARMA(p,q) models (these were already given in Table 2 but are reproduced here for the reader's convenience), reports the H statistics of the test that predictability of the estimated model, captured by $\hat{R}^2$, does not exceed the predictability bound, as well as p-values of the asymptotic distribution of the H statistic, under the null of the test.

The finite sample properties of the $\hat{R}^2$ sampling error estimate provided by Hosking's (1979) asymptotic distribution, however, are not known. Therefore, to check the extent to which the asymptotic distribution is valid in the context of our application, we conduct a bootstrapping exercise. As part of the latter, as explained in detail in Appendix C, we bootstrap the distribution of the coefficient of determination $\hat{R}^2$ of the estimated predictive regressions and use it to construct two types of 2-tailed confidence intervals for $\hat{R}^2$, as well as an estimate of the $\hat{R}^2$ sampling error so as to compute a bootstrap version of the H statistic. We resort to both a parametric and a non-parametric procedure, each described in Appendix (which also introduces the necessary notation), involving a number B of bootstrap simulations, with $B = 1{,}000$ and $B = 10{,}000$ in the parametric and non-parametric case, respectively.

The results of the bootstrapping exercise for the full sample period are reported in Panel B of Table 5. The bootstrapped confidence intervals suggest that the evidence against the null of no excess-predictability is somewhat stronger than indicated by the H tests based on Hosking's (1979) asymptotic distribution, with values of the bootstrap H statistics larger than when computed using the asymptotic variance of estimated predictability. The lower end of the confidence interval of the latter is always above the predictability bound under RRA_V = 2.5 (which is 1.28 percent, as per Table 3) and, with the exception of the confidence interval of the predictability of the Swiss Franc based on the nonparametric bootstrap, also above the predictability bound under RRA_V = 5.0 (which is 5.10 percent, as per Table 3). Hence, under the nonparametric bootstrap, we reject the null of no excess-predictability in all cases except for the Swiss Franc. Therefore, inferences in terms of rejection of the null of no excess-predictability are identical whether we use the asymptotic distribution of H or the $\hat{R}^2$ distribution under the non-parametric bootstrap.

Overall, the fact that inferences are the same under the bootstrap distribution as under the asymptotic distribution is reassuring with respect to the validity of the latter. This conclusion is reinforced by visual inspection of the histograms of the non-parametric bootstrap distribution of $\hat{R}_i^2$ for each currency, shown in Figure 5. The histograms all appear symmetric around the sample mean (i.e., the bootstrap estimate of the mean of $\hat{R}^2$ and therefore the bootstrap estimate of the true predictability R^2) and largely resembling normal distributions. The two different confidence intervals we consider (namely the one with endpoints given by the 5th and 95th percentiles and the one to which we referred as the MV bootstrap confidence interval, as explained in Appendix) are indeed very similar. This fact also suggests that the bootstrap distribution is close to normal, as this assumption is implicitly imposed in the construction of the second type of interval, and therefore in line with the asymptotic distribution derived by Hosking (1979). The exception is represented by the confidence intervals of the Japanese Yen in the parametric bootstrap (and, to a much lesser extent, the Swiss Franc), in the parametric case. It is not obvious why, for this currency, there is a discrepancy between the parametric bootstrap distribution and the asymptotic distribution of predictability. The exploration of circumstances under which this happens, pointing to a possible break-down of the asymptotic result, is a question we leave for future work.

To save space, we do not report test results (whether using the asymptotic or the bootstrap distribution) for the sub-sample periods considered in Table 2. In all cases and with the exception of the Japanese Yen, the evidence of statistically significant violations of the predictability bounds is limited to the first sub-sample period. It would be wrong, however, to conclude that the bulk of the predictability found in the full sample period, namely over 1972-2012, is due to early inefficiency in currency pricing. Instead, it simply means that the currencies (except the Japanese Yen) were not mispriced at the beginning (i.e., t_0 in the notation introduced earlier) of each of the three post-1982 sub-periods, though they might be mispriced at other times throughout the sample period. Moreover, currency mispricing might occur infrequently enough for our tests to detect it. Even episodes of large but temporary mispricing may result in limited (though positive) excess-profitability and therefore limited, though positive, excess-predictability if occurring infrequently enough over a given sample period. The problem in this situation is the possibly limited power of tests against the null of no excess-predictability (including our test as well as tests focussing on the profitability of trading rules employed by other authors). That is, excess-predictability might become diluted enough for our test to fail to reject a false null of no excess-predictability. These are problems in which previous studies might have incurred too. To gain a more exhaustive picture of the evolution of excess-predictability and mispricing over time, we therefore construct versions of the rolling estimates of predictability adjusted for sampling error. The rolling nature of the estimation windows allows mispricing to be estimated throughout the sample period, rather than at the beginning of a handful of sub-sample periods, and the fact that the estimation windows are relatively short (5 years) should help increase the power against the null of no excess-predictability. To adjust $\hat{R}^2_{i,t\to t+l}$ for sampling error, we use its asymptotic distribution and standard error, both given in Appendix B. For each currency, we use sample auto-covariances (as explained in Appendix) estimated over rolling 5-year windows to construct a series of rolling standard errors, which we denote as $\hat{\sigma}(\hat{R}^2_{i,t\to t+l})$, and use the latter to construct a version of $\hat{R}^2_{i,t\to t+l}$ adjusted for sampling error at the 95 percent confidence level under the null of a predictability upper bound given by $\text{RRA}_{\text{V}} = 5.0$, namely $\hat{R}^2_{i,t\to t+l,adj} \equiv \hat{R}^2_{i,t\to t+l} - 1.64 \times \hat{\sigma}(\hat{R}^2_{i,t\to t+l})$. We then use the latter to construct analogues of *BVI* and implied RRA adjusted for sampling error, namely $BVI_{i,t\to t+l,adj} \equiv \hat{R}^2_{i,t\to t+l,adj} - \phi_{t\to t+l}$, and

$$RRA_{i,t\to t+l,adj} = \sqrt{\hat{R}^2_{i,t\to t+l,adj} / \hat{\sigma}^2_{t,t\to t+l}(r_{m,t+s})}, \tag{15}$$

respectively, where $\hat{\sigma}_{t,t\to t+l}(r_{m,t+s})$ is the volatility of the market portfolio proxy previously obtained. The series of implied RRA adjusted for sampling error thus obtained is plotted, together with a superimposed smoothed HP filter, in Figure 6 (the version of BVI adjusted for sampling error is not reported to save space, as all information it conveys is also conveyed by the corresponding implied RRA series). Visual inspection of the Figure suggests that statistically significant excess-predictability remains a recurring feature of currency markets with no apparent sign that it is (or has been) declining over time. To reconcile this fact with the findings of disappearing profitability of technical trading rules from the early 1990s onwards reported by Olson (2004) and Neely, Weller and Ulrich (2009), as well as with the declining trend of daily profitability seen in Figure 1, one must posit that neither the rules considered by these authors nor daily predictability capture all predictability. One possibility is that markets have learned to exploit the predictability captured by relatively traditional trading strategies, e.g. the trading rules examined by Olson (2004) and Neely, Weller and Ulrich (2009), but not the predictability captured by the more flexible ARMA(p,q) rolling specifications considered in this study or the momentum strategies studied by Okunev and White (2003) and Harris and Yilmaz (2009). Evidence provided by Pukthuanthong, Levich and Thomas (2007) support this conjecture. These authors report that once profitable trend-following rules now lose money, whereas the corresponding counter-trending rules, i.e. rules that do exactly the opposite, are increasingly profitable. Our measure of excess-predictability, especially the rolling version, captures the sources of profitability of both rules.

Table 6 shows that, net of sampling error, the predictability bound is violated in about 10 to 15 percent of the estimation windows for most currencies, and somewhat more often in the case of the Euro. This means that, at the beginning of typically more than a tenth of the 5-year estimation windows and from the perspective of a RE investor, the currencies under consideration were mispriced against the USD. It is not all bad news, however, for the RE-efficient market perspective. In fact, the Table also shows that the number of average consecutive estimation windows characterized by a statistically positive BVI is a relatively small fraction of the total number of violations. Take, for example, the Canadian Dollar in 1984-1995. It was mispriced in about 18.8 percent of the months but only about 18.6 percent of the episodes of monthly mispricing were followed by another month of mispricing. Therefore, simplifying somewhat, the unconditional probability of two or more months of mispricing in a row can be estimated as just 3.5 percent (i.e., $18.8\% \times 18.6\% \cong 3.5\%$) and the unconditional probability of three or more months of mispricing in a row is just $3.5\% \times 18.6\% \cong 0.65\%$. That is, long-lasting episodes of mispricing are unlikely, suggesting that currency markets correct to within a level consistent with ruling out statistically significant "good-deals" relatively quickly after episodes of mispricing.

7. In-Sample vs. Out-of-Sample Predictability

So far we have examined in-sample predictability. An important question is how our measures of in-sample predictability relate to out-of sample predictability because in sample and out-of-sample estimates of predictability pick up different components of the overall true predictability.[14] In Figure 7, we compare in-sample and out-of-sample predictability estimates generated by the same reduced form representations

[14] Out-of-sample tests are based on forecasts that exploit only information contained in past prices (i.e. currency returns) and therefore they can only be used to make inferences on the EMH in its weak form, whereas in-sample tests are powerful, at least in principle, against weak and strong formulations of the EMH since the regressors in the reduced form model for the DGP, i.e. in (11), should pick-up both public and private available information not yet embedded in prices but that manifest themselves through the subsequent price action. In-sample tests, however, can detect mispricing only to the extent that exchange rates revert to their RE fundamental valuation, and that they do so not too slowly before the end of the sample period, whereas out-of-sample tests pick up predictability that results in protracted momentum, even in the absence of mean-reversion to RE by the end of the sample period.

of the DGP, namely the ARMA(p,q) with orders p and q selected by the AIC, estimated over the same 5-years rolling windows. The difference, in the out-of-sample case, is that estimates of the DGP are used to generate 1 step-ahead forecasts of the currency return. Following Campbell and Thompson (2008), we collect these 1 step-ahead forecasts in time series and regress, again over rolling 5-year windows, the actual currency return series against the predicted series. This yields, for each currency, the series of rolling out-of-sample $\hat{R}^2_{i,t\rightarrow t+l}$ coefficients shown in the Figure, which we denote as $\hat{R}^2_{o;i,t\rightarrow t+l}$, analogous to the out-of-sample R^2 considered by Campbell and Thompson (2008), where l = 60 months as for the in-sample rolling predictability series. Each pair of corresponding points on the out-of-sample time series thus obtained and their (previously introduced) in-sample counterparties are comparable as they represent the amount of out-of-sample predictability and in-sample predictability, respectively, that can be exploited at time t over the following 5 years for each currency. Aiming to cover as much as possible of the post 2007 period, both series are constructed using the extended sample period, i.e. using an extra year of data up to July 2013. The last month for which a one-step ahead forecast is available is therefore July 2008, as we use l = 5 years of data to generate each out of sample forecast. Accordingly, the predictability series run from 1972 to July 2008.

As shown in the Figure, in-sample predictability typically exceeds out-of-sample predictability though, over large portions of the overall-sample period, they tend to move together. In Table 7, we report the results of the regression of the out-of-sample series on the in-sample series (the regression is shown at the top of the Table). The regressions confirm the tight link between the two estimates of predictability, in that the coefficient of the out-of-sample series is highly significant and the coefficient of determination of the regression is relatively high for all the currencies. From the Figure, however, the strength of the link does not appear to be constant over time.[15]

In Panel A of Figure 8, we report the equally weighted average of the out-of-sample R^2 series across currencies, namely $\frac{1}{6}\sum_{i=1}^{6}\hat{R}^2_{o;i,t\rightarrow t+l}$ $\forall t \in [1,\ldots,T]$, alongside the predictability bound. In Panel B of the same Figure, we report the difference between the former and the latter, as a synthetic measure of excess out-of-sample predictability. The figure confirms the drop in out-of-sample predictability in the early and mid-90s detected by numerous authors but also shows that, coherently with the in-sample analysis, excess-predictability has returned to a level that is comparable to before the late 80s and early 90s peaks. Interestingly, while there was a surge in average predictability after 2006, excess-predictability did not undergo such an increase, due to the concurrent increase of the predictability bound (greater market volatility). That is, the post-2006 years were not times of abruptly increasing excess-predictability, though they were times of abruptly increasing predictability.

[15] We conjecture it might depend on the volatility of predictability itself, in that during times of more volatile predictability it might be harder for our rolling ARMA(p,q) procedure to generate accurate forecasts. We therefore added to the figure shaded areas that identify times when the volatility of the BVI index is larger than its own unconditional 75th percentile, i.e. times of large volatility of excess-predictability, but no clear relation between the former and the latter is apparent. It would be interesting to explore further the relation between in-sample and out-of-sample predictability. It would be, however, outside the scope of the present paper and we therefore leave it for future research.

8. Conclusions and Final Remarks

As pointed out by Taylor (2005), currency strategies have tended to be, by far, more profitable than strategies that attempt to exploit the predictability of other asset classes. A natural question is then whether such profitability stems from inefficient pricing. In this paper, we assess the statistical and economic significance of predictability in currency returns over the period 1972-2012 by analysing the frequency and magnitude of violations of a boundary consistent with rational pricing and the absence of "good deals". We find that, even under a relatively wide bound on relative risk-aversion, predictability often violates the attendant theoretically motivated upper bound. This happens in as many as 10 to 15 percent of the rolling estimation windows, though typically only briefly. This evidence implies the availability of "good deals" and thus violation of the EMH under a broad class of asset pricing models, with conservatively high values of the marginal investor's RRA and with realistic levels of transaction costs. Crucially, this excess-predictability does not disappear after the mid-1990s, contrary to the conclusions of several recent studies. Taken together, our findings pose a challenge to the EMH but they are consistent with Lo's (2004) AMH.[16] Offering confirmation that technical trading is still alive in the currency domain, Pojarliev and Levich (2008) have shown that currency hedge funds behave as if they follow standard technical trading strategies. Menkhoff and Taylor (2007) note the "obstinate passion of foreign exchange

[16] On a similar note, Lo (2005) offers, on pp. 35-36, a suggestive discussion of the cyclical behaviour of the first-order autocorrelation of the S&P Composite Index. In particular, on p. 35, Lo (2005) argues: "Rather than the inexorable trend to higher efficiency predicted by the EMH, the AMH implies considerably more complex market dynamics, with cycles as well as trends, and panics, manias, bubbles, crashes and other phenomena that are routinely witnessed in natural market ecologies. These dynamics provide the motivation for active management."

professionals" for technical analysis. Our results suggest that currency market professionals have been advocates of technical analysis in FX for years not out of blind faith, but because FX predictability is genuinely a recurring phenomenon.

In previous versions of the paper, we showed that the strategies that rationally exploit this predictability are closely related to, though not spanned by, popular currency trading benchmarks, including the momentum-based AFX index and the carry trade factors proposed by proposed by Lequeux and Acar (1998) and Lustig et al. (2011), respectively. This suggests that technical trading rules represent *heuristics* deployed by imperfectly rational market participants to supplement their pricing abilities, which in some cases have offered a successful means to achieve more desired trading outcomes. While this is an intriguing possibility, we leave the investigation of the role of technical analysis in currency market learning to parallel research.

Appendix A

The expectation of excess-returns in equation (2) in the main text of the article is conditional on public information, whether already reflected in prices or otherwise, as well as on private information, but we only observe a sequence of subsets of I_t, i.e. $J_t \subseteq I_t$ with $t \in [1, 2, \dots T]$. In this circumstance, from the econometrician's point of view, the error is

$$\varepsilon_{t+1} = \mu_{t+1} + u_{t+1} - E(r_{t+1}|J_t) = u_{t+1} + \mu_{t+1} - E(\mu_{t+1}|J_t)$$

Proposition I here below enumerates some key properties of ε_{t+1}.

Proposition I: when the forecaster uses J_t instead of I_t, (a) the prediction is unbiased with respect to J_t but (b) the errors ε_{t+1} are not zero-mean innovations with respect to I_t and (c) they are more volatile, i.e. $\sigma^2(\varepsilon_{t+1}) \geq \sigma^2(u_{t+1})$.

Proof: Since $E(\varepsilon_{t+1}|J_t) = 0$, the prediction is unbiased, which proves (a). Also, since $J_t \subseteq I_t$,

$$E(\varepsilon_{t+1}|I_t) = E(r_{t+1} - E(r_{t+1}|J_t)|I_t) = \mu_{t+1} - E(E(r_{t+1}|J_t)|I_t)$$
$$= \mu_{t+1} - E(E(\mu_{t+1}|J_t)|I_t) \neq 0$$

That is, the errors ε_{t+1} are not zero-mean innovations with respect to I_t and therefore (b) is proved. This also implies that the unconditional variance of ε_{t+1} is larger than the unconditional variance of the true errors. Hence, (c) is proved too.

Therefore, since J_t includes the sigma-field generated by the past of ε_{t+1}, the latter is, conditional on J_t, a zero-mean innovation, but, as per Proposition I.c., the use of J_t instead of I_t entails a loss of power in tests of the RE/EMH. Unfortunately, the loss of power cannot be quantified because the difference between J_t and $I_t$is, by definition, unknown.

Appendix B: Hosking's (1979) R^2 Asymptotic Distribution

Hosking (1979) derived the asymptotic distribution of the coefficient of determination $\hat{R}^2$ of the ARMA(p,q) model, valid when the model parameters are estimated[17] and the estimated model encompasses the true one,

$$\hat{R}^2 \sim N\left(R^2, \frac{4(1-R^2)^2}{T} \sum_{k=1}^{\infty} \rho_k^2 \right) \qquad \text{(B.1)}$$

Here, $R^2 \equiv \frac{\sigma_\mu^2}{\sigma_r^2}$ is the coefficient of determination in the DGP and $\rho_k = \frac{E(y_t y_{t-k})}{E(y_t^2)}$ denotes the k-th order autocorrelation of the series y_t. In our case, y_t is a currency return and R^2 is bounded from above by the predictability upper bound, i.e. $R^2 \leq \phi$. Letting $R^2 = \phi$, and thus under the null that the coefficient of determination equals (and hence does not exceed) the bound, the above result can be rewritten to obtain a convenient statistic for one-tailed tests that estimated predictability does not exceed the predictability upper bound ϕ, i.e.

$$H = \frac{\hat{R}^2 - \phi}{\sigma(\hat{R}^2)} \equiv \frac{BVI}{\sigma(\hat{R}^2)} \sim N(0,1) \qquad \text{(B.2)}$$

Here, the quantity $\sigma(\hat{R}^2) = \sqrt{\frac{4(1-\phi)^2}{T} \sum_{k=1}^{\infty} \rho_k^2}$ denotes the variance of the predictability estimate under the null that $R^2 = \phi$, whereas it represents a lower bound to such a quantity under the null that $R^2 \leq \phi$. The use of this lower bound is a test configuration *least favourable* to the excess-predictability alternative

[17] In the original article by Hosking (1979), the term $(1 - R^2)$ was not squared but this is an error due to referring to the terms r_k^y, in the two paragraphs just above equation (2) in the article, as (kth order) autocorrelations whereas they should be the square thereof.

(simplifying somewhat, it implies a smaller test statistic), thereby ensuring that the nominal size does not underestimate the true size of the test. To construct an estimate for $\sigma(\hat{R}^2)$, we use $\frac{1}{T}\sum_{k=1}^{m}\hat{\rho}_k^2$ as a sample counterpart of $\frac{1}{T}\sum_{k=1}^{\infty}\rho_k^2$, where $m = \min[l/4, 2\sqrt{l}]$, e.g. $m = 22$ for $l = 60$. We do this because the computation of the variance of the coefficient of determination requires a consistent[18] estimate of the terms of $\sum_{k=1}^{\infty}\rho_k^2$.

One possible criticism of a test of excess-predictability based on the H statistic asymptotic distribution in (B.2) is that it does not take into account the sampling error of the market portfolio volatility. This is because, in practice, ϕ must be computed from the assumed upper bound on RRA, namely RRA_V, and an estimate of the volatility of the market portfolio. Therefore, in (B.2), we typically cannot use $\phi \equiv RRA_V \sigma^2(r_{m,t+1})$ directly but rather $\hat{\phi} = RRA_V \hat{\sigma}^2(r_{m,t+1})$. From this point of view, the null that is tested is not that predictability does not excess ϕ but rather that, given an estimate of the market portfolio variance provided by $\hat{\sigma}^2(r_{m,t+1})$, it does not imply a RRA in excess of RRA_V. It can be argued, however, that sampling error of the market portfolio volatility is negligible in that the variance of returns is notoriously estimated with considerably less error than the mean return.

[18] If we estimated the latter using $m = \infty$, we would have very few observations at our disposal to estimate autocorrelations of high orders, i.e. with k large and close to T. This would lead to inconsistent estimates of ρ_k and thus of the sampling error of R^2.

Appendix C: Parametric and Non-Parametric Bootstrap R^2 Distribution

In the parametric bootstrap[19], we do the following:

1. We generate B = 1,000 bootstrapped currency returns samples by re-sampling with replacement, using the stationary bootstrap of Politis and Romano (1994), from the residuals of the selected ARMA(p,q) model (where p and q are given in both Table 2 and Panel A of Table 5);
2. We use these residuals, together with the point estimates of the model, to generate the bootstrap currency returns samples;
3. We estimate the selected ARMA(p,q) model over each bootstrap sample and each time record the coefficient of determination $\hat{R}_b^2$ of the estimated model;
4. We use the resulting set of bootstrap observations on $\hat{R}^2$ to construct the bootstrap distribution of the latter.

In step 1, to preserve any serial dependence of the errors not captured by the estimated ARMA(p,q) model, the resampling is done in blocks with expected length equal to 10. In the non-parametric bootstrap, we do the following:

1. We generate B = 10,000 bootstrapped currency returns samples by re-sampling with replacement directly from the currency excess-return series, using again the stationary bootstrap of Politis and Romano (1994);
2. We then use the AIC to select, for each bootstrap sample, the appropriate ARMA(p,q) model, we estimate the latter and each time record the coefficient of determination $\hat{R}_b^2$ of the estimated model;

[19] This approach to bootstrapping is also known as estimation-based bootstrap. It has been introduced by Freedman and Peters (1984) and Peters and Freedman (1984), and has been used by Karolyi and Kho (2004) to test the profitability of momentum strategies.

3. We use the resulting set of bootstrap observations on $\hat{R}^2$ to construct the bootstrap distribution of the latter.

In step 1, to preserve the serial dependence of the return series, the resampling is done in blocks with expected length equal to 20. With the bootstrap distribution of $\hat{R}^2$ in hand, whether obtained through the parametric or the non-parametric procedure, we then compute bootstrap estimates of the mean of the $\hat{R}^2$ distribution, namely $\hat{E}_b(\hat{R}^2) = \frac{1}{B}\sum_{b=1}^{B} \hat{R}_b^2$, and its variance, namely $\widehat{Var_b}(\hat{R}^2) = \frac{1}{B}\sum_{b=1}^{B}\left(\hat{R}_b^2 - \hat{E}(\hat{R}^2)\right)^2$. For each currency, we use the latter of these two moments to construct the bootstrap analogue of the excess-predictability statistic H, namely $H = \frac{\hat{R}^2-\phi}{\sqrt{\widehat{Var_b}(\hat{R}^2\,)}}$, so as to permit a comparison with the value of this statistic (reported in Panel A of the Table) computed using the asymptotic estimate of $\widehat{Var}(\hat{R}^2\,)$. We also construct two types of bootstrap 90-percent confidence intervals. The first type of confidence interval is given directly by the 5th and 95th percentiles of the empirical distribution of $\hat{R}_b^2$ (which is the bootstrap distribution of $\hat{R}^2$). The second type, to which we refer as the Mean-variance (MV) bootstrap confidence interval, is obtained as $\hat{E}_b(\hat{R}^2) \pm \sqrt{\widehat{Var}_b(\hat{R}^2)}$, imposing the assumption that, as in the asymptotic case, the $\hat{R}^2$ distribution is normal and therefore can be described in full by its mean and variance. In either case, in a one-sided test, we reject the null that $R^2 - \phi \leq 0$ at the 5 percent level when the lower end of the confidence interval exceeds the predictability bound.

Table 1
Daily Predictability vs. Bound
ARMA(5,0)

Sample Period	AUD	CAD	JPY	GBP	CHF	ECU/ EUR	Bound	SR Bound p.a.
				Predictability (R^2)				
1971-2012	0.22	0.08	0.04	0.24	0.02	0.12		
1971-1976	-	1.62	0.98	1.52	0.76	-		
1977-1982	1.06	0.96	0.27	0.48	0.26	-		
1983-1988	0.64	0.79	0.99	1.07	0.36	0.19		
1989-1994	0.56	0.28	0.19	0.38	0.19	0.74		
1995-2000	0.43	0.55	0.12	0.94	0.24	0.19		
2001-2006	0.53	0.81	0.31	0.10	0.89	0.67		
2007-2012	0.98							
				Annualized Excess-Predictability under RRA_V = 2.5 ($\gamma_{RRA=2.5}$)				
1971-2012	61.4	15.9	-	63.5	-	35.5	0.08	44.9
1971-1976	-	198.3	152.3	191.8	132.8	-	0.06	38.9
1977-1982	159.5	151.4	74.5	104.1	72.7	-	0.05	35.5
1983-1988	117.7	132.8	150.6	157.1	82.5	50.2	0.09	47.6
1989-1994	114.5	77.8	61.5	92.6	61.5	132.8	0.04	31.7
1995-2000	95.2	110.0	35.5	148.1	65.5	55.0	0.07	42.0
2001-2006	107.7	136.6	77.8	27.5	143.7	123.0	0.07	42.0
2007-2012	144.0	29.4	114.7	121.9	32.5	53.0	0.16	63.5
				Annualized Excess-Predictability under RRA_V = 5 ($\gamma_{RRA=5}$)				
1971-2012	-	-	-	-	-	-	0.30	87.0
1971-1976	-	187.2	137.5	180.3	115.6	-	0.23	76.1
1977-1982	148.9	140.2	47.6	86.9	44.9	-	0.18	67.3
1983-1988	86.9	106.5	128.0	135.6	22.4	-	0.34	92.6
1989-1994	101.6	57.2	31.7	76.1	31.7	121.9	0.15	61.5
1995-2000	61.5	82.5	-	129.0	-	-	0.28	84.0
2001-2006	85.5	119.8	42.0	-	128.0	104.1	0.24	77.8
2007-2012	94.3	-	36.3	55.0	-	-	0.63	126.0

Notes. This table reports the percentage coefficient of determination R^2 for each currency, the predictability upper bounds under RRA upper bounds equal to 2.5 and 5, the percentage bounds and versions thereof expressed as annualized SRs ('Bound' and "SR Bound p.a.", respectively), and a measure of excess-predictability, namely $\lambda_{i,t_0 \rightarrow t_1}$,under a RRA upper bound set to either 2.5 or 5, converted to annualized SR units. The estimation method is maximum likelihood.

Table 2
Monthly Predictability and Excess-Predictability

	AUD	*CAD*	*JPY*	*GBP*	*CHF*	*ECU/EUR*
1971-2012						
p	0	5	4	5	0	0
q	1	5	5	5	1	1
R^2	11.80	10.98	15.21	20.01	8.54	11.17
$BVI_{RRA=2.5}$	10.53	9.71	13.93	18.73	7.26	9.90
$BVI_{RRA=5.0}$	6.70	5.88	10.10	14.90	3.44	6.10
$\gamma_{RRA=2.5}$	112.39	107.92	129.30	149.92	93.36	109.01
$\gamma_{RRA=5.0}$	89.66	83.98	110.11	133.72	64.20	85.54
1971-1982						
p	2	2	4	2	1	1
q	1	4	4	0	0	0
R^2	23.01	6.83	21.58	22.84	10.66	5.00
$BVI_{RRA=2.5}$	21.66	5.48	20.23	21.49	9.31	3.65
$BVI_{RRA=5.0}$	17.61	1.43	16.18	17.44	5.26	-
$\gamma_{RRA=2.5}$	161.22	81.09	155.81	160.59	105.70	66.18
$\gamma_{RRA=5.0}$	145.37	41.42	139.34	144.67	79.45	-
1983-1994						
p	0	3	3	0	1	0
q	4	4	2	1	2	1
R^2	16.09	6.51	12.77	17.72	12.90	12.47
$BVI_{RRA=2.5}$	14.91	5.33	11.59	16.54	11.72	11.29
$BVI_{RRA=5.0}$	11.35	1.77	8.03	12.98	8.16	7.73
$\gamma_{RRA=2.5}$	133.76	79.97	117.93	140.88	118.59	116.40
$\gamma_{RRA=5.0}$	116.70	46.09	98.16	124.80	98.95	96.31
1995-2006						
p	0	0	4	2	0	0
q	2	1	2	0	1	1
R^2	9.99	4.98	20.45	5.20	8.91	13.34
$BVI_{RRA=2.5}$	8.85	3.84	19.31	4.06	7.77	12.20
$BVI_{RRA=5.0}$	5.43	0.42	15.89	0.64	4.35	8.78
$\gamma_{RRA=2.5}$	103.05	67.88	152.22	69.80	96.56	121.00
$\gamma_{RRA=5.0}$	80.72	22.45	138.09	27.71	72.25	102.65
2007-2012						
p	1	1	3	1	1	1
q	0	0	2	0	0	4
R^2	18.90	8.01	24.72	16.83	1.42	25.98
$BVI_{RRA=2.5}$	17.18	6.29	23.00	15.11	-0.30	24.26
$BVI_{RRA=5.0}$	12.01	1.12	17.83	9.94	-5.47	19.09
$\gamma_{RRA=2.5}$	143.58	86.88	166.13	134.66	-	170.62
$\gamma_{RRA=5.0}$	120.05	36.66	146.27	109.22	-	151.35

Notes. This table reports, for the full sample period 1971-2012 and four sub-sample periods, the autoregressive *p* and moving average *q* terms order lags selected by the Akaike Information Criterion (AIC) and the percentage coefficient of determination R^2 of the chosen ARMA(p,q) predictive regressions. The table also reports excess predictability measures BVI and (annualized) γ computed under a RRA upper bound equal to 2.5. The estimation method is a Gauss-Newton (GN) algorithm with numerical derivatives (the default choice in RATS™) or, when this procedure fails to converge, the Broyden, Fletcher, Goldfarb and Shanno (AFGS) method described in Press et al. (1988) or a genetic search (GEN) algorithm. The data frequency is monthly.

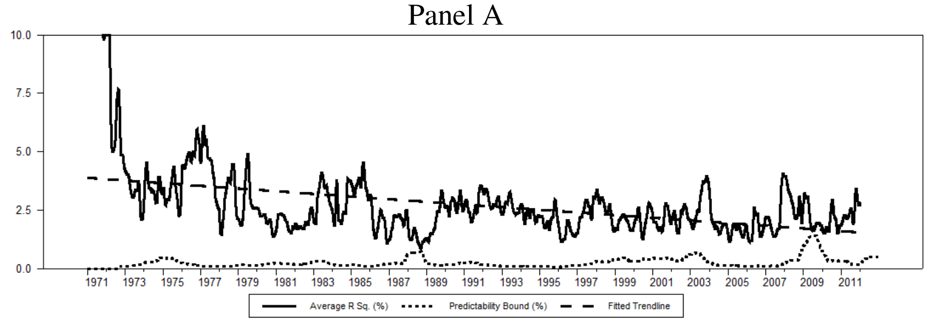
Table 3
Monthly Predictability Bound

RRA_V	**Bounds**	**Bound p.a.**
	1971-2012	
2.5	1.28	39.13
5.0	5.10	78.27
	1971-1982	
2.5	1.35	40.2
5.0	5.40	80.5
	1983-1994	
2.5	1.18	37.7
5.0	4.74	75.4
	1995-2006	
2.5	1.14	37.0
5.0	4.56	74.0
	2007-2012	
2.5	1.72	45.48
5.0	6.89	90.96

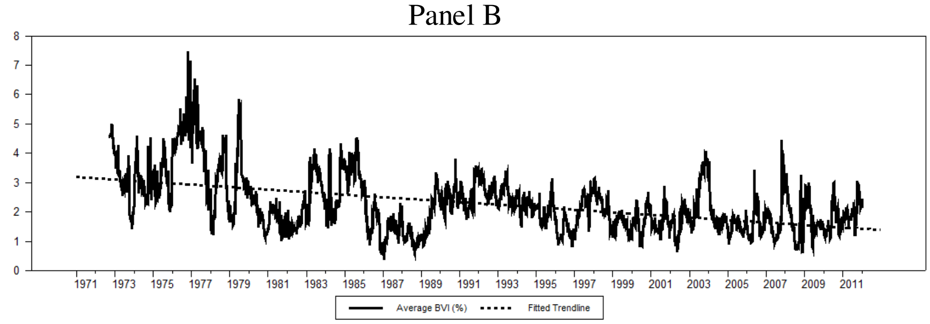
Notes. This table reports, for the full sample period and for four sub-periods of about equal length, monthly and annualized (p.a.) percentage predictability upper bounds under RRA upper bounds equal to 2.5 and 5.00.

Figure 1
Daily Excess-Predictability

Panel A

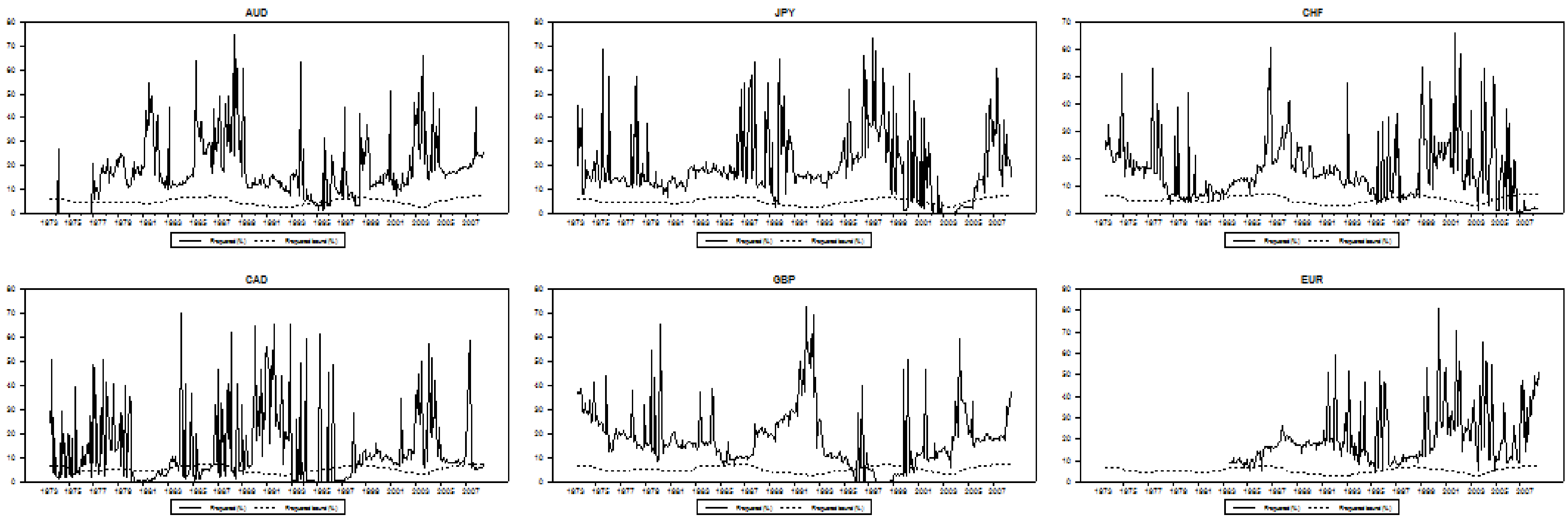


Panel B



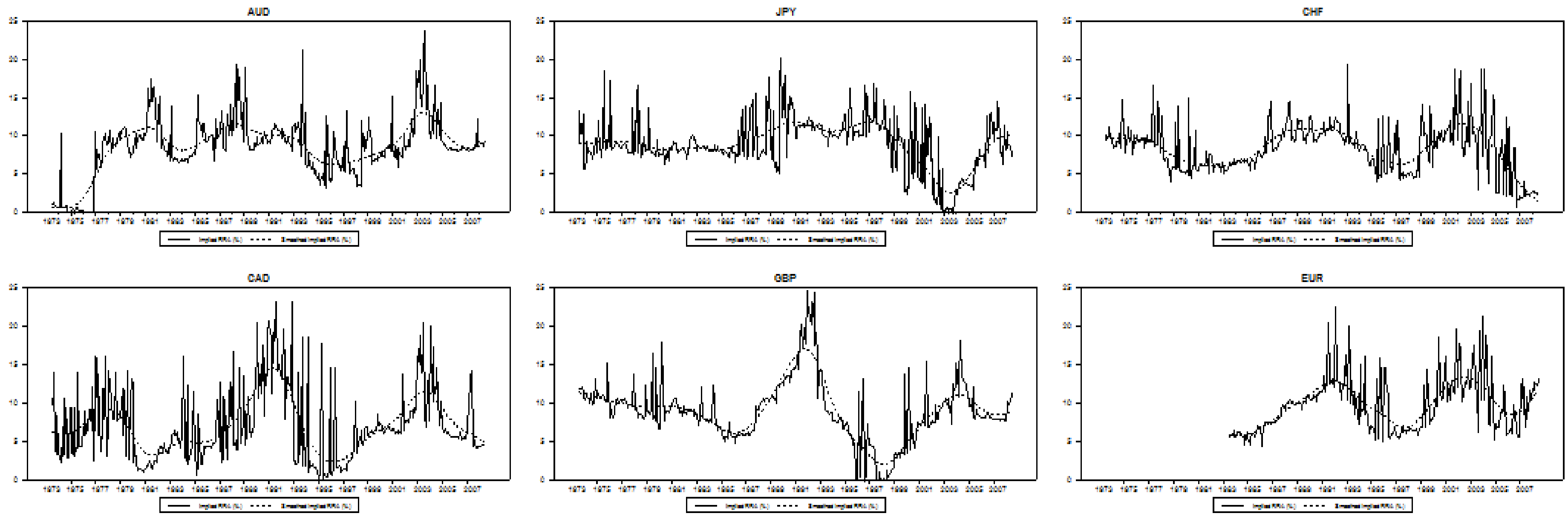
Notes. Panel A of this figure plots, for each point in our sample period, the average of the percentage R^2 of the predictive AR(5) regressions across all currencies in our sample, as well as the predictability bound calculated under a RRA upper bound of 5, i.e. $RRA_V = 5$. Panel B plots the corresponding average BVI. The estimation window of each auto-regression is one year and the sample period is 1971-2012. The average BVI series has been cut off at 10.0 for improved visual clarity.

Figure 2
Monthly ARMA(p,q) Predictability vs. Predictability Bound



Notes. These figures plot the sequences of the percentage coefficients of determinations (shown by the solid thin lines) of rolling ARMA(p,q) models of the monthly return on each currency in our sample against their upper bound (the thick dotted lines). The bound for each currency is computed under a relative risk aversion upper bound of 5. The estimation window of each predictive regression is 5 years and they run from 1972 to 2012. The estimation method is maximum likelihood.

Figure 3
Implied RRA



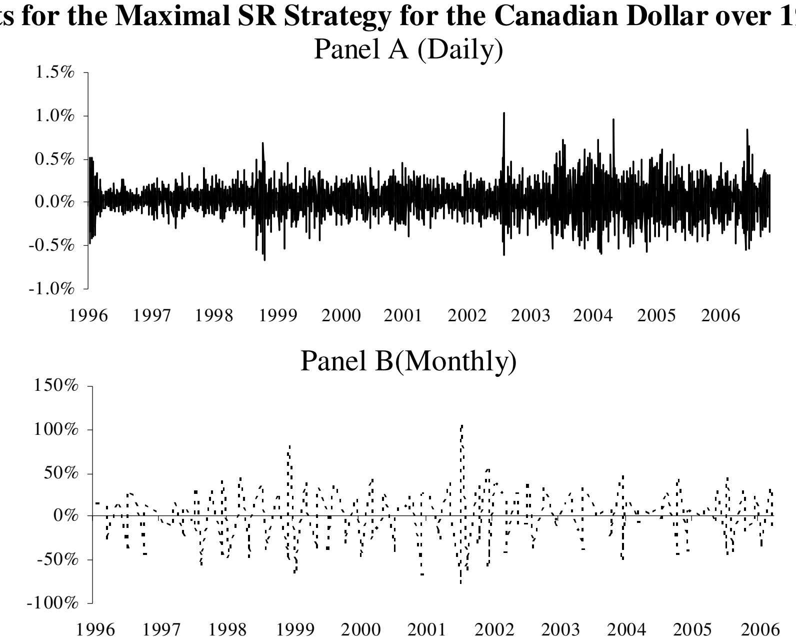
Notes. These figures plot, for each point in our sample period and each currency in our sample, the RRA bound implied (given the estimated S&P500 volatility) by the coefficient of determination $\hat{R}^2_{i,t\rightarrow t+l,adj}$ of the selected ARMA(p,q) predictive regressions (the same as in Figure 2) estimated over rolling estimation windows, with p and q selected by the AIC within each window. The estimation window of each predictive regression is 5 years of monthly data, i.e. $l = 60$ months, from 1971 to 2012 (hence the mispricing or forward excess-predictability estimates refer to 5-year periods from 1971 to 2007). The super-imposed smoothed line is a HP filter. The estimation is conducted by maximum likelihood and, when this method fails to converge, using in a sequential order the Broyden, Fletcher, Goldfarb and Shanno method described in Press et al. (1988), a simplex method or a genetic search algorithm.

Table 4
Impact of Transaction Costs

Transaction costs (bps)	**0**	**2**	**3**	**5**	**25**	**Bound RRA_V = 2.5**	**Bound RRA_V = 5.0**
		Daily				46.0	88.0
AUD	*57.3	17.4	-2.3	-41.7			
CAD	**130.1	*47.1	5.62	-77.4			
JPY	*49.1	-11.0	-41.1	-101.2			
GBP	*48.4	20.0	5.7	-22.7			
CHF	**104.3	*47.7	19.6	-36.7			
ECU/EUR	*82.1	22.7	-7.1	-66.6			
		Monthly				39.2	78.3
AUD	*43.3	*40.9	*39.8	37.4	14.0		
CAD	*39.5	34.0	31.1	25.6	-30.7		
JPY	*53.0	*51.4	*50.6	*48.9	32.2		
GBP	37.4	35.5	3.5	32.5	12.7		
CHF	*60.2	*58.0	*57.0	*54.8	32.7		

Notes. This Table reports percentage annualized maximal Sharpe ratios of strategies that rationally exploit the estimated predictability of daily and monthly currency returns, as a function of various levels of transaction costs (in basis points in the top row). The estimated daily predictive regression models are ARMA(5,0) for all currencies. The estimated monthly predictive regression models are ARMA(5,2) for all currencies. The last two columns report the annualized maximal SR bounds under RRA upper bounds equal to 2.5 and 5. The SR bound is computed by taking the square root of the predictability bound and annualizing. One and two asterisks are used to draw attention to SRs in excess of the bound corresponding to RRA = 2.5 and RRA = 5, respectively. The sample period is 1972-2012.

Figure 4
Weights for the Maximal SR Strategy for the Canadian Dollar over 1996-2006



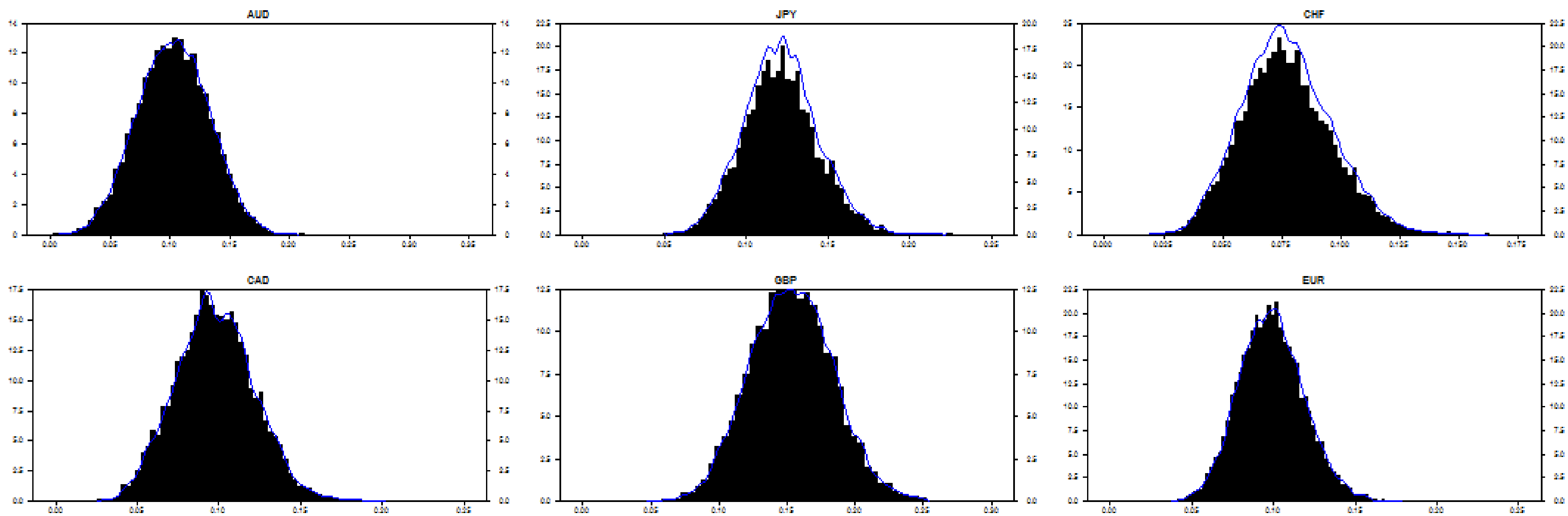
Notes. Panel A and B of this Figure plot the time-varying weights of the rational trading rules that exploit the predictability of daily and monthly, respectively, Canadian Dollar returns, based on estimates from an ARMA(5,0) model for daily returns and ARMA(5,2) for monthly returns. The weights are rescaled in such a way that they add up to 1 over the sample-period.

Table 5
Monthly Excess-Predictability Tests
1972-2012

	AUD	***CAD***	***JPY***	***GBP***	***CHF***	***ECU/ EUR***
			Panel A **Asymptotic distribution**			
p	0	5	4	5	0	0
q	1	5	5	5	1	1
$\boldsymbol{R^2}$ (%)	11.80	10.98	15.21	20.01	8.54	11.17
$BVI_{RRA=2.5}$ p.a. (%)	10.53	9.71	13.93	18.73	7.26	9.90
$\lambda_{RRA=2.5}$ p.a. (%)	112.39	107.92	129.30	149.92	93.36	109.01
$\boldsymbol{H_{RRA=2.5}}$	2.89	2.56	3.06	4.59	2.15	2.67
p-value	(0.002)	(0.005)	(0.001)	(0.000)	(0.016)	(0.004)
$BVI_{RRA=5.0}$ p.a. (%)	6.70	5.88	10.10	14.90	3.44	6.10
$\lambda_{RRA=5.0}$ p.a. (%)	89.66	83.98	110.11	133.72	64.20	85.54
$\boldsymbol{H_{RRA=5.0}}$	1.91	1.61	2.31	3.80	1.06	1.71
p-value	(0.028)	(0.053)	(0.011)	(0.000)	(0.145)	(0.043)
			Panel B **Parametric stationary bootstrap** **(block mean length = 10, bootstrap iterations = 1,000)**			
$\hat{R}^2$ (%) distr. 5th - 95th percentile	6.50-16.83	7.75-16.91	9.64-26.24	12.44-23.13	5.47-12.13	7.94-14.77
$\hat{R}^2$ mean (%)	11.66	12.32	15.89	17.80	8.64	11.25
$\hat{R}^2$ variance (%)	0.10	0.08	0.27	0.10	0.04	0.04
$\hat{R}^2$ st. err. (%)	3.13	2.83	5.16	3.23	2.03	2.08
$\boldsymbol{H_{RRA=2.5}}$	3.36	3.43	2.70	5.80	3.58	4.76
$\boldsymbol{H_{RRA=5.0}}$	2.14	2.08	1.96	4.61	1.69	2.93
$\hat{R}^2$ (%) MV distr. 5th - 95th percentile	6.52-16.80	7.68-16.96	7.43-24.35	12.50-23.10	5.31-11.96	7.84-14.66
			Panel C **Non-parametric stationary bootstrap** **(block mean length = 20, bootstrap iterations = 10,000)**			
$\hat{R}^2$ (%) distr. 5th - 95th percentile	5.44-15.15	5.86-13.76	8.46-15.96	10.40-20.39	4.73-10.99	6.77-13.25
$\hat{R}^2$ mean (%)	10.28	9.78	12.13	15.36	7.71	9.89
$\hat{R}^2$ variance (%)	0.09	0.06	0.05	0.09	0.04	0.04
$\hat{R}^2$ st. err. (%)	2.96	2.40	2.26	3.04	1.89	1.97
$\boldsymbol{H_{RRA=2.5}}$	3.56	4.04	6.17	6.16	3.85	5.04
$\boldsymbol{H_{RRA=5.0}}$	2.27	2.45	4.47	4.90	1.82	3.10
$\hat{R}^2$ (%) MV distr. 5th - 95th percentile	5.43-15.13	5.84-13.72	8.43-15.84	10.37-20.34	4.62-10.81	6.67-13.12

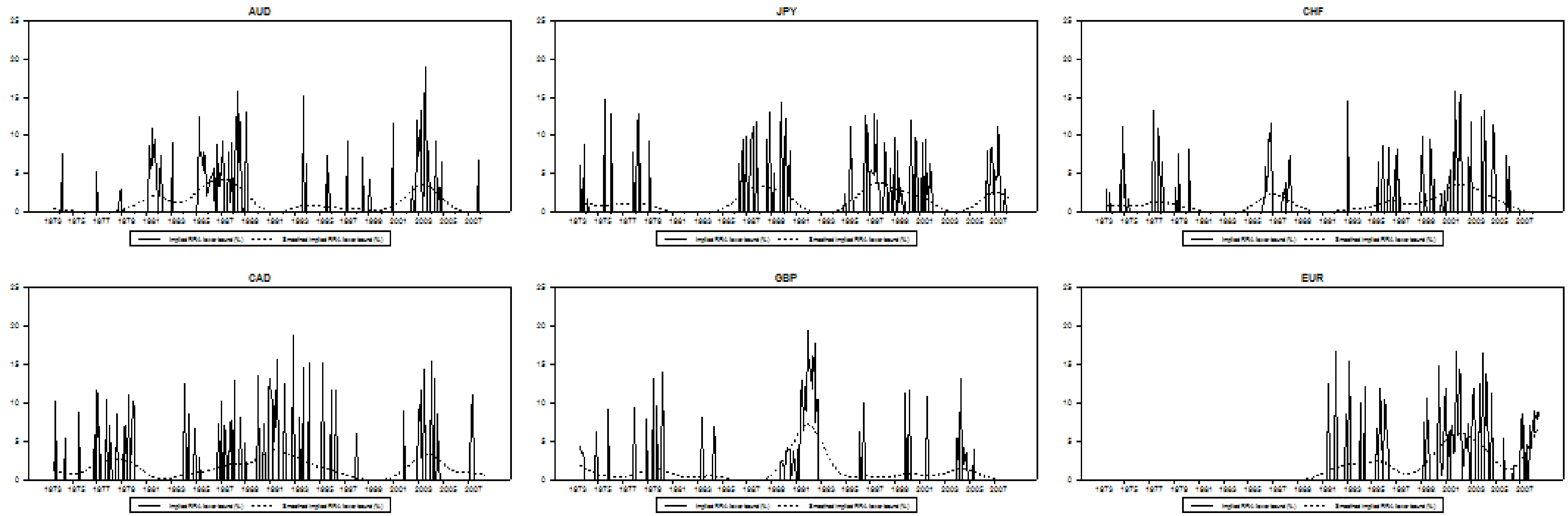
Notes. Panel A of this table reports, for the sample period 1972-2012, the autoregressive p and moving average q terms order lags selected by the Akaike Information Criterion (AIC), the percentage coefficient of determination R^2 of the chosen ARMA(p,q) predictive regressions, the excess predictability measures BVI and (annualized) γ, computed under both RRA upper bounds, as well as the corresponding H statistic and p-value under the asymptotic distribution. In the bottom panels, it reports parametric and non-parametric bootstrapped confidence intervals of the coefficient of determination, of the mean and variance of the latter and bootstrap versions of the H statistic. The data frequency is monthly. The predictability bounds for this sample-period are 1.28 and 5.10 per cent.

Figure 5
Bootstrap Distribution of R^2 of Estimated ARMA(p,q)
(Histogram and density estimate based on the Epanechnikov kernel)



Notes. This figure plots, for each currency, the histogram of the nonparametric bootstrap distribution of the estimated predictability, $\hat{R}^2$, with the order of the predictive ARMA(p,q) selected using the AIC, based on a non-parametric stationary bootstrap with 10,000 replications and blocks with expected size of 20. The superimposed lines are density estimated using the Epanechnikov kernel. The sample period is 1972-2012.

Figure 6
Implied RRA
(Adjusted for R^2 Asymptotic Sampling Error)



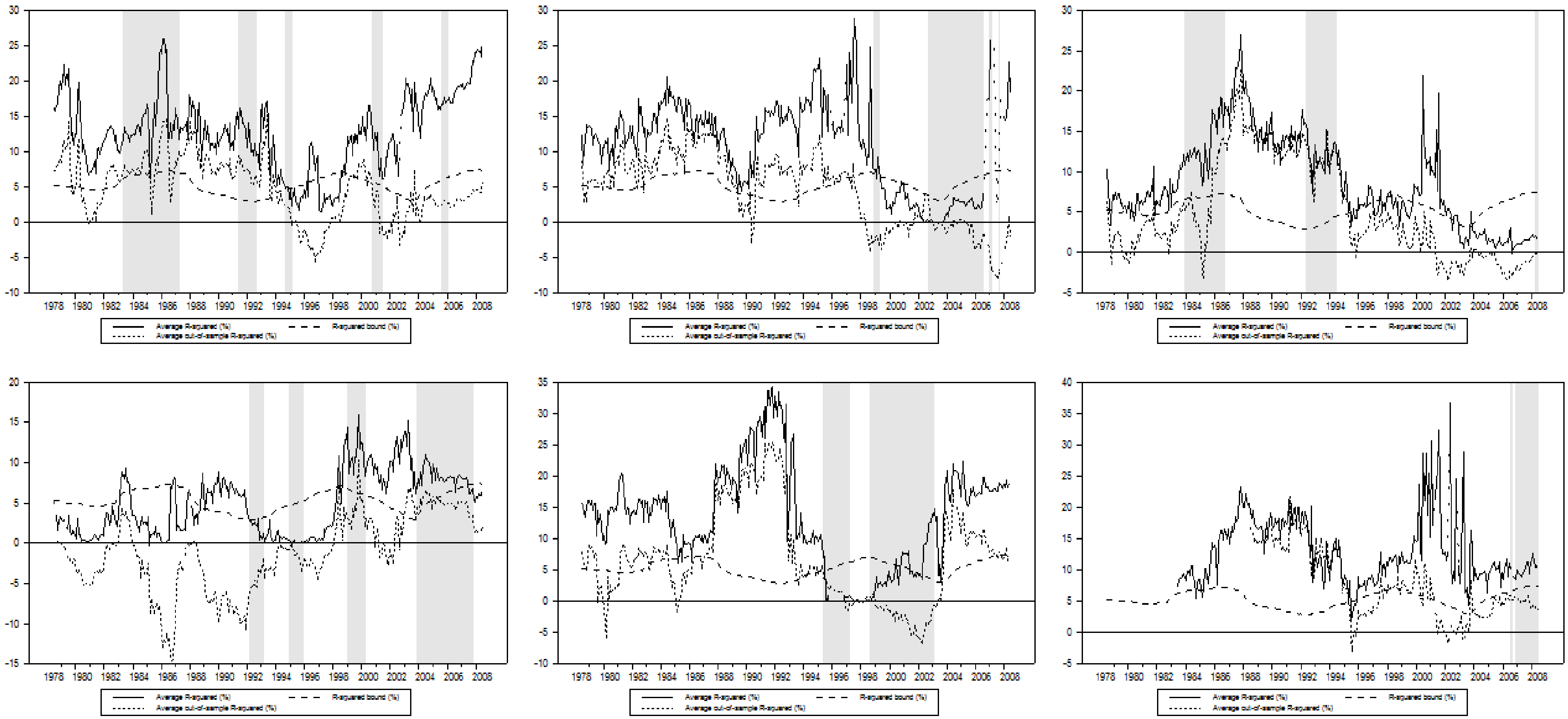
Notes. These figures plot, for each point in our sample period and each currency in our sample, the RRA implied (given the estimated S&P500 volatility) by the coefficient of determination $\hat{R}^2_{i,t\to t+l,adj}$ of the selected ARMA(p,q) predictive regressions (the same as in Figure 2, which forms also the basis for Figure 3) estimated over rolling estimation windows, with p and q selected by the AIC and adjusted for sampling error using Hosking's standard errors. The estimation window of each predictive regression is 5 years of monthly data, i.e. $l = 60$ months, from 1971 to 2012 (hence the mispricing or forward excess-predictability estimates refer to 5-year periods from 1971 to 2007). The superimposed smoothed line is a HP filter.

Table 6
Descriptive Statistics of Significant Boundary Violations Occurrences (Monthly Data)

		AUD	CAD	JPY	GBP	CHF	ECU /EUR
1972-2007	(1)	414	414	414	414	414	294
	(2)	33	54	42	30	32	39
	(3)	8.0	13.0	10.1	7.2	7.7	13.3
	(4)	2.2	3.4	2.2	3.4	2.4	5.4
	(5)	27.5	26.2	21.8	47.2	31.2	40.6
1972-1983	(1)	126	126	126	126	126	6
	(2)	5	13	7	7	7	0
	(3)	4.0	10.3	5.6	5.6	5.6	0.0
	(4)	0.0	2.4	0.0	0.0	0.8	0.0
	(5)	0.0	23.3	0.0	0.0	14.3	0.0
1984-1995	(1)	144	144	144	144	144	144
	(2)	19	27	16	17	6	9
	(3)	13.2	18.8	11.1	11.8	4.2	6.3
	(4)	4.9	3.5	3.5	9.0	2.1	1.4
	(5)	37.1	18.6	31.5	76.3	50.0	22.2
1996-2007	(1)	144	144	144	144	144	144
	(2)	9	14	19	6	19	30
	(3)	6.3	9.7	13.2	4.2	13.2	20.8
	(4)	1.4	4.2	2.8	0.7	4.2	9.7
	(5)	22.2	43.3	21.2	16.7	31.8	46.6

Notes. This table reports, for the rolling predictive regressions considered in Figure 6 for which the estimation procedure converged, (1) the number of windows over which the estimation converged for the full sample period and in each of 3 sub-sample periods, (2) the number and the (3) percentage frequency of positive BVI values, i.e. (2) over (1), as well as the percentage of consecutive instances of positive BVI values as a fraction (4) of the number of instances in which the estimation procedure converged, given in (1), and as a fraction of the times in which BVI is significantly positive, given in (2). BVI is calculated, as explained in the text, under a RRA upper-bound equal to 5.

Figure 7
In-sample and out-of-sample predictability vs. predictability bound



Notes. This figure plots, for each point in our sample period and each currency in our sample (in the same order as in the preceding Figures), the in-sample (thicker line) and out-of-sample (dotted thinner line) $\hat{R}^2_{i,t\rightarrow t+l}$ of ARMA(p,q) predictive regressions, with p and q selected by the AIC, together with the predictability bound under $RRA_V = 5.0$. The estimation window of each predictive regression is 5 years of monthly data, i.e. $l = 60$ months, from 1971 to July 2013 (hence the mispricing or forward excess-predictability estimates refer to 5-year periods from 1971 to July 2008). The estimation is conducted by maximum likelihood and, when this method fails to converge, using in a sequential order the Broyden, Fletcher, Goldfarb and Shanno method described in Press et al. (1988), a simplex method or a genetic search algorithm.

Table 7
Regression of Out-of-Sample on In-Sample R^2

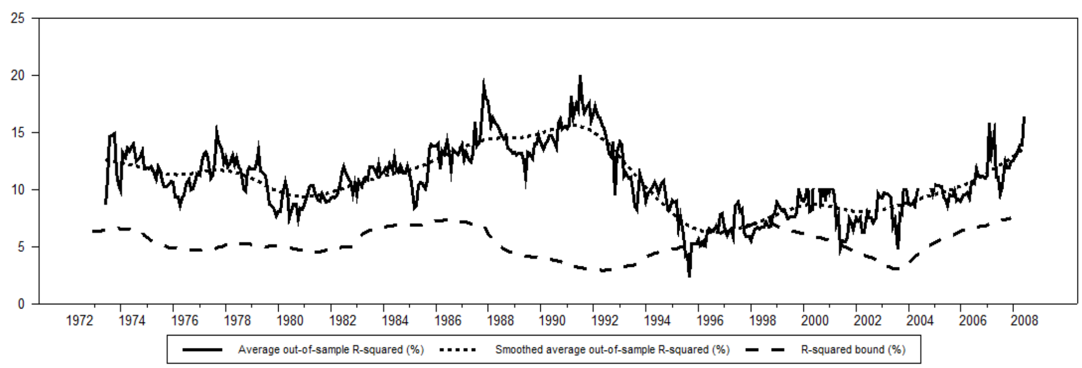
$$\hat{R}^2_{o;i,t\to t+l} = \boldsymbol{a} + \boldsymbol{b}\hat{R}^2_{i,t\to t+l} + \epsilon_{i,t\to t+l}$$

	AUD	*CAD*	*JPY*	*GBP*	*CHF*	*ECU/EUR*
a	0.00	-0.04	-0.01	-0.04	-0.03	0.01
	[-0.76]	[-13.04]	[-2.57]	[-9.34]	[-11.68]	[1.40]
b	0.41	0.66	0.53	0.79	0.95	0.50
	[11.44]	[12.19]	[16.94]	[32.16]	[33.91]	[8.48]
R^2	0.27	0.30	0.46	0.74	0.76	0.24

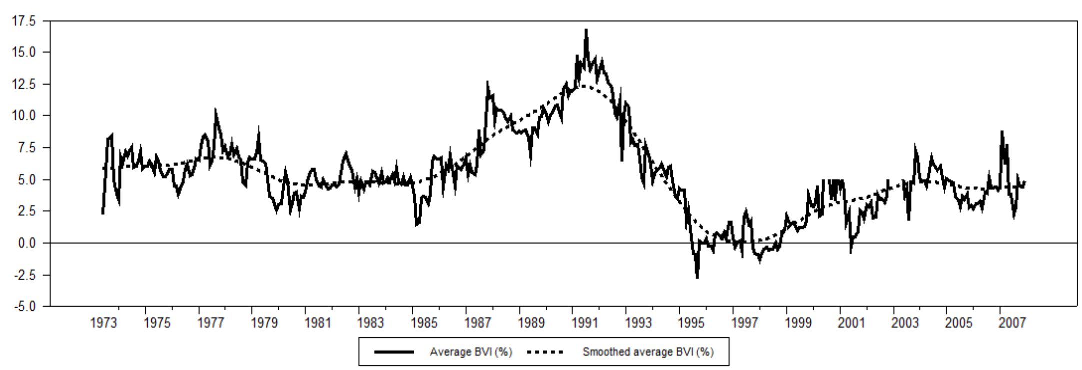
Notes. This table reports, for each currency in our sample, the estimated coefficients and associated t-statistics based on OLS standard errors (in square brackets) of the regression shown above the table, together with its coefficient of determination (below the t-statistics). The dependent and independent variables, namely $\hat{R}^2_{o;i,t\to t+l}$ and $\hat{R}^2_{i,t\to t+l}$, respectively, are those plotted in the preceding figure.

Figure 8
Average Out-of-Sample Predictability and Excess-Predictability
(Rolling 5-Year Estimation Windows, extended sample period)

Panel A



Panel B



Notes. Panel A plots the average out-of-sample monthly predictability across each currency in our sample, based on ARMA(p,q) predictive regressions, with p and q selected by the AIC, and a predictability bound calculated under a RRA upper bound of 5, i.e. $\text{RRA}_\text{V} = 5$. The estimation window of each predictive regression is 5 years of monthly data. Panel B plots the corresponding percentage average BVI index. The overall sample period is from 1971 to July 2013. The superimposed dotted lines are smoothed HP filters. The estimation is conducted by maximum likelihood and, when this method fails to converge, using in a sequential order the Broyden, Fletcher, Goldfarb and Shanno method described in Press et al. (1988), a simplex method or a genetic search algorithm.

Bibliography

Abhyankar, A., Basu, D. and A. Stremme (2012), The Optimal Use of Return Predictability: An Empirical Study, Journal of Financial and Quantitative Analysis 47, 973–1001.

Berger, D.W., Chaboud, A.P., Chernenko, S.V., Howorka E. and J.H. Write, 2008, Order Flow and Exchange Rate Dynamics in Electronic Brokerage System Data, Journal of International Economics 75, 93-109.

Brennan, M.J. and Y. Xia, 2006, International Capital Markets and Foreign Exchange Risk, Review of Financial Studies 19, 753 - 795.

Campbell, J.Y. and S.B. Thompson, 2008, Predicting the Equity Premium Out of Sample: Can Anything Beat the Historical Average? Review of Financial Studies 21, 1509-1531.

Cerný, A. and S.D. Hodges, 2001, The Theory of Good-Deal Pricing in Incomplete Markets, in Mathematical Finance-Bachelier Congress 2000, H. Geman, D. Madan, S. Pliska and T. Vorst, eds. Berlin: Spring, 175-202.

Chang, P. H. K. and C.L. Osler, 1999, Methodical Madness: Technical Analysis and the Irrationality of Exchange-Rate Forecasts, The Economic Journal 109, 636-661.

Cochrane, J. H. (1999). "Portfolio advice for a multifactor world", National Bureau of Economic Research (NBER) Working Paper no w7170.

Cochrane, J.H., 2005, Asset Pricing, 2nd Ed., Princeton University Press, Princeton.

Cochrane, J.H. and J. Saà-Requejo, 2000, Beyond Arbitrage: Good Deal Asset Price Bounds in Incomplete Markets, Journal of Political Economy 108, 79-119.

Deutsche Bank, 2008. "DB Currency Returns: Weekly Update," October 20.

Dooley, M.P. and J. Shafer, 1976, Analysis of Short Run Exchange Rate Behavior: March 1973 – September 1975, International Finance Discussion Papers, No. 76. Washington, D.C., Federal Reserve System.

Dooley, M.P. and J. Shafer, 1984, Analysis of Short-Run Exchange Rate Behaviour: March 1973–November 1981, in Bigman, D. and T. Taya (eds.), Exchange Rate and Trade Instability, Ballinger, Cambridge, MA.

Evans, M.D.D., and R.K. Lyons, 2002, Order flow and exchange rate dynamics, Journal of Political Economy 110, 170–180.

Fama, E., 1970, Efficient Capital Markets: a Review of Theory and Empirical Work, Journal of Finance 25, 383-417.

Freedman, D.A. and S.C. Peters, 1984, Bootstrapping an Econometric Model: Some Empirical Results, Journal of Business and Economic Statistics 2, 150-158.

Gencay, R., 1999, Linear, Non-Linear and Essential Foreign Exchange Rate Prediction with Simple Technical Trading Rules, Journal of International Economics 47, 91-107.

Griffin, J.M., Kelly, P.J. and F. Nardari (2010), Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets, Review of Financial Studies 23, 3225-3277.

Harris, R.D.F. and F. Yilmaz, 2009, A Momentum Trading Strategy Based on the Low Frequency Component of the Exchange Rate, Journal of Banking and Finance 33, 1575-1585.

Hosking, J.R.M., 1979, The Asymptotic Distribution of R^2 for Autoregressive-Moving Average Time Series Models When Parameters Are Estimated, Biometrika 66, 156-7.

Inoue, A., and L. Kilian, 2004, In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use?, Econometric Reviews 23, 371–402.

Karolyi, G.A. and B.-C. Kho, 2004, Momentum Strategies: Some Bootstrap Tests, Journal of Empirical Finance 11, 509-536.

Kirby, C., 1998, The Restrictions on Predictability Implied by Rational Asset Pricing Models, Review of Financial Studies 11, 343–382.

LeBaron, B., 1999, Technical Trading Rule Profitability and Foreign Exchange Intervention, Journal of International Economics 49, 125-143.

Lequeux, P. and E. Acar, 1998, A Dynamic Index for Managed Currencies Funds Using CME Currency Contracts, European Journal of Finance 4, 311-330.

Levich, R. M. and L.R. Thomas III, 1993, The Significance of Technical Trading-Rule Profits in the Foreign Exchange Market: A Bootstrap Approach, Journal of International Money and Finance 12, 451-74.

Ljung, G.M. and G.E.P. Box, 1978, On a Measure of Lack of Fit in Time Series Models, Biometrika 67, 297-303.

Lo, A.W., 2004, The Adaptive Market Hypothesis: Market Efficiency from an Evolutionary Perspective, Journal of Portfolio Management, 30th Anniversary Issue, 15-29.

Lo, A.W., 2005, Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis, Journal of Investment Consulting 7, 21-44.

Lo, A. and A.C. MacKinlay (1997), Maximizing Predictability in the Stock and Bond Markets, Macroeconomic Dynamics 1, 102-134.

Lustig, H.N., Roussanov, N.L. and A. Verdelhan, 2011, Common Risk Factors in Currency Markets, Review of Financial Studies 24, 3731-3777.

Menkhoff, L., Sarno, L., Schmeling, M. and A. Schrimpf, 2012, Currency Momentum Strategies, CEPR Discussion Paper 8747 and Journal of Financial Economics (forthcoming).

Menkhoff, L. and M.P. Taylor (2007). The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis, Journal Of Economic Literature 45, 936-972

Meyer, D.J. and J. Meyer, 2005, Relative Risk Aversion: What Do We Know? Journal of Risk and Uncertainty 31, 243-262.

Muth, J.F., 1961, Rational Expectations and the Theory of Price Movements, Econometrica 29, 315-335.

Neely, C., Weller, P., and R. Dittmar, 1997, Is Technical Analysis in the Foreign Exchange Market Profitable? A Genetic Programming Approach, Journal of Financial and Quantitative Analysis 32, 405-426.

Neely, C.J., Weller, P.A. and J. Ulrich, 2009, The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market, Journal of Financial and Quantitative Analysis 44, 467-488.

Nelson, C.R., 1976, The Interpretation of R^2 in Autoregressive-Moving Average Time Series Models, The American Statistician 30, 175-180.

Okunev, J. and D. White, 2003, Do Momentum-based Strategies Still Work in Foreign Currency Markets? Journal of Financial and Quantitative Analysis 38, 425-447.

Olson, D., 2004, Have Trading Rule Profits in the Foreign Exchange Markets declined through time? Journal of Banking and Finance 28, 85-105.

Pesaran, M.H. and A. Timmermann, 1995, Predictability of Stock Returns: Robustness and Economic Significance, Journal of Finance 50, 1201-1228.

Peters, S.C. and D.A. Freedman, 1984, Some Notes on the Bootstrap in Regression Problems, Journal of Business & Economic Statistics 2, 406-409.

Pojarliev, M. and R.M. Levich. 2008, Do Professional Currency Managers Beat the Benchmark?, Financial Analysts Journal (Sept/Oct.), 18-32.

Poti, V. and A. Siddique, 2013, What Drives Currency Predictability?, Journal of International Money and Finance 36, 86-106.

Press, W.H., Flannery, B.P., Teukolsky, S.A. and W.T. Vettering, 1988, Numerical Recipes in C, Cambridge University Press, New York.

Pukthuanthong, K., Levich, R. M. and L.R. Thomas III, 2007, Do Foreign Exchange Markets Still Trend? Journal of Portfolio Management 34, 114-28.

Ross, S. A., 2005, Neoclassical Finance, Princeton University Press, Princeton, New Jersey.

Sargent, T.J. (1979), A Note on Maximum Likelihood Estimation of the Rational Expectations Model of the Term Structure, Journal of Monetary Economics 1, 133–143

Schulmeister, S., 2006, The Interaction Between Technical Currency Trading and Exchange Rate Fluctuations, Finance Research Letters 3, 212-233.

Shibata, R., 1976, Selection of the order of an autoregressive model by Akaike's information criterion, Biometrika 63, 117-126.

Stremme, A., Abhyankar, A and D. Basu, 2007, Portfolio Efficiency and Discount Factor Bounds with Conditioning Information: An Empirical Study, Journal of Banking and Finance 31, 419-437.

Sweeney, R. J., 1986, Beating the Foreign Exchange Market, Journal of Finance 41, 163-182.

Taylor, S.J., 1994, Trading Futures Using a Channel Rule: A Study of the Predictive Power of Technical Analysis with Currency Examples, Journal of Futures Markets 14, 215-235.

Taylor, S.J., 2005, Asset Price Dynamics, Volatility and Prediction, Princeton University Press, Princeton, NJ.