

Discussion:

What Drives Trading in Financial Markets? A Big Data Perspective

Shikun Ke and Anton Lines

Yinan Su

Johns Hopkins University Carey Business School

AFA paper session “Asset Pricing: Machine Learning”
Jan. 5, 2025, San Francisco

Motivation

“What drives trading in financial markets?”

Very important for asset pricing research:

- 1 how information is incorporated into asset prices?
- 2 how non-fundamental trading affects prices?
- 3 where does non-fundamental trading come from?

...

Choice of empirical strategy (and criteria for claiming empirical success) depend on the research goal

Lots of potential here!

What to explain? (y)

- ▶ Ideal goal: “what drives trading?”
buy/sell(investor, stock, time)

What to explain? (y)

- ▶ Ideal goal: “what drives **trading**?”
buy/sell(investor, stock, time)
(one-more dimension than return(stock, time))

What to explain? (y)

- ▶ Ideal goal: “what drives trading?”
 - buy/sell(investor, stock, time)
 - (one-more dimension than return(stock, time))
- some aggregation can be necessary (depending on the research goal)

What to explain? (y)

This paper:

volume(investor_group, stock, day)

1. this paper categorizes investors to five groups
 - " $R^2 = 29\%$ " for the *group's* volume
 - R^2 mechanically depends on the degree of aggregation

What to explain? (y)

This paper:

volume(investor_group, stock, day)

1. this paper categorizes investors to five groups
 - " $R^2 = 29\%$ " for the *group's* volume
 - R^2 mechanically depends on the degree of aggregation
2. buy/sell is lumped together as volume

“Trading Volume Alpha”

Ruslan Goyenko, Bryan Kelly, Tobias Moskowitz, Yinan Su, Chao Zhang

Main message:

- ▶ daily stock-level trading volume is highly predictable with ML
- ▶ volume predictability has significant economic value:
transfer learning: from volume forecast to portfolio implementation

“Trading Volume Alpha”

Ruslan Goyenko, Bryan Kelly, Tobias Moskowitz, Yinan Su, Chao Zhang

Simple findings that are relevant to this research:

- ▶ log dollar volume (stock-day) is highly persistent
lagged moving average: $R^2 \approx 90\%$
...report R^2 relative to change in log dollar volume

“Trading Volume Alpha”

Ruslan Goyenko, Bryan Kelly, Tobias Moskowitz, Yinan Su, Chao Zhang

Simple findings that are relevant to this research:

- ▶ log dollar volume (stock-day) is highly persistent
lagged moving average: $R^2 \approx 90\%$
...report R^2 relative to change in log dollar volume
- ▶ some simple calendar dates strongly predict volume
index rebalancing, triple witching, holidays

“Trading Volume Alpha”

Ruslan Goyenko, Bryan Kelly, Tobias Moskowitz, Yinan Su, Chao Zhang

Simple findings that are relevant to this research:

- ▶ log dollar volume (stock-day) is highly persistent
lagged moving average: $R^2 \approx 90\%$
...report R^2 relative to change in log dollar volume
- ▶ some simple calendar dates strongly predict volume
index rebalancing, triple witching, holidays
- ▶ earnings announcement days are highly predictive
(...not surprising)

“Quantity, Risk, and Return”

Yu An, Yinan Su, and Chen Wang

- ▶ expected stock return explained by not just risk exposure (β) but also “quantity”

“Quantity, Risk, and Return”

Yu An, Yinan Su, and Chen Wang

- ▶ expected stock return explained by not just risk exposure (β) but also “quantity”
- ▶ rationale:
when sophisticated investors absorb more factor risk, they demand higher factor premiums

“Quantity, Risk, and Return”

Yu An, Yinan Su, and Chen Wang

- ▶ expected stock return explained by not just risk exposure (β) but also “quantity”
- ▶ rationale:
when sophisticated investors absorb more factor risk, they demand higher factor premiums
- ▶ empirical results highlight:
predicts monthly stock returns, OOS $R^2 \approx 1\%$, comparable to ML return forecasts

“Quantity, Risk, and Return”

Yu An, Yinan Su, and Chen Wang

Points that are relevant to this research:

- ▶ Non-fundamental flow matters to asset prices
 - need to explain “volume” with direction (buy vs. sell between investor groups)
 - need to focus on flow aggregated along the directions of risk (concentrated trading on characteristic)

“Quantity, Risk, and Return”

Yu An, Yinan Su, and Chen Wang

Points that are relevant to this research:

- ▶ Non-fundamental flow matters to asset prices
 - need to explain “volume” with direction (buy vs. sell between investor groups)
 - need to focus on flow aggregated along the directions of risk (concentrated trading on characteristic)
- ▶ cross-sectional APT still holds
 - who resolves mis-pricing? (sophisticated investors...who exactly?)
 - how do they do it?
can we observe arbitrage taking place?

Discussion:

What Drives Trading in Financial Markets? A Big Data Perspective

Shikun Ke and Anton Lines

Yinan Su

Johns Hopkins University Carey Business School

AFA paper session “Asset Pricing: Machine Learning”
Jan. 5, 2025, San Francisco