

# Discussion of “Noise Trading and Asset Pricing Factors”

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# Outline

1. Motivation: why are factors “compensation for risk”?
  - An important research question
2. This paper:
  - Shows novel evidence that noise trader risk in factors is priced
3. Some comments

# 1. Motivation

# Motivation

- Empirical asset pricing makes heavy use of “factors”:
  - Factor movements are called “risk”
  - Expected factor returns are “compensations for risk”
- However, what “risk” do factor movements represent?
  - Traditional view: cash flow variation + rational discount rate variation
  - New view: factor movements driven by **uninformed demand**
    - Noise trader risk: De Long, Shleifer, Summers, and Waldmann (1990)
    - Style-level demand: Barberis Shleifer (2003), Kojen Yogo (2019)
- This paper shows evidence for the new view

# Key messages in this paper

1. Asset pricing factors (anomalies) are exposed to noise-trader risk
    - Uninformed mutual fund flows cause temporary price pressures
    - Teo and Woo (2004), Wahal and Yavuz (2013), Ben-David et al (2020)
  2. Noise-trader risk is priced
    - **To my best knowledge, this is entirely new**
- I'll start by presenting the paper using a framework based on my own understanding

## 2. This paper

# Conceptual framework

- Trading at time 0 of assets maturing at time 1
- There are  $K$  long-short factor portfolios (e.g. HML) with a supply of  $\frac{1}{K}$  units each:  $w_0 = (1/K, \dots, 1/K)$
- Time 1 payoff is subject to “fundamentals” and flows:
  - $\pi_i = V_i + \text{Flow}_i$
  - Vector of payoffs:  $\pi \sim N(\mu_V, \text{Var}(V + \text{Flow}))$
  - **Key:**  $\text{Var}_{t=0}(\text{Flow})$  is time-varying and predictable
- Market clearing at time 0 to solve for prices
  - All factors need to be absorbed by arbitrageurs (e.g. hedge funds)
  - Assume CARA utility with risk aversion  $\gamma$

# Asset pricing implications

- Arbitrageurs hold all factors. Their wealth portfolio return:

$$R^W = \frac{1}{K} \sum_i R_i = \frac{1}{K} \sum_i (\text{Flow}_i + R_i^{\text{no flow}}) = \text{Flow}^W + R^{W, \text{no flow}}$$

- 1) Time series result:

$$E(R^W) = \gamma \cdot \text{Var}(\text{Flow}^W + R^{W, \text{no flow}})$$

- In periods with high  $\text{Var}(\text{Flow}^W)$ ,  $E(R^W)$  is higher

- 2) Cross-sectional result:

$$E(R_i) = \beta_i \cdot E(R^W)$$

- Factors with higher  $\beta_i$  have higher return



# Empirical results

# Preliminaries

- Mutual fund flows cause uninformed price pressures in factors
  - Very plausible: most mutual fund investors are retail and unsophisticated
  - Consistent with prior literature
- Flow volatility ( $Var(Flow)$ ) is predictable
  - As a consequence, factor return volatility and covariance can be better predicted using past flows
  - The authors call the predictability risks “fragility” (Greenwood Thesmar (2011))

# 1. Time series results

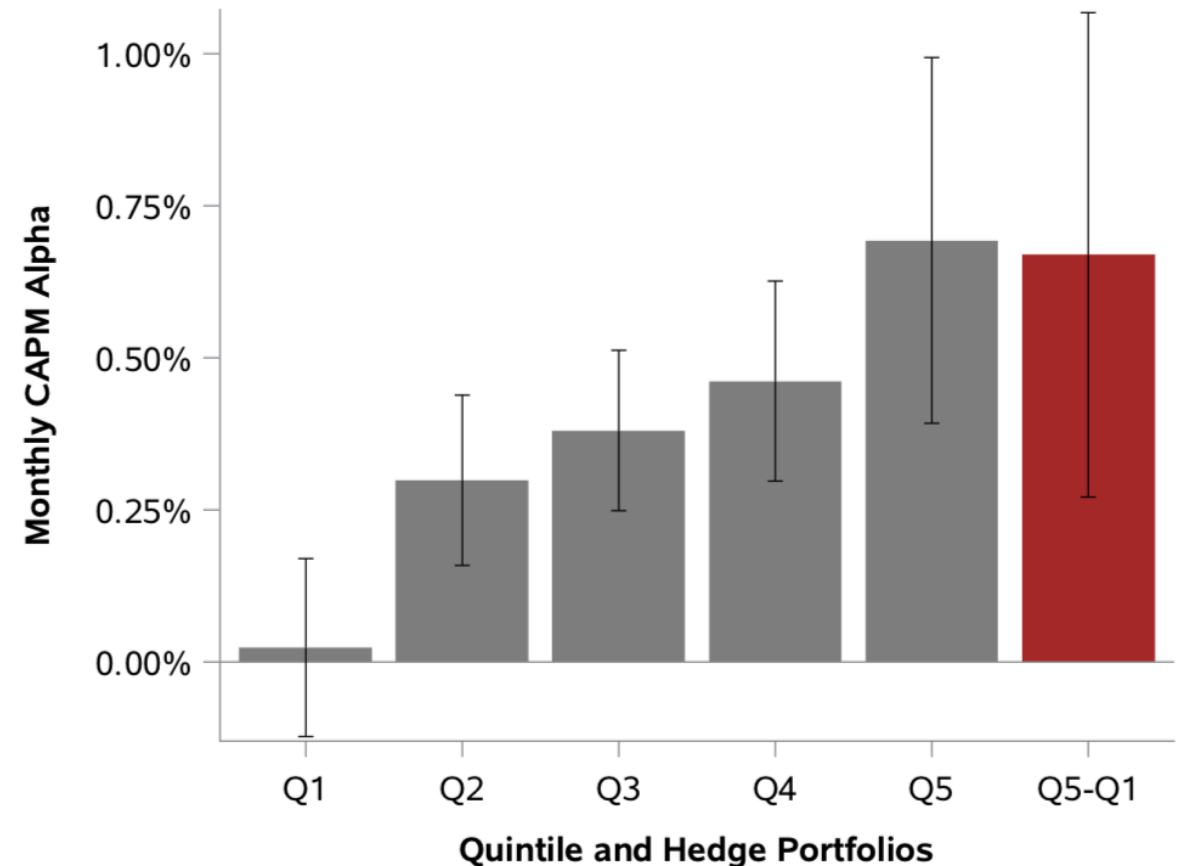
Table 5: Aggregate fragility and future average factor premia

- When average factor “fragility” (expected flow-induced volatility) is high, factor returns are high
- Additional results:
  1. This predictability holds *out-of-sample*
    - Thus, the predictability is sufficiently stable to be useful in actual return predictability implementation (Goyal Welch)
  2. Results are stronger when focusing on large cap stocks and those more heavily traded by hedge funds
    - ... HFs and institutions are more likely the relevant arbitrageurs

	(8)
Aggregate Fragility	0.42** (2.12)
Avg Covariance	0.13 (0.34)
BW Sentiment	0.18 (0.59)
Avg Value Spread	0.31 (0.70)
Avg Factor Ret	0.22 (1.04)
Mkt Volatility	-0.42** (-2.07)
No. Obs.	144
Adj. R <sup>2</sup>	0.16

## 2. Cross-sectional results

- The authors sort factors by “co-fragility”, which is effectively the predicted values of  $Cov(Flow_i, Flow^W)$
- As predicted, factors with higher co-fragility have higher returns



# 3. Comments

# Comment 1: specification

- The conceptual framework suggests that the cross-sectional results need a different specification
- The relevant beta should be with respect to the aggregate arbitrageur portfolio:

$$\begin{aligned}\beta_i &\propto \text{Cov}(Ret_i, Ret^W) \\ &= \text{Cov}(Ret_i^{no\ flow} + Flow_i, Ret^{W,no\ flow} + Flow^W)\end{aligned}$$

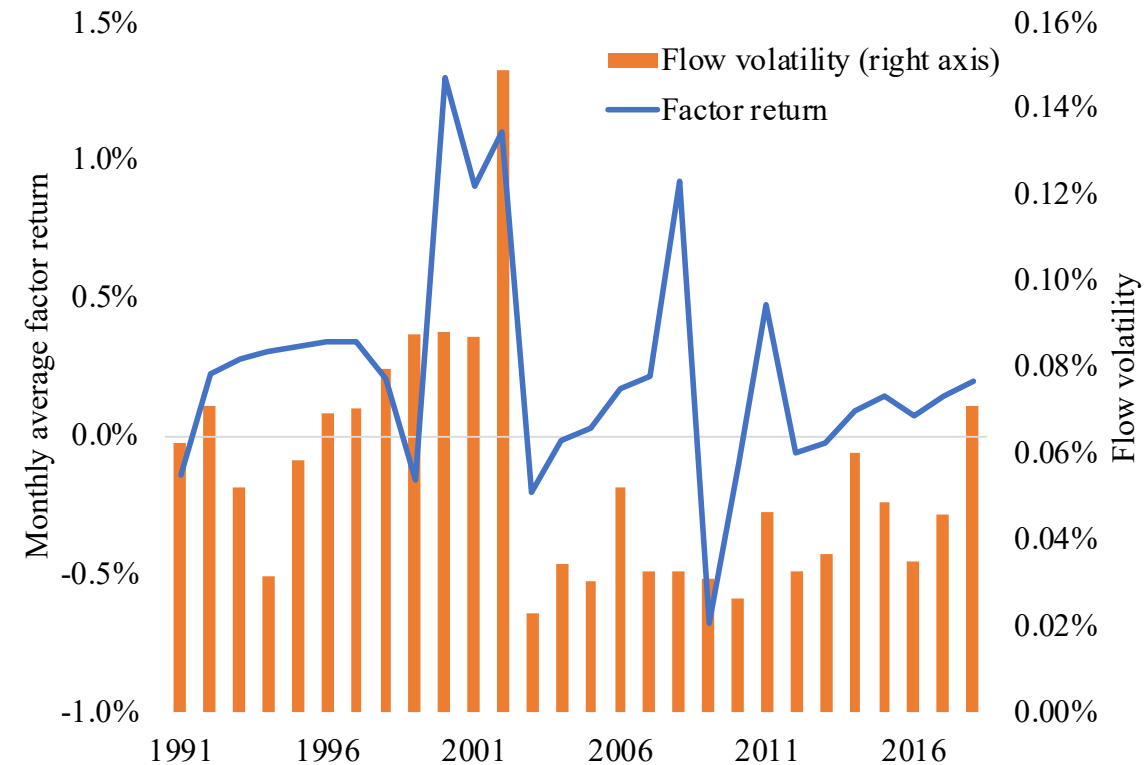
- The current specification focuses on the **flow-related component**
  - It is entirely possible that the other components do not differ much across factors, but it would be good to show

## Comment 2: more evidence for the mechanism?

- In general, establishing risk-based asset pricing results is challenging because it *requires an additional layer of rationality*
  - The maintained hypothesis in this paper: marginal arbitrageurs 1) recognize that flows impact returns, and 2) incorporate flow volatility estimates (perhaps heuristically) into their portfolio decisions
- It is impossible to get into the heads of investors, but anecdotal evidence could help
  - For instance, do risk-forecast models (e.g. MSCI/Barra) on Wall Street incorporate flows? Or do they incorporate it through some heuristics? (I don't know)
- This challenge on “showing investors knew” is almost never addressed in asset pricing
  - *Thus, this cannot be held as a “must-have” standard for publication*

# Comment 3: intermediary asset pricing

- The story in this paper is about time-varying *quantity* of (flow) risk
- The intermediary asset pricing literature emphasizes shocks to arbitrageur capital, which effectively induces *time-varying risk aversion*
  - For instance, in periods of high flow volatility, arbitrageurs have unstable funding and thus become unwilling to hold factors
  - Extreme: think “quant melt-down” in 2007





# Summary

- Very important research topic
- Believable hypothesis
- Novel empirical evidence
- Perhaps more can be done to pin down mechanism