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Exchange rate predictability and economic value: a long-short currency strategy using country-level signals

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Abstract. This paper examines whether country-level macroeconomic, valuation, momentum, positioning, volatility, and financial-market signals can predict future monthly exchange rate returns and generate economic value in a long-short currency strategy. This paper constructs monthly returns for 46 currencies and matches them with country-level predictive signals. After stationarity tests and signal transformation, this paper then uses univariate regression models as an initial screening step and builds country-level multivariate forecasting regression models under two model selection approaches: a strict statistical selection method and a category-protected selection method. The selected signals are then used in an expanding-window forecasting framework to construct long-short portfolios. Results show substantial cross-country heterogeneity: no single signal or common signal set consistently predicts all currencies. However, the selected signals can generate meaningful portfolio economic value. Among all the specifications, the Top/Bottom 2 portfolio under the category-protected approach provides the best overall balance between return, volatility, and drawdown. It also outperforms the passive Equal-Weighted FX benchmark and has low correlation with the global equal-weighted local equity benchmark. Overall, the findings suggest that exchange rate predictability should be evaluated not only through regression statistics, but also through portfolio performance, risk control, and diversification value.

Keywords: exchange rate predictability, currency returns, long-short strategy, country-level signals, diversification

1. Introduction

As time has progressed, more and more countries have begun to engage in global trade. And in global markets, the exchange rate is one of the most important concepts because it determines the value of cross-border trade, foreign investment, and international portfolio returns. Actually, in global trade, for traders and investors, the exchange rate change is not only a foreign risk, but also a potential source of returns. Therefore, many people may try to predict exchange rate changes precisely to earn extra returns, as they do in stock markets.

However, forecasting exchange rate movements has long been one of the most difficult questions in international finance. This difficulty is closely related to the classic Meese-Rogoff puzzle [1], showing that many exchange rate models based on macroeconomic fundamentals have historically struggled to outperform a simple random walk benchmark, especially in short-horizon out-of-sample forecasts. Therefore, although exchange rates are affected by macroeconomic conditions, interest rates, investor expectations, and financial market conditions, it remains challenging to transform these economic relationships into stable and profitable return forecasts.

This paper mainly focuses on whether many different kinds of signals can predict the monthly returns of different currencies, instead of the prediction of long-run exchange rate levels. This distinction is important because exchange rate levels are the price of one currency in terms of another currency, and they are often persistent and non-stationary, while exchange rate returns measure the change in one currency, which is usually more stationary and can be used for predictive regressions and to show investment performance.

This paper chooses signals that contain information from 10 categories, including Macroeconomics, Exchange Rate Valuation & REER, FX Strategies, Financial Market Sentiment & Risk Appetite, Fund Flows & Positioning, Equity Market Valuation, Yield & Dividends, Volatility & Options Market, Corporate & Financial Health, and Market Trading Activity as the candidate signals. These variable selections are motivated by existing studies on exchange rate predictability, currency risk premium, momentum, valuation adjustment, capital flows, global risk appetite, and so on.

The empirical analysis proceeds in several steps. First, this paper builds monthly log returns from exchange rate price data for 46 currencies and matches each currency with a set of country-level signals. Second, this paper applies stationarity tests and transforms signals so that these candidate variables can be used for regression analysis. Third, univariate predictive regression models with next-month returns as dependent variables are used as an initial screening step to identify signals with preliminary predictive power. Fourth, using selected variables, country-level multivariate regression models are built to decide the final signals. There are two model selection methods: Approach 1, a strict statistical selection method based on VIF screening and backward elimination, and Approach 2, a category-protected selection method that preserves economically meaningful signal categories. Finally, the final selected signals are used in an expanding-window forecasting framework to construct a long-short strategy across countries.

The long-short strategy ranks currencies each month by their predicted next-month returns and goes long the currencies with the highest predicted returns and short the currencies with the lowest ones. To make a better comparison, this paper separately evaluates Top/Bottom 1, Top/Bottom 2, and Top/Bottom 3 portfolio specifications under both model selection approaches. In addition, transaction costs are also added to make the strategy more realistic.

Finally, this paper evaluates the strategy performance by using cumulative returns, annualized returns and volatility, Sharpe Ratio, maximum drawdowns, and comparisons with passive FX and global equity benchmarks. Empirical results show that among all the specifications, the Top/Bottom 2 portfolio under Approach 2 has the best overall balanced performance with an annualized return of 7.37%, an annualized volatility of 6.41%, a Sharpe Ratio of 1.15, and a maximum drawdown of -7.05%. In addition, compared with a Global Equal-weighted Local Equity Benchmark (Global LEQ) and a passive equal-weighted foreign exchange benchmark (Equal-Weighted FX), the long-short strategy has a stronger risk-adjusted performance and a much lower drawdown. The correlation examination also shows that the long-short strategy has a near-zero correlation with Global LEQ, which can suggest that the strategy is not simply driven by global equity market movements.

All in all, this paper focuses on exchange rate predictability by combining regression models and signals that contain some predictive information. Rather than only testing whether individual signals are statistically significant, this paper further examines whether selected signals can be used to construct a long-short currency strategy with meaningful risk-adjusted performance and diversification value.

2. Literature review

2.1. Exchange rate predictability and economic value

Exchange rate predictability is always an important problem in international finance, but it's still difficult to correctly predict them, especially in the short run. But as time goes on, researchers have gradually found some useful evidence and theories that can transmit predictive information to some extent, which is really helpful in exchange rate research. Della Corte et al. [2] provide a useful framework for this paper because they also develop a strategy for monthly exchange-rate returns, similar to this paper's, and evaluate the short-run predictive ability of economic fundamentals and forward premiums for these returns. They also suggest that exchange rate predictability should be assessed not only by statistical significance but also by its economic value to investors, for example, whether it can help investors earn additional returns.

Their idea is closely related to the objective of this paper. The empirical analysis not only examines whether individual signals have statistically significant predictive power, but also aims to see whether these signals can help build strategies and earn stable returns. Therefore, this paper follows the broader logic of economic evaluation by connecting predictive regressions with long-short currency strategy returns.

2.2. Macroeconomic fundamentals, inflation expectations, and exchange rate valuation

Macroeconomic fundamentals and inflation expectations may influence exchange rate returns as currencies reflect relative economic conditions across countries and can be easily influenced by national policies, interest rates, and so on. Signals related to inflation expectations, economic surprises, and trade balances can change investors' expectations about this country's current economy and then influence the relative value of the domestic currency. For example, an increase in expected inflation may reduce real purchasing power or put pressure on monetary policy, which may lead to domestic currency depreciation.

Bems et al. [3] show that the anchoring of inflation expectations affects the persistence of inflation. They found that when inflation expectations are weakly anchored, external shocks such as terms-of-trade shocks have more persistent effects on inflation. More importantly, under flexible exchange rate regimes, a negative terms-of-trade shock may trigger domestic currency depreciation, which can pass through to consumer prices. Therefore, it builds a channel between the exchange rate and inflation, which then provides an idea for using inflation signals to predict exchange rate returns.

Meanwhile, exchange rate valuation provides another macroeconomic channel for predicting future currency returns. Valuation-based measures, such as real exchange rate misalignment and deviations from long-run purchasing power, can reflect whether a currency appears overvalued or undervalued relative to its fundamentals. Rogoff [4] discusses the purchasing power parity puzzle and shows that although real exchange rate deviations can be highly persistent, long-run mean reversion is still an important feature of real exchange rate behavior. Therefore, this paper also considers exchange rate valuation as an important signal category in forecasting future currency returns.

2.3. Currency risk premium, carry, and common risk factors

What's more, many studies also found that currency returns are related to carry trade and global risk factors and can reflect risk premiums. Lustig et al. [5] show that currency excess returns are related to common risk factors in currency markets. In particular, they find that the return difference between high-interest-rate and low-interest-rate currency portfolios can be explained by a carry-trade risk factor. This implies that interest rate differentials and carry-related variables may capture exposure to global currency risk.

This literature is really helpful for this paper. First, it provides a theoretical foundation for the carry and forward-yield signals in forecasting models. Second, it also suggests that profitable currency strategies may reflect the compensation for bearing systematic risk, which can commonly be observed in the stock market, not the real excess returns the models make. Therefore, a long-short currency investing strategy should not be directly interpreted as pure alpha without further analysis. To address this issue, this paper compares the long-short strategy with sample equal-weighted Foreign Exchange (FX) and equity benchmarks and examines whether its returns are less correlated with global risk-on assets after accomplishing the final strategy.

2.4. Momentum signals and trading frictions

Similar to those factors in the stock markets, there are also momentum signals and trading frictions in the FX market. Menkhoff et al. [6] found significant cross-sectional momentum returns in foreign exchange markets. Their results show that currencies with higher past returns tend to outperform currencies with lower past returns, suggesting that past currency performance may contain information about future returns. This provides motivation for including momentum-related signals in exchange rate return forecasting.

At the same time, currency momentum strategies are sensitive to trading frictions. Menkhoff et al. [6] show that transaction costs reduce the profitability of momentum strategies, but they do not fully eliminate the positive excess returns. In fact, when investing or trading, transaction costs are almost everywhere, and it's common to pay these costs. And it's especially important when the strategy needs a higher portfolio turnover. Therefore, this paper decides to evaluate strategy performance after applying transaction cost adjustments.

2.5. Capital flows, risk appetite, and financial market signals

Exchange rates may also be affected by capital flows and the financial market. Gabaix and Maggiori [7] develop a theory of exchange rate determination based on capital flows in imperfect financial markets. In their framework, capital flows affect exchange rates by changing the balance sheets and risk-bearing capacity of financiers who absorb currency risk. Therefore, when financial intermediaries face problems like balance sheet constraints, changes in asset demand can affect both exchange rate levels and exchange rate volatility.

This perspective provides a theoretical foundation for the use of financial market signals such as equity-market valuation, investor sentiment, positioning, volatility, trading activity, and so on. These variables can be understood as investor demand for domestic assets, global risk appetite, or the current states of financial and stock markets. For example, stronger equity market valuations or more optimistic sentiment may be associated with capital inflows and stronger domestic currency demand. Conversely, during recession periods, investors may rebalance assets toward safe-haven currencies such as the U.S. dollar.

All in all, as these references suggested, exchange rate return prediction may be associated with macroeconomic fundamentals, inflation expectations, currency risk premium, carry, momentum, valuation adjustment, capital flows, positioning, equity market valuation, and investor sentiment. According to these factors, this paper collects a broad set of predictive signals and evaluates whether they can make sense in predicting next-month exchange rate returns across countries.

3. Data & methodology

After discussing and determining the relationship between exchange rates and many different kinds of signals that may make sense, these data are collected to continue this research.

3.1. Exchange rate returns

This paper collects daily exchange rate price data for 46 currencies from the Bloomberg Professional Service, using Bloomberg Generic Prices (BGN), from January 1st, 2000, to October 27th, 2022. The raw exchange rates are originally quoted as units of local currency per U.S. dollar, and this paper converts them into units of U.S. dollars per local currency. This paper then uses the exchange rate price on the final available trading day of each month as the monthly exchange rate price, which helps calculate the monthly returns next.

In this paper, monthly returns are computed as shown in Equation (1):

$$R_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1}) \tag{1}$$

where $R_{i,t}$ is the monthly exchange rate return for country (i) in month (t), and $P_{i,t}$ is the exchange rate price level for country (i) at the end of month (t).

Therefore, this paper finally gets the 46 currencies' monthly log returns from February 2000 to October 2022. Compared to traditional Simple Returns, Logarithmic Returns are widely used in financial research due to their time-additive property and analytical tractability, and it will be much more convenient when calculating cumulative returns [8]. Since exchange rates are expressed as units of U.S. dollars per local currency, a positive return indicates an appreciation of the local currency against the U.S. dollar and vice versa.

3.2. Candidate signals

This paper collects 62 types of candidate signal data across 74 countries from January 1st, 2000, to October 27th, 2022, which corresponds to the exchange rate price sample period. The equity-market valuation metrics, including the Bloomberg BEST consensus series, option-implied volatility measures, and sentiment indicators, are sourced from Bloomberg. The REER signal series are compiled from the J.P. Morgan Currency Index and Citigroup Economic and Market Systems databases. Long-term macroeconomic baseline variables, such as PPP Z-scores, use purchasing power parity data from the OECD and the IMF International Financial Statistics (IFS) database.

Table 1. 62 candidate signals with 10 categories in 74 countries

Category	Signal	Number
Macroeconomics	InfConsensusChg	30
	EconSurprise	30
	PPP Z-score	49
	InfSurprise	30
	TradeBalance	46
	TermsTrade	39
	BudgetBalanceFcast	35
	GDPFcast	32
	CurrentAcctFcast	37
	InfFcast	33
	UnempFcast	36
	GlobalEconSurprise	1
Exchange Rate Valuation & REER	CitiBroadREER	37

Table 1. Continued

Exchange Rate Valuation & REER	CitiNarrowREER	37
	JPM_CPI_REER	39
	JPM_PPI_REER	43
	Citi-Broad-REER/ToT Z-score	34
	Citi-Narrow-REER/ToT Z-score	34
	JPM-CPI-REER/ToT Z-score	36
	JPM-PPI-REER/ToT Z-score	36
	OECD.PPP	49
	BigMac	35
FX Strategies	1m FX MOM	46
	3y FX MOM	46
	1mFwdYield	36
	vol-adj carry	39
	FX seasonality	46
Financial Market Sentiment & Risk Appetite	AGGR Sentiment	25
	BUY Sentiment	12
	RSI_30D	44
	PCT_MEMB_MACD_GT_BASE_LINE_0	44
	HOLD Sentiment	12
	SELL Sentiment	12
Fund Flows & Positioning	Equity Index Uncertainty	11
	Fixed Income Real Money Positioning	24
	Fixed Income Leveraged Positioning	24
	Fixed Income Total Positioning	24
	Fixed Income Uncertainty	37
	Equity Index Real Money Positioning	14
	Equity Index Retail Positioning	10
	Equity Index Leveraged Positioning	13
	Equity Index Total Positioning	14
Equity Market Valuation	BEST_PX_SALES_RATIO	44
	BEST_PX_CPS_RATIO	44
	BEST_PX_BPS_RATIO	44
	PX_TO_TANG_BV_PER_SH	44
	LONG_TERM_PRICE_EARNINGS_RATIO	44
	BEST_EPS	44
	PROF_MARGIN	44
	OPER_MARGIN	44
	EST_PX_EBITDA_FY3_AGGTE	44
	EV_EST_EBITDA_NEXT_YR_AGGTE	44
	EST_PX_CASHFLOW_FY3_AGGTE	44
	PX_TO_CASH_FLOW	44

Table 1. Continued

Yield & Dividends	IDX_EST_DVD_YLD	44
	ETF Sharpe	48
Volatility & Options Market	1M_CALL_IMP_VOL_50DELTA_DFLT	44
	1M_PUT_IMP_VOL_50DELTA_DFLT	44
	IVOL_MONEYNESS	44
Corporate & Financial Health	CUR_RATIO	44
	TOT_DEBT_TO_EBITDA	44
Market Trading Activity	INDX_ADV_VOL	44

Then, as Table 1 has shown, these signals are divided into 10 categories: Macroeconomics, Exchange Rate Valuation & REER, FX Strategies, Financial Market Sentiment & Risk Appetite, Fund Flows & Positioning, Equity Market Valuation, Yield & Dividends, Volatility & Options Market, Corporate/Financial Health, and Market Trading Activity. The number of each signal under different categories is also displayed. But after conducting Augmented Dickey–Fuller (ADF) tests and univariate regressions on these signals, this paper finally filters 50 signals to be used in multivariate regressions and the long-short strategy.

3.3. Stationarity and signal processing

Then, for the signal database, this paper groups them based on frequency of update and conducts ADF on monthly and daily updated signals. This paper divides these signals into four groups: daily, monthly, yearly, and other. The other group means some signals have insufficient observations, irregular updating frequency, or very low variation. This paper finds 1,685, 169, 259, and 82 signal data in the daily, monthly, other, and yearly groups. This paper only chooses daily and monthly updated data to conduct the ADF examination and omits the others.

For these daily updated data, this paper chooses the data on the last day of each month to be their monthly data, as this paper did for the exchange rate price, and combines them with the monthly updated data. To examine the stationarity of the predictor variables, an ADF test is applied to each signal series. In this specification, the ADF regression includes an intercept but does not include a deterministic time trend. The lag length k is automatically determined according to the default rule used in Equation (2):

$$k = \lfloor (n-1)^{1/3} \rfloor \tag{2}$$

where n denotes the number of observations in the series. This lag structure helps account for potential serial correlation in the residuals.

The null hypothesis of the ADF test is that the series contains a unit root, indicating that the series is non-stationary. If the p-value of the test is less than 0.1, the null hypothesis is rejected and the series is classified as stationary. Otherwise, the series is treated as non-stationary and is transformed using the first difference before being used in subsequent regressions. In addition, series with fewer than 24 observations are not tested, since the ADF test may produce unreliable results with very short samples.

For variables that are identified as non-stationary, a first-difference transformation is applied before they are used in the regression analysis. The first difference is calculated using the simple difference between consecutive observations. Specifically, the transformed series is constructed as shown in Equation (3):

$$\Delta x_t = x_t - x_{t-1} \tag{3}$$

where x_t represents the value of the signal at time t. This transformation removes potential stochastic trends and helps ensure that the predictor variables are stationary.

And for each signal, the following rule applies: If, within a given signal type, more than 50% of the data points have been subjected to first differencing, then the entire data series for that signal is transformed accordingly into its first-difference form. This approach ensures consistency in the economic interpretation of the variable across the entire group. Conversely, if the proportion is less than or equal to 50%, this paper keeps the individual ADF test results for each signal, meaning that stationary series are kept in levels while non-stationary series are differenced separately. After conducting all these steps, this paper finally gets 948 first-difference signals and 906 level signals.

4. Univariate analysis

Before estimating the multivariate forecasting models, this paper first conducts univariate predictive regressions to examine the individual forecasting power of each signal. The purpose of this step is to identify which signals contain preliminary predictive information for future exchange rate returns and to provide a foundation for the later multivariate model selection process.

For each country and each signal instance, the univariate time-series regression specified is estimated in Equation (4):

$$R_{i,t+1} = \alpha_{i,j} + \beta_{i,j} X_{i,j,t} + \varepsilon_{i,j,t+1} \tag{4}$$

where $R_{i,t+1}$ is the next-month exchange rate return for country i, $X_{i,j,t}$ is signal j observed for country i in month t, $\alpha_{i,j}$ is the intercept, $\beta_{i,j}$ measures the predictive effect of signal j for country i, and $\varepsilon_{i,j,t+1}$ is the error term.

In this regression, $t+1$ timing convention ensures that only available information in the current month is used to predict the following month's return, preventing the use of future data. A signal instance is defined by the combination of DataType, Ticker, and Name, rather than DataType alone. This distinction is important because the same DataType may contain multiple underlying series that measure related but not identical market information.

The regressions are estimated separately for each country and signal. To ensure that the estimated relationship is based on a minimum amount of information, a regression is only estimated when the sample contains at least 36 non-missing monthly observations. Besides, signal series with no meaningful variation, or return series with insufficient variation, are excluded from valid estimation. For each valid regression, the model records the estimated coefficient, t-statistic, in-sample R^2, adjusted R^2, and the number of observations.

The sign of the estimated coefficient shows the predictive relationship between signals and next-month exchange rate returns. Since exchange rate returns are defined as changes in U.S. dollars per unit of local currency, a positive coefficient means that a higher value of the signal can predict local currency appreciation against the U.S. dollar. In contrast, a negative one means that a higher value of the signal predicts local currency depreciation next month.

To filter which signals can be used in the following steps, this paper classifies signals as statistically significant based on the absolute value of their t-statistics. If $|t| > 1.645$, a signal is treated as significant at the 10% level. The filtered results are organized by country and signal type and are used as candidate predictors for the subsequent multivariate model selection process.

Table 2. Most frequent (> 4) significant signals in univariate regressions

DataType	Category	Number
InfConsensusChg	Macroeconomics	10
FX seasonality	FX Strategies	9
1m FX MOM	FX Strategies	7
1mFwdYield	FX Strategies	7
3y FX MOM	FX Strategies	7
vol-adj carry	FX Strategies	7
BEST_PX_SALES_RATIO	Equity Market Valuation	7
JPM_PPI_REER	Exchange Rate Valuation & REER	7
PCT_MEMB_MACD_GT_BASE_LINE_0	Financial Market Sentiment & Risk Appetite	7
PPP Z-score	Macroeconomics	6
EconSurprise	Macroeconomics	6
Fixed Income Real Money Positioning	Fund Flows & Positioning	6
Fixed Income Uncertainty	Fund Flows & Positioning	6
IDX_EST_DVD_YLD	Yield & Dividends	6
CitiBroadREER	Exchange Rate Valuation & REER	6
CitiNarrowREER	Exchange Rate Valuation & REER	5
JPM_CPI_REER	Exchange Rate Valuation & REER	5
InfSurprise	Macroeconomics	5
RSI_30D	Financial Market Sentiment & Risk Appetite	5

As shown in Table 2, several signals are statistically significant in more than four country-level univariate regressions. After filtering, there are a total of 35 countries and 50 kinds of signals remaining, which suggests that exchange rate predictability is highly heterogeneous across countries and no single signal can consistently predict all the currencies. However, there are still several significant signals appearing repeatedly among different currencies. For example, Macroeconomics signals, such as InfConsensusChg, PPP Z-score, and EconSurprise, FX Strategies signals, like FX seasonality, 1m FX MOM, 1mFwdYield, and so on, Exchange Rate Valuation & REER signals, and Fund Flows & Positioning show predictive power in some country-level regressions.

These findings are consistent with the theoretical foundation that this paper has discussed earlier: macroeconomic expectations, currency risk premia, valuation adjustment, momentum, and financial market conditions may contain information that can predict exchange rate changes. Meanwhile, the strong cross-country heterogeneity also suggests that building a universal signal model may be too difficult and restrictive. Therefore, the univariate results are used as an initial screening step for the later multivariate model selection process, where country-specific combinations of signals are considered.

5. Multivariate model selection

5.1. Multivariate model set and signal screening

After the univariate filter step, this paper further estimates country-level multivariate time-series regression forecasting models based on significant signals. The purpose of this stage is not to examine whether each signal has predictive power in multivariate regressions, but to filter and screen signals for constructing country-level multivariate forecasting models, as multivariate regressions can contain more information and predict more precisely compared to univariate regressions. And then it can provide a more stable and predictive set of variables in each country for conducting the long-short strategy in the next step.

For each country, the candidate variables are selected from the signals that pass the univariate screening procedure. The multivariate predictive regression is specified in Equation (5):

$$R_{i,t+1} = \alpha_i + \sum_{k \in S_i} \beta_{i,k} X_{i,k,t} + \varepsilon_{i,t+1} \quad (5)$$

where $R_{i,t+1}$ is the next-month exchange rate return for country i, $X_{i,k,t}$ is candidate signal k observed for country i in month t, S_i denotes the set of selected predictors for country i, and $\varepsilon_{i,t+1}$ is the error term.

The model is estimated separately for each country, which allows the final predictor set to vary across currencies. This country-specific design is consistent with the earlier univariate results, which show that exchange rate predictability is heterogeneous across countries. During data processing, observations with missing values in the dependent variable or candidate predictors are removed, and only if the complete sample contains at least 50 valid monthly observations is a country included in the multivariate estimation.

5.2. Approach 1: strict statistical selection

Next, this paper considers two multivariate model selection approaches. The first approach is a strict statistical selection procedure. For each country, this paper mainly applies the Variance Inflation Factor (VIF) screening and backward stepwise selection to filter these signals. According to Kutner et al. [9], the VIF is a rule to control for multicollinearity, which measures how strongly one predictor can be explained by the other predictors. A high VIF indicates that the coefficient estimate may be unstable because of overlapping information among regressors. In this paper, if more than one candidate variable is available, VIF is computed for the predictor set. Following the common regression diagnostic rule discussed by Kutner et al. [9], variables with high VIF values are removed iteratively until the maximum VIF is no greater than 10.

After the VIF screening step, a backward elimination procedure is applied. Following the backward selection logic described by Kutner et al. [9], the model begins with the remaining candidate predictors and iteratively removes the least statistically significant variable. In each iteration, an OLS regression is estimated, and the variable with the highest *p*-value is removed if its *p*-value is greater than 0.10. The process continues until all remaining variables satisfy the *p*-value threshold or only one variable remains. The remaining variables are determined to be the ultimate signal sets across countries and then used in the long-short strategy in the next stage.

5.3. Approach 2: category-protected selection

The second approach is a category-protected model selection procedure. This approach follows the same general logic as the first approach, but it adds an economic category protection rule: if one signal is the last remaining variable within its economic category, it will not be removed. The categories are those listed in Table 1, where all candidate signals are divided into 10 types. The reason why this paper decides to add Approach 2 is that strict statistical selection focuses too much on statistical significance and multicollinearity control, so it may remove an entire category of economically meaningful signals.

Under the category-protected approach, it also applies the same VIF screening and backward elimination logic as in Approach 1, but both steps must obey the category protection rule. For instance, if one country has 10 candidate signals and they are all from different categories, none of the signals will be removed during the filter process. Specifically, a variable with a high VIF or a *p*-value above 0.10 can be removed only if at least one other variable from the same economic category remains in the model. Therefore, Approach 2 will retain some variables that would be removed under Approach 1 and preserve broader economic information from many different aspects.

5.4. Model comparison

For both approaches, the resulting country-level models report the selected variables and standard regression statistics, including estimated coefficients, t-statistics, p-values, in-sample R^2, adjusted R^2, number of observations, and the p-value of the model-level F-statistic.

And they serve different purposes. Approach 1 provides a much more concise model with fewer signal sets and focuses on strict multicollinearity control and in-sample statistical significance. In contrast, Approach 2 keeps signal diversity and allows statistical imperfection instead of conducting a strict screening process, trying to retain broader information to make the model have better predictive ability.

Comparing these two approaches allows this paper to examine whether a strict statistical model selection process is sufficient, or whether preserving economically different information can lead to more robust forecasting and strategy performance. The selected variables from both approaches will then be used in the expanding-window forecasting and long-short portfolio strategies in the next section.

6. Strategy construction

After constructing the multivariate forecasting models, this paper further evaluates whether predicted exchange rate returns with the selected signals have economic value in a tradable long-short currency strategy. In this section, this paper converts the predicted country-level returns into actual portfolio positions and then examines the final performance.

6.1. Expanding forecast construction

The variable sets this paper uses are from the "Multivariate Model Selection" section, but the corresponding estimated coefficients are not used. Instead, this paper uses expanding historical window to re-estimate the regression coefficients recursively for each forecast month. For each signal month t, the regression coefficients are estimated using completed historical signal and return data up to X_{t-1} and R_t. The expanding estimation begins only after a minimum training window of 120 months is available. This expanding-window design helps avoid using future information and has adequate data to improve precision. Therefore, the selected variables across countries remain fixed, while the coefficient estimates are updated over time using only completed historical signal and return data.

The timing convention follows the same structure as the multivariate regression analysis: signals observed in month t are used to predict exchange rate returns in month $t+1$. For each country i, the predicted next-month exchange rate return is computed using Equation (6):

$$\widehat{R}_{i,t+1} = \widehat{\alpha}_{i,t} + \sum_{k \in S_i} \widehat{\beta}_{i,k,t} X_{i,k,t} \tag{6}$$

where $\widehat{R}_{i,t+1}$ is the predicted next-month exchange rate return, S_i is the selected predictor set for country i, and $\widehat{\alpha}_{i,t}$ and $\widehat{\beta}_{i,k,t}$ are estimated using the expanding training sample available at the forecast formation date. The predicted return is then matched with the actual exchange rate return in month $t+1$.

6.2. Long-short portfolio formation

Then, each month, all the currencies are ranked by their predicted next-month returns, and the strategy goes long the currencies with the highest predicted returns and short the currencies with the lowest ones. As this paper discussed above, higher positive returns mean local currency appreciation relative to the U.S. dollar, and lower negative returns show local currency depreciation. In addition, this paper also evaluates three portfolio specifications: Top/Bottom 1, Top/Bottom 2, and Top/Bottom 3, which can help compare the portfolio performance under different numbers of currencies.

In each month, the long side receives a total weight of +0.5 and is allocated across the selected long currencies, while the short side receives a total weight of (-0.5), equally allocated across the selected short currencies. For example, in the Top/Bottom 2 portfolio, each long currency receives a weight of (+0.25), and each short currency receives a weight of (-0.25). The monthly gross portfolio return is calculated using the selected currencies' actual next-month exchange rate returns. Since the exchange rate returns are calculated as log returns, this paper converts them into simple returns before portfolio returns are computed, which can make the calculation more precise and is conducive to the subtraction of transaction costs.

6.3. Transaction costs and strategy output

To make the strategy more realistic, this paper adds transaction costs and turnover. Turnover is calculated as the sum of the absolute monthly changes in portfolio weights, and the transaction cost in each month is computed using Equation (7):

$$Transaction\,Cost_i = Turnover_i \times 0.001 \tag{7}$$

where 0.001 represents a 10-basis point trading cost. The net portfolio return is then calculated by subtracting the transaction cost from the gross portfolio return.

Finally, the strategy performance is evaluated using monthly net portfolio returns, cumulative returns, net asset value, and drawdowns. The main performance statistics include annualized return, annualized volatility, Sharpe ratio, maximum drawdown, average monthly turnover, and transaction costs. These statistics are calculated separately for the Top/Bottom 1, Top/Bottom 2, and Top/Bottom 3 portfolios.

In addition, this strategy construction framework is applied separately to Approach 1, the strict statistical selection method, and Approach 2, the category-protected selection method. This allows the paper to compare portfolio performance across different long-short specifications within each approach, and also to examine which approach produces signals with stronger economic value in the long-short strategy. Meanwhile, this paper will report all the results and further compare the strategy performance with the global LEQ equal-weighted benchmark and FX equal-weighted benchmark in the next section.

7. Empirical results and comparison

After discussing the theoretical foundation, methodology, univariate and multivariate regressions, and the Long-Short Strategy, this section will present and evaluate the strategy's empirical performance under Approaches 1 and 2. In addition, this paper will determine the ultimate result, compare it with two benchmarks: a Global Equal-weighted Local Equity Benchmark (Global LEQ) and a passive Equal-Weighted Foreign Exchange Benchmark (Equal-Weighted FX), and examine the correlation between them to evaluate whether the strategy captures independent currency alpha rather than simply reflecting broad global risk exposure.

7.1. Long-Short Strategy performance in approach 1 and 2

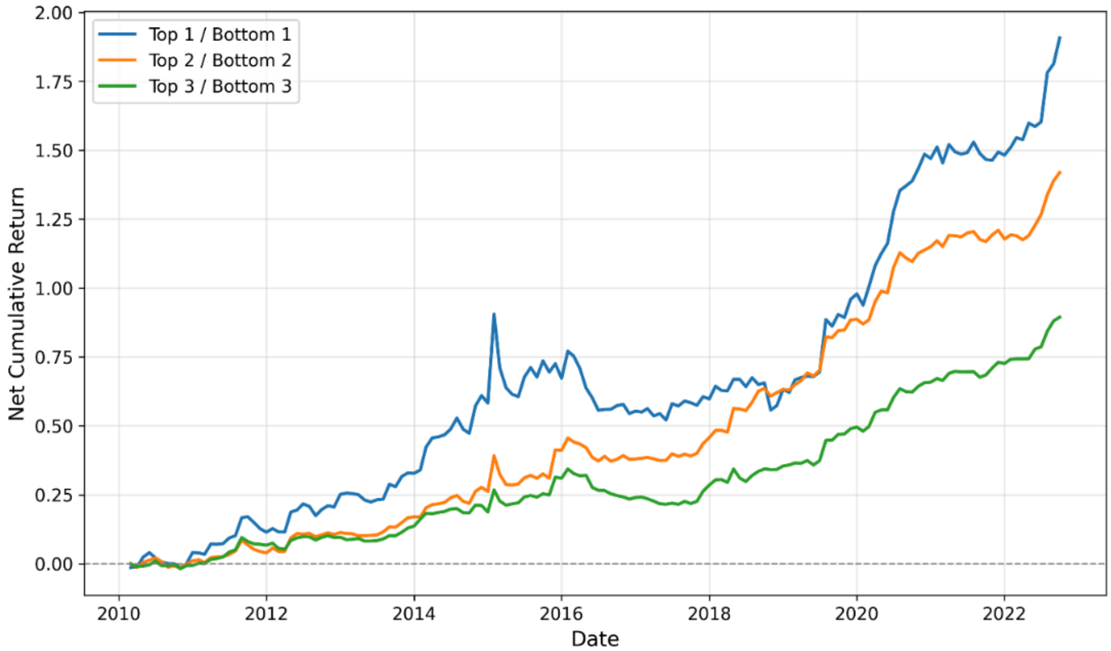

Figure 1. Net cumulative returns of Long-Short Strategy portfolios under approach 1

Note: This figure reports the net cumulative returns of the Top/Bottom 1, Top/Bottom 2, and Top/Bottom 3 long-short currency portfolios under Approach 1. Returns are calculated after applying a 10-basis-point transaction cost adjustment.

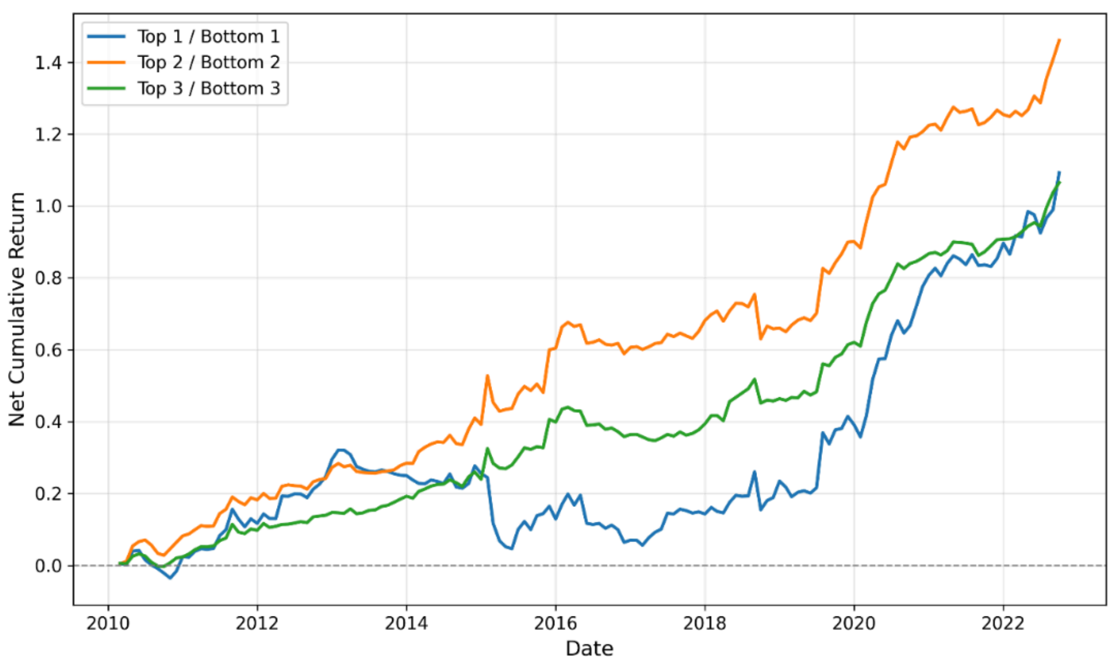

Figure 2. Net cumulative returns of Long-Short Strategy portfolios under approach 2

Note: This figure reports the net cumulative returns of the Top/Bottom 1, Top/Bottom 2, and Top/Bottom 3 long-short currency portfolios under Approach 2. Returns are calculated after applying a 10-basis-point transaction cost adjustment.

Figures 1 and 2 show the net cumulative returns of the long-short strategies under Approach 1 and Approach 2. Although there are many fluctuations over time, all the strategies show overall increasing trends and generate positive cumulative returns. This suggests that the selected signals and Long-Short Strategy across all three portfolio specifications have economic and investment value.

Table 3. Strategy performance across portfolio specifications under approaches 1 and 2

	Approach 1			Approach 2		
Top/Bottom *N*	1	2	3	1	2	3
Annualized Return	8.79%	7.22%	5.17%	6.00%	7.37%	5.89%
Annualized Volatility	10.38%	6.32%	4.89%	9.03%	6.41%	4.81%
Sharpe Ratio	0.85	1.14	1.06	0.66	1.15	1.23
Maximum Drawdown	-20.13%	-7.64%	-9.54%	-20.79%	-7.05%	-6.48%
Average Monthly Turnover	1.44	1.31	1.26	1.49	1.39	1.34
Average Monthly Transaction Cost	0.14%	0.13%	0.13%	0.15%	0.14%	0.13%
Total Transaction Cost	21.90%	19.85%	19.17%	22.70%	21.15%	20.30%

Note: Top/Bottom *N* indicates the number of currencies held on each side of the long-short portfolio. Transaction costs are calculated using a 10-basis-point cost rate multiplied by monthly portfolio turnover.

Table 3 shows the strategy performance including Annualized Return, Annualized Volatility, Sharpe Ratio, Maximum Drawdown, Average Monthly Turnover, Average Monthly Transaction Cost, and Total Transaction Cost in three portfolio specifications under Approaches 1 and 2. Under Approach 1, the Top/Bottom 1 portfolio achieves the highest annualized return of 8.79%, but it has the highest annualized volatility of 10.38% and the deepest maximum drawdown, about -20.13%. In contrast, the Top/Bottom 2 portfolio has a lower annualized return of 7.22%, but it has a much higher Sharpe Ratio, approximately 1.14, and a smaller maximum drawdown of -7.64%, indicating better risk-adjusted performance. Besides, the Top/Bottom 3 portfolio has a middle result, with a lower return of 5.17% and a lower volatility of 4.89%. Therefore, this result suggests that the most concentrated portfolio can gain a stronger return, but it is also more exposed to short-term volatility and drawdown risk. Instead, the less concentrated one can balance the return and risk better.

A similar situation also happens on Approach 2. Under Approach 2, the Top/Bottom 1 portfolio has the lowest Sharpe Ratio at 0.66 and the deepest maximum drawdown of -20.79%, which indicates relatively weak risk-adjusted performance. Although the Top/Bottom 3 portfolio has the highest Sharpe Ratio and best maximum drawdown, its annualized return is too low. Therefore, in contrast, the Top/Bottom 2 portfolio performs and balances particularly well, with an annualized return of 7.37%, an annualized volatility of 6.41%, a Sharpe ratio of 1.15, and a maximum drawdown of only -7.05%.

In addition, in Table 3, this paper also lists average monthly turnover, average monthly transaction cost, and total transaction cost across all the portfolio specifications under Approaches 1 and 2. Through comparing and evaluating these data, this paper finds that these results are similar, for example, with an average monthly turnover ranging from approximately 1.2 to 1.5 and an average monthly transaction cost of about 0.13%, 0.14%, and 0.15%, and they are close to realistic trade, which can prove the rationality of this strategy to some extent.

Therefore, based on these discussions, this paper selects the Top/Bottom 2 portfolio specification under Approach 2 as the main long-short strategy of this paper and uses it in the following benchmark comparison and correlation analysis. This choice is also consistent with the purpose of the category-protected model selection method. By keeping more diverse signals, the models can contain more information and improve the stability of strategy performance without giving up too much return.

7.2. Comparison with Global LEQ and Equal-Weighted FX

After deciding the ultimate main strategy portfolio, this paper then compares the performance with a Global Equal-weighted Local Equity Benchmark (Global LEQ) and a passive Equal-Weighted Foreign Exchange Benchmark (Equal-Weighted FX) over the same period.

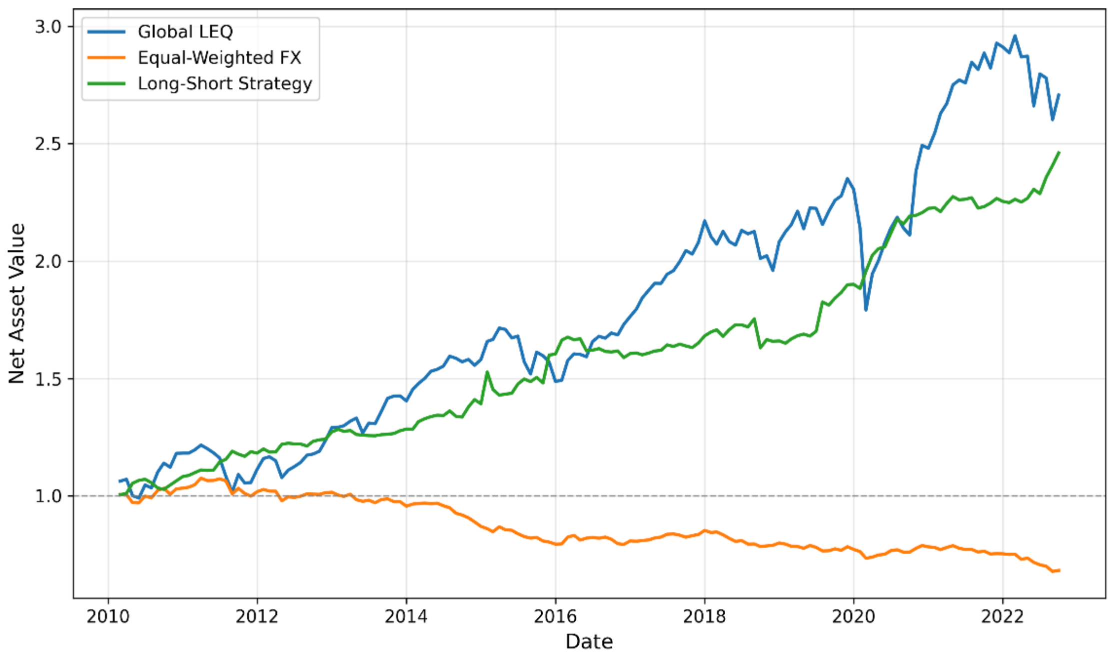

Figure 3. Net asset value comparison across Global LEQ, Equal-Weighted FX, and Long-Short Strategy

Note: This figure compares the net asset value of Global LEQ, Equal-Weighted FX, and the selected Long-Short Strategy over the common sample period. Each series is normalized to 1 at the beginning of the sample.

Figure 3 shows the net asset value of three portfolios between 2010 and 2022. Long-Short Strategy and Global LEQ groups both show an increasing trend, and the Global LEQ group reaches a higher point at the end of this period, while the Equal-Weighted FX group displays a decreasing trend over time.

Table 4. Performance comparison across Global LEQ, Equal-Weighted FX, and Long-Short Strategy

	Global LEQ	Equal-Weighted FX	Long-Short Strategy
Cumulative Return	170.73%	-31.70%	146.08%
Annualized Return	8.18%	-2.97%	7.37%
Annualized Volatility	12.12%	5.02%	6.41%
Sharpe Ratio	0.67	-0.59	1.15
Max Drawdown	-23.80%	-36.94%	-7.05%

Note: Performance statistics are calculated over the common sample period for Global LEQ, Equal-Weighted FX, and the selected Long-Short Strategy.

Table 4 displays the performance results of these three portfolios from five aspects of cumulative return, annualized return, annualized volatility, Sharpe Ratio, and maximum drawdown. Corresponding to Figure 3, Global LEQ reaches a 170.73% cumulative return and Long-Short Strategy reaches 146.08%, but Equal-Weighted FX only gets a -31.7% cumulative return, which means that the basket of foreign currencies depreciated against the U.S. dollar and had a bad performance over the sample period.

More importantly, the Long-Short Strategy has a lower annualized return at 7.37%, which is lower by 0.81%, but suffers lower risk than Global LEQ. Its annualized volatility is 6.41%, compared with 12.12% for Global LEQ, and its maximum drawdown is also much smaller, at -7.05%, compared with -23.80% for Global LEQ. In addition, the Long-Short Strategy has a Sharpe ratio of 1.15, which is higher than both Global LEQ and Equal-Weighted FX. This trade-off suggests that a modest reduction in return is accompanied by substantially improved stability and lower risk.

Therefore, these results suggest that the Long-Short Strategy provides meaningful economic value compared to passive equal-weighted FX. Although equal-weighted FX shows a negative cumulative return, this paper can still use predicted returns to form long positions in currencies with higher expected returns and short positions in currencies with lower expected returns to capture the relative disparities across currencies and gain returns. Meanwhile, the comparison with Global LEQ shows that the Long-Short Strategy achieves equity-like cumulative performance and annualized return with lower volatility and drawdown. Therefore, it also raises a question: is the Long-Short Strategy closely related to broad global equity market movements?

7.3. All-Sample and rolling correlation with Global LEQ

To examine this problem, this paper calculates the Pearson correlation coefficient between the monthly returns of Global LEQ, Equal-Weighted FX, and the Long-Short Strategy in this section. The Pearson correlation coefficient is commonly used to measure the linear relationship between two return series, with values ranging from -1 to 1 [10]. A positive correlation means that two return series tend to move in the same direction, while a negative correlation means that they tend to move in opposite directions. A correlation close to zero suggests that the two series have little linear relationship. Therefore, if the Long-Short Strategy has a low correlation with Global LEQ, it would suggest that the strategy can capture independent currency alpha rather than simply reflecting broad global risk exposure.

Table 5. All-sample correlation across Global LEQ, Equal-Weighted FX, and Long-Short Strategy

	Global LEQ	Equal-Weighted FX	Long-Short Strategy
Global LEQ	1	0.6822	-0.0748
Equal-Weighted FX	0.6822	1	-0.0885
Long-Short Strategy	-0.0748	-0.0885	1

Note: The table reports Pearson correlations based on monthly portfolio returns.

Table 5 shows the all-sample correlation matrix among Global LEQ, Equal-Weighted FX, and Long-Short Strategy. It shows that the Equal-Weighted FX has a high positive all-sample correlation with Global LEQ, at 0.6822, while the Long-Short Strategy has very low all-sample correlations with Global LEQ and Equal-Weighted FX, separately at -0.0748 and -0.0885. Therefore, this Long-Short Strategy is hardly related to Global LEQ in the all-sample.

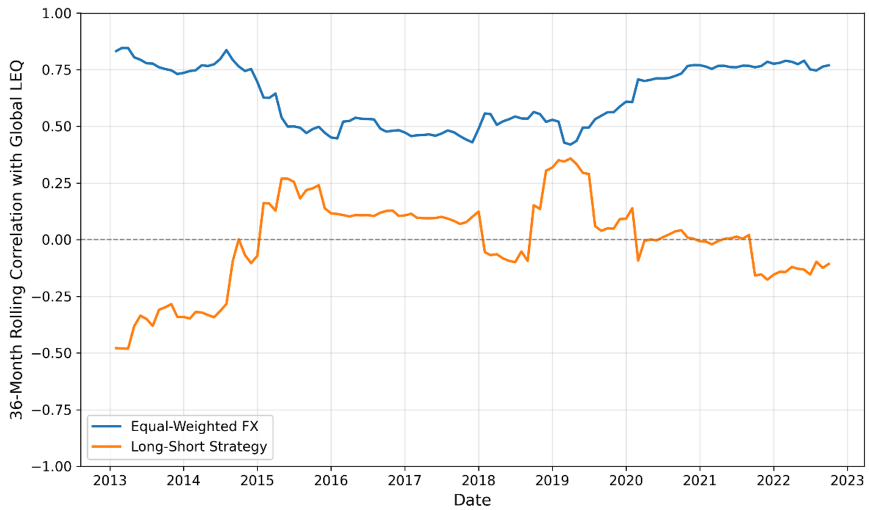

Figure 4. 36-month rolling correlations of Equal-Weighted FX and Long-Short Strategy with Global LEQ

Note: This figure reports 36-month rolling correlations between Global LEQ and two currency return series: Equal-Weighted FX and the Long-Short Strategy. Correlations are calculated using monthly portfolio returns.

Then, Figure 4 shows the 3-year rolling correlations of Equal-Weighted FX and the Long-Short Strategy with Global LEQ. The results show that the rolling correlation between Equal-Weighted FX and Global LEQ remains positive and relatively high for most of the sample period: most of the correlation is higher than 0.5 and approximately two-fifths is higher than 0.75. This suggests that passive exposure to a basket of foreign currencies is strongly related to global risk-on market conditions.

In contrast, the rolling correlation between Long-Short Strategy and Global LEQ is lower, mostly being lower than 0.25 and close to 0, and sometimes even negative. Combining with previous all-sample results, it suggests that the Long-Short Strategy is not mainly driven by global equity market exposure or passive foreign currency exposure. Instead, its returns are more likely generated by relative differences across currencies, which is captured by the forecasting signals.

Overall, the correlation results indicate that the Long-Short Strategy can indeed capture relatively independent currency alpha beyond global LEQ. Combined with the earlier performance comparison, the strategy not only balances return and risk, but also provides diversification value relative to global equity exposure.

8. Conclusion

This paper mainly examines whether a broad set of macroeconomic, valuation, momentum, positioning, volatility, and financial-market signals can predict future monthly exchange rate returns and generate economic value in a long-short currency strategy. The analysis first constructs monthly exchange rate returns and country-level predictive signals, then applies stationarity tests, univariate regressions, multivariate model selection, expanding-window strategy construction, and finally displays consequences and makes comparisons.

The empirical results show that exchange rate predictability is obviously heterogeneous across countries. No single signal can consistently predict all currencies, but several categories of signals appear repeatedly in the univariate screening results, such as macroeconomic expectations, FX strategy variables, valuation measures, and so on. This suggests that exchange rate return predictability cannot be done by one factor. Instead, using country-specific combinations of economic and financial information may have stronger effects in predicting exchange rates.

The multivariate model selection results also show the importance of balancing statistical discipline with economic interpretation. In the process, Approach 1 applies a strict statistical selection process based on multicollinearity control and significance screening, while Approach 2 preserves broader economic information from different signal categories through the category-protected selection rule. The final strategy results suggest that preserving economically diverse information can improve strategy performance to some extent.

Among the tested portfolio specifications, the Top/Bottom 2 portfolio under Approach 2 is selected as the main Long-Short Strategy because it provides the best overall balance of return, volatility, and drawdown. This strategy achieves an annualized return of 7.37%, an annualized volatility of 6.41%, a Sharpe ratio of 1.15, and a maximum drawdown of -7.05%. Although its annualized return is slightly lower than the Global LEQ benchmark, it has much lower volatility and a much smaller maximum drawdown. In addition, it also clearly outperforms the Equal-Weighted FX benchmark, which has a negative cumulative return over the same sample period.

What's more, the correlation analysis provides additional evidence that the Long-Short Strategy has diversification value. The comparison shows that Equal-Weighted FX has a high positive correlation with Global LEQ, which suggests that passive foreign currency exposure is strongly related to global risk-on market conditions. In contrast, the Long-Short Strategy has a near-zero correlation with Global LEQ and Equal-Weighted FX. This can indicate that the strategy is not mainly driven by broad global equity market exposure or passive currency exposure. Instead, its returns are more likely generated by relative differences across currencies captured by the forecasting signals.

Overall, this paper shows that exchange rate predictability can be better understood when statistical forecasting evidence is connected with portfolio-level economic evaluation. The results suggest that selected country-level signals do contain useful information about future currency returns, but this information is most meaningful when it can be translated into a long-short strategy. The comparison across model selection approaches also shows that preserving economically diverse signals can be helpful to some extent. Therefore, exchange rate predictability should be evaluated through both statistical evidence and portfolio-level performance, because signals are only economically meaningful if they can be translated into a more stable and useful investment strategy.

At the same time, this paper has several limitations that leave room for future research. Although the expanding-window coefficient estimation in strategy construction avoids using future return information when predicting next-month returns, the signal sets are selected before the expanding strategy implementation. Therefore, the results should be interpreted as back-tested evidence rather than fully out-of-sample trading. In addition, the analysis relies on simplified transaction cost assumptions and monthly rebalancing. Future research could consider currency-specific bid-ask spreads, forward-implied carry, funding costs, and alternative rebalancing frequencies to make the strategy closer to real trading conditions. Regularized models such as LASSO or Ridge regression can also be used to reduce overfitting when using a large number of variables, and machine learning methods or nonlinear specifications are good ideas in capturing more complex relationships among signals. Finally, more formal asset-pricing factor regressions, alternative portfolio weighting methods, and longer out-of-sample periods could be used to further test the robustness and sources of the Long-Short Strategy's performance.

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