Currency Anomalies

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Abstract

This paper is the first to study the cross-section of currency anomalies to explore alternative explanations for their existence. Using real-time data, currency anomalies are profitable during in-sample and out-of-sample periods, both before and after transaction costs, but trading profits decrease substantially after the publication of the underlying academic research. The decline is greater for anomalies with larger in-sample profits and lower arbitrage costs, and signal ranks and performance decay quickly, suggesting that currency anomalies reflect mispricing rather than compensation for risk or statistical bias. Mispricing is systematically related to mistakes and changes in analysts' currency forecasts. In particular, analysts expect anomaly payoffs that are too low compared with actual anomaly profits. However, analysts update their forecasts to incorporate lagged anomaly information. These results are consistent with a behavioral explanation for currency anomalies.

Keywords: Exchange rates, anomalies, mispricing, analysts, market efficiency, real-time, point-in-time, arbitrage costs
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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.[1] Yet, investors in currency markets have been shown to be able to generate systematic trading profits using various investment strategies, such as momentum (Burnside et al., 2011; Menkhoff et al., 2012), value (Asness et al., 2013; Menkhoff et al., 2017), term spread (Ang and Chen, 2010), and output gap (Riddiough and Sarno, 2018).[2]

In contrast to the focus on risk premia of individual predictors in this currency literature, this is the first paper studying the cross-section of currency anomalies and testing alternative hypotheses for their occurrence. In particular, we construct all currency anomalies 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. We consider data snooping and behavioral biases, in addition to risk premia, as possible rationales of these anomalies. In order to distinguish between different rationales, we examine whether the predictive power of anomalies remains after the underlying academic research has been publicly disseminated. If anomaly profits are the result of data snooping, they should not exist in post-sample periods before publication,

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

[2] Our paper is related to a recent, small but growing body of research that is focused on cross-sectional prediction of currency excess returns documenting a number of variables that systematically predict excess returns across currencies (see, e.g., Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2014; Verdelhan, 2018). To illustrate, trading signals that predict the cross-section of currency excess returns are changes in interest rates and term spreads (Ang and Chen, 2010) and currency value, measured as the 5-year change in purchasing power parity (Asness, Moskowitz, and Pedersen, 2013) or real exchange rates, especially when adjusting real exchange rates for key fundamentals (Menkhoff et al., 2017). Recent research shows that business cycles are a powerful predictor of currency excess returns (Riddiough and Sarno, 2018).

and if they reflect compensation for risk, they should not change after publication. In contrast, if predictors of currency excess returns reflect mispricing and market inefficiencies that are likely the result of behavioral biases, anomalies should become weaker after publication. Similarly, anomaly profits should decrease when delaying the trading signal.

To analyze behavioral explanations directly, we use a unique and in part hand-collected data set of currency forecasts to study behavioral biases by relating currency mispricing to the exchange rate expectations formed by analysts, their forecast errors or mistakes, and revisions to their forecasts. Since we study many anomalies, we can again take a realistic investment perspective by combining them into aggregate mispricing measures yielding investment strategies with improved signal to noise ratios. Moreover, we can test the predictive power of aggregate mispricing alongside the exchange rate predictions made by analysts.

Our results provide evidence consistent with behavioral explanations for currency anomalies, as opposed to them being the result of data mining or capturing risk premia. In particular, currency anomalies remain profitable in out-of-sample periods pre-publication, but in line with them reflecting mispricing, their profitability decreases significantly after the academic research has been published.[3] Also consistent with mispricing, we observe significant decay in anomaly profits for stale trading signals, and the autocorrelations of signal ranks are low. The post-publication decline in anomaly profits is greater for anomalies with larger in-sample profits and lower arbitrage costs.

Mispricing captured by anomalies is systematically related to mistakes and changes in analysts' currency forecasts. Specifically, analysts typically expect anomaly profits that are too low compared with realized profits. In fact, analysts' forecasts of currency excess returns can even be in the opposite direction to those suggested by anomalies, i.e. analysts expect higher anomaly

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

excess returns for the short portfolios than for the long portfolios. These effects are largely driven by expectations of future exchange rate movements as analysts often expect losses from exchange rate changes (which reduce currency excess returns).

While analysts' forecasts are, thus, inconsistent with currency anomalies, lagged mispricing predicts forecast revisions, indicating that analysts incorporate information from anomaly variables into their exchange rate expectations with a delay. Moreover, analysts' forecasts of currency excess returns predict future currency excess returns controlling for anomaly-based mispricing.

This paper is the first to study the cross-section of currency anomalies, which allows drawing more general conclusions about exchange rate predictability, in contrast to extant work that has to date focused on individual predictors. Our approach permits entertaining and testing alternative rationales for currency anomalies, beyond the focus on risk in the literature. 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 of analysts documented for other assets classes such as equities. Consequently, the approach and data employed in this paper allow us to generate new inferences about the economics of currency markets.

To investigate alternative potential sources of predictability in currency markets, we first examine the profits of anomaly strategies in out-of-sample and post-publication periods. If return predictability reflects mispricing, and publication leads to investors learning about anomalies and trading to exploit mispricing, the predictability of anomalies should decline post-publication (McLean and Pontiff, 2016), and anomaly profits should decay when lagging the trading signal. Consistent with mispricing but not risk as the source of predictability, payoffs associated with currency anomalies significantly decrease (or even disappear) after the academic research has been

published. Post-publication declines are greater for strategies with economically or statistically larger in-sample profits and with smaller arbitrage costs. Trading profits decrease for lagged trading signals, and anomaly signals decay quickly. In contrast, there is no drop in the profitability of currency anomalies in out-of-sample periods before publication and thus no evidence of statistical bias or data mining as the origin of anomaly profits.

We combine anomalies into measures of average mispricing and extreme mispricing (alternatively across all anomalies and three groups of anomalies) that generate significant quintile spreads of realized currency excess returns both gross and net of transaction costs. However, analysts expect payoffs to mispricing based strategies that are lower than realized profits, and across all anomalies they even expect significant losses. To illustrate, the forecast excess return for the first quintile based on average mispricing (i.e. the short portfolio) is 143 basis points ("bp") per month, while it is –116 bp for the fifth quintile (i.e. the long portfolio). The expected quintile spread is thus –259 bp per month, contrasting with a realized quintile spread of 80 bp (or –31.0% vs. 9.7% on an annualized basis). Similarly, the realized profit of a trading strategy based on extreme mispricing is 73 bp per month, while analysts expect a loss of –251 bp. These results are opposite to what one would expect *a priori*. Across groups of anomalies, analysts expect significant positive trading profits only from mispricing tied to macroeconomic fundamentals. The expected losses are, to a large extent, the result of analysts frequently expecting negative quintile spreads on the currency return component.

Evidence from panel regressions of currency excess returns on mispricing are consistent with these results. If analysts considered anomaly variables, their expectations about currency excess returns would be positively related to mispricing, while the regressions yield significant negative coefficients on mispricing (except for fundamentals). These results demonstrate that analysts' foreign exchange forecasts are often inconsistent with the information in anomaly variables,

providing evidence of mispricing in currency markets. Investors following the advice of analysts may well be contributing to this mispricing and making currency markets less efficient.

The apparent mistakes that analysts make can be measured directly as the difference between forecast and realized excess returns. They are negatively associated with mispricing, 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, for anomalies based on interest rates and fundamentals, analysts' mistakes become smaller over time. In fact, for anomalies tied to fundamentals, the effect is so large that on average analysts' forecasts are in line with realized anomaly profits. Furthermore, lagged mispricing predicts changes in analysts' foreign exchange forecasts, suggesting that analysts predictably update their forecasts based on information captured in anomalies.

We perform a number of additional tests to establish the robustness of our results. While all currencies in our sample have quotes in the spot and forward market and the respective spreads capture the relative liquidity of currencies, we alternatively limit the sample to several smaller sets of currencies. For instance, we consider the 40 most liquid currencies based on Bank for International Settlements (BIS) turnover statistics, or just the so-called "G10" currencies. Our main results pertaining to publication effects and analysts' biases are robust to these alternative samples. Results are also qualitatively similar when excluding carry trade and dollar carry trade from the set of anomalies, given that they might be perceived as risk factors rather than anomalies.

While practitioners may have traded on some of the currency anomalies before they were popularized by academic research, this should bias against finding significant effects for later publication of the underlying research. Moreover, we still find significant publication effects of academic currency research even after explicitly controlling for possible earlier dissemination of the anomaly strategies in practitioner publications, newspaper articles, or academic publications on different but related effects in currency markets as well as academic publications on corresponding anomalies in other asset classes. Other robustness tests consider the recent low interest rate

environment, control for aggregate measures of macroeconomic risk, or use final vintage data to construct anomalies based on macroeconomic data, which yield stronger performance but otherwise similar results compared to using real-time data for the affected anomalies.

Our study provides a fresh view on excess return predictability in currency markets. Related work that tries to explain the existence of anomalies cross-sectionally mostly exists for equities. To illustrate, empirical evidence suggests that stock market anomalies are attenuated after publication (McLean and Pontiff, 2016) and in recent years due to increased trading activity of hedge funds and lower trading costs (Chordia et al., 2014). Studies of the relation of stock market anomalies with equity analysts' recommendations and target prices find them to be consistent (Jegadeesh et al., 2004), inconsistent (Engelberg et al., 2017; Guo et al., 2020), or conditional on credit quality (Grinblatt, Jostova, and Philipov, 2018). Given this mixed evidence, our paper provides important out-of-sample evidence for related questions in currency markets, where it is also easier to take a more realistic investment perspective by adjusting anomaly profits for transactions costs.

Moreover, while equity markets have many assets and anomalies compared to currency markets, they might be less efficient due to higher transactions costs, lower turnover, market closures, short selling constraints, etc. Additionally, data on analysts' forecasts for next months' stock returns do not exist. Instead, researchers have to use forecasts of annual or quarterly earnings or annual target prices, which exhibit horizon and seasonality effects, may require adjustments for 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.

The paper is organized as follows. Section 2 defines the sample and describes the data. Section 3 analyzes post-sample and post-publication predictability. Section 4 examines the relationship between anomalies and foreign exchange forecasts, analysts' mistakes, and forecast revisions. Section 5 provides robustness tests. The paper concludes in Section 6.

2 Sample and Data

The empirical analysis uses monthly data for anomaly signals and exchange rates of 76 countries (Table A5 in the Appendix). For each of the 570 months between December 1970 to May 2018, we construct eleven widely used currency anomalies that have been documented in the literature as distinct predictors of currency excess returns: momentum based on prior one, three, or twelve months currency returns, a filter rule combination, carry trade, dollar carry trade, dollar exposures, term spread, currency value, output gap, and the Taylor Rule. They represent all anomalies that can be constructed with publicly available data for a large number of currencies.

Since we are analyzing the ability of these anomaly variables to predict future currency returns, we construct all anomalies using real-time data. This ensures that the information from the trading signals was available to market participants at the point in time the signal was constructed and thus avoids a look-ahead bias. To this end, we source monthly spot exchange rates, one-month forward exchange rates, short-term interest rates (interbank or Treasury Bill rates), and long-term interest rates (ten-year or five-year government bond yields) from Datastream. We further obtain monthly real-time data on industrial production and consumer prices from the Original Release Data and Revisions Database of the OECD, which has been rarely used in the cross-sectional currency prediction literature.[4] Appendix A provides detailed descriptions of the anomalies, their construction, and references to the literature.

[4] 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,

Individual anomalies have low correlations between each other, with an average correlation of 0.15. However, correlations can be as low as –0.39 and as high as 0.92, suggesting they provide a wide range of differing mispricing signals (Table A4 in the Appendix).[5] Consequently, our calculation of standard errors takes the dependence between anomalies into account. Based on their characteristics and inputs, we classify anomalies into three broad groups (or "families"). The first group, Trend Following, comprises 1month, 3-months and 12-months momentum, and the filter rule combination, because they are based on prior months' returns. We group carry trade, dollar carry trade, dollar exposures, and term spread into a second category, Interest Rates, since these anomalies use a form of interest rate differential or forward discount. The third group, Fundamentals, includes currency value, output gap, and the Taylor Rule, i.e. anomalies that use macroeconomic variables (consumer price inflation and industrial production).[6]

We relate these anomalies to currency returns and analysts' expectations in the following month, so that the anomalies are lagged by one month relative to future actual currency (excess) returns and analysts' expected currency (excess) returns. Anomaly profits are calculated as quintile spreads of the excess returns of equally weighted currency portfolios. We build a unique and in part hand-collected data set of foreign exchange rate expectations using mean forecasts from surveys undertaken by Consensus Economics for the period December 1989 and June 2018. All spot and forecast exchange rates are in units of foreign currency per unit of a U.S. Dollar. For some currencies and time periods, raw data on analysts' exchange rate expectations are quoted relative

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.

[5] Similarly, for equity markets, McLean and Pontiff (2016) find average correlations between 97 predictor variables of 0.033, ranging from –0.895 to 0.933. Green, Hand and Zhang (2013) report an average correlation of 0.09 among 60 quantitative portfolios.

[6] The classification follows similar principles applied in the literature (e.g. McLean and Pontiff, 2016). A cluster analysis generates fairly similar groupings, except that the Taylor Rule becomes part of the Interest Rates group due to high correlation with carry.

to the Deutschmark or Euro, and we convert these forecasts to quotes against the U.S. Dollar using the corresponding Deutschmark or Euro forecasts.[7]

Following the literature (e.g. Lustig, Roussanov, and Verdelhan, 2014; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012) we define next month's currency return as the *negative* log difference between the spot exchange rates of months $t+1$ and t, so that a positive value represents an appreciation of the foreign currency with respect to the U.S. Dollar and a positive contribution from the spot exchange rate movement to the currency excess return.[8] 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, Rime, and Sarno, 2008). Gross currency (excess) returns are based on mid-point exchange rate quotes. However, a more realistic measurement of trading profits needs to consider the frictions involved in realizing these profits. To this end, we calculate currency (excess) returns net of transaction costs by using bid-ask quotes for spot and forward exchange rates.

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. The excess return expected by analysts is the expected exchange rate return plus the one-month interest differential. The mistake (or forecast error) that analysts make in forecasting exchange rates is the difference between the expected currency return for month $t+1$ and its realization during that month. Finally, we measure the forecast revision as the log difference in analysts' forecasts between month t and month $t+1$. Appendix A provides

[7] The surveys draw on 250 forecasters in 27 countries covering 65 currencies, mostly affiliated with investment banks (BNP Paribas, Commerzbank, Citigroup, Goldman Sachs, Deutsche Bank, Royal Bank of Canada, Royal Bank of Scotland, Santander, Société Générale, etc.), but also consultancies (e.g. Oxford Economics, EIU) and research institutes (such as WIIW, NIESR). The number of survey participants ranges from 100 for the more traded currencies Euro, Japanese Yen, British Pound and Canadian Dollar, to around 20 for Chinese Renminbi and Indian Rupee, and still more than 10 for less liquid currencies such as Czech Krona, Russian Ruble, Argentinian Peso and Brazilian Real (all quoted against the U.S. Dollar).

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

details of all variable definitions. Table A6 in the Appendix shows detailed summary statistics of actual and forecast currency (excess) returns and analysts' mistakes.

3 Post-Publication Profits

To examine possible explanations for the existence of systematic currency investment strategies, such as risk premia, statistical biases, and mispricing, we analyze their ability to predict currency excess returns in out-of-sample and post-publication periods. In particular, we compare anomaly profits from the sample period of the original academic research (i.e. the in-sample period) with profits in the period after the in-sample period but before the publication of the academic research (referred to as the out-of-sample period) as well as with profits after the publication of the research (i.e. the post-publication period).[9] If currency excess return predictability in published academic research originates solely from in-sample statistical bias or data mining, predictability should not exist in the out-of-sample period (McLean and Pontiff, 2016; Fama, 1991).[10]

Differences between the predictive power of anomalies in the in-sample period and post-publication period could be the result of statistical bias or learning by investors from the publication. If return predictability reflects mispricing, and publication allows sophisticated investors to exploit mispricing by trading on the anomalies, the returns associated with anomalies should decrease after anomalies become publicly known through their dissemination. Frictions, however, might prevent anomaly profits from disappearing completely. In contrast, anomaly profits should not change after publication if they reflect compensation for risk, conditional on no fundamental change in the risk-return trade-off or pricing of risk (Cochrane, 1999).

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

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

Profits of individual currency investment strategies are generally positive and significant over the full sample period before accounting for transaction costs as documented in the literature, while net profits are naturally smaller (Table A1 in the Appendix). Since the academic research discovering cross-sectional currency strategies is very recent, we use the date of the first posting of the respective working papers on SSRN as their publication dates (Appendix B).[11] We create a Post-Sample dummy that is equal to one for the months after the end of the sample period used in the original study (but before publication), and zero otherwise. The indicator variable Post-Publication is equal to one for months after the publication date, and zero otherwise. The average monthly anomaly payoff before transaction costs is 56 bp per month in the in-sample period, 64 bp in the out-of-sample pre-publication period, and 19 bp in the post-publication period. The average length of the in-sample, out-of-sample and post-publication periods are 461, 11, and 99 months, respectively.

In order to study post-publication and out-of-sample anomaly profits, we estimate the following panel regression:

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

where the dependent variable is the monthly quintile spread of excess returns on currency anomaly *j* in month *t*, and Post-Sample and Post-Publication are indicator variables for the respective time periods. Anomaly profits are alternatively gross or net of transaction costs. The regression includes anomaly fixed effects, and standard errors are computed using feasible generalized least squares (FGLS) under the assumption of contemporaneous cross-correlation between returns.[12]

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

[12] Results are similar when clustering standard errors by date and anomaly.

The results show two interesting findings. First, there is no evidence that anomaly profits decline in the out-of-sample period, since the coefficients on the Post-Sample variable are insignificant in all specifications (Table 1 Panel A). This indicates that data mining is likely not a source of currency anomalies. If return predictability in published studies resulted from statistical bias, predictability should disappear out-of-sample. We do not find this to be the case.[13] Second, there is strong evidence that anomaly profits decrease after the underlying academic research has been disseminated. In particular, in specification (1), gross returns are lower by 38 bp per month after publication compared with the in-sample period, which is both statistically and economically significant. Given that anomalies generate on average in-sample payoffs of 56 bp, this result implies that currency anomalies are no longer profitable post publication, and we cannot reject the hypothesis that return predictability disappears completely (p-value = 0.128).

Results using anomaly profits net of transaction costs, arguably a more realistic measure, also show strong publication effects with a reduction of 33 bp after publication in specification (1) (Table 1 Panel A). These publication effects are bigger for anomalies that have economically or statistically larger in-sample profits, as shown in specifications (2) and (3), respectively, and the overall publication effect is always significant.[14] For net profits we similarly cannot reject the hypothesis that anomalies disappear post publication (p-value = 0.122). The analysis provides evidence that the returns associated with anomalies decrease after dissemination of the underlying academic research, consistent with the view that investors learn about and trade to exploit mispricing.

[13] Another way of studying the effect of data mining would be to measure anomaly profits before the in-sample period of the original research. However, pre-sample profits cannot be calculated for several of the anomalies studied in this paper because of unavailability of real-time fundamentals data (currency value, output gap, Taylor rule) or bid-ask spreads (carry trade) in the periods before the respective in-sample. In addition, exchange rates were fixed prior to August 1971 under the Bretton Woods system. A pre-sample indicator variable that is equal to one for the months before the sample period used in the original study (and zero otherwise) for anomalies where the necessary data is available has an insignificant (significant) negative coefficient for gross (net) anomaly profits in the regressions in Table 1 Panel A.

[14] As shown in Table A7 in the Appendix, the interaction terms involving in-sample profits are always negative and significant for profits gross and net of transactions costs using alternative samples with different sets of currencies.

The publication effect can be illustrated graphically by plotting the incremental change of anomaly profits post publication against anomaly in-sample profits: Anomalies with larger in-sample profits show larger declines in anomaly returns after publication (Figure 1 Panels A and B). In a related vein, there is also a negative relation between in-sample *t*-statistics and post-publication effects (Figure 1 Panels C and D). Similar results have recently been documented for the U.S. equity market, where gross portfolio returns are 58% lower post-publication, but already decrease by 26% in the out-of-sample period (McLean and Pontiff, 2016). In contrast, our results show no effect in the out-of-sample period and a larger decrease in the post-publication period (both for gross and net returns), which is in line with higher efficiency of deep and active currency markets.

The effect of publication on anomaly profits can be studied in more detail by replacing the post-publication indicator in the regressions in Table 1 Panel A by separate indicators for each of the first three years after publication as well as a single indicator variable for all months that are at least three years after publication. The coefficients on these variables show that gross profits drop quickly as they are lower by 24 bp in the first year after publication compared to the in-sample period (Figure 2, Panel A). In the following years, they are lower by 39 bp and 40 bp, and on average 42 bp lower than in the in-sample period thereafter. The regression also includes an indicator variable for the last year of the in-sample period. Its coefficient of –0.29 indicates that the last 12 months of the sample period have lower profits than other in-sample months, while anomaly profits are (insignificantly) higher in the post-sample period. Net profits (Figure 2, Panel B) exhibit similar patterns. These results provide no support for the concern of researchers choosing in-sample periods opportunistically to report stronger results.

One explanation for lower anomaly 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. To investigate this conjecture, we construct a time trend variable that is equal to 1/100 in January 1971 (the first anomaly signal is in December 1970, hence the first realized

return associated with that signal is in January 1971) and increases by 1/100 each month in our sample period. The estimated coefficient on the time trend is negative in specification (1), but only (marginally) significant for gross profits (Table 1 Panel B). When we relate anomaly profits to the time trend and post-publication variables in specification (2), the time trend is positive (and significant for net profits). Importantly, the post-publication coefficient remains negative and statistically significant, hence, the documented publication effect survives allowing for the presence of a time trend.

The publication effect is also robust to controlling for macro-economic risk and monetary policy in specification (3) as captured by within-month exchange rate volatility and the level of interest rates, alternatively for the currencies in the long/short portfolios (as reported in the table), or the G10 currencies, or just the level of the 3-months U.S. interbank rate and the volatility of a multilateral U.S. exchange rate, as well as indicator variables for the post-crisis period (2009-2011) and NBER recessions. The publication effect remains negative and significant in the presence of these additional controls.

We also investigate whether anomaly returns are persistent, and whether such persistence has an effect on the publication effect (Moskowitz, Ooi, and Pedersen, 2013). We implement this by including the anomalies' profits over the prior 1 and 12 months, respectively (specifications (4) and (5)). Only anomaly profits over the prior 12 months are significant, and the post-publication coefficient remains negative and significant in each of these specifications. There is a robust and economically sizable post-publication effect of at least 31 bp per month for gross profits and 27 bp for net profits of anomalies once persistence is controlled for.

The dissemination of research documenting profitable investment strategies based on anomalies should attract arbitrageurs who exploit these strategies leading to lower mispricing and reduced anomaly profits post publication. However, if trading is costly due to frictions, arbitrage may not fully eliminate all profits before accounting for these costs (Shleifer and Vishny, 1997;

Pontiff 1996, 2006). Thus, the reduction in profitability should be smaller for anomalies that involve taking positions in currencies that are more costly to trade. In order to test this hypothesis, we measure the arbitrage cost of an anomaly as the in-sample mean of the average bid-ask spread of the currencies in its long and short portfolios.

Similarly, we also condition the analysis on various proxies of limits to arbitrage related to exchange rate convertibility. In particular, for the currencies in the long and short portfolios, we consider the average in-sample exchange rate turnover (from the BIS, 2019), an index of average money market restrictions for inflows and outflows (from Fernández et al., 2015), a measure of capital account openness (Chinn and Ito, 2008), measures on the severity of restrictions to capital account and financial current account liberalization (Quinn and Toyoda, 2008), a measure of functional capital market efficiency (Eklund and Desai, 2013), and a proxy of the capital allocation efficiency (Wurgler, 2000). Note that these measures are typically capturing the exchange of one currency with regards to all other currencies, while our analysis only requires the conversion of U.S. Dollars into foreign currency and vice versa. Our main measure averages the percentile ranks of those with best coverage (FX turnover, money market restrictions, capital account openness) into a single index.

Including limits to arbitrage and their interaction with the post-publication indicator in the regressions provides evidence that they affect the size of the publication effect (Table 1 Panel C). In particular, the interaction terms on bid/ask spreads and the index of capital restrictions are positive and significant indicating that the post-publication reduction in anomaly 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 anomaly profits can also be rejected for bid/ask spreads (p-value = 0.002) and exchange rate convertibility (p-value = 0.039). By the same token, trading profits from equity market anomalies have approximately halved since

decimalization and are generally larger for stocks with larger arbitrage costs (Chordia et al., 2014; McLean and Pontiff, 2016).

We also examine the variation of the publication effect across anomaly groups. In particular, we regress anomaly profits on indicator variables representing the three anomaly families, the post-publication dummy, and the interaction between the post-publication and the anomaly family dummies. The coefficients on these interaction terms indicate whether publication effects vary across anomaly groups. While the post-publication coefficients are consistently negative and significant in all specifications (and show similar magnitudes as in Table 1), the interaction terms are insignificant for all three anomaly groups (specifications (2)-(4) in Table 2). Thus, there is no discernible difference in the publication effect across groups. Similarly, anomaly families do not significantly differ in terms of their in-sample profits, since the coefficients on the anomaly group indicators are insignificant in all specifications. These findings are interesting since one might have expected that some anomalies are more likely to be related to risk than others suggesting differential post-publication effects.

Overall, these results indicate that statistical bias or data mining is not a prominent explanation for currency anomalies. They are more consistent with currency anomalies being the result of mispricing, with anomaly profits decreasing or even disappearing after the research is disseminated. Therefore, we subsequently focus on behavioral explanations or mispricing as a possible explanation of currency anomalies, a subject not yet studied in the literature.

4 Analysts and Currency Anomalies

4.1 Anomalies, Mispricing, and Currency (Excess) Returns

If there is a behavioral explanation for the existence of currency anomalies, their trading profits should reflect (temporary) mispricing, and one should be able to relate them to the behavior of market participants and biases in their views. In order to mimic alpha models of institutional investors that summarize different trading signals into a combined alpha score and to make more

general statements about the relationship between currency mispricing and analysts' forecasts, we combine anomalies into two aggregate mispricing measures. This contrasts with the currency literature that has so far focused on the analysis of individual anomalies.

In particular, we create a measure of average mispricing by averaging each month for each currency the percentile ranks of all available anomalies, resulting in values of the aggregate measure between 0 and 1. This approach gives equal weight to each anomaly and thus assumes no information regarding their relative forecasting power. It also reduces the noise across currency predictors.[15] The second aggregate is a measure of extreme mispricing defined as the difference between the number of long and short anomaly-portfolios that a currency belongs to in a given month, divided by the number of anomalies. This normalized score ranges between –1 and +1. A high score indicates that a currency should be bought based on many anomalies and shorted based on few anomalies. It thus reflects extreme mispricing or a high conviction of mispricing.[16] We create average and extreme mispricing measures for all anomalies as well as the three anomaly families.[17]

The correlation of 0.90 between average and extreme mispricing indicates that they measure similar dimensions, but are not identical. Sorting currencies on either mispricing measure yields currency excess returns in the following month that monotonically increase across quintiles from the short to the long portfolio (Table 3 Panel A). Trading strategies based on mispricing are profitable before and after transaction costs. To illustrate, quintile spreads of gross currency excess returns are 80 bp per month for average mispricing and 73 bp for extreme mispricing (equivalent to 9.7% and 8.7% per year), and net profits are still 48 bp and 39 bp, respectively. Both gross and

[15] A similar approach has been used to measure mispricing in equity markets (Stambaugh et al., 2012).

[16] A similar approach has recently been used to aggregate equity market anomalies (McLean and Pontiff, 2016).

[17] Table A2 in the Appendix provides detailed summary statistics of these measures. The mispricing measures for the category of all anomalies require available signals of at least four anomalies, while the mispricing measures for the anomaly subgroups require at least two available anomaly signals.

net profits are statistically significant, and they are of similar magnitude to anomaly profits in equity markets.

Plotting cumulative profits from mispricing over the full sample period shows distinct upward trends (Figure 3), indicating (mostly) positive returns underlying the average profits reported in Table 3. Annualized Sharpe ratios of up to 1.3 for gross profits and 0.6 for net profits are also economically significant (Table A3 in the Appendix). Trading strategies based on average and extreme mispricing for the three anomaly groups are profitable as well (Table 3 Panel A); in fact, their profitability is often statistically and economically more significant than that of the underlying individual anomalies due to improved signal to noise ratios (Table A1 in the Appendix).[18]

Assessing the "alpha decay" of mispricing signals provides further support for the view that anomaly profits are not compensation for risk. If anomalies were to capture risk, one would expect high autocorrelations of signal ranks over time as well as significant persistence of anomaly profits when lagging the trading signal. However, the average Spearman rank correlation between the vector of mispricing at month t and month $t-1$ is 0.72 (0.67) for average (extreme) mispricing, and it is 0.39 (0.37) for mispricing in months t and $t-6$. In addition, anomaly profits from stale signals show a steady decline both before and after transaction costs, with net returns declining toward zero within just two months (Figure 4). Thus, while the existence of anomaly profits suggest that currency markets may not be completely efficient, the inefficiencies seem to be arbitraged away quickly. The low persistence of profits, particularly net of transaction costs, suggests that anomaly profits are not providing compensation for risk, but rather reflect mispricing (Cochrane, 1999).[19]

[18] Note that Table 3 is based on the shorter sample period December 1989 to June 2018 to match Table 4.

[19] However, the results could be consistent with dynamic risk models (Patton and Verado, 2012; Savor and Wilson, 2016).

Profits from currency anomalies are measured using currency excess returns that are the sum of the negative change in the spot exchange rate and the interest rate differential. Different to currency excess returns, the pattern of currency returns shows more an inverted u-shape across portfolios stratified by mispricing (Table 3 Panel B).[20] Quintile spreads are often negative, and are mostly insignificant. Thus, comparing currency returns and currency excess returns indicates that the profits of trading strategies based on currency mispricing are largely, if not entirely, attributable to the associated interest differentials, while the currency appreciation component is negligible or negative.

4.2 Mispricing and Analysts' Forecasts

We use the aggregate mispricing measures to investigate whether analysts incorporate the information reflected in anomalies when making their exchange rate forecasts. If analysts' forecasts capture the information contained in anomaly variables, currencies with high values of aggregate anomalies should have higher forecast excess returns than currencies with low values, and the expected profits should be similar to realized profits. Interestingly, this is not always the case.

In particular, average forecast currency excess returns before transaction costs decrease monotonically from low to high mispricing quintiles based on all anomalies (Table 4 Panel A). They are 143 bp per month for the short portfolio and –116 bp for the long portfolio, yielding an expected quintile spread of –259 bp for strategies based on average mispricing, with a *t*-statistic of –19.2. The pattern is similar for extreme mispricing with expected profits from mispricing of –251 bp (*t*-statistic = –18.7). Thus, analysts erroneously expect negative profits from trading on mispricing even though these strategies yield significant positive actual gross profits of 80 bp and 73 bp per month for average and extreme mispricing, respectively (comparing Panel A of Table 4 with Panel A of Table 3).

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

Analysts appear to be particularly mistaken about trend following anomalies, where they expect significant losses despite the actual profitability of these strategies (–364 bp vs. +62 bp for average mispricing). While analysts expect profits for anomalies based on interest rates, forecast profits are smaller than actual profits (19 bp vs. 59 bp). Only for anomalies tied to fundamentals are expected profits broadly in line with realized profits (89 bp vs. 84 bp). Similar results obtain for extreme mispricing. Hence, the expectations of analysts with regard to currency excess returns appear to not always align with the relations of anomaly variables with next months' currency returns that have been widely documented in academic research and observed in historical data. Analysts often expect anomaly payoffs that are too low or even negative compared with positive realized profits.

The results for expected mispricing profits are largely accounted for by the expectations that analysts have about future exchange rate movements. Specifically, average forecast currency returns, which abstract from interest rate differentials, decrease monotonically from low to high mispricing quintiles based on all anomalies (Table 4 Panel B). The difference in currency returns between the fifth and first quintile is –324 bp per month for average mispricing and –320 bp for extreme mispricing. In contrast, realized currency return spreads are much smaller and mostly indistinguishable from zero (Table 3 Panel B). This effect is particularly pronounced in the Trend Following group, where analysts expect a loss of –407 bp for average mispricing, while the actual currency return spread is insignificant. In contrast, analysts are better at predicting the currency return for anomalies related to interest rates (–60 bp vs. –20 bp) and fundamentals (48 bp vs. 43 bp), where the sign and order of magnitude of the spread correspond more closely between actual and expected currency returns.

These results can be illustrated graphically (Figure 5). Across all anomalies, analysts' forecasts of currency excess returns are monotonically decreasing from the first quintile to the fifth quintile (Panel A), and analysts expect short portfolio currencies to appreciate and long portfolio

currencies to depreciate (Panel B). The results are robust across alternative measures of mispricing. These findings provide evidence that foreign exchange forecasts calculated by analysts are inconsistent with the information in anomaly variables. Analogous to these findings, forecast returns are higher (lower) among U.S. stocks that anomaly variables suggest will have lower (higher) returns (Engelberg et al., 2017). However, systematic forecast errors may be more surprising in currency markets where analysts are less likely to have a stake in views about the underlying asset compared equity markets.

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

$$\begin{aligned} Forecast\ (Excess)\ Return_{i,t+1} = a + \beta_1\ Mispricing_{i,t} + \beta_2\ Number\ of\ Forecasters_{i,t} \\ +\beta_3\ Single\ Forecast_{i,t} + \varepsilon_t + e_{i,t} \end{aligned} \tag{2}$$

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

The regressions confirm the results of the portfolio sorts, as the relation between mispricing and forecast currency excess returns is negative and significant (Table 5 Panel A). Specifically, the coefficients on average and extreme mispricing are –7.763 and –3.527 (first column for all anomalies in each panel) respectively, and both are statistically significant. The size of the coefficient for average mispricing means that a currency with an average mispricing value that is one standard deviation above the sample mean has a forecast excess return that is 121 bp per month lower than a currency with an average mispricing value at the sample mean. In the case of extreme

mispricing, the incremental forecast excess return would be 112 bp. This contrasts with the higher realized currency excess returns for currencies with higher mispricing scores.

The results by anomaly family suggest that, as in the univariate analyses, the patterns are particularly pronounced for trend following anomalies where mispricing has a strong negative relation with forecast currency excess returns (contrasting the positive relation between mispricing and realized excess returns). The coefficients for the Interest Rates group are insignificant, suggesting that analysts' forecasts have no relation with the predictions from mispricing, while the results for the Fundamentals category are consistent with analysts correctly predicting the direction of anomaly profits. With respect to the control variables, forecast currency excess returns are lower for currencies with more analysts. Thus, analysts tend to be more bullish when they are smaller in numbers.[21]

For forecast currency returns, the mispricing coefficients are negative and significant for all anomalies as well as those in the Trend Following and Interest Rates categories (Table 5 Panel B). In contrast, but consistent with the portfolio sorts, only for anomalies tied to macroeconomic fundamentals do analysts expect a positive contribution to trading profits from currency movements, though the positive coefficient is not significant for extreme mispricing.

If analysts considered anomaly variables, they should expect higher currency excess returns (and possibly currency returns) for portfolios on the long side of a mispricing based trading strategy than for portfolios on the short side. This implies the expectation of a positive trading profit, in line with the historical performance of these strategies. The results show that analysts' forecasts for currency anomaly payoffs are often too low and sometimes even negative, contrasting with positive realized anomaly profits. These results suggest that analysts appear to regularly make mistakes in their forecasts.

[21] Note that there are always multiple forecasts in the sample of the regressions for anomalies tied to fundamentals, so that the Single Forecast variable is dropped.

While our database does not contain forecasts of individual analysts or detailed monthly data on the distribution of forecasts for all currencies, the available annual data on the expected probabilities of changes in selected currencies falling into coarse ranges does not suggest that analysts' forecasts are generally skewed in a particular way. However, the monthly standard deviations of the forecasts across analysts document significant dispersion in opinion. In fact, when using the lowest forecast for currencies in the short mispricing portfolio and the highest forecast for those in the long portfolio, negative expected excess returns obtain for the short side and positive expected excess returns obtain for the long side, yielding a large positive quintile spread. While these high and low forecasts may not come from the same analyst, they document that there is a range of forecasts underlying the mean, with some forecasts reflecting expectations that are in line with predictions from currency anomalies. However, as a whole, analysts appear to be making predictions that do not align with them.

4.3 Analysts' Mistakes

If analysts on average expect negative profits for mispricing-based trading strategies that yield positive actual (i.e. realized) profits, their expectations must frequently be wrong, and their forecast errors or mistakes should be systematically related to mispricing. 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. Table A6

in the Appendix provides detailed summary statistics of analysts' mistakes.

The patterns in realized currency (excess) returns (Table 3) and forecast currency (excess) returns (Table 4) across quintiles suggest that the mistakes in analysts' expectations of future exchange rates are systematically related to mispricing. Indeed, mistakes decrease across mispricing quintile portfolios, with positive mistakes in the first quintile and negative mistakes in the fifth quintile, on average and over time (Figure 6 Panels A and B).

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

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

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

As expected, currency mispricing predicts mistakes in currency return forecasts (Table 6). Estimated coefficients for average and extreme mispricing based on all anomalies are –9.584 and –4.359, respectively, and are significant at the 1% level. This indicates that if a currency has a higher value of average or extreme mispricing, its realized excess return tends to be higher than its forecast excess return (yielding a negative forecast error). Thus, analysts' currency return forecasts are too low compared with realized returns for currencies that tend to be in the long mispricing portfolio, while they are too high for currencies in the short mispricing portfolio. The regression coefficients imply that a currency with a mispricing value that is one standard deviation above the sample mean has a forecast excess return that is 149 bp (139 bp) per month lower than its realized return compared with a currency with an average (extreme) mispricing value at the sample average.

Across anomaly families, the coefficient on average mispricing and extreme mispricing is large, negative, and significant for trend following anomalies. It is also negative for anomalies based on interest rates, though economically and statistically smaller. While the coefficient is insignificant

for anomalies in the Fundamentals family, this group captures fewer, more recently discovered anomalies, so that the sample is smaller compared with the other groups.

The finding that analysts make systematic errors may seem surprising, and one would expect them to incorporate anomaly information into their forecasts over time. If this was the case, one should observe the relation between mistakes and mispricing to become weaker, which can be analyzed by adding an interaction term between mispricing and a time trend to the regression:

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

where Time is equal to 1/100 during the first month of our sample and increases by 1/100 each month. As before, the regression includes the number of forecasters, an indicator variable for a single forecaster, and month fixed effects as controls. Standard errors are clustered by country.

The augmented regressions suggest a significant negative relation between mispricing and analysts' mistakes for all anomalies and all three anomaly families, with coefficients on average mispricing ranging from –2.836 for anomalies based on interest rates to –5.542 for trend following anomalies (Table 7). Thus, across all sub-samples analysts make predictable mistakes by forecasting too low (high) currency returns for currencies in the long (short) portfolio based on average and extreme mispricing.

The interaction between mispricing and the time trend is positive and significant for anomalies tied to interest rates and fundamentals, and the economic magnitudes are important as well. The positive coefficients reduce the negative relation between mistakes and mispricing and indicate that analysts on average improve their forecasts over time, implying smaller mistakes. For anomalies related to macroeconomic fundamentals, the effect is sufficiently large to render the average mispricing coefficient insignificant (Table 6). In contrast, the interaction is negative and significant for trend following anomalies, suggesting that mistakes become in fact larger over time. Thus, the evidence of analysts learning over time is mixed across different types of anomalies, and as a result,

for regressions based on all anomalies, the interaction between mispricing and the time trend is insignificant for extreme mispricing and only marginally significant for average mispricing. The coefficients on the number of forecasters are negative and mostly significant (as in Table 6). Overall, the documented biases in analysts' forecasts and their mistakes in predicting future currency movements are consistent with a behavioral explanation for the existence of currency anomalies.

4.4 Changes in Exchange Rate Forecasts

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

This conjecture can be tested empirically by regressing monthly changes in analysts' forecasts on mispricing lagged by one to three months. Specifically, we estimate the following regression model:

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

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 mispricing (lagged by one to three months), the number of analysts, a single forecaster indicator variable, and month fixed effects. Standard errors are again clustered by country.

The results provide evidence that analysts indeed incorporate mispricing information into their forecast revisions. To illustrate, the coefficients on average and extreme mispricing lagged by one month are 2.360 and 1.030 respectively, and both are statistically significant (Table 8). The

regression coefficients indicate that a currency with a mispricing value that is one standard deviation above the sample mean is expected to appreciate by 37 bp (33 bp) more per month compared with a currency with an average (extreme) mispricing value at the sample mean. The magnitudes of the mispricing coefficients decrease monotonically with lag length: The economic and statistical significance of mispricing lagged by two months is much smaller than for one month, while the coefficients on mispricing lagged by three months are insignificant. Thus, analysts do not use information contained in mispricing variables from months before the most recent two. The coefficient on the number of forecasters are positive and significant, indicating more positive revisions for currencies that are followed by more analysts.

In summary, while analysts miss important information in mispricing variables that help predict currency excess returns, this information is incorporated with a reasonably short lag and fully reflected after two months. This contrasts with evidence that lags of anomaly signals of up to 18 months predict changes in target prices for equities (Engelberg et al., 2017), which is again consistent with currency markets exhibiting higher degrees of informational efficiencies than stock markets.

4.5 Analysts' Forecasts and Predictability of Currency Excess Returns

Finally, we consider whether analysts' forecasts are useful to predict future exchange rate excess returns. Given that analysts seem to make predictable mistakes in forecasting the excess returns associated with mispricing, it could be that their forecasts contain other information that outweighs these forecast errors and that is informative in predicting future currency excess returns. For market participants, it is important to understand which variables are most useful for predicting future currency excess returns to generate the largest trading profit. To this end, we estimate Fama-MacBeth (1973) regressions that have the monthly currency excess return in the next period (i.e. month t+1) as dependent variable and current period (i.e. month t) mispricing and analysts' forecast currency excess returns as explanatory variables, both of which are known to investors at the time of

putting the trade on.[22] 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.

Mispricing and analysts' forecasts are both found to be useful in predicting future currency excess returns (Table 9). In particular, the coefficients on the quintile dummies increase monotonically from low to high quintiles, for both average and extreme mispricing. For quintiles based on analysts' forecast excess currency returns, the pattern in the indicators is also almost monotonic but with slightly weaker significance. In regressions with average mispricing, the quintile spread on mispricing is 99 bp per month, while the quintile spread on forecast excess returns from analysts is 41 bp per month. Magnitudes are similar but slightly smaller for regressions with extreme mispricing, with quintile spreads of 84 bp and 31 bp for mispricing and analysts' forecasts, respectively. Thus, while the forecasts that analysts make are inconsistent with currency anomalies, they are useful in predicting future currency excess returns over and above anomaly-based mispricing.

5 Robustness Tests

We carry out several additional tests to document the robustness of our results. One set of robustness tests considers the potential sensitivity of our results to the sample definition. The broad set of 76 currencies in our sample has the advantage of generating better contrasts in mispricing between currency portfolios and providing diversification within portfolios. At the same time, some of the currencies from less developed markets may not be liquidly tradable at all times, which could affect mispricing profits (e.g. Menkhoff et al., 2012). Therefore, we perform all of our analyses for a smaller set of 62 currencies, a set of 54 currencies representing all currencies covered by the BIS

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

Triennial Surveys (1995–2019), the 40 currencies with the highest FX turnover according to the BIS Triennial Surveys, and the G10 currencies (see Ang and Chen, 2010). The publication effect is robust to these alternative samples (Table A7 in the Appendix). In fact, the magnitude of the coefficient is larger when using smaller sets of currencies, and the interaction term of the post-publication dummy with in-sample anomaly profits is always significant for profits both gross and net of transaction costs. The interaction of the post-publication indicator with in-sample bid/ask spreads is only significant for larger samples (of 76, 62 and 54 currencies), likely because these offer more heterogeneity in terms of arbitrage costs.

The relation between analysts' mistakes and mispricing is similarly robust to alternative sets of currencies (Table A8 in the Appendix). Note that the number of currencies differs from Table A7 due to the more limited availability of analysts' forecasts. Coefficients on mispricing are always negative and significant for all anomalies and for trend following anomalies. They are also negative and significant for most samples in the Interest Rates group, and always negative when significant for anomalies based on fundamentals. For specifications that include the interaction between mispricing and a time trend, the coefficient on mispricing is negative and significant for all sets of currencies and all anomaly groups (except in the fundamentals group using the G10 currencies). The robustness of our tests for the G10 currencies also further addresses potential concerns about limitations to currency convertibility. In the same vein, the results are robust to the subsample of observations with deliverable forward contracts.

Carry trade and dollar carry trade might be considered risk factors rather than anomalies (Lustig, Roussanov and Verdelhan, 2011, 2014; Verdelhan, 2018). While the carry trade shows strong in-sample profits and no reduction after publication, which would fit the profile of a risk factor, the profitability of the dollar carry trade is significantly smaller after publication (Figure 1). When excluding these two strategies from the set of anomalies, publication effects tend to be stronger, while results overall are similar to those reported in the paper.

In other tests, we control for the possibility that market participants traded on the anomaly strategies that we study already before they were popularized by academic studies. To illustrate, Asness, Moskowitz, and Pedersen (2013) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012) are generally cited for documenting cross-sectional momentum strategies in currency markets. However, these strategies are related to earlier papers using filter rules in currency markets (e.g. Sweeney, 1986). Investors might have also considered adapting momentum strategies developed in other asset classes (e.g. Jegadeesh and Titman (1993) for momentum in equities), mentioning of currency momentum strategies in newspaper articles (e.g. an article in the Financial Times in October 2009, see Smith (2009)), or in fact read and implemented currency momentum strategies documented in practitioner research publications (e.g. on the Deutsche Bank Currency Momentum Index that started in January 2000). In the same vein, we use the posting of the paper by Lustig and Verdelhan on SSRN in January 2005 and published in the AER in March 2007 as the first documented source of cross-sectional carry trade strategies. However, the carry trade was mentioned, for instance, in a Financial Times article in February 1997 (see Riley (1997)). Also, there are related earlier academic papers, such as Hansen and Hodrick (1980) studying the relation between the forward discount and future exchange rates, but only in time-series analysis.

Of course, as noted in the literature, trading by practitioners on these strategies should lead to lower or even zero anomaly profits and thus bias against any later publication effect of the underlying academic research (e.g. McLean and Pontiff, 2016). Nevertheless, we research several potential sources of earlier information relevant to the eleven anomalies studied in this paper. First, we look for earlier papers in the currency literature that develop trading strategies or economic relations that might be related to a particular anomaly. Second, we identify earlier practitioner research publications or currency indices based on related strategies. Third, we look for mentions of the anomaly strategies in newspaper articles. Finally, we also identify earlier papers suggesting corresponding strategies in equity or bond markets. Table A9 in the Appendix summarizes these sources. We do not list sources of alternative publication dates if they occur after the date for the

corresponding currency anomaly. In a few cases, the earliest source of alternative publication dates is before the beginning of our sample period, so that our analysis is unaffected. We then control for the respective publication dates (using the earlier of journal publication date, or where available SSRN dates), either by using indicator variables for each individual paper dissemination date, or by pooling them by type. The results in Table A10 in the Appendix show that there is only limited evidence of earlier dissemination being associated with lower anomaly profits, and that our main finding of significant publication effects of the underlying academic paper remains after controlling for other potential sources of anomaly information. Thus, although some practitioners may know about these strategies before publication, the results suggest that publication makes the effects more widely known.

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. The first, Thomson Reuters, provides forecasts of one-month horizon for 37 currencies over the period May 1993 to June 2018. The second, analysts' forecasts from Bloomberg, are available for 41 currencies between December 2006 and June 2018, but forecast horizons of one month are only available for March, June, September and December of each year since forecasts are limited to exchange rates at the end of each calendar quarter. Using mean and median consensus forecasts from these alternative data sources with more limited coverage shows similar results to those reported in the paper using either the full data available from each source or the subsample of currency-months common across data sources.

Finally, most research in the literature on currency anomalies uses final vintage data for macroeconomic data, such as Asness et al. (2013) and Menkhoff et al. (2017) for currency value and Riddiough and Sarno (2018) for output gap.[23] In order to allow for better comparability of our results with the literature, we repeat our analysis for the same sample period and currencies,

[23] Riddiough and Sarno (2018) utilize real-time industrial production data in a robustness test.

but replace signals using real-time data for macroeconomic variables with those using final vintage data. This only affects the currency value, output gap, and Taylor Rule strategies. While the performance of these three strategies is stronger, results using final vintage data are qualitatively similar to those reported in the paper using real-time data.

6 Conclusion

This paper studies, for the first time, all widely used systematic investment strategies in currency markets that can be constructed with publicly available data. The study of the cross-section of currency anomalies allows it to offer more general conclusions than prior studies that focus on single predictors of currency excess returns. Currency anomalies are implemented in a realistic way using novel real-time data that investors could have employed at a historical point in time and combined into aggregate mispricing scores that generate investment strategies with improved signal to noise ratios. The paper tests alternative explanations pertaining to risk, data mining and behavioral bias as *raison d'être* of anomaly payoffs. While currency investment strategies generate significant trading profits, both before and after transaction costs, anomaly profits significantly decrease and even disappear after the underlying academic research has been published. The decline is greater for strategies with larger in-sample profits and lower arbitrage costs. In contrast, profits remain in the out-of-sample period before publication lending no support to the concern that they might be the result of data mining.

The evidence of a publication effect is more consistent with a behavioral explanation, suggesting that anomalies reflect mispricing that is ultimately traded away. This view is supported by low autocorrelations of mispricing signal ranks, and by a relatively fast decay of trading profits when delaying mispricing signals. Moreover, aggregate mispricing can be directly related to forecasts by market participants using a unique dataset of analysts' forecasts. Analysts often have currency expectations that imply anomaly payoffs that are too low compared with the realized profits of these strategies. Across all anomalies, they expect higher anomaly excess returns on short

portfolios than on long portfolios, yielding an expected loss. This result is driven by the expected currency return component, as analysts expect negative quintile spreads from currency returns. Thus, analysts appear to make systematic mistakes.

Since currency anomalies are widely documented and the information is publicly available, it seems that analysts miss some of the information they capture. However, they quickly and predictably incorporate useful information reflected in anomalies within the following two months. Overall, this paper paints a picture of relatively efficient global currency markets, where inefficiencies arise as the result of biased expectations by analysts, but are ultimately traded away as the underlying research is published. The evidence complements findings of publication effects and analysts mistakes as a source of inefficiencies in U.S. equity markets, and provides out-of-sample evidence from a different asset class (Chordia et al., 2014; McLean and Pontiff, 2016; Engelberg et al., 2017). Mispricing in currency markets suggests that investors who follow analysts' advice contribute to anomaly mispricing.

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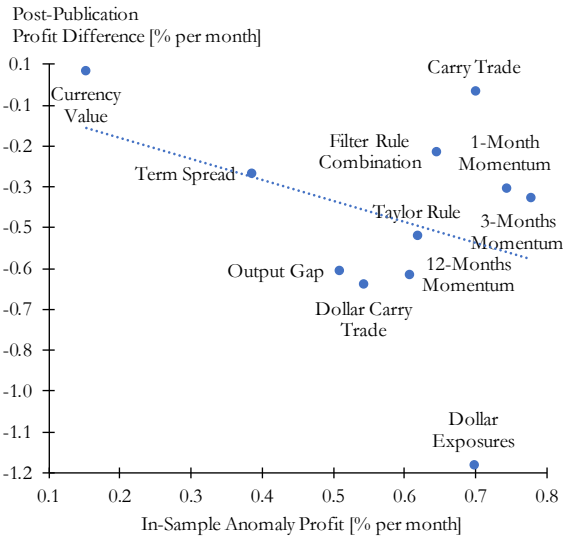
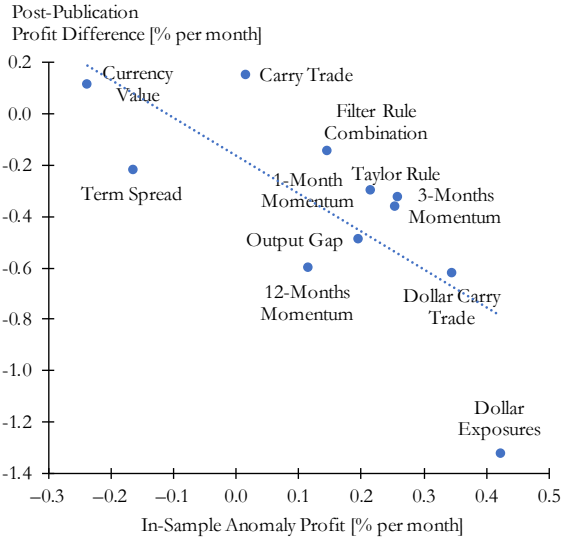
Figure 1: Relation between In-Sample and Post-Publication Anomaly Profits

The figure plots the relation between monthly in-sample currency anomaly profits and changes in profits after publication (post-publication profit differences), as well as the relation between in-sample currency anomaly *t*-statistics and changes in *t*-statistics after publication. In particular, it shows the following eleven currency anomalies: (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 anomaly profits are the mean returns (in percent) of the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1) from January 1971 to end of the sample period of the original study. Post-publication profits are the mean returns (in percent) of the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1) for the period after the study has been published (through June 2018). 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 June 2018. Appendix A provides details on variable definitions. Appendix B provides details on the anomalies' original sample period used in the paper as well as date of publication.

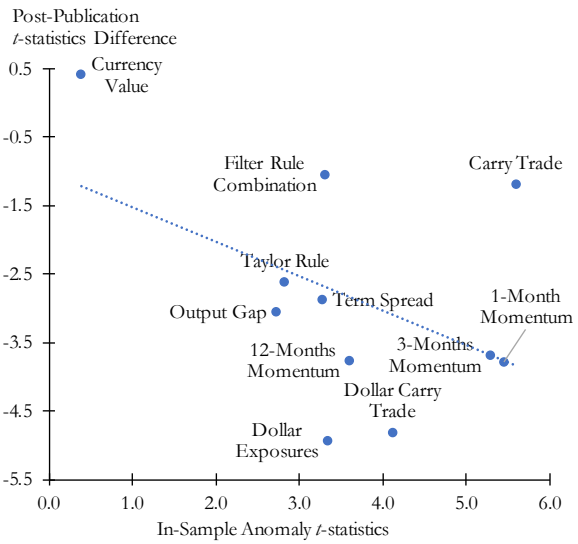
Panel A: Profits Gross of Transaction Costs



Panel B: Profits Net of Transaction Costs



Panel C: *t*-statistics for Anomaly Gross Profits



Panel D: *t*-statistics for Anomaly Net Profits

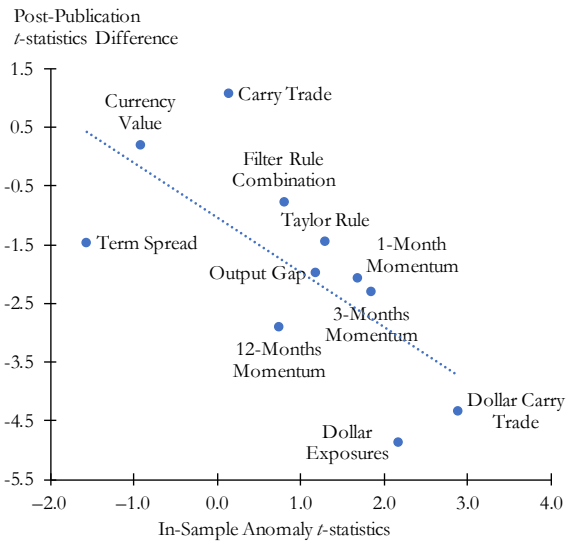
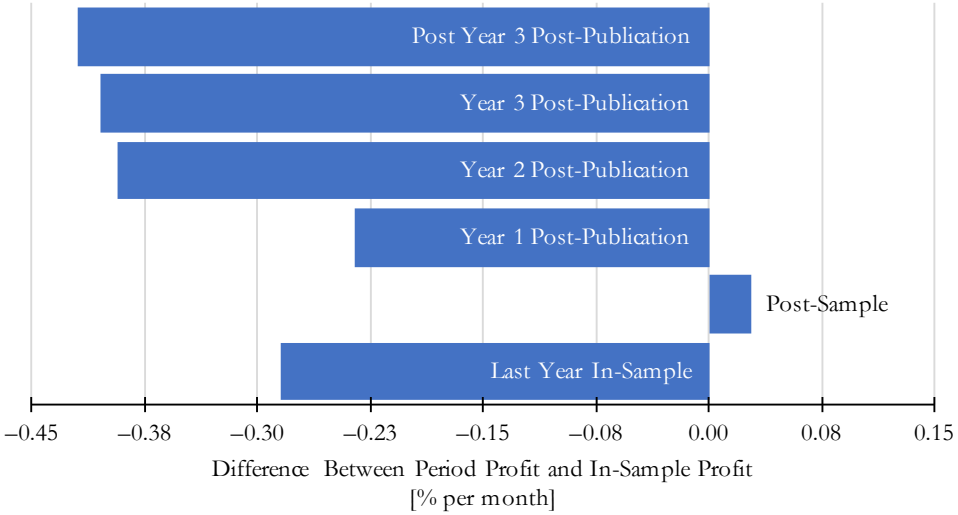


Figure 2: Anomaly Profits Around End-of-Sample and Publication Dates

The figure plots the coefficients from a regression of currency anomaly 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 anomaly profits gross and net of transaction costs, where transactions costs are calculated using bid and ask quotations. Separately for each anomaly, 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 an anomaly 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 anomalies: (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 anomaly fixed effects. The sample includes 76 currencies. The sample period is from January 1971 to June 2018. Appendix A provides details on variable definitions. Appendix B provides details on the anomalies' 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

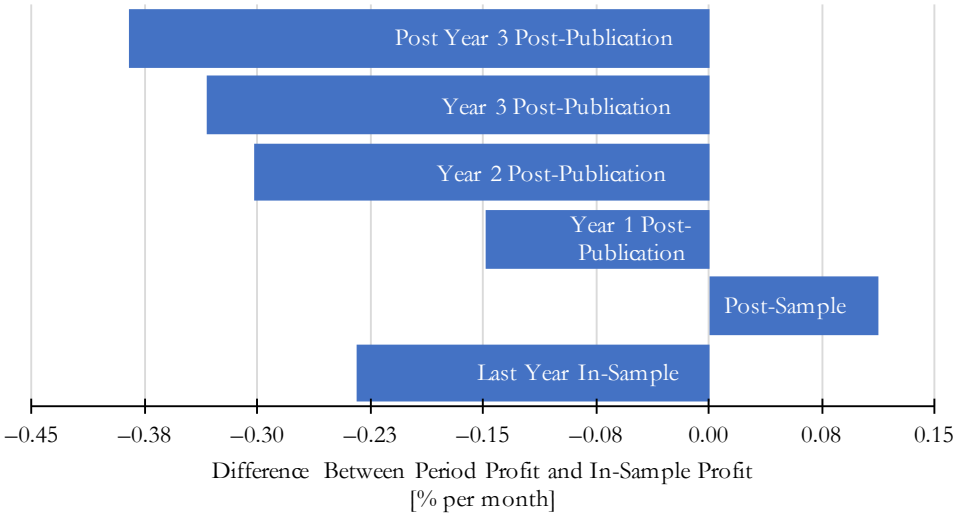
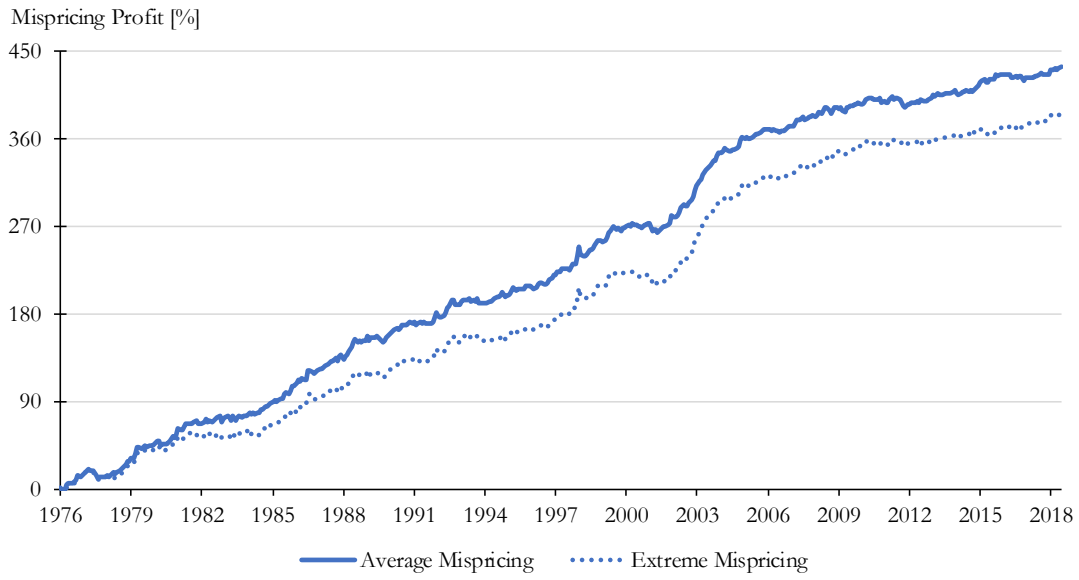


Figure 3: Cumulative Profits of Currency Mispricing Strategies

The figure shows the cumulative sum of trading profits (in percent) of investment strategies based on average mispricing (solid line) and extreme mispricing (dotted line). At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average mispricing and extreme mispricing and combined into equally weighted portfolios. The difference between the currency excess returns of portfolios Q5 and Q1 for each month is summed cumulatively from the first to the last month of the sample period. Average mispricing is the average of the percentile ranks of currencies with respect to the following eleven anomalies: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior three months, (iii) momentum based on the currency excess return over the prior twelve months, (iv) filter rule combination, (v) carry trade, (vi) dollar carry trade, (vii) dollar exposures, (viii) term spread, (ix) currency value, (x) output gap, and (xi) the Taylor Rule. Extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven anomaly strategies, divided by the total number of strategies. Panel A shows trading profits gross of transaction costs, while Panel B shows trading profits net of transaction costs. Transaction costs are calculated using bid and ask quotations. The sample includes 76 currencies. The sample period is from January 1976 to June 2018. Appendix A provides details on variable definitions.

Panel A: Profits Gross of Transaction Costs



Panel B: Profits Net of Transaction Costs

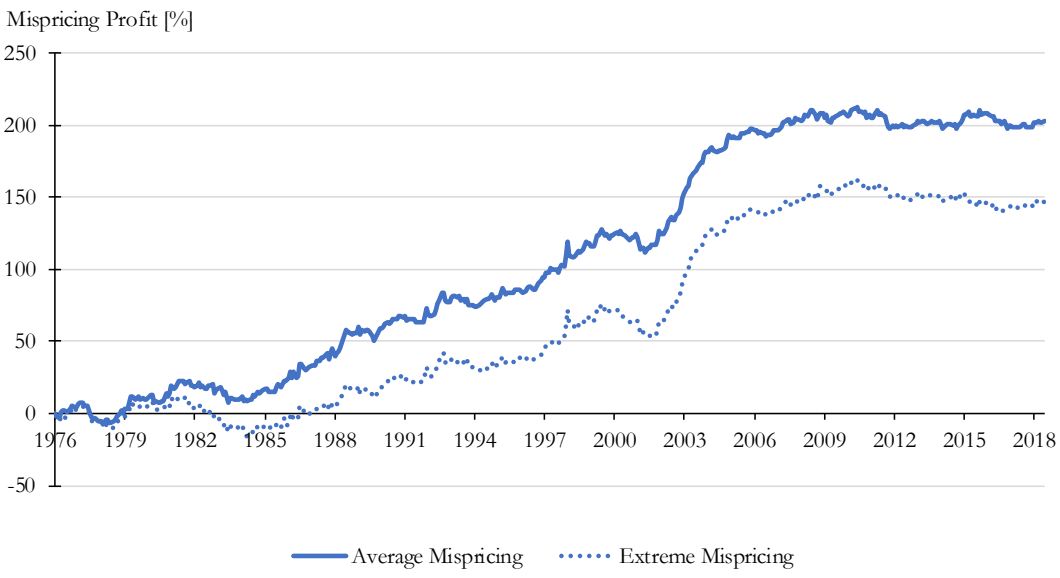
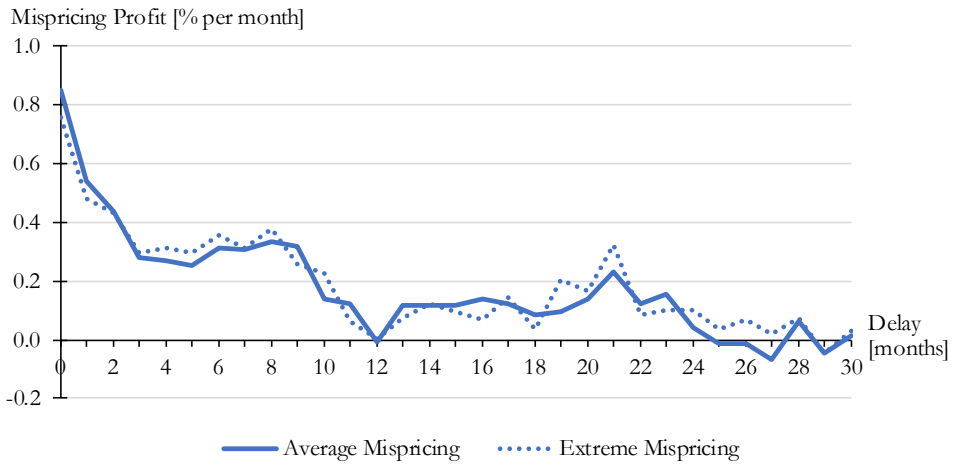


Figure 4: Decay of Mispricing Signals

The figure shows trading profits (in percent per month) for investment strategies based on average mispricing (solid line) and extreme mispricing (dashed line). At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average mispricing and extreme mispricing and combined into equally weighted portfolios. The mispricing signal is lagged from zero to 30 months. The difference between the currency excess returns of portfolios Q5 and Q1 for each month is averaged over the sample period. Average mispricing is the average of the percentile ranks of currencies with respect to the following eleven anomalies: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior three months, (iii) momentum based on the currency excess return over the prior twelve months, (iv) filter rule combination, (v) carry trade, (vi) dollar carry trade, (vii) dollar exposures, (viii) term spread, (ix) currency value, (x) output gap, and (xi) the Taylor Rule. Extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven anomaly 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 July 1978 to June 2018 in Panel A and from July 1976 to June 2018 in Panel B to ensure the same period of analysis in each panel across strategies with different lag lengths. Appendix A provides details on variable definitions.

Panel A: Profits Gross of Transaction Costs



Panel B: Profits Net of Transaction Costs

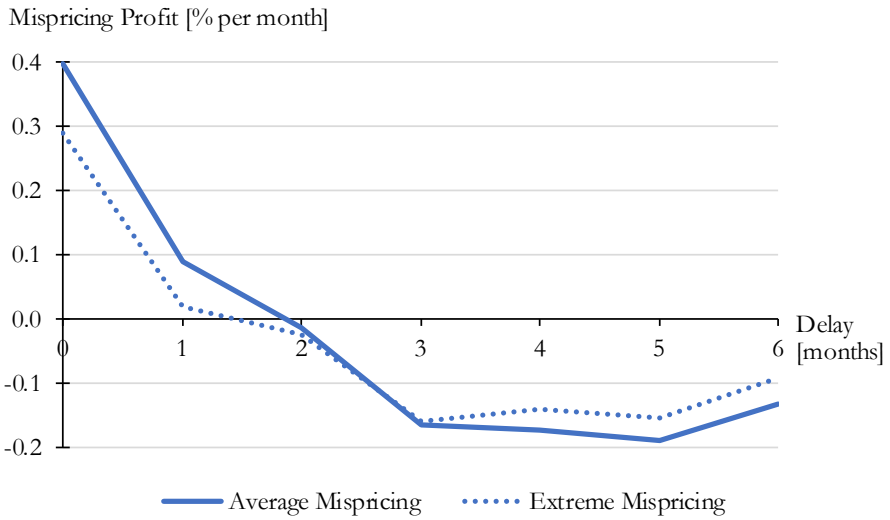
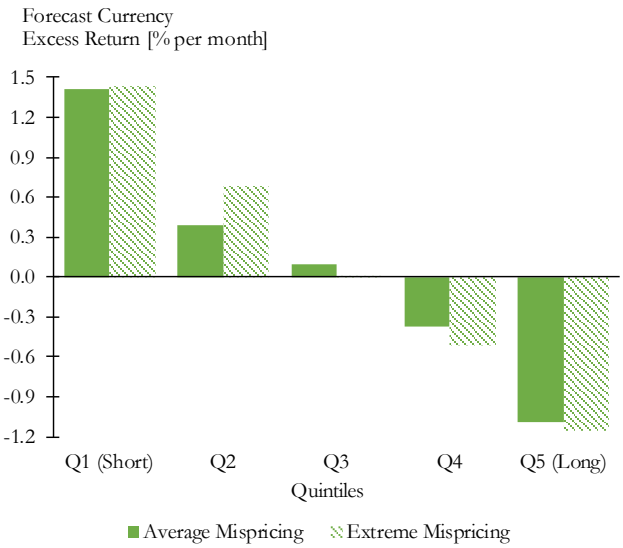


Figure 5: Analysts' Forecast Currency Returns of Currency Mispricing Strategies

The figure shows analysts' forecast currency returns and currency excess returns (in percent per month) for investment strategies based on average mispricing and extreme mispricing. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average mispricing and extreme mispricing and combined into equally weighted portfolios. The forecast currency (excess) returns of each quintile are averaged over the sample period. Forecast currency returns are the negative log difference of a foreign currency's one-month forecast in month *t* and its spot rate in month *t*. Forecast currency excess returns are the sum of forecast currency returns and interest rate differentials. Average mispricing is the average of the percentile ranks of currencies with respect to the following eleven anomalies: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior three months, (iii) momentum based on the currency excess return over the prior twelve months, (iv) filter rule combination, (v) carry trade, (vi) dollar carry trade, (vii) dollar exposures, (viii) term spread, (ix) currency value, (x) output gap, and (xi) the Taylor Rule. Extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven anomaly 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 June 2018. Appendix A provides details on variable definitions.

Panel A: Forecast Currency Excess Returns



Panel B: Forecast Currency Returns

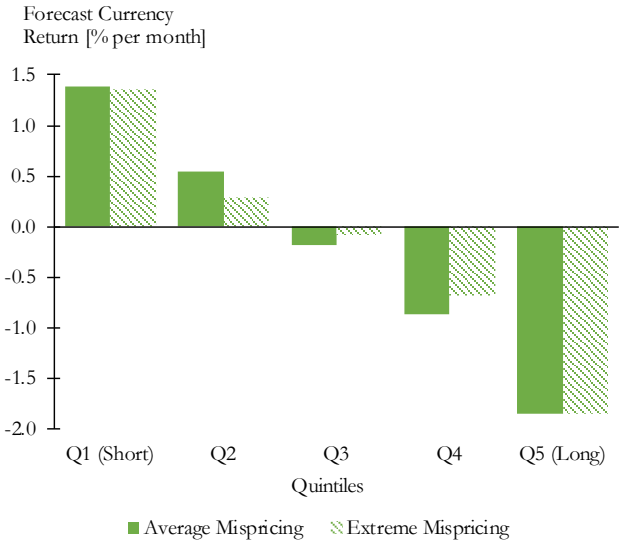
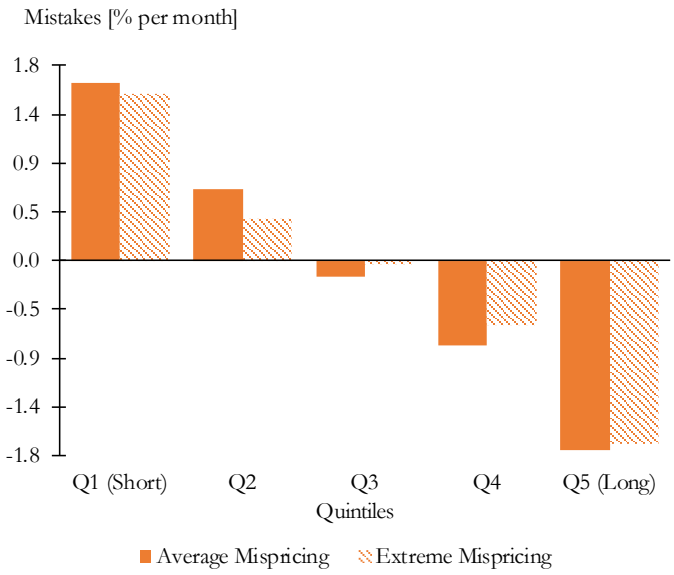


Figure 6: Analysts' Mistakes of Currency Mispricing Strategies

The figure shows analysts' mistakes (in percent) for investment strategies based on average mispricing and extreme mispricing. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average mispricing and extreme mispricing and combined into equally weighted portfolios. Analysts' mistakes of each quintile are averaged over the sample period. Mistakes are the difference between forecast currency returns and actual (i.e. realized) currency returns. Forecast currency returns are the negative log difference of a foreign currency's one-month forecast in month *t* and its spot rate in month *t*. Average mispricing is the average of the percentile ranks of currencies with respect to the following eleven anomalies: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior three months, (iii) momentum based on the currency excess return over the prior twelve months, (iv) filter rule combination, (v) carry trade, (vi) dollar carry trade, (vii) dollar exposures, (viii) term spread, (ix) currency value, (x) output gap, and (xi) the Taylor Rule. Extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven anomaly strategies, divided by the total number of strategies. Panel A shows analysts' mistakes by quintile, while Panel B shows the monthly time series of the differences between the mistakes of portfolios Q5 and Q1. The sample includes 62 currencies. The sample period is from December 1989 to June 2018. Appendix A provides details on variable definitions.

Panel A: Mistakes by Quintile



Panel B: Quintile Spreads of Mistakes Over Time

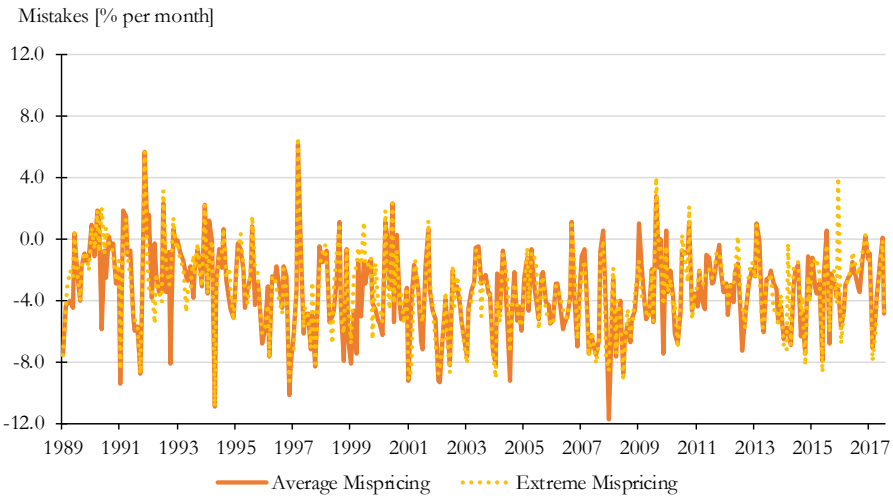


Table 1: Regression of Anomaly Profits on Post-Publication Indicators

The table reports results from regressions of currency anomaly 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 (Panel A), time trends (Panel B) and limits to arbitrage (Panel C). Results in Panel A and Panel B are shown alternatively for anomaly profits gross and net of transaction costs, where transactions costs are calculated using bid and ask quotations. Results in Panel C are shown for anomaly profits gross of transaction costs. Separately for each anomaly, 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 an anomaly 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. 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 an anomaly is the average of the short-term interest rates of the currencies in its long and short portfolios. The exchange rate volatility of an anomaly is the average of the within-month standard deviation of the currencies in its long and short portfolios. Post Crisis is an indicator variable that take the value 1 for the years 2009-2011 and 0 otherwise. NBER U.S. Business Cycle Contractions is an indicator variable that takes the value 1 for U.S. recessions and 0 otherwise. 1-Month Anomaly Profit and 12-Month Anomaly Profit are the anomaly's profit from the previous month and the cumulative return over the prior 12 months. Limits to arbitrage of an anomaly are measured alternatively as the in-sample mean of the average bid-ask spread of the currencies in its long and short portfolios, or the in-sample mean of the average percentile rank of exchange rate turnover (from the BIS, 2019), an index of average money market restrictions for inflows and outflows (from Fernández et al., 2015), and a measure of capital account openness (Chinn and Ito, 2008) of the currencies in its long and short portfolios. The analysis is based on the following eleven currency anomalies: (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 anomaly 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 anomalies, 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 June 2018. Appendix A provides details on variable definitions. Appendix B provides details on the anomalies' original sample period used in the paper as well as date of publication.

(continued)

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

Panel A: Post-Publication and Post-Sample Indicators

	Anomaly Profits Gross of Transaction Costs			Anomaly Profits Net of Transaction Costs		
	(1)	(2)	(3)	(1)	(2)	(3)
Post-Sample	0.040	0.054	0.075	0.123	0.150	0.158
	(0.237)	(0.237)	(0.236)	(0.236)	(0.232)	(0.232)
Post-Publication	–0.379***	–0.058	–0.145	–0.330***	–0.132	–0.149*
	(0.119)	(0.227)	(0.192)	(0.119)	(0.087)	(0.089)
Post-Publication x Average Anomaly In-Sample Profits		–0.540			–1.432***	
		-0.472			(0.504)	
Post-Publication x Average Anomaly In-Sample *t*-statistics			–0.048			–0.184***
			(0.052)			(0.069)
Average Anomaly In-Sample Profits		0.998***			0.946***	
		(0.108)			(0.253)	
Average Anomaly In-Sample *t*-statistics			0.136***			0.136***
			(0.014)			(0.034)
Observations	4,483	4,483	4,483	4,483	4,483	4,483
R–Squared	0.01	0.04	0.04	0.01	0.01	0.01
Number of Anomalies	11	11	11	11	11	11
Anomaly Fixed Effects	Yes	No	No	Yes	No	No
Standard Errors	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
Null: Post-Publication = –1 x Average Anomaly In-Sample Profits	0.128			0.122		
Null: Post-Publication + (Post-Publication x Average Anomaly In-Sample Profits) = 0		0.036			0.002	
Null: Post-Publication + (Post-Publication x Average Anomaly In-Sample *t*-statistics) = 0			0.199			0.002

(continued)

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

Panel B: Time Trend, Macro-Economic Risk, and Persistence in Currency Anomalies

	Anomaly Profits Gross of Transaction Costs					Anomaly Profits Net of Transaction Costs				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Post-Publication		–0.460***	–0.334***	–0.373***	–0.312***		–0.590***	–0.391***	–0.326***	–0.269**
		(0.142)	(0.127)	(0.118)	(0.117)		(0.141)	(0.126)	(0.118)	(0.116)
Time	–0.067*	0.035				–0.019	0.113**			
	(0.039)	(0.048)				(0.039)	(0.047)			
Level of Interest Rates			0.027					–0.001		
			(0.017)					(0.017)		
Exchange Rate Volatility			–0.761***					–0.981***		
			(0.247)					(0.244)		
Post-Crisis (2009–2011)			–0.083					–0.058		
			(0.206)					(0.204)		
NBER U.S. Business Cycle Contractions			–0.180					–0.149		
			(0.176)					(0.174)		
1-Month Anomaly Profit				0.013					0.020	
				(0.019)					(0.019)	
12-Months Anomaly Profit					0.017***					0.019***
					(0.005)					(0.005)
Observations	4,483	4,483	4,475	4,472	4,351	4,483	4,483	4,475	4,472	4,351
R–Squared	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01
Number of Anomalies	11	11	11	11	11	11	11	11	11	11
Anomaly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS

(continued)

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

Panel C: Limits to Arbitrage

	Bid/Ask Spreads	Capital Restrictions
	(1)	(2)
Post-Publication	–1.525***	–2.386**
	(0.526)	(1.092)
Post-Publication x Limits to Arbitrage	6.962**	3.096*
	(3.038)	(1.775)
Limits to Arbitrage	1.413	–0.104
	(1.376)	(1.175)
Intercept	0.338	0.683
	(0.234)	(0.726)
Observations	4,483	2,904
R–Squared	0.01	0.01
Number of Anomalies	11	11
Standard Errors	FGLS	FGLS
Null: (Post-Publication x Arbitrage Costs) + Arbitrage Costs = 0	0.002	0.039

Table 2: Publication Effects Across Anomaly Types

The table reports results from regressions of currency anomaly profits (in percent per month) on a post-publication period indicator variable and its interaction with indicator variables for anomaly groups. Results are shown alternatively for anomaly profits gross and net of transaction costs, which are calculated using bid and ask quotations. Separately for each anomaly, 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 an anomaly 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 anomalies: (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. Trend Following is an indicator variable that takes the value 1 if the currency anomaly is 1-month, 3-months, 12-months momentum, or the filter rule combination, and zero otherwise. Interest Rates is an indicator variable that takes the value 1 if the currency anomaly is carry trade, dollar carry trade, dollar exposures, or term spread, and zero otherwise. Fundamentals is an indicator variable that takes the value 1 if the currency anomaly is currency value, output gap, or the Taylor Rule, and zero otherwise. 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 anomalies, and the R-Squared. Regressions include anomaly fixed effects as indicated in the table. 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 June 2018. Appendix A provides details on variable definitions. Appendix B provides details on the anomalies' original sample period used in the paper as well as date of publication.

(continued)

Table 2: Publication Effects Across Anomaly Types (continued)

	Anomaly Profits Gross of Transaction Costs				Anomaly Profits Net of Transaction Costs			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Post-Publication	–0.377***	–0.404***	–0.334**	–0.392***	–0.337***	–0.358***	–0.296**	–0.353***
	(0.109)	(0.130)	(0.140)	(0.127)	(0.109)	(0.130)	(0.140)	(0.127)
Trend Following		0.118				0.035		
		(0.115)				(0.115)		
Trend Following x Post-Publication		0.053				0.043		
		(0.221)				(0.221)		
Interest Rates			–0.019				–0.009	
			(0.103)				(0.103)	
Interest Rates x Post-Publication			–0.106				–0.100	
			(0.200)				(0.201)	
Fundamentals				–0.184				–0.049
				(0.134)				(0.132)
Fundamentals x Post-Publication				0.083				0.107
				(0.286)				(0.285)
Intercept	0.563***	0.513***	0.571***	0.592***	0.152**	0.137**	0.156**	0.160**
	(0.060)	(0.067)	(0.079)	(0.066)	(0.060)	(0.067)	(0.078)	(0.067)
Observations	4,483	4,483	4,483	4,483	4,483	4,483	4,483	4,483
R–Squared	0.004	0.005	0.004	0.005	0.003	0.003	0.003	0.003
Number of Anomalies	11	11	11	11	11	11	11	11
Standard Errors	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
Null: Anomaly Type + (Anomaly Type x Post-Publication) = 0		0.396	0.481	0.692		0.697	0.543	0.816

Table 3: Quintile Performance of Portfolios Sorted on Currency Mispricing

The table reports actual (i.e. realized) currency returns and currency excess returns (in percent per month) of portfolios sorted on average mispricing and extreme mispricing across all anomalies or groups of anomalies, alternatively gross of transaction costs and net of transaction costs. Transaction costs are calculated using bid and ask quotations. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average mispricing and extreme mispricing and combined into equally weighted portfolios. The table shows the time series average of the currency (excess) returns of the quintile portfolios. It also shows the time series average and associated *t*-statistic (in square brackets, computed using the method of Newey and West (1987) with three lags) of the difference between the currency (excess) returns of portfolios Q5 and Q1 (Q5-Q1). Currency returns are the negative log difference of spot exchange rates from month *t+1* and month *t*. Currency excess returns are the sum of currency returns and interest rate differentials. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying anomalies, while extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying anomalies, divided by the number of anomalies. The analysis is based on the following eleven currency anomalies: (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. Trend Following is a group of anomalies that contains momentum based on the currency excess return over the prior one, three, and twelve months, as well as the filter rule combination. Interest Rates is a group of anomalies that contains carry trade, dollar carry trade, dollar exposures, and term spread. Fundamentals is a group of anomalies that contains currency value, output gap, and the Taylor Rule. Panel A shows results for currency excess returns, while Panel B shows results for currency returns. The sample includes 62 currencies. The sample period is from December 1989 to June 2018. Appendix A provides details on variable definitions.

Panel A: Currency Excess Returns

	Gross of Transaction Costs							Net of Transaction Costs	
	Quintiles								
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1	*t*-statistic	Q5–Q1	*t*-statistic
Average Mispricing									
All Anomalies	–0.207	0.023	0.146	0.261	0.597	0.804	[6.57]	0.479	[3.93]
Trend Following	–0.141	0.033	0.156	0.273	0.475	0.617	[4.64]	0.286	[2.14]
Interest Rates	–0.096	0.004	0.129	0.310	0.489	0.585	[3.80]	0.289	[1.87]
Fundamentals	–0.117	0.147	0.117	0.199	0.724	0.841	[4.00]	0.583	[2.92]
Extreme Mispricing									
All Anomalies	–0.125	0.011	0.123	0.221	0.602	0.727	[5.81]	0.385	[3.10]
Trend Following	–0.115	0.065	0.143	0.187	0.519	0.634	[4.75]	0.295	[2.22]
Interest Rates	–0.030	–0.009	0.114	0.283	0.480	0.510	[3.42]	0.195	[1.31]
Fundamentals	0.014	0.160	0.088	0.153	0.682	0.668	[3.46]	0.403	[2.21]

(continued)

Table 3: Quintile Performance of Portfolios Sorted on Currency Mispricing (continued)

Panel B: Currency Returns

	Gross of Transaction Costs							Net of Transaction Costs	
	Quintiles								
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1	*t*-statistic	Q5–Q1	*t*-statistic
Average Mispricing									
All Anomalies	–0.249	–0.110	–0.043	–0.091	–0.101	0.148	[1.25]	–0.085	[–0.72]
Trend Following	–0.293	–0.129	–0.068	–0.017	–0.103	0.190	[1.48]	–0.051	[–0.40]
Interest Rates	–0.082	–0.100	–0.051	–0.072	–0.286	–0.203	[–1.29]	–0.411	[–2.59]
Fundamentals	–0.214	–0.018	–0.169	–0.067	0.213	0.427	[2.66]	0.236	[1.51]
Extreme Mispricing									
All Anomalies	–0.191	–0.096	–0.055	–0.088	–0.156	0.035	[0.29]	–0.208	[–1.71]
Trend Following	–0.289	–0.074	–0.017	–0.124	–0.114	0.175	[1.37]	–0.069	[–0.54]
Interest Rates	–0.070	–0.093	–0.037	–0.046	–0.349	–0.279	[–1.91]	–0.501	[–3.40]
Fundamentals	–0.081	–0.060	–0.130	–0.066	0.105	0.186	[1.28]	–0.017	[–0.12]

Table 4: Forecast Currency Returns across Currency Mispricing Quintiles

The table reports average forecast currency returns and currency excess returns (in percent per month) of portfolios sorted on average mispricing and extreme mispricing across all anomalies or groups of anomalies. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average mispricing and extreme mispricing and combined into equally weighted portfolios. The table shows the time series average of the forecast currency returns and forecast currency excess returns of the quintile portfolios. It also shows the time series average and associated *t*-statistic (in square brackets, computed using the method of Newey and West (1987) with three lags) of the difference between the forecast currency returns and forecast currency excess returns of portfolios Q5 and Q1 (Q5-Q1). Forecast currency returns are the negative log difference of a foreign currency's one-month forecast in month *t* and its spot rate in month *t*. Forecast currency excess returns are the sum of forecast currency returns and interest rate differentials. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying anomalies, while extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying anomalies, divided by the number of anomalies. The analysis is based on the following eleven currency anomalies: (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. Trend Following is a group of anomalies that contains momentum based on the currency excess return over the prior one, three, and twelve months, as well as the filter rule combination. Interest Rates is a group of anomalies that contains carry trade, dollar carry trade, dollar exposures, and term spread. Fundamentals is a group of anomalies that contains currency value, output gap, and the Taylor Rule. 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 June 2018. Appendix A provides details on variable definitions.

Panel A: Forecast Currency Excess Returns

	Quintiles					Q5–Q1	
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Average	*t*-statistic
Average Mispricing							
All Anomalies	1.431	0.684	0.004	–0.517	–1.155	–2.586	[–19.2]
Trend Following	2.053	0.665	–0.028	–0.651	–1.586	–3.639	[–20.7]
Interest Rates	0.019	–0.021	–0.028	0.232	0.212	0.193	[1.25]
Fundamentals	–0.264	–0.175	–0.007	0.039	0.627	0.891	[4.15]
Extreme Mispricing							
All Anomalies	1.418	0.391	0.092	–0.372	–1.089	–2.507	[–18.7]
Trend Following	2.048	0.406	–0.027	–0.468	–1.491	–3.539	[–20.7]
Interest Rates	–0.053	0.019	0.136	0.052	0.241	0.295	[1.97]
Fundamentals	–0.286	–0.069	–0.009	0.199	0.359	0.645	[3.19]

Panel B: Forecast Currency Returns

	Quintiles					Q5–Q1	
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Average	*t*-statistic
Average Mispricing							
All Anomalies	1.389	0.552	–0.185	–0.868	–1.854	–3.243	[–22.2]
Trend Following	1.901	0.503	–0.251	–0.942	–2.165	–4.066	[–22.0]
Interest Rates	0.032	–0.126	–0.208	–0.150	–0.563	–0.595	[–4.10]
Fundamentals	–0.362	–0.340	–0.293	–0.227	0.115	0.477	[2.14]
Extreme Mispricing							
All Anomalies	1.351	0.285	–0.085	–0.681	–1.847	–3.198	[–21.6]
Trend Following	1.874	0.268	–0.187	–0.779	–2.124	–3.997	[–22.0]
Interest Rates	–0.093	–0.066	–0.015	–0.277	–0.588	–0.494	[–3.43]
Fundamentals	–0.381	–0.290	–0.227	–0.019	–0.218	0.163	[0.75]

Table 5: Currency Mispricing and Forecast Returns

The table reports results from regressions of forecast currency returns and currency excess returns (in percent per month) on average mispricing and extreme mispricing across all anomalies or groups of anomalies 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 sum of forecast currency returns and interest rate differentials. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying anomalies, while extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying anomalies, divided by the number of anomalies. The analysis is based on the following eleven currency anomalies: (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. Trend Following is a group of anomalies that contains momentum based on the currency excess return over the prior one, three, and twelve months, as well as the filter rule combination. Interest Rates is a group of anomalies that contains carry trade, dollar carry trade, dollar exposures, and term spread. Fundamentals is a group of anomalies that contains currency value, output gap, and 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. 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 June 2018. Appendix A provides details on variable definitions.

Panel A: Forecast Currency Excess Returns

	Average Mispricing				Extreme Mispricing			
	All Anomalies	Trend Following	Interest Rates	Fundamentals	All Anomalies	Trend Following	Interest Rates	Fundamentals
Mispricing	–7.763***	–6.351***	0.515	1.328***	–3.527***	–3.017***	0.246	0.510***
	(0.606)	(0.293)	(0.362)	(0.403)	(0.300)	(0.145)	(0.162)	(0.181)
Number of Forecasters	–0.013***	–0.011***	–0.005***	–0.004*	–0.011***	–0.011***	–0.005***	–0.005**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Single Forecast	–0.090	0.130	0.160		–0.021	0.145	0.155	
	(0.335)	(0.271)	(0.172)		(0.323)	(0.274)	(0.173)	
Intercept	5.580***	4.290***	–0.181	0.564	1.547***	1.072***	0.083	1.274*
	(0.721)	(0.658)	(0.440)	(0.674)	(0.342)	(0.202)	(0.367)	(0.651)
Observations	11,083	11,056	11,095	4,470	11,083	11,056	11,095	4,470
R–Squared	0.44	0.56	0.33	0.48	0.43	0.54	0.33	0.48
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country	Country	Country	Country	Country

(continued)

Table 5: Currency Mispricing and Forecast Returns (continued)

Panel B: Forecast Currency Returns

	Average Mispricing				Extreme Mispricing			
	All Anomalies	Trend Following	Interest Rates	Fundamentals	All Anomalies	Trend Following	Interest Rates	Fundamentals
Mispricing	–9.536***	–6.990***	–1.409***	0.796**	–4.411***	–3.346***	–0.622***	0.249
	(0.623)	(0.321)	(0.364)	(0.385)	(0.309)	(0.157)	(0.177)	(0.179)
Number of Forecasters	–0.007***	–0.005**	–0.000	0.001	–0.006**	–0.005**	–0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Single Forecast	–0.177	0.092	0.008		–0.095	0.109	0.028	
	(0.253)	(0.157)	(0.115)		(0.242)	(0.160)	(0.117)	
Intercept	6.500***	4.393***	0.930**	0.357	1.577***	0.859***	0.184	0.791
	(0.735)	(0.678)	(0.406)	(0.588)	(0.225)	(0.161)	(0.329)	(0.491)
Observations	11,083	11,056	11,095	4,470	11,083	11,056	11,095	4,470
R–Squared	0.52	0.63	0.33	0.47	0.50	0.61	0.33	0.47
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country	Country	Country	Country	Country

Table 6: Analysts' Mistakes and Currency Mispricing

The table reports results from regressions of analysts' mistakes (in percent per month) on average mispricing and extreme mispricing across all anomalies or groups of anomalies 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*. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying anomalies, while extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying anomalies, divided by the number of anomalies. The analysis is based on the following eleven currency anomalies: (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. Trend Following is a group of anomalies that contains momentum based on the currency excess return over the prior one, three, and twelve months, as well as the filter rule combination. Interest Rates is a group of anomalies that contains carry trade, dollar carry trade, dollar exposures, and term spread. Fundamentals is a group of anomalies that contains currency value, output gap, and 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 June 2018. Appendix A provides details on variable definitions.

	Average Mispricing				Extreme Mispricing			
	All Anomalies	Trend Following	Interest Rates	Fundamentals	All Anomalies	Trend Following	Interest Rates	Fundamentals
Mispricing	–9.584***	–7.099***	–0.823*	0.300	–4.359***	–3.359***	–0.377*	0.083
	(0.657)	(0.334)	(0.445)	(0.508)	(0.321)	(0.163)	(0.194)	(0.233)
Number of Forecasters	–0.011***	–0.008***	–0.003*	–0.001	–0.009***	–0.008***	–0.003*	–0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Single Forecast	–0.138	0.137	0.087		–0.052	0.154	0.097	
	(0.313)	(0.213)	(0.158)		(0.299)	(0.217)	(0.159)	
Intercept	5.753***	3.685***	–0.285	3.358***	0.776	0.084	–0.714	3.523***
	(0.950)	(0.645)	(1.099)	(0.696)	(0.883)	(0.711)	(1.062)	(0.660)
Observations	11,083	11,056	11,095	4,470	11,083	11,056	11,095	4,470
R–Squared	0.45	0.50	0.36	0.51	0.44	0.49	0.36	0.51
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country	Country	Country	Country	Country

Table 7: Analysts' Mistakes and Currency Mispricing Over Time

The table reports results from regressions of analysts' mistakes (in percent per month) on the interaction between average mispricing and extreme mispricing (across all anomalies or groups of anomalies) and Time, mispricing, and control variables. Mistakes are the difference between forecast currency returns and actual (i.e. realized) currency returns. Forecast currency returns are the negative log difference of a foreign currency's one-month forecast in month *t* and its spot rate in month *t*. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying anomalies, while extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying anomalies, divided by the number of anomalies. The analysis is based on the following eleven currency anomalies: (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. Trend Following is a group of anomalies that contains momentum based on the currency excess return over the prior one, three, and twelve months, as well as the filter rule combination. Interest Rates is a group of anomalies that contains carry trade, dollar carry trade, dollar exposures, and term spread. Fundamentals is a group of anomalies that contains currency value, output gap, and the Taylor Rule. Time is equal to 1/100 during the first month of the sample and increases by 1/100 each month. 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 June 2018. Appendix A provides details on variable definitions.

(continued)

Table 7: Analysts' Mistakes and Currency Mispricing Over Time (continued)

	Average Mispricing				Extreme Mispricing			
	All Anomalies	Trend Following	Interest Rates	Fundamentals	All Anomalies	Trend Following	Interest Rates	Fundamentals
Mispricing	–7.906***	–5.542***	–2.836***	–3.727*	–3.990***	–2.714***	–1.137***	–2.024**
	(0.957)	(0.542)	(0.748)	(1.861)	(0.479)	(0.286)	(0.362)	(0.978)
Mispricing x Time	–0.828*	–0.740***	0.989***	1.619**	–0.178	–0.304**	0.359**	0.841**
	(0.442)	(0.260)	(0.366)	(0.686)	(0.214)	(0.138)	(0.175)	(0.359)
Number of Forecasters	–0.011***	–0.008***	–0.003**	–0.002	–0.009***	–0.008***	–0.003*	–0.002
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Single Forecast	–0.140	0.151	0.108		–0.051	0.170	0.110	
	(0.320)	(0.216)	(0.154)		(0.301)	(0.219)	(0.157)	
Intercept	4.630***	2.717***	1.157	4.496***	0.649	–0.077	–0.382	3.631***
	(0.975)	(0.694)	(1.186)	(0.894)	(0.896)	(0.777)	(1.090)	(0.676)
Observations	11,083	11,056	11,095	4,470	11,083	11,056	11,095	4,470
R–Squared	0.45	0.51	0.36	0.51	0.44	0.49	0.36	0.51
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country	Country	Country	Country	Country

Table 8: Mispricing and Changes in Currency Forecasts

The table reports results from regressions of changes in analysts' forecasts of currencies that are made from month *t* to month *t*+1 (in percent per month) on lags of average mispricing and extreme mispricing, respectively, and control variables. Average mispricing is the average of the percentile ranks of currencies with respect to the following eleven currency anomalies: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior three months, (iii) momentum based on the currency excess return over the prior twelve months, (iv) filter rule combination, (v) carry trade, (vi) dollar carry trade, (vii) dollar exposures, (viii) term spread, (ix) currency value, (x) output gap, and (xi) the Taylor Rule. Extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven anomaly 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 June 2018. Appendix A provides details on variable definitions.

	Average Mispricing			Extreme Mispricing		
	(1)	(2)	(3)	(1)	(2)	(3)
Mispricing (lagged by 1 month)	2.360***			1.030***		
	(0.250)			(0.130)		
Mispricing (lagged by 2 months)		0.573**			0.243*	
		(0.249)			(0.125)	
Mispricing (lagged by 3 months)			–0.293			–0.157
			(0.261)			(0.125)
Number of Forecasters	0.005***	0.004***	0.003**	0.005***	0.004***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Single Forecast	0.035	–0.013	–0.052	0.011	–0.019	–0.050
	(0.131)	(0.100)	(0.090)	(0.127)	(0.099)	(0.091)
Intercept	–1.269*	1.705*	0.606	–0.026	2.010**	0.464
	(0.670)	(0.901)	(1.142)	(0.703)	(0.889)	(1.117)
Observations	10,996	10,928	10,860	10,996	10,928	10,860
R–Squared	0.34	0.32	0.32	0.33	0.32	0.32
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country	Country	Country

Table 9: Analysts' Forecasts and Mispricing

The table reports results from Fama-MacBeth (1973) regressions of actual (i.e. realized) currency excess returns (in percent per month) from month t to t+1 on dummy variables for quintiles Q2, Q3, Q4 and Q5 of average or extreme mispricing and analysts' forecasts of currency excess returns that are made in month t. At the end of each month, all available currencies are sorted independently into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on mispricing and analysts' forecasts of currency excess returns. Forecast currency excess returns are the sum of forecast currency returns and interest rate differentials. Average mispricing is the average of the percentile ranks of currencies with respect to the following eleven currency anomalies: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior three months, (iii) momentum based on the currency excess return over the prior twelve months, (iv) filter rule combination, (v) carry trade, (vi) dollar carry trade, (vii) dollar exposures, (viii) term spread, (ix) currency value, (x) output gap, and (xi) the Taylor Rule. Extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven anomaly 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 June 2018. Appendix A provides details on variable definitions.

	Average Mispricing		Extreme Mispricing	
	Coefficient	t-statistic	Coefficient	t-statistic
Mispricing Q2	0.241	[2.88] ***	0.169	[1.92] *
Mispricing Q3	0.344	[3.20] ***	0.264	[2.45] **
Mispricing Q4	0.551	[4.46] ***	0.444	[3.63] ***
Mispricing Q5	0.987	[7.18] ***	0.842	[6.56] ***
Forecast Excess Return Q2	0.201	[2.43] **	0.136	[1.51]
Forecast Excess Return Q3	0.229	[2.29] **	0.127	[1.14]
Forecast Excess Return Q4	0.298	[2.44] **	0.108	[0.82]
Forecast Excess Return Q5	0.409	[2.81] ***	0.313	[2.19] **
Intercept	–0.490	[–3.55] ***	–0.313	[–2.05] **
Average Number of Observations	32		32	
Average R–Squared	0.42		0.41	

Appendix A: 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. Data are from Datastream.
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.
Currency Excess Return	Currency Return + Interest Rate Differential. 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	Forecast Currency Return + Interest Rate Differential.
Mistakes	Forecast Currency Return – Currency Return.
Currency Anomalies	
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., 2012).
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., 2012).
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).
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.

(continued)

Appendix A: Variable Definitions (continued)

Variable	Definition
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. Riddiough and Sarno, 2018). 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. Riddiough and Sarno, 2018). 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.
Anomaly Groups	
Trend Following	Group of anomalies containing 1-Month Momentum, 3-Months Momentum, 12-Months Momentum, and Filter Rule Combination.
Interest Rates	Group of anomalies containing Carry Trade, Dollar Carry Trade, Dollar Exposures, and Term Spread.
Fundamentals	Group of anomalies containing Currency Value, Output Gap, and Taylor Rule.
Mispricing	
Average Mispricing	Average mispricing is calculated as the average percentile rank of currencies with respect to the underlying anomalies.
Extreme Mispricing	Extreme mispricing is calculated as the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying anomaly strategies, divided by the number of anomalies.
Profits	
Anomaly Profit	The anomaly profit in a month is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1) based on an anomaly signal.
Mispricing Profit	The mispricing profit in a month is the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1) based on average mispricing or extreme mispricing.
Control Variables	
Post-Sample	An indicator variable that takes the value 1 if the month is after the sample period used in the original study, but still pre-publication, and zero otherwise.
Post-Publication	An indicator variable that takes the value 1 if the month is after posting on SSRN, and zero otherwise.
Time	Time is equal to 1/100 during the first month of the sample and increases by 1/100 each month.

(continued)

Appendix A: Variable Definitions (continued)

Variable	Definition
1-Month Anomaly Profit	The quintile spread of the anomaly based on excess returns in the prior month.
12-Months Anomaly Profit	The quintile spread of the anomaly based on excess returns in the prior 12 months.
Level of Interest Rates	The average of the short-term interest rates of the currencies that are in the portfolios Q5 and Q1 for an anomaly.
Exchange Rate Volatility	The average of the within-month standard deviation of the currencies that are in the portfolios Q5 and Q1 for an anomaly using daily currency returns.
Post-Crisis (2009–2011)	An indicator variable with value 1 for the years 2009-2011, and zero otherwise.
NBER US Business Cycle Contractions	An indicator variable that takes the value 1 for U.S. recessions, and zero otherwise.
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 an anomaly. We calculate the average of each time-series over the in-sample period to estimate a single costly arbitrage variable for each anomaly.
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 an anomaly. The index is the average percentile rank of exchange rate turnover (from the BIS, 2016), an index of average money market restrictions for inflows and outflows (from Fernández et al., 2015), and a measure of capital account openness (Chinn and Ito, 2008). We calculate the average of each time-series over the in-sample period to estimate a single costly arbitrage variable for each anomaly.
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.

Appendix B: Anomalies, Authors, and Details of Publication

The table reports the currency anomaly, 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
Anomaly	Authors (Journal)	Start Date	End Date	Posting on SSRN	Start Date	End Date	Publication
Trend Following							
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
Interest Rates							
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			
Fundamentals							
Currency Value	Asness, Moskowitz, and Pedersen (*Journal of Finance*)	January 1979	October 2008	March 2009	January 1979	July 2011	June 2013
Output Gap	Riddiough and Sarno (Working Paper)	October 1983	January 2016	January 2017			
Taylor Rule	Riddiough and Sarno (Working Paper)	October 1983	January 2016	January 2017			

Table A1: Quintile Performance of Portfolios Sorted on Currency Anomalies

The table reports actual (i.e. realized) excess returns (in percent per month) of portfolios sorted on currency anomalies, alternatively gross of transaction costs and net of transaction costs. Transaction costs are calculated using bid and ask quotations. Individual anomalies 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 anomalies 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, computed using the method of Newey and West (1987) with three lags) 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 June 2018. Appendix A 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	–0.201	0.034	0.147	0.195	0.411	0.612	7.343	0.006	–0.151	–0.057	–0.011	0.151	0.145	1.737
	[–1.63]	[0.29]	[1.25]	[1.79]	[3.41]	[5.59]		[0.05]	[–1.29]	[–0.48]	[–0.10]	[1.25]	[1.32]	
3-Months Momentum	–0.163	–0.057	0.120	0.195	0.497	0.659	7.911	0.035	–0.249	–0.080	–0.005	0.227	0.192	2.300
	[–1.25]	[–0.49]	[1.08]	[1.73]	[4.07]	[5.91]		[0.27]	[–2.13]	[–0.71]	[–0.04]	[1.88]	[1.71]	
12-Months Momentum	–0.037	–0.004	0.048	0.108	0.377	0.415	4.977	0.137	–0.182	–0.119	–0.075	0.108	–0.028	–0.341
	[–0.28]	[–0.04]	[0.37]	[0.87]	[2.90]	[3.19]		[1.03]	[–1.51]	[–0.91]	[–0.59]	[0.85]	[–0.22]	
Filter Rule Combination	[–0.13]	[–0.08]	[0.11]	[0.17]	[0.34]	[0.46]	5.539	[0.09]	[–0.28]	[–0.08]	[–0.02]	[0.13]	[0.05]	0.561
	[–0.88]	[–0.59]	[0.91]	[1.41]	[2.82]	[3.83]		[0.62]	[–2.15]	[–0.67]	[–0.17]	[1.13]	[0.38]	
Carry Trade	–0.165	–0.031	0.143	0.240	0.547	0.712	8.540	0.026	–0.208	–0.049	0.021	0.161	0.135	1.619
	[–1.58]	[–0.30]	[1.39]	[2.29]	[4.11]	[7.06]		[0.24]	[–2.00]	[–0.47]	[0.20]	[1.20]	[1.32]	
Dollar Carry Trade						0.365	4.376						0.218	2.618
						[3.65]							[2.18]	
Dollar Exposures	0.075	0.248	0.318	0.489	0.445	0.370	4.439	0.209	0.055	0.126	0.350	0.320	0.110	1.322
	[1.56]	[2.69]	[2.40]	[3.21]	[2.69]	[2.20]		[4.20]	[0.59]	[0.96]	[2.32]	[1.93]	[0.64]	
Term Spread	0.033	–0.005	0.072	0.119	0.308	0.276	3.306	0.266	–0.189	–0.106	–0.080	0.057	–0.210	–2.517
	[0.30]	[–0.04]	[0.61]	[1.02]	[2.23]	[2.66]		[2.43]	[–1.61]	[–0.89]	[–0.68]	[0.41]	[–1.92]	
Currency Value	0.284	0.139	0.063	0.159	0.440	0.157	1.884	0.431	0.024	–0.045	0.046	0.288	–0.143	–1.710
	[1.51]	[0.72]	[0.34]	[0.81]	[2.09]	[0.88]		[2.29]	[0.13]	[–0.24]	[0.23]	[1.39]	[–0.82]	
Output Gap	0.093	0.047	0.166	0.395	0.432	0.339	4.067	0.206	–0.058	0.056	0.258	0.292	0.086	1.032
	[0.49]	[0.24]	[0.82]	[1.64]	[2.04]	[2.08]		[1.10]	[–0.30]	[0.28]	[1.10]	[1.38]	[0.54]	
Taylor Rule	0.156	–0.017	0.054	0.295	0.690	0.534	6.403	0.263	–0.102	–0.045	0.165	0.500	0.238	2.853
	[0.93]	[–0.09]	[0.26]	[1.42]	[2.58]	[2.45]		[1.55]	[–0.55]	[–0.22]	[0.80]	[1.93]	[1.13]	

Table A2: Summary Statistics of Average Mispricing and Extreme Mispricing

The table reports summary statistics for average mispricing and extreme mispricing across all anomalies or groups of anomalies. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying anomalies, while extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying anomalies, divided by the number of anomalies. The analysis is based on the following eleven currency anomalies: (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. Trend Following is a group of anomalies that contains momentum based on the currency excess return over the prior one, three, and twelve months, as well as the filter rule combination. Interest Rates is a group of anomalies that contains carry trade, dollar carry trade, dollar exposures, and term spread. Fundamentals is a group of anomalies that contains currency value, output gap, and the Taylor Rule. The sample includes 76 currencies. The sample period is from January 1976 to June 2018. Appendix A provides details on variable definitions.

		Standard				Percentiles								Number of
	Mean	Deviation	Skewness	Kurtosis	Minimum	1st	5th	25th	Median	75th	95th	99th	Maximum	Observations
Average Mispricing														
All Anomalies	0.527	0.155	0.087	2.670	0.068	0.195	0.273	0.417	0.526	0.636	0.788	0.889	1.000	16,936
Trend Following	0.515	0.234	–0.018	2.151	0.017	0.050	0.129	0.335	0.518	0.696	0.897	0.975	1.000	16,902
Interest Rates	0.544	0.194	0.036	2.350	0.037	0.150	0.236	0.393	0.549	0.683	0.861	0.967	1.000	17,113
Fundamentals	0.524	0.193	–0.231	2.407	0.042	0.083	0.191	0.384	0.542	0.667	0.826	0.899	0.987	4,527
Extreme Mispricing														
All Anomalies	0.029	0.318	0.087	3.099	–1.000	–0.714	–0.500	–0.182	0.000	0.250	0.571	0.800	1.000	16,936
Trend Following	0.005	0.474	–0.037	2.875	–1.000	–1.000	–0.750	–0.250	0.000	0.250	0.750	1.000	1.000	16,902
Interest Rates	0.064	0.407	0.002	2.528	–1.000	–0.750	–0.500	–0.250	0.000	0.333	0.750	1.000	1.000	17,113
Fundamentals	0.007	0.397	–0.369	3.036	–1.000	–1.000	–0.667	–0.333	0.000	0.333	0.667	0.667	1.000	4,527

Table A3: Quintile Performance of Portfolios Sorted on Average Mispricing and Extreme Mispricing

The table reports actual (i.e. realized) excess returns (in percent per month) of portfolios sorted on average mispricing and extreme mispricing, alternatively gross of transaction costs and net of transaction costs. Transaction costs are calculated using bid and ask quotations. At the end of each month, all available currencies are sorted into quintiles from Q1 (short portfolio) to Q5 (long portfolio) based on alternatively average mispricing and extreme mispricing and combined into equally weighted portfolios. The table shows the time series average of the currency excess returns of the quintile portfolios. It also shows the time series average of the difference between the currency excess returns of portfolios Q5 and Q1 (Q5-Q1). Average mispricing is the average of the percentile ranks of currencies with respect to the following eleven currency anomalies: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior three months, (iii) momentum based on the currency excess return over the prior twelve months, (iv) filter rule combination, (v) carry trade, (vi) dollar carry trade, (vii) dollar exposures, (viii) term spread, (ix) currency value, (x) output gap, and (xi) the Taylor Rule. Extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the eleven anomaly strategies, divided by the total number of strategies. The table reports average returns and associated *t*-statistic (in square brackets, computed using the method of Newey and West (1987) with three lags). It also shows the Sharpe ratio, calculated as the average currency excess return divided by its standard deviation, as well as the standard deviation, skewness and kurtosis of the portfolio returns, and the average level of mispricing. The sample includes 76 currencies. The sample period is from January 1971 to June 2018. Appendix A provides details on variable definitions.

	Gross of Transaction Costs						Net of Transaction Costs					
	Quintiles						Quintiles					
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1
Average Mispricing												
Average Currency Excess Return (t+1)	–0.324	0.047	0.129	0.220	0.526	0.851	–0.147	–0.147	–0.065	–0.002	0.252	0.399
t-statistic	[–2.98]	[0.41]	[1.14]	[1.83]	[4.22]	[8.56]	[–1.37]	[–1.29]	[–0.57]	[–0.02]	[2.03]	[4.01]
Sharpe Ratio	–0.137	0.020	0.056	0.090	0.212	0.373	–0.062	–0.063	–0.028	–0.001	0.102	0.175
Standard Deviation	2.369	2.351	2.311	2.451	2.477	2.281	2.365	2.345	2.319	2.465	2.474	2.285
Skewness	–0.588	–0.154	–0.235	–0.332	–0.305	0.020	–0.485	–0.195	–0.268	–0.382	–0.369	–0.064
Kurtosis	6.601	5.221	4.365	4.579	4.449	5.199	6.540	5.202	4.333	4.678	4.489	5.341
Mispricing (t)	0.323	0.438	0.533	0.623	0.746	0.424	0.323	0.438	0.533	0.623	0.746	0.424
Extreme Mispricing												
Average Currency Excess Return (t+1)	–0.239	0.027	0.098	0.207	0.517	0.756	–0.059	–0.159	–0.099	–0.004	0.230	0.290
t-statistic	[–2.21]	[0.24]	[0.86]	[1.76]	[4.16]	[7.21]	[–0.56]	[–1.38]	[–0.87]	[–0.03]	[1.87]	[2.76]
Sharpe Ratio	–0.102	0.012	0.042	0.085	0.213	0.329	–0.025	–0.068	–0.042	–0.002	0.095	0.125
Standard Deviation	2.339	2.331	2.347	2.434	2.432	2.301	2.334	2.332	2.356	2.437	2.432	2.308
Skewness	–0.445	–0.225	–0.367	–0.331	–0.223	0.097	–0.341	–0.264	–0.422	–0.364	–0.321	–0.001
Kurtosis	6.386	4.802	4.770	4.407	4.774	5.555	6.358	4.805	4.849	4.391	4.805	5.618
Mispricing (t)	–0.399	–0.124	0.030	0.182	0.477	0.876	–0.399	–0.124	0.030	0.182	0.477	0.876

Table A4: Correlations of Currency Anomalies and Mispricing

The table reports correlations between time series of monthly returns of investment strategies based on currency anomalies. 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 anomalies and combined into equally weighted portfolios. The investment 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 anomalies are 1-Month Momentum (momentum based on the currency excess return over the prior month), 3-Months Momentum (momentum based on the currency excess return over the prior three months), 12-Months Momentum (momentum based on the currency excess return over the prior twelve months), Filter Rule Combination, Carry Trade, Dollar Carry Trade, Dollar Exposures, Term Spread, Currency Value, Output Gap, and the Taylor Rule. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying anomalies, while extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying anomalies, divided by the number of anomalies. The sample includes 76 currencies. The sample period is from January 2000 to June 2018. Appendix A provides details on variable definitions.

	1-Month Momentum	3-Months Momentum	12-Months Momentum	Filter Rule Combination	Carry Trade	Dollar Carry Trade	Dollar Exposures	Term Spread	Currency Value	Output Gap	Taylor Rule	Average Mispricing
3-Months Momentum	0.641											
12-Months Momentum	0.372	0.461										
Filter Rule Combination	0.709	0.762	0.590									
Carry Trade	–0.040	0.137	0.340	–0.070								
Dollar Carry Trade	0.131	0.129	0.065	0.079	0.192							
Dollar Exposures	0.095	0.071	0.059	0.067	0.133	0.922						
Term Spread	0.005	0.084	0.185	0.025	0.340	0.256	0.253					
Currency Value	–0.102	–0.067	–0.387	–0.172	–0.140	–0.016	0.018	0.019				
Output Gap	0.147	0.101	0.094	0.115	–0.153	0.108	0.138	0.116	0.204			
Taylor Rule	–0.056	0.014	0.244	0.010	0.530	0.064	0.060	0.324	0.010	0.152		
Average Mispricing	0.594	0.668	0.667	0.714	0.320	0.250	0.231	0.362	–0.169	0.160	0.317	
Extreme Mispricing	0.642	0.719	0.666	0.741	0.343	0.233	0.201	0.342	–0.149	0.136	0.352	0.902

Table A5: 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	June 2018
Australia	Australian Dollar	December 1984	June 2018
Austria	Austrian Schilling	December 1970	December 1998
Bahrain	Bahrain Dinar	March 2004	June 2018
Belgium	Belgian Franc	December 1970	December 1998
Brazil	Brazilian Real	March 2004	June 2018
Bulgaria	Bulgarian Lev	March 2004	June 2018
Canada	Canadian Dollar	December 1970	June 2018
Chile	Chilean Peso	March 2004	June 2018
China	Chinese Renminbi	February 2002	June 2018
Colombia	Colombian Peso	March 2004	June 2018
Croatia	Croatian Kuna	March 2004	June 2018
Cyprus	Cypriot Pound	March 2004	December 2007
Czech Republic	Czech Koruna	December 1996	June 2018
Denmark	Danish Krone	December 1970	June 2018
Egypt	Egyptian Pound	March 2004	June 2018
Estonia	Estonian Kroon	March 2004	December 2010
Euro Area	Euro	January 1999	June 2018
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	June 2018
Greece	Greek Drachma	December 1996	December 2000
Hong Kong	Hong Kong Dollar	October 1983	June 2018
Hungary	Hungarian Forint	October 1997	June 2018
Iceland	Iceland Krona	March 2004	June 2018
India	Indian Rupee	October 1997	June 2018
Indonesia	Indonesian Rupiah	December 1996	June 2018
Ireland	Irish Punt	December 1970	December 1998
Israel	Israeli Shekel	March 2004	June 2018
Italy	Italian Lira	December 1970	December 1998
Japan	Japanese Yen	June 1978	June 2018
Jordan	Jordanian Dinar	March 2004	June 2018
Kazakhstan	Kazakhstani Tenge	March 2004	June 2018
Kenya	Kenyan Schilling	March 2004	June 2018
Kuwait	Kuwaiti Dinar	January 1994	June 2018
Latvia	Latvian Lats	March 2004	December 2013
Lithuania	Lithuanian Litas	March 2004	December 2014
Malaysia	Malaysian Ringgit	December 1996	June 2018
Malta	Maltese Lira	March 2004	December 2007
Mexico	Mexican Peso	December 1996	June 2018

(continued)

Table A5: Currency Sample Periods (continued)

		Sample Period	
Country	Currency	Start Date	End Date
Morocco	Moroccan Dirham	March 2004	June 2018
Netherlands	Netherlands Guilder	December 1970	December 1998
New Zealand	New Zealand Dollar	December 1984	June 2018
Nigeria	Nigerian Naira	April 2011	June 2018
Norway	Norwegian Krone	December 1970	June 2018
Oman	Omani Rial	March 2004	June 2018
Pakistan	Pakistani Rupee	March 2004	June 2018
Peru	Peruvian New Sol	March 2004	June 2018
Philippines	Philippine Peso	December 1996	June 2018
Poland	Polish Zloty	February 2002	June 2018
Portugal	Portuguese Escudo	January 1981	December 1998
Qatar	Qatar Rial	March 2004	June 2018
Romania	Romanian Leu	March 2004	June 2018
Russia	Russian Rouble	March 2004	June 2018
Saudi Arabia	Saudi Arabian Riyal	December 1996	June 2018
Serbia	Serbian Dinar	July 2011	June 2018
Singapore	Singaporean Dollar	December 1984	June 2018
Slovakia	Slovakian Koruna	February 2002	December 2008
Slovenia	Slovenian Tolar	March 2004	December 2006
South Africa	South African Rand	October 1983	June 2018
South Korea	South Korean Won	February 2002	June 2018
Spain	Spanish Peseta	December 1970	December 1998
Sri Lanka	Sri Lankan Rupee	July 2011	June 2018
Sweden	Swedish Krona	December 1970	June 2018
Switzerland	Swiss Franc	December 1970	June 2018
Taiwan	Taiwanese Dollar	December 1996	June 2018
Thailand	Thai Baht	December 1996	June 2018
Tunisia	Tunisian Dinar	March 2004	June 2018
Turkey	Turkish Lira	December 1996	June 2018
Uganda	Ugandan Shilling	July 2011	June 2018
Ukraine	Ukrainian Hryvnia	March 2004	June 2018
United Arab Emirates	UAE Dirham	December 1996	June 2018
United Kingdom	United Kingdom Pound	December 1970	June 2018
Vietnam	Vietnamese Dong	July 2011	June 2018
Zambia	Zambia Kwacha	July 2011	June 2018

Table A6: Summary Statistics of Actual and Forecast Currency Returns and Analysts' Mistakes

The table reports summary statistics on actual (i.e. realized) and forecast currency returns and analysts' mistakes (in percent per month). In particular, the table shows the means, standard deviations, skewness, kurtosis, minimum, maximum and various percentiles. 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. Mistakes are the difference between forecast currency returns and actual (i.e. realized) currency returns. The sample period is from January 1971 to June 2018. Appendix A provides details on variable definitions.

		Standard				Percentiles							
	Mean	Deviation	Skewness	Kurtosis	Minimum	1st	5th	25th	Median	75th	95th	99th	Maximum
Actual Currency Returns	–0.14	3.18	–2.28	40.5	–69.4	–9.66	–5.01	–1.31	0.00	1.21	4.52	7.33	34.2
Forecast Currency Returns	–0.24	2.96	0.39	7.61	–16.7	–7.97	–4.89	–1.64	–0.17	1.01	4.57	8.38	24.6
Actual Currency Excess Returns	0.14	3.18	–1.32	27.8	–63.9	–9.13	–4.72	–1.08	0.08	1.52	4.89	7.95	38.8
Forecast Currency Excess Returns	0.05	3.04	0.88	9.76	–15.9	–7.40	–4.55	–1.40	–0.00	1.24	4.96	9.32	28.7
Analysts' Mistakes	–0.09	4.37	1.27	15.1	–27.8	–10.2	–6.63	–2.28	–0.17	1.71	6.96	13.2	66.8

Table A7: Publication Effects for Alternative Samples

The table reports results from regressions of currency anomaly 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 (specifications (1) and (2)) and in-sample anomaly bid/ask spreads (specification (3)). The regression specifications are the same as specifications (1) and (2) in Table 1 Panel A and specification (1) in Table 1 Panel C, but for brevity, the table only displays the coefficients on selected variables. Except for estimations with arbitrage costs, results are shown alternatively for anomaly profits gross and net of transaction costs, which are calculated using bid and ask quotations. Separately for each anomaly, 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 an anomaly 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 in-sample bid/ask spreads is measured as the in-sample mean of the average bid-ask spread of the currencies in its long and short portfolios. The analysis is based on the following eleven currency anomalies: (i) momentum based on the currency excess return over the prior month, (ii) momentum based on the currency excess return over the prior three months, (iii) momentum based on the currency excess return over the prior twelve months, (iv) filter rule combination, (v) carry trade, (vi) dollar carry trade, (vii) dollar exposures, (viii) term spread, (ix) currency value, (x) output gap, and (xi) the Taylor Rule. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels. Standard errors are computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between returns. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes alternatively 62 currencies, 54 currencies covered by the 2019 BIS Triennial Survey, 40 currencies with the most turnover according to the BIS Triennial Survey, and the G10 currencies (USD, EUR, DEM, GBP, JPY, AUD, NZD, CAD, CHF, NOK, SEK, see Ang and Chen, 2010). The sample period is from January 1971 to June 2018. Appendix A provides details on variable definitions. Appendix B provides details on the anomalies' original sample period used in the paper as well as date of publication.

	Anomaly Profits Gross of Transaction Costs			Anomaly Profits Net of Transaction Costs	
	Table 1A, Specification (1)	Table 1A, Specification (2)	Table 1C, Specification (1)	Table 1A, Specification (1)	Table 1A, Specification (2)
	(1)	(2)	(3)	(1)	(2)
62 currencies					
Post-Publication	–0.394***	0.065	–1.443**	–0.304**	–0.078
	(0.119)	(0.221)	(0.564)	(0.119)	(0.090)
Post-Publication x Average Anomaly In-Sample Profits		–0.789*			–1.500***
		(0.446)			(0.471)
Post-Publication x In-Sample Bid/Ask Spreads			6.327*		
			(3.250)		

(continued)

Table A7: Publication Effects for Alternative Samples (continued)

	Anomaly Profits Gross of Transaction Costs			Anomaly Profits Net of Transaction Costs	
	Table 1A, Specification (1)	Table 1A, Specification (2)	Table 1C, Specification (1)	Table 1A, Specification (1)	Table 1A, Specification (2)
	(1)	(2)	(3)	(1)	(2)
54 currencies					
Post-Publication	–0.456***	0.106	–1.305**	–0.236*	0.012
	(0.128)	(0.204)	(0.529)	(0.127)	(0.097)
Post-Publication x Average Anomaly In-Sample Profits		–0.919**			–1.457***
		(0.404)			(0.452)
Post-Publication x In-Sample Bid/Ask Spreads			5.348*		
			(3.066)		
40 currencies					
Post-Publication	–0.553***	0.120	–1.200**	–0.363***	0.002
	(0.125)	(0.240)	(0.575)	(0.124)	(0.105)
Post-Publication x Average Anomaly In-Sample Profits		–1.094**			–1.667***
		(0.444)			(0.514)
Post-Publication x In-Sample Bid/Ask Spreads			4.309		
			(3.597)		
10 currencies					
Post-Publication	–0.494***	0.121	–0.094	–0.335**	–0.012
	(0.140)	(0.204)	(0.483)	(0.139)	(0.120)
Post-Publication x Average Anomaly In-Sample Profits		–1.203***			–1.411***
		(0.429)			(0.495)
Post-Publication x In-Sample Bid/Ask Spreads			–3.173		
			(4.123)		

Table A8: Mispricing and Analysts' Mistakes for Alternative Samples

The table reports results from regressions of analysts' mistakes (in percent per month) on average mispricing and extreme mispricing (across all anomalies or groups of anomalies), and their interaction with Time, and control variables. The regression specifications are the same as Tables 6 and 7, but for brevity, the table only displays the coefficients on the mispricing variable. Mistakes are the difference between forecast currency returns and actual (i.e. realized) currency returns. Forecast currency returns are the negative log difference of a foreign currency's one-month forecast in month *t* and its spot rate in month *t*. Average mispricing is the average of the percentile ranks of currencies with respect to the underlying anomalies, while extreme mispricing is the difference between the number of long and the number of short portfolios a currency belongs to in a given month across the underlying anomalies, divided by the number of anomalies. All Anomalies refers to the following eleven anomalies: (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. Trend Following is a group of anomalies that contains momentum based on the currency excess return over the prior one, three, and twelve months, as well as the filter rule combination. Interest Rates is a group of anomalies that contains carry trade, dollar carry trade, dollar exposures, and term spread. Fundamentals is a group of anomalies that contains currency value, output gap, and the Taylor Rule. Time is equal to 1/100 during the first month of the sample and increases by 1/100 each month. Regressions include the number of forecasters providing forecasts for a currency and an indicator for a single forecast as controls. All regressions also include month fixed effects. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels. Standard errors are clustered by country. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The sample includes 52 currencies that are covered in the 2019 BIS Triennial Survey, 40 currencies with the most turnover according to the BIS Triennial Survey, and the G10 currencies (USD, EUR, DEM, GBP, JPY, AUD, NZD, CAD, CHF, NOK, SEK, see Ang and Chen, 2010). The sample period is from December 1989 to June 2018. Appendix A provides details on variable definitions.

(continued)

Table A8: Mispricing and Analysts' Mistakes for Alternative Samples (continued)

		Average Mispricing				Extreme Mispricing			
		All Anomalies	Trend Following	Interest Rates	Fundamentals	All Anomalies	Trend Following	Interest Rates	Fundamentals
52 currencies									
Table 6	Mispricing	–10.012***	–7.226***	–1.072**	0.300	–4.660***	–3.468***	–0.520**	0.083
		(0.644)	(0.329)	(0.474)	(0.508)	(0.307)	(0.159)	(0.201)	(0.233)
Table 7	Mispricing	–7.369***	–5.291***	–2.780***	–3.727*	–3.681***	–2.523***	–1.209***	–2.024**
		(0.946)	(0.522)	(0.710)	(1.861)	(0.483)	(0.273)	(0.369)	(0.978)
40 currencies									
Table 6	Mispricing	–10.323***	–7.338***	–1.336***	0.329	–4.859***	–3.564***	–0.562***	0.077
		(0.683)	(0.348)	(0.487)	(0.510)	(0.312)	(0.166)	(0.204)	(0.240)
Table 7	Mispricing	–7.732***	–5.574***	–2.765***	–3.607*	–3.877***	–2.718***	–1.134***	–2.094**
		(1.042)	(0.565)	(0.737)	(1.842)	(0.528)	(0.306)	(0.375)	(1.002)
10 currencies									
Table 6	Mispricing	–8.208***	–5.665***	–1.186	0.685	–4.152***	–2.911***	–0.533	0.054
		(0.652)	(0.321)	(0.750)	(0.555)	(0.378)	(0.178)	(0.293)	(0.278)
Table 7	Mispricing	–6.046***	–4.263***	–2.086***	1.742	–2.737***	–2.201***	–0.730*	0.406
		(1.170)	(0.356)	(0.410)	(1.875)	(0.544)	(0.193)	(0.391)	(1.143)

Table A9: Publication Dates of Earlier Related Research

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

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

Table A10: Publication Effects Controlling for Earlier Related Research

The table reports results from regressions of currency anomaly profits (in percent per month) on an indicator variable for post-publication periods, and control variables for the dissemination of earlier related research. Alternative groups of relevant research are academic publications on related FX strategies, practitioner articles on FX strategies, newspaper articles on FX strategies, academic publications on corresponding equity strategies, and academic publications on corresponding fixed income strategies. Controls are for dissemination of earlier related research are either pooled across anomalies or for each individual paper. Results are shown alternatively for anomaly profits gross and net of transaction costs, where transactions costs are calculated using bid and ask quotations. Separately for each anomaly, 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 an anomaly 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 anomalies: (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 anomaly 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 anomalies, 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 June 2018. Appendix A provides details on variable definitions. Appendix B provides details on the anomalies' original sample period used in the paper as well as date of publication. Table A9 provides details on the dissemination of earlier related research.

	Anomaly Profits Gross of Transaction Costs		Anomaly Profits Net of Transaction Costs	
	Pooled	Individual	Pooled	Individual
Post-Publication	–0.408***	–0.347***	–0.466***	–0.380***
	(0.129)	(0.122)	(0.129)	(0.121)
Academic Publications on Related FX Strategies	–0.274**		–0.104	
	(0.137)		(0.137)	
Practitioner Articles on FX Strategies	0.570***		0.632***	
	(0.193)		(0.192)	
Newspaper Articles on FX Strategies	–0.149		–0.115	
	(0.158)		(0.156)	
Academic Publications on Corresponding Equity Strategies	0.365**		0.422**	
	(0.164)		(0.164)	
Academic Publications on Corresponding Fixed Income Strategies	0.029		0.081	
	(0.173)		(0.173)	
Observations	4,483	4,483	4,483	4,483
R–Squared	0.01	0.02	0.01	0.02
Number of Anomalies	11	11	11	11
Anomaly Fixed Effects	Yes	Yes	Yes	Yes
Standard Errors	FGLS	FGLS	FGLS	FGLS