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Predictability, trading rule profitability and learning in currency markets☆

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ABSTRACT

This paper studies currency predictability over time. We assess predictability by testing for the presence of exploitable patterns in currency returns. To do so, we first generate consistent and parsimonious reduced-form estimates of currency expected returns and variances and then use these estimates to form dynamic trading strategies that maximize the multi-period Sharpe ratio. Our results show that currency predictability is time-varying and, for a number of currencies, has increased substantially in recent times, casting doubt on the widespread view that currency pricing may be on a path of convergence towards efficiency. We find, however, that currency markets learn in an efficient manner and a close relation between our strategies and indices that track popular technical trading rules, namely moving average cross-over rules and the carry trade, suggesting that the technical rules represent heuristics by which professional market participants exploit currency mispricing.

1. Introduction

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), LeBaron (1999), and Schulmeister (2006), among others, various studies have reported that filter and moving average crossover rules, as well as other technical trading rules, often result in statistically significant trading profits in currency markets, to an extent that casts doubts on the efficient market hypothesis (henceforth, EMH). More recently, and contrary to the bulk of these earlier findings, a number of authors, including Olson (2004) and Pukthuanthong, Levich, and Thomas (2007), find evidence of diminishing profitability of currency trading over time. In a comprehensive re-evaluation of past studies of filter and moving average (MA) rules, Neely, Weller, and Dittmar (2009) also find evidence of declining profitability. There is, however, evidence that other strategies, such as the carry trade, continue to generate returns that appear to be large and relatively uncorrelated with known risk factors. See, among others, Burnside, Eichenbaum, Kleschelski, and Rebelo (2007) and Brunnermeir, Nagel, and Pedersen (2008), as well as Neely et al. (2009) who note that less popular and relatively more sophisticated strategies continued to generate excess-profitability even as the profitability of the simpler and more popular ones declined.

Ultimately, these studies provide alternative and to some extent conflicting views on foreign exchange market efficiency. Their common trait is the emphasis on the EMH and the attempt to use estimates of currency trading profitability to make inferences either on whether the foreign exchange market is efficient. In light of the changing strength of the evidence on currency trading profitability over time, however, it is possible that market efficiency is itself time-varying. An obvious driver of time-varying efficiency, and the one on which we focus in this paper, is learning. For example, under Lo's (2004) adaptive market hypothesis (AMH), bursts of predictability would occur whenever shifts in market conditions required market participants to re-

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learn how to make efficient forecasts.[5] The possibility of learning is considered, in a currency market setting, by Neely et al. (2009), who interpret the declining profitability of traditional currency trading rules as evidence of a trend towards increasing market efficiency, but these authors formally tests only for violations of the EMH rather than for efficient learning. The latter, as defined by Muth (1961) and later further formalized by Sargent (1993), makes the assumption that the markets' belief about the data generating process of asset returns are correct up to the realization of a random shock. Efficient learning, instead, admits error in prior beliefs as long as the latter are subsequently updated efficiently, as in Bossaerts' (2004) formulation of the efficient learning market hypothesis (ELM, henceforth) and consistent with how beliefs are modelled in the work of Hansen (2007) and Hansen and Sargent (2007, 2010).

In this paper, we test for both currency market efficiency (EMH) and efficient learning (ELM). As in previous studies, a central role in our inferences is played by tests of whether currency trading can generate abnormal returns relative to known risk factors. Unlike previous studies, however, we consider Bossaerts' (2004)' (2004) *modified* risk-adjusted returns alongside traditional measures of abnormal returns, so as to be able to test for ELM as well as for the EMH. The currency strategies we consider in our tests are directly based on maximum likelihood (ML) reduced form estimates of the data generating process of currency return. We use these estimates of the data generating process to form out-of-sample forecasts and then translate the forecasts into optimal trading rules, which we label "*rational* trading rules". These rules maximize ex-ante a given criterion, namely the period-by-period conditional Sharpe ratio and the multi-period unconditional Sharpe ratio. They attempt to mimic the dynamic trading strategies that would have been deployed, at the time of making the trading decision, by an investor endowed with RE and interested in maximizing the Sharpe ratio of her currency portfolio. As argued by the literature on rational dynamic general equilibrium models, e.g. Sargent (1993), ML estimates replicate ex-post the understanding of the process that a RE trader would have formed in real time. Our approach, therefore, naturally imposes the null of RE and seeks to replicate the manner in which a rational agent would use RE forecasts in generating the trading strategies. This mitigates the danger of data-snooping, because it avoids extensive searches across arbitrary and possibly ad hoc (i.e., known to perform well over a particular sample period) sets of strategies. It does so while in principle permitting powerful tests, as long as the predictive model estimated by ML to generate the forecasts is sufficiently flexible to offer a reduced form representation of the true data generating process.

Our empirical results offer evidence of violations of the EMH at the beginning of the sample period, i.e. in the early 90s, and in its final part, in coincidence with the outbreak of the financial turbulence that characterized the period 2007–2010. This is not only the case of emerging currencies, such as the Russian Rouble, the Brazilian Real and the Polish Zloty, but also of the Euro. This suggests that the conclusion in favour of vanishing profitability of technical trading rules, which has gained support in recent years in the empirical literature, may be premature. We find, however, that we cannot reject ELM and therefore that the currency market learns efficiently. Moreover, our *rational* rules are to a large extent tracked, over different portions of the sample period, by popular *technical* rules. The technical rules we consider are the momentum strategy, tracked by the AFX currency management index constructed by Lequeux and Acar (1998) by combining filter moving average rules[6] on the major currencies, and the carry trade, captured by the HML index of Lustig, Roussanov, and Verdelhan (2011). This suggests that technical trading, far from being an irrational and wasteful endeavour, is a way for currency portfolio managers to exploit, and hence eventually correct, mispricing relative to a RE benchmark. It should be noticed that, because we use monthly data, our results are robust to issues that crop up at higher-frequencies. For example, because of the low frequency of the strategies we consider, it is unlikely that non-proportional transaction costs arising as a result of 'price pressure', e.g. Evans and Lyons (2002), play an important role.

The remainder of our paper is structured as follows. In the next Section, we outline the relation between predictability and time-varying expected returns and illustrate the rational trading rules, which play a key role in our analysis. In Section 3, we describe our dataset. In Sections 4, 5 and 6, we present our empirical results on out-sample predictability and tests of market efficiency and efficient market learning. Section 7 offers an analysis of the correlation of strategies that exploit predictability with popular portfolio allocation benchmarks and risk factors. In the final Section, we summarize our main findings and offer conclusions.

2. Currency predictability and rational trading rules

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 currency excess-returns as follows:

$$r_{t+1} = \mu_t + \varepsilon_{t+1}. \quad (1)$$

Here $\mu_t \equiv E(r_{t+1}|I_t)$, I_t is the information set at time t and ε_{t+1} is a conditionally zero-mean innovation, i.e. a (non-degenerate) random variable unpredictable with respect to the information set I_t, i.e. $E_t(\varepsilon_{t+1}) = 0$, with finite but possibly time-varying variance $\sigma^2_{\varepsilon,t}$. Conditioning down, this implies $E(E_t(\varepsilon_{t+1})) = E(\varepsilon_{t+1} z_t) = 0 \; \forall \; z_t \in I_t$. In this setup, the EMH boils down to the requirement that the expected excess-return μ_t equals the discount rate demanded by the marginal investor to hold the asset, i.e. the currency. In the context of our tests of the weak-form EMH, I_t includes the sigma-field generated by the past of ε_{t+1}, which belongs to the information set J_t available to the econometrician and we thus have $J_t = I_t$, but it may also include, in tests of the semi-strong and strong form EMH, other available public and private information, in which case we might have $J_t \subseteq I_t$, but this does not need to concern us here as these forms of the EMH are outside the scope of the present paper.

Our approach to testing the EMH in currency markets is based on the back-testing of trading rules that seek to mimic the strategies that would have been followed by an optimizing risk-averse currency trader endowed with RE. At any one time, the simulated rational trading rule invests in the ith currency an amount of wealth proportional to the expected excess-return and inversely to its conditional variance. That is, the net amount of numeraire currency, i.e. the USD, invested in the ith currency at any one time t under the rule is[7]

$$w_{i,t} = \lambda \frac{\mu_{i,t}}{\sigma^2_{i,t}}. \quad (2)$$

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

[6] Menkhoff, Sarno, Schmeling, and Schrimpf (in press) point out that moving average rules do not capture in full the profitability that can be generated by exploiting currency momentum but, as implicitly acknowledged by the same authors, they are indeed representative of the strategies that have been traditionally employed by currency managers and academics alike to do so.

[7] In-sample versions of these rules have been already used by Levich and Potì (2008).

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