PROJECT REPORT: FACTOR CLUSTERING MODEL IN EMPIRICAL ASSET PRICING

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BACKGROUND & MOTIVATION

- Prevalence in empirical pricing of Factor models as extensions from the Capital Asset Pricing Model (CAPM)
- Replication Crisis in finance
 - Internal Validity
 - External Validity
- This project focuses on the discovery of significant global factors using a Bayesian model of factor replication utilizing linear approach such as Principal Component Regression, and non-linear approach such as Hierarchical Agglomerative Clustering

FOUNDATIONS – FACTOR MODEL

An extension from the Capital Asset Pricing Model:

$$ER_i = R_f + \beta_i (ER_m - R_f)$$

- Where:
 - *ER*_i= Expected rate of return
 - R_f = Risk-free rate
 - **ß** = Factor's coefficient (sensitivity)
 - Market Factor: $(r_m r_f)$ = Market risk premium

FAMA-FRENCH 3-FACTOR MODEL

$$r = r_f + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \varepsilon$$

- Where:
 - r = Expected rate of return
 - r_f = Risk-free rate
 - **ß** = Factor's coefficient (sensitivity)
 - Market Factor: $(r_m r_f)$ = Market risk premium
 - Size Factor: SMB (Small Minus Big) = Historic excess returns of small-cap companies over large-cap companies
 - Value Factor: HML (High Minus Low) = Historic excess returns of value stocks (high book-to-price ratio) over growth stocks (low book-to-price ratio)

HIERARCHICAL BAYESIAN MODEL

$$f_t = \alpha + \beta r_t^m + \varepsilon_t$$

- Where:
 - f_t = Factor's net performance
 - r^m_t = Excess market factor
 - α = Posterior α , (Prior $\alpha \sim N(0,\tau^2)$)
 - ε_t = Error term, $\varepsilon_t \sim N(0, \sigma^2)$
 - **ß** = Factor's coefficient (sensitivity)

MULTI-LEVEL HIERARCHICAL BAYESIAN – POSTERIOR

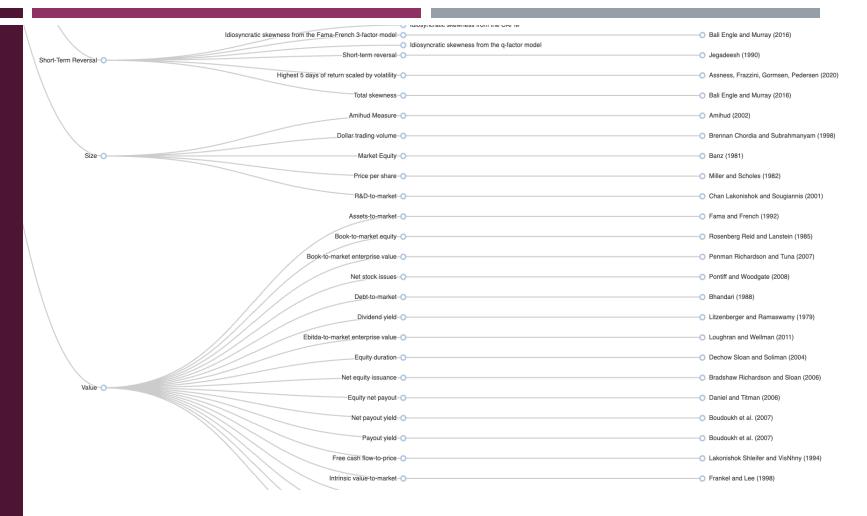
$$\alpha^i = \alpha^o + c^j + s^n + w^i$$

Where:

- α^i = Individual factor *i*
- α^0 = Component common to all factors
- c^{j} = Cluster specific component, $c^{j} \sim N(0,\tau_{c}^{2})$
- s^n = Signal specific component, $s^n \sim N(0,\tau_n^2)$
- w^i = Idiosyncratic component, $w^i \sim N(0,\tau_w^2)$

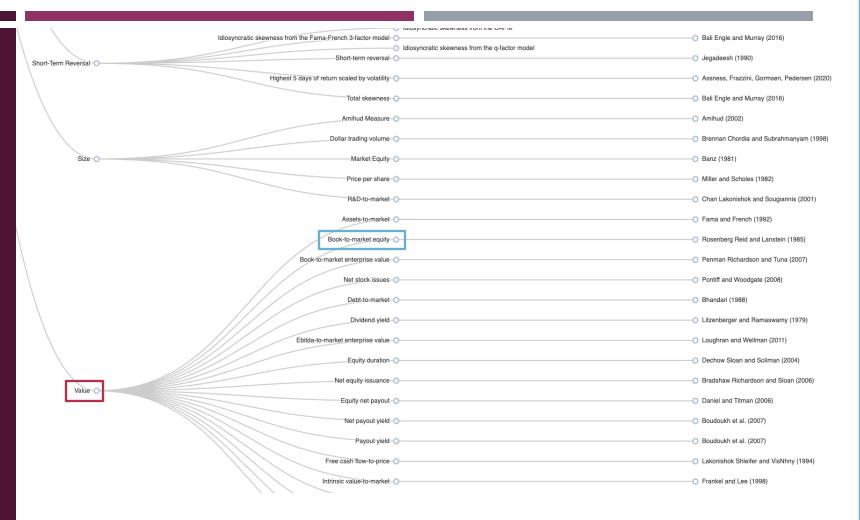
FACTOR ZOO – CLUSTERING

- Jensen, T. I., Kelly, B. T. & Pedersen, L. H. (n.d.). (2023). Is there a replication crisis in finance?, The Journal of Finance (forthcoming) 78 (5): 2465–2518.
- Divides factors into 13 clustered themes
- Source



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DATASET

- Global dataset with 153 factors in 93 countries (subset of Global Factor dataset, Jensen, Kelly, and Pedersen (2022)),
 with direction and magnitude
- Global Market Returns Data
- Country classification data for regional analysis(US, World, Frontier, Developed...)
- Factor Returns HML(High Minus Low) Data

CRSP for the United States (beginning in 1926) and from Compustat for all other countries

DATA CONSTRUCTION

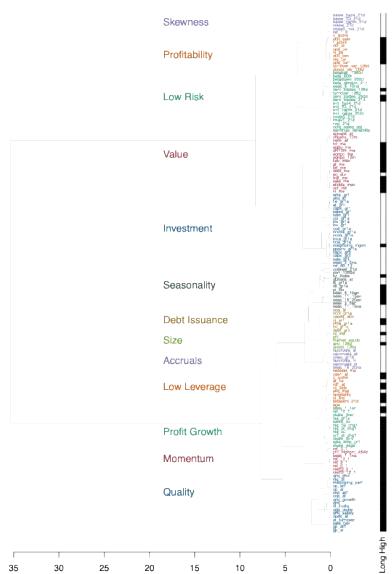
- focus on a one-month holding period for all factors, and only include the version that updates with the most recent accounting data
- in each country and month, sort stocks into characteristic terciles (top/middle/bottom third) with breakpoints based on non-micro stocks in that country
- for each tercile, compute its "capped value weight" return, meaning that stocks are weighted by their market equity winsorized at the NYSE 80th percentile
- factor is then defined as the high-tercile return minus the low-tercile return, corresponding to the excess return
 of a long-short zero-net-investment strategy

FACTOR GROUPING

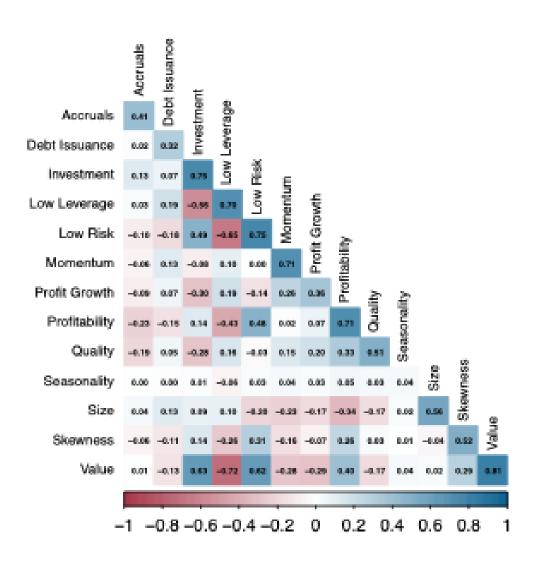
- group factors into clusters using Hierarchical Agglomerative Clustering (HAC)
- define the distance between factors as one minus their pairwise correlation and use the linkage criterion of Ward (1963).

HIERARCHICAL CLUSTERING

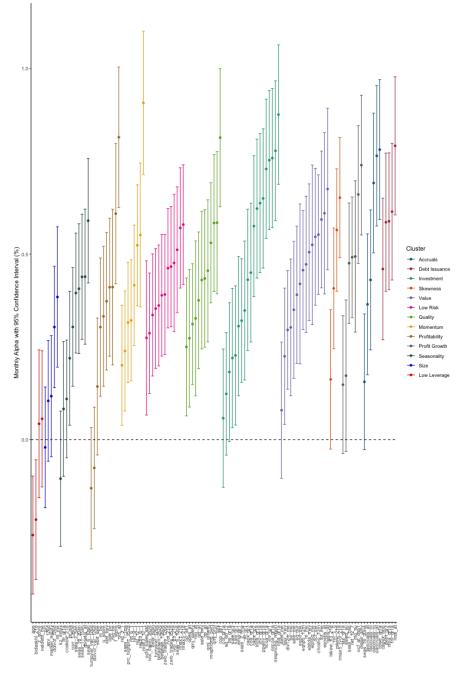
Distance Calculation –
 Cophenetic correlation
 between dendrogram and
 distance(var-cov) matrix



12



VARIANCE-COVARIANCE MATRIX



MONTHLY ALPHA, BY FACTOR

JOINT-FACTOR BAYESIAN APPROACH TO THE MT PROBLEM

- Multiple Testing problem to the frequentist approach
- Allows simultaneous inference of factor alphas
- Zero-alpha prior shrinks alpha estimates of all factors, thereby leading to fewer discoveries (i.e., a lower replication rate)
- Allows knowledge about the alpha of any individual factor, borrowing estimation strength across all factors (i.e., a higher replication rate)

2 KEY MODEL FEATURES

■ Feature 1. Model prior: anchors the researcher's beliefs to a sensible default (e.g., all alphas are zero)

$$f_t = \alpha + \beta r_t^m + \varepsilon_t, \ \alpha \sim N(0, \tau^2)$$

Derive the posterior alpha distribution via Bayes' rule, posterior alpha is normal with mean

$$E(\alpha|\hat{\alpha}) = \kappa \hat{\alpha}, \qquad \kappa = \frac{\tau^2}{\tau^2 + \sigma^2/T} = \frac{1}{1 + \frac{\sigma^2}{\tau^2 T}} \in (0, 1)$$

2 KEY MODEL FEATURES

Hierarchical (alpha) structure: each alpha is shrunk toward its posterior cluster mean (i.e., toward related factors)

$$E(\alpha^{i}|\hat{\alpha}^{1},\dots,\hat{\alpha}^{N}) = \frac{1}{1 + \frac{\rho\sigma^{2}}{\tau_{c}^{2}T} + \frac{\tau_{w}^{2} + (1-\rho)\sigma^{2}/T}{\tau_{c}^{2}N}} \hat{\alpha}^{\cdot} + \frac{1}{1 + \frac{(1-\rho)\sigma^{2}}{\tau_{w}^{2}T}} \left(\hat{\alpha}^{i} - \frac{1}{1 + \frac{\tau_{w}^{2} + (1-\rho)\sigma^{2}/T}{(\tau_{c}^{2} + \rho\sigma^{2}/T)N}} \hat{\alpha}^{\cdot}\right)$$

where $\hat{\alpha} = \frac{1}{N} \sum_{j} \hat{\alpha}^{j}$ is average alpha. When the number of factors N grows, the limit is

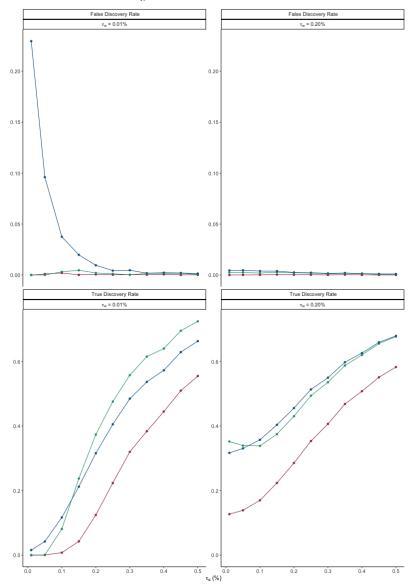
$$\lim_{N \to \infty} E(\alpha^i | \hat{\alpha}^1, \dots, \hat{\alpha}^N) = \frac{1}{1 + \frac{\rho \sigma^2}{\tau_c^2 T}} \hat{\alpha}^{\cdot} + \frac{1}{1 + \frac{(1 - \rho)\sigma^2}{\tau_w^2 T}} \left(\hat{\alpha}^i - \hat{\alpha}^{\cdot} \right)$$

 Intuitively, the posterior for any individual alpha depends on all of the other observed alphas because they are all informative about the common alpha component

FDR CONTROL – EMPIRICAL BAYES

 Compared to Benjamini & Yukutieli and ordinary OLS(Harvey et al. (2016).)

Type: → OLS → Benjamini and Yekutieli → Empirical Bayes



REPLICATION RATE IDENTICAL TO THE OLS-BASED RATE

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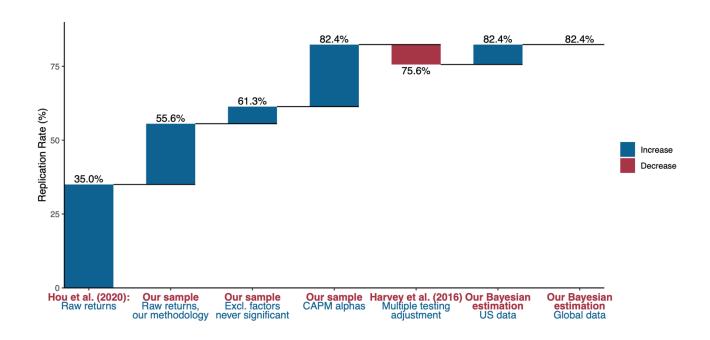


Figure 1: Replication Rates Versus the Literature

CONCLUSION & OUTLOOK

- In summary, the joint model with hierarchical alphas has the dual benefits of identifying the common component in alphas and tightening confidence intervals by sharing information among factors.
- The Empirical Bayes model help establish stable and replicable discovery rate, regionally and globally.
- Implementing CNN for more precise distance calculation for clustering correlation matrix
- Testing the out-of-sample replication rate globally country specific idiosyncratic factor component
- Additional/end use for model:
 - look for evidence of alpha-hacking
 - compute the expected number of false discoveries based on the posterior
 - analyze portfolio choice taking into account both estimation uncertainty and return volatility
 - evaluate asset pricing models