Mispricing and Risk Premia in Currency Markets

Söhnke M. Bartram,[*] Leslie Djuranovik,[†] Anthony Garratt,[‡] and Yan Xu[§]

Abstract

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

JEL classification: F31, G12, G15

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Abstract

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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") in order to investigate alternative rationales for their existence. To this end, we construct all major cross-sectional predictors of currency excess returns documented in the literature that do not require proprietary data, using novel real-time data to ensure investors could have implemented these strategies at a historical point in time.

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

[1] Currency markets are generally viewed as extremely liquid and efficient relative to other asset classes. Average daily turnover is estimated at $7.5 trillion in 2022, which makes the currency market 31 times larger than world exports and imports, 19 times larger than world Gross Domestic Product (GDP), and 13 times larger than exchange-traded equity turnover (World Bank, 2022; BIS, 2022; WFE, 2022). 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), noise traders, and tourists are likely to leave money on the table in currency markets.

ranks, and fast decay of risk-adjusted returns (or "alphas") (e.g., Bartram and Grinblatt, 2021, 2018).

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

Our analysis adopts an agnostic perspective on the importance of alternative explanations for the presence of currency predictors. While some researchers place strong emphasis on the existence of currency predictors (especially carry) 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; Okunev and White, 2003; 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 in the literature to distinguish between alternative explanations for return predictability, we study the effect of both research publication and risk adjustment on currency strategy profits. Our results provide evidence that currency return predictability is at least in part due to mispricing. First, the risk-adjusted profitability of systematic currency trading strategies decreases significantly in periods after the underlying academic research has been published, suggesting some market participants learn about mispricing from research publications. Consistent with mispricing, the post-publication decline is greater for strategies with larger in-sample profits and lower arbitrage costs. Second, the effect of comprehensive, state-of-the art risk adjustments on predictor payoffs is limited, there is significant decay in risk-adjusted profits for stale trading signals, and the autocorrelations of signal ranks are low.

Analysis of possible sources of mispricing reveals that forecasts of currency analysts are inconsistent with currency predictors, which implies that investors trading on them contribute to mispricing, motivating biased expectations as an explanation for mispricing-based return predictability.[2] In particular, investors following analysts' forecasts would be selling (buying) the currencies in the fifth (first) portfolio of currencies sorted based on predictors. Consequently, investors trading on these predictors can buy (sell) the currencies in the fifth (first) portfolio at a lower (higher) price, which increases the excess returns on their strategies.

While extant work has documented each of the currency predictors and their properties individually, this paper is the first to study patterns across predictors, which allows more general conclusions to be drawn. 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 shown for equity analysts. Consequently, the approach and data employed in this paper allow generating new inferences about the economics of currency markets.

To investigate alternative sources of predictability in currency markets, we employ two approaches commonly used to distinguish between mispricing and risk premium explanations. The first approach examines predictor profits in periods before and after the dissemination of research

[2] While the literature on behavioral effects in currency markets is fairly scant to date, concepts from behavioral finance can be used to understand phenomena in currency markets as well (e.g., Burnside et al., 2011; Neely et al., 2009).

publicizing the trading strategies. If profits reflect mispricing and publication leads to investors learning about strategies and trading on them to exploit mispricing, currency excess return predictability should decline post publication (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 that risk-adjusted payoffs associated with currency strategies significantly decrease after the academic research has been published and that post-publication declines are greater for strategies with economically or statistically larger in-sample profits and smaller limits to arbitrage.

The staggering of publication dates for currency predictors provides identification for tests of changes in profitability 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 crisis, or recession. The publication effect remains significant in the presence of controls for time trends, crisis periods, and variables capturing monetary policy and macro-economic risk more generally. Finally, we include a host of risk factors in currency, equity, and bond markets and show that risk-adjusted profits also drop significantly after the publication of the underlying research. The literature refers to predictor variables with these characteristics that cannot be explained by risk as "anomalies" (e.g., McLean and Pontiff, 2016; Schwert, 2003; Fama, 1991; Froot and Thaler, 1990; Jensen 1978; Ball 1978).

While academic research has only recently documented many cross-sectional currency predictors, market participants may have traded on some of them before they were popularized by academic research. Importantly, trading by investors on these strategies should lead to lower or even zero portfolio returns in-sample and bias against any later publication effect if predictors reflect mispricing, while having no effect if they reflect risk (e.g., McLean and Pontiff, 2016; Schwert, 2003; Cochrane, 1999). 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 our tests biasing against finding significant effects.

The second approach to distinguishing between mispricing and risk as alternative rationales for return predictability involves risk adjustments to 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 predictors into aggregate measures with improved signal to noise ratios. Specifically, we combine individual currency predictors into average predictor (Stambaugh et al., 2012) and extreme predictor signals (Engelberg et al., 2020, 2018) that generate significant quintile spreads of realized currency excess returns of up to 74 basis points ("bp") and 45 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 nineteen-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 predictors we study, despite controlling for time-varying risk premia and factor exposures tied to the individual predictors themselves. In particular, risk-adjusted quintile spreads remain highly statistically significant, with factor model intercepts and IPCA-adjusted spreads of up to 53 bp and 43 bp per month, respectively. The literature has traditionally interpreted the existence of significant risk-adjusted returns that we document in currency markets as evidence of mispricing, i.e. anomalies, which is buttressed by fast decay of signal ranks and alphas.

Despite their limitations, publication effect and risk adjustment analyses have been commonly used in the asset pricing literature to distinguish between risk and mispricing. Given that both provide evidence in support of market inefficiencies, we explore possible sources of mispricing-based return predictability using analysts' forecasts. Currency predictors represent publicly available information that skilled analysts should be able to take advantage of (e.g., Engelberg et al., 2020, 2018; Guo et al., 2020; Grinblatt et al., 2018). If currency analysts are sophisticated and informed, they should exploit these well-documented sources of currency predictability for their predictions, while biased forecasts could give rise to mispricing. To this end, we use a unique and in part hand-collected data set of currency forecasts to investigate the relation between currency predictors and the exchange rate expectations formed by analysts, which provides a setting unaffected by the joint-hypothesis problem of risk models (Engelberg et al., 2018).

Our results show that analysts' forecasts are inconsistent with currency predictors, as analysts are expecting losses for strategies based on predictors that yield realized profits. To illustrate, the forecast excess return for the first quintile based on the average predictor variable (i.e. the short portfolio) is +152 bp per month, while it is –116 bp for the fifth quintile (i.e. the long portfolio). The expected quintile spread is thus –268 bp per month, contrasting with a realized quintile spread of +74 bp. Similarly, the realized profit of a trading strategy based on the extreme predictor variable is +68 bp per month, while analysts expect a loss of –262 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. Thus, it is not the case that analysts' forecasts are incorrect; they just 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 (Engelberg et al., 2020, 2018; Guo et al., 2020; Grinblatt et al., 2018). Since investors following analysts' forecasts reinforce currency predictors, biased expectations can rationalize mispricing as a source of return predictability.

Our paper makes several contributions to the literature. It is the first to study the cross-section of currency predictors, building on related work that tries to explain the existence of predictors cross-sectionally for equities. To illustrate, empirical evidence suggests that stock market predictability is attenuated after publication (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). However, while equity and bond markets have many assets and predictors compared with currency markets, they might be less efficient due to higher transactions costs, lower turnover, market closures, short selling constraints, etc. A contribution of our paper is to show that the risk-adjusted profits of systematic currency trading strategies decrease after the publication of the underlying research, especially for strategies with larger and more significant in-sample profits and lower arbitrage costs.

The evidence in our paper on publication effects complements findings for time-series predictors in currency markets by Neely et al. (2009), who replicate different types of published technical trading rules such as filter rules, moving averages, channel rules, ARIMA rules, genetic program rules, and Markov rules, based on Sweeney (1986), Levich and Thomas (1993), Taylor (1994), Neely et al. (1997), and Dueker and Neely (2007), and study their performance in the "ex post periods" after the end of the original samples. They find that the performance of trading rules in the ex post sample deteriorates, in some cases to the point where they earn significantly negative returns, and that risk and data mining cannot explain strategy profits. While Neely et al. (2009) employ different tests and methodologies and do not perform tests across the different types of strategies or apply comprehensive risk adjustments, their evidence of lower out-of-sample performance of published technical trading rules is consistent with publication effects and investor learning. A number of other studies also show evidence that profits of technical trading have declined over time (e.g., Cialenco and Protopapadakis, 2011; Qi and Wu, 2006; Olson, 2004).[3]

[3] Pukthuanthong-Le et al. (2007) and Pukthuanthong-Le and Thomas (2008) conclude that investor learning is consistent with the erosion of profits from technical trading rules in major, more liquid currencies and their cross exchange rates as well as evidence of significant profits for new strategies using more sophisticated technical models on more complex relationships or applied at higher frequencies or trading in more exotic and newly liquid exchange

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; Burnside et al., 2011a; Ang and Chen, 2010). Early research often eschews risk adjustments altogether, and they are still fairly parsimonious in recent studies and often limited to equity factors or the dollar and carry factors (e.g., Della Corte et al., 2021). Consequently, a contribution of our paper is its application of comprehensive, state-of-the art risk adjustments to delineate between mispricing and risk as sources of return predictability in currency markets.

Our paper is also the first to relate analysts' currency forecasts to currency predictors and currency excess returns documenting contradictions between currency predictors and analysts' forecasts that motivate biased expectations as a possible mechanism for mispricing-based return predictability. 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 contributes to the literature by providing important out-of-sample evidence for related questions in currency markets, where no prior evidence exists.

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

rates, since learning takes time. To the extent that trading in strategies not covered in our paper, such as technical trading rules, reduces the profits of these strategies and enhances currency market efficiency, this should bias against finding significant profits and significant declines in profits of the cross-sectional strategies in our paper.

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, while Section 4 examines risk-adjusted predictor profits and alpha decay. 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).[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 620 months between December 1970 to July 2022, 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 (Table A3). They represent all cross-sectional predictors that can be constructed with publicly available data for a large number of currencies. In line with the asset pricing literature (e.g., Chordia et al., 2014; McLean and Pontiff, 2016; Harvey et al., 2016; Guo et al., 2020), we do not study time-series predictability.[5] The long sample period averages out variation in strategy profits across economic cycles, policy regimes, risk on/off periods, crisis events, and other episodes in currency markets. While the number of strategies is relatively small, the resultant lower power of the tests biases against finding significant effects.[6]

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

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[4] For comparison, Lustig and Verdelhan (2007), Della Corte 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 A9 and A10.

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

[6] 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), 15 (Kozak et al., 2018), 34 (Tian, 2021), 97 (Engelberg et al., 2020; McLean and Pontiff, 2016).

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 rarely been used in the currency literature.[7] Individual predictors have low correlations between each other, with an average correlation of 0.14. However, correlations can be as low as –0.39 and as high as +0.92, suggesting they provide a wide range of differing trading signals (Table A4).[8] 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 (Appendix A). The forecasts are made every month for the exchange rates at the end of the following month. All spot and forecast exchange rates are in units of foreign currency per unit of a U.S. Dollar. We convert analysts' forecasts quoted relative to the Deutschmark or Euro to quotes against the U.S. Dollar using the corresponding Deutschmark or Euro forecasts.[9] Actual currency (excess) returns cover the period January 1971 to August 2022, while analysts' expected currency (excess) returns are available for December 1989 to August 2022.

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[7] 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, 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.

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

[9] 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

We define next month's currency return as the *negative* log difference between the spot exchange rates of months t+1 and t. Furthermore, next month's currency excess return is defined as the log difference between the 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 et al., 2021; Karnaukh et al., 2015; Lyons, 2001), net currency excess returns understate 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. Available for our full sample period are factors capturing dollar risk and carry trade risk (Lustig et al., 2011), currency volatility risk (Menkhoff et al., 2012b), currency skewness risk (Burnside, 2012; Rafferty, 2012), and network centrality (Richmond, 2019). Factors with shorter history capture correlation risk (Mueller et al., 2017), political risk (Filippou et al., 2018), and global imbalance risk (Della Corte et al., 2016).

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

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).

[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). Alternatively, we exclude countries with the largest 1% of the absolute cross-currency basis (alternatively including or excluding countries without available interest rates) and find that results using currency excess returns are robust to large CIP violations.

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 forecast error (or analyst mistake) is the difference between the expected currency return for month $t+1$ and its realization during that month. Finally, we measure the forecast revision as the log difference in analysts' forecasts between month t and month $t+1$. Table A3 provides details of all variable definitions. Table A5 shows detailed summary statistics of actual and forecast currency (excess) returns and analysts' mistakes.

3 Predictor Profits and Publication

3.1 Publication Effects of Academic Research

The first approach we employ to investigate mispricing and risk as alternative explanations for the existence of systematic currency trading strategies is the analysis of publication effects, which assesses the ability of trading signals to predict currency excess returns in different time periods. In particular, we compare trading profits from the sample period of the original academic research (i.e. the in-sample period) with profits in the period after the in-sample period but before the publication of the academic research (referred to as the out-of-sample period) as well as with profits after the publication of the research (i.e. the post-publication period).[11]

The analysis of publication effects allows distinguishing between mispricing and risk premium (and data mining) explanations. In particular, differences between the predictive power of currency predictors in the in-sample and post-publication periods could be the result of statistical bias or learning by investors from the publication. If return predictability reflects mispricing and publication allows sophisticated investors to learn about predictors and exploit mispricing by trading on predictor signals, their returns should decrease after these become publicly known. Frictions, however, might prevent trading profits from disappearing completely. In contrast, trading

[11] Academic studies may use different sets of currencies. For output gap, currency value, and 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.

profits should not change after publication if they reflect compensation for risk, conditional on no fundamental change in the risk-return trade-off or pricing of risk (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 1998, 1991).[12]

Profits of individual predictors are generally positive and significant over the full sample period before accounting for transaction costs as documented in the literature, while net profits are naturally smaller (Table A6). 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 date (Table A7).[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 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 gross predictor payoff is 56 bp, 64 bp, and 19 bp per month in the in-sample, out-of-sample, and the post-publication periods, respectively. The average length of these periods is 461, 11, and 149 months, respectively (which is similar to the 323, 56, and 156 months in McLean and Pontiff, 2016).

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

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

where the dependent variable is the monthly quintile spread of excess returns on currency predictor *j* in month *t*, and Post-Sample and Post-Publication are indicator variables for the respective periods. The regression has predictor fixed effects, and standard errors are computed using feasible

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

generalized least squares (FGLS) under the assumption of contemporaneous cross-correlation between returns (results are similar when clustering standard errors by date and predictor).

The results show two interesting findings. First, with the caveat of a relatively short out-of-sample period, there is little evidence that trading profits decline in the out-of-sample period, since the coefficients of the Post-Sample variable are insignificant in all but one specification (Table 1). This indicates that data mining is likely not a primary source of trading profits in currency markets, since predictability should disappear out-of-sample otherwise. We do not find this to be the case.[14] Second, there is strong evidence that trading profits decrease after the underlying academic research has been disseminated. In particular, in specification (1), gross returns are lower by 37 bp per month after publication, which is both statistically and economically significant. However, we can reject the hypothesis that return predictability disappears completely (*p*-value = 0.05).

Results using trading profits net of transaction costs also show strong publication effects with a reduction by 34 bp in specification (1) (Table 1). Publication effects are bigger for predictors that have economically or statistically larger in-sample profits (specifications (2) and (3)), respectively, and the overall publication effect is always significant.[15] For net profits we cannot reject the hypothesis that trading profits disappear completely post publication (*p*-value = 0.26). Finally, overfitting explanations of predictability suggest that predictors with smaller in-sample profits or *t*-statistics are more likely subject to data mining and thus should have a larger drop in performance out-of-sample, while the results suggest the opposite.[16] The analysis provides evidence that the returns associated with currency predictors decrease in periods after dissemination of the underlying research, consistent with the view that investors learn about and trade to exploit mispricing.

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[14] Confidence intervals for the parameter estimates of the post-sample indicator 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.

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

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

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).[17] 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 effect is indeed stronger when excluding these two strategies.

The publication effect can be illustrated by plotting the change in trading profits after publication against in-sample profits (Figure 1). The effect exists for almost all strategies individually, without an obvious bias towards a particular type of predictor, and those with larger in-sample profits show larger declines in portfolio returns (Panels A and B). Similarly, 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, but no reduction after publication, and thus bears the hallmarks of a risk factor, while the profitability of the dollar carry trade deteriorates significantly. Currency value has low in-sample profits and no significant publication effect.

The effect of publication on trading profits can be studied in more detail by replacing the post-publication indicator in Table 1 with separate indicators for each of the first three years after publication as well as a single indicator variable for all months that are at least three years after publication (Figure 2). Gross profits are lower by 23 bp, 38 bp, and 40 bp in the three years after publication compared with the in-sample period, and on average by 39 bp thereafter (Panel A). The last 12 months of the in-sample period have lower profits (by –0.28 bp) than other in-sample months, while trading profits are insignificantly higher in the post-sample period. Net profits exhibit similar patterns (Panel B). These results provide no support for the concern that researchers choose in-sample periods opportunistically to report stronger results. Average detrended cumulative profits are fairly stable before publication but decline afterwards (Figure 3).

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[17] 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.

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

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 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.

Lower trading profits could also be related to periods of low interest rates, high exchange rate volatility, economic business cycle contractions, or financial crisis. However, the staggering of publication dates ranging from 2001 to 2017 for currency predictors provides identification for tests of changes in their profitability that compare their average payoffs before and after the publication of the underlying research. The in-sample period covers years of high/low interest rates, various business cycles, risk on/off periods, and several economic and currency crises (e.g., EMS 1992, Mexico in 1994, Asia in 1997, Russia in 1998, Argentina 1999–2002). Similarly, the post-publication period extends until August 2022 and thus includes periods well before and after the recent global financial crisis (which was not a currency crisis).[18] 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.

[18] 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, crisis, and monetary policy in specification (3) such as the level of interest rates, within-month exchange rate volatility, and indicators for NBER recessions and financial crises (Nguyen et al., 2022; Laeven and Valencia, 2020; Reinhart and Rogoff, 2014), 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. The publication effect remains negative and significant in the presence of these additional controls. Predictor profits are on average not significantly lower in recessions or crisis periods.[19]

In order to further consider possible risk premia explanations for currency predictors, we estimate regressions that control for risk factors available for the full sample period, i.e., dollar, carry trade, currency volatility, currency skewness, network centrality factors, a global equity market risk factor, eight U.S. equity market risk factors, and two bond market risk factors. Specification (4) shows that while currency risk factors are significantly related to predictor profits, the publication effect is smaller but robust to these risk controls. Since all risk factors are tradable, self-financing portfolios, the results can be interpreted as significant drops in risk-adjusted returns.[20] Finally, specification (5) shows that the publication effect is also robust to predictor persistence when including trading profits over the prior 1 and 12 months (Moskowitz, Ooi, and Pedersen, 2013).

3.3 Limits to Arbitrage

The dissemination of research documenting profitable trading strategies should attract arbitrageurs who exploit these strategies leading to lower mispricing and trading profits. 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, while it should not be related to arbitrage costs if predictor returns are the outcome of rational asset pricing. In order to test this hypothesis, we measure the arbitrage cost of a predictor as the in-sample

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

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

mean of the average bid-ask spread of the currencies in its long and short portfolios.

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

Including limits to arbitrage and their interaction with the post-publication indicator in the regressions provides evidence that they moderate the size of the publication effect (Table 3). In particular, the interaction terms on bid/ask spreads and capital restrictions are positive and significant indicating that the post-publication reduction in trading profits is smaller for strategies that are more expensive to implement and/or face larger restrictions to convertibility. The hypothesis that limits to arbitrage do not matter for expected trading profits can also be rejected for bid/ask spreads (p-value < 0.01) and exchange rate convertibility (p-value < 0.01). Similarly, trading profits from equity market predictors have approximately halved since decimalization and are generally larger for stocks with larger arbitrage costs (Bartram and Grinblatt, 2021; 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 studying the effect of risk adjustments on currency predictor profits more generally using alternative risk models.

4 Predictor Profits and Risk Adjustments

4.1 Aggregate Currency Predictors

The second approach we employ to investigate mispricing and risk as alternative explanations for the existence of systematic currency trading strategies is the application of risk models. If profits to trading strategies based on currency predictors reflect compensation for risk, they should disappear after adjusting for risk, while profits in excess of factor risk would reflect market inefficiencies (e.g., Fama 1998, 1991; Jensen 1978). To this end, we use comprehensive, state-of-the-art risk models and control for time-varying risk premia and factor exposures to address concerns that mispricing might simply reflect omitted factor risk. In order to study the average effect of risk adjustment on currency predictor profits, we follow the asset pricing literature without discretion and combine currency predictors into aggregate measures, mimicking alpha models of institutional investors that summarize different trading signals into combined predictor scores (e.g., Engelberg et al., 2020, 2018; Guo et al., 2020; Stambaugh et al., 2015, 2014, 2012).

In particular, we create a variable "average predictor" by averaging each month, for each currency, the percentile ranks of all available predictors, resulting in values of the aggregate measure between 0 and 1. This approach gives equal weight to each predictor and thus assumes no information regarding their relative forecasting power. It also reduces the noise across currency predictors.[21] The second aggregate variable "extreme predictor" is defined as the difference between the number of long and short predictor-portfolios that a currency belongs to in a given month, divided by the number of predictors. This normalized score ranges between –1 and +1. A high score indicates that a currency should be bought based on many predictors and shorted based on few predictors. It thus reflects extreme values or a high conviction across predictors.[22]

The correlation of 0.89 between average and extreme predictor variables indicates that they measure similar dimensions but are not identical.[23] Sorting currencies on either measure yields currency excess returns in the following month that increase across quintiles from the short to the

[21] Stambaugh et al. (2012) refer to a similar measure aggregating equity market predictors as "Mispricing".
[22] Engelberg et al. (2020) refer to a similar measure aggregating equity market predictors as "Net".
[23] Aggregate predictors require at least four available signals. Table A5 provides detailed summary statistics.

long portfolio (Table 4 Panel A); monotonicity tests are highly significant (Patton and Timmermann, 2010). Trading strategies based on predictors are profitable before and after transaction costs. To illustrate, quintile spreads of gross currency excess returns are 74 bp and 68 bp per month when sorting by average and extreme predictor variables (equivalent to 8.9% and 8.2% per year), and net profits are 45 bp and 38 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 transaction costs is 62% and 63% for average and extreme predictors, both significantly higher than 50% (p-value < 0.01). Hit ratios for gross returns are even larger at 66% and 69%, respectively, and highly significant. Annualized Sharpe ratios of up to 1.3 (0.7) for gross (net) profits are economically significant (Table A8); in 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).[24] Diversification across predictors is also harder to reconcile with pure risk-based explanations.

4.2 Risk-Adjustments and Alpha Decay

To adjust predictor profits for risk, we employ both Black et al. (1972) time-series factor models and cross-sectional Fama-MacBeth (1973) regressions, which are well established methods in the finance literature. In particular, we estimate factor model regressions with tradable long/short factors so that the intercepts can be interpreted as risk-adjusted returns. Our nineteen-factor model includes eight currency factors, nine equity and two bond market factors, subsuming the Lustig et al. (2011) two-factor model, the Fama and French (2014) five-factor model, and the factors in Menkhoff et al. (2012a).

The results in Panel B of Table 4 show that the effect of risk adjustment using factor models on trading profits is limited.[25] In particular, for sorts by average and extreme predictor, monthly gross alphas are 53 bp and 45 bp per month, respectively. Risk-adjusted profits net of transaction costs are smaller but still economically and statistically significant, with nineteen-factor

[24] Table 4 is based on the shorter sample period 12/1989 to 12/2019 to compare actual and forecast currency returns.
[25] Burnside et al. (2011a) documents a lack of a relationship between currency trading strategies and equity factors.

alphas of 28 bp (*t*-statistic = 2.52) and 21 bp (*t*-statistic = 1.85) for average and extreme predictors, respectively. Note that we use the full bid-ask spread, while recent papers (e.g., Colacito et al., 2020; Menkhoff et al., 2016) employ 50% of the quoted spread and suggest that even 25% could be appropriate (Cespa et al., 2021). Alphas increase monotonically from the first to the fifth quintile, documenting the systematic nature of the relation between sorting variables and next period excess returns. Moreover, both the first and the fifth portfolio make significant and about equal contributions to the quintile spread.

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

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

Assessing the alpha decay of predictor signals provides further support for the view that trading profits reflect mispricing. If predictors capture mispricing, one would expect low autocorrelations of signal ranks over time as well as low persistence of alphas (Bartram and Grinblatt, 2021, 2018; Bartram et al., 2021). Indeed, the average Spearman rank correlation between the vector of predictors at month t and month $t-1$ is only 0.71 (0.67) for the average (extreme) predictor, and it is 0.39 (0.37) for predictors in months t and $t-6$. In addition, nineteen-factor model alphas from stale signals decay quickly, with net returns declining toward zero within just one month (Figure 4). Thus, while the existence of currency predictors suggest that currency markets may not be completely efficient, inefficiencies seem to be arbitraged away quickly. Rapid decay of alphas, particularly net of transaction costs, suggests that they reflect in part mispricing (Cochrane, 1999).[26]

[26] 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 predictor strategies and (lagged) AUM, consistent with market inefficiencies and arbitrage capital reducing strategy profits as suggested by the theoretical and empirical results in these prior studies for returns to the carry trade, an optimized currency strategy, and equity market predictors.

Consistent with the results from publication effects, 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, at least to an extent, result from market inefficiencies. That said, tests using risk models are always subject to the joint hypothesis problem, and one cannot rule out that an unknown factor or risk not captured by risk models explains strategy returns. Either way, currency predictors should be related to the forecasts of currency analysts, which we examine next. Evidence of mispricing does not necessarily imply arbitrage opportunities because limits to arbitrage could constrain the ability of market participants to exploit them, explaining why profits exist in a seemingly competitive market.

5 Analysts and Mispricing-based Return Predictability

5.1 Mispricing and Analysts' Forecasts

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

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

In particular, average forecast currency excess returns before transaction costs decrease monotonically from low to high predictor quintiles (Table 4 Panel D). They are +152 bp per month for the short portfolio and –116 bp for the long portfolio, yielding an expected quintile spread of

–268 bp for strategies based on the average predictor, with a *t*-statistic of –27.7. The pattern is similar for the extreme predictor with expected profits of –262 bp (*t*-statistic = –27.1). Analysts erroneously expect losses from trading on predictors even though these strategies yield significant positive actual profits of 74 bp and 68 bp per month for average and extreme predictors, respectively (Panels A and D). Hence, the expectations of analysts with regard to currency excess returns conflict with the relations of predictor variables with next 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. As we show later, this does however not imply that the forecasts by analysts are generally wrong and not useful in forecasting currencies – it is just that they do not reflect currency predictors.

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

These results can be illustrated graphically (Figure 5). Analysts' forecasts of currency excess returns are monotonically decreasing from the first quintile to the fifth quintile (Panel A), and analysts expect short portfolio currencies to appreciate and long portfolio currencies to depreciate (Panel B). Consequently, 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 suggested by predictor variables to 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.

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

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

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

The regressions confirm the results of the portfolio sorts, as the relation between predictors and forecast currency excess returns is negative and significant (Table 5). Specifically, the coefficients on average and extreme predictors are –8.024 and –3.663, respectively, and both are statistically significant. The size of the coefficient for the average predictor variable means that a currency with an average predictor value one standard deviation above the sample mean has a forecast excess return that is 124 bp per month lower than a currency with an average predictor value at the sample mean. With the extreme predictor, the incremental forecast excess return would be 115 bp. This contrasts with higher realized currency excess returns for currencies with higher predictor scores. Regarding the control variables, forecast currency excess returns are lower for currencies with more analysts, i.e., analysts tend to be more bullish when they are fewer in numbers. For forecast currency returns, the predictor coefficients are also negative and significant.[27]

If analysts considered predictor variables for their exchange rate forecasts, they should expect higher currency excess returns for portfolios on the long side of a predictor-based trading strategy than for portfolios on the short side. This implies the expectation of a positive trading profit, in line with the historical performance of these strategies. In contrast, the results show that analysts' forecasts of currency strategy payoffs are negative, suggesting that analysts regularly make

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

mistakes in their forecasts. Biased forecasts imply that they may contribute to mispricing if investors trading on them naively or strategically exert price impact, as their trades will reinforce or amplify predictors. Put differently, biases in analysts' forecasts could be a source of market friction that impedes the efficient correction of mispricing (Guo et al., 2020; Engelberg et al., 2020).

5.2 Analysts' Mistakes

If analysts on average expect losses for currency trading strategies that yield actual (i.e. realized) profits, their expectations must frequently be wrong (with 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.

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

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

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

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

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

The finding that analysts make systematic errors may seem surprising, but it could be that analysts are simply unaware of the information contained in predictors until their discovery by academics. Consequently, one would expect them to incorporate predictor information into their forecasts after the dissemination of research publicizing them. If this was the case, the relation between mistakes and predictors should become weaker, which can be analyzed by adding an interaction term between the predictor and a publication variable to the regression:

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

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

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

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

In sum, analysts have currency expectations that contradict currency predictors, since they expect higher excess returns on short portfolios than on long portfolios, yielding an expected loss. Consequently, analysts make systematic mistakes that are in line with 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).

5.3 Changes in Analysts' Forecasts

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

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

$$Change\ in\ Currency\ Forecast_{i,(t|t+1),(t+1|t+2)} = a + \sum_{\tau=0}^{2} \beta_{\tau+1} Predictor_{i,t-\tau} + \beta_4 Number\ of\ Forecasters_{i,t} + \beta_5 Single\ Forecast_{i,t} + \varepsilon_t + e_{i,t} \tag{6}$$

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 predictor variables (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 predictor information into their forecast revisions. To illustrate, the coefficients on the average and extreme predictor lagged by one month are 2.230 and 0.976 respectively, both statistically significant (Table 7). The regression coefficients indicate that a currency with a predictor value one standard deviation above the sample mean is expected to appreciate by 34 bp (31 bp) more per month compared with a currency with an average (extreme) predictor value at the sample mean.[28] The magnitudes of the coefficients decrease monotonically with lag length, and coefficients lagged by two and three months are insignificant. Thus, analysts do not use information contained in predictor variables from months before the most recent. The coefficient on the number of forecasters are positive and significant, indicating more positive revisions for currencies that are followed by more analysts.

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

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

predictors, it could be that their forecasts contain other information that outweighs these forecast errors and that is informative in predicting future currency excess returns. To this end, we estimate Fama-MacBeth (1973) regressions that have monthly currency excess return as the dependent variable and lagged predictors and analysts' forecast currency excess returns as explanatory variables, both of which are known to investors at the time of putting the trade on.[29] In order to be able to compare economic magnitudes, we use quintile dummies (Q2, Q3, Q4, and Q5, with Q1 omitted due to the regression intercept) for both variables. Coefficients from regressing excess returns on Q2–Q5 dummy variables can be interpreted as the added return from belonging to the respective characteristic quintile compared with the Q1 quintile.

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

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 between predictor sorted currency portfolios and providing diversification within portfolios. Nevertheless, we perform all of our analyses for smaller sets of 62, 54, 40, and 10 currencies. The publication effect is

[29] Analysts' forecasts are published around the 2nd week of the month and, thus, available to investors by month end.

robust to these alternative samples (Table A9). In fact, the magnitude of the coefficient is larger with fewer currencies, and the interaction term of the post-publication dummy with in-sample trading profits is always significant both gross and net of transaction costs.

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

We also investigate whether the results for analysts' mistakes are driven by the source of the forecast data. To this end, we obtain analysts' consensus forecasts from two alternative databases (Appendix A). Results are similar 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 the efficiency of the currency market and the rationales for trading profits of systematic trading strategies with focus on risk and mispricing using, for the first time, all widely used cross-sectional trading strategies in currency markets that can be constructed for many currencies with publicly available data. The study of the cross-section of currency predictors allows for more general conclusions than prior studies that document and analyze one of the predictors of currency excess returns at a time. Currency trading strategies are implemented in a realistic way using novel real-time data that investors could have employed at a historical point in time. With an agnostic perspective, the paper tests alternative explanations for the *raison d'être* of currency predictors pertaining to risk and mispricing using a range of methods suggested in the literature.

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

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

Moreover, analysts have currency expectations that contradict currency predictors, since they expect higher excess returns on short portfolios than on long portfolios, yielding an expected loss. Consequently, analysts make systematic mistakes that are in line with biased expectations as a source of mispricing-based return predictability. Overall, this 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). At the same time, existing methods in the literature to delineate between mispricing and risk have limitations, and better tests are needed to draw conclusions about the source of predictability of a particular predictor.

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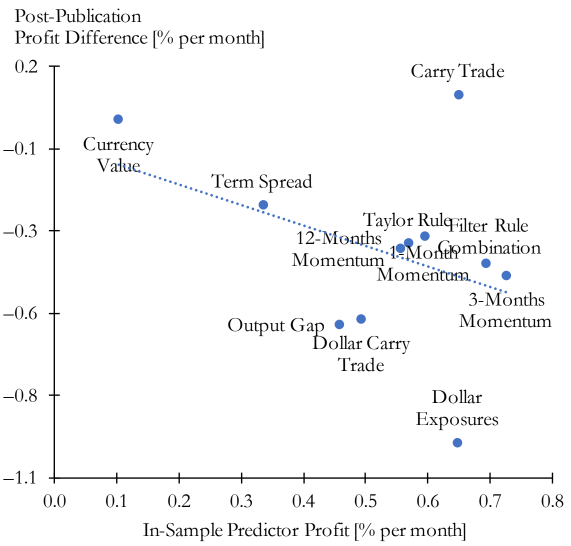
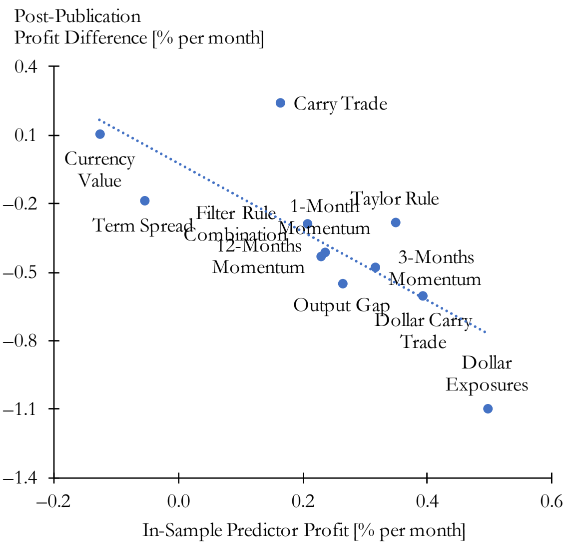
Figure 1: Relation between In-Sample and Post-Publication Trading Profits

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 the end of the sample period of the original study. Post-publication profits are the mean returns (in percent) of the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1) for the period after the study has been published (through August 2022). Post-publication profit differences are the difference between in-sample profits and post-publication profits. Post-publication *t*-statistic differences are the difference between in-sample *t*-statistics and post-publication *t*-statistics. 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 August 2022. 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.

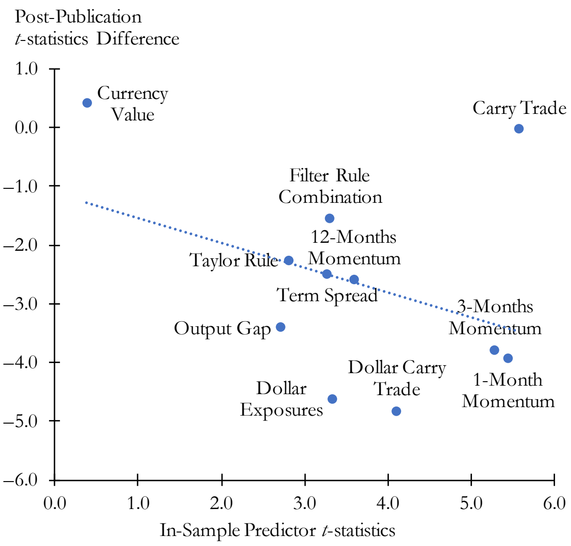
Panel A: Profits Gross of Transaction Costs



Panel B: Profits Net of Transaction Costs



Panel C: *t*-statistics for Gross Profits



Panel D: *t*-statistics for Net Profits

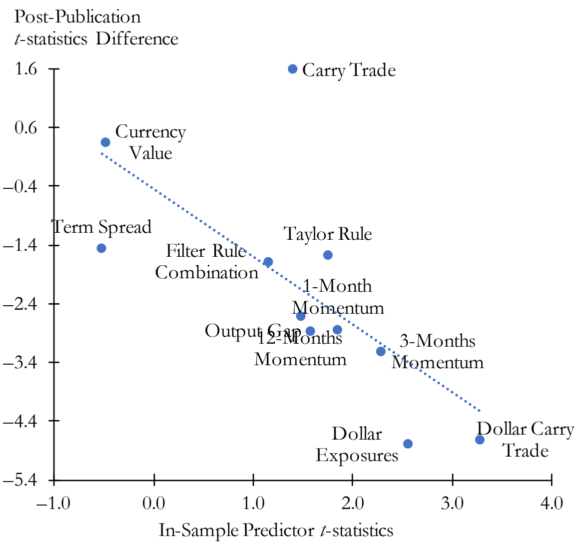
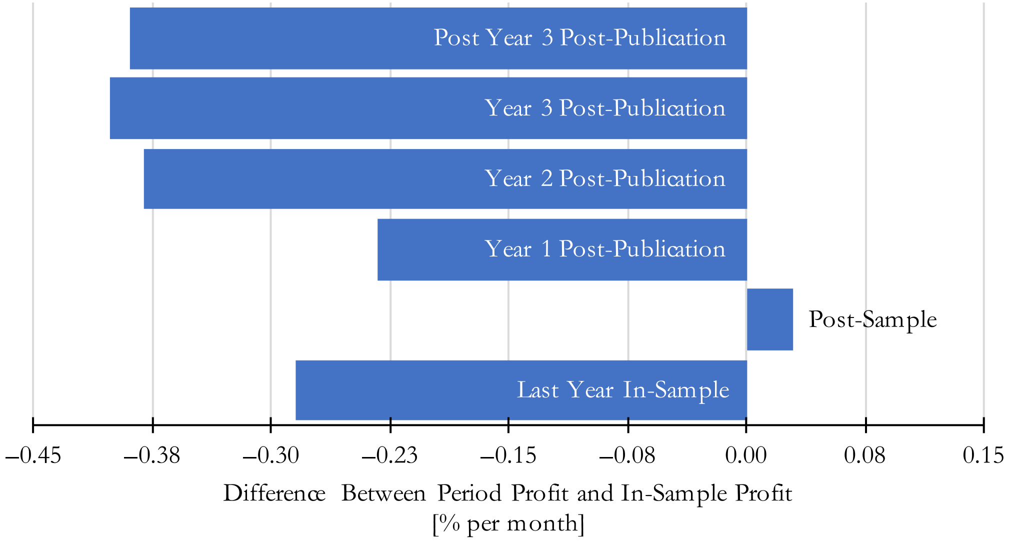


Figure 2: Predictor Profits Around End-of-Sample and Publication Dates

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 transaction costs are calculated using bid and ask quotations. Separately for each predictor, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) at the end of each month and combined into 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 August 2022. 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

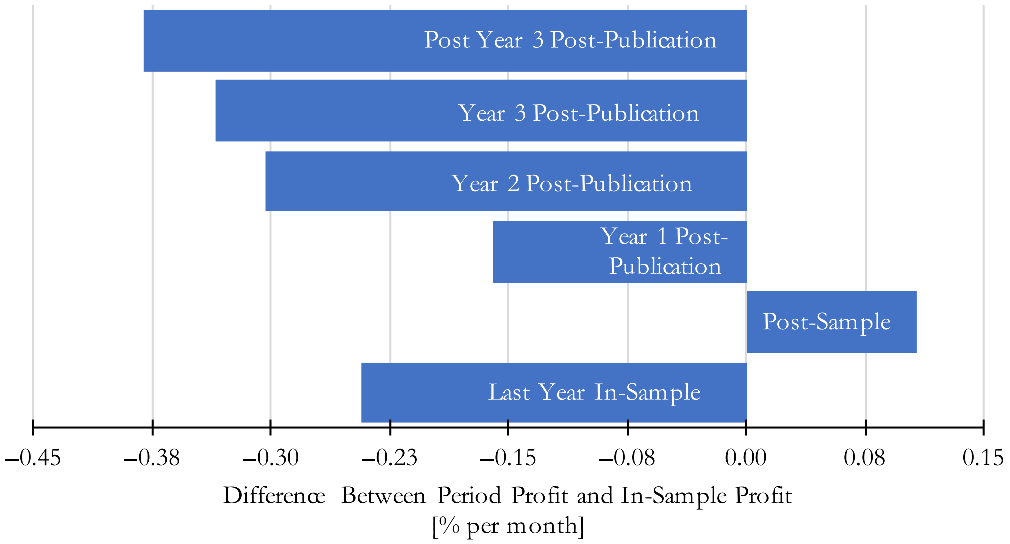


Figure 3: Strategy Profits in Event Time

The figure shows detrended average predictor profits in event time. In particular, the cumulative profits of the predictors in the five years before and after their publication are averaged and detrended by regressing the average cumulative profits on a constant and a linear trend for the five years before and after publication. Results are shown separately for profits gross and net of transaction costs. 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 76 currencies. The sample period is from January 1971 to August 2022. 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.

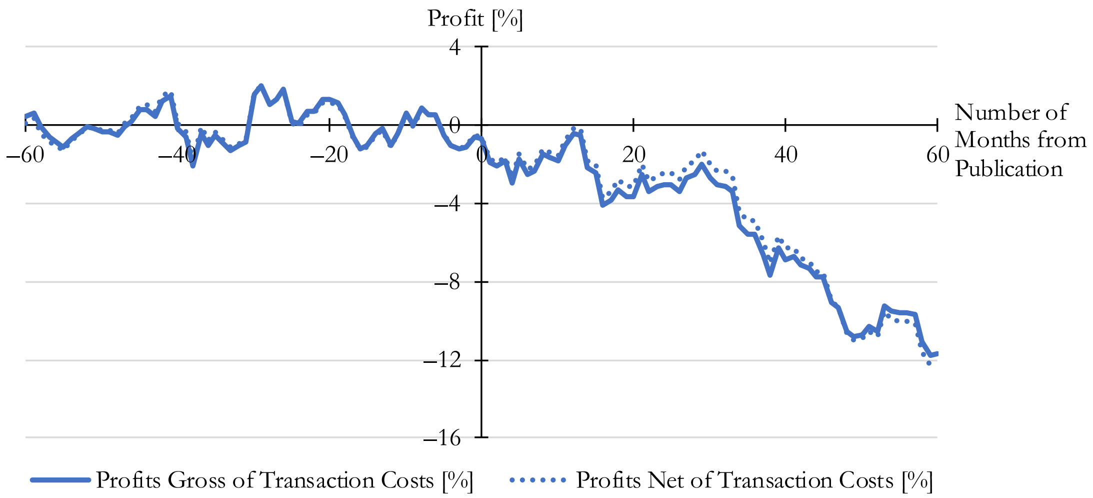
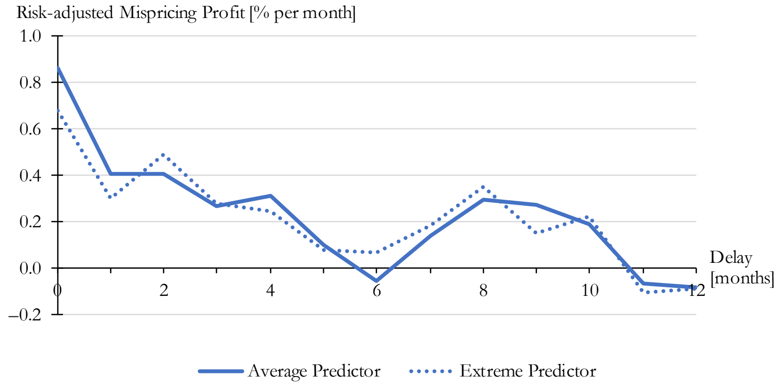


Figure 4: Alpha Decay

The figure shows risk-adjusted trading profits (in percent per month) for trading strategies based on average predictor (solid line) and extreme predictor (dashed line) variables. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average and extreme predictors and combined into equally weighted portfolios. The predictor 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 eight currency risk factors, nine equity market risk factors, and two bond market risk factors. The eight currency risk factors are the dollar risk factor and the carry trade risk factor (Lustig et al., 2011), a volatility risk factor (Menkhoff et al., 2012b), a skewness risk factor (Burnside, 2012; Menkhoff et al., 2012b; Rafferty, 2012), and a network centrality factor (Richmond, 2019). The nine equity market factors are the excess return on the world market portfolio as well as eight U.S. equity market factors, namely the excess return on the market portfolio (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), obtained from Amit Goyal's website (https://sites.google.com/view/agoyal145. Average predictor is the average of the percentile ranks of currencies with respect to the following eleven predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. 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 February 1985 to August 2022 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

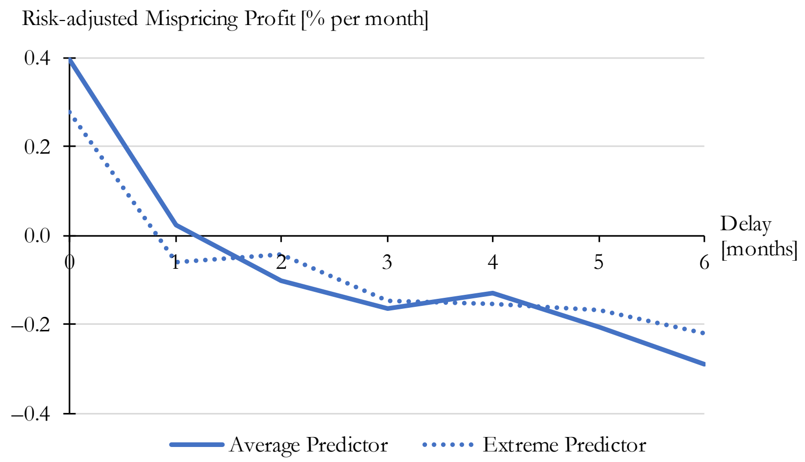
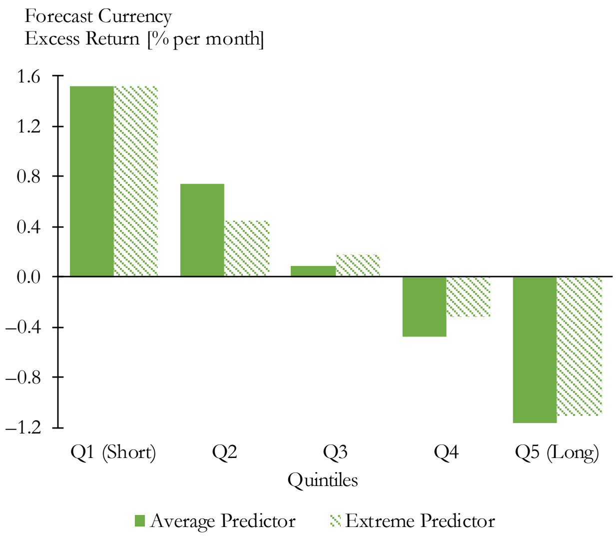


Figure 5: Currency Analysts' Forecasts and Predictors

The figure shows analysts' forecast currency returns and currency excess returns (in percent per month) for trading strategies based on average and extreme predictor variables. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average and extreme predictors and combined into 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 predictor is the average of the percentile ranks of currencies with respect to the following eleven predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. 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 August 2022. Table A3 in the Appendix provides details on variable definitions.

Panel A: Forecast Currency Excess Returns



Panel B: Forecast Currency Returns

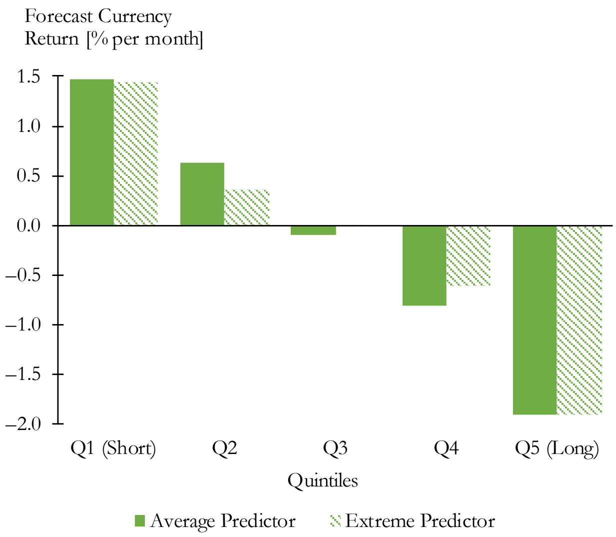
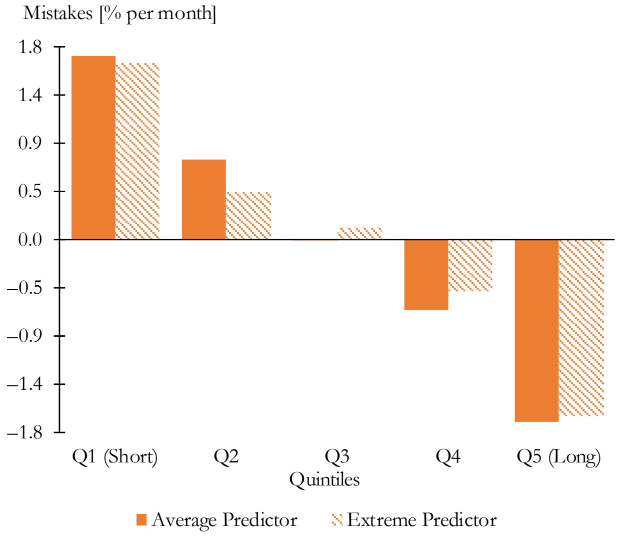


Figure 6: Currency Analysts' Mistakes and Predictors

The figure shows analysts' mistakes (in percent) for trading strategies based on individual and aggregate 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 aggregate (i.e., average and extreme) predictors 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 predictor is the average of the percentile ranks of currencies with respect to the following eleven predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. Panel A shows analysts' mistakes by aggregate predictor 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 August 2022. Table A3 in the Appendix provides details on variable definitions.

Panel A: Mistakes by Aggregate Predictor Quintile



Panel B: Mistakes by Individual Predictor Quintile

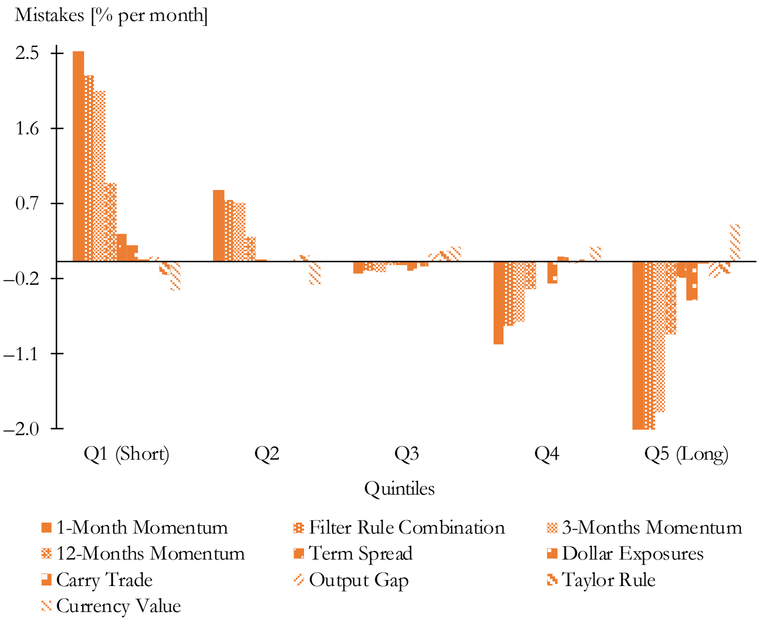


Table 1: Regression of Predictor Profits on Post-Publication Indicators

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 transaction costs are calculated using bid and ask quotations. Separately for each predictor, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) at the end of each month and combined into 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 August 2022. 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	0.041	0.054	0.075	–0.528*	0.118	0.141	0.140	–0.452
	(0.235)	(0.235)	(0.235)	(0.299)	(0.235)	(0.233)	(0.233)	(0.299)
Post-Publication	–0.365***	–0.031	–0.150	–0.414***	–0.341***	–0.000	–0.039	–0.405***
	(0.100)	(0.196)	(0.160)	(0.112)	(0.100)	(0.090)	(0.091)	(0.112)
Post-Publication x Average Predictor In-Sample Profits		–0.583				–1.509***		
		(0.405)				(0.462)		
Post-Publication x Predictor In-Sample *t*-statistics			–0.045				–0.196***	
			(0.044)				(0.065)	
Average Predictor In-Sample Profits		0.998***				0.978***		
		(0.104)				(0.216)		
Predictor In-Sample *t*-statistics			0.136***				0.145***	
			(0.014)				(0.031)	
Observations	5,033	5,033	5,033	3,948	5,033	5,033	5,033	3,948
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	0.051			0.191	0.261			0.114
Null: Post-Publication + (Post-Publication x Average Predictor In-Sample Profits) = 0		0.012				0.000		
Null: Post-Publication + (Post-Publication x Predictor In-Sample t-statistics) = 0			0.120				0.003	

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, equity, and bond market risk factors, and prior predictor profits. Results are shown alternatively for trading profits gross and net of transaction costs, where transaction costs are calculated using bid and ask quotations. Separately for each predictor, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) at the end of each month and combined into 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 (Nguyen et al., 2022; 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), the skewness risk factor following Burnside (2012), Menkhoff et al. (2012b) and Rafferty (2012), and the network centrality factor as in Richmond (2019). The nine equity market risk factors are the excess return on the world market portfolio as well as eight U.S. equity market factors, namely the excess return on the market portfolio (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), obtained from Amit Goyal's website (https://sites.google.com/view/agoyal145). 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 August 2022. 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		–0.471***	–0.330***	–0.318***	–0.302***		–0.597***	–0.388***	–0.288***	–0.285***
		(0.131)	(0.108)	(0.087)	(0.099)		(0.130)	(0.107)	(0.087)	(0.098)
Time	–0.072**	0.043				–0.043	0.103**			
	(0.033)	(0.043)				(0.033)	(0.043)			
Level of Interest Rates			0.030*					0.005		
			(0.017)					(0.017)		
Exchange Rate Volatility			–0.668***					–0.849***		
			(0.227)					(0.225)		
NBER U.S. Business Cycle Contractions			–0.164					–0.144		
			(0.166)					(0.164)		
Crisis			–0.225					–0.248		
			(0.622)					(0.617)		
Dollar Risk Factor				–0.351***					–0.379***	
				(0.053)					(0.054)	
Carry Trade Risk Factor				–0.189***					–0.239***	
				(0.059)					(0.063)	
Volatility Risk Factor				–0.036					–0.048	
				(0.037)					(0.038)	
Skewness Risk Factor				0.181***					0.199***	
				(0.022)					(0.023)	
Network Centrality Risk Factor				–0.021					–0.030	
				(0.029)					(0.029)	
1-Month Predictor Profit					–0.017					–0.013
					(0.019)					(0.019)
12-Months Predictor Profit					0.017***					0.018***
					(0.005)					(0.005)
Observations	5,033	5,033	5,025	5,024	4,901	5,033	5,033	5,025	5,024	4,901
R–Squared	0.01	0.01	0.01	0.06	0.01	0.00	0.01	0.01	0.06	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 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 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 August 2022. 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	–1.336***	–2.252***
	(0.416)	(0.849)
Post-Publication x Limits to Arbitrage	6.024**	3.392**
	(2.460)	(1.617)
Limits to Arbitrage	1.413	0.698
	(1.370)	(0.901)
Intercept	0.338	0.214
	(0.232)	(0.474)
Observations	5,033	4,987
R–Squared	0.01	0.01
Number of Predictors	11	11
Standard Errors	FGLS	FGLS
Null: (Post-Publication x Arbitrage Costs) + Arbitrage Costs = 0	0.000	0.002

Table 4: Quintile Performance of Portfolios Sorted on Currency Predictors

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 and extreme predictors, alternatively gross of transaction costs and net of transaction costs. Transaction costs are calculated using bid and ask quotations. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average and extreme predictors and combined into 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 eight currency factors, nine equity market factors and two bond market factors (19-Factor Model). The eight currency factors are the dollar risk factor and the carry trade risk factor (Lustig et al., 2011), a volatility risk factor (Menkhoff et al., 2012b), a skewness risk factor (Burnside, 2012; Menkhoff et al., 2012b; Rafferty, 2012), and a network centrality factor (Richmond, 2019). The nine equity market factors are the excess return on the world market portfolio as well as eight U.S. equity market factors, namely the excess return on the market portfolio (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), obtained from Amit Goyal's website (https://sites.google.com/view/agoyal145). 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 nineteen currency, equity and bond factors from Panel B as observable factors (M = 19). Fama MacBeth regressions regress currency excess returns cross-sectionally on dummies for predictor quintiles as well as the predicted excess return for the currency in a month from the IPCA (Bartram and Grinblatt, 2021). Risk-adjusted quintile portfolio excess returns are from 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 predictor 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 predictor is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying predictors, divided by the number of predictors. The analysis is based on the following eleven currency predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 August 2022. Table A3 in the Appendix provides details on variable definitions.

(continued)

Table 4: Quintile Performance of Portfolios Sorted on Currency Predictors (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 Predictor	–0.193	–0.001	0.093	0.189	0.545	0.738	[7.09]	0.453	[4.35]
Extreme Predictor	–0.133	0.002	0.068	0.160	0.549	0.682	[6.61]	0.383	[3.72]
Currency Returns									
Average Predictor	–0.240	–0.122	–0.094	–0.142	–0.195	0.045	[0.43]	0.273	[2.59]
Extreme Predictor	–0.204	–0.093	–0.110	–0.133	–0.247	–0.043	[–0.41]	0.208	[1.97]
Panel B: Factor Model Time-Series Regressions with Realized Excess Returns									
19-Factor Model									
Average Predictor	–0.243	–0.026	0.025	0.118	0.290	0.532	[4.36]	0.283	[2.52]
Extreme Predictor	–0.170	0.020	0.021	0.035	0.280	0.450	[3.72]	0.207	[1.85]
Panel C: Fama-MacBeth Cross-sectional Regressions with Realized Excess Returns									
Unconstrained IPCA Model									
Average Predictor	–0.130	–0.013	0.128	0.150	0.296	0.426	[4.82]		
Extreme Predictor	–0.115	0.020	0.021	0.113	0.227	0.343	[4.20]		
Constrained IPCA Model									
Average Predictor	–0.078	-0.065	0.035	0.010	0.078	0.156	[1.95]		
Extreme Predictor	–0.084	–0.018	–0.016	0.015	0.089	0.172	[2.18]		
Panel D: Forecast Returns									
Currency Excess Returns									
Average Predictor	1.517	0.748	0.092	–0.472	–1.163	–2.681	[–27.7]		
Extreme Predictor	1.517	0.450	0.177	–0.322	–1.107	–2.624	[–27.1]		
Currency Returns									
Average Predictor	1.470	0.627	–0.096	–0.804	–1.904	–3.374	[–34.0]		
Extreme Predictor	1.446	0.355	–0.000	–0.615	–1.903	–3.349	[–33.6]		

Table 5: Currency Analysts' Forecasts and Predictors

The table reports results from regressions of forecast currency returns and currency excess returns (in percent per month) on average and extreme predictors and control variables. Forecast currency returns are the negative log difference of a foreign currency's 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 predictor is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying predictors, divided by the number of predictors. The analysis is based on the following eleven currency predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 August 2022. Table A3 in the Appendix provides details on variable definitions.

	Forecast Currency Excess Returns		Forecast Currency Returns	
	Average Predictor	Extreme Predictor	Average Predictor	Extreme Predictor
Predictor	–8.024***	–3.663***	–9.958***	–4.611***
	(0.658)	(0.327)	(0.706)	(0.349)
Number of Forecasters	–0.013***	–0.012***	–0.008***	–0.006***
	(0.003)	(0.003)	(0.002)	(0.002)
Single Forecast	–0.198	–0.140	–0.250	–0.180
	(0.333)	(0.325)	(0.256)	(0.248)
Intercept	5.775***	1.612***	6.794***	1.653***
	(0.770)	(0.354)	(0.802)	(0.239)
Observations	13,333	13,333	13,333	13,333
R–Squared	0.42	0.41	0.49	0.48
Month Fixed Effects	Yes	Yes	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country

Table 6: Currency Analysts' Mistakes and Predictors

The table reports results from regressions of analysts' mistakes (in percent per month) on predictors and control variables. Mistakes are the difference between forecast currency returns and actual (i.e. realized) currency returns. Forecast currency returns are the negative log difference of a foreign currency's 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 predictor is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying predictors, divided by the number of predictors. The analysis is based on the following eleven currency predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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. Predictor (out-of-sample) is average or extreme predictor using individual predictors only in periods after their respective in-sample periods. Regressions include the number of forecasters providing forecasts for a currency and an indicator for a single forecast as controls. All regressions also include month fixed effects. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels as well as the number of observations and the R-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 August 2022. Table A3 in the Appendix provides details on variable definitions.

	Average Predictor				Extreme Predictor			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Predictor	–9.724***	–9.540***	–8.142***		–4.443***	–4.590***	–3.714***	
	(0.688)	(0.888)	(0.653)		(0.334)	(0.435)	(0.324)	
Predictor x Publication		2.453**				1.475***		
		(1.088)				(0.509)		
Publication		–1.184**				0.175		
		(0.585)				(0.150)		
Realized Excess Returns			–0.931***				–0.934***	
			(0.028)				(0.028)	
Predictor (out-of-sample)				–11.009***				–5.065***
				(0.938)				(0.449)
Number of Forecasters	–0.011***	–0.009***	–0.013***	–0.011***	–0.010***	–0.008***	–0.012***	–0.006**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Single Forecast	–0.207	–0.202	–0.199	0.309	–0.136	–0.178	–0.139	0.169
	(0.306)	(0.230)	(0.331)	(0.300)	(0.295)	(0.220)	(0.322)	(0.285)
Intercept	5.857***	5.181***	5.781***	1.161	0.813	0.194	1.560***	2.823***
	(0.972)	(0.552)	(0.768)	(0.718)	(0.879)	(0.143)	(0.374)	(0.715)
Observations	13,333	13,333	13,333	11,043	13,333	13,333	13,333	11,043
R–Squared	0.42	0.08	0.71	0.40	0.41	0.07	0.71	0.39
Month Fixed Effects	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country	Country	Country	Country	Country

Table 7: Predictors 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 and extreme predictors, respectively, and control variables. Average predictor is the average of the percentile ranks of currencies with respect to the following eleven currency predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. Regressions include the number of forecasters providing forecasts for a currency and an indicator for a single forecast as controls. All regressions also include month fixed effects. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels as well as the number of observations and the R-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 August 2022. Table A3 in the Appendix provides details on variable definitions.

	Average Predictor			Extreme Predictor		
	(1)	(2)	(3)	(1)	(2)	(3)
Predictor (lagged by 1 month)	2.230***			0.976***		
	(0.305)			(0.153)		
Predictor (lagged by 2 months)		0.389			0.152	
		(0.307)			(0.151)	
Predictor (lagged by 3 months)			–0.499			–0.242
			(0.317)			(0.150)
Number of Forecasters	0.006***	0.004***	0.003**	0.005***	0.004***	0.003**
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Single Forecast	0.079	0.028	–0.009	0.061	0.024	–0.006
	(0.140)	(0.110)	(0.102)	(0.137)	(0.110)	(0.103)
Intercept	–1.190*	1.824*	0.741	–0.016	2.035**	0.488
	(0.686)	(0.914)	(1.151)	(0.706)	(0.892)	(1.118)
Observations	12,979	12,911	12,843	12,979	12,911	12,843
R–Squared	0.32	0.31	0.31	0.32	0.31	0.31
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country	Country	Country

Table 8: Currency Excess Returns, Analysts' Forecasts, and Predictors

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 predictors and analysts' forecasts of currency excess returns that are made in month t. At the end of each month, all available currencies are sorted independently into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on predictors and analysts' forecasts of currency excess returns. Forecast currency excess returns are the log difference between the one-month forward exchange rate of month t and the foreign currency's one-month forecast in month t. Average predictor is the average of the percentile ranks of currencies with respect to the following eleven currency predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. The table reports 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 August 2022. Table A3 in the Appendix provides details on variable definitions.

	Average Predictor			Extreme Predictor		
	Coefficient	t-statistic		Coefficient	t-statistic	
Predictor Q2	0.240	[3.15]	***	0.173	[2.17]	**
Predictor Q3	0.311	[3.15]	***	0.247	[2.52]	**
Predictor Q4	0.497	[4.41]	***	0.409	[3.72]	***
Predictor Q5	0.940	[7.42]	***	0.827	[6.90]	***
Forecast Excess Return Q2	0.202	[2.63]	***	0.166	[2.00]	**
Forecast Excess Return Q3	0.229	[2.53]	**	0.154	[1.52]	
Forecast Excess Return Q4	0.285	[2.52]	**	0.144	[1.19]	
Forecast Excess Return Q5	0.459	[3.26]	***	0.396	[2.86]	***
Intercept	–0.508	[–4.02]	***	–0.372	[–2.67]	***
Average Number of Observations	34			34		
Average R–Squared	0.40			0.39		

Internet Appendix

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 $\alpha_{i,t}$ is a linear combination of the characteristics, where the weights are defined by the matrix Γ_α.

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 $M \times 1$ vector of observable factors. Currencies are allowed to have dynamic loadings $\delta_{i,\,t}$ on these factors conditional on the same set of instruments that are mapped into loadings by the $L \times M$ 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	August 2022
Australia	Australian Dollar	December 1984	August 2022
Austria	Austrian Schilling	December 1970	December 1998
Bahrain	Bahrain Dinar	March 2004	August 2022
Belgium	Belgian Franc	December 1970	December 1998
Brazil	Brazilian Real	March 2004	August 2022
Bulgaria	Bulgarian Lev	March 2004	August 2022
Canada	Canadian Dollar	December 1970	August 2022
Chile	Chilean Peso	March 2004	August 2022
China	Chinese Renminbi	February 2002	August 2022
Colombia	Colombian Peso	March 2004	August 2022
Croatia	Croatian Kuna	March 2004	August 2022
Cyprus	Cypriot Pound	March 2004	December 2007
Czech Republic	Czech Koruna	December 1996	August 2022
Denmark	Danish Krone	December 1970	August 2022
Egypt	Egyptian Pound	March 2004	August 2022
Estonia	Estonian Kroon	March 2004	December 2010
Euro Area	Euro	January 1999	August 2022
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	August 2022
Greece	Greek Drachma	December 1996	December 2000
Hong Kong	Hong Kong Dollar	October 1983	August 2022
Hungary	Hungarian Forint	October 1997	August 2022
Iceland	Iceland Krona	March 2004	August 2022
India	Indian Rupee	October 1997	August 2022
Indonesia	Indonesian Rupiah	December 1996	August 2022
Ireland	Irish Punt	December 1970	December 1998
Israel	Israeli Shekel	March 2004	August 2022
Italy	Italian Lira	December 1970	December 1998
Japan	Japanese Yen	June 1978	August 2022
Jordan	Jordanian Dinar	March 2004	August 2022
Kazakhstan	Kazakhstani Tenge	March 2004	August 2022
Kenya	Kenyan Schilling	March 2004	August 2022
Kuwait	Kuwaiti Dinar	January 1994	August 2022
Latvia	Latvian Lats	March 2004	December 2013
Lithuania	Lithuanian Litas	March 2004	December 2014
Malaysia	Malaysian Ringgit	December 1996	August 2022

(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	August 2022
Morocco	Moroccan Dirham	March 2004	August 2022
Netherlands	Netherlands Guilder	December 1970	December 1998
New Zealand	New Zealand Dollar	December 1984	August 2022
Nigeria	Nigerian Naira	April 2011	August 2022
Norway	Norwegian Krone	December 1970	August 2022
Oman	Omani Rial	March 2004	August 2022
Pakistan	Pakistani Rupee	March 2004	August 2022
Peru	Peruvian New Sol	March 2004	August 2022
Philippines	Philippine Peso	December 1996	August 2022
Poland	Polish Zloty	February 2002	August 2022
Portugal	Portuguese Escudo	January 1981	December 1998
Qatar	Qatar Rial	March 2004	August 2022
Romania	Romanian Leu	March 2004	August 2022
Russia	Russian Rouble	March 2004	August 2022
Saudi Arabia	Saudi Arabian Riyal	December 1996	August 2022
Serbia	Serbian Dinar	July 2011	August 2022
Singapore	Singaporean Dollar	December 1984	August 2022
Slovakia	Slovakian Koruna	February 2002	December 2008
Slovenia	Slovenian Tolar	March 2004	December 2006
South Africa	South African Rand	October 1983	August 2022
South Korea	South Korean Won	February 2002	August 2022
Spain	Spanish Peseta	December 1970	December 1998
Sri Lanka	Sri Lankan Rupee	July 2011	August 2022
Sweden	Swedish Krona	December 1970	August 2022
Switzerland	Swiss Franc	December 1970	August 2022
Taiwan	Taiwanese Dollar	December 1996	August 2022
Thailand	Thai Baht	December 1996	August 2022
Tunisia	Tunisian Dinar	March 2004	August 2022
Turkey	Turkish Lira	December 1996	August 2022
Uganda	Ugandan Shilling	July 2011	August 2022
Ukraine	Ukrainian Hryvnia	March 2004	August 2022
United Arab Emirates	UAE Dirham	December 1996	August 2022
United Kingdom	United Kingdom Pound	December 1970	August 2022
Vietnam	Vietnamese Dong	July 2011	August 2022
Zambia	Zambia Kwacha	July 2011	August 2022

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. Della Corte, Ramadorai, and Sarno, 2016; Menkhoff et al., 2016; Menkhoff et al., 2012a; 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 a foreign currency's one-month forecast in month t and the spot exchange rate of month $t+1$.
Interest Rate Differential	When Covered Interest Parity holds, the interest rate differential equals the forward discount. The forward discount is the log difference of a foreign currency's one-month forward rate in month t and its spot rate in month t. Data 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.
Predictors	
Average Predictor	Average predictor is calculated as the average percentile rank of currencies with respect to the underlying predictors.
Extreme Predictor	Extreme predictor 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	Predictor profit in a month is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1) based on an individual or aggregate predictor signal.
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 (Nguyen et al., 2022; Laeven and Valencia, 2020; Reinhart and Rogoff, 2014) in the respective country and 0 otherwise. In a very small number of cases, we extend crisis data due to missing observations. Results are similar for inclusion of individual or joint controls for different types of crises.
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	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 the 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	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).
Political Risk Factor	We obtain monthly political risk measure from the International Country Risk Guide (ICRG) published by the PRS Group. We calculate the political risk measure as the standardized sum of differences in political risk between all countries and the United States. We then calculate political risk innovations by estimating an AR(1) for the political risk measure and take the residuals. To obtain the political risk factor, we regress political risk innovations on six momentum portfolio excess returns, and take the projections on the five portfolios (Filippou et al., 2018).
International Correlation Risk Factor	We sort currencies into portfolios based on the exposure (beta) of currency excess returns to innovations in their dispersion measure. Then nine G10 currencies can be sorted into three portfolios according to their estimated exposure (beta). Finally, the international correlation risk factor is constructed by taking a long position in the top tercile and a short position in the bottom tercile (Mueller et al., 2017).
Global Imbalance Risk Factor	We construct portfolios based on net foreign asset position and external liabilities in domestic currency. The global imbalance factor is the return difference between portfolio 5 and portfolio 1 (Della Corte et al., 2016).
Network Centrality Risk Factor	We build four portfolios sorted by annual values of trade network centrality provided by Robert Richmond. The Network Centrality factor is the return difference between portfolio 4 and portfolio 1 (Richmond, 2019).
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)

(continued)

Table A3: Variable Definitions (continued)

Variable	Definition
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 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

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 predictor is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying predictors, divided by the number of predictors. The sample includes 76 currencies. The sample period is from January 2000 to August 2022. 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 Predictor
3-Months Momentum	0.606											
12-Months Momentum	0.331	0.460										
Filter Rule Combination	0.697	0.748	0.567									
Carry Trade	–0.053	0.075	0.311	–0.134								
Dollar Carry Trade	0.084	0.110	0.073	0.070	0.175							
Dollar Exposures	0.045	0.053	0.068	0.075	0.099	0.920						
Term Spread	0.014	0.077	0.184	0.013	0.313	0.194	0.153					
Currency Value	–0.106	–0.150	–0.386	–0.238	–0.005	–0.036	–0.051	0.082				
Output Gap	0.148	0.115	0.121	0.152	–0.153	0.097	0.133	0.111	0.098			
Taylor Rule	–0.096	–0.041	0.201	–0.067	0.576	0.023	–0.010	0.356	0.143	0.126		
Average Predictor	0.544	0.628	0.632	0.633	0.344	0.188	0.138	0.378	–0.100	0.152	0.347	
Extreme Predictor	0.629	0.684	0.648	0.701	0.340	0.194	0.139	0.359	–0.107	0.149	0.342	0.890

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 and extreme predictors. 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 predictor is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying predictors, divided by the number of predictors. The analysis is based on the following eleven currency predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 predictors. All series end in August 2022. 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	–0.179	3.165	–2.332	39.54	–69.40	–9.754	–4.927	–1.317	0.000	1.125	4.395	7.193	34.21
Forecast Currency Returns	–0.158	3.044	0.529	12.150	–28.14	–8.202	–4.818	–1.545	–0.129	1.091	4.608	8.500	37.53
Actual Currency Excess Returns	0.107	3.178	–1.364	28.08	–63.94	–9.136	–4.658	–1.081	0.069	1.453	4.795	7.884	38.78
Forecast Currency Excess Returns	0.136	3.112	1.219	14.863	–22.38	–7.520	–4.483	–1.278	0.016	1.326	4.998	9.414	40.35
Analysts' Mistakes	0.043	4.420	1.223	16.76	–40.92	–10.13	–6.474	–2.118	–0.073	1.872	6.971	13.34	66.77
Average Predictor	0.520	0.154	0.129	2.708	0.068	0.194	0.270	0.411	0.516	0.625	0.781	0.883	1.000
Extreme Predictor	0.015	0.315	0.137	3.108	–1.000	–0.714	–0.500	–0.182	0.000	0.222	0.556	0.778	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 August 2022. 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	–0.186	0.020	0.132	0.159	0.381	0.567	6.803	0.012	–0.157	–0.063	–0.041	0.131	0.118	1.420
	[–1.66]	[0.20]	[1.37]	[1.68]	[3.74]	[5.44]		[0.11]	[–1.60]	[–0.65]	[–0.43]	[1.28]	[1.13]	
3-Months Momentum	–0.147	–0.071	0.094	0.174	0.461	0.608	7.300	0.028	–0.246	–0.091	–0.016	0.225	0.197	2.365
	[–1.29]	[–0.73]	[0.96]	[1.79]	[4.56]	[5.47]		[0.25]	[–2.53]	[–0.92]	[–0.16]	[2.22]	[1.76]	
12-Months Momentum	–0.058	–0.019	0.033	0.077	0.381	0.439	5.269	0.073	–0.167	–0.110	–0.077	0.167	0.094	1.127
	[–0.49]	[–0.19]	[0.31]	[0.76]	[3.71]	[3.66]		[0.62]	[–1.64]	[–1.03]	[–0.77]	[1.63]	[0.78]	
Filter Rule Combination	–0.101	–0.100	0.094	0.154	0.292	0.393	4.720	0.083	–0.286	–0.084	–0.022	0.116	0.033	0.393
	[–0.83]	[–0.96]	[0.94]	[1.60]	[2.97]	[3.42]		[0.68]	[–2.72]	[–0.84]	[–0.23]	[1.18]	[0.28]	
Carry Trade	–0.190	–0.048	0.110	0.216	0.563	0.753	9.034	–0.052	–0.190	–0.048	0.039	0.264	0.316	3.790
	[–2.09]	[–0.55]	[1.27]	[2.33]	[5.30]	[8.57]		[–0.57]	[–2.17]	[–0.55]	[0.42]	[2.48]	[3.58]	
Dollar Carry Trade						0.320	3.842						0.219	2.626
						[3.42]							[2.33]	
Dollar Exposures	0.059	0.203	0.267	0.426	0.378	0.319	3.826	0.159	0.054	0.133	0.330	0.293	0.134	1.608
	[1.56]	[2.74]	[2.31]	[3.23]	[2.44]	[2.02]		[4.14]	[0.73]	[1.15]	[2.50]	[1.89]	[0.84]	
Term Spread	0.021	–0.017	0.047	0.087	0.289	0.268	3.221	0.208	–0.171	–0.104	–0.077	0.100	–0.108	–1.297
	[0.22]	[–0.17]	[0.47]	[0.86]	[2.70]	[3.29]		[2.20]	[–1.70]	[–1.04]	[–0.76]	[0.93]	[–1.30]	
Currency Value	0.185	0.072	0.002	0.092	0.338	0.153	1.840	0.278	–0.010	–0.084	0.001	0.241	–0.036	–0.437
	[1.25]	[0.48]	[0.01]	[0.58]	[1.97]	[1.01]		[1.88]	[–0.07]	[–0.56]	[0.01]	[1.41]	[–0.24]	
Output Gap	0.069	0.007	0.029	0.298	0.314	0.245	2.943	0.155	–0.078	–0.063	0.188	0.222	0.067	0.805
	[0.40]	[0.05]	[0.17]	[1.70]	[1.89]	[1.79]		[0.92]	[–0.51]	[–0.37]	[1.08]	[1.34]	[0.50]	
Taylor Rule	0.067	–0.065	–0.002	0.195	0.549	0.481	5.777	0.141	–0.136	–0.081	0.101	0.426	0.285	3.418
	[0.48]	[–0.42]	[–0.01]	[1.14]	[2.78]	[2.82]		[0.99]	[–0.88]	[–0.51]	[0.59]	[2.17]	[1.68]	

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: Quintile Performance of Portfolios Sorted on Average and Extreme Predictors

The table reports actual (i.e. realized) excess returns (in percent per month) of portfolios sorted on average and extreme predictors, alternatively gross of transaction costs and net of transaction costs. Transaction costs are calculated using bid and ask quotations. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average and extreme predictors and combined into 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 predictor is the average of the percentile ranks of currencies with respect to the following eleven currency predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven strategies, divided by the total number of strategies. The table reports 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 the predictor variable. The sample includes 76 currencies. The sample period is from January 1976 to August 2022. 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 Predictor												
Average Currency Excess Return (t+1)	–0.316	0.036	0.104	0.190	0.501	0.817	–0.164	–0.143	–0.078	–0.019	0.265	0.429
t-statistic	[–3.23]	[0.38]	[1.09]	[1.88]	[4.90]	[8.64]	[–1.68]	[–1.48]	[–0.82]	[–0.18]	[2.59]	[4.53]
Sharpe Ratio	–0.136	0.016	0.046	0.080	0.207	0.365	–0.071	–0.063	–0.035	–0.008	0.109	0.191
Standard Deviation	2.314	2.287	2.247	2.390	2.421	2.236	2.311	2.281	2.254	2.404	2.424	2.243
Skewness	–0.610	–0.155	–0.215	–0.322	–0.301	0.083	–0.525	–0.200	–0.252	–0.375	–0.353	0.013
Kurtosis	6.713	5.381	4.482	4.669	4.514	5.284	6.657	5.357	4.454	4.784	4.569	5.418
Predictor (t)	0.321	0.435	0.527	0.616	0.740	0.419	0.321	0.435	0.527	0.616	0.740	0.419
Extreme Predictor												
Average Currency Excess Return (t+1)	–0.230	0.020	0.076	0.165	0.497	0.727	–0.071	–0.149	–0.104	–0.030	0.249	0.320
t-statistic	[–2.37]	[0.21]	[0.80]	[1.63]	[4.96]	[7.65]	[–0.74]	[–1.57]	[–1.08]	[–0.30]	[2.48]	[3.35]
Sharpe Ratio	–0.100	0.009	0.034	0.069	0.210	0.323	–0.031	–0.066	–0.046	–0.013	0.105	0.141
Standard Deviation	2.296	2.257	2.271	2.394	2.370	2.250	2.292	2.257	2.281	2.397	2.379	2.264
Skewness	–0.470	–0.218	–0.348	–0.328	–0.213	0.125	–0.392	–0.255	–0.404	–0.356	–0.289	0.047
Kurtosis	6.485	5.007	4.963	4.403	4.863	5.608	6.484	5.001	5.047	4.398	4.920	5.678
Predictor (t)	–0.401	–0.131	0.019	0.170	0.465	0.866	–0.401	–0.131	0.019	0.170	0.465	0.866

Table A9: 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 2022 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 August 2022. 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	–0.375***	0.090	–0.308***	0.066
	(0.102)	(0.193)	(0.101)	(0.096)
Post-Publication x Average Predictor In-Sample Profits		–0.824**		–1.607***
		(0.387)		(0.446)

(continued)

Table A9: 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	–0.476***	0.098	–0.297***	0.078
	(0.106)	(0.178)	(0.106)	(0.094)
Post-Publication x Average Predictor In-Sample Profits		–0.971***		–1.493***
		(0.354)		(0.419)
40 currencies				
Post-Publication	–0.569***	0.141	–0.415***	0.069
	(0.104)	(0.203)	(0.104)	(0.117)
Post-Publication x Average Predictor In-Sample Profits		–1.180***		–1.607***
		(0.377)		(0.457)
10 currencies				
Post-Publication	–0.533***	0.083	–0.404***	–0.085
	(0.116)	(0.159)	(0.116)	(0.109)
Post-Publication x Average Predictor In-Sample Profits		–1.254***		–1.174***
		(0.354)		(0.405)

Table A10: Currency Analysts' Mistakes and Predictors for Alternative Samples

The table reports results from regressions of analysts' mistakes (in percent per month) on predictors, the interaction of predictors with publication, and control variables. The regression specifications are the same as in Table 6, but for brevity, the table only displays the coefficients on the predictor 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 predictor is the average of the percentile ranks of currencies with respect to the underlying predictors, while extreme predictor is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying predictors, divided by the number of predictors. The analysis is based on the following eleven currency predictors: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior 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 2022 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 August 2022. Table A3 in the Appendix provides details on variable definitions.

	Average Predictor		Extreme Predictor	
	Table 6, Specification (1)	Table 6, Specification (2)	Table 6, Specification (1)	Table 6, Specification (2)
52 currencies				
Predictor	–10.30***	–9.585***	–4.806***	–4.652***
	(0.681)	(0.915)	(0.328)	(0.450)
40 currencies				
Predictor	–10.491***	–10.039***	–4.948***	–4.881***
	(0.706)	(1.023)	(0.331)	(0.471)
10 currencies				
Predictor	–8.051***	–8.762***	–4.054***	–4.441***
	(0.688)	(0.918)	(0.378)	(0.465)