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Dynamic Currency Mispricing and Arbitrage Profits*

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Abstract

We find that mispricing is prevalent in individual currency returns by employing a conditional latent factor model that captures short-lived mispricing under general assumptions on systematic risk. An arbitrage portfolio based on currency mispricing can achieve an annualized Sharpe ratio around 0.8, and its performance cannot be explained by canonical currency factors. The results also suggest that: currency characteristics contribute more significantly to currency mispricing than macroeconomic fundamentals; mispricing is closely related to country-specific limits to arbitrage; and the currency arbitrage portfolio is related to shifts in global financial conditions.

Keywords: Currency Markets; Mispricing; PPCA; IPCA; Machine Learning; Limits to Arbitrage; Global Financial Conditions.

JEL Classification: F31, G12, G15.

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1. Introduction

The global currency market is the largest and most liquid financial market, with an average daily turnover exceeding \$7.5 trillion (BIS, 2022). It attracts a diverse range of participants, including professional investors, multinational corporations, policy makers, and retail investors, each with distinct objectives and skills. Moreover, there are no natural short-selling constraints in currency markets, which makes it easier for prices to adjust in response to demand shifts and to new relevant information. A vast literature has studied the currency investment strategies employed by market participants, and has shown that several common factors, such as Carry (Lustig, Roussanov, and Verdelhan, 2011), Momentum (Menkhoff et al., 2012), and Value (Kroencke et al., 2014; Menkhoff et al., 2017) can effectively capture time-series variation in currency portfolio returns and explain the cross-sectional spreads in their expected returns. Furthermore, employing unconditional latent factor approaches, Nucera, Sarno, and Zinna (2024) and Li, Sarno, and Zinna (2025) also identify these factors as key drivers of the currency pricing kernel.

However, a growing body of evidence indicates that the profitability of numerous currency strategies cannot be fully explained by common observable risk factors (see, e.g., Barroso and Santa-Clara, 2015; Bartram et al., 2023), and that these common risk factors exhibit limited explanatory power when applied to individual currencies rather than currency portfolios (Chernov, Dahlquist, and Lochstoer, 2023; Feng, He, Li, Sarno, and Zhang, 2024), suggesting the existence of potential mispricing. In this paper, we implement a comprehensive examination of whether individual currencies are mispriced, under general assumptions regarding systematic risk.¹

Inspired by the international arbitrage pricing theory (IAPT) of Solnik (1983), we consider a conditional latent factor model in which both mispricing (alpha) and factor loadings (beta) are functions of conditioning information, with the number of latent fac-

¹To be clear, we refer to mispricing as the notion that significant excess returns that exceed expected risk compensation can be generated, and not riskless arbitrage profits.

tors optimally determined by the data. The primary objective of this paper is to model and estimate mispricing, which is inherently short-lived; this design allows for one type of mispricing to disappear quickly, and to be followed by a completely different type of mispricing. Also, when focusing on pricing individual currencies rather than currency portfolios, factor loadings can also experience large changes in response to market conditions. In this setting, the dependence structures of mispricing and factor loadings on conditioning information may vary over time.

Therefore, we employ the projected principal component analysis (PPCA), first proposed by [Fan, Liao, and Wang \(2016\)](#) and then extended by [Kim, Korajczyk, and Neuhierl \(2021\)](#), to estimate the model. A distinct property of PPCA is that it does not require a long time-series sample (only requiring a large cross section) for consistency, but assumes relatively stable conditioning variables. Therefore, our conditional latent factor model can be estimated using a rolling-window approach with a small window size (say, 12 months), which introduces time-varying dependence structures of mispricing and systematic risk on conditioning information. Using this rolling-window estimation allows us to study both the cross-sectional and temporal relations of conditioning variables with both mispricing and systematic risk. Importantly, PPCA estimates the model by first giving conditioning variables maximal explanatory power for systematic risk before attributing any explanatory power to mispricing, making it orthogonal to factor loadings.

To quantify mispricing in currency markets, we employ a sample of 49 individual currencies, with data sampled at a monthly frequency and ranging from January 1986 to December 2023. We take the US dollar as the home currency and express the exchange rate as units of the US dollar per unit of the foreign currency. We consider two types of conditioning variables: country-specific macroeconomic fundamentals and currency-specific characteristics. In total, there are 12 conditioning variables, with 6 macroeconomic fundamentals and 6 currency characteristics. Using these data and the rolling-window PPCA procedure, we estimate the mispricing function at each time, and

construct the currency arbitrage portfolio in real time.

The main empirical findings can be summarized as follows. First, for the number of latent factors ranging from one to five, we find that all corresponding arbitrage portfolios generate positive mean returns and high Sharpe ratios. The annualized Sharpe ratio varies from 0.77 to 0.83. By comparison, we find that in our sample, the Carry strategy achieves an annualized Sharpe ratio of 0.89, and the short-term momentum strategy yields a Sharpe ratio of only 0.55. The arbitrage portfolio demonstrates stable long-term performance, outperforming most currency strategies. Although the Carry strategy performs comparably, it can exhibit large drawdowns, in particular during states characterized by high aggregate volatility. However, after the 2008 global financial crisis, the increase of the arbitrage portfolio cumulative returns slowed down, and since the onset of the COVID-19 pandemic, its performance has lagged behind the Carry strategy.

Second, we examine whether commonly used currency risk factors can explain the performance of the arbitrage portfolio, and find that they cannot do so. Specifically, we employ a four-factor model that includes the dollar, carry, short-term momentum, and value as pricing factors. In unconditional spanning regressions of the arbitrage portfolio returns on these four factors, the risk-adjusted returns remain economically substantial and statistically highly significant, regardless of the number of latent factors considered. Additionally, we reconstruct the arbitrage portfolio by incorporating the pre-specified observable factors in the PPCA framework. This approach allows for conditional factor loadings on observable factors when estimating the mispricing function. Even under this conditional specification, the arbitrage portfolio continues to achieve a high Sharpe ratio. These findings provide further evidence in support of the prevalence of mispricing in currency markets.

Another approach to estimating the conditional latent factor model is the instrumental principal component analysis (IPCA) of [Kelly, Pruitt, and Su \(2019\)](#). Unlike PPCA, IPCA requires both a large cross section and a long time series for consistent estimators,

and it assumes that the dependence structures of mispricing and factor loadings on conditioning variables remain constant over time. We construct an alternative long-short arbitrage portfolio in an out-of-sample setting based on a measure of expected mispricing in the IPCA framework, similar to [Bali, Beckmeyer, and Wiedemann \(2023\)](#). Although this long-short arbitrage portfolio yields a statistically significant average annualized return of 3.30%, with an annualized Sharpe ratio of 0.55, its performance can be fully explained by the aforementioned four-factor model. Hence, while the out-of-sample procedure alleviates concerns of time-invariant dependence structures in IPCA, it remains unclear whether mispricing is orthogonal to factor loadings, which is a distinct feature of PPCA.

Third, we explore potential sources of currency mispricing. This analysis starts from examining the variables that mostly contribute to mispricing and systematic risk, and how their contributions evolve over time. We find that the contributions of currency characteristics overshadow those of macroeconomic fundamentals in both factor loadings and mispricing. This finding aligns with the literature suggesting that while macroeconomic fundamentals may influence the long-term behavior of exchange rates, a short-term disconnect often exists between the two (see, e.g., [Meese and Rogoff, 1983](#); [Rossi, 2013](#); [Fratzscher, Rime, Sarno, and Zinna, 2015](#); [Nucera, Sarno, and Zinna, 2024](#)). The time-varying contributions of conditioning variables indicate that, compared to systematic risk, no single variable consistently plays a dominant role in mispricing. Instead, many variables contribute to mispricing, but only for a short period.

We also find that emerging market currencies are much more severely mispriced than developed market currencies. No currency can remain consistently overvalued or undervalued over an extended period, and each currency switches between overvalued and undervalued groups over time. The most mispriced currencies are characterized by low exchange rate stability, relatively independent monetary policies, limited financial openness, high arbitrage costs, and large bid-ask spreads. We find that when financial conditions

worsen, imposing greater limits on arbitrage and reducing trading activity, currency mispricing remains uncorrected and the arbitrage portfolio generates higher returns. Finally, we find that speculative traders tend to increase their current and future positions in currencies with high mispricing.

Our paper closely relates to the literature on the asset pricing of currency markets. Since [Lustig, Roussanov, and Verdelhan \(2011\)](#), many papers focus on the factor structure of currency returns (see, e.g., [Verdelhan, 2018](#); [Chernov, Dahlquist, and Lochstoer, 2023](#); [Nucera, Sarno, and Zinna, 2024](#); [Li, Sarno, and Zinna, 2025](#); [Liu, Maurer, Vedolin, and Zhang, 2024](#)). However, this paper shifts the focus to mispricing with general assumptions on systematic risk at the individual currency level. [Du, Tepper, and Verdelhan \(2018\)](#) examine the violation of Covered Interest Parity (CIP) and identify significant and persistent arbitrage opportunities in currency markets after the global financial crisis, attributing these to constraints on financial intermediaries and persistent international imbalances in investment demand and funding supply. [Barroso and Santa-Clara \(2015\)](#) constructs optimal currency portfolios combining multiple currency strategies, finding that the outperformance of these portfolios can be gradually corrected by speculative capital. [Bartram et al. \(2023\)](#) show that currency return predictability can be attributed to mispricing. Our paper extends this literature by employing a conditional latent factor model that is capable of capturing short-lived mispricing at the individual currency level.

Many studies try to relate currency risk premia to economic conditions (see, e.g., [Lustig and Verdelhan, 2007](#); [Richmond, 2019](#); [Zeng, 2023](#)). [Nucera, Sarno, and Zinna \(2024\)](#) revisit macro-financial determinants of currency risk premia, revealing a disconnect between currency excess returns and macroeconomic fundamentals. In contrast, [Bybee, Gomes, and Valente \(2023\)](#) employ macroeconomic fundamentals as instruments in the IPCA framework and find that they are relevant for explaining currency risk premia. Relying on machine learning methods, [Filippou et al. \(2023\)](#) show that macroeconomic fundamentals are valuable predictors for currency returns. Our paper examines

the relative importance of macroeconomic fundamentals and currency characteristics for currency mispricing and systematic risk, respectively. We show that, for both mispricing and systematic risk, currency characteristics play a more important role than macroeconomic fundamentals, suggesting a short-term disconnect between currency returns and macroeconomic fundamentals.

The rest of the paper proceeds as follows. Section 2 introduces the methodology for modeling and estimating currency mispricing. Section 3 presents the data used in the empirical analysis. Section 4 presents the main empirical findings on currency mispricing. Section 5 discusses potential sources of currency mispricing. Finally, Section 6 concludes the paper.

2. Methodology

In this section, we present our methodology for measuring currency mispricing. Subsection 2.1 briefly reviews international arbitrage pricing theory and introduces the conditional latent-factor model. Subsection 2.2 discusses how to model and estimate currency mispricing relying on PPCA. Subsection 2.3 describes how to construct the currency arbitrage portfolio based on currency mispricing.

2.1. International APT

We start by reviewing the international arbitrage pricing theory (IAPT) of Solnik (1983). Without modeling the heterogeneity of national investors, IAPT establishes that an arbitrage portfolio that is riskless in a currency is also riskless in any other currency and that the factor structure in international capital markets is invariant to the choice of the numeraire currency.

Assume that there are $N + 1$ currencies, with currency 0 being the home currency. The exchange rate is defined as units of the home currency per unit of the foreign currency. Therefore, an increase in the exchange rate represents an appreciation of the foreign

currency or a depreciation of the home currency. From the home investor's perspective, the excess return of currency i with respect to the home currency 0 is determined by a K -factor model as follows,

$$rx_{i,t+1} = \alpha_i + \beta_i f_{t+1} - \epsilon_{i,t+1} + \epsilon_{0,t+1}, \quad i = 1, \dots, N, \quad (1)$$

where α_i is a constant representing mispricing; β_i is a $1 \times K$ vector of factor loadings representing the difference between exposures of currency i and the home currency to K common (latent) risk factors (f_t); and $\epsilon_{i,t}$ and $\epsilon_{0,t}$ represent currency i and home currency-specific idiosyncratic noises, respectively, which are mutually independent and uncorrelated to common latent factors, i.e., $E[\epsilon_{j,t}] = E[\epsilon_{j,t}f_t] = 0$, for $j = 0, \dots, N$. Under some mild conditions, the IAPT shows that there exist constants, λ_f , representing factor risk premia, such that the currency risk premium is determined by $E[rx_{i,t}] = \beta_i \lambda_f$, suggesting that the pricing error, α_i , should be equal to zero.

Consider a home investor who forms a well-diversified portfolio (with weights ω_i) in currency markets by borrowing in the home currency and investing in all available risk-free assets denominated in foreign currencies. Her portfolio return is then given by

$$R_{p,t+1}^c \equiv \sum_{i=1}^N \omega_i rx_{i,t+1} = \sum_{i=1}^N \omega_i \alpha_i + \sum_{i=1}^N \omega_i \beta_i f_{t+1} + \epsilon_{0,t+1}, \quad (2)$$

where the foreign currency-specific risk averages out when N becomes large. Therefore, the home investor bears two types of risk: (1) the home currency-specific risk ($\epsilon_{0,t+1}$), and (2) the difference between the average exposure of all foreign currencies and the home currency exposure to common risk factors. [Lustig, Roussanov, and Verdelhan \(2014\)](#) find similar implications and empirically show that for U.S. investors, aggregate returns in currency markets are highly predictable, and U.S. macro variables are powerful predictors determining the time-variation of expected currency returns.

The IAPT of [Solnik \(1983\)](#) is an unconditional model which also holds as a conditional

one:

$$rx_{i,t+1} = \alpha_{i,t} + \beta_{i,t}f_{t+1} - \epsilon_{i,t+1} + \epsilon_{0,t+1}, \quad (3)$$

which allows for both mispricing and factor loadings to be time-varying and conditional on information available to the home investor at time t . Empirically, we aim to quantify $\alpha_{i,t}$ in real time, and examine whether an arbitrage portfolio based on it is profitable. However, home idiosyncratic shocks are unobservable and hard to estimate, and this complicates the estimation of pricing errors in Equation (3). In particular, using an unbalanced panel of currencies, for those currencies with shorter time series samples, the estimated pricing errors could be affected considerably by home-specific risk. For this reason, similar to [Bybee, Gomes, and Valente \(2023\)](#), we modify the above model in Equation (3) by first constructing a Dollar factor, $\bar{r}x_{t+1}$, defined as the equal-weight average return across all currencies,

$$\bar{r}x_{t+1} \equiv \frac{1}{N} \sum_{i=1}^N rx_{i,t+1} = \frac{1}{N} \sum_{i=1}^N \alpha_{i,t} + \frac{1}{N} \sum_{i=1}^N \beta_{i,t}f_{t+1} + \epsilon_{0,t+1} = \bar{\alpha}_t + \bar{\beta}_t f_{t+1} + \epsilon_{0,t+1}, \quad (4)$$

and then subtracting the Dollar factor from each individual currency's excess return in each period, yielding the modified IAPT as follows:

$$\begin{aligned} rx_{i,t+1} - \bar{r}x_{t+1} &= (\alpha_{i,t} - \bar{\alpha}_t) + (\beta_{i,t} - \bar{\beta}_t)f_{t+1} - \epsilon_{i,t+1} \\ \implies \tilde{r}x_{i,t+1} &= \tilde{\alpha}_{i,t} + \tilde{\beta}_{i,t}f_{t+1} - \epsilon_{i,t+1}, \end{aligned} \quad (5)$$

where the individual currency excess return in excess of the dollar factor return in each period consists of three terms: a mispricing term, the risk factor premia, and the idiosyncratic return. All three terms are immune to the home idiosyncratic risk.

2.2. Modeling and Estimating Mispricing

We rewrite the modified IAPT in Equation (5) by stacking all currencies into matrix form as

$$\widetilde{\mathbf{R}\mathbf{X}}_{t+1} = \tilde{\boldsymbol{\alpha}}_t + \tilde{\boldsymbol{\beta}}_t f_{t+1} + \mathbf{e}_{t+1}, \quad (6)$$

for $t = 1, \dots, T$. Assume that at each time t , the conditioning information is represented by variables $\mathbf{Z}_t$, an $N \times L$ matrix, which may contain macroeconomic fundamentals of each country and currency-specific characteristics. We model $\tilde{\boldsymbol{\alpha}}_t$ and $\tilde{\boldsymbol{\beta}}_t$ with the following specifications,

$$\tilde{\boldsymbol{\alpha}}_t = \mathbf{Z}_t \boldsymbol{\theta} + \boldsymbol{\Gamma}_{\alpha,t}, \quad \tilde{\boldsymbol{\beta}}_t = \mathbf{Z}_t \boldsymbol{\beta} + \boldsymbol{\Gamma}_{\beta,t}, \quad (7)$$

where the $N \times 1$ vector $\boldsymbol{\Gamma}_{\alpha,t}$ and the $N \times K$ matrix $\boldsymbol{\Gamma}_{\beta,t}$ are cross-sectionally orthogonal to conditioning variables $\mathbf{Z}_t$. The above specifications show that $\mathbf{Z}_t \boldsymbol{\theta}$ and $\mathbf{Z}_t \boldsymbol{\beta}$ capture mispricing and factor loadings, respectively, which can be explained by conditioning variables, whereas $\boldsymbol{\Gamma}_{\alpha,t}$ and $\boldsymbol{\Gamma}_{\beta,t}$ represent sources of alpha and beta that are unrelated to conditioning variables. Such a setup allows for currency return predictability to arise from conditioning variables predicting either mispricing, systematic risk, or both.

Combining Equations (6) and (7), we have

$$\widetilde{\mathbf{R}\mathbf{X}}_{t+1} = \left(\mathbf{Z}_t \boldsymbol{\theta} + \boldsymbol{\Gamma}_{\alpha,t} \right) + \left(\mathbf{Z}_t \boldsymbol{\beta} + \boldsymbol{\Gamma}_{\beta,t} \right) f_{t+1} + \mathbf{e}_{t+1}. \quad (8)$$

One approach to estimate this conditional latent-factor model is IPCA of [Kelly, Pruitt, and Su \(2019\)](#). IPCA requires both a large cross-section (i.e., $N \rightarrow \infty$) and a long time series (i.e., $T \rightarrow \infty$) for consistent estimators, and the latent factors and model parameters are estimated via alternating least squares. In the IPCA framework, conditioning variables, $\mathbf{Z}_t$, can vary freely over time, whereas model parameters, $\boldsymbol{\theta}$ and $\boldsymbol{\beta}$, are time-invariant. Our primary aim is to model and estimate mispricing which is in essence short-lived, i.e., one type of mispricing could disappear very quickly, and may be followed

by a completely different type of mispricing. In addition, as we focus on pricing individual currencies instead of currency portfolios, the factor loadings can also display large changes with respect to market conditions. This suggests that the dependence structures of alpha and beta on conditioning variables, captured by $\boldsymbol{\theta}$ and $\boldsymbol{\beta}$ respectively, may vary over time.

Therefore, we employ PPCA, firstly proposed by [Fan, Liao, and Wang \(2016\)](#) and then extended by [Kim, Korajczyk, and Neuhierl \(2021\)](#). A distinct property of PPCA is that it does not require a large T for consistency, but assumes that conditioning variables are relatively stable. Hence, the model in Equation (8) can be estimated using a rolling-window approach with a small window size (e.g., $T = 12$ months). Such a rolling-window approach introduces time-varying dependence structures of mispricing and systematic risk on conditioning information. [Kim, Korajczyk, and Neuhierl \(2021\)](#) interpret this recursive approach as a locally unconditional approximation to a conditional model. Within each short estimation window, the relationships of alpha and beta with conditioning variables remain constant. However, using a rolling-window estimation allows us to study both the cross-sectional and temporal relations of conditioning variables with both mispricing and systematic risk.

PPCA estimates the conditional latent-factor model in Equation (8) by first giving conditioning variables maximal explanatory power for systematic risk before attributing any explanatory power to mispricing. Under some standard regularity conditions of latent-factor models, PPCA is repeatedly implemented in each (short) time window. As discussed above, conditioning variables are assumed to be constant in each window but allowing them to freely vary across windows. Here we provide an intuitive description, whereas more technical details can be found in the Internet Appendix (Section A1). First, currency excess returns are demeaned to remove the alpha component in Equation (6) and then project demeaned excess returns on conditioning variables to obtain projected demeaned currency excess returns that solely depend on factor loadings related to condi-

tioning variables ($\mathbf{Z}\beta$) and demeaned latent factors. Second, we estimate factor loadings ($\mathbf{Z}\beta$) by applying the standard PCA procedure to projected demeaned currency excess returns. At this stage, PPCA first gives maximal explanatory power to conditioning variables for systematic risk. Third, Equation (8) suggests that currency average excess returns ($\widetilde{\mathbf{R}\mathbf{X}}$) can be written as

$$\widetilde{\mathbf{R}\mathbf{X}} = (\mathbf{Z}\boldsymbol{\theta} + \boldsymbol{\Gamma}_\alpha) + (\mathbf{Z}\beta + \boldsymbol{\Gamma}_\beta)\bar{f} + \bar{e}. \quad (9)$$

Mispricing can then be estimated by regressing average excess returns of individual currencies in the window on conditioning variables orthogonal to estimated factor loadings.

To be specific, we estimate $\boldsymbol{\theta}$ by

$$\hat{\boldsymbol{\theta}} = \arg \min (\widetilde{\mathbf{R}\mathbf{X}} - \mathbf{Z}\boldsymbol{\theta})'(\widetilde{\mathbf{R}\mathbf{X}} - \mathbf{Z}\boldsymbol{\theta}), \quad s.t. \quad (\mathbf{Z}\beta)' \mathbf{Z}\boldsymbol{\theta} = 0, \quad (10)$$

which is an ordinary least square problem with linear constraints and the closed-form solution can be obtained. Clearly, mispricing estimated in this way is orthogonal to factor loadings.

2.3. Currency Arbitrage Portfolio

With the estimated mispricing function, we construct a currency arbitrage portfolio based on conditioning variables observed at the end of each window as

$$\hat{\mathbf{w}}_{\alpha,T} = \frac{1}{N_T} \mathbf{Z}_T' \hat{\boldsymbol{\theta}}. \quad (11)$$

In the empirical implementation, for a given time window, $t = 1, \dots, T$ (e.g., $T = 12$ months), we use currency excess returns in the window and T -period averages of conditioning variables to estimate $\boldsymbol{\theta}$. The currency arbitrage portfolio weights at time T , $\hat{\mathbf{w}}_{\alpha,T}$, are then computed as in Equation (11) using the window-end conditioning

variables ($\mathbf{Z}_T$). We hold the portfolio to the next period and compute its return as $\hat{\mathbf{w}}_{\alpha,T} \mathbf{R} \mathbf{X}_{t+1}$. We then move on to the next window, $t = 2, \dots, T + 1$, and construct the arbitrage portfolio weights and return, $\hat{\mathbf{w}}_{\alpha,T+1}$ and $\hat{\mathbf{w}}_{\alpha,T+1} \mathbf{R} \mathbf{X}_{t+2}$, in the same way. This procedure is repeated recursively each time up to the end of the sample.

All conditioning variables are cross-sectionally standardized to have a mean of zero, ensuring that the portfolio weights $\hat{\mathbf{w}}_{\alpha,T}$ sum to zero, and the currency arbitrage portfolio is a zero-cost investment. The portfolio constructed in this way is an arbitrage portfolio based on pure alpha related to conditioning information without exposure to systematic risk (when $N \rightarrow \infty$). The design is completely out of sample, and thus can serve as a realization of mispricing in currency markets.

3. Data

In this section, we describe the data on currency excess returns, macroeconomic fundamentals, currency characteristics, and observable currency factors used in the empirical analysis.

3.1. Currency Excess Returns

We collect spot and one-month forward exchange rates with respect to the U.S. Dollar (USD) from Barclays Bank International (BBI) and WM/Reuters, available via *Datstream*. We take the U.S. dollar as the home currency, and define the exchange rate as units of USD per unit of the foreign currency (FCU), i.e., FCU/USD. Therefore, an increase in the spot and forward exchange rate indicates an appreciation of the foreign currency or a depreciation of the US dollar.

Our dataset spans from January 1986 to December 2023, and includes a total of 49 currencies: Australia (AUD), Austria (ATS), Belgium (BEF), Brazil (BRL), Bulgaria (BGN), Canada (CAD), Croatia (HRK), Cyprus (CYP), Czech Republic (CZK), Denmark (DKK), Egypt (EGP), Euro area (EUR), Finland (FIM), France (FRF), Germany

(DEM), Greece (GRD), Hong Kong (HKD), Hungary (HUF), Iceland (ISK), India (INR), Indonesia (IDR), Ireland (IEP), Israel (ILS), Italy (ITL), Japan (JPY), Kuwait (KWD), Malaysia (MYR), Mexico (MXN), Netherlands (NLG), New Zealand (NZD), Norway (NOK), Philippines (PHP), Poland (PLN), Portugal (PTE), Russia (RUB), Saudi Arabia (SAR), Singapore (SGD), Slovakia (SKK), Slovenia (SIT), South Africa (ZAR), South Korea (KRW), Spain (ESP), Sweden (SEK), Switzerland (CHF), Taiwan (TWD), Thailand (THB), Turkey (TRY), Ukraine (UAH) and the United Kingdom (GBP). The euro series starts in January 1999. After this date, we exclude the euro area countries and only keep the euro series. In line with previous studies, we remove observations for a given currency that coincide with large deviations from Covered Interest Parity (CIP) (see, e.g., [Nucera, Sarno, and Zinna, 2024](#), and references therein).

Monthly currency excess returns are calculated by sampling the end-of-month spot and forward exchange rates. Specifically, the excess return on buying a foreign currency in the forward market at month t and then selling it in the spot market at month $t + 1$ is given by

$$rx_{i,t+1} = \frac{S_{i,t+1} - F_{i,t}}{S_{i,t}}, \quad (12)$$

where $S_{i,t+1}$ denotes the spot exchange rate of currency i at time $t + 1$, and $F_{i,t}$ denotes its one-month forward exchange rate at month t . The excess return can be decomposed into its spot return and forward-premium components. Under the CIP condition, the forward premium approximates the interest rate differential such that

$$rx_{i,t+1} = \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \frac{S_{i,t} - F_{i,t}}{S_{i,t}} \approx r_{i,t+1} + (i_{i,t} - i_{0,t}), \quad (13)$$

where $r_{i,t+1}$ represents the spot exchange rate return, and $i_{i,t}$ and $i_{0,t}$ denote the foreign and US interest rates, respectively. Following common practice, we use the quoted prices of traded forward contracts, rather than interest rate differentials, to compute currency excess returns. To estimate the pricing error, we subtract from individual currency excess

returns ($rx_{i,t}$) the cross-sectional average return ($\bar{r}x_t$) at each time t , to remove the effect of US-specific shocks as discussed previously.

Table [A1](#) in the Internet Appendix presents the start and end dates, and the number of observations for each currency. Notably, individual currency returns data are unbalanced. The sample includes 23 currencies of developed markets, and 26 currencies of emerging markets. It is important to employ a relatively large cross-section of individual currencies when estimating mispricing and factor loadings in currency markets, given that latent-factor asset pricing models typically require a large cross-section for consistent estimators. Also, a recent study by [Chernov, Dahlquist, and Lochstoer \(2024\)](#) shows that including emerging market currencies substantially enlarges the investment frontier.

3.2. Macroeconomic Fundamentals and Currency Characteristics

We consider two types of conditioning variables. It is well understood that exchange rate fluctuations of two currencies are driven by the relative strength and variability of their macroeconomic fundamentals. Therefore, the first type of conditioning variables includes country-specific macroeconomic fundamentals. We focus on those macroeconomic variables that prior literature has studied and/or found to have predictive power in the cross-section of currency excess returns. Thus, we take into account variables related to inflation, output, global trade, and monetary policy. To be specific, we include the inflation rate (yoy), GDP growth (yoy), GDP level, trade balance over GDP, net foreign assets, and term spread. [Molodtsova, Nikolsko-Rzhevskyy, and Papell \(2008\)](#) show that inflation has predictive power for changes in spot exchange rates. [Lustig, Stathopoulos, and Verdelhan \(2019\)](#) examine the term structure of carry strategies and find that carry trade profits decrease with the maturity of foreign bonds. Additionally, [Dahlquist and Hasseltoft \(2020\)](#) construct economic momentum based on five economic fundamentals related to economic activity and inflation, and show that it can explain the cross-sectional variation in currency excess returns. We also include global imbalances, measured by net

foreign assets, in our set of conditioning variables. Della Corte, Riddiough, and Sarno (2016) show that the dispersion in countries’ foreign imbalances and external liabilities helps explain the cross-sectional variation in currency excess returns. Net debtor countries provide a currency risk premium as compensation for investors financing these negative imbalances, since their currencies tend to depreciate during adverse economic periods. Additionally, building on Richmond (2019), who uncovers that currency risk premia are related to global trade networks, we introduce the ratio of trade balance to GDP as a potential variable reflecting the impact of global trade.

The second type of conditioning variables is related to currency characteristics. We focus on those characteristics that have been shown in the literature to be able to explain the cross-sectional variation of expected currency returns. The first characteristic is the Dollar beta, which measures the exposure of an individual currency to the level of risk in currency markets. Since Lustig and Verdelhan (2007), the literature documents various profitable currency investment strategies. The most prominent strategies include currency Carry (Lustig, Roussanov, and Verdelhan, 2011), currency momentum (Menkhoff et al., 2012; Asness et al., 2013), currency value (Asness et al., 2013; Kroencke et al., 2014; Menkhoff et al., 2017), and currency volatility (Li et al., 2025). Therefore, we also include those currency characteristics: carry based on interest rate differentials, short-term (1-month) and long-term (12-month) momentum based on past currency returns, currency value based on past five-year nominal exchange rate returns, and currency realized variance based on previous three-month daily exchange rate returns.²

Table 1 provides a brief description of both macroeconomic fundamentals and currency characteristics. All variables are lagged to ensure that they are available to investors at the time they are constructed, and thus avoid look-ahead-bias. In the empirical analysis, in each month, we cross-sectionally rank all variables and normalize them in the range of $[-0.5, 0.5]$, with their cross-sectional median equal to 0. One advantage of using the

²While we acknowledge that there are potentially many other relevant currency characteristics, the limited size of the cross-section of currency returns leads us to consider only the most common ones.

Table 1: Conditioning Variables and Long-Short Portfolios

This table lists the conditioning variables used in our PPCA specification and the summary statistics of their long-short portfolios. These conditioning variables include six country-specific macroeconomic fundamentals and six currency characteristics. Columns 4-6 report the long-short portfolios' annualized average return and Sharpe ratios. Newey-West adjusted t -ratios (Newey and West, 1987) are presented in parentheses. The sample period is from January 1986 to December 2023.

Acronym	Variables	Freq.	Mean	t -ratio	SR
Panel A. Macroeconomic Fundamentals					
CPI	YoY Inflation Rate	Monthly/Quarterly	5.04	(3.91)	0.68
GDP Growth	YoY Growth of GDP	Quarterly	1.76	(1.51)	0.26
GDP_per	GDP per capita	Annual	2.11	(1.69)	0.28
Trade_GDP	Trade Balance over GDP	Annual	1.62	(1.83)	0.31
NFA	Net Foreign Asset	Annual	2.93	(2.55)	0.44
Term Spread	Term Spread	Monthly	3.16	(2.39)	0.42
Panel B. Currency Characteristics					
Dollar Beta	Risk Exposure to Dollar Factor	Monthly	0.60	(0.35)	0.06
Carry	Carry (Forward Discount)	Monthly	6.99	(4.97)	0.89
Mom1m	Short-term Momentum	Monthly	4.69	(3.62)	0.55
Mom12m	Long-term Momentum	Monthly	3.05	(2.37)	0.36
Value	Value	Monthly	3.07	(2.43)	0.38
RV	Realized Variance	Monthly	2.04	(1.32)	0.22

cross-sectional ranks is that the impact of potential data errors and outliers in individual variables can be largely alleviated.

Next, we construct long-short portfolios based on individual conditioning variables. Specifically, at the end of each month, we sort all currencies into quintile portfolios on the basis of each conditioning variable, and then form a long-short portfolio that buys the portfolio with the highest values of the sorting variable and shorts the portfolio with the lowest values of the sorting variable. We hold these portfolios to the next month and compute their realized equal-weighted mean excess returns. The last three columns of Table 1 report annualized average returns, t -ratios, and annualized Sharpe ratios of all long-short portfolios. We adjust the direction of the long and short positions to ensure that the long-short portfolios yield positive mean returns. We see that almost all portfolios based on macroeconomic fundamentals except GDP growth produce positive

average returns which are statistically significant at least at the 10% significance level. We also note that consistent with the literature, except for the Dollar beta and RV portfolios, the long-short portfolios based on carry, momentum, and value all generate statistically significant mean excess returns. The Carry portfolio produces the largest Sharpe ratio in Table 1 (0.89), followed by the CPI-based portfolio (0.68) and the short-term momentum portfolio (0.55).

3.3. Observable Currency Risk Factors

Relying on a large cross-section of currency portfolios, [Nucera, Sarno, and Zinna \(2024\)](#) show that at least three and potentially four latent factors should enter the currency stochastic discount factor. These latent factors appear to be closely related (albeit not identical) to some tradable factors. The dominant latent factors relate to carry and short-term momentum, while the evidence for a fourth value-like latent factor is weaker. The other factor is essentially a Dollar factor. Therefore, in this paper, we consider four observable currency factors for a benchmark model: Dollar, Carry, Short-term Momentum, and Value.

As previously described, the Dollar factor is simply the equal-weighted cross-sectional average of currency excess returns and serves as a level factor. In contrast, the factors of carry, short-term momentum, and value are slope factors, constructed as long-short portfolios based on quintile portfolios, as detailed in the previous subsection and Table 1. Note that we measure currency value using the past five-year nominal exchange rate returns rather than real returns. The calculation of real returns requires information on each country’s purchasing power relative to the US. However, for many countries in our sample, consumer price index data are sparse and infrequently updated. Furthermore, previous studies find that the variability of the value signal is predominantly driven by the nominal exchange rate component ([Menkhoff, Sarno, Schmeling, and Schrimpf, 2017](#)).

4. Empirical Results

In this section, we present our main empirical findings. We begin by evaluating the performance of the arbitrage portfolio constructed using the PPCA method in Subsection 4.1. We then show that the arbitrage portfolio already integrates information contained in currency characteristics and macroeconomic fundamentals, and it cannot be explained by commonly used observable currency factors in Subsection 4.2. In Subsection 4.3, we construct an alternative arbitrage portfolio based on IPCA estimates of mispricing and examine its performance relative to the PPCA-based currency arbitrage portfolio.

4.1. Performance of Currency Arbitrage Portfolios

Table 2 presents summary statistics of arbitrage portfolios, which are derived from estimates of mispricing related to conditioning variables. Following the PPCA procedure outlined in Section 2.2, we construct arbitrage portfolios for various numbers of latent factors (K) employing a rolling-window approach with a 12-month window size. Within each window, conditioning variables are treated as constant, with their values set to their window averages. The arbitrage portfolio weights are updated based on model parameter estimates for this window and the out-of-sample values of conditioning variables. To ensure comparability over time, we normalize the annualized standard deviation of in-sample arbitrage portfolio returns to 5% for each window.

When examining the number of latent factors ranging from one to five, we find that all arbitrage portfolios generate positive mean returns and high Sharpe ratios. The annualized Sharpe ratio varies from 0.77 to 0.83. Specifically, with only one latent factor, the annualized Sharpe ratio of the arbitrage portfolio is 0.81. It then declines to a value of 0.77 when the number of latent factors equals two. Subsequently, the Sharpe ratio rebounds slightly, peaking at 0.83 when the number of latent factors increases to four. We observe that all arbitrage portfolio returns are right-skewed and platykurtic. The Sharpe

Table 2: Performance of Arbitrage Portfolios

This table reports the summary statistics of the arbitrage portfolio, including the annualized percentage means, annualized percentage standard deviations, annualized Sharpe ratios, skewness, kurtosis, the minimum return, 10% quantile return, 25% quantile return, 75% quantile return, 90% quantile return, and the maximum return. The estimation window is 12 months, and the number of latent factors ranges from one to five. The last row presents the summary statistics of the arbitrage portfolio constructed using the optimal number of latent factors. The sample period is from January 1987 to December 2023.

K	Mean	SD	SR	Skew	Kurt	Min	Q10	Q25	Q75	Q90	Max
1	4.39	5.39	0.81	0.27	1.40	-5.16	-1.45	-0.59	1.28	2.28	6.63
2	4.24	5.53	0.77	0.16	1.43	-5.74	-1.53	-0.61	1.31	2.32	6.89
3	4.50	5.54	0.81	0.27	0.98	-4.37	-1.62	-0.63	1.37	2.26	7.18
4	4.73	5.66	0.83	0.20	0.68	-4.46	-1.62	-0.62	1.47	2.36	6.32
5	4.96	6.01	0.82	0.25	1.08	-5.08	-1.66	-0.67	1.42	2.37	7.48
K^*	4.43	5.48	0.81	0.24	1.17	-4.97	-1.51	-0.58	1.28	2.25	6.78

ratios of these arbitrage portfolios are quite comparable to those of common currency trading strategies, as shown in Table 1. For instance, the Carry factor achieves a higher Sharpe ratio of 0.89, and the short-term momentum factor yields a more modest Sharpe ratio of 0.55. In contrast, the Sharpe ratios of the Dollar strategy, the volatility strategy, and the value strategy are all well below 0.5.

The optimal number of latent factors in each window may be different. Too few latent factors cannot ensure orthogonality between mispricing and factor loadings, while too many may lead to less accurate estimates of model parameters, harming the performance of the arbitrage portfolio. We therefore follow the projected-PC eigenvalue-ratio method of [Fan, Liao, and Wang \(2016\)](#) to estimate the number of latent factors for each window by maximizing the ratio of adjacent eigenvalues of the demeaned projected currency returns. We observe that the optimal number of latent factors ranges from one to three. We then construct a currency arbitrage portfolio based on the optimal number of latent factors for each window (K^*). As we see in the last row in Table 2, this arbitrage portfolio yields

an annualized Sharpe ratio of 0.81.^{3,4}

In Figure 1, we plot the time series of log cumulative returns of the arbitrage portfolios with three latent factors (as a representative case) and optimally chosen factors, alongside those of commonly used currency risk factors. To ensure comparability, all strategies are normalized to have the same standard deviation as the Dollar factor. We observe that the arbitrage portfolios demonstrate stable long-term performance, outperforming most currency strategies. Although the Carry factor performs comparably with the arbitrage portfolios, it exhibits frequent ups and downs, in particular during market downturns. We notice that after the 2008 global financial crisis, the increase of arbitrage portfolio cumulative returns slows down, and since the onset of the COVID-19 pandemic, its performance has lagged behind the Carry factor.

Both Table 2 and Figure 1 suggest that mispricing in currency markets is prevalent. As discussed, the arbitrage portfolio in the PPCA is constructed based on alpha estimates related to conditioning variables by first giving them maximal explanatory power for systematic risk. Theoretically, as the cross-section of currencies expands, the exposures of the arbitrage portfolio to systematic risk should approach zero. Therefore, the high Sharpe ratio and stable long-term performance of the arbitrage portfolio can be interpreted as the existence of mispricing in currency markets.

4.2. Arbitrage Portfolios and Risk Factors

While the arbitrage portfolio is constructed by orthogonalizing mispricing and factor loadings to ensure that systematic risk is controlled for, this can be achieved only when

³Several currencies in our sample are pegged to the US dollar, including HKD, BGN, DKK, KWD, and SAR. Therefore, we examine how the currency arbitrage portfolio performs when excluding those pegged currencies. We see in Table A2 in the Internet Appendix that the Sharpe ratio of the currency arbitrage portfolio remains high, varying from 0.68 to 0.75 for different numbers of latent factors.

⁴An important question is whether the currency arbitrage portfolio remains profitable when we take into account transaction costs. To this end, we measure the transaction cost as a certain percentage of the effective bid-ask spread. We consider 25%, 50%, and 75%. Table A3 in the Internet Appendix shows that the currency arbitrage portfolio remains profitable after transaction costs. For example, for the arbitrage portfolio with three latent factors, its Sharpe ratios are 0.67, 0.52, and 0.37, respectively, for the aforementioned three levels of transaction costs.

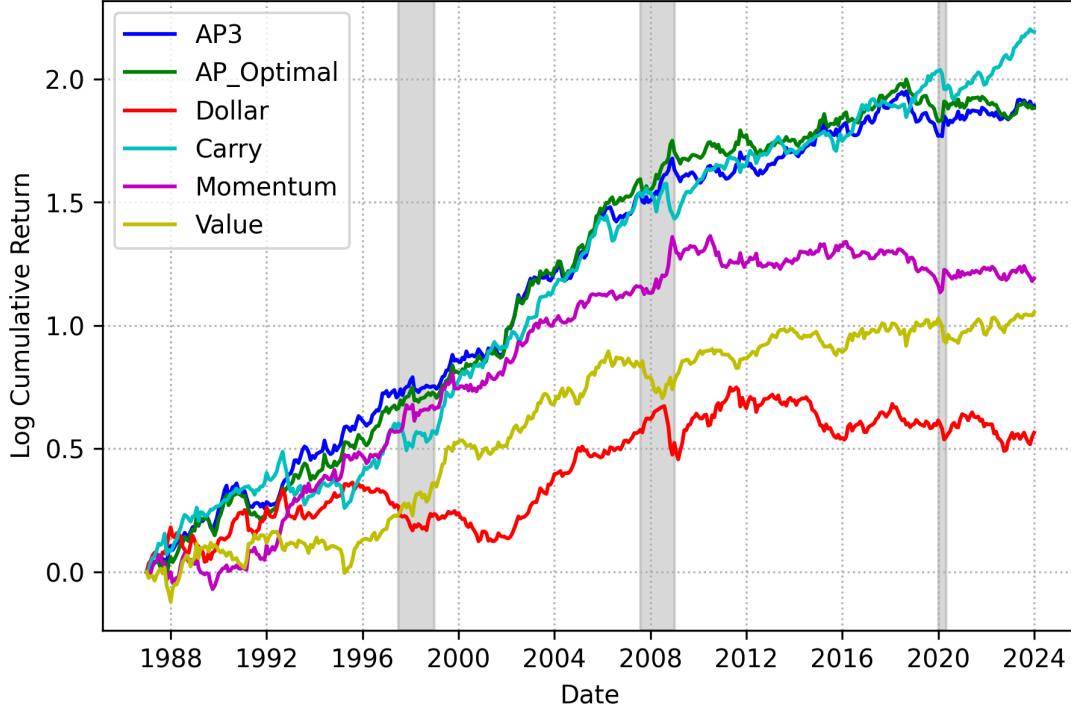


Figure 1: Cumulative Returns of Arbitrage Portfolios

This figure shows the logarithm of the price path (i.e., the cumulative returns) of the arbitrage portfolios and commonly used observable factors. AP3 represents the arbitrage portfolio with three latent factors, and AP_Optimal represents the arbitrage portfolio that uses the optimally selected factors in each window.

the cross section is large enough in PPCA. However, in currency markets, we do not have large cross-sections of individual currencies compared to, say, equity markets. Therefore, in this subsection, we examine whether the performance of the arbitrage portfolio can be explained by commonly used currency factors. We first implement unconditional spanning regressions in Subsection 4.2.1, and then conduct a conditional spanning test in Subsection 4.2.2.

4.2.1. Spanning Regressions

We start by performing unconditional spanning regressions of the arbitrage portfolio returns on observable currency factors. As discussed in Section 3.3, we take the four-factor model, which includes the factors of the dollar, carry, short-term momentum, and value as the benchmark model.

Table 3 presents the results of the spanning regressions. We regress the arbitrage portfolio returns for the number of latent factors ranging from one to five on the aforementioned four observable currency factors. A key finding is that no matter how many latent factors we use in constructing the arbitrage portfolio, the risk-adjusted annualized returns are all economically substantial and statistically highly significant. We note that the coefficients on the three slope factors are all statistically significant, suggesting that they contain relevant information on currency mispricing. The estimated coefficients on Carry and Momentum are both positive, indicating that the arbitrage portfolio returns are positively related to these two dominant slope factors. Interestingly, the estimated coefficient on the Value factor is negative, which suggests that the arbitrage portfolio returns are related to a growth-type currency strategy rather than conventional value. In contrast, the dollar factor barely has any explanatory power, which is not surprising. The adjusted R^2 in the spanning regressions varies from 28% to 52% for various numbers of latent factors. In Section 5, we will further examine variable importance for both mispricing and systematic risk.

4.2.2. PPCA with Observable Factors

The spanning regressions above demonstrate that the risk-adjusted returns of the arbitrage portfolios are both economically substantial and statistically significant. However, these regressions assume constant exposures to observable factors, whereas the arbitrage portfolio is constructed using a model with time-varying factor loadings. Therefore, we reconstruct the arbitrage portfolio by incorporating the pre-specified observable factors in the PPCA framework. To be specific, we introduce the observable factors in Equation (6) as follows

$$\widetilde{\mathbf{R}}\mathbf{X}_{t+1} = \tilde{\boldsymbol{\alpha}}_t + \tilde{\boldsymbol{\beta}}_t f_{t+1} + \tilde{\boldsymbol{\gamma}}_t g_{t+1} + \mathbf{e}_{t+1}, \quad (14)$$

where the new term represents risk premia captured by observable factors, g_{t+1} . We estimate the above model using a procedure similar to that outlined in Section 2, with the

Table 3: Unconditional Spanning Regressions

This table presents the results from implementing the spanning regressions of arbitrage portfolio returns on the risk factor model. The risk factor model includes the Dollar, Carry, Momentum, and Value factors. The risk-adjusted returns (Intercept) are presented in annualized percentage. The sample period ranges from January 1987 to December 2023. Newey-West adjusted t -ratios (Newey and West, 1987) are shown in parentheses.

K	1	2	3	4	5
Intercept	2.04 (3.21)	1.88 (2.97)	2.53 (3.61)	2.94 (3.55)	3.35 (3.76)
Dollar	-0.03 (-0.87)	-0.04 (-1.01)	-0.02 (-0.5)	-0.02 (-0.54)	-0.00 (-0.10)
Carry	0.11 (2.89)	0.13 (3.22)	0.11 (2.84)	0.12 (2.64)	0.10 (1.94)
Mom	0.46 (15.5)	0.44 (14.4)	0.40 (11.7)	0.37 (9.47)	0.35 (8.59)
Value	-0.09 (-2.03)	-0.12 (-2.79)	-0.15 (-3.29)	-0.17 (-3.59)	-0.17 (-3.08)
$Adj\ R^2$	0.52	0.48	0.40	0.34	0.28

additional assumptions that, within each window, $\tilde{\gamma}_t$ is also a function of conditioning variables and the mispricing function must also be orthogonal to both the latent factors and the pre-specified observable factors. The estimation of factor loadings on the latent factors then follows the same procedure as in the previous section except that the projected demeaned currency return is replaced with the projected demeaned returns in excess of the observable factor premium and $\tilde{\beta}_t$ is required to be orthogonal to $\tilde{\gamma}_t$.

Table 4 presents the performance of the arbitrage portfolio constructed by including the factors of carry, short-term momentum, and value in the model. For the number of latent factors ranging from one to five, the new arbitrage portfolio maintains strong performance, with the annualized Sharpe ratio varying from 0.85 ($K = 3$) to 0.93 ($K = 2$). Similarly, all arbitrage portfolio returns are right-skewed and platykurtic.

Both Table 3 and Table 4 provide further evidence in support of the conclusion that mispricing is prevalent in currency markets. This mispricing can be exploited by constructing an arbitrage portfolio based on alpha estimates related to various types of condi-

Table 4: Arbitrage Portfolios from PPCA Combined with Observable Factors

This table reports the summary statistics of the arbitrage portfolio constructed by the PPCA approach combined with observable factors, including the annualized percentage means, annualized percentage standard deviations, annualized Sharpe ratios, skewness, kurtosis, the minimum return, 10% quantile return, 25% quantile return, 75% quantile return, 90% quantile return, and the maximum return. The estimation window is 12 months and the number of latent factors ranges from one to five. The sample period is from January 1987 to December 2023.

K	Mean	SD	SR	Skew	Kurt	Min	Q10	Q25	Q75	Q90	Max
1	5.06	5.75	0.88	0.15	0.95	-5.44	-1.64	-0.61	1.44	2.30	6.22
2	5.35	5.78	0.93	0.21	1.13	-5.40	-1.61	-0.53	1.41	2.31	7.50
3	4.98	5.89	0.85	0.39	1.37	-4.61	-1.62	-0.71	1.38	2.39	7.65
4	5.48	6.15	0.89	0.34	1.10	-4.60	-1.61	-0.73	1.44	2.58	7.53
5	5.45	6.30	0.86	0.31	0.85	-4.78	-1.68	-0.74	1.52	2.61	7.54

tioning variables, including country-specific macroeconomic fundamentals and currency-specific characteristics.

4.3. What Does IPCA Say?

So far, we have showed that an arbitrage portfolio based on mispricing related to conditioning variables in PPCA achieves a high Sharpe ratio and its performance cannot be explained by commonly used observable factors. Another approach to estimating our conditional latent factor model is IPCA of [Kelly, Pruitt, and Su \(2019\)](#), which however assumes both a large cross section and a long time series for consistent estimators. As discussed, the construction of the arbitrage portfolios is essentially an out-of-sample procedure. In this part, we rely on a measure of expected mispricing in the IPCA framework to construct an alternative arbitrage portfolio, in a way similar to [Bali, Beckmeyer, and Wiedemann \(2023\)](#).

Specifically, we first compute realized mispricing at each time starting from January 1996 as residual returns by estimating the restricted IPCA model (i.e., $\tilde{\alpha}_t = 0$ in Equation (6)) with three latent factors⁵ in an out-of-sample setting using the standard expanding-

⁵The results remain quantitatively similar when using four IPCA latent factors. See Table A4 in the Internet Appendix.

window approach, i.e., at time t , we estimate the restricted model using returns and conditioning variables data only up to time t , and hold the model parameter estimates $\hat{\beta}$ fixed over the next period to obtain factor realizations ($\hat{f}_{t+1}$). Relying on both model parameter estimates and factor realizations, we define realized mispricing as

$$mp_{i,t+1} = r\tilde{x}_{i,t+1} - z_{i,t}\hat{\beta}\hat{f}_{t+1}. \quad (15)$$

With realized mispricing estimated, we then implement a forecasting procedure to construct expected mispricing as follows

$$E_t[mp_{i,t+1}] = g(z_{i,t}), \quad (16)$$

where $g(\cdot)$ is a function mapping current conditioning variables to expected mispricing. We learn this function using three types of machine learning methods, including gradient-boosted regression trees (Friedman, 2001), random forests (Breiman, 2001), and neural network with three hidden layers (Gu, Kelly, and Xiu, 2020). Expected mispricing is then constructed as the equal-weighted average of those three types of forecasts.⁶

Our first out-of-sample period begins in January 1996, with the first sample comprising 10 years of data. At each time, we use the data of the first 70% of months to train the model of Equation (16), and the remaining 30% to validate the hyperparameters. Based on expected mispricing at each time, we form quintile currency portfolios and a high-

⁶A feed-forward neural network (FFNN) is an artificial neural network with an input layer, one or more hidden layers, and an output layer. The input layer receives conditioning variables, while the hidden layers apply non-linear transformations (e.g., ReLU) to capture the complex relationships between conditioning variables and mispricing. The output layer generates predictions of the realized mispricing. Gradient-Boosted Regression Trees (GBRT), introduced by Friedman (2001), combine multiple weak learners, typically decision trees, into a strong predictive model. Trees are built sequentially, with each new tree correcting the errors of the previous one by fitting residuals. The model minimizes a loss function through gradient descent, and the final prediction is an additive model of all trees. Random Forests (RF), introduced by Breiman (2001), aggregate predictions from multiple decision trees constructed via bootstrapping, with each tree trained on a random subset of the data and features. The final output is the average of all trees' predictions. Unlike GBRT, RF trains trees independently and does not use boosting, making it less prone to overfitting, particularly with noisy data. Each method has distinct strengths: FFNN captures complex non-linear relationships, GBRT is more interpretable and focuses on iterative improvement, and RF ensures stability and robustness through ensemble averaging.

Table 5: Expected Mispricing and Arbitrage Portfolio

This table reports the performance of alternative arbitrage portfolios constructed under the IPCA framework, using three latent factors. Panel A shows annualized expected mispricing, annualized realized mispricing, annualized portfolio excess returns, annualized Sharpe ratios, skewness, and kurtosis for quintile portfolios. Panel B reports the spanning regression of annualized high-minus-low portfolio returns, sorted by expected mispricing, on the risk factor model that includes Dollar, Carry, Momentum, and Value factors. Newey-West adjusted t -ratios (Newey and West, 1987) are shown in parentheses. The sample period is from January 1996 to December 2023.

Panel A. Portfolio Statistics						
	E[mp]	mp	Ret	SR	Skew	Kurt
Low	-1.41	-1.14	-0.69	-0.08	-0.03	0.94
2	-0.57	-0.09	0.93	0.13	-0.02	0.69
3	-0.09	-0.20	0.54	0.08	-0.05	1.97
4	0.39	0.25	1.54	0.25	-0.07	1.25
High	1.43	1.24	2.60	0.39	-0.99	3.26
HML	2.84 (40.6)	2.37 (2.98)	3.30 (2.75)	0.55	-0.31	1.26
Panel B. Risk-Adjusted Return						
	Intercept	Dollar	Carry	MoM	Value	Adj R^2
HML	0.68 (0.61)	-0.29 (-4.33)	0.39 (6.66)	0.19 (3.19)	-0.19 (-2.91)	0.29

minus-low portfolio, as an alternative arbitrage portfolio and hold them to the next period.

Panel A of Table 5 reports the performance of the arbitrage portfolio based on expected mispricing in the IPCA framework. We find that the average annualized expected mispricing spread is 2.84%, which is highly statistically significant and slightly larger than the average annualized realized mispricing spread (2.37%). The high-minus-low arbitrage portfolio based on expected mispricing generates a statistically significant average annualized return of 3.30% ($t = 2.75$), with an annualized Sharpe ratio of 0.55.

We then examine whether the IPCA arbitrage portfolio returns can be explained by commonly used observable currency factors. Panel B of Table 5 presents the result of the spanning regression. We note that the four-factor model, which includes the Dollar, Carry, Momentum, and Value factors, can fully account for the IPCA arbitrage portfolio

returns. The annualized risk-adjusted return (Intercept) is only 0.68% (compared to an average annualized return of 3.30%) and is not statistically significant. All factor loadings are highly statistically significant, and the adjusted R^2 is about 29%. These findings contrast sharply with those in Section 4.2, where we show that the PPCA arbitrage portfolio returns cannot be explained by these observable factors in both unconditional and conditional setups.⁷ While the two-step out-of-sample procedure alleviates concerns of time-invariant dependence structures of both mispricing and factor loadings on conditional variables in IPCA, it remains unclear whether mispricing is orthogonal to factor loadings. This orthogonality is a distinct feature of PPCA, where mispricing is estimated by ensuring it is orthogonal to factor loadings.

5. Interpreting Currency Mispricing

In this section, we explore potential sources of currency mispricing. We evaluate the importance of conditioning variables that significantly contribute to systematic risk and mispricing, respectively, in Subsection 5.1. We then implement empirical analyses to investigate which currencies are most mispriced in Subsection 5.2. We examine how the arbitrage portfolio performs under various market conditions and how it relates to global financial conditions in Subsection 5.3. Finally, in Subsection 5.4, we show how net positions of speculators relate to currency mispricing.

5.1. Which Variables Mostly Contribute to Mispricing?

In PPCA, both mispricing and factor loadings are functions of conditioning variables, which include currency characteristics and macroeconomic fundamentals. We investigate which variables mostly contribute to mispricing and systematic risk and the relative

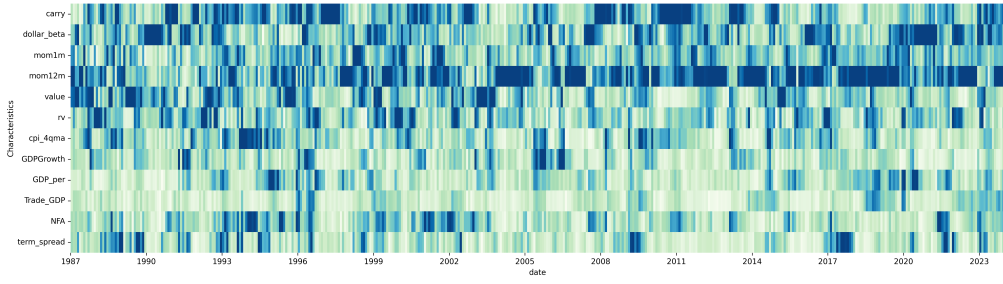
⁷For the same period from January 1996 to December 2023, we further show in Table A5 and Table A6 in the Internet Appendix that the arbitrage portfolio in the PPCA framework generates an annualized Sharpe ratio of 0.73 (for three latent factors) and its performance cannot be explained by the observable currency factors also during this shorter sample period.

importance of currency characteristics to macroeconomic fundamentals. Given that the PPCA procedure is implemented using a rolling-window approach, it allows us to compute the time-series contributions of each variable to mispricing and factor loadings and examine how those contributions vary over time.

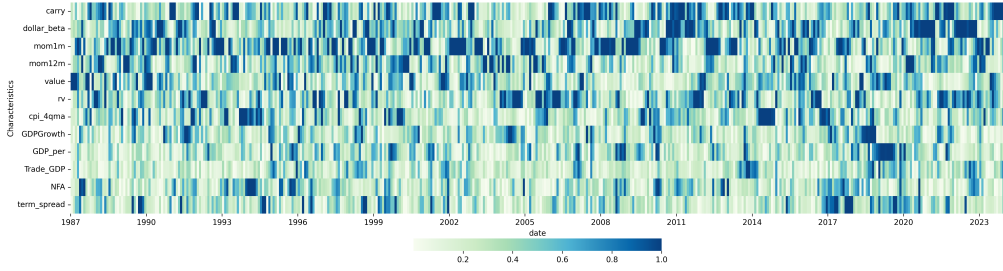
We regress the estimated factor loadings and mispricing on conditioning variables in each period, and hence, the estimated $\hat{\beta}$ and $\hat{\theta}$ capture the relationships between conditioning variables and systematic risk and mispricing, respectively, in that period. The estimated coefficients of $\hat{\beta}$ and $\hat{\theta}$ are an $L \times K$ matrix and an $L \times 1$ vector, respectively. We evaluate the contribution of variable l to systematic risk as $\sum_{k=1}^K |\hat{\beta}_{k,l}|$ and to mispricing as $|\hat{\theta}_l|$. To ensure the contributions of conditioning variables are comparable over time, we normalize them cross-sectionally in each period so that the largest contribution is always equal to one. This approach allows us not only to identify the key conditioning variables that impact expected returns but also to understand how their impacts vary over time.

We consider a three-factor model in PPCA. The top panel of Figure 2 presents a heatmap illustrating the contributions of conditioning variables to systematic risk. It is evident that these contributions vary both in the cross section and in the time series. In the cross section, currency characteristics appear to play more important roles than macroeconomic fundamentals. Notably, among all currency characteristics, carry and 12-month momentum emerge as the most critical variables. We also note that the contributions change over time. The time-varying contributions of conditioning variables suggest that the temporal dependence of factor loadings on conditioning variables is not constant.

The bottom panel of Figure 2 displays a heatmap of the contributions of conditioning variables to mispricing. Again, we see that these contributions change both cross-sectionally and temporally. However, compared to the heatmap for systematic risk, no single variable consistently plays a dominant role in mispricing. Instead, many variables



(a) Factor Loadings



(b) Mispricing

Figure 2: Heatmap of Contributions of Conditioning Variables to Beta and Alpha

The heatmap shows the contributions of conditioning variables on Beta (PPCA factor loadings) and Alpha (Mispricing). The number of latent factors is three, and the size of the estimation window is 12 months. For the Beta heatmap (Upper Figure), we regress the Beta estimated by PPCA on the conditioning variables each month. Then, we take the eigenvalue-weighted summation of the absolute value of the coefficient and normalize it by the maximum so that the largest one equals one. For the Alpha heatmap, we regress the Alpha estimated by PPCA on conditioning variables each month. Then, we take the absolute value of the coefficient and normalize it by the maximum so that the largest one equals one. The darker (lighter) mark represents that the contribution of conditioning variables is large (small) and close to one (zero).

are related to mispricing, but only for a few periods and there is a clear “on-and-off” pattern, reflecting that mispricing is short-lived, with one type of mispricing disappearing quickly and being followed by another type of mispricing.

The heatmaps above offer a convenient way to visually assess the cross-sectional and temporal variations in the relationships between systematic risk/mispricing and conditioning variables. We further quantify the aggregate contributions of conditioning variables to both mispricing and systematic risk by calculating their time-series averages. Table 6 presents the aggregate contributions of various variables. The top five contributors

to factor loadings include 12-month momentum, carry, dollar beta, 1-month momentum, and value, which align closely with findings in the literature (see, e.g., [Nucera, Sarno, and Zinna, 2024](#); [Li, Sarno, and Zinna, 2025](#); [Bartram, Djuranovik, Garratt, and Xu, 2023](#)). Their contributions vary from 0.50 to 0.74. We notice a similar set of variables also contribute to mispricing, although their overall contributions are smaller compared to the contributions for systematic risk. This observation is consistent with our findings above that a variable cannot consistently contribute to mispricing over an extended period. The most important macroeconomic fundamentals for both factor loadings and mispricing are CPI, NFA and Term spread. However, consistent with what we have observed in the heatmaps above, the contributions of currency characteristics overshadow those of macroeconomic fundamentals in both factor loadings and mispricing. This finding aligns with the literature suggesting that while macroeconomic fundamentals may influence the long-term behavior of exchange rates, a short-term disconnect often exists between the two.

To further investigate the relative importance of currency characteristics to macroeconomic fundamentals in estimating currency mispricing, we apply the PPCA method separately to two types of conditioning variables. The first set of conditioning variables includes only currency characteristics, and the other contains carry, dollar beta, and all macroeconomic fundamentals. We note that when using the set of conditioning variables including only carry, dollar beta, and macroeconomic fundamentals, the arbitrage portfolio exhibits weaker performance, whereas the arbitrage portfolio based solely on currency characteristics (without macroeconomic fundamentals) generates comparable performance to that constructed with the full set of conditioning variables.⁸

⁸See Tables [A7](#) and [A8](#) in the Internet Appendix.

Table 6: Contributions of Conditioning Variables to Factor loadings and Mispricing

This table presents the average contribution of conditioning variables to Beta (Factor loadings) and Alpha (Mispricing) over the sample period. The number of latent factors is three. The estimation window is 12 months. Each month, we regress the Beta (Alpha) estimated by PPCA onto conditioning variables. Then, we take the eigenvalue-weighted summation of the absolute value of the coefficient and normalize it by the maximum so that the largest one equals one. Finally, we calculate the time-series average of the contribution.

Factor Loadings			Mispricing		
Variables	Contribution	Category	Variables	Contribution	Category
<i>Mom12m</i>	0.74	Momentum	<i>Mom1m</i>	0.56	Momentum
<i>Carry</i>	0.59	Carry	<i>Carry</i>	0.50	Carry
<i>Dollar Beta</i>	0.57	Dollar	<i>Dollar Beta</i>	0.49	Dollar
<i>Mom1m</i>	0.53	Momentum	<i>RV</i>	0.46	Trading Friction
<i>Value</i>	0.50	Value	<i>Mom12m</i>	0.42	Momentum
<i>RV</i>	0.49	Trading Friction	<i>Value</i>	0.40	Value
<i>CPI</i>	0.42	Macro	<i>CPI</i>	0.40	Macro
<i>NFA</i>	0.41	Macro	<i>Term Spread</i>	0.35	Macro
<i>GDP_per</i>	0.36	Macro	<i>NFA</i>	0.34	Macro
<i>Term Spread</i>	0.36	Macro	<i>GDP_per</i>	0.34	Macro
<i>GDP Growth</i>	0.35	Macro	<i>GDP Growth</i>	0.34	Macro
<i>Trade_GDP</i>	0.27	Macro	<i>Trade_GDP</i>	0.29	Macro

5.2. Which Currencies are Mostly Mispriced?

The cross-section of individual currencies contains both developed market and emerging market currencies. Including emerging market currencies is important as they expand the investment frontier substantially relative to major currencies (Chernov, Dahlquist, and Lochstoer, 2024). A natural question then arises: how are emerging market currencies mispriced relative to developed market currencies? To explore this question, we construct an emerging market currency arbitrage portfolio and a developed market currency arbitrage portfolio. We first implement PPCA using the entire universe of individual currencies, as previously described, to obtain estimates of mispricing related to conditioning variables, and then construct these two types of arbitrage portfolios based solely on their respective mispricing estimates.

Table 7 presents the performance of developed and emerging market currency arbitrage portfolios for various numbers of latent factors in PPCA. Regardless of how many

Table 7: Arbitrage Portfolios: Developed vs. Emerging Markets

This table reports the performance of arbitrage portfolios constructed from developed and emerging market currencies. It includes annualized mean returns, annualized standard deviations, and annualized Sharpe ratios. For comparability, both portfolios cover the sample period from 1998 to 2023. The rightmost column shows the statistical significance of the Sharpe ratio differences between developed and emerging currency portfolios.

K	Developed Markets			Emerging Markets			SR Diff (p -value)
	Mean	Std	SR	Mean	Std	SR	
1	0.15	1.98	0.07	3.07	4.00	0.77	0.00
2	0.00	2.07	0.00	3.02	4.38	0.69	0.01
3	0.38	2.12	0.18	2.94	4.63	0.64	0.07
4	0.38	2.25	0.17	3.37	4.70	0.72	0.03
5	0.28	2.49	0.11	3.91	4.95	0.79	0.01

latent factors are selected, the Sharpe ratio of the emerging market arbitrage portfolio is consistently much higher than that of the developed markets. The Sharpe ratio difference is statistically significant (at least at the level of 10%) according to the test of [Jobson and Korkie \(1981\)](#) and [Mennel \(2003\)](#) for each number of latent factors. This finding suggests that emerging market currencies are much more severely mispriced than developed market currencies. This is understandable because, compared to emerging market currencies, developed market currencies are traded more frequently and with higher liquidity in the global currency market.

Next, we examine the most overvalued and undervalued currencies in the arbitrage portfolio. To this end, we divide the currency sample into five groups based on mispricing estimates at each time. The first group contains the most overvalued currencies (those with the most negative mispricing), while the fifth group contains the most undervalued currencies (those with the most positive mispricing). We then calculate the frequency of each currency that appears in the first and fifth groups, respectively.

Panel A of Table 8 lists the five most undervalued and overvalued currencies. The most overvalued currencies are JPY, CHF, ILS, ZAR, and SAR, while the most undervalued currencies include EGP, BRL, TRY, ISK, and MXN. It appears that developed market currencies tend to be overvalued, whereas emerging market currencies are often under-

Table 8: Overvalued and Undervalued Currencies

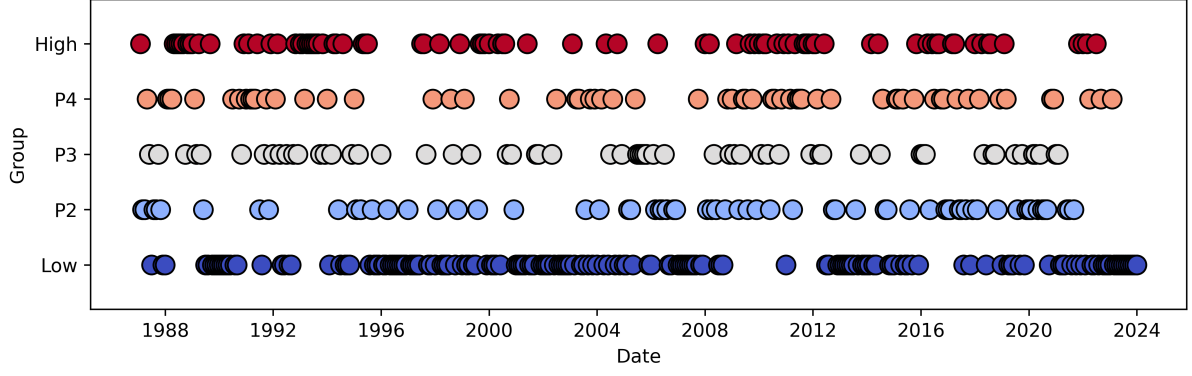
The table presents the top five constituents of the corner portfolios, including the short-side P1 and the long-side P5, for the estimated weight from PPCA and the Carry factor. The top constituents are the currencies that display the highest time series frequency (Freq) of appearance in the selected portfolio. The number of latent factors is three, and the size of the estimation window is 12 months.

Panel A: AP				Panel B: Carry			
P1	P1 Freq	P5	P5 Freq	P1	P1 Freq	P5	P5 Freq
JPY	0.39	EGP	0.46	JPY	0.87	TRY	0.98
CHF	0.30	BRL	0.43	CHF	0.81	EGP	0.88
ILS	0.28	TRY	0.43	TWD	0.60	BRL	0.81
ZAR	0.28	ISK	0.36	SGD	0.50	ZAR	0.78
SAR	0.28	MXN	0.34	DEM	0.50	UAH	0.68

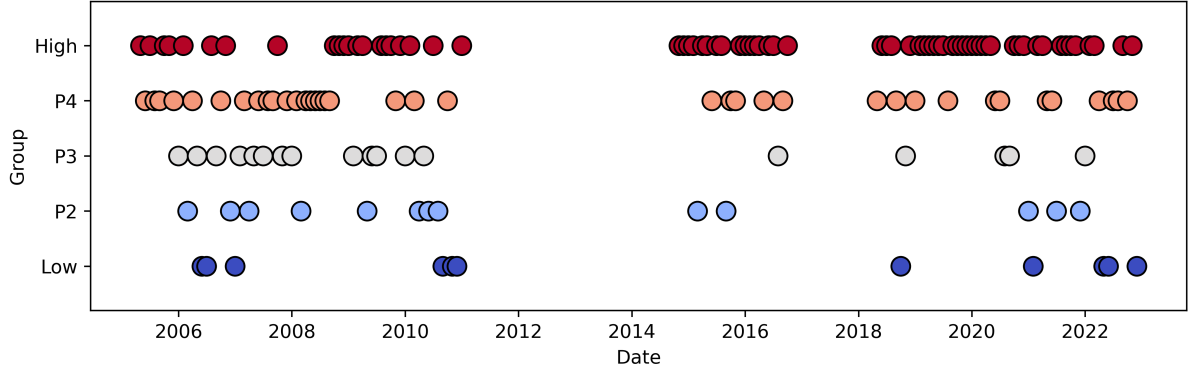
valued. However, their appearance frequencies are relatively low. For example, although the Japanese Yen is the most frequently overvalued currency, its appearance frequency in the most overvalued group is only about 0.39. Similarly, the Egyptian Pound is the most undervalued currency, yet its appearance frequency in the most undervalued group is about 0.46. Figure 3 illustrates over(under)-valuation of the Japanese Yen and Egyptian Pound at each time. For both currencies, we see clear switches between the overvalued and undervalued groups over time. These results suggest that a currency cannot remain consistently overvalued or undervalued over an extended period; it may be overvalued at one time and undervalued at another.⁹

We further investigate how limits to arbitrage affect currency mispricing. We divide the currency sample into three groups based on absolute mispricing estimates at each time: the first group consists of currencies with the smallest absolute mispricing (least mispriced), while the third group includes those currencies with the largest absolute mispricing (most mispriced). For each group, we examine exchange rate stability (ERS, [Aizenman et al., 2013](#)), monetary independence (MI, [Aizenman et al., 2013](#)), financial

⁹For comparison, we examine the constituents of long and short legs in the Carry factor, which is often regarded as the key systematic factor in currency markets. Panel B of Table 8 presents the top five constituents. The long position predominantly contains emerging market currencies, whereas the short leg includes developed market currencies. Notably, their appearance frequencies are significantly higher. The Japanese Yen consistently appears in the short leg with a frequency of 0.87, and the Turkish Lira consistently appears in the long leg with a frequency close to 100%. This result clearly indicates that the arbitrage portfolio is distinct from the carry factor and captures short-lived mispricing.



(a) JPY



(b) EGP

Figure 3: Time-series Variation of Estimated Mispricing of JPY and EGP

The scatter plots show the time-series variation of estimated alphas for JPY and EGP. The number of latent factors is three, and the size of the estimation window is 12 months. Each month, we sort the estimated alphas into five groups based on their magnitude and present the time-series variation, indicating whether a currency is overvalued or undervalued. Circles represent currencies assigned to each group for that month.

openness (OPEN, [Chinn and Ito, 2006](#)), bid-ask spreads (BAS, [Bartram et al., 2023](#)), and measures of arbitrage cost: capital controls (KA, [Fernández et al., 2016](#)), capital controls on inflows (KAI, [Fernández et al., 2016](#)), and controls on outflows (KAO, [Fernández et al., 2016](#)). All measures are cross-sectionally standardized to the interval of $[-0.5, 0.5]$ to ensure comparability over time. Table 9 presents the time-series averages of these measures. We see that the mispricing difference between the least and most mispriced currencies is highly statistically significant. We find statistically significant evidence that markets with the most mispriced currencies exhibit characteristics of low exchange rate stability, relatively independent monetary policy, limited financial openness, large bid-ask

Table 9: Limits to Arbitrage and Mispricing

The table presents descriptive statistics for portfolios sorted by our absolute estimated weight using the PPCA procedure. We report the average values for each portfolio, including absolute weight, exchange rate stability (ERS), monetary independence (MI), financial openness (OPEN), capital controls (KA), capital controls on inflows (KAI), capital controls on outflows (KAO) and bid-ask spread (BAS). All characteristics have been cross-sectionally rank-standardized to the interval $[-0.5, 0.5]$. Newey-West adjusted t -ratios (Newey and West, 1987) are shown in parentheses.

	$ \hat{\omega}_\alpha $	ERS	MI	OPEN	KA	KAI	KAO	BAS
Low	0.03	0.06	-0.01	0.19	0.02	0.03	0.1	-0.02
Middle	0.08	0.03	-0.01	0.21	0.02	0.03	0.1	-0.01
High	0.17	-0.05	0.02	0.16	0.04	0.05	0.12	0.03
HML	0.14	-0.11	0.03	-0.03	0.02	0.02	0.02	0.05
	(18.3)	(-10.4)	(3.29)	(-1.97)	(2.14)	(2.24)	(2.37)	(4.53)

spreads, and high arbitrage costs.

5.3. Market Conditions and Mispricing

We also examine how the arbitrage portfolio performs in periods with different market conditions. We first consider recession/non-recession periods and pre-/post-financial crisis periods. Recession periods are identified using the NBER recession index, and the period before September 2009 is defined as the pre-crisis period.

Different market conditions. Table 10 presents the performance of the arbitrage portfolios under various types of market conditions. The arbitrage portfolio performs notably well during recession periods, with Sharpe ratios being 0.65, 0.65, and 0.84, respectively, for two, three, and four latent factors. During non-recession periods, it also performs well, with the Sharpe ratio being 0.78, 0.83, and 0.83 for two, three, and four latent factors, respectively. In comparison, we note that the carry strategy performs poorly during recession periods, with a Sharpe ratio close to zero, and as compensation, it performs much better during non-recession periods, achieving a Sharpe ratio around 1, which reflects its nature capturing systematic risk, i.e., a high Sharpe ratio in non-recession periods as a compensation for its poor performance in bad times.

Table 10: Arbitrage Portfolio Performance and Market Conditions

This table presents the subsample performance of arbitrage portfolios and Carry factor. The summary statistics include the annualized percentage means, annualized percentage standard deviations, and annualized Sharpe ratios. AP2-AP4 represents the arbitrage portfolios constructed using the number of latent factors in estimation from two to four. Carry is the carry trade strategy that buys (sells) the top 20% of all currencies with the highest (lowest) interest rate differential. The full sample period covers monthly data from 1987 to 2023. The subsamples are the National Bureau of Economic Research (NBER) recession periods (from July 1990 to March 1991, from March 2001 to November 2001, from December 2007 to June 2009 and from February 2020 to April 2020) in Panel A, the non-NBER recession periods in Panel B, the pre-crisis period (from January 1998 to December 2006) in Panel C, and the post-crisis period (from January 2007 to December 2013) in Panel D.

	Mean	STD	SR		Mean	STD	SR
Panel A: NBER recession periods				Panel B: Non-NBER recession periods			
AP2	4.32	6.68	0.65	AP2	4.23	5.42	0.78
AP3	4.36	6.74	0.65	AP3	4.51	5.41	0.83
AP4	5.62	6.69	0.84	AP4	4.64	5.56	0.83
Carry	0.41	9.50	0.04	Carry	7.62	7.64	1.00
Panel C: Pre-crisis period				Panel D: Post-crisis period			
AP2	6.38	5.78	1.10	AP2	1.72	5.15	0.33
AP3	6.34	5.70	1.11	AP3	2.34	5.28	0.44
AP4	6.96	5.92	1.18	AP4	2.11	5.27	0.40
Carry	8.25	8.40	0.98	Carry	5.43	7.05	0.77

The arbitrage portfolio performs much better during the pre-crisis period compared to the post-crisis period. For two-, three-, and four-factor arbitrage portfolios, the Sharpe ratios are 1.10, 1.11, and 1.18, respectively, during the pre-crisis period, whereas they drop to 0.33, 0.44, and 0.40, respectively, during the post-crisis period. This can also be seen in Figure 1. It is tempting to infer, although there is no formal proof, that the reduced performance of the arbitrage portfolio can be attributed to policy-makers' and industry efforts to improve the global financial system and enhance the efficiency of the global currency market.

CIP deviations. A number of studies have documented the failure of covered interest rate parity (CIP), revealing large and persistent arbitrage opportunities, particularly during and after the global financial crisis (see, e.g., [Baba and Packer, 2009](#); [Du, Tepper, and Verdelhan, 2018](#); [Cerutti, Obstfeld, and Zhou, 2021](#)). We therefore examine whether

the profitability of the arbitrage portfolio arises from the CIP deviations (cross-currency basis). [Du and Schreger \(2022\)](#) show that there exist strong comovements in cross-currency bases. Therefore, we use the average of cross-currency bases as the overall basis. Model (1) in Table 11 runs a regression of the three-factor arbitrage portfolio returns on a constant and overall basis. The coefficient on the overall basis is not statistically significant, suggesting that the CIP deviations cannot explain the performance of the currency arbitrage portfolio.

Financial conditions. We further examine how financial conditions affect the arbitrage portfolio performance. We measure financial conditions using dollar strength, VIX, BBB-Treasury spread, and intermediary capital ratio, as in [Du and Schreger \(2022\)](#). Model (2) in Table 11 runs a regression of the arbitrage portfolio returns on a constant and the Federal Reserve Board’s broad dollar index, a trade-weighted measure of the US dollar’s exchange rate against its major trading partners. The coefficient on the dollar index is positive and statistically significant. A stronger dollar affects banks’ risk-taking capacity and leads to a contraction in cross-border dollar-denominated lending. [Avdjiev et al. \(2019\)](#) show that the strength of the dollar is positively related to the cost of dollar liquidity, which represents the shadow cost of bank balance sheet capacity. This increase in liquidity cost restricts the availability of dollar credit and cross-border flows, thereby being associated with potential arbitrage opportunities.

Models (3)-(5) present regression results for the VIX, credit spread, and the intermediary capital ratio. The BBB-Treasury spread serves as a proxy for credit spread. However, the coefficient on credit spread is not statistically significant. An increase in the VIX is linked to a decline in cross-border dollar flows ([Rey, 2015](#)). The positive coefficient (marginally significant) on VIX suggests that high VIX tends to deter market participants from exploiting arbitrage opportunities and currencies are more likely to be mispriced during periods of high volatility. The coefficient on the intermediary capital

Table 11: Arbitrage Portfolio and Financial Conditions

This table presents the results of time-series regressions. The dependent variable is the monthly return on the arbitrage portfolio. The independent variables include the average cross-currency basis deviation from CIP (Basis), the monthly percentage change in the Federal Reserve Board broad dollar index (Dollar-Sth), the monthly percentage change in the BBB-Treasury spread (BBB-Tsy), the monthly percentage change in implied volatility of S&P options (VIX), and the monthly innovations to the intermediary capital ratio (Capital). The sample period spans from January 1990 to December 2023 in Column 1, February 2006 to December 2023 in Columns 2 and 6-12, February 1990 to December 2023 in Column 3, February 1997 to December 2023 in Column 4, and January 1987 to December 2023 in Column 5. Newey-West adjusted t -ratios (Newey and West, 1987) are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.37 (3.41)	0.17 (1.59)	0.31 (3.38)	0.34 (4.08)	0.38 (4.86)	0.24 (1.27)	0.26 (1.40)	0.25 (1.31)	0.21 (1.10)	0.19 (1.02)	0.19 (0.99)
Basis	-3.11 (-0.29)					-21.4 (-0.93)	-20.6 (-0.89)	-22.6 (-0.91)	-13.1 (-0.58)	-14.1 (-0.62)	-12.8 (-0.56)
Dollar		19.7 (2.17)				5.32 (0.62)	5.12 (0.55)	6.38 (0.73)	12.3 (1.38)	14.5 (1.60)	11.0 (1.22)
BBB-Tsy			2.13 (1.45)			-0.14 (-0.10)	1.01 (0.66)	1.09 (0.76)	-0.99 (-0.61)	-1.56 (-0.98)	0.03 (0.02)
VIX				1.20 (1.74)		-0.04 (-0.06)	0.01 (0.02)	0.15 (0.22)	0.01 (0.01)	0.09 (0.14)	-0.11 (-0.16)
Capital					-28.0 (-1.48)	-35.1 (-1.00)	-29.1 (-0.84)	-21.8 (-0.64)	-28.5 (-0.83)	-27.4 (-0.80)	-24.9 (-0.73)
Dol_BBB						106.0 (2.81)					
Dol_VIX							38.6 (1.84)				
Dol_Capital								-39.7 (-2.63)			
BBB_VIX									2.84 (3.77)		
BBB_Capital										-3.35 (-4.32)	
VIX_Capital											-1.54 (-2.73)
Adj R^2	0.02	3.19	2.28	2.16	0.68	12.6	9.89	11.01	12.1	13.1	10.4
Obs.	408	215	323	407	444	215	215	215	215	215	215

ratio is negative but insignificant.¹⁰

Overall, it seems that the arbitrage portfolio generates higher returns during periods of tighter financial conditions. However, its performance is not related to CIP deviations, reflecting that it captures a very different type of currency mispricing.

¹⁰The remaining models in Table 11 present results of several multivariate regressions that include all individual financial condition variables and their interactions. These variables are highly correlated as they reflect the aggregate variation of financial conditions. While insignificant in multivariate regressions, these individual variables retain their expected signs; importantly, their interactions are statistically significant, reinforcing the aggregate effect of the financial condition on currency mispricing.

5.4. Net Positions of Speculators and Mispricing

In this section, we examine how speculative trading relates to currency mispricing. We use futures position data from the Commodity Futures Trading Commission (CFTC) to measure the activity of speculators, as in [Brunnermeier, Nagel, and Pedersen \(2008\)](#) and [Zeng \(2023\)](#). Specifically, for each currency, speculative trading activity is quantified as the net positions (long positions minus short positions) of noncommercial traders in that currency, normalized by the total open interest across all traders. Noncommercial traders are typically regarded as speculators, as they are classified by the CFTC as engaging in futures contracts for speculative rather than hedging purposes. A positive position in this context indicates a currency trade where the foreign currency acts as the investment asset and the U.S. dollar serves as the funding currency. Net positions can be seen as proxies for speculation and are thought to capture similar information to currency order flow ([Klitgaard and Weir, 2004](#)).

We implement pooled panel regressions with both currency and time fixed effects. We also include currency characteristics including carry, short-term momentum and value as control variables. Table [12](#) presents the regression results. The results in Panel A are consistent with our previous findings and confirm that currencies with higher PPCA-weights tend to generate higher future returns and mispricing is short-lived and disappears quickly.

Panel B reports the results from the regression of net positions on currency mispricing. The positive and statistically significant relationship between mispricing and current net positions in currency markets suggests that speculators, acting as arbitrage traders, are able to capitalize on mispricing opportunities. Furthermore, we observe that the estimated coefficients remain positive and statistically significant for the subsequent three periods, although they gradually decrease.

We further investigate how net positions change over time. We sort currencies into

Table 12: Net Positions of Speculators and Currency Mispricing

This table presents the results of panel regressions incorporating both currency and time fixed effects. Panel A presents regressions with the currency monthly excess returns as the dependent variable, while Panel B presents regressions with the net position of speculators as the dependent variable. The independent variable in both panels is the individual currency weights, estimated using the PPCA approach. Newey-West adjusted t -ratios (Newey and West, 1987) are shown in parentheses.

	$T + 0$	$T + 1$	$T + 2$	$T + 3$	$T + 4$	$T + 5$
Panel A: Currency Returns						
PPCA-weight ($\hat{\omega}_\alpha$)		0.62 (2.40)	0.33 (1.20)	0.38 (1.68)	0.27 (1.24)	0.14 (0.53)
Panel B: Net Positions of Speculators						
PPCA-weight ($\hat{\omega}_\alpha$)	0.29 (4.03)	0.27 (3.71)	0.23 (2.89)	0.14 (1.85)	0.11 (1.63)	0.07 (1.13)

three groups based on estimated mispricing, and then calculate the 12-month average net positions of non-commercial traders for each group. Figure A1 in the Internet Appendix displays the time-series spreads of net position between high- and low-mispricing groups. The positive net position spreads suggest that speculators buy currencies with high alphas and sell those with low alphas.

Taken together, these results provide strong support that speculative activity aligns with mispricing estimates in currency markets. Non-commercial traders tend to increase their positions in currencies exhibiting high mispricing.

6. Conclusion

The global currency market is generally regarded as a well-functioning over-the-counter market: highly liquid, trading around the clock, and characterized by efficient execution. Yet, many observable factor models in currency markets exhibit limited explanatory power for currency returns, especially at the individual currency level, suggesting the potential existence of mispricing. In this paper, we implement a comprehensive examination of whether individual currencies are mispriced, while making very general assumptions regarding systematic risk. Inspired by the international arbitrage pricing theory (IAPT),

we propose a conditional latent factor model, in which both mispricing (α) and factor loadings (β) are functions of conditioning information. To effectively capture short-lived mispricing, we estimate the model using the projected principal component analysis method (Fan, Liao, and Wang, 2016; Kim, Korajczyk, and Neuhierl, 2021).

We find that the arbitrage portfolios based on currency mispricing achieve high Sharpe ratios ranging from 0.77 to 0.83, depending on the number of latent factors. The strong performance of the arbitrage portfolio provides uncontroversial evidence that mispricing is prevalent in currency markets. Notably, the arbitrage portfolio returns cannot be explained by commonly used observable risk factors. Even when we incorporate these pre-specified factors into the PPCA estimation process, the arbitrage portfolio continues to exhibit strong performance.

We examine potential sources of currency mispricing. The contributions of currency characteristics overshadow those of macroeconomic fundamentals in both factor loadings and mispricing. The time-varying contributions of conditioning variables indicate that many variables contribute to mispricing, but only for a short period. Emerging market currencies are much more severely mispriced than developed market currencies. The most mispriced currencies are characterized by low exchange rate stability, relatively independent monetary policies, limited financial openness, high arbitrage costs, and large bid-ask spreads. When financial conditions worsen, imposing greater limits on arbitrage and reducing trading activity, currency mispricing remains uncorrected and the arbitrage portfolio generates higher returns. Speculative traders tend to increase their current and future positions in currencies with high mispricing.

In summary, this paper establishes a new set of facts about mispricing in currency markets. A notable feature of our study is the flexibility of the model and estimation method, which can effectively accommodate the short-lived nature of mispricing. These results pose new challenges to currency pricing models, which have primarily focused on characterizing the factor structure of portfolio currency returns.

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Internet Appendix

(not for publication)

Dynamic Currency Mispricing and Arbitrage Profits

A1. PPCA: Technical Details

We assume that the return-generating process for individual currencies remains stable and conditioning variables are constant over a short time window, $t = 1, \dots, T$ (e.g., $T = 12$ months), while allowing them to vary across different periods. For each window, we rewrite the model in matrix form as in Equation (A1). By setting T to a short horizon, the model of Equation (A1) can be interpreted as a locally unconditional approximation of the conditional model,

$$\widetilde{\mathbf{R}}\mathbf{X} = \left(\mathbf{L}_\alpha(\mathbf{Z}) + \mathbf{\Gamma}_\alpha\right)\mathbf{1}'_T + \left(\mathbf{L}_\beta(\mathbf{Z}) + \mathbf{\Gamma}_\beta\right)\mathbf{F}' + \mathbf{E}, \quad (\text{A1})$$

where as discussed in the main text, $\mathbf{L}_\alpha(\mathbf{Z}) = \mathbf{Z}\boldsymbol{\theta}$ and $\mathbf{L}_\beta(\mathbf{Z}) = \mathbf{Z}\boldsymbol{\beta}$. By estimating Equation (A1) over rolling windows, we can capture the time-varying dependence structures of factor loadings and mispricing on conditioning variables.

In our paper, we construct the arbitrage portfolio to test the presence of significant mispricing, which implies that the cross-sectional mean of the squared mispricing function, $\mathbf{L}_\alpha(\mathbf{Z})$, may deviate from zero, since the $0 \leq \frac{\mathbf{L}_\alpha(\mathbf{Z})'\mathbf{L}_\alpha(\mathbf{Z})}{N} \leq \frac{\boldsymbol{\alpha}'\boldsymbol{\alpha}}{N}$.

Assumption 1. As $N \rightarrow \infty$,

$$\frac{\mathbf{L}_\alpha(\mathbf{Z})'\mathbf{L}_\alpha(\mathbf{Z})}{N} \rightarrow \delta \geq 0$$

The assumption above states that the conditioning variables in $\mathbf{Z}$ may contain information about mispricing, $\boldsymbol{\alpha}$. By leveraging the joint relation between the conditioning

variables $\mathbf{Z}$ and both $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, we construct arbitrage portfolios that generate abnormal returns (when $\delta > 0$) while simultaneously hedging out systematic risk related to the conditioning variables.

We also impose a series of cross-sectional orthogonality assumptions among the mispricing function, its residuals, the factor loading function, its residuals, and the residual returns.

Assumption 2. As $N \rightarrow \infty$,

$$\begin{aligned} (i) \quad & \frac{\widetilde{\mathbf{R}\mathbf{X}}' \widetilde{\mathbf{R}\mathbf{X}}}{N} \xrightarrow{p} \mathbf{Q}_{\widetilde{\mathbf{R}\mathbf{X}}} \text{ and } \frac{\mathbf{Z}' \mathbf{Z}}{N} \rightarrow \mathbf{Q}_{\mathbf{Z}}, \text{ where } \mathbf{Q}_{\widetilde{\mathbf{R}\mathbf{X}}} \text{ and } \mathbf{Q}_{\mathbf{Z}} \text{ are positive definite matrices,} \\ (ii) \quad & \frac{\mathbf{L}_{\beta}(\mathbf{Z})' \boldsymbol{\Gamma}_{\alpha}}{N} \xrightarrow{p} \mathbf{0}_K, \quad \frac{\mathbf{L}_{\beta}(\mathbf{Z})' \boldsymbol{\Gamma}_{\beta}}{N} \xrightarrow{p} \mathbf{0}_{K \times K}, \quad \frac{\mathbf{Z}' \boldsymbol{\Gamma}_{\alpha}}{N} \xrightarrow{p} \mathbf{0}_L, \quad \frac{\mathbf{Z}' \boldsymbol{\Gamma}_{\beta}}{N} \xrightarrow{p} \mathbf{0}_{L \times K}, \quad \frac{\mathbf{L}_{\beta}(\mathbf{Z})' \mathbf{E}}{N} \xrightarrow{p} \mathbf{0}_{K \times T} \\ & \text{and } \frac{\mathbf{Z}' \mathbf{E}}{N} \xrightarrow{p} \mathbf{0}_{L \times T}. \end{aligned}$$

In addition, we impose a cross-sectional orthogonality restriction between the mispricing function and the factor loading function to separate the effect of mispricing and factor loadings. To address the rotational indeterminacy inherent in latent factor models, we also impose minor yet essential modifications to the standard identification restrictions commonly used in the literature. These adjustments are required to ensure the separate identification of $\mathbf{L}_{\beta}(\mathbf{Z})$.

Assumption 3. As $N \rightarrow \infty$,

$$\begin{aligned} (i) \quad & \frac{\mathbf{L}_{\beta}(\mathbf{Z})' \mathbf{L}_{\alpha}(\mathbf{Z})}{N} \rightarrow \mathbf{0}_K \\ (ii) \quad & \frac{\mathbf{L}_{\beta}(\mathbf{Z})' \mathbf{L}_{\beta}(\mathbf{Z})}{N} \rightarrow \mathbf{I}_K \\ (iii) \quad & \text{Define the matrix } \mathbf{J}_T = (\mathbf{I}_T - \frac{1}{T} \mathbf{1}_T \mathbf{1}_T'), \text{ which removes the time-series mean. We} \\ & \text{assume that } \mathbf{F}' \mathbf{J}_T \mathbf{F} \text{ is a full-rank diagonal matrix with distinct diagonal elements.} \end{aligned}$$

We construct the arbitrage portfolio in five steps as follows.

(1) First, we need to estimate $\boldsymbol{\beta}$. We demean the returns in Equation (A1) to eliminate the effect of $\boldsymbol{\alpha}$.

$$\begin{aligned} \widetilde{\mathbf{R}\mathbf{X}} \mathbf{J}_T &= (\mathbf{L}_{\alpha}(\mathbf{Z}) + \boldsymbol{\Gamma}_{\alpha}) \mathbf{1}_T' \mathbf{J}_T + (\mathbf{L}_{\beta}(\mathbf{Z}) + \boldsymbol{\Gamma}_{\beta}) \mathbf{F}' \mathbf{J}_T + \mathbf{E} \mathbf{J}_T \\ &= (\mathbf{L}_{\beta}(\mathbf{Z}) + \boldsymbol{\Gamma}_{\beta}) \mathbf{F}' \mathbf{J}_T + \mathbf{E} \mathbf{J}_T \end{aligned} \tag{A2}$$

where $\mathbf{J}_T = (\mathbf{I}_T - \frac{1}{T}\mathbf{1}_T\mathbf{1}_T')$ represents the process of time-series demeaning.

(2) We project the demeaned returns in Equation (A2) onto the span of $\mathbf{Z}$ by premultiplying with the corresponding projection matrix.

$$\begin{aligned}\widehat{\mathbf{R}\mathbf{X}} &= \mathbf{P}\mathbf{L}_\beta(\mathbf{Z})\mathbf{F}'\mathbf{J}_T + \mathbf{P}\mathbf{\Gamma}_\beta\mathbf{F}'\mathbf{J}_T + \mathbf{P}\mathbf{E}\mathbf{J}_T, \\ \text{when } N \rightarrow \infty, \quad \widehat{\mathbf{R}\mathbf{X}} &\xrightarrow{p} \mathbf{L}_\beta(\mathbf{Z})\mathbf{F}'\mathbf{J}_T,\end{aligned}\tag{A3}$$

where $\mathbf{P} = \mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'$. The orthogonality between $\mathbf{\Gamma}_\beta$ and $\mathbf{Z}$, together with the Assumption 2 make $\mathbf{P}\mathbf{\Gamma}_\beta\mathbf{F}'\mathbf{J}_T$ and $\mathbf{P}\mathbf{E}\mathbf{J}_T$ can be negligible for $N \rightarrow \infty$.

(3) Next, we apply standard principal component analysis to (A3) to estimate the factor loadings and factors. When $N \rightarrow \infty$,

$$\frac{1}{N}\widehat{\mathbf{R}\mathbf{X}}\widehat{\mathbf{R}\mathbf{X}}' \xrightarrow{p} \frac{\mathbf{L}_\beta(\mathbf{Z})}{\sqrt{N}}\mathbf{F}'\mathbf{J}_T\mathbf{J}_T'\mathbf{F}\frac{\mathbf{L}_\beta(\mathbf{Z})'}{\sqrt{N}}\tag{A4}$$

From Assumptions 3, we have that $\frac{\mathbf{L}_\beta(\mathbf{Z})\mathbf{L}_\beta(\mathbf{Z})'}{\sqrt{N}} \xrightarrow{p} \mathbf{I}_K$ and that $\mathbf{F}'\mathbf{J}_T\mathbf{J}_T'\mathbf{F}$ is a diagonal matrix. It implies that the eigenvectors of $\frac{1}{N}\widehat{\mathbf{R}\mathbf{X}}\widehat{\mathbf{R}\mathbf{X}}'$ are given by $\mathbf{L}_\beta(\mathbf{Z})$. According to Theorem 1 in Kim, Korajczyk, and Neuhierl (2021), as $N \rightarrow \infty$, the estimated loading matrix converges in probability, that is, $\widehat{\mathbf{L}}_\beta(\mathbf{Z}) \xrightarrow{p} \mathbf{L}_\beta(\mathbf{Z})$.

(4) Next, we estimate $\mathbf{L}_\alpha(\mathbf{Z})$, by taking the mean of $\widetilde{\mathbf{R}\mathbf{X}}$ in (A1).

$$\widetilde{\mathbf{R}\mathbf{X}} = \left(\mathbf{L}_\alpha(\mathbf{Z}) + \mathbf{\Gamma}_\alpha\right) + \left(\mathbf{L}_\beta(\mathbf{Z}) + \mathbf{\Gamma}_\beta\right)\overline{\mathbf{F}} + \overline{\mathbf{E}}\tag{A5}$$

The mispricing function, $\mathbf{L}_\alpha(\mathbf{Z})$, can be estimated by projecting the average excess returns of individual currencies in the window on conditioning variables orthogonal to estimated factor loadings. By assuming that both $\mathbf{L}_\alpha(\mathbf{Z})$ and $\mathbf{L}_\beta(\mathbf{Z})$ are linear functions of conditioning variables, we have

$$\hat{\boldsymbol{\theta}} = \arg \min_{\boldsymbol{\theta}} \left(\widetilde{\mathbf{R}\mathbf{X}} - \mathbf{Z}\boldsymbol{\theta}\right)' \left(\widetilde{\mathbf{R}\mathbf{X}} - \mathbf{Z}\boldsymbol{\theta}\right) \quad \text{subject to} \quad \widehat{\mathbf{L}}_\beta(\mathbf{Z})'\mathbf{Z}\boldsymbol{\theta} = \mathbf{0}_K\tag{A6}$$

which is an ordinary least squares problem with linear constraints and the closed-form solution can be obtained. Clearly, mispricing estimated in this way is orthogonal to factor loadings. According to the Theorem 2 in [Kim, Korajczyk, and Neuhierl \(2021\)](#), as $N \rightarrow \infty$, $\widehat{\mathbf{L}}_\alpha(\mathbf{Z}) \xrightarrow{p} \mathbf{L}_\alpha(\mathbf{Z})$.

(5) With the estimated mispricing function, we construct a currency arbitrage portfolio based on conditioning variables observed at the end of each window as

$$\hat{\mathbf{w}}_{\alpha,T} = \frac{1}{N_T} \widehat{\mathbf{L}}_\alpha(\mathbf{Z}_T) = \frac{1}{N_T} \mathbf{Z}_T' \hat{\boldsymbol{\theta}}_\alpha. \quad (\text{A7})$$

We hold the portfolio to the next period and compute its return as follows, $\hat{\mathbf{w}}_{\alpha,T} \mathbf{R}\mathbf{X}_{t+1}$. We can also rewrite the returns of arbitrage portfolio in the matrix form,

$$\begin{aligned} \mathbf{R}_{AP} = \mathbf{w}\mathbf{R}\mathbf{X} &= \left(\frac{1}{N} \mathbf{L}_\alpha(\mathbf{Z})' \mathbf{L}_\alpha(\mathbf{Z}) + \frac{1}{N} \mathbf{L}_\alpha(\mathbf{Z})' \boldsymbol{\Gamma}_\alpha \right) \mathbf{1}_T' \\ &+ \left(\frac{1}{N} \mathbf{L}_\alpha(\mathbf{Z})' \mathbf{L}_\beta(\mathbf{Z}) + \frac{1}{N} \mathbf{L}_\alpha(\mathbf{Z})' \boldsymbol{\Gamma}_\beta \right) \mathbf{F}' + \frac{1}{N} \mathbf{L}_\alpha(\mathbf{Z})' \mathbf{E} \end{aligned} \quad (\text{A8})$$

Under Assumptions [1](#), [2](#), and [3](#), as $N \rightarrow \infty$, $\mathbf{R}_{AP}$ converges to $\frac{\mathbf{L}_\alpha(\mathbf{Z})' \mathbf{L}_\alpha(\mathbf{Z})}{N}$, that is $\mathbf{R}_{AP} \xrightarrow{p} \delta \mathbf{1}_T'$. According to the Theorem 3 in [Kim, Korajczyk, and Neuhierl \(2021\)](#), weighted by $\widehat{\mathbf{L}}_\alpha(\mathbf{Z})$, the arbitrage portfolio can earn the return of $\widehat{\mathbf{R}}_{AP} = \hat{\mathbf{w}}\mathbf{R}\mathbf{X} \xrightarrow{p} \delta \mathbf{1}_T'$.

A2. Additional Tables and Figures

Table A1: List of Currencies

This table lists the 49 currencies used in the empirical analysis, indicating the currency identifier/code, corresponding country, as well as the start/end dates, and the number of monthly observations for each currency.

Code	Country	Start	End	Obs	Code	Country	Start	End	Obs
Panel A: Developed Markets									
ATS	Austria	Jan-97	Dec-98	24	HKD	Hong Kong	Jan-86	Dec-23	456
AUD	Australia	Jan-86	Dec-23	456	IEP	Ireland	Nov-93	Dec-98	62
BEF	Belgium	Jan-97	Dec-98	24	ILS	Israel	Apr-04	Dec-23	237
CAD	Canada	Jan-86	Dec-23	456	ITL	Italy	Jan-86	Dec-98	156
CHF	Switzerland	Jan-86	Dec-23	456	JPY	Japan	Jan-86	Dec-23	456
DEM	Germany	Jan-86	Dec-98	156	NLG	Netherlands	Jan-86	Dec-98	156
DKK	Denmark	Jan-86	Dec-23	456	NOK	Norway	Jan-86	Dec-23	456
ESP	Spain	Jan-97	Dec-98	24	NZD	New Zealand	Jan-86	Dec-23	456
EUR	Euro	Feb-99	Dec-23	299	PTE	Portugal	Jan-97	Dec-98	24
FIM	Finland	Jan-97	Dec-98	24	SEK	Sweden	Jan-86	Dec-23	456
FRF	France	Jan-86	Dec-98	156	SGD	Singapore	Jan-86	Dec-23	456
GBP	United Kingdom	Jan-86	Dec-23	456					
Panel B: Emerging Markets									
BGN	Bulgaria	Apr-04	Dec-23	237	MXN	Mexico	Jan-97	Dec-23	324
BRL	Brazil	Apr-04	Dec-23	237	MYR	Malaysia	Jan-97	Dec-23	237
CYP	Cyprus	Apr-04	Dec-07	45	PHP	Philippines	Jan-97	Dec-23	324
CZK	Czech Republic	Jan-97	Dec-23	324	PLN	Poland	Mar-02	Dec-23	262
EGP	Egypt	Apr-04	Nov-22	185	RUB	Russia	Apr-04	Jan-22	204
GRD	Greece	Jan-97	Dec-00	48	SAR	Saudi Arabia	Jan-97	Dec-23	324
HRK	Croatia	Apr-04	Dec-22	225	SIT	Slovenia	Apr-04	Dec-06	33
HUF	Hungary	Nov-97	Dec-23	314	SKK	Slovakia	Mar-02	Dec-08	82
IDR	Indonesia	Jan-97	Dec-23	235	THB	Thailand	Jan-97	Dec-23	324
INR	India	Nov-97	Dec-23	314	TRY	Turkey	Jan-97	Dec-23	310
ISK	Iceland	Apr-04	Dec-23	237	TWD	Taiwan	Jan-97	Dec-23	324
KRW	South Korea	Mar-02	Dec-23	262	UAH	Ukraine	Apr-04	Oct-14	127
KWD	Kuwait	Jan-97	Dec-23	324	ZAR	South Africa	Jan-86	Dec-23	414

Table A2: Arbitrage Portfolio Performance: Excluding Pegged Currencies

This table reports the summary statistics of the arbitrage portfolio of the subsample that excludes pegged currencies, specifically HKD, BGN, DKK, KWD, and SAR. This table presents the annualized percentage means, annualized percentage standard deviations, annualized Sharpe ratios, skewness, kurtosis, the minimum return, 10% quantile return, 25% quantile return, 75% quantile return, 90% quantile return, and the maximum return. The estimation window is 12 months and the number of latent factors ranges from one to five. The sample period is from January 1987 to December 2023.

K	Mean	SD	SR	Skew	Kurt	Min	Q10	Q25	Q75	Q90	Max
1	3.57	4.77	0.75	0.16	2.11	-5.26	-1.35	-0.47	1.10	1.93	6.75
2	3.37	4.95	0.68	0.13	2.36	-5.97	-1.38	-0.57	1.11	1.95	6.83
3	3.65	5.11	0.71	0.26	1.80	-4.49	-1.55	-0.56	1.11	2.04	7.14
4	3.81	5.31	0.72	0.26	1.25	-4.06	-1.63	-0.55	1.27	1.96	6.25
5	4.05	5.67	0.71	0.30	1.26	-4.24	-1.64	-0.64	1.33	2.21	6.68

Table A3: Performance of Arbitrage Portfolio with Transaction Costs

This table reports the summary statistics of the arbitrage portfolio with transaction costs. Specifically, we consider a range of possible transaction costs as a fraction of quoted bid-ask spreads (25%, 50%, and 75%) (Chernov et al., 2024). This table presents the annualized percentage means, annualized percentage standard deviations, annualized Sharpe ratios, and the significance. Adjusted t-statistics, calculated following Newey and West (1987), are shown in parentheses. The estimation window is 12 months and the number of latent factors ranges from two to four. The sample period is from January 1987 to December 2023.

$K = 2$				
TC	Mean	SD	SR	T-value
25%	3.51	5.53	0.64	(3.86)
50%	2.78	5.52	0.50	(3.06)
75%	2.05	5.51	0.37	(2.26)
$K = 3$				
TC	Mean	SD	SR	T-value
25%	3.68	5.52	0.67	(3.96)
50%	2.86	5.51	0.52	(3.08)
75%	2.04	5.51	0.37	(2.2)
$K = 4$				
TC	Mean	SD	SR	T-value
25%	3.84	5.65	0.68	(3.95)
50%	2.94	5.63	0.52	(3.04)
75%	2.05	5.62	0.36	(2.12)

Table A4: Expected Mispricing and Arbitrage Portfolio with Four Latent Factors

This table reports the performance of alternative arbitrage portfolios constructed under the IPCA framework, using four latent factors. Panel A shows the average expected mispricing, realized mispricing, the excess return, the Sharpe ratio, the skewness and the kurtosis for quantile portfolios. Panel B reports the spanning regression of the high-minus-low portfolios, sorted by expected mispricing, on the risk factor model that includes Dollar, Carry, Momentum, and Value factors. Adjusted t-statistics, calculated following [Newey and West \(1987\)](#), are shown in parentheses. The sample period is from January 1996 to December 2023.

Panel A. Portfolio Statistics						
	E[mp]	mp	Ret	SR	Skew	Kurt
Low	-1.43	-1.0	-0.75	-0.09	-0.21	1.10
2	-0.54	-0.37	0.48	0.07	0.00	0.84
3	-0.05	0.17	0.56	0.08	-0.14	1.5
4	0.44	-0.11	0.94	0.15	-0.68	2.38
High	1.46	1.30	3.62	0.53	-0.3	1.25
HML	2.88	2.30	4.37	0.75	-0.06	0.79
	(45.30)	(2.86)	(3.34)			
Panel B. Risk-Adjusted Return						
	Intercept	Dollar	Carry	MoM	Value	Adj R^2
HML	1.34	-0.24	0.37	0.21	-0.08	0.27
	(1.10)	(-4.25)	(5.51)	(3.52)	(-1.34)	

Table A5: Performance of Arbitrage Portfolios: From 1996 to 2023

This table reports the summary statistics of the arbitrage portfolio, including the annualized percentage means, annualized percentage standard deviations, annualized Sharpe ratios, skewness, kurtosis, the minimum return, 10% quantile return, 25% quantile return, 75% quantile return, 90% quantile return, and the maximum return. The estimation window is 12 months, and the number of latent factors ranges from one to five. The last row presents the summary statistics of the arbitrage portfolio constructed using the optimal number of latent factors. The sample period is from January 1996 to December 2023.

K	Mean	SD	SR	Skew	Kurt	Min	Q10	Q25	Q75	Q90	Max
1	4.00	5.16	0.77	0.49	2.03	-5.16	-1.32	-0.59	1.09	2.15	6.63
2	3.64	5.32	0.68	0.37	1.93	-4.38	-1.48	-0.62	1.18	2.18	6.89
3	4.04	5.51	0.73	0.40	1.48	-4.37	-1.63	-0.63	1.22	2.24	7.18
4	4.44	5.62	0.79	0.25	0.92	-4.46	-1.62	-0.61	1.43	2.25	6.32
5	4.81	5.93	0.81	0.26	1.42	-5.08	-1.68	-0.63	1.41	2.28	7.48
K^*	4.17	5.28	0.79	0.34	1.52	-4.38	-1.43	-0.56	1.22	2.13	6.78

Table A6: Unconditional Spanning Regressions: From 1996 to 2023

This table presents the results from implementing the spanning regressions of arbitrage portfolio returns on the risk factor model. The risk factor model includes the Dollar, Carry, Momentum, and Value factors. The sample period ranges from January 1996 to December 2023. Adjusted t -statistics, calculated following [Newey and West \(1987\)](#), are shown in parentheses.

K	1	2	3	4	5
Intercept	1.88 (2.60)	1.44 (2.05)	1.84 (2.47)	2.03 (2.52)	2.61 (2.83)
Dollar	-0.05 (-1.31)	-0.06 (-1.34)	-0.03 (-0.64)	-0.02 (-0.45)	0.01 (0.22)
Carry	0.10 (2.30)	0.14 (3.09)	0.15 (3.07)	0.18 (3.60)	0.17 (3.16)
Mom	0.50 (15.33)	0.47 (13.57)	0.47 (12.57)	0.46 (13.36)	0.44 (12.22)
Value	-0.07 (-1.65)	-0.12 (-2.61)	-0.13 (-3.15)	-0.14 (-3.13)	-0.16 (-3.26)
$Adj\ R^2$	0.57	0.50	0.46	0.42	0.36

Table A7: Subperiod Analysis: AP with Only Macro Variables

This table presents the subsample performance of arbitrage portfolios and the Carry factor. The arbitrage portfolios are constructed by the characteristics space with only carry, dollar beta and macroeconomic fundamentals. The summary statistics include the annualized percentage means, annualized percentage standard deviations, and annualized Sharpe ratios. AP2-AP4 represents the arbitrage portfolios constructed using the number of latent factors in estimation from two to four. Carry is the carry trade strategy that buys (sells) the top 20% of all currencies with the highest (lowest) interest rate differential. The full sample period covers monthly data from 1987 to 2023. The subsamples are the National Bureau of Economic Research (NBER) recession periods (from July 1990 to March 1991, from March 2001 to November 2001, from December 2007 to June 2009 and from February 2020 to April 2020) in Panel A, the non-NBER recession periods in Panel B, the pre-crisis period (from January 1998 to December 2006) in Panel C, and the post-crisis period (from January 2007 to December 2013) in Panel D.

	Mean	STD	SR		Mean	STD	SR
Panel A: NBER recession periods				Panel B: non-NBER recession periods			
AP2	2.20	6.72	0.33	AP2	3.85	5.69	0.68
AP3	2.96	6.94	0.43	AP3	4.08	5.93	0.69
AP4	3.14	7.15	0.44	AP4	4.35	5.91	0.74
Carry	0.41	9.50	0.04	Carry	7.62	7.64	1.00
Panel C: pre-crisis period				Panel D: post-crisis period			
AP2	5.60	5.91	0.95	AP2	1.47	5.58	0.26
AP3	5.97	6.26	0.95	AP3	1.64	5.66	0.29
AP4	6.20	6.12	1.01	AP4	1.95	5.86	0.33
Carry	8.25	8.40	0.98	Carry	5.43	7.05	0.77

Table A8: Subperiod Analysis: AP with Only Currency Characteristics

This table presents the subsample performance of arbitrage portfolios and the Carry factor. The arbitrage portfolios are constructed by the characteristics space of currency characteristics (without macroeconomic fundamentals). The summary statistics include the annualized percentage means, annualized percentage standard deviations, and annualized Sharpe ratios. AP2-AP4 represents the arbitrage portfolios constructed using the number of latent factors in estimation from two to four. Carry is the carry trade strategy that buys (sells) the top 20% of all currencies with the highest (lowest) interest rate differential. The full sample period covers monthly data from 1987 to 2023. The subsamples are the National Bureau of Economic Research (NBER) recession periods (from July 1990 to March 1991, from March 2001 to November 2001, from December 2007 to June 2009 and from February 2020 to April 2020) in Panel A, the non-NBER recession periods in Panel B, the pre-crisis period (from January 1998 to December 2006) in Panel C, and the post-crisis period (from January 2007 to December 2013) in Panel D.

	Mean	STD	SR		Mean	STD	SR
Panel A: NBER recession periods				Panel B: non-NBER recession periods			
AP2	4.99	6.92	0.72	AP2	3.72	5.18	0.72
AP3	7.64	6.69	1.14	AP3	4.28	5.18	0.83
AP4	9.05	6.92	1.31	AP4	3.80	5.55	0.68
Carry	0.41	9.50	0.04	Carry	7.62	7.64	1.00
Panel C: pre-crisis period				Panel D: post-crisis period			
AP2	5.77	5.58	1.03	AP2	1.56	4.99	0.31
AP3	6.65	5.61	1.19	AP3	2.14	4.91	0.44
AP4	6.78	5.92	1.14	AP4	1.32	5.30	0.25
Carry	8.25	8.40	0.98	Carry	5.43	7.05	0.77

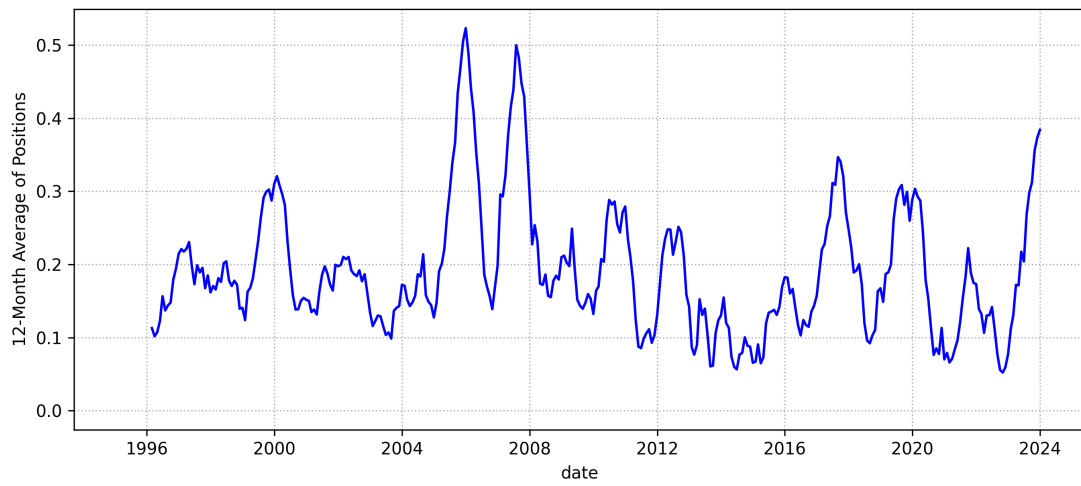


Figure A1: Spreads of Net Positions and Mispricing

This figure shows the relationship between the mispricing signal and the net positions of non-commercial traders, as reported by the CFTC. We categorize the currencies into three groups based on the estimated PPCA-alphas and calculate the average net positions for each group. The spread in net positions is calculated as the difference between the group with the highest and lowest PPCA-alphas.