Essays in International Financial Markets

by

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Contents

List of Figures

List of Tables

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Declarations

This thesis is submitted to the University of Warwick in support of the requirements for the degree of Doctor of Philosophy. I confirm that I have not submitted the thesis for a degree at another university.

I further declare that Chapters 1 and 2 of this thesis are based on collaborative work with Söhnke M. Bartram and Anthony Garratt.

Leslie Djuranovik

Abstract

This thesis studies explanations for the existence of currency anomalies and time-varying parameter effects of exchange-rate predictability within the context of currency markets. The thesis comprises three essays.

The first essay examines the relation between currency anomalies and academic research. 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 academic research. The decline is greater for anomalies with larger in-sample period profits and lower arbitrage costs, and signal performance decays quickly. This finding is consistent with the idea that academic research draws trading attention to currency anomalies.

The second essay relates currency anomalies and foreign exchange analysts, where mispricing is systematically found related to mistakes and changes in analysts' currency forecasts. In particular, analysts expect anomaly payoffs that are too low or even negative compared to actual anomaly profits. While analysts' mistakes decrease after anomaly publication and analysts update their forecasts to incorporate lagged anomaly information, trading profits from mispricing are more than three times those using analysts' forecasts. These results are consistent with a behavioral explanation for currency anomalies.

The third essay constructs bilateral measures of cyclical external imbalances to predict exchange-rate returns in a framework that allows for the parameters of the forecasting regression to vary over time. A strategy using bilateral measures of cyclical external imbalances exhibits high economic value relative to the random walk benchmark in short horizons of one quarter ahead. Predictive regressions employing constant parameter models are found to be inferior to time varying coefficient parameter models, suggesting a dynamic relationship between bilateral cyclical imbalances and exchange-rate returns that vary over time.

Overview

This thesis consists of three essays in international financial markets, with a focus on the currency markets. The first two chapters discuss currency anomalies, while the last chapter examines the time-varying effects of macroeconomic fundamentals, i.e., the international financial adjustment model, when predicting exchange-rate changes.

Cross-sectional currency excess return predictability has been the subject of a recent and expanding literature. As currency markets are populated by sophisticated professional investors and characterized by high liquidity, large transaction volumes and low transaction costs, one would expect them to be highly informationally efficient. However, investors in currency markets have been shown capable of exploiting exchange-rate predictability using various investment strategies. Generally, these studies try to rationalize the systematic profits generated by currency investment strategies as compensation for risk.

Chapters 1 and 2 are related to this more recent, small, but growing, body of research focusing on the cross-sectional prediction of currency excess returns, documenting a number of variables or anomalies systematically predicting excess returns across currencies. We aim to investigate behavioral explanations for the existence of currency anomalies. To this end, Chapter 1 examines whether the predictive power of anomalies remains after publication of the underlying academic research. If these 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. Chapter 2 analyzes behavioral explanations directly, and we relate currency mispricing via the anomalies to exchange-rate expectations formed by analysts, their forecast errors or mistakes, and revisions to their forecasts.

Anomaly profits could be the result of mispricing, risk, or statistical biases arising in estimation (McLean and Pontiff, 2016). To investigate these different explanations as sources of predictability in currency markets, Chapter 1 examines the profits of anomaly strategies 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) and with profits after the publication of the research (i.e., the post-publication period). If currency excess return predictability in published academic research originates solely from in-sample period statistical bias or data mining, predictability should not exist in the out-of-sample period (McLean and Pontiff, 2016; Fama, 1991).

If however 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 the 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).

The empirical analysis uses real-time monthly data for a comprehensive set of currencies and anomaly strategies and the exchange rates of a large cross-section of countries. We construct ten widely used currency anomalies that have been documented in the literature as predictors of currency excess returns. They are momentum based on prior one, three or twelve months currency returns, carry trade, dollar carry trade, dollar exposures, term spread, currency value, output gap, and the Taylor Rule.

Since we seek to analyze the ability of these anomaly variables to predict future currency returns, constructing all the anomalies using real-time data makes sense. This procedure ensures the information from the trading signals is available to market participants at the point in time the signal was constructed; thus, it avoids a look-ahead bias. Data are sourced from Datastream and the Original Release Data and Revisions Database of the OECD covering the period from December 1970 to June 2018. As a measure of foreign exchange rate expectations, we use mean forecasts from surveys undertaken by Consensus Economics, which are available from December 1989 to June 2018.

Consistent with mispricing, but not with risk, as the source of predictability, payoffs associated with anomalies significantly decrease (or even disappear) after academic research has been published. Post-publication declines are greater for currencies with economically or statistically larger in-sample period profits and with smaller arbitrage costs. Trading profits decrease for lagged trading signals, and anomaly signals decay quickly. In contrast, the profitability of currency anomalies does not drop in out-of-sample periods before publication; thus, no evidence exists of statistical bias or data mining as the origin of anomaly profits.

Nevertheless, mispricing might not be the sole explanation for some anomalies. The literature on the cross-sectional predictability of currency returns is not very old and is still growing. As a result, post-publication periods for the various anomalies often overlap and coincide with the zero lower bound period. Under these circumstances, disentangling the reasons for the disappearing profitability is difficult.

In Chapter 2 we investigate whether the existence of currency anomalies has a behavioral explanation. If this were the case, their trading profits should reflect (temporary) mispricing, and one should be able to relate the anomalies to the behaviors of investors and biases in investors' market views or forecasts. To mimic the alpha models of institutional investors summarizing 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. These two measures of average and extreme mispricing (across all anomalies and across three groups of anomalies) are generated using the quintile spreads of realized currency excess returns both gross and net of transactions costs. We investigate whether analysts incorporate the information reflected in these anomalies and examine evidence of their ability to predict currency excess returns cross-sectionally when making their exchange-rate forecasts, given that this information is widely disseminated and publicly available. 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 do, and expected profits should be similar to realized profits. This situation contrasts with the currency literature focused to date on the analysis of individual anomalies.

The measure of average mispricing is constructed 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; thus, it assumes no information regarding each anomaly's relative forecasting power. It also reduces the noise across currency predictors. The second aggregate is a measure of extreme mispricing defined as the difference between the number of long- and short-anomaly portfolios to which a currency belongs in a given month, divided by the number of anomalies. This normalized score ranges between –1 and +1. A high score indicates 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. We create average and extreme mispricing measures for all anomalies as well as three anomaly families based on trend following, interest rates, and fundamentals.

We find that analysts expect payoffs to mispricing-based strategies lower than realized profits, and across all anomalies they even expect significant losses. These results are the converse of a priori expectations. Across groups of anomalies, analysts expect significant positive trading profits only from mispricing tied to macroeconomic fundamentals. The expected losses are, largely, the result of analysts frequently expecting large negative quintile spreads on the currency return component.

Evidence from panel regressions of currency excess returns on average and extreme 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 negative and significant coefficients on mispricing (except for fundamentals). These results demonstrate analysts' foreign exchange forecasts are often at odds 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, 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 decrease over time as analysts learn and improve their predictions. For anomalies tied to fundamentals, the learning effect is so large that, on average, analysts' forecasts are in line with realized anomaly profits. Similarly, lagged mispricing predicts changes in analysts' foreign exchange forecasts, suggesting analysts predictably update their forecasts based on initially overlooked information captured in anomalies. Nevertheless, while analysts are skilled information processors and aggregators, the profits from long-short currency strategies based on analysts' currency expectations yield much lower profits compared to trading on mispricing-based signals.

Analysts could still follow investors, as currency markets are dominated by presumably sophisticated investors. As we do not have direct information about investors' foreign exchange forecasts, aggregating analysts' forecasts is our attempt to explore the biased expectation as a source of currency predictability, which, to the best of our knowledge, is the first such attempt made in the literature.

Chapters 1 and 2 provide a fresh view on excess return predictability in currency markets from the perspective of behavioral finance. This view is closely related to recent research for equity markets documenting that the profitability of 97 anomalies decreases after publication of the academic research (McLean and Pontiff, 2016). Average returns to prominent equity market anomalies have declined in recent years, a fact attributed to increased trading activity of hedge funds and lower trading costs (Chordia et al., 2014). Moreover, analysts' recommendations agree with half of 12 equity anomalies (Jegadeesh et al., 2004), and analysts' price targets and recommendations contradict stock return anomaly variables (Engelberg et al., 2017). For firms with better credit quality, analysts' biases are unrelated to subsequent stock returns, while among stocks with poor credit quality, the quintile predicted to have the most conservative forecasts outperforms the quintile with the most optimistic forecasts (Grinblatt, Jostova, and Philipov, 2016). This thesis is the first to explore similar questions in currency markets.

Chapter 3 is more related to a large literature on predicting exchange rates in time-series analyses (e.g., Mark, 1995, Molodtsova, Nikolsko-Rzhevskyy, and Papell, 2008, and Rossi, 2013). It seeks to explore the established consensus that exchange rates are very difficult to predict using economic models (Meese and Rogoff, 1983), that economic fundamentals are of little use, and that exchange rates are well approximated by a naive random walk model (Engel et al., 2007). The chapter also tries to address another issue in exchange rate predictability with regards to parameter estimation, arguing that parameter instability may rationalize the poor forecasting performance of exchange rate models (Meese and Rogoff, 1983).

Specifically, Chapter 3 uses macroeconomic fundamentals and allows for time varying parameters in the models used. The underlying idea is that macroeconomic conditions should have useful information on exchange rate movements, but change over-time. In particular, this chapter employs Bayesian methods to estimate a state-space model in which regression parameters are time varying, following a random walk process. Bayesian methods are appealing as all the unknown parameters in the system are treated as jointly distributed random variables (Kim and Nelson, 1999), so each estimated parameter reflects uncertainty about the other parameters.

The macroeconomic fundamentals used in this chapter follow the international financial adjustment theoretical model of Gourinchas and Rey (2007), where bilateral external imbalances between the U.S. and foreign countries are constructed by combining stationary components of the (trend) share of exports and imports in the trade balance and the (trend) share of foreign assets and liabilities in the net foreign assets respectively. This approach has been used previously (Della Corte, Sarno, and Sestieri, 2012), but this chapter extends previous investigation based on a single-equation constant-parameter model to estimate the predictability regression by allowing for time-variation in the parameters. The predictive power of net foreign assets for currency returns has also been examined recently (Della Corte, Riddiough, and Sarno, 2016). This chapter provides further investigation by combining information from net foreign assets and net exports, which are found to provide more economic gain for exchange-rate predictability in the out-of-sample period than the use of net foreign assets only.

Interest has been growing in evaluating exchange-rates predictability using several economic evaluation criteria by which researchers look for tangible economic gains using dynamic forecasts in active portfolio management. For example, assessments of the economic value of exchange-rate predictability are made in a decision-making environment (Garratt and Lee, 2010) or in terms of investment profits (Kouwenberg et al., 2017). I opt to focus on economic as opposed to statistical evaluation in this chapter, with a focus on a one-step ahead horizon.

The evaluation is done by using the following economic performance criteria. First, a maximum performance fee that a risk-averse investor with quadratic utility would be willing to pay to have access to the additional information available in a strategy relative to a benchmark random walk model. Second, the excess premium return of a fundamentals-based portfolio relative to the random walk portfolio. Third, the break-even proportional transaction cost that renders investors indifferent between two alternative strategies.

The empirical analysis provides evidence that bilateral external imbalances have strong in-sample and out-of-sample period predictive ability for exchange-rate returns based on economic performance measures. Allowing for time-varying bilateral external imbalances improves upon the random walk at short horizons of one quarter. Time-varying regressions also perform much better than constant parameter linear regressions employed in a rolling-window forecasting approach. The investor can find large economic value using the predictive information in bilateral external imbalances.

1 Currency Anomalies and Academic Research

1.1 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. Average daily turnover of spot and forward is estimated at $2.4 trillion in 2016, which makes the currency market 36 times larger than world exports and imports, 15 times larger than world GDP or exchange-traded equity turnover (IMF 2018a,b; World Bank, 2018; BIS, 2016; WFE, 2016). Nevertheless, investors in currency markets have been shown to be able to generate systematic trading profits using various investment strategies.

To illustrate, a carry trade strategy that invests in high interest rate currencies and borrows in low interest rate currencies yields positive currency excess returns in violation of uncovered interest rate parity (Lustig and Verdelhan, 2007). A dollar carry trade strategy that goes long a basket of foreign currencies and short the dollar whenever the average foreign short-term interest rate is above the U.S. interest rate, while it shorts all foreign currencies and takes long positions in the dollar otherwise, also delivers excess returns (Lustig, Roussanov, and Verdelhan, 2014). Sorting countries by their dollar currency betas produces currency excess returns as well (Verdelhan, 2018). Other 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., 2016). Recent research shows that business cycles are a powerful predictor of currency excess returns (Riddiough and Sarno, 2018). Generally, those studies rationalize profits as compensation for risk.

In this chapter, we explore alternative explanations by relating return predictability with underlying academic research that publishes the strategy. More specifically, by examining the return predictability during its in-sample period in the academic research and periods after publication, we shall be able to differentiate between explanations whether the cross-sectional currency return predictability is from risk compensation, statistical biases, or mispricing. If anomaly profits reflect compensation for risk, conditional on no fundamental change in the risk-return trade-off or pricing of risk, then its predictability is likely to persist (Cochrane, 1999). In contrast, if anomalies are a product of statistical biases, then their predictability should disappear out-of-sample (Fama, 1991; McLean and Pontiff, 2016). Lastly, if the anomaly reflects mispricing, its publication leads investors to learn about and trade against the mispricing (McLean and Pontiff, 2016). We can expect returns from the anomaly to be weaker or even to disappear after the research is published, although frictions might prevent anomaly profits from disappearing completely. This is consistent with behavioral explanations for the existence of currency anomalies.

Using real-time data for a comprehensive set of currencies and anomaly strategies, we provide evidence supporting mispricing as 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. The post-publication decline in anomaly profits is greater for anomalies with larger in-sample profits and lower arbitrage costs.

Our study is comprehensive as we construct a wide range of currency anomaly variables underlying popular currency strategies found in academic research and widely practiced by investors. We conduct an extensive empirical analysis that evaluates the relation of anomalies with realized excess returns. The sample includes 76 currencies over the period from January 1971 to June 2018.

To investigate mispricing as a potential source of predictability in currency markets, we 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. Consistent with mispricing but not risk as the source of predictability, payoffs associated with anomalies significantly decrease (or even disappear) after the academic research has been published. Post-publication declines are greater for currencies with economically or statistically larger in-sample profits and with smaller arbitrage costs. 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.

Over the years, transaction costs have declined due to more efficient trading technologies (King, Osler, and Rime, 2012). Hence the decline in profitability post-publication might be attributed to a time trend that captures decreasing costs of corrective trading. Our results are robust when we relate anomaly profits to the time trend. In relation to that, we also find economically sizable post-publication effect controlling for persistence in the anomalies. Moreover, when we examine anomaly profits during periods of distress in the U.S., anomaly profits are lower during recessions. Post-publication effect remains significant once crisis periods are controlled for and its economic size is consistent across different specifications.

The publication of academic research showing profitable investment strategies should attract arbitrageurs that exploit the strategies leading to lower mispricing and reduced anomaly profits post publication. In subsequent analysis we find that the reduction in profitability is smaller for anomalies that involve taking positions in currencies that are more costly to trade.

Lastly, as our study covers a wide range of anomalies, we examine the variation of the publication effect across anomaly families of Trend following, Interest Rates, and Fundamentals. Interestingly, anomaly families do not significantly differ in terms of their in-sample and post-publication profits, as one might expect that some anomalies are more likely to be related to risk than others.

Our study provides a fresh view on excess return predictability in currency markets from the perspective of behavioral finance. It is closely related to recent research for equity markets documenting that the profitability of 97 anomalies decreases after publication of the academic research (McLean and Pontiff, 2016). Average returns to prominent equity market anomalies have declined in recent years, which has been attributed to increased trading activity of hedge funds and lower trading costs (Chordia et al., 2014). Our paper is the first to explore similar questions in currency markets.

The chapter is organized as follows. Section 1.2 defines the sample and describes the data. Section 1.3 provides empirical results for post-sample and post-publication predictability across different specification, including robustness tests. The chapter concludes in Section 1.4.

1.2 Sample and Data

The empirical analysis uses monthly data for anomaly signals and exchange rates of 76 countries (Table 1.1) around the world that consist of those from developed and emerging markets. For each of the 570 months between December 1970 to May 2018, we construct ten widely used currency anomalies that have been documented in the literature as predictors of currency excess returns. They are momentum based on prior one, three or twelve months currency returns, carry trade, dollar carry trade, dollar exposures, term spread, currency value, output gap, and the Taylor Rule. This is a broad set of anomalies, where some are with strong theoretical motivation such as dollar carry trade and term spread, while others use information from macroeconomic fundamental derived from time-series based macroeconomic variables such as currency value and output gap.

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.[1] Appendix 1.A provides detailed descriptions of the anomalies, their construction and references to the literature.

In terms of sample, Figure 1.1 shows the number of currencies with available data for each month and each anomaly of our sample. Our sample does not cover all 76 currencies at the same time since data availability varies due to inclusion and exclusion of currencies, such as the adoption of Euro in 1999. The minimum number of currencies in the cross-sectional portfolio at each month is 11 currencies i.e. in the early periods of our sample, while the maximum number is 60 currencies in the periods of 2011–2014. The time variation in the sample is in line with other studies such as Menkhoff et al (2012).

We relate these anomalies to currency returns in the following month, so that the anomalies are lagged by one month relative to future actual currency excess returns. Anomaly profits are calculated as quintile spreads of the excess returns of equally-weighted currency portfolios. All spot exchange rates are in units of foreign currency per unit of a U.S. dollar. More specifically, next month's gross currency excess return is defined as the log difference between the one-month forward exchange rate (f) of month t and the spot exchange rate of month t+1:

$$\text{Currency excess return}_{t+1} = f_t - s_{t+1}. \tag{1.1}$$

[1] Specifically, we retrieve real-time data (or monthly vintages, as the series contain revisions) for CPI (starting in February 1999) and IPI (starting in December 1999). The database covers all countries in our sample, except Argentina, Bahrain, Bulgaria, Colombia, Croatia, Cyprus, Egypt, Ghana, Hong Kong, Jordan, Kazakhstan, Kenya, Kuwait, Latvia, Lithuania, Malaysia, Malta, Morocco, Nigeria, Oman, Pakistan, Peru, Philippines, Qatar, Romania, Saudi Arabia, Serbia, Singapore, Sri Lanka, Taiwan, Thailand, Tunisia, Uganda, Ukraine, United Arab Emirates, Vietnam, and Zambia. Real-time data for these countries are 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.

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 net excess return for a currency that enters a portfolio at time *t* and exits the portfolio at the end of the month is computed as

$$\textit{Currency excess return}\,_{t+1}^{long} = f_t^{bid} - s_{t+1}^{ask} \tag{1.2}$$

for a long position. Hence, an investor who goes long in a foreign currency buys the foreign currency at the bid price (f^{bid}) in period *t*, and sells the foreign currency at the ask price (s^{ask}) in the spot market in period *t* + 1. Similarly for a short position:

$$\textit{Currency excess return}\,_{t+1}^{short} = f_t^{ask} - s_{t+1}^{bid}. \tag{1.3}$$

An investor who is short the foreign currency sells the foreign currency at the ask price (f^{ask}) in period *t*, and buys the foreign currency at the bid price (s^{bid}) in the spot market in period *t* + 1.

1.3 Empirical Results

To examine possible explanations for the existence of currency anomalies, 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).[2] 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).

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.

Profits of individual currency anomalies are generally positive and significant over the full sample period before accounting for transaction costs as documented in the literature (Table 1.2). In general, there is a monotonically increasing profitability in average excess returns. The strategy that has minimum gross profit is currency value that delivers return of 0.16% per month or 1.88% in annualized basis, while the maximum gross profit is carry trade strategy with returns of 0.71% per month or 8.54% per annum. On average, all anomalies have 5.33% returns per annum, which is a sizeable magnitude economically. Taking account transaction costs, we impose the full quoted bid–ask spread and end up with net profits that are naturally smaller. Note here that the full spread is known to be too large relative to actual effective spreads (Lyons, 2001). Hence, these results are likely to provide a lower bound on profitability.

Individual anomalies have low correlations between each other, with an average correlation of 0.14 (Table 1.3). There are both higher and negative correlations among

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

the anomalies. The minimum is –0.39 between currency value and twelve months momentum, while the maximum is 0.92 between dollar exposures and dollar carry trade. We control for such cross-correlations when computing the standard errors of statistics in our regressions.

1.3.1 Anomaly and Post-Publication Profits

Since the academic research discovering currency anomalies is very recent, we use the date of the first posting of the respective working papers on SSRN as their publication dates (Appendix 1.B).[3] 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 55 basis points ("bp") per month in the in-sample period, 80 bp in the out-of-sample pre-publication period, and 14 bp in the post-publication period. The average length of the in-sample, out-of-sample and post-publication periods are 471, 11 and 88 months, respectively.

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

$$Anomaly\ Profit_{j,t} = a_j + \beta_1\ Post\text{-}Sample_{j,t} + \beta_2\ Post\text{-}Publication_{j,t} + e_{j,t} \qquad (1.4)$$

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

[3] 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 publication. However, for those anomalies that have already been published, we alternatively use the dates when the research appeared in peer-reviewed journals. Some investors may not know about the anomalies until years after their publication, reducing the speed of alpha decay (McLean and Pontiff, 2016).

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.

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 1.4). 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. 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 41 bp per month after publication compared to the in-sample period, which is both statistically and economically significant. Given that anomalies generate on average in-sample payoffs of 55 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 = 0.238). Results using anomaly profits net of transaction costs, arguably a more realistic measure, also show strong publication effects with a reduction of 37 bp after publication in specification (1) (Table 1.4).

Specifications (2) and (3) include interactions between the in-sample mean profits and *t*-statistics of each anomaly. The interactions test whether anomaly profits with higher in-sample means decline more post-publication. We include the in-sample mean in the regression, but note here anomaly fixed effects are excluded. The interaction coefficients for profits net of transaction costs show that the publication effects are bigger for anomalies that have economically or statistically larger in-sample profits. Furthermore, the overall publication effect is always significant, and we reject the hypothesis that anomalies disappear completely post publication (*p*-value = 0.068). The analysis provides evidence that the returns associated with anomalies decrease after dissemination of the research, consistent with the view that investors learn about and trade to exploit mispricing.

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 1.2 Panels A and B). In a related vein, there is also a negative relation between in-sample *t*-statistics and post-publication effects (Figure 1.3 Panels A and B). Similar results have recently been documented for the U.S. equity market, where portfolio returns are 58% lower post-publication and already decrease in the out-of-sample period (by 26%) (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, which is in line with higher efficiency of deep and active currency markets.

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.

1.3.2 Controlling for Time Trends and Persistence

One explanation for the results is the possibility that they are caused by a time trend, for example capturing decreasing costs of corrective trading, rather than a publication effect. Over the years transaction costs have declined due to more efficient trading technologies such as electronic trading networks operated by, e.g., Electronic Broking Services (EBS) and Reuters, and have made arbitrage less costly (Goldstein et al., 2009 and Anand et al., 2012).

To investigate this conjecture, we construct a time trend variable that is equal to 1/100 in January 1971 (the first 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. We regress the monthly quintile spread of excess returns on currency anomaly to the time trend variable, as well as post-publication indicator, which includes anomaly fixed effects and FGLS estimation.

The estimated coefficient on the time trend is negative but not significant in specification (1) (Table 1.5). 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.

We also investigate whether anomaly returns are persistent, and whether such persistence has an effect on the publication effect (Moskowitz, Ooi, and Pedersen, 2013). This is relevant to the extent that some anomalies such as those of trend-following type may exhibit some degree of persistence or predictability that is shown in recognizable patterns. We implement this by including the anomalies' profits over the prior 1 and 12 months, respectively (specifications (3) and (4)). Only anomaly profits over the prior 12 months are significant, where the estimated coefficients are –0.02 for both profits gross and net of transaction costs. The post-publication coefficient remains negative and significant in each of these specifications, where there is a robust and economically sizable post-publication effect of at least 35 bp per month for gross profits and 31 bp for net profits of anomalies once persistence is controlled for.

1.3.3 Anomaly and Crisis Periods

Widely practiced short-term multicurrency investment strategies can contain substantial tail risks, and they do not perform uniformly during distress periods in global markets. In that regard, anomalies' returns post-publication drops may be related to crisis periods.

We examine this possibility by relating anomaly profits with periods of distress in the U.S. Specifically, we retrieve the dates of U.S. crisis periods from NBER and assign a value of one if the month is during crisis periods and zero otherwise. As our sample starts from January 1971, it covers six episodes of crisis, most recently the global financial crisis in 2008–2009. As before, we perform a regression of the anomaly profits on the crisis variable and on the post-publication indicator with other variables such as time trend and persistence.

Table 1.6 shows the crisis coefficient is negative. Although the coefficient is not significant when anomaly profits are regressed using the crisis dummy as the sole explanatory variable in specification (1), it is significant in specifications (2) to (5). Anomaly profits are approximately 30–32 bp lower during crisis periods, and they are significant at the 10% level for profits both gross and net of transaction costs. This result is consistent with previous literature documenting that some anomalies saw a sharp drop as volatility and uncertainty increase during financial crises (Gyntelberg and Schrimpf, 2011), particularly when trades in those strategies are crowded (Pojarliev and Levich, 2011).

The post-publication effect remains significant once crisis periods are controlled for. The effect is also robust when time trend and persistence variables are added as explanatory variables. Moreover, the post-publication coefficient size is similar to the estimated coefficient reported previously.

However, post-publication periods (Appendix 1.B) may coincide with a fundamental change in the economy. For example, during the post-crisis period considered in the analysis, global interest rates largely remained at or near the zero lower bound. The interest rate differential often significantly affects the profitability of certain anomalies, and because the post-publication period often overlaps with the zero lower bound period the reasons for the disappearing profitability are more difficult to disentangle.

1.3.4 Arbitrage Costs

The dissemination of research documenting profitable investment strategies based on anomalies should attract arbitrageurs that 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. Alternatively, we use the fraction of currencies in these portfolios that are among the five currencies with the most turnover according to the 2016 BIS Triennial Survey, or that are currencies from developed markets,[4] both of which may be expected to have lower limits to arbitrage.

We estimate the following regression,

---

[4] Developed countries 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, the United Kingdom and the United States according to the classification by Morgan Stanley Capital International (as of May 2018).

$$
\begin{aligned}
&\textit{Anomaly Profit}_{j,t} = a_j + \beta_1 \textit{ Post-Publication}_{j,t} \\
&+\beta_2 \textit{ Post-Publication}_{j,t} \times \textit{Arbitrage Cost}_j + \beta_3 \textit{Arbitrage Cost}_j + e_{j,t}.
\end{aligned} \tag{1.5}
$$

Including arbitrage costs and their interaction with the post-publication indicator in the regression provides some evidence that limits to arbitrage affect the profitability of anomalies and the size of the publication effect (Table 1.7). While the coefficients on different proxies for arbitrage costs are only significant for the fraction of developed country currencies, they do have the expected sign, i.e. positive for bid/ask spreads (specification (1)) and negative for major/developed currency variables (specifications (2) and (3)), consistent with larger in-sample returns of anomalies that are more costly to trade pre-publication. Moreover, the interaction term on bid/ask spreads is positive and significant indicating that the post-publication reduction in anomaly profits is smaller for strategies that are more expensive to implement. In contrast, the interaction terms for major/developed currencies are not significant.

The sum of the coefficient on the interaction between the post-publication indicator and the arbitrage cost variable (β_2) plus the costly arbitrage coefficient (β_3) reflect higher expected returns for anomalies that are more costly to arbitrage. The last row of Table 1.7 shows the null hypothesis that arbitrage costs (i.e. the sum of the two coefficients) do not matter for expected anomaly profits is rejected for bid/ask spreads with a *p*-value of 0.002. 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).

1.3.5 Anomaly Returns across Family Groups

We also examine the variation of the publication effect across anomaly groups. We classify anomalies into three groups (or "families"). The first group, Trend Following, comprises 1-month, 3-months and 12-months momentum, 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 differentials 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). The classification is based on similar characteristics that underlie each anomaly. The similarity can be seen from correlation among anomalies in each group (Table 1.3), where some groups exhibit a relatively sizeable correlation. The average cross-correlation of anomalies for the Trend Following, Interest Rates, and Fundamentals group respectively are 0.49, 0.35, and 0.12.

We regress anomaly profits on the post-publication dummy, indicator variables representing the three anomaly families, and the interaction between the post-publication and the anomaly family dummies, as the following:

$$\begin{aligned} &Anomaly\ Profit_{j,t} = a_j + \beta_1\ Post\text{-}Publication_{j,t} + \beta_2\ Anomaly\ Family_{j,t} \\ &+ \beta_3\ Post\text{-}Publication_{j,t} \times Anomaly\ Family_{j,t} + e_{j,t}. \end{aligned} \tag{1.6}$$

The coefficients on these interaction terms (β_3) indicate whether publication effects vary across anomaly families. Meanwhile, differences in post-publication profits are given by the sum of the family's coefficient and the interaction coefficient $\beta_2 + \beta_3$.

The regression results are shown in Table 1.8. While the post-publication coefficients are consistently negative and significant in all specifications (and show similar magnitudes as in Table 1.4), the interaction terms are insignificant for all three anomaly groups (specifications (2)-(4) in Table 1.8). 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. The last row also shows the null hypothesis of no differences in post-publication profits cannot be rejected, where the *p*-value is greater than 0.1 for all three anomaly families. These findings are interesting since one might have expected that some anomalies are more likely to be related to risk than others.

1.3.6 Robustness Tests

We carry out several additional tests to document the robustness of our results. 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. (2016) for currency value and Riddiough and Sarno (2018) for output gap[5]. In order to allow for better comparability of our results with the literature, we repeat our analysis for the same sample period and currencies, 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. We find the performance of these three strategies is stronger (Table 1.A in the Appendix). The average gross profits using final vintage data is 0.43% per month or 5.13% in annualized basis, higher than the gross profits using real-time data of 0.34% per month or 4.12% per annum (Table 1.2). We repeat the whole analysis and conduct the same regressions, and overall the results using final vintage data are qualitatively similar to those reported using real-time data.

A further 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

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

profits (e.g. Menkhoff et al., 2012). Therefore, we perform all of our analyses for a smaller set of sixty-two currencies, a set of fifty-three currencies representing all currencies covered by the BIS Triennial Surveys (1995-2016), and for the forty currencies with the highest foreign exchange turnover according to the BIS Triennial Surveys. The publication effect is robust to these alternative samples (Table 1.9). In fact, the magnitude of the coefficient is larger for 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. While always positive, the interaction of the post-publication indicator with in-sample bid/ask spreads is only significant for larger samples (of 76 and 62 currencies), likely because these offer more dispersion in terms of arbitrage costs.

1.4 Conclusion

This paper studies widely used investment strategies in currency markets, commonly referred to as currency anomalies. It is distinguished from similar developing literature by exploring behavioral bias as the raison d'être of currency anomalies. Consistent with the presumed efficiency of currency markets, the profitability of currency strategies significantly deteriorates or even disappears after the underlying academic research is published. In contrast, profits remain in the out-of-sample period before publication, lending no support to the concern that data mining might be the driver of anomalies. Thus, institutional investors face real-world limitations when they seek to exploit the patterns in currency markets uncovered by academic studies.

The decline in trading profits is greater for anomalies with larger in-sample period profits and lower arbitrage costs, which is consistent with asset managers focusing on the most profitable opportunities and those with the lowest limits to arbitrage (and thus the highest net profits). While some research has suggested that payoffs of currency anomalies may be compensation for risk, the fact that profits decline after the publication of the research suggests some or all of the currency anomalies are the result of mispricing. The results are robust when we control for the existence of a time trend, persistence, and distress periods across anomaly families, as well as using sub samples of the currency set.

However, a significant publication effect in our finding does not mean every anomaly is a result of mispricing. We are aware that as literature in currency anomalies has only recently been expanding, post-publication periods are clustered during the last decade for most anomalies. While we perform some robustness tests, such as controlling for distress periods, we cannot disentangle the mispricing effect from fundamental changes in the economy, where, for example, the last decade was nuanced by a zero lower bound environment (see, among others, Marco and Kacperczyk (2017) or Amador, Bianchi, Bocola, and Perri (2017)). This limitation is especially relevant to anomalies tied to interest rates. Furthermore, we do not eliminate another explanation, which is that our results could be consistent with dynamic risk models (Patton and Verado, 2012).

Behavioral explanations for currency anomalies can be investigated more directly by studying the currency forecasts of market participants. We explore this topic in the subsequent chapter.

Figure 1.1: Number of Available Currencies

The figure plots the number of available currencies for the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) The Taylor Rule. The sample includes 76 currencies. The sample period is from January 1971 to June 2018. Appendix 1.A provides details on variable definitions. Appendix 1.B provides details on the anomalies' original sample period used in the paper as well as date of publication.

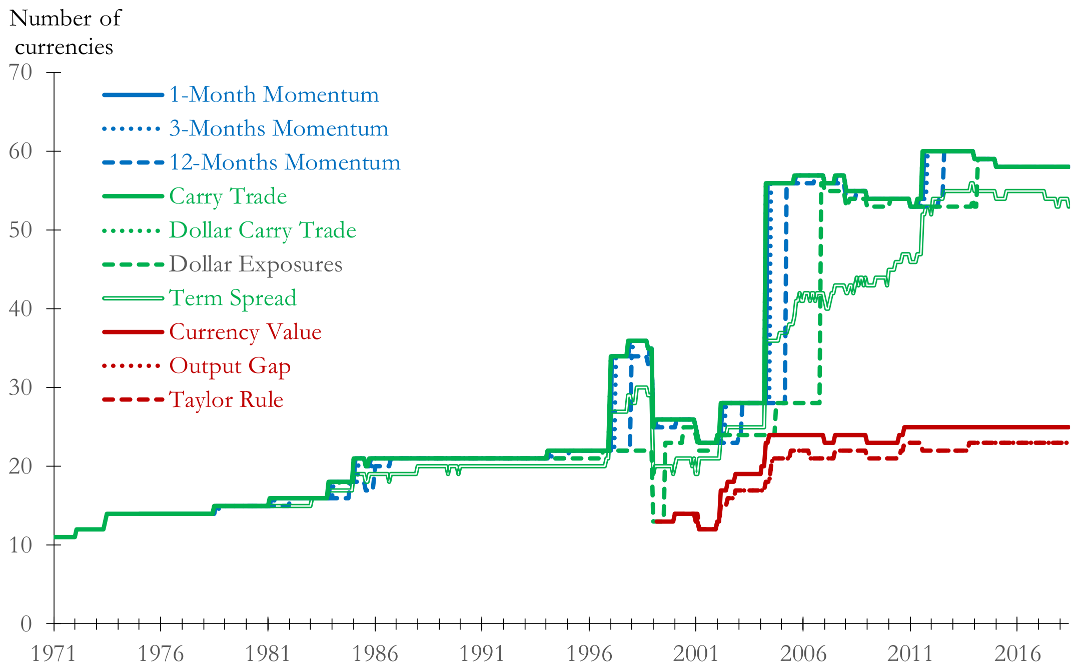
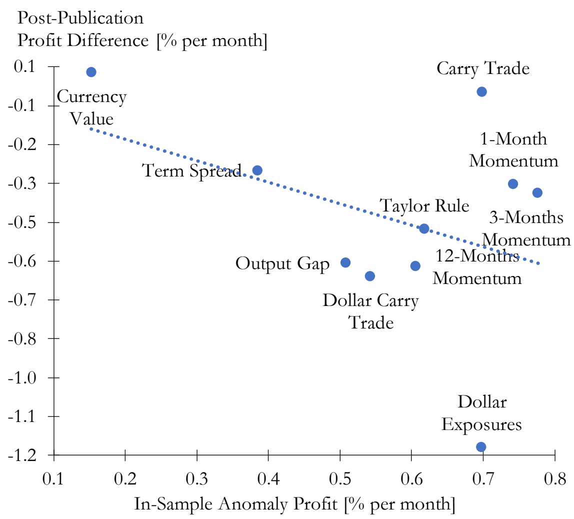


Figure 1.2: Relation between In-Sample and Post-Publication Anomaly Profits

The figure plots the relation between monthly in-sample currency anomaly profits and changes in profits after publication (post-publication profit differences). In particular, it shows the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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. Panel A shows trading profits gross of transaction costs, and Panel B shows trading profits net of transaction costs. The sample includes 76 currencies. The sample period is from January 1971 to June 2018. Appendix 1.A provides details on variable definitions. Appendix 1.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

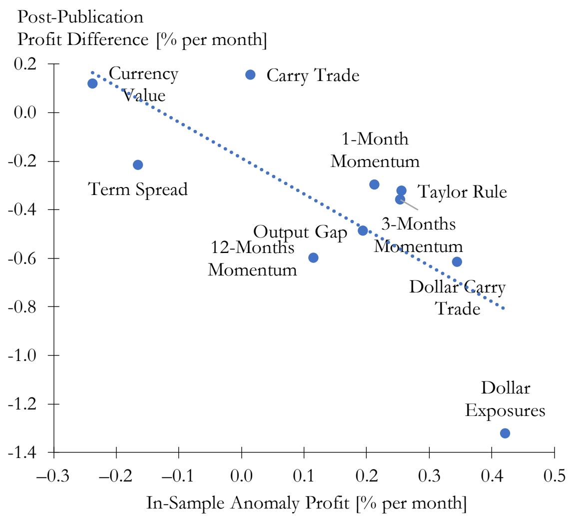
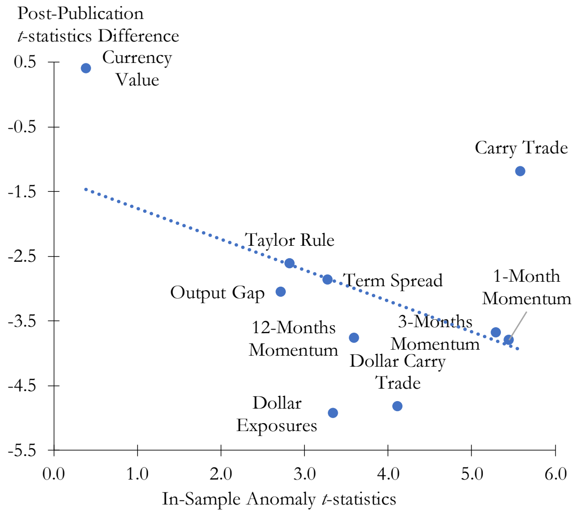


Figure 1.3: Relation between In-Sample and Post-Publication Anomaly *t*-Statistics

The figure plots the relation between in-sample currency anomaly *t*-statistics and changes in *t*-statistics after publication. In particular, it shows the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 *t*-statistic differences are the difference between in-sample *t*-statistics and post-publication *t*-statistics. Panel A shows *t*-statistics for trading profits gross of transaction costs, and Panel B 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 1.A provides details on variable definitions. Appendix 1.B provides details on the anomalies' original sample period used in the paper as well as date of publication.

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



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

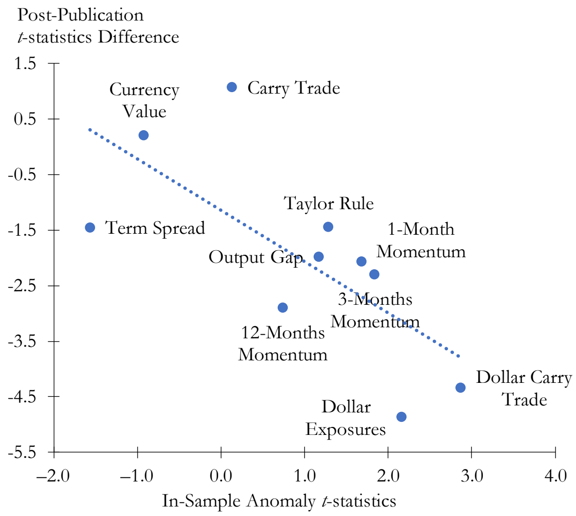


Table 1.1: Currency Sample Periods

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 1.1: 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 1.2: 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), 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 1.A provides details on variable definitions.

(continued)

Table 1.2: Quintile Performance of Portfolios Sorted on Currency Anomalies (continued)

	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]	
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 1.3: Correlations of Currency Anomalies

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 (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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) The Taylor Rule. The sample includes 76 currencies. The sample period is from January 2000 to June 2018. Appendix 1.A provides details on variable definitions.

	1-Month Momentum	3-Months Momentum	12-Months Momentum	Carry Trade	Dollar Carry Trade	Dollar Exposures	Term Spread	Currency Value	Output Gap
3-Months Momentum	0.641								
12-Months Momentum	0.372	0.461							
Carry Trade	–0.040	0.137	0.340						
Dollar Carry Trade	0.131	0.129	0.065	0.192					
Dollar Exposures	0.095	0.071	0.059	0.133	0.922				
Term Spread	0.005	0.084	0.185	0.340	0.256	0.253			
Currency Value	–0.102	–0.067	–0.387	–0.140	–0.016	0.018	0.019		
Output Gap	0.147	0.101	0.094	–0.153	0.108	0.138	0.116	0.204	
Taylor Rule	–0.056	0.014	0.244	0.530	0.064	0.060	0.324	0.010	0.152

Table 1.4: 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. 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-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. The analysis is based on the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 1.A provides details on variable definitions. Appendix 1.B provides details on the anomalies' original sample period used in the paper as well as date of publication.

(continued)

Table 1.4: Regression of Anomaly Profits on Post-Publication Indicators (continued)

	Anomaly Profits Gross of Transaction Costs			Anomaly Profits Net of Transaction Costs		
	(1)	(2)	(3)	(1)	(2)	(3)
Post-Sample	0.204	0.217	0.236	0.289	0.317	0.324
	(0.249)	(0.250)	(0.250)	(0.249)	(0.245)	(0.245)
Post-Publication	–0.413***	–0.058	–0.243	–0.370***	–0.175*	–0.192**
	(0.122)	(0.227)	(0.211)	(0.122)	(0.092)	(0.094)
Post-Publication x Average Anomaly In-Sample Profits		–0.615			–1.472***	
		(0.474)			(0.506)	
Post-Publication x Average Anomaly In-Sample t-statistics			–0.034			–0.184***
			(0.054)			(0.069)
Average Anomaly In-Sample Profits		0.998***			0.941***	
		(0.105)			(0.247)	
Average Anomaly In-Sample t-statistics			0.133***			0.134***
			(0.014)			(0.033)
Observations	4,021	4,021	4,021	4,021	4,021	4,021
R–Squared	0.01	0.04	0.04	0.01	0.01	0.01
Number of Anomalies	10	10	10	10	10	10
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	0.238			0.068		
Null: Post-Publication + (Post-Publication x Average Anomaly In-Sample Profits) = 0		0.021			0.001	
Null: Post-Publication + (Post-Publication x Average Anomaly In-Sample t-statistics) = 0			0.098			0.001

(continued)

Table 1.5: Time Trend and Persistence in Currency Anomalies

The table reports results from regressions of currency anomaly profits (in percent per month) on an indicator variable for post-publication periods, time trends, as well as persistence variables of 1-Month Anomaly Profit and 12-Month Anomaly Profit. 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. Time is equal to 1/100 during the first month of the sample and increases by 1/100 each month. 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. The analysis is based on the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) The Taylor Rule. Regressions include anomaly fixed effects. 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 1.A provides details on variable definitions. Appendix 1.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			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Post-Publication		–0.550***	–0.411***	–0.349***		–0.687***	–0.368***	–0.309***
		(0.155)	(0.121)	(0.120)		(0.154)	(0.121)	(0.118)
Time	–0.059	0.057			–0.009	0.136***		
	(0.038)	(0.048)			(0.038)	(0.047)		
1-Month Anomaly Profit			0.016				0.024	
			(0.019)				(0.019)	
12-Months Anomaly Profit				0.017***				0.020***
				(0.005)				(0.005)
Observations	4,021	4,021	4,011	3,901	4,021	4,021	4,011	3,901
R–Squared	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01
Number of Anomalies	10	10	10	10	10	10	10	10
Anomaly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS

Table 1.6: Publication Effects and Crisis Periods in Currency Anomalies

The table reports results from regressions of currency anomaly profits (in percent per month) on an indicator variable for post-publication periods, crisis periods, time trends, as well as persistence variables of 1-Month Anomaly Profit and 12-Month Anomaly Profit. 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. Time is equal to 1/100 during the first month of the sample and increases by 1/100 each month. 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. The analysis is based on the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) The Taylor Rule. Regressions include anomaly fixed effects. 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 1.A provides details on variable definitions. Appendix 1.B provides details on the anomalies' original sample period used in the paper as well as date of publication.

(continued)

Table 1.6: Publication Effects and Crisis Periods in Currency Anomalies (continued)

	Anomaly Profits Gross of Transaction Costs					Anomaly Profits Net of Transaction Costs				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Post-Publication		–0.455***	–0.586***	–0.446***	–0.384***		–0.414***	–0.724***	–0.403***	–0.344***
		(0.122)	(0.155)	(0.122)	(0.121)		(0.122)	(0.154)	(0.121)	(0.119)
Crisis	–0.234	–0.316*	–0.318*	–0.316*	–0.294*	–0.242	–0.316*	–0.320*	–0.314*	–0.297*
	(0.171)	(0.167)	(0.166)	(0.167)	(0.166)	(0.170)	(0.167)	(0.165)	(0.167)	(0.164)
Time			0.058					0.137***		
			(0.047)					(0.047)		
1-Month Anomaly Profit				0.016					0.023	
				(0.019)					(0.019)	
12-Months Anomaly Profit					0.017***					0.020***
					(0.005)					(0.005)
Observations	4,021	4,021	4,021	4,011	3,901	4,021	4,021	4,021	4,011	3,901
R–Squared	0.01	0.01	0.01	0.01	0.02	0.00	0.01	0.01	0.01	0.01
Number of Anomalies	10	10	10	10	10	10	10	10	10	10
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

Table 1.7: Arbitrage Costs

The table reports results from regressions of currency anomaly profits (in percent per month) on arbitrage costs. Results 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-Publication indicator takes the value 1 if the month is after the posting date on SSRN, and zero otherwise. The arbitrage costs 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 fraction of currencies in these portfolios that are among the five currencies with the most turnover according to the 2016 BIS Triennial Survey, or that are currencies from developed markets. The analysis is based on the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) The Taylor Rule. The table reports the regression coefficients and associated standard errors (in parentheses) and significance levels as well as the number of observations, the number of 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 1.A provides details on variable definitions. Appendix 1.B provides details on the anomalies' original sample period used in the paper as well as date of publication.

	In-Sample Bid/Ask Spreads	Major Currencies	Developed Countries
	(1)	(2)	(3)
Post-Publication	–1.522***	–0.478**	–0.834***
	(0.526)	(0.197)	(0.260)
Post-Publication x Arbitrage Costs	6.716**	0.257	1.254
	(3.014)	(1.438)	(0.891)
Arbitrage Costs	1.451	–0.307	–0.303*
	(1.360)	(0.394)	(0.180)
Intercept	0.336	0.624***	0.768***
	(0.234)	(0.092)	(0.134)
Observations	4,021	4,021	4,021
R–Squared	0.01	0.01	0.01
Number of Anomalies	10	10	10
Standard Errors	FGLS	FGLS	FGLS
Null: (Post-Publication x Arbitrage Costs) + Arbitrage Costs = 0	0.002	0.971	0.275

Table 1.8: 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 ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) The Taylor Rule. Trend Following is an indicator variable that takes the value 1 if the currency anomaly is 1-Month, 3-Months, or 12-Months Momentum, 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 1.A provides details on variable definitions. Appendix 1.B provides details on the anomalies' original sample period used in the paper as well as date of publication.

(continued)

Table 1.8: 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	–0.425***	–0.404***	–0.406***	–0.448***	–0.387***	–0.358***	–0.376**	–0.416***
	(0.115)	(0.130)	(0.150)	(0.136)	(0.114)	(0.130)	(0.148)	(0.136)
Trend Following		0.140				0.054		
		(0.111)				(0.111)		
Trend Following x Post-Publication		–0.040				–0.081		
		(0.246)				(0.246)		
Interest Rates			–0.026				–0.020	
			(0.099)				(0.099)	
Interest Rates x Post-Publication			–0.034				–0.021	
			(0.203)				(0.203)	
Fundamentals				–0.190				–0.056
				(0.133)				(0.131)
Fundamentals x Post-Publication				0.139				0.170
				(0.291)				(0.290)
Intercept	0.566***	0.513***	0.578***	0.598***	0.158***	0.137**	0.167**	0.167***
	(0.058)	(0.067)	(0.075)	(0.065)	(0.058)	(0.067)	(0.074)	(0.065)
Observations	4,021	4,021	4,021	4,021	4,021	4,021	4,021	4,021
R–Squared	0.01	0.01	0.01	0.01	0.004	0.004	0.004	0.004
Number of Anomalies	10	10	10	10	10	10	10	10
Standard Errors	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
Null: Anomaly Type + (Anomaly Type x Post-Publication) = 0		0.652	0.740	0.843		0.905	0.820	0.657

Table 1.9: 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)). For brevity, the table only displays the coefficients on selected variables of interest but not control 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 ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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, 53 currencies covered by the 2016 BIS Triennial Survey, and 40 currencies with the most turnover according to the BIS Triennial Survey. The sample period is from January 1971 to June 2018. Appendix 1.A provides details on variable definitions. Appendix 1.B provides details on the anomalies' original sample period used in the paper as well as date of publication.

(continued)

Table 1.9: Publication Effects for Alternative Samples (continued)

		Anomaly Profits Gross of Transaction Costs			Anomaly Profits Net of Transaction Costs	
		Table 1.4, Specification (1)	Table 1.4, Specification (2)	Table 1.7, Specification (1)	Table 1.4, Specification (1)	Table 1.4, Specification (2)
		(1)	(2)	(3)	(1)	(2)
62 currencies	Post-Publication	–0.417***	0.084	–1.442**	–0.321***	–0.112
		(0.122)	(0.220)	(0.564)	(0.122)	(0.094)
	Post-Publication x Average Anomaly In-Sample Profits		–0.887*			–1.682***
			(0.457)			(0.505)
	Post-Publication x In-Sample Bid/Ask Spreads			6.146*		
				(3.226)		
53 currencies	Post-Publication	–0.500***	0.262	–1.215**	–0.273**	–0.050
		(0.126)	(0.216)	(0.528)	(0.126)	(0.097)
	Post-Publication x Average Anomaly In-Sample Profits		–1.391***			–1.814***
			(0.448)			(0.497)
	Post-Publication x In-Sample Bid/Ask Spreads			4.288		
				(3.012)		
40 currencies	Post-Publication	–0.550***	0.212	–1.243**	–0.331***	–0.034
		(0.128)	(0.242)	(0.551)	(0.128)	(0.105)
	Post-Publication x Average Anomaly In-Sample Profits		–1.307***			–1.848***
			(0.458)			(0.492)
	Post-Publication x In-Sample Bid/Ask Spreads			4.276		
				(3.222)		

Appendix 1.A: Variable Definitions

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

Variable	Definition
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).
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, each currency's change in 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 60-months rolling windows. The carry factor is the average change in exchange rate between high interest rate countries and low interest rate countries. The dollar factor is the average change in exchange rate across all other currencies. Currencies are sorted into five quintiles (Q1 to Q5) from low to high based on the slope coefficients on the dollar factor and combined into equally weighted portfolios. Each month and for each quintile, the Dollar Exposures strategy goes long when the AFD of developed countries is positive and goes short otherwise (e.g. Verdelhan, 2018).

(continued)

Appendix 1.A: Variable Definitions (continued)

Variable	Definition
Term Spread	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on the difference between their long-term interest rates and short-term interest rates and combined into equally weighted portfolios. The Term Spread strategy goes long portfolio Q5 and short Q1 (e.g. Ang and Chen, 2010). Short-term rates are three months interest rates (interbank or Treasury bills) and long-term rates are ten year (or if unavailable five year) Government bond rates sourced from Datastream.
Currency Value	At the end of each month, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on the real exchange rate return (RER) over the prior five years and combined into equally weighted portfolios. The log RER is given by $q_t = -s_t + p_k{}^t - p_t$ where s denotes the exchange rate (in foreign currency units per USD), p^k denotes the price level in country k, and p denotes the U.S. price level. All variables are in logs. Following Asness et al. (2013), we calculate the lagged five-year ($5y$) real exchange rate return as $\Delta^{(5y)}q_t = q_t - q_{t-5y} = -\Delta^{(5y)} s_t + \pi^{(5y),k} - \pi^{(5y)}$. The Currency Value strategy goes long portfolio Q5 and short Q1 (e.g. Menkhoff et al., 2016). Real time data on Consumer Price Indices (CPI) to calculate real exchange rates are from OECD's Original Release Data and Revisions Database.
Output Gap	At the end of each month, currencies are sorted into quintiles (Q1 to Q5) from low to high based on the output gap and combined into equally weighted portfolios. The output gap is calculated from detrending the monthly industrial production index (IPI) for each country. Specifically, the residuals from a regression of IPI_t on a constant and IPI_{t-13}, IPI_{t-14}, ..., IPI_{t-24} (corresponding to p=12 and h=24 in Hamilton (2017)) 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.
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.

(continued)

Appendix 1.A: Variable Definitions (continued)

Variable	Definition
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.
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.
In-Sample 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.
Major Currencies	At the end of each month, we take the fraction of currencies in the portfolios Q5 and Q1 that are among the five currencies with the highest foreign exchange turnover according to the BIS Triennial Central Bank Survey (2016), i.e. Euro, Japanese Yen, British Pound, Australian Dollar, and Canadian Dollar.
Developed Countries	At the end of each month, we take the fraction of currencies in the portfolios Q5 and Q1 that are from developed countries according to the MSCI classification as of May 2018.

Appendix 1.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 (Title and Journal)	Start Date	End Date	Posting on SSRN	Start Date	End Date	Publication
Trend Following							
1-Month Momentum	Menkhoff, Sarno, Schmeling, and Schrimpf (Currency Momentum Strategies, *Journal of Financial Economics*)	January 1976	January 2010	April 2011	January 1976	January 2010	December 2012
3-Months Momentum	Menkhoff, Sarno, Schmeling, and Schrimpf (Currency Momentum Strategies, *Journal of Financial Economics*)	January 1976	January 2010	April 2011	January 1976	January 2010	December 2012
12-Months Momentum	Asness, Moskowitz, and Pedersen (Value and Momentum Everywhere, *Journal of Finance*)	January 1979	October 2008	March 2009	January 1979	July 2011	June 2013
Interest Rates							
Carry Trade	Lustig and Verdelhan (The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk, *American Economic Review*)	January 1971	December 2002	January 2005	January 1971	December 2002	March 2007
Dollar Carry Trade	Lustig, Roussanov, and Verdelhan (Countercyclical Currency Risk Premia, *Journal of Financial Economics*)	November 1983	January 2009	January 2010	November 1983	June 2010	March 2014
Dollar Exposures	Verdelhan (The Share of Systematic Variation in Bilateral Exchange Rates, *Journal of Finance*)	November 1983	December 2010	November 2011	November 1983	December 2010	February 2018
Term Spread	Ang and Chen (Yield Curve Predictors of Foreign Exchange Returns)	January 1975	August 2009	January 2010			
Fundamentals							
Currency Value	Asness, Moskowitz, and Pedersen (Value and Momentum Everywhere, *Journal of Finance*)	January 1979	October 2008	March 2009	January 1979	July 2011	June 2013
Output Gap	Riddiough and Sarno (Business Cycles and Currency Returns)	October 1983	January 2016	January 2017			
Taylor Rule	Riddiough and Sarno (Business Cycles and Currency Returns)	October 1983	January 2016	January 2017			

Table 1.A1: Quintile Performance using Final Vintage Data

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, that uses final vintage data for macroeconomic data. Transaction costs are calculated using bid and ask quotations. Individual anomalies are 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 sample includes 76 currencies. The sample period is from February 1999 to June 2018. Appendix 1.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
Currency Value	0.262	0.185	0.067	0.115	0.462	0.200	2.400	0.408	0.072	–0.043	0.001	0.308	–0.101	–1.207
	[1.43]	[1.00]	[0.36]	[0.59]	[2.15]	[1.14]		[2.22]	[0.40]	[–0.23]	[0.01]	[1.46]	[–0.59]	
Output Gap	0.035	0.075	0.066	0.416	0.551	0.516	6.192	0.146	–0.030	–0.038	0.268	0.403	0.258	3.091
	[0.17]	[0.39]	[0.34]	[1.73]	[2.48]	[2.72]		[0.72]	[–0.16]	[–0.19]	[1.15]	[1.85]	[1.41]	
Taylor Rule	0.121	–0.005	–0.027	0.409	0.688	0.567	6.802	0.237	–0.085	–0.128	0.283	0.492	0.255	3.059
	[0.61]	[–0.03]	[–0.12]	[2.08]	[2.40]	[2.44]		[1.17]	[–0.52]	[–0.58]	[1.44]	[1.76]	[1.12]	

2 Currency Anomalies and Analysts

2.1 Introduction

We continue the investigation from Chapter 1 to assess behavioral explanations for the existence of currency anomalies. To analyze behavioral explanations directly, we study the behavioral biases of analysts by relating currency mispricing to the exchange rate expectations formed by analysts, their forecast errors or mistakes, and revisions to their forecasts. 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 investors and biases in their market views or forecasts.

The major participants in currency trading are asset managers, dealers, central banks, retail traders, and high frequency traders (King, Osler, and Rime, 2012). These investors might be sophisticated, trading based on their own forecasts. Since investors' forecasts are unobservable, we collect analysts' forecasts of foreign exchange from around the world. The majority of analysts are prominent financial forecasters; hence, their forecasts may reflect investors' view when investors perform currency trading. In this study, we show that investors who follow analysts' forecast may contribute to mispricing, although we do not rule out the fact that analysts may also follow investors who presumably have more information about currencies trading.

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.

These two measures, of average mispricing and extreme mispricing (alternatively across all anomalies and three groups of anomalies) are generated using the quintile spreads of realized currency excess returns both gross and net of transactions costs. We investigate whether analysts incorporate the information reflected in these anomalies and to examine evidence of their ability to predict currency excess returns cross-sectionally when making their exchange rate forecasts, given that this information is widely disseminated and publicly available. 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. This contrasts with the currency literature that has so far focused on the analysis of individual anomalies.

The measure of average mispricing is constructed 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. 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.

We find that analysts expect payoffs to mispricing based strategies that are lower than the 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 116 basis points ("bp") per month, while it is –88 bp for the fifth quintile (i.e. the long portfolio). The expected quintile spread is –204 bp per month, contrasting with a realized quintile spread of 74 bp (or –24.5% vs. 8.9% on an annualized basis). Similarly, the realized profit of a trading strategy based on extreme mispricing is 68 bp per month, while analysts expect a loss of –186 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 large negative quintile spreads on the currency return component.

Furthermore, evidence from panel regressions of currency excess returns on average and extreme 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 negative and significant coefficients on mispricing (except for fundamentals). These results demonstrate that analysts' foreign exchange forecasts are often at odds 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 as analysts learn and improve their predictions. In fact, for anomalies tied to fundamentals, the learning effect is so large that on average analysts' forecasts are in line with realized anomaly profits. Furthermore, the mistakes that analysts make reduce after the publication of the academic research for all anomalies. In the same vein, lagged mispricing predicts changes in analysts' foreign exchange forecasts, suggesting that analysts predictably update their forecasts based on initially overlooked information captured in anomalies. Nevertheless, while analysts could be perceived as skilled information processors and aggregators, the profits from long-short currency strategies based on their currency expectations yield much lower profits compared to trading on mispricing based signals.

This chapter complements the view from previous chapter on excess return predictability in currency markets from the perspective of behavioral finance. In literature, this is the first paper links the currency markets and analysts, to the best of our knowledge. In equity markets, numerous papers linking analyst information to stock returns, which include Elton, Gruber, and Grossman (1986), Stickel (1995) Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), Brav and Lehavy (2003), Asquith, Mikhail, and Au (2005), Jegadeesh et al. (2004), and Da and Schaumburg (2011). This literature finds that changes in recommendations, changes in price targets, and newly initiated targets and recommendations all predict returns in the direction intended by the analyst. This literature also finds that sell recommendations predict lower returns, but buys do not predict higher returns.

Study in this chapter is also related to a stream of literature that examine sophisticated investors who use anomaly strategies. For example, institutions are found to contribute to anomalies (Edelen, Ince, and Kadlec, 2016), and institutional investors may fail to take advantage of anomalies when forming their portfolios (Lewellen, 2011). Moreover, there is evidence that institutions especially hedge funds, do follow anomaly strategies, but only after an anomaly is highlighted in an academic publication (Calluzzo, Moneta, and Topaloglu, 2017).

With regards recommendations, there is evidence that analysts' recommendations agree with half of 12 equity anomalies (Jegadeesh et al., 2004) as well as that analysts' price targets and recommendations contradict stock return anomaly variables (Engelberg et al., 2017). For better credit quality firms, analysts' biases are unrelated to subsequent stock returns, while among stocks with poor credit quality, the quintile predicted to have the most conservative forecasts outperforms the quintile with the most optimistic forecasts (Grinblatt, Jostova, and Philipov, 2016).

The chapter is organized as follows. Section 2.2 defines the sample and describes the data. Section 2.3 examines the relationship between anomalies and foreign exchange forecasts, analysts' mistakes and forecast revisions. The chapter concludes in Section 2.4.

2.2 Sample and Data

The empirical analysis uses monthly data for anomaly signals and exchange rates of 76 countries as in Chapter 1. For each of the 570 months between December 1970 to May 2018, we construct ten widely used currency anomalies which are momentum based on prior one, three or twelve months currency returns, carry trade, dollar carry trade, dollar exposures, term spread, currency value, output gap, and the Taylor Rule. We construct all anomalies using real-time data. See Chapter 1 for the detail of exchange rates and other data that are used to construct the anomalies.

We classify anomalies into three groups (or "families"). The first group, Trend Following, comprises 1-month, 3-months and 12-months momentum, 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 differentials 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).

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 measure foreign exchange rate expectations using mean forecasts from surveys undertaken by Consensus Economics, which are available between December 1989 to 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 to the Deutschmark or Euro, and we convert these forecasts to quotes against the U.S. Dollar using the corresponding Deutschmark or Euro forecasts.

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 (s) 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, as follows:

$$Currency\ return_{t+1} = -\Delta s_{t+1} = -(s_{t+1} - s_t). \tag{2.1}$$

Furthermore, next month's currency excess return is defined as the log difference between the one-month forward (f) exchange rate of month t and the spot exchange rate of month $t+1$, assuming covered interest parity:

$$\begin{aligned} &\textit{Currency excess return}_{t+1} = f_t - s_{t+1} = f_t - s_t - \Delta s_{t+1} \\ &\approx \textit{Interest rate differential}_t + \textit{Currency return}_{t+1} \end{aligned}. \tag{2.2}$$

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 ($\hat{s}$) at the end of month *t* and the spot exchange rate at the end of month *t*,

$$\textit{Forecast currency return}_{t+1} = -(\hat{s}_{t+1} - s_t). \tag{2.3}$$

The excess return expected by analysts is the expected exchange rate return plus the one-month interest differential:

$$\begin{aligned} &\textit{Forecast currency excess return}_{t+1} \\ &= \textit{Interest rate differential}_t + \textit{Forecast currency return}_{t+1}. \end{aligned} \tag{2.4}$$

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 2.A provides details of all variable definitions. Table 2.1 shows detailed summary statistics of actual and forecast currency (excess) returns and analysts' mistakes.

2.3 Analysis and Empirical Results

2.3.1 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 investors and biases in their market 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.[1] 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.[2] We create average and extreme mispricing measures for all anomalies as well as the three anomaly families. 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. Table 2.2 provides detailed summary statistics of these measures.

The correlation of 0.89 between average and extreme mispricing indicates that they measure similar dimensions, but are not identical (Table 2.3). Plotting cumulative profits from mispricing over the full sample period shows distinct upward trends (Figure

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

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

2.1), indicating (mostly) positive returns underlying the average profits reported in Table 2.4. Annualized Sharpe ratios of up to 1.2 for gross profits and 0.5 for net profits are also economically significant.

Trading strategies based on average and extreme mispricing for the three anomaly groups are profitable as well, (Table 2.5 Panel A); in fact their profitability is often statistically and economically more significant than that of the underlying individual anomalies (see Table 1.2 in Chapter 1).[3] 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. Trading strategies based on mispricing are profitable before and after transactions costs. To illustrate, quintile spreads of gross currency excess returns are 74 bp per month for average mispricing and 68 bp for extreme mispricing (equivalent to 8.9% and 8.1% per year), and net profits are still 41 bp and 34 bp, respectively. Both gross and net profits are statistically significant, and they are of similar magnitude to anomaly profits in equity markets.

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 0.75 (0.70) for average (extreme) mispricing, and it is 0.48 (0.45) 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 towards zero within just two months (Figure 2.2). Thus, while the existence of anomaly profits suggest that currency markets may not be completely efficient, the inefficiencies seem to

[3] Note that Table 2.5 is based on the shorter sample period December 1989 to June 2018 to match Table 2.6.

be arbitraged away quickly. The low persistence of profits, particularly net of transactions costs, suggests that anomaly profits are not providing compensation for risk, but rather reflect mispricing (Cochrane, 1999).[4]

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 is more an inverted u-shape across portfolios stratified by mispricing (Table 2.5 Panel B).[5] Quintile spreads are often negative, and mostly are 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.

2.3.2 Mispricing and Analysts' Forecasts

We use the aggregate mispricing measures to investigate whether analysts incorporate the information reflected in anomalies and the existing evidence of their ability to predict currency excess returns cross-sectionally when making their exchange rate forecasts, given that this information is widely disseminated and publicly available. 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.

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

[5] 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.

In particular, average forecast currency excess returns before transactions costs decrease monotonically from low to high mispricing quintiles based on all anomalies (Table 2.6 Panel A). They are 116 bp per month for the short portfolio and –88 bp for the long portfolio, yielding an expected quintile spread of –204 bp for strategies based on average mispricing, with a *t*-statistic of –17.3. The pattern is similar for extreme mispricing with expected profits from mispricing of –186 bp (*t*-statistic = –16.0). Thus, analysts erroneously expect negative profits from trading on mispricing even though these strategies yield significant positive actual gross profits of 74 bp and 68 bp per month for average and extreme mispricing, respectively (comparing Panel A of Table 2.6 with Panel A of Table 2.5).

Analysts appear to be particularly mistaken about trend following anomalies, where they expect significant losses despite the actual profitability of these strategies (–344 bp vs. +75 bp for average mispricing). While analysts expect profits for anomalies based on interest rates, forecast profits are significantly 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 regards 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 to 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 2.6

Panel B). The difference in currency returns between the fifth and first quintile is –285 bp per month for average mispricing and –268 bp for extreme mispricing. In contrast, realized currency returns are much smaller and mostly indistinguishable from zero (Table 2.5 Panel B). This effect is particularly pronounced in the Trend Following group, where analysts expect a loss of –402 bp for average mispricing, while the actual currency return 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 2.3). 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 the different measures of mispricing. These findings provide evidence that foreign exchange forecasts calculated by analysts are at odds 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). In fact, systematic forecast errors may be less 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:

$$\begin{aligned} \textit{Forecast (Excess) Return}_{i,t+1} &= a + a_t + \beta_1 \textit{ Mispricing}_{i,t} + \beta_2 \textit{ Number of Forecasters}_{i,t} \\ &+ \beta_3 \textit{ Single Forecast}_{i,t} + e_{i,t} \end{aligned} \tag{2.5}$$

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 2.7 Panel A). Specifically, the coefficients on average and extreme mispricing are –6.521 and –2.833 (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 100 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 90 bp. This is opposite to 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.[6]

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 2.7 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 positive realized anomaly profits. These results suggest that analysts appear to regularly make mistakes in their forecasts.

While the 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

[6] 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.

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.

2.3.3 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:

$$\begin{aligned} Mistake_{i,t+1} &= Forecast\ Currency\ Excess\ Return_{i,t+1} - Realized\ Currency\ Excess\ Return_{i,t+1} \\ &= Forecast\ Currency\ Return_{i,t+1} - Realized\ Currency\ Return_{i,t+1} \end{aligned} \tag{2.6}$$

Negative mistakes reflect that the (excess) return forecast was too low, and vice versa. Table 2.1 provides detailed summary statistics of analysts' mistakes.

The patterns in realized currency (excess) returns (Table 2.5) and forecast currency (excess) returns (Table 2.6) 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 2.4 Panels A and B).

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

$$\begin{aligned} Mistake_{i,t+1} = a + a_t + \beta_1 \, Mispricing_{i,t} + \beta_2 \, Number\ of\ Forecasters_{i,t} \\ + \beta_3 \, Single\ Forecast_{i,t} + e_{i,t} \end{aligned} . \tag{2.7}$$

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 2.8). Estimated coefficients for average and extreme mispricing based on all anomalies are –8.575 and –3.757, 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 131 bp (119 bp) per month lower than its realized return compared to 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 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 to the other groups.

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

$$\begin{aligned} Mistake_{i,t+1} &= a + a_t + \beta_1\ Mispricing_{i,t} + \beta_2\ (Mispricing_{i,t} \times Time_t) \\ &\quad + \beta_3\ Number\ of\ Forecasters_{i,t} + \beta_4\ Single\ Forecast_{i,t} + e_{i,t} \end{aligned} \tag{2.8}$$

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 –5.872 for trend following anomalies (Table 2.9 Panel A). 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. For regressions based on all anomalies, the interaction between mispricing and the time trend is not significant. However, the interaction terms are 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 learning effect is sufficiently large to render the average mispricing effect insignificant (Table 2.8). The coefficients on the number of forecasters are negative and mostly significant (as in Table 2.8).

If the publication of research allows analysts to learn about mispricing, their mistakes should decrease after anomalies become publicly known. We investigate this by splitting mispricing into a post-publication mispricing and a pre-publication mispricing that include only the anomalies that have or have not yet been published in a particular month, respectively. We relate these two mispricing variables to mistakes in the following regression:

$$\begin{aligned} Mistake_{i,t+1} &= a + a_t + \beta_1\ Pre\text{-}Publication\ Mispricing_{i,t} + \beta_2\ Post\text{-}Publication\ Mispricing_{i,t} \\ &+ \beta_3\ Number\ of\ Forecasters_{i,t} + \beta_4\ Single\ Forecast_{i,t} + e_{i,t}. \end{aligned} \tag{2.9}$$

As before, the regression includes the number of forecasters, a single forecaster indicator, and month fixed effects as controls. Standard errors are clustered by country.

While the mistakes that analysts make are related to mispricing both before and after the publication of anomalies, the relationship tends to be weaker after the dissemination of the academic research (Table 2.9 Panel B). In particular, the coefficient on average mispricing is –8.851 for unpublished anomalies, but –8.051 for published anomalies; however the increase in the coefficient is not large enough to be significant. For extreme mispricing, the change in coefficients is larger (from –4.248 to –2.964), indicating significant reductions in analysts' mistakes associated with anomalies (p-value < 0.01).

The same pattern holds across anomaly groups, where the coefficients are significantly larger (less negative) for post-publication mispricing. For trend following anomalies, analysts' mistakes are still significantly related to mispricing after publication, while the significant pre-publication relation turns insignificant post-publication for interest rate anomalies. For anomalies tied to fundamentals, neither mispricing coefficient is significant. Thus, analysts appear to be learning about anomalies through the publication of the underlying academic research and making smaller mistakes in predicting future excess returns. 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.

2.3.4 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 to incorporate in their forecasts, 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:

$$\begin{aligned} \textit{Change in Currency Forecast}_{i,t+1|t,t+2|t+1} &= a + a_t + \sum_{\tau=0}^{2} \beta_{\tau+1}\ \textit{Mispricing}_{i,t-\tau} \\ &+ \beta_4\ \textit{Number of Forecasters}_{i,t} + \beta_5\ \textit{Single Forecast}_{i,t} + e_{i,t} \end{aligned} \tag{2.10}$$

where the dependent variable is the monthly revision in the one-month ahead log exchange rate forecast for 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, but only from the previous month. To illustrate, the coefficients on average and extreme mispricing lagged by one month are 1.836 and 0.748 respectively, and both are statistically significant (Table 2.10). 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 28 bp (24 bp) more per month compared to a currency with an average (extreme) mispricing value at the sample mean. Analysts do not use information contained in mispricing variables from months before the most recent, i.e. the coefficients on mispricing lagged by two and three months are insignificant. The magnitudes of the coefficients decrease monotonically with lag length.

The coefficients on the number of forecasters are positive and significant, indicating more positive revisions for currencies that are followed by more analysts. The results suggest that mistakes become smaller over time, i.e. analysts learn or markets become more efficient. Thus, 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 incorporated after one month. 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.

2.3.5 Analysts Forecasts and Predictability of Currency Excess Returns

Finally, we consider whether analysts' forecasts are useful to predict future excess exchange rate returns. Given that analysts seem to make predictable mistakes in forecasting the excess returns associated with mispricing, it could be that they 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.[7] 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 2.11). 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 weaker significance. In regressions with average mispricing, the quintile spread on mispricing is 89 bp per month, while the quintile spread on forecast excess returns from analysts is 25 bp per month. Magnitudes are similar but slightly smaller for regressions with extreme mispricing, with quintile spreads of 76 bp and 22 bp for mispricing and analysts' forecasts, respectively. Thus, the forecasts that analysts make are useful in predicting future currency excess returns, but the associated profits are much smaller compared to mispricing, which could be related to the biases of analysts with regards to the future currency excess returns from mispricing.

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

2.3.6 Mispricing and Analysts' Mistakes for Alternative Samples

As in Chapter 1, a further set of robustness tests considers the potential sensitivity of our results to the sample definition. In particular, we perform all of our analyses for a smaller set of fifty-two currencies representing all currencies covered by the BIS Triennial Surveys (1995-2016), and for the forty currencies with the highest foreign exchange turnover according to the BIS Triennial Surveys.

The relation between analysts' mistakes and mispricing is similarly robust to alternative sets of currencies (Table 2.12). Note that the number of currencies are smaller compared to Table 1.9 due to the availability of analysts' forecasts. Coefficients on mispricing are always negative and significant for all anomalies and for trend following anomalies. With rare exceptions, they are also negative for the Interest Rates and Fundamentals groups, and they are often significant. 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.

2.4 Conclusion

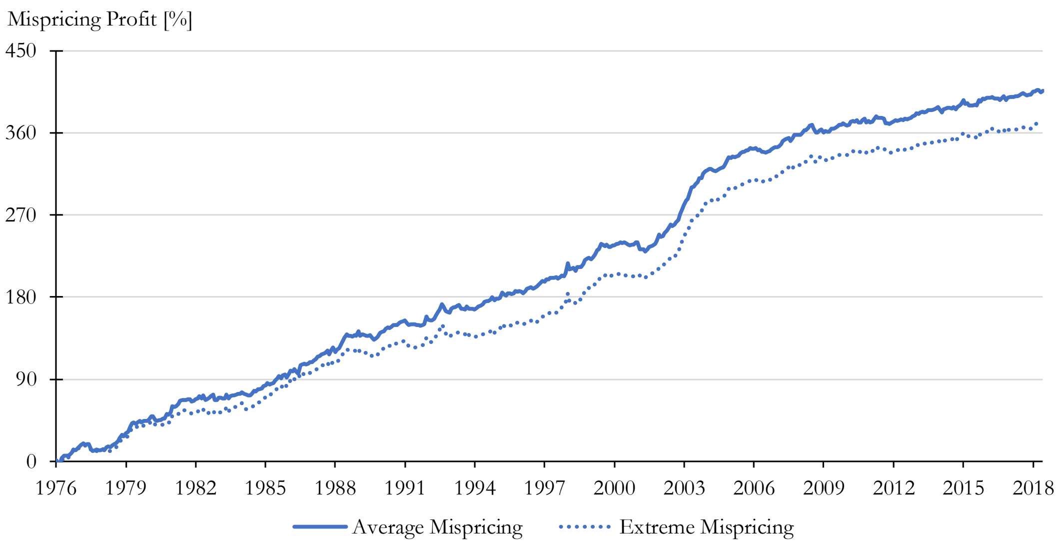
This chapter continues to explore behavioral bias as the explanation of currency anomalies. A behavioral explanation suggesting that anomalies can be combined to measure aggregate mispricing that is ultimately traded away. This view is supported by low autocorrelations of mispricing signal ranks, and by a relatively fast decay of trading profits when delaying mispricing signals. Moreover, aggregate mispricing can be directly related to forecasts by market participants. Analysts often have currency expectations that imply anomaly payoffs that are too low compared to 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 and thus be causing anomalies.

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 month. Similarly, analysts make smaller mistakes after the academic research documenting anomalies has been published. Nonetheless, trading on mispricing signals yields more than three times the profits compared to trading on analysts' forecasts. Overall, Chapter 1 and Chapter 2 paint 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 and market participants learn. 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.

Figure 2.1: 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 ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 ten 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 2.A provides details on variable definitions.

Panel A: Profits Gross of Transaction Costs



Panel B: Profits Net of Transaction Costs

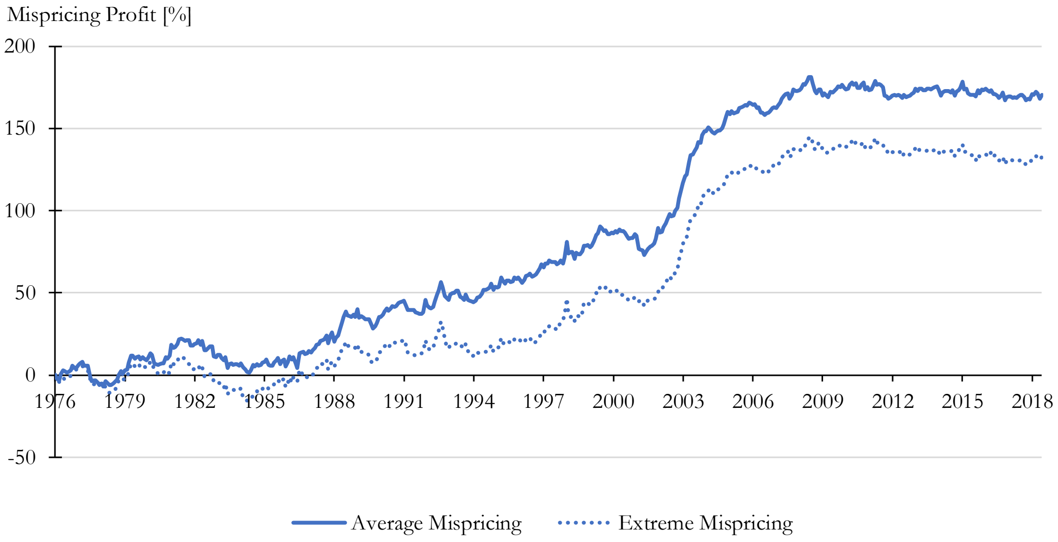
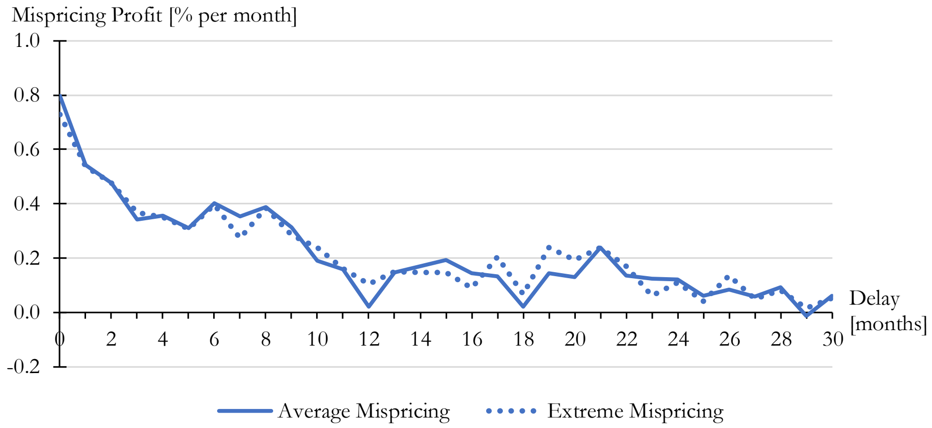


Figure 2.2: Decay of Mispricing Signals

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 ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 ten 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 2.A provides details on variable definitions.

Panel A: Profits Gross of Transaction Costs



Panel B: Profits Net of Transaction Costs

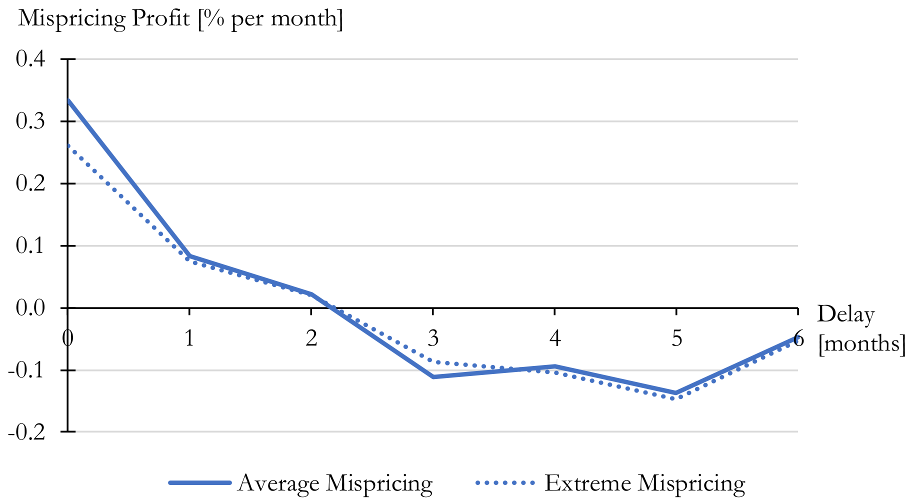
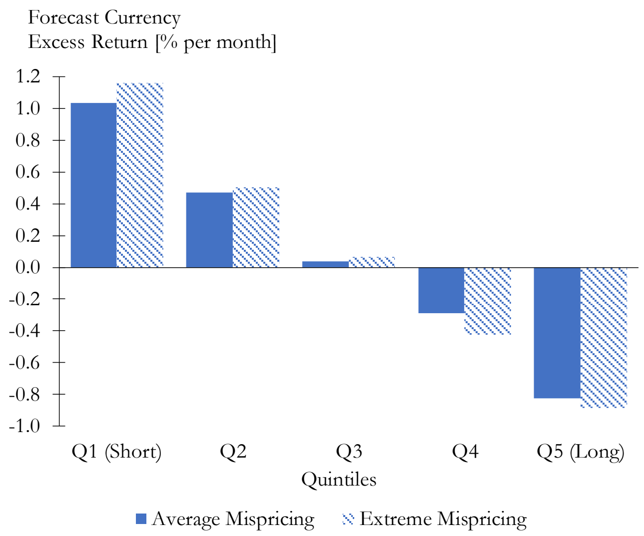


Figure 2.3: Analysts' Forecast Currency Returns of Currency Mispricing Strategies

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 ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 ten 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 2.A provides details on variable definitions.

Panel A: Forecast Currency Excess Returns



Panel B: Forecast Currency Returns

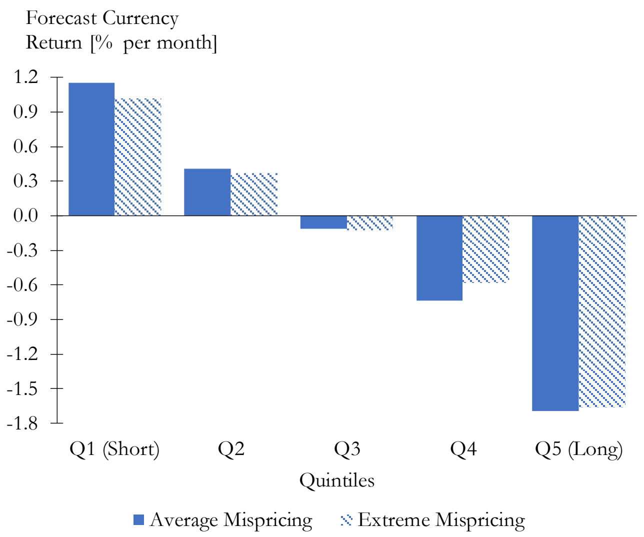
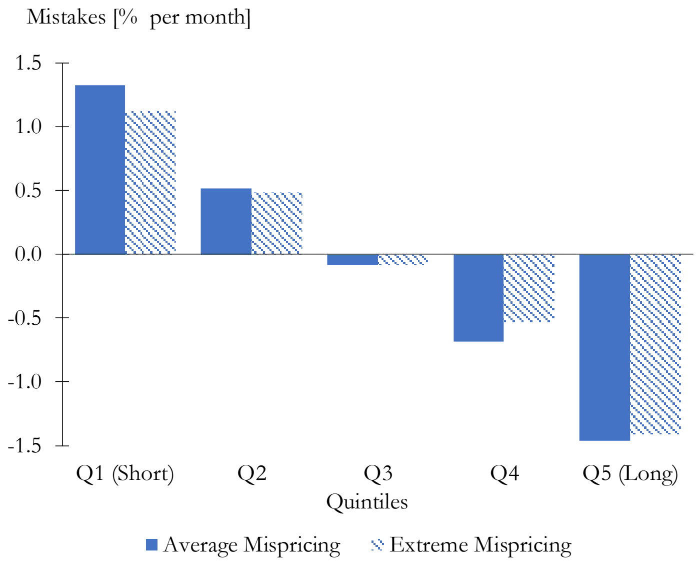


Figure 2.4: Analysts' Mistakes of Currency Mispricing Strategies

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 ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 ten 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 2.A provides details on variable definitions.

Panel A: Mistakes by Quintile



Panel B: Quintile Spreads of Mistakes Over Time

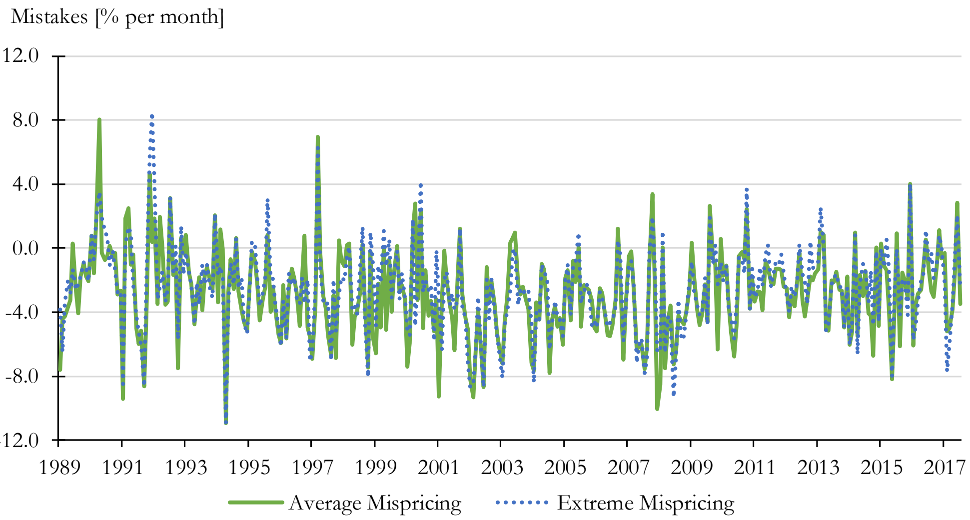


Table 2.1: Summary Statistics of Actual and Forecast Currency Returns and Analysts' Mistakes

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 2.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	9.75	–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 2.2: 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. All Anomalies refers to the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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. 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 2.A provides details on variable definitions.

	Mean	Standard Deviation	Skewness	Kurtosis	Minimum	Percentiles 1st	5th	25th	Median	75th	95th	99th	Maximum	Number of Observations
Average Mispricing														
All Anomalies	0.529	0.153	0.122	2.747	0.074	0.200	0.283	0.420	0.526	0.634	0.786	0.890	1.000	16,845
Trend Following	0.515	0.229	0.011	2.243	0.017	0.052	0.135	0.345	0.515	0.685	0.901	0.978	1.000	16,772
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	0.031	0.317	0.110	3.099	–1.000	–0.714	–0.500	–0.167	0.000	0.222	0.571	0.833	1.000	16,845
Trend Following	0.005	0.474	0.003	2.929	–1.000	–1.000	–1.000	–0.333	0.000	0.333	1.000	1.000	1.000	16,772
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 2.3: 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 (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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 2.A provides details on variable definitions.

	1-Month Momentum	3-Months Momentum	12-Months Momentum	Carry Trade	Dollar Carry Trade	Dollar Exposures	Term Spread	Currency Value	Output Gap	Taylor Rule	Average Mispricing
Average Mispricing	0.487	0.597	0.612	0.450	0.256	0.226	0.444	–0.128	0.146	0.395	
Extreme Mispricing	0.529	0.606	0.591	0.477	0.281	0.257	0.432	–0.032	0.224	0.391	0.887

Table 2.4: 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 ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 ten 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 2.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)	–0.283	0.025	0.084	0.260	0.515	0.798	–0.112	–0.159	–0.107	0.040	0.222	0.334
t-statistic	[–2.75]	[0.24]	[0.71]	[2.16]	[3.96]	[7.85]	[–1.11]	[–1.49]	[–0.90]	[0.33]	[1.72]	[3.27]
Sharpe Ratio	–0.127	0.011	0.036	0.105	0.200	0.358	–0.050	–0.069	–0.045	0.016	0.087	0.149
Standard Deviation	2.219	2.286	2.365	2.474	2.569	2.226	2.216	2.283	2.376	2.485	2.569	2.237
Skewness	–0.506	–0.357	–0.366	–0.282	–0.362	0.041	–0.389	–0.400	–0.423	–0.308	–0.432	–0.050
Kurtosis	6.272	5.669	4.579	4.559	4.286	4.845	6.058	5.641	4.681	4.545	4.356	4.906
Mispricing (t)	0.335	0.445	0.533	0.618	0.743	0.408	0.335	0.445	0.533	0.618	0.743	0.408
Extreme Mispricing												
Average Currency Excess Return (t+1)	–0.202	0.010	0.102	0.167	0.527	0.729	–0.032	–0.177	–0.093	–0.041	0.229	0.261
t-statistic	[–2.02]	[0.09]	[0.88]	[1.38]	[4.09]	[7.22]	[–0.33]	[–1.60]	[–0.80]	[–0.34]	[1.78]	[2.59]
Sharpe Ratio	–0.093	0.004	0.043	0.068	0.209	0.333	–0.015	–0.077	–0.039	–0.017	0.090	0.119
Standard Deviation	2.172	2.303	2.372	2.461	2.525	2.188	2.169	2.301	2.381	2.461	2.527	2.192
Skewness	–0.383	–0.189	–0.399	–0.221	–0.379	0.004	–0.250	–0.232	–0.451	–0.261	–0.459	–0.117
Kurtosis	6.844	4.528	4.763	4.472	4.625	5.462	6.759	4.503	4.845	4.464	4.660	5.496
Mispricing (t)	–0.380	–0.119	0.033	0.182	0.471	0.851	–0.380	–0.119	0.033	0.182	0.471	0.851

Table 2.5: Quintile Performance of Portfolios Family 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. All Anomalies refers to the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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. 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 2.A provides details on variable definitions.

(continued)

Table 2.5: Quintile Performance of Portfolios Family Sorted on Currency Mispricing (continued)

Panel A: Currency Excess Returns

	Gross of Transaction Costs							Net of Transaction Costs	
	Quintiles								
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Q5–Q1	t-stat	Q5–Q1	t-stat
Average Mispricing									
All Anomalies	–0.162	–0.011	0.149	0.261	0.578	0.740	[5.84]	0.408	[3.24]
Trend Following	–0.181	0.051	0.121	0.245	0.570	0.751	[5.89]	0.414	[3.30]
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	–0.094	–0.017	0.118	0.239	0.583	0.677	[5.08]	0.340	[2.56]
Trend Following	–0.146	0.078	0.147	0.182	0.534	0.679	[5.39]	0.332	[2.66]
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 2.5: Quintile Performance of Portfolios Family 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*-stat	Q5–Q1	*t*-stat
Average Mispricing									
All Anomalies	–0.171	–0.106	–0.033	–0.051	–0.235	–0.065	[–0.52]	–0.298	[–2.36]
Trend Following	–0.302	–0.098	–0.047	–0.019	–0.130	0.173	[1.40]	–0.068	[–0.55]
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	–0.109	–0.123	–0.042	–0.056	–0.256	–0.147	[–1.13]	–0.384	[–2.94]
Trend Following	–0.282	–0.052	0.011	–0.088	–0.198	0.084	[0.68]	–0.164	[–1.32]
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 2.6: 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. All Anomalies refers to the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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. 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 2.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	1.163	0.506	0.068	–0.424	–0.884	–2.047	[–17.3]
Trend Following	1.975	0.680	–0.038	–0.665	–1.466	–3.442	[–20.5]
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	1.034	0.473	0.036	–0.290	–0.825	–1.859	[–16.0]
Trend Following	1.892	0.449	–0.072	–0.443	–1.332	–3.223	[–20.3]
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]

(continued)

Table 2.6: Forecast Currency Returns across Currency Mispricing Quintiles (continued)

Panel B: Forecast Currency Returns

	Quintiles					Q5–Q1	
	Q1 (Short)	Q2	Q3	Q4	Q5 (Long)	Average	t-statistic
Average Mispricing							
All Anomalies	1.155	0.411	–0.114	–0.737	–1.698	–2.852	[–21.5]
Trend Following	1.854	0.530	–0.206	–0.929	–2.166	–4.020	[–22.5]
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	1.019	0.367	–0.124	–0.585	–1.664	–2.683	[–20.2]
Trend Following	1.755	0.319	–0.209	–0.713	–2.063	–3.819	[–22.4]
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 2.7: 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. All Anomalies refers to the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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. 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 2.A provides details on variable definitions.

(continued)

Table 2.7: Currency Mispricing and Forecast Returns

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	–6.521***	–6.140***	0.515	1.328***	–2.833***	–2.785***	0.246	0.510***
	(0.683)	(0.338)	(0.362)	(0.403)	(0.331)	(0.166)	(0.162)	(0.181)
Number of Forecasters	–0.012***	–0.012***	–0.005***	–0.004*	–0.011***	–0.011***	–0.005***	–0.005**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Single Forecast	–0.081	0.153	0.160		–0.012	0.161	0.155	
	(0.325)	(0.300)	(0.172)		(0.306)	(0.297)	(0.173)	
Intercept	4.776***	4.182***	–0.181	0.564	1.330***	1.032***	0.083	1.274*
	(0.703)	(0.661)	(0.440)	(0.674)	(0.397)	(0.331)	(0.367)	(0.651)
Observations	11,037	10,972	11,095	4,470	11,037	10,972	11,095	4,470
R–Squared	0.40	0.54	0.33	0.48	0.39	0.51	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 2.7: 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	–8.827***	–7.064***	–1.409***	0.796**	–3.939***	–3.239***	–0.622***	0.249
	(0.661)	(0.323)	(0.364)	(0.385)	(0.324)	(0.159)	(0.177)	(0.179)
Number of Forecasters	–0.008***	–0.006***	–0.000	0.001	–0.006**	–0.006***	–0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Single Forecast	–0.195	0.107	0.008		–0.107	0.117	0.028	
	(0.255)	(0.185)	(0.115)		(0.235)	(0.183)	(0.117)	
Intercept	6.086***	4.475***	0.930**	0.357	1.464***	0.862***	0.184	0.791
	(0.702)	(0.705)	(0.406)	(0.588)	(0.286)	(0.298)	(0.329)	(0.491)
Observations	11,037	10,972	11,095	4,470	11,037	10,972	11,095	4,470
R–Squared	0.48	0.63	0.33	0.47	0.46	0.60	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 2.8: 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. All Anomalies refers to the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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. 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 2.A provides details on variable definitions.

(continued)

Table 2.8: Analysts' Mistakes and Currency Mispricing (continued)

	Average Mispricing				Extreme Mispricing			
	All Anomalies	Trend Following	Interest Rates	Fundamentals	All Anomalies	Trend Following	Interest Rates	Fundamentals
Mispricing	–8.575***	–7.037***	–0.823*	0.300	–3.757***	–3.185***	–0.377*	0.083
	(0.721)	(0.353)	(0.445)	(0.508)	(0.346)	(0.173)	(0.194)	(0.233)
Number of Forecasters	–0.011***	–0.009***	–0.003*	–0.001	–0.009***	–0.009***	–0.003*	–0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Single Forecast	–0.138	0.163	0.087		–0.048	0.173	0.097	
	(0.312)	(0.245)	(0.158)		(0.290)	(0.242)	(0.159)	
Intercept	5.128***	3.679***	–0.285	3.358***	0.610	0.067	–0.714	3.523***
	(1.040)	(0.731)	(1.099)	(0.696)	(0.995)	(0.873)	(1.062)	(0.660)
Observations	11,037	10,972	11,095	4,470	11,037	10,972	11,095	4,470
R–Squared	0.42	0.50	0.36	0.51	0.42	0.48	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 2.9: 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 (Panel A), as well as on pre-publication mispricing, post-publication mispricing, and control variables (Panel B). 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. Pre-publication mispricing is based only on anomalies of research that has not yet been posted on SSRN in a particular month, while post-publication mispricing is based only on anomalies of research that has been posted on SSRN in that month. All Anomalies refers to the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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. 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 2.A provides details on variable definitions.

(continued)

Table 2.9: Analysts' Mistakes and Currency Mispricing Over Time (continued)

Panel A: Analysts' Mistakes and Time Trend

	Average Mispricing				Extreme Mispricing			
	All Anomalies	Trend Following	Interest Rates	Fundamentals	All Anomalies	Trend Following	Interest Rates	Fundamentals
Mispricing	–7.793***	–5.872***	–2.836***	–3.727*	–3.783***	–2.705***	–1.137***	–2.024**
	(1.078)	(0.653)	(0.748)	(1.861)	(0.527)	(0.341)	(0.362)	(0.978)
Mispricing x Time	–0.387	–0.554	0.989***	1.619**	0.012	–0.226	0.359**	0.841**
	(0.492)	(0.336)	(0.366)	(0.686)	(0.231)	(0.171)	(0.175)	(0.359)
Number of Forecasters	–0.011***	–0.009***	–0.003**	–0.002	–0.009***	–0.009***	–0.003*	–0.002
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Single Forecast	–0.138	0.179	0.108		–0.048	0.190	0.110	
	(0.316)	(0.246)	(0.154)		(0.289)	(0.242)	(0.157)	
Intercept	4.600***	2.954***	1.157	4.496***	0.619	–0.053	–0.382	3.631***
	(1.102)	(0.783)	(1.186)	(0.894)	(0.998)	(0.896)	(1.090)	(0.676)
Observations	11,037	10,972	11,095	4,470	11,037	10,972	11,095	4,470
R–Squared	0.42	0.50	0.36	0.51	0.42	0.48	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

(continued)

Table 2.9: Analysts' Mistakes and Currency Mispricing Over Time (continued)

Panel B: Analysts' Mistakes and Anomaly Publication

	Average Mispricing				Extreme Mispricing			
	All Anomalies	Trend Following	Interest Rates	Fundamentals	All Anomalies	Trend Following	Interest Rates	Fundamentals
Pre-Publication Mispricing	–8.851***	–7.483***	–1.281**	–0.000	–4.248***	–3.406***	–0.645***	–0.089
	(0.712)	(0.356)	(0.503)	(0.548)	(0.362)	(0.175)	(0.238)	(0.249)
Post-Publication Mispricing	–8.051***	–6.309***	–0.233	1.302	–2.964***	–2.829***	–0.083	0.619
	(1.100)	(0.567)	(0.658)	(0.888)	(0.453)	(0.279)	(0.259)	(0.399)
Number of Forecasters	–0.010***	–0.009***	–0.003*	–0.001	–0.009***	–0.009***	–0.003*	–0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)
Single Forecast	–0.166	0.128	0.078		–0.099	0.135	0.085	
	(0.305)	(0.234)	(0.156)		(0.276)	(0.231)	(0.157)	
Intercept	5.312***	3.960***	0.041	3.547***	0.792	0.126	–0.599	3.558***
	(1.035)	(0.733)	(1.090)	(0.707)	(0.983)	(0.866)	(1.061)	(0.660)
Observations	11,037	10,972	11,095	4,470	11,037	10,972	11,095	4,470
R–Squared	0.42	0.50	0.36	0.51	0.42	0.48	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
Null: Pre-Publication ≥ Post-Publication Mispricing	0.217	0.020	0.084	0.098	0.002	0.022	0.039	0.060

Table 2.10: 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 ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 ten 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 2.A provides details on variable definitions.

	Average Mispricing			Extreme Mispricing		
	(1)	(2)	(3)	(1)	(2)	(3)
Mispricing (lagged by 1 month)	1.836***			0.748***		
	(0.351)			(0.172)		
Mispricing (lagged by 2 months)		0.260			0.093	
		(0.333)			(0.158)	
Mispricing (lagged by 3 months)			–0.499			–0.249
			(0.332)			(0.156)
Number of Forecasters	0.005***	0.003***	0.003**	0.004***	0.003***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Single Forecast	0.032	–0.025	–0.073	0.009	–0.029	–0.070
	(0.124)	(0.095)	(0.087)	(0.118)	(0.095)	(0.088)
Intercept	–0.919	1.921**	0.755	0.071	2.066**	0.504
	(0.729)	(0.938)	(1.164)	(0.734)	(0.902)	(1.120)
Observations	10,949	10,881	10,813	10,949	10,881	10,813
R–Squared	0.33	0.32	0.32	0.33	0.32	0.33
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Error Clustering	Country	Country	Country	Country	Country	Country

Table 2.11: 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 average mispricing, extreme 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 ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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 ten 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 2.A provides details on variable definitions.

	Average Mispricing			Extreme Mispricing		
	Coefficient	*t*-statistic		Coefficient	*t*-statistic	
Mispricing Q2	0.114	[1.24]		0.103	[1.21]	
Mispricing Q3	0.294	[2.88]	***	0.216	[2.21]	**
Mispricing Q4	0.450	[3.73]	***	0.321	[2.93]	***
Mispricing Q5	0.893	[7.10]	***	0.756	[5.94]	***
Forecast Excess Return Q2	0.118	[1.36]		0.185	[2.24]	**
Forecast Excess Return Q3	0.132	[1.31]		0.074	[0.71]	
Forecast Excess Return Q4	0.151	[1.22]		0.143	[1.12]	
Forecast Excess Return Q5	0.248	[1.76]	*	0.215	[1.51]	
Intercept	–0.312	[–2.31]	**	–0.239	[–1.81]	*
Average Number of Observations	32			32		
Average R–Squared	0.42			0.41		

Table 2.12: 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. For brevity, the table only displays the coefficients on the mispricing variable but not 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. All Anomalies refers to the following ten 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) carry trade, (v) dollar carry trade, (vi) dollar exposures, (vii) term spread, (viii) currency value, (ix) output gap, and (x) 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. 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 2016 BIS Triennial Survey and 40 currencies with the most turnover according to the BIS Triennial Survey. The sample period is from December 1989 to June 2018. Appendix 2.A provides details on variable definitions.

			Average Mispricing				Extreme Mispricing			
			All Anomalies	Trend Following	Interest Rates	Fundamentals	All Anomalies	Trend Following	Interest Rates	Fundamentals
52 currencies	Table 6	Mispricing	–9.140***	–7.285***	–1.072**	0.300	–4.136***	–3.358***	–0.520**	0.083
			(0.704)	(0.326)	(0.474)	(0.508)	(0.331)	(0.161)	(0.201)	(0.233)
	Table 7	Mispricing	–7.155***	–5.419***	–2.780***	–3.727*	–3.457***	–2.435***	–1.209***	–2.024**
			(1.044)	(0.593)	(0.710)	(1.861)	(0.521)	(0.313)	(0.369)	(0.978)
40 currencies	Table 6	Mispricing	–8.997***	–7.298***	–0.924*	0.329	–4.107***	–3.360***	–0.390	0.084
			(0.805)	(0.360)	(0.536)	(0.510)	(0.386)	(0.179)	(0.251)	(0.241)
	Table 7	Mispricing	–6.824***	–5.241***	–2.601***	–3.592*	–3.339***	–2.473***	–1.008***	–2.021*
			(1.059)	(0.619)	(0.701)	(1.848)	(0.531)	(0.329)	(0.328)	(1.005)

Appendix 2.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).
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).

(continued)

Appendix 2.A: Variable Definitions (continued)

Variable	Definition
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, each currency's change in 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 60-months rolling windows. The carry factor is the average change in exchange rate between high interest rate countries and low interest rate countries. The dollar factor is the average change in exchange rate across all other currencies. Currencies are sorted into five quintiles (Q1 to Q5) from low to high based on the slope coefficients on the dollar factor and combined into equally weighted portfolios. Each month and 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.
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.

(continued)

Appendix 2.A: Variable Definitions (continued)

Variable	Definition
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 (2017)) 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, and 12-Months Momentum.
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	
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.

(continued)

Appendix 2.A: Variable Definitions (continued)

Variable	Definition
Control Variables	
Time	Time is equal to 1/100 during the first month of the sample and increases by 1/100 each month.
Major Currencies	Five currencies with the highest foreign exchange turnover according to the BIS Triennial Central Bank Survey (2016), i.e. Euro, Japanese Yen, British Pound, Australian Dollar, and Canadian Dollar.
Developed Countries	Developed countries according to the MSCI classification as of May 2018.
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.

3 Time Varying Effects of External Imbalances when Forecasting Exchange Rates

3.1 Introduction

It is widely known that exchange rates are very difficult to predict using economic models (Meese and Rogoff, 1983). In particular, a simple, a-theoretical model such as the random walk is frequently found to generate better exchange rate forecasts than economic models. The consensus is that economic fundamentals are of little use and exchange rates are well approximated by a naive random walk model (Engel et al., 2007). Numerous empirical applications in international finance have attempted to resolve whether exchange rates are predictable. Recent developments (see Rossi, 2013, for a survey) suggest several economic fundamentals that are argued to have out-of-sample predictive power in explaining exchange rate returns, such as net foreign assets (Gourinchas and Rey, 2007) or Taylor Rule fundamentals (Engel and West, 2006, and Molodtsova and Papell, 2009).

With regards to net foreign assets, a theoretical model of international financial adjustment shows that net foreign assets capture global imbalances that require exchange rate adjustments as part of the mechanism that leads to sustainable current account positions. As such, it provides useful insights linking the U.S. global imbalances to future movements in the U.S. dollar exchange rate (Gourinchas and Rey, 2007). A related literature also shows that a country's exchange rate has a cointegrated relation with international investors' net foreign holdings of its assets (Gelman, Jochem, Reitz, and Taylor, 2015). Moreover as global markets have been more integrated, there have been increases in asset and liabilities transactions among countries (Hau and Rey, 2004). This lends a support to utilize the international financial adjustment model to forecast exchange rates, which is one of the aims of this chapter.

Another issue in exchange rate predictability involves parameter estimation, where it is argued that parameter instability may rationalize the poor forecasting performance of exchange rate models (Meese and Rogoff, 1983). Previous studies have attempted to account for time-variation in parameters when forecasting exchange rates. For example, Wolff (1987) and Rossi (2006) show that time varying parameter estimation using the Kalman filter can be used to improve the predictive performance of monetary exchange rate models. And recently, Byrne et. al (2016) examine the predictive power of adopting time varying parameters using Taylor rule fundamentals. Although the problem with regards conjecture that the lack of dynamic in regression parameters causes the poor performance when forecasting exchange rates has not yet been fully resolved (Rossi, 2013; Rogoff and Stavrakeva, 2008), there is a growing consensus that instabilities can be exploited to improve exchange rate forecasts.

This chapter addresses both issues of forecasting exchange rates using macroeconomic fundamentals and accommodating time variation in the parameters of the models. The underlying idea is that macroeconomic conditions have useful information on the exchange rate movements, but the informational content varies over time in a way not captured by constant parameter based models. The time varying parameter models are used and estimated using Bayesian methods, which allows for changing dynamics between macroeconomic fundamentals and the path of the exchange rate. The information in the likelihood and using Bayesian methods helps achieve efficiency when estimating the parameters. Moreover, the Bayesian methods are appealing because it treats all the unknown parameters in the system as jointly distributed random variables (Kim and Nelson, 1999), such that each estimated parameter reflects uncertainty about the other parameters. In contrast, estimates based on classical maximum likelihood are prone to errors, since a large number of likelihood functions have to be evaluated. Hence unlike the previous literature, this chapter does not rely on classical maximum likelihood methods (Rossi, 2006) or calibration (e.g. Bacchetta et al., 2010), which can also be subjective and may deliver less accurate parameter estimates and inferior forecasting performance.

With regards forecast accuracy, literature on statistical measures of the accuracy of exchange rate forecasts is very extensive. Nevertheless, an accurate forecast that minimizes the forecast error falls short of measuring whether there are tangible economic gains from using dynamic forecasts in active portfolio management (Della Corte and Tsiakas, 2012). Related papers assess the economic value of exchange rate predictability, for example under a decision-making environment (Garratt and Lee, 2010) or in terms of investment profits (Kouwenberg et. al, 2017). The work in this area is growing but is still limited, hence following this, I opt to focus on economic as opposed to statistical evaluation in this chapter.

The macroeconomic fundamentals used in this chapter are bilateral external imbalances between the U.S. and foreign countries, following the international financial adjustment theoretical model of Gourinchas and Rey (2007). The bilateral external imbalances are measured as a linear combination of stochastic trend-deviations of bilateral exports, imports, assets and liabilities, normalized with respect to national wealth. The model is theoretically robust and has a simple structural derivation, but nonetheless evidence examining its performance is still limited. This chapter extends previous investigation based on a single equation constant parameter model to estimate the predictability regression (Della Corte, Sarno, and Sestieri, 2012), but allows for time-variation in the parameters. Another related literature is Della Corte, Riddiough, and Sarno (2016) who examine the predictive power of net foreign assets for currency returns, but they do not use information from net exports and moreover predictability is examined in a cross-sectional setting. The exercise in this chapter shows that combining information from net foreign assets and net exports provide more economic gain for exchange rate predictability in out-of-sample.

The dataset consists of quarterly exchange rates from 1983Q1 to 2015Q1, for nine countries relative to the U.S. dollar. Bilateral external imbalances measures are constructed for each country, by combining the stationary components of the (trend) share of exports and imports in the trade balance and the (trend) share of foreign assets and liabilities in the net foreign assets respectively. Time varying parameter models are estimated using Bayesian estimation. The analysis is employed both in-sample and out-of-sample.[1]

The ability of the time varying model to forecast major exchange rates is examined using several economic evaluation criteria, with a focus on the one-step ahead forecast horizon. Using statistical criteria, typically root mean square error, fundamental

[1] Note that the in-sample and out-of-sample definition in this chapter is different from the definition as in Chapter 1. In this chapter, in-sample refers to estimation of a regression using the whole observations in the data. Out-of-sample refers to estimation of a regression using a certain period of observations in the data, and the estimation is done recursively. The in-sample and out-of-sample estimations are done in Section 3.5.

models are known to be outperformed by the random walk at this short horizon. Hence our perspective is to examine whether a fundamental-based model can outperform random walk for the predictability, in the context of allowing for time-variation.

The economic evaluation takes the form of a comparison of portfolio performance between a portfolio formulated on the basis of exchange rate forecasts formed using a random walk model, versus the performance of a portfolio formulated on the basis of a time-varying parameters bilateral external imbalances model. Transactions costs associated with the second more active investment strategy are taken into account when making the comparison. The empirical analysis provides evidence that bilateral external imbalances have strong in-sample and out-of-sample predictive ability for exchange rate returns on the basis of economic performance measures. Allowing for time-varying bilateral external imbalances improves upon the driftless random walk at short horizons of one quarter. The time varying regressions also perform much better than standard linear regressions employed in a rolling window forecasting approach. There is a large gain in economic value to the investor using the predictive information in bilateral external imbalances. This result contributes to the empirical examination of exchange rate forecasting by delivering meaningful relationship of macroeconomic information in predicting the exchange rate returns.

It is worth noting that this chapter does not intend to find a new strategy for currency trading or propose a new risk factor that may underlie cross-sectional predictability of exchange rates. Rather, this chapter aims to examine the ability of macroeconomic fundamentals in explaining exchange rate movements. The models are constructed on a time-series dimension that involves bilateral relation between a foreign currency and the U.S. dollar.[2]

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[2] Preliminary assessment in Section 3.3 uses estimations of panel regression.

In the following, in Section 3.2, I discuss time varying bilateral external imbalances and exchange rates, followed by discussion on the data and estimated imbalances measures in Section 3.3. Section 3.4 provides an overview of economic evaluation and Section 3.5 covers the empirical results. This chapter concludes in Section 3.6.

3.2 Bilateral External Imbalances and Time Varying Parameter Regression

Gourinchas and Rey (2007) construct a measure of global external imbalances by filtering out the trend component in exports, imports, foreign assets and liabilities, relative to domestic wealth. They show that the global external imbalances measure has significant out-of-sample predictive power at horizons from one to sixteen quarters for two series of multilateral nominal exchange rates i.e. the foreign direct investment (FDI)-weighted *effective* exchange rate, and the Federal Reserve trade-weighted *effective* exchange rate for the U.S. dollar against major currencies. The detail mechanism of global external imbalances is provided in Appendix 3.B.

In contrast to the focus on effective exchange rates, in this chapter, following Della Corte, Sarno and Sestieri (2012), I use the Gourinchas and Rey's framework but estimate a *bilateral* measure of cyclical external imbalances. The bilateral measure is desirable because they are directly tradable, while effective exchange rates are not. In practice, investors form expectations and allocate their wealth on the basis of bilateral exchange rates, since these are the prices they observe and are important to their portfolio returns. The global measure can be used as a proxy for the bilateral measure, however this may not be appropriate since global external imbalances capture not only information related to the bilateral exchange rate of interest but also about other trading partners. Hence it can be argued that by using global external imbalances as predictive variables in a regression for bilateral exchange rate returns, an errors-in-variable problem would raise as an issue which potentially leading to inconsistent least square estimates. Della Corte et al. highlight this problem and estimate the bilateral external imbalances by using fitted values from an instrumental variable (IV) regression. They regress the U.S. global external imbalances on the foreign global external imbalances and the bilateral detrended net exports between the U.S. and the foreign country.

There are differences however, that distinguish this paper from Della Corte et al.'s earlier work. First, direct measures of bilateral foreign asset and foreign liabilities are used, instead of estimation results from an IV regression. The data (as will be explained in the next Section) is retrieved from Kubelec and Sá (2012)'s study, and is updated to include recent period. This provides a cleaner measure of bilateral external imbalances, and avoid any errors-in-variable problem that is still raised from an estimation using the IV regression. Second, the parameters from predictive regression of exchange rate changes using information from bilateral external imbalances are time varying. This addresses parameter instability that is commonly found in the exchange rate literature, where it is argued that such instability causes macroeconomic fundamentals to fail to outperform a random walk when predicting exchange rate changes. And lastly, this paper does not limit the sample size to include major currencies from developed markets, but also those from emerging markets.

The construction of bilateral external imbalances measure is as follows. The measure is defined as a linear combination of stochastic trend-deviations of bilateral exports, imports, assets and liabilities, normalized with respect to national wealth (see Appendix 3.B). To construct the measure, first, the variables entering the bilateral external imbalances are normalized using net worth. Second, the trend components of each variable are estimated using the Hodrick-Prescott filter.[3]

By filtering out low-frequency trends, we are able to decompose each normalized variable into a deterministic trend component, and a stationary component, representing the stochastic deviations from the long-run estimated trend. For each country, the measure of external imbalances linearly combines these stationary components in bilateral assets, liabilities, exports and imports. The weights used for this combination take into account the relative share of bilateral exports/imports in the detrended net export, and the relative share of bilateral assets/liabilities in the detrended net foreign assets. The time-varying shares are replaced with their sample average values, and then their absolute values are taken to construct the country-specific bilateral measures of external imbalances.

Specifically, the bilateral measure of cyclical external imbalances between the domestic economy and the foreign country i at time t ($nxa_t^{(i)}$) is computed as

$$nxa_t^{(i)} \equiv \frac{|\mu_t^{a(i)}|}{|\mu_t^{x(i)}|}\varepsilon_t^{a(i)} - \frac{|\mu_t^{l(i)}|}{|\mu_t^{x(i)}|}\varepsilon_t^{l(i)} + \varepsilon_t^{x(i)} - \frac{|\mu_t^{m(i)}|}{|\mu_t^{x(i)}|}\varepsilon_t^{m(i)} \tag{3.1}$$

where

$$\mu_t^{a(i)} = \frac{\overline{A_t^{(i)}}}{\overline{A_t^{(i)}} - \overline{L_t^{(i)}}}, \qquad \mu_t^{l(i)} = \mu_t^{a(i)} - 1, \tag{3.2}$$

$$\mu_t^{x(i)} = \frac{\overline{X_t^{(i)}}}{\overline{X_t^{(i)}} - \overline{M_t^{(i)}}}, \qquad \mu_t^{m(i)} = \mu_t^{x(i)} - 1. \tag{3.3}$$

[3] The Hodrick-Prescott filter and the constant weights are based on the full-sample information in the in-sample analysis. In the out-of-sample however, the Hodrick-Prescott filter is performed and the weights are computed only using information available at the time of the forecast to avoid any look-ahead bias.

$\overline{Z}^{(i)} = \{\overline{A_t^{(i)}}, \overline{L_t^{(i)}}, \overline{X_t^{(i)}}, \overline{M_t^{(i)}}\}$ comprises bilateral assets, liabilities, exports and imports normalized with respect to net worth, $\varepsilon_t^{z(i)}$ is the stationary component we are interested in, the weight $\mu_t^{a(i)}$ is the (trend) share of bilateral assets in the net foreign assets, and the weight $\mu_t^{x(i)}$ is the (trend) share of bilateral exports in the trade balance. The weights are normalized with respect to $\mu_t^{x(i)}$ such that the weight on bilateral exports is unity, and $nxa_t^{(i)}$ can be interpreted as the percentage increase in bilateral exports needed to restore a country's external equilibrium. In the same vein, the bilateral cyclical net foreign assets can be constructed as:

$$na_t^{(i)} \equiv \frac{|\mu_t^{a(i)}|}{|\mu_t^{x(i)}|}\varepsilon_t^{a(i)} - \frac{|\mu_t^{l(i)}|}{|\mu_t^{x(i)}|}\varepsilon_t^{l(i)}, \tag{3.4}$$

and the bilateral cyclical net exports as:

$$nx_t^{(i)} \equiv \varepsilon_t^{x(i)} - \frac{|\mu_t^{m(i)}|}{|\mu_t^{x(i)}|}\varepsilon_t^{m(i)}. \tag{3.5}$$

Having the bilateral external imbalances measure, the following regression is estimated to forecast exchange rates:

$$\Delta_k s_{t+k}^{(i)} / k = a_t + b_t \; nxa_t^{(i)} + \varepsilon_{t+k}, \qquad \varepsilon_{t+k} \sim N(0, R), \tag{3.6}$$

where $s_t^{(i)}$ is the log-nominal exchange rate at time t, defined as the domestic price of foreign currency i; and $\Delta_k s_{t+k}^{(i)} = s_{t+k}^{(i)} - s_t^{(i)}$ is the nominal exchange rate return between time t and $t+k$. The U.S. is the domestic economy. The time-subscripts t attached to the coefficients $\beta_t = [a_t, b_t]$ characterize them as changing over time. I assume a random walk time-varying parameter process (Stock and Watson, 1996; and Rossi, 2006):

$$\beta_t = \beta_{t-1} + v_t, \qquad v_t \sim N(0, Q), \tag{3.7}$$

where the error term v_t is assumed to be homoskedastic, uncorrelated with ε_{t+k} in Equation (3.6), and with a diagonal covariance matrix Q. Equations (3.6) and (3.7) make up a state-space model, where (3.6) is the measurement equation and (3.7) the transition equation.

For the empirical assessment, the b_t value is expected to be *negative*. Theoretically, time variation in bilateral external imbalances must forecast either future portfolio returns, or future net export growth, or both. In a country with a cyclical debt position and a cyclical trade deficit, a negative value of bilateral external imbalances anticipates an increase in future returns of net foreign assets and future trade surpluses. Assuming local currency return is constant, a foreign currency depreciation increases the domestic return on foreign assets, hence the *negative* relation between bilateral external imbalances and future exchange rate movements (Appendix 3.B).

Bayesian methods are used to estimate the parameters of the state-space model. Using the Kalman filter with maximum likelihood is another potential method, but the evaluation of a large number of likelihood functions may undermine the estimates (Kim and Nelson, 1999). With the method of maximum likelihood there is potential for accumulation of errors, as estimation of the state variables is conditional upon maximum likelihood estimates of the other parameters of the system. There is also the issue of identifying objective priors to initialize the Kalman filter. The solution to this latter issue involves setting diffuse priors or using a training sample, but solving the problem of obtaining efficient parameter estimates is more challenging. Bayesian methods, in contrast, treat all the unknown parameters in the system as jointly distributed random variables, such that the estimate of each of them reflects uncertainty about the others. The detail of the procedure to estimate the state-space model is explained in Appendix

3.C. In the estimation process, I take 20,000 draws, discarding the first 10,000 draws and save the last 10,000 draws for inference.

3.3 Data and Estimated Bilateral External Imbalances

I collect a data set that consists of quarterly observations from 1983Q1 to 2015Q4, comprising nine spot exchange rates relative to the U.S. Dollar (USD) i.e. the Australian Dollar (AUD), the Canadian dollar (CAD), the Euro (EUR), the Japanese yen (JPY), the British pound (GBP), the Singaporean Dollar (SGD), the Indian Rupee (INR), the Korean Won (KRW), and the Mexican Peso (MXN). The exchange rate data are from the International Monetary Fund's International Financial Statistics (IFS) database. For the economic evaluation, I use the Eurocurrency deposit rates with three-month maturity, obtained from Datastream, as a proxy for the riskless rate of return.

Bilateral asset and liabilities between the U.S. and the nine foreign countries are from Kubelec and Sá (2012), who provide the data set until 2005Q4. I update the data set using databases from the IMF Coordinated Portfolio Investment Survey (CPIS), UNCTAD, and the IMF Coordinated Direct Investment Survey (CDIS). Because the asset/liabilities data are in annual frequency, I construct quarterly observations by linear interpolation.

Quarterly data on bilateral exports and imports of goods and services between the United States and each of nine foreign countries (Germany is used as the country for Euro) are from the U.S. Bureau of Economic Analysis (BEA). These exports and imports data are seasonally adjusted using dummy-variable regressions. To construct bilateral external imbalances, I use nominal GDP as a proxy of countries' wealth.

The descriptive statistics for all variables of interest are presented in Table 3.A in the Appendix, which are quarterly percentage changes in log bilateral (i) foreign assets,

(ii) foreign liabilities, (iii) exports and (iv) imports, constructed measures of bilateral cyclical (i) net foreign assets, (ii) net exports, and (iii) external imbalances, as well as quarterly percentage changes in exchange rates. Foreign assets and liabilities have lower volatility and higher serial correlation than exports and imports. The three cyclical variables have a sample mean of zero, a large standard deviation, and high serial correlation that indicates persistency of the respective measures.

The bilateral cyclical imbalances between the U.S. and each country are shown in Figure 1.1. Some countries such as Germany, India, and Australia show smooth pattern cyclical imbalances and are quite persistent overtime. Meanwhile, other countries such as Canada, U.K., and Singapore depict more volatile bilateral imbalances. Moreover, India, Mexico, and Australia show positive imbalances with respect to the U.S. in recent periods. On the other hand, Germany and Japan have negative imbalances in the last few years.

With regards co-movement of the cyclical imbalances, Canada, Germany, Japan and the U.K. are positively correlated with a correlation coefficient of at least 0.4 among each other (Table 3.1). Furthermore, Germany and Japan have positive correlations of more than 0.5 with South Korea. Australia is positively correlated with India and South Korea by 0.3 and 0.5 respectively. This co-movement might have some determining factors for the economic evaluation assessment. In terms of portfolio allocation, an efficient portfolio will generate a higher return if it takes account of more diversifying assets in the portfolio basket. The co-movement between the bilateral imbalances can also influence the exchange rate changes, where depreciation of a foreign currency can induce a spillover effect of depreciation to another foreign currency.

To examine the statistical significance of relationship between bilateral external imbalances and exchange rate changes, I firstly run a panel regression (of constant parameter) with the following specification:

$$\Delta_k s_{t+k}^{(i)} / k = a^{(i)} + b\, nxa_t^{(i)} + \varepsilon_{t+k}^{(i)}, \tag{3.8}$$

i.e. a regression with country fixed effect, where the dependent variable is exchange rate changes that are varied from $k = 1, 2, 3, 4, 8,$ and 12 quarter changes, and the dependent variable is the bilateral external imbalances of respective foreign countries. To account for the possibility of contemporaneous cross-correlation between changes in exchange rates, the regression is estimated using feasible generalized least squares (FGLS).

The international financial adjustment mechanism suggests the b coefficient of bilateral external imbalances from the regression should be *negative*. Table 3.2 Panel A shows that is the case empirically. The b coefficient is significant, ranging from –0.007 (a quarter change in exchange rates) to –0.081 (three years change in exchange rates). When a one-sided test is performed for each coefficient, we reject the null at 1% level that b is greater than or equal to zero. This confirms the predictive ability of bilateral external imbalances, and furthermore, the predictive power increases as the number of lags increases from 1 (R-squared of 6%) to 12 quarters (R-squared of 28%). The results are in line with previous studies (Gourinchas and Rey, 2007[4]; Della Corte et al., 2012[5]).

Moreover, the bilateral external imbalances at the right hand side of Equation (3.8) can be decomposed into two components, cyclical net foreign assets and net exports. Regressing the exchange rate changes on the two components show that both have significant predictive power, as presented in Table 3.2 Panel B. Consistent with the

[4] Using multilateral weighted effective exchange rate.

[5] The estimation involves four major currencies of Euro, British Pound, Canadian Dollar, and Japanese Yen.

results in Panel A, the coefficient of each variable increases from $k=1$ to 12 quarters, and a one-sided test indicates that they are significantly less than zero. The coefficients of net exports are higher than those of net foreign assets, in line with the descriptive statistics (Table 3.A in the Appendix) that the former is more volatile than the latter. This initial assessment describes that valuation channel (through net foreign assets) and trade channel (through net exports) play significant roles for the bilateral external adjustment in predicting exchange rates.

3.4 Economic Evaluation Methods

Using predictive variables that measure cyclical external imbalances for country pairs, I assess the ability of the time varying parameter model to forecast major exchange rates using various economic evaluation criteria. The forecast horizon is one step ahead, as fundamental model is known to be outperformed by the random walk at this horizon. The setting for the economic evaluation is as follows.

A U.S. investor builds a portfolio by allocating his wealth between the domestic bond and foreign bonds. The yield of the foreign bonds is riskless in their local currency but risky in terms of U.S. investor's domestic currency. Therefore the return that the investor enjoys from investing in a foreign bond between t and $t+1$ is equal to the foreign riskless return known at time t adjusted by the exchange rate return observed at time $t+1$. Using this setting, at time t, the only risk that the investor is exposed to is foreign exchange risk.

Each period the investor performs the following two steps. Firstly, he uses the predictive model as in Equation (3.6) to forecast the exchange rate returns, and utilizes the unconditional covariance matrix at time t as the forecast of the covariance matrix for the next period. Secondly, having the forecasts, he dynamically rebalances his portfolio by computing new optimal portfolio weights based on a mean-variance strategy.

In the mean-variance strategy, the investor maximizes his expected portfolio returns while achieving a desired portfolio volatility. The maximum return strategy leads to a portfolio allocation on the efficient frontier, where the dynamic portfolio weights are computed by implementing the strategy using the forecasts of conditional mean and covariance matrix.

More specifically, let r_{t+1} denote the $N\times 1$ vector of risky asset returns; $\mu_{t+1|t}$ = $E_t[r_{t+1}]$ is the conditional expectation of r_{t+1}; and $\Sigma_{t+1|t} = E_t[(r_{t+1}-\mu_{t+1})(r_{t+1}-\mu_{t+1})']$ is the conditional variance-covariance matrix of r_{t+1}. At each period t, the investor solves the following problem:

$$\begin{aligned}&\max_{w_t} \quad \{\mu_{p,t+1|t} = w_t'\mu_{t+1|t} + (1-w_t'\iota)r_f\}\\&\text{subject to } (\sigma_p^*)^2 = w_t'\Sigma_{t+1|t}w_t,\end{aligned} \tag{3.9}$$

where w_t is the $N\times 1$ vector of portfolio weights on the risky assets, ι is an $N\times 1$ vector of 1s, $\mu_{t+1|t}$ is the conditional expected return of the portfolio, σ_p^* is the target volatility of the portfolio returns, and r_f is the domestic riskless return. The solution to this optimization problem is the risky asset weights,

$$w_t = \frac{\sigma_p^*\,\Sigma_{t+1|t}^{-1}(\mu_{t+1|t}-\iota r_f)}{\sqrt{(\mu_{t+1|t}-\iota r_f)'\Sigma_{t+1|t}^{-1}(\mu_{t+1|t}-\iota r_f)}}, \tag{3.10}$$

while the weight on the riskless asset is $(1-w_t'\iota)$. The gross portfolio return at time $t+1$ is

$$\mathrm{R}_{p,t+1} = 1 + w_t'r_{t+1} + (1-w_t'\iota)r_f = \mathrm{R}_f + w_t'(\mathrm{R}_t - \iota\mathrm{R}_f), \tag{3.11}$$

where R_t is the $N \times 1$ vector of gross risky returns and R_f is the gross domestic riskless return. The conditional covariance matrix of exchange returns is not modelled explicitly. $\Sigma_{t+1|t}$ is simply set to be equal to Σ_t, which is the unconditional covariance matrix of the exchange rate returns at time t.

A driftless random walk (RW) is used as a benchmark model, by setting $a = b = 0$ in the Equation (3.6). With this setup, the conditional expectation of exchange rate returns will be equal to zero. The two models are firstly compared in terms of the Sharpe Ratio, calculated as the ratio of the average realized portfolio excess return to the standard deviation of the portfolio returns.

The model to predict exchange rates based on international financial adjustment are examined in terms whether it provides economically higher gains than the random walk model using a utility-based criterion. The economic performance of the two models are compared using the following metrics: maximum performance fee, excess premium, and break-even transaction costs.

The maximum performance fee indicates the level of fee that a risk-averse investor with quadratic utility would be willing to pay to have access to the additional information available in bilateral external imbalances relative to the benchmark random walk model (West et al., 1993 and Fleming et al., 2001). Suppose that holding the optimal portfolio based on the random walk model generates the same average utility as holding the optimal portfolio based on bilateral external imbalances strategy that is subject to quarterly expenses Φ. Since the investor would be indifferent between these two strategies, Φ can be interpreted as the maximum performance fee he will pay to switch from the first strategy to the second strategy. The performance fee is the value Φ that satisfies:

$$\sum_{t=0}^{T-1}\left\{(R^*_{p,t+1}-\Phi)-\frac{\delta}{2(1+\delta)}(R^*_{p,t+1}-\Phi)^2\right\}=\sum_{t=0}^{T-1}\left\{R_{p,t+1}-\frac{\delta}{2(1+\delta)}R^2_{p,t+1}\right\}, \qquad (3.12)$$

where $R^*_{p,t+1}$ is the gross portfolio return constructed using the bilateral external imbalances strategy, $R_{p,t+1}$ is the gross portfolio return implied by the benchmark RW strategy, and δ is the investor's constant degree of relative risk aversion. In the empirical section, the relative risk aversion is set equal to 6.

The second performance measure, the excess premium, does not require an assumption of any particular utility function. In particular, a manipulation-proof performance measure (Goetzmann et al., 2007) is defined as:

$$M(R_p)=\frac{1}{1-\delta}\ln\left\{\frac{1}{T}\sum_{t=0}^{T-1}\left(\frac{R_{p,t+1}}{R_f}\right)^{1-\delta}\right\}, \qquad (3.13)$$

where $M(R_p)$ is an estimate of the portfolio's premium return after adjusting for risk and can be interpreted as the certainty equivalent of the excess portfolio returns. The difference between manipulation-proof performance measures for competing portfolios can be computed as follows:

$$\Theta = M(R^*_p)-M(R_p), \qquad (3.14)$$

which can be interpreted as the excess premium return of the bilateral external imbalances strategy relative to the RW strategy.

To measure the impact of transaction costs, we can compute the break-even proportional transaction cost τ^{be} that renders investors indifferent between two alternative strategies (Han, 2006). Assume that transaction costs equal a fixed proportion (τ) of the value traded in each bond: $\tau\,|\,w_t - w_{t-1}(R_t / R_{p,t})\,|$. Comparing the dynamic bilateral external imbalances strategy with the RW strategy, an investor who pays transaction costs lower than τ^{be} will prefer the former strategy.

3.5 Economic Evaluation of Time Varying Bilateral External Imbalances

This section provides empirical results of bilateral external imbalances' economic performance in predicting exchange rate changes. The regression is a state-space model, estimated using Bayesian technique as presented in the Appendix 3.C. The analysis is employed both in-sample and out-of-sample, as it is known that significant in-sample predictability does not guarantee significant out-of-sample predictability (Inoue and Kilian, 2005).

The first five years (20 observations) rolling data is used as a training sample to estimate via ordinary least square (OLS) estimator a fixed coefficient model as in Equation (3.6). Therefore, the evaluation for in-sample covers the period from 1988Q1 to 2015Q4. Out-of-sample analysis uses a further fifteen years (60 observations) rolling data that start from 2003Q1 through 2015Q4. To avoid any look-ahead bias, bilateral external imbalances variable for each foreign country is reestimated at each point in time using only available information. This ensures that the rolling-window forecasts are always constructed conditioning on an information set that is available at the time of the forecast.

The economic evaluation is based on four criteria: the Sharpe Ratio, the maximum performance fee, the excess premium return, and the break-even transaction cost. Each strategy uses a quarterly rebalancing period and three target annualized portfolio volatilities of 8%, 10%, 12%, and a degree of relative risk aversion of 6. The estimates of maximum fee and excess premium are reported in annualized basis points ("bp"), whereas the estimates of break-even transaction costs are given in quarterly bp.

3.5.1 Main Results

Table 3.3 Panel A presents risk-return performances of the time varying parameter (TVP) external imbalances and the RW strategies. The in-sample results show that at the target volatility of 8%, the external imbalances strategy delivers higher annual return (13.8%) and Sharpe ratio (0.93) than the RW's annual return (11.3%) and Sharpe ratio (0.68). The performance fee a U.S. investor is willing to pay for switching from the RW strategy to the external imbalances strategy is 247 annual bp, whereas the premium return the external imbalances strategy yields in excess to the RW strategy is 280 annual bp.

The TVP external imbalances strategy retains the significant profitability in the out-of-sample. At the target volatility of 8%, the strategy offers annual return of 7.3% and Sharpe ratio of 0.77. The RW strategy meanwhile, posts an annual return of 4.3% and Sharpe ratio of 0.25. Other target volatilities of 10% and 12% show the same Sharpe ratio both for the TVP external imbalances and the RW. These figures are encouraging, considering the fact that periods between 2003 and 2015 were marked by low interest rate regime, where the average 3 months USD deposit (as an alternative outlet for asset allocation) is around 1.8% during the period.[6] Note that in all target volatilities, the Sharpe ratios for the external imbalances are about three times than the Sharpe ratios for the RW, which in economic terms is a large difference (this contrasts with the comparison of the two strategies in the in-sample analysis, where the Sharpe ratios of external imbalances are only about 40% higher than the RW's Sharpe ratios). The maximum performance fee a U.S. investor is willing to pay for switching from the RW to

[6] The raw data is from Datastream.

the external imbalances is 440 annual bp, and the external imbalances' premium return in excess to the RW is 444 annual bp.

Furthermore, if transaction costs are sufficiently high, the fluctuations in the dynamic weights of the external imbalances strategy would render the strategy too costly to implement relative to the RW strategy. This issue is addressed by computing the break-even transaction cost as the proportional transaction cost that cancels out the positive performance fee of the external imbalances strategy relative to the RW strategy. A U.S. investor who pays a transaction cost lower than the break-even cost will continue to prefer a strategy that delivers a positive performance fee. Table 3.3 Panel A shows that break even cost is generally high. At the target portfolio volatility of 8%, the costs are 132 and 103 quarterly bp respectively for the in-sample and out-of-sample periods. This means that a U.S. investor can bear paying a transaction cost of up to 132 (102) quarterly bp during the in-sample (out-of-sample) period to execute the external imbalances strategy. To put it in the perspective, the spread on exchange rates was generally very low, never higher than 20 bp for the major exchange rates (Akram et al., 2008). The exercise in this paper allows portfolio rebalancing once per quarter, hence it is unlikely that transaction costs can offset the positive performance fees from using the external imbalances strategy.

Evaluating TVP external imbalances, one can obtain the density for each economic performance metric of maximum fee, excess premium, and break-even transaction cost. For each draw and each quarter t, the distribution of the unconditional variance-covariance matrix Σ_t (as a substitute for the conditional matrix of $\Sigma_{t+1|t}$) can be retrieved. Combining the variance-covariance matrix with the median forecast of risky asset returns as described in Section 3.4, the density for each of the three measures of economic performance has positive median and narrow standard deviation. Out-of-sample results show that at the target volatility of 8%, the medians of the maximum fee, excess premium, and break-even transaction cost are 423, 426, and 93 bp, with standard deviations of 27, 26 and 7 bp respectively (Figure 3.2). Hence the median values are still positive, even when one takes a spread of three standard deviations. This suggests the economic performance measures are significantly different from zero, rendering the benefit of employing TVP external imbalances to predict exchange rate returns. Similar results are obtained for other target volatilities.

Allowing the parameters in Equation (3.6) to be time varying has created more dynamic relationship between bilateral external imbalances and exchange rate changes. A further analysis shows that the TVP external imbalances strategy is indeed found to outperform a strategy where the parameters in Equation (3.6) are restricted to be constant. The strategy based on prediction of exchange rate returns using TVP has higher return and Sharpe ratio than the strategy if the prediction is based on fixed coefficients of parameters (Table 3.3 Panel B) both in the in-sample and out-of-sample. Out-of-sample have more significant results than the in-sample, which indicates that TVP estimation works well when one considers the strategy implementation. For the out-of-sample, at the target volatility of 8%, the maximum performance fee a U.S. investor is willing to pay for switching from the constant parameters to the TVP external imbalances is 198 annual bp, the TVP-based strategy's premium return in excess to the constant parameters-based strategy's is 187 annual bp, and the average break-even transaction cost of the two strategies is 72 quarterly bp.

Hence, forecasting using time varying parameters allow the model to be adaptable in capturing the relationship between the U.S. bilateral external imbalances and the foreign exchange rates, which afterwards provide more economically useful exchange rates forecasts. It is the differences in the estimated-parameters that render the benefit of

TVP in comparison to constant-parameters. For the out-of-sample, these differences of the estimated parameters between the two regressions of each country are shown graphically in Figure 3.3.[7] The dynamics of the estimated coefficients are worth mentioning here. Take Japan as an example. In the entire out-of-sample period, the coefficients of external imbalances from constant parameters estimation are positive, which are in contrast with a prediction from the theoretical model of bilateral external imbalances. The coefficients from TVP estimation on the other hand, results in negative values during the entire period, which are in line with the theory. Germany shows similar results. In some other cases nevertheless, for example the U.K., the TVP coefficients are shown to have positive values in the second half of the period (in contrast with the negative values from constant parameter estimation). This can be addressed by imposing a restriction on the estimated coefficients, which will be discussed in the latter part of this chapter.

All in all, the above results suggest that exploiting time varying relationship between bilateral measures of U.S. external imbalances and foreign exchange rates deliver economically and significantly valuable information for investors in currency market.

3.5.2 Exchange Rate Returns Predictability

The theoretical model of international financial adjustment provides a framework to predict exchange rate changes. Economic evaluation meanwhile, by construction involves interest rate differentials where an investor is compensated not only from exchange rate returns, but also from the foreign interest rates by buying foreign bonds. To decompose the performance of external imbalances model in predicting exchange rates, one could calculate the returns that are solely from exchange rate changes, hence

[7] Note that the variation in the constant-parameters are resulted from the rolling window analysis. At each point in time, both regressions of constant parameters as well as TVP are reestimated using the available information up to quarter *t*.

without any assumptions on interest rate differentials.

When interest rate differentials are excluded (Table 3.4), the RW strategy delivers negative returns (for example, –3.3% for in-sample and –3.9% for out-of-sample at the target volatility of 8%). Hence the previous positive performances of the RW strategy (Table 3.3) are mostly compensations from foreign bonds.

The TVP external imbalances strategy meanwhile consistently delivers positive economic performance net of interest rate differentials. The contribution from interest rate differentials is more apparent for the in-sample results. At the target volatility of 8%, in-sample results show that the strategy has an annual return of 6.9% and a Sharpe ratio of 0.24 (Table 3.4), lower than the previous annual return of 13.8% and Sharpe ratio of 0.93 (Table 3.3). This is consistent with the fact that in-sample covers period of high interest rates from late 1980s and 1990s. For the out-of-sample period however, in contrast, the TVP external imbalances have similar return properties whether interest rate differentials are included (Table 3.3) or excluded (Table 3.4). This suggests that the total returns from TVP external imbalances are mostly from exchange rate returns.

In these instances, when we observe the portfolio solely from exchange rate returns, the fall in the returns from the RW strategy suggests that TVP external imbalances is even more favorable. The three economic performance measures of maximum fee, excess premium, and break-even transaction costs (Table 3.4) are significantly higher than the results when interest rate differentials are taken into account (Table 3.3). Out-of-sample results for example, show that at the target volatility of 8% the maximum performance fee a U.S. investor is willing to pay for switching from the RW strategy to the TVP external imbalances strategy is 1260 annual bp, the excess premium return of the TVP external imbalances relative to the RW is 1290 annual bp, and the average break-even transaction cost of the TVP and the RW strategies is 282 quarterly bp.

The above results suggest the bilateral external imbalances significantly predict exchange rate changes in a consistent manner, where increases of such measures are found to predict appreciation of foreign currencies and vice versa.

3.5.3 Valuation and Trade Channels

One can examine the relative importance of cyclical net foreign assets and net exports in determining the predictive power of bilateral external imbalances. Dissecting the two also sheds some light with regards transmission of valuation channel and trade channel to predict exchange rate changes. In this subsection, investment strategies that use either TVP cyclical net foreign assets or TVP net exports as the predictive variable are considered and compared with the strategy that uses TVP external imbalances.

Consistent with initial assessment of statistical significance in Section 3.3, using information from either net foreign assets or net exports deliver positive economic performance both in-sample and out-of-sample (Table 3.5). The three measures of maximum fee, excess premium and break-even transaction costs are all positive. This indicates that any strategy is favorable than the random walk strategy. In-sample results show that bilateral cyclical net foreign assets and net exports yield similar positive performance fees and excess premium. It is worth noting that the bilateral external imbalances strategy is dominated by its component, as shown by lower fee and excess premium. Out-of-sample however, which arguably is a more realistic exercise, depicts that the bilateral external imbalances outperforms significantly both strategies of the net foreign assets or the net exports. All three economic performance measures of the bilateral external imbalances are higher than the measures that use the net foreign assets or the net exports. For example, the maximum performance fee at the target volatility of 8% is 440 annual bp for the bilateral external imbalances, whereas the net foreign assets' and the net exports' performance fees are nearly half of that i.e. 272 and 271 annual bp respectively. Moreover, at the same target volatility, the bilateral external imbalances' return premium (in excess of the RW) is 444 annual bp, while the net foreign assets and the net exports deliver excess premium of 273 and 278 annual bp. Break-even transaction costs are also in line with the other two measures: 103, 85, and 69 quarterly bp for the composite external imbalances measure and two of its components respectively.

The above results suggest that the asset/liability component plays similar role as the export/imports component in driving the forecasting power of cyclical external imbalances for exchange rates. This is in contrast with results in previous literature using single equation constant parameter model that show the net foreign assets component has significantly more important role than the net exports component in driving the forecasting power of exchange rates (Della Corte et al., 2012).

3.5.4 Additional Results and Robustness Tests

Various Rolling Windows. TVP external imbalances strategy is built using an information set of twenty years data and is evaluated for the out-of-sample period from 2003Q1 to 2015Q4. If the rolling window size is expanded from fifteen to nineteen years of data, we have an out-of-sample period that begins just before the global financial turmoil i.e. from 2007Q1 to 2015Q4. This period is particularly important given the substantial instabilities that characterized the period with consequences for the volatilities in the exchange rates. Focusing on this out-of-sample period, TVP external imbalances strategy that employs the default rolling window of fifteen years of data delivers Sharpe ratio of about 0.70 (Table 3.6). This does not differ substantially when the exercise is done for the out-of-sample period previously from 2003Q1 to 2015Q4 (Table 3.3). The random walk strategy however suffers as the Sharpe ratio decreases to 0.06 (from 0.25, Table 3.3). As a result, the economic value measurements increase by several percentage points. This test suggests the TVP external imbalances' robustness and random walk's instabilities with regards out-of-sample period.

Moreover, taking the out-of-sample period 2007Q1–2015Q4 as fixed, we can see the impact of different window size from fifteen – as the default size – to be reduced to as short as ten years or expanded to nineteen years of data. Reducing the rolling window size from fifteen to ten years means there is less information in the estimated imbalances measure, hence the cyclical imbalances between the U.S. and foreign countries might not fully capture the whole dynamics. The three economic performance measures as a result, decrease by few percentage points. Meanwhile, the Sharpe ratio of the TVP external imbalances strategy increases when the rolling window size is expanded to seventeen years, but decreases for nineteen years rolling window size. In this case, more information for the bilateral external imbalances does not necessarily translates into more beneficial exchange rate forecasts. This analysis indicates that a certain number of observations are needed to capture business cycles, to produce meaningful bilateral cyclical imbalances measures that are able to predict exchange rates.

Economic Restrictions. I examine the impact of imposing meaningful economic restrictions on the forecasts of exchange rate returns in the spirit of Campbell and Thompson (2008). Specifically, the performance measures are replicated under the following restriction. The slope in the predictive regression (3.6) is set to zero when it is estimated with a positive sign. This restriction is justified by the negative relation suggested by the theoretical model (Appendix 3.B). The TVP external imbalances investment strategy still shows valuable economic performance relative to the RW strategy (Table 3.7). Consider 8% as target volatility, the maximum performance fees are still positive and at a good margin, which are 232 annual bp for the in-sample and 245 annual bp for the out-of-sample. The other performance measures confirm these findings, indicating that the TVP external imbalances strategy is still performing well when meaningful, theoretically-consistent restrictions are imposed in the predictive regressions (although the strategy performance relative to unrestricted case is slightly worsen for the out-of-sample).

Implementation Lags. The data set employed in this study are not in real time, i.e. we cannot guarantee that the data used to construct bilateral external imbalances were available in a timely fashion to an investor at time t to generate forecasts of exchange rate returns at time $t+1$. This issue is addressed by lagging the bilateral external adjustment in the conditioning information set available to the investor. When the predictive variable is available with a delay of 2 and 4 quarters (corresponding to a six-month and one-year time difference between the predictive variable and the return to forecast), the economic value tends to decrease (Table 3.8) which is expected. Although all three measures of maximum fee, excess premium, and break-even transaction costs at all target volatilities are slightly lower than the same measures when the predictive variable is used without delay (Table 3.3 Panel A), they show a persistent performance to outperform the RW strategy even with 4 quarter lags in the information set.

Currencies Set. By design, the dynamic foreign exchange strategy invests in nine foreign bonds and thus exploits predictability in nine exchange rates. Since we economically evaluate the performance of portfolios rather than individual exchange rates, it would be interesting to assess whether the superior portfolio performance of one versus another empirical model is driven by one particular currency. When one of the currencies (and hence one of the bonds) from the investment opportunity set is excluded from the investment opportunity set, all three economic performance measures have positive values both in-sample and out-of-sample (Table 3.9). This empirical evidence suggests that previous results are not driven by any one particular currency.

3.6 Conclusion

Recent literature shows that international financial adjustment is helpful in predicting exchange rates. Furthermore, an established literature documents time-evolving macroeconomic conditions and relationships among macroeconomic variables (Stock and Watson, 1996). Taken together, these observations raise the possibility that accounting for time-evolving dynamics may be fundamental to improve exchange rate models' forecasting ability.

In this chapter, I construct bilateral measures of cyclical external imbalances and use the measures to predict exchange rate returns in a framework that allows for the parameters of the forecasting regression to change over time. Evaluation of the model is done in terms of economic significance from the perspective of a U.S. investor who employs the model for the purpose of building a portfolio that consists of investment in foreign countries. The economic evaluation compares the performances of a portfolio formulated on the basis of exchange rate forecasts formed using a random walk model, versus the performance of a portfolio formulated on the basis of a time-varying parameters bilateral external imbalances model.

Empirical evidence shows that bilateral external imbalances have strong in-sample and out-of-sample predictive ability for exchange rate returns. The time varying regressions are found to outperform the random walk and standard linear regressions employed in a rolling window forecasting approach, in short horizon of one quarter ahead. The cyclical net foreign assets and net exports, which are two main components of bilateral external imbalances, contribute similarly to the predictive power of exchange rate changes.

The findings in this chapter contributes to the literature for the support of macroeconomic fundamentals to forecast exchange rates, in an environment when we allow the predictive regression coefficients to be time-varying.

Figure 3.1: Bilateral External Imbalances

The figure plots the time series of bilateral external imbalances between the United States and nine foreign countries of Australia, Canada, Germany, India, Japan, South Korea, Mexico, Singapore, and the United Kingdom. The bilateral external imbalances measure linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports, between the United States and respective countries. The data set covers quarterly data from 1983Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

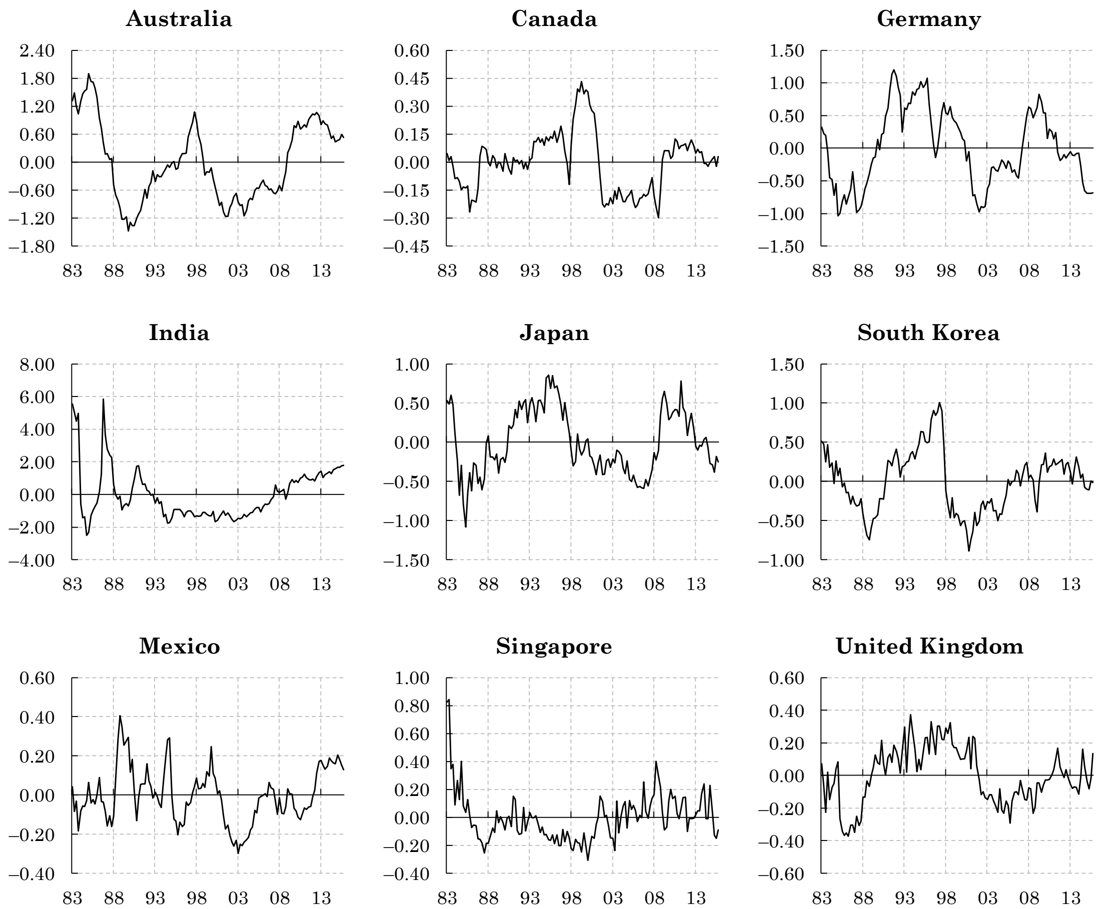
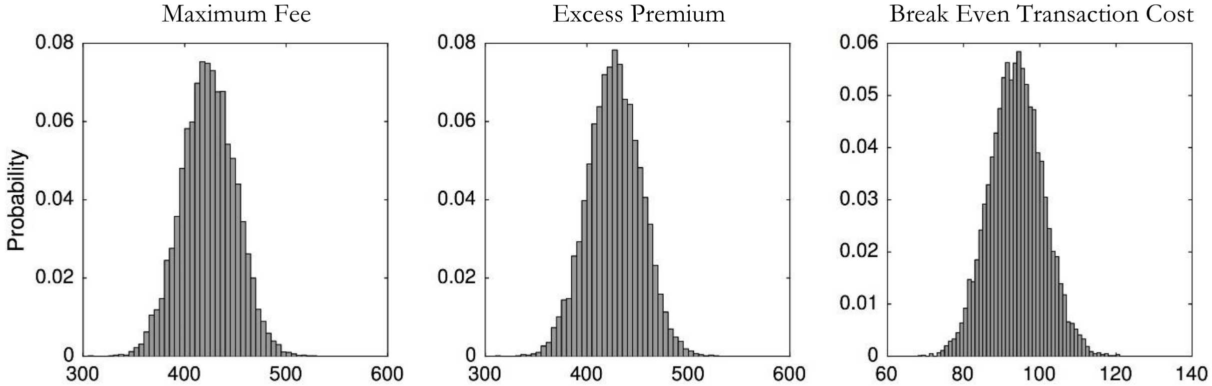


Figure 3.2: Out-of-Sample Economic Performance Metrics Density

The figure plots the density of out-of-sample three economic performance measures to invest in nine foreign currencies relative to the USD. The economic performance measures are (i) the maximum performance fee (in annual basis points) a risk-averse investor with quadratic utility and a degree of relative risk aversion equal to 6 is willing to pay for switching from the Random Walk (RW) to Time Varying Parameter (TVP) external imbalances strategy, (ii) the excess premium return (in annual basis points) of TVP external imbalances relative to RW strategy, and (iii) the break-even proportional transaction cost (in quarterly basis points) which cancels out the utility advantage of the TVP external imbalances relative to RW strategy. RW is an investment strategy that uses the driftless random walk model to forecast nominal exchange rate returns. The TVP external imbalances is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical external imbalances between the United States and nine foreign counterparts to forecast nominal exchange rate returns. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. The TVP is estimated using Bayesian technique as in Appendix 3.C. Each strategy considers a U.S. investor who dynamically rebalances his wealth every quarter between the domestic bond in USD and nine foreign bonds in foreign currencies. The exchange rate forecasts are used to convert the foreign bond returns in USD. The strategy maximizes expected returns subject to a given target volatility of 8%. The figure provides the median and standard deviation of each economic performance measure. The height of each bar is the relative number of observations, i.e. number of observations in bin divided by total number of observations. The sum of the bar heights is 1. The out-of-sample analysis uses a rolling window of twenty years and runs from 2003Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.



Median = 423
Standard Deviation = 27

Median = 426
Standard Deviation = 26

Median = 93
Standard Deviation = 7

Figure 3.3: Out-of-Sample Coefficients of Constant and Time Varying Parameters

The figure plots the coefficients of constant (dashed lines) parameters and time varying parameters (solid lines) regressions of exchange rate changes on bilateral external imbalances between the United States and nine foreign countries of Australia, Canada, Germany, India, Japan, South Korea, Mexico, Singapore, and the United Kingdom. The regressions are out-of-sample, conditioning on an information set that is available at the time of the forecast. At each point in time, constant parameters regressions are reestimated using fixed coefficient models, and time varying parameters regressions are reestimated using Bayesian technique as in Appendix 3.C. The time varying parameters coefficients are from non-smoothed Kalman filter estimation. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports, between the United States and respective countries. The out-of-sample analysis uses a rolling window of twenty years and runs from 2003Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

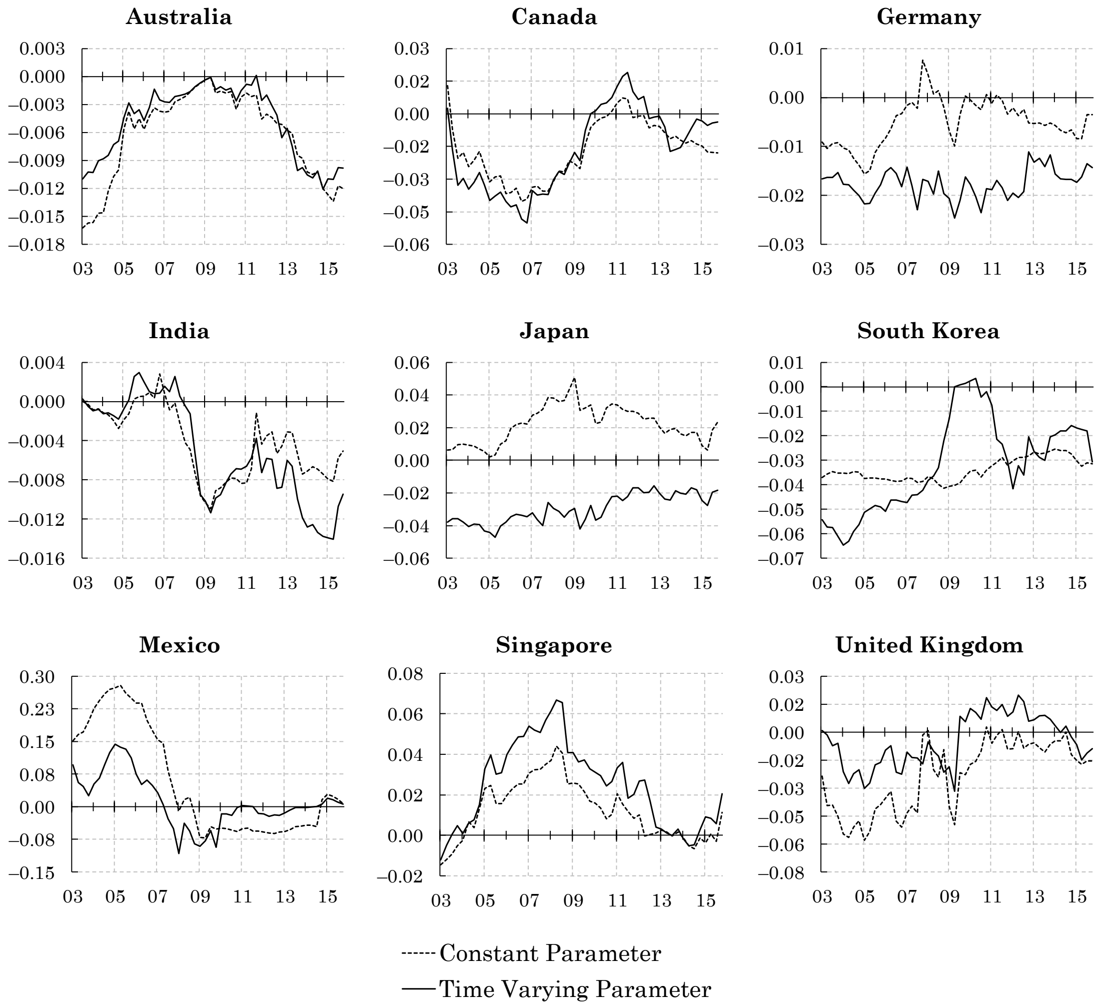


Table 3.1: Correlation of Bilateral External Imbalances between Foreign Countries

The table reports correlations of bilateral external imbalances between the United States and nine foreign countries. The bilateral external imbalances measure linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports, between the United States and respective countries. The data set covers quarterly data from 1983Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

	Australia	Canada	Germany	India	Japan	Korea	Mexico	Singapore
Canada	0.113							
Germany	–0.112	0.408						
India	0.299	0.012	–0.024					
Japan	0.113	0.440	0.723	0.166				
Korea	0.460	0.058	0.460	0.164	0.594			
Mexico	0.036	0.327	0.162	0.063	–0.026	–0.089		
Singapore	0.254	–0.369	–0.025	0.389	0.021	0.199	–0.091	
United Kingdom	–0.113	0.602	0.527	–0.261	0.497	0.282	0.210	–0.199

Table 3.2: Bilateral External Imbalances and Changes in Exchange Rates

The table reports results from regressions of changes (i.e. log differences) in exchange rates on the bilateral measure of cyclical external imbalances in Panel A, and on the bilateral measure of cyclical net foreign assets and net exports in Panel B. The number of quarters for exchange rate changes is denoted as *k*, which varies from 1, 2, 3, 4, 8, and 12 quarters. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. The bilateral measure of cyclical net foreign assets linearly combines stationary components in bilateral foreign assets and liabilities. The bilateral measure of cyclical net exports linearly combines stationary components in bilateral exports and imports. All regressions include country 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 computed using feasible generalized least squares under the assumption of contemporaneous cross-correlation between changes in exchange rates. The table also reports the *p*-value of one-sided test of null hypothesis that the respective regression coefficient is greater than or equal to zero. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data set covers quarterly data of nine countries from 1983Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

Panel A: Regressions of Changes in Exchange Rates to Bilateral External Imbalances

	Changes in Exchange Rates					
Number of quarters (*k*)	1	2	3	4	8	12
Bilateral External Imbalances	–0.007***	–0.017***	–0.026***	–0.036***	–0.067***	–0.081***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)	(0.009)
Observations	1,179	1,170	1,161	1,152	1,116	1,080
R–Squared	0.06	0.10	0.14	0.16	0.24	0.28
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
Null: Bilateral External Imbalances ≥ 0	0.001	0.000	0.000	0.000	0.000	0.000

(continued)

Table 3.2: Bilateral External Imbalances and Changes in Exchange Rates (continued)

Panel B: Regressions of Changes in Exchange Rates to Bilateral Cyclical Net Foreign Assets and Net Exports

	Changes in Exchange Rates					
Number of quarters (*k*)	1	2	3	4	8	12
Bilateral Cyclical Net Foreign Assets	–0.005*	–0.010**	–0.016***	–0.021***	–0.036***	–0.039***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.009)	(0.010)
Bilateral Cyclical Net Exports	–0.016**	–0.041***	–0.066***	–0.087***	–0.176***	–0.230***
	(0.008)	(0.011)	(0.013)	(0.016)	(0.021)	(0.025)
Observations	1,179	1,170	1,161	1,152	1,116	1,080
R–Squared	0.06	0.11	0.15	0.17	0.25	0.30
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors	FGLS	FGLS	FGLS	FGLS	FGLS	FGLS
Null: Bilateral Cyclical Net Foreign Assets ≥ 0	0.036	0.006	0.001	0.000	0.000	0.000
Null: Bilateral Cyclical Net Exports ≥ 0	0.017	0.000	0.000	0.000	0.000	0.000

Table 3.3: Economic Value of Time Varying Parameter Regression

The table reports the in-sample and out-of-sample economic performance of currency strategies investing in nine foreign currencies relative to the USD. Random walk (RW) is an investment strategy that uses the driftless random walk model to forecast nominal exchange rate returns. The time varying parameter (TVP) external imbalances is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical external imbalances between the United States and nine foreign counterparts to forecast nominal exchange rate returns, using TVP regression. The constant parameter external imbalances is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical external imbalances between the United States and nine foreign counterparts to forecast nominal exchange rate returns, using constant parameter regression. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. The TVP is estimated using Bayesian technique as in Appendix 3.C. Each strategy considers a U.S. investor who dynamically rebalances his wealth every quarter between the domestic bond in USD and nine foreign bonds in foreign currencies. The exchange rate forecasts are used to convert the foreign bond returns in USD. The strategy maximizes expected returns subject to a given target volatility of 8%, 10%, and 12%. The table shows the annualized percentage mean, percentage volatility, and Sharpe ratio of each portfolio. The table also shows three economic performance measures comparing two strategies. In Panel A, the economic performance measures are (i) the maximum performance fee (in annual basis points) a risk-averse investor with quadratic utility and a degree of relative risk aversion equal to 6 is willing to pay for switching from the RW to TVP external imbalances strategy, (ii) the excess premium return (in annual basis points) of TVP external imbalances relative to RW strategy, and (iii) the break-even proportional transaction cost (in quarterly basis points) which cancels out the utility advantage of the TVP external imbalances relative to RW strategy. In Panel B, the economic performance measures are (i) the maximum performance fee (in annual basis points) a risk-averse investor with quadratic utility and a degree of relative risk aversion equal to 6 is willing to pay for switching from the constant parameter to TVP external imbalances strategy, (ii) the excess premium return (in annual basis points) of TVP external imbalances relative to constant parameter external imbalances strategy, and (iii) the break-even proportional transaction cost (in quarterly basis points) which cancels out the utility advantage of the TVP external imbalances relative to constant parameter external imbalances strategy. The in-sample analysis covers quarterly data from 1988Q1 to 2015Q4. The out-of-sample analysis uses a rolling window of twenty years and runs from 2003Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

(continued)

Table 3.3: Economic Value of Time Varying Parameter Regression (continued)

Panel A: Time Varying Parameter External Imbalances vs Random Walk

	Random Walk (RW)			TVP External Imbalances			TVP External Imbalances vs RW		
Target volatility	Mean	Volatility	Sharpe Ratio	Mean	Volatility	Sharpe Ratio	Maximum Fee	Excess Premium	Break Even Transaction Cost
In sample									
8%	11.3	9.9	0.68	13.8	9.9	0.93	247	280	132
10%	13.0	12.2	0.69	16.1	12.3	0.94	310	373	132
12%	14.6	14.6	0.69	18.4	14.6	0.95	374	481	133
Out of sample									
8%	4.3	9.8	0.25	7.3	7.2	0.77	440	444	103
10%	4.9	12.2	0.25	8.7	9.0	0.77	595	605	109
12%	5.5	14.7	0.25	10.1	10.8	0.77	767	788	115

Panel B: Time Varying Parameter vs Constant Parameter External Imbalances

	Constant Parameter External Imbalances			TVP External Imbalances			TVP vs Constant Parameter External Imbalances		
Target volatility	Mean	Volatility	Sharpe Ratio	Mean	Volatility	Sharpe Ratio	Maximum Fee	Excess Premium	Break Even Transaction Cost
In sample									
8%	12.5	9.4	0.85	13.8	9.9	0.93	85	97	56
10%	14.5	11.5	0.87	16.1	12.3	0.94	89	116	50
12%	16.5	13.7	0.88	18.4	14.6	0.95	86	133	44
Out of sample									
8%	6.1	8.7	0.49	7.3	7.2	0.77	198	187	72
10%	7.2	10.8	0.50	8.7	9.0	0.77	271	254	78
12%	8.2	12.9	0.50	10.1	10.8	0.77	354	332	83

Table 3.4: Economic Value from Exchange Rate Returns

The table reports the in-sample and out-of-sample economic performance of currency strategies investing in nine foreign currencies relative to the USD, where the strategies' return does not include interest rate differentials. Random walk (RW) is an investment strategy that uses the driftless random walk model to forecast nominal exchange rate returns. The time varying parameter (TVP) external imbalances is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical external imbalances between the United States and nine foreign counterparts to forecast nominal exchange rate returns. The TVP is estimated using Bayesian technique as in Appendix 3.C. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. Each strategy considers a U.S. investor who dynamically rebalances his wealth every quarter between the domestic bond in USD and nine foreign bonds in foreign currencies. The exchange rate forecasts are used to convert the foreign bond returns in USD. The strategy maximizes expected returns subject to a given target volatility of 8%, 10%, and 12%. The table shows the annualized percentage mean, percentage volatility, and Sharpe ratio of each portfolio. The table also shows three economic performance measures comparing the two strategies, which are (i) the maximum performance fee (in annual basis points) a risk-averse investor with quadratic utility and a degree of relative risk aversion equal to 6 is willing to pay for switching from the RW to TVP external imbalances strategy, (ii) the excess premium return (in annual basis points) of TVP external imbalances relative to RW strategy, and (iii) the break-even proportional transaction cost (in quarterly basis points) which cancels out the utility advantage of the TVP external imbalances relative to RW strategy. The in-sample analysis covers quarterly data from 1988Q1 to 2015Q4. The out-of-sample analysis uses a rolling window of twenty years and runs from 2003Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

	Random Walk (RW)			TVP External Imbalances			TVP External Imbalances vs RW		
Target volatility	Mean	Volatility	Sharpe Ratio	Mean	Volatility	Sharpe Ratio	Maximum Fee	Excess Premium	Break Even Transaction Cost
In sample									
8%	–3.3	9.6	–0.82	6.9	9.7	0.24	1013	1052	526
10%	–5.3	12.0	–0.82	7.5	12.2	0.24	1266	1344	526
12%	–7.2	14.4	–0.82	8.1	14.6	0.24	1518	1655	528
Out of sample									
8%	–3.9	10.1	–0.57	7.3	7.3	0.76	1260	1290	282
10%	–5.3	12.6	–0.57	8.7	9.0	0.77	1613	1677	283
12%	–6.7	15.1	–0.57	10.1	10.8	0.77	1978	2097	286

Table 3.5: Value from Decomposition of Time Varying Parameter Regression

The table reports the in-sample and out-of-sample economic performance of currency strategies investing in nine foreign currencies relative to the USD. Random walk (RW) is an investment strategy that uses the driftless random walk model to forecast nominal exchange rate returns. The time varying parameter (TVP) external imbalances is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical external imbalances between the United States and nine foreign counterparts to forecast nominal exchange rate returns. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. The TVP net foreign assets is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical net foreign assets between the United States and nine foreign counterparts to forecast nominal exchange rate returns. The bilateral measure of cyclical net foreign assets linearly combines stationary components in bilateral foreign assets and liabilities. The TVP net exports is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical net exports between the United States and nine foreign counterparts to forecast nominal exchange rate returns. The bilateral measure of cyclical net exports linearly combines stationary components in bilateral foreign exports and imports. The TVP is estimated using Bayesian technique as in Appendix 3.C. Each strategy considers a U.S. investor who dynamically rebalances his wealth every quarter between the domestic bond in USD and nine foreign bonds in foreign currencies. The exchange rate forecasts are used to convert the foreign bond returns in USD. The strategy maximizes expected returns subject to a given target volatility of 8%, 10%, and 12%. The table shows the annualized percentage mean, percentage volatility, and Sharpe ratio of each portfolio. The table also shows three economic performance measures comparing the two strategies, which are (i) the maximum performance fee (in annual basis points) a risk-averse investor with quadratic utility and a degree of relative risk aversion equal to 6 is willing to pay for switching from the RW to TVP external imbalances strategy, (ii) the excess premium return (in annual basis points) of TVP external imbalances relative to RW strategy, and (iii) the break-even proportional transaction cost (in quarterly basis points) which cancels out the utility advantage of the TVP external imbalances relative to RW strategy. The in-sample analysis covers quarterly data from 1988Q1 to 2015Q4. The out-of-sample analysis uses a rolling window of twenty years and runs from 2003Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

	TVP External Imbalances vs RW			TVP Net Foreign Assets vs RW			TVP Net Exports vs RW		
Target volatility	Maximum Fee	Excess Premium	Break Even Transaction Cost	Maximum Fee	Excess Premium	Break Even Transaction Cost	Maximum Fee	Excess Premium	Break Even Transaction Cost
In sample									
8%	247	280	132	379	387	286	373	383	124
10%	310	373	132	503	521	302	487	511	128
12%	374	481	133	641	677	318	612	657	133
Out of sample									
8%	440	444	103	272	273	85	271	278	69
10%	595	605	109	382	387	94	370	386	75
12%	767	788	115	508	520	103	482	511	80

Table 3.6: Out-of-Sample Economic Value with Different Window Lengths

The table reports out-of-sample economic performance of currency strategies investing in nine foreign currencies relative to the USD for different window lengths of 10, 13, 15, 17, and 19 years. Random walk (RW) is an investment strategy that uses the driftless random walk model to forecast nominal exchange rate returns. The time varying parameter (TVP) external imbalances is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical external imbalances between the United States and nine foreign counterparts to forecast nominal exchange rate returns. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. The TVP is estimated using Bayesian technique as in Appendix 3.C. Each strategy considers a U.S. investor who dynamically rebalances his wealth every quarter between the domestic bond in USD and nine foreign bonds in foreign currencies. The exchange rate forecasts are used to convert the foreign bond returns in USD. The strategy maximizes expected returns subject to a given target volatility of 8%, 10%, and 12%. The table shows the annualized percentage mean, percentage volatility, and Sharpe ratio of each portfolio. The table also shows three economic performance measures comparing the two strategies, which are (i) the maximum performance fee (in annual basis points) a risk-averse investor with quadratic utility and a degree of relative risk aversion equal to 6 is willing to pay for switching from the RW to TVP external imbalances strategy, (ii) the excess premium return (in annual basis points) of TVP external imbalances relative to RW strategy, and (iii) the break-even proportional transaction cost (in quarterly basis points) which cancels out the utility advantage of the TVP external imbalances relative to RW strategy. The in-sample analysis covers quarterly data from 1988Q1 to 2015Q4. The out-of-sample analysis uses a rolling window of twenty years and runs from 2007Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

(continued)

Table 3.6: Out-of-Sample Economic Value with Different Window Lengths (continued)

		Random Walk (RW)			TVP External Imbalances			TVP External Imbalances vs RW		
Window length	Target volatility	Mean	Volatility	Sharpe Ratio	Mean	Volatility	Sharpe Ratio	Maximum Fee	Excess Premium	Break Even Transaction Cost
10 years	8%	3.0	9.1	0.17	4.8	7.3	0.45	269	255	50
	10%	3.4	11.4	0.17	5.6	9.1	0.45	364	342	53
	12%	3.8	13.7	0.17	6.4	10.9	0.45	470	437	56
13 years	8%	2.4	10.3	0.08	2.9	7.4	0.19	203	216	60
	10%	2.6	12.8	0.08	3.3	9.3	0.19	301	327	68
	12%	2.8	15.4	0.08	3.6	11.1	0.19	417	463	76
15 years	8%	2.2	10.3	0.06	6.7	7.4	0.70	608	622	122
	10%	2.3	12.9	0.06	8.0	9.2	0.70	812	837	127
	12%	2.5	15.5	0.06	9.3	11.0	0.71	1034	1079	132
17 years	8%	1.9	10.0	0.04	8.6	7.8	0.91	788	800	151
	10%	2.0	12.5	0.04	10.3	9.7	0.91	1024	1049	156
	12%	2.1	15.1	0.04	12.1	11.6	0.91	1275	1320	161
19 years	8%	2.1	10.2	0.06	5.1	6.7	0.54	474	480	109
	10%	2.3	12.7	0.06	6.0	8.4	0.54	647	661	119
	12%	2.4	15.3	0.06	6.9	10.0	0.54	841	869	128

Table 3.7: Value with Economic Restrictions

The table reports the in-sample and out-of-sample economic performance of currency strategies investing in nine foreign currencies relative to the USD, when economically meaningful restrictions are imposed on the forecasts of the predictive regression underlying the time varying parameter (TVP) external imbalances strategy. More specifically, the slope of the predictive regression in the TVP external imbalances is set to zero when it is estimated with positive sign. Random walk (RW) is an investment strategy that uses the driftless random walk model to forecast nominal exchange rate returns. The TVP external imbalances is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical external imbalances between the United States and nine foreign counterparts to forecast nominal exchange rate returns. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. The TVP is estimated using Bayesian technique as in Appendix 3.C. Each strategy considers a U.S. investor who dynamically rebalances his wealth every quarter between the domestic bond in USD and nine foreign bonds in foreign currencies. The exchange rate forecasts are used to convert the foreign bond returns in USD. The strategy maximizes expected returns subject to a given target volatility of 8%, 10%, and 12%. The table shows the annualized percentage mean, percentage volatility, and Sharpe ratio of each portfolio. The table also shows three economic performance measures comparing the two strategies, which are (i) the maximum performance fee (in annual basis points) a risk-averse investor with quadratic utility and a degree of relative risk aversion equal to 6 is willing to pay for switching from the RW to TVP external imbalances strategy, (ii) the excess premium return (in annual basis points) of TVP external imbalances relative to RW strategy, and (iii) the break-even proportional transaction cost (in quarterly basis points) which cancels out the utility advantage of the TVP external imbalances relative to RW strategy. The in-sample analysis covers quarterly data from 1988Q1 to 2015Q4. The out-of-sample analysis uses a rolling window of twenty years and runs from 2003Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

	Random Walk (RW)			TVP External Imbalances			TVP External Imbalances vs RW		
Target volatility	Mean	Volatility	Sharpe Ratio	Mean	Volatility	Sharpe Ratio	Maximum Fee	Excess Premium	Break Even Transaction Cost
In sample									
8%	11.3	9.9	0.68	13.6	9.9	0.92	232	264	121
10%	13.0	12.2	0.69	15.9	12.3	0.93	291	353	121
12%	14.6	14.6	0.69	18.2	14.6	0.93	351	456	122
Out of sample									
8%	4.3	9.8	0.25	5.8	8.0	0.49	245	248	108
10%	4.9	12.2	0.25	6.7	10.0	0.49	337	346	118
12%	5.5	14.7	0.25	7.7	12.1	0.49	441	461	129

Table 3.8: The Economic Value with Implementation Lags

The table reports the out-of-sample economic performance of currency strategies investing in nine foreign currencies relative to the USD, when the conditioning variable in the predictive regression is released with a given delay. Random walk (RW) is an investment strategy that uses the driftless random walk model to forecast nominal exchange rate returns. The time varying parameter (TVP) external imbalances is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical external imbalances between the United States and nine foreign counterparts to forecast nominal exchange rate returns. The TVP external imbalances strategy uses a predictive regression where the conditioning variable is available with a delay of 2 and 4 quarters, respectively. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. The TVP is estimated using Bayesian technique as in Appendix 3.C. Each strategy considers a U.S. investor who dynamically rebalances his wealth every quarter between the domestic bond in USD and nine foreign bonds in foreign currencies. The exchange rate forecasts are used to convert the foreign bond returns in USD. The strategy maximizes expected returns subject to a given target volatility of 8%, 10%, and 12%. The table shows the annualized percentage mean, percentage volatility, and Sharpe ratio of each portfolio. The table also shows three economic performance measures comparing the two strategies, which are (i) the maximum performance fee (in annual basis points) a risk-averse investor with quadratic utility and a degree of relative risk aversion equal to 6 is willing to pay for switching from the RW to TVP external imbalances strategy, (ii) the excess premium return (in annual basis points) of TVP external imbalances relative to RW strategy, and (iii) the break-even proportional transaction cost (in quarterly basis points) which cancels out the utility advantage of the TVP external imbalances relative to RW strategy. The analysis is out-of-sample, that uses a rolling window of twenty years and runs from 2003Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

	Random Walk (RW)			TVP External Imbalances			TVP External Imbalances vs RW		
Target volatility	Mean	Volatility	Sharpe Ratio	Mean	Volatility	Sharpe Ratio	Maximum Fee	Excess Premium	Break Even Transaction Cost
				Lag 2					
8%	4.3	9.8	0.25	7.2	7.2	0.75	431	435	59
10%	4.9	12.2	0.25	8.6	9.0	0.75	583	593	63
12%	5.5	14.7	0.25	9.9	10.8	0.75	752	775	67
				Lag 4					
8%	4.4	9.9	0.26	7.5	8.1	0.70	416	419	57
10%	5.0	12.4	0.26	8.9	10.1	0.71	553	562	60
12%	5.6	14.8	0.26	10.3	12.1	0.71	704	722	62

Table 3.9: The Economic Value of TVP Bilateral External Imbalances when Removing One Currency

The table reports the in-sample and out-of-sample economic performance of currency strategies investing in foreign currencies relative to the USD when one of nine foreign currencies is removed from the investment opportunity set. The nine exchange rates include the Australian Dollar (AUD), the Canadian dollar (CAD), the Euro (EUR), the Japanese yen (JPY), the British pound (GBP), the Singaporean Dollar (SGD), the Indian Rupee (INR), the Korean Won (KRW), and the Mexican Peso (MXN). For example, AUD denotes an investment strategy that invests in all currencies except for AUD. The table shows three economic performance measures comparing two strategies of random walk (RW) and TVP external imbalances: (i) the maximum performance fee (in annual basis points) a risk-averse investor with quadratic utility and a degree of relative risk aversion equal to 6 is willing to pay for switching from the RW to TVP external imbalances strategy, (ii) the excess premium return (in annual basis points) of TVP external imbalances relative to RW strategy, and (iii) the break-even proportional transaction cost (in quarterly basis points) which cancels out the utility advantage of the TVP external imbalances relative to RW strategy. RW is an investment strategy that uses the driftless random walk model to forecast nominal exchange rate returns. The time varying parameter (TVP) external imbalances is a dynamic investment strategy that exploits the predictive information in the bilateral measure of cyclical external imbalances between the United States and foreign counterparts to forecast nominal exchange rate returns. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. The TVP is estimated using Bayesian technique as in Appendix 3.C. Each strategy considers a U.S. investor who dynamically rebalances his wealth every quarter between the domestic bond in USD and foreign bonds in foreign currencies. The exchange rate forecasts are used to convert the foreign bond returns in USD. The strategy maximizes expected returns subject to a given target volatility of 8%, 10%, and 12%. The in-sample analysis covers quarterly data from 1988Q1 to 2015Q4. The out-of-sample analysis uses a rolling window of twenty years and runs from 2003Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

		In sample			Out of sample		
Excluded Currency	Target Volatility	Maximum Fee	Excess Premium	Break Even Transaction Cost	Maximum Fee	Excess Premium	Break Even Transaction Cost
AUD	8%	252	281	130	393	403	96
	10%	313	367	129	530	551	102
	12%	373	465	128	683	722	108
CAD	8%	267	297	151	252	252	64
	10%	338	396	152	372	374	74
	12%	410	510	154	513	522	83
EUR	8%	225	273	160	305	311	75
	10%	282	368	162	429	440	84
	12%	338	481	164	573	590	92
INR	8%	229	248	144	662	663	176
	10%	293	336	148	855	863	180
	12%	361	442	153	1060	1079	184
JPY	8%	249	285	147	346	356	80
	10%	312	380	147	474	491	86
	12%	376	490	149	620	646	92
KRW	8%	158	184	106	248	249	54
	10%	202	251	110	347	354	60
	12%	248	333	114	461	480	66

(continued)

Table 3.9: The Economic Value of TVP Bilateral External Imbalances when Removing One Currency (continued)

		In sample			Out of sample		
Excluded Currency	Target Volatility	Maximum Fee	Excess Premium	Break Even Transaction Cost	Maximum Fee	Excess Premium	Break Even Transaction Cost
MXN	8%	196	237	88	279	283	62
	10%	221	293	78	393	399	68
	12%	235	354	69	525	535	75
SGD	8%	131	194	105	31	39	11
	10%	158	272	101	79	98	24
	12%	182	371	97	145	183	38
GBP	8%	289	326	155	412	416	105
	10%	363	435	156	547	556	109
	12%	438	563	157	694	712	113

Appendix 3.A: Variable Definitions

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

Variable	Definition
Macroeconomic Fundamentals	
Bilateral Cyclical Net Foreign Assets	Linear combination of stationary components in bilateral foreign assets, and foreign liabilities. Bilateral asset and liabilities between the U.S. and foreign countries are from Kubelec and Sá (2012), updated using databases from the IMF Coordinated Portfolio Investment Survey (CPIS), UNCTAD, and the IMF Coordinated Direct Investment Survey (CDIS).
Bilateral Cyclical Net Exports	Linear combination of stationary components in bilateral exports and imports. Bilateral exports and imports between the U.S. and foreign countries are from the U.S. Bureau of Economic Analysis (BEA).
Bilateral Cyclical External Imbalances	Linear combination of stationary components in bilateral foreign assets, liabilities, exports and imports.
Economic Performance Measures	
Maximum Fee	The level of fee that a risk-averse investor with quadratic utility would be willing to pay to have access to the additional information available in a predictive economic model relative to a benchmark (West et al., 1993 and Fleming et al., 2001).
Excess Premium	An estimate of a portfolio's risk-adjusted premium return in excess of a benchmark portfolio's return (Goetzmann et al., 2007).
Break Even Transaction	The break-even proportional transaction cost that renders investors indifferent between two alternative strategies (Han, 2006).
Countries	
Domestic	United States (U.S.).
Foreign	Australia, Canada, Germany, India, Japan, South Korea, Mexico, Singapore, and the United Kingdom.
Regressions	
Constant Parameter	Parameters are constant, estimated using Ordinary Least Squares (OLS) regression.
Time Varying Parameter	Parameters are time-varying, following a random walk process, estimated using Bayesian method.

Appendix 3.B: International Financial Adjustment

Mechanism. Consider the following external budget constraint of a country between time t and $t+1$:

$$NA_{t+1} \equiv R_{t+1}(NA_t + NX_t), \tag{3.A1}$$

where NA_t denotes net foreign assets, defined as external assets minus external liabilities; NX_t is net exports, defined as the difference between exports and imports of goods and services; and R_{t+1} is the gross return on the net foreign asset portfolio, a combination of the gross return on assets and the gross return on liabilities. Equation (3.A1) states that the net foreign asset position improves with the return on the net foreign asset portfolio and positive net exports. The exports, imports, as well as external assets and liabilities in the external budget constraint above are then normalized relative to domestic wealth, and adjusted for slow-moving trends attributed to structural changes such as financial and trade integration in the world economy. Under fairly general assumptions, the first-order approximation of equation (3.A1) around its trend satisfies

$$nxa_{t+1} \approx \frac{1}{\rho} nxa_t + r_{t+1} + \Delta nx_{t+1}. \tag{3.A2}$$

The term nxa_t is a linear combination of stationary components of exports, imports, and foreign assets and liabilities relative to domestic wealth, where all variables are in log. It is a measure of cyclical external imbalances, which contains information from both the trade balance and the foreign asset position. The trade balance is a flow variable, while the foreign asset position is a stock variable. The ρ is a discount factor that depends on the steady-state average ratio of net exports to net foreign assets. The r_{t+1} is the real return on net foreign assets. The term Δnx_{t+1} denotes detrended net export growth between t and $t+1$, which increases with cyclical export growth and decreases with cyclical import growth. Equation (3.A2) shows that a country can increase its net foreign asset position via either high returns on its net foreign asset portfolio ($r_{t+1} > 0$) or trade surpluses (Δnx_{t+1}).

Assume that the economy settles into a balanced-growth path, solving forward equation (3.A2) will result in an intertemporal external constraint in deviation from its trend, which must hold both ex post and ex ante along every sample path, implying that it will also hold in expectation

$$nxa_t \approx -\sum_{j=1}^{+\infty} \rho^j E_t(r_{t+j} + \Delta nx_{t+j}). \tag{3.A3}$$

This equation is a key role in the model of international financial adjustment, which suggests that time variation in *nxa* must forecast either future portfolio returns (valuation channel), or future net export growth (trade channel), or both. In a country with a cyclical debt position and a cyclical trade deficit, a negative value of *nxa* anticipates an increase in future returns of net foreign assets ($E_t r_{t+j} > 0$) and future trade surpluses ($E_t \Delta nx_{t+j} > 0$).

The above mechanism of financial adjustment involves the role of exchange rate which naturally implies a prediction power of exchange rate movements. Consider a case of United States in which foreign assets are denominated in foreign currency while foreign liabilities are all denominated in domestic currency. The real return on the net foreign portfolio between time t and $t+1$ will be

$$r_{t+1} = |\mu^a|(r_{t+1}^{*a} + \Delta s_{t+1}) - |\mu^l| r_{t+1}^l - \pi_{t+1}, \tag{3.A4}$$

where r_{t+1}^{*a} denotes the nominal return on foreign assets in foreign currency and r_{t+1}^l denotes the nominal return on foreign liabilities in domestic currency, Δs_{t+1} is the rate of appreciation/depreciation of the nominal exchange rate (defined as the domestic price of the foreign currency), π_{t+1} is the realized domestic inflation rate, and μ^a μ^l is the (trend) share of assets and liabilities respectively in the net foreign asset portfolio. Assuming local currency return is constant, a currency depreciation increases the domestic return on foreign assets. The negative correlation between nxa_t and future exchange rate movements is magnified by the degree of leverage of the net foreign asset portfolio if $|\mu^a| > 1$.

Appendix 3.C: Bayesian Estimation of Time Varying Parameter Model

The following describes the Bayesian approach that is used to estimate the time-varying parameter model, and presents the prior hyperparameters, the conditional posterior distributions, and the steps or algorithm used to draw from these conditional distributions. The exposition draws mainly from Kim and Nelson (1999, Ch.8) and Blake and Mumtaz (2012, Ch.3).

The time varying parameter model has the following general state-space representation:

$$y_t = H_t \beta_t + \varepsilon_t, \quad \text{observation equation;} \tag{3.A5}$$

$$\beta_t = \beta_{t-1} + v_t, \quad \text{transition equation;} \tag{3.A6}$$

where $\varepsilon_t \sim i.i.d.(0, R), v_t \sim i.i.d.(0, Q)$, and $cov(\varepsilon_t, v_t) = 0$. Further, $y_t = \Delta_k s_{t+k}^{(i)} / k$ is a $(T \times 1)$ vector of observations on the regressand; $\beta_t = [a_t, b_t]$ is a (2×1) vector of unobserved state variables (e.g. the time-varying coefficients); $H_t = [\mathbf{1}\; nxa_t^{(i)}]$ contains the explanatory variables.

Prior Hyperparameters and Initial Conditions

The time varying model suggests that we need priors for the variance R of the measurement or observation equation and the variance-covariance matrix Q of the transition equation. In addition, to recover the unobserved state variable β_t we need initial conditions or starting values for the Kalman filter (i.e., the initial state, $\beta_{0|0}$, and its initial variance $P_{0|0}$. See Kim and Nelson (1999, Ch.3) for details about the Kalman filter.

To parameterize the prior distributions and initial conditions I use pre-sample information. Specifically, I use a training sample of $T_0 = 20$ observations to estimate via OLS estimator a fixed-coefficient model which is counterpart to Equation (3.A5). The estimated coefficients and their corresponding covariance matrix are set as initial conditions for the Kalman filter. In notation:

$$\beta_{0|0} \equiv \beta_{OLS} = (H_{0t}' H_{0t})^{-1} (H_{0t}' y_{0t}), \tag{3.A7}$$

$$P_{0|0} \equiv P_{OLS} = \Sigma_0 \otimes (H_{0t}' H_{0t})^{-1}, \tag{3.A8}$$

where $\beta_{0|0}$ and $P_{0|0}$ are, respectively, the coefficients' vector and covariance matrix from an OLS regression, and $\Sigma_0 = (y_0 - H_{0t}\beta_0)'(y_0 - H_{0t}\beta_0)/(T_0 - k)$.

The prior for Q is inverse Wishart, with T_0 degrees of freedom and Q_0 scale matrix, i.e., $P(Q) \sim IW(Q_0, T_0)$. This prior influences the amount of time-variation in the coefficients. A large value for the scale matrix Q_0 is consistent with more fluctuation in the coefficients. I set $Q_0 = P_{0|0} \times T_0 \times \tau$, where τ is a scaling factor that reflects our beliefs about the preciseness of $P_{0|0}$. Since the training sample T_0 is small, the estimate of

$P_{0|0}$ is very imprecise hence I set $\tau = 3.5\times10^{-6}$. This reasoning accords with Blake and Mumtaz (2012, Ch.3).

The prior for the variance of the measurement equation is $P(R) \sim IG(R_0, T_0 - k)$, where $R_0 = \Sigma_{OLS}$ is the scale parameter, and $(T_0 - k)$ is the prior degree of freedom. To initialize the first step of the Gibbs sampling we need starting values for R and Q. I set them to $R_0 = \Sigma_{OLS}$ and $Q_0 = P_{0|0} \times T_0 \times \tau$.

Conditional Posterior Distribution

In addition to priors and initial conditions, the method necessitates the forms of the conditional posterior distributions. The conditional posterior distribution for the state variable (β_T) given the other parameters is given by:

$$H(\beta_T \mid y_T, R, Q) = H(\beta_T \mid y_T)\prod_{t=1}^{T-1} H(\beta_t \mid \beta_{t+1}, y_t), \tag{3.A9}$$

where $\beta_T = [\beta_1, \beta_2, \ldots, \beta_T]$ and $y_T = [y_1, y_2, \ldots, y_T]$. The conditional posterior distribution of R given a draw of the state variable β_t and the other parameters is given by:

$$H(R \mid \beta_t, y_t, Q) \sim \Gamma^{-1}\left(\frac{T_0 - k + T}{2}, \frac{R_0 + (y_t - \beta_t H)'(y_t - \beta_t H)}{2}\right). \tag{3.A10}$$

The conditional posterior distribution of Q given a draw of the state variable β_t and the other parameters is:

$$H(Q \mid \beta_t, y_t, R) \sim IW(\bar{Q}, T + T_0), \tag{3.A11}$$

where $\bar{Q} = Q_0 + (\beta_t - \beta_{t-1})'(\beta_t - \beta_{t-1})$.

Sampling from The Conditional Posterior Distribution

To draw samples from the conditional posterior distributions, the Carter and Kohn (1994) algorithm with the Gibbs sampler is employed. The Carter and Kohn algorithm provide us with the draws of the state variable β_T from its conditional posterior distribution. The key updating equations are:

$$\beta_{t|t,\beta_{t+1}} = \beta_{t|t} + K^* \times (\beta_{t+1} - \beta_{t|t}), \tag{3.A12}$$

$$P_{t|t,\beta_{t+1}} = P_{t|t} + K^* \times H^* \times P_{t|t}, \tag{3.A13}$$

where $\beta_{t|t}$ and $P_{t|t}$ are obtained from the Kalman filter and $K^* = P_{t|t} \times H^* \times f_{t+1|t}^{-1}$. Equations (3.A12) and (3.A13) are substituted backwards from $(T-1)$, and iterating backwards to period 1. This step is an integral part of the Gibbs sampling algorithm, which proceeds as follows:

1. Conditional on R and Q, draw β_t from its conditional posterior distribution given in Equation (3.A9) using the Kalman filter and the Carter and Kohn algorithm.

2. Conditional on β_t, sample R from its conditional posterior distributions given in Equation (3.A10).
3. Conditional on β_t, sample Q from its conditional posterior distribution given by Equation (3.A11).
4. Repeat steps 1 – 3 a sufficient number of times.

In the empirical work I take 20,000 draws, discarding the first 10,000 draws and save the last 10,000 draws for inference.

Table 3.A1: Descriptive Statistics

The table reports the descriptive statistics (mean and standard deviation in percentage points, and correlation of respective time series between time t and lag of 1, 2, 4, 8, and 12) for the quarterly changes of bilateral (i) foreign assets, (ii) foreign liabilities, (iii) exports, (iv) imports, the bilateral measure of cyclical (i) net foreign assets, (ii) net exports, (iii) external imbalances, and the quarterly changes of bilateral nominal exchange rate return with the US dollar as pricing currency. The bilateral measure of cyclical net foreign assets linearly combines stationary components in bilateral foreign assets and liabilities. The bilateral measure of cyclical net exports linearly combines stationary components in bilateral exports and imports. The bilateral measure of cyclical external imbalances linearly combines stationary components in bilateral foreign assets, liabilities, exports and imports. The data set covers quarterly data of nine countries from 1983Q1 to 2015Q4. Appendix 3.A provides details on variable definitions.

	Quarterly changes in bilateral				Bilateral cyclical measure of			Quarterly changes in exchange rates
	Foreign assets	Foreign liabilities	Exports	Imports	Net foreign assets	Net exports	External Imbalances	
Australia								
Mean	2.913	3.581	1.585	1.259	–0.000	–0.000	–0.000	–0.128
Standard Deviation	5.714	5.852	11.693	12.966	0.833	0.121	0.838	5.823
Correlation $(t, t-1)$	–0.056	0.056	–0.316	–0.172	0.989	0.627	0.979	0.038
$(t, t-2)$	0.076	0.121	–0.099	–0.223	0.960	0.562	0.947	0.036
$(t, t-4)$	–0.067	0.064	0.219	0.206	0.863	0.486	0.848	–0.055
$(t, t-8)$	–0.088	–0.037	0.037	0.238	0.591	0.202	0.569	–0.173
$(t, t-12)$	–0.026	0.101	0.069	0.436	0.222	0.217	0.192	–0.011
Canada								
Mean	2.224	2.743	1.638	1.421	–0.000	–0.000	–0.000	–0.088
Standard Deviation	7.600	3.485	8.000	7.277	0.156	0.119	0.157	3.440
Correlation $(t, t-1)$	0.563	0.256	–0.354	–0.242	0.965	0.931	0.931	0.152
$(t, t-2)$	0.291	0.040	0.065	0.196	0.888	0.873	0.837	–0.061
$(t, t-4)$	–0.105	0.206	0.682	0.377	0.691	0.777	0.638	0.097
$(t, t-8)$	–0.043	–0.015	0.664	0.431	0.373	0.599	0.317	–0.044
$(t, t-12)$	–0.260	–0.101	0.713	0.481	0.140	0.382	0.082	–0.068
Germany								
Mean	2.475	1.686	1.297	1.743	0.000	–0.000	0.000	0.056
Standard Deviation	6.201	5.970	9.704	8.724	0.328	0.375	0.583	5.531
Correlation $(t, t-1)$	0.170	0.136	–0.140	–0.316	0.931	0.945	0.954	0.082
$(t, t-2)$	–0.001	–0.031	–0.278	0.262	0.787	0.908	0.891	–0.096
$(t, t-4)$	–0.020	0.023	0.412	0.357	0.427	0.804	0.724	0.048
$(t, t-8)$	0.194	–0.059	0.353	0.309	0.097	0.533	0.450	0.010
$(t, t-12)$	–0.031	0.055	0.288	0.203	0.019	0.230	0.237	0.023

(continued)

Table 3.A1: Descriptive Statistics (continued)

	Quarterly changes in bilateral				Bilateral cyclical measure of			Quarterly changes in exchange rates
	Foreign assets	Foreign liabilities	Exports	Imports	Net foreign assets	Net exports	External Imbalances	
India								
Mean	6.174	10.084	3.009	3.730	–0.000	0.000	–0.000	–1.447
Standard Deviation	7.547	48.909	18.019	13.276	1.382	0.396	1.562	3.698
Correlation $(t, t-1)$	0.431	0.119	–0.282	–0.441	0.872	0.780	0.876	0.141
$(t, t-2)$	0.289	0.079	–0.164	0.112	0.701	0.687	0.735	0.231
$(t, t-4)$	–0.229	0.027	0.222	0.541	0.226	0.626	0.361	–0.041
$(t, t-8)$	0.166	–0.224	0.051	0.550	–0.189	0.518	0.068	0.131
$(t, t-12)$	0.147	0.230	0.054	0.579	0.250	0.368	0.375	0.033
Japan								
Mean	2.315	2.602	0.339	0.392	–0.000	0.000	–0.000	0.527
Standard Deviation	8.719	6.358	8.482	8.710	0.163	0.331	0.413	6.128
Correlation $(t, t-1)$	0.307	0.053	–0.046	–0.015	0.891	0.894	0.895	0.061
$(t, t-2)$	0.086	–0.190	–0.113	–0.143	0.782	0.813	0.805	–0.170
$(t, t-4)$	–0.003	0.069	–0.029	0.164	0.639	0.664	0.663	0.135
$(t, t-8)$	–0.009	0.040	–0.008	0.076	0.395	0.337	0.371	–0.020
$(t, t-12)$	–0.243	–0.130	–0.133	0.009	0.069	0.032	0.141	–0.192
Korea								
Mean	3.513	4.447	1.834	2.154	–0.000	–0.000	–0.000	–0.327
Standard Deviation	9.190	7.466	11.220	11.157	0.233	0.310	0.386	6.889
Correlation $(t, t-1)$	0.104	0.220	–0.418	–0.146	0.968	0.906	0.923	–0.129
$(t, t-2)$	0.151	0.172	0.048	–0.154	0.894	0.834	0.841	0.013
$(t, t-4)$	–0.135	–0.114	0.115	0.321	0.698	0.724	0.687	–0.159
$(t, t-8)$	–0.018	–0.072	0.086	0.370	0.349	0.515	0.370	–0.129
$(t, t-12)$	–0.090	0.078	–0.001	0.355	0.035	0.239	0.050	0.115

(continued)

Table 3.A1: Descriptive Statistics (continued)

	Quarterly changes in bilateral				Bilateral cyclical measure of			Quarterly changes in exchange rates
	Foreign assets	Foreign liabilities	Exports	Imports	Net foreign assets	Net exports	External Imbalances	
Mexico								
Mean	5.578	7.491	6.427	6.141	–0.000	0.000	–0.000	–3.878
Standard Deviation	8.527	11.016	10.200	10.221	0.167	0.190	0.140	8.524
Correlation $(t, t-1)$	0.409	0.528	0.208	0.232	0.963	0.936	0.864	0.433
$(t, t-2)$	0.266	0.313	0.215	0.186	0.880	0.868	0.715	0.301
$(t, t-4)$	0.293	0.094	0.445	0.356	0.641	0.719	0.388	0.363
$(t, t-8)$	0.210	0.074	0.373	0.288	0.243	0.457	0.071	0.219
$(t, t-12)$	0.040	0.158	0.259	0.040	–0.007	0.252	–0.020	0.091
Singapore								
Mean	3.238	2.921	1.262	1.307	–0.000	–0.000	–0.000	0.300
Standard Deviation	4.463	3.207	10.748	9.200	0.005	0.174	0.177	2.686
Correlation $(t, t-1)$	0.313	0.229	–0.353	–0.113	0.961	0.742	0.750	0.013
$(t, t-2)$	0.190	0.123	0.061	–0.230	0.869	0.608	0.620	–0.047
$(t, t-4)$	–0.139	0.012	0.048	0.285	0.605	0.439	0.453	–0.032
$(t, t-8)$	–0.043	–0.118	–0.025	0.359	0.143	0.265	0.274	0.014
$(t, t-12)$	–0.016	0.099	–0.200	0.275	0.086	0.111	0.118	0.063
United Kingdom								
Mean	2.785	2.271	1.249	1.200	0.000	0.000	0.000	–0.002
Standard Deviation	6.014	5.728	10.853	8.824	0.088	0.161	0.172	5.124
Correlation $(t, t-1)$	0.339	0.266	–0.054	–0.423	0.989	0.822	0.841	0.103
$(t, t-2)$	0.102	–0.005	–0.404	0.222	0.964	0.731	0.750	–0.227
$(t, t-4)$	0.093	0.085	0.370	0.256	0.886	0.686	0.692	–0.006
$(t, t-8)$	–0.097	–0.122	0.267	0.400	0.702	0.518	0.530	–0.043
$(t, t-12)$	–0.071	–0.044	0.181	0.378	0.506	0.274	0.325	0.008

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