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Mispricing and Risk Premia in Currency Markets

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Abstract

Using real-time data, we show that currency excess return predictability is in part due to mispricing. First, the risk-adjusted profitability of systematic trading strategies decreases after dissemination of the underlying academic research, suggesting that market participants learn about mispricing from publications. Moreover, the decline is greater for strategies with larger in-sample profits and lower arbitrage costs. Second, the effect of comprehensive risk adjustments on trading profits is limited, and signal ranks and alphas decay quickly. The finding that analysts' forecasts are inconsistent with currency predictors implies that investors' trading contributes to mispricing and suggests biased expectations as a possible explanation.

I. Introduction

Cross-sectional currency excess return predictability has been the subject of a recent and expanding literature. Given that currency markets are populated by sophisticated professional investors and characterized by high liquidity, large transaction volumes, low transaction costs, and the absence of natural short-selling

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constraints, one would expect them to be highly informationally efficient. Yet, investors have been shown to be able to generate profits using various systematic trading strategies, such as momentum, value, term spread, and output gap.[1]

In contrast to the focus in this currency literature on individual predictors, asset pricing research in other asset classes, particularly equities, has recently studied patterns across many predictors (e.g., McLean and Pontiff (2016), Engelberg, McLean, and Pontiff (2018), (2020), Calluzzo, Moneta, and Topaloglu (2019), and Guo, Li, and Wei (2020)). Consequently, this is the first article studying the cross section of predictors of currency excess returns (hereafter, "currency predictors") in order to investigate alternative rationales for their existence. To this end, we construct all major cross-sectional predictors of currency excess returns documented in the literature that do not require proprietary data, using novel real-

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[1]Currency markets are generally viewed as extremely liquid and efficient. Average daily turnover is estimated at $7.5 trillion in 2022, which is 31 times larger than world exports and imports, 19 times larger than world Gross Domestic Product (GDP), and 13 times larger than exchange-traded equity turnover (Bank for International Settlements (BIS) (2022), World Bank (2022), and World Federation of Exchanges (WFE) (2022)). At the same time, official market participants (such as central banks that are not profit maximizing), fixed income managers (who want to hedge the currency exposure), corporate treasuries (who are transacting because of underlying hedging needs), noise traders, and tourists are likely to leave money on the table.

time data to ensure investors could have implemented these strategies at a historical point in time.

To delineate between alternative explanations, primarily risk and mispricing, we study the effect of research dissemination and risk adjustment on predictor profits employing established asset pricing tests and methodologies. In particular, the literature suggests that if strategy profits reflect mispricing, they should diminish after the underlying academic research has been publicly disseminated, while they should not change if portfolio returns reflect compensation for risk (e.g., Cochrane (1999), Schwert (2003), Chordia, Subrahmanyam, and Tong (2014), and McLean and Pontiff (2016)). Mispricing as a source of currency predictability would also be evidenced by significant predictor profits in excess of factor risk premia (e.g., Jensen (1978), Fama (1991), and Schwert (2003)), low persistence of signal ranks, and fast decay of risk-adjusted returns (or "alphas") (e.g., Bartram and Grinblatt (2018), (2021)).

In order to explore possible underlying mechanisms of currency excess return predictability, we study the relation between currency predictors and forecasts by currency analysts. If analysts form their forecasts by incorporating publicly available information about currency predictors or analyzing the market and fundamental data used to construct them, their predictions about future exchange rate returns should align with currency predictors. In contrast, conflicting views of currency analysts would be consistent with explanations where predictors reflect mispricing based on biased expectations (e.g., Engelberg et al. (2020), Guo et al. (2020)).

Our analysis adopts an agnostic perspective on the importance of alternative explanations for the presence of currency predictors. While some researchers place strong emphasis on the existence of currency predictors (especially carry trade) as capturing risk (e.g., Lustig, Roussanov, and Verdelhan (2011)), others suggest that risk does not provide a full explanation, motivating alternative rationales such as market inefficiencies (e.g., Froot and Thaler (1990), Okunev and White (2003), Burnside, Eichenbaum, and Rebelo (2011), and Barroso and Santa-Clara (2015)). We control for time-varying risk premia and factor exposures as comprehensively as possible in order to address concerns that mispricing might simply reflect omitted factor risk. In the same vein, our approach is non-discretionary with regard to the sample of currency predictors and the inclusion of potentially risk-based predictors. In line with prior asset pricing literature, the focus of our article is on the cross section of predictors similar to Chordia et al. (2014), McLean and Pontiff (2016), Engelberg et al. (2018), (2020), and Guo et al. (2020).

Given the lack of a single, generally accepted procedure in the literature to distinguish between alternative explanations for return predictability, we study the effect of both research publication and risk adjustment on currency strategy profits. Our results provide evidence that currency return predictability is at least in part due to mispricing. First, the risk-adjusted profitability of systematic currency trading strategies decreases significantly in periods after the underlying academic research has been published, suggesting some market participants learn about mispricing from research publications. Consistent with mispricing, the post-publication decline is greater for strategies with larger in-sample profits and lower arbitrage costs. Second, the effect of comprehensive, state-of-the-art risk adjustments is limited, there is significant decay in risk-adjusted profits for stale trading signals, and the autocorrelations of signal ranks are low.

Analysis of possible sources of mispricing reveals that the forecasts of currency analysts are inconsistent with currency predictors, which implies that investors trading on them contribute to mispricing, motivating biased expectations as a possible explanation. In particular, investors following analysts' forecasts would be selling (buying) the currencies in the fifth (first) predictor-sorted portfolio. Consequently, investors trading on these predictors can buy (sell) the currencies in the fifth (first) portfolio at a lower (higher) price, increasing their excess returns.

While extant work has documented each of the currency predictors and their properties individually, this article is the first to study patterns across predictors, which allows more general conclusions. Our approach permits entertaining and testing alternative rationales for currency predictability. The currency market is a particularly well-suited environment for this analysis, since one would expect it to be more efficient than other asset classes. Moreover, analysts provide monthly forecasts of the expected value of the underlying asset at the end of the following month, allowing a direct comparison of expected and realized returns. Consequently, our approach and data allow generating new inferences about the economics of currency markets.

The first approach to investigate alternative sources of predictability in currency markets examines predictor profits in periods before and after the dissemination of research publicizing the trading strategies. If profits reflect mispricing and publication leads to investors learning about strategies and trading on them to exploit mispricing, currency excess return predictability should decline post publication (Cochrane (1999), Schwert (2003), Chordia et al. (2014), and McLean and Pontiff (2016)). Consistent with mispricing as a source of predictability, we show that risk-adjusted payoffs associated with currency strategies significantly decrease after the academic research has been published and that post-publication declines are greater for strategies with economically or statistically larger in-sample profits and smaller limits to arbitrage.

The staggering of publication dates for currency predictors provides identification for tests of changes in profitability. However, the publication effect also remains significant in the presence of controls for alternative explanations such as a secular decline in trading profits or a compression of risk premia in periods of low interest rates, high exchange rate volatility, financial crisis, or recession. Finally, we include a host of risk factors in currency, equity, and bond markets and show that risk-adjusted profits also drop significantly after the publication of the underlying research. The literature refers to predictor variables with these characteristics that cannot be explained by risk as "anomalies" (e.g., Ball (1978), Jensen (1978), and Fama (1991)).

The second approach to distinguishing between mispricing and risk as alternative rationales for return predictability involves risk adjustments to predictor payoffs. Following the literature, we combine individual currency predictors into average predictor (Stambaugh, Yu, and Yuan (2012)) and extreme predictor signals (Engelberg et al. (2018), (2020)) that generate significant quintile spreads of up to 74 basis points (bps) and 45 bps per month gross and net of transaction costs, respectively. In the absence of a universally accepted risk model for currency markets, we adjust these quintile spreads for risk with comprehensive risk models using time-series regressions with 19-factor risk models as well as the instrumented principal component analysis (IPCA) technique developed in Kelly, Pruitt, and Su (2019) (thus representing its first application to currency markets).

While many major anomaly portfolios in equity markets have insignificant IPCA alphas (e.g., Kelly, Moskowitz, and Pruitt (2021)), these risk adjustments have only a limited effect on the profitability of the predictors we study, despite controlling for time-varying risk premia and factor exposures tied to the individual predictors themselves. In particular, risk-adjusted quintile spreads remain highly statistically significant, with factor model intercepts and IPCA-adjusted spreads of up to 53 bps and 43 bps per month, respectively. This evidence of mispricing is buttressed by fast decay of signal ranks and alphas.

Given the evidence in support of market inefficiencies from publication effect and risk adjustment analyses, we explore possible sources of mispricing using analysts' forecasts. Currency predictors represent publicly available information that skilled analysts should be able to take advantage of (e.g., Engelberg et al. (2020), Guo et al. (2020)). Currency analysts should exploit these well-documented sources of currency predictability for their own predictions, while biased forecasts could give rise to mispricing. To this end, we use a unique and in part hand-collected data set of currency forecasts to investigate the relation between currency predictors and the exchange rate expectations formed by analysts, which provides a setting unaffected by the joint-hypothesis problem of risk models (Engelberg et al. (2018)).

Our results show that analysts' forecasts are inconsistent with currency predictors, as analysts are expecting losses for strategies based on predictors that yield realized profits. To illustrate, the forecast excess return for the first quintile based on the average predictor variable (i.e., the short portfolio) is +152 bps per month, while it is −116 bps for the fifth quintile (i.e., the long portfolio). The expected quintile spread is thus −268 bps per month, contrasting with a realized quintile spread of +74 bps. Similarly, the realized profit of a trading strategy based on the extreme predictor variable is +68 bps per month, while analysts expect a loss of −262 bps. These results are opposite to what one would expect if analysts made use of predictor information.

The apparent mistakes that analysts make (i.e., the difference between forecast and realized excess returns) are negatively associated with currency predictors, indicating that analysts' excess return forecasts are too low for currencies in the long portfolio and too high for those in the short portfolio. Nevertheless, analysts appear to have superior (private) information such that, even as they contradict currency predictors, their forecasts predict future currency excess returns. Thus, it is not the case that analysts' forecasts are incorrect; they just do not reflect currency predictors. Since investors following analysts' forecasts reinforce currency predictors, biased expectations can rationalize mispricing as a source of return predictability (Engelberg et al. (2020), Guo et al. (2020)).

Our article makes several contributions to the literature. It is the first to study the cross section of currency predictors, building on related work that tries to explain the existence of predictors cross-sectionally for equities. To illustrate, empirical evidence suggests that stock market predictability is attenuated after publication (Schwert (2003), McLean and Pontiff (2016)), following increased predictor-based institutional trading (Calluzzo et al. (2019)), and due to lower trading costs (Chordia et al. (2014)). However, while equity and bond markets have many assets and predictors compared with currency markets, they might be less efficient due to higher transactions costs, lower turnover, market closures, short selling constraints, etc.

The evidence in our article on publication effects complements findings for time-series predictors in currency markets by Neely, Weller, and Ulrich (2009), who replicate different types of published technical trading rules. They find that the performance of trading rules in the "ex post periods" after the end of the original samples deteriorates, and that risk and data mining cannot explain strategy profits. While Neely et al. (2009) employ different tests and methodologies and do not perform tests across the different types of strategies or apply comprehensive risk adjustments, their evidence of lower out-of-sample performance of published technical trading rules is consistent with publication effects and investor learning. A number of other studies also show evidence that profits of technical trading have declined over time (e.g., Pukthuanthong-Le and Thomas (2008), Cialenco and Protopapadakis (2011)).

While risk-adjusted predictor payoffs have been widely studied in equity and bond markets for decades, early currency research often eschews risk adjustments altogether, and they are still fairly parsimonious in recent studies and often limited to equity factors or the dollar and carry factors. Consequently, a contribution of our article is its application of comprehensive, state-of-the-art risk adjustments.

Our article is also the first to relate analysts' currency forecasts to currency predictors and currency excess returns. Studies of the relation between stock market predictors and analysts' earnings forecasts, recommendations, and target prices find them to be inconsistent (Engelberg et al. (2018), (2020), Guo et al. (2020)), consistent (Jegadeesh, Kim, Krische, and Lee (2004)), or conditional on credit quality (Grinblatt, Jostova, and Philipov (2023)). Given this mixed evidence, our article contributes to the literature by providing important out-of-sample evidence for related questions in currency markets, where no prior evidence exists.

Additionally, data on analysts' forecasts for next month's stock or bond prices do not exist. Instead, researchers have to use forecasts of annual or quarterly earnings or annual target prices, which exhibit horizon and seasonality effects, can be stale, may require adjustments for expected payouts (such as dividends), etc., that might induce measurement error. In contrast, our unique data set allows directly estimating the monthly return that analysts expect on each currency every month. Furthermore, the forecasts of equity analysts have been shown to be biased upward reflecting analyst optimism due to conflicts of interest originating from investment banking and brokerage activities (La Porta (1996)). In contrast, forecasts for exchange rates always involve opposite views on the two currencies involved.

II. Sample and Data

The empirical analysis uses monthly data for trading signals and exchange rates of 76 countries (Table A2 in the Supplementary Material).[2] The number of

[2]For comparison, Lustig and Verdelhan (2007), Della Corte, Riddiough, and Sarno (2016), and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) use 81, 55, and 48 currencies, respectively.

currencies varies over time as a function of data availability, with 20 to 30 currencies in a typical month. For each of the 620 months between Dec. 1970 to July 2022, we construct eleven distinct predictors of currency excess returns that have been documented in the literature: momentum based on prior 1, 3, or 12 months' currency returns, a filter rule combination, carry trade, dollar carry trade, dollar exposures, term spread, currency value, output gap, and the Taylor Rule (Table A3 in the Supplementary Material). They represent all cross-sectional predictors that can be constructed with publicly available data for a large number of currencies. In line with the asset pricing literature (e.g., Chordia et al. (2014), Harvey, Liu, and Zhu (2016), McLean and Pontiff (2016), and Guo et al. (2020)), we do not study time-series predictability.[3] The long sample period averages out variation in strategy profits across economic cycles, policy regimes, risk on/off periods, crisis events, and other episodes in currency markets. While the number of strategies is relatively small, the resultant lower power of the tests biases against finding significant effects.[4]

Since we are analyzing the ability of these variables to predict future currency excess returns, we construct all trading signals using real-time data. This ensures that the information from the trading signals was available to market participants at the point in time the signal was constructed and thus avoids a look-ahead bias. To this end, we source monthly spot exchange rates, 1-month forward exchange rates, short-term interest rates (interbank or Treasury Bill rates), and long-term interest rates (10-year or 5-year government bond yields) from Datastream. We further obtain monthly real-time data on industrial production and consumer prices from the Original Release Data and Revisions Database of the Organization for Economic Co-operation and Development (OECD), which has rarely been used in the currency literature.[5] Individual predictors have low correlations between each

We report results for subsamples of 62, 54, 40, and 10 currencies in Tables A9 and A10 in the Supplementary Material.

[3]The cross-sectional implementation is in line with benchmark indices constructed by the financial industry, such as the DB FX Momentum, DB FX Valuation, and DB FX Carry indices. To illustrate, the DB G10 Currency Future Harvest ETF tracks the carry index, which goes long the three highest and short the three lowest yielding currencies. Studies of technical trading rules often differ in terms of data and research design from cross-sectional trading signals. In particular, trading rules in currency markets typically use daily (sometimes intra-day or weekly) data, either from the spot or futures market, for one or a small number of currencies. The trading/rebalancing frequencies are often irregular. Strategies typically do not involve hedge portfolios (i.e., long/short positions) but are dollar exposed.

[4]The number of predictors studied in equity research is, for instance, 11 (Daniel et al. (2020), Guo et al. (2020), Stambaugh, Yu, and Yuan (2012)), 12 (Chordia et al. (2014)), 14 (Calluzzo et al. (2019), Grinblatt et al. (2023)), 15 (Kozak, Nagel, and Santosh (2018)), 34 (Tian (2021)), and 97 (McLean and Pontiff (2016), Engelberg et al. (2020)).

[5]Specifically, we retrieve real-time data (or monthly vintages, as the series contain revisions) for the consumer price index (CPI) (starting in Feb. 1999) and the industrial production index (IPI) (starting in Dec. 1999). The database covers all countries in our sample, except Argentina, Bahrain, Bulgaria, Colombia, Croatia, Cyprus, Egypt, Ghana, Hong Kong, Jordan, Kazakhstan, Kenya, Kuwait, Latvia, Lithuania, Malaysia, Malta, Morocco, Nigeria, Oman, Pakistan, Peru, Philippines, Qatar, Romania, Saudi Arabia, Serbia, Singapore, Sri Lanka, Taiwan, Thailand, Tunisia, Uganda, Ukraine, United Arab Emirates, Vietnam, and Zambia. Real-time data for these countries is neither available from the OECD database or other data sources, nor could it be obtained from the respective country's central bank or national statistics office.

other, with an average correlation of 0.14. However, correlations can be as low as −0.39 and as high as +0.92, suggesting they provide a wide range of differing trading signals (Table A4 in the Supplementary Material).[6] Our calculation of standard errors takes the dependence between predictors into account.

We relate these trading signals to exchange rates and analysts' expectations in the following month, so that the predictors are lagged by 1 month relative to future actual currency (excess) returns and analysts' expected currency (excess) returns. We build a unique and in part hand-collected data set of foreign exchange rate expectations using mean consensus forecasts from surveys undertaken by Consensus Economics (Appendix A of the Supplementary Material). The forecasts are made every month for the exchange rates at the end of the following month. All spot and forecast exchange rates are in units of foreign currency per unit of a U.S. dollar. We convert analysts' forecasts quoted relative to the Deutschmark or Euro to quotes against the U.S. dollar using the corresponding Deutschmark or Euro forecasts.[7] Actual currency (excess) returns cover the period Jan. 1971 to Aug. 2022, while analysts' expected currency (excess) returns are available for Dec. 1989 to Aug. 2022.

We define next month's currency return as the *negative* log difference between the spot exchange rates of months $t+1$ and t. Furthermore, next month's currency excess return is defined as the log difference between the 1-month forward exchange rate of month t and the spot exchange rate of month $t+1$, assuming covered interest parity.[8] Gross currency (excess) returns are based on mid-point exchange rate quotes, while currency (excess) returns net of transaction costs use bid–ask quotes for spot and forward exchange rates. Since average dealer quoted spreads by World Market/Reuters exceed effective spreads actually paid by a factor of more than 2 (Lyons (2001), Karnaukh, Ranaldo, and Soderlind (2015)), net profitability is understated. Profits of trading strategies are calculated as quintile spreads of the excess returns of equal-weighted currency portfolios from sorts based on the respective predictor variable.

In order to adjust trading profits for risk, we employ a comprehensive set of factors. Available for our full sample period are factors capturing dollar risk and

[6]Similarly, for equity markets, McLean and Pontiff (2016) find average correlations between predictor variables of 0.033, ranging from −0.895 to +0.933, while Green, Hand, and Zhang (2013) report average correlations of 0.09.

[7]The surveys draw on 250 forecasters in 27 countries covering 93 currencies, mostly affiliated with investment banks (e.g., BNP Paribas, Citigroup, Commerzbank, Deutsche Bank, Goldman Sachs, Royal Bank of Canada, Royal Bank of Scotland, Santander, Société Générale), but also consultancies (e.g., Oxford Economics, EIU) and research institutes (e.g., WIIW, NIESR). The number of survey participants ranges from 100 for the more traded currencies (Euro, Japanese Yen, British Pound, and Canadian Dollar), to around 20 for Chinese Renminbi and Indian Rupee, and still more than 10 for less liquid currencies such as Czech Koruna, Russian Rouble, Argentinian Peso, and Brazilian Real (all quoted against the U.S. Dollar). See Appendix A of the Supplementary Material for details.

[8]In line with prior research (e.g., Lustig et al. (2011), Lustig, Roussanov, and Verdelhan (2014)), we drop observations of countries/periods with large failures of covered interest parity (South Africa: 7/1985–8/1985; Malaysia: 9/1998–6/2005; Indonesia: 1/2001–5/2007; Turkey 2/2001–11/2001). Alternatively, we exclude countries with the largest 1% of the absolute cross-currency basis (alternatively including or excluding countries without available interest rates) and find that results using currency excess returns are robust to large covered interest rate parity (CIP) violations.

carry trade risk (Lustig et al. (2011)), currency volatility risk (Menkhoff, Sarno, Schmeling, and Schrimpf (2012b)), currency skewness risk (Burnside (2012), Rafferty (2012)), and network centrality (Richmond (2019)). Factors with shorter history capture correlation risk (Mueller, Stathopoulos, and Vedolin (2017)), political risk (Filippou, Gozluklu, and Taylor (2018)), and global imbalance risk (Della Corte, Riddiough, and Sarno (2016)).

Full coverage also have the excess return on the world stock market portfolio, eight U.S. equity market risk factors (i.e., the market portfolio (Rm_RF), size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), momentum (Mom), short-term reversal (ST_Rev), and long-term reversal (LT_Rev)), obtained from the Ken French data library, as well as the term spread (TERM) and the default spread (DEF) (Fama and French (1993)) from Amit Goyal's website.

The 1-month return that analysts expect on a currency during month $t+1$ is calculated as the *negative* log difference between the foreign currency's forecast at the end of month t and the spot exchange rate at the end of month t (similar to Engelberg et al. (2018), (2020)). The excess return expected by analysts is the expected exchange rate return plus the 1-month interest differential, proxied by the forward discount. The forecast error (or analyst mistake) is the difference between the expected currency return for month $t+1$ and its realization during that month. Finally, we measure the forecast revision as the log difference in analysts' forecasts between month t and month $t+1$. Table A3 in the Supplementary Material provides details of all variable definitions. Table A5 in the Supplementary Material presents detailed summary statistics of actual and forecast currency (excess) returns and analysts' mistakes.

III. Predictor Profits and Publication

A. Publication Effects of Academic Research

The first approach to investigate mispricing and risk as alternative explanations for the existence of systematic currency trading strategies is the analysis of publication effects, which assesses the ability of trading signals to predict currency excess returns in different time periods. In particular, we compare trading profits from the sample period of the original academic research (i.e., the in-sample period) with profits in the period after the in-sample period but before the publication of the academic research (referred to as the out-of-sample period) as well as with profits after the publication of the research (i.e., the post-publication period).[9]

The analysis of publication effects allows distinguishing between mispricing and risk premium (and data mining) explanations. In particular, differences between the predictive power of currency predictors in the in-sample and post-publication periods could be the result of statistical bias or learning by investors from the publication. If return predictability reflects mispricing and publication allows sophisticated investors to learn about predictors and exploit mispricing by trading

[9]Academic studies may use different sets of currencies. For output gap, currency value, and the Taylor Rule, our in-sample period starts later than in the original studies since real-time data has a shorter history than final vintage data.

on predictor signals, their returns should decrease after these become publicly known.[10] Frictions, however, might prevent trading profits from disappearing completely. In contrast, trading profits should not change after publication if they reflect compensation for risk, conditional on no fundamental change in the risk–return trade-off or pricing of risk (Cochrane (1999), Schwert (2003), Chordia et al. (2014), and McLean and Pontiff (2016)). If currency excess return predictability originates solely from in-sample statistical bias or data mining, predictability should not exist in the out-of-sample period (Fama (1991), (1998), Cochrane (1999), Schwert (2003), and McLean and Pontiff (2016)).[11]

Profits of individual predictors are generally positive and significant over the full sample period before accounting for transaction costs as documented in the literature, while net profits are naturally smaller (Table A6 in the Supplementary Material). Since the academic research discovering cross-sectional currency strategies is very recent, we use the date of the first posting of the respective working papers on the Social Science Research Network (SSRN) as their publication date (Table A7 in the Supplementary Material).[12] We create an indicator variable Post-Publication that is equal to 1 for months after the publication date, and 0 otherwise. Conversely, the Post-Sample dummy is equal to 1 for the months after the end of the sample period used in the original study (but before publication), and 0 otherwise. The average gross predictor payoff is 56 bps, 64 bps, and 19 bps per month in the in-sample, out-of-sample, and post-publication periods, respectively. The average length of these periods is 461, 11, and 149 months, respectively (which is similar to the 323, 56, and 156 months in McLean and Pontiff (2016)).

In order to study the publication effect of academic research, we estimate the following panel regression:

$$\text{Predictor Profit}_{j,t} = a_j + \beta_1 \text{Post-Sample}_{j,t} + \beta_2\text{\_Post-Publication}_{j,t} + e_{j,t}, \tag{1}$$

where the dependent variable is the monthly quintile spread of excess returns on currency predictor j in month t, and Post-Sample and Post-Publication are indicator variables for the respective periods. The regression has predictor fixed effects, and standard errors are computed using feasible generalized least squares (FGLS) under the assumption of contemporaneous cross-correlation between returns (results are similar when clustering standard errors by date and predictor).

[10]Trading by investors on currency predictors before they were popularized by academic research should lower portfolio returns in-sample and bias against any later publication effect if predictors reflect mispricing, while having no effect if they reflect risk (e.g., Cochrane (1999), Schwert (2003), and McLean and Pontiff (2016)).

[11]Lower profits in the out-of-sample period would also be consistent with investors learning about predictors even before the research is published.

[12]Institutional investors regularly follow SSRN postings to identify new predictors. Thus, investors will typically know already about the predictors (or correlated trading strategies) prior to formal journal publication. In robustness tests, we use the dates when the research appeared in peer-reviewed journals for those strategies that have already been published. At the same time, some investors may not know about the predictors until years after their publication, reducing the speed of alpha decay (McLean and Pontiff (2016)).

The results show two interesting findings. First, with the caveat of a relatively short out-of-sample period, there is little evidence that trading profits decline in the out-of-sample period, since the coefficients of the Post-Sample variable are insignificant in all but one specification (Table 1). This indicates that data mining is likely not a primary source of trading profits in currency markets, since predictability should disappear out-of-sample otherwise. We do not find this to be the case.[13] Second, there is strong evidence that trading profits decrease after the underlying academic research has been disseminated. In particular, in specification 1, gross returns are lower by 37 bps per month after publication, which is both statistically and economically significant. However, we can reject the hypothesis that return predictability disappears completely (p-value = 0.05).

Results using trading profits net of transaction costs also show strong publication effects with a reduction by 34 bps in specification 1 (Table 1). Publication effects are bigger for predictors that have economically or statistically larger in-sample profits (specifications 2 and 3), respectively, and the overall publication effect is always significant.[14] For net profits, we cannot reject the hypothesis that trading profits disappear completely post publication (p-value = 0.26). Finally, overfitting explanations of predictability suggest that predictors with smaller in-sample profits or t-statistics are more likely subject to data mining and thus should have larger drops in performance out-of-sample, while the results suggest the opposite.[15] The analysis provides evidence that the returns associated with currency predictors decrease in periods after dissemination of the underlying research, which is consistent with the view that investors learn about and trade to exploit mispricing.

The set of trading strategies includes predictors that are sometimes considered risk factors, such as the carry trade or the dollar carry trade (e.g., Lustig et al. (2011), Lustig, Roussanov, and Verdelhan (2014), and Verdelhan (2018)).[16] If the expected returns of these trading strategies are the bona-fide result of a rational expectations equilibrium and there is no data snooping, then including them in the sample should bias the slope estimate of the Post-Publication variable toward 0. This is borne out empirically in specification 4, as the publication effect is indeed stronger when excluding these two strategies.

The publication effect can be illustrated by plotting the change in trading profits after publication against in-sample profits (Figure 1). The effect exists for almost all strategies individually, without an obvious bias toward a particular type of predictor, and those with larger in-sample profits show larger declines (Graphs A

[13]Confidence intervals for the parameter estimates of the post-sample indicator from a nonparametric bootstrap (Patton and Timmermann (2010)) to address a potential bias due to the small out-of-sample period are similar to those reported in the table.

[14]The publication effect and the interaction terms involving in-sample profits are always negative and significant for profits gross and net of transaction costs using alternative samples with different sets of currencies (Table A9 in the Supplementary Material).

[15]Tests using a combined proxy as in Falck, Rej, and Thesmar (2022) also show no evidence of overfitting.

[16]Similarly, research studying publication effects in equity markets (e.g., Chordia et al. (2014), McLean and Pontiff (2016)) includes predictors such as market beta, firm size, book-to-market, profitability, investment, and so forth, that are often considered risk factors and are part of the Fama and French (2014) 5-factor model.

TABLE 1

Regression of Predictor Profits on Post-Publication Indicators

Table 1 reports results from regressions of currency predictor profits (in percent per month) on an indicator variable for post-sample periods, and an indicator variable for post-publication periods and its interaction with average in-sample profits as well as *t*-statistics. Results are shown alternatively for trading profits gross and net of transaction costs, where transaction costs are calculated using bid and ask quotations. Separately for each predictor, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) at the end of each month and combined into equal-weighted portfolios. The profit of a predictor in a month is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5 − Q1). The Post-Sample indicator takes the value 1 if the month is after the sample period used in the original study, but still pre-publication, and 0 otherwise. The Post-Publication indicator takes the value 1 if the month is after the posting date on SSRN, and 0 otherwise. Regressions in specifications 1–3 are based on the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Regressions in specification 4 exclude the carry trade and dollar carry trade. Regressions include predictor fixed effects as indicated in the table. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels as well as the number of observations, the number of predictors, and the R^2. Standard errors are computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between returns. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample includes 76 currencies. The sample period is from Jan. 1971 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions. Table A7 in the Supplementary Material provides details on the predictors' original sample period used in the article as well as date of publication.

	Predictor Profits Gross of Transaction Costs				Predictor Profits Net of Transaction Costs			
	1	2	3	4	1	2	3	4
Post-Sample	0.041	0.054	0.075	−0.528*	0.118	0.141	0.140	−0.452
	(0.235)	(0.235)	(0.235)	(0.299)	(0.235)	(0.233)	(0.233)	(0.299)
Post-Publication	−0.365***	−0.031	−0.150	−0.414***	−0.341***	−0.000	−0.039	−0.405***
	(0.100)	(0.196)	(0.160)	(0.112)	(0.100)	(0.090)	(0.091)	(0.112)
Post-Publication × Average Predictor In-Sample Profits		−0.583				−1.509***		
		(0.405)				(0.462)		
Post-Publication × Predictor In-Sample *t*-Statistics			−0.045				−0.196***	
			(0.044)				(0.065)	
Average Predictor In-Sample Profits		0.998***				0.978***		
		(0.104)				(0.216)		
Predictor In-Sample *t*-Statistics			0.136***				0.145***	
			(0.014)				(0.031)	
No. of obs.	5,033	5,033	5,033	3,948	5,033	5,033	5,033	3,948
R^2	0.01	0.04	0.04	0.01	0.01	0.01	0.01	0.01
No. of predictors	11	11	11	9	11	11	11	9
Predictor fixed effects	Yes	No	No	Yes	Yes	No	No	Yes
Standard errors	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
Null: Post-Publication = −1 × Average Predictor In-Sample Profits	0.051			0.191	0.261			0.114
Null: Post-Publication + (Post-Publication × Average Predictor In-Sample Profits) = 0		0.012				0.000		
Null: Post-Publication + (Post-Publication × Predictor In-Sample *t*-Statistics) = 0			0.120				0.003	

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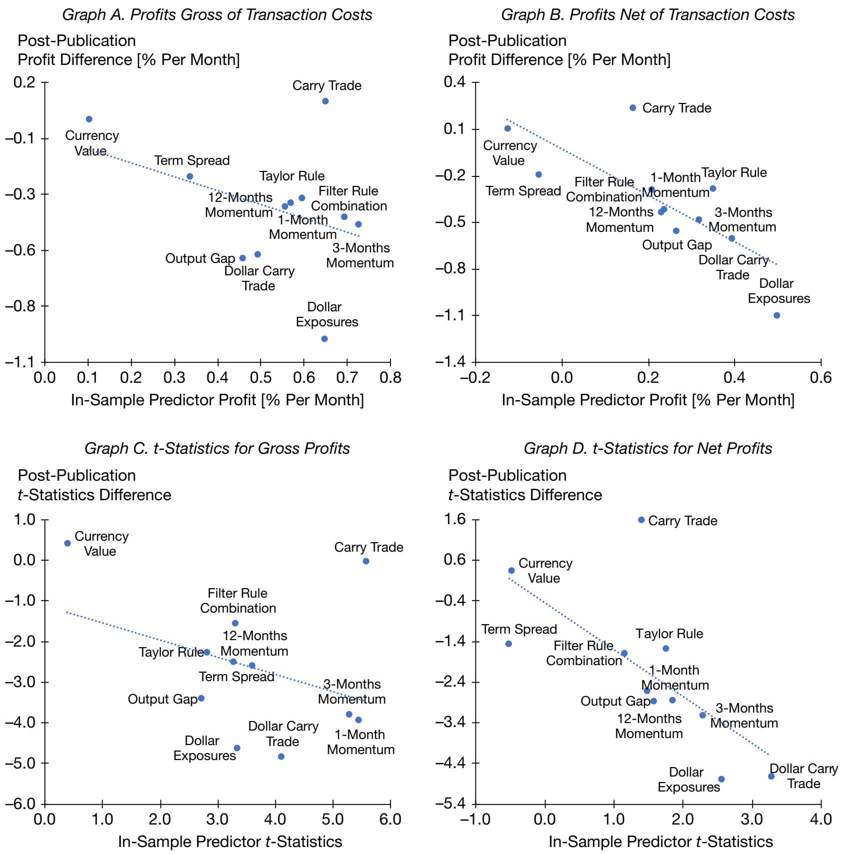
FIGURE 1

Relation Between In-Sample and Post-Publication Trading Profits

Figure 1 plots the relation between monthly in-sample currency predictor profits and changes in profits after publication (post-publication profit differences), as well as the relation between in-sample currency predictor *t*-statistics and changes in *t*-statistics after publication. In particular, it shows the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. In-sample predictor profits are the mean returns (in percent) of the difference between the currency excess returns of portfolios Q5 and Q1 (Q5 – Q1) from Jan. 1971 to the end of the sample period of the original study. Post-publication profits are the mean returns (in percent) of the difference between the currency excess returns of portfolios Q5 and Q1 (Q5 – Q1) for the period after the study has been published (through Aug. 2022). Post-publication profit differences are the difference between in-sample profits and post-publication profits. Post-publication *t*-statistic differences are the difference between in-sample *t*-statistics and post-publication *t*-statistics. Graph A shows trading profits gross of transaction costs, Graph B shows trading profits net of transaction costs, Graph C shows *t*-statistics for trading profits gross of transaction costs, and Graph D shows *t*-statistics for trading profits net of transaction costs. Transaction costs are calculated using bid and ask quotations. The sample includes 76 currencies. The sample period is from Jan. 1971 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions. Table A7 in the Supplementary Material provides details on the predictors' original sample period used in the article as well as date of publication.



and B). Similarly, there is a negative relation between in-sample *t*-statistics and post-publication effects (Graphs C and D). Note that the carry trade shows strong in-sample (gross) profits, but no reduction after publication, and thus bears the hallmarks of a risk factor, while the profitability of the dollar carry trade deteriorates

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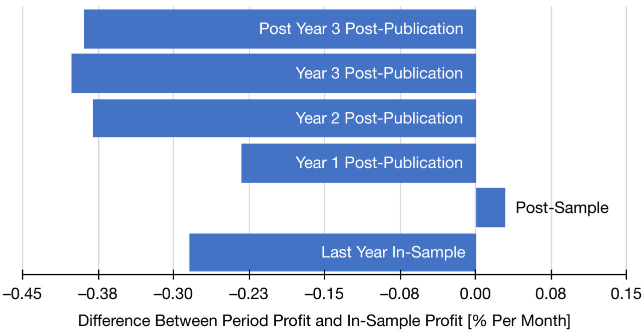
FIGURE 2

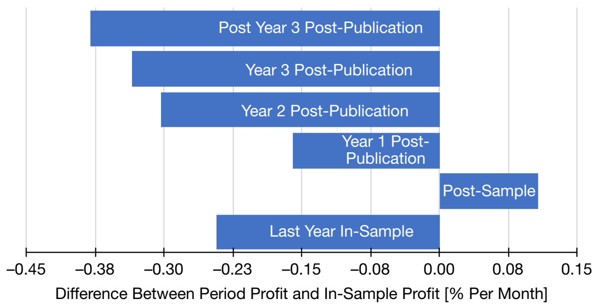
Predictor Profits Around End-of-Sample and Publication Dates

Figure 2 plots the coefficients from a regression of currency predictor profits (in percent per month) on indicator variables for the last year of the original sample period, the post-sample period, the first 1, 2, and 3 years post publication, and all months that are at least 3 years after publication. Results in Graph A and Graph B are shown alternatively for trading profits gross and net of transaction costs, where transaction costs are calculated using bid and ask quotations. Separately for each predictor, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) at the end of each month and combined into equal-weighted portfolios. The profit of a predictor in a month is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5 – Q1). The analysis is based on the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Regressions include predictor fixed effects. The sample includes 76 currencies. The sample period is from Jan. 1971 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions. Table A7 in the Supplementary Material provides details on the predictors' original sample period used in the article as well as date of publication.

Graph A. Profits Gross of Transaction Costs



Graph B. Profits Net of Transaction Costs



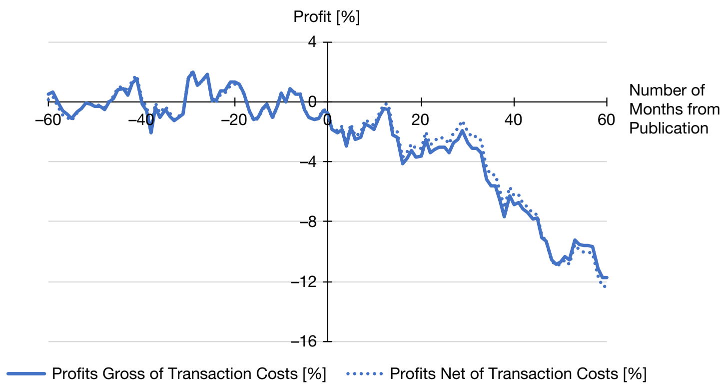
significantly. Currency value has low in-sample profits and no significant publication effect.

The effect of publication on trading profits can be studied in more detail by replacing the Post-Publication indicator in Table 1 with separate indicators for each of the first 3 years after publication as well as a single indicator variable for all months that are at least 3 years after publication (Figure 2). Gross profits are lower by 23 bps, 38 bps, and 40 bps in the 3 years after publication compared with the in-sample period, and on average by 39 bps thereafter (Graph A). The last 12 months of the in-sample period have lower profits (by −0.28 bps) than other in-sample months, while trading profits are insignificantly higher in the post-sample period.

FIGURE 3

Strategy Profits in Event Time

Figure 3 shows detrended average predictor profits in event time. In particular, the cumulative profits of the predictors in the 5 years before and after their publication are averaged and detrended by regressing the average cumulative profits on a constant and a linear trend for the 5 years before and after publication. Results are shown separately for profits gross and net of transaction costs (solid and dashed line, respectively). The analysis is based on the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. The sample includes 76 currencies. The sample period is from Jan. 1971 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions. Table A7 in the Supplementary Material provides details on the predictors' original sample period used in the article as well as date of publication.



Net profits exhibit similar patterns (Graph B). These results provide no support for the concern that researchers choose in-sample periods opportunistically to report stronger results. Average detrended cumulative profits are stable before publication but decline afterward (Figure 3).

For the U.S. equity market, recent research shows that portfolio returns are 58% lower after publication, but decrease already by 26% in the out-of-sample period (McLean and Pontiff (2016)). In contrast, our results show no effect in the out-of-sample period and a larger decrease in the post-publication period in line with higher efficiency of deep and active currency markets.

B. Time Trends, Crises, Risk Premia, and Persistence in Currency Predictors

One explanation for lower trading profits after publication is the possibility that the decay is caused by a time trend (e.g., capturing decreasing costs of corrective trading) rather than a publication effect (see Goldstein, Irvine, Kandel, and Weiner (2009), Anand, Irvine, Puckett, and Venkataraman (2012)). To investigate this conjecture, we construct a time trend variable that is equal to 1/100 in Jan. 1971 and increases by 1/100 each month in our sample period. The estimated coefficient on the time trend is negative in specification 1, but only significant for gross profits (Table 2). When we relate trading profits to the time trend and Post-Publication variables in specification 2, the time trend is positive (and significant for net profits). Importantly, the Post-Publication coefficients remain negative and statistically significant.

TABLE 2

Time Trends, Crises, Risk Premia, and Persistence in Currency Predictors

Table 2 reports results from regressions of currency predictor profits (in percent per month) on an indicator variable for post-publication periods, time trends, macro-economic risks, currency, equity, and bond market risk factors, and prior predictor profits. Results are shown alternatively for trading profits gross and net of transaction costs, where transaction costs are calculated using bid and ask quotations. Separately for each predictor, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) at the end of each month and combined into equal-weighted portfolios. The profit of a predictor in a month is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5 – Q1). The Post-Publication indicator takes the value 1 if the month is after the posting date on SSRN, and 0 otherwise. Time is equal to 1/100 during the first month of the sample and increases by 1/100 each month. The level of interest rates for a predictor is the average of the short-term interest rates of the currencies in its long and short portfolios. The exchange rate volatility of a predictor is the average of the within-month standard deviation of the returns of the currencies in its long and short portfolios. NBER U.S. Business Cycle Contractions is an indicator variable that takes the value 1 for U.S. recessions, and 0 otherwise. The Crisis variable is the average of crisis indicator variables of the currencies in the long and short portfolios of a predictor that take the value of 1 in years with a financial crisis (currency, inflation, banking, systemic, sovereign debt, and so forth as identified in the literature (Reinhart and Rogoff (2014), Laeven and Valencia (2020), and Nguyen et al. (2022))) in the respective country, and 0 otherwise. The dollar risk factor and carry trade risk factor are constructed as in Lustig et al. (2011), the volatility risk factor as in Menkhoff et al. (2012b), the skewness risk factor following Burnside (2012) and Rafferty (2012), and the network centrality factor as in Richmond (2019). The nine equity market risk factors are the excess return on the world market portfolio as well as eight U.S. equity market factors, namely the excess return on the market portfolio, SMB (small minus big), HML (high minus low), CMA (conservative minus aggressive), RMW (robust minus weak), momentum, short-term reversal, and long-term reversal, obtained from the Kenneth French data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The two bond market risk factors are the term spread and the default spread (Fama and French (1993)), obtained from Amit Goyal's website (https://sites.google.com/view/agoyal145). 1-Month Predictor Profit and 12-Months Predictor Profit are the predictor's profit from the previous month and the cumulative return over the prior 12 months. The analysis is based on the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Regressions include predictor fixed effects as indicated in the table. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels as well as the number of observations, the number of predictors, and the R^2. Standard errors are computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between returns. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample includes 76 currencies. The sample period is from Jan. 1971 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions. Table A7 in the Supplementary Material provides details on the predictors' original sample period used in the article as well as date of publication.

	Predictor Profits Gross of Transaction Costs					Predictor Profits Net of Transaction Costs				
	1	2	3	4	5	1	2	3	4	5
Post-Publication		−0.471***	−0.330***	−0.318***	−0.302***		−0.597***	−0.388***	−0.288***	−0.285***
		(0.131)	(0.108)	(0.087)	(0.099)		(0.130)	(0.107)	(0.087)	(0.098)
Time	−0.072**	0.043				−0.043	0.103**			
	(0.033)	(0.043)				(0.033)	(0.043)			
Level of Interest Rates			0.030*					0.005		
			(0.017)					(0.017)		
Exchange Rate Volatility			−0.668***					−0.849***		
			(0.227)					(0.225)		
NBER U.S. Business Cycle Contractions			−0.164					−0.144		
			(0.166)					(0.164)		
Crisis			−0.225					−0.248		
			(0.622)					(0.617)		
Dollar Risk Factor				−0.351***					−0.379***	
				(0.053)					(0.054)	

(continued on next page)

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TABLE 2 (continued)

Time Trends, Crises, Risk Premia, and Persistence in Currency Predictors

	Predictor Profits Gross of Transaction Costs					Predictor Profits Net of Transaction Costs				
	1	2	3	4	5	1	2	3	4	5
Carry Trade Risk Factor				−0.189*** (0.059)					−0.239*** (0.063)	
Volatility Risk Factor				−0.036 (0.037)					−0.048 (0.038)	
Skewness Risk Factor				0.181*** (0.022)					0.199*** (0.023)	
Network Centrality Risk Factor				−0.021 (0.029)					−0.030 (0.029)	
1-Month Predictor Profit					−0.017 (0.019)					−0.013 (0.019)
12-Months Predictor Profit					0.017*** (0.005)					0.018*** (0.005)
No. of obs.	5,033	5,033	5,025	5,024	4,901	5,033	5,033	5,025	5,024	4,901
R^2	0.01	0.01	0.01	0.06	0.01	0.00	0.01	0.01	0.06	0.01
No. of predictors	11	11	11	11	11	11	11	11	11	11
Predictor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nine equity market risk factors	No	No	No	Yes	No	No	No	No	Yes	No
Two bond market risk factors	No	No	No	Yes	No	No	No	No	Yes	No
Standard errors	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS

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Lower trading profits could also be related to periods of low interest rates, high exchange rate volatility, economic business cycle contractions, or financial crisis. However, the staggering of publication dates ranging from 2001 to 2017 for currency predictors provides identification for tests of changes in their profitability that compare their average payoffs before and after the publication of the underlying research. The in-sample period covers years of high/low interest rates, various business cycles, risk on/off periods, and several economic and currency crises (e.g., EMS 1992, Mexico in 1994, Asia in 1997, Russia in 1998, Argentina 1999–2002). Similarly, the post-publication period extends until Aug. 2022 and thus includes periods well before and after the recent global financial crisis (GFC, which was not a currency crisis).[17] More generally, if the publication effect reflected time-varying risk premia, a similar effect should obtain in the out-of-sample period and show up as data snooping bias, which is not observed in the data.

Nevertheless, we include controls for macro-economic risk, crises, and monetary policy in specification 3 such as the level of interest rates, within-month exchange rate volatility, and indicators for NBER recessions and financial crises (Reinhart and Rogoff (2014), Laeven and Valencia (2020), and Nguyen, Castro, and Wood (2022)); we include alternatively the average for the currencies in the long/short portfolios (as reported in Table 2), or the G10 currencies, or only the United States. The publication effect remains negative and significant in the presence of these additional controls. Predictor profits are on average not significantly lower in recessions or crisis periods.[18]

In order to further consider possible risk premia explanations for currency predictors, we estimate regressions that control for risk factors available for the full sample period (i.e., dollar, carry trade, currency volatility, currency skewness, network centrality factors, a global equity market risk factor, eight U.S. equity market risk factors, and two bond market risk factors). While currency risk factors are significantly related to predictor profits, the publication effect is smaller but robust to these risk controls (specification 4). Since all risk factors are tradable, self-financing portfolios, the results can be interpreted as significant drops in risk-adjusted returns.[19] Finally, specification 5 shows that the publication effect is also robust to predictor persistence when including trading profits over the prior 1 and 12 months (Moskowitz, Ooi, and Pedersen (2012)).

C. Limits to Arbitrage

The dissemination of research documenting profitable trading strategies should attract arbitrageurs who exploit these strategies leading to lower mispricing

[17]Burnside et al. (2011) note that, e.g., momentum performed well during the 2008 crisis, carry and momentum had positive risk-adjusted returns outside of the crisis period, and in early 1991 and late 1992, carry trades took heavy losses while momentum was highly profitable. The largest drawdowns of the carry trade did not occur in the recent financial crisis. Value also did well in the 2008 crisis (Barroso and Santa-Clara (2015)).

[18]There is also a significant drop in strategy profits after publication outside of a post-GFC period, i.e., the publication effect is not simply part of a post-GFC downward trend.

[19]We also find that mean post-publication returns fall into the left tail of the bootstrapped strategy return distributions (with the exception of value and carry), suggesting they are not due to short sample concerns.

and trading profits. However, if trading is costly due to frictions, arbitrage may not fully eliminate all profits before accounting for these costs (Pontiff (1996), (2006), Shleifer and Vishny (1997)). Thus, the reduction in profitability should be smaller for predictors that involve taking positions in currencies that are costlier to trade, while it should not be related to arbitrage costs if predictor returns are the outcome of rational asset pricing. In order to test this hypothesis, we measure the arbitrage cost of a predictor as the in-sample mean of the average bid–ask spread of the currencies in its long and short portfolios.

Similarly, we also condition the analysis on various proxies for limits to arbitrage related to exchange rate convertibility. In particular, for the currencies in the long and short portfolios, we consider the in-sample average of money market restrictions for inflows and outflows (from Fernández, Klein, Rebucci, Schindler, and Uribe (2015)), capital account openness (Chinn and Ito (2008)), and severity of restrictions to capital account and financial current account liberalization (Quinn and Toyoda (2008)). Note that these measures typically capture the exchange of one currency with regard to all other currencies, while our analysis only requires the conversion of U.S. dollars into foreign currency. Our main measure averages the percentile ranks of those with best coverage.

Including limits to arbitrage and their interaction with the Post-Publication indicator in the regressions shows that the interaction terms on bid–ask spreads and capital restrictions are positive and significant, indicating that the post-publication reduction in trading profits is smaller for strategies that are more expensive to implement and/or face larger restrictions to convertibility (Table 3). The hypothesis that limits to arbitrage do not matter for expected trading profits can also be rejected for bid–ask spreads (p-value < 0.01) and exchange rate convertibility (p-value < 0.01). Similarly, trading profits from equity market predictors have approximately halved since decimalization and are generally larger for stocks with larger arbitrage costs (Chordia et al. (2014), McLean and Pontiff (2016), and Bartram and Grinblatt (2021)).

Overall, these results mirror those for anomalies in equity markets. However, in line with currency markets being more efficient, the decline in predictor profits is larger and faster. The evidence is consistent with investors learning about these strategies via academic publications and profits being arbitraged away through institutional trading. It suggests that predictor profits may not, on average, entirely provide compensation for risk, but reflect at least in part mispricing. The next section further delineates between these two competing explanations by studying the effect of risk adjustments more generally using alternative risk models.

IV. Predictor Profits and Risk Adjustments

A. Aggregate Currency Predictors

The second approach to investigate mispricing and risk as alternative explanations for the existence of systematic currency trading strategies is the application of risk models. If profits of trading strategies based on currency predictors reflect compensation for risk, they should disappear after adjusting for risk, while profits in excess of factor risk would reflect market inefficiencies (e.g., Jensen (1978), Fama

TABLE 3

Publication Effects and Limits to Arbitrage

Table 3 reports results from regressions of currency predictor profits (in percent per month) on an indicator variable for post-publication periods and its interaction with limits to arbitrage. Limits to arbitrage of a predictor are measured alternatively as the in-sample mean of the average bid–ask spread of the currencies in its long and short portfolios, or the in-sample mean of the average percentile rank of an index of average money market restrictions for inflows and outflows (from Fernández et al. (2015)) and a measure of capital account openness (Chinn and Ito (2008)) of the currencies in its long and short portfolios. Results are shown for trading profits gross of transaction costs. Separately for each predictor, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) at the end of each month and combined into equal-weighted portfolios. The profit of a predictor in a month is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5 – Q1). The Post-Publication indicator takes the value 1 if the month is after the posting date on SSRN, and 0 otherwise. The analysis is based on the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels as well as the number of observations, the number of predictors, and the R^2. Standard errors are computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between returns. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample includes 76 currencies. The sample period is from Jan. 1971 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions. Table A7 in the Supplementary Material provides details on the predictors' original sample period used in the article as well as date of publication.

	Bid–Ask Spreads	Capital Restrictions
	1	2
Post-Publication	−1.336***	−2.252***
	(0.416)	(0.849)
Post-Publication × Limits to Arbitrage	6.024**	3.392**
	(2.460)	(1.617)
Limits to Arbitrage	1.413	0.698
	(1.370)	(0.901)
Intercept	0.338	0.214
	(0.232)	(0.474)
No. of obs.	5,033	4,987
R^2	0.01	0.01
No. of predictors	11	11
Standard errors	FGLS	FGLS
Null: (Post-Publication × Arbitrage Costs) + Arbitrage Costs = 0	0.000	0.002

(1991), (1998)). To this end, we use comprehensive, state-of-the-art risk models and control for time-varying risk premia and factor exposures to address concerns that mispricing might simply reflect omitted factor risk. In order to study the average effect of risk adjustment on currency predictor profits, we follow the asset pricing literature without discretion and combine currency predictors into aggregate measures, mimicking alpha models of institutional investors that summarize different trading signals into combined predictor scores.

In particular, we create a variable "average predictor" by averaging each month, for each currency, the percentile ranks of all available predictors, resulting in values of the aggregate measure between 0 and 1. This approach gives equal weight to each predictor and thus assumes no information regarding their relative forecasting power. It also reduces the noise across currency predictors.[20] The second aggregate variable "extreme predictor" is defined as the difference between the number of long and short predictor portfolios that a currency belongs to in a given month, divided by the number of predictors. This normalized score ranges between −1 and +1. A high score indicates that a currency should be bought based

[20]Stambaugh et al. (2012) refer to a similar measure aggregating equity market predictors as "Mispricing."

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on many predictors and shorted based on few, thus reflecting extreme values or a high conviction across predictors.[21]

The correlation of 0.89 between average and extreme predictor variables indicates that they measure similar dimensions but are not identical.[22] Sorting currencies on either measure yields currency excess returns in the following month that increase across quintiles from the short to the long portfolio (Panel A of Table 4); monotonicity tests are highly significant (Patton and Timmermann (2010)). Trading strategies based on predictors are profitable before and after transaction costs. To illustrate, quintile spreads of gross currency excess returns are 74 bps and 68 bps per month when sorting by average and extreme predictor variables (equivalent to 8.9% and 8.2% per year), and net profits are 45 bps and 38 bps, respectively. Both gross and net profits are statistically significant, and they are of similar magnitude to predictor profits in equity markets.

The fraction of positive quintile spreads net of transaction costs is 62% and 63% for average and extreme predictors, both significantly higher than 50% (p-value < 0.01). Hit ratios for gross returns are even larger at 66% and 69%, respectively, and highly significant. Annualized Sharpe ratios of up to 1.3 (0.7) for gross (net) profits are economically significant (Table A8 in the Supplementary Material); in fact, their profitability is often statistically and economically more significant than that of the underlying individual predictors, reflecting improved signal to noise ratios (Table A6 in the Supplementary Material).[23] Diversification across predictors is also harder to reconcile with pure risk-based explanations.

B. Risk Adjustments and Alpha Decay

To adjust predictor profits for risk, we employ both Black, Jensen, and Scholes (1972) time-series factor models and cross-sectional Fama and MacBeth (FM) (1973) regressions. In particular, we estimate factor model regressions with tradable long/short factors so that the intercepts can be interpreted as risk-adjusted returns. Our 19-factor model includes eight currency factors, nine equity factors, and two bond market factors.

The results in Panel B of Table 4 show that the effect of risk adjustment using factor models on trading profits is limited. In particular, for sorts by average and extreme predictor, monthly gross alphas are 53 bps (t-stat = 4.36) and 45 bps (t-stat = 3.72) per month, respectively. Risk-adjusted profits net of transaction costs (using the full bid–ask spread) are smaller but still economically and statistically significant, with 19-factor alphas of 28 bps (t-stat = 2.52) and 21 bps (t-stat = 1.85) for average and extreme predictors, respectively. Alphas increase monotonically from the first to the fifth quintile, documenting the systematic nature of the relation between sorting variables and next period excess returns. Moreover, both the first and the fifth portfolio make significant and about equal contributions to the quintile spread.

[21]Engelberg et al. (2020) refer to a similar measure aggregating equity market predictors as "Net."

[22]Aggregate predictors require at least four available signals. Table A5 in the Supplementary Material provides detailed summary statistics.

[23]Table 4 is based on the period 12/1989 to 8/2022 to be able to compare actual and forecast currency returns.

TABLE 4

Quintile Performance of Portfolios Sorted on Currency Predictors

Table 4 reports raw and risk-adjusted actual (i.e., realized) and forecast currency returns and currency excess returns (in percent per month) of portfolios sorted on average and extreme predictors, alternatively gross of transaction costs and net of transaction costs. Transaction costs are calculated using bid and ask quotations. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average and extreme predictors and combined into equal-weighted portfolios. The table reports the time-series average of the currency (excess) returns of the quintile portfolios. It also shows the time-series average and associated *t*-statistic of the difference between the currency (excess) returns of portfolios Q5 and Q1 (Q5 – Q1). Panel A shows raw realized currency (excess) returns. Currency returns are the negative log difference of spot exchange rates from month $t + 1$ and month t. Currency excess returns are the log difference between the 1-month forward exchange rate of month t and the spot exchange rate of month $t + 1$. Panel B shows realized currency excess returns adjusted for risk using factor model time-series regressions. Risk-adjusted currency excess returns are the intercept from time-series regressions of currency excess returns on eight currency factors, nine equity market factors, and two bond market factors (19-factor model). The eight currency factors are the dollar risk factor and the carry trade risk factor (Lustig et al. (2011)), a volatility risk factor (Menkhoff et al. (2012b)), a skewness risk factor (Burnside (2012), Rafferty (2012)), and a network centrality factor (Richmond (2019)). The nine equity market factors are the excess return on the world market portfolio as well as eight U.S. equity market factors, namely the excess return on the market portfolio, SMB (small minus big), HML (high minus low), CMA (conservative minus aggressive), RMW (robust minus weak), momentum, short-term reversal, and long-term reversal, obtained from the Kenneth French data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The two bond market risk factors are the term spread and the default spread (Fama and French (1993)), obtained from Amit Goyal's website (https://sites.google.com/view/agoyal145). Panel C shows realized currency excess returns adjusted for risk using Fama and MacBeth (FM) (1973) cross-sectional regressions with expected currency excess returns from instrumented principal component analysis (IPCA) (Kelly et al. (2019)). The IPCA is implemented with 11 instruments ($L = 11$), namely a constant, momentum (over 1, 3, and 12 months), the filter rule combination, carry trade, dollar exposures, term spread, currency value, output gap, and the Taylor Rule. The scale of the instruments is transformed cross-sectionally each month with affine functions that force each instrument to lie between −0.5 and +0.5; missing characteristics are imputed to take a value of 0. The IPCA model has two latent factors ($K = 2$) and the 19 currency, equity, and bond factors from Panel B as observable factors ($M = 19$). FM regressions regress currency excess returns cross-sectionally on dummies for predictor quintiles as well as the predicted excess return for the currency in a month from the IPCA (Bartram and Grinblatt (2021)). Risk-adjusted quintile portfolio excess returns are from FM regressions of currency excess returns on IPCA expected returns and dummy variables for quintiles 1 to 5 (and no regression intercept), while the risk-adjusted excess returns of the quintile spread portfolios are from FM regressions of currency excess returns on IPCA expected returns, dummies for predictor quintiles 2 to 5, and a regression intercept. The unconstrained model places no constraints on the regression coefficients, while the constrained model forces the coefficient on the IPCA return prediction to be 1 (Bartram and Grinblatt (2021)). Panel D shows forecast currency (excess) returns. Forecast currency returns are the negative log difference of a foreign currency's 1-month forecast in month t and its spot rate in month t. Forecast currency excess returns are the sum of forecast currency returns and interest rate differentials. Average predictor is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying predictors, divided by the number of predictors. The analysis is based on the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. The sample includes 62 currencies. The sample period is from Dec. 1989 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions.

	Gross of Transaction Costs							Net of Transaction Costs	
	Quintiles								
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5 – Q1	*t*-Statistic	Q5 – Q1	*t*-Statistic
Panel A. Raw Realized Returns									
Currency Excess Returns									
Average Predictor	−0.193	−0.001	0.093	0.189	0.545	0.738	[7.09]	0.453	[4.35]
Extreme Predictor	−0.133	0.002	0.068	0.160	0.549	0.682	[6.61]	0.383	[3.72]
Currency Returns									
Average Predictor	−0.240	−0.122	−0.094	−0.142	−0.195	0.045	[0.43]	0.273	[2.59]
Extreme Predictor	−0.204	−0.093	−0.110	−0.133	−0.247	−0.043	[−0.41]	0.208	[1.97]
Panel B. Factor Model Time-Series Regressions with Realized Excess Returns									
19-Factor Model									
Average Predictor	−0.243	−0.026	0.025	0.118	0.290	0.532	[4.36]	0.283	[2.52]
Extreme Predictor	−0.170	0.020	0.021	0.035	0.280	0.450	[3.72]	0.207	[1.85]
Panel C. Fama–MacBeth Cross-Sectional Regressions with Realized Excess Returns									
Unconstrained IPCA Model									
Average Predictor	−0.130	−0.013	0.128	0.150	0.296	0.426	[4.82]		
Extreme Predictor	−0.115	0.020	0.021	0.113	0.227	0.343	[4.20]		
Constrained IPCA Model									
Average Predictor	−0.078	−0.065	0.035	0.010	0.078	0.156	[1.95]		
Extreme Predictor	−0.084	−0.018	−0.016	0.015	0.089	0.172	[2.18]		
Panel D. Forecast Returns									
Currency Excess Returns									
Average Predictor	1.517	0.748	0.092	−0.472	−1.163	−2.681	[−27.7]		
Extreme Predictor	1.517	0.450	0.177	−0.322	−1.107	−2.624	[−27.1]		
Currency Returns									
Average Predictor	1.470	0.627	−0.096	−0.804	−1.904	−3.374	[−34.0]		
Extreme Predictor	1.446	0.355	−0.000	−0.615	−1.903	−3.349	[−33.6]		

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We also use cross-sectional FM regressions as an alternative approach to risk adjustment. To this end, we use the IPCA, developed by Kelly et al. (2019), which allows for latent factors and time-varying factor betas by introducing observable characteristics as instruments for unobservable dynamic factor betas. To the best of our knowledge, we are the first to apply this risk-adjustment methodology to currency research. Our IPCA implementation uses 11 instruments (L = 11): a constant, momentum (over 1, 3, and 12 months), the filter rule combination, carry trade, dollar exposures, term spread, currency value, output gap, and the Taylor Rule. Following Kelly et al. (2019), we cross-sectionally transform the scale of the instruments each month with affine functions that force each instrument to lie between −0.5 and +0.5 and impute missing predictor characteristics to take a value of 0 (the cross-sectional median). We estimate a 21-factor IPCA model with two latent factors ($K = 2$) and 19 observable currency, equity, and bond market factors ($M = 19$). The model allows not only factor premia to vary over time, but also factor betas as a function of changes in the individual currency predictors. Thus, time-varying risk premia associated with the ability of the individual currency predictors to proxy for risk are fully controlled for. Appendix B of the Supplementary Material summarizes the IPCA methodology.

In order to control for risk using the IPCA model, we estimate FM regressions that cross-sectionally regress currency excess returns on the predicted excess return for the currency in a month from the IPCA as well as dummies for predictor quintiles. As in Bartram and Grinblatt (2021), the unconstrained model places no constraints on the coefficients, while the constrained model forces the coefficient on the IPCA return prediction to be 1.

The results in Panel C of Table 4 show that both aggregate predictor variables yield significant quintile spreads between the IPCA-controlled currency excess returns. In particular, the unconstrained regression yields a highly significant spread of 43 bps and 34 bps per month between the two extreme quintiles of average and extreme predictors, respectively. The coefficients on the predictor quintile dummies are (nearly) monotonic, lending further support to the conjecture that the predictors capture pricing inefficiencies since these regressions control for factor risk associated with the individual predictors. The constrained regression also exhibits a significant and nearly monotonic effect from the predictors (separate from their effect on factor betas). The coefficients on the average and extreme predictor quintiles are smaller than those in the unconstrained regression, but are still economically and statistically significant.

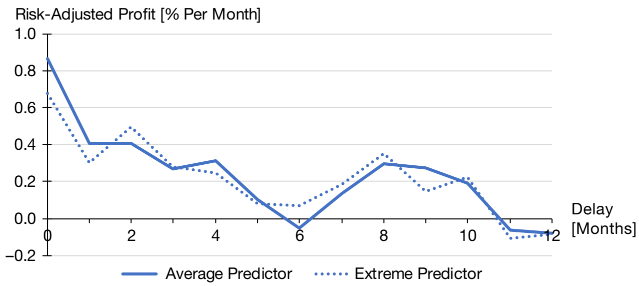
If predictors capture mispricing, one would expect low autocorrelations of signal ranks over time as well as low persistence of alphas (Bartram and Grinblatt (2018), (2021), Bartram, Grinblatt, and Nozawa (2024)). Indeed, the average Spearman rank correlation between the vector of predictors at month t and month $t-1$ is only 0.71 (0.67) for the average (extreme) predictor, and it is 0.39 (0.37) for predictors in months t and $t-6$. In addition, 19-factor model alphas from stale signals decay quickly, with net returns declining toward 0 within just 1 month (Figure 4). Thus, while the existence of currency predictors suggests that currency markets may not be completely efficient, inefficiencies seem to be arbitraged away

FIGURE 4

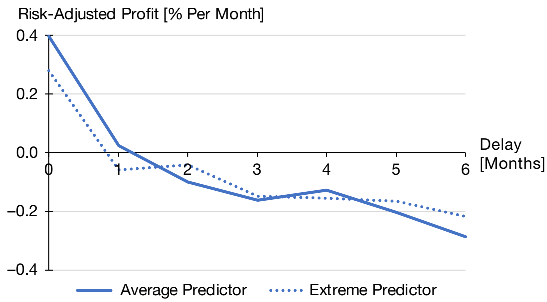
Alpha Decay

Figure 4 shows risk-adjusted trading profits (in percent per month) for trading strategies based on average predictor (solid line) and extreme predictor (dashed line) variables. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average and extreme predictors and combined into equal-weighted portfolios. The predictor signal is lagged from 0 to 12 months (Graph A) and 6 months (Graph B), respectively. Risk-adjusted quintile spreads are the intercept from time-series regressions of the difference of the currency excess returns of portfolios Q5 and Q1 on eight currency risk factors, nine equity market risk factors, and two bond market risk factors. The eight currency risk factors are the dollar risk factor and the carry trade risk factor (Lustig et al. (2011)), a volatility risk factor (Menkhoff et al. (2012b)), a skewness risk factor (Burnside (2012), Rafferty (2012)), and a network centrality factor (Richmond (2019)). The nine equity market factors are the excess return on the world market portfolio as well as eight U.S. equity market factors, namely the excess return on the market portfolio, SMB (small minus big), HML (high minus low), CMA (conservative minus aggressive), RMW (robust minus weak), momentum, short-term reversal, and long-term reversal. The two bond market risk factors are the term spread and the default spread (Fama and French (1993)), obtained from Amit Goyal's website (https://sites.google.com/view/agoyal145). Average predictor is the average of the percentile ranks of currencies with respect to the following eleven predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. Graph A shows trading profits gross of transaction costs, while Graph B shows trading profits net of transaction costs. Transaction costs are calculated using bid and ask quotations. The sample includes 76 currencies. The sample period is from Feb. 1985 to Aug. 2022 to ensure the same period of analysis in each graph across strategies with different lag lengths. Table A3 in the Supplementary Material provides details on variable definitions.

Graph A. Alphas Gross of Transaction Costs



Graph B. Alphas Net of Transaction Costs



quickly. Rapid decay of alphas suggests that they reflect in part mispricing (Cochrane (1999)).[24]

[24]While arbitrage capital is difficult to measure empirically (e.g., Edelman, Fung, and Hsieh (2013), Joenväärä, Kauppila, Kosowski, and Tolonen (2019)), we construct monthly time series of global currency hedge fund Assets Under Management (AUM) and flows (from Hedge Fund Research (HFR)), alternatively scaled by global M1 and M3 indices (from OECD) or global equity market capitalization (from Datastream), following, e.g., Jylhä and Suominen (2011), Chordia et al. (2014), and Barroso and Santa-Clara (2015). While the results have to be taken with a great deal of caution given

Consistent with the results from publication effects, the findings of significant risk-adjusted profits and fast decay of signal ranks and alphas for lagged trading signals suggest the existence of currency anomalies, where predictors are on average not fully explained by risk and, at least to an extent, result from market inefficiencies. That said, tests using risk models are always subject to the joint hypothesis problem, and one cannot rule out that an unknown factor or risk not captured by risk models explains strategy returns. Either way, currency predictors should be related to the forecasts of currency analysts, which we examine next. Evidence of mispricing does not necessarily imply arbitrage opportunities because limits to arbitrage could constrain the ability of market participants to exploit them, explaining why profits exist in a seemingly competitive market.

V. Analysts and Mispricing-Based Return Predictability

A. Mispricing and Analysts' Forecasts

In order to explore possible underlying mechanisms for mispricing-based currency return predictability, we study the relation between predictors and analysts' forecasts. Given the systematic relation of predictors with future excess returns, they should be related to the views and behavior of market participants. In particular, they would seem an important source of information for analysts who are trying to forecast exchange rates. If analysts build their forecasts based on predictors or analysis of the underlying fundamentals and trends in currency markets, their forecasts should be consistent with predictors. Alternatively, biases in the views of analysts could lead to investors trading on their forecasts reinforcing mispricing.

Guided by the literature (e.g., Engelberg et al. (2018), (2020), Guo et al. (2020)), we investigate whether analysts incorporate the information reflected in currency predictors when making their exchange rate forecasts. If analysts' forecasts capture the information contained in predictor variables, currencies with high values of aggregate predictors should have higher forecast excess returns than currencies with low values. Interestingly, this is not the case.

In particular, average forecast currency excess returns before transaction costs decrease monotonically from low to high predictor quintiles (Panel D of Table 4). They are +152 bps per month for the short portfolio and −116 bps for the long portfolio, yielding an expected quintile spread of −268 bps for strategies based on the average predictor, with a t-statistic of −27.7. The pattern is similar for the extreme predictor, with expected profits of −262 bps (t-stat = −27.1). Analysts erroneously expect losses from trading on predictors even though these strategies yield significant positive actual profits of 74 bps and 68 bps per month for average and extreme predictors, respectively (Panels A and D). Hence, the expectations of analysts with regard to currency excess returns conflict with the relations of predictor variables with next month's currency returns that have been widely

the data limitations, there is evidence of a negative relation between profits to average and extreme predictor strategies and (lagged) AUM, consistent with market inefficiencies and arbitrage capital reducing strategy profits as suggested by the theoretical and empirical results in these prior studies for returns of the carry trade, an optimized currency strategy, and equity market predictors.

documented in academic research and observed in historical data. Analysts expect predictor payoffs that are negative compared with positive realized profits and thus do not seem to incorporate currency predictors into their forecasts. As we show later, this does, however, not imply that the forecasts by analysts are generally wrong and not useful in forecasting currencies (it is just that they do not reflect currency predictors).

The results for expected predictor profits are largely accounted for by the expectations that analysts have about future exchange rate movements. Specifically, average forecast currency returns, which abstract from interest rate differentials, decrease monotonically from low to high predictor quintiles (Panel D of Table 4). The difference in currency returns between the fifth and first quintile is −337 bps per month for the average predictor and −335 bps for the extreme predictor. In contrast, realized spreads are much smaller and indistinguishable from 0 (Panel A).

These results can be illustrated graphically (Figure 5). Analysts' forecasts of currency excess returns are monotonically decreasing from the first quintile to the fifth quintile (Graph A), and analysts expect short portfolio currencies to appreciate and long portfolio currencies to depreciate (Graph B). Consequently, forecasts by analysts are inconsistent with the information in predictor variables. Analogous to these findings, forecast returns are higher (lower) among U.S. stocks suggested by predictor variables to have lower (higher) returns (Engelberg et al. (2020), Guo et al. (2020)). However, systematic forecast errors may be more surprising in currency markets where analysts are less likely to have a stake in views about the underlying asset.

The relation between forecast currency (excess) returns and predictor variables can be further investigated in panel regressions to assess if analysts take information contained in predictor variables into account. In particular, we estimate the following regression model:

$$\text{(2)} \qquad \begin{aligned} \text{Forecast (Excess) Return}_{i,t+1} = a &+ \beta_1 \text{Predictor}_{i,t} \\ &+ \beta_2 \text{Number of Forecasters}_{i,t} \\ &+ \beta_3 \text{Single Forecast}_{i,t} + \varepsilon_t + e_{i,t+1}, \end{aligned}$$

where the dependent variable is the monthly forecast return or forecast excess return on currency i in month $t+1$, and Predictor is the aggregate predictor variable of interest. The regression includes the number of analysts providing forecasts, an indicator variable for whether or not there is only a single forecast, and month fixed effects as controls. Standard errors are clustered by country.

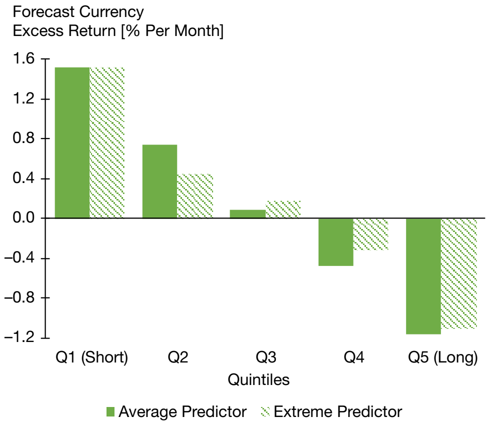
The regressions confirm the results of the portfolio sorts, as the relation between predictors and forecast currency excess returns is negative and significant (Table 5). Specifically, the coefficients on average and extreme predictors are −8.024 and −3.663, respectively, and both are statistically significant. The size of the coefficient for the average predictor variable means that a currency with an average predictor value 1 standard deviation above the sample mean has a forecast excess return that is 124 bps per month lower than a currency with an average predictor value at the sample mean. With the extreme predictor, the incremental

FIGURE 5

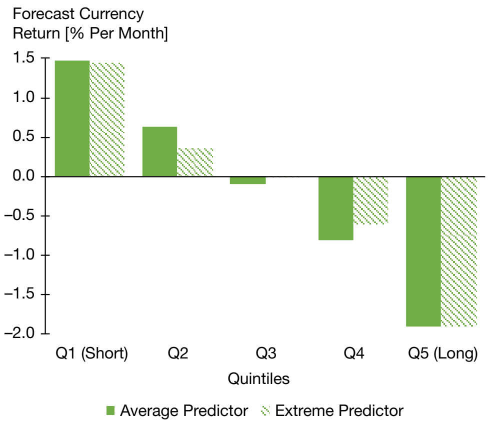
Currency Analysts' Forecasts and Predictors

Figure 5 shows analysts' forecast currency returns and currency excess returns (in percent per month) for trading strategies based on average and extreme predictor variables. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average and extreme predictors and combined into equal-weighted portfolios. The forecast currency (excess) returns of each quintile are averaged over the sample period. Forecast currency returns are the negative log difference of a foreign currency's 1-month forecast in month *t* and its spot rate in month *t*. Forecast currency excess returns are the log difference between the 1-month forward exchange rate of month *t* and the foreign currency's 1-month forecast in month *t*. Average predictor is the average of the percentile ranks of currencies with respect to the following eleven predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. Graph A shows results for forecast currency excess returns, while Graph B shows results for forecast currency returns. The sample includes 62 currencies. The sample period is from Dec. 1989 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions.

Graph A. Forecast Currency Excess Returns



Graph B. Forecast Currency Returns



forecast excess return would be 115 bps. This contrasts with higher realized currency excess returns for currencies with higher predictor scores. Regarding the control variables, forecast currency excess returns are lower for currencies with more analysts, that is, analysts tend to be more bullish when they are fewer in

TABLE 5

Currency Analysts' Forecasts and Predictors

Table 5 reports results from regressions of forecast currency returns and currency excess returns (in percent per month) on average and extreme predictors and control variables. Forecast currency returns are the negative log difference of a foreign currency's 1-month forecast in month t and its spot rate in month t. Forecast currency excess returns are the log difference between the 1-month forward exchange rate of month t and the foreign currency's 1-month forecast in month t. Average predictor is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying predictors, divided by the number of predictors. The analysis is based on the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Regressions include the number of forecasters providing forecasts for a currency and an indicator for a single forecast as controls. All regressions also include month fixed effects. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels as well as the number of observations and the R^2. Standard errors are clustered by country. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample includes 62 currencies. The sample period is from Dec. 1989 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions.

	Forecast Currency Excess Returns		Forecast Currency Returns	
	Average Predictor	Extreme Predictor	Average Predictor	Extreme Predictor
Predictor	−8.024***	−3.663***	−9.958***	−4.611***
	(0.658)	(0.327)	(0.706)	(0.349)
Number of Forecasters	−0.013***	−0.012***	−0.008***	−0.006***
	(0.003)	(0.003)	(0.002)	(0.002)
Single Forecast	−0.198	−0.140	−0.250	−0.180
	(0.333)	(0.325)	(0.256)	(0.248)
Intercept	5.775***	1.612***	6.794***	1.653***
	(0.770)	(0.354)	(0.802)	(0.239)
No. of obs.	13,333	13,333	13,333	13,333
R^2	0.42	0.41	0.49	0.48
Month fixed effects	Yes	Yes	Yes	Yes
Standard error clustering	Country	Country	Country	Country

number. For forecast currency returns, the predictor coefficients are also negative and significant.[25]

If analysts considered predictor variables for their exchange rate forecasts, they should expect higher currency excess returns for portfolios on the long side of a predictor-based trading strategy than for portfolios on the short side. This implies the expectation of a positive trading profit, in line with the historical performance of these strategies. In contrast, the results show that analysts' forecasts of currency strategy payoffs are negative, suggesting that analysts regularly make mistakes in their forecasts. Biased forecasts imply that they may contribute to mispricing if investors trading on them naively or strategically exert price impact, as their trades will reinforce or amplify predictors. Put differently, biases in analysts' forecasts could be a source of market friction that impedes the efficient correction of mispricing (Guo et al. (2020)).

B. Analysts' Mistakes

If analysts on average expect losses for currency trading strategies that yield actual (i.e., realized) profits, their expectations must frequently be wrong (with regard to currency predictors), and their forecast errors or mistakes should be systematically related to currency predictors. Note that expectations about currency

[25]The results in Table 5 are robust to controlling for the forecast (excess) return at time t.

excess returns are driven by the forecasts that analysts make about exchange rates, since 1-month interest rates are known. Thus, their forecast errors for currency returns and currency excess returns are identical, where mistakes for currency excess returns are all attributed to analysts' exchange rate forecast errors.

In particular, analysts' mistakes can be calculated as the difference between the forecast currency (excess) return and the realized currency (excess) return for currency i in month $t+1$:

$$\begin{aligned} \text{Mistake}_{i,t+1} &= \text{Forecast Currency Excess Return}_{i,t+1} \\ &\quad - \text{Realized Currency Excess Return}_{i,t+1} \\ &= \text{Forecast Currency Return}_{i,t+1} \\ &\quad - \text{Realized Currency Return}_{i,t+1}. \end{aligned} \tag{3}$$

Negative mistakes reflect that the (excess) return forecast was too low, and vice versa.

The patterns in realized currency (excess) returns and forecast currency (excess) returns across quintiles (in Panels A and D of Table 4) suggest that the mistakes in analysts' expectations of future exchange rates are systematically related to predictors. Indeed, mistakes decrease across predictor quintile portfolios, with positive mistakes in the first quintile and negative mistakes in the fifth quintile (Graph A of Figure 6). These univariate patterns exist for aggregate predictors, but also for the individual currency predictors (Graph B).

Consequently, we regress monthly mistakes by analysts for currency i in month $t+1$ on predictors and control variables:

$$\begin{aligned} \text{Mistake}_{i,t+1} = a + \beta_1 \text{Predictor}_{i,t} + \beta_2 \text{Number of} \\ \text{Forecasters}_{i,t} + \beta_3 \text{Single Forecast}_{i,t} \\ + \varepsilon_t + e_{i,t+1}. \end{aligned} \tag{4}$$

The regression includes the number of analysts or forecasters, a dummy for a single forecaster, and month fixed effects as controls. Standard errors are clustered by country.

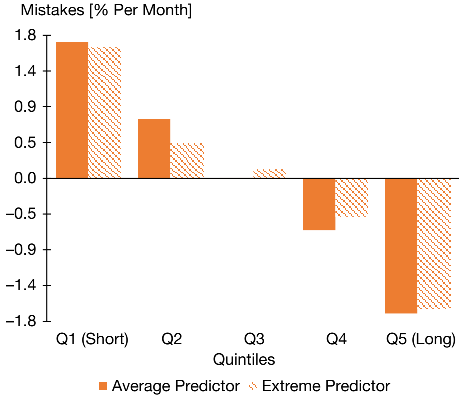
As expected, currency predictors predict mistakes in return forecasts of individual currencies (Table 6). In specification 1, estimated coefficients for average and extreme predictors are −9.724 and −4.443, respectively, and are significant at the 1% level. This indicates that if a currency has a higher value for the average or extreme predictor, its realized excess return tends to be higher than its forecast excess return (yielding a negative forecast error). Thus, analysts' currency return forecasts are too low compared with realized returns for currencies in the long predictor portfolio, while they are too high for currencies in the short predictor portfolio. The regression coefficients imply that a currency with a predictor value 1 standard deviation above the sample mean has a forecast excess return that is 150 bps (140 bps) per month lower than its realized return compared with a currency with an average (extreme) predictor value at the sample average.

FIGURE 6

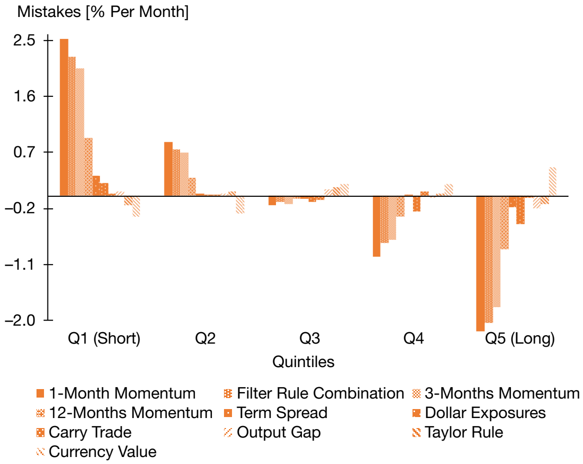
Currency Analysts' Mistakes and Predictors

Figure 6 shows analysts' mistakes (in percent) for trading strategies based on individual and aggregate currency predictors. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively aggregate (i.e., average and extreme) predictors and individual currency predictors and subsequently combined into equal-weighted portfolios. Analysts' mistakes of each quintile are averaged over the sample period. Mistakes are the difference between forecast currency returns and actual (i.e., realized) currency returns. Forecast currency returns are the negative log difference of a foreign currency's 1-month forecast in month *t* and its spot rate in month *t*. Average predictor is the average of the percentile ranks of currencies with respect to the following eleven predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. Graph A shows analysts' mistakes by aggregate predictor quintile, while Graph B shows analysts' mistakes by individual currency predictor quintile. The sample includes 62 currencies. The sample period is from Dec. 1989 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions.

Graph A. Mistakes by Aggregate Predictor Quintile



Graph B. Mistakes by Individual Predictor Quintile



The finding that analysts make systematic errors may seem surprising, but it could be that analysts are simply unaware of the information contained in predictors until their discovery by academics. Consequently, one would expect them to incorporate predictor information into their forecasts after the dissemination of

TABLE 6

Currency Analysts' Mistakes and Predictors

Table 6 reports results from regressions of analysts' mistakes (in percent per month) on predictors and control variables. Mistakes are the difference between forecast currency returns and actual (i.e., realized) currency returns. Forecast currency returns are the negative log difference of a foreign currency's 1-month forecast in month t and its spot rate in month t. Currency returns are the negative log difference of spot exchange rates from month $t+1$ and month t. Average predictor is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying predictors, divided by the number of predictors. The analysis is based on the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Publication measures the fraction of predictors that have been published by posting the underlying research on SSRN. Realized excess return is the contemporaneous actual currency excess return. Predictor (out-of-sample) is the average or extreme predictor using individual predictors only in periods after their respective in-sample periods. Regressions include the number of forecasters providing forecasts for a currency and an indicator for a single forecast as controls. All regressions also include month fixed effects. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels as well as the number of observations and the R^2. Standard errors are clustered by country. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample includes 62 currencies. The sample period is from Dec. 1989 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions.

	Average Predictor				Extreme Predictor			
	1	2	3	4	1	2	3	4
Predictor	−9.724***	−9.540***	−8.142***		−4.443***	−4.590***	−3.714***	
	(0.688)	(0.888)	(0.653)		(0.334)	(0.435)	(0.324)	
Predictor × Publication		2.453**				1.475***		
		(1.088)				(0.509)		
Publication		−1.184**				0.175		
		(0.585)				(0.150)		
Realized Excess Return			−0.931***				−0.934***	
			(0.028)				(0.028)	
Predictor (out-of-sample)				−11.01***				−5.065***
				(0.938)				(0.449)
Number of Forecasters	−0.011***	−0.009***	−0.013***	−0.011***	−0.010***	−0.008***	−0.012***	−0.006**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Single Forecast	−0.207	−0.202	−0.199	0.309	−0.136	−0.178	−0.139	0.169
	(0.306)	(0.230)	(0.331)	(0.300)	(0.295)	(0.220)	(0.322)	(0.285)
Intercept	5.857***	5.181***	5.781***	1.161	0.813	0.194	1.560***	2.823***
	(0.972)	(0.552)	(0.768)	(0.718)	(0.879)	(0.143)	(0.374)	(0.715)
No. of obs.	13,333	13,333	13,333	11,043	13,333	13,333	13,333	11,043
R^2	0.42	0.08	0.71	0.40	0.41	0.07	0.71	0.39
Month fixed effects	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Standard error clustering	Country	Country	Country	Country	Country	Country	Country	Country

research publicizing them. If this was the case, the relation between mistakes and predictors should become weaker, which can be analyzed by adding an interaction term between the predictor and a publication variable to the regression:

$$\text{Mistake}_{i,t+1} = a + \beta_1 \text{Predictor}_{i,t} + \beta_2 (\text{Predictor}_{i,t} \times \text{Publication}_t) + \beta_3 \text{Publication}_t + \beta_4 \text{Number of Forecasters}_{i,t} + \beta_5 \text{Single Forecast}_{i,t} + e_{i,t+1}, \tag{5}$$

where Publication measures the fraction of predictors that have been published at time t. As before, the regression includes control variables, and standard errors are clustered by country.

The regressions show again a significant negative relation between predictors and analysts' mistakes, indicating that analysts make predictable mistakes by forecasting too low (high) currency returns for currencies in the long (short) predictor portfolios (Table 6, specification 2). The interaction between predictors and publication is positive and significant for both aggregate predictors in line with analysts improving their forecasts as predictors become widely known.

The finding that analysts' excess return forecasts are too low (high) for currencies in the long (short) predictor portfolio is not only consistent with biased expectations, but also with data mining as an explanation for predictability, since a spurious predictor may just by chance be long (short) in currencies that have low (high) forecasts. To control for this data-mining effect, we include the contemporaneous currency excess return in regression specification 3, following Engelberg et al. (2018). This variable is negative and significant, indicating that analysts' forecasts are indeed too low (high) for currencies with high (low) returns. Nevertheless, the predictor variables remain negative and significant, contradicting the idea that data mining explains the predictability of analysts' mistakes by currency predictors. In the same vein, the negative relation between predictors and analysts' mistakes also exists for versions of aggregate predictor variables constructed using predictors only after their respective in-sample periods in specification 4.

In sum, analysts have expectations that contradict currency predictors, since they expect higher excess returns on short portfolios than on long portfolios, yielding an expected loss. Consequently, analysts make systematic mistakes that are in line with explanations for predictors based on biased expectations, but not risk, as it is difficult to rationalize biases in analysts' forecasts even with dynamic risk exposures (e.g., Engelberg et al. (2020), Guo et al. (2020)).

C. Changes in Analysts' Forecasts

A possible explanation for the finding that forecasts are not always in line with the currency movements predicted by predictors could be that analysts overlook information captured by predictors (Engelberg et al. (2020)). Since predictor variables predict currency excess returns, their information content would seem useful for analysts, and forecasters should include missed information from predictors in subsequent updates of their predictions. If this is the case, forecast revisions should change in a predictable way as a function of past predictors.

We test this conjecture empirically by regressing monthly changes in analysts' forecasts on predictors lagged by 1–3 months. Specifically, we estimate the following regression model:

$$
\begin{aligned}
(6)\qquad & \text{Change in Currency Forecast}_{i,(t|t+1),(t+1|t+2)} \\
& = a + \sum_{\tau=0}^{2} \beta_{\tau+1}\text{Predictor}_{i,t-\tau} + \beta_4 \text{Number of Forecasters}_{i,t} \\
& \quad + \beta_5 \text{Single Forecast}_{i,t} + \varepsilon_t + e_{i,t},
\end{aligned}
$$

where the dependent variable is the monthly revision in the 1-month ahead log exchange rate forecast of currency i from month t to month $t+1$, and the independent variables are predictor variables (lagged by 1–3 months), the number of analysts, a single forecaster indicator variable, and month fixed effects. Standard errors are again clustered by country.

TABLE 7

Predictors and Changes in Currency Forecasts

Table 7 reports results from regressions of changes in analysts' forecasts of currencies that are made from month t to month $t+1$ (in percent per month) on lags of average and extreme predictors, respectively, and control variables. Average predictor is the average of the percentile ranks of currencies with respect to the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. Regressions include the number of forecasters providing forecasts for a currency and an indicator for a single forecast as controls. All regressions also include month fixed effects. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels as well as the number of observations and the R^2. Standard errors are clustered by country. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample includes 62 currencies. The sample period is from Dec. 1989 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions.

	Average Predictor			Extreme Predictor		
	1	2	3	1	2	3
Predictor (lagged by 1 month)	2.230***			0.976***		
	(0.305)			(0.153)		
Predictor (lagged by 2 months)		0.389			0.152	
		(0.307)			(0.151)	
Predictor (lagged by 3 months)			−0.499			−0.242
			(0.317)			(0.150)
Number of Forecasters	0.006***	0.004***	0.003**	0.005***	0.004***	0.003**
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Single Forecast	0.079	0.028	−0.009	0.061	0.024	−0.006
	(0.140)	(0.110)	(0.102)	(0.137)	(0.110)	(0.103)
Intercept	−1.190*	1.824*	0.741	−0.016	2.035**	0.488
	(0.686)	(0.914)	(1.151)	(0.706)	(0.892)	(1.118)
No. of obs.	12,979	12,911	12,843	12,979	12,911	12,843
R^2	0.32	0.31	0.31	0.32	0.31	0.31
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard error clustering	Country	Country	Country	Country	Country	Country

The results provide evidence that analysts indeed incorporate predictor information into their forecast revisions. To illustrate, the coefficients on the average and extreme predictor lagged by 1 month are 2.230 and 0.976, respectively, both statistically significant (Table 7). The regression coefficients indicate that a currency with a predictor value 1 standard deviation above the sample mean is expected to appreciate by 34 bps (31 bps) more per month compared with a currency with an average (extreme) predictor value at the sample mean.[26] The magnitudes of the coefficients decrease monotonically with lag length, and coefficients lagged by 2 and 3 months are insignificant. Thus, analysts only use information contained in predictor variables from the most recent month. The coefficient on the number of forecasters is positive and significant, indicating more positive revisions for currencies followed by more analysts.

In summa, while analysts make predictable forecasting errors, their mistakes become smaller after predictors are popularized via publication. Even though analysts miss important information in predictor variables that help predict currency excess returns, they incorporate that information with a short lag. This contrasts with evidence that lags of predictor signals of up to 18 months predict

[26]Predictor variables remain significant even after controlling for the realized currency excess return in month t.

changes in target prices for equities (Engelberg et al. (2020)) (consistent with currency markets exhibiting higher degrees of informational efficiencies than stock markets).

D. Analysts' Forecasts and Predictability of Currency Excess Returns

Finally, we consider whether analysts' forecasts are useful to predict future currency excess returns. While analysts seem to make predictable mistakes in forecasting the excess returns associated with predictors, it could be that their forecasts contain other information that outweighs these forecast errors and that is informative in predicting future currency excess returns. To this end, we estimate FM regressions that have monthly currency excess returns as the dependent variable and lagged predictors and analysts' forecast currency excess returns as explanatory variables, both of which are known to investors at the time of putting the trade on.[27] In order to be able to compare economic magnitudes, we use quintile dummies (Q2, Q3, Q4, and Q5, with Q1 omitted due to the regression intercept) for both variables. Coefficients from regressing excess returns on Q2–Q5 dummy variables can be interpreted as the added return from belonging to the respective characteristic quintile compared with the Q1 quintile.

TABLE 8

Currency Excess Returns, Analysts' Forecasts, and Predictors

Table 8 reports results from Fama and MacBeth (FM) (1973) regressions of actual (i.e., realized) currency excess returns (in percent per month) from month *t* to *t* + 1 on dummy variables for quintiles Q2, Q3, Q4, and Q5 of average or extreme predictors and analysts' forecasts of currency excess returns that are made in month *t*. At the end of each month, all available currencies are sorted independently into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on predictors and analysts' forecasts of currency excess returns. Forecast currency excess returns are the log difference between the 1-month forward exchange rate of month *t* and the foreign currency's 1-month forecast in month *t*. Average predictor is the average of the percentile ranks of currencies with respect to the following eleven currency predictors: i) momentum based on the currency excess return over the prior month, ii) momentum based on the currency excess return over the prior 3 months, iii) momentum based on the currency excess return over the prior 12 months, iv) filter rule combination, v) carry trade, vi) dollar carry trade, vii) dollar exposures, viii) term spread, ix) currency value, x) output gap, and xi) the Taylor Rule. Extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. The table reports the FM regression coefficients, associated *t*-statistic (in square brackets) and significance levels, as well as the average number of observations and the average R^2. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample includes 62 currencies. The sample period is from Dec. 1989 to Aug. 2022. Table A3 in the Supplementary Material provides details on variable definitions.

	Average Predictor		Extreme Predictor	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
Predictor Q2	0.240	[3.15]***	0.173	[2.17]**
Predictor Q3	0.311	[3.15]***	0.247	[2.52]**
Predictor Q4	0.497	[4.41]***	0.409	[3.72]***
Predictor Q5	0.940	[7.42]***	0.827	[6.90]***
Forecast Excess Return Q2	0.202	[2.63]***	0.166	[2.00]**
Forecast Excess Return Q3	0.229	[2.53]**	0.154	[1.52]
Forecast Excess Return Q4	0.285	[2.52]**	0.144	[1.19]
Forecast Excess Return Q5	0.459	[3.26]***	0.396	[2.86]***
Intercept	−0.508	[−4.02]***	−0.372	[−2.67]***
Average no. of obs.	34		34	
Average R^2	0.40		0.39	

[27]Analysts' forecasts are published around the second week of the month and, thus, available to investors by month end.

Predictor variables and analysts' forecasts are both useful in predicting future currency excess returns (Table 8). In particular, the coefficients on the quintile dummies increase monotonically from low to high quintiles for both aggregate predictors. For quintiles based on analysts' forecast excess currency returns, the pattern in the indicators is also almost monotonic with slightly weaker significance. In regressions with the average predictor, the quintile spread on the predictor is 94 bps per month (t-stat = 7.42), while the quintile spread on forecast excess returns is 46 bps per month (t-stat = 3.26). Magnitudes are similar but slightly smaller for regressions with the extreme predictor, with spreads of 83 bps and 40 bps for predictor variable and analysts' forecasts, respectively. Thus, while the forecasts that analysts make contradict predictors, they are useful in predicting currency excess returns over and above predictors.

VI. Robustness Tests

We carry out several additional tests to document the robustness of our results. One set of robustness tests considers the potential sensitivity of our results to the sample definition. The broad set of 76 currencies in our sample has the advantage of generating better contrasts between predictor-sorted currency portfolios and providing diversification within portfolios. Nevertheless, we perform all of our analyses for smaller sets of 62, 54, 40, and 10 currencies. The publication effect is robust to these alternative samples (Table A9 in the Supplementary Material). In fact, the publication effect is larger with fewer currencies, and the interaction term of the Post-Publication dummy with in-sample trading profits is always significant both gross and net of transaction costs.

The relation between analysts' mistakes and aggregate predictors is similarly robust to alternative sets of currencies (Table A10 in the Supplementary Material). Coefficients on predictor variables are negative and significant for specifications with and without the interaction between predictors and publication. The robustness of our tests for the G10 currencies also further addresses potential concerns about limitations to currency convertibility or liquidity. In the same vein, the results are robust to the subsample of observations with deliverable forward contracts.

We also investigate whether the results for analysts' mistakes are driven by the source of the forecast data. To this end, we obtain analysts' consensus forecasts from two alternative databases (Appendix A of the Supplementary Material). Results are similar to those reported in the article using either the full data available from each source or the subsample of currency-months common across data sources.

VII. Conclusion

This article studies the efficiency of the currency market and the rationales for trading profits of systematic trading strategies with focus on risk and mispricing using, for the first time, all widely used cross-sectional trading strategies in currency markets that can be constructed for many currencies with publicly available data. The study of the cross section of currency predictors allows for more general conclusions than prior studies that document and analyze one of the predictors of currency excess returns at a time. Currency trading strategies are implemented in a realistic way using novel real-time data that investors could have employed at a historical point in time. With an agnostic perspective, the article tests alternative explanations for the *raison d'être* of currency predictors using a range of methods suggested in the literature.

First, profits of currency strategies significantly decrease after the underlying academic research has been published, and the decline is greater for strategies with larger or more significant in-sample profits and lower arbitrage costs. The findings obtain despite possible knowledge and use of the strategies prior to publication biasing the tests against rejecting the null and the relatively small number of strategies entailing low power of tests.

Second, trading profits remain statistically and economically significant after applying state-of-the-art risk adjustments using 19-factor models (up to 53 bps per month) and IPCA (up to 43 bps per month), allowing for dynamic factor betas derived from the individual currency predictors themselves. Autocorrelations of predictor signal ranks are low, and alpha decay is relatively fast. The evidence from these two approaches of studying rationales for return predictors has been interpreted in the literature as consistent with predictability being at least to some extent due to them reflecting mispricing as opposed to just risk.

Moreover, analysts have currency expectations that contradict currency predictors, since they expect higher excess returns on short portfolios than on long portfolios, yielding an expected loss. Consequently, analysts make systematic mistakes that are in line with biased expectations as a source of mispricing-based return predictability. Overall, this article paints a picture of relatively efficient global currency markets, where inefficiencies arise but are ultimately traded away as the underlying research is published. The evidence complements findings of publication effects, risk-adjusted returns of anomalies, and analysts' mistakes as a source of inefficiencies in U.S. and international markets for equities and bonds, providing out-of-sample evidence from a different asset class. At the same time, existing methods in the literature to delineate between mispricing and risk have limitations, and better tests are needed to draw conclusions about the source of predictability of a particular predictor.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023001400.

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