Asymmetric Risks: Alphas or Betas?

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Outline

Motivation

- **Anomaly zoo** – Large number of factors proposed to price the cross-section of stock returns.
- **Characteristics vs covariances** – *Risk vs anomaly* – Characteristics should be priced because they are related to the common behavior of stocks.
- Much of the progress was made in recent years, but...
- ...those studies usually do not include **asymmetric risk measures** (ARMs): implementation costs?
- ARMs posses a special place among characteristics because:
    - They capture joint behavior of stock return and some aggregate measure of risk (e.g., return on the whole market)
    - But the measured dependence goes beyond linearity of standard covariances:
        - either a non-linear measure of dependence
        - or non-linear factors

Risk vs Anomaly

Beta vs Alpha

- The most important equation in asset pricing

$$\mathbb{E}_t[r_{i,t+1} m_{t+1}] = 0 \tag{1}$$

is further exploited by linearity of the SDF: $m_{t+1} = \delta \frac{u'(c_{t+1})}{u'(c_t)} \approx a + b' f_{t+1}$, which leads to

$$\begin{aligned} \mathbb{E}_t[r_{i,t+1}] &= \alpha_{i,t} + \lambda' \beta_{i,t} \\ r_{i,t+1} &= \alpha_{i,t} + \beta'_{i,t} f_{t+1} + \epsilon_{i,t+1} \end{aligned} \tag{2}$$

and if a factor model is successful, then $\alpha_{i,t} = 0$.

- If we assume asymmetry of the SDF in the factors, this changes to

$$\begin{aligned} \mathbb{E}_t[r_{i,t+1}] &= \delta' g(r_{i,t+1}, f^*_{t+1}) + \lambda' \beta_{i,t} \\ r_{i,t+1} &= \delta' g(r_{i,t+1}, f^*_{t+1}) + \beta'_{i,t} f_{t+1} + \epsilon_{i,t+1} \end{aligned} \tag{3}$$

where g is a function of asset return and some, potentially non-linear, factor f^*_t – *asymmetric risk measure* (ARM).

Example of an ARM

- Consider economic agent with disappointment aversion utility of Gul (1991) given by

$$U(\mu_W) = K^{-1}\left(\int_{-\infty}^{\mu_W} U(W)dF(W) + A\int_{\mu_W}^{\infty} U(W)dF(W)\right) \tag{4}$$

  where $U(W)$ is the power utility over end-of-period wealth W, $0 < A \leq 1$ is the coefficient of disappointment aversion, $F(\cdot)$ is *cdf* of wealth, μ_W is the certainty equivalent, and K is a normalizing scalar.

- According to Ang et al. (2006), the *downside* beta should be priced in the cross-section of asset returns

$$\beta^i \equiv \frac{\mathbb{C}ov(r_i, r_m|r_m < \mu_m)}{\mathbb{V}ar(r_m|r_m < \mu_m)}. \tag{5}$$

Questions & Answers

- Are the ARMs alphas or betas?
  - Relation between ARMs and expected returns due to being a proxy for a linear or non-linear exposure to some factors?
  - Is there *any* set of linear factors with $K \ll L$ that can explain the abnormal returns?

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  - Can the abnormal returns of the ARMs be explained by some combination of other factors?
    - Answer 1: Characteristics-based factors can explain most of the single ARM's abnormal returns.
    - Answer 2: Combinations of the ARMs that hedge common exposures to systematic risk cannot be explained by other factor models. Sizeable exposure to the momentum factor, though.

Instrumented Principal Component Analysis

- I employ the ***Instrumented principal component analysis*** (IPCA) model proposed by Kelly et al. (2019, 2020) defined for an excess return $r_{i,t+1}$ as

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1}$$
$$\alpha_{i,t} = z'_{i,t}\Gamma_\alpha + \nu_{\alpha,i,t}, \quad \beta_{i,t} = z'_{i,t}\Gamma_\beta + \nu_{\beta,i,t}$$

  where we model system of N assets over T periods.
- f_t is a $Kx1$ vector of latent factors.
- The factor loadings $\beta_{i,t}$ are dynamic and potentially depend on $Lx1$ vector of observable characteristics $z_{i,t}$.
- The mapping between potentially many characteristics and small number of factor exposures facilitate LxK matrix Γ_β.
- The mapping between characteristics and anomaly returns capture $Lx1$ vector Γ_α.
- I use the ARMs as the instruments that proxy for the exposures to the common factors and form anomaly alphas – hence ***ARM-IPCA***.

Testing Hypotheses

- I use two specifications of the IPCA model

$$r_{i,t+1} = z'_{i,t}\Gamma_\alpha + z'_{i,t}\Gamma_\beta f_{t+1} + \nu_{i,t+1} \tag{6}$$

  the **restricted** model assumes $\Gamma_\alpha = 0$, the **unrestricted** model assumes $\Gamma_\alpha \neq 0$.
- To decide the **alpha vs beta** debate regarding the ARMs:

$$H_0 : \Gamma_\alpha = \mathbf{0}_{Lx1} \quad \text{against} \quad H_1 : \Gamma_\alpha \neq \mathbf{0}_{Lx1} \tag{7}$$

  - *In-sample*, I use Wald-type test statistic $W_\alpha = \hat{\Gamma}'_\alpha \hat{\Gamma}_\alpha$ and wild bootstrap.
  - *Out-of-sample*, I evaluate ***arbitrage portfolio*** of the unrestricted model – conditionally factor neutral with stock-level weights

$$w_t = Z_t(Z'_t Z_t)^{-1}\Gamma_\alpha \tag{8}$$

Performance Measures

- Ability to explain *return behavior* using the total R^2:

$$\text{Total } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - z'_{i,t}(\hat{\Gamma}_\alpha + \hat{\Gamma}_\beta \hat{f}_{t+1})\right)^2}{\sum_{i,t} r^2_{i,t+1}} \tag{9}$$

- Ability to explain *conditional expected returns (risk compensation)* using the predictive R^2

$$\text{Predictive } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - z'_{i,t}(\hat{\Gamma}_\alpha + \hat{\Gamma}_\beta \hat{\lambda})\right)^2}{\sum_{i,t} r^2_{i,t+1}}. \tag{10}$$

  Similarly as PCA, the estimation of the IPCA model targets to maximize the ability of model to explain return behavior.

- ***Tangency portfolio*** of the restricted model that combines latent factors using weights proportional to

$$\Sigma_t^{-1}\mu_t \tag{11}$$

Estimation

- Estimation of $f_{t+1}, \Gamma_\alpha, \Gamma_\beta$ is numerically solved via *alternating least squares* by iterating by the first-order conditions for Γ_β and f_{t+1}

$$f_{t+1} = \left(\hat{\Gamma}'_\beta Z'_t Z_t \hat{\Gamma}_\beta\right)^{-1} \hat{\Gamma}'_\beta Z'_t r_{t+1}, \quad \forall t \tag{12}$$

and

$$\mathrm{vec}(\hat{\Gamma}'_\beta) = \left(\sum_{t=1}^{T-1} Z'_t Z_t \otimes \hat{f}_{t+1} \otimes \hat{f}'_{t+1}\right)^{-1} \left(\sum_{t=1}^{T-1} \left[Z_t \otimes \hat{f}'_{t+1}\right]' r_{t+1}\right) \tag{13}$$

- In the case of the unrestricted version of the model with $\Gamma_\alpha \neq 0$, the estimation proceeds similarly, the only difference is that we augment the vector of factors to include a constant.
- Computational burden is similar as in the case of simple PCA estimation.

Asymmetric risk measures

Aim: To employ a representative set of asymmetric risk measures that were proven to significantly predict the cross-section of stock returns.

- Coskewnes of Harvey and Siddique (2000)
- Cokurtosis of Dittmar (2002)
- Downside beta of Ang et al. (2006)
- Downside correlation of Hong et al. (2006)
- Hybrid tail covariance risk of Bali et al. (2014)
- Tail risk beta of Kelly and Jinag (2014)
- Exceedance coentropy of Backus et al. (2018)
- Predicted systematic coskewness of Langlois (2020)
- Negative semibeta of Bollerslev et al. (2022)
- Multivariate crash risk of Chabi-Yo et al. (2022)
- Downside common idiosyncratic quantile risk beta of Baruník and Nevrla (2023)

Data

- 11 ARMs estimated from daily or monthly return data from the CRSP database.
- Monthly updated characteristics of the CRSP stocks are from Freyberger et al. (2020). Those include
  - 32 characteristics including beta, book-to-market, capital intensity, idiosyncratic volatility, gross profitability, Tobin's Q, return on equity, etc.
- Full merged dataset yields 1,519,754 stock-month observations of 12,505 unique stocks.
- Dataset spans time period between January 1968 and December 2018.
- Each period, variables are cross-sectionally ranked and standardized into interval $[-0.5, 0.5]$.
- Many results presented in terms of managed portfolios

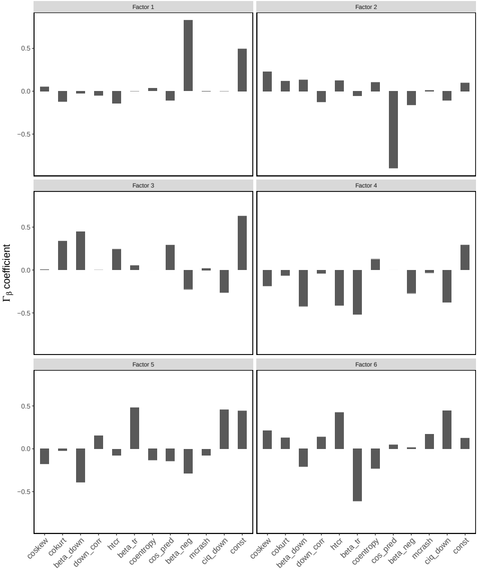
$$x_{t+1} = \frac{Z_t' r_{t+1}}{N_{t+1}} \tag{14}$$

In-Sample Results

Table: *IPCA Results – ARM variables.*

		ARM-IPCA(K)							
		1	2	3	4	5	6	7	8
Individual stocks									
Total R^2	$\Gamma_\alpha = 0$	15.95	17.30	17.99	18.46	18.70	18.83	18.94	19.02
	$\Gamma_\alpha \neq 0$	16.02	17.36	18.00	18.47	18.71	18.83	18.94	19.02
Predictive R^2	$\Gamma_\alpha = 0$	0.29	0.31	0.35	0.35	0.36	0.36	0.35	0.36
	$\Gamma_\alpha \neq 0$	0.37	0.37	0.36	0.36	0.36	0.36	0.36	0.36
Managed portfolios									
Total R^2	$\Gamma_\alpha = 0$	96.28	98.35	99.45	99.66	99.79	99.85	99.90	99.94
	$\Gamma_\alpha \neq 0$	96.35	98.41	99.46	99.67	99.79	99.85	99.90	99.94
Predictive R^2	$\Gamma_\alpha = 0$	1.85	1.88	1.95	1.94	1.95	1.95	1.94	1.95
	$\Gamma_\alpha \neq 0$	1.97	1.96	1.96	1.96	1.96	1.96	1.96	1.95
Asset pricing test									
W_α p-value		0.00	0.00	4.70	0.80	2.50	16.40	7.60	77.60

Γ_β Estimates – Factor Loadings



Variable Importance

Table: *Variable Importance of the ARMs.* The table reports p-values of the bootstrap test with 1,000 replications that given ARM do not significantly contribute to the ARM-IPCA model's fit.

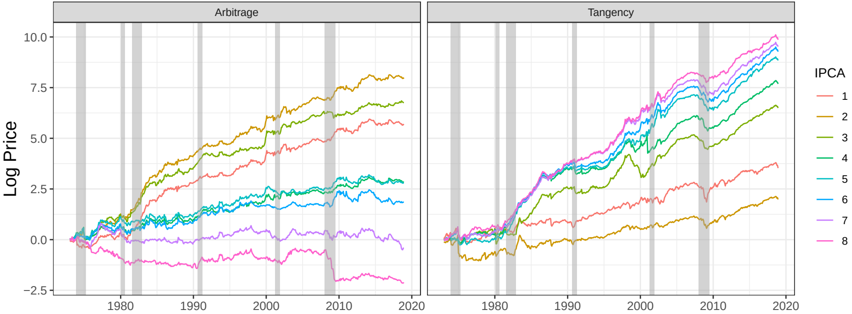
	IPCA1	IPCA2	IPCA3	IPCA4	IPCA5	IPCA6	IPCA7	IPCA8
coskew	22.60	16.90	9.10	2.30	3.30	59.90	46.90	0.00
cokurt	17.70	18.30	9.80	4.80	7.10	55.60	1.90	0.50
beta_down	9.90	4.90	0.20	0.30	0.10	**0.80**	0.00	0.00
down_corr	0.00	3.00	18.40	7.30	9.20	13.80	33.30	64.90
htcr	0.00	4.20	0.10	0.80	0.40	**0.00**	0.30	0.00
beta_tr	97.80	8.60	18.80	21.70	0.00	**0.00**	0.00	0.00
coentropy	2.50	2.90	25.70	17.10	18.10	18.20	40.40	51.40
cos_pred	0.10	26.60	46.30	0.00	0.00	**0.00**	0.00	0.00
beta_neg	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00
mcrash	49.40	6.40	2.80	3.60	2.90	**1.40**	4.70	8.90
ciq_down	75.40	8.90	13.30	4.00	0.00	**0.00**	0.00	0.00

Out-of-Sample Results

Table: *Out-of-Sample IPCA Results – ARM variables.*

		IPCA(K)							
		1	2	3	4	5	6	7	8
Individual stocks									
Total R^2	$\Gamma_\alpha = 0$	15.49	16.81	17.47	17.99	18.25	18.38	18.49	18.57
	$\Gamma_\alpha \neq 0$	15.47	16.80	17.37	17.98	18.24	18.36	18.48	18.57
Predictive R^2	$\Gamma_\alpha = 0$	0.23	0.23	0.26	0.26	0.27	0.28	0.28	0.28
	$\Gamma_\alpha \neq 0$	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28
Managed portfolios									
Total R^2	$\Gamma_\alpha = 0$	96.30	98.35	99.28	99.63	99.77	99.83	99.89	99.93
	$\Gamma_\alpha \neq 0$	95.91	98.04	99.08	99.56	99.74	99.81	99.88	99.92
Predictive R^2	$\Gamma_\alpha = 0$	1.55	1.56	1.64	1.67	1.69	1.69	1.69	1.69
	$\Gamma_\alpha \neq 0$	1.69	1.69	1.69	1.69	1.69	1.69	1.69	1.70
Tangency portfolios									
Mean		9.74	6.64	16.36	19.11	21.37	22.37	22.93	23.68
t-stat		3.10	2.27	4.45	6.00	6.06	6.66	7.10	7.43
Sharpe		0.49	0.33	0.82	0.96	1.07	1.12	1.15	1.18
Pure-alpha portfolios									
Mean		**14.36**	**19.36**	**16.78**	**8.20**	**8.06**	5.97	1.07	-2.53
t-stat		**4.73**	**6.27**	**5.35**	**3.04**	**2.86**	2.05	0.34	-0.81
Sharpe		**0.72**	**0.97**	**0.84**	**0.41**	**0.40**	0.30	0.05	-0.13

IPCA Model Performances



Variable Importance for the Pure-Alpha Portfolios

Table: *Variable Importance of the ARMs for the pure-alpha portfolios.* The table reports decreases of the out-of-sample Sharpe ratios of the pure-alpha portfolios from the leave-one-variable-out procedure. For each ARM, I report difference (in % points) between Sharpe ratio obtained without the ARM and Sharpe ratio obtained from the model with all ARMs.

	IPCA1	IPCA2	IPCA3	IPCA4	IPCA5	IPCA6
Sharpe ratio	0.72	0.97	0.84	0.41	0.40	0.30
	Decrease of Sharpe ratio in %					
`coskew`	15.17	9.19	7.21	26.12	14.21	34.82
`cokurt`	11.24	-1.56	-14.72	4.65	-6.52	26.40
`beta_down`	5.96	0.48	-10.53	-40.93	-47.86	-71.74
`down_corr`	-15.21	-4.98	-13.34	-26.57	-29.53	-57.84
`htcr`	-5.44	-6.91	-22.21	3.71	15.90	21.43
`beta_tr`	0.09	2.27	3.97	-3.61	-66.96	-142.62
`coentropy`	-39.70	-32.00	-25.15	-2.26	-16.14	-41.76
`cos_pred`	1.35	-21.29	-7.45	25.48	11.38	32.18
`beta_neg`	-1.99	0.64	7.24	-12.51	-61.93	-51.72
`mcrash`	1.27	-1.63	-1.61	-0.07	0.03	-10.14
`ciq_down`	-31.39	-25.61	-15.85	-22.89	-15.85	-74.26

Alphas of the Pure-Alpha Portfolios, 1

Table: *Annualized alphas of the ARM-IPCA pure-alpha portfolios to the IPCA model with original 32 characteristics.*

	IPCA1	IPCA2	IPCA3	IPCA4	IPCA5	IPCA6
ARM-IPCA1	14.12	14.60	12.95	8.60	10.62	12.07
	(4.77)	(4.99)	(2.71)	(2.01)	(2.34)	(2.69)
ARM-IPCA2	18.85	19.50	18.83	12.15	13.65	18.33
	(6.30)	(6.89)	(3.57)	(2.54)	(2.74)	(3.62)
ARM-IPCA3	16.40	16.95	21.09	16.29	16.42	18.87
	(5.26)	(6.07)	(4.12)	(3.21)	(3.03)	(3.25)
ARM-IPCA4	7.12	7.47	3.29	3.04	7.94	10.61
	(2.62)	(2.94)	(0.88)	(0.81)	(2.03)	(2.16)
ARM-IPCA5	7.25	7.40	4.44	3.82	7.96	11.83
	(2.58)	(2.76)	(1.24)	(1.05)	(2.12)	(2.58)
ARM-IPCA6	5.47	4.52	1.90	3.12	2.12	4.50
	(1.92)	(1.65)	(0.65)	(0.98)	(0.64)	(1.22)

Alphas of the Pure-Alpha Portfolios, 2

Table: *Annualized alphas and exposures of the ARM-IPCA pure-alpha portfolios to the 6-factor model.*

IPCA(K)	α	Mkt	SMB	HML	CIV	BAB	MOM
1	**6.27**	0.07	0.13	0.06	-0.02	0.42	0.33
	(1.85)	(1.01)	(0.81)	(0.47)	(-0.57)	(3.49)	(2.69)
2	**10.63**	0.03	0.17	0.15	-0.02	0.39	0.43
	(3.15)	(0.48)	(1.08)	(1.06)	(-0.72)	(3.32)	(3.28)
3	**10.03**	0.04	0.11	0.09	0.00	0.22	0.46
	(3.46)	(0.55)	(0.64)	(0.52)	(0.19)	(1.80)	(4.29)
4	**5.22**	0.04	-0.11	0.33	-0.04	0.10	0.07
	(1.88)	(0.57)	(-0.72)	(1.82)	(-1.24)	(0.93)	(0.78)
5	**5.61**	0.10	-0.10	0.30	-0.02	0.00	0.10
	(1.94)	(1.49)	(-0.70)	(1.66)	(-0.52)	(0.00)	(0.99)
6	4.57	0.02	0.08	0.35	-0.01	-0.01	-0.03
	(1.52)	(0.41)	(0.86)	(2.79)	(-0.37)	(-0.08)	(-0.33)
7	-0.02	0.07	0.14	0.44	-0.04	-0.12	-0.01
	(-0.01)	(1.10)	(1.36)	(3.05)	(-1.14)	(-1.30)	(-0.10)
8	-2.60	-0.08	0.14	0.30	0.02	-0.19	0.14
	(-0.68)	(-1.05)	(1.50)	(1.81)	(0.77)	(-1.66)	(1.12)

ARMs' Individual Alphas

Table: *Alphas of the ARM managed portfolios when regressing on IPCA factors estimated using original 32 characteristics.*

	All-IPCA(K)					
variable	1	2	3	4	5	6
`coskew`	-0.20	-0.21	-0.40	0.05	0.18	0.19
	(-1.48)	(-1.50)	(-1.98)	(0.23)	(0.72)	(0.76)
`cokurt`	-0.50	-0.16	-0.18	-0.57	0.57	0.14
	(-2.49)	(-0.81)	(-1.14)	(-2.91)	(2.11)	(0.69)
`beta_down`	-0.79	-0.68	-0.02	-0.92	-0.07	-0.20
	(-3.20)	(-3.14)	(-0.10)	(-2.98)	(-0.21)	(-0.59)
`down_corr`	0.05	0.08	0.36	-0.10	-0.28	-0.19
	(0.53)	(0.81)	(2.84)	(-0.69)	(-1.61)	(-1.09)
`htcr`	0.04	0.41	-0.10	-0.36	0.61	0.36
	(0.18)	(2.51)	(-0.67)	(-1.62)	(1.85)	(1.36)
`beta_tr`	0.22	0.33	0.21	-0.09	0.01	-0.04
	(1.48)	(2.31)	(0.72)	(-0.50)	(0.03)	(-0.14)
`coentropy`	0.01	0.03	0.31	-0.08	-0.32	-0.25
	(0.15)	(0.32)	(2.57)	(-0.53)	(-1.96)	(-1.53)
`cos_pred`	-0.32	-0.01	-1.54	-0.68	0.34	-0.15
	(-1.30)	(-0.05)	(-4.57)	(-1.51)	(0.66)	(-0.39)
`beta_neg`	-0.81	-0.96	0.20	-0.77	-0.27	-0.19
	(-2.19)	(-4.11)	(0.71)	(-1.62)	(-0.50)	(-0.42)
`mcrash`	-0.02	0.11	0.08	-0.22	0.20	0.10
	(-0.16)	(0.98)	(0.82)	(-2.16)	(1.61)	(0.81)
`ciq_down`	0.48	0.40	0.19	0.28	0.34	0.42
	(3.27)	(3.00)	(0.74)	(1.33)	(1.60)	(2.11)

Preview of the Full Results

In the paper, I also include:

- Deeper look at the univariate performances of the ARMs
- Investigation of the latent factors
- Robustness check based on split samples
- Time-varying risk premium of the ARMs using Projected PCA
- No-penny dataset (probably will be gone in the next version of the paper)

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