# Predictability and 'Good Deals' in Currency Markets

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This paper studies predictability of currency returns over the period 1971-2006. To assess the economic significance of 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 evidence that predictability often exceeds this bound. 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 serious 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. Strategies that attempt to exploit excess-predictability are very sensitive to transaction costs but those that exploit monthly predictability remain attractive even after realistic levels of transaction costs are taken into account and are not spanned either by the Fama and French (1993) equity-based factors or by the AFX Currency Management Index.

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# Predictability and ‘Good Deals’ in Currency Markets

This paper studies predictability of currency returns over the period 1971-2006. To assess the economic significance of 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 evidence that predictability often exceeds this bound. 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 serious 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. Strategies that attempt to exploit excess-predictability are very sensitive to transaction costs but those that exploit monthly predictability remain attractive even after realistic levels of transaction costs are taken into account and are not spanned either by the Fama and French (1993) equity-based factors or by the AFX Currency Management Index.

## 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), Olson (2004), 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, Pukthuanthong, Levich and Thomas (2007) find evidence of diminishing profitability of currency trading rules over time. In a comprehensive re-evaluation of the evidence hitherto provided by the extant literature, Neely, Weller and Ulrich (2007), also find evidence of declining profitability of technical trading rules.

In this paper, we directly assess whether currency returns are predictable to an extent that implies violation of the efficient market hypothesis (henceforth, EMH) and whether the evidence against the EMH has changed over time. To this end, we test whether, conditional on sensible restrictions on the volatility of the kernel that prices the assets, currency return predictability can be exploited to generate "good deals". The latter, following the terminology introduced by Cochrane and Saà Requeio (2000), Cerný and Hodges (2001) and Cochrane (2001), are investment opportunities that offer unduly high Sharpe ratios. To check on the availability of "good deals," we construct a theoretical time-varying upper bound on the explanatory power of predictive regressions. This bound, following Ross (2005), is ultimately a function of the volatility of the kernel that prices the assets traded in the economy, and it makes precise the intuitive connection between predictability, risk and reward for risk. In an efficient market, predictability should never exceed the bound as violations would imply the availability of "good deals," i.e. the possibility of exploiting predictability to generate unduly high Sharpe ratios. We thus test for violations of the EMH by comparing the explanatory power of predictive regressions with the theoretical "no good deal" bound. In doing so, we examine how predictability has varied over time and we compare and contrast predictability patterns with historical patterns in the profitability of technical trading rules considered by the extant literature.

In a stock market setting, related empirical literature includes the work of Campbell and Thompson (2005) and, with an emphasis on the role of conditioning information, of Stremme, Basu, and Abhyankar (2005). Pesaran and Timmermann (1995) study the empirical link between predictability and risk (and thus reward for risk) by examining stock predictability at times of high and low market volatility. While these authors empirically exploit the link between the economy's maximal Sharpe ratio and the amount of admissible predictability, they do not directly test for violations of the EMH. This is the approach we take here and it represents the main contribution of the paper. As pointed out by Taylor (2005), currency strategies tend to be, by far, more profitable than strategies that attempt to exploit the predictability of other asset classes. It is therefore rather surprising that this approach has not been previously attempted in a study of the efficiency of the currency market.

Empirically, we find evidence of recurring violations of the EMH. While such violations are especially severe in the initial part of the sample period, excess-predictability has not disappeared from the mid-1990s onwards, in contrast with the vanishing profitability of many popular technical trading rules reported in some recent studies, e.g. Neely, Weller and Ulrich (2007) and Pukthuanthong, Levich and Thomas (2007). Importantly, we find that the extent to which predictability exceeds the no good-deal upper bound varies over time in a roughly cyclical manner. Suggestively, while this 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 occur each time that a shift in market conditions requires market participants to re-learn how to make efficient forecasts. While realistic levels of transaction costs, especially those arising as a result of ‘price pressure,’ e.g. Evans and Lyons (2002), can account for part of these violations and daily predictability is difficult to exploit as it would require frequent trading, strategies that exploit monthly predictability are much less sensitive to transaction costs and they expand the investment opportunity set, thus rationalizing the enduring market participants’ tendency to engage in technical analysis and other active currency management practices.

In the next section, we outline the theoretical relation between predictability and time varying expected returns, on the one hand, and trading rule profitability, on the other hand. We also introduce Ross’ (2005) upper bound on pricing kernel volatility and we discuss its implications for the maximum amount of explanatory power of currency returns predictive regressions (AR) compatible with foreign exchange market efficiency. In Section 3, we describe our dataset. In Section 4, we describe the simple rolling auto-regressions and autoregressive moving average models (ARMA) that we employ to capture predictability and how we construct empirical upper bounds, based on Ross’ (2005) theoretical bound, as a function of the coefficient of determination. In Section 5, in the spirit of White’s (2000) reality checks, we assess the possible impact of sampling error on our inferences on the presence of excess-predictability. In Section 6, we consider the strategies that exploit estimated predictability to generate maximal Sharpe Ratios and we evaluate the impact of transaction costs on their profitability. In Section 7, we adopt an explicit multi-factor asset pricing perspective to assess to what extent strategies that exploit predictability expand the investment opportunity set of an investor endowed with rational expectations. In the final Section, we summarize our main findings and offer conclusions.

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

Trading rules profitability implies that returns are to some extent predictable. This predictability, in turn, can stem either from time varying expected returns, thus representing an equilibrium reward for risk, or from information contained in past prices unexploited by market participants. The former possibility is consistent with the notion of currency market efficiency, whereas the latter is not. Clearly, being able to fully discriminate between these two possibilities requires an equilibrium asset pricing model. More formally, consider the following model of excess returns:

$$r_{t+1} = \mu_{t+1} + \varepsilon_{t+1} \tag{1}$$

Where

$$\mu_{t+1} = E(r_{t+1} \mid I_t) = \mu(I_t) \tag{2}$$

Here, $I_t$ is the information set at time $t$ and $\varepsilon_{t+1}$ is a conditionally zero-mean innovation. Then, following Ross (2005), we can write:

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

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

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

Variation in mean excess returns, in turn, can either come from variation in equilibrium risk premia, 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 specify what constitutes the model of the rational expected excess returns, and thus the rational component of $\sigma_\mu^2$. An equivalent way of representing this fact is to recognize that $\sigma_\mu^2 = E[\mu_{t+1} - E(\mu_{t+1})]^2 \leq E(\mu_{t+1}{}^2)$ and that, as noted by Ross (2005), we can write:

$$\sigma_\mu^2 \leq E(\mu_{t+1}{}^2) \leq (1+R_f)^2 \sigma^2(r_{t+1}) \sigma^2(m_{t+1}) \tag{5}$$

The first inequality in (5) is based on an elementary result from descriptive statistics. The second inequality follows from the fact that, under no-arbitrage and in a frictionless economy, the pricing kernel satisfies $\mu_{t+1} = (1+R_f) Cov(r_{t+1}, m_{t+1} \mid I_t)$, while the correlation between the kernel and the asset excess return is bounded from above, in absolute value, by one. Using (5) in (4), we see that predictability is bounded from above by $\phi$, a quantity that depends on the amount of volatility of the kernel that prices the assets:

$$R^2 \leq (1+R_f)^2 \sigma^2 (m_{t+1}) \equiv \phi \tag{6}$$

Notably, the restriction in (6) holds unconditionally and thus for the in-sample coefficient of determination of any predictive regression. By a familiar Hansen and Jagannathan (1991) result, the maximal Sharpe ratio (*SR*), and thus the maximum amount of profitability per unit of risk from any trading strategy is bounded from above by the volatility of the pricing kernel:

$$\frac{E(\mu_{t+1})}{\sigma \ \ (r_{t+1})} = SR \ \ \leq (1+R_f)\sigma(m_{t+1}) \tag{7}$$

Thus, from (6) and (7), it is clear that the volatility of the pricing kernel places an upper bound on both predictability and the maximal SR of the economy. Under the rational expectations (RE) assumption originally formulated by Muth (1961), there exists a tight link between the pricing kernel $m_{t+1}$ and investors' marginal utility. The RE assumption, in turn, is a necessary condition for the EMH to hold. These considerations suggest one way to mitigate the stark alternative between conducting a joint test of market efficiency and of a particular asset pricing model and not being able to discriminate between time-variation in equilibrium returns and abnormal profitability. A possible solution is to impose just enough restrictions on preferences to be able to restrict the volatility of the pricing kernel. This then yields restrictions on the maximal SR of the economy and on predictability.

To draw testable implications of the EMH for return predictability without having to fully specify an equilibrium asset pricing model, we may therefore start by assuming that there exist a group of risk-averse investors endowed with RE. Ross (2005) argues that, if they are sufficiently homogeneous and wealthy, they can be seen as a marginal investor whose inter-temporal marginal rate of substitution volatility provides an upper bound to the volatility of the pricing kernel. If we make the simplifying assumption that the preferences of the marginal investor can be modelled using a constant relative risk aversion utility function defined over wealth, we can then place the following upper bound on the volatility of the kernel $m_{t+1}$ that prices the assets:

$$\sigma^2(m_{t+1}) \leq \sigma^2(m_{V,t+1}) \cong RRA_V^2 \sigma^2(r_{m,t+1}) \tag{8}$$

Here, $m_{V,t+1}$ is the inter-temporal marginal rate of substitution between present and future wealth of an investor with relative risk aversion $RRA_V$ , the latter is the relative risk aversion upper bound, and $\sigma(r_{m,t+1})$ is the volatility of the market excess-return $r_{m,t+1}$. Based on (6), the pricing kernel volatility bound in (8) implies the following upper bound on the explanatory power of any predictive regression of asset returns:

$$\phi = (1+R_f)^2 RRA_V^2 \sigma^2(r_{m,t+1}) \cong RRA_V^2 \sigma^2(r_{m,t+1}) \tag{9}$$

Thus, under the EMH, we should observe $R^2 \le \phi$ and hence $R^2 \le RRA_V^2 \sigma^2(r_{m,t+1})$. At this point, to fix ideas, we may define a 'boundary violation index,' henceforth *BVI*, as the difference between the coefficient of determination of the estimated predictive regression and the predictability bound, i.e. $BVI = R^2 - \phi$. The inequality in (6) implies that *BVI* should be non-positive for all predictive regressions of the returns on all traded assets priced by the kernel *m*.

To operationalize (9), 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. $RRA_V \le 5$. Among the motivations advanced by Ross (2005) to do so, the one that most easily applies to a world with possibly non-normally distributed returns and non-quadratic utility is the simple observation that a relative risk aversion higher than 5 implies that the marginal investor would be willing to pay more than 10 percent per annum to avoid a 20 percent volatility of his wealth (i.e., about the unconditional volatility of the S&P from 1926) which, by introspection, seems large. We will also experiment with a lower value for the RRA upper bound, i.e. $RRA_V = 2.5$, as this is just above the relative risk aversion of the marginal investor in the stock market, if we assume that this investor's preferences are described by a power utility function and we estimate the mean and volatility of the stock market using the historical average and standard deviation of the returns on the S&P index since 1926. This bound implies that the marginal investor would be willing to pay up to 5 percent per annum, arguably still a relatively large amount, to avoid a 20 percent volatility of his wealth.

## 3. Data

Our data comprise daily and monthly returns on the spot exchange rate against the US Dollar of the major currencies (except those that were replaced by the Euro) for the period 1971-2006 taken by Bloomberg at the close of business in London at 6:00 p.m. GMT.[1] These currencies are 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). To proxy for the return on the market portfolio we use daily and monthly returns on the S&P500 index constructed from last traded price and dividend data provided by Datastream.

## 4. Predictability of Currency Returns

To conduct our tests of currency market efficiency, we estimate simple predictive regressions of the returns on the currencies in our sample. Next, we construct empirical counterparts to the predictability bound in (9) and we compare the coefficient of determination of the estimated predictive regressions with the constructed bound. To visualize periods of high and low excess-predictability, we construct empirical counterparts of the BVI. As shown by Taylor (1994), among

[1] We also use daily data, provided by Bloomberg, on the front month futures contract on the exchange rate of each of the above currencies against the US Dollar traded on the Chicago Mercantile Exchange (CME), but the results are not reported because they are qualitatively indistinguishable from, and quantitatively very similar to, the results for the underlying currencies.

others, ARIMA models of exchange rates, and thus ARMA models of currency returns, capture substantial predictability. Our estimated models are thus specifications of the general ARMA(p,q) model, where *p* denotes the autoregressive lag order and *q* denotes the order of the moving average term:

$$y_t = const. + b_1 y_{t-1} + ..... + b_p y_{t-p} + c_1 u_{t-1} + ..... + c_q u_{t-q} + u_t \qquad (10)$$

We apply versions of (10) to both currency returns and to returns adjusted by the interest[2] differential (i.e. the differential between the funding cost in US Dollars and the return from reinvesting the funds in each one of the foreign currencies). 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 duplication of indistinguishable predictability estimates, in the remainder of this study we work with currency return data only.

We start by estimating specifications of (10) over rolling windows of daily and monthly data for all currency returns in our sample, and recording their coefficients of determination. The predictive models are ARMA(5,0) or, equivalently, AR(5), for daily returns, and ARMA(5,2) for monthly returns. This yields daily and monthly

[2] 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.

series of coefficients of determination $R^2_{i,t}(r_{i,(t-l)\to t})$ for each currency. Here, $r_{i,(t-l)\to t}$ denotes the series of currency *i* return realizations between time *t-l* and *t*, with *l* that denotes the estimation window. The latter is one year, i.e. *l* = 252 trading days, for daily data and 5 years, i.e. $l = 5\times 12 = 60$ months, for monthly data. In other word, each predictive auto-regression is estimated over a window that runs between *t-l* and *t*, where window length *l* equals 252 for daily data and 60 for monthly data. To estimate a time-varying predictability bound $\phi_t$ at the daily (monthly) frequency, we proxy for the variance of the market return between *t-l* and *t*, i.e. $\sigma^2_t(r_{m,(t-l)\to t})$, as the average, over rolling windows of 1 year (5 years) of daily (monthly) GARCH(1,1) S&P500 returns variance estimates. To compute $\phi_t$, as prescribed by (8), we then multiply $\sigma^2_t(r_{m,(t-l)\to t})$ by the square of the chosen RRA upper bound, i.e. by the square of the chosen value of $RRA_V$. Finally, to construct BVI, we subtract $\phi_t$ from $R^2_{i,t}(r_{i,(t-l)\to t})$.

The resulting daily time-series of the rolling coefficients of determination for each currency are plotted in Figure 1, against the time series of the rolling predictability bound $\phi_t$ computed setting $RRA_V$ = 5. The corresponding monthly series are qualitatively indistinguishable and they are not shown to save space.[3] Visual inspection of Figure 1 reveals that the coefficients of determination of the estimated auto-regressions are almost always above the bound. In fact, perhaps surprisingly, sub-periods when the bound is not violated represent the exception rather than the norm. As a consequence, as detailed in Panel A of Table 1, the BVI is positive in more than 90 percent of the yearly rolling estimation windows for all currencies over the period 1971-2006 and three sub-periods of roughly equal length 1971-1983, 1984-1995, 1996-2006. For most currencies and sub-periods, the frequency of positive BVI values, and thus predictability upper bound violations, is almost 100 percent. To help appreciate the magnitude and economic significance of the estimated predictability, we create an excess-predictability measure based on the BVI and express it in annualized Sharpe ratios units. To do so, we compute the square root of the 'annualized' average value for the BVI, conditional on the BVI itself being positive,

$$\gamma_{i,t_0 \to t_1} \equiv \sqrt{\sum_{t=t_0}^{t_1} \frac{BVI_{i,t} I_{i,t}}{t_1 - t_0} \frac{l}{years}}$$

Here, $t_0$ and $t_1$ are the beginning and end points, respectively, of the sub-periods over which we compute $\gamma_{i,t_0 \to t_1}$, i.e. 1972-1977, 1978-1983, 1984-1989, 1990-1995, 1996-2001 and 2002-2006, and $I_{i,t}$ is an indicator function that takes value one when $BVI_{i,t} > 0$ and value zero otherwise. The quantity under the square root is multiplied by the ratio of the number of observations to the number of years in the estimation window length, i.e. $\frac{l}{years}$, to 'annualize' (thus, $\frac{l}{years} = 252$ when working with 1-year estimation windows of daily data and $\frac{l}{years} = \frac{60}{5} = 12$ when using 5-year windows of monthly data). The quantity $\gamma_{i,t_0 \to t_1}$ has an appealing economic

[3] They are however available upon request from the authors.

interpretation. Based on (6) and (7), it can be seen as the annualized excess-SR that can be earned by exploiting predictability, assuming that one trades at the indicated frequency (i.e. daily or monthly) only when excess-predictability is present. The value taken by $\gamma_{i,t_0 \to t_1}$, therefore, can be seen as a measure of “good deal” availability.

In Panel B of Table 1, we report the computed values of $\gamma_{i,t_0 \to t_1}$ based on estimates obtained using daily data.[4] They are often positive and economically sizable. Excess-predictability is especially high in the initial part of the sample periods, i.e. in 1972-1977. In subsequent periods, the computed values of $\gamma_{i,t_0 \to t_1}$ are often lower, but a clear declining pattern can be detected only in the values taken by the $\gamma_{i,t_0 \to t_1}$ of AUD and, to a lesser extent, JPY and in its arithmetic average across all currencies, reported in the last column. Excess-predictability of GBP and CHF also appears to be generally declining across the sub-sample periods under consideration, except for a burst in 1990-95 in the case of GBP and a smaller increase in 2002-2006 for CHF. On the contrary, CAD exhibits increasing excess-predictability while, in the case of ECU/EUR, there is a burst of predictability between 1984 and 1994, probably in relation to market adjustments leading to the adoption of the Euro.

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

[4] Again, the values of this quantity computed using monthly data are qualitatively similar and they are not tabulated to save space. They are however available upon request.

also that excess-profitability disappeared after 1991. Neely, Weller and Ulrich (2007) examine a more comprehensive set of trading rules and report similar findings. Large values of our measure of excess-predictability $\gamma_{i,t_0 \to t_1}$, over the periods 1972-1977, 1978-1983 and 1984-1989, are consistent with Olson's (2004) and Neely, Weller and Ulrich's (2007) findings. As shown in Figure 2, the average BVI across our currencies declines over time and this is also broadly consistent with evidence of diminishing abnormal profitability of technical trading rules reported by these authors, in that decreasing excess-predictability presumably makes it more difficult for technical trading rules to spot profitable trends.

Our findings, however, do not support the view that excess-predictability might have disappeared from the early 1990s onwards, or at least that it might have been steadily declining since then. The increase, in the latter part of the sample period, of the excess-predictability of AUD, CAD, CHF and its surge around 1990-1995 for GBP are in contrast with this conclusion. To reconcile our evidence with the findings of diminishing profitability of technical trading rules reported by Olson (2004) and Neely, Weller and Ulrich (2007), one must posit that the rules considered by these authors do not capture all predictability. Evidence provided by Pukthuanthong, Levich and Thomas (2007) suggests that trend-following rules that were once profitable now lose money, whereas the corresponding counter-trending rules, i.e. rules that do exactly the opposite, are increasingly profitable. Our excess-predictability measure would capture the excess-profitability of both types of strategies. Our results, contrary to Olson's (2004) and Neely, Weller and Ulrich's (2007) findings, are also consistent with evidence of high trading profits from momentum strategies during the 1990s reported by Okunev and White (2003), as we generally do not find evidence of declining excess-predictability after 1991.

On balance, our findings represent intriguing *prima facie* evidence that there is non-negligible excess-predictability in currency markets and that this excess-predictability, in recent years, has declined from its 1970s peaks without disappearing entirely. This implies that there might be good reasons why currency traders, in their pursuit of profitability and against academic advice, have long engaged in technical analysis and other practices aimed at exploiting predictable patterns in currency returns. Taken at face value, these results represent evidence against the EMH. There is the possibility, however, that our estimates of the coefficient of determination $R^2$ might be inflated because of sampling error and that high transaction costs might have to be incurred to exploit the estimated predictability. We now investigate these important possibilities.

## 5. The Impact of Sampling Error

To gain insight into the impact of sampling error on our assessment of excess-predictability, we compare the estimated BVI with a measure of sampling error of the coefficient of determination of the estimated predictive regressions. To this end, we construct a modified version of the *BVI*, i.e. $BVI_{adj}$, by reducing *BVI* by an amount that reflects an estimate of sampling error at a specified confidence level,

$$BVI_{adj} = BVI - s.e._{R^2,95\%}$$

Here, $s.e._{R^2,95\%}$ denotes the sampling error, at the 95 percent confidence level, of the estimated coefficient of determination $R^2$ of the predictive regression. It is well known that, under mild regularity conditions and the null that $R^2$ equals zero, $\frac{R^2(T-k-1)}{(1-R^2)K} \sim F_{K,T-K-1}$, where $F_{K,T-K-1}$ denotes an F-distribution with $K$ and $T-K-1$ degrees of freedom, $T$ denotes the sample size and $K$ denotes the number of parameters of the estimated regression model. Since $R^2 \geq 0$, at least when the predictive regression includes an intercept, $\frac{1}{(1-R^2)} > 1$. As a consequence, the distribution of $\frac{K}{(T-K-1)} F_{K,T-K-1}$ provides an upper bound to the distribution of the coefficient of determination $R^2$ under the null that the latter is equal to zero, and its 5th percentile thus provides an upper bound to $s.e._{R^2,95\%}$, under the null that excess-predictability equals zero.[5] The times series of $BVI_{adj}$, based on ARMA(5,2) predictive regressions estimated using rolling 5-year windows of monthly data, i.e. letting $l$ = 60 and *years* = 5, are plotted in Figure 3.[6] Bursts of excess-predictability occurred at various points over the sample period, for example between 1985 and 1986 and between 1996 and 1997 for the JPY, and shortly after the 1992 EMS crisis in the case of the ECU/EUR and the GBP (with a longer episode in the case of the latter). In the more recent part of the sample period, the return on a number of

[5] We define the percentile of the F-distribution in a manner consistent with the popular convention of defining its critical value at the level α as the integral from the critical value to infinity, i.e. an integral 'over the right tail' of the distribution.

[6] The corresponding series constructed using daily data, i.e. using the coefficient of determination of ARMA(5,0) predictive regressions estimated over rolling 1-year windows of daily data, are qualitatively similar and are not plotted to save space.

currencies, especially the AUD, CAD and CHF, also experienced episodes of increasing excess-predictability. Overall, as emphasized by the 12-month moving average superimposed to the BVI series, excess-predictability displays a cyclical pattern, i.e. periods of high and low predictability alternate over time, consistent with Lo's (2004) AMH.

Next, to reduce the sampling error of our predictability estimates and as a robustness check, we select the p and q lag orders of the predictive ARMA(p,q) model in (10) using the Akaike Information Criterion (AIC) and, more importantly, we increase the estimation window, i.e. we estimate our predictive regressions over sample periods longer than the yearly windows of daily data and 5-year windows of monthly data used so far. In particular, we compute $BVI_{adj}$ over the entire 1972-2006 sample period and three non-overlapping sub-sample periods of roughly equal length, i.e. 1971-1982, 1983-1994, and 1995-2006. To facilitate the interpretation of the economic magnitude of the computed $BVI_{adj}$ values, we 'translate' them into annualized SRs units, i.e. we construct a version of $\gamma_{i,t_0 \to t_1}$ adjusted for sampling error,

$$\gamma_{adj;i,t_0 \to t_1} \equiv \sqrt{BVI_{adj,i,t} I_{i,t} \frac{t_1 - t_0}{l \cdot years}}$$

As before, $t_0$ and $t_1$ are the beginning and end points, respectively, of the sub-periods over which we compute $\gamma_{i,t_0 \to t_1}$, in this case 1971-2006 as well as 1971-1982, 1983-1994 and 1995-2006, $I_{i,t}$ is an indicator function that takes value one when $BVI_{i,t} > 0$ and value zero otherwise. We estimate $BVI_{adj}$ and $\gamma_{adj;i,t_0 \to t_1}$ using both daily and monthly data. Accordingly, the ratio $\frac{t_1 - t_0}{l \cdot years}$, that serves to annualize, equals 252 for daily data and 12 for monthly data. The quantity $\gamma_{adj;i,t_0 \to t_1}$ can be seen as the minimum annualized excess-SR that can be earned, at the 95 percent confidence level, by exploiting excess predictability, assuming that one trades at the indicated frequency (i.e. daily or monthly). The values of $\gamma_{adj;i,t_0 \to t_1}$ constructed using daily and monthly data are reported in Table 2 and 3, respectively. They suggest the presence of high daily excess-predictability at the beginning of the sample period, i.e. in the 1970s and early 1980s. For example, under RRA = 5, excess-predictability over the period 1971-1982 implies an annualized excess-SR of 91.2 percent in the case of GBP and larger than 100 percent in the case of CAD and CHF. Subsequently, there are fewer and generally less prolonged episodes of daily excess-predictability and statistically significant violations of the predictability bound are less severe. The evidence of monthly excess-predictability is instead still strong in the central part of the sample period for CAD and JPY, with SRs in excess of the RRA = 5 bound as large as 76.5 and 49.3 percent, respectively, and in the case of JPY high statistically significant excess-predictability persists in the last sub-sample period, implying a SR of 55.5 percent in excess of the RRA = 5 bound. AUD also exhibits high statistically significant excess-predictability.

The OLS estimate of sampling error used to construct $BVI_{adj}$ might be biased or not converge fast enough to provide a reliable estimate of sampling error of the coefficient of determinations of the estimated predictive regressions. In fact, Kurz-Kim and Loretan (2007) show that this might be a concrete danger when the normality assumption fails and the regression variables have fat tails distributions, as it is often the case for regressions involving currency returns. To double-check on our assessment of sampling error and especially as a further robustness check on our inferences about the presence of excess-predictability, we bootstrap 2-tailed confidence intervals for the coefficient of determination of the estimated predictive regressions. This allows us to take sampling error of the coefficient of determination into account without having to rely on OLS assumptions. To conduct our bootstrapping experiment, we estimate the parameters of the chosen predictive ARMA(p,q) model and store the residuals. We then re-sample 1,000 times, with replacement, blocks of 5 consecutive realizations from the stored residuals time-series, i.e. we employ 'block re-sampling' to capture any residual serial correlation not explained by the estimated predictive regression. Using the time-series of the re-sampled residuals and the point estimates of the predictive regression parameters, we generate 1,000 separate bootstrapped currency return series, for which we then re-estimate the chosen predictive ARMA(p,q) model and record the coefficient of determination $R^2$. This generates a bootstrapped distribution of the latter.

In Table 4, we report the daily predictability upper bounds and the bootstrapped confidence intervals for the coefficient of determination of the selected ARMA(p,q) model of the daily return on each currency, estimated over the whole sample period and the three sub-periods 1971-1983, 1984-1995, 1996-2006. The chosen ARMA(p,q) specification is AR(5) for all currencies.[7] Under the 2.5 upper bound on

[7] This specification captures reasonably well daily predictability of the currencies in our sample, as shown by tests based on the Ljung-Box (1978) Q-statistic of residuals serial correlation, on the Akaike Information Criterion and the Swartz Bayesian Criterion (not reported to save space but available upon request).

relative risk aversion, i.e. under $RRA_V$ = 2.5, we can reject at the 5 percent significance level the null that the estimated predictability does not violate the bound for almost all currencies in the sample. In other words, under $RRA_V$ = 2.5, we can reject the null of no excess-predictability, i.e. there is statistically significant evidence that predictability exceeds the upper bound even after taking possible sampling error into account. Under $RRA_V$ = 5 instead, we can reject the null of no excess-predictability only in 3 out of 17 cases. Thus, the evidence that the estimated daily predictability violates market efficiency is considerably weaker under the less restrictive risk aversion bound. In agreement with our prior analysis of the evolution of the amount of predictability over time, the 5 percent critical values of the bootstrapped confidence intervals are generally higher in the first part of the sample period, i.e. in 1971-1982, they decrease in 1983-1994, to increase again somewhat for CAD, CHF and ECU/EUR in the latter part of the sample period, i.e. in 1995-2006.

In Table 5, we report monthly predictability upper bounds and bootstrapped confidence intervals for the coefficient of determination of predictive regressions estimated using monthly data. The predictive regressions are ARMA(5,0), to facilitate comparison with the estimates obtained using daily data, and ARMA(5,2), to eliminate residual serial dependence in the regression errors.[8] As before, the predictive regressions are estimated over the whole sample period and the three sub-periods 1971-1983, 1984-1995, 1996-2006. When the predictive model is ARMA(5,0), evidence of excess-predictability is somewhat weaker than in the

[8] Tests for residual serial correlation, similarly to the daily case, are conducted using Ljung-Box (1978) Q-statistic.

estimates obtained using daily data. When one considers the explanatory power of ARMA(5,2) models, however, the bootstrapped confidence intervals are almost always in excess of the tightest bound, i.e. the bound corresponding to $RRA_V = 2.5$. The wider bound, i.e. the bound corresponding to $RRA_V = 5.0$, is violated in the case of CAD and JPY in the initial 1971-1982 sub-sample period and in the case of JPY also in the final sub-sample period, i.e. in 1995-2006.

To interpret these results, it is useful to consider that, when the 95$^{th}$ percentile of the bootstrapped coefficient of determination distribution exceeds the predictability bound for a given risk aversion bound $RRA_V$, it means that an investor endowed with rational expectations and RRA no larger than $RRA_V$ could have exploited currency predictability to reliably (i.e., with 95 percent confidence) generate SRs in excess of the square root of the predictability bound. For example, under $RRA_V = 2.5$, such an investor could have earned SRs in excess of the square root of 1.28 percent by exploiting the monthly ARMA(5,2) predictability of AUD, JPY and CHF over the period 1971-2006. This amounts to a SR in excess of 39.2 percent per annum. Similar calculations show that the same investor could have earned SRs in excess of 40.1, 44.0 and 38.6 over the periods 1971-1983, 1984-1995, 1996-2006, respectively, by exploiting the predictability of either currency in our sample (except, of course, ECU/EUR over the initial sample period). The monthly predictability of CAD and JPY over the period 1971-1983 and of JPY in 1996-2006 exceeds the predictability bound even under $RRA_V = 5.0$. Thus, optimally exploiting the monthly predictability of CAD and JPY over the period 1971-1983 and of JPY in 1996-2006 would have allowed for SRs in excess of 80.1 and 77.1, respectively.

Overall, the bootstrapped distributions of the coefficient of determination of predictive regressions reported in Tables 4 and 5 provide evidence that, over large portions of the 1971-2006 sample period, an investor endowed with rational expectations could have exploited daily and monthly predictability to reliably generate SRs in excess, before transaction costs, of the good-deal thresholds corresponding to $RRA_V$ = 2.5 or even $RRA_V$ = 5. Evidence of excess-predictability does not disappear in the more recent part of the sample period. This contrasts with the emerging view (in Taylor (2005) and Neely, Weller and Ulrich (2007)) that the markets of the major currencies no longer allow for trading profits.

## 6. The Impact of Transaction Costs

To gain insights into the impact of transaction costs, it is necessary to consider the strategies that would have to be implemented in order to exploit the estimated predictability. To this end, we use an elementary statistical result that relates the variance of a random variable to its second moment and the square of its mean, and re-write the coefficient of determination in (4) as follows:

$$R^2 = \frac{\sigma_\mu^2}{\sigma_r^2} = \frac{1}{\sigma_r^2}\left(\frac{\mu'\mu}{T} - \bar{\mu}^2\right) = \frac{1}{T}\mu'\left(\frac{DD'}{T}\right)^{-1}\mu - \frac{\bar{\mu}^2}{\sigma_r^2} = \mu'(DD')^{-1}\mu - \frac{\bar{\mu}^2}{\sigma_r^2} \quad (11)$$

Here, $\mu$ is the $T \times 1$ vector that stacks the conditional means of the currency return at each point in time $t$, $t$ = 1, ....$T$, $\bar{\mu}$ is the unconditional mean return (a scalar) and

$D$ denotes a $T \times T$ diagonal matrix with elements along the main diagonal that contain the conditional standard deviation of the currency return at each point in time $t$. In using this notation, we are essentially interpreting a strategy aimed at exploiting predictability as a portfolio made up of as many positions as data points in the sample period, each with its own 'conditional' SR. Recognising that, especially in monthly and higher frequency data, the second term on the far right-hand side of (11) is negligible, as it is the square of a typically small percentage number, we can approximate the coefficient of determination as follows,

$$R^2 \cong \mu'(DD')^{-1}\mu \tag{12}$$

Interestingly, if one neglects the possible temporal interdependencies across conditional volatilities, i.e. if one neglects GARCH effects, (12) can be interpreted as the squared maximal SR attainable by forming 'portfolios,' i.e. strategies, of one-period positions in the currency under consideration. The weights with which each one-period position enters such strategy are then

$$W = (DD')^{-1}\mu \tag{13}$$

Intuitively, a trading strategy based on the above inter-temporal weights amounts to using a predictive model that combines a directional signal, the conditional mean $\mu_t$, with a volatility filter, i.e. the elements $\sigma_t\,(y_{t+1})$ of $D$. In the context of our ARMA(p,q), the mean vector equals the conditional mean of (10), i.e. $\mu_t = y_t - u_t$, while $DD'$ collapses to the currency return sample variance times a $T \times T$ identity matrix, i.e. $\sigma^2(y_{t+1})I_{T\times T}$. We use the weights in (13) to calculate the returns of maximal SR strategies for each currency. 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 Figure 4, to illustrate, we plot the time-varying weights, calculated using (13) and normalized to add up to unity, of the maximal SR strategies that exploit the daily and monthly predictability of the Canadian Dollar, based on AR(5) and ARMA(5,2) specifications, respectively, estimated over the period 1995-2006. The corresponding plots for the other currencies and predictive models are not reported to save space. In all cases, there is substantial variation in the weights of the (daily) positions entailed by the maximal SR strategies that optimally exploit daily predictability, as a result of the conditional time-variation of the mean of the return process. There is much less variation in the weights of the (monthly) positions entailed by strategies that exploit monthly predictability. This means that strategies that exploit daily predictability are rebalanced more frequently than those that exploit monthly predictability and therefore transaction costs are likely to have a greater impact on the former than on the latter. Notably, in classic filter and moving-average strategies, trading positions change relatively infrequently.[9] This is because such strategies often exploit predictability at low frequency and thus avoid the burden of high transaction costs.

In Table 6, we report the SRs offered by maximal SR strategies that exploit daily and monthly predictability. The predictive model for daily returns is ARMA(5,0) for all currencies. The predictive model for monthly returns is ARMA(5,2) for all currencies. For all the currencies under consideration, except the Swiss Franc, 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 and the maximal SRs of strategies based on the daily predictability of Australian Dollar, Japanese Yen and ECU/Euro become negative. With transaction costs of five basis points, the maximal SRs of daily strategies are negative for all currencies. The strategies that exploit monthly predictability, however, are much less sensitive to transaction costs. In all sub-sample periods, the SRs for the maximal SR monthly strategies are positive even with transaction costs of 5 basis points. More importantly, they often exceed the threshold implied by the predictability bound, even under $RRA_V = 5$. Crucially, this happens in the latter sample period too, contrary to studies cited earlier which find that certain popular trading strategies are not profitable from the 1990s onwards.

Overall, our empirical evidence suggests that while daily predictability cannot be exploited because of high transaction costs, lower frequency (monthly) predictability is amenable to generate high SRs because trading frequency and transaction costs are reduced. As shown in Table 6, SRs of strategies that exploit predictability decrease

[9] 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.

slowly in transaction costs. This means that the evidence of statistically significant violations of the monthly predictability bound reported in Table 3 and 5 are likely to imply the availability of "good deals" both before and after transaction costs. The latter circumstance means failure of the EMH, as in an efficient market investors endowed with rational expectations should have detected excess-predictability and recognized and exploited the attendant "good deal" opportunities, thereby bringing predictability within the bound provided by the volatility of the pricing kernel. In turn, this means that trading strategies based on low-frequency currency predictability can be attractive for professional investors, at least for those who can use available information better than the representative investor and face moderate yet realistic levels of transaction costs.

A word of caution is in order at this point 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, Chernenko, Howorka and Write (2006), at least for trades executed over a daily horizon. As shown in Table 6, 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 $RRA_V = 5$, and often below the level implied by the tighter predictability bound, i.e. the bound corresponding to $RRA_V = 2.5$. Similar or higher levels of transaction costs, as implied by the evidence provided by the literature on "price pressure," are to be expected for large transactions.

High transaction costs by themselves generate apparent excess-predictability. Roll (1984), for example, show that the bid-ask bounce induces an amount of predictability that depends on the relative magnitude of the bid-ask spread and exchange rate variability. This predictability is not exploitable by construction, because any attempt to exploit it would be costly. The evidence of high predictability and these considerations on the impact of transaction costs on the profitability of large-size transaction, taken together, allow one to rationalize, on the one hand, the frequent occurrence of studies that find abnormally profitable strategies and, on the other hand, the persistence of excess-profitability. We conjecture that available "good deal" opportunities might persist over time because, though in principle advantageous, they do not attract enough investors or investors with enough risk capital due to the presence of a fixed component of transaction costs, e.g. entry costs. We leave, however, a formal investigation of this issue, i.e. the link between transaction costs, transaction size and persistence of profit opportunities, for future research.

## 7. Currency Predictability and the Investment Opportunity Set

To more explicitly assess to what extent predictability-based strategies expand the investment opportunity set, we first combine the maximal SR strategies for the individual currencies into an overall maximal SR strategy. We then compare the performance of the latter to a benchmark currency management strategy, i.e. the AFX index introduced by Lequeux and Acar (1998) and designed to track the performance of technical analysis rules commonly followed by active currency managers. To take a conservative stance on the amount of exploitable or detectable predictability, we consider the maximal SR strategies that exploit the predictability implied by parsimonious ARMA(5,0) models of monthly currency returns. We denote by $r^*$ the excess return on the overall maximal SR strategy. The weights with which the maximal SR strategies for the individual currencies enter the overall maximal SR strategy are calculated as follows:

$$w^* = \Sigma^{*-1}\overline{\mu}^* \tag{14}$$

Here, $\Sigma^*$ denotes the variance-covariance matrix of the returns on the individual currencies maximal SR strategies and $\overline{\mu}^*$ denotes the vector of their unconditional expected returns. As reported in Table 7, the SR of $r^*$ is considerably higher than the SR of the individual currencies maximal SRs strategies. Especially in the more recent sub-sample period, it is also much higher than the SR of the AFX currency management index. Interestingly, the correlation of the AFX index and $r^*$ is not perfect. As shown in Table 8, their correlation drops from 52.36 percent in 1985-1990 to just over 41 percent in 2003-2006. At the same time, while the SR of the AFX index becomes negative, the SR of r* exceeds 106 percent per annum. Taken together, these results suggest that the combination of moving-average rules and currencies considered by the AFX index does not fully capture the estimated amount of currency predictability, especially in recent times. In fact, while the SR of the

AFX currency management index is lower in 1996-2006 than in 1986-2006, the SR of $r^*$ is actually much higher in the more recent sub-sample period. Figure 4 shows the 12-month SR of the AFX index and r*. These series move remarkably closely until about 1996 but subsequently their correlation breaks down. As shown in Table 8, their correlation becomes negative in 2003-2006. This suggests that, while the excess-profitability of the specific moving average rules considered by the AFX index might have dried up as market participants have employed them in their trading strategies, alternative and not yet fully exploited sources of excess-profitability have emerged and manifest themselves as excess-predictability. Again, this is consistent with the Adaptive Market Hypothesis (AMH) perspective put forth by Lo (2004) and advocated, in a currency market setting, by Neely, Weller and Ulrich (2007).

Finally, we take an explicit asset pricing perspective and we ask whether maximal SR predictability-based strategies are spanned by known equity market factors, which some studies suggest span the investment opportunity set. To this end, we simply regress the excess return on each one of the individual currencies maximal SR strategies, the overall SR strategy and, for comparison, the AFX currency management index against the Fama and French (1993) factors, i.e. we estimate

$$r_{i,t} = \alpha_i + \beta_{i,m} r_{m,t} + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t} \quad (15)$$

Here, $r_{i,t}$ is the excess return on either the overall maximal SR strategy, $r_t^*$, an individual currency maximal SR strategy or the AFX currency management index, $\alpha_i$ denotes either the regression intercept or the pricing error if (15) is estimated without a constant term, $r_{m,t}$, $SMB_t$ and $HML_t$ are the excess-returns on the Fama and French (1993) market, size and book-to market factor mimicking portfolios, respectively, and $\beta_{i,m}$, $\beta_{i,SMB}$ and $\beta_{i,HML}$ denote their corresponding factor loadings, while $\varepsilon_{i,t}$ denotes the regression error term. As shown in Table 7, the maximal SR strategies for a number of individual currencies and the overall maximal SR strategy display a positive and statistically significant $\alpha_i$ term, especially over the period 1984-2006. Perhaps more interestingly, the factor loadings on these strategies are always either very small and statistically insignificant or negative and statistically significant. This implies that the strategies either carry little systematic risk or they act as a hedge against the latter.[10] This fact, coupled with the signs and magnitude of the factor loadings and the significance of the 'alpha' terms, suggest that the strategies that exploit currency predictability expand the investment opportunity set, i.e. they are not spanned by the Fama and French (1993) factors.

To formally test whether these strategies expand the investment opportunity set, we use their 'alphas' to compute a Gibson, Ross and Shanken (1989) test-statistic, i.e. we form

$$GRS = \frac{T-N-K}{K}\left[1+E(f)'\Omega^{-1}E(f)\right]^{-1}\alpha'\Sigma^{-1}\alpha \sim F_{K,T-N-K} \tag{16}$$

Here, $T$ is the sample size, $N$ is the number of factors $f$, $E()$ denotes the unconditional expectation operator, $\Omega$ denotes the factor variance-covariance matrix,

[10] A recent study by Burnside, et al. (2006) also shows that currency returns are uncorrelated with

$\alpha$ is the vector of the intercepts from (15), and $\Sigma$ is the variance-covariance matrix of the strategies residuals not explained by the factor model, i.e. the error terms $\varepsilon_t$ in (15).

In our application, there are 6 maximal SR strategies that exploit the predictability of AUD, CAD, JPY, GBP, CHF and ECU/EUR and thus $K = 6$, while the factors $f$ are the excess-returns on the Fama and French (1993) market, size and book-to market factor mimicking portfolios and thus $N = 3$. The GRS statistics for the periods 1986-2006 and 1996-2006, reported in the last column of Table 7, are both highly statistically significant. In computing (16), we estimate population moments using their sample counterparts, i.e. in (16) we replace $E()$ with the vector of sample averages of the excess-returns on the factors. Gibson, Ross and Shanken (1989) demonstrate that comparing the GRS statistic with the 5 percent critical value of its finite sample distribution (under the null that pricing errors are equal to zero), i.e. the F distribution with $K$ and $T - N - K$ degrees of freedom, amounts to testing whether the factors are on the ex-post mean-variance frontier. The significance of the GRS statistic in our tests thus implies that the Fama and French (1993) factors do not span the predictability-based strategies and, therefore, that the latter expand the efficient frontier, at least from the point of view of a rational mean-variance investor.

## 8. Conclusions, Final Remarks and Future Work

In this paper, we assess the statistical and, more importantly, economic significance of predictability in currency returns over the period 1971-2006. We find that, even

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other asset classes.

under a relatively wide bound on relative risk aversion, predictability often violates a theoretically motivated upper bound. Closer scrutiny reveals that the performance of strategies that attempt to optimally exploit daily predictability is very sensitive to the level of transaction costs and this limits the extent to which it can be exploited to generate genuine "good deals." On the other hand, the performance of strategies that attempt to optimally exploit monthly predictability is robust to the level of transaction costs. Taken at face value, this evidence implies the availability of "good deals," at least at the monthly frequency, and thus violation of the EMH under a broad class of asset pricing models, for conservative values of the marginal investor's relative risk aversion and for moderate yet realistic levels of transaction costs. Excess-predictability is highest in the 1970s and, for most currencies in our sample, tends to decreases over time without disappearing. In addition, we find that strategies based on monthly predictability expand the investment opportunity set, even after transaction costs. This effect is also present in the latter part of the sample period and, crucially, it does not disappear after the mid-1990s, contrary to the conclusions of several recent studies. Taken together, our findings pose a serious challenge to the EMH but they are consistent with Lo's (2004) AMH.[11]

Our inferences about market efficiency are based on estimates of 'in sample' predictability. This is fully warranted by our specification of the predictability bound, in that the bound itself should hold unconditionally. Given that it holds unconditionally, it should *a fortiori* also hold conditionally, because conditional

[11] 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,

moments are defined over a coarse information set. Therefore, a natural extension of our analysis would be the assessment, that we leave for future research, of whether the predictability bound is violated out of sample as well as in sample. Another possible avenue of future research is a more formal investigation of whether the estimated $R^2$ series contains a time trend, a cyclical component and one or more structural breaks. Considering cross-rates and a wider sample of countries might also allow the estimation of possible time trends and structural breaks, perhaps adopting a panel approach (a random coefficient model, along the lines of Swamy (1970), would appear particularly promising to accommodate the difficulty of modelling of possible sources of cross-sectional variation in the predictability of currency returns). Another obvious extension is to consider emerging economies currencies. These extensions would make it possible to better address the important question of whether predictability in excess of a level that can be judged consistent with the EMH has become milder over time as a result of learning by economic agents, or whether excess-predictability exhibits a persistently cyclical pattern that can be more easily explained by Lo's (2004) AMH.

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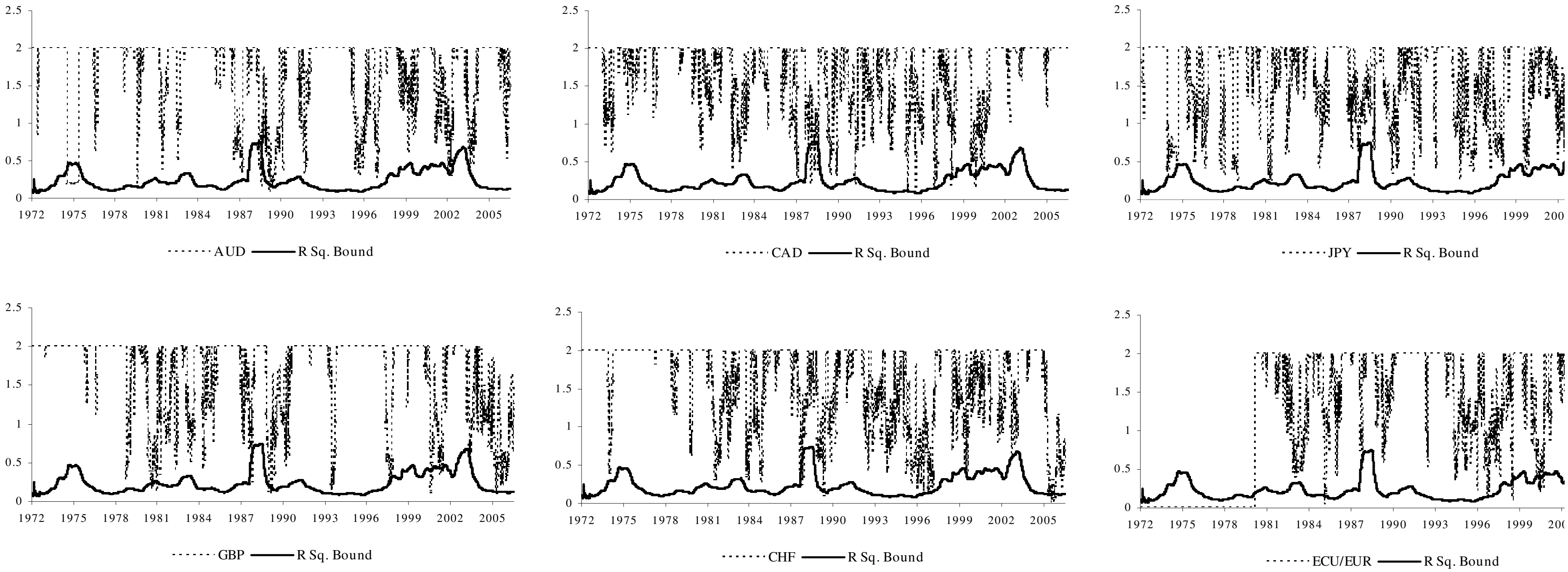
manias, bubbles, crashes and other phenomena that are routinely witnessed in natural market ecologies. These dynamics provide the motivation for active management."

**Figure 1**
**Daily AR(5) Predictability vs. Predictability Bound**




**Notes**. These figures plot the sequences of the percentage coefficients of determinations (shown by the dotted line) of rolling AR(5) auto-regressions for each currency in our sample against their upper bound (shown by the solid line). The latter is computed under a relative risk aversion upper bound of 5. The estimation window of each auto-regression is one year and the sample period is 1971-2006. The values of all the series have been cut off at 2.0 to improve visual clarity.

**Table 1**
**Boundary Violation Index**

Panel A
(Frequency of Boundary Violations – Daily Data)

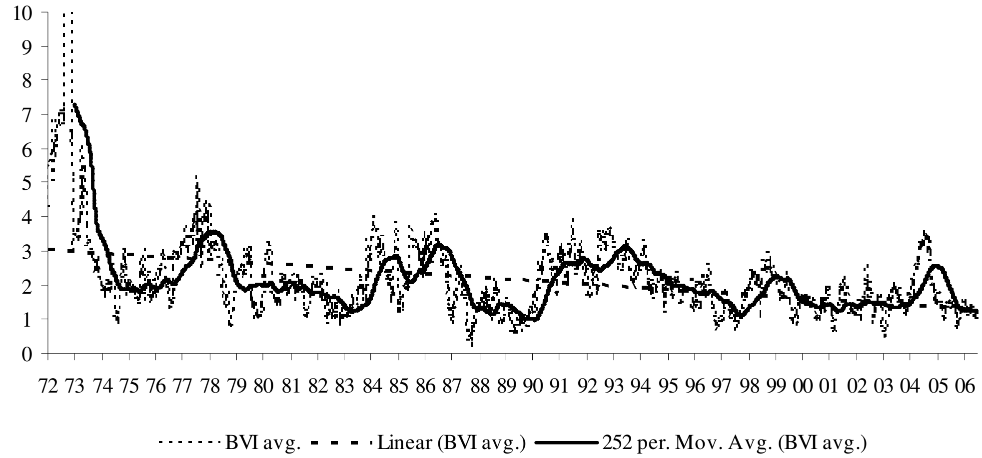
| | | 1971-2006 | 1971-1983 | 1984-1995 | 1996-2006 |
|---|---|---|---|---|---|
| AUD | (1) | 9001 | 3056 | 3130 | 2815 |
| | (2) | 8686 | 2809 | 3067 | 2810 |
| | (3) | 96.5 | 91.9 | 98.0 | 99.8 |
| CAD | (1) | 9001 | 3056 | 3130 | 2815 |
| | (2) | 8923 | 3056 | 3081 | 2786 |
| | (3) | 99.1 | 100.0 | 98.4 | 99.0 |
| JPY | (1) | 9001 | 3056 | 3130 | 2815 |
| | (2) | 8995 | 3053 | 3129 | 2813 |
| | (3) | 99.9 | 99.9 | 100.0 | 99.9 |
| GBP | (1) | 9001 | 3056 | 3130 | 2815 |
| | (2) | 8890 | 3045 | 3102 | 2743 |
| | (3) | 98.8 | 99.6 | 99.1 | 97.4 |
| CHF | (1) | 9001 | 3056 | 3130 | 2815 |
| | (2) | 8902 | 3056 | 3111 | 2735 |
| | (3) | 98.9 | 100.0 | 99.4 | 97.2 |
| ECU/EUR | (1) | 6751 | 806 | 3130 | 2815 |
| | (2) | 6675 | 805 | 3118 | 2752 |
| | (3) | 98.9 | 99.9 | 99.6 | 97.8 |

Panel B
(Percent Square Root of Average BVI Given Violation – Daily Data)

| | AUD | CAD | JPY | GBP | CHF | ECU/ EUR | Avg. |
|---|---|---|---|---|---|---|---|
| 1972-1977 | 40.6 | 26.4 | 28.1 | 33.6 | 43.7 | NA | 29.5 |
| 1978-1983 | 29.2 | 23.4 | 23.3 | 23.8 | 26.0 | 14.7 | 22.7 |
| 1984-1989 | 26.6 | 21.9 | 26.0 | 23.7 | 20.1 | 21.9 | 23.3 |
| 1990-1995 | 25.5 | 20.4 | 22.5 | 30.0 | 20.4 | 28.1 | 25.2 |
| 1996-2001 | 22.5 | 21.7 | 20.4 | 26.7 | 18.7 | 16.1 | 20.9 |
| 2002-2006 | 21.8 | 29.3 | 17.2 | 18.8 | 20.8 | 15.4 | 20.9 |

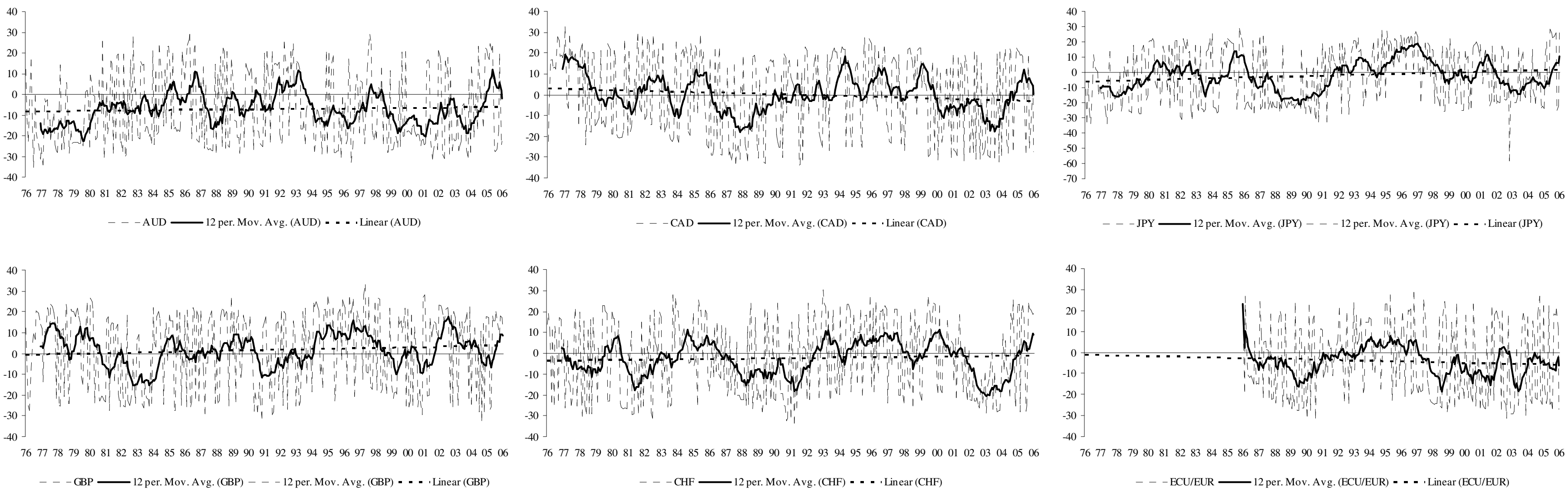
**Notes**. Panel A of this table reports (1) the number of rolling yearly $R^2$ estimates for each currency over the full sample period and in each sub-sample period, (2) the number and the (3) percentage frequency of positive BVI values, i.e. (2) over (1). Panel B reports the percentage square root of the annualized average BVI conditional on the BVI itself being positive, for each currency and its average across currencies. The BVI is calculated as explained in the text, under a RRA upper-bound equal to 5. The predictive regressions are estimated over rolling 1-year windows of daily data, throughout the sub-sample periods specified in the first column.

**Figure 2**
**Daily Excess-Predictability**




**Notes**. This figure plots, for each point in our sample period, the average across the cross-section of the currencies in our sample of the percentage BVI. The latter is based, for all currencies, on rolling AR(5) auto-regressions and a RRA upper bound of 5, i.e. $RRA_V = 5$. The estimation window of each auto-regression is one year and the sample period is 1971-2006. The values of the average BVI series have been cut off at 10.0 for improved visual clarity. The solid and dotted lines in bold are a 252-day moving average and a linear interpolation, respectively, of the average BVI series.

# Figure 3
# Monthly Excess-Predictability
# (Adjusted for Sampling Error)




**Notes**. These figures plot, for each point in our sample period and each currency on our sample, the percentage sampling error-adjusted BVI based on rolling AR(5,2) predictive regressions and a RRA upper bound of 5, i.e. $RRA_V = 5$. The estimation window of each auto-regression is 5 years of monthly data from 1971 to 2006. The values of all the BVI series have been cut off at 10.0 for improved visual clarity. The solid and dotted lines in bold are a 252-day moving average and a linear interpolation, respectively, of the BVI series.

**Table 2**
**Boundary Violation Index and Excess-Maximal SRs**
**Daily Excess Predictability**

| | | **AUD** | **CAD** | **JPY** | **GBP** | **CHF** | **ECU/ EUR** | **Bound $RRA_V$ = 2.5** | **Bound $RRA_V$ = 5.0** |
|---|---|---|---|---|---|---|---|---|---|
| 1971-2006 | | | | | | | | 0.06 | 0.24 |
| | p,q | 3,0 | 3,0 | 1,1 | 4,2 | 2,2 | | | |
| | $R^2$ | 0.07 | 0.12 | 0.15 | 0.29 | 0.09 | | | |
| | Q(36-p-q) | 35.27 | 43.6 | 43.8 | 39.6 | 38.2 | | | |
| | (p-value) | (0.361) | (0.102) | (0.121) | (0.112) | (0.209) | | | |
| | $BVI_{RRA=2.5} > 0$ | 0.01 | *0.06 | *0.09 | *0.23 | 0.03 | | | |
| | $BVI_{RRA=5.0} > 0$ | - | - | - | 0.05 | - | | | |
| | $F_{K,T\text{-}K\text{-}1,\ 95\%}$ | 0.06 | 0.06 | 0.05 | 0.10 | 0.07 | | | |
| | $\gamma_{adj,RRA=2.5}$ | - | - | 31.7 | 57.2 | - | | | |
| | $\gamma_{adj,RRA=5.0}$ | - | - | - | - | - | | | |
| 1971-1982 | | | | | | | | 0.05 | 0.20 |
| | p,q | 4,2 | 4,2 | 1,1 | 4,2 | 3,2 | | | |
| | $R^2$ | 0.54 | 1.05 | 0.38 | 0.84 | 0.90 | | | |
| | Q(36-p-q) | 16.27 | 29.3 | 42.7 | 63.3 | 59.34 | | | |
| | (p-value) | (0.979) | (0.499) | (0.145) | (0.000) | (0.001) | | | |
| | $BVI_{RRA=2.5} > 0$ | *0.49 | *1.00 | *0.33 | *0.79 | *0.85 | | | |
| | $BVI_{RRA=5.0} > 0$ | *0.34 | *0.85 | *0.18 | *0.64 | *0.70 | | | |
| | $F_{K,T\text{-}K\text{-}1,\ 95\%}$ | 0.31 | 0.31 | 0.15 | 0.31 | 0.08 | | | |
| | $\gamma_{adj,RRA=2.5}$ | 67.3 | 131.8 | 67.3 | 109.9 | 139.3 | | | |
| | $\gamma_{adj,RRA=5.0}$ | 27.5 | 116.6 | 27.5 | 91.2 | 125.0 | | | |
| 1983-1994 | | | | | | | | 0.05 | 0.21 |
| | p,q | 2,2 | 5,1 | 2,2 | 1,0 | 3,2 | 4,2 | | |
| | $R^2$ | 0.34 | 0.41 | 0.44 | 0.12 | 0.67 | 0.48 | | |
| | Q(36-p-q) | 47.26 | 14.4 | 43.7 | 30.4 | 32.2 | 28.9 | | |
| | (p-value) | (0.040) | (0.992) | (0.082) | (0.691) | (0.409) | (0.524) | | |
| | $BVI_{RRA=2.5} > 0$ | *0.29 | *0.36 | *0.39 | 0.07 | *0.60 | *0.43 | | |
| | $BVI_{RRA=5.0} > 0$ | 0.13 | 0.20 | 0.23 | - | 0.46 | 0.27 | | |
| | $F_{K,T\text{-}K\text{-}1,\ 95\%}$ | 0.22 | 0.29 | 0.22 | 0.09 | 0.25 | 0.29 | | |
| | $\gamma_{adj,RRA=2.5}$ | 42.0 | 42.0 | 65.4 | - | 93.9 | 59.4 | | |
| | $\gamma_{adj,RRA=5.0}$ | - | - | 15.9 | - | 72.7 | - | | |
| 1995-2006 | | | | | | | | 0.07 | 0.30 |
| | p,q | 3,2 | 3,2 | 3,2 | 3,2 | 1,0 | 1,0 | | |
| | $R^2$ | 0.44 | 0.73 | 0.52 | 0.69 | 0.38 | 0.21 | | |
| | Q(36-p-q) | 34.6 | 27.7 | 30.2 | 26.2 | 28.9 | 25.6 | | |
| | (p-value) | (0.299) | (0.635) | (0.505) | (0.710) | (0.756) | (0.878) | | |
| | $BVI_{RRA=2.5} > 0$ | *0.37 | *0.66 | *0.45 | *0.62 | *0.31 | *0.14 | | |
| | $BVI_{RRA=5.0} > 0$ | 0.14 | *0.43 | 0.22 | *0.39 | 0.08 | - | | |
| | $F_{K,T\text{-}K\text{-}1,\ 95\%}$ | 0.26 | 0.26 | 0.26 | 0.26 | 0.09 | 0.09 | | |
| | $\gamma_{adj,RRA=2.5}$ | 52.6 | 100.4 | 69.2 | 95.2 | 74.4 | 35.5 | | |
| | $\gamma_{adj,RRA=5.0}$ | - | 65.4 | - | 57.2 | - | - | | |

**Notes**. This table reports, for the entire sample period 1971-2006 and three sub-samples of about equal length, 1971-1982, 1983-1994, 1995-2006, the AR and MA order lags, denoted by p and q, selected by the AIC and the percentage coefficient of determination and Ljung-Box Q(36-p-q) statistic, and associated p-value, of the corresponding ARMA(p,q) model estimated using daily data. The table also reports the BVI, when positive, under RRA = 2.5 and RRA = 5, the 95th percentile of the F- distribution with K and T-K-1 degrees of freedom, where K = p + q and T denotes the sample size, and the corresponding $\gamma_{adj}$.

**Table 3**
**Boundary Violation Index and Excess-Maximal SRs**
**Monthly Excess Predictability**

| | | **AUD** | **CAD** | **JPY** | **GBP** | **CHF** | **ECU/ EUR** | **Bound $RRA_V$ = 2.5** | **Bound $RRA_V$ = 5.0** |
|---|---|---|---|---|---|---|---|---|---|
| 1971-2006 | | | | | | | | 1.28 | 5.11 |
| | p,q | | **4,2** | 5,2 | 1,0 | 3,2 | | | |
| | $R^2$ | | 3.28 | 3.80 | 0.50 | 3.12 | | | |
| | Q(36-p-q) | | 40.1 | 23.6 | 29.2 | 18.2 | | | |
| | (p-value) | | (0.102) | (0.749) | (0.745) | (0.967) | | | |
| | $BVI_{RRA=2.5} > 0$ | | *2.00 | *2.52 | - | *1.84 | | | |
| | $BVI_{RRA=5.0} > 0$ | | - | - | - | - | | | |
| | $F_{K,T\text{-}K\text{-}1,\ 95\%}$ | | 1.17 | 1.31 | 0.35 | 1.03 | | | |
| | $\gamma_{adj,\mathrm{RRA}=2.5}$ | | - | - | - | - | | | |
| | $\gamma_{adj,\mathrm{RRA}=5.0}$ | | - | - | - | - | | | |
| 1971-1982 | | | | | | | | 1.34 | 5.35 |
| | p,q | | 5,2 | 5,2 | 0,2 | **1,0** | | | |
| | $R^2$ | | 13.81 | 11.39 | 2.91 | 0.16 | | | |
| | Q(35-p-q) | | 29.6 | 16.6 | 33.6 | 29.6 | | | |
| | (p-value) | | (0.380) | (0.955) | (0.439) | (0.682) | | | |
| | $BVI_{RRA=2.5} > 0$ | | *12.47 | *10.05 | *1.68 | - | | | |
| | $BVI_{RRA=5.0} > 0$ | | *8.46 | *6.04 | - | - | | | |
| | $F_{K,T\text{-}K\text{-}1,\ 95\%}$ | | 4.01 | 4.01 | 1.67 | 1.07 | | | |
| | $\gamma_{adj,\mathrm{RRA}=2.5}$ | | 31.5 | 38.1 | - | 31.2 | | | |
| | $\gamma_{adj,\mathrm{RRA}=5.0}$ | | - | - | - | - | | | |
| 1983-1994 | | | | | | | | 1.61 | 6.43 |
| | p,q | **2,2** | 4,2 | 5,2 | **1,0** | **2,2** | **1,0** | | |
| | $R^2$ | 7.20 | 10.20 | 13.93 | 1.01 | 7.01 | 0.58 | | |
| | Q(35-p-q) | 29.2 | 27.0 | 34.9 | 27.1 | 35.0 | 33.4 | | |
| | (p-value) | (0.556) | (0.570) | (0.170) | (0.793) | (0.282) | (0.499) | | |
| | $BVI_{RRA=2.5} > 0$ | *5.59 | *8.59 | *12.32 | - | *5.40 | - | | |
| | $BVI_{RRA=5.0} > 0$ | 0.77 | *3.77 | *7.50 | - | 0.58 | - | | |
| | $F_{K,T\text{-}K\text{-}1,\ 95\%}$ | 2.68 | 3.58 | 4.01 | 1.07 | 2.68 | 1.07 | | |
| | $\gamma_{adj,\mathrm{RRA}=2.5}$ | - | 103.3 | 85.1 | 24.5 | - | - | | |
| | $\gamma_{adj,\mathrm{RRA}=5.0}$ | - | 76.5 | 49.3 | - | - | - | | |
| 1995-2006 | | | | | | | | 1.24 | 4.95 |
| | p,q | **1,2** | **0,1** | 3,2 | 2,0 | **1,1** | **0,1** | | |
| | $R^2$ | 7.76 | 0.08 | 10.7 | 2.99 | 5.8 | 1.27 | | |
| | Q(35-p-q) | 27.2 | 31.43 | 33.1 | 28.7 | 42.7 | 29.7 | | |
| | (p-value) | (0.560) | (0.641) | (0.316 | (0.681) | (0.145) | (0.718) | | |
| | $BVI_{RRA=2.5} > 0$ | *6.52 | - | *9.46 | *1.75 | *4.56 | 0.03 | | |
| | $BVI_{RRA=5.0} > 0$ | *2.81 | - | *5.75 | - | 0.85 | - | | |
| | $F_{K,T\text{-}K\text{-}1,\ 95\%}$ | 2.23 | 1.08 | 3.18 | 1.67 | 1.67 | 1.08 | | |
| | $\gamma_{adj,\mathrm{RRA}=2.5}$ | 71.7 | - | 86.8 | 9.8 | 58.9 | - | | |
| | $\gamma_{adj,\mathrm{RRA}=5.0}$ | 26.4 | - | 55.5 | - | - | - | | |

**Notes**. This table reports, for the entire sample period 1971-2006 and three sub-samples of about equal length, 1971-1982, 1983-1994, 1995-2006, the AR and MA order lags, denoted by p and q, selected by the AIC and the percentage coefficient of determination and Ljung-Box Q(36-p-q) statistic, and associated p-value, of the corresponding ARMA(p,q) model estimated using monthly data. The table also reports the BVI, when positive, under RRA = 2.5 and RRA = 5, and the 95$^{th}$ percentile of the F- distribution with K and T-K-1 degrees of freedom, where K = p + q and T denotes the sample size, and the corresponding $\gamma_{adj}$.

**Table 4**
**Bootstrapped Percent $R^2$ Distribution**
**Daily Predictability**

| | | 1971-2006 | | 1971-1982 | | 1983-1994 | | 1995-2006 | |
|---|---|---|---|---|---|---|---|---|---|
| $Bound_{RRA=2.5}$ | | | 0.06 | | 0.05 | | 0.05 | | 0.07 |
| $Bound_{RRA=5}$ | | | 0.24 | | 0.20 | | 0.21 | | 0.30 |
| AUD | $R^2$ | | | | | | 0.29 | | 0.14 |
| | Conf. Interval | | | | | *0.16 | 0.89 | *0.08 | 0.61 |
| CAD | $R^2$ | | 0.13 | | 0.90 | | 0.20 | | 0.60 |
| | Conf. Interval | *0.06 | 0.33 | **0.52 | 1.72 | *0.11 | 0.75 | **0.34 | 1.30 |
| JPY | $R^2$ | | 0.07 | | 0.11 | | 0.12 | | 0.09 |
| | Conf. Interval | 0.04 | 0.25 | *0.06 | 0.61 | *0.07 | 0.59 | 0.06 | 0.52 |
| GBP | $R^2$ | | 0.21 | | 0.70 | | 0.41 | | 0.17 |
| | Conf. Interval | *0.12 | 0.45 | **0.40 | 1.46 | *0.19 | 1.02 | *0.10 | 0.67 |
| CHF | $R^2$ | | 0.01 | | 0.24 | | 0.14 | | 0.34 |
| | Conf. Interval | 0.01 | 0.15 | *0.08 | 0.61 | *0.09 | 0.62 | *0.18 | 0.94 |
| ECU/EUR | $R^2$ | | | | | | 0.18 | | 0.30 |
| | Conf. Interval | | | | | *0.09 | 0.69 | *0.14 | 0.90 |

**Notes**. This table reports, for the entire sample period 1971-2006 and three sub-samples of about equal length, 1971-1982, 1983-1994, 1995-2006, boot-strapped confidence intervals for the percentage coefficient of determination of ARMA(5,0) models. The first two rows report percentage unconditional upper bounds on the explanatory power of predictive regressions under a relative risk aversion upper bound equal to 2.5 and 5, respectively. The other rows report, for each currency, the estimated predictive regression coefficient of determination and 90 percent two-tailed confidence intervals around the latter (in percentage). The estimated predictive models are 5-lag auto-regressions. In the table, one and two asterisks denote when the upper bound is violated at the significance level corresponding to the value reported in the left-most column under a RRA bound of 2.5 and 5, respectively. Confidence intervals for AUD in 1971-1982 are not available due to a failure of the bootstrapping procedure, caused by a lack of a sufficiently continuous series of return observations.

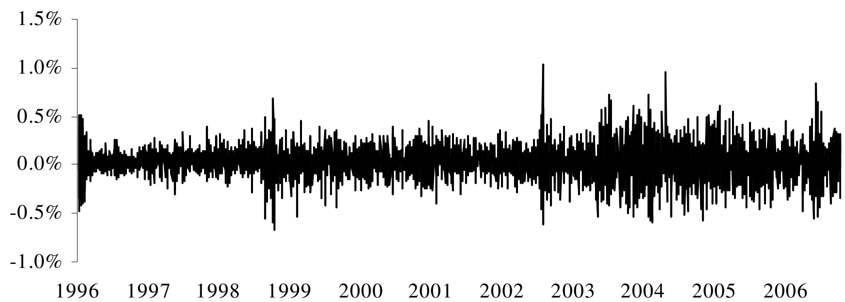
**Table 5**
**Bootstrapped Percent $R^2$ Distribution**
**Monthly Predictability**

| | | 1971-2006 | 1971-1982 | 1983-1994 | 1995-2006 |
|---|---|---|---|---|---|
| $Bound_{RRA=2.5}$ | | 1.28 | 1.34 | 1.61 | 1.24 |
| $Bound_{RRA=5}$ | | 5.11 | 5.35 | 6.43 | 4.95 |
| | | ARMA(5,0) | | | |
| AUD | $R^2$ | 0.83 | 2.41 | 5.25 | 1.44 |
| | Conf. Interval | 0.51 4.17 | *1.51 12.17 | *2.49 15.90 | *1.28 10.18 |
| CAD | $R^2$ | 0.71 | 8.42 | | 1.97 |
| | Conf. Interval | 0.47 3.77 | *4.81 19.29 | | *1.36 11.71 |
| JPY | $R^2$ | 1.03 | 3.23 | 1.54 | 7.65 |
| | Conf. Interval | 0.57 4.28 | *1.52 12.89 | 1.00 10.06 | *3.96 18.18 |
| GBP | $R^2$ | 0.58 | 4.90 | 1.86 | 3.73 |
| | Conf. Interval | 0.42 3.63 | *2.55 15.03 | 1.29 10.61 | *2.23 14.08 |
| CHF | $R^2$ | 0.95 | 1.41 | 1.51 | 2.48 |
| | Conf. Interval | 0.52 4.22 | 1.09 10.51 | 1.18 9.78 | *1.43 12.02 |
| ECU/EUR | $R^2$ | | | 1.30 | 2.04 |
| | Conf. Interval | | | 1.04 9.17 | *1.37 11.62 |
| | | ARMA(5,2) | | | |
| AUD | $R^2$ | 1.19 | 2.82 | 5.51 | 3.82 |
| | Conf. Interval | *1.38 24.15 | *2.93 17.43 | *5.15 23.39 | *3.55 28.81 |
| CAD | $R^2$ | 0.90 | 13.58 | 4.17 | 2.26 |
| | Conf. Interval | 1.12 6.09 | **9.37 30.36 | *3.34 17.95 | *3.33 15.52 |
| JPY | $R^2$ | 3.85 | 14.41 | 8.74 | 11.49 |
| | Conf. Interval | *2.94 64.38 | **6.89 63.83 | *4.23 27.30 | **8.05 25.03 |
| GBP | $R^2$ | 1.54 | 5.71 | 2.35 | 6.72 |
| | Conf. Interval | 1.24 7.21 | *4.80 18.05 | *3.14 16.04 | *3.93 18.26 |
| CHF | $R^2$ | 2.52 | 3.22 | 3.41 | 6.68 |
| | Conf. Interval | *1.76 8.31 | *3.17 17.25 | *3.92 19.55 | *4.25 17.07 |
| ECU/EUR | $R^2$ | | | 4.81 | 4.45 |
| | Conf. Interval | | | *3.87 20.13 | *3.36 14.62 |

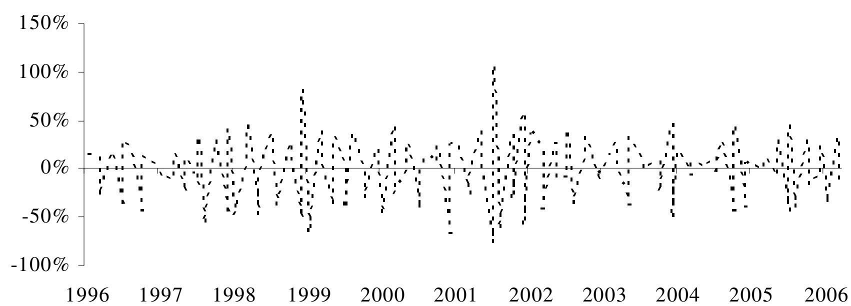
**Notes**. The first two rows of this table report percentage unconditional upper bounds on the explanatory power of predictive regressions under a relative risk aversion upper bound equal to 2.5 and 5, respectively. The other rows report, for each currency, the percentage coefficient of determination of the estimated regression model and the bootstrapped 90 percent two-tailed confidence intervals around the latter (in percentage). The bootstrapping experiment is conducted by re-sampling 1,000 times, in blocks of 5 at a time, the residuals of the estimated predictive model. The latter is AR(5), for the top panel, and ARMA(5,2) for the bottom panel. The sample periods are 1971-2006 and three sub-samples of about equal length, 1971-1982, 1983-1994, 1995-2006. In the table, one and two asterisks denote when the upper bound is violated at the significance level corresponding to the value reported in the left-most column under a RRA bound of 2.5 and 5, respectively. Confidence intervals for CAD in 1983-1994 are not available due to a lack of convergence of regressions on bootstrapped data.

**Figure 4**
**Time Varying Weights for the Maximal SR Strategy for the Canadian Dollar**

Panel A
(Daily)




Panel B
(Monthly)




**Notes**. Panel A and B of this Figure plot the time-varying weights of the maximal SR strategies 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 1995-2006 sample period.

## Table 6
## Impact of Transaction Costs on Percentage SRs of Predictability-Based Strategies

| Transaction costs (bps) | 0 | 2 | 3 | 5 | 25 | Bound $RRA_V$ = 2.5 | Bound $RRA_V$ = 5.0 |
|---|---|---|---|---|---|---|---|
| | | Daily (1995-2006) | | | | 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 (1972-2006) | | | | 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 | | |
| ECU/EUR | | | | | | | |
| | | (1972-1982) | | | | 40.1 | 80.1 |
| AUD | *52.3 | *50.6 | *49.6 | *47.7 | 27.3 | | |
| CAD | **130.9 | **123.8 | **120.3 | **113.0 | 35.7 | | |
| JPY | **128.0 | **126.4 | **125.7 | **124.2 | **109.2 | | |
| GBP | **181.4 | **179.2 | **178.1 | **175.9 | **154.0 | | |
| CHF | *76.01 | *74.3 | *73.4 | *71.7 | *54.1 | | |
| ECU/EUR | | | | | | | |
| | | (1983-1994) | | | | 44.0 | 87.8 |
| AUD | *75.5 | *73.7 | *72.8 | *71.0 | *52.8 | | |
| CAD | *74.4 | *69.8 | *67.5 | *62.9 | 16.2 | | |
| JPY | **93.4 | **91.3 | **90.3 | **88.2 | *66.8 | | |
| GBP | *54.6 | *52.9 | *52.1 | *51.3 | 33.6 | | |
| CHF | *63.0 | *60.8 | *59.7 | *57.5 | 34.8 | | |
| ECU/EUR | *85.8 | *83.0 | *81.5 | *78.7 | 49.4 | | |
| | | (1995-2006) | | | | 38.6 | 77.1 |
| AUD | *81.5 | *79.2 | *78.0 | *75.7 | *51.9 | | |
| CAD | *72.0 | *68.1 | *66.1 | *62.0 | 20.3 | | |
| JPY | **106.4 | **105.0 | **104.4 | **103.0 | **89.6 | | |
| GBP | **78.6 | *75.0 | *73.3 | 69.8 | 34.1 | | |
| CHF | *56.0 | *54.9 | *54.4 | *53.4 | *43.7 | | |
| ECU/EUR | *63.9 | *62.2 | *61.3 | *59.7 | *42.8 | | |

**Notes**. This Table reports percentage annualized Sharpe ratios of strategies that optimally exploit 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. 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.

## Table 7
## SRs, Correlations and Factor Structure of Maximal-SR Strategies

| | w* | SR | Corr. vs. r* | Corr. vs. AFX | alpha | $R_m$-$R_f$ | SMB | HML | GRS |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Panel A (1984-2006) | | | | | *2.79 (0.012) |
| AUD | 46.1 | 43.9 | 58.8 | 22.5 | *0.45 | *-5.17 | *-11.78 | *-8.86 | |
| | | | | | (2.54) | (-2.27) | (-2.44) | (-2.04) | |
| CAD | 15.9 | 15.4 | 20.7 | 4.3 | 0.16 | 6.52 | 5.49 | 0.85 | |
| | | | | | (0.57) | (1.09) | (0.49) | (0.10) | |
| JPY | 31.6 | 43.9 | 58.8 | 19.1 | *0.59 | *-12.44 | -5.41 | *-15.19 | |
| | | | | | (2.22) | (-2.09) | (-0.80) | (-2.01) | |
| GBP | 4.4 | 24.3 | 32.5 | 21.8 | 0.52 | *-14.55 | 2.12 | -10.91 | |
| | | | | | (1.30) | (-3.06) | (0.19) | (-1.45) | |
| CHF | -15.6 | 35.3 | 47.3 | 41.8 | *0.19 | *-3.75 | -3.99 | *-6.37 | |
| | | | | | (2.71) | (-2.17) | (-1.70) | (-2.42) | |
| ECU-EUR | 17.6 | 39.6 | 53.1 | 45.0 | *0.85 | -6.27 | -10.27 | -17.62 | |
| | | | | | (2.60) | (-0.59) | (-0.73) | (-1.23) | |
| r* | 100.0 | 74.7 | 100.0 | 46.9 | *0.56 | *-6.44 | -7.39 | *-11.38 | |
| | | | | | (4.11) | (-1.97) | (-1.59) | (-2.67) | |
| AFX | | 56.7 | 46.9 | 100.0 | *0.34 | 0.52 | *-4.71 | -3.60 | |
| | | | | | (2.72) | (0.17) | (-1.11) | (-0.92) | |
| | | | | Panel B (1996-2006) | | | | | *2.73 (0.016) |
| AUD | 6.9 | 44.2 | 31.8 | 10.2 | 0.34 | 7.68 | -2.22 | 5.47 | |
| | | | | | (1.18) | (1.11) | (-0.18) | (0.77) | |
| CAD | 12.5 | 42.7 | 30.7 | 11.2 | 0.38 | -0.54 | 14.27 | -12.52 | |
| | | | | | (1.58) | (-0.12) | (1.70) | (-1.35) | |
| JPY | 30.9 | 74.4 | 53.5 | 4.8 | 0.38 | 3.19 | *-17.93 | 2.11 | |
| | | | | | (1.59) | (1.58) | (-3.23) | (0.32) | |
| GBP | 22.9 | 64.6 | 46.4 | -3.0 | *0.45 | 3.15 | 10.25 | 1.29 | |
| | | | | | (2.71) | (0.89) | (1.90) | (0.16) | |
| CHF | 21.7 | 59.3 | 42.6 | 23.5 | *0.30 | 2.38 | -1.54 | 1.84 | |
| | | | | | (2.07) | (0.77) | (-0.25) | (0.26) | |
| ECU-EUR | 5.1 | 53.4 | 38.3 | 40.7 | *0.86 | 16.61 | -5.42 | -25.72 | |
| | | | | | (2.21) | (1.19) | (-0.20) | (-1.55) | |
| r* | 100.0 | 139.2 | 100.0 | 27.9 | *0.40 | 3.53 | -2.19 | -1.14 | |
| | | | | | (4.16) | (1.47) | (-0.52) | (-0.25) | |
| AFX | | 35.8 | 27.9 | 100.0 | 0.20 | 1.01 | 9.52 | *-11.65 | |
| | | | | | (1.40) | (0.29) | (1.56) | (-1.77) | |

**Notes**. The first column of this table reports the percentage weights w* with which the maximal Sharpe Ratio predictability-based strategies for each currency enter the overall maximal Sharpe Ratio strategy, denoted by r*. The other columns report annualized Sharpe ratios of these strategies and of the AFX currency management index. The annualized maximal SR bound under a RRA upper bound equal to 2.5 and 5 is 44 and 85 percent, respectively. The other columns reports the intercept and factor loadings estimated (marked with an asterisk when significant at the 5 percent level) and, in brackets, the associated t-static based on Newy and West (1987) autocorrelation and heteroskedasticity adjusted standard errors. An asterisk denotes significance at the 5 percent level. The last column reports the GRS statistic (and its p-value in brackets) for the 6 individual currencies maximal SR strategies. The hypothesized level of transaction costs is two basis points per transaction and the predictive model, to simplify our computational task, is ARMA(5,0) for all currencies. The data frequency of the underlying return series is monthly.

## Table 8
## AFX vs. Maximal SR Strategy

| Period | Corr. AFX vs. r* | $SR_{AFX}$ | $SR_{r*}$ | Corr. $SR_{AFX}$ vs. $SR_{r*}$ |
|---|---|---|---|---|
| 1985-1990 | 52.36 | 97.17 | 115.89 | 52.92 |
| 1991-1996 | 46.29 | 38.38 | 58.62 | 45.64 |
| 1997-2002 | 50.20 | 49.53 | 20.00 | 11.62 |
| 2003-2006 | 41.08 | -5.44 | 106.14 | -44.55 |

**Notes**. This Table reports, for four 5-year periods between 1985 and 2006, the percentage coefficient of correlation between the AFX Currency Management index return and the maximal SR strategy return r*, their SR and the correlation between their 12-month moving.

## Figure 4
## AFX vs. Maximal SR Strategy


**Notes**. This Figure plots the rolling 12-month SR of the maximal SR strategy r* that exploits monthly predictability, based on estimates from an ARMA(5,0) model, and of the AFX Currency Management Index. The sample period is 1984-2006.

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