Dynamic Beta Variability in Foreign Exchange Returns Using Instrumented PCA

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Abstract

Forecasting foreign exchange market prices poses significant challenges, often due to the assumption of constant beta coefficients over time. Utilizing the Instrumented Principal Component Analysis (IPCA) method, this study [1,2,3] constructs a flexible factor model that reduces the dimensionality of diverse information sets involving FX data and various risk factors from G10 countries. The IPCA model accommodates time-varying betas while maintaining traceability. Our findings reveal that the IPCA model offers superior out-of-sample predictability compared to the random-walk model and traditional PCA, demonstrating both statistical and economic significance. Key components for predicting returns include the medium-term interest rate differential, stock market momentum, and idiosyncratic volatility.

1. Introduction

Building an effective predictive model for foreign exchange (FX) market prices is a notably difficult task. One possible reason for this difficulty is the inherent assumption in many models that beta coefficients remain constant over time. Contrary to this assumption, we follow the methodology outlined by Kelly et al. (2019) and apply the Instrumented Principal Component Analysis (IPCA) to construct a more flexible factor model. This approach not only reduces the dimensionality of the vast and varied datasets from FX markets but also accommodates time-varying betas, ensuring model traceability [4].

The predictability of FX returns has long been debated, with some suggesting that FX returns follow a random walk process, as proposed by Meese and Rogoff (1983). Others argue that the set of predictors relevant to FX returns changes over time, influenced by evolving economic conditions (Engel et al., 2015; Rossi, 2013). Despite these challenges, the continuous rise in currency trading volumes driven by various investment strategies underscores the ongoing interest from both academic researchers and market practitioners in developing models with robust predictive capabilities.

In equity markets, the predictability of returns has been well documented through various regression models, especially over short horizons (Rapach et al., 2010, 2013). However, similar predictability in FX markets [5]. remains contentious (Kilian and Taylor, 2003; Filippou et al., 2023). This paper aims to enhance our understanding of cross-sectional risk premiums in FX markets by applying a dimension reduction technique to extract valuable information from potential predictors, including macroeconomic fundamentals and risk premium proxies derived from stock markets.

Peer Reviewed by Undergraduate Research Committee, Abu Dhabi University - 2022.

Inspired by the two-factor model of Lustig et al. (2011), our study employs the IPCA methodology to introduce diverse sources of information into the model while maintaining tractability. The IPCA approach, as refined by Kelly et al. (2019), allows for time-varying beta coefficients, offering both econometric flexibility and theoretical consistency with the Euler equation for asset pricing (Ross, 1976; Hansen and Richard, 1987). Additionally, the extensive literature on the forward premium puzzle highlights significant deviations from the Uncovered Interest Rate Parity (UIP), which remain largely unexplained. Our study posits that time-varying beta coefficients may introduce bias in commonly used linear regression models, providing a plausible explanation for these deviations.

The IPCA model's ability to allow beta coefficients to vary according to macroeconomic conditions is a critical feature. Specifically, the IPCA model defines beta coefficients as functions of a country's characteristics, enabling them to adapt based on the macroeconomic conditions specific to each country. This dual-purpose specification not only establishes a statistical link between different countries' macroeconomic conditions and expected currency returns but also incorporates additional data as instruments, thereby improving the efficiency of return factor model estimations.

Our dataset comprises FX data from G10 countries, collected monthly from January 2008 to December 2020. The risk factors considered align with those identified by Filippou et al. (2023), including market volatility and various macroeconomic variables. Our results indicate that while PCA explains the cross-sectional returns better in-sample, IPCA demonstrates superior out-of-sample performance, highlighting the overfitting issues inherent in PCA models. The predictive R-squared values show that IPCA outperforms the random walk model consistently when a moderate number of latent factors are used. [6,7].

Furthermore, the IPCA framework supports statistical inference, allowing for the testing of model intercepts and evaluating the importance of variables contributing to latent factors. Our findings suggest [8]. that the medium-term interest rate differential and idiosyncratic volatility are significant predictors of FX returns, while traditional equity market factors like dividend yield and price-earnings ratio do not show significant impact.

In summary, this study contributes to the literature by employing a dimension-reduction method to predict the cross-section of FX returns, demonstrating enhanced in-sample explanatory power and superior out-of-sample predictability compared to benchmark models. Our approach also enables formal testing of risk factors, identifying the medium-term interest rate differential and idiosyncratic volatility as key components in predicting FX returns.

2. Methodology

In this section, we provide a review of the Instrumented Principal Component model. Consider the factor model for the currency return $r_{i,t+1}$ of N assets over T periods, incorporating a K × 1 vector of latent factors f_{t+1}:

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1}. \tag{1}$$

Following the Euler equation for investment returns the factor framework (1) is the setting for most empirical analyses of expected returns across as-sets. While applying this framework, the factor loadings $\beta_{i,t}$ and the intercept $\alpha_{i,t}$ are typically constrained to be static. Many studies either treat the factors $\{f_{t+1}\}$ as completely observable, estimating betas and alphas through regression or regard the fac-tors $\{f_{t+1}\}$ as entirely latent, simultaneously estimating betas, alphas, and the factors using factor techniques like the principal component analysis

The IPCA model allows for the dynamic factor loadings $\beta_{i,t}$ and the intercept $\alpha_{i,t}$ to depend on observable L × 1 country characteristics $z_{i,t}$:

$$\alpha_{i,t} = z_{i,t}^{\top} \Gamma_{\alpha} + \nu_{\alpha,i,t}, \text{ and } \beta_{i,t} = z_{i,t}^{\top} \Gamma_{\beta} + \nu_{\beta,i,t}.$$

The specification of $\beta_{i,t}$ and $\alpha_{i,t}$ serves as a statistical linkage between country's characteristics and expected currency returns. Furthermore, it becomes possible to incorporate additional data to estimate the factor model for returns more efficiently by instrumenting the latent factor loadings with observable characteristics $z_{i,t}$. By aggregating L characteristics into K linear combinations, the IPCA model also effectively averages out the characteristics' noise and reduces the characteristic space's dimensionality. For the estimation of the model, combining equations (1) and (2) yields:

$$r_{i,t+1} = z_{i,t}^{T}\Gamma_{\alpha} + z_{i,t}^{T}\Gamma_{\beta} f_{t+1} + \epsilon^{*}_{i,t+1}, \quad (3)$$

where $\epsilon^{*}_{i,t+1} = \epsilon_{i,t+1} + v_{\alpha,i,t} + v_{\beta,i,t} f_{t+1}$ denotes the composite error. Equation (3) can be further written in a vector form:

$$r_{t+1} = Z_t\Gamma_{\alpha} + Z_t\Gamma_{\beta} f_{t+1} + \epsilon^{*}_{t+1}, \quad (4)$$

3. Data Collection And Variable Definition

This section details the data sources, variable definitions, and preliminary findings of our study. Our dataset encompasses monthly foreign exchange (FX) spot and forward rates from January 2008 to December 2020, covering G10 countries. These data are crucial for examining the dynamics and predictability of FX returns using the Instrumented Principal Component Analysis (IPCA) model.
We collected the FX spot and forward rates from Datastream, ensuring monthly frequency data spanning from January 2008 to December 2020. All exchange rates are denominated in US dollars, with the price currency always being the US dollar and the base currency being the non-US country. This structure ensures that the signs of exchange rate returns reflect the strength of the non-US currency: a positive return indicates an appreciation of the foreign currency relative to the US dollar, while a negative return indicates a depreciation. [10,11,12,13,14,15].

Following Filippou et al. (2023), we considered ten country-specific characteristics computed using macroeconomic and financial data from multiple sources. These characteristics are defined as follows:

Inflation Differential (INF): The difference in inflation rates between a G10 country and the United States, calculated using consumer price index data. Sources include the International Financial Statistics (IFS) database of the International Monetary Fund (IMF), Bloomberg for New Zealand, and the Organization for Economic Co-operation and Development (OECD) for the euro zone.

Unemployment Rate Gap Differential (UN): The difference in unemployment rate gaps between a G10 country and the United States, where the gap is the cyclical component extracted from unemployment data using the Christiano and Fitzgerald (2003) band-pass filter. Unemployment data are sourced from the same institutions as inflation data.

Bill Yield Differential (BILL): The difference in three-month government bill yields between a G10 country and the United States, sourced from the OECD, representing short-term interest rate differentials.

Note Yield Differential (NOTE) and Bond Yield Differential (BOND): The differences in five-year (note) and ten-year (bond) government debt yields between a G10 country and the United States, sourced from Bloomberg, representing medium- and long-term interest rate differentials.

Dividend Yield Differential (DP): The difference in dividend yields between a G10 country and the United States, primarily sourced from Datastream, with supplementary data from Bloomberg for Canada and Norway to ensure complete coverage.

Price-Earnings Differential (PE): The difference in price-earnings ratios between a G10 country and the United States, sourced similarly to dividend yield data.

Stock Market Momentum Differential (SRET12): The difference in cumulative 12-month returns of stock indices, collected from MSCI, between a G10 country and the United States. [4].

Idiosyncratic Volatility (IV) and Idiosyncratic Skewness (IS): Integrated volatility and skewness computed using the residuals from the two-factor model by Lustig et al. (2011), estimated with daily currency returns data for each month.

The annualized average return across the 10 currencies is 1.2%, with a standard deviation of 10.9%, consistent with existing literature. The skewness values are mostly positive, indicating a higher frequency of negative returns, while positive kurtosis suggests that the return distributions do not suffer from significant tail risks.The panel data correlation matrices can be calculated in two ways: across country characteristics (Panel A) and across currencies (Panel B).

In Panel A, we observe high correlations among bond-based variables. The average correlations between bill yield (BILL) and bond yield (BOND), BILL and note yield (NOTE), and BOND and NOTE are 80.5%, 84.3%, and 96.8%, respectively. Stock market momentum (SRET12) has a moderate negative correlation with dividend yield (DP), and idiosyncratic volatility (IV) is moderately correlated with bond yield (BOND) and inflation (INF). Interestingly, the correlation between bond yield and inflation is relatively weak, implying that these differentials likely capture risk premium dynamics more effectively. [16].

Panel B shows strong positive correlations among G10 currencies, generally above 50%, with some correlations as high as 67.8%. The only pair with a correlation below 20% is between Japan and New Zealand, consistent with the use of the Japanese yen as a funding currency in carry trades, which diversifies risk due to its low correlation with other countries.

To investigate the time-varying nature of beta coefficients, we create beta-sorting currency portfolios using in-sample data divided into two equal-length subsamples: 2008–2012 (Period 1) and 2013–2017 (Period 2). First, we estimate an Ordinary Least Squares (OLS) regression without intercept for each subsample. Currencies are then ranked by their beta for each characteristic in Period 1, and assigned into three portfolios: low-beta (Portfolio 1), medium-beta (Portfolio 2), and high-beta (Portfolio 3). Portfolios 1 and 3 contain three currencies each, while Portfolio 2 contains four.

During Period 1, average betas increase monotonically due to the sorting process. In Period 2, we observe that betas generally revert, with high group betas decreasing and low group betas increasing, confirming the time-varying nature of beta coefficients. Only two exceptions do not follow this pattern, marked with a star. [17].

The IPCA model allows for time-varying betas within a linear framework, linking beta variation to macroeconomic conditions. This specification provides insights into the macroeconomic drivers of FX returns. By using country characteristics as instruments rather than explanatory factors, the IPCA model explains exchange rate returns more effectively than conventional linear regression models with static betas. This approach is intuitive, aligning with real business cycle theories and improving the interpretability and performance of the asset pricing model.

4. Findings

This section elaborates on the empirical results obtained from applying the IPCA model to FX returns. We assess the model's performance through various metrics and compare its in-sample and out-of-sample efficacy. Additionally, we discuss the economic significance of our findings based on the IPCA predictions.

To evaluate the performance of the K-factor IPCA model, we use two R^2 statistics: the Total R^2 and the Predictive R^2. which measures the fraction of return variance explained by both the dynamic behavior of conditional loadings and the contemporaneous factor realizations, aggregated over all currencies and time periods.

Our dataset is divided into an in-sample period (2008–2017) and an out-of-sample period (2018–2020) to evaluate the model's predictive power. We begin by assessing the in-sample performance. The Total R^2 for the IPCA model is compared with the conventional PCA model across different numbers of latent factors (K).

Table 4 shows that the PCA model consistently yields higher Total R^2 values, indicating a better in-sample fit. For instance, with one latent factor (K=1), the PCA model achieves a Total R^2 of 68.21% compared to IPCA's 51.11%. However, as the number of latent factors increases, the performance gap narrows. When K=5, the PCA's Total R^2 is 92.18%, while IPCA's is 83.81%.

The Predictive R^2 provides a stark contrast. The PCA model shows systematically negative Predictive R^2 values, suggesting overfitting. Conversely, the IPCA model delivers positive Predictive R^2 in some cases, indicating its superior out-of-sample predictability. For instance, in the in-sample period, IPCA achieves a Predictive R^2 of 1.93% with two latent factors (K=2).

Out-of-sample tests reinforce these findings. Table 4 reveals that the PCA model's out-of-sample Total R^2 is often lower than its in-sample R^2, while IPCA maintains more consistent performance. For example, with three latent factors (K=3), IPCA achieves an out-of-sample Predictive R^2 of 0.28%, outperforming PCA and the random walk benchmark.

The IPCA model's better out-of-sample performance suggests it avoids the overfitting issues inherent in PCA. Despite some negative Predictive R^2 values, IPCA models consistently outperform PCA and regression-based models in forecasting FX returns.

To demonstrate the economic significance of the IPCA model, we compare trading strategies based on its predictions against those from the PCA model. We construct these strategies by taking long positions in currencies with positive predicted returns and short positions in those with negative predicted returns. [4].

Table 5 presents the annualized returns of these strategies. The IPCA-based strategy outperforms the PCA-based strategy in both full-sample and out-of-sample periods. For example, the IPCA strategy yields higher returns for most G10 currencies, with notable outperformance in the Swiss Franc and Australian Dollar.

The economic significance is further illustrated in Figure 1, which plots the difference in cumulative returns between IPCA and PCA strategies [4].. The IPCA model consistently outperforms the PCA model across most currencies, with the differences being more pronounced in the out-of-sample period. This suggests that IPCA's ability to handle time-varying betas and utilize macroeconomic instruments enhances its predictive power.

The IPCA model's robustness and economic relevance are underscored by its ability to capture and exploit the time-varying nature of FX returns. This performance advantage is crucial for practitioners seeking reliable models for trading and risk management in the FX markets.

Overall, our empirical findings highlight the IPCA model's superior in-sample and out-of-sample performance, its capacity to mitigate overfitting, and its practical utility in developing profitable trading strategies. The model's ability to adapt to macroeconomic conditions and provide robust predictions makes it a valuable tool for understanding and forecasting FX returns.

5. Understanding IPCA Trends

In this section, we delve into the interpretation of the factors derived from the Instrumented Principal Component Analysis (IPCA) model. We explore which country characteristics are most influential, compare the IPCA model with existing models, and examine the representation of each latent factor.

To determine the significance of each country characteristic in the IPCA model, we evaluate the incremental contribution of these characteristics while holding others constant. We test the statistical significance by setting specific rows in the \(\Gamma_\beta\) matrix to zero and recalculating the Total R^2. A substantial drop in Total R^2 indicates the importance of the characteristic.

Table 6 shows the results of this analysis for models with one and three latent factors. We find that Note yield, Idiosyncratic volatility, and Stock market momentum are the top three significant characteristics. In the model with one latent factor, Note yield accounts for 43.62% of the Total R^2 reduction, followed by Idiosyncratic volatility and Stock market momentum. Similar patterns are observed in the model with three latent factors, where Note yield again dominates with a 40.64% reduction.

These findings reaffirm the critical role of medium-term interest rates and stock market conditions in predicting FX returns. The high importance of Note yield aligns with the profitability of carry trades in international currency markets, where interest rate differentials drive returns.

However, the Total R^2 reduction does not provide directional insights. The IPCA model allows us to estimate the \(\Gamma_\beta\) coefficients, whose signs reveal the direction of influence for each characteristic. In the model with one latent factor, most \(\Gamma_\beta\) coefficients are either positive or negative, reflecting the straightforward relationship between characteristics and returns. In contrast, the model with three latent factors shows mixed signs, indicating complex interactions among factors.

A formal test using bootstrapped p-values provides further insights. In the model with one latent factor, most characteristics pass the significance test at the 10% level, except for Bond yield and Price-earnings ratio. With three latent factors, only the Price-earnings ratio fails to pass the relevance test. These results highlight the robustness of the IPCA model in leveraging macro-finance indicators to explain FX returns.

We compare the IPCA model's performance with traditional regression models, including Ordinary Least Squares (OLS) and fixed-effects regressions. Table 7 reports the Total and Predictive R^2 for these models, along with the significance of their coefficients.

The OLS regression, shown in Regression (1), performs poorly, with only the in-sample Total R^2 being positive at 11.09%. The constant term is significantly positive, indicating an unexplained risk premium. Fixed-effects regressions, presented in Regressions (2) and (3), incorporate country and calendar month fixed effects but do not improve the model's explanatory power significantly. The Total R^2 decreases slightly with the inclusion of fixed effects, contradicting the common expectation that fixed effects enhance model performance.

Predictive R^2 values are negative for both in-sample and out-of-sample periods in the fixed-effects models, indicating their inability to outperform the random walk benchmark. This highlights the limitations of traditional regression approaches in capturing the dynamics of FX returns.

The IPCA model, on the other hand, demonstrates superior performance. It consistently achieves higher Predictive R^2 values, particularly when using a moderate number of latent factors. This underscores the advantage of IPCA in handling time-varying betas and exploiting macroeconomic information.

To better understand the latent factors in the IPCA model, we analyze the product of \(\Gamma_\beta\) and the latent factors \(f\), which captures the association between country characteristics and FX returns.

Figure 2 presents time-series plots of \(\Gamma_\beta \times f\) for the top three characteristics: Note yield, Idiosyncratic volatility, and Stock market momentum. The plots reveal that Note yield consistently has the highest exposure, reinforcing its importance in driving FX returns. During periods of financial crisis, such as 2008 and 2012, Idiosyncratic volatility shows heightened exposure, reflecting increased risk premiums during times of market uncertainty.

Figure 3 illustrates the \(\Gamma_\beta \times f\) values for individual latent factors. Each factor primarily represents one of the top three characteristics. Factor one is dominated by Note yield, factor two by Stock market momentum, and factor three by Idiosyncratic volatility. This clean separation indicates that the IPCA model effectively captures distinct sources of risk and their contributions to FX returns.

Overall, the IPCA model provides a nuanced understanding of the drivers behind FX returns. By accommodating time-varying betas and utilizing macroeconomic instruments, it offers robust and interpretable insights into the dynamics of currency markets. This analysis highlights the model's ability to distill complex interactions into meaningful factors, enhancing both statistical and economic predictability.

6. Discussions

In this section, we examine the robustness of our IPCA model's findings and discuss its limitations. We extend our analysis to currency excess returns and address potential limitations that could impact our study's conclusions.

Our primary analysis focuses on gross returns, but the literature often emphasizes understanding foreign exchange (FX) risk premiums through excess returns. To test the robustness of our IPCA model, we analyze currency excess returns by incorporating the forward premium, defined by the Covered Interest Rate Parity (CIRP):

$$xr_{i,t+1} = \ln(S_{i,t+1}) - \ln(S_{i,t}) - f\,p_{i,t}.$$

Table 8 presents the results for currency excess returns. The patterns are consistent with our baseline findings for gross returns. The IPCA model with moderate latent factors, particularly \(K = 1\) and \(K = 3\), continues to exhibit superior predictive performance. The Predictive R^2 values for PCA models remain negative, confirming their inability to beat the random walk benchmark. However, the IPCA model achieves positive Predictive R^2 values, albeit modest, indicating its robustness in predicting currency excess returns.

The consistency between the results for gross and excess returns validates the IPCA model’s effectiveness in capturing the risk dynamics of the FX market. This robustness across different return measures underscores the model's capability to enhance our understanding of currency risk premiums.

Despite the IPCA model's strong performance, several limitations could affect our study's findings. These limitations highlight areas for future research and potential improvements in the model.

Selection of Latent Factors: One significant challenge in our analysis is determining the optimal number of latent factors (\(K\)). While our results suggest that a moderate number of latent factors (e.g., \(K = 1\) or \(K = 3\)) performs well, the selection is data-dependent and not intuitive. The relationship between \(K\) and model performance is nonlinear, indicating that increasing the number of factors does not always lead to better results. Future research could develop more systematic methods for selecting \(K\) to enhance model robustness.

Negative Out-of-Sample R^2 Values: Another limitation is the occurrence of negative out-of-sample R^2 values, which may be attributed to the relatively small cross-section of FX returns. Unlike studies involving a large number of firms, our dataset is limited to ten currencies. Many currencies are subject to capital controls and have limited return histories, leading to discontinuities and non-stationarity in the time series. These characteristics introduce idiosyncratic risks that can negatively impact predictive performance. While the IPCA model consistently outperforms PCA and regression-based models, the modest cross-section limits the generalizability of our results.

Government Intervention and Market Conditions: The FX market is heavily influenced by government interventions, monetary policies, and macroeconomic conditions. These factors can introduce structural breaks and regime changes that are challenging to model. Our analysis assumes stable relationships between macroeconomic variables and FX returns, but real-world conditions may vary. Future research could explore incorporating regime-switching models or structural break detection to improve predictive accuracy under different market conditions.

Sample Period and Economic Events: Our study period (2008–2020) includes significant economic events, such as the 2008 financial crisis and the European debt crisis. While these events provide valuable insights into the model's performance under stress conditions, they may also introduce biases. The model’s predictive power might differ in more stable periods. Extending the analysis to longer timeframes and including more varied economic conditions could provide a more comprehensive assessment of the IPCA model's robustness.

Comparison with Other Models: While we compare the IPCA model with PCA and regression-based models, there are other advanced models, including nonlinear and machine learning approaches, that could offer additional insights. Future research could benchmark the IPCA model against a broader range of models to further validate its performance.

In summary, while our study demonstrates the IPCA model’s effectiveness in predicting FX returns and capturing time-varying risk premiums, acknowledging its limitations is crucial. Addressing these limitations through extended datasets, advanced modeling techniques, and systematic factor selection methods will enhance the robustness and applicability of the IPCA model in FX market analysis.

7. Conclusion

Building a reliable predictive model for foreign exchange (FX) market prices remains a formidable challenge. This difficulty is often attributed to the assumption of constant beta coefficients over time, which fails to capture the dynamic nature of FX returns. By adopting the Instrumented Principal Component Analysis (IPCA) approach, this study addresses this issue, offering a flexible and robust model that incorporates time-varying betas and effectively reduces the dimensionality of complex information sets.

Our research demonstrates the superiority of the IPCA model over traditional methods, including the random walk and conventional Principal Component Analysis (PCA) models. The IPCA model's ability to handle time-varying betas provides a significant improvement in out-of-sample predictability, showcasing both statistical and economic significance. The model's flexibility allows it to accommodate the diverse and evolving macroeconomic conditions that influence FX markets, making it a powerful tool for predicting currency returns.

One of the key findings of this study is the identification of critical components for predicting FX returns. The medium-term interest rate differential, stock market momentum, and idiosyncratic volatility emerge as significant predictors, highlighting the importance of these factors in the FX market. The IPCA model's ability to capture these predictors underscores its robustness and enhances our understanding of the underlying drivers of FX returns.

The empirical results provide strong evidence of the IPCA model's effectiveness. The model consistently delivers higher predictive R-squared values compared to the random walk and PCA models, particularly in out-of-sample tests. This superior performance is attributed to the IPCA model's capacity to mitigate overfitting and utilize macroeconomic instruments more effectively. By doing so, the IPCA model offers more accurate and reliable forecasts, which are crucial for both academic researchers and market practitioners.

Our analysis also highlights the economic significance of the IPCA model's predictions. Trading strategies based on the IPCA model's forecasts outperform those based on PCA, demonstrating the practical utility of the model in real-world applications. The IPCA model's ability to generate profitable trading signals underscores its value in the FX market, providing actionable insights for investors and traders.

Despite the promising results, this study acknowledges several limitations. The selection of the optimal number of latent factors remains a challenge, with the relationship between the number of factors and model performance being nonlinear. Additionally, the occurrence of negative out-of-sample R-squared values suggests that the relatively small cross-section of FX returns may limit the generalizability of our findings. Moreover, the FX market's susceptibility to government interventions and macroeconomic shocks presents further challenges, as these factors can introduce structural breaks and regime changes that are difficult to model.

To address these limitations, future research could explore more systematic methods for selecting the number of latent factors, incorporate regime-switching models, and extend the analysis to longer timeframes with more varied economic conditions. Comparing the IPCA model with a broader range of advanced models, including nonlinear and machine learning approaches, could also provide additional insights and validate its performance.

In conclusion, this study makes a significant contribution to the literature by demonstrating the effectiveness of the IPCA model in predicting FX returns. The model's flexibility, robustness, and superior predictive power offer valuable insights into the dynamics of the FX market. By capturing time-varying betas and utilizing macroeconomic instruments, the IPCA model enhances our understanding of currency returns and provides a powerful tool for both academic research and practical applications. Future research should continue to build on these findings, addressing the identified limitations and exploring new avenues for improving the predictive accuracy and applicability of the IPCA model in FX market analysis.

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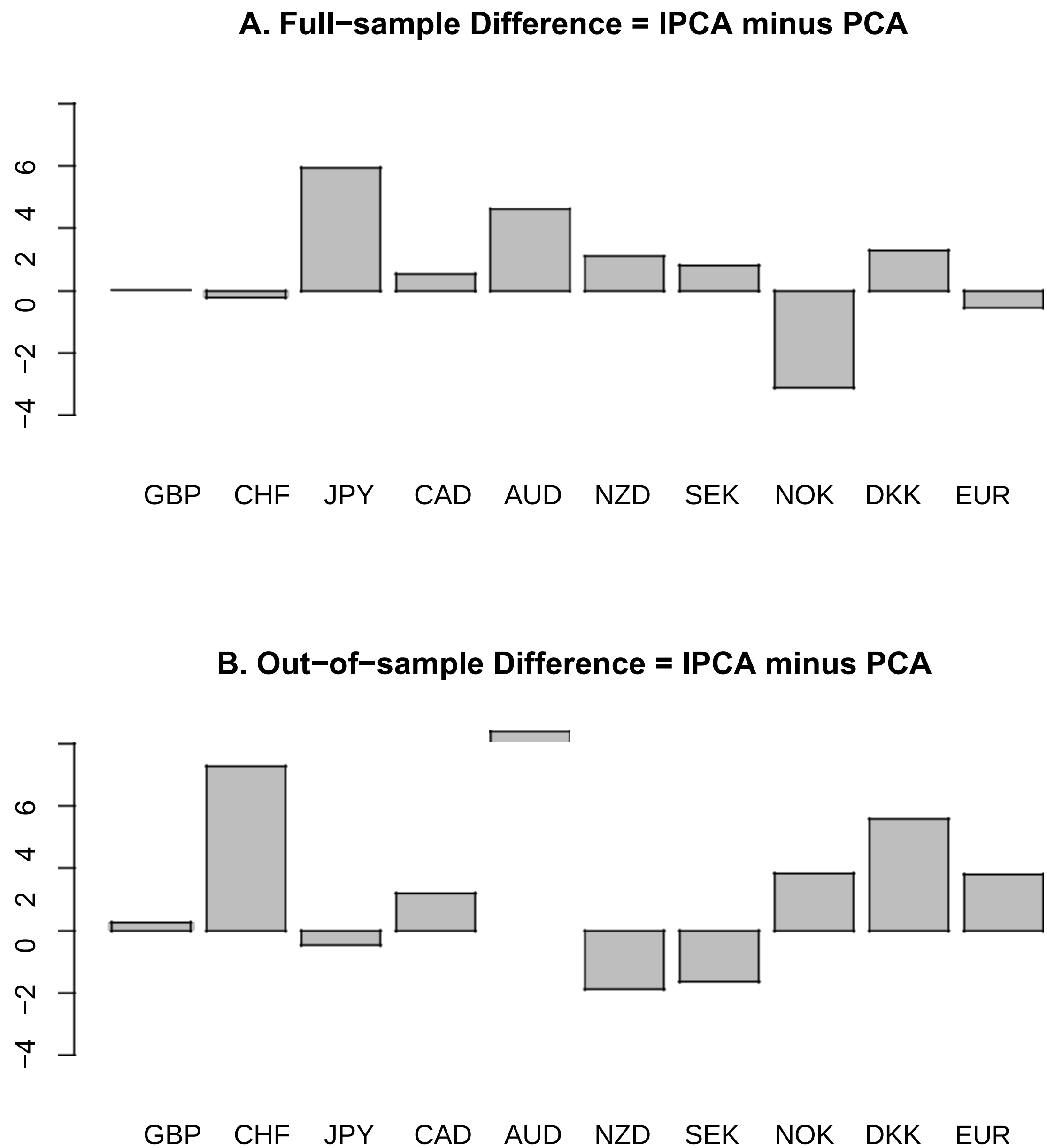

Figure 1. Performance difference of trading strategies: PCA vs. IPCA

This chart compares the performance of trading strategies based on the predictions of the PCA and IPCA models. The difference is obtained by subtracting the cumulative returns of IPCA from PCA models. Panel A uses the full-sample predictions while Panel B only processes the out-of-sample predictions. To ensure comparability, both models have three latent factors (K = 3) and the cumulative returns are annualized and expressed in percentage point.

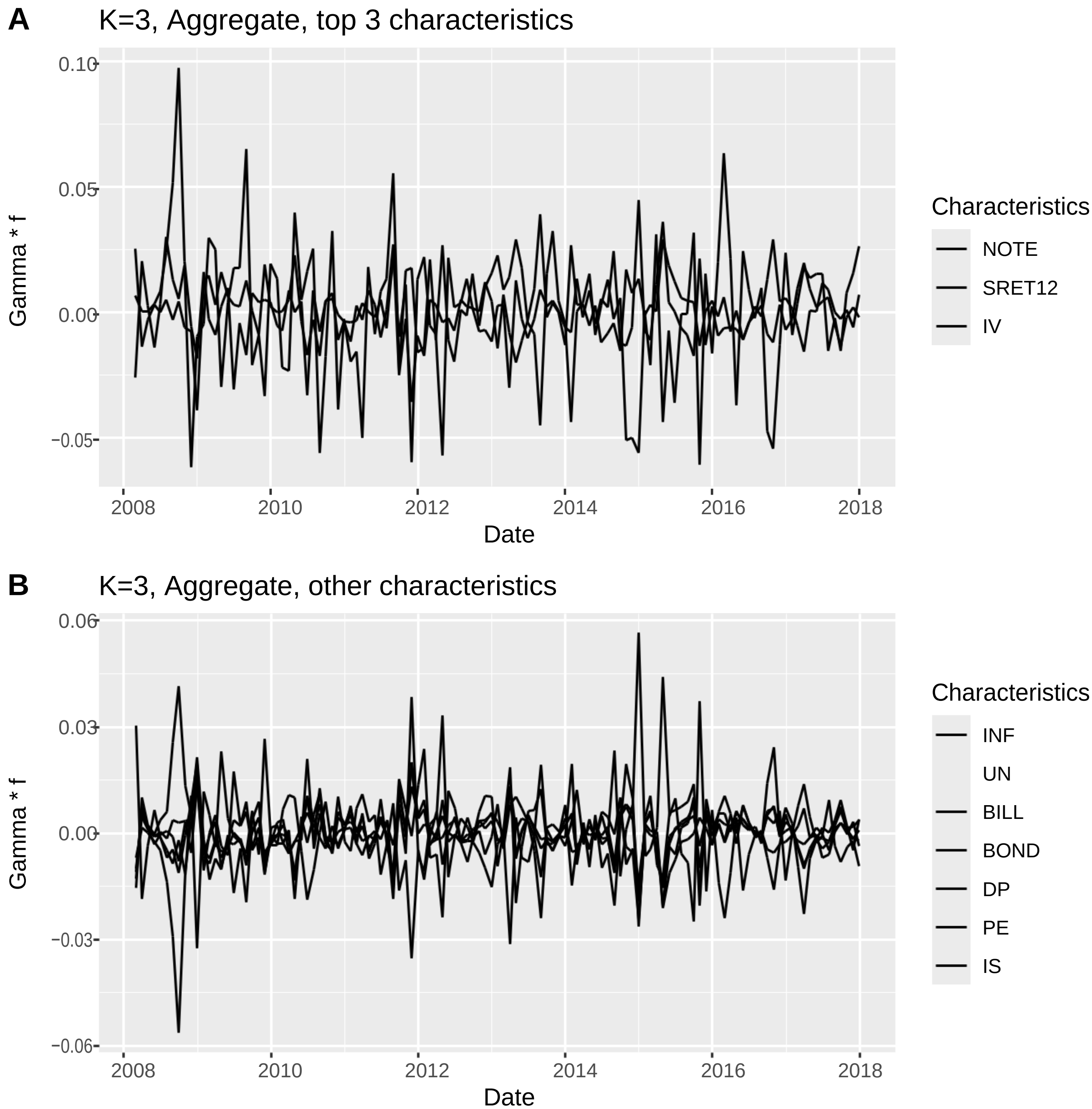

Figure 2. Time-varying beta by characteristic: Aggregate latent factors

This chart presents the time-series coefficients, i.e. the product of Γ_{β} and f in Equation (3), for each country characteristic based on the IPCA model with three latent factors (K = 3).

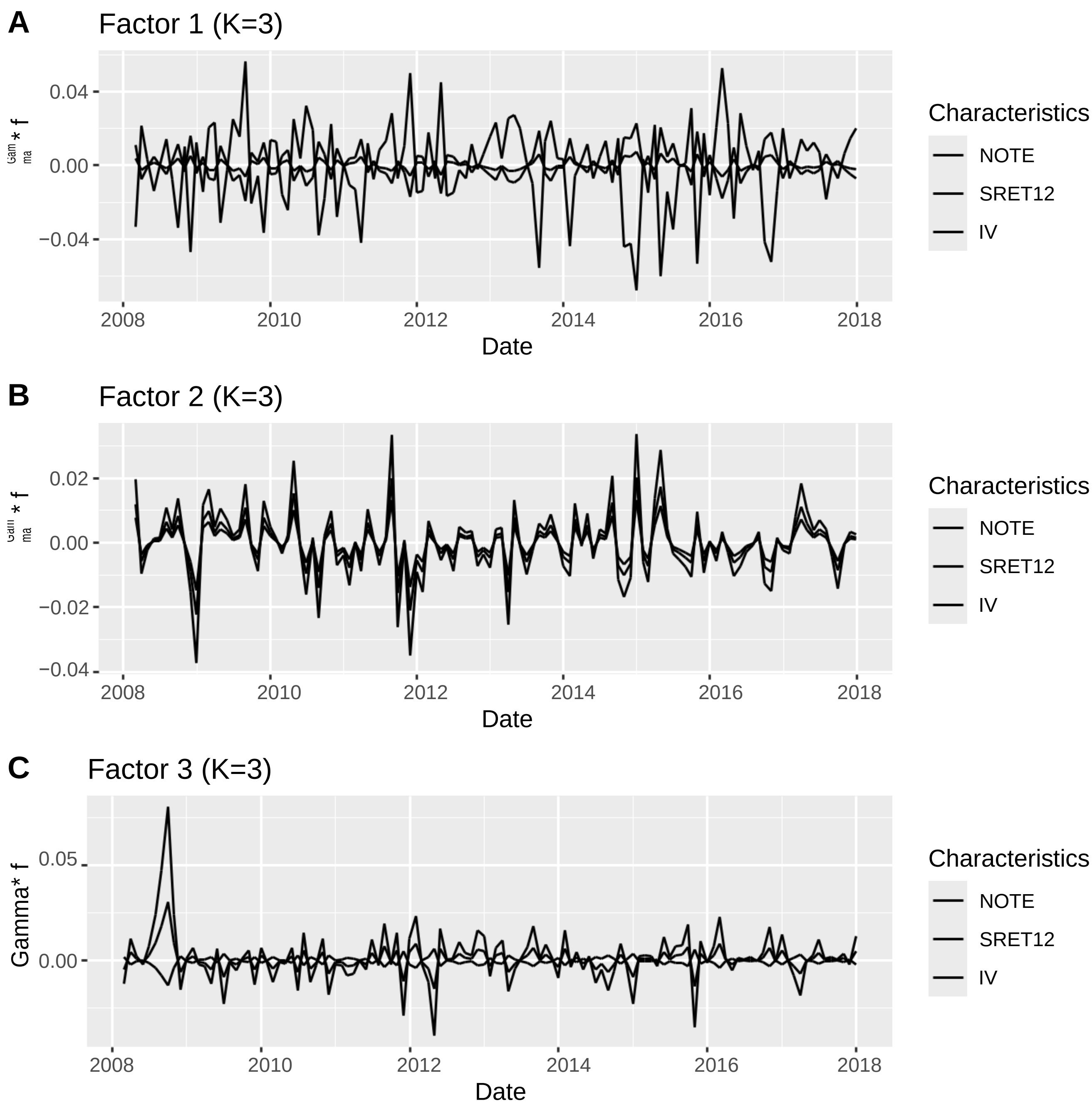

Figure 3. Time-varying beta by characteristic: individual latent factors

This chart presents the time-series coefficients, i.e. the product off and $\Gamma_{\beta j}$ for j = 1, 2, 3 in Equation (3), for each country characteristic based on the IPCA model with three latent factors (K = 3).

Table 1. Summary Statistics

This table presents the summary statistics of the US dollar denominated foreign exchange spot rate returns from the G10 member country. The last row shows the equally-weighted returns across 10 currencies. The reported mean (Column 'Mean') and standard deviation (Column 'Std') are annualized. The characteristics of higher moments are also recorded. Skewness measures the degree of asymmetry. Particularly, negative skewness indicates a distribution with an asymmetric tail extending toward more negative values. Addition-ally, Kurtosis characterizes the relative peakedness of the currency return distribution compared with the normal distribution, where the positive kurtosis indicates the absence of fat tails on the distribution. The monthly returns are from January of 2008 to December 2020. In total, there are 165 observations for each currency. The data is collected from Datastream.

Currency	Code	Mean	Std	Skewness	Kurtosis
Australian Dollar	AUD	0.029	0.094	0.392	1.507
Canadian Dollar	CAD	0.019	0.104	−0.099	3.073
Swiss Franc	CHF	−0.006	0.094	0.370	1.223
Danish Krone	DKK	0.019	0.095	0.505	2.995
Euro	EUR	0.010	0.133	0.626	2.168
British Pound	GBP	0.005	0.138	0.333	1.452
Japanese Yen	JPY	0.018	0.115	0.127	0.462
Norwegian Krone	NOK	0.035	0.122	0.335	0.711
New Zealand Dollar	NZD	0.013	0.098	0.311	1.667
Swedish Krona	SEK	0.014	0.099	0.346	1.621
Equally-Weighted Mean		0.012	0.109	0.325	1.688

Table 2. Correlation Structures

This table presents the correlation structures of the explanatory variables used in this paper. The correlation among the country's characteristics is reported in Panel A while the cross-currency correlation is shown in Panel B. All the correlation matrices are calculated at the currency or characteristics levels. Each correlation matrix is the average of 10 currencies or characteristics. The full variable names of the country's character-istics and currencies can be found in Tables 6 and 1, respectively. The monthly returns are from January of 2008 to December 2020. In total, there are 1650 currency-month observations. The data is sourced from multiple databases, including Bloomberg, Datastream, International Financial Statistics database of International Monetary Fund, OECD and MSCI stock returns.

Panel A: Correlation matrix of country characteristics

	BILL	BOND	DP	INF	IS	IV	NOTE	PE	SRET12	UN
BILL	1	0.805	0.099	0.076	0.007	0.140	0.843	0.110	0.067	0.077
BOND		1	-0.072	0.129	0.016	0.222	0.968	0.051	0.133	0.047
DP			1	-0.039	0.034	0.003	0.096	-0.217	0.396	0.029
INF				1	-0.024	0.232	0.066	0.082	0.145	0.096
IS					1	-0.037	-0.009	0.010	0.029	0.002
IV						1	0.190	0.004	-0.113	0.155
NOTE							1	0.074	0.162	0.016
PE								1	0.136	0.030
SRET12									1	-0.009
UN										1

Panel B: Correlation matrix of G10 currencies

	GBP	CHF	JPY	CAD	AUD	NZD	SEK	NOK	DKK	EUR
GBP	1	0.449	0.367	0.495	0.644	0.498	0.520	0.557	0.535	0.593
CHF		1	0.412	0.417	0.439	0.377	0.595	0.539	0.508	0.499
JPY			1	0.418	0.283	0.165	0.277	0.366	0.256	0.313
CAD				1	0.522	0.283	0.490	0.498	0.456	0.378
AUD					1	0.593	0.586	0.514	0.547	0.584
NZD						1	0.473	0.413	0.491	0.530
SEK							1	0.557	0.623	0.530
NOK								1	0.499	0.549
DKK									1	0.678
EUR										1

Table 3. Beta-sorting portfolios

This table demonstrates the time-varying nature of beta with the beta-sorting currency portfolios in two subsamples of equal lengths. Period 1 and 2 use the data from the first and last five years of the in-sample period, i.e. 2008:01–2017:12. Column ‘Char.’ represents the country’s characteristics and column ‘Port.’ numerates the portfolios from 1 (Low-beta) to 3 (High-beta). In Period 1, an linear regression model without intercept is estimated at currency level and the currencies are ranked according to the beta of each country’s characteristics. Specifically, Portfolios 1 and 3 contain three currencies and the middle portfolio contains four. * denotes the absence of beta-reversal in a specific portfolio. The monthly currency return data are collected from Datastream while the input variables are sourced from multiple databases, including Datastream, Bloomberg, IMF, OECD, and MSCI.

		Period 1	Period 2			Period 1	Period 2
Char.	Port.	2008–2012	2013–2017	Char.	Port.	2008–2012	2013–2017
Bill yield	1	−1.631	1.694	Idiosyncratic volatility	1	−2.111	1.504
	2	0.783	1.863		2	4.444	3.107
	3*	2.497	2.593		3	16.214	2.545
Bond yield	1	6.199	0.706	Price-earning ratio	1	0.060	0.018
	2	1.117	2.334		2	0.002	0.001
	3	4.925	4.216		3	0.150	0.024
Dividend-price ratio	1	2.599	−2.004	Stock momentum	1	0.183	0.109
	2	0.004	0.002		2	0.107	0.037
	3*	0.022	0.032		3	0.013	0.022
Inflation	1	1.843	1.631	Unemployment gap	1	0.027	0.012
	2	1.055	0.419		2	0.007	0.010
	3	0.274	0.714		3	0.014	0.014
Idiosyncratic skewness	1	0.016	0.005	Note yield	1	7.947	4.816
	2	−0.005	0.009		2	−1.337	3.104
	3	0.007	−0.002		3	1.531	−1.535

Table 4. Model's performance

This table shows both the model's in-sample and out-of-sample performance across two models. First, PCA represents the Principal Component Analysis model, and second, IPCA represents the Instrumented Principal Component Analysis. We record Total R^2 and Predictive R^2 in Panel A and B, using the equations (10) and (11), respectively. The R^2 statistics of each model are presented in percentage and calculated up to five latent factors. In the second column, we also show the p-value corresponding to the constrained model where the null hypothesis is $\Gamma_\alpha = 0$. The monthly currency return data are collected from Datastream while the input variables are sourced from multiple databases, including Datastream, Bloomberg, IMF, OECD, and MSCI. We use the first ten years, i.e. from January of 2008 to December 2017, as our in-sample period and the rest of three years as our out of sample. In total, there are 120 and 36 observations for each currency during the in-sample and out-of-sample periods.

	In-sample 2008:01–2017:12			Out of Sample 2018:01–2020:12	
K	$H_0:\Gamma_\alpha=0$ p-value	PCA	IPCA	PCA	IPCA
		Panel A: Total R^2			
1	0.42	68.40	51.11	66.58	43.87
2	0.83	77.36	66.07	73.59	56.22
3	0.98	83.73	73.82	80.84	62.43
4	0.15	88.72	79.89	85.44	74.62
5	0.23	92.22	83.81	89.41	75.64
		Panel B: Predictive R^2			
1		4.07	0.14	0.37	0.03
2		4.92	1.93	0.31	2.31
3		5.31	1.62	0.36	0.28
4		5.55	0.95	0.36	−4.27
5		−5.70	−3.57	−0.42	−16.20

Table 5. Trading strategies based on PCA vs. IPCA models

This table compares the trading strategy performance between the PCA and IPCA models for each G10 currency. We compute the cumulative returns depending on the model's predictions. Specifically, the trading strategy buys the foreign currency (sells the US dollar) when the predicted returns are positive, and sells the foreign currency (buys the US dollar) when the predicted returns are negative. Both full sample and out-of-sample returns are annualized and expressed in percentage point. The last row shows the equally-weighted returns across 10 currencies. The monthly returns are from February of 2008 to December 2020 in the full sample, while the out-of-sample exercise began from February of 2018. The foreign exchange rate data is collected from Datastream.

		Full sample 2008:02–2018:01		Out-of-sample 2018:02–2020:12	
Currency	Code	PCA	IPCA	PCA	IPCA
Australian Dollar	AUD	4.216	1.595	1.532	7.912
Canadian Dollar	CAD	0.662	0.139	1.195	2.396
Swiss Franc	CHF	0.633	0.863	−1.718	3.565
Danish Krone	DKK	0.509	0.789	0.562	4.155
Euro	EUR	−0.516	−1.075	0.567	2.363
British Pound	GBP	1.559	1.571	1.308	1.566
Japanese Yen	JPY	0.020	3.955	1.895	1.435
Norwegian Krone	NOK	2.915	−0.220	3.609	5.435
New Zealand Dollar	NZD	0.248	0.843	0.852	1.019
Swedish Krona	SEK	0.630	0.175	1.466	−0.169
Equally-Weighted Mean	EWR	−0.292	0.344	1.127	2.764

Table 6. Characteristic contribution

This table reports the contribution of each country characteristic to overall model fit in the restricted IPCA specification when K = 1 and 3 in Panel A and B, respectively. The recorded R^2 reductions are presented in percentage when setting all Γ_β elements pertaining to that characteristic to zero. 'Std' standardize the R^2 reduction values to 100% while the original R^2 reduction is reported in the column 'Non-Std'. Columns 'Γ_β' report the estimated Γ coefficient(s) of latent factor(s). The shaded rows indicate the top three country characteristics according to the standardized R^2 reduction. We also present the coefficient andp-value of the test $H_0 : \Gamma_\beta = 0$.

Panel A: R^2 reduction (K = 1)				Gamma Coefficient	H_0:Γ_β=0
		Non-Std	Std	Γ_β	p-value
Inflation	INF	1.58	3.08	0.16	0.003
Unemployment gap	UN	2.91	5.69	−0.21	0.001
Bill yield	BILL	1.55	3.04	0.16	0.020
Note yield	NOTE	22.30	43.62	0.67	0.004
Bond yield	BOND	1.54	3.01	0.19	0.329
Dividend-price ratio	DP	0.70	1.38	0.10	0.008
Price-earning ratio	PE	0.02	0.04	−0.02	0.620
Stock momentum	SRET12	5.60	10.96	0.33	0.001
Idiosyncratic volatility	IV	14.61	28.58	0.54	0
Idiosyncratic skewness	IS	0.31	0.61	−0.08	0.034

Panel B: R^2 reduction (K = 3)				Gamma Coefficients (Γ_β)			H_0:Γ_β=0
		Non-Std	Std	β_1	β_2	β_3	p-value
Inflation	INF	1.97	2.67	0.02	0.25	0.09	0.006
Unemployment gap	UN	0.97	1.31	0.01	0.11	0.16	0.007
Bill yield	BILL	7.22	9.78	0.32	0.42	−0.22	0.009
Note yield	NOTE	30.00	40.64	−0.86	−0.34	0.27	0.021
Bond yield	BOND	6.50	8.81	0.09	0.34	0.41	0.051
Dividend-price ratio	DP	2.66	3.61	0.00	0.30	0.03	0.005
Price-earning ratio	PE	4.37	5.91	−0.19	0.19	0.39	0.303
Stock momentum	SRET12	8.89	12.04	0.10	0.57	−0.12	0.001
Idiosyncratic volatility	IV	9.29	12.58	0.29	−0.22	0.71	0.066
Idiosyncratic skewness	IS	1.95	2.64	−0.17	0.16	0.03	0.009

Table 7. Time-invariant β in fixed effects regression

This table reports the results of the fixed effects regression models. Panel A shows the model's performance measures of in-sample (Panel A.1) and out-of-sample (Panel A.2) periods. Next, Panel B presents the coefficient results of the fixed effects regressions. Note that the Total and PredictiveR^2 follow the definition in Equation (10) and (11), respectively. The shaded rows highlight the country characters with significance according to the R^2-reduction results in the feature importance exercise of Table 6. Standard errors (in parentheses) are clustered by country and time (calendar month) dimension. The superscripts *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

	(1)	(2)	(3)
Panel A.1: In-sample R^2			
Total R^2	11.093	7.453	7.170
Predictive R^2	0.597	4.732	=1.907
Panel A.2: Out-of-sample R^2			
Total R^2	0.686	0.286	4.329
Predictive R^2	=1.346	=7.974	=3.388
Panel B: In-sample Regressions			
Bill yield	0.828***	0.984***	0.703***
	(0.196)	(0.184)	(0.205)
Bond yield	0.352	=1.065*	0.842
	(0.483)	(0.574)	(0.464)
Dividend-price ratio	0.000	0.000	=0.001
	(0.001)	(0.003)	(0.001)
Inflation	0.458***	0.517**	0.010
	(0.101)	(0.181)	(0.087)
Idiosyncratic skewness	=0.006***	=0.006*	=0.006**
	(0.001)	(0.003)	(0.002)
Idiosyncratic volatility	2.887***	4.206**	1.521
	(0.999)	(1.648)	(1.230)
Note yield	=1.008**	=0.249	=0.205
	(0.455)	(0.387)	(0.413)
Price-earning ratio	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Stock momentum	=0.048***	=0.049***	=0.034***
	(0.008)	(0.008)	(0.008)
Unemployment gap	0.000	0.000	0.003
	(0.004)	(0.005)	(0.003)
α	=0.016***		
	(0.004)		
Calendar Month Fixed Effects			✓
Country Fixed Effects		✓	✓

Table 8. Robustness test: currency excess returns

This table shows both the model's in-sample and out-of-sample performance across two models using currency excess returns as dependent variable. First, PCA represents the Principal Component Analysis model, and second, IPCA represents the Instrumented Principal Component Analysis. We record Total R^2 and Predictive R^2 in Panel A and B, using the equations (10) and (11), respectively. The R^2 statistics of each model are presented in percentage and calculated up to five latent factors. In the second column, we also show the p-value corresponding to the constrained model where the null hypothesis is $\Gamma_\alpha = 0$. The monthly currency return data are collected from Datastream while the input variables are sourced from multiple databases, including Datastream, Bloomberg, IMF, OECD, and MSCI. We use the first ten years, i.e. from January of 2008 to December 2017, as our in-sample period and the rest of three years as our out of sample. In total, there are 120 and 36 observations for each currency during the in-sample and out-of-sample periods.

		In-sample 2008:01–2017:12		Out of Sample 2018:01–2020:12	
K	$H_0{:}\Gamma_\alpha=0$ p-value	PCA	IPCA	PCA	IPCA
		Panel A: Total R^2			
1	0.43	68.55	51.13	66.46	43.69
2	0.88	77.34	66.17	73.29	56.33
3	0.80	83.81	73.98	80.61	59.05
4	0.06	88.78	80.02	85.26	73.77
5	0.62	92.25	84.33	89.05	77.02
		Panel B: Predictive R^2			
1		4.21	0.23	0.24	0.68
2		5.05	2.18	0.20	2.91
3		5.32	2.05	0.27	0.38
4		5.59	2.13	0.22	−9.54
5		−5.73	−1.03	0.14	−13.66