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Currency Anomalies

Abstract

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JEL Classification: F31, G12, G15

Keywords: predictors, Anomalies, mispricing, Analysts, Market Efficiency, Real-time, arbitrage costs, IPCA, principal components

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Currency Anomalies

Abstract

This paper is the first to study the cross-section of currency excess return predictors. Using real-time data, the results provide evidence that currency excess return predictability is at least in part due to mispricing. First, the risk-adjusted profitability of systematic currency trading strategies decreases significantly after the publication of the underlying academic research, suggesting that market participants learn about mispricing from research publications. Consistent with mispricing, the 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 on trading profits is limited, and signal ranks and alphas decay quickly. Third, in line with biased expectations as opposed to risk as a source of return predictability, analysts' forecasts are inconsistent with currency predictors, implying that investors trading on them contribute to mispricing.

Keywords: Predictors, anomalies, mispricing, analysts, market efficiency, real-time, point-in-time, arbitrage costs, IPCA, instrumented principal components analysis

JEL classification: F31, G12, G15

1 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 absence of natural short-selling constraints, one would expect them to be highly informationally efficient. Yet, investors in currency markets 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., Guo et al., 2020; Engelberg et al., 2020, 2018; Calluzzo et al., 2019; McLean and Pontiff, 2016). Consequently, this is the first paper studying the cross-section of predictors of currency excess returns (hereafter "currency predictors"). 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-time data to ensure investors could have implemented these strategies at a historical point in time. To delineate between alternative explanations, primarily risk and market inefficiencies, as rationales for currency predictors, we employ established asset pricing tests and methodologies assessing the effect of research dissemination and risk adjustment on predictor profits as well as their relation to the views and behavior of market participants.

In particular, the literature suggests that if strategy profits reflect mispricing and market inefficiencies, 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., McLean and Pontiff, 2016; Chordia et al., 2014; Schwert, 2003; Cochrane, 1999). Moreover, mispricing as a source of currency predictability would be evidenced by significant predictor profits

[1] Currency markets are generally viewed as extremely liquid and efficient relative to other asset classes. Average daily turnover is estimated at $3.0 trillion in 2019, which makes the currency market 37 times larger than world exports and imports, 17 times larger than world Gross Domestic Product (GDP), or 21 times larger than exchange-traded equity turnover (IMF 2019; World Bank, 2020; BIS, 2019; WFE, 2018). At the same time, official market participants (such as central banks that are not profit maximizing), fixed income managers (who typically do not want the currency exposure and simply hedge it), corporate treasuries (who are transacting because of underlying hedging needs), and tourists are likely to leave money on the table in currency markets.

in excess of factor risk premia (see e.g., Schwert, 2003; Fama, 1991; Jensen 1978). It should also manifest in low persistence of signal ranks and fast alpha decay when delaying the trading signal (e.g., Bartram and Grinblatt, 2018, 2021). Finally, if analysts form their forecasts by incorporating publicly available information about currency predictors or by analyzing the market and fundamental data used to construct them, their predictions about future exchange rate returns should align with currency predictors, while conflicting views of currency analysts would be consistent with explanations for predictors based on biased expectations, but not risk (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 a strong emphasis on the existence of currency predictors (especially carry) as capturing risk (e.g. Lustig et al., 2011), others suggest that risk does not provide a full explanation, motivating alternative rationales such as market inefficiencies (e.g. Barroso and Santa-Clara, 2015; Menkhoff et al., 2012a; Burnside et al., 2011a,b; Froot and Thaler, 1990). 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 regards 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 paper is on the cross-section of predictors similar to Falck et al. (2021), Engelberg et al. (2020, 2018), Guo et al. (2020), Calluzzo et al. (2019), McLean and Pontiff (2016), and Chordia et al. (2014).

Given the lack of a single, generally accepted procedure, we employ a variety of tests and methodologies used in the literature to distinguish between alternative explanations for currency excess return predictability. Our results provide evidence that it 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 that some market participants learn about mispricing from research publications.[2] Consistent with mispricing explanations, 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 on predictor payoffs is limited, there is significant decay in risk-adjusted strategy profits for stale trading signals, and the autocorrelations of signal ranks are low. Third, consistent with biased expectations as opposed to risk as a source of return predictability, analysts' forecasts are inconsistent with currency predictors, implying that investors trading on them contribute to mispricing.

While extant work that has documented each of the currency predictors and their properties individually,[3] this paper is the first to study patterns across predictors, which allows drawing more general conclusions about exchange rate predictability. 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. Currency forecasts also do not suffer from the optimism bias of analysts documented for other assets classes such as equities. Consequently, the approach and data employed in this paper allow us to generate new inferences about the economics of currency markets.

To investigate and delineate between alternative potential sources of predictability in currency markets, we employ three commonly used approaches in the literature. The first approach examines predictor profits in periods before and after the dissemination of research publicizing the trading strategies. If strategy 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 (Falck et al., 2021; McLean and Pontiff, 2016; Chordia et al., 2014; Schwert, 2003; Cochrane, 1999). Consistent with mispricing as a source of predictability, we show

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[2] Given the recent nature of this literature, we use the date of the first posting of the respective working paper on SSRN as publication date in our main tests.

[3] We document and discuss these predictors and the relevant literature later in the paper and the appendices.

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 with smaller limits to arbitrage.

The staggering of publication dates 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. However, we also consider alternative explanations such as a secular decline in trading profits or a potential compression of risk premia in periods of low interest rates, high exchange rate volatility, financial crises, or recessions. Consequently, we include controls for time trends, crises periods, and variables capturing monetary policy and macro-economic risk more generally. The publication effect remains significant in the presence of these additional controls. Finally, we include a host of risk factors in currency, equity, and bond markets and show that risk-adjusted profits drop significantly after the publication of the underlying research as well. The literature refers to predictor variables with these characteristics that cannot be explained by risk as "anomalies" (see, for instance, McLean and Pontiff, 2016; Schwert, 2003; Fama, 1991; Froot and Thaler, 1990; Jensen 1978; Ball 1978).

While academic research has documented many cross-sectional currency predictors only fairly recently, they are sometimes related to earlier publications by practitioners or academics, and market participants may have traded on some of them before they were popularized by academic research. This biases against finding significant effects for later publication of the underlying research if predictors reflect mispricing, while it should not affect predictability reflecting risk premia. Moreover, the publication effect of academic currency research remains significant even after explicitly controlling for possible earlier dissemination of the trading strategies in practitioner publications, newspaper articles, or academic publications on different but related effects in currency markets as well as academic publications on corresponding trading strategies in other asset classes such as equities and fixed income. By the same token, while the number of strategies is relatively small, it is similar to that in related research (e.g., Daniel et al., 2020; Guo et al., 2020; Chordia et al., 2014; Stambaugh et al., 2015, 2014, 2012), and we are able to reject the null of no publication effect despite the resultant low power of the tests biasing against finding significant effects.

The second approach of distinguishing between alternative rationales for return predictability studies the effect of risk adjustments on currency predictor payoffs. Following the literature (e.g., Engelberg et al., 2020, 2018; Guo et al., 2020; Stambaugh et al., 2015, 2014, 2012), we again take a realistic investment perspective by combining currency predictors into aggregate measures yielding trading strategies with improved signal to noise ratios. Specifically, we combine currency predictors into measures of average mispricing (Stambaugh et al., 2012) and extreme mispricing (Engelberg et al., 2020, 2018) that generate significant quintile spreads of realized currency excess returns of up to 76 basis points ("bp") and 43 bp per month gross and net of transaction costs, respectively. In the absence of a universally accepted risk model for currency markets (e.g., Menkhoff et al., 2012b), we adjust these quintile spreads for risk with comprehensive risk models using time-series regressions with four- and fifteen-factor risk models as well as the instrumented principal components analysis (IPCA) technique developed in Kelly et al. (2019)—thus representing its first application to currency markets. This new approach to modelling risk allows for latent factors and dynamic factor betas by introducing observable characteristics as instruments for unobservable dynamic factor betas.

While many major anomaly portfolios in equity markets have insignificant IPCA alphas (Kelly et al., 2021; Kelly et al., 2019), these risk-adjustments have only a limited effect on the profitability of the trading strategies we study, despite controlling for time-varying risk premia and factor exposures tied to the individual currency predictors themselves. In particular, risk-adjusted quintile spreads remain highly statistically significant, with factor model intercepts of similar magnitude as unadjusted spreads and IPCA-adjusted spreads of up to 55 bp per month. The literature has traditionally interpreted the existence of significant risk-adjusted returns (or "alphas") that we document in currency markets as evidence of mispricing, i.e. anomalies, which is buttressed by evidence of fast decay of signal ranks and alphas for lagged trading signals.

The third approach that has been used in the literature to investigate sources of return predictability makes use of analysts' forecasts. Irrespective of the sources of return predictability, currency predictors represent publicly available information that skilled analysts should be able to take advantage of (e.g., Engelberg et al., 2020, 2018; Guo et al., 2020; Grinblatt et al., 2018). If currency analysts are truly sophisticated and informed, they should exploit these well-documented sources of currency predictability for their exchange rate forecasts. 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, resulting in analysts expecting losses for strategies based on currency predictors that yield realized profits. To illustrate, the forecast excess return for the first quintile based on average mispricing (i.e. the short portfolio) is +147 bp per month, while it is –115 bp for the fifth quintile (i.e. the long portfolio). The expected quintile spread is thus –262 bp per month, contrasting with a realized quintile spread of +76 bp. Similarly, the realized profit of a trading strategy based on extreme mispricing is +68 bp per month, while analysts expect a loss of –255 bp. These results are opposite to what one would expect *a priori* if analysts made use of the information in currency predictors.

The apparent mistakes that analysts make can be measured directly as the difference between forecast and realized excess returns. They 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 controlling for mispricing. Thus, it is not the case that analysts' forecasts are incorrect, they just but do not reflect currency predictors. The contradiction of analysts' forecasts and predictors has been interpreted in the literature as evidence of anomalies that predict future returns due to biased expectations as opposed to risk (Engelberg et al., 2020, 2018; Guo et al., 2020; Grinblatt et al., 2018). Consequently, all three approaches that have been commonly used in the asset pricing literature to distinguish between alternative rationales provide evidence suggesting that currency excess return predictability is at least in part due to market inefficiencies.

We perform a number of additional tests to establish the robustness of our results. While all currencies in our sample have quotes in the spot and forward market and the respective spreads capture the relative liquidity of currencies, we alternatively limit the sample to several smaller sets of currencies. For instance, we consider the 40 most liquid currencies based on Bank for International Settlements (BIS) turnover statistics, or just the so-called "G10" currencies. Our main results are robust to these alternative samples. Similarly, while the inclusion of risk-based currency predictors biases against our findings (see, for instance, McLean and Pontiff, 2016), results are qualitatively similar when excluding predictors such as carry trade and dollar carry trade that might a priori be perceived as risk factors.

Our study provides a fresh view on excess return predictability in currency markets. While currency research has not studied effects across many predictors to date, related work that tries to explain the existence of predictors cross-sectionally exists for equities. To illustrate, empirical evidence suggests that stock market predictability is attenuated after publication (McLean and Pontiff, 2016; Schwert, 2003), following increased predictor-based institutional trading (Calluzzo et al., 2019), and in recent years due to increased trading activity of hedge funds and lower trading costs (Chordia et al., 2014). While risk-adjusted predictor payoffs have been widely studied in equity and bond markets for decades, the use of risk-adjustments in currency markets is scant (e.g. Menkhoff et al., 2012a; Menkhoff et al., 2012b; Ang and Chen, 2010). Studies of the relation of stock market predictors with analysts' earnings forecasts, recommendations and target prices find them to be inconsistent (Engelberg et al., 2020, 2018; Guo et al., 2020), consistent (Jegadeesh et al., 2004), or conditional on credit quality (Grinblatt et al., 2018). Given this mixed evidence, our paper provides important out-of-sample evidence for related questions in currency markets, where no prior evidence exists and where it is also easier to take a more realistic investment perspective by employing real time data and adjusting trading profits for transactions costs.

Moreover, while equity markets have many assets and predictors compared to currency markets, they might be less efficient due to higher transactions costs, lower turnover, market closures, short selling constraints, etc. Additionally, data on analysts' forecasts for next months' stock 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.

While the carry trade has long standing prominence and continues to be a much studied and used investment strategy with currency researchers and practitioners alike, it is not the focus of our paper. On the contrary, while we include carry for completeness, it is not representative of our results. To illustrate, we show that the carry trade exhibits no publication effect and, thus, bears the hallmarks of a risk factor, consistent with related prior evidence in the literature. Consequently, our tests control for time varying excess return premia tied to the carry trade, and our results are stronger when we exclude it, since it biases against evidence of mispricing.

The paper is organized as follows. Section 2 defines the sample and describes the data. Section 3 analyzes the effect of academic research publication on predictor profits. Section 4 examines risk-adjusted predictor profits and alpha decay, while Section 5 investigates the relationship between predictors and foreign exchange forecasts, analysts' mistakes, and forecast revisions. Section 6 provides robustness tests. The paper concludes in Section 7.

2 Sample and Data

The empirical analysis uses monthly data for trading signals and exchange rates of 76 countries

(Table A2 in the Appendix).[4] The number of currencies varies over time as a function of data availability, with twenty to thirty currencies in a typical month. For each of the 588 months between December 1970 to November 2019, we construct eleven distinct predictors of currency excess returns that have been documented in the literature: momentum based on prior one, three, or twelve months' currency returns, a filter rule combination, carry trade, dollar carry trade, dollar exposures, term spread, currency value, output gap, and the Taylor Rule. They represent all cross-sectional predictors that can be constructed with publicly available data for a large number of currencies; we do not study time-series predictability. The long sample period averages out variation in the profitability of these trading strategies 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.[5]

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, one-month forward exchange rates, short-term interest rates (interbank or Treasury Bill rates), and long-term interest rates (ten-year or five-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 OECD, which has been rarely used in the cross-sectional currency prediction literature.[6] Table A3 in the Appendix provides detailed descriptions of the currency predictors, their construction, and references to the literature.

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[4] For comparison, Lustig and Verdelhan (2007), Sarno et al. (2016), and Menkhoff et al. (2012a) use 81, 55, and 48 currencies, respectively. We report results for subsamples of 62, 54, 40 and 10 currencies in Tables A10 and A11.

[5] The number of predictors studied in equity research is, for instance, 11 (Daniel et al., 2020; Guo et al., 2020; Stambaugh and Yuan, 2017; Stambaugh et al., 2015, 2014, 2012), 12 (Chordia et al., 2014), 14 (Calluzzo et al., 2019; Grinblatt et al., 2018), 97 (Engelberg et al., 2020; McLean and Pontiff, 2016).

[6] Specifically, we retrieve real-time data (or monthly vintages, as the series contain revisions) for Consumer Price Index (CPI) (starting in February 1999) and Industrial Production Index (IPI) (starting in December 1999). The database covers all countries in our sample, except Argentina, Bahrain, Bulgaria, Colombia, Croatia, Cyprus, Egypt, Ghana,

Individual predictors have low correlations between each other, with an average correlation of 0.15. However, correlations can be as low as –0.42 and as high as +0.92, suggesting they provide a wide range of differing trading signals (Table A4 in the Appendix).[7] Consequently, 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 one 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. 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. For some currencies and time periods, raw data on analysts' exchange rate expectations are quoted relative to the Deutschmark or Euro, and we convert these forecasts to quotes against the U.S. Dollar using the corresponding Deutschmark or Euro forecasts (see Appendix A for details on exchange rate forecasts data).[8] Actual currency (excess) returns cover the period January 1971 to December 2019, while analysts' expected currency (excess) returns are available for December 1989 to December 2019.

Following the literature (e.g., Menkhoff et al., 2016; Okunev and White, 2003) we define next month's currency return as the *negative* log difference between the spot exchange rates of months t+1 and t, so that a positive value represents an appreciation of the foreign currency with

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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 not 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.

[7] Similarly, for equity markets, McLean and Pontiff (2016) find average correlations between predictor variables of 0.033, ranging from –0.895 to +0.933. Green et al. (2013) report an average correlation of 0.09 among quantitative portfolios.

[8] The surveys draw on 250 forecasters in 27 countries covering 93 currencies, mostly affiliated with investment banks (e.g., BNP Paribas, Commerzbank, Citigroup, Goldman Sachs, Deutsche Bank, Royal Bank of Canada, Royal Bank of Scotland, Santander, Société Générale, etc.), but also consultancies (e.g., Oxford Economics, EIU) and research institutes (such as 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 Krona, Russian Ruble, Argentinian Peso and Brazilian Real (all quoted against the U.S. Dollar).

respect to the U.S. Dollar and a positive contribution from the spot exchange rate movement to the currency excess return.[9] Furthermore, as customary in the literature (e.g., Menkhoff et al., 2016; Lustig et al., 2014; Menkhoff et al., 2012a), next month's currency excess return is defined as the log difference between the one-month forward exchange rate of month *t* and the spot exchange rate of month *t*+1, assuming covered interest parity (Akram et al., 2008).[10] 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 WM/R exceed effective spreads actually paid by a factor of more than two (Cespa, 2021; Karnaukh et al., 2015; Lyons, 2001), results using net currency excess returns are undercutting the lower bound of actual profitability. Profits of trading strategies are calculated as quintile spreads of the excess returns of equally 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 covering our sample period. Our four-factor model includes the dollar risk factor and the carry trade risk factor defined in Lustig, Roussanov, and Verdelhan (2011). We add a currency volatility risk factor constructed as a factor-mimicking portfolio of currency volatility innovations as in Menkhoff et al. (2012b). We also consider a factor-mimicking currency skewness risk factor, following Burnside (2012) and Rafferty (2012), given skewness and crash risk explanations of the carry trade (see, e.g., Brunnermeier et al., 2009). As with the volatility risk factor we construct the factor-mimicking portfolio using the method in Menkhoff et al. (2012b). Moreover, we use a fifteen-factor model that adds the excess return on the world stock market portfolio as well as eight U.S. equity market risk factors to the four-factor model. The U.S. equity market factors are those of the Fama and French (2014) five-factor model, i.e. the excess return on the market portfolio

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[9] Currency returns capture changes in the spot exchange rate and therefore ignore interest rate differentials or forward discounts.

[10] In line with prior research (e.g. Lustig et al., 2011; Lustig et al., 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).

(Mkt_RF), size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), augmented by momentum (Mom), short-term reversal (ST_Rev), and long-term reversal (LT_Rev), obtained from the Ken French data library. Finally, we add the term spread (TERM) and the default spread (DEF) (Fama and French, 1993). These fifteen factors also serve as observable factors in the IPCA.

The one-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., 2020, 2018) The excess return expected by analysts is the expected exchange rate return plus the one-month interest differential, proxied by the forward discount. The mistake (or forecast error) that analysts make in forecasting exchange rates 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 Appendix provides details of all variable definitions. Table A5 in the Appendix shows detailed summary statistics of actual and forecast currency (excess) returns and analysts' mistakes.

3 Post-Publication Profits

3.1 Publication Effects of Academic Research

To start examining alternative explanations for the existence of systematic currency trading strategies, we analyze the ability of their 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).[11]

[11] The 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.

Differences between the predictive power of currency predictors in the in-sample period and post-publication period 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 currency predictors and exploit mispricing by trading on predictor signals, the returns associated with them should decrease after they become publicly known. Frictions, however, might prevent trading profits from disappearing completely. In contrast, trading profits should not change after publication on average if they reflect compensation for risk, conditional on no fundamental change in the risk-return trade-off or pricing of risk (McLean and Pontiff, 2016; Schwert, 2003; Chordia et al., 2014; Cochrane, 1999). 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 (Falck et al., 2021; McLean and Pontiff, 2016; Schwert, 2003; Cochrane, 1999; Fama, 1991).[12]

Profits of individual currency trading strategies 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 Appendix). 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 SSRN as their publication dates (Table A7 in the Appendix).[13] We create an indicator variable Post-Publication that is equal to one for months after the publication date, and zero otherwise. Conversely, the Post-Sample dummy that is equal to one for the months after the end of the sample period used in the original study (but before publication), and zero otherwise. The average monthly predictor payoff before transaction costs is 56 bp per month in the in-sample period, 64 bp in the out-of-sample pre-publication period, and 17 bp in the post-

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

[13] Institutional investors regularly follow SSRN postings to identify new predictors of currency excess returns. Thus, investors will typically know about the predictors (or correlated trading strategies) already 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).

publication period. The average length of the in-sample, out-of-sample, and post-publication periods are 461, 11, and 117 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:

$$Predictor\ Profit_{j,t} = a_j + \beta_1 Post\text{-}Sample_{j,t} + \beta_2 Post\text{-}Publication_{j,t} + e_{j,t}, \quad (1)$$

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 time periods. Predictor profits are alternatively gross or net of transaction costs. The regression also includes predictor fixed effects, and standard errors are computed using feasible generalized least squares (FGLS) under the assumption of contemporaneous cross-correlation between returns.[14]

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 on the Post-Sample variable are insignificant in all but one specification (Table 1). This indicates that data mining is likely not a source of trading profits in currency markets. If return predictability in published studies resulted from statistical bias, predictability should disappear out-of-sample. We do not find this to be the case.[15] 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 40 bp per month after publication compared

[14] Results are similar when clustering standard errors by date and predictor.

[15] Confidence intervals for the post-sample indicator parameter estimates from a non-parametric bootstrap (Patton and Timmerman, 2010) to address a potential bias due to the small out-of-sample period are similar to those reported in the table. Another way of studying the effect of data mining would be to measure trading profits before the in-sample period of the original research (Linnainmaa and Roberts, 2018). However, pre-sample profits cannot be calculated for several of the predictors studied in this paper because of unavailability of real-time fundamentals data (currency value, output gap, Taylor rule) or bid-ask spreads (carry trade) in the periods before the respective in-sample. In addition, exchange rates were fixed prior to August 1971 under the Bretton Woods system. A pre-sample indicator variable that is equal to one for the months before the sample period used in the original study (and zero otherwise) for predictors where the necessary data is available has an insignificant (significant) negative coefficient for gross (net) trading profits in the regressions in Table 1.

with the in-sample period, which is both statistically and economically significant. Given that predictors generate on average in-sample payoffs of 56 bp, this result implies that currency trading strategies are no longer profitable post publication, and we cannot reject the hypothesis that return predictability disappears completely (*p*-value = 0.140).

Results using trading profits net of transaction costs also show strong publication effects with a reduction by 35 bp after publication in specification (1) (Table 1). These publication effects are bigger for predictors that have economically or statistically larger in-sample profits, as shown in specifications (2) and (3), respectively, and the overall publication effect is always significant.[16] For net profits we can reject the hypothesis that trading profits disappear completely post publication (*p*-value = 0.065). 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 a larger drop in performance out-of-sample, while the results suggest the opposite.[17] The analysis provides evidence that the returns associated with currency predictors decrease on average in periods after dissemination of the underlying academic research, consistent with the view that investors learn about and trade to exploit mispricing, and thus that predictability reflects currency anomalies.

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, 2014; Verdelhan, 2018).[18] 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 towards zero. This is borne out empirically in specification (4), as the publication effects are indeed stronger when excluding these two strategies.

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[16] As shown in Table A10 in the Appendix, the publication effect, and the interaction terms involving in-sample profits are always negative and significant for profits gross and net of transactions costs using alternative samples with different sets of currencies.

[17] Test using a combined proxy as in Falck et al. (2021) also show no evidence of overfitting.

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

The publication effect can be illustrated by plotting the incremental change of trading profits post publication against in-sample profits (Figure 1). The effect exists for almost all strategies individually, and those with larger in-sample profits show larger declines in portfolio returns after publication (Panels A and B). In a related vein, there is a negative relation between in-sample *t*-statistics and post-publication effects (Panels C and D). Note that the carry trade shows strong in-sample (gross) profits and no reduction after publication and thus bears the hallmarks of a risk factor, while the profitability of the dollar carry trade is significantly smaller after publication. Currency value has low in-sample profits and no significant publication effect.

Similar effects of the publication of academic research on return predictability have recently been documented for the U.S. equity market, where gross portfolio returns are 58% lower post-publication, but already decrease 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 (both for gross and net returns), which is in line with higher efficiency of deep and active currency markets.

The effect of publication on trading profits can be studied in more detail by replacing the post-publication indicator in the regressions in Table 1 by separate indicators for each of the first three years after publication as well as a single indicator variable for all months that are at least three years after publication (Figure 2). The coefficients on these variables show that gross profits drop quickly as they are lower by 24 bp in the first year after publication compared to the in-sample period (Panel A). In the following years, they are lower by 39 bp and 41 bp, and on average 44 bp lower than in the in-sample period thereafter. The regression also includes an indicator variable for the last year of the in-sample period. Its coefficient of –0.29 indicates that the last 12 months of the sample period have lower profits than other in-sample months, while trading profits are (insignificantly) higher in the post-sample period. Net profits (Panel B) exhibit similar patterns. These results provide no support for the concern of researchers choosing in-sample periods opportunistically to report stronger results.

3.2 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, for example capturing decreasing costs of corrective trading, rather than a publication effect (see Goldstein et al., 2009; Anand et al., 2012). To investigate this conjecture, we construct a time trend variable that is equal to 1/100 in January 1971 (the first predictor signal is in December 1970, hence the first realized return associated with that signal is in January 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 coefficient remains negative and statistically significant, hence, the documented publication effect survives allowing for the presence of time decay.

Lower trading profits could also be related to periods of low interest rates, high exchange rate volatility, economic business cycle contractions, or financial crises. 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, etc.). Similarly, the post-publication period extends until the end of the sample period in December 2019 and thus includes periods well before and after the recent global financial crisis (which was not a currency crisis).[19] More generally, if the publication effect reflected 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.

[19] Burnside et al. (2011a,b) note that, for example, 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).

Nevertheless, we include controls for macro-economic risk, crises, and monetary policy in specification (3) as captured by the level of interest rates, within-month exchange rate volatility, and indicators for NBER recessions and financial crises, alternatively the average for the currencies in the long/short portfolios (as reported in the table), or the G10 currencies, or just the United States. Indicators for financial crises are based on various crises (currency, inflation, banking, systemic, sovereign debt, etc.) identified in the literature (Laeven and Valencia, 2020; Reinhart and Rogoff, 2014).[20] The publication effect remains negative and significant in the presence of these additional controls. Predictor profits are not significantly lower in recessions or crisis periods.

In order to further consider possible risk premia explanations for currency predictors, we estimate regressions that control for the dollar risk factor, carry trade risk factor, currency volatility risk factor, currency skewness risk factor, a global equity market risk factor, eight U.S. equity market risk factors, and two bond market risk factors. Specification (4) shows that while currency risk factors are significantly related to currency predictor profits, the publication effect is robust to these risk controls (coefficients on the equity and bond market risk factors are mostly insignificant and not reported for brevity). Since all risk factors are tradable, self-financing portfolios, the results can be interpreted as significant drops in risk-adjusted returns post publication.

We also investigate whether predictor returns are persistent, and whether such persistence has an effect on the publication effect (Moskowitz, Ooi, and Pedersen, 2013). We implement this by including the trading profits over the prior 1 and 12 months in specification (5). Only trading profits over the prior 12 months are significant, and there is a robust and economically sizable post-publication effect once persistence is controlled for.

3.3 Earlier Related Research

It is possible that market participants traded on the currency strategies that we study already before they were popularized by academic studies. To illustrate, Asness et al. (2013) and Menkhoff et al.

[20] Results are similar for inclusion of individual or joint controls for different types of crises.

(2012a) are generally cited for documenting cross-sectional momentum strategies in currency markets. However, these strategies are related to earlier papers using filter rules in currency markets (e.g., Sweeney, 1986). Investors might have also considered adapting momentum strategies developed in other asset classes (e.g., Jegadeesh and Titman (1993) for momentum in equities), learnt about currency momentum strategies from newspaper articles (e.g., an article in the Financial Times in October 2009; see Smith, 2009), or implemented currency momentum strategies documented in practitioner research publications (e.g., on the Deutsche Bank Currency Momentum Index that started in January 2000).

In the same vein, our tests use the posting of the paper by Lustig and Verdelhan on SSRN in January 2005 and published in the AER in March 2007 as the first documented source of cross-sectional carry trade strategies. However, the carry trade was mentioned, for instance, in a Financial Times article in February 1997 (see Riley, 1997). Also, there are related earlier academic papers, such as Hansen and Hodrick (1980), studying the relation between the forward discount and future exchange rates, though only in time-series analyses.

Importantly, as noted in the literature, trading by investors on these strategies should lead to lower or even zero portfolio returns in-sample and bias against any later publication effect of the underlying academic research if predictors reflect mispricing, while having no effect if they reflect risk (e.g., McLean and Pontiff, 2016; Schwert, 2003; Cochrane, 1999). Nevertheless, we research several potential sources of earlier information relevant to the predictors studied in this paper. First, we look for earlier papers in the currency literature that develop trading strategies or economic relations that might be related to a particular predictor. Second, we identify earlier practitioner research publications or currency indices based on related strategies. Third, we look for mentions of the trading strategies in newspaper articles. Finally, we also search for earlier papers suggesting corresponding strategies in equity or bond markets. Table A8 in the Appendix summarizes the sources that we can identify; we do not list sources of alternative publication dates if they occur after the date for the corresponding currency predictor. In a few cases, the earliest source of alternative publication dates is before the beginning of our sample period, so that our analysis is unaffected.

We then control for the respective publication dates (using the earlier of publication date, or where available SSRN dates), either using indicator variables for each individual paper dissemination date, or pooling them by publication type. Consequently, publication effects in these tests are measured over and above changes in strategy profits associated with these controls. The results in Table 3 show that there is only limited evidence of earlier dissemination being associated with lower trading profits, and that a significant publication effect of the underlying academic paper remains after controlling for other potential sources of predictor information. Thus, although some practitioners may know about these strategies before publication, biasing the tests against rejecting the null, the results suggest that publication does make the strategies more widely known.

3.4 Limits to Arbitrage

The dissemination of research documenting profitable trading strategies should attract arbitrageurs who exploit these strategies leading to lower mispricing and reduced trading profits post publication. However, if trading is costly due to frictions, arbitrage may not fully eliminate all profits before accounting for these costs (Shleifer and Vishny, 1997; Pontiff 1996, 2006). Thus, the reduction in profitability should be smaller for predictors that involve taking positions in currencies that are costlier to trade. Nevertheless, if predictor returns are the outcome of rational asset pricing, then the post-publication decline should not be related to arbitrage costs. 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 average in-sample exchange rate turnover (from the BIS, 2019), an index of average money market restrictions for inflows and outflows (from Fernández et al., 2015), a measure of capital account openness (Chinn and Ito, 2008), measures on the severity of restrictions to capital account and financial current account liberalization (Quinn and Toyoda, 2008), a measure of functional capital market efficiency (Eklund and Desai, 2013), and a proxy of the capital allocation efficiency (Wurgler, 2000). Note that these measures are typically capturing the exchange of one currency with regards to all other currencies, while our analysis only requires the conversion of U.S. Dollars into foreign currency and vice versa. Our main measure averages the percentile ranks of those with best coverage (FX turnover, money market restrictions, capital account openness) into a single index.

Including limits to arbitrage and their interaction with the post-publication indicator in the regressions provides evidence that they moderate the size of the publication effect (Table 4). In particular, the interaction terms on bid/ask spreads and the index of 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. The hypothesis that limits to arbitrage do not matter for expected trading profits can also be rejected for bid/ask spreads (p-value = 0.002) and exchange rate convertibility (p-value = 0.017). By the same token, trading profits from equity market predictors have approximately halved since decimalization and are generally larger for stocks with larger arbitrage costs (McLean and Pontiff, 2016; Chordia et al., 2014).

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 applying risk adjustments to predictor profits using factor models.

4 Predictor Profits, Risk Adjustments, and Alpha Decay

4.1 Currency Predictor Profits

If profits to trading strategies based on currency predictors reflect compensation for risk, they should disappear after adjusting for risk (e.g., Fama 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 using discretion and combine currency predictors into aggregate measures, mimicking alpha models of institutional investors that summarize different trading signals into combined predictor scores (e.g., Engelberg et al., 2020, 2018; Guo et al., 2020; Stambaugh et al., 2015, 2014, 2012).

In particular, we create a measure of average mispricing 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.[21] The second aggregate is a measure of extreme mispricing 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 on many predictors and shorted based on few predictors. It thus reflects extreme mispricing or a high conviction of mispricing.[22]

The correlation of 0.90 between average and extreme mispricing indicates that they measure similar dimensions but are not identical.[23] Sorting currencies on either mispricing measure yields currency excess returns in the following month that increase across quintiles from the short to the long portfolio (Table 5 Panel A); monotonicity tests are highly significant (Patton and Timmermann, 2010). Trading strategies based on mispricing are profitable before and after transaction costs. To illustrate, quintile spreads of gross currency excess returns are 76 bp per month for average mispricing and 68 bp for extreme mispricing (equivalent to 9.1% and 8.2% per year), and

[21] A similar approach has been used to measure mispricing in equity markets (e.g., Stambaugh et al., 2012).
[22] A similar approach has recently been used to aggregate equity market predictors (e.g., Engelberg et al., 2020).
[23] Table A5 in the Appendix provides detailed summary statistics of these measures. The mispricing measures require available signals of at least four predictors.

net profits are still 43 bp and 34 bp, 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 transactions costs is 61% and 62% for average and extreme mispricing, which is significantly higher than 50% (p-value < 0.001). Hit ratios for gross returns are even larger at 67% and 70%, respectively, and highly significant. Different to currency excess returns, the pattern of currency returns shows an inverted u-shape across portfolios stratified by mispricing.[24] (Gross) Quintile spreads are not significantly different from zero.

Annualized Sharpe ratios of up to 1.3 for gross profits and 0.6 for net profits are economically significant (Table A9 in the Appendix); 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 Appendix).[25] The diversification across predictors is also harder to reconcile with a pure risk based explanation.

4.2 Risk-Adjustments and Alpha Decay

To adjust currency predictor profits for risk, we employ both Black et al. (1972) time-series factor model regressions and cross-sectional Fama-MacBeth (1973) regressions, which are well established methods in the finance literature. In particular, we estimate factor model time-series regressions with tradable long/short factors so that the intercepts can be interpreted as risk-adjusted returns. We employ the same set of factors as in Table 2. Our four-factor model includes dollar and carry trade risk factors, a volatility risk factor, and a skewness risk factor. Our fifteen-factor model further adds a global equity market risk factor, eight U.S. equity market factors, and two bond market risk factors. It includes all four factors used in Menkhoff et al. (2012a) and subsumes the Lustig et al. (2011) two-factor model and the Fama and French (2014) five-factor model.[26]

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[24] Note that following the literature, the currency return in the table is defined as is the negative of the log difference in spot rates to allow assessing the contribution of the exchange rate change to the currency excess return more easily.

[25] Note that Table 5 is based on the shorter sample period December 1989 to December 2019 to compare actual and forecast currency returns.

[26] The fifteen factors we employ throughout the paper are available for the full sample period. While only available for a more limited time period, we also construct the global imbalance risk factor of Della Corte, Riddiough, and Sarno (2016) as well as the sovereign risk factor of Della Corte, Sarno, Schmeling, and Wagner (2021). In addition,

The results in Panel B of Table 5 show that the effect of risk adjustment using factor models on the size of trading profits is very limited. In particular, for average mispricing, monthly gross alphas are 93 bp with the four-factor model, and 92 bp with the fifteen-factor model. Risk-adjusted returns for trading strategies based on extreme mispricing are 77 bp for both the four- and fifteen-factor models. These payoffs are slightly larger than the simple quintile spreads without risk adjustment of 76 bp and 68 bp in Panel A. Risk-adjusted profits net of transactions costs are smaller but still economically and statistically significant, with fifteen-factor alphas of 39 bp (*t*-statistic = 3.61) and 29 bp (*t*-statistic = 2.70) for average and extreme mispricing, respectively. Intercepts for portfolios sorted by mispricing increase monotonically from the first to the fifth quintile, documenting the systematic nature of the relation between mispricing and next period excess returns. Moreover, both the first and the fifth portfolio make significant and about equal contributions to the quintile spread.

We also use cross-sectional Fama-MacBeth regressions as an alternative approach of risk adjustment. To this end, we make use of Instrumented Principal Component Analysis (IPCA), developed by Kelly et al. (2019),[27] 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 excess returns. Our IPCA implementation uses eleven instruments (L = 11): a constant, and all ten individual currency predictors with cross-sectional characteristics available for the sample period of Table 5, namely 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 zero (the cross-sectional median). We estimate a seventeen-

Chernov, Dahlquist, and Lochstoer (2022) kindly shared their UMVE portfolio's estimated SDF series. Adding these risk factors yields alphas similar to those of the factor models and IPCA in Table 5 estimated over this shorter period.

[27] We are grateful to the authors for use of their code. Appendix B summarizes the IPCA methodology.

factor IPCA model with two latent factors (K = 2) and the fifteen currency, equity and bond market factors as observable factors (M = 15).[28] 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.

In order to control for risk using the IPCA model, we estimate Fama MacBeth 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 mispricing quintiles (Bartram and Grinblatt, 2021). In particular, we obtain the quintile portfolio alphas from regressions with the IPCA expected return and dummy variables for quintiles one to five (and no regression intercept), while the alpha of the quintile spread portfolio is obtained from regressions with IPCA expected return, dummies for mispricing quintiles two to five, and a regression intercept. As in Bartram and Grinblatt (2021), 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.

The results in Panel C of Table 5 show that average and extreme mispricing yield highly significant quintile spreads between the IPCA-controlled currency excess returns. In particular, the unconstrained regression yields a highly significant spread of 55 bp and 48 bp per month between the two extreme quintiles of average and extreme mispricing, respectively. The coefficients on the mispricing quintile dummies are monotonic, lending further support to the conjecture that the aggregate currency predictors capture pricing inefficiencies since these regressions control for factor risk associated with mispricing itself. The constrained regression also exhibits a significant and nearly monotonic effect from mispricing – separate from the effect of mispricing on factor betas. The coefficients on the average and extreme mispricing quintiles are smaller than those in the unconstrained regression, but are still economically and statistically significant.

[28] Results excluding observable factors or without filling in missing values are highly similar.

Assessing the alpha decay of mispricing signals provides further support for the view that trading profits reflect mispricing. If predictors capture mispricing and market inefficiencies, one would expect low autocorrelations of signal ranks over time as well as low persistence of alphas when lagging the trading signal (Bartram and Grinblatt, 2021, 2018; Bartram et al., 2021). Indeed, the average Spearman rank correlation between the vector of mispricing at month t and month $t-1$ is only 0.71 (0.67) for average (extreme) mispricing, and it is just 0.39 (0.37) for mispricing in months t and $t-6$. In addition, fifteen-factor model alphas from stale signals decline quickly, with net returns declining toward zero within just one month (Figure 3). Thus, while the existence of currency predictors suggest that currency markets may not be completely efficient, the inefficiencies seem to be arbitraged away quickly. The low persistence of profits, particularly net of transaction costs, suggests that trading profits reflect mispricing (Cochrane, 1999).[29]

Overall, the findings of significant risk-adjusted profits, 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 are, at least to an extent, the result of market inefficiencies. Either way, currency predictors should be related to the forecasts of currency analysts, which we examine next. Importantly, studying analysts' forecast errors provides a setting that cannot be affected by static or dynamic risk (Engelberg et al., 2018).

5 Analysts and Currency Predictors

5.1 Mispricing and Analysts' Forecasts

Given the systematic relation of currency predictors with future currency 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 currency predictors or analysis of the underlying fundamentals

[29] While arbitrage capital is difficult to measure empirically (e.g., Joenväärä, et al., 2022; Edelman et al., 2013), we construct monthly time-series of global currency hedge fund AUM and flows (from 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), Barroso and Santa-Clara (2015), and Chordia et al. (2014). While the results have to be taken with a great deal of caution given the data limitations, there is evidence of a negative relation between profits to average and extreme mispricing 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 to the carry trade, an optimized currency strategy, and equity market predictors.

and trends in currency markets, their forecasts should be consistent with currency predictors. Alternatively, biases in the views of currency analysts could lead to investors trading on analysts' forecasts reinforcing mispricing and thus help explain the existence of currency predictors.

Guided by the literature (e.g., Engelberg et al., 2020, 2018; Guo et al., 2020), we use the aggregate measures to 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 mispricing quintiles (Table 5 Panel D). They are +147 bp per month for the short portfolio and –115 bp for the long portfolio, yielding an expected quintile spread of –262 bp for strategies based on average mispricing, with a *t*-statistic of –26.8. The pattern is similar for extreme mispricing with expected profits from mispricing of –255 bp (*t*-statistic = –26.1). Analysts erroneously expect negative profits from trading on mispricing even though these strategies yield significant positive actual gross profits of 76 bp and 68 bp per month for average and extreme mispricing, respectively (comparing Panels A and D). Hence, the expectations of analysts with regard to currency excess returns conflict with the relations of predictor variables with next months' currency returns that have been widely 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. Note, however, that this does not imply that the forecasts by analysts are generally wrong and not useful in forecasting currencies (as we show later) – it is just that they do not reflect currency predictors.

The results for expected mispricing 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 mispricing quintiles (Panel D). The difference in currency returns between the fifth and first quintile is –327 bp per month for average mispricing and –324 bp for extreme mispricing. In contrast, realized currency return spreads are much smaller and indistinguishable from zero (Panel A).

These results can be illustrated graphically (Figure 4). Analysts' forecasts of currency excess returns are monotonically decreasing from the first quintile to the fifth quintile (Panel A), and analysts expect short portfolio currencies to appreciate and long portfolio currencies to depreciate (Panel B). The results are robust across alternative measures of mispricing. These findings provide evidence that foreign exchange forecasts by analysts are inconsistent with the information in predictor variables. Analogous to these findings, forecast returns are higher (lower) among U.S. stocks that predictor variables suggest will have lower (higher) returns (Engelberg et al., 2020, 2018; 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 compared equity markets.

The relation between forecast currency (excess) returns and mispricing 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:

$$\begin{aligned} \textit{Forecast (Excess) Return}_{i,t+1} = a + \beta_1 \textit{Mispricing}_{i,t} + \beta_2 \textit{Number of Forcasters}_{i,t} \\ + \beta_3 \textit{Single Forecast}_{i,t} + \varepsilon_t + e_{i,t} \end{aligned} \tag{2}$$

where the dependent variable is the monthly forecast return or forecast excess return on currency *i* in month *t*, and Mispricing is the mispricing variable of interest (average mispricing or extreme mispricing). The regression includes the number of analysts providing forecasts, an indicator variable of 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 mispricing and forecast currency excess returns is negative and significant (Table 6). Specifically, the coefficients on average and extreme mispricing are –7.851 and –3.571, respectively, and both are statistically significant. The size of the coefficient for average mispricing means that a currency with an average mispricing value that is one standard deviation above the sample mean has a forecast excess return that is 121 bp per month lower than a currency with an average mispricing value at the sample mean. In the case of extreme mispricing, the incremental forecast excess return would be 113 bp. This contrasts with the higher realized currency excess returns for currencies with higher mispricing scores. With respect to the control variables, forecast currency excess returns are lower for currencies with more analysts. Thus, analysts tend to be more bullish when they are smaller in numbers. For forecast currency returns, the mispricing coefficients are also negative and significant.[30]

If analysts considered predictor variables for their exchange rate forecasts, they should expect higher currency excess returns (and possibly currency returns) for portfolios on the long side of a mispricing-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 for currency strategy payoffs are negative, suggesting that analysts regularly make mistakes in their forecasts. Trading by investors on these forecasts could contribute to and reinforce mispricing (Guo et al., 2020; Engelberg et al., 2020).

5.2 Analysts' Mistakes

If analysts on average expect losses for currency trading strategies that yield positive actual (i.e. realized) profits, their expectations must frequently be wrong (with regards to currency predictors), and their forecast errors or mistakes should be systematically related to currency predictors (Engelberg et al., 2020, 2018). Note that expectations about currency excess returns are driven by the forecasts that analysts make about exchange rates, since one-month interest rates are known. Thus, their forecast errors for currency returns and currency excess returns are identical, where mistakes for currency excess return are all attributed to analysts' exchange rate forecast errors.

[30] The results in Table 6 are robust to controlling for the forecast (excess) return at time *t*.

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:

$$\begin{aligned} Mistake_{i,t+1} &= Forecast\ Currency\ Excess\ Return_{i,t+1} - Realized\ Currency\ Excess\ Return_{i,t+1} \\ &= Forecast\ Currency\ Return_{i,t+1} - Realized\ Currency\ Return_{i,t+1} \end{aligned} \tag{3}$$

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 5) suggest that the mistakes in analysts' expectations of future exchange rates are systematically related to mispricing. Indeed, mistakes decrease across mispricing quintile portfolios, with positive mistakes in the first quintile and negative mistakes in the fifth quintile (Figure 5 Panel A). These univariate patterns exist for aggregate mispricing measures, but also for the individual currency predictors (Panel B).

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

$$\begin{aligned} Mistake_{i,t+1} &= a + \beta_1 Mispricing_{i,t} + \beta_2 Number\ of\ Forecasters_{i,t} \\ &+ \beta_3 Single\ Forecast_{i,t} + \varepsilon_t + e_{i,t} \end{aligned} \tag{4}$$

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 mispricing predicts mistakes in return forecasts of individual currencies (Table 7). Estimated coefficients for average and extreme mispricing are –9.563 and –4.359, respectively, in specification (1) and are significant at the 1% level. This indicates that if a currency has a higher value of average or extreme mispricing, 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 that tend to be in the long mispricing portfolio, while they are too high for currencies in the short mispricing portfolio. The regression coefficients imply that a currency with a mispricing value that is one standard deviation above the sample mean has a forecast excess return that is 148 bp (138 bp) per month lower than its realized return compared with a currency with an average (extreme) mispricing value at the sample average.

The finding that analysts make systematic errors may seem surprising, and one would expect them to incorporate predictor information into their forecasts after the dissemination of research publicizing the trading strategies. If this was the case, the relation between mistakes and mispricing should become weaker, which can be analyzed by adding an interaction term between mispricing and a publication variable to the regression:

$$\begin{aligned} Mistake_{i,t+1} &= a + \beta_1 Mispricing_{i,t} + \beta_2 (Mispricing_{i,t} \times Publication_t) \\ &+ \beta_3 Publication_t + \beta_4 Number\ of\ Forecasters_{i,t} + \beta_5 Single\ Forecast_{i,t} + e_{i,t} \end{aligned} \tag{5}$$

where Publication measures the fraction of predictors that have been published at time *t*. As before, the regression includes the number of forecasters, and an indicator variable for a single forecaster. Standard errors are clustered by country.

The augmented regressions show again a significant negative relation between mispricing and analysts' mistakes, indicating that analysts make predictable mistakes by forecasting too low (high) currency returns for currencies in the long (short) portfolio based on average and extreme mispricing (Table 7, specification (2)). The interaction between mispricing and publication is positive and significant for both average and extreme mispricing in line with analysts improving their forecasts as predictors become widely known. The coefficients on the number of forecasters are negative and significant.

The finding that analysts' excess return forecasts are too low (high) for currencies in the long (short) mispricing 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 in specification (3) the contemporaneous currency excess return in the regression, 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 mispricing variables remain negative and significant, which is evidence contradicting the idea of data mining explaining the predictability of analysts' mistakes by currency predictors. In the same vein, the negative relation between mispricing and analysts' mistakes also exists for versions of average and extreme mispricing constructed using predictors only after their respective in-sample periods in specification (4).

5.3 Changes in Exchange Rate Forecasts

A possible explanation for the finding that foreign exchange forecasts are not always in line with the currency movements predicted by predictor variables could be that analysts overlook information captured by currency predictors (Engelberg et al., 2020). Since mispricing 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 mispricing.

We test this conjecture empirically by regressing monthly changes in analysts' forecasts on mispricing lagged by one to three months. Specifically, we estimate the following regression model:

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

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

The results provide evidence that analysts indeed incorporate mispricing information into their forecast revisions. To illustrate, the coefficients on average and extreme mispricing lagged by one month are 2.358 and 1.037 respectively, both statistically significant (Table 8). The regression coefficients indicate that a currency with a mispricing value that is one standard deviation above the sample mean is expected to appreciate by 36 bp (33 bp) more per month compared with a currency with an average (extreme) mispricing value at the sample mean.[31] The magnitudes of the mispricing coefficients decrease monotonically with lag length: The economic and statistical significance of mispricing lagged by two months is much smaller than for one month, while the coefficients on mispricing lagged by three months are insignificant. Thus, analysts do not use information contained in mispricing variables from months before the most recent two. The coefficient on the number of forecasters are positive and significant, indicating more positive revisions for currencies that are followed by more analysts.

In summary, while analysts appear to make predictable forecasting errors, their mistakes become smaller after predictors are popularized via publication. Even though analysts miss important information in mispricing variables that help predict currency excess returns, they incorporate this information with a short lag. This contrasts with evidence that lags of predictor signals of up to 18 months predict changes in target prices for equities (Engelberg et al., 2020)—consistent with currency markets exhibiting higher degrees of informational efficiencies than stock markets.

5.4 Analysts' Forecasts and Predictability of Currency Excess Returns

Finally, we consider whether analysts' forecasts are useful to predict future exchange rate excess returns. While analysts seem to make predictable mistakes in forecasting the excess returns associated with mispricing, it could be that their forecasts contain other information that outweighs these forecast errors and that is informative in predicting future currency excess returns. For market participants, it is important to understand which variables are most useful for predicting future currency excess returns to generate the largest trading profit. To this end, we estimate Fama-MacBeth (1973) regressions that have monthly currency excess return as dependent variable and lagged mispricing and analysts' forecast currency excess returns as explanatory variables, both of which are known to investors at the time of putting the trade on.[32] In order to be able to compare economic magnitudes, we use quintile dummies (Q2, Q3, Q4, and Q5, with Q1 omitted due to the

[31] Mispricing remains significant even after controlling for the realized currency excess return in month t.
[32] Analysts' forecasts are published around the 2nd week of the month and, thus, are available to investors by the end of the month.

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.

Mispricing and analysts' forecasts are both useful in predicting future currency excess returns (Table 9). In particular, the coefficients on the quintile dummies increase monotonically from low to high quintiles, for both average and extreme mispricing. 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 average mispricing, the quintile spread on mispricing is 96 bp per month (t-statistic = 7.20), while the quintile spread on forecast excess returns from analysts is 46 bp per month (t-statistic = 3.24). Magnitudes are similar but slightly smaller for regressions with extreme mispricing, with quintile spreads of 83 bp and 38 bp for mispricing and analysts' forecasts, respectively. Thus, while the forecasts that analysts make contradict currency predictors, they are useful in predicting currency excess returns over and above predictor-based mispricing.

In summary, 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 appear to 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).

6 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 in mispricing between currency portfolios and providing diversification within portfolios. Nevertheless, we perform all of our analyses for a smaller set of 62 currencies, a set of 54 currencies representing all currencies covered by the BIS Triennial Surveys (1995–2019), the 40 currencies with the highest FX turnover according to the BIS Triennial Surveys, and the G10 currencies (see Ang and Chen, 2010). The publication effect is robust to these alternative samples (Table A10 in the Appendix).

In fact, the magnitude of the coefficient is larger when using smaller sets of currencies, and the interaction term of the post-publication dummy with in-sample trading profits is always significant for profits both gross and net of transaction costs.

The relation between analysts' mistakes and mispricing is similarly robust to alternative sets of currencies (Table A11 in the Appendix). Note that the number of currencies differs from Table A10 due to the more limited availability of analysts' forecasts. Coefficients on mispricing are negative and significant for specifications with and without the interaction between mispricing 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 described in Appendix A. The first, Refinitiv Consensus FX Forecasts, provides forecasts of one-month horizon for 36 currencies starting in May 1993. The second, analysts' forecasts from Bloomberg, are available for 41 currencies from December 2006 onward, but forecast horizons of one month are only available for March, June, September and December of each year since forecasts are limited to exchange rates at the end of each calendar quarter. While these datasets cover fewer currencies and have shorter histories compared to Consensus Economics, they do provide not just mean but also median consensus forecasts. Using these alternative data sources shows similar results to those reported in the paper using either the full data available from each source or the subsample of currency-months common across data sources.

7 Conclusion

This paper studies, for the first time, all widely used systematic 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 us to offer 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 paper tests alternative explanations as a *raison d'être* for currency predictors pertaining to risk and market inefficiencies employing a range of methods suggested in the literature.

First, profits of currency strategies significantly decrease on average after the underlying academic research has been published. The decline is greater for strategies with larger in-sample profits and lower arbitrage costs. The findings obtain despite possible knowledge 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 15-factor models (up to 93 bp per month) and IPCA (up to 55 bp per month) allowing for dynamic factor betas derived from the individual currency predictors themselves. Autocorrelations of mispricing signal ranks are low and alpha decay is relatively fast.

Third, 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 appear to make systematic mistakes that are in line with biased expectations as opposed to risk as a source of return predictability. The evidence from these three 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 predictors reflecting mispricing as opposed to just risk.

Overall, this paper 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 (Engelberg et al., 2020, 2018; Guo et al., 2020; McLean and Pontiff, 2016; Chordia et al., 2014).

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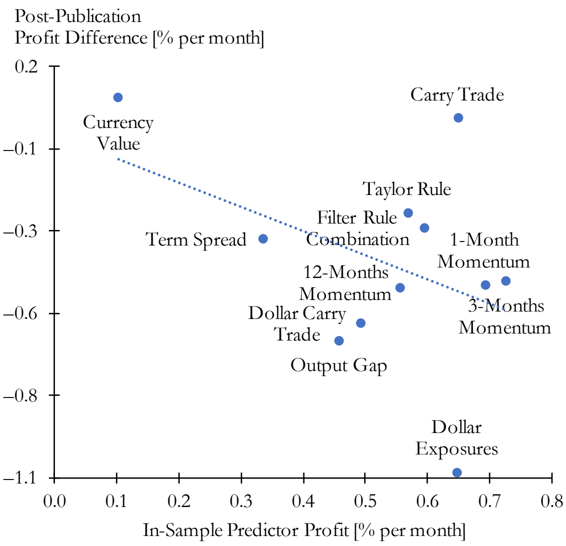
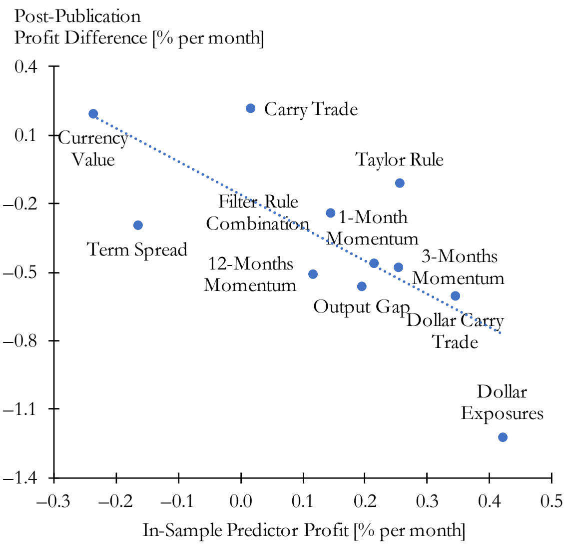
Figure 1: Relation between In-Sample and Post-Publication Trading Profits

The figure 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 January 1971 to 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 December 2019). 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. Panel A shows trading profits gross of transaction costs, Panel B shows trading profits net of transaction costs, Panel C shows *t*-statistics for trading profits gross of transaction costs, and Panel 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 January 1971 to December 2019. Table A3 in the Appendix provides details on variable definitions. Table A7 in the Appendix provides details on the predictors' original sample period used in the paper as well as date of publication.

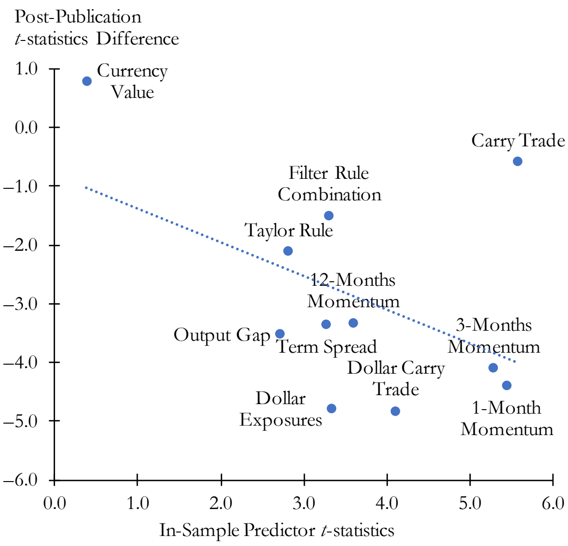
Panel A: Profits Gross of Transaction Costs



Panel B: Profits Net of Transaction Costs



Panel C: *t*-statistics for Gross Profits



Panel D: *t*-statistics for Net Profits

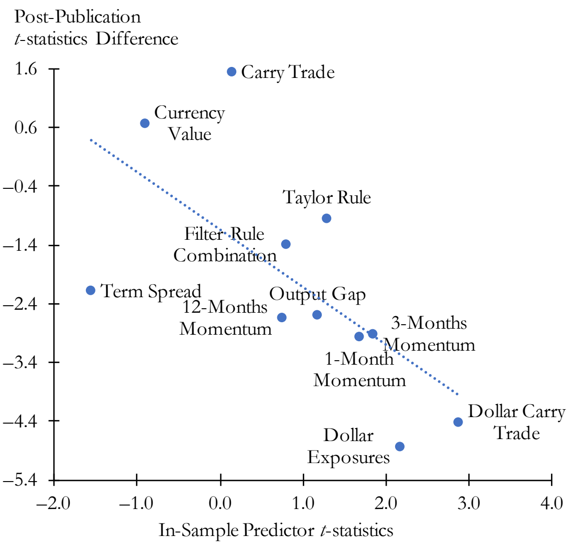
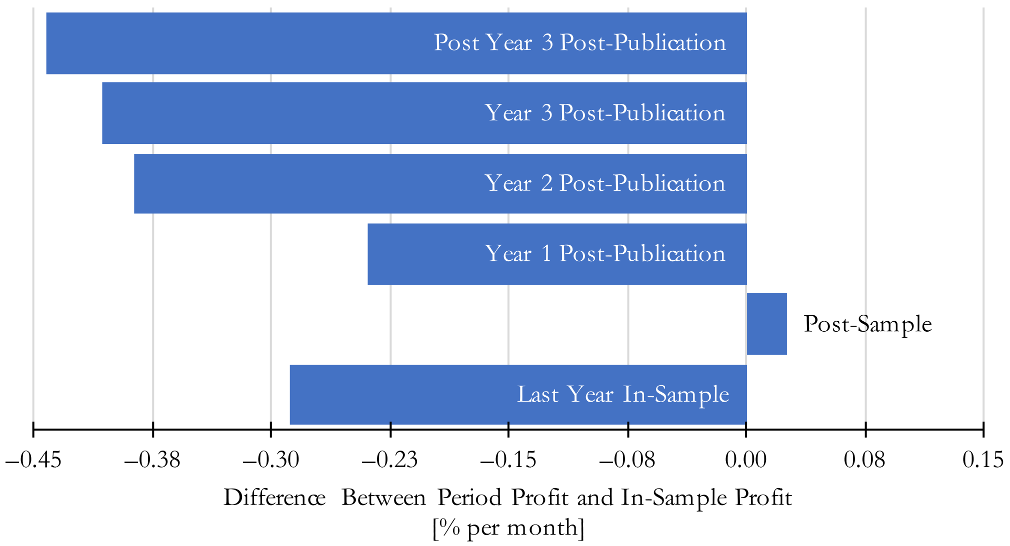


Figure 2: Predictor Profits Around End-of-Sample and Publication Dates

The figure 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 three years after publication. Results in Panel A and Panel B are shown alternatively for trading profits gross and net of transaction costs, where transactions 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 equally 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 January 1971 to December 2019. Table A3 in the Appendix provides details on variable definitions. Table A7 in the Appendix provides details on the predictors' original sample period used in the paper as well as date of publication.

Panel A: Profits Gross of Transaction Costs



Panel B: Profits Net of Transaction Costs

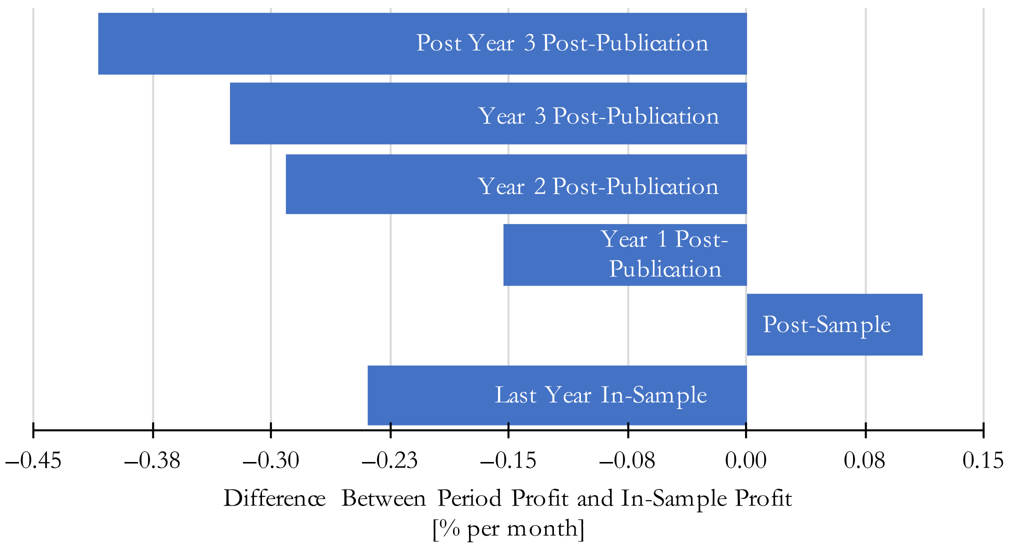
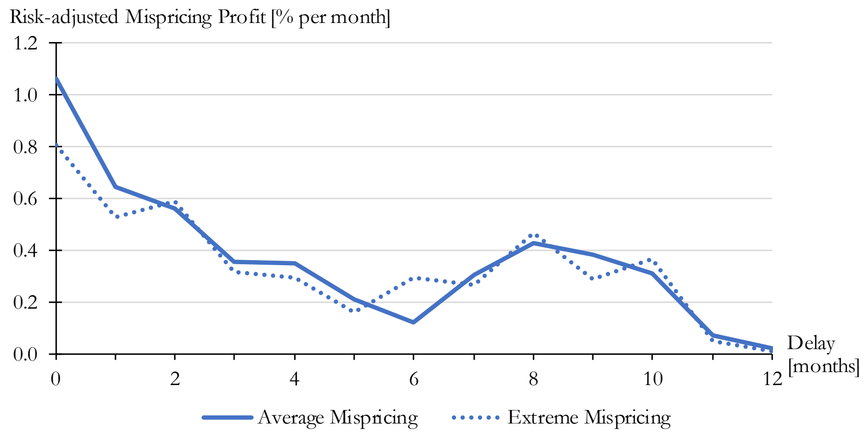


Figure 3: Decay of Mispricing Signals

The figure shows risk-adjusted trading profits (in percent per month) for trading strategies based on average mispricing (solid line) and extreme mispricing (dashed line). 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 mispricing and extreme mispricing and combined into equally weighted portfolios. The mispricing signal is lagged from zero to 12 months (Panel A) and 6 months (Panel 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 four currency risk factors, nine equity market risk factors, and two bond market risk factors. The four 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), and a skewness risk factor (Burnside, 2012; Menkhoff et al., 2012b; Rafferty, 2012). 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 (Mkt_RF), 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). Average mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 mispricing 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. Panel A shows trading profits gross of transaction costs, while Panel 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 January 1977 to December 2019 in Panel A and from July 1976 to December 2019 in Panel B to ensure the same period of analysis in each panel across strategies with different lag lengths. Table A3 in the Appendix provides details on variable definitions.

Panel A: Alphas Gross of Transaction Costs



Panel B: Alphas Net of Transaction Costs

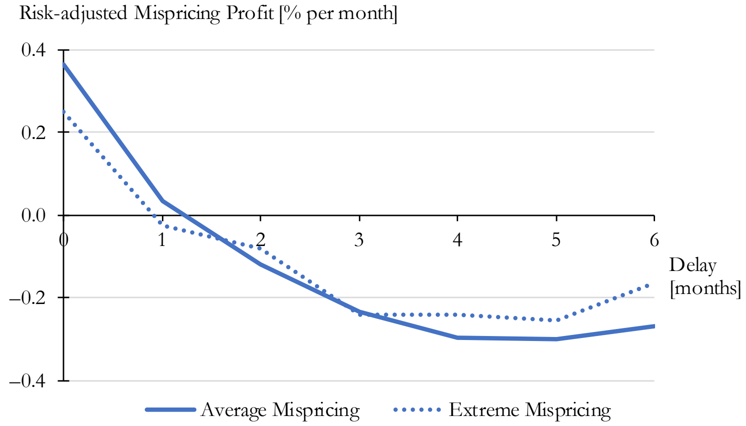
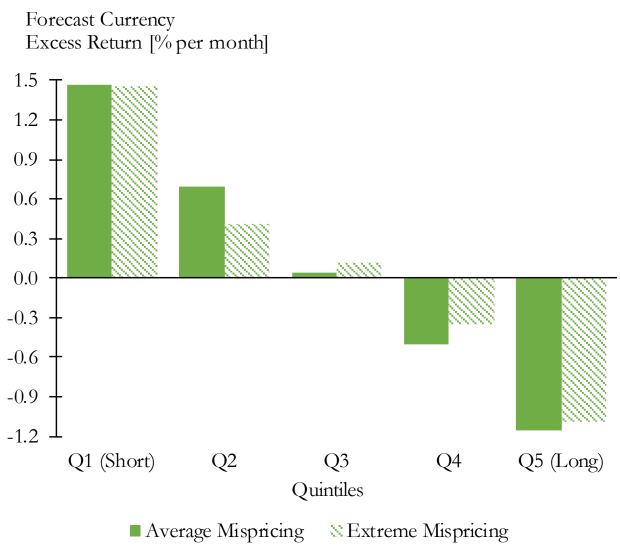


Figure 4: Analysts' Forecast Currency Returns of Currency Mispricing Strategies

The figure shows analysts' forecast currency returns and currency excess returns (in percent per month) for trading strategies based on average mispricing and extreme mispricing. 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 mispricing and extreme mispricing and combined into equally 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 one-month forecast in month *t* and its spot rate in month *t*. Forecast currency excess returns are the log difference between the one-month forward exchange rate of month *t* and the foreign currency's one-month forecast in month *t*. Average mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 mispricing 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. Panel A shows results for forecast currency excess returns, while Panel B shows results for forecast currency returns. The sample includes 62 currencies. The sample period is from December 1989 to December 2019. Table A3 in the Appendix provides details on variable definitions.

Panel A: Forecast Currency Excess Returns



Panel B: Forecast Currency Returns

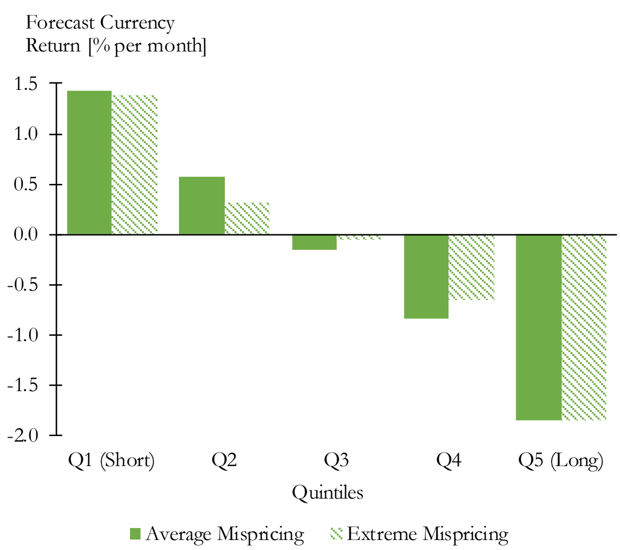
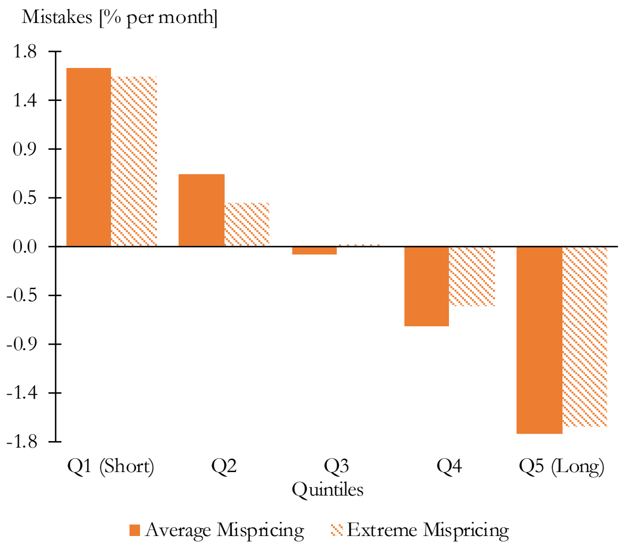


Figure 5: Analysts' Mistakes of Currency Mispricing Strategies

The figure shows analysts' mistakes (in percent) for trading strategies based on mispricing and 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 average mispricing, extreme mispricing and individual currency predictors and subsequently combined into equally 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 one-month forecast in month *t* and its spot rate in month *t*. Average mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 mispricing 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. Panel A shows analysts' mistakes by mispricing quintile, while Panel B shows analysts' mistakes by individual currency predictor quintile. The sample includes 62 currencies. The sample period is from December 1989 to December 2019. Table A3 in the Appendix provides details on variable definitions.

Panel A: Mistakes by Mispricing Quintile



Panel B: Mistakes by Predictor Quintile

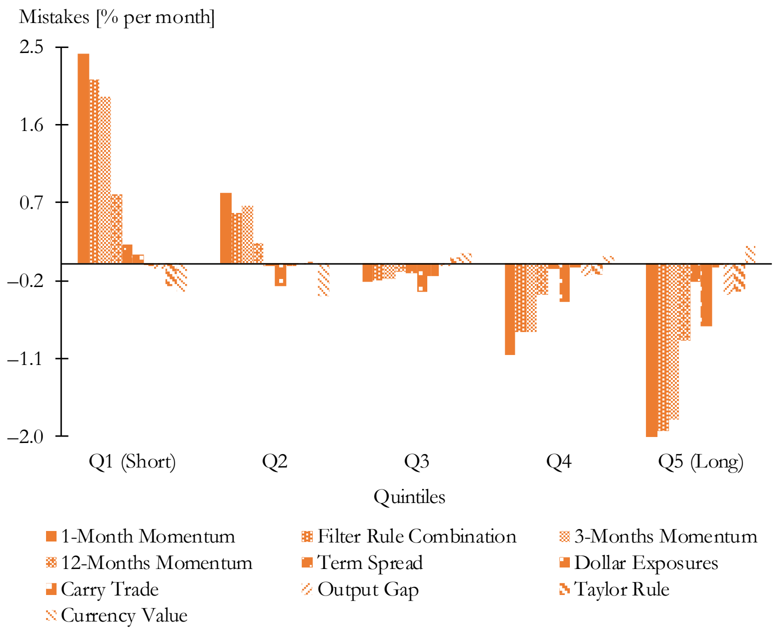


Table 1: Regression of Predictor Profits on Post-Publication Indicators

The table 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 transactions 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 equally 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 zero otherwise. The Post-Publication indicator takes the value 1 if the month is after the posting date on SSRN, and zero 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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-Squared. Standard errors are computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between returns. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 76 currencies. The sample period is from January 1971 to December 2019. Table A3 in the Appendix provides details on variable definitions. Table A7 in the Appendix provides details on the predictors' original sample period used in the paper as well as date of publication.

(continued)

Table 1: Regression of Predictor Profits on Post-Publication Indicators (continued)

	Predictor Profits Gross of Transaction Costs				Predictor Profits Net of Transaction Costs			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Post-Sample	0.038	0.054	0.075	–0.536*	0.120	0.150	0.158	–0.443
	(0.233)	(0.233)	(0.233)	(0.298)	(0.233)	(0.229)	(0.229)	(0.297)
Post-Publication	–0.398***	0.005	–0.096	–0.446***	–0.350***	–0.140*	–0.158*	–0.417***
	(0.110)	(0.214)	(0.177)	(0.124)	(0.110)	(0.081)	(0.082)	(0.124)
Post-Publication x Average Predictor In-Sample Profits		–0.696				–1.473***		
		(0.446)				(0.480)		
Post-Publication x Average Predictor In-Sample t-statistics			–0.066				–0.190***	
			(0.049)				(0.066)	
Average Predictor In-Sample Profits		0.998***				0.946***		
		(0.106)				(0.251)		
Average Predictor In-Sample t-statistics			0.136***				0.136***	
			(0.014)				(0.034)	
Observations	4,681	4,681	4,681	3,660	4,681	4,681	4,681	3,660
R–Squared	0.01	0.04	0.04	0.01	0.01	0.01	0.01	0.01
Number 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 x Average Predictor In-Sample Profits	0.140			0.359	0.065			0.029
Null: Post-Publication + (Post-Publication x Average Predictor In-Sample Profits) = 0		0.010				0.001		
Null: Post-Publication + (Post-Publication x Average Predictor In-Sample t-statistics) = 0			0.242				0.000	

Table 2: Time Trends, Crises, Risk Premia, and Persistence in Currency Predictors

The table 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 and equity market risk factors, and prior predictor profits. Results are shown alternatively for trading profits gross and net of transaction costs, where transactions 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 equally 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 zero 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, etc. as identified in the literature (Laeven and Valencia, 2020; Reinhart and Rogoff, 2014)) 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), and the skewness risk factor following Burnside (2012), Menkhoff et al. (2012b) and Rafferty (2012). 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 (Mkt_RF), 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). 1-Month Predictor Profit and 12-Month 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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-Squared. Standard errors are computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between returns. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 76 currencies. The sample period is from January 1971 to December 2019. Table A3 in the Appendix provides details on variable definitions. Table A7 in the Appendix provides details on the predictors' original sample period used in the paper as well as date of publication.

(continued)

Table 2: Time Trends, Crises, Risk Premia, and Persistence in Currency Predictors (continued)

	Predictor Profits Gross of Transaction Costs					Predictor Profits Net of Transaction Costs				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Post-Publication		–0.466***	–0.389***	–0.346***	–0.329***		–0.594***	–0.441***	–0.305***	–0.287***
		(0.136)	(0.118)	(0.097)	(0.109)		(0.135)	(0.117)	(0.096)	(0.108)
Time	–0.080**	0.029				–0.036	0.103**			
	(0.037)	(0.046)				(0.037)	(0.046)			
Level of Interest Rates			0.036**					0.007		
			(0.018)					(0.017)		
Exchange Rate Volatility			–0.752***					–0.965***		
			(0.238)					(0.235)		
NBER U.S. Business Cycle Contractions			–0.172					–0.140		
			(0.171)					(0.170)		
Crisis			–0.905					–0.872		
			(0.727)					(0.720)		
Dollar Risk Factor				–0.346***					–0.402***	
				(0.054)					(0.057)	
Carry Trade Risk Factor				–0.217***					–0.335***	
				(0.065)					(0.079)	
Volatility Risk Factor				–0.050					–0.100*	
				(0.047)					(0.052)	
Skewness Risk Factor				0.178***					0.205***	
				(0.024)					(0.025)	
1-Month Predictor Profit					–0.013					–0.010
					(0.020)					(0.020)
12-Months Predictor Profit					0.018***					0.020***
					(0.005)					(0.005)
Observations	4,681	4,681	4,673	4,672	4,549	4,681	4,681	4,673	4,672	4,549
R–Squared	0.01	0.01	0.01	0.06	0.01	0.00	0.01	0.02	0.07	0.01
Number 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
9 Equity Market Risk Factors	No	No	No	Yes	No	No	No	No	Yes	No
2 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

Table 3: Publication Effects Controlling for Earlier Related Research

The table reports results from regressions of currency predictor profits (in percent per month) on an indicator variable for post-publication periods, and control variables for the dissemination of earlier related research. Alternative groups of relevant research are academic publications on related FX strategies, practitioner articles on FX strategies, newspaper articles on FX strategies, academic publications on corresponding equity strategies, and academic publications on corresponding fixed income strategies. Controls are for dissemination of earlier related research are either pooled across types of earlier publications or for each individual paper. Results are shown alternatively for trading profits gross and net of transaction costs, where transactions 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 equally 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 zero 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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-Squared. Standard errors are computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between returns. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 76 currencies. The sample period is from January 1971 to December 2019. Table A3 in the Appendix provides details on variable definitions. Table A7 in the Appendix provides details on the predictors' original sample period used in the paper as well as date of publication. Table A8 in the Appendix provides details on the dissemination of earlier related research.

	Predictor Profits Gross of Transaction Costs		Predictor Profits Net of Transaction Costs	
	Pooled	Individual	Pooled	Individual
Post-Publication	–0.422***	–0.408***	–0.479***	–0.427***
	(0.122)	(0.118)	(0.122)	(0.118)
Academic Publications on Related FX Strategies	–0.262**		–0.095	
	(0.133)		(0.133)	
Practitioner Articles on FX Strategies	0.617***		0.676***	
	(0.187)		(0.185)	
Newspaper Articles on FX Strategies	–0.152		–0.116	
	(0.150)		(0.149)	
Academic Publications on Corresponding Equity Strategies	0.356**		0.414**	
	(0.162)		(0.162)	
Academic Publications on Corresponding Fixed Income Strategies	–0.014		0.032	
	(0.169)		(0.168)	
Observations	4,681	4,681	4,681	4,681
R–Squared	0.01	0.02	0.01	0.02
Number of Predictors	11	11	11	11
Earlier Related Publication Fixed Effects	No	Yes	No	Yes
Predictor Fixed Effects	Yes	Yes	Yes	Yes
Standard Errors	FGLS	FGLS	FGLS	FGLS

Table 4: Publication Effects and Limits to Arbitrage

The table 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 exchange rate turnover (from the BIS, 2019), 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 equally 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 zero 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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-Squared. Standard errors are computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between returns. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 76 currencies. The sample period is from January 1971 to December 2019. Table A3 in the Appendix provides details on variable definitions. Table A7 in the Appendix provides details on the predictors' original sample period used in the paper as well as date of publication.

	Bid/Ask Spreads	Capital Restrictions
	(1)	(2)
Post-Publication	–1.361***	–2.779**
	(0.468)	(1.144)
Post-Publication x Limits to Arbitrage	5.925**	3.688**
	(2.725)	(1.871)
Limits to Arbitrage	1.413	–0.079
	(1.354)	(1.299)
Intercept	0.338	0.669
	(0.231)	(0.796)
Observations	4,681	3,102
R–Squared	0.01	0.02
Number of Predictors	11	11
Standard Errors	FGLS	FGLS
Null: (Post-Publication x Arbitrage Costs) + Arbitrage Costs = 0	0.002	0.017

Table 5: Quintile Performance of Portfolios Sorted on Currency Mispricing

The table 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 mispricing and extreme mispricing, 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 mispricing and extreme mispricing and combined into equally weighted portfolios. The table shows 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 one-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 four currency factors (4-Factor Model), or four currency factors, nine equity market factors and two bond market factors (15-Factor Model). The four 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), and a skewness risk factor (Burnside, 2012; Menkhoff et al., 2012b; Rafferty, 2012). 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 (Mkt_RF), 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). Panel C shows realized currency excess returns adjusted for risk using Fama-MacBeth cross-sectional regressions with expected currency excess returns from Instrumented Principal Component Analysis (IPCA) (Kelly et al., 2019). The IPCA is implemented with eleven 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 zero. The IPCA model has two latent factors (K = 2) and the fifteen currency, equity and bond factors from Panel B as observable factors (M = 15). Fama MacBeth regressions regress currency excess returns cross-sectionally on dummies for mispricing 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 Fama-MacBeth regressions of currency excess returns on IPCA expected returns and dummy variables for quintiles one to five (and no regression intercept), while the risk-adjusted excess returns of the quintile spread portfolios are from Fama-MacBeth regressions of currency excess returns on IPCA expected returns, dummies for mispricing quintiles two to five, 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 one-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 mispricing is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 December 1989 to December 2019. Table A3 in the Appendix provides details on variable definitions.

(continued)

Table 5: Quintile Performance of Portfolios Sorted on Currency Mispricing (continued)

	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 Mispricing	–0.184	0.025	0.118	0.238	0.575	0.759	[6.91]	0.434	[3.95]
Extreme Mispricing	–0.105	0.009	0.102	0.200	0.578	0.683	[6.34]	0.343	[3.19]
Currency Returns									
Average Mispricing	–0.228	–0.098	–0.070	–0.103	–0.123	0.105	[0.96]	–0.129	[–1.17]
Extreme Mispricing	–0.173	–0.088	–0.077	–0.099	–0.177	–0.004	[–0.03]	–0.247	[–2.26]
Panel B: Factor Model Time-Series Regressions with Realized Excess Returns									
4-Factor Model									
Average Mispricing	–0.462	–0.046	0.062	0.218	0.463	0.925	[7.32]	0.393	[3.94]
Extreme Mispricing	–0.334	–0.059	0.069	0.155	0.431	0.765	[6.03]	0.294	[2.94]
15-Factor Model									
Average Mispricing	–0.501	–0.045	0.036	0.251	0.423	0.924	[6.83]	0.385	[3.61]
Extreme Mispricing	–0.377	–0.027	0.068	0.132	0.393	0.770	[5.69]	0.288	[2.70]
Panel C: Fama-MacBeth Cross-sectional Regressions with Realized Excess Returns									
Unconstrained IPCA Model									
Average Mispricing	–0.147	0.031	0.091	0.147	0.402	0.549	[5.30]		
Extreme Mispricing	–0.103	0.085	0.034	0.099	0.378	0.481	[5.26]		
Constrained IPCA Model									
Average Mispricing	–0.095	0.018	–0.035	-0.018	0.165	0.260	[2.66]		
Extreme Mispricing	–0.096	0.043	–0.054	–0.042	0.191	0.288	[3.01]		
Panel D: Forecast Returns									
Currency Excess Returns									
Average Mispricing	1.466	0.697	0.038	–0.503	–1.153	–2.620	[–26.8]		
Extreme Mispricing	1.459	0.407	0.120	–0.355	–1.092	–2.551	[–26.1]		
Currency Returns									
Average Mispricing	1.422	0.574	–0.151	–0.844	–1.852	–3.274	[–33.1]		
Extreme Mispricing	1.391	0.310	–0.060	–0.655	–1.847	–3.238	[–32.6]		

Table 6: Currency Mispricing and Forecast Returns

The table reports results from regressions of forecast currency returns and currency excess returns (in percent per month) on average mispricing and extreme mispricing and control variables. Forecast currency returns are the negative log difference of a foreign currency's one-month forecast in month *t* and its spot rate in month *t*. Forecast currency excess returns are the log difference between the one-month forward exchange rate of month *t* and the foreign currency's one-month forecast in month *t*. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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-Squared. Standard errors are clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 62 currencies. The sample period is from December 1989 to December 2019. Table A3 in the Appendix provides details on variable definitions.

	Forecast Currency Excess Returns		Forecast Currency Returns	
	Average Mispricing	Extreme Mispricing	Average Mispricing	Extreme Mispricing
Mispricing	–7.851***	–3.571***	–9.618***	–4.450***
	(0.630)	(0.311)	(0.655)	(0.325)
Number of Forecasters	–0.013***	–0.012***	–0.007***	–0.006**
	(0.003)	(0.003)	(0.002)	(0.002)
Single Forecast	–0.134	–0.074	–0.186	–0.115
	(0.330)	(0.319)	(0.253)	(0.243)
Intercept	5.643***	1.566***	6.553***	1.588***
	(0.741)	(0.346)	(0.754)	(0.229)
Observations	11,893	11,893	11,893	11,893
R–Squared	0.43	0.42	0.51	0.49
Month Fixed Effects	Yes	Yes	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country

Table 7: Analysts' Mistakes and Currency Mispricing

The table reports results from regressions of analysts' mistakes (in percent per month) on mispricing 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 one-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 mispricing is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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. Mispricing (out-of-sample) is average or extreme mispricing using 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-Squared. Standard errors are clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 62 currencies. The sample period is from December 1989 to December 2019. Table A3 in the Appendix provides details on variable definitions.

	Average Mispricing				Extreme Mispricing			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Mispricing	–9.563***	–9.633***	–7.973***		–4.359***	–4.647***	–3.624***	
	(0.653)	(0.880)	(0.627)		(0.318)	(0.435)	(0.309)	
Mispricing x Publication		3.197***				1.912***		
		(1.000)				(0.476)		
Publication		–1.755***				–0.008		
		(0.573)				(0.173)		
Realized Excess Returns			–0.928***				–0.932***	
			(0.028)				(0.028)	
Mispricing (out-of-sample)				–11.02***				–5.064***
				-0.93				-0.434
Number of Forecasters	–0.011***	–0.009***	–0.013***	–0.010***	–0.009***	–0.008***	–0.011***	–0.005*
	(0.003)	(0.002)	(0.003)	-0.003	(0.003)	(0.002)	(0.003)	-0.003
Single Forecast	–0.148	–0.170	–0.135	0.465	–0.075	–0.149	–0.074	0.285
	(0.304)	(0.225)	(0.328)	-0.302	(0.292)	(0.215)	(0.317)	-0.276
Intercept	5.737***	5.248***	5.649***	3.154***	0.775	0.214	1.513***	5.151***
	(0.952)	(0.549)	(0.740)	-0.741	(0.882)	(0.144)	(0.368)	-0.75
Observations	11,893	11,893	11,893	9,603	11,893	11,893	11,893	9,603
R–Squared	0.44	0.08	0.72	0.41	0.43	0.07	0.72	0.41
Month Fixed Effects	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country	Country	Country	Country	Country

Table 8: Mispricing and Changes in Currency Forecasts

The table 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 mispricing and extreme mispricing, respectively, and control variables. Average mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 mispricing 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-Squared. Standard errors are clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 62 currencies. The sample period is from December 1989 to December 2019. Table A3 in the Appendix provides details on variable definitions.

	Average Mispricing			Extreme Mispricing		
	(1)	(2)	(3)	(1)	(2)	(3)
Mispricing (lagged by 1 month)	2.358***			1.037***		
	(0.244)			(0.127)		
Mispricing (lagged by 2 months)		0.598**			0.253**	
		(0.242)			(0.123)	
Mispricing (lagged by 3 months)			–0.227			–0.123
			(0.250)			(0.120)
Number of Forecasters	0.005***	0.004***	0.003**	0.005***	0.004***	0.003**
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Single Forecast	0.058	0.013	–0.022	0.037	0.007	–0.021
	(0.133)	(0.107)	(0.100)	(0.130)	(0.106)	(0.100)
Intercept	–1.272*	1.682*	0.555	–0.033	2.000**	0.445
	(0.671)	(0.897)	(1.140)	(0.704)	(0.888)	(1.115)
Observations	11,827	11,759	11,691	11,827	11,759	11,691
R–Squared	0.33	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

Table 9: Analysts' Forecasts and Mispricing

The table reports results from Fama-MacBeth (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 mispricing 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 mispricing and analysts' forecasts of currency excess returns. Forecast currency excess returns are the log difference between the one-month forward exchange rate of month *t* and the foreign currency's one-month forecast in month *t*. Average mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 mispricing 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 Fama-MacBeth coefficients, associated *t*-statistic (in square brackets) and significance levels, as well as the average number of observations and the average R-Squared. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 62 currencies. The sample period is from December 1989 to December 2019. Table A3 in the Appendix provides details on variable definitions.

	Average Mispricing			Extreme Mispricing		
	Coefficient	*t*-statistic		Coefficient	*t*-statistic	
Mispricing Q2	0.227	[2.83]	***	0.171	[2.01]	**
Mispricing Q3	0.311	[2.95]	***	0.252	[2.39]	**
Mispricing Q4	0.527	[4.44]	***	0.432	[3.69]	***
Mispricing Q5	0.955	[7.20]	***	0.833	[6.74]	***
Forecast Excess Return Q2	0.195	[2.44]	**	0.137	[1.59]	
Forecast Excess Return Q3	0.224	[2.35]	**	0.133	[1.24]	
Forecast Excess Return Q4	0.287	[2.45]	**	0.125	[0.98]	
Forecast Excess Return Q5	0.457	[3.24]	***	0.381	[2.75]	***
Intercept	–0.484	[–3.66]	***	–0.334	[–2.28]	**
Average Number of Observations	33			33		
Average R–Squared	0.41			0.40		

Appendix A: Exchange Rate Forecasts Data

This appendix describes details and sources of the exchange rate forecast data we use to measure analysts exchange rate expectations. All datasets are based on surveys of currency analysts. The appendix first describes our main data set, provided by Consensus Economics, a specialist firm who undertake a wide range of surveys. It subsequently contrasts it with two well-known alternative FX forecast survey data sets, Refinitiv Consensus FX Forecasts (Thomson Reuters Polls) and Bloomberg FX Forecasts, which are used for robustness checks. Table A1 summarizes some of the key features.

A.1 Consensus Economics Forecasts

Consensus Economics conducts a monthly survey asking FX analysts in financial markets and economic institutions for their currency exchange rate projections. At the beginning of each month, participants are asked for forecasts of their home country's nominal spot exchange rate, in most cases with respect to the U.S. dollar (or the Euro). Analysts in larger more internationally orientated contributing institutions may also provide forecasts for other currencies. Consensus Economics specify a day in the month by which a response is required, typically the same for all participants: the first Monday in each month until March 1994, and the second Monday since April 1994. Forecasts are made for 1, 3, 12 and 24 months ahead. The earliest data available is from October 1989 for major currencies and (mostly) the mid to late 1990s otherwise. For each currency pair and horizon, the survey reports the mean, standard deviation (from January 2003), the highest and lowest predictions and the number of forecasters.

The survey draws on around 250 forecasters in 27 countries covering up to 37 major and 56 additional currencies, mostly with respect to the U.S. dollar and Euro. The number of survey participants ranges considerably according to the currency, from approximately 100 for the more traded currencies, to around 20 for the Chinese Renminbi and Indian Rupee. Numbers may be lower for less liquid currencies such as Czech Krona, Russian Ruble, Argentinian Peso and Brazilian Real. Survey participants include a wide range of financial and economic institutions, e.g., BNP Paribas, Commerzbank, Citigroup, Goldman Sachs, Deutsche Bank, Royal Bank of Canada, Royal Bank of Scotland, Santander, Société Générale, Oxford Economics, EIU, WIIW, NIESR.

A.2 Refinitiv Consensus FX Forecasts (Thomson Reuters Polls)

The first of the alternative FX forecast data sources, Refinitiv Consensus FX Forecasts*,* provides FX forecasts based on Reuters polls, which are surveys of expert forecasts for bilateral exchange rates, mostly with respect to the U.S. dollar. Refinitiv send an electronic questionnaire to a selected set of contributors asking for their forecast of the currency pairs. The poll is generally published during the first week of the month, although there are exceptions whereby the poll maybe delayed to the middle of the month, or in rare occasions are not published if the response rate is very low. The Refinitiv survey is a snap poll, and a fresh or new poll is conducted every month. Respondents are required to provide their forecast only during the window while the poll is open. The responses are published once the poll is closed. Thus, participants cannot see other forecasts until the close of the poll. Unlike Bloomberg, surveys by Refinitiv (and Consensus Economics) do not use rolling time windows. Most of the currencies are polled once a month, though there are some that are polled once a quarter (13 out of the 61 currencies/currency pairs).

Forecasts are reported for horizons of 1, 3, 6 and 12 months ahead, where the earliest date data is available from is May 1993. The survey reports the mean, median, high, low, and standard deviation of the responses, as well as the number of forecasters. Refinitiv Forecasts have a narrower range of currencies compared to the Consensus Economics FX forecasts, with 36 currencies and 25 cross currency pairs. The total number of contributors to the poll varies across currencies, from approximately 85 for the major currencies, falling to as low as 5 for the less traded currencies for Vietnam, Kenya, or Zambia.

The participants are chosen in order to represent a wide range of views. They include economists and financial markets strategists from the sell-side as well as buy-side, plus independent researchers, and some academics. Some examples include Rabobank, ZKB, Westpac, DZ Bank, Continuum Economics, Wells Fargo Julius Baer, Barclays, Citigroup, Desjardins, MUFG, ANZ, DNB, JP Morgan, Société Générale, Commerzbank and many more.

A.3 Bloomberg FX Forecasts

The second set of alternative FX forecasts are those available from Bloomberg. On any given day FX forecasts, produced by a wide range of major banks and financial institutions, are quoted on Bloomberg Terminals. Summary consensus measures on the last trading of a month are calculated as the mean and median of all the contributor's forecasts reported on Bloomberg Terminals in the prior 36 days. The use of a rolling time window causes the aggregate measures to vary from day to day. The 36-day time frame also potentially increases the heterogeneity in the information set of the individual forecasters, as compared with the Consensus Economics and Refinitiv data sets that have much narrower time windows over which the forecasts are made.

In contrast to Consensus Economics and Refinitiv the forecast horizons are for calendar quarters rather than months. Forecasts reported in March, June, September, and December are for the next four calendar quarters and for the remaining months are for the current and next three calendar quarters. Forecasts for the next four years are also reported. The earliest date data is available from is from December 2006. Surveys report the mean, median, high, and low forecasts. Bloomberg reports forecasts for more than 41 currencies (60 currency pairs), most with respect to the U.S. dollar, including all major traded currencies. The number of participants varies over time and currencies. For major currencies including the Euro, Pound, Yen, Australian Dollar, New Zealand Dollar and Danish Krona with respect to the U.S. Dollar the approximate number of participants increases from around 30 in 2006 to 50 in 2012 and 75 in 2018.

As with Consensus Economics and Refinitiv, survey participants include a wide range of financial and economic institutions. Among many others the range of contributing institutions include: Barclays, Bank of America, Merrill Lynch, Commerzbank, Morgan Stanley, X-Trade Brokers, Citigroup, China Construction Bank (Asia), Lloyds Bank Commercial, PKO Bank Polski, Validus Risk Management, BNP Paribas, DZ Bank, Mizuho Bank, Maybank Singapore, Standard Chartered, ABN Amro, JPMorgan Chase, Investment Capital Ukraine, Banco Santander, Vadilal Forex, Standard Bank Group.

Appendix B: Instrumented Principal Components Analysis

This appendix summarizes the main features of Instrumented Principal Components Analysis (IPCA), developed in Kelly et al. (2019) and used, among others, for U.S. stock returns (Kelly et al., 2021; Gu et al., 2020; Kelly et al., 2019), international stock returns (Bartram and Grinblatt, 2021), corporate bond returns (Kelly et al., 2020), and option returns (Büchner and Kelly, 2022).

The general IPCA model specifies an excess return as

$$
\begin{aligned}
r_{i,t+1} &= \alpha_{i,t} + \beta_{i,t} f_{t+1} + \varepsilon_{i,t+1}, \\
\alpha_{i,t} &= z'_{i,t}\Gamma_{\alpha} + \nu_{\alpha,i,t}, \quad \beta_{i,t} = z'_{i,t}\Gamma_{\beta} + \nu_{\beta,i,t},
\end{aligned}
\tag{B.1}
$$

where $r_{i,\,t+1}$ is the excess return of currency i (i = 1,…,N) in month t + 1 (t = 1, …, T). A key feature is individual currencies having dynamic factor loadings, $\beta_{i,t}$, on a vector of K latent factors, f_{t+1}. Factor loadings are parameterized to depend on observable currency characteristics in the $L \times 1$ vector of instruments $z_{i,\,t}$ (which includes a constant). The use of time-varying instruments allows estimating dynamic factor loadings. The space of currency characteristics is reduced by the matrix Γ_β that maps a larger number of characteristics into a smaller number of risk exposures ($K < L$). The term $\nu_{\beta,i,t}$ allows for risk exposures that are not perfectly captured by observable characteristics. Analogously, the structure of $a_{i,\,t}$ is a linear combination of the characteristics, where the weights are defined by the matrix Γ_a.

The IPCA framework can further accommodate observable factors to nest commonly studied factor models with pre-specified factors. A general specification of the resulting model augments equation (B.1) by an additional term capturing the return component related to observable factors:

$$
\begin{aligned}
r_{i,t+1} &= \alpha_{i,t} + \beta_{i,t} f_{t+1} + \delta_{i,t} g_{t+1} + \varepsilon_{i,t+1}, \\
\delta_{i,t} &= z'_{i,t}\Gamma_{\delta} + \nu_{\delta,i,t},
\end{aligned}
\tag{B.2}
$$

where g_{t+1} is an M × 1 vector of observable factors. Currencies are allowed to have dynamic loadings $\delta_{i,\,\mathrm{t}}$ on these factors conditional on the same set of instruments that are mapped into loadings by the L × M matrix Γ_δ.

Table A1: Foreign Exchange Forecasts Data Sets

The table reports details on foreign exchange rate forecasts from alternative data sources (Consensus Economics, Refinitiv, Bloomberg).

	Consensus Economics	Refinitiv	Bloomberg
Number of currencies	93 currencies (with respect to the dollar, Euro or Yen)	36 currencies and 25 cross currency pairs (mostly with respect to US dollar)	41 currencies (60 currency pairs)
Frequency	Monthly	Monthly	Daily/Real-time
Start date	December 1989	May 1993	December 2006
Number of participants	100 (for major traded currencies)	85 (for major traded currencies)	75 (for major traded currencies)
Forecasters time window	First two weeks of the month	First week of the month	Prior 36 days
Forecast horizons	1, 3, 12 and 24 months	1, 3, 6, and 12 months	1, 2, 3 and 4 quarters; 1, 2, 3 and 4 years
Statistics	Mean, high, low, standard deviation, number of forecasters	Mean, median, high, low, standard deviation, number of forecasters	Mean, median, high, low
Types of participants	Financial and economic institutions	Financial and economic institutions	Financial and economic institutions
Common set of currencies	Argentine Peso, Australian Dollar, Brazilian Real, Canadian Dollar, Chilean Peso, Chinese Renminbi, Colombian Peso, Czech Koruna, Egyptian Pound, Euro, Hong Kong Dollar, Hungarian Forint, Indian Rupee, Indonesian Rupiah, Japanese Yen, Kazakhstani Tenge, Malaysian Ringgit, Mexican Peso, , New Zealand Dollar, Norwegian Krone, Peruvian New Sol, Philippine Peso, Polish Zloty, Romanian Leu, Russian Rouble, Serbian Dinar, Singaporean Dollar, South African Rand, South Korean Won, Swedish Krona, Swiss Franc, Taiwanese Dollar, Thai Baht, Turkish Lira, Ukrainian Hryvnia, United Kingdom Pound, Vietnamese Dong		
Additional currencies	Austrian Schilling, Belgian Franc, Bulgarian Lev, Croatian Kuna, Cypriot Pound, Danish Krone, Estonian Kroon, Finnish Markka, French Franc, Deutschemark, Greek Drachma, Irish Punt, Israeli Shekel, Italian Lira, Latvian Lats, Lithuanian Litas, Netherlands Guilder, Nigerian Naira, Pakistani Rupee, Portuguese Escudo, Saudi Arabian Riyal, Slovakian Koruna, Slovenian Tolar, Spanish Peseta, Sri Lankan Rupee	Nigeria Naira, Kenyan Shilling, Ghanaian Cedi, Zambian Kwacha	Bulgarian Lev, Danish Krona, Israeli Shekel, Saudi Arabian Riyal

Table A2: Currency Sample Periods

The table reports details on currency data series. For each country, it reports the start date and end date of its currency data.

		Sample Period	
Country	Currency	Start Date	End Date
Argentina	Argentine Peso	March 2004	December 2019
Australia	Australian Dollar	December 1984	December 2019
Austria	Austrian Schilling	December 1970	December 1998
Bahrain	Bahrain Dinar	March 2004	December 2019
Belgium	Belgian Franc	December 1970	December 1998
Brazil	Brazilian Real	March 2004	December 2019
Bulgaria	Bulgarian Lev	March 2004	December 2019
Canada	Canadian Dollar	December 1970	December 2019
Chile	Chilean Peso	March 2004	December 2019
China	Chinese Renminbi	February 2002	December 2019
Colombia	Colombian Peso	March 2004	December 2019
Croatia	Croatian Kuna	March 2004	December 2019
Cyprus	Cypriot Pound	March 2004	December 2007
Czech Republic	Czech Koruna	December 1996	December 2019
Denmark	Danish Krone	December 1970	December 2019
Egypt	Egyptian Pound	March 2004	December 2019
Estonia	Estonian Kroon	March 2004	December 2010
Euro Area	Euro	January 1999	December 2019
Finland	Finnish Markka	December 1996	December 1998
France	French Franc	December 1970	December 1998
Germany	Deutschemark	December 1970	December 1998
Ghana	Ghana Cedi	July 2011	December 2019
Greece	Greek Drachma	December 1996	December 2000
Hong Kong	Hong Kong Dollar	October 1983	December 2019
Hungary	Hungarian Forint	October 1997	December 2019
Iceland	Iceland Krona	March 2004	December 2019
India	Indian Rupee	October 1997	December 2019
Indonesia	Indonesian Rupiah	December 1996	December 2019
Ireland	Irish Punt	December 1970	December 1998
Israel	Israeli Shekel	March 2004	December 2019
Italy	Italian Lira	December 1970	December 1998
Japan	Japanese Yen	June 1978	December 2019
Jordan	Jordanian Dinar	March 2004	December 2019
Kazakhstan	Kazakhstani Tenge	March 2004	December 2019
Kenya	Kenyan Schilling	March 2004	December 2019
Kuwait	Kuwaiti Dinar	January 1994	December 2019
Latvia	Latvian Lats	March 2004	December 2013
Lithuania	Lithuanian Litas	March 2004	December 2014
Malaysia	Malaysian Ringgit	December 1996	December 2019

(continued)

Table A2: Currency Sample Periods (continued)

		Sample Period	
Country	Currency	Start Date	End Date
Malta	Maltese Lira	March 2004	December 2007
Mexico	Mexican Peso	December 1996	December 2019
Morocco	Moroccan Dirham	March 2004	December 2019
Netherlands	Netherlands Guilder	December 1970	December 1998
New Zealand	New Zealand Dollar	December 1984	December 2019
Nigeria	Nigerian Naira	April 2011	December 2019
Norway	Norwegian Krone	December 1970	December 2019
Oman	Omani Rial	March 2004	December 2019
Pakistan	Pakistani Rupee	March 2004	December 2019
Peru	Peruvian New Sol	March 2004	December 2019
Philippines	Philippine Peso	December 1996	December 2019
Poland	Polish Zloty	February 2002	December 2019
Portugal	Portuguese Escudo	January 1981	December 1998
Qatar	Qatar Rial	March 2004	December 2019
Romania	Romanian Leu	March 2004	December 2019
Russia	Russian Rouble	March 2004	December 2019
Saudi Arabia	Saudi Arabian Riyal	December 1996	December 2019
Serbia	Serbian Dinar	July 2011	December 2019
Singapore	Singaporean Dollar	December 1984	December 2019
Slovakia	Slovakian Koruna	February 2002	December 2008
Slovenia	Slovenian Tolar	March 2004	December 2006
South Africa	South African Rand	October 1983	December 2019
South Korea	South Korean Won	February 2002	December 2019
Spain	Spanish Peseta	December 1970	December 1998
Sri Lanka	Sri Lankan Rupee	July 2011	December 2019
Sweden	Swedish Krona	December 1970	December 2019
Switzerland	Swiss Franc	December 1970	December 2019
Taiwan	Taiwanese Dollar	December 1996	December 2019
Thailand	Thai Baht	December 1996	December 2019
Tunisia	Tunisian Dinar	March 2004	December 2019
Turkey	Turkish Lira	December 1996	December 2019
Uganda	Ugandan Shilling	July 2011	December 2019
Ukraine	Ukrainian Hryvnia	March 2004	December 2019
United Arab Emirates	UAE Dirham	December 1996	December 2019
United Kingdom	United Kingdom Pound	December 1970	December 2019
Vietnam	Vietnamese Dong	July 2011	December 2019
Zambia	Zambia Kwacha	July 2011	December 2019

Table A3: Variable Definitions

The table reports the definitions of the variables used in the study.

Variable	Definition
Currency Returns and Excess Returns	
Currency Return	Negative log difference of spot exchange rates in month $t+1$ and month t (see e.g. Menkhoff et al., 2016; Okunev and White, 2003). Data are from Datastream.
Currency Excess Return	Log difference between the one-month forward exchange rate of month t and the spot exchange rate of month $t+1$ (see e.g. Menkhoff et al., 2016; Lustig, Roussanov, and Verdelhan, 2014; Menkhoff et al., 2012a). Data are from Datastream.
Forecast Currency Return	Negative log difference of a foreign currency's one-month forecast in month t and its spot rate in month t. Foreign currency's one-month ahead forecast data are from Consensus Economics. Spot exchange rates are from Datastream.
Forecast Currency Excess Return	Log difference between the one-month forward exchange rate of month t and the foreign currency's one-month forecast in month t. Foreign currency's one-month ahead forecast data are from Consensus Economics. Forward exchange rates are from Datastream.
Mistakes	Forecast Currency Return – Currency Return.
Currency Predictors	
1-Month Momentum	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on lagged excess returns over the prior month, and combined into equally weighted portfolios. The 1-Month Momentum strategy goes long portfolio Q5 and short Q1 (e.g. Menkhoff et al., 2012a).
3-Months Momentum	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on lagged excess returns over the prior three months and combined into equally weighted portfolios. The 3-Months Momentum strategy goes long portfolio Q5 and short Q1 (e.g. Menkhoff et al., 2012a).
12-Months Momentum	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on lagged excess returns over the prior twelve months and combined into equally weighted portfolios. The 12-Months Momentum strategy goes long portfolio Q5 and short Q1 (e.g. Asness et al., 2013).
Filter Rule Combination	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on the average percentile rank of 354 moving average rules (i.e. are combined using equal weights). The 354 moving average rules are based on the difference between short-run (SR) and long-run (LR) moving averages of currency returns, where SR ranges from 1 – 12 months and LR ranges from 2 – 36 months. The Filter Rule Combination strategy goes long portfolio Q5 and short Q1 (e.g. Okunev and White, 2003).
Carry Trade	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on forward discounts and combined into equally weighted portfolios. The Carry Trade strategy goes long portfolio Q5 and short Q1 (e.g. Lustig et al., 2011).
Dollar Carry Trade	At the end of each month, we calculate the average forward discount (AFD) of developed countries. We categorize a country as developed if it was considered "developed" by Morgan Stanley Capital International (MSCI) as of May 2018, which are Australia, Austria, Belgium, Canada, Denmark, Euro Area, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom and United States. The Dollar Carry Trade strategy goes long all foreign (i.e. non-U.S.) currencies when the AFD is greater than zero and short all foreign currencies when the AFD is equal or less than zero (e.g. Lustig, Roussanov, and Verdelhan, 2014). All currencies are equally weighted.
Dollar Exposures	At the end of each month, for each currency, the change in the exchange rate is regressed on a constant, the interest rate differential, the carry factor, the interaction between interest rate differential and carry factor, and the dollar factor using a 60-month rolling window. The carry factor is the average change in exchange rates between high interest rate countries and low interest rate countries based on quintiles. The dollar factor is the average change in exchange rates across all currencies. Currencies are sorted into five quintiles (Q1 to Q5), from low to high, based on the slope coefficients for the dollar factor and combined into equally weighted portfolios. Each month, for each quintile, the Dollar Exposures strategy goes long when the AFD of developed countries is positive and goes short otherwise (e.g. Verdelhan, 2018).

(continued)

Table A3: Variable Definitions (continued)

Variable	Definition
Term Spread	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on the difference between their long-term interest rates and short-term interest rates and combined into equally weighted portfolios. The Term Spread strategy goes long portfolio Q5 and short Q1 (e.g. Ang and Chen, 2010). Short-term rates are three months interest rates (interbank or Treasury bills) and long-term rates are ten year (or if unavailable five year) Government bond rates sourced from Datastream.
Currency Value	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on the real exchange rate return (RER) over the prior five years and combined into equally weighted portfolios. The log RER is given by $q_t = -s_t + p^k{}_t - p_t$ where s denotes the exchange rate (in foreign currency units per USD), p^k denotes the price level in country k, and p denotes the U.S. price level. All variables are in logs. Following Asness et al. (2013), we calculate the lagged five-year ($5y$) real exchange rate return as $\Delta^{(5y)}q_t = q_t - q_{t-5y} = -\Delta^{(5y)}s_t + \pi^{(5y),k} - \pi^{(5y)}$. The Currency Value strategy goes long portfolio Q5 and short Q1 (e.g. Menkhoff et al., 2016). Real time data on Consumer Price Indices (CPI) to calculate real exchange rates are from OECD's Original Release Data and Revisions Database.
Output Gap	At the end of each month, currencies are sorted into quintiles (Q1 to Q5) from low to high based on the output gap and combined into equally weighted portfolios. The output gap is calculated from detrending the monthly industrial production index (IPI) for each country. Specifically, the residuals from a regression of IPI_t on a constant and IPI_{t-13}, IPI_{t-14}, ..., IPI_{t-24} (corresponding to p=12 and h=24 in Hamilton (2018)) are a measure of detrended output gap. The procedure is implemented recursively conditioning on data available at the time of sorting. The Output Gap strategy goes long portfolio Q5 and short Q1 (e.g. Colacito, Riddiough and Sarno, 2020). Real time data on industrial production are from OECD's Original Release Data and Revisions Database.
Taylor Rule	At the end of each month, currencies are sorted into quintiles (Q1 to Q5) from low to high based on 1.5 times inflation and 0.5 times the output gap, and combined into equally weighted portfolios. The output gap is calculated following the procedure in the Output Gap strategy. The Taylor Rule strategy goes long portfolio Q5 and short Q1 (e.g. Colacito, Riddiough and Sarno, 2020). Real time data on CPI to calculate inflation and real time data on industrial production are from OECD's Original Release Data and Revisions Database.
Mispricing	
Average Mispricing	Average mispricing is calculated as the average percentile rank of currencies with respect to the underlying Predictors.
Extreme Mispricing	Extreme mispricing is calculated as the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying Predictor strategies, divided by the number of Predictors.
Profits	
Predictor Profit	The Predictor profit in a month is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1) based on a predictor signal.
Mispricing Profit	The mispricing profit in a month is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1) based on average mispricing or extreme mispricing.
Control Variables	
Post-Sample	An indicator variable that takes the value 1 if the month is after the sample period used in the original study, but still pre-publication, and zero otherwise.
Post-Publication	An indicator variable that takes the value 1 if the month is after posting on SSRN, and zero otherwise.
Time	Time is equal to 1/100 during the first month of the sample and increases by 1/100 each month.
Level of Interest Rates	The average of the short-term interest rates of the currencies that are in the portfolios Q5 and Q1 for a predictor.
Exchange Rate Volatility	The average of the within-month standard deviation of the currencies that are in the portfolios Q5 and Q1 for a predictor using daily currency returns.
NBER US Business Cycle Contractions	An indicator variable that takes the value 1 for U.S. recessions, and zero otherwise.

(continued)

Table A3: Variable Definitions (continued)

Variable	Definition
Crisis	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, or systemic as identified in the literature (Laeven and Valencia, 2020; Reinhart and Rogoff, 2014) in the respective country and 0 otherwise.
Dollar Risk Factor	At the end of each month, we take the average of currency excess returns. (Lustig et al., 2011).
Carry Trade Risk Factor	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on forward discounts and combined into equally weighted portfolios. The Carry Trade Risk Factor is the difference between the currency excess returns of portfolios Q5 and Q1. (Lustig et al., 2011).
Volatility Risk Factor	Monthly volatility risk factor. We calculate the absolute daily log return for each currency on each day, and average over all currencies available on any given day and average daily values up to the monthly. We then calculate volatility innovations by estimating an AR(1) for the average volatility level and take the residuals. To obtain volatility risk factor, we regress volatility innovations on the five carry trade portfolio excess returns, and take the projections on the five portfolios. (Menkhoff et al., 2012b).
Skewness Risk Factor	Monthly skewness risk factor. At the end of each month, currencies are sorted into two groups: one with positive forward discounts and one with negative forward discounts. Next, we calculate the realized within-month skewness of the currencies in the first group, and the negative of the within-month skewness of the currencies in the second group. We take the average of the two skewness statistics across available currencies. To obtain skewness risk factor, we regress the average on the five carry trade portfolio excess returns, and take the projections on the five portfolios. (Burnside, 2012; Rafferty, 2012; Menkhoff et al., 2012b).
Global Equity Risk Factor	Monthly MSCI world market index return net of risk-free rate. The MSCI return data is from Datastream, risk-free rate data is from Ken French website.
Excess Return on Market Portfolio	Monthly US market index return net of risk-free rate (Mkt_RF) (Ken French website)
SMB	Monthly Small Minus Big (SMB) portfolio return (size factor) (Ken French website)
HML	Monthly High Minus Low (HML) portfolio return (value factor) (Ken French website)
CMA	Monthly Conservative Minus Aggressive (CMA) portfolio return (investment factor) (Ken French website)
RMW	Monthly Robust Minus Weak (RMW) portfolio return (profitability factor) (Ken French website)
Momentum	Monthly Momentum (Mom) portfolio return (Ken French website)
Short-term Reversal	Monthly Short-term Reversal (ST_Rev) portfolio return (Ken French website)
Long-term Reversal	Monthly Long-term Reversal (LT_Rev) portfolio return (Ken French website)
Term Spread	Term Spread (TERM) is the difference between the monthly long-term government bond return (Amit Goyal website) and the one-month Treasury bill rate (Ken French website) (Fama and French, 1993)
Default Spread	Default Spread (DEF) is the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return (Amit Goyal website) (Fama and French, 1993)
1-Month Predictor Profit	The quintile spread of the Predictor based on excess returns in the prior month.
12-Months Predictor Profit	The quintile spread of the Predictor based on excess returns in the prior 12 months.
Bid/Ask Spreads	At the end of each month, we take the average of bid-ask spreads of currencies that are in the portfolios Q5 and Q1 for a predictor. We calculate the average of each time-series over the in-sample period to estimate a single costly arbitrage variable for each Predictor.
Capital Restrictions	At the end of each month, we take the average of an index of limits to arbitrage of currencies that are in the portfolios Q5 and Q1 for a predictor. The index is the average percentile rank of exchange rate turnover (from the BIS, 2016), 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). We calculate the average of each time-series over the in-sample period to estimate a single costly arbitrage variable for each Predictor.
Number of Forecasters	The number of analysts who provide forecasts for a currency. If the number of analysts is not available for a particular currency, we retrieve the number of analysts as reported by Consensus Economics in the section of forecasts for economic growth.
Single Forecast	Single Forecast is an indicator variable that takes the value 1 if there is only one forecast available for the currency in a month and zero otherwise. We assume that there is only a single forecast if the number of forecasts is not reported.

Table A4: Correlations of Currency Predictors and Mispricing

The table reports correlations between time series of monthly returns of trading strategies based on 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 different currency predictors and combined into equally weighted portfolios. The trading strategy return is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1). Trading profits are gross of transaction costs. Individual predictors are 1-Month Momentum (momentum based on the currency excess return over the prior month), 3-Months Momentum (momentum based on the currency excess return over the prior three months), 12-Months Momentum (momentum based on the currency excess return over the prior twelve months), Filter Rule Combination, Carry Trade, Dollar Carry Trade, Dollar Exposures, Term Spread, Currency Value, Output Gap, and the Taylor Rule. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme mispricing 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 sample includes 76 currencies. The sample period is from January 2000 to December 2019. Table A3 in the Appendix provides details on variable definitions.

	1-Month Momentum	3-Months Momentum	12-Months Momentum	Filter Rule Combination	Carry Trade	Dollar Carry Trade	Dollar Exposures	Term Spread	Currency Value	Output Gap	Taylor Rule	Average Mispricing
3-Months Momentum	0.621											
12-Months Momentum	0.362	0.472										
Filter Rule Combination	0.700	0.767	0.597									
Carry Trade	–0.038	0.095	0.296	–0.090								
Dollar Carry Trade	0.127	0.144	0.086	0.104	0.158							
Dollar Exposures	0.091	0.093	0.089	0.097	0.102	0.923						
Term Spread	0.025	0.056	0.152	0.025	0.341	0.257	0.248					
Currency Value	–0.109	–0.120	–0.417	–0.212	–0.074	–0.052	–0.033	0.046				
Output Gap	0.155	0.114	0.106	0.129	–0.185	0.123	0.150	0.103	0.152			
Taylor Rule	–0.056	–0.029	0.179	–0.027	0.555	0.030	0.018	0.338	0.088	0.100		
Average Mispricing	0.599	0.656	0.641	0.702	0.311	0.228	0.205	0.347	–0.162	0.152	0.305	
Extreme Mispricing	0.647	0.702	0.651	0.735	0.324	0.224	0.191	0.339	–0.155	0.137	0.329	0.898

Table A5: Summary Statistics

The table reports summary statistics on actual (i.e. realized) and forecast currency returns, analysts' mistakes (in percent per month) as well as average mispricing and extreme mispricing. In particular, the table shows the means, standard deviations, skewness, kurtosis, minimum, maximum and various percentiles. 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 one-month forward exchange rate of month *t* and the spot exchange rate of month *t*+1. Forecast currency returns are the negative log difference of a foreign currency's one-month forecast in month *t* and its spot rate in month *t*. Forecast currency excess returns are the log difference between the one-month forward exchange rate of month *t* and the foreign currency's one-month forecast in month *t*. Mistakes are the difference between forecast currency returns and actual (i.e. realized) currency returns. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 period starts in January 1971 for actual (excess) returns, in December 1989 for analysts' mistakes, and in January 1976 for average and extreme mispricing. All series end in December 2019. Table A3 in the Appendix provides details on variable definitions.

		Standard				Percentiles							
	Mean	Deviation	Skewness	Kurtosis	Minimum	1st	5th	25th	Median	75th	95th	99th	Maximum
Actual Currency Returns	–0.147	3.155	–2.352	40.77	–69.40	–9.573	–4.918	–1.296	0.000	1.176	4.458	7.215	34.21
Forecast Currency Returns	–0.199	2.954	0.463	8.558	–16.75	–8.007	–4.816	–1.585	–0.145	1.046	4.552	8.355	28.99
Actual Currency Excess Returns	0.130	3.159	–1.358	27.93	–63.94	–9.073	–4.658	–1.067	0.076	1.496	4.847	7.939	38.78
Forecast Currency Excess Returns	0.087	3.039	1.057	11.844	–15.92	–7.388	–4.505	–1.330	0.004	1.261	4.933	9.259	34.06
Analysts' Mistakes	–0.040	4.335	1.327	15.77	–27.83	–10.13	–6.506	–2.195	–0.123	1.745	6.836	13.15	66.77
Average Mispricing	0.523	0.155	0.115	2.674	0.068	0.196	0.273	0.412	0.520	0.631	0.785	0.885	1.000
Extreme Mispricing	0.021	0.316	0.117	3.097	–1.000	–0.714	–0.500	–0.182	0.000	0.250	0.571	0.800	1.000

Table A6: Quintile Performance of Portfolios Sorted on Currency Predictors

The table reports actual (i.e. realized) excess returns (in percent per month) of portfolios sorted on currency predictors, alternatively gross of transaction costs and net of transaction costs. Transaction costs are calculated using bid and ask quotations. Individual predictors are 1-Month Momentum (momentum based on the currency excess return over the prior month), 3-Months Momentum (momentum based on the currency excess return over the prior three months), 12-Months Momentum (momentum based on the currency excess return over the prior twelve months), Filter Rule Combination, Carry Trade, Dollar Carry Trade, Dollar Exposures, Term Spread, Currency Value, Output Gap, and the Taylor Rule. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternative currency predictors and combined into equally weighted portfolios. The table shows the time series average of the currency excess returns of the quintile portfolios. It also shows the time series average (in percent per month as well as annualized) and associated *t*-statistic (in square brackets) of the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1). The table does not report quintiles for the Dollar Carry Trade since the strategy goes long and short all foreign currencies based on average forward discount of developed countries. The sample includes 76 currencies. The sample period is from January 1971 to December 2019. Table A3 in the Appendix provides details on variable definitions.

	Currency Excess Returns Gross of Transaction Costs							Currency Excess Returns Net of Transaction Costs						
	Quintiles						Annualized	Quintiles						Annualized
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1	Q5–Q1	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1	Q5–Q1
1-Month Momentum	–0.181	0.036	0.142	0.184	0.390	0.571	6.852	0.025	–0.146	–0.058	–0.020	0.130	0.105	1.259
	[–1.57]	[0.35]	[1.41]	[1.85]	[3.68]	[5.32]		[0.22]	[–1.42]	[–0.58]	[–0.20]	[1.23]	[0.98]	
3-Months Momentum	–0.142	–0.058	0.113	0.182	0.483	0.625	7.500	0.055	–0.246	–0.085	–0.015	0.213	0.158	1.897
	[–1.20]	[–0.57]	[1.09]	[1.78]	[4.58]	[5.38]		[0.46]	[–2.43]	[–0.82]	[–0.15]	[2.02]	[1.36]	
12-Months Momentum	–0.038	–0.009	0.041	0.102	0.385	0.423	5.073	0.134	–0.184	–0.125	–0.079	0.113	–0.021	–0.250
	[–0.31]	[–0.09]	[0.37]	[0.96]	[3.57]	[3.35]		[1.08]	[–1.73]	[–1.11]	[–0.75]	[1.05]	[–0.16]	
Filter Rule Combination	–0.094	–0.077	0.100	0.152	0.321	0.415	4.977	0.116	–0.275	–0.086	–0.032	0.116	–0.000	–0.006
	[–0.75]	[–0.70]	[0.94]	[1.50]	[3.15]	[3.46]		[0.93]	[–2.49]	[–0.81]	[–0.31]	[1.14]	[–0.00]	
Carry Trade	–0.175	–0.035	0.135	0.236	0.554	0.729	8.753	0.012	–0.208	–0.055	0.021	0.167	0.155	1.857
	[–1.87]	[–0.38]	[1.49]	[2.49]	[5.02]	[8.20]		[0.13]	[–2.28]	[–0.61]	[0.22]	[1.51]	[1.73]	
Dollar Carry Trade						0.347	4.167						0.202	2.419
						[3.54]							[2.05]	
Dollar Exposures	0.074	0.220	0.298	0.476	0.425	0.351	4.209	0.213	0.025	0.108	0.339	0.301	0.088	1.053
	[1.83]	[2.82]	[2.43]	[3.40]	[2.64]	[2.14]		[5.18]	[0.32]	[0.88]	[2.43]	[1.87]	[0.53]	
Term Spread	0.044	–0.014	0.068	0.110	0.299	0.254	3.053	0.282	–0.195	–0.107	–0.085	0.050	–0.233	–2.792
	[0.46]	[–0.13]	[0.65]	[1.04]	[2.67]	[3.04]		[2.89]	[–1.85]	[–1.02]	[–0.80]	[0.44]	[–2.71]	
Currency Value	0.227	0.129	0.047	0.137	0.419	0.192	2.299	0.372	0.017	–0.058	0.028	0.272	–0.100	–1.204
	[1.42]	[0.81]	[0.29]	[0.82]	[2.33]	[1.21]		[2.34]	[0.11]	[–0.36]	[0.17]	[1.52]	[–0.64]	
Output Gap	0.105	0.047	0.118	0.342	0.396	0.291	3.497	0.216	–0.054	0.011	0.211	0.263	0.047	0.563
	[0.58]	[0.29]	[0.66]	[1.83]	[2.18]	[1.99]		[1.20]	[–0.33]	[0.06]	[1.15]	[1.45]	[0.33]	
Taylor Rule	0.123	–0.024	0.035	0.256	0.655	0.532	6.389	0.226	–0.106	–0.061	0.131	0.473	0.247	2.964
	[0.80]	[–0.15]	[0.20]	[1.42]	[3.15]	[3.04]		[1.47]	[–0.64]	[–0.35]	[0.73]	[2.29]	[1.43]	

Table A7: Predictors, Authors, and Details of Publication

The table reports the currency predictor, authors of the paper, and original sample period used in the paper as well as date of publication, alternatively on SSRN and peer-reviewed journal articles.

		Working Paper			Journal Article		
		Sample Period		Date of First	Sample Period		Date of Journal
Predictor	Authors (Journal)	Start Date	End Date	Posting on SSRN	Start Date	End Date	Publication
1-Month Momentum	Menkhoff, Sarno, Schmeling, and Schrimpf (*Journal of Financial Economics*)	January 1976	January 2010	April 2011	January 1976	January 2010	December 2012
3-Months Momentum	Menkhoff, Sarno, Schmeling, and Schrimpf (*Journal of Financial Economics*)	January 1976	January 2010	April 2011	January 1976	January 2010	December 2012
12-Months Momentum	Asness, Moskowitz, and Pedersen (*Journal of Finance*)	January 1979	October 2008	March 2009	January 1979	July 2011	June 2013
Filter Rule Combination	Okunev and White (*Journal of Financial and Quantitative Analysis*)	January 1980	June 2000	June 2001	January 1980	June 2000	June 2003
Carry Trade	Lustig and Verdelhan (*American Economic Review*)	January 1971	December 2002	January 2005	January 1971	December 2002	March 2007
Dollar Carry Trade	Lustig, Roussanov, and Verdelhan (*Journal of Financial Economics*)	November 1983	January 2009	January 2010	November 1983	June 2010	March 2014
Dollar Exposures	Verdelhan (*Journal of Finance*)	November 1983	December 2010	November 2011	November 1983	December 2010	February 2018
Term Spread	Ang and Chen (Working Paper)	January 1975	August 2009	January 2010			
Currency Value	Asness, Moskowitz, and Pedersen (*Journal of Finance*)	January 1979	October 2008	March 2009	January 1979	July 2011	June 2013
Output Gap	Colacito, Riddiough and Sarno (*Journal of Financial Economics*)	October 1983	January 2016	January 2017	October 1983	January 2016	September 2020
Taylor Rule	Colacito, Riddiough and Sarno (*Journal of Financial Economics*)	October 1983	January 2016	January 2017	October 1983	January 2016	September 2020

Table A8: Publication Dates of Earlier Related Research

The table reports the date of publication, alternatively on SSRN and peer-reviewed journal articles, of research related to currency predictors. We only list relevant cases that are strictly before the SSRN posting dates listed in Table A3 in the Appendix. Alternative groups of relevant research are academic publications on related FX strategies, practitioner articles on FX strategies, newspaper articles on FX strategies, academic publications on corresponding equity strategies, and academic publications on corresponding fixed income strategies.

Currency Predictor	Authors (Journal)	Date of First Posting on SSRN	Date of (Journal) Publication
Academic Publications on Related FX Strategies			
1-Month Momentum	Sweeney (*Journal of Finance*)		March 1986
3-Months Momentum	Sweeney (*Journal of Finance*)		March 1986
12-Months Momentum	Sweeney (*Journal of Finance*)		March 1986
Filter Rule Combination	Sweeney (*Journal of Finance*)		March 1986
Carry Trade	Hansen and Hodrick (*Journal of Political Economy*)		October 1980
Dollar Exposures	Lustig, Roussanov, and Verdelhan (*Journal of Financial Economics*)	January 2010	March 2014
Term Spread	Backus, Foresi and Telmer (*Journal of Finance*)	April 1998	February 2001
Currency Value	Bilson (*Journal of Finance*)		July 1984
Taylor Rule	Molodtsova, Nikolsko-Rzhevskyy and Papell (*Journal of Monetary Economics*)	February 2009	October 2008
Practitioner Articles on FX Strategies			
12-Months Momentum	The Deutsche Bank Momentum (USD) Index (*Deutsche Bank*)		January 2000
Carry Trade	DB Currency Carry Index (*Deutsche Bank*)		December 1999
Currency Value	The Deutsche Bank Valuation (USD) Index (*Deutsche Bank*)		January 2000
Newspaper Articles on FX Strategies			
1-Month Momentum	Smith (*Financial Times*)		October 2009
3-Months Momentum	Smith (*Financial Times*)		October 2009
12-Months Momentum	Smith (*Financial Times*)		October 2009
Carry Trade	Riley (*Financial Times*)		February 1997
Currency Value	Smith (*Financial Times*)		October 2009
Output Gap	Smith (*Financial Times*)		October 2009
Academic Publications on Corresponding Equity Strategies			
1-Month Momentum	Jegadeesh (*Journal of Finance*)		July 1990
3-Months Momentum	Jegadeesh and Titman (*Journal of Finance*)		March 1993
12-Months Momentum	Jegadeesh and Titman (*Journal of Finance*)		March 1993
Term Spread	Chen, Roll and Ross (*Journal of Business*)		July 1986
Currency Value	Stattman (*The Chicago MBA: A journal of selected papers*)		December 1980
Academic Publications on Corresponding Fixed Income Strategies			
1-Month Momentum	Khang and King (*Journal of Banking and Finance*)		March 2004
3-Months Momentum	Khang and King (*Journal of Banking and Finance*)		March 2004
Term Spread	Fama and French (*Journal of Financial Economics*)		February 1993

Table A9: Quintile Performance of Portfolios Sorted on Average Mispricing and Extreme Mispricing

The table reports actual (i.e. realized) excess returns (in percent per month) of portfolios sorted on average mispricing and extreme mispricing, 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 mispricing and extreme mispricing and combined into equally weighted portfolios. The table shows the time series average of the currency excess returns of the quintile portfolios. It also shows the time series average of the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1). Average mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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 mispricing 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 average returns and associated t-statistic (in square brackets). It also shows the Sharpe ratio, calculated as the average currency excess return divided by its standard deviation, as well as the standard deviation, skewness and kurtosis of the portfolio returns, and the average level of mispricing. The sample includes 76 currencies. The sample period is from January 1971 to December 2019. Table A3 in the Appendix provides details on variable definitions.

	Gross of Transaction Costs						Net of Transaction Costs					
	Quintiles						Quintiles					
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1
Average Mispricing												
Average Currency Excess Return (t+1)	–0.302	0.045	0.119	0.206	0.515	0.817	–0.125	–0.147	–0.072	–0.013	0.241	0.366
t-statistic	[–2.96]	[0.44]	[1.20]	[1.95]	[4.81]	[8.31]	[–1.23]	[–1.46]	[–0.72]	[–0.13]	[2.26]	[3.72]
Sharpe Ratio	–0.129	0.019	0.052	0.085	0.210	0.362	–0.054	–0.063	–0.031	–0.006	0.098	0.162
Standard Deviation	2.340	2.320	2.285	2.424	2.459	2.259	2.336	2.314	2.293	2.438	2.455	2.263
Skewness	–0.608	–0.151	–0.232	–0.330	–0.306	0.046	–0.504	–0.195	–0.267	–0.383	–0.369	–0.038
Kurtosis	6.724	5.320	4.421	4.649	4.470	5.246	6.659	5.303	4.393	4.750	4.510	5.383
Mispricing (t)	0.322	0.437	0.530	0.619	0.743	0.421	0.322	0.437	0.530	0.619	0.743	0.421
Extreme Mispricing												
Average Currency Excess Return (t+1)	–0.219	0.026	0.090	0.190	0.510	0.728	–0.040	–0.157	–0.106	–0.018	0.223	0.263
t-statistic	[–2.17]	[0.26]	[0.89]	[1.81]	[4.87]	[7.36]	[–0.39]	[–1.57]	[–1.05]	[–0.17]	[2.13]	[2.64]
Sharpe Ratio	–0.095	0.011	0.039	0.079	0.212	0.320	–0.017	–0.068	–0.046	–0.007	0.093	0.115
Standard Deviation	2.314	2.299	2.318	2.416	2.407	2.275	2.309	2.299	2.326	2.419	2.407	2.281
Skewness	–0.456	–0.225	–0.361	–0.334	–0.217	0.122	–0.353	–0.267	–0.418	–0.368	–0.315	0.024
Kurtosis	6.475	4.905	4.850	4.433	4.819	5.639	6.444	4.908	4.935	4.417	4.852	5.698
Mispricing (t)	–0.401	–0.128	0.024	0.175	0.471	0.872	–0.401	–0.128	0.024	0.175	0.471	0.872

Table A10: Publication Effects for Alternative Samples

The table 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. The regression specifications are the same as specifications (1) and (2) in Table 1, but for brevity, the table only displays the coefficients on selected variables. Results are shown alternatively for trading profits gross and net of transaction costs, which 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 equally 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 zero 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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. Standard errors are computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between returns. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes alternatively 62 currencies, 54 currencies covered by the 2019 BIS Triennial Survey, 40 currencies with the most turnover according to the BIS Triennial Survey, and the G10 currencies (USD, EUR, DEM, GBP, JPY, AUD, NZD, CAD, CHF, NOK, SEK, see Ang and Chen, 2010). The sample period is from January 1971 to December 2019. Table A3 in the Appendix provides details on variable definitions. Table A7 in the Appendix provides details on the predictors' original sample period used in the paper as well as date of publication.

	Predictor Profits Gross of Transaction Costs		Predictor Profits Net of Transaction Costs	
	Table 1, Specification (1)	Table 1, Specification (2)	Table 1, Specification (1)	Table 1, Specification (2)
	(1)	(2)	(1)	(2)
62 currencies				
Post-Publication	–0.403***	0.137	–0.304***	–0.063
	(0.111)	(0.207)	(0.110)	(0.084)
Post-Publication x Average Predictor In-Sample Profits		–0.945**		–1.581***
		(0.421)		(0.450)
Post-Publication x In-Sample Bid/Ask Spreads				

(continued)

Table A10: Publication Effects for Alternative Samples (continued)

	Predictor Profits Gross of Transaction Costs		Predictor Profits Net of Transaction Costs	
	Table 1, Specification (1)	Table 1, Specification (2)	Table 1, Specification (1)	Table 1, Specification (2)
	(1)	(2)	(1)	(2)
54 currencies				
Post-Publication	–0.510***	0.197	–0.285**	–0.017
	(0.118)	(0.193)	(0.117)	(0.090)
Post-Publication x Average Predictor In-Sample Profits		–1.190***		–1.587***
		(0.386)		(0.434)
Post-Publication x In-Sample Bid/Ask Spreads				
40 currencies				
Post-Publication	–0.582***	0.245	–0.387***	0.007
	(0.116)	(0.221)	(0.115)	(0.098)
Post-Publication x Average Predictor In-Sample Profits		–1.367***		–1.797***
		(0.413)		(0.483)
Post-Publication x In-Sample Bid/Ask Spreads				
10 currencies				
Post-Publication	–0.520***	0.123	–0.358***	–0.053
	(0.129)	(0.183)	(0.129)	(0.108)
Post-Publication x Average Predictor In-Sample Profits		–1.291***		–1.392***
		(0.393)		(0.458)
Post-Publication x In-Sample Bid/Ask Spreads				

Table A11: Mispricing and Analysts' Mistakes for Alternative Samples

The table reports results from regressions of analysts' mistakes (in percent per month) on mispricing, the interaction of mispricing with publication, and control variables. The regression specifications are the same as in Table 7, but for brevity, the table only displays the coefficients on the mispricing variable. 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 one-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 mispricing is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme mispricing 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 three months, (iii) momentum based on the currency excess return over the prior twelve 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. 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. Standard errors are clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 52 currencies that are covered in the 2019 BIS Triennial Survey, 40 currencies with the most turnover according to the BIS Triennial Survey, and the G10 currencies (USD, EUR, DEM, GBP, JPY, AUD, NZD, CAD, CHF, NOK, SEK, see Ang and Chen, 2010). The sample period is from December 1989 to December 2019. Table A3 in the Appendix provides details on variable definitions.

	Average Mispricing		Extreme Mispricing	
	(1)	(2)	(1)	(2)
52 currencies				
Mispricing	–10.01***	–9.708***	–4.670***	–4.719***
	(0.637)	(0.900)	(0.303)	(0.448)
40 currencies				
Mispricing	–10.27***	–10.14***	–4.831***	–4.935***
	(0.671)	(1.010)	(0.304)	(0.472)
10 currencies				
Mispricing	–8.031***	–8.649***	–4.037***	–4.382***
	(0.681)	(0.906)	(0.393)	(0.470)