

What Drives Currency Predictability?

Valerio Potì^a

Akhtar Siddique^b

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In this paper, we study predictability of exchange rates and explore determinants of its dynamics over time. We model the admissible amount of predictability in two ways, each corresponding in a stylized manner to a broad class of rational currency pricing models, namely those under which the marginal currency trader can diversify away currency risk and alternative specifications under which this possibility is precluded. Under the null of Rational Expectations, we find strong evidence against the former class of models but little evidence against the latter, except that predictability itself is predictable. Our results pose a challenge to Fama's (1970) Efficient Market Hypothesis, but are consistent with microstructure models of foreign exchange markets in which a capital-constrained undiversified marginal currency trader seeks reward for total risk instead of systematic risk alone and sluggish risk capital mobility drives predictable time-variation in currency predictability.

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Contact details:

^a Valerio Potì, Room Q233, Dublin City University Business School, Glasnevin, Dublin 9, Ireland; Tel: 3531-7005823, Fax: 3531- 7005446; Email: valerio.poti@dcu.ie.

^b Akhtar Siddique, Comptroller of the Currency, 250 E St., Washington, DC 20219 Email: Akhtarur.siddique@occ.treas.gov

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In this paper, we study predictability of exchange rates and explore determinants of its dynamics over time. We model the admissible amount of predictability in two ways, each corresponding in a stylized manner to a broad class of rational currency pricing models, namely those under which the marginal currency trader can diversify away currency risk and alternative specifications under which this possibility is precluded. Under the null of Rational Expectations, we find strong evidence against the former class of models but little evidence against the latter, except that predictability itself is predictable. Our results pose a challenge to Fama's (1970) Efficient Market Hypothesis, but are consistent with microstructure models of foreign exchange markets in which a capital-constrained undiversified marginal currency trader seeks reward for total risk instead of systematic risk alone and sluggish risk capital mobility drives predictable time-variation in currency predictability.

1. Introduction

Evidence of currency predictability was initially documented in studies that sought to evaluate the profitability of technical trading rules. See, for example, Levich and Thomas (1993), Neely, Weller and Dittmar (1997), Gencay (1999), LeBaron (1999). More recent studies found diminishing profitability, e.g. Olson (2004), Pukthuanthong, Levich and Thomas (2006) and Neely, Weller and Joshua (2009), though the latter authors also found that newer and relatively more sophisticated rules were still profitable. Recent studies have also shown that rules that exploited the "forward premium puzzle", most notably the carry trade, generated for over a decade returns that were large and relatively uncorrelated with known risk factors. See, among others, Burnside et al. (2007), Brunnermeir et al. (2008), Jylha et al. (2008) and Jylha and Suominen (2010). Overall, these studies suggest the presence of predictability, possibly itself of a predictably time-varying nature, in foreign exchange markets.

Direct or indirect attempts to explain such predictability include the work of Brennan and Xia (2006), Burnside et al. (2007), Lustig et al. (2008), Hochradl and Wagner (2009), Neely et al. (2009), Jylha and Suominen (2010). Such attempts, however, have either focused on the predictability exploited by specific trading rules, most prominently the carry trade except in the paper of Neely et al (2009) who consider momentum and filter rules, or they have not emphasized the possibly time-varying nature of predictability, with the notable exceptions of Neely et al (2009) and Jylha and Suominen (2010). Our paper draws insight from this literature and especially from the paper of Jylha and Suominen (2010), to offer a comprehensive assessment of the evolution through time of currency predictability and, more importantly, explore its determinants. That is, a key concern in our study is predictability of predictability and what drives it. We rely on the recent literature on limits to speculation, especially Jylha and Suominen (2010), Adrian and Shin (2010) and Garleanu and Pedersen (2011), and capital mobility, i.e. Duffie (2010) and Duffie and Strulovici (2011).

On one hand, we find that the level of estimated currency predictability can be largely explained as the by-product of plausible temporal variation of expected returns demanded by a marginal currency trader who seeks reward for total risk, whereas it is difficult to account for it if we posit that it is systematic risk only that matters. Because of the close link between predictability and excess-volatility, this is in contrast with classical formulations of Fama's (1970) Efficient Market Hypothesis (EMH) but is consistent with rational expectations, and hence rational currency pricing, in the presence of "limits to speculation" as in models à la Lyon's (2001) and "speculative efficiency" à la Wagner

(2009). On the other hand, we find that predictability varies over time in a manner that depends on the availability of risk capital. This predictability of predictability cannot be easily reconciled with these models unless we posit limited risk capital mobility as in Duffie (2010) and Duffie and Strulovici (2011) or some other mechanism that may result in time-varying “limits to speculation”.

The rest of the paper is structured as follows. In the next section, we characterize rational currency pricing and predictability under two stylized models corresponding to two broad classes of rational asset pricing models, which essentially differ with respect to whether the marginal currency trader can hold a diversified market portfolio or otherwise. In Section 3, we describe our dataset. In Section 4, we provide an empirical characterization of currency predictability by checking whether it can be rationalized in a model that allows for diversification of the marginal currency trader or otherwise. In Sections 5, 6 and 7, we study the evolution of predictability over time and the drivers of its variation, showing that short-term deviations from the level that can be rationalized by postulating an undiversified marginal currency trader are themselves predicted by the availability of risk capital. In the final Section, we summarize our main findings and offer conclusions.

2. Rational Currency Pricing and Marginal Currency Trader Diversification

We interpret an exchange rate as the price of a particular security, i.e. a default-free interest-bearing deposit denominated in a foreign currency, with price and payoffs expressed in terms of units of the domestic currency, i.e. the US Dollar, which in our

study acts as the numeraire. For ease of exposition, we will refer to such deposits as the currencies in which they are denominated, e.g. the Canadian Dollar will be a unit deposit denominated in such currency (and funded in USD). We represent the data-generating process (DGP) of the excess-returns on a generic asset in the economy, including currencies, as follows:

$$r_{t+1} = \mu_{t+1}(I_t) + u_{t+1} \quad (1)$$

$$\mu_{t+1} \equiv E(r_{t+1}|I_t) \equiv \mu_{t+1}(I_t) \quad (2)$$

Here, I_t is the information set at time t and u_{t+1} is a zero-mean innovation, which is unpredictable with respect to the information set I_t . The information set includes not only the sigma-field generated by the past of u_{t+1} but also all other available public and private information. Under rational valuation, the expected excess-return μ_{t+1} equals the discount rate at which the marginal investor, assumed endowed with Rational Expectations (RE), discounts the excess return r_{t+1} . We define RE as the ability to formulate ex-ante forecasts that do not systematically diverge from ex-post Maximum Likelihood (ML) estimates of the DGP. This definition is consistent with Muth's (1961) seminal article and the subsequent generalizations in Lucas (1978) and Sargent (1993).

We focus on 'predictability-based' strategies that allow an investor endowed with RE to take advantage of discrepancies between the expected rate or return and the discount rate by exploiting the resulting predictability. We denote the excess-return on a generic member of this class of strategies as r_{t+1}^* . We will characterize one such strategy later. For the moment, we derive the implications of RE for the entire class under two alternative stylized models, namely the '*diversified marginal trader*' model (DMTM,

henceforth), and the ‘*undiversified marginal trader*’ model (*UMTM*, henceforth), each corresponding to a relatively broad class of rational currency pricing models. In both models, we assume that investors are greedy, risk-averse individuals bent on maximizing expected utility of lifetime wealth and endowed with Muth’s (1961) RE. We now illustrate each model in turn.

DMTM

In the *DMTM*, investors have access at no cost to the public and private information required to formulate rational forecasts. In this frictionless economy, investors will trade away all arbitrage opportunities. This implies that there exists a positive kernel m_{t+1} such that $E(r_{t+1}m_{t+1}|I_t) = 0$ holds for all traded payoffs. Under RE, this restriction must also hold unconditionally, i.e.

$$E(r_{t+1}m_{t+1}) = E[E(r_{t+1}m_{t+1}|I_t)] = 0 \quad (3)$$

When pricing excess-returns, and for realistically low levels of the risk free rate, the mean of the kernel is essentially not identified and thus it can be well approximated by setting it to unity. From (3), we thus have

$$E(r_{t+1}) = -\frac{\text{Cov}(r_{t+1}, m_{t+1})}{E(m_{t+1})} \cong -\text{Cov}(r_{t+1}, m_{t+1}) \quad (4)$$

For a given set of traded assets, (3) and (4) must hold for any admissible kernel, including the kernel with minimum variance, and all strategies, including the predictability-based strategies introduced earlier. These strategies, with excess return r_{t+1}^* , will be our focus from now on. The minimum-variance kernel that satisfies (3) for all traded payoffs is the

marginal investor's Inter-temporal marginal Rate of Substitution (IMRS)¹, φ_{t+1} , which we model as a linear function² of a set of factors f_{t+1} and setting its mean equal to one (again, this is legitimate because we are working with excess-returns):

$$\varphi_{t+1} = a + b' f_{t+1} = 1 + b' f_{t+1} \quad (5)$$

Then, from (4) and (5), we have

$$E(r_{t+1}^*) \cong -Cov(r_{t+1}^*, \varphi_{t+1}(f_{t+1})) = -b' Cov(r_{t+1}^*, f_{t+1}) = \beta' \lambda \quad (6)$$

Here, the elements of the vector β are the coefficients of the regression of r_{t+1}^* on the factors and $\lambda \cong -b' Var(f)^{-1} Cov(r_{t+1}^*, f_{t+1})$ is a conformable vector of risk-premia.

UMTM

In the *UMTM*, we allow for frictions by assuming that (a) investors are capital-constrained, in the sense that the risk capital supply curve they face is upward-sloping, and (b), in trading currencies, they face fixed transaction costs in gathering and processing information³, as well as limited asset divisibility⁴. These frictions all impact

¹ This must be the case for every investor and for every payoff that each investor can trade. If the market is complete, the IMRSs of all investors must be the same and equal to the minimum-variance kernel that prices all assets. In incomplete but otherwise frictionless markets, this restriction applies with respect to the projections of the IMRSs onto the span of the traded asset payoffs.

² The representative investor's IMRS will be a function of the payoff on a portfolio of risky assets that represents the efficient allocation for all investors. Such a function will be unconditionally linear (static CAPM) or non linear (e.g., higher-moment versions of the static CAPM, conditional CAPM) depending, in general, on the functional specification of the investors' utility functions and their wealth allocations.

³ Ideally, we should also consider the implications for the investors' problem of economies of scope that arise in the gathering of information. This would, however, complicate our discussion and we therefore leave it for future research. We note, however, that, to the extent that such economies of scope pertain to the gathering of information that is idiosyncratic to the currency market, possibly in a multi-currency setting à la Lyons and Moore (2009), they would typically create additional incentives to increase the scale. For example, traders often cite the usefulness of being a large player in that this allows to "see the flows", thereby gaining an informational advantage. This creates an incentive for large dealers to develop large currency trading operations, effectively becoming market makers. See, on this mechanism, the comprehensive discussion offered by Lyons (2001).

⁴ For example, in order to exploit informational advantages resulting from being able to "see the flows", currency traders must stand ready to enter large size transactions, thereby acting as market makers.

the investors' problem in the same direction, i.e. increase the optimal scale of currency trading, thus creating an entry barrier. The incumbent is, by definition, the investor who trades currencies at the margin and its risk capital is defined, as in Adrian and Shin (2010), as "balance sheet size". We also assume that (c) fixed transaction costs are large enough and (d) capital constraints are binding enough that, due to the need to exploit economies of scale while coping with capital-constraints, this investor will prefer not to form diversified portfolios. Furthermore, for ease of argument but without loss of generality, we assume that (e) average unit fixed transaction costs and asset indivisibility are, at the incumbent's optimal scale, negligible. Thus, at such scale, the incumbent can invest at the margin in the currency strategy even though she cannot optimally hold a diversified portfolio. Then maximization of the incumbent's expected utility implies the following restriction on the currency strategy expected excess-returns:

$$E(r_{t+1}^*) \cong -Cov(r_{t+1}^*, \varphi_{i,t+1}) = \sigma(r_{t+1}^*)\sigma(\varphi_{i,t+1}) \quad (7)$$

Here, $\varphi_{i,t+1}$ denotes the incumbent's IMRS. The right-most equality follows from the fact that $\varphi_{i,t+1}$ is perfectly negatively correlated to the currency strategy since the latter makes up her entire portfolio. In this stylized model, the currency market is *segmented* from the rest of the capital market due to the entry barrier, leading to (7) with, in general, $\varphi_{i,t+1} \neq \varphi_{t+1}$ at the equilibrium allocation. But the investor that holds at the margin the portfolio of risky assets traded in the wider capital market can always choose to undertake the fixed costs and become an undiversified currency trader. Unless the optimal scale of currency trading allows for only a limited number of incumbents, which seems implausible given the scale of the foreign exchange market, and if the incumbent's risk capital is large enough, competitive pressure and the threat posed by potential

entrants will rule out $\sigma(\varphi_{i,t+1}) > \sigma(\varphi_{t+1})$ because, as implied by Proposition I in Ross (2005)⁵, investors with concave and non decreasing utility of wealth prefer an investment opportunity set priced by a more volatile minimum-variance kernel. At the resulting equilibrium, it must be that

$$\sigma(\varphi_{i,t+1}) \leq \sigma(\varphi_{t+1}) \quad (8)$$

For the same reason, i.e. preference for a volatile kernel, the incumbents will not trade currencies if $\sigma(\varphi_{i,t+1}) < \sigma(\varphi_{t+1})$ and will choose instead to invest their capital in the capital market portfolio of risky asset. This turns the weak inequality in (8) into an equality. That is, in equilibrium, we have

$$\sigma(\varphi_{i,t+1}) = \sigma(\varphi_{t+1}) \quad (9)$$

Therefore, while in general (6) will not hold, (7) and (9) will and jointly they imply

$$SR(r_{t+1}^*) \equiv \frac{E(r_{t+1}^*)}{\sigma(r_{t+1}^*)} \cong \sigma(\varphi_{i,t+1}) = \sigma(\varphi_{t+1}) \quad (10)$$

That is, since the strategy cannot be traded at the margin by a diversified investor, we should observe a quest for reward for total risk, instead of systematic risk alone. We use (5) and (10), as well as the well known duality between the volatility of the minimum-variance kernel and the economy maximal SR, and obtain the following more practical restriction

$$SR(r_{t+1}^*) \cong \sigma(\varphi_{i,t+1}) = \sqrt{b'\sigma^2(f_{t+1})b} = \sqrt{\lambda'\sigma^{-2}(f_{t+1})\lambda} \quad (11)$$

⁵ The volatility of the minimum-variance kernel, as an implication of the familiar Hansen and Jagannathan (1991) bound, coincides with the SR attainable by trading the available assets. Therefore, if this weak inequality did not hold, the unconditional maximal SR attainable by trading the currency would exceed the unconditional maximal SR attainable in the wider capital markets. For the investor holding the market portfolio, this would represent an opportunity to increase expected utility by switching risk capital to currency trading. As shown by Ross (2005), this is true even if the investor's preferences are defined over third and higher order moments of her portfolio return. In this case, the investor can simply use a dynamic trading strategy to trade off the conditional SR for conditional higher moments to achieve a more desirable combination. This is the intuition behind Ross' (2005) Proposition I. For a formal statement and proof, see pp. 28-29 in Ross (2005).

This can be seen as the hurdle SR that trades must offer to be entered into by proprietary traders. A higher hurdle rate would imply, for the providers of risk capital, missing out on investment opportunities that are more advantageous than those they typically undertake. While the model is admittedly stylized, its implications are plausible. Lyons (2001) and, more recently, Hochradl and Wagner (2009), also noted the need, by capital-constrained currency traders, to develop economies of scale and scope in the processing of information and the management of inventory risk, and argued that this leads to the emergence of the SR as the appropriate performance measure. The equilibrium SR in the left-hand side of (11) should be seen as net of all transaction costs, including the price impact of trades. As in the model of Lyons and Moore (2009), professional currency traders will choose the optimal amount of currency mispricing to arbitrage away so as to maximize their objective function, taking into account the price impact of their own trades.

For the UMTM equilibrium to arise, the information needed for the pricing of currencies should be, at least to some extent, currency-specific, so as to generate enough incentive to specialize. Evidence provided by the microstructure literature, e.g. Lyons (2001), Killeen et al. (2006) and Lyons and Moore (2009), suggests that this is likely the case in that the bulk of currency volatility is explained by order flows, typically carrying currency-specific cash flow and discount rate information, rather than macroeconomic news or even returns on other asset classes. The acquisition costs that give rise to economies of scale pertain to both public and private information. In either case, they should be seen as more similar to the costs that Mankiw and Ricardo (2002) view as the main culprit for the

slow diffusion of information (“sticky information”) than to those that determine the limited-information channel problem (“noisy-information”) in the model of Woodford (2001). In fact, what matters in the context of the UMTM is that the quality of the information acquisition performed by traders depends on how much they are willing to invest in such task. As Mankiw and Ricardo (2002) put it, thinking is costly and therefore “people do it only once in a while”. In their model, agents do so at random times whereas, in the UMTM, they specialize and chose whether to become undiversified currency traders, so as to achieve economies of scale in gathering and processing information, or invest in the wider capital market, thus dispensing with the need to acquire currency-specific information.

UMTM and Limited Capital Mobility

It cannot be ruled out that the incumbents, in spite of committing all their risk capital to currency trading, may still face a binding capital constraint when $\sigma(\varphi_{i,t+1}) > \sigma(\varphi_{t+1})$. Thus, in a (perhaps more realistic) version of the UMTM that allows for such possibility, SRs would exceed the bound in (10) by a non-negative amount until enough new risk capital arrives, i.e. until potential entrants decide to undertake the fixed entry cost. Due to limited capital mobility à la Duffie (2010) and Duffie and Strulovici (2011), this may take some time and occur somewhat sluggishly, giving rise to predictable co-variation with the availability of risk-capital⁶. As a result, due to the well-known duality⁷ between the coefficient of determination R^2 of predictive regressions and the (squared) SR of

⁶ Of course, the economy maximal SR also likely co-varies with risk-capital but the testable implication here is that currency strategies SRs should co-vary more with risk capital than the economy maximal SR does.

⁷ See for example Cochrane (1999) or Appendix A (available on-line as a web-appendix).

strategies that exploit the predictability picked up by the R^2 , predictability would be driven, in a predictable manner, by the time-varying availability of risk-capital.

From this point of view, the UMTM is also related to the work of Garleanu and Pedersen (2011). Just like the high margin securities considered by these authors, the predictability-based strategies on which we focus absorb risk capital, and the availability of the latter determines their mispricing. Related work includes also the model put forth by Adrian, Etula et al. (2010), who show that funding liquidity in a given currency predicts returns in that currency and the latter co-varies with the leverage of funding intermediaries. It is, however, the availability of risk capital committed to currency trading that plays the crucial role in the determination of equilibrium predictability, rather than either availability of risk capital in the wider capital market or funding liquidity. Under the UMTM, the availability of risk capital committed to currency trading drives down excess-predictability of currency returns, i.e. deviations from the equilibrium described by (11). Availability of risk capital in the wider capital market drives instead fluctuations in the economy-wide SR, i.e. in the right-hand side of (11), whereas funding liquidity in any given currency predicts spot returns on holdings of that currency, as shown by Adrian, Etula et al. (2010). That is, while availability of risk capital in the wider capital market determines admissible predictability under RE and the availability of funding liquidity in a given currency predicts spot returns on holdings of that currency, the availability of risk capital committed to trading of a currency predicts excess-predictability of the currency returns.⁸

⁸ The other key difference between the UMTS and the models put forth by Garleanu and Pedersen (2011) and Adrian et al (2010) is, of course, our emphasis on total risk rather than diversifiable risk only.

3. Data

Our dataset includes the exchange rates against the USD and prices of front-month futures contracts, denominated in US Dollars (USD) and traded at the Chicago Mercantile Exchange (CME), of the Australian and Canadian Dollar (AUD and CAD, respectively), Japanese Yen (JPY), British Pound (GPB), Swiss Franc (CHF) and Deutsche Mark/Euro (DEM/EUR, because we combine data on the Deutsche Mark, including its futures, before the introduction of the Euro in 1999 and on the latter after its launch), over the period 1971-2010 for the exchange rates and 1988-2010 for the currency futures. The futures are characterized by the following Bloomberg tickers: AD1, CD1, JY1, BP1, SF1, respectively. The futures prices are ‘chained’ to ensure comparability over time. We construct monthly (excess-)return series by calculating the monthly rate of change of the futures prices whereas we subtract the interest rate differential, when available, in calculating currency excess-returns from the exchange rates series. To proxy for the factors in (5), remaining consistent with the perspective of the American marginal investor, we use the time series of excess-returns on the market, size and book-to market Fama and French (1993) portfolios⁹ of US stocks augmented by a US bond index¹⁰. The latter is the popular and widely tracked Salomon Investment

⁹ This data was downloaded from the website of Kenneth French, whose kindness we gratefully acknowledge.

¹⁰ While this model does not explicitly link the specification of the kernel to the IMRS of the representative investor, it has proven reasonably successful in explaining differences in average returns across widely traded investment strategies, overcoming some of the empirical shortcomings of the CAPM. Most importantly, a number of plausible risk-based arguments have been offered in the literature to motivate the choice of factors, thus linking variation in the kernel to variation in investors’ IMRSs. Moreover, at least from the point of view of the typical professional investor, the factors correspond to strategies that are easy to implement. Hence, we can use them as attainable benchmarks against which performance of currency strategies can be reasonably evaluated, without the need to model the effect of frictions as it might be the

Grade US bond index known as “Big”. We use the percentage flow of asset under management in the hedge fund industry, denoted as *AUM*, as a proxy for the availability of risk capital. This choice is motivated by to the relatively specialized profile of the typical player in this industry and the sophisticated nature of investors who act as capital providers, bent on being the first to move capital to the best investment opportunities, which closely resembles the professional currency trader and her financiers, respectively, in the context of the UMTM. It should be noted that, to be consistent with the definition of risk capital, which coincides with the notion of ‘balance sheet size’ put forth by Adrian and Shin (2010), our proxy for risk capital availability should also take into account a measure of leverage. It is however extremely difficult to acquire data on hedge fund leverage and therefore we use *AUM* alone, under the simplifying assumption that hedge fund leverage does not greatly change over time.

4. Tests of the *DMTM* and *UMTM*

To test the *DMTM* and *UMTM*, we check whether strategies that exploit currency predictability satisfy the restrictions in (6) and (9), respectively. For a powerful test of the RE null, the predictability-based strategies should mimic the trading action that would have been pursued by a rational trader based on her knowledge of the DGP. Obvious candidates as proxies for such strategies are *technical trading rules* traditionally followed by currency traders. Another approach to identifying predictability-based strategies is to derive the trading rule that would allow a rational trader to attain a given objective. One such strategy, described in Appendix A, is characterized by the goal of maximizing the

case if we were to pick at will from the endless list of factors considered over time by the empirical asset pricing literature.

unconditional SR and an inter-temporal allocation akin to the “dynamic strategies” of Ferson and Siegel (2001). It generates the largest SR attainable by exploiting the predictability of the currency under consideration. We label such strategy as a *rational trading rule*.

We pursue both approaches to identifying predictability-based strategies. The technical trading rules we consider are those tracked by the AFX Index, i.e. the basket of moving-average technical trading rules used by Lequeux and Acar (1998) to track the performance of momentum currency traders, and the HML_{FX} index used by Lustig et al. (2008) to track the performance of carry trades, based on currencies of developed economies. To construct the rational trading rules, we estimate time series of ‘time-weights’

$$w_t = \lambda \frac{\hat{\mu}_{t+1}}{\sigma_t^2}, \quad (11),$$

where λ represents an arbitrary constant of proportionality and $\hat{\mu}_{t+1}$ and σ_t^2 are the estimated conditional mean and variance, respectively, of the excess-return. These weights, up to the scaling factor given by λ , represent the amount invested in the currency under consideration at time t under the rule and are a simplified version of those derived by Ferson and Siegel (2001).¹¹ Intuitively, a hypothetical trading strategy based on such inter-temporal weights would amount to using a directional signal, i.e. the conditional mean combined with a volatility filter. To obtain estimates of the inputs of

¹¹ In the formulation of Ferson and Siegel (2001), given by equation (4) in their paper, the conditional variance of excess-returns is replaced by the sum of two terms, i.e. the squared conditional mean excess-return and the conditional variance of its innovations. We illustrated using a simplified version for ease of exposition.

the weights formula in (11), we specify the following reduced form representation of the DGP of currency futures returns:

$$r_t = \text{const.} + b_1 r_{t-1} + \dots + b_p r_{t-p} + c_1 u_{t-1} + \dots + c_q u_{t-q} + u_t \quad (12)$$

Here, p denotes the autoregressive (AR) lag order and q denotes the order of the moving average (MA) term¹². While we experiment with various GARCH specifications for the error process u_t , we eventually settle, in a pursuit of parsimony so as to minimize the risk of over-fitting, on a white noise i.i.d. specification. This implies that the variance input in the weights w_t is a constant¹³, i.e. the unconditional variance of the currency excess-return process. We estimate the model parameters by Quasi Maximum Likelihood (QML). This method is asymptotically equivalent to Maximum Likelihood (ML) even in the presence of non-normally distributed errors, assuming stationarity of r_{t+1} and ergodicity of the DGP. In large samples, it is thus consistent with the implications of the RE null and appropriate to generate consistent estimates of $\mu_{t+1}(I_t)$, under relatively mild distributional assumptions. We use the ‘small sample’ version of the AIC, i.e. $\text{AIC}_{\text{small}} = \text{AIC} + 2k(k + 1)/(1 - k - 1)$, where $k = p + q$, to choose the order of the ARMA(p, q) in (12).¹⁴ Table 1 reports the coefficient of determination R^2 of the estimated ARMA(p, q) models. We then use the series of time-varying conditional means of the

¹² This choice of functional specification for the DGP is motivated by the flexibility of this class of models, which makes it more likely that it encompasses a reduced form representation of the DGP. Also, Taylor (1994) shows that ARIMA models of exchange rates and thus ARMA models of currency returns capture substantial predictability.

¹³ And therefore could be subsumed into the arbitrary constant λ and hence omitted.

¹⁴ This version of the AIC was formulated by Sugiura (1978) and later used by Hurvich and Tsai (1989). Just like the AIC, its small sample version adjusts the sample estimator of twice the expected log-likelihood for its bias but, in doing so, it uses an expansion of the bias of higher order than the AIC. The bias-adjustment of the AIC, coupled with the fact that we specify the mean of r_t as a parametric function of only a constant and variables observed at time t , should ensure that we do not over-fit r_{t+1} while, as explained by Diebold and Kilian (2001), the AIC is less likely to underestimate the lag order in small samples than alternative criteria. The latter property is crucial in preserving higher-order dynamics of the conditional mean of the process.

estimated ARMA(p,q) model as estimates of the currency excess-return conditional mean and therefore as inputs in the time-weights w_t .¹⁵ Figure 1, as an illustration, plots the resulting time series of weights, normalized to add up to unity, for the strategy that exploits the monthly predictability of GBP futures. We use these time-weights series and 2 bps transaction costs to construct the return of the rational trading rule for each currency futures in our sample. We also combine the rational trading rules for each currency into an equally-weighted rational trading rule. We denote its excess-return as $r_{avg,t+1}^*$. It should be noticed that, in constructing the rational trading rules, we exploit in-sample predictability. That is, following the advice of Inoue and Kilian (2004), we estimate (12) over the entire sample period, i.e. using observations available up to time T rather than to time t only.¹⁶ We do this to gain power against the null of RE, compared to the test based on the predictability captured by the technical trading rules (which are, of course, out-of-sample). In fact, in tests of this null, the econometrician suffers from a possibly imperfect knowledge of the information set that would have been available to professional currency traders at the time of making the investment decisions, i.e. it is possible that $I_t^* \subseteq I_t$ where I_t^* denotes the econometrician's information set. In this case, as explained in Appendix B (available on-line as a web-appendix), the test suffers an essentially unquantifiable but possibly severe loss of power. For example, there is no guarantee that the momentum and carry trade technical trading rules capture all predictability, leading to a loss of power in our tests based on the out-of-sample predictability captured by these rules. The typical remedy to this problem, i.e. engaging

¹⁵ While setting the variance input equal to the sample variance of the currency futures returns.

¹⁶ Using observations available up to time t only, the same approach yields rational trading rules that exploit out-of-sample predictability (and will be used later this way) and can be even used to implement a trading strategy in real time.

in an extensive search across rules, would expose our inferences to the danger of data snooping.¹⁷ Resorting to in-sample estimates of predictability, while carefully avoiding over-fitting, represents a partial way around both problems.

Table 2 reports the ‘alphas’ of both the technical (out-of-sample) and rational (in-sample) trading rules, i.e. the intercepts of the regression of their excess-returns on the Fama and French factors augmented by the bond factor. The alphas of most strategies are statistically significant. The only exceptions are the carry trade and the rational rules based on the JPY and ECU/EUR in 1988-2010,¹⁸ as well as the rational rule based on the GBP futures both in this period and in the sub-period 1988-2006. In any case, the intercept of the momentum technical rule tracked by the AFX index and of the equally-weighted rational trading rule $r_{avg,t+1}^*$ are significant both in 1988-2006 and 1988-2010 and, as shown in Table 3, the GRS tests statistic, constructed following Gibbons, Ross and Shanken (1989), is highly significant for the rational trading rules. On balance, these results imply that the DMTM is rejected.

¹⁷ Estimating a different ‘out-of-sample’ forecasting model for each point in the sample period, each time searching over a large set of observed candidate predictive variables, raises the issue of composite hypothesis testing. Often much of the apparent power gain does not survive the “reality check” (RC) suggested by White (2000). The RC power does approach one as the number of cases in the evaluation set grows larger (that is, the best rule is eventually detected with certainty) when there is a forecasting rule that truly beats the benchmark among the set of rules tested. In practice, however, this requires the econometrician’s ability to identify the rules to include in the evaluation set and thus knowledge of I_t , though the mapping of the latter onto μ_{t+1} needs to be estimated. Intuitively, the power of the test depends on the extent to which the rules in the set offer an improvement, in terms of the chosen loss function, over the benchmark (roughly speaking, the larger the improvement, the easier it is to detect it). This concern surfaces in the work of Hansen (2005), who proposes a test for superior predictive ability that is less sensitive to poor and irrelevant alternatives and hence more powerful than Whites’ (2000) RC. This test is not optimal, as acknowledged by Hansen (2005), nor could it be without knowledge of I_t .

¹⁸ But in the latter case we suspect a lack of power due to the inability of our ARMA(p,q) to pick up all predictability.

Next, we turn to examining the SRs of the technical and rational rules. In Table 4, we report both the SRs and excess-SRs. The latter are the excess of the former over a threshold consistent with the UMTM. According to the SR bound in (10), we set this threshold equal to the sample estimates of the unconditional SR, reported in Table 5, attainable by investing in the factor-mimicking portfolios. To test for the significance of each excess-SR, we conducted a two-tailed test of the null that the difference between the squared SR of the trading rule and the square of the threshold SR is equal to zero. In the test, we used HAC standard errors constructed following Ledoit and Wolf (2008). Notably, as shown by the p-value of such tests reported in Table 4, the excess-SRs are in all cases negative, implying that the SRs are lower than the SR attainable by investing in the factors, when the latter include the bond index. Also, even when the bond factor is not included, excess-SRs are in no case significantly positive and, in most cases, they are significantly negative. The lack of positive and statistically significant excess-SRs is in stark contrast with the statistically positive alphas. Taken together, and especially considering the strikingly different picture that emerges by comparing Table 2, which focuses on ‘alphas’, with Table 4, which reports SRs, our results lend support to the UMTM against the DMTM, in that they imply a marginal currency trader who ‘leaves alphas on the table’ but does not stand idle when the opportunity to earn a high SR presents itself.

5. Currency Predictability Over Time

To gain perspective on the behaviour of predictability over time, we construct for each currency a time series of predictability estimates. As a consequence of the tight link between the R^2 of predictive regressions and the (squared) SR attainable by exploiting the predictability captured by such regressions, as in Cochrane (1999) and further formalized in Appendix A (available on-line), there is a close relation between the SR of rational trading rules and the R^2 of the predictive regression on which they are based, in that the square of the former can be decomposed in the latter and the squared SR of a static ‘buy-and-hold’ position in the currency under consideration, i.e.

$$SR(r_{t+1}^*)^2 = \frac{SR^2(r_{t+1}) + R^2}{1 - R^2} \quad (12)$$

Therefore, the R^2 captures the portion of the rational trading rule (squared) SR directly related to predictability, i.e. the volatility of conditional mean returns, and hence the part of of greatest interest. For each currency, we thus construct times series of coefficients of determination $R_{i,t}^2$ of ARMA(p,q) predictive regressions estimated using rolling 5-year windows of monthly data from $t - 60$ to t . The ARMA(p,q) regressions are estimated by maximum likelihood and, when this method fails to converge, using in sequential order the Broyden, Fletcher, Goldfarb and Shanno method described in Press et al. (1988), the simplex method and a genetic search procedure. As before, p and q are selected using the ‘small sample’ AIC. To expand as much as possible the period under study, we fit the selected ARMA(p,q) models to raw currency returns rather than excess-returns (i.e. raw returns adjusted by the interest differential) or currency futures returns. This is because currency exchange rate data is available for longer than both currency futures data

(starting in 1987) and good quality interest rate data (missing for most of the '70) and, most importantly, 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.¹⁹ Since each estimation window is 5-year long, the associated coefficient of determination $R_{i,t}^2$ represents an estimate of predictability from the point of view of $t - 60$. Therefore, to obtain predictability estimates that come as close as possible to the end of the sample period considered in the paper, i.e. June 2010, we use data on currency returns until July 2011, the very last available data point at the time of conducting the analysis. Next, to isolate the component of predictability that cannot be explained under the UMTM, we first construct a measure of explained predictability under such model. The measure is the following:

$$\phi \equiv RRA_V^2 \sigma_t^2(r_{m,t+1}) = RRA_V^2 \sigma_t^2(r_{m,t+1}) \quad (13)$$

Here, RRA_V is an upper bound on the relative risk aversion (RRA) of the marginal currency trader and $\sigma_t^2(r_{m,t+1}) = \sigma^2(r_{m,t+1}|I_t)$ is the conditional variance of the market portfolio, i.e. the portfolio held by the potential entrant. The rationale of (13) is that, as explained in more detail by Potì and Wang (2010) and in Appendix C, its right-hand side bounds from above the variance of discount rates and therefore represents an upper bound to the variance of the kernel that prices the assets in the wider capital market.

¹⁹ For periods when interest rate data is available, we constructed predictability estimates using both raw returns and basis-adjusted excess-returns and found that indeed they are indistinguishable. 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.

Given the duality between pricing kernel volatility and the economy maximal SR, it therefore bounds from above the squared maximal SR attainable by exploiting predictability, i.e. $SR(r_{t+1}^*)^2$, and hence the coefficient of determination R^2 of the corresponding predictive regression since, using (12) and the fact that $R^2 \leq 1$,

$$R^2 \leq SR(r_{t+1}^*)^2. \quad (13)$$

To operationalize the bound, we follow Potì and Wang (2010) and let $RRA_V = 5.0$. This is, conservatively, about twice the RRA implied by the US stock market equity premium, to allow for possible steep increase of RRA during bad economic times. Also, remaining consistent with the perspective of the American marginal investor, we use the CRSP VW Index as a proxy for her portfolio of risky assets. Over the period 1971-2010, the resulting monthly bound is 4.34 percent, i.e. $R^2 \leq 4.34\%$, corresponding to a maximal SR of 72.20 percent on an annualized basis. This is roughly the same as the maximal SR attainable by investing in the portfolios mimicked by the Fama and French (1993) factors and is also right in the middle of the range for SR targets identified by Lyons (2001). This author, while reporting that currency traders interviewed by him declared that their target SR is in the region of 100 percent per annum, suggests that a more realistic figure, net of the traders' desire to present their activity in a more positive light, is in the region of 50 percent per annum. As in Levich and Potì (2008), our measure of excess-predictability is the difference between the in-sample coefficient of determination R^2 of the rolling predictive regressions and the bound in (13), i.e.

$$BVI_t = R_t^2 - \phi_t \quad (14)$$

The $BVI_{i,t-60}$ time-series, i.e. the series of the excess-predictability estimates for each currency and 'back-dated' by 5 years since this is the length of the rolling estimation

windows, are plotted in Figure 2. As seen in the Figure, the series display considerable time variation. The Figure shows that bursts of statistically significant excess-predictability occurred at various points over the sample period, for example in the 1970s and 1980s, around the European Monetary System (EMS) crisis of the early 1990s and at the time of the Asian Financial Crisis in the second half of the 1990s. In the more recent part of the sample period, a number of currencies, especially AUD, JPY, CHF and EUR, also experienced short-lived episodes of significant excess-predictability.

6. What Drives Excess-Predictability

To test whether excess-predictability is predictable, we regress a measure of excess-predictability on variables that may explain its time-variation, most notably the availability of risk capital. More specifically, we regress BVI_t on its lags, AUM , which serves as a proxy for the availability of risk capital, and other variables whose role is to control for un-modelled time-variation in risk premia and behavioural effects:

$$\begin{aligned}
 BVI_{i,t} = & \omega + \beta_{AUM} AUM_{t-60} \\
 & + \gamma_1 BVI_{i,t-1} + \gamma_2 BVI_{i,t-2} + \gamma_3 BVI_{i,t-3} + \gamma_4 BVI_{i,t-4} \\
 & + \delta_1 rrel_{t-60} + \delta_2 TED_{t-60} + \delta_3 sento_{t-60} + \delta_4 |sento_{t-60}| + \delta_5 VIX_{t-60} + e_{i,t}
 \end{aligned} \tag{15}$$

Here, AUM denotes the percentage flow of asset under management in the hedge fund industry, $rrel$ denotes the stochastically de-trended US risk free rate, TED is the TED spread, $sento$ denotes Wurgler and Baker's (2006) Sentiment index and VIX is the DJ implied option volatility index. We estimate (15) as a panel regression random coefficient model, along the lines of Swamy (1970), and also, as a robustness check, using other panel estimation methods.

Estimates of unrestricted and restricted versions of the model in (15) for the periods 1972-2006 and 1972-2010 are reported in Table 6 and Table 7, respectively. The Tables show that the availability of risk capital, which is proxied by *AUM*, is the single most important explanatory variable of the variation in our measure of excess-predictability. The latter also displays serial correlation, picked up by the statistically significant coefficients on its four lags. In the 1971-2006 period, the sign of the trend coefficient is negative but insignificant whereas, in the 1971-2010 period that includes the recent financial market turbulence, it is significantly positive, casting doubt on the widely held view that predictability might be declining over time, and the coefficient of the *AUM* is insignificant only in the model that includes the VIX volatility index and the TED spread. The coefficients of the latter, however, are insignificant and, unlike for the more parsimonious models that do not include these variables, the Durbin-Watson statistic suggests misspecification. We therefore discard the unrestricted model in Panel A.

Interestingly, comparing the estimates of the restricted specifications in Panel B with those in Panels C and D, it emerges that stock market sentiment, proxied by the sentiment index constructed by Baker and Wurgler (2006), is a significant determinant of excess-predictability but not in the way that behavioural economics would predict. In fact, the latter views sentiment as a determinant of mispricing. As such, if we conjecture that the mispricing in currency and stock markets stem from the same economic causes, excess-predictability should be related to the absolute value of the sentiment index rather than the sentiment index itself. It is instead the latter to be significantly related to excess-

predictability. Our interpretation is that the level of sentiment determines the availability of risk capital, typically more plentiful during ‘good times’, as shown by Adrian and Shin (2010), and therefore is inversely related to mispricing. This is consistent with our conjecture that it is the availability of risk-capital the key determinant of the extent to which currency markets absorb mispricing, and ultimately consistent with Lyon’s (2001) “limits to speculation” perspective coupled with imperfect capital mobility à la Duffie (2010) and Duffie and Strulovici (2011). Table 8 presents estimates of the restricted model from Panel D obtained using alternative panel estimation methods, namely a fixed effect estimator, random effect, first differences (i.e., using cross-sectionally demeaned observations). While the autoregressive coefficient estimates vary depending on the estimation methodology, the estimate of the coefficient of the risk capital availability proxy is remarkably stable. This circumstance is all the more remarkable when one considers that it is beginning-of-period risk capital availability, i.e. flow of asset under management to the hedge fund industry in month t , that explains the (excess-)R² over the following 5 years, i.e. from month t to month $t + 60$. This means that risk capital availability predicts in-sample predictability.

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

As a final exercise, we check whether the predictive relation between risk capital and predictability holds also for out-of-sample predictability. It is worth emphasizing, however, that in-sample and out-of-sample excess-predictability capture two very different type of mispricing relative to the RE benchmark. In-sample excess-

predictability, when consistently estimated (i.e. paying attention not to over-fit the DGP), implies violation of the EMH in its strong and semi-strong form. To the contrary, out-of-sample excess-predictability implies violation of the weak-form EMH only.

Nonetheless, it is of interest to establish whether the impact of risk capital availability on predictability is confined to in-sample predictability holds with respect to out-of-sample predictability too. To do so, we used the 6 portfolios of currencies sorted according to the level of the interest rate made available for download by Lustig et al. (2011) to form an out-of-sample rational trading strategy that could be implemented in real time by the marginal currency investor. These are the same portfolios that Lustig et al. (2011) combine to form a traditional carry trade strategy benchmark (every 12 months, they form an equally weighted portfolio long in the currency with the largest interest rate and another one short the currencies with the lowest interest rate). One benefit of using these portfolios in forming the rational rules is that we will be able to directly gauge the benefit of implementing the RE-mimicking approach that underpins the rational rules. To form our out-of-sample rational trading rules, we combined the 6 currency portfolios using time-varying weights that reflect out-of-sample predictability. The weights w_{it} for the i th portfolio, $i = 1, 2, \dots, 6$, are a multivariate version of those in (11), that is

$$w_t = \lambda \sigma_t^{-2} \mu_{t+1},$$

where w_t is the vector of weights for the 6 currency portfolios, with elements w_{it} , and $\sigma_{u,t}^2$ denotes the (conditional) variance-covariance matrix of the portfolios returns. As before, λ is an arbitrary constant which is related to the amount of financial leverage. As estimates for the conditional mean and variance-covariance matrix in the expression

above we used the one-month forecast generated by the estimated ARMA(p,q) models and the sample variance-covariance matrix of the portfolio returns, respectively. Both the ARMA(p,q) models and the variance-covariance matrices are estimated over 5 year rolling windows ending in t . We consider also versions of such strategy that limit the absolute value of the position in each currency portfolio to a given multiple c of the allocated capital. The return on the latter strategy, assuming 10 bps per each way trade and a limit on the position in each currency given by $c = 100$ percent of the allocated capital, is plotted in Figure 3 and compared with the corresponding plot for the carry trade strategy.

Out-of-sample, the relatively less restricted (i.e., with $c \geq 4$) rational trading strategies offer comparable SRs²⁰ but much higher alphas than the traditional carry trade based on the same currency portfolios considered by Lustig et al (2011), as summarized in Table 9. In fact, the alpha of the former remains positive and statistically significant even after including the latter as a factor in a performance attribution regression, implying that the carry trade does not span the rational trading strategy. The alpha of the latter, however, comes at the price of requiring the trader to take positions characterized by extreme variation over time. In practice, this means that only traders who can invest in the strategy truly at the margin would be able to reap this large alpha. To the contrary, investors who had to take non-marginal positions in such strategy would exceed any realistic VaR limit due to wild variation in the position to be taken in each currency over time. Therefore, only investors without capital-constraints can attain those alphas. These

²⁰ As seen in Table 4, the monthly SR of the carr trade benchmark is 11.35 percent, or 39.32 percent on an annualized basis.

results suggest that, just like in the case of in-sample predictability, there is more downwards pressure on excess-SRs than on alphas, likely because currency traders seek reward for total risk and thus consistently with the UMTM, and also that constraints on risk-capital availability matter, consistently with the UMTM augmented by limited capital mobility.

To check whether the predictive power of risk capital holds also for out-of-sample predictability, we estimate a VAR (vector autoregression) including, among the endogenous variables, the risk-capital availability proxy and the one-month SRs of rational trading rules that exploit out-of-sample predictability of the futures on each currency. The rational trading rules are based on ARMA(p,q) models estimated using rolling windows of 5 years of monthly data on currency futures and assuming 2 bps transaction costs for each way trade. The VAR estimates are reported in Table 10 and the implied impulse responses of the SRs to shocks to AUM, based on a straightforward ‘triangular’ Cholesky decomposition of the error covariance matrix, are reported in Figure 4, together with 95 percent confidence intervals constructed using a Monte Carlo integration procedure and 10,000 simulations. The figure shows that, consistently with our earlier finding, the SRs react negatively to AUM shocks, and to a statistically significant degree, either immediately or after some delay. The only exception is the reaction of the SR of the rational trading rule based on the CD1 futures, i.e. the futures on the Canadian Dollar. In any case, the effect mostly dies out after 12 months.

8. Conclusions and Final Remarks

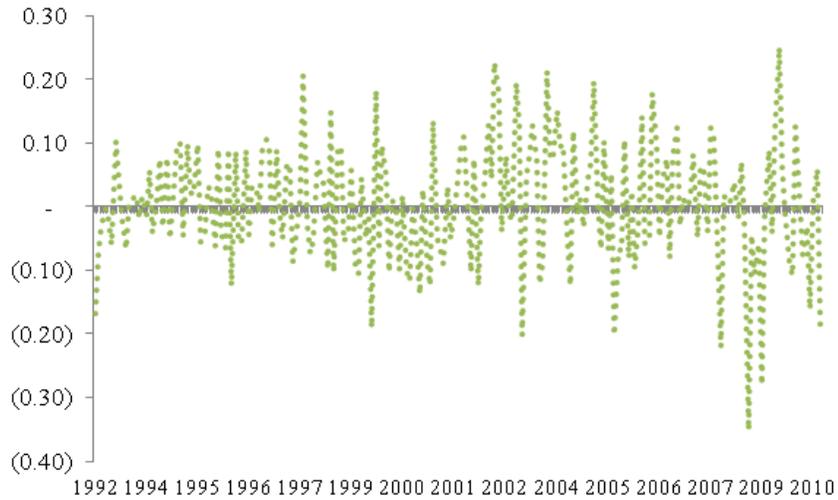
In this paper, we assess the statistical and economic significance of predictability in currency returns over the period 1971-2010. Our findings imply violation of the RE/EMH under a broad class of asset rational pricing models, represented in a stylized manner by the DMTM. The case against the RE/EMH rests, however, on relatively large alphas but not on unduly large SRs. Taken together, these findings pose a challenge to the EMH but they are compatible “limits to speculation” models in which a capital-constrained marginal trader, as in the UMTM, holds undiversified portfolios of currency strategies. This circumstance implies the emergence of the Sharpe ratio as the relevant risk-reward measure. Excess-predictability, however, is time-varying and predicted by risk-capital availability, consistently with recent theories on limited mobility of risk capital put forth by Duffie (2010) and Duffie and Strulovici (2011). A concurrent effect might be learning, as in Lo’s (2004) AMH, possibly coupled with un-modelled microstructure effects or outright investors’ error. Attempts to discriminate between these possibilities would be a valuable extension of this work. This would require a more detailed structural model of exchange rate determination, characterized, at a minimum, by the presence of capital-constrained marginal traders and a plausible learning scheme.

Table 1
Currency Futures Return In-Sample Predictability

	AUD	CAD	JPY	GBP	CHF	DEM/ EUR
Panel A (1988-2006)						
p,q	5,2	3,2	4,4	2,2	1,1	2,4
R ²	5.81	4.10	6.06	3.29	2.57	3.43
Panel B (1988-2010)						
p,q	5,2	4,5	3,2	3,2	3,3	1,1
R ²	4.17	8.16	1.78	6.10	5.63	2.80

Notes. This table reports, for the 1988-2006 and 1988-2010 sample periods, the autoregressive p and moving average q terms order lags and percentage coefficient of determination R^2 of the chosen ARMA(p,q) predictive regressions as selected using the Akaike Information Criterion (AIC). The estimation method is a Gauss-Newton (GN) algorithm with numerical derivatives (the default choice in RATSTM). The data frequency is monthly.

Figure 1
Weights for the British Pound Rational Trading Rule



Notes. This Figure plots the time-varying weights of the rational trading rules that exploit the predictability of monthly returns on the British Pound futures traded at the CME, based on estimates from an ARMA(p,q) model, with p and q selected using the AIC. The weights are rescaled in such a way that they add up to 1 over the 1992-2010 sample period.

Table 2
Percentage Alphas of Benchmark Technical Trading Rules and In-Sample Rational Trading Rules

Model	AFX	HML _{FX}	AUD	CAD	JPY	GBP	CHF	ECU/ EUR	r_{avg}^*
Panel A (1988-2006)									
FF	2.67 (5.08) (0.000)	5.48 (2.19) (0.014)	2.17 (2.49) (0.006)	1.59 (3.69) (0.000)	2.33 (4.55) (0.000)	1.65 (1.29) (0.098)	1.44 (1.93) (0.027)	69.16 (2.10) (0.018)	12.61 (2.30) (0.011)
FF+Bond	2.69 (5.52) (0.000)	5.85 (2.45) (0.007)	2.26 (2.19) (0.014)	1.35 (2.83) (0.002)	2.35 (4.65) (0.000)	1.15 (1.12) (0.131)	1.53 (2.15) (0.016)	69.81 (2.44) (0.007)	12.64 (2.67) (0.004)
Panel B (1988-2010)									
FF	0.27 (2.72) (0.003)	0.14 (0.73) (0.230)	0.02 (3.71) (0.000)	0.01 (2.04) (0.021)	0.00 (.91) (0.182)	0.01 (1.16) (0.124)	0.01 (2.21) (0.013)	0.01 (1.35) (0.088)	0.02 (3.71) (0.000)
FF+Bond	0.26 (2.61) (0.004)	0.17 (0.85) (0.196)	0.03 (3.30) (0.000)	0.01 (1.94) (0.026)	0.00 (1.22) (0.111)	0.01 (0.86) (0.195)	0.01 (1.97) (0.024)	0.00 (1.02) (0.153)	0.03 (3.30) (0.000)

Notes. This table reports percentage annualized alphas of the predictability-based strategies, i.e. the benchmark technical trading rules (represented by the momentum strategy tracked by the AFX index and carry trade tracked by the HML_{FX} index of Lustig et al.), and the rational trading rules, together with their t-statistics and corresponding p -values (both in brackets) based on HAC standard errors. The hypothesized level of transaction costs is two basis points per each way transaction. The predictive model for the rational trading rules is ARMA(p,q) with p and q selected by the ‘small sample’ AIC. The data frequency of the underlying return series is monthly. The performance attribution models are the Fama and French 3-factor model and the same model augmented by a bond factor mimicking an investment in the bond portfolio tracked by the Salomon US index known as “BIG”.

Table 3
GRS Test of Alphas

Model	Out of sample (AFX + HML_{FX})	In sample (Rational Trading Rules)
Panel A 1988-2006		
FF	4.60 (0.011)	23.20 (0.000)
FF+Bond	4.90 (0.008)	22.79 (0.000)
Panel B 1988-2010		
FF	2.61 (0.075)	9.52 (0.000)
FF+Bond	2.27 (0.105)	9.42 (0.000)

Notes. This table reports GRS tests of the alphas of predictability-based strategies (technical and rational rules) reported in the previous Table. The performance attribution models are the Fama and French 3-factor model and the same model augmented by a bond factor mimicking an investment in the bond portfolio tracked by the Salomon US index known as “BIG”.

Table 4
SRs of Benchmark Technical Trading Rules and In-Sample Rational Trading Rules

Model	AFX	Carry	AUD	CAD	JPY	GBP	CHF	DEM/ EUR
Panel A								
1988-2006								
SR	10.54	21.86	22.66	20.21	28.13	11.77	11.39	12.76
Excess SR _{FF}	-1.15	0.00	0.13	-0.21	0.98	-1.79	-1.43	0.00
	(0.125)	(0.500)	(0.447)	(0.416)	(0.165)	(0.037)	(0.077)	(0.499)
Excess-SR _{FF+Bond}	-0.63	-0.15	-1.13	-1.35	-0.35	-1.23	-1.85	0.00
	(0.265)	(0.440)	(0.130)	(0.089)	(0.363)	(0.110)	(0.033)	(0.500)
Panel B								
1988-2010								
SR	11.19	11.35	28.17	14.35	6.42	5.73	11.45	8.28
Excess SR _{FF}	-0.55	-0.52	1.99	-0.07	-1.26	-1.36	-0.51	-0.98
	(0.293)	(0.301)	(0.023)	(0.471)	(0.104)	(0.087)	(0.306)	(0.164)
Excess-SR _{FF+Bond}	-2.53	-2.51	-0.03	-2.07	-3.24	-3.34	-2.49	-2.96
	(0.006)	(0.006)	(0.488)	(0.019)	(0.001)	(0.000)	(0.006)	(0.002)

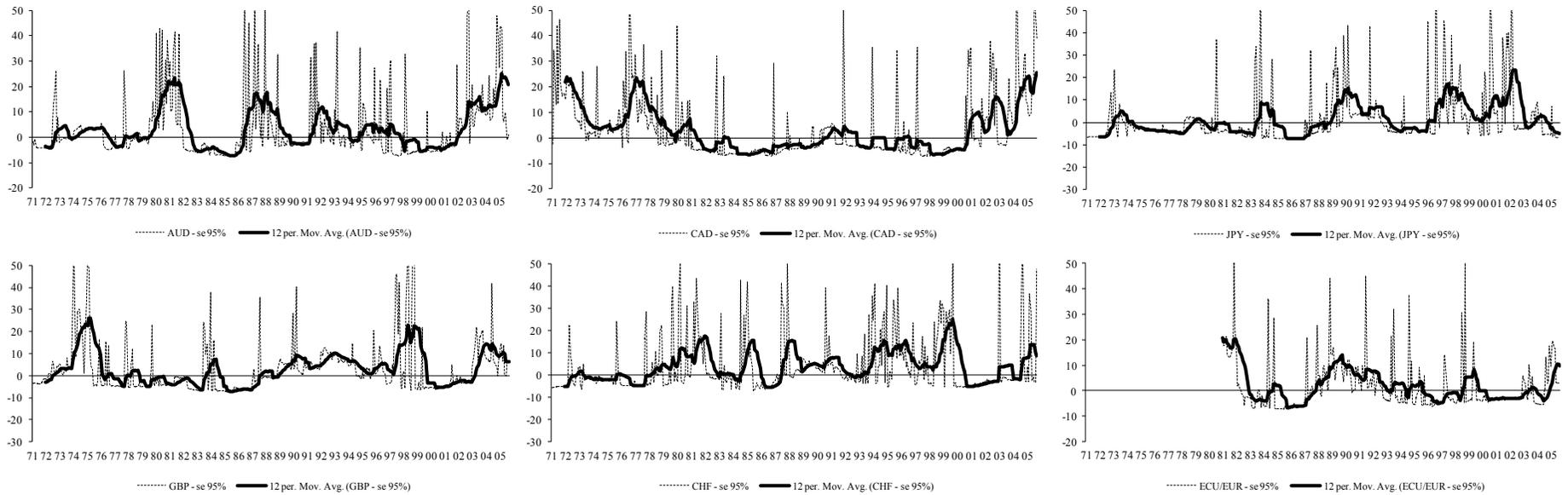
Notes. This table reports, in the first row of each Panel, percentage monthly SRs of predictability-based strategies, i.e. the benchmark technical trading rules (represented by the momentum strategy tracked by the AFX index and carry trade tracked by the HML_{FX} index of Lustig et al.), and the rational trading rules. The predictive model for constructing the latter is ARMA(p,q) with p and q selected by the AIC. In the other rows, the Table reports, in brackets, t-statistics and p-values based on Newy and West (1987) standard errors adjusted for heteroskedasticity and autocorrelation (HAC) under the null that the strategy SR equals the maximal SR spanned by the factors of the given performance attribution model. These are the Fama and French (1996) factors (model denoted by FF) and the same factors augmented by Salomon US bond index known as “BIG” (model denoted by FF+Bond). The percent monthly SR of these set of factors is, in Panel A, 21.85 (75.71 p.a.) and 30.35 (105.12 p.a.), respectively, and in Panel B, 14.84 (51.41 p.a.) and 28.37 (98.28 p.a.), respectively. The hypothesized level of transaction costs is two basis points per each way transaction. The data frequency of the underlying return series is monthly.

Table 5
Factors Maximal SRs and SR Bounds

	Monthly	Annualized
CRSP VW	11.43	39.58
FF	21.90	75.87
FF+Bond	30.35	105.12

Notes. This table reports, for the period 1988-2010 the percentage SR of the CRSP VW portfolio and the maximal SR attainable by investing in the Fama and French (1996) market, size and book-to-market factor mimicking portfolios and in these same portfolios augmented by the bond portfolio tracked by the Salomon US bond index “Big”.

Figure 2
Excess-Predictability Over Time



Notes. These figures plot, for each point in our sample period and each currency in our sample, the percentage BVI based on ARMA(p,q) predictive regressions, with p and q selected by the AIC, and a RRA upper bound of 5, i.e. $RRA_V = 5$. The estimation window of each predictive regression is 5 years of monthly data from 1971 to 2010. The solid lines formatted in bold are 12-month moving averages. 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 6
Swamy's Random Coefficients Panel Regressions
1972-2006

Const.	Trend	BVI _{t-1}	BVI _{t-2}	BVI _{t-3}	BVI _{t-4}	AUM _{t-60}	rrel _{t-60}	TED _{t-60}	sent _{t-60}	sent _{t-60}	VIX _{t-60}	DW
Panel A												
3.91	-0.03	0.19	-0.00	0.01	0.04	15.15	-1.05	3.24	0.59	0.59	0.05	1.86
4.69	0.023	0.035	0.036	0.036	0.035	29.02	0.61	2.81	1.76	1.76	0.10	
(0.403)	(0.172)	(0.000)	(0.973)	(0.690)	(0.186)	(0.601)	(0.087)	(0.250)	(0.737)	(0.737)	(0.625)	
Panel B												
-1.42	0.00	0.24	0.05	0.08	0.05	-31.40			-1.14	0.18		1.98
0.95	0.00	0.02	0.02	0.02	0.02	11.34			0.54	0.74		
(0.132)	(0.553)	(0.000)	(0.078)	(0.001)	(0.052)	(0.005)			(0.033)	(0.808)		
Panel C												
-0.84	0.00	0.25	0.05	0.08	0.05	-28.21				-0.83		1.99
0.90	0.00	0.02	0.02	0.02	0.02	11.22				0.57		
(0.350)	(0.853)	(0.000)	(0.042)	(0.000)	(0.027)	(0.011)				(0.149)		
Panel D												
-1.26	0.00	0.25	0.04	0.08	0.05	-30.89			-1.03			1.99
0.74	0.00	0.02	0.02	0.02	0.02	11.29			0.40			
(0.088)	(0.571)	(0.000)	(0.052)	(0.000)	(0.031)	(0.006)			(0.010)			

Notes. This table reports the estimates of panel regressions of our excess--predictability measure, i.e. BVI, for all the currencies in our dataset against its own lags and two alternative sets of regressors (Panel A, B and C) which include 60 month lags of the percentage flow of asset under management in the hedge fund industry (AUM), the stochastically de-trended US risk free rate (rrel), the TED spread, Wurgler and Baker's (2006) Sentiment index together with its absolute value and the VIX volatility index. All variables are denoted as in the text. The BVIs are estimated using rolling windows of 5 years of data over the period 1972-2006. The estimation method is Swamy's (1970) Random Coefficient panel regression with GLS standard errors. Standard errors p-values (in brackets) are reported below the corresponding coefficient estimates. The last column reports the Durbin-Watson statistic for each model.

Table 7
Swamy's Random Coefficients Panel Regressions
1972-2010

Const.	Trend	BVI _{t-1}	BVI _{t-2}	BVI _{t-3}	BVI _{t-4}	AUM _{t-60}	rrel _{t-60}	TED _{t-60}	sent _{t-60}	sent _{t-60}	VIX _{t-60}	DW
Panel A												
-6.57	0.03	0.27	0.00	0.05	0.04	-3.92	-0.51	1.43	-2.55	-0.80	-0.08	1.89
2.48	(0.01)	0.03	0.03	0.03	0.03	26.09	0.53	2.08	0.79	1.09	0.07	
(0.08)	(0.000)	(0.000)	(0.829)	(0.106)	(0.162)	(0.880)	(0.337)	(0.491)	(0.001)	(0.462)	(0.277)	
Panel B												
-2.13	0.01	0.29	0.04	0.10	0.05	-29.66			-1.30	0.18		2.00
0.83	0.00	0.02	0.02	0.02	0.02	10.91			0.46	0.66		
(0.010)	(0.000)	(0.000)	(0.035)	(0.000)	(0.011)	(0.06)			(0.004)	(0.785)		
Panel C												
-1.71	0.01	0.29	0.05	0.10	0.06	-24.64				-0.84		2.00
0.82	0.00	0.02	0.02	0.02	0.02	10.74				0.55		
(0.037)	(0.001)	(0.000)	(0.019)	(0.000)	(0.006)	(0.021)				(0.127)		
Panel D												
-1.95	0.01	0.29	0.05	0.10	0.05	-29.18			-1.23			2.00
0.66	0.00	0.02	0.02	0.02	0.02	10.82			-0.38			
(0.003)	(0.000)	(0.000)	(0.027)	(0.000)	(0.008)	(0.007)			(0.001)			

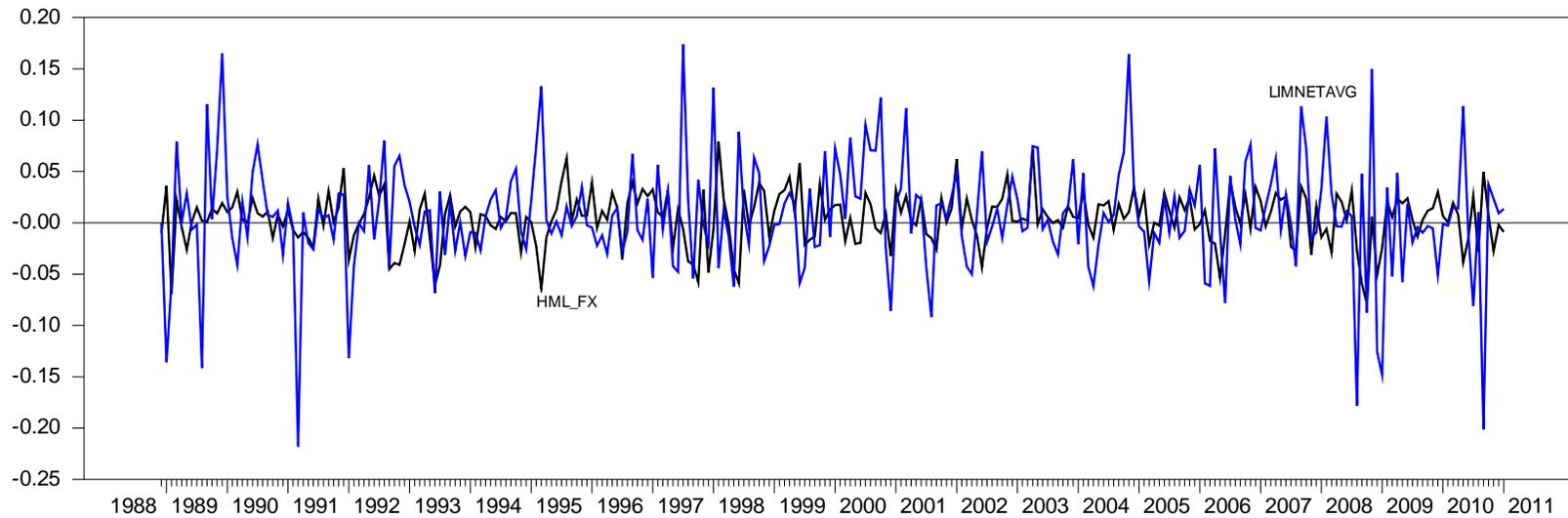
Notes. This table reports the estimates of panel regressions of our excess--predictability measure, i.e. BVI, for all the currencies in our dataset against its own lags and two alternative sets of regressors (Panel A, B and C) which include 60 month lags of the percentage flow of asset under management in the hedge fund industry (AUM), the stochastically de-trended US risk free rate (rrel), the TED spread, Wurgler and Baker's (2006) Sentiment index together with its absolute value and the VIX volatility index. All variables are denoted as in the text. The BVIs are estimated using rolling windows of 5 years of data over the period 1972-2010. The estimation method is Swamy's (1970) Random Coefficient panel regression with GLS standard errors. Standard errors p-values (in brackets) are reported below the corresponding coefficient estimates. The last column reports the Durbin-Watson statistic for each model.

Table 8
Alternative Panel Regression Estimators

Estimator	Const.	Trend	BVI _{t-1}	BVI _{t-2}	BVI _{t-3}	BVI _{t-4}	AUM _{t-60}	sent _{t-60}	Adj. R ²
1971-2006									
Fixed effect		0.01	0.25	0.07	0.09	0.06	-22.89	-0.79	14.39
		0.00	0.02	0.02	0.02	0.02	10.99	0.40	
		(0.000)	(0.000)	(0.002)	(0.000)	(0.009)	(0.037)	(0.046)	
Random effect	-1.04	0.01	0.25	0.07	0.09	0.066	-22.58	-0.78	
	0.43	0.00	0.02	0.02	0.02	0.02	10.97	0.40	
	(0.017)	(0.000)	(0.000)	(0.002)	(0.000)	(0.006)	(0.039)	(0.051)	
First differences		0.01					-18.93	4.43	30.93
		0.00					9.22	1.86	
		(0.000)					(0.040)	(0.017)	
1971-2010									
Fixed effect		0.01	0.29	0.07	0.10	0.07	-19.90	-1.07	20.19
		0.00	0.02	0.02	0.02	0.02	10.73	0.38	
		(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.063)	(0.005)	
Random effect	-2.05	0.01	0.29	0.08	0.11	0.07	-19.63	-1.07	
	0.65	0.00	0.02	0.02	0.02	0.02	10.71	0.38	
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.067)	(0.005)	
First differences							-18.77	2.72	28.70
							-2.07	1.41	
							(0.0037)	(0.157)	

Notes. This table reports the estimates of panel regressions of our excess--predictability measure, i.e. BVI, for all the currencies in our dataset against its own lags and, the 60 month lags of the percentage flow of asset under management in the hedge fund industry (AUM) and Wurgler and Baker's (2006) Sentiment index. All variables are denoted as in the text. The BVIs are estimated using rolling windows of 5 years of data over the periods 1972-2006 and 1972-2010. The estimation method is Swamy's (1970) Random Coefficient panel regression with GLS standard errors. Standard errors p-values (in brackets) are reported below the corresponding coefficient estimates. The last column reports the coefficient of determination for each model.

Figure 3
Out-of-Sample Rational Trading Rules vs Carry Trade



Notes. This figure plots the return on the rational trading strategy denoted by LIMNETAVG and constructed by optimally dynamically rebalancing a portfolio made up of the 6 portfolios of currencies sorted according to the level of the interest rate constructed and made available for download by Lustig et al. (2011), as well as the return on the carry trade strategy, denoted by HML_fx, formed by the same authors using these currency portfolios. The assumed level of transaction costs is 10 bps per each way trade and positions in each currency portfolio are limited in absolute value to 100 percent of allocated capital.

Table 9
Out-of-Sample Rational Trading Rules vs Carry Trade

<i>c</i> (limit)	<i>SR p.a. gross</i>	<i>SR p.a. net</i>	<i>Alpha</i> (net)	β_{rm}	β_{SMB}	β_{HML}	β_{HMLfc}
1	56.79	42.16	0.07 (0.071)	-0.10 (0.216)	-0.11 (0.280)	-0.02 (0.810)	0.30 (0.104)
2	58.08	41.66	0.01 (0.068)	-0.20 (0.205)	-0.24 (0.266)	-0.04 (0.841)	0.57 (0.116)
3	59.32	41.86	0.01 (0.061)	-0.31 (0.194)	-0.36 (0.268)	-0.06 (0.848)	0.82 (0.125)
4	60.91	43.11	0.02* (0.049)	-0.40 (0.196)	-0.46 (0.283)	-0.07 (0.861)	0.98 (0.162)
5	62.72	44.76	0.03* (0.040)	-0.47 (0.215)	-0.58 (0.272)	-0.07 (0.882)	1.14 (0.193)
10	65.52	46.83	0.05* (0.032)	-0.80 (0.256)	-1.02 (0.282)	0.08 (0.934)	2.12 (0.214)
20	66.63	47.39	0.09* (0.028)	-1.38 (0.221)	-1.54 (0.282)	0.00 (0.995)	3.51 (0.205)
30	63.31	44.84	0.10* (0.034)	-1.69 (0.216)	-1.80 (0.283)	0.00 (0.999)	4.12 (0.186)
50	58.80	41.52	0.11* (0.038)	-2.19 (0.183)	-2.11 (0.266)	-0.15 (0.948)	4.17 (0.215)
100	54.46	37.98	0.13* (0.039)	-2.95 (0.155)	-2.82 (0.194)	-0.96 (0.718)	4.10 (0.283)
∞	53.56	37.00	0.13* (0.045)	-3.08 (0.150)	-2.87 (0.194)	-0.93 (0.727)	4.404 (0.274)

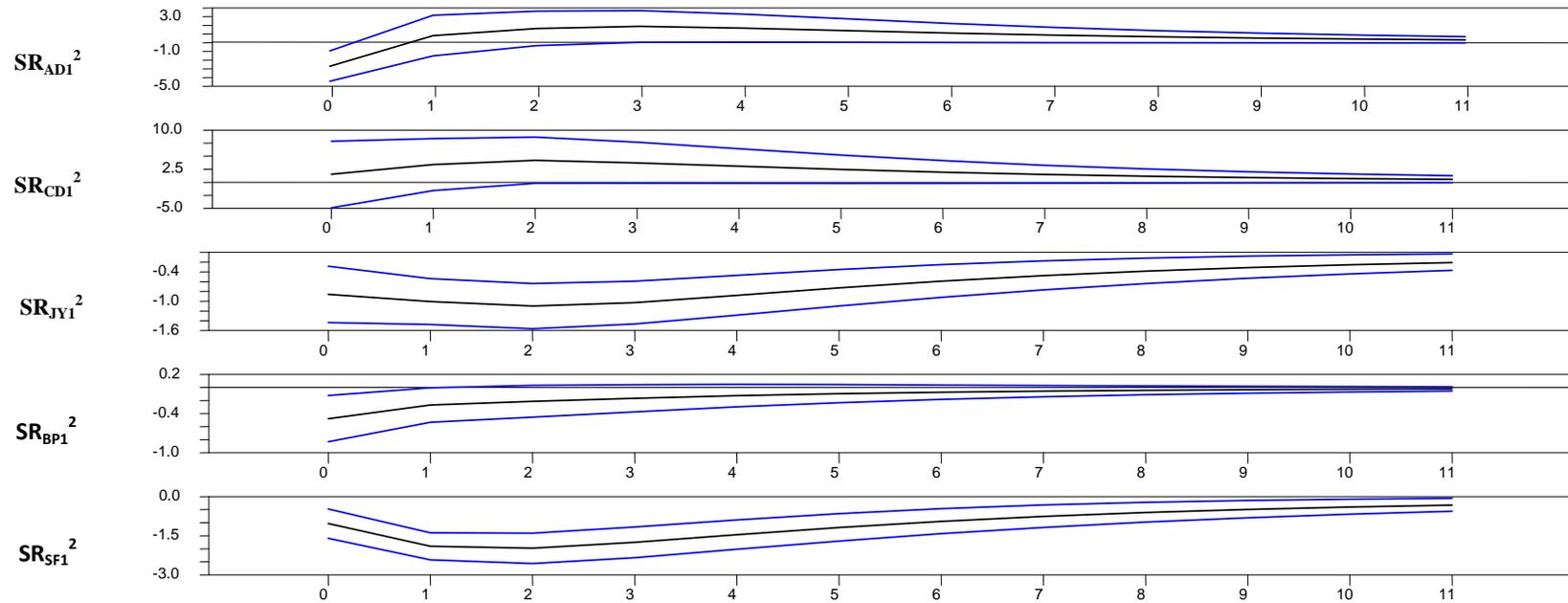
Notes. This table reports percentage annualized SRs, alphas and factor loadings of rational trading strategies based on the currency portfolios considered by Lustig et al (2011) and on the carry trade strategy constructed by the same authors using such currency portfolios. The rational trading strategies are constructed by rebalancing the same portfolios based on time-varying weights that reflect the out-of-sample predictability picked by ARMA(p,q) models, where p and q are selected using the small sample version of the AIC, and subject to a given limit on the position taken in each currency portfolio. The limit is specified by *c*, reported in the first column, as a multiple of the allocated capital. The annualized SR of the latter over the same period, i.e. 1988-2010, is 57.63 percent. The factors are the Fama and French factor-mimicking portfolios augmented by the carry trade strategy considered by Lustig et al. (2011).

Table 10
VAR(1) of AUD and One-Month SRs of Out-of-Sample of Rational Trading Rules

Dependent variable	Constant	AUM _{t-1}	SR _{ADI,t-1} ²	SR _{CDI,t-1} ²	SR _{JY1,t-1} ²	SR _{GB1,t-1} ²	SR _{SF1,t-1} ²
AUM _{t-1}	0.00	0.70	0.00	0.00	0.00	0.00	0.00
	2.64 (0.009)	12.81 (0.000)	0.42 (0.675)	-3.58 (0.000)	-2.84 (0.005)	2.00 (0.047)	0.03 (0.973)
SR _{ADI,t-1} ²	4.32	26.79	0.08	0.30	-0.09	-0.15	-0.11
	1.71 (0.088)	0.24 (0.810)	1.62 (0.107)	14.79 (0.000)	-0.39 (0.694)	-0.39 (0.696)	-0.37 (0.715)
SR _{CDI,t-1} ²	6.45	404.21	0.29	0.09	0.19	2.45	-0.61
	0.70 (0.485)	1.00 (0.321)	1.57 (0.117)	1.24 (0.218)	0.23 (0.817)	1.77 (0.079)	-0.57 (0.570)
SR _{JY1,t-1} ²	2.47	-48.46	0.02	0.00	0.18	-0.18	0.30
	3.07 (0.002)	-1.36 (0.174)	1.21 (0.229)	-0.51 (0.611)	2.53 (0.012)	-1.44 (0.151)	3.16 (0.002)
SR _{GB1,t-1} ²	1.94	-14.67	0.00	0.00	-0.05	0.17	0.05
	3.93 (0.000)	-0.68 (0.500)	0.27 (0.788)	-0.47 (0.638)	-1.11 (0.267)	2.26 (0.025)	0.81 (0.421)
SR _{SF1,t-1} ²	3.13	-124.51	-0.01	0.00	0.01	-0.09	0.50
	3.84 (0.000)	-3.47 (0.001)	-0.85 (0.395)	0.60 (0.548)	0.17 (0.867)	-0.77 (0.445)	5.26 (0.000)

Notes. This table reports estimates of a VAR(1) that includes as endogenous variables the percentage capital flow and the squared out-of-sample SRs of the rational trading rules on the indicated currency futures. The trading rules exploit the predictability captured by an ARMA(p,q) where p and q are selected using the small sample version of the AIC. For each estimated equation and each included variable, we report the point estimate of the associated coefficient, its OLS t-statistic and, in brackets, the corresponding p-value. The data frequency is monthly and the sample period is 1992-2010.

Figure 4
Impulse Responses of Out-Of-Sample Squared SRs to Capital Flow Shock



Notes. This figure reports the impulse responses to percentage capital flow shocks of the squared out-of-sample SRs of the rational trading rules based on the predictability of the indicated currencies. The impulse responses are based on a VAR(1) with including a constant, the percentage flow of asset under management in the hedge fund industry (AUM) and the out-of-sample SRs of the indicated currencies. The sample period is 1992-2010 and the data frequency is monthly. The out-of-sample SRs are those of the strategies that exploit the predictability captured by an ARMA(p,q) where p and q are selected using the small sample version of the AIC. Confidence intervals are constructed using a Monte Carlo integration procedure.

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