# Investigating Latent Factors in Currencies

Applied Finance Project
Team 18

Rodney Chabuda, Saurabh Kelkar, Amrit Prasad, Joanna Wang

University of California, Berkeley

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*Supervisors:*
Prof. Martin Lettau
Prof. Eric Reiner

# Outline

# Introduction

# Introduction

## Factor Construction

- Macro Factors
  - Risk premium from changes in macroeconomic variables.
  - Typically not directly tradable.
- Dynamic Factors
  - Based on prior understanding of drivers of asset returns - constructed using portfolio sorts.
  - Prior understanding is partial.
  - Method of portfolio construction is arbitrary.
- Latent Factors
  - Factors are latent: utilize decomposition techniques.
  - Lack of interpretability.

# Executive Summary

## Problem Statement

Can we find a technique that allows us to explicitly learn latent factors that drive asset returns while incorporating established domain knowledge in currency markets?

- Instrumented PCA (IPCA).

## Key Results

- IPCA yields factors that explain returns better than Fama-French (FFR) style factors and PCA factors.
- IPCA and FFR factors have comparable Sharpe ratios ex-ante that are much higher than PCA factors.

# Factor Modeling

# Factor Modeling

## Framework

- Undiversifiable systematic risk factors vs diversifiable idiosyncratic risk.
- Factor modeling attempts to describe and estimate the systematic factors.

## Generic Factor Equation

$$r_{i,t} = \alpha_i + \beta_{1,i,t} F_{1,i,t} + ... + \beta_{k,i,t} F_{k,i,t} + \epsilon_{i,t}$$

# Link with Stochastic Discount Factor (SDF)

## SDF

SDF can be used to price any traded asset using:

$$1 = E[\tilde{m} \times (1 + r_i)]$$

SDFs and asset pricing can be linked by:

$$E(r_i) - r_f = \beta_{i,\tilde{m}} \lambda_{\tilde{m}}$$

where, $\lambda_{\tilde{m}} = -\frac{\text{var}(\tilde{m})}{E(\tilde{m})}$ and $\beta_{i,\tilde{m}}$ is asset $i$'s exposure to $\tilde{m}$ risk.

# Generalization

## Multifactor Models

The generalized multi factor models can be expressed as:

$$r_i - r_f = \beta_i^T f + \epsilon_i$$
$$E(r_i) - r_f = \beta_i^T \lambda$$

Assuming the factors linearly span the SDF vector space, it can be expressed as:

$$\tilde{m}_t = 1 - b^T (f_t - \lambda)$$

Expression linking b and $\beta$ obtained as:

$$b = \Sigma_f^{-1} \lambda$$

*b* can be interpreted as the factor weights that maximize the mean-variance utility for a fixed risk-aversion coefficient.

# FX Market

## Dynamics

- Price quotes
  - Quoted in terms of relative rates.
  - Base currency US Dollar.
- Interest rates
  - Analogous to dividend on a stock.
  - Worth noting base currency also has a dividend yield.
- Excess returns
  - Log excess returns: $rx_{t+1} = \ln\left(\frac{e^{r_{X,t}} S_t}{S_{t+1}}\right) - r_{\$,t} = r_{X,t} - r_{\$,t} - \Delta \ln S_{t+1}$
  - Assuming covered interest rate parity holds: $rx_{t+1} = \ln F_t - \ln S_{t+1}$

## Dynamics Cont'd

- Numeraire
  - A good model should be numeraire invariant.
  - Difficult to observe due to frictions such as currency supply/demand differences, public policy, liquidity.
  - Example: Egyptian Pound-Russian Ruble executed indirectly through US Dollar.
- Systematic vs idiosyncratic risk
  - **Systematic**: Undiversifiable risk of currencies co-moving, similar to CAPM market factor. The US Dollar Index is a real-life example of an index that captures this.
  - **Idiosyncratic**: Idiosyncratic risk from country specific events such as political turmoil, macro factor shocks.

# Data

# FX Data

## Data Description

- **Universe**: 47 currencies including both fully and partially converted currencies.
- **Begin date**: Different countries in Europe began adopting the Euro at different points in time.
- **Contemporaneous data**: FX market trades 24 $\times$ 7 - no notion of "closing" price. Used monthly data.
- **Interest rate parity exclusions**: Assumed interest rate parity holds. Excluded some periods for South African Rand, Malaysian Ringgit, Indonesian Rupiah, Turkish Lira and UAE Dirham.

# FX Data

## Challenges

- Cross-section size changes over time.
  - Adoption of the Euro at different points in time.
  - Poor quality of forwards data.
  - Interest rate parity exclusions.
- **PCA**: Use portfolios sorts instead of individual currencies. Cannot incorporate data apart from returns.
- **IPCA**: Can handle individual currencies directly. Can incorporate data apart from returns.

# Framework and Data Exploration

# Factor Modeling: Generalized Framework

## Generalized Framework

$$r_t = \beta_t f_t + \epsilon_t$$

- $r_t \in \mathbb{R}^{N \times 1}$: cross-section of N asset returns at time t
- $f_t \in \mathbb{R}^{K \times 1}$: contemporaneous returns of K factors
- $\beta_t \in \mathbb{R}^{N \times K}$: factor exposures or loadings for each asset

## Estimation

- Different approaches to estimate the $\beta_t$ and $f_t$
- For constructing tradable factors, information upto time t is used for creating the portfolios that realize returns at t+1, i.e.

$$\begin{aligned} \hat{f}_{t+1} &= (\hat{\beta}_t^T \hat{\beta}_t)^{-1} \hat{\beta}_t^T r_{t+1} \\ &= w_t^T r_{t+1} \end{aligned}$$

# Factor Modeling in FX: FFR

## Fama French Approach (FFR)

- Take a characteristic such as currencies with higher relative interest rates appreciate (carry), and construct quantile portfolios.
  - Identify a quantifiable characteristic for carry.
  - Sort currencies on the basis of it into a fixed number of equal-weighted portfolios.
- $f_t$ is long-short the extreme bucket portfolios.
- $\beta$ estimated by regressing each currency against the factors on a rolling basis. Assumed to be constant over the estimation period.

## Characteristic for Each Factor

- **Carry**: Forward Discount
- **Value**: $\frac{<S_t^{X/USD}>}{PPP_{t-12}^{X/USD}}$
- **Momentum**: $r_{t-1}$

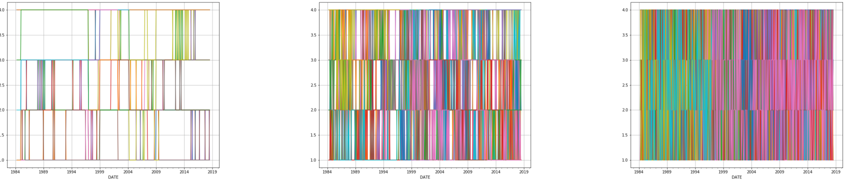
# Characteristics Ranks

## Time Variation and Turnover

The value characteristic is the slowest moving while momentum has the highest variation. These translate into turnovers that follow:

$$TO_{value} < TO_{carry} < TO_{momentum}$$

Figure 1: Ranks vs Time



(a) Value (b) Carry (c) Momentum

# Factor Modeling in FX: PCA

## Principal Component Analysis (PCA)

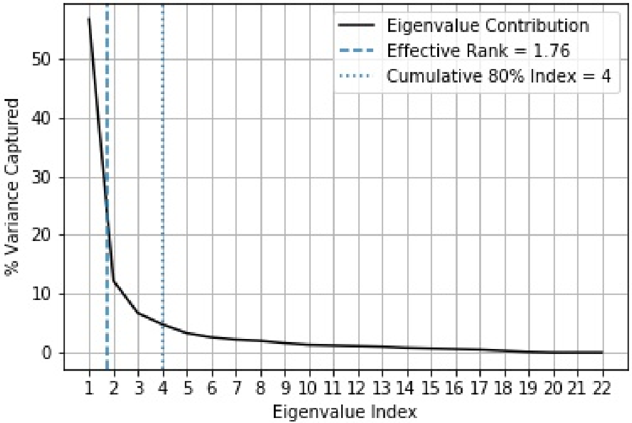
PCA specification given by:

$$
\begin{aligned}
r_t &= \beta f_t + \epsilon_t \\
\implies X = \begin{bmatrix} r_1 & \dots & r_T \end{bmatrix}^T &= \begin{bmatrix} \beta f_1 & \dots & \beta f_T \end{bmatrix}^T + \begin{bmatrix} \epsilon_1 & \dots & \epsilon_T \end{bmatrix}^T \\
&= F\beta^T + \epsilon \\
\text{subject to } \beta^T\beta &= I_K
\end{aligned}
$$

- Factor portfolio weights are the loadings which are estimated from the data.
- Factor exposures are also the loadings estimated simultaneously for the entire panel. This gives the constructed factors greater ability to explain the cross-section.
  - Assumed to be static in the estimation window.

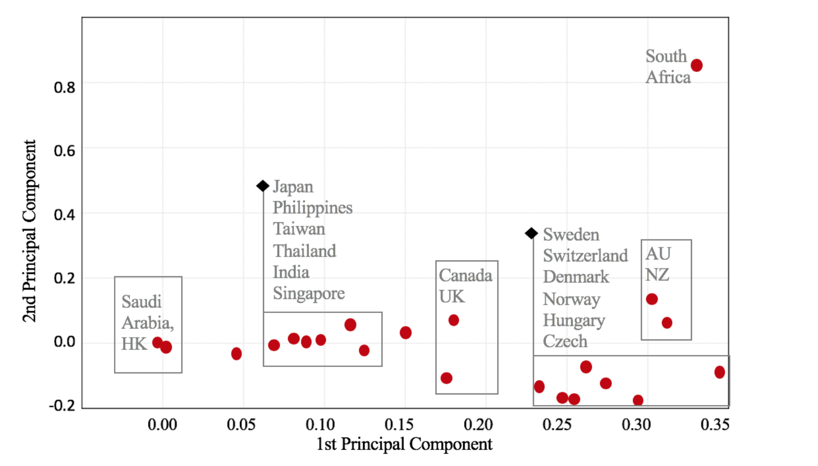
# Data Exploration: Latent Factor Structure

## A Clear Latent Factor Structure in the Data

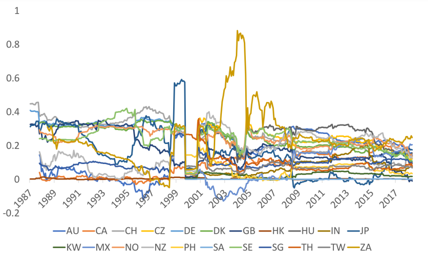


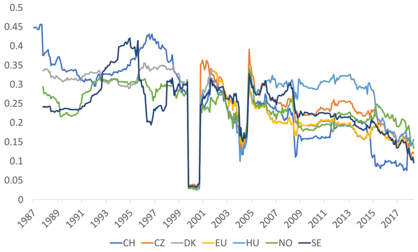
# Data Exploration: Clustering

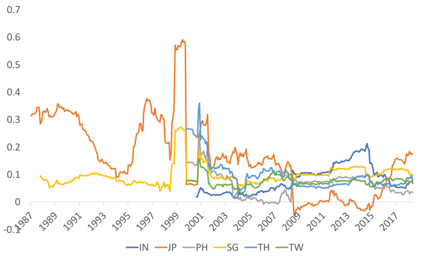
## Five Major Clusters



# Data Exploration: Time Variation




# Preliminary Exploration Summary and Motivation for IPCA

## Dimensionality in FX Market

The incorporation of domain knowledge could potentially help with the small dimensionality in FX Market. For example, with 30 currencies and T = 36 months, we observe that the number of data points per parameter increases from 2.3 for PCA to 32.7 for IPCA in the model.

## Latent Factors with Domain Knowledge

We observed a clear latent factor structure by running PCA, suggesting the viability of the latent factor construction approach.

## Time Variation

Exposure of currencies to the latent factors are unstable across time. IPCA handles this by making the loadings an explicit function of the time-varying characteristics.

# Instrumented-PCA

# Factor Modeling in FX: IPCA

## Instrumented Principal Component Analysis (IPCA)

IPCA specification given by:

$$r_{t+1} = \beta_t f_{t+1} + \epsilon_{t+1}$$
$$\beta_t = Z_t \Gamma_\beta + \nu_{\beta,t}$$
$$\text{subject to } \Gamma_\beta^T \Gamma_\beta = I_K; \; FF^T = \text{diagonal matrix}$$

where

$$F = \begin{bmatrix} f_1 & \dots & f_T \end{bmatrix}^T$$

- Factor portfolio weights determined solely by the loadings.
- Factor exposures (or loadings) are estimated simultaneously for the entire panel. This preserves the greater ability to explain the cross-section similar to the PCA factors.
  - Allowed to vary in the estimation window as per the chosen characteristics.

# Factor Modeling in FX: IPCA

## PCA Constraints

- PCA has an additional degree of freedom compared to FFR.
- General solution belongs to the family $\beta R^{-1}$ and $FR$ where $R$ is a rotation matrix.
- Factor portfolio weights given by $\beta$. Solution chosen after imposing orthonormality on $\beta$. This ensures leverage is not massive.
- SVD ensures the constraint is met. The constructed factors are also orthogonal.

## IPCA Constraints

- IPCA has two additional degrees of freedom compared to FFR.
- The constraints are chosen to ensure that the properties of PCA portfolios are preserved.
- The constructed factors should be orthogonal.
- Factor portfolio weights given by $(\hat{\Gamma}_\beta^T Z_t^T Z_t \hat{\Gamma}_\beta)^{-1} \hat{\Gamma}_\beta^T Z_t^T$, should have sensible leverage.
- The constraints are chosen accordingly. $\Gamma_\beta^T \Gamma_\beta = I_K$ and $FF^T =$ diagonal matrix.
- This is still not enough since the $Z_t$ matrices are derived from real data and could have very large eigenvalues leading to non-sensible weights.

# Factor Modeling in FX: IPCA

## IPCA Normalization

The columns of $Z_t$ (cross-sectional characteristics) can be normalized using the following approaches:

- **Orthonormalization**: $Z_t$ becomes an orthonormal matrix and the weights reduce to $\Gamma_\beta^T Z_t^T$. This leads to loss of interpretability since all preceding columns of $Z_t$ are used to normalize each of its columns.
- **Unit L2 norm**: Columns of $Z_t$ are unit normalized with respect to the L2 norm resulting in a matrix that is reasonably well behaved and interpretable.
- **Z-Score**: Similar to above except that the columns are de-meaned prior to being normalized to unit norm.
- **X-Rank**: Columns converted to rank indices to remove impact of outliers. Needs to be combined with one of the above techniques to ensure that eigenvalues do not explode.

## Alternating Minimization

The objective function is given by:

$$\min_{\Gamma_\beta, f} \sum_{t=1}^{T-1} (r_{t+1} - Z_t \Gamma_\beta f_{t+1})^T (r_{t+1} - Z_t \Gamma_\beta f_{t+1})$$

- Cannot leverage SVD to solve the above. Need to use Alternating Minimization.
- Initial values provided assuming that $Z_t$ is orthonormal.

$$r_{t+1} = Z_t \Gamma_\beta f_{t+1} + \epsilon_{t+1}$$
$$Z_t^T r_{t+1} = \Gamma_\beta f_{t+1} + \epsilon^*_{t+1}$$

This can be solved using SVD.

# Factor Modeling in FX: Comparison setup

## Rolling Estimation

- The time variation of the factor exposures could be potentially captured by estimating them in a rolling window fashion for FFR and PCA.
- For FFR, regress currency returns against the factors in a rolling window of 36 months. The last day of the window gets assigned the exposure.
- For PCA, estimate the loadings in a rolling window of 36 months. Use them to calculate portfolio weights for the last day of the window. The factor return is realized in the next period.
- For IPCA, replicate the PCA process.

# Results

# Results: Outline

## $R^2$ Metrics

- Analysis to evaluate how well the factors explain returns.

## Performance Metrics: SDF

- Construct Stochastic Discount Factor (SDF) for various factor combinations using mean variance optimization for a risk target of 1%.
- Compare Sharpe ratios of the SDFs across techniques.

## IPCA Factors Interpretation

- Interpret IPCA Factors in terms of the known FFR factors.
- Contrast interpretations across combinations of characteristics.

## $R^2$ Metrics

- Total $R^2$
  - Quantify how well the estimated factors and currency exposures to them fit the panel of returns
  - Total $\mathrm{R}^2 = 1 - \frac{\Sigma_t ||r_{t+1} - \hat{\beta}_t \hat{f}_{t+1}||_2^2}{\Sigma_t ||r_{t+1}||_2^2}$
  - $r_{t+1} \in \mathbb{R}^{N \times 1}$, $\hat{\beta}_t \in \mathbb{R}^{N \times K}$, $\hat{f}_{t+1} \in \mathbb{R}^{K \times 1}$
- Predictive $R^2$
  - Quantify how well the estimated factors explain the cross-section of returns
  - Predictive $\mathrm{R}^2 = 1 - \frac{\Sigma_t ||r_{t+1} - \hat{\beta}_t \hat{\lambda}_t||_2^2}{\Sigma_t ||r_{t+1}||_2^2}$
  - $\hat{\lambda}_t = \frac{1}{t} \Sigma_{k=1}^t \hat{f}_k$, price to take factor risk

# Results: $R^2$ Metrics

| | FFR | | PCA | | IPCA | |
|---|---|---|---|---|---|---|
| | *Predictive Rsq* | *Total Rsq* | *Predictive Rsq* | *Total Rsq* | *Predictive Rsq* | *Total Rsq* |
| Carry | -0.38% | 17.55% | - | - | 1.04% | 86.00% |
| Momentum | 0.01% | 9.97% | - | - | 1.13% | 44.23% |
| Value | -0.23% | 17.50% | - | - | 1.18% | 40.74% |
| Curr Acc | 0.07% | 24.80% | - | - | 0.55% | 26.37% |
| GDP Growth | -0.21% | 4.20% | - | - | 0.71% | 24.86% |
| Carry, Momentum | -0.19% | 23.56% | - | - | 1.29% | 48.03% |
| Carry, Value | 1.09% | 38.03% | - | - | 1.33% | 45.66% |
| Curr Acc, GDP Growth | -0.35% | 29.49% | - | - | 1.13% | 42.98% |
| Momentum, Value | -0.58% | 25.30% | - | - | 0.87% | 46.33% |
| Carrry, Momentum, Value | 0.54% | 41.95% | - | - | 1.29% | 49.06% |
| All Factors Combined | 0.44% | 56.20% | - | - | 1.32% | 49.12% |
| 2nd Moment Matrix | - | - | 0.82% | 76.49% | - | - |
| Correlation Matrix | - | - | 0.58% | 63.66% | - | - |
| Covariance Matrix | - | - | 0.81% | 75.91% | - | - |

# Results: $R^2$ Metrics

## $R^2$ Metrics

- Total PCA $R^2$: PCA $>$ IPCA $>$ FFR
  - PCA and IPCA objective functions explicitly maximize this.
- Predictive $R^2$: IPCA $>$ PCA $>$ FFR
  - FFR is inconsistent likely because its measure of exposure (regression coefficients) are estimated separately for each currency.
  - Time variation of IPCA exposures seems to boost its performance.
- PCA results are comparable for the 2nd Moment and Covariance Matrices. Both are better than the Correlation Matrix. This suggests that it is indeed covariance that is priced and not correlations.

# Results: SDF Performance Metrics

## SDF Performance Metrics

- The ex-ante performance for FFR and IPCA is almost similar.
  - No clear winner in terms of Sharpe ratio, ex-ante.
- The ex-post Sharpe ratio is better for IPCA factors than FFR factors.
  - Ex-post is hypothetical case unlikely to be realized
  - Outperformance indicates research to forecast returns of IPCA factors could yield a good benchmark
- Tunover and Leverage are at comparable levels ex-ante and ex-post.
- Very low Sharpe ratios for PCA SDFs. This is because it is not able to pick consistent exposure to anomalies known to have steady risk premia.

# Results: SDF Performance Metrics (FFR)

| **Approach** | **SDF (ex-ante)** | | | | | **SDF (ex-post)** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Leverage* | *Mean* | *Sharpe* | *Std Dev* | *Turnover* | *Leverage* | *Mean* | *Sharpe* | *Std Dev* | *Turnover* |
| Carry | 1.98 | 0.24% | 0.22 | 1.10% | 0.26 | 1.98 | 0.28% | 0.27 | 1.04% | 0.26 |
| Momentum | 1.88 | 0.18% | 0.17 | 1.05% | 1.19 | 1.88 | 0.23% | 0.23 | 0.98% | 1.19 |
| Value | 2.64 | 0.05% | 0.05 | 1.17% | 0.17 | 2.63 | 0.12% | 0.12 | 1.05% | 0.18 |
| Curr Acc | 2.22 | 0.00% | 0.00 | 1.02% | 0.23 | 2.22 | 0.15% | 0.15 | 0.97% | 0.24 |
| GDP Growth | 1.99 | 0.08% | 0.07 | 1.03% | 0.37 | 1.99 | 0.15% | 0.15 | 0.97% | 0.37 |
| Carry, Momentum | 2.13 | 0.33% | 0.28 | 1.16% | 0.73 | 2.13 | 0.41% | 0.39 | 1.06% | 0.73 |
| Carry, Value | 2.64 | 0.24% | 0.18 | 1.31% | 0.28 | 2.65 | 0.39% | 0.35 | 1.11% | 0.28 |
| Carry, Curr Acc | 2.40 | 0.25% | 0.19 | 1.27% | 0.29 | 2.40 | 0.37% | 0.33 | 1.12% | 0.29 |
| Carry, GDP Growth | 2.21 | 0.22% | 0.20 | 1.11% | 0.37 | 2.21 | 0.35% | 0.37 | 0.96% | 0.37 |
| Momentum, Value | 2.45 | 0.20% | 0.18 | 1.11% | 0.77 | 2.45 | 0.33% | 0.32 | 1.01% | 0.77 |
| Curr Acc, GDP Growth | 2.29 | 0.05% | 0.05 | 1.08% | 0.35 | 2.29 | 0.22% | 0.23 | 0.95% | 0.36 |
| Carry, Momentum, Value | 2.61 | 0.33% | 0.27 | 1.25% | 0.56 | 2.62 | 0.49% | 0.46 | 1.07% | 0.57 |
| All Factors Combined | 2.99 | 0.32% | 0.24 | 1.30% | 0.58 | 2.99 | 0.57% | 0.55 | 1.04% | 0.58 |

Figure 6: SDF Performance Metrics: FFR

# Results: SDF Performance Metrics (PCA)

| SVD Matrix | | SDF (ex-ante) | | | | | SDF (ex-post) | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Leverage* | *Mean* | *Sharpe* | *Std Dev* | *Turnover* | *Leverage* | *Mean* | *Sharpe* | *Std Dev* | *Turnover* |
| Second Moment | 2.04 | -0.06% | -0.05 | 1.30% | 0.47 | 2.04 | 0.31% | 0.32 | 0.99% | 0.46 |
| Correlation | 2.32 | 0.03% | 0.02 | 1.42% | 0.59 | 2.30 | 0.40% | 0.37 | 1.09% | 0.58 |
| Covariance | 2.01 | -0.05% | -0.03 | 1.41% | 0.51 | 2.00 | 0.35% | 0.32 | 1.08% | 0.50 |

Figure 7: SDF Performance Metrics: PCA

# Results: SDF Performance Metrics (IPCA)

| Approach | SDF (ex-ante) | | | | | SDF (ex-post) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Leverage* | *Mean* | *Sharpe* | *Std Dev* | *Turnover* | *Leverage* | *Mean* | *Sharpe* | *Std Dev* | *Turnover* |
| Carry | 2.07 | 0.26% | 0.22 | 1.14% | 0.38 | 2.09 | 0.38% | 0.37 | 1.02% | 0.37 |
| Momentum | 1.72 | 0.16% | 0.16 | 1.01% | 1.05 | 1.72 | 0.31% | 0.34 | 0.93% | 1.04 |
| Value | 2.32 | 0.15% | 0.13 | 1.13% | 0.32 | 2.31 | 0.28% | 0.27 | 1.03% | 0.33 |
| Curr Acc | 2.61 | 0.12% | 0.10 | 1.18% | 0.39 | 2.61 | 0.29% | 0.27 | 1.08% | 0.40 |
| GDP Growth | 2.11 | 0.11% | 0.1 | 1.10% | 0.51 | 2.11 | 0.27% | 0.27 | 0.99% | 0.51 |
| Carry, Momentum | 2.27 | 0.32% | 0.27 | 1.18% | 0.79 | 2.28 | 0.49% | 0.47 | 1.03% | 0.77 |
| Carry, Value | 2.70 | 0.29% | 0.24 | 1.18% | 0.43 | 2.70 | 0.46% | 0.45 | 1.02% | 0.43 |
| Carry, Curr Acc | 2.65 | 0.29% | 0.23 | 1.25% | 0.44 | 2.64 | 0.48% | 0.46 | 1.05% | 0.44 |
| Carry, GDP Growth | 2.34 | 0.28% | 0.21 | 1.30% | 0.5 | 2.35 | 0.48% | 0.43 | 1.11% | 0.51 |
| Momentum, Value | 2.42 | 0.15% | 0.13 | 1.08% | 0.85 | 2.43 | 0.0034 | 0.35 | 0.0098 | 0.85 |
| Curr Acc, GDP Growth | 2.62 | 0.10% | 0.09 | 1.21% | 0.51 | 2.6 | 0.0037 | 0.36 | 0.0102 | 0.49 |
| Carry, Momentum, Value | 2.24 | 0.31% | 0.26 | 1.20% | 0.84 | 2.24 | 0.48% | 0.46 | 1.05% | 0.84 |
| All Factor Combined | 2.09 | 0.24% | 0.20 | 1.22% | 0.85 | 2.10 | 0.44% | 0.43 | 1.03% | 0.85 |

Figure 8: SDF Performance Metrics: IPCA

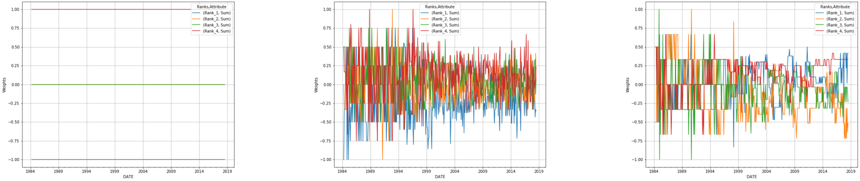
# Results: IPCA Factor Interpretations

## Coefficient Weights

- Sum of weights bucketed by carry rank buckets:
  - The FFR sum of weights indicate clear separation by design.
  - Negative bias in single characteristic based IPCA factors coincide with carry drawdowns.
  - Bias disappears on including a constant characteristic.
  - First component of IPCA similar to FFR carry.
- IPCA factors with three characteristics: constant, carry, value
  - First 2 components very similar to the constant, carry case.
- IPCA cumulative returns by carry ranks
  - Cumulative weighted returns in the carry rank buckets.
  - Major returns extracted from the extreme ranked portfolios.

# Results: IPCA Factor Interpretations

Figure 9: FFR factors: Sum of weights bucketed by carry ranks

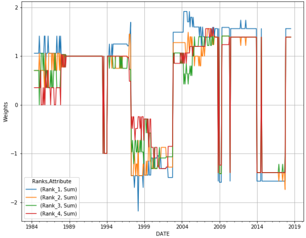



(a) FFR carry

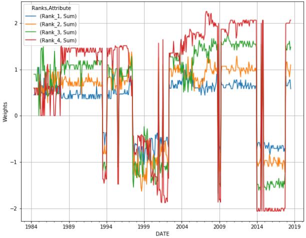
(b) FFR momentum

(c) FFR value

Figure 11: IPCA factors: Sum of weights bucketed by carry ranks



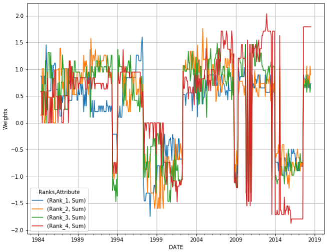

(a) IPCA, Characteristics: constant



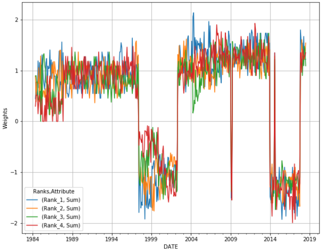

(b) IPCA, Characteristics: carry

# Results: IPCA Factor Interpretations

Figure 13: IPCA factors: Sum of weights bucketed by carry ranks




(a) IPCA, Characteristics: value



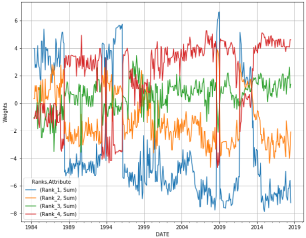

(b) IPCA, Characteristics: momentum

Figure 15: Sum of weights bucketed by carry ranks (IPCA factor) and Cumulative Returns (FFR carry)

# Results: IPCA Factor Interpretations

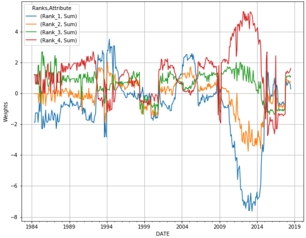
Figure 16: IPCA factors: Sum of weights bucketed by carry ranks


(a) IPCA Component 1, Characteristics: constant, carry

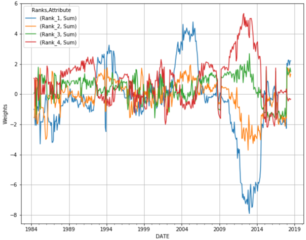



(b) IPCA Component 1, Characteristics: constant, carry, value

Figure 18: IPCA factors: Sum of weights bucketed by carry ranks




(a) IPCA Component 2, Characteristics: constant, carry




(b) IPCA Component 2, Characteristics: constant, carry, value

# Results: IPCA Factor Interpretations

Figure 20: IPCA factors: Sum of weights bucketed by value ranks

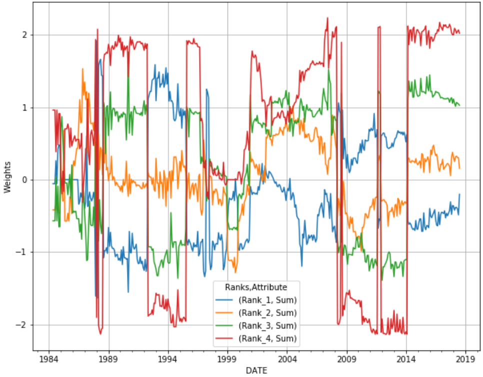



Figure 21: IPCA Component 3, Characteristics: constant, carry, value

# Results: IPCA Factor Interpretations

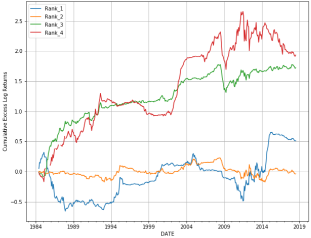
Figure 22: IPCA factors: Cumulative returns bucketed by carry ranks


(a) IPCA Component 1, Characteristics: constant, carry

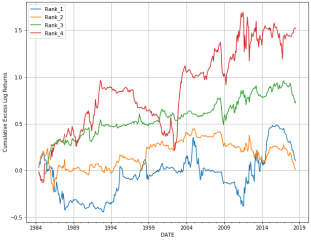

(b) IPCA Component 1, Characteristics: constant, carry, value

# Results: IPCA Factor Interpretations

Figure 24: IPCA factors: Cumulative returns bucketed by carry ranks



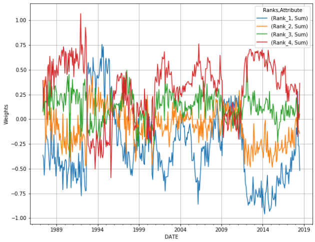

(a) IPCA Component 2, Characteristics: Constant, Carry



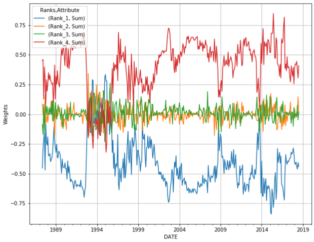

(b) IPCA Component 2,Characteristics: Constant, Carry, Value

# Results: SDF Interpretations

Figure 26: SDF: Sum of weights bucketed by carry ranks

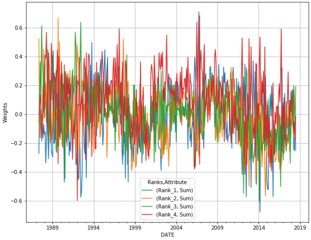



(a) IPCA SDF, Characteristics: constant, carry, momentum

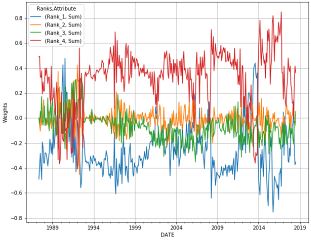



(b) FFR SDF, Characteristics: carry, momentum

Figure 28: SDF: Sum of weights bucketed by momentum ranks




(a) IPCA SDF, Characteristics: constant, carry, momentum




(b) FFR SDF, Characteristics: carry, momentum

# Conclusion

# Conclusion

## Main Results

- IPCA and PCA factors explain the cross-section better than FFR as measured by the predictive $R^2$.
- IPCA and FFR factors have comparable Sharpe ratios ex-ante that are much higher than PCA.

## Summary

- FFR factors have good Sharpe ratios, but do not seem to have a consistent ability to explain the cross-section.
- PCA factors are likely risk factors since they are able to explain the cross-section to some extent. They do not seem to have a consistent risk premium and are unlikely to be traded.
- IPCA factors are likely priced factors due to their superior ability to price currencies and Sharpe ratios comparable to FFR factors.

# Conclusion

## Wrap Up

- IPCA and FFR SDFs show that carry seems to have consistent risk premia. They differ in the exact weighting, but the trends are similar.
- PCA factors are able to explain the cross-section better than FFR, but do not have consistent risk premia.
- IPCA by can take other characteristics that affect currency markets:
  - Macro Factors: Volatility, inflation, trade deficit
  - Technical Indicators: 52 week high, moving average etc.
- Observing the sum of weights bucketed by characteristic rank buckets is a way to interpret the constructed latent factors leading to greater confidence in using them.

# Thank You!