

Discussions on Missing Financial Data

Svetlana Bryzgalova Sven Lerner Martin Lettau Markus Pelger

Comments by Guofu Zhou

AI & BIG DATA IN FINANCE RESEARCH FORUM

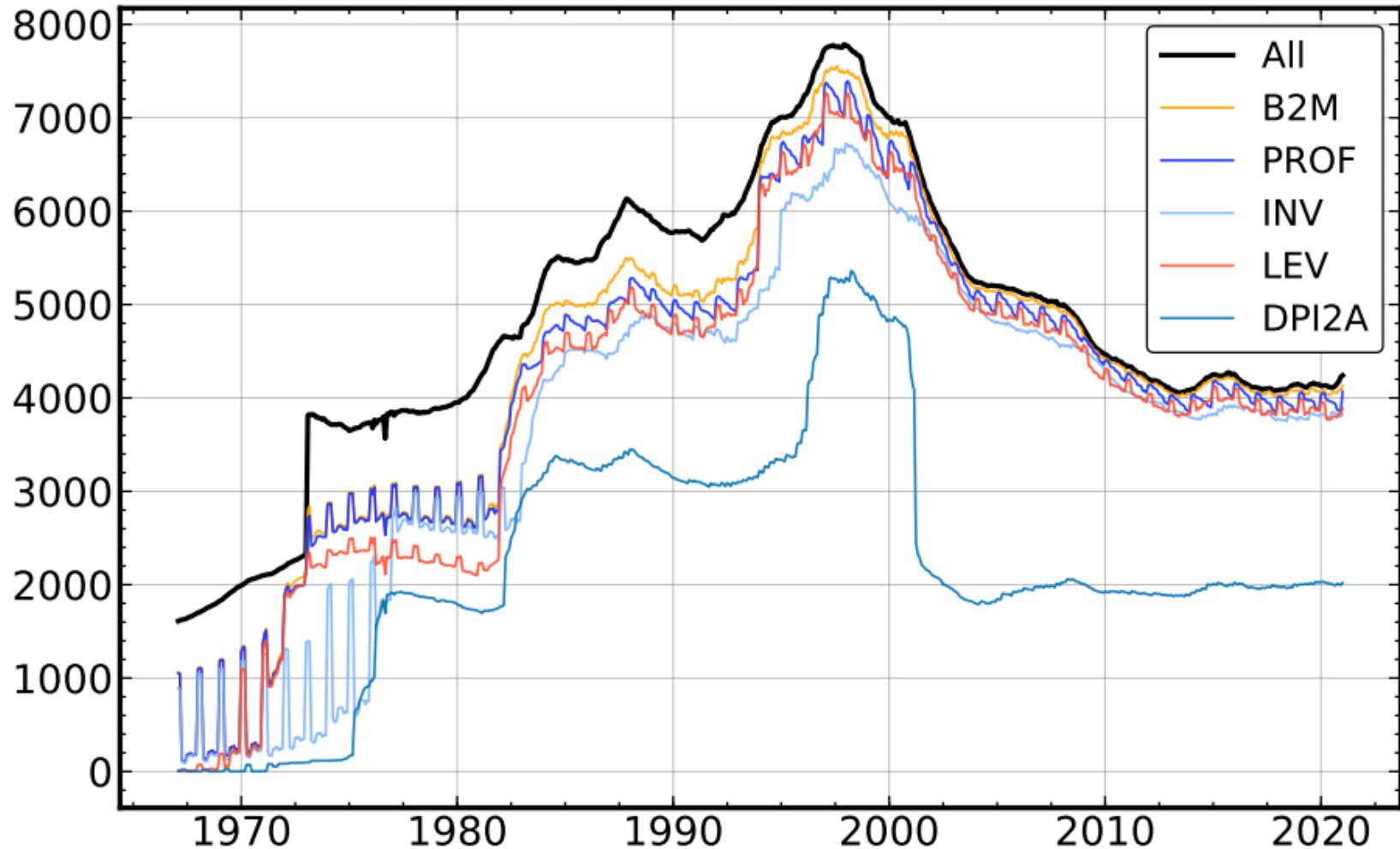
ABFR Webinar, April 28, 2022



Is there really a problem?

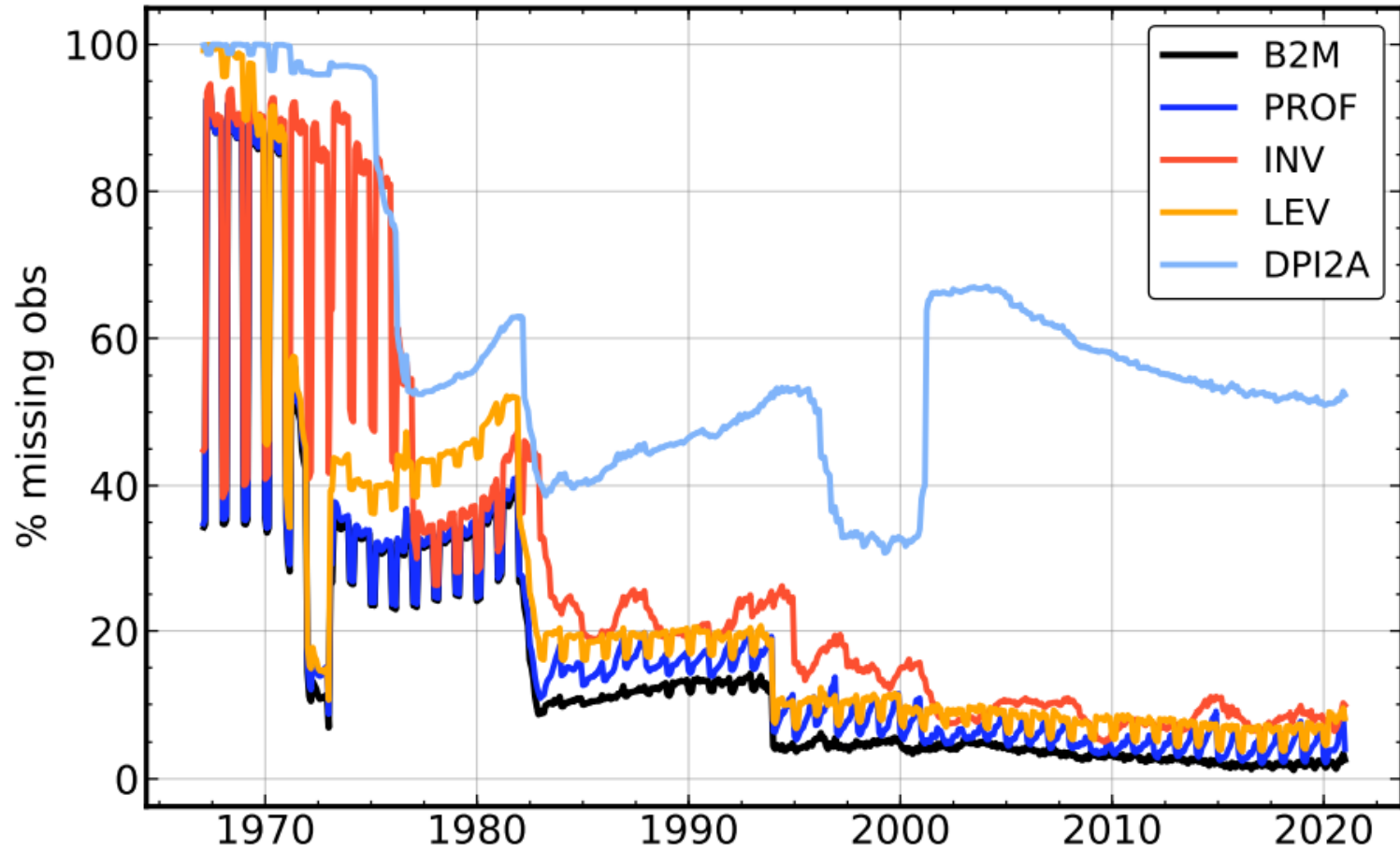
Problem of Missing Values: A

(a) Number of Stocks



Problem of Missing Values: B

(e) Missing Percentage



Why Is It Important ?

- **Thousands of Studies** reply on firm characteristics
 - ☞ Fama and French 3-factor models, ...
 - ☞ Hundreds of anomalies
 - ☞ Empirical corporate; Accounting
- **Potential issues:** under- or over-estimate
- **What about machine learning?**
 - ◆ Panel approach: selection bias
 - ◆ Exception: Han, et al, 2022, “Expected Stock Returns ... E-LASSO ...”
 - ☞ univariate XS: replacing missing forecasts by others; competitive to NN.
 - ◆ **Literature** correction: Rapach, Strauss and Zhou (2013, JF) is perhaps the first academic study (published in a top finance journal) that applies LASSO, Enet in finance.
- **Pathbreaking !**
 - ◆ a generic approach dealing with missing data
 - ◆ Another paper, Freyberger, et al, 2021, “Missing Data in asset pricing”
 - ◆ Both offer unique insights



How to solve the problem?

The Idea

At time t , Let $C_{i,l}^t$ be firm i 's characteristic l .

Assume a factor model for the $N_t \times L$ matrix:

$$C_{i,l}^t = F_i^t \Lambda_l^{t\top} + e_{i,l}^t$$

PCA with all data:

$$\tilde{\Sigma}_t^{XS} = \frac{1}{L} \sum_{l=1}^L C_l^t C_l^{t\top}, \quad N_t \times N_t$$

PCA with missing:

$$\hat{\Sigma}_t^{XS} = \frac{1}{|Q_{i,j}^t|} \sum_{l \in Q_{i,j}^t} C_l^t C_l^{t\top},$$

summing over observed data.

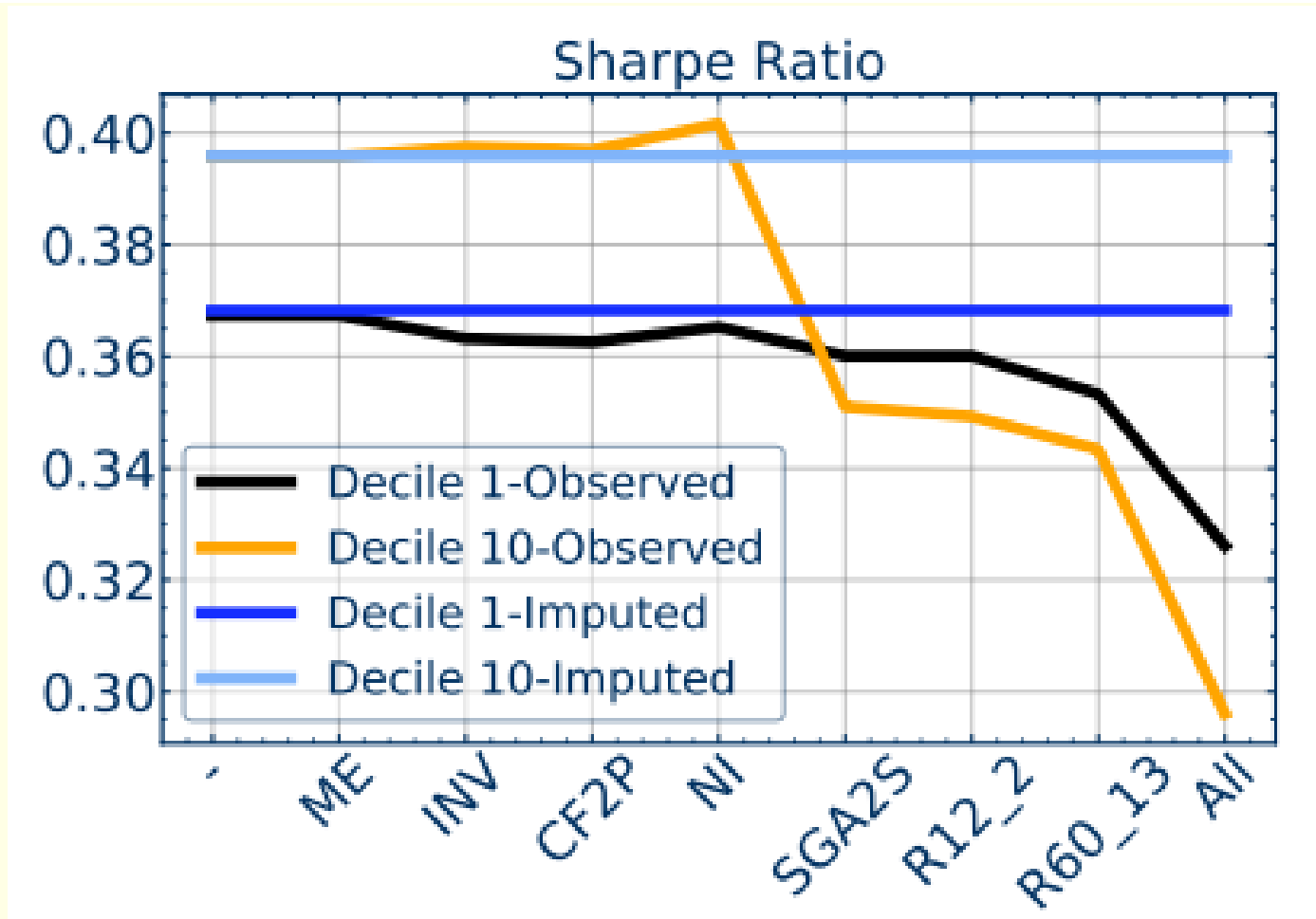
Major Results: 1

Table 3: Imputation Error for Different Imputation Methods

Method	In-Sample			OOS MAR			OOS Block		
	all	quarterly	monthly	all	quarterly	monthly	all	quarterly	monthly
global BF-XS	0.11	0.10	0.13	0.15	0.15	0.14	0.17	0.16	0.19
global F-XS	0.10	0.07	0.14	0.16	0.17	0.16	0.18	0.17	0.20
global B-XS	0.15	0.15	0.14	0.16	0.16	0.15	0.19	0.18	0.20
global XS	0.19	0.18	0.21	0.23	0.22	0.24	0.22	0.21	0.24
global B	0.16	0.17	0.15	0.17	0.17	0.15	0.21	0.20	0.22
local B-XS	0.15	0.16	0.14	0.16	0.17	0.15	0.19	0.19	0.20
local XS	0.21	0.20	0.22	0.23	0.22	0.24	0.23	0.22	0.24
prev	0.18	0.18	0.18	0.19	0.19	0.19	0.23	0.21	0.25
local B	0.16	0.17	0.15	0.17	0.17	0.15	0.21	0.20	0.22
XS-median	0.29	0.29	0.29	0.29	0.29	0.29	0.28	0.28	0.29
ind-median	0.29	0.29	0.29	0.29	0.29	0.29	0.28	0.28	0.29

Major Results: 2

Figure 15: Univariate Sorts With and Without Missing Values



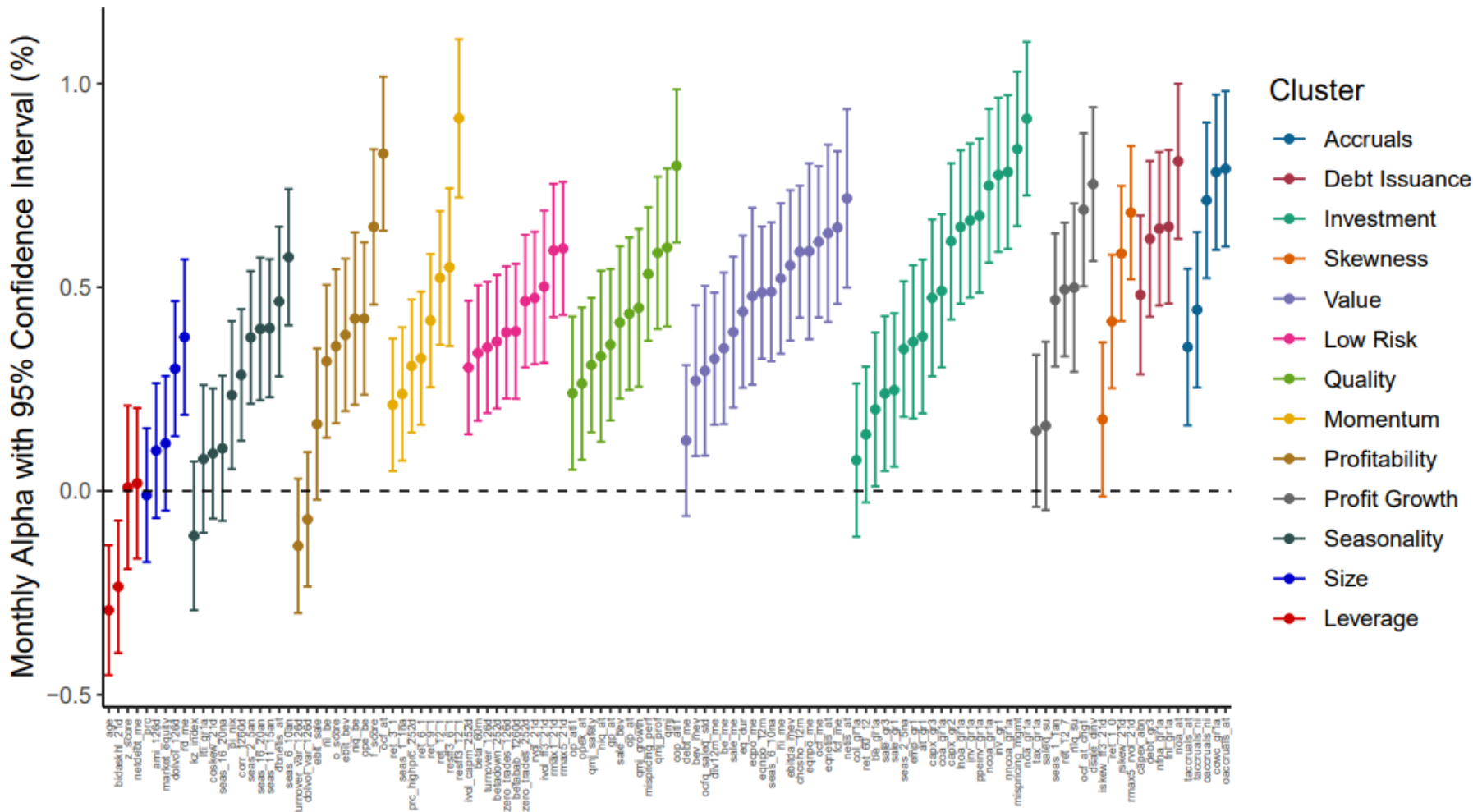
Book-to-Mkt: sequentially to have more characteristics available.

Model Assumptions?

- Doing PCA on characteristics
 - ◆ more discussions on the types of missing?
 - ☞ missing at random
 - ☞ missing completely at random
 - ◆ simple:
 - ☞ given firm, it can miss 50% of the data?
 - ☞ Given characteristic, 75% of firm should not miss?
- The impact of different missing
 - ◆ Errors in identifying K?
 - ◆ Errors in estimating the eigenvalues/vectors?

Interpretation of PCs?

- Given, say, 10 PCs:
 - ◆ What are the economic interpretations ?
 - ☞ data-driven grouping
 - ◆



Source: Jensen, Kelly, and Pedersen (2021, Is There a Replication Crisis in Finance?).

Interpretation of PCs?

- Given, say, 10 PCs:
 - ◆ What are the economic interpretation?
 - ☞ data-driven grouping
 - ◆ Which one is the most important? The least?
- If hard to explain, sparse PCA?
 - ◆ Pelger and Xiong (2021)
 - ◆ Rapach and Zhou (2021)
 - ☞ Get interpretable macro factors
 - Each PC is a combination of a few highly related macros
 - ☞ The factors are competitive to Fama-French factors!

s-PCA

PCA on:

$$\hat{\Sigma}_t^{XS} = \frac{1}{|Q_{i,j}^t|} \sum_{l \in Q_{i,j}^t} C_l^t C_l^{t\top},$$

PCA+
LASSO

$$\max_{\mathbf{u}_1, \mathbf{v}_1} \mathbf{u}_1' \mathbf{X} \mathbf{v}_1 \quad \text{subject to } \|\mathbf{u}_1\|_2^2 = 1, \|\mathbf{v}_1\|_2^2 = 1, \|\mathbf{v}_1\|_1 \leq c,$$

Q: 1st PC about trading friction characteristics?

Source: Witten, D. M., R. Tibshirani, and T. Hastie (2009), A Penalized Matrix Decomposition, with Applications to Sparse Principal Components and Canonical Correlation Analysis. *Biostatistics* 10, 515–534.

WTH exploit the biconvexity to develop an efficient iterative algorithm.

Asset Pricing Implications

- Given K characteristic factors,
 - ◆ do they contain all the info of the characteristic to price all stocks?
 - ◆ only K categories of anomalies?
 - ◆ is the largest risk of characteristics carry the most risk premium?
 - ◆ which imputation method does the best in explaining the expected returns?
 - ◆ the Sharpe ratio?

Timely Forecasts?

- In cross-section forecasting, one often lags the characteristics a few months.
- No longer necessary!
 - ◆ if missing only a small amount, why “throw out the baby with the bath water”?
 - ☞ more **timely** info should be more valuable.
 - ◆ if in doubt, impute them. How will this affect the results?

A Paper to cite ?

- Liu, Tang and Zhou (2022, JFE, forth)
 - ◆ “Recovering the FOMC Risk Premium”
- Anything in common ?
 - ◆ missing data
 - ◆ options with expiration right after the FOMC
 - ◆ early years unavailable options
 - ☞ matrix completion via implied volatility surface
- Why cite ?
 - ◆ missing data problem too in option pricing
 - ◆ an alternative solution to a different problem
 - ◆ that paper does cite this one (in the last minute; good to inform readers on general approaches dealing with missing data).

Overall

- Thought provoking paper !
- Impressive results !
- Wide applications !
 - ◆ Bonds, FXs, mutual funds, etc.
 - ◆ Corporate, Accounting