# Understanding momentum and reversal

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# 1. Introduction

## Background

- Jegadeesh and Titman (1993)
- The basis of strategies implemented throughout the asset management industry.
- One of the few reliable violators of prevailing empirical asset pricing models.
- People try to explain this mysterious phenomenon both behaviorally and rationally but none are widely accepted.
- Consequently, momentum is often the center piece for debates of market efficiency.

# 1. Introduction

## Motivation: momentum, the violators.

- we begin with a generic conditional factor pricing model of the form:

$$r_{i,t+1} = \beta'_{i,t} f_{t+1} + \epsilon_{i,t+1}$$
$$\mathrm{E}_t(r_{i,t+1}) = \beta'_{i,t}\lambda_t$$

- In this framework, conditional expected returns $(\mu_{i,t})$ are restricted to derive only from exposures $(\beta_{i,t})$ to a set of common risk factors and the associated factor premia$\left(\lambda_t \equiv \mathrm{E}_t(f_{t+1})\right)$.

# 1. Introduction

## Motivation: momentum, the violators.

- At a minimum, a successful model will need to explain three facts associated with past return anomalies:
    - A large spread in average returns for stocks in the highest quintile of past one year returns over those in the lowest quintile (or a Sharpe ratio)
    - A 12-2-month moving average produces better return predictions than alternative moving average windows.
    - The marginally significant long term reversal pattern that occurs beyond a year

# 1. Introduction

Motivation: momentum, the violators.

- Consider for a moment a static version of equation:

$$r_{i,t+1} = \beta_{i,t}' f_{t+1} + \epsilon_{i,t+1}, \quad \mathrm{E}_t\left(r_{i,t+1}\right) = \beta_{i,t}' \lambda_t$$

which means $\mu_{i,t} = \beta_i' \lambda$ for all $t$.

- One condition alone—a sufficiently large spread in $\beta_i$—could match momentum's large average return spread.
- This condition would also imply that a very long moving average window would provide the best estimate of $\beta_i$.
- Cannot match Fact (2) : Turnover

# 1. Introduction

Motivation: momentum, the violators.

- Holding the factor premia fixed, dynamic betas $(\beta_{i,t})$:

$$r_{i,t+1} = \beta_{i,t}' f_{t+1} + \epsilon_{i,t+1}, \quad \mathrm{E}_t(r_{i,t+1}) = \beta_{i,t}' \lambda_t$$

- The conditional factor models offer a potential conceptual explanation for momentum and other price trend patterns.
- We need to use observable factors and estimate rolling betas, but observable factors may be misspecified.
- “staleness bias”: they only slowly incorporate conditioning information (may be higher frequency?)

# 1. Introduction

## Motivation: momentum, the violators.

- Now we utilize IPCA methods introduced by Kelly et al. (2019), to estimate latent factors and factor exposures by parameterizing $\beta_{i,t}$ as a function of observable asset characteristics.
- we treat the expected factor return as constant:

$$\mu_{i,t}^{IPCA} = \beta_{i,t}'\lambda, \quad \mathrm{E}_t(f_{t+1}) = \lambda$$

- To be more specific, we consider that:
  - $\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T} f_t$, for in-sample calculation.
  - $\hat{\lambda} = \frac{1}{T}\sum_{\tau=1}^{t} f_t$, for out-of-sample calculations

# 1. Introduction

Question:

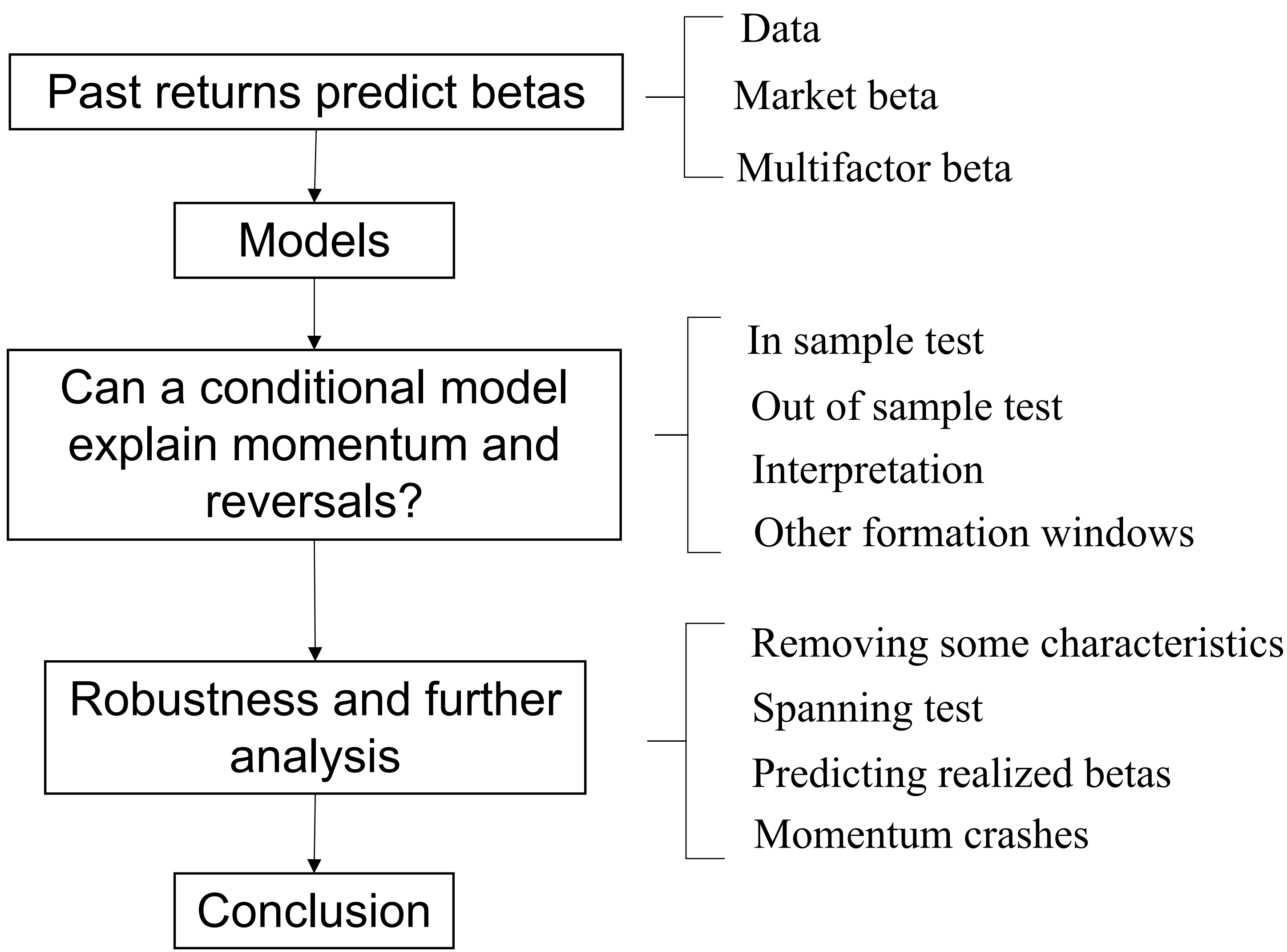
Can a conditional model explain momentum and reversals?

# 1. Introduction

## Research contents

- We first explore the relationships between stock’s recent past return and its realized beta through a multifactor model.
- We introduce some models (IPCA and instrumented FF-models) and show how we construct them.
- We evaluate IPCA’s ability to explain momentum in a host of specifications and data sets, both in sample and out of sample.
- The paper also considers the robustness of our results.

# 1. Introduction



# 1.Introduction

Related researches

- Conrad and Kaul (1998) suggest that differences in stocks' expected returns can explain momentum.
- Jegadeesh and Titman (2002) argue against this interpretation because it is based on unconditional expectations that they show are not dispersed enough to explain momentum returns.
- Grundy and Martin (2001) decompose returns into a systematic risk component and stock-specific residuals and find that the momentum phenomenon is driven entirely by momentum in residual returns.
- Chordia and Shivakumar (2002) conclude that momentum returns are best captured through the conditional expected returns predicted by macroeconomic variables rather than through the residual.

# 1.Introduction

## Contribution

- We show that these past return characteristics are strongly predictive of a stock's realized exposures to common risk factors.
- The results offer a new risk-based interpretation to some of the return predictability from momentum and reversal strategies and provide insights into how to improve return predictability using our model.
- Future research may pin down what economic risks or state variables our latent factors capture, but past return sorts appear to be good predictors of future factor exposure that is priced in equilibrium.

# 2. Data & Models

## 1) Data

- Our data set is the one studied in KPS, composed of stock returns and 36 characteristics from Freyberger et al. (2020)
- That sample spans 1966 to 2014, restricts attention to stock-month observations and ultimately includes 12,813 unique stocks and 1,403,544 stock-month observations.

## 2) Details

- To deal with outliers, each characteristic is cross-sectionally ranked, then these ranks are divided by the number of stocks in that cross section, and then they are cross-sectionally demeaned so that they live in the [−0.5, 0.5] interval

# 2. Data & Models

**Table A.1**
Characteristics.

- Assets
- Assets-to-market
- Bid-ask spread
- Book-to-market
- Capital intensity
- Capital turnover
- Cash-flow-to-book
- Cash-to-short-term-inv.
- Earnings-to-price
- FF3 Idio. vol.
- Fixed costs-of-sales
- Gross profitability
- Intermed. mom. (*)
- Investment
- Leverage
- Long-term reversal (*)
- Market beta
- Market cap.
- Momentum (*)
- Net operating assets
- Operating accruals
- Operating leverage
- PPE-chg-to-assets
- Price rel. 52wk high
- Price-to-cost-margin
- Profit margin
- Return on NOA
- Return on assets
- Return on equity
- SGA-to-sales
- Sales-to-assets
- Sales-to-price
- Short-term reversal
- Tobin's Q
- Turnover
- Unexplained volume

# 2. Data & Models

## 3) Instrumented principal component analysis

- KPS provide a detailed analysis of the IPCA model, which we summarize here.

$$r_{i,t+1} = \left(z'_{i,t}\Gamma\right) f_{t+1} + \epsilon_{i,t+1}$$

- Assets are exposed to a set of $K$ unobservable factors, which are denoted $f_{t+1}$.
- $z_{i,t}$, which includes a constant, is the $L \times 1$ vector defined by observable asset characteristics
- $\Gamma$ is the $L \times K$ matrix, defining the mapping between a potentially large number of characteristics and a small number of risk factor exposures. (minimizing the sum of squared model errors)

# 2. Data & Models

## 4) Instrumented Fama–French model

- We replaces $f_{t+1}$ with the FF5 factors rather than treating $f_{t+1}$ as laten

$$r_{i,t+1} = \text{vec}(\Gamma)'\left(f_{t+1} \otimes z_{i,t}\right) + \epsilon_t$$

- The term $f_{t+1} \otimes z_{i,t}$ is the $KL\times 1$ vector of each factor interacted with each characteristic.
- Because the factors are observable, an OLS regression of returns onto the factor/characteristic interactions recovers $\Gamma$ and in turn recovers the conditional loadings, $\beta_{i,t}$ (robustness)

# 3. Empirical results

## 1) Market beta prediction results

$$\beta_{t,t+h} = a + b_h r_{t-12,t-2} + C_h' X_{t-1} + \epsilon_{t,t+h}$$

where $s_{i,t}$ represents either 2–12 return momentum $(\bar{r})$, the model-based expected return $\beta'\lambda$ or momentum in model residuals $\bar{\epsilon}$.

- We also consider other betas (SMB, HML, RMW, CMA) ,and we see the similar pattern except short-term reversal.

- Factor betas are significantly time-varying, and stock characteristics appear useful for tracking that beta variation
- This finding hints at a route to reconciling the average return patterns associated with stock characteristics based on past returns within a dynamic conditional model of risk and return.

| Characteristic | Realized beta | | | |
| --- | --- | --- | --- | --- |
| | One-month | Three-month | Six-month | Twelve-month |
| Assets | −0.28*** | −0.31*** | −0.33*** | −0.32*** |
| Assets-to-market | 0.16*** | 0.14*** | 0.14*** | 0.14*** |
| Bid-ask spread | 0.08*** | 0.05** | 0.03* | 0.02 |
| Book-to-market | −0.02 | −0.02 | 0.01 | 0.03 |
| Capital intensity | 0.02 | 0.01 | 0.01 | 0.01 |
| Capital turnover | 0.21*** | 0.18*** | 0.14*** | 0.11*** |
| Cash-flow-to-book | −0.01 | −0.01 | −0.01 | −0.01 |
| Cash-to-short-term-inv. | 0.01 | 0.01 | 0.02 | 0.02 |
| Earnings-to-price | 0.02 | 0.01 | −0.00 | −0.01 |
| FF3 Idio. vol. | 0.07*** | 0.08*** | 0.08*** | 0.07*** |
| Fixed costs-of-sales | 0.12*** | 0.11*** | 0.11*** | 0.11*** |
| Gross profitability | −0.05* | −0.05** | −0.05* | −0.04 |
| Intermed. mom | −0.02 | −0.02 | −0.02* | −0.03** |
| Investment | −0.01 | 0.00 | 0.01 | 0.02* |
| Leverage | 0.03 | 0.04* | 0.04** | 0.05*** |
| Long-term reversal | 0.11*** | 0.11*** | 0.10*** | 0.08*** |
| Market beta | 0.77*** | 0.76*** | 0.75*** | 0.72*** |
| Market cap. | 0.83*** | 0.81*** | 0.81*** | 0.80*** |
| Momentum | 0.23*** | 0.23*** | 0.23*** | 0.20*** |
| Net operating assets | −0.03* | −0.03* | −0.02 | −0.02 |
| Operating accruals | 0.01 | 0.01* | 0.01* | 0.02** |
| Operating leverage | −0.17*** | −0.16*** | −0.13*** | −0.10*** |
| PPE-chg-to-Assets-chg | −0.03** | −0.02** | −0.02* | −0.01 |
| Price rel. 52wk high | −0.20*** | −0.18*** | −0.16*** | −0.14*** |
| Price-to-cost-margin | −0.01 | −0.01 | −0.01 | −0.01 |
| Profit margin | 0.01 | 0.01 | 0.01 | −0.00 |
| Return on NOA | −0.04** | −0.05*** | −0.05*** | −0.05*** |
| Return on assets | −0.13*** | −0.16*** | −0.17*** | −0.17*** |
| Return on equity | 0.05* | 0.08*** | 0.09*** | 0.10*** |
| SGA-to-sales | −0.13*** | −0.11*** | −0.10*** | −0.12*** |
| Sales-to-assets | 0.03* | 0.04** | 0.04** | 0.04** |
| Sales-to-price | 0.06 | 0.06 | 0.07* | 0.08* |
| Short-term reversal | 0.03** | 0.04*** | 0.05*** | 0.04*** |

# 3. Empirical results

## 2) Can the model explain momentum and reversals?

$$r_{i,t+1} = c_0 + c_1 s_{i,t} + e_{i,t+1}$$

where $s_{i,t}$ represents either 2–12 return momentum $(\bar{r})$, the model-based expected return $\beta'\lambda$ or momentum in model residuals $\bar{\epsilon}$.

- First predictor: traditional momentum signal,

$$\mathrm{E}_t\left[r_{i,t+1}\right], with\ \bar{r}_{i,t} = \sum_{j=2}^{12} r_{i,t-j}$$

- Second predictor: model-based predictor,

$$\beta_{i,t}'\lambda_t\ , with\ \lambda_t = \mathrm{E}_t[f_{t+1}]$$

  - $\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T} f_t$, for in-sample calculation.
  - $\hat{\lambda} = \frac{1}{T}\sum_{\tau=1}^{t} f_t$, for out-of-sample calculations

- Third predictor: moving average of model residuals

$$\bar{\epsilon}_{i,t} = \sum_{j=2}^{12} \epsilon_{i,t-j}$$

# In-sample test

**A. Univariate regressions**

| | Raw signal | | | Rank signal | | |
|---|---|---|---|---|---|---|
| | $\bar{r}$ | $\beta'\lambda$ | $\bar{\epsilon}$ | $\bar{r}$ | $\beta'\lambda$ | $\bar{\epsilon}$ |
| Constant | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 |
| ($t$-stat) | (3.59) | (0.13) | (3.70) | (3.70) | (3.70) | (3.70) |
| Coeff | –0.00 | 0.99 | –0.00 | 0.72 | 3.24 | 0.30 |
| ($t$-stat) | (–0.29) | (14.02) | (–0.18) | (2.52) | (13.91) | (1.26) |
| $R^2$ (%) | 0.00 | 0.37 | 0.00 | 0.02 | 0.32 | 0.00 |

**B. Portfolio sorts**

| | Average return | | | Sharpe ratio | | |
|---|---|---|---|---|---|---|
| | $\bar{r}$ | $\beta'\lambda$ | $\bar{\epsilon}$ | $\bar{r}$ | $\beta'\lambda$ | $\bar{\epsilon}$ |
| Q1 | 7.96 | –4.59 | 10.17 | 0.30 | –0.22 | 0.38 |
| Q2 | 8.59 | 5.59 | 10.14 | 0.43 | 0.29 | 0.51 |
| Q3 | 10.26 | 9.76 | 10.21 | 0.55 | 0.49 | 0.55 |
| Q4 | 12.64 | 15.93 | 10.61 | 0.67 | 0.75 | 0.57 |
| Q5 | 16.25 | 29.01 | 14.57 | 0.69 | 1.14 | 0.64 |
| Q5–Q1 | 8.29 | 33.59 | 4.39 | 0.48 | 2.39 | 0.30 |
| ($t$-stat) | (3.30) | (16.47) | (2.09) | (3.29) | (14.81) | (1.88) |

**C. Bivariate regressions**

| | Raw signal | | | Rank signal | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Constant | 0.00 | –0.00 | 0.01 | 0.01 | 0.01 | 0.01 |
| ($t$-stat) | (0.11) | (–0.03) | (3.24) | (3.70) | (3.70) | (3.70) |
| $\bar{r}$ | –0.01 | | –0.00 | –0.14 | | 3.10 |
| ($t$-stat) | (–1.45) | | (–0.29) | (–0.42) | | (3.13) |
| $\beta'\lambda$ | 1.06 | 1.03 | | 3.27 | 3.30 | |
| ($t$-stat) | (11.83) | (12.96) | | (11.88) | (12.62) | |
| $\bar{\epsilon}$ | | –0.00 | 0.00 | | –0.34 | –2.57 |
| ($t$-stat) | | (–2.40) | (0.28) | | (–1.29) | (–2.90) |
| $R^2$ (%) | 0.40 | 0.39 | 0.00 | 0.32 | 0.32 | 0.05 |

# Out-of-sample test

**A. Univariate regressions**

| | Raw signal | | | Rank signal | | |
|---|---|---|---|---|---|---|
| | $\bar{r}$ | $\beta'\lambda$ | $\bar{\epsilon}$ | $\bar{r}$ | $\beta'\lambda$ | $\bar{\epsilon}$ |
| Constant | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 |
| ($t$-stat) | (3.73) | (1.42) | (3.81) | (3.82) | (3.82) | (3.82) |
| Coeff | −0.00 | 0.77 | −0.00 | 0.69 | 3.03 | 0.35 |
| ($t$-stat) | (−0.49) | (12.15) | (−0.00) | (2.37) | (13.46) | (1.45) |
| $R^2$ (%) | 0.00 | 0.28 | 0.00 | 0.01 | 0.28 | 0.00 |

**B. Portfolio sorts**

| | Average return | | | Sharpe ratio | | |
|---|---|---|---|---|---|---|
| | $\bar{r}$ | $\beta'\lambda$ | $\bar{\epsilon}$ | $\bar{r}$ | $\beta'\lambda$ | $\bar{\epsilon}$ |
| Q1 | 9.24 | −2.90 | 10.63 | 0.34 | −0.14 | 0.40 |
| Q2 | 9.19 | 7.03 | 10.48 | 0.46 | 0.37 | 0.53 |
| Q3 | 11.12 | 10.85 | 11.25 | 0.61 | 0.56 | 0.62 |
| Q4 | 13.35 | 16.48 | 11.73 | 0.72 | 0.79 | 0.64 |
| Q5 | 16.55 | 27.99 | 15.36 | 0.71 | 1.13 | 0.69 |
| Q5–Q1 | 7.30 | 30.89 | 4.74 | 0.42 | 2.29 | 0.33 |
| ($t$-stat) | (2.79) | (15.17) | (2.16) | (2.78) | (13.76) | (1.96) |

**C. Bivariate regressions**

| | Raw signal | | | Rank signal | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Constant | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 |
| ($t$-stat) | (1.45) | (1.33) | (3.46) | (3.82) | (3.82) | (3.82) |
| $\bar{r}$ | −0.01 | | −0.01 | −0.08 | | 2.74 |
| ($t$-stat) | (−1.56) | | (−0.62) | (−0.24) | | (2.66) |
| $\beta'\lambda$ | 0.84 | 0.80 | | 3.05 | 3.07 | |
| ($t$-stat) | (11.26) | (11.45) | | (11.60) | (12.19) | |
| $\bar{\epsilon}$ | | −0.00 | 0.01 | | −0.24 | −2.20 |
| ($t$-stat) | | (−1.97) | (0.66) | | (−0.91) | (−2.40) |
| $R^2$ (%) | 0.32 | 0.30 | 0.01 | 0.28 | 0.28 | 0.03 |

# 3. Empirical results

## 2) Can the model explain momentum and reversals?

- Our results imply that the momentum characteristic (past 12-month return) picks up time-varying exposure to latent factor risk, defined through the covariance matrix of returns.
- Sorting on past 12-month returns is a noisy measure of sorting on conditional beta exposure to priced factors in the economy.
- Hence, controlling for an accurate measure of this time-varying exposure captures the bulk of momentum’s premium.

# 3. Empirical results

## 2) Can the model explain momentum and reversals?

- High-frequency reversal is at least partially driven by illiquidity of small firms, and therefore part of the effect does not stem from systematic risk compensation.

| Formation | | Rank signal regressions | | | | |
|---|---|---|---|---|---|---|
| | | Univariate | | Bivariate | | |
| | | $\bar{r}$ | $R^2$ (%) | $\bar{r}$ | $\beta'\lambda$ | $R^2$ (%) |
| 2 | 12 | 0.72 | 0.02 | −0.14 | 3.27 | 0.32 |
| | | (2.52) | | (−0.42) | (11.88) | |
| 13 | 24 | −0.67 | 0.01 | −0.30 | 3.12 | 0.32 |
| | | (−3.34) | | (−1.54) | (13.91) | |
| 25 | 36 | −0.42 | 0.01 | 0.00 | 3.08 | 0.32 |
| | | (−2.52) | | (0.01) | (14.13) | |
| 1 | 1 | −2.04 | 0.12 | −1.02 | 4.08 | 0.34 |
| | | (−7.08) | | (-2.76) | (14.61) | |

# 3. Empirical results

## 3) Robustness and further analysis

| | Univariate regression | | Average return | Q5-Q1 Sharpe ratio | FF 5-factor |
|---|---|---|---|---|---|
| | $\bar{r}$ | | $R^2$ (%) | | Alpha |
| Return momentum ($\bar{r}$) | | | | | |
| Estimate | 0.72 | 0.02 | 8.29 | 0.48 | 9.18 |
| $t$-stat | (2.52) | | (3.30) | (3.29) | (2.95) |

| | Bivariate regression | | | Average return | | Q5-Q1 Sharpe ratio | | IPCA 5-factor |
|---|---|---|---|---|---|---|---|---|
| | $\beta'\lambda$ | $\bar{r}$ | $R^2$ (%) | $\beta'\lambda$ | $\bar{\epsilon}$ | $\beta'\lambda$ | $\bar{\epsilon}$ | Alpha |
| **Panel A: Main** | | | | | | | | |
| Estimate | 3.27 | −0.14 | 0.32 | 33.60 | 4.40 | 2.39 | 0.30 | −3.20 |
| $t$-stat | (11.88) | (0.42) | | (16.48) | (2.10) | (14.82) | (1.89) | (−1.23) |
| **Panel B: Main OOS** | | | | | | | | |
| Estimate | 3.05 | −0.08 | 0.28 | 30.88 | 4.75 | 2.29 | 0.33 | 2.00 |
| $t$-stat | (11.60) | (−0.24) | | (15.17) | (2.17) | (13.75) | (1.97) | (0.48) |
| **Panel C: Excluding momentum and reversal OOS** | | | | | | | | |
| Estimate | 2.85 | 0.51 | 0.26 | 29.76 | 4.51 | 2.16 | 0.31 | 5.09 |
| $t$-stat | (11.82) | (1.69) | | (14.31) | (2.06) | (13.11) | (1.89) | (1.25) |
| **Panel D: Excluding all return variables OOS** | | | | | | | | |
| Estimate | 1.54 | 0.78 | 0.09 | 14.97 | 3.87 | 0.93 | 0.27 | 0.91 |
| $t$-stat | (6.04) | (2.66) | | (6.13) | (1.76) | (6.03) | (1.73) | (0.23) |
| **Panel E: Fama–French instrumented** | | | | | | | | |
| Estimate | 1.83 | 0.45 | 0.12 | 19.82 | 7.46 | 1.56 | 0.54 | |
| $t$-stat | (8.79) | (1.52) | | (10.70) | (3.73) | (10.21) | (3.56) | |
| **Panel F: Fama–French rolling** | | | | | | | | |
| Estimate | 0.09 | 0.93 | 0.03 | 2.34 | 8.02 | 0.23 | 0.70 | |
| $t$-stat | (0.54) | (3.68) | | (1.58) | (4.84) | (1.58) | (4.84) | |

# 3. Empirical results

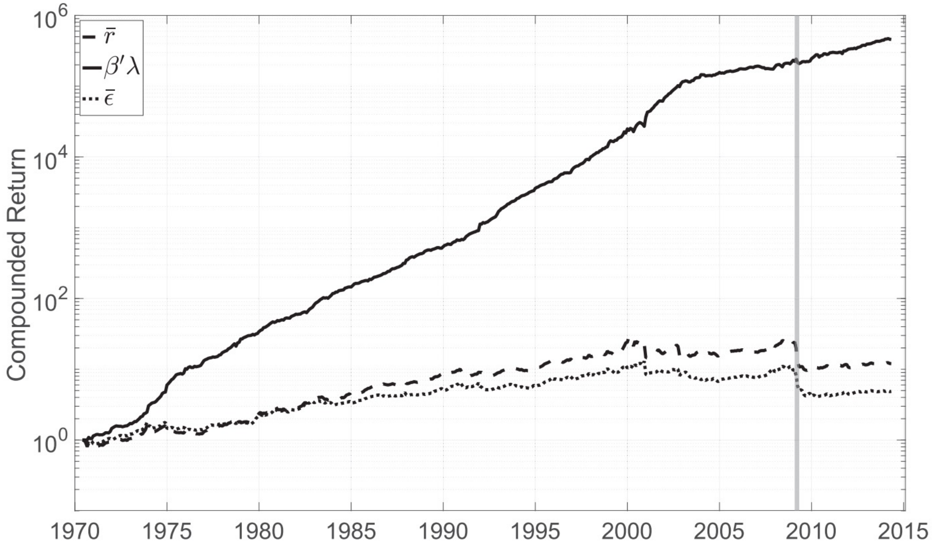
## 3) Robustness and further analysis

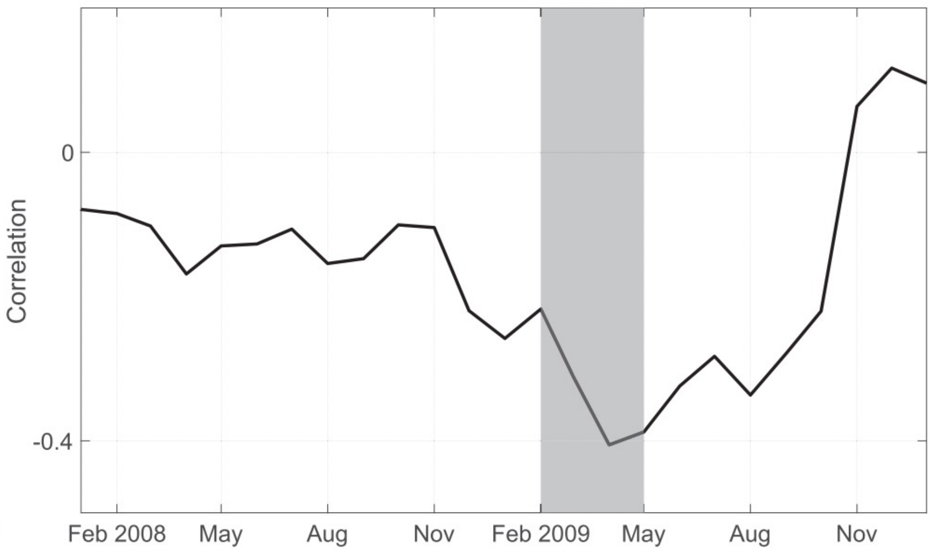
$$RealBeta^{oos} = a + b\beta + \epsilon$$

| | Factor | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| **A: One-month** *$RealBeta^{OOS}$* | | | | | |
| Constant | −0.00 | −0.01 | 0.00 | −0.00 | −0.00 |
| ($t$-stat) | (−0.61) | (−3.14) | (0.42) | (−0.21) | (−1.03) |
| Slope | 1.00 | 1.01 | 1.00 | 1.00 | 1.00 |
| ($t$-stat) | (479.12) | (183.32) | (158.53) | (144.74) | (143.95) |
| $[t : \beta = 1]$ | [0.26] | [1.77] | [0.18] | [−0.03] | [0.44] |
| $R^2$ (%) | 7.88 | 2.11 | 1.62 | 2.16 | 1.29 |
| **B: Three-month** *$RealBeta^{OOS}$* | | | | | |
| Constant | 0.00 | −0.01 | 0.00 | −0.00 | −0.00 |
| ($t$-stat) | (0.45) | (−2.90) | (1.19) | (−0.04) | (−1.04) |
| Slope | 1.00 | 1.02 | 1.01 | 1.00 | 1.01 |
| ($t$-stat) | (388.46) | (134.51) | (133.23) | (136.79) | (122.62) |
| $[t : \beta = 1]$ | [−0.25] | [2.20] | [1.22] | [0.16] | [1.03] |
| $R^2$ (%) | 25.86 | 7.15 | 4.97 | 7.25 | 4.38 |
| **C: Six-month** *$RealBeta^{OOS}$* | | | | | |
| Constant | 0.00 | −0.01 | 0.00 | −0.00 | −0.00 |
| ($t$-stat) | (1.35) | (−3.81) | (1.82) | (−0.12) | (−1.25) |
| Slope | 1.00 | 1.03 | 1.02 | 1.00 | 1.02 |
| ($t$-stat) | (366.51) | (118.06) | (120.31) | (128.50) | (111.91) |
| $[t : \beta = 1]$ | [−0.73] | [3.49] | [2.86] | [0.41] | [1.77] |
| $R^2$ (%) | 37.02 | 9.22 | 7.64 | 11.00 | 6.39 |
| **D: Twelve-month** *$RealBeta^{OOS}$* | | | | | |
| Constant | 0.00 | −0.01 | 0.01 | −0.00 | −0.01 |
| ($t$-stat) | (2.70) | (−5.00) | (2.20) | (−0.40) | (−1.86) |
| Slope | 1.00 | 1.05 | 1.05 | 1.01 | 1.03 |
| ($t$-stat) | (339.69) | (91.38) | (99.47) | (119.90) | (90.77) |
| $[t : \beta = 1]$ | [−1.55] | [4.56] | [4.65] | [0.67] | [2.63] |
| $R^2$ (%) | 43.73 | 9.21 | 9.56 | 13.95 | 6.99 |

# 3. Empirical results

## 3) Robustness and further analysis




2009 momentum crash largely comes from the large market rebound coupled with the fact that at that time, the momentum strategy was doing the opposite—shorting high market beta stocks and going long low beta stocks.

IPCA aggregates information across a wide range of conditioning characteristics, only one of which is momentum.

# 4. Conclusion

- We show that these past return characteristics are strongly predictive of a stock's realized exposures to common risk factors.
- Using IPCA to estimate latent risk factors and assets' time-varying betas on these factors, we show that the momentum and long-term reversal effects are capturing conditional risk premia largely explained by conditional betas in our no-arbitrage factor pricing model.