“Which Investors Drive Factor Returns?”
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Discussion
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Summary

Comments

Conclusion
Theory

▶ Theoretical model with $T$-period myopic mean-variance portfolio selection with one risky-asset, which pays

\[
F_t = \mu + \epsilon_t \quad \forall t
\]

where $\mu \sim N(0, \sigma_{\mu})$ and $\epsilon_t \sim N(0, \sigma_{\epsilon})$

▶ Investors differ in terms of signal processing capacity, which they allocate to two signals associated with $\mu$ and $\epsilon_t$, in every period:

▶ factor selection: learning about $\mu$.
▶ factor timing: learning about $\epsilon_t$

→ solve for optimal precision and portfolio choice, as well as equilibrium prices.

▶ Main findings:

▶ In absolute terms, investors with more capacity allocate more to both signals.
▶ In relative terms investors with more capacity allocate more to factor timing, the greater the uncertainty about the underlying factor.

⇒ Investors with more capacity have more variable portfolio allocation and contribute more to price discovery.

▶ Test these predictions empirically by combining:

▶ Investor holdings data from 13F filings from FactSet from 1999 to 2018.
▶ 55 accounting and price characteristics that have been shown to predict returns cross-sectionally (Harvey et al. 2016, McLean and Pontiff (2016)).
Empirics

- Consider 8 investor groups: Brokers, Hedge Funds, Investment Advisors, Long term (insurance and pension funds), Mutual funds, Private Banking, and short-seller, and households (residual).

- Attribute each security $s$ to a characteristic $c$ (e.g., Momentum) decile $d_{s,t}^c$ portfolio. Then for each investor $i$’s portfolio weight $w_{i,s,t}$ compute

$$q_{i,t}^c = \sum_{s=1}^{S_t} w_{i,s,t} d_{s,t}^c - \bar{d}_t^c,$$

$$d_{s,t}^c = \frac{\sum_s ME_{s,t} d_{s,t}^c}{\sum_s ME_{s,t}}$$

where

- Decompose average investor investing skill into factor selection and factor timing:

$$FSkill_i = \frac{1}{NT} \sum_{c=1}^{N} \sum_{t=1}^{T} q_{i,t}^c (f_i^c - \bar{f})$$

$$= \frac{1}{N} \sum_{c=1}^{N} q_{i,t}^c (\bar{f}^c - \bar{f}) + \frac{1}{N} \sum_{c=1}^{N} \left[ \frac{1}{T} \sum_{t=1}^{T} \left( q_{i,t}^c - \bar{q}_i^c \right) (f_i^c - \bar{f}^c) \right],$$

$$\equiv FSelection_i$$

$$\equiv FTiming_{i,c}$$

- Find that hedge funds have highest total Factor skill, mostly from Factor timing.

- Instead, long-term investors and brokers have least.

- HF have more dispersed, most volatile, and least auto-correlated portfolios and contribute most to price discovery:

- using counterfactual based on Koijen-Yogo demand system, $1$ Trillion in additional HF assets, decreases risk-premia by 3.35% per year and volatility by 3% per year.
Closer connection between theory and empirics?

- Demand system equation (32) is straight from Koijen and Yogo (2019), which is derived
  - for a log-investor,
  - under no short-sale constraints,
  - heterogeneous beliefs,
  - assuming that only four characteristics matter for investors (Book to Market, profitability, asset growth, dividend yield, market beta).

- This paper has a theoretical framework where heterogeneous investor holdings arise because they differ in terms of signal processing capacities and focuses on 55 long-short anomaly portfolios.

⇒ Why not estimate the demand system consistent with the theoretical model setup?

⇒ Is the Koijen-Yogo demand equation consistent with the endogenously derived optimal investor demands in the paper?

⇒ Could the model be used to do the counter-factual experiment rather than the KY system?
What set of characteristics?

- Koijen-Yogo assume only four characteristics matter for cross-section of returns.
- This paper assumes investors allocate to 55 factors based on 55 long-short anomaly portfolios that have been shown to predict the cross-section of returns (Harvey et al. 2016, McLean and Pontiff (2016)).

Q? Because it is easier to estimate demand for 55 factor portfolios than for 3000 stocks.

- However, does it describe investors’ actual demand function (conscious or unconscious)? Does it matter?
- Do the 55 factors better explain the cross-section of returns than the 5 picked by KY? Should you expand their set of factors?
- Many hedge funds use price-based signals (momentum, reversal, . . .). How to integrate these signals in the demand-based system of KY (while dealing with the price endogeneity)?
- Long-short portfolios in the KY model (which assumes no-short sale constraints)?
- Does the constraint that $\beta < 1$ apply to momentum traders? How much does it affect estimation?
What investor groups?

- Most investors hold very few stocks (unbalanced panel for the demand system).
  - Useful to aggregate investors and consider groups with larger security ‘mandates.’
- What is the optimal aggregation/group size?
  - If aggregation is too broad, then group holdings $\sim$ market and get no variation in holdings (so group will not contribute to price-discovery), even if within the group there may be substantial heterogeneity and trading (e.g., households, brokers?).

Figure 1: Portfolio Characteristics by Investor Type

![Figure 1: Portfolio Characteristics by Investor Type](image1)

Note: This figure plots the average characteristic decile (relative to the market portfolio) by investor type. Each quarter, firms are assigned into deciles for each of the 55 characteristics considered. An investor’s decile score is defined as the difference between the value-weighted average decile of her portfolio and the score of the market portfolio. A positive value indicates exposure to the long side of the characteristic relative to the market portfolio. Characteristics are sorted on the x-axis by the average hedge fund exposure. Details about the characteristics and their construction are given in Appendix D. The sample is from 1999Q1 to 2019Q4.

Figure 2: Percent Ownership by Investor Type

![Figure 2: Percent Ownership by Investor Type](image2)

Note: This figure plots percent ownership by investor type over the sample period. Investor classifications come from FactSet. Investor types (excluding Households and Short-Sellers) are sorted by the final ownership share. Households are constructed from the residual of institutional ownership and market capitalizations. Short-Sellers are the aggregate class of short interest. Ownership shares sum to more than 1 due to the presence of Short-Sellers. The sample is from 1999Q1 to 2019Q4.

→ What is optimal group size?
Conclusion

- Nice theoretical framework to think about what drives differences in investor portfolio composition.

- KY focus on differences in beliefs. Here focus on differences in learning, and signal processing capabilities.

- Nice way to extract measures of factor timing and factor selection ability.

- Interesting results.

Questions

- Develop demand-based system based on your model rather than using KY?
- Think about refining the broad investor categories?
- How do we assess the counterfactual experiment validity? For example: *hedge funds reduce expected returns of factors by 40% and reduce volatility by 0.9% per year per $ trillion invested.*

→ Is it possible to use this to predict factor expected returns out of sample? or volatility?