Job Market Presentation

Matěj Nevrla

Institute of Economic Studies
Charles University

University of Liverpool Management School
February 8, 2024

Outline

RESEARCH INTEREST

- Main areas of interest: empirical asset pricing, financial econometrics

Research Interest

- Main areas of interest: empirical asset pricing, financial econometrics
- Better understand investors' *aversion to large losses* using:
  - Machine learning tools
  - Quantile regression framework
  - Factor modeling
  - Frequency domain econometrics

Research Interest

- Main areas of interest: empirical asset pricing, financial econometrics
- Better understand investors' *aversion to large losses* using:
  - Machine learning tools
  - Quantile regression framework
  - Factor modeling
  - Frequency domain econometrics
- Research outlook:
  - Large set of firm characteristics to better understand:
    - Downside risk – horizon features
    - Factor risk premiums – relation to cross-sectional stock features
    - Momentum returns – continuation of long-run predictions
    - Non-linear factor modeling
  - Any other interesting asset pricing or financial econometrics topic

Research Interest

- Main areas of interest: empirical asset pricing, financial econometrics
- Better understand investors' *aversion to large losses* using:
  - Machine learning tools
  - Quantile regression framework
  - Factor modeling
  - Frequency domain econometrics
- Research outlook:
  - Large set of firm characteristics to better understand:
    - Downside risk – horizon features
    - Factor risk premiums – relation to cross-sectional stock features
    - Momentum returns – continuation of long-run predictions
    - Non-linear factor modeling
  - Any other interesting asset pricing or financial econometrics topic
- Value for the group:
  - Enthusiasm regarding:
    - Empirical asset pricing research
    - Computational challenges

Papers

My dissertation consists of three papers:

Quantile Spectral Beta: A Tale of Tail Risks, Investment Horizons, and Asset Prices
Baruník, J., Nevrla, M. (2023)
Journal of Financial Econometrics 21(5), 1590–1646. Summary

Common Idiosyncratic Quantile Risk
Baruník, J., Nevrla, M. (2023)
Revise & Resubmit in the *Review of Finance*. Summary

Asymmetric Risks: Alphas or Betas?
Nevrla, M. (2023)
Job market paper.

TEACHING

- Courses taught:
  - Introductory Statistics, Statistics (Bachelor)
  - Applied Econometrics, Advanced Econometrics (Master)

Teaching

- Courses taught:
  - Introductory Statistics, Statistics (Bachelor)
  - Applied Econometrics, Advanced Econometrics (Master)
- Teaching outlook:
  - Ideal course: *Empirical Asset Pricing*

TEACHING

- Courses taught:
  - Introductory Statistics, Statistics (Bachelor)
  - Applied Econometrics, Advanced Econometrics (Master)
- Teaching outlook:
  - Ideal course: *Empirical Asset Pricing*
  - Empirical methods with respect to:
    - Asset pricing
    - Investments
    - Any other finance area
  - Special emphasis on implementation using
    - R (preferable) and interactive Jupyter notebooks
    - Other options: Python, Matlab, Julia

JMP: Asymmetric Risks: Alphas or Betas?

- How **systematic asymmetric risk measures** (ARMs) relate to linear factor pricing models?

JMP: ASYMMETRIC RISKS: ALPHAS OR BETAS?

- How **systematic asymmetric risk measures** (ARMs) relate to linear factor pricing models?
  - ARM = (non-linear) measure of dependence between stock returns and some (non-linear) risk factor
  - E.g., coskewness, downside beta, tail risk beta.

JMP: Asymmetric Risks: Alphas or Betas?

- How **systematic asymmetric risk measures** (ARMs) relate to linear factor pricing models?
  - ARM = (non-linear) measure of dependence between stock returns and some (non-linear) risk factor
  - E.g., coskewness, downside beta, tail risk beta.
- Non-linear properties of ARMs important for asset prices?

JMP: Asymmetric Risks: Alphas or Betas?

- How **systematic asymmetric risk measures** (ARMs) relate to linear factor pricing models?
  - ARM = (non-linear) measure of dependence between stock returns and some (non-linear) risk factor
  - E.g., coskewness, downside beta, tail risk beta.
- Non-linear properties of ARMs important for asset prices?
- Can their pricing information be **efficiently combined**?
  - ...without being spanned by linear pricing factors?

Related Literature

Cross-sectional return predictability in relation to:

- **Anomaly zoo** – Large number of factors and asset features proposed to price the cross-section of stock returns (Harvey et al., 2016; Kozak et al., 2020).

Related Literature

Cross-sectional return predictability in relation to:

- **Anomaly zoo** – Large number of factors and asset features proposed to price the cross-section of stock returns (Harvey et al., 2016; Kozak et al., 2020).
- **Characteristics vs covariances** – *Risk vs anomaly* – Characteristics should be priced because they are *linearly* related to the common behavior of stocks (Kelly et al., 2019; Kim et al., 2020).

Related Literature

Cross-sectional return predictability in relation to:

- **Anomaly zoo** – Large number of factors and asset features proposed to price the cross-section of stock returns (Harvey et al., 2016; Kozak et al., 2020).
- **Characteristics vs covariances** – *Risk vs anomaly* – Characteristics should be priced because they are *linearly* related to the common behavior of stocks (Kelly et al., 2019; Kim et al., 2020).
- **Non-linear risks** – Various deviations from the expected utility framework and factor linearity assumption proposed to explain cross-section of stock returns (Ang et al., 2006; Farago and Tédongap, 2018).

Alpha vs Beta

- **Linear factor pricing models** are usually based on two assumptions:

$$\mathbb{E}_t[r_{i,t+1} m_{t+1}] = 0 \qquad \text{(expected utility)}$$

$$m_{t+1} = \delta \frac{u'(c_{t+1})}{u'(c_t)} \approx a + b' f_{t+1} \qquad \text{(linearity of the SDF)}$$

Alpha vs Beta

- **Linear factor pricing models** are usually based on two assumptions:

$$\mathbb{E}_t[r_{i,t+1} m_{t+1}] = 0 \qquad \text{(expected utility)}$$

$$m_{t+1} = \delta \frac{u'(c_{t+1})}{u'(c_t)} \approx a + b' f_{t+1} \quad \text{(linearity of the SDF)}$$

which lead to the prediction regarding the behavior of returns

$$\mathbb{E}_t[r_{i,t+1}] = \alpha_{i,t} + \lambda' \beta_{i,t}$$

$$r_{i,t+1} = \alpha_{i,t} + \beta'_{i,t} f_{t+1} + \epsilon_{i,t+1}.$$

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

Alpha vs Beta

- **Linear factor pricing models** are usually based on two assumptions:

$$\mathbb{E}_t[r_{i,t+1} m_{t+1}] = 0 \qquad \text{(expected utility)}$$

$$m_{t+1} = \delta \frac{u'(c_{t+1})}{u'(c_t)} \approx a + b' f_{t+1} \quad \text{(linearity of the SDF)}$$

which lead to the prediction regarding the behavior of returns

$$\mathbb{E}_t[r_{i,t+1}] = \alpha_{i,t} + \lambda' \beta_{i,t}$$

$$r_{i,t+1} = \alpha_{i,t} + \beta'_{i,t} f_{t+1} + \epsilon_{i,t+1}.$$

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

- If we assume some **non-linear deviations**, predictions change to

$$\mathbb{E}_t[r_{i,t+1}] = \delta' g(r_{i,t+1}, f^*_{t+1}) + \lambda' \beta_{i,t}$$

$$r_{i,t+1} = \delta' g(r_{i,t+1}, f^*_{t+1}) + \beta'_{i,t} f_{t+1} + \epsilon_{i,t+1}$$

where g is a function of return and some, potentially non-linear, factor f^*_t – **ARM**.

Instrumented Principal Component Analysis

- ***Instrumented principal component analysis*** (IPCA) model proposed by Kelly et al. (2019, 2020) defined for system of N assets over T periods 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
- f_t is a $Kx1$ vector of latent factors
- Γ_β is an LxK matrix that maps L observable characteristics $z_{i,t}$ into K factor loadings $\beta_{i,t}$
- Γ_α captures relation between characteristics and anomaly returns via $\alpha_{i,t}$

Instrumented Principal Component Analysis

- ***Instrumented principal component analysis*** (IPCA) model proposed by Kelly et al. (2019, 2020) defined for system of N assets over T periods 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
  - f_t is a $Kx1$ vector of latent factors
  - Γ_β is an LxK matrix that maps L observable characteristics $z_{i,t}$ into K factor loadings $\beta_{i,t}$
  - Γ_α captures relation between characteristics and anomaly returns via $\alpha_{i,t}$
- ***ARM-IPCA*** model – ARMs as the instruments that proxy for the exposures to the common factors and form anomaly alphas.

ARM-IPCA PORTFOLIOS

- ***Pure-alpha portfolio*** with stock-level weights

$$w_{t-1} = Z_{t-1}(Z'_{t-1}Z_{t-1})^{-1}\hat{\Gamma}_\alpha$$

yields conditionally factor neutrality $\implies$ combination of the pricing information above ability to proxy for linear exposures.

  - Pure relation between ARMs and their anomaly premium.

ARM-IPCA Portfolios

- ***Pure-alpha portfolio*** with stock-level weights

$$w_{t-1} = Z_{t-1}(Z'_{t-1}Z_{t-1})^{-1}\hat{\Gamma}_{\alpha}$$

  yields conditionally factor neutrality $\implies$ combination of the pricing information above ability to proxy for linear exposures.
  - Pure relation between ARMs and their anomaly premium.

- Portfolios formed based on an **out-of-sample** setting with
  - Expanding-window estimation and 60-month initial estimation period

Estimation

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

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

  and

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

  where the vector of factors contains a constant to facilitate the estimation of the $\Gamma_\alpha$vector.
- Computational burden is similar as in the case of simple PCA estimation.
- No need for a balanced panel!

ARMs & Data

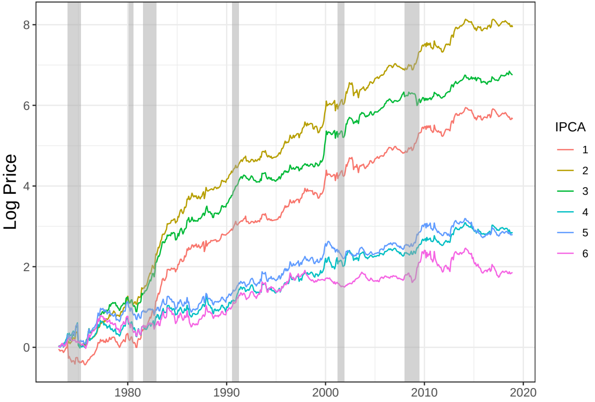
- 11 ARMs estimated from daily or monthly return data from the CRSP and Compustat databases:
  - Coskewnes of Harvey and Siddique (2000)
  - Cokurtosis of Dittmar (2002)
  - Downside beta of Ang et al. (2006)
  - Downside correlation of Hong et al. (2006)
  - Hybrid tail covariance risk of Bali et al. (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)
- Full dataset yields 1,519,754 stock-month observations of 12,505 unique U.S. stocks between January 1968 and December 2018.
- Each period, variables are cross-sectionally ranked and standardized into the interval $[-0.5, 0.5]$.

Pure-Alpha Portfolios

Table: Out-of-sample pure-alpha portfolio returns.

K factors	Mean	t-stat	SR	Skewness	Kurtosis	Maximum drawdown	Worst month	Best month
1	14.36	4.73	0.72	0.09	3.59	41.40	-31.14	25.53
2	19.36	6.27	0.97	0.15	2.87	31.17	-25.47	27.23
3	16.78	5.35	0.84	-0.00	6.59	43.45	-39.64	25.67
4	8.20	3.04	0.41	-0.12	5.41	45.88	-40.07	24.14
5	8.06	2.86	0.40	0.34	3.69	38.36	-32.42	27.70
6	5.97	2.05	0.30	0.79	3.20	51.45	-17.98	27.29

Performances of the Pure-Alpha Portfolios



Risk-Adjusted Returns

Table: Risk-adjusted returns of the pure-alpha portfolios with respect to model combinations of Fama and French (1993), Carhart (1997), Fama and French (2015), **CIV** shocks of Herskovic et al. (2016), and **BAB** factor of Frazzini and Pedersen (1993).

K factors	CAPM	FF3	FF3+MOM	FF3+MOM +CIV	FF3+MOM +CIV+BAB	FF5	FF5+MOM	FF5+MOM +CIV	FF5+MOM +CIV+BAB
1	14.31	13.58	9.12	9.16	6.27	12.38	8.77	8.79	6.87
	(4.75)	(4.54)	(2.71)	(2.74)	(1.85)	(3.69)	(2.53)	(2.54)	(2.00)
2	19.65	18.70	13.28	13.31	10.63	17.39	13.00	13.02	11.18
	(6.54)	(6.19)	(3.95)	(3.98)	(3.15)	(5.02)	(3.73)	(3.73)	(3.23)
3	17.04	16.88	11.49	11.50	10.03	15.97	11.59	11.60	10.34
	(5.68)	(5.41)	(4.23)	(4.22)	(3.46)	(4.65)	(4.06)	(4.03)	(3.51)
4	8.44	6.68	5.87	5.90	5.22	6.67	6.02	6.03	5.37
	(3.27)	(2.55)	(2.27)	(2.28)	(1.88)	(2.67)	(2.32)	(2.32)	(1.91)
5	7.89	6.57	5.59	5.60	5.61	7.41	6.54	6.55	6.14
	(2.94)	(2.32)	(1.94)	(1.94)	(1.94)	(2.76)	(2.33)	(2.33)	(2.13)
6	6.07	4.14	4.51	4.52	4.57	5.90	6.07	6.07	5.61
	(2.13)	(1.47)	(1.48)	(1.48)	(1.52)	(2.13)	(2.01)	(2.01)	(1.88)

Additional results: Q-models, IPCA factors

Exposures of the Pure-Alpha Portfolios

Table: Exposures of the ARM-IPCA pure-alpha portfolios to the model of Fama and French (2015), augmented by momentum factor of Carhart (1997), **CIV** shocks of Herskovic et al. (2016), and **BAB** factor of Frazzini and Pedersen (1993).

K	α	Mkt	SMB	HML	RMW	CMA	MOM	CIV	BAB
1	6.87	0.05	0.06	0.06	-0.21	-0.06	0.33	-0.02	0.48
	(2.00)	(0.69)	(0.38)	(0.39)	(-0.97)	(-0.30)	(2.73)	(-0.47)	(3.63)
2	11.18	0.02	0.08	0.10	-0.27	0.02	0.42	-0.02	0.46
	(3.23)	(0.26)	(0.53)	(0.57)	(-1.39)	(0.12)	(3.35)	(-0.62)	(3.88)
3	10.34	0.04	-0.03	-0.05	-0.42	0.27	0.44	0.01	0.31
	(3.51)	(0.57)	(-0.21)	(-0.24)	(-2.19)	(1.12)	(4.50)	(0.33)	(2.76)
4	5.37	0.04	-0.21	0.27	-0.27	0.16	0.06	-0.04	0.17
	(1.91)	(0.59)	(-1.12)	(1.13)	(-1.61)	(0.60)	(0.67)	(-1.14)	(1.37)
5	6.14	0.09	-0.23	0.26	-0.40	0.11	0.09	-0.01	0.10
	(2.13)	(1.24)	(-1.38)	(1.16)	(-2.75)	(0.48)	(0.88)	(-0.37)	(0.98)
6	5.61	-0.01	-0.05	0.35	-0.46	-0.07	-0.04	0.00	0.11
	(1.88)	(-0.17)	(-0.55)	(2.50)	(-3.20)	(-0.37)	(-0.45)	(-0.10)	(1.09)

Significant relation with the **momentum factor** – many ARMs proxy for the stock's exposure to this factor.

Robustness Checks

Results regarding the pure-alpha portfolios are robust with respect to

- Other factor pricing models
- Split samples
- Annual returns
- Dataset without penny stocks
- Volatility targeting

ARMs and Latent Factors

- The **restricted version** of the IPCA model where there is no mapping between ARMs and alphas, i.e., $\Gamma_\alpha = 0$ is

$$\begin{aligned} r_{i,t+1} &= \beta_{i,t} f_{t+1} + \epsilon_{i,t+1} \\ \beta_{i,t} &= z'_{i,t}\Gamma_\beta + \nu_{\beta,i,t}. \end{aligned}$$

ARMs and Latent Factors

- The **restricted version** of the IPCA model where there is no mapping between ARMs and alphas, i.e., $\Gamma_\alpha = 0$ is

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

- ***All-IPCA model*** – 11 ARMs and 32 characteristic from Freyberger et al. (2020) and Kelly et al. (2019) as instruments.

Table: ARMs' p-values (in %) from variable importance tests regarding the All-IPCA models.

	coskew	cokurt	beta_down	down_corr	htcr	beta_tr	coentropy	cos_pred	beta_neg	mcrash	ciq_down	Joint test
All-IPCA(5)	6.8	28.7	0.6	28.6	1.8	8	22.5	16.9	2.2	58.6	26.1	6.7
All-IPCA(6)	24.2	37.3	2.5	23.9	2.4	11.7	26.2	8.2	1.2	94.9	17	6.8

Preview of the Full Results

In the paper, I also include

- Deeper look at the univariate performances of the ARMs
- Alternative options for combining ARMs into an investment strategy
- Investigation regarding the importance of each ARM for the performance of the pure-alpha portfolios
- Time-varying risk premium of the ARMs using Projected PCA
- More thorough investigation regarding the ARMs and latent factors

Contribution

I investigate ARMs in their multivariate context and show that

- ARMs can be efficiently combined.
  - ...without being explained by linear factor models.
  - $\Longrightarrow$ **asymmetries and non-linearities important for asset prices!**

CONTRIBUTION

I investigate ARMs in their multivariate context and show that

- ARMs can be efficiently combined.
  - ...without being explained by linear factor models.
  - $\Longrightarrow$ **asymmetries and non-linearities important for asset prices!**
- Some of the ARMs capture exposure to the linear factor structure.
  - There is a clear relation between ARMs and linear exposure to the momentum factor.
  - Some ARMs capture exposure to the latent factors even when controlling for other characteristics.

Contribution

I investigate ARMs in their multivariate context and show that

- ARMs can be efficiently combined.
  - ...without being explained by linear factor models.
  - $\implies$ **asymmetries and non-linearities important for asset prices!**
- Some of the ARMs capture exposure to the linear factor structure.
  - There is a clear relation between ARMs and linear exposure to the momentum factor.
  - Some ARMs capture exposure to the latent factors even when controlling for other characteristics.
- Answer to the question from the title of the paper: **Some measures are alphas, some are betas.**

References I

Ang, A., Chen, J., Xing, Y. (2006) Downside Risk. *The Review of Financial Studies* 19(4), 1191–1239.

Backus, D., N. Boyarchenko, and M. Chernov (2018) Term structures of asset prices and returns. *Journal of Financial Economics* 129(1), 1–23.

Bali, T. G., Cakici, N., Whitelaw, R. F. (2014) Hybrid Tail Risk and Expected Stock Returns: When Does the Tail Wag the Dog? *The Review of Asset Pricing Studies* 4(2), 206–246.

Baruník, Jozef and Nevrla, Matěj (2023) Common Idiosyncratic Quantile Risk. *Available at SSRN 4204916*.

Bollerslev, T., Patton, A.J., Quaedvlieg R. (2022) Realized semibetas: Disentangling "good" and "bad" downside risks. *Journal of Financial Economics* 144(1), 227–246.

Carhart, Mark M. (1997) On Persistence in Mutual Fund Performance. *The Journal of Finance* 52, 57–82.

Chabi-Yo, F., M. Huggenberger, and F. Weigert (2022) Multivariate crash risk. *Journal of Financial Economics* 145(1), 129–153.

Liang Chen, Juan J. Dolado and Jesús Gonzalo (2021) Quantile Factor Models. *Econometrica* 89(2), 875–910.

Dittmar, Robert F.. (2002) Nonlinear Pricing Kernels, Kurtosis Preference, and Evidence from the Cross Section of Equity Returns. *The Journal of Finance* 57, 369–403.

Fama, Eugene F. and French, Kenneth R. (1993) Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1), 3–56.

Fama, Eugene F. and French, Kenneth R. (2015) A five-factor asset pricing model. *Journal of Financial Economics* 116(1), 1–22.

Adam Farago and Roméo Tédongap (2018) Downside risks and the cross-section of asset returns. *Journal of Financial Economics* 129(1), 69–86.

Frazzini, A. and Pedersen, Lasse Heje (2014) Betting against beta. *Journal of Financial Economics* 111(1), 1–25.

Freyberger, J., Neuhierl, A., and Weber, M. (2020) Dissecting characteristics nonparametrically. *The Review of Financial Studies* 33(5), 2326–2377.

References II

Harvey, C.R. and Siddique, A. (2000) Conditional Skewness in Asset Pricing Tests. *The Journal of Finance* 55, 1263–1295.

Harvey, Campbell R. and Liu, Yan and Zhu, Heqing (2016) . . . and the Cross-Section of Expected Returns. *The Review of Financial Studies* 29(1), 5–68.

Herskovic, B., Kelly, B., Lustig, H., Van Nieuwerburgh, S. (2016) The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics* 119(2), 249–283.

Hong, Y., J. Tu, and G. Zhou (2006) Asymmetries in Stock Returns: Statistical Tests and Economic Evaluation. *The Review of Financial Studies* 20(5), 1547–1581.

Hou, K., C. Xue, and L. Zhang (2014) Digesting Anomalies: An Investment Approach. *The Review of Financial Studies* 28(3), 650–705.

Hou, K., C. Xue, and L. Zhang (2020) An Augmented q-Factor Model with Expected Growth. *Review of Finance* 25(1), 1–41.

Kelly, Bryan and Jiang, Hao (2014) Tail risk and asset prices. *The Review of Financial Studies* 27(10), 2841–2871.

Kelly, B. T., S. Pruitt, and Y. Su (2019) Characteristics are covariances: A unified model of risk and return. *Journal of Financial Economics* 134(3), 501–524.

Kelly, B. T., S. Pruitt, and Y. Su (2020) Instrumented principal component analysis. *Available at SSRN 2983919*.

Kim, S., R. A. Korajczyk, and A. Neuhierl (2020) Arbitrage Portfolios. *The Review of Financial Studies* 34(6), 2813–2856.

Kozak, S., S. Nagel, and S. Santosh (2020) Shrinking the cross-section. *Journal of Financial Economics* 135(2), 271–292.

Langlois, H. (2020) Measuring skewness premia. *Journal of Financial Economics* 135(2), 399–424.

Nakamura, E., J. Steinsson, R. Barro, and J. Ursúa (2013) Crises and recoveries in an empirical model of consumption disasters. *American Economic Journal: Macroeconomics* 5(3), 35–74.

Paper 1: Quantile Spectral Beta

- Assuming that dependences during *bad and good times* and over *long and short horizon* are priced the same may be too restrictive.
- A new measure of risk: ***Quantile spectral*** (QS) beta

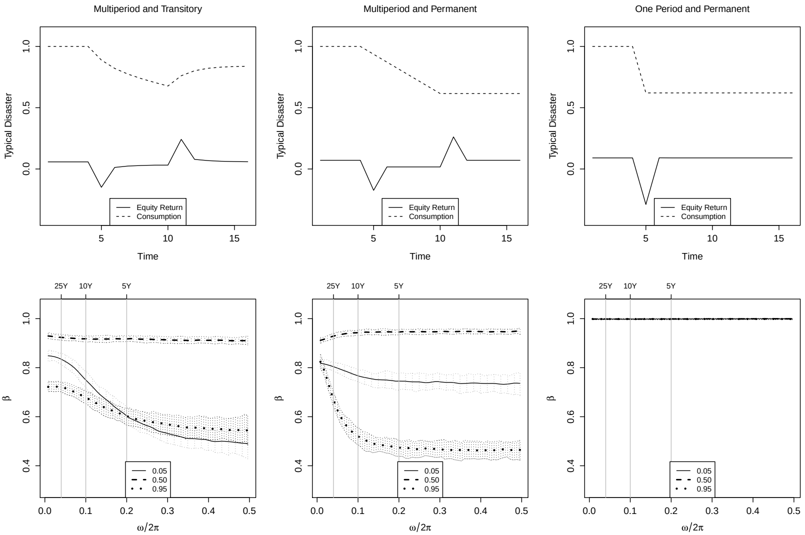
$$\beta^{m,r}(\omega; \tau_m, \tau_r) \equiv \frac{f^{m,r}(\omega; \tau_m, \tau_r)}{f^{m,m}(\omega; \tau_m, \tau_m)},$$

$$f^{m,r}(\omega; \tau_m, \tau_r) \equiv \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \mathbb{C}ov\Big(I\{m_{t+k} \leq q_m(\tau_m)\}, I\{r_t \leq q_r(\tau_r)\}\Big) e^{-\mathrm{i}k\omega}$$

where

  - $\tau_m, \tau_r \in [0, 1] =$ Part of their joint distribution
  - $\omega \in \mathbb{R} =$ Investment horizon
- Quantile spectral betas employed to measure
  - *Tail market risk*: $\tau_m, \tau_r \leq 0.25$ and $m = r_m$
    - $\Longrightarrow$ generalization of the CAPM beta.
  - *Extreme volatility risk*: $\tau_m, \tau_r \leq 0.25$ and $m = \Delta\sigma^2$
- Main empirical results:
  - QS risks priced *heterogeneously* across asset classes.
  - In the case of stocks, *short-term* tail market risk and *long-term* extreme volatility risk are priced.

Paper 1: QS Betas and Nakamura et al. (2013) Model



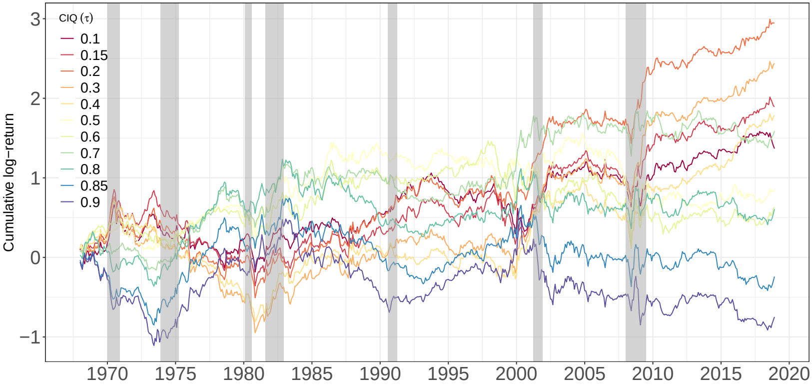
Paper 2: Common Idiosyncratic Quantile Risk

- Linear pricing models (PCA, Fama and French (1993)) capture significant portion of average time-series variability of returns.
  - ...But they do not capture extreme common events!
- We assume a common *quantile-dependent* structure in idiosyncratic stock returns

$$r_{i,t} = \alpha_i + \beta_i^\top F_t + \epsilon_{i,t},$$
$$\epsilon_{i,t} = \gamma_i(\tau) f_t(\tau) + u_{i,t}(\tau)$$

  with $P[u_{i,t}(\tau) < 0 | f_t(\tau)] = \tau$ almost surely for all $\tau \in (0,1)$. We coin $f_t(\tau)$ ***common idiosyncratic quantile*** (CIQ) factors.
- CIQ factors estimated using the Quantile Factor Analysis of Chen et al. (2021).
- Main results:
  - Significant asymmetry in significance of the CIQ factors:
    - Only common *downside* movements matter for asset prices!
  - Time-series predictability:
    - Downside CIQ factors robustly predict one-month-ahead market return.
  - Cross-sectional predictability:
    - Stocks' exposure to the downside CIQ factors significantly priced.

Paper 2: CIQ Portfolio Performances



Risk-Adjusted Returns – Q-Models

Table: *Q-model risk-adjusted returns of the pure-alpha portfolios.* The table reports annualized alphas and their HAC *t*-statistics with six lags obtained by regressing the pure-alpha portfolio returns on factor models of Hou et al. (2014) and Hou et al. (2020), augmented by momentum factor, CIV shocks, and BAB factor. Data cover the period between January 1973 and December 2018.

K factors	Q4	Q5	Q5+MOM	Q5+MOM +CIV	Q5+MOM +CIV+BAB
1	8.03	7.40	7.81	7.64	6.29
	(2.23)	(2.15)	(2.42)	(2.37)	(1.95)
2	12.22	11.05	11.58	11.41	10.16
	(3.27)	(3.13)	(3.60)	(3.51)	(3.17)
3	11.39	8.69	9.29	9.24	8.54
	(2.98)	(2.57)	(3.06)	(3.00)	(2.74)
4	5.98	6.00	6.04	5.91	5.37
	(2.01)	(1.93)	(1.96)	(1.89)	(1.69)
5	6.11	6.50	6.63	6.59	6.39
	(1.97)	(2.03)	(2.11)	(2.08)	(2.04)
6	6.33	6.81	6.83	6.81	6.40
	(2.16)	(2.16)	(2.18)	(2.18)	(2.08)

Risk-Adjusted Returns – IPCA Models

Table: *IPCA risk-adjusted returns of the pure-alpha portfolios.* The table reports annualized alphas and their HAC t-statistics with six lags obtained by regressing the pure-alpha portfolio returns on out-of-sample IPCA factors with one to six latent factors and 32 characteristics from Kelly et al. (2019) as instruments. Data cover the period between January 1973 and December 2018.

K factors	IPCA1	IPCA2	IPCA3	IPCA4	IPCA5	IPCA6
1	14.12	14.60	12.95	8.60	10.62	12.07
	(4.77)	(4.99)	(2.71)	(2.01)	(2.34)	(2.69)
2	18.85	19.50	18.83	12.15	13.65	18.33
	(6.30)	(6.89)	(3.57)	(2.54)	(2.74)	(3.62)
3	16.40	16.95	21.09	16.29	16.42	18.87
	(5.26)	(6.07)	(4.12)	(3.21)	(3.03)	(3.25)
4	7.12	7.47	3.29	3.04	7.94	10.61
	(2.62)	(2.94)	(0.88)	(0.81)	(2.03)	(2.16)
5	7.25	7.40	4.44	3.82	7.96	11.83
	(2.58)	(2.76)	(1.24)	(1.05)	(2.12)	(2.58)
6	5.47	4.52	1.90	3.12	2.12	4.50
	(1.92)	(1.65)	(0.65)	(0.98)	(0.64)	(1.22)