Cross-stock momentum and factor momentum

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Cross-stock linkages to Momentum Effect

Cross-stock linkages:

Own-stock momentum (constancy of stock returns);

Symmetry: The co-movements of linked Stocks (Factor Momentum);

Asymmetry: The ‘lead-lag’ relationship of linked stocks. (Cross-stock Momentum)

Cross-stock(C-S) Momentum: **Directional** and **Strength difference**

- If i is the industry leader, its past performance can predict j's future returns, while j cannot predict i's performance in reverse.

Motivation

Limitation: Previous research neglected the asymmetric relationship between stocks.

- Cross-stock momentum comes from factor momentum. (Arnott et al., 2023)
- Hard to distinguish own-stock momentum/factor momentum. (Ehsani and Linnainmaa 2022)

Why is it interesting?

- Co-movements and asymmetry assures more accurate identifying “leaders” of market information, thereby optimizing investment decisions.
- Asymmetry may help distinguish between C-S MoM and factor momentum.

Research Questions

Key Questions:

1. Can asymmetric relationships bring significant positive returns?

- Does stock momentum have non factor driven predictive ability and economic significance?

2. Is this feature making C-S MoM differ from factor momentum?

- Will data-driven method(PP) captures it?

Contributions

1. Literature on Cross-stock Momentum and Factor Momentum

Prior: Industry momentum stems from factor momentum.(Arnott, 2023)

- Factor momentum profit mainly comes from co-movements. (Lee et al., 2019)

Extend: Seperating symmetric and asymmetric components.

- C-S MoM strategy consistently generates excess returns.
- Industry momentum becomes significant after reducing the weight of the largest stock.

2. Literature on feature extraction and dimension reduction

Prior: PP: Efficiency in researching firm-networks(cross-stock linkages). (Kelly, 2023)

Extend: Verified time-varying co-movement and cross-sectional asymmetry are important features of cross stock linkages.

Design

How to extract asymmetric components?

1. **Data driven approach**: Principal Portfolio (PP) (Kelly et al. 2023)
   - The **Prediction matrix**: Predicting future returns using past returns.
   - The **Optimal Portfolio**: Closed form portfolio based on prediction matrix.
2. **Cross Stock linkages**: Asymmetric/Symmetric component.
   - The **Lead-Lag Relationships**: Cross-section, Time series features.
3. **Empirical analysis**: Stock returns from CRSP monthly from 1926 to 2018.

Theoretical Framework Principal Portfolio

$$\boldsymbol{\Pi}_t = E(\boldsymbol{R}_{t+1}\boldsymbol{S}_t') = \begin{bmatrix} R_{0,t+1}S_{0,t}' & R_{1,t+1}S_{0,t}' & \dots & R_{N,t+1}S_{0,t}' \\ R_{0,t+1}S_{1,t}' & R_{1,t+1}S_{1,t}' & \dots & R_{N,t+1}S_{1,t}' \\ \dots & \dots & \dots & \dots \\ R_{0,t+1}S_{N,t}' & R_{1,t+1}S_{N,t}' & \dots & R_{N,t+1}S_{N,t}' \end{bmatrix}$$

Prediction Matrix: Use past returns to predict future returns:

$$\Pi_t = \frac{1}{T}\sum_{\tau=t-T+1}^{t} R_\tau S_{\tau-1}' = \frac{1}{T}\sum_{\tau=t-T+1}^{t} R_\tau R_{\tau-1}'$$

Exact covariance matrix Σ (overall correlation between stocks) based on prediction matrix.

Theoretical Framework C-S MoM

Covariance decomposition: $\Sigma_{ij} = \textsf{Cov}(R_i, R_j)$

$$\textsf{Cov} = \underbrace{\frac{1}{2}\left[\textsf{Cov}(R_{i,t}, R_{j,t-1}) + \textsf{Cov}(R_{j,t}, R_{i,t-1})\right]}_{\text{Symmetric Component}} + \underbrace{\frac{1}{2}\left[\textsf{Cov}(R_{i,t}, R_{j,t-1}) - \textsf{Cov}(R_{j,t}, R_{i,t-1})\right]}_{\text{Asymmetric Component}}$$

SYM Component: Not focusing on directionality, reflecting co-movements of stock groups.

ASY Component:

$$\Sigma_{\textsf{ASY}} = \frac{1}{2}(\Sigma - \Sigma') \approx \frac{1}{2}\left[\textsf{Cor}(r_t^i, r_{t-1}^j) - \textsf{Cor}(r_t^j, r_{t-1}^i)\right]\sigma_i\sigma_j$$

Singular Value Decomposition(SVD)

1. SVD for the Asymmetric component $\Sigma_{\text{Asymmetric}} = U\Sigma V'$

U and V: Representing directional principal components.

Σ: **SVD diagonal matrix**: representing importance of principal component.

2. Select top K largest singular values and construct a dimensionality reduced prediction matrix L: $w_t = L'S_t$

Thus, the optimal portfolio return is:

$$w_t' R_{t+1} = S_t' L R_{t+1} = S_t' \sum_{k=1}^{K} (\lambda_k v_{k,t-1} u_{k,t-1}') R_{t+1}$$

Return of C-S MoM Strategy

	Excess returns	CAPM alpha	FF3 alpha	FF3 + m alpha	FF3 + mr alpha	FF5 alpha	FF7 alpha
Optimal PP	1.16	1.17	1.15	1.17	1.62	1.35	1.95
	(7.15)	(7.13)	(6.97)	(6.96)	(10.03)	(5.49)	(8.68)
PP1-1	0.51	0.51	0.48	0.53	0.78	0.69	1.08
	(3.11)	(3.14)	(2.92)	(3.16)	(4.64)	(2.98)	(4.79)
PP1–3	0.65	0.65	0.61	0.62	0.92	0.77	1.18
	(3.99)	(3.96)	(3.74)	(3.69)	(5.51)	(3.23)	(5.15)
PP1–5	0.76	0.76	0.73	0.77	1.10	0.83	1.37
	(4.70)	(4.65)	(4.44)	(4.61)	(6.63)	(3.41)	(6.02)
PP1–10	0.93	0.90	0.86	0.92	1.25	1.00	1.59
	(5.71)	(5.52)	(5.28)	(5.47)	(7.55)	(4.13)	(7.03)
PP1–20	1.05	1.04	1.00	1.06	1.45	1.18	1.81
	(6.47)	(6.32)	(6.09)	(6.32)	(8.82)	(4.81)	(8.07)
2-norm PP	0.80	0.81	0.78	0.88	1.27	1.08	1.71
	(4.93)	(4.91)	(4.74)	(5.22)	(7.74)	(4.19)	(7.18)

- PP portfolios have significant returns and alpha compared to classical models.

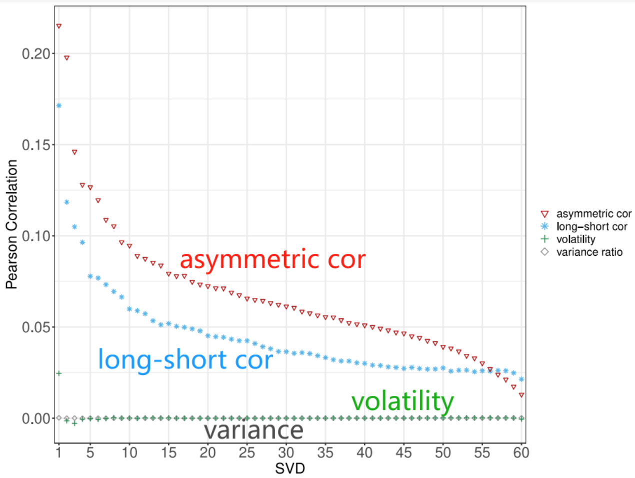
Components of Symmetric/Asymmetric Terms

组成部分	公式	含义
long-short cor	$COR(2) - COR(1)$	对称性影响
asymmetric cor	$Cor(r_t^i, r_{t-1}^j) - Cor(r_t^j, r_{t-1}^i)$	非对称性影响
volatility	σ_i	当期价格波动
variance ratio	VR_i	个股时序动量

Correlation between components of $SYM_{i,j}$ & $ASY_{i,j}$ and SVD matrix indicates that:

SVD matrix mainly reflects features of asymmetric terms in C-S MoM.

Asymmetry matters for PP(C-S MoM strategy)



C-S Momentum does not come from factor momentum

	Excess returns	CAPM alpha	FF3 alpha	FF3 + m alpha	FF3 + mr alpha	FF5 alpha	FF7 alpha
Asymmetric							
asymmetric cor	0.56	0.46	0.43	0.95	0.80	0.57	1.07
	(3.47)	(2.86)	(2.65)	(6.36)	(5.26)	(2.30)	(5.02)
asymmetric cor $\cdot \sigma_i \sigma_j$	0.50	0.41	0.38	0.88	0.72	0.55	1.04
	(3.08)	(2.51)	(2.35)	(5.82)	(4.67)	(2.22)	(4.87)
ASY	0.49	0.40	0.37	0.87	0.71	0.53	1.02
	(3.04)	(2.46)	(2.30)	(5.72)	(4.58)	(2.17)	(4.75)
Symmetric							
long-short cor	0.75	0.73	0.69	0.89	1.20	0.93	1.50
	(4.69)	(4.54)	(4.27)	(5.46)	(7.46)	(4.00)	(6.87)
long-short cor $\cdot \sigma_i \sigma_j$	0.63	0.61	0.58	0.76	1.05	0.82	1.37
	(3.95)	(3.81)	(3.62)	(4.66)	(6.42)	(3.49)	(6.17)
SYM	0.61	0.60	0.58	0.74	1.00	0.80	1.33
	(3.86)	(3.77)	(3.61)	(4.48)	(6.09)	(3.43)	(6.02)

Factor momentum affected by cross-asymmetric linkages

TSFM:

$$R^f_{t-1} R^f_t = \frac{1}{N}\sum_{i=1}^{N} R_{i,t} = \underbrace{\frac{1}{N}\sum_{i=1}^{N}\sum_{j \neq i} \rho_{ij} R_{j,t-1}}_{\text{High Cross-Stock Link}} + \underbrace{\frac{1}{N}\sum_{i=1}^{N}\sum_{j \neq i} (1-\rho_{ij}) R_{j,t-1}}_{\text{Low Cross-Stock Link}} + \underbrace{\frac{1}{N}\sum_{i=1}^{N} R_{i,t-1}}_{\text{Own-Stock Lead-Lag}}$$

CSFM: $\left(R^f_{t-1} - \overline{R_{t-1}}\right)\left(R^f_t - \overline{R_t}\right)$

$$= \underbrace{\frac{1}{N}\sum_{i=1}^{N}\sum_{j \neq i}^{N} \rho_{ij}(R_{j,t-1} - R_{t-1})}_{\text{High Cross-Stock Link}} + \underbrace{\frac{1}{N}\sum_{i=1}^{N}\sum_{j \neq i}^{N} (1-\rho_{ij})(R_{j,t-1} - R_{t-1})}_{\text{Low Cross-Stock Link}} + \underbrace{\frac{1}{N}\sum_{i=1}^{N} (R_{i,t-1} - R_{t-1})}_{\text{Own-Stock Lead-Lag}}$$

Factor momentum affected by cross-asymmetric linkages

Factor Mom		Own-stock lead-lag	Cross-stock link Low	Cross-stock link High	High - Low
15 factors	TimeSeries	0.01	−0.68	1.10	1.78
		(0.63)	(−2.53)	(3.78)	(3.43)
	CrossSection	0.01	−0.75	1.15	1.90
		(0.59)	(−2.81)	(3.88)	(3.63)
43 factors	TimeSeries	0.05	−0.75	1.07	1.83
		(0.84)	(−2.52)	(3.50)	(3.11)
	CrossSection	0.05	−0.92	1.23	2.15
		(0.84)	(−2.89)	(3.70)	(3.38)

Profits of *TSFM* and *CSFM* mainly come from high cross-stock linkages:

The driving force of factor momentum lies in the information transmission between stocks.

Factor Momentum and Industry Momentum: Asymmetric Analysis

	Excess return	CAPM alpha	FF3 alpha	FF5 alpha	FF7 alpha
Asymmetry					
all stocks	0.47	0.47	0.46	0.44	0.53
	(5.87)	(5.83)	(5.64)	(5.26)	(6.32)
top size decile stocks	−0.26	−0.27	−0.28	−0.25	−0.56
	(−1.64)	(−1.7)	(−1.75)	(−1.51)	(−3.96)
other stocks	0.66	0.68	0.66	0.63	0.82
	(6.47)	(6.57)	(6.29)	(5.88)	(8.25)
Symmetry	0.67	0.73	0.73	0.76	1.07
	(4.74)	(5.18)	(5.11)	(5.13)	(9.78)

Value Weighted: Industry momentum mainly reflects performance of large stocks within the industry, while ignoring contribution of small stocks;

Industry momentum becomes significant after excluding top 10.

Conclusions

1. **Introduced asymmetry to distinguish cross-stock and factor momentum**.
   - Asymmetry refelcts the 'lead-lag' relationship between stocks.
2. **Improved prediction accuracy with a data-driven approach**.
   - PP method with SVD captures the asymmetric terms.
3. **Showed cross-stock momentum's (asymmetry) role in factor momentum formation**.

探讨 & 未来方向

应用数据驱动策略于更广泛的资产类别（如债券、衍生品）。

探索其他动态关系（如流动性、宏观变量对跨股动量的影响）。

- 探索宏观因子与股票间动量的交互作用。

股票间联系的动态性可能要求资产定价模型引入时变因子，而非仅依赖静态的行业、地理等因子。

- 动态联系的发现可以为因子模型的改进提供新思路。

Appendix: Scenario-Connection between Stocks in Technology Industry

Three companies: A: upstream leader, B: midstream, and C: downstream.

Symmetry(Co-movement):

Long run: In same industry, returns will be affected by similar macro-factors (global demand fluctuations), showing long-term co-movements.

Short run: certain sudden policies may make their short-term gains highly correlated.

Asymmetry(Lead-lag):

A's performance may predict future returns of B and C, but B and C cannot predict A in reverse.

"Upstream leading, downstream following" pattern reflects the **asymmetry between stocks**.