Fundamental Anomalies

Erica X.N. Li, Guoliang Ma, Shujing Wang, and Cindy Yu

Discussant: **Andrei S. Gonçalves**

2021 UConn Finance Conference

Outline

The Paper

My Comments

Final Remarks

$\mathbb{E}[R]$ from Firm's Perspective

- Firm's Net Present Value (NPV) Rule:

q-theory formalizes this logic and implies: $\boxed{R^S = R^F}$

$\mathbb{E}[R]$ from Firm's Perspective

- Firm's Net Present Value (NPV) Rule:

$$
\begin{aligned}
\text{NPV} &= \text{Inv } \partial\text{Benefit} - \text{Inv } \partial\text{Cost} \\
&= \widehat{CF}(I)/(1+WACC) - Cost(I) \\
0 &= \mathbb{E}[CF(I^*)]/\mathbb{E}[R] - Cost(I^*) \\
&\Downarrow \\
\mathbb{E}[R] &= \mathbb{E}[CF(I^*)]\ /\ Cost(I^*)
\end{aligned}
$$

q-theory formalizes this logic and implies: $\boxed{R^S = R^F}$

$\mathbb{E}[R]$ from Firm's Perspective

- Firm's Net Present Value (NPV) Rule:

$$\text{NPV} = \text{Inv } \partial\text{Benefit} - \text{Inv } \partial\text{Cost}$$

$$= \widehat{CF}(I)/(1+WACC) - Cost(I)$$

$$0 = \mathbb{E}[CF(I^*)]/\mathbb{E}[R] - Cost(I^*)$$

$$\Downarrow$$

$$\mathbb{E}[R] = \mathbb{E}[CF(I^*)] \,/\, Cost(I^*)$$

q-theory formalizes this logic and implies: $\boxed{R^S = R^F}$

$\mathbb{E}[R]$ from Firm's Perspective

- Firm's Net Present Value (NPV) Rule:

$$
\begin{aligned}
\text{NPV} &= \text{Inv } \partial\text{Benefit} && - \quad \text{Inv } \partial\text{Cost} \\
&= \widehat{CF}(I)/(1+WACC) && - \quad Cost(I) \\
0 &= \mathbb{E}[CF(I^*)]/\mathbb{E}[R] && - \quad Cost(I^*) \\
&\Downarrow \\
\mathbb{E}[R] &= \mathbb{E}[CF(I^*)] \,/\, Cost(I^*)
\end{aligned}
$$

q-theory formalizes this logic and implies: $\boxed{R^S = R^F}$

$\mathbb{E}[R]$ from Firm's Perspective

- Firm's Net Present Value (NPV) Rule:

$$\begin{aligned}
\text{NPV} &= \text{Inv } \partial\text{Benefit} - \text{Inv } \partial\text{Cost} \\
&= \widehat{CF}(I)/(1+WACC) - Cost(I) \\
0 &= \mathbb{E}[CF(I^*)]/\mathbb{E}[R] - Cost(I^*)
\end{aligned}$$

$$\Downarrow$$

$$\mathbb{E}[R] = \mathbb{E}[CF(I^*)] \,/\, Cost(I^*)$$

q-theory formalizes this logic and implies: $R^S = R^F$

$\mathbb{E}[R]$ from Firm's Perspective

- Firm's Net Present Value (NPV) Rule:

$$
\begin{aligned}
\text{NPV} &= \text{Inv } \partial\text{Benefit} &&- \text{Inv } \partial\text{Cost} \\
&= \widehat{CF}(I)/(1+WACC) &&- Cost(I) \\
0 &= \mathbb{E}[CF(I^*)]/\mathbb{E}[R] &&- Cost(I^*) \\
&\Downarrow \\
\mathbb{E}[R] &= \mathbb{E}[CF(I^*)] \;/\; Cost(I^*)
\end{aligned}
$$

q-theory formalizes this logic and implies: $R^S = R^F$

$\mathbb{E}[R]$ from Firm's Perspective

- Firm's Net Present Value (NPV) Rule:

$$
\begin{aligned}
\text{NPV} &= \text{Inv } \partial\text{Benefit} &&- \text{Inv } \partial\text{Cost} \\
&= \widehat{CF}(I)/(1+WACC) &&- Cost(I) \\
0 &= \mathbb{E}[CF(I^*)]/\mathbb{E}[R] &&- Cost(I^*) \\
&\Downarrow \\
\mathbb{E}[R] &= \mathbb{E}[CF(I^*)] \;/\; Cost(I^*)
\end{aligned}
$$

q-theory formalizes this logic and implies: $\boxed{R^S = R^F}$

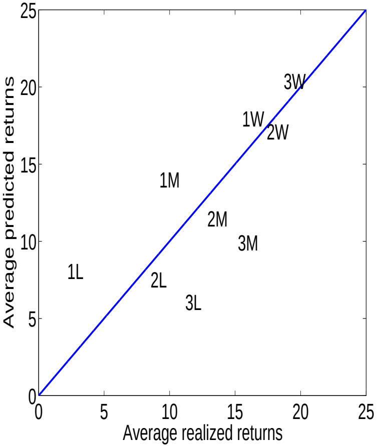
The Empirical Challenge of $\mathbb{E}[R^S] = \mathbb{E}[R^F]$

The Empirical Challenge of $\mathbb{E}[R^S] = \mathbb{E}[R^F]$

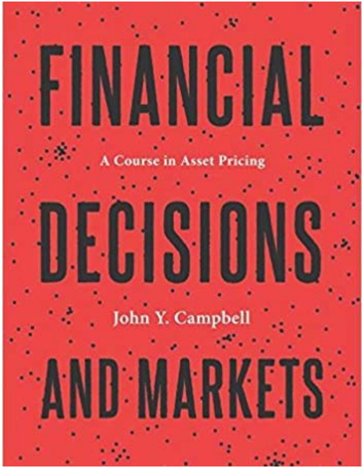
	SUE	B/M	CI
	Matching Expected Returns		
a	7.7	22.3	1.0
	[1.7]	[25.5]	[.3]
α	.3	.5	.2
	[.0]	[.3]	[.0]

The Empirical Challenge of $\mathbb{E}[R^S] = \mathbb{E}[R^F]$

	SUE	B/M	CI
Matching Expected Returns			
a	7.7	22.3	1.0
	[1.7]	[25.5]	[.3]
α	.3	.5	.2
	[.0]	[.3]	[.0]



Campbell (2017): The Empirical Challenge Matters



"This problem, that different parameters are needed to fit each anomaly, is a pervasive one in the q-theoretic asset pricing literature (p. 275)."

Gonçalves, Xue, and Zhang (2020, RFS)

$$r_p^F = r^F \left(r_p^{Ba} \, ; \, w_p^B \, ; \, \frac{I_p}{K_p} \, ; \, \frac{Y_p}{K_p} \, ; \, \delta_p \right)$$

$$r_p^F = \sum_{i=1}^{N_p} w_{ip} \times r^F \left(r_i^{Ba} \, ; \, w_i^B \, ; \, \frac{I_i}{K_i} \, ; \, \frac{I_i}{K_i} \, ; \, \frac{Y_i}{K_i + W_i} \, ; \, \frac{K_i}{K_i + W_i} \, ; \, \delta_i \right)$$

Gonçalves, Xue, and Zhang (2020, RFS)

$$r_p^F = r^F\left(r_p^{Ba};\, w_p^B;\, \frac{I_p}{K_p};\, \frac{Y_p}{K_p};\, \delta_p\right)$$

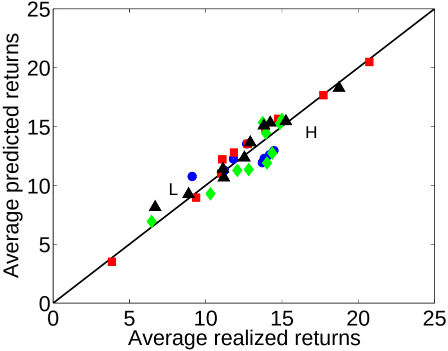
$$r_p^F = \sum_{i=1}^{N_p} w_{ip} \times r^F\left(r_i^{Ba};\, w_i^B;\, \frac{I_i}{K_i};\, \frac{I_i}{K_i};\, \frac{Y_i}{K_i + W_i};\, \frac{K_i}{K_i + W_i};\, \delta_i\right)$$

Gonçalves, Xue, and Zhang (2020, RFS)

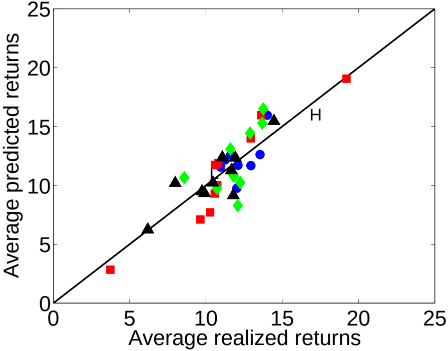
$$r_p^F = r^F\left(r_p^{Ba};\ w_p^B;\ \frac{I_p}{K_p};\ \frac{Y_p}{K_p};\ \delta_p\right)$$

$$r_p^F = \sum_{i=1}^{N_p} w_{ip} \times r^F\left(r_i^{Ba};\ w_i^B;\ \frac{I_i}{K_i};\ \frac{I_i}{K_i};\ \frac{Y_i}{K_i + W_i};\ \frac{K_i}{K_i + W_i};\ \delta_i\right)$$

Equal-Weighted Portfolios



Value-Weighted Portfolios



This Paper

$$r_i^F = r^F\left(r_i^{Ba}; w_i^B; \frac{I_i}{K_i}; \frac{I_i}{K_i}; \frac{Y_i}{K_i+W_i}; \frac{K_i}{K_i+W_i}; \delta_i\right)$$

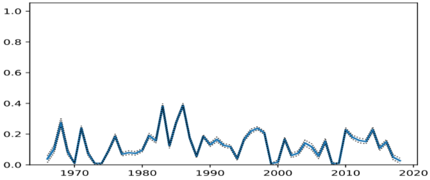
This Paper

$$r_i^F = r^F\left(r_i^{Ba}\,;\,w_i^B\,;\,\frac{I_i}{K_i}\,;\,\frac{I_i}{K_i}\,;\,\frac{Y_i}{K_i+W_i}\,;\,\frac{K_i}{K_i+W_i}\,;\,\delta_i\right)$$

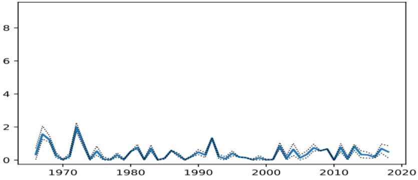
This Paper

$$r_i^F = r^F\left(r_i^{Ba}\,;\,w_i^B\,;\,\frac{I_i}{K_i}\,;\,\frac{I_i}{K_i}\,;\,\frac{Y_i}{K_i+W_i}\,;\,\frac{K_i}{K_i+W_i}\,;\,\delta_i\right)$$

Consumer Nondurables: γ



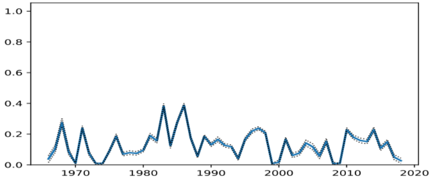
Consumer Nondurables: a



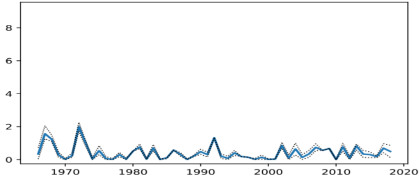
This Paper

$$r_i^F = r^F \left(r_i^{Ba} \, ; \, w_i^B \, ; \, \frac{I_i}{K_i} \, ; \, \frac{I_i}{K_i} \, ; \, \frac{Y_i}{K_i + W_i} \, ; \, \frac{K_i}{K_i + W_i} \, ; \, \delta_i \right)$$

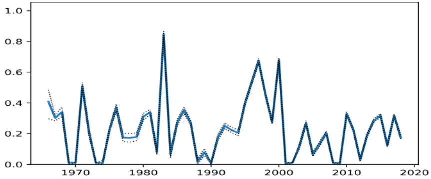
Consumer Nondurables: γ



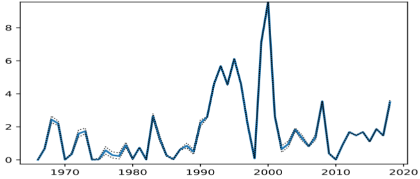
Consumer Nondurables: a



Business Equipment: γ



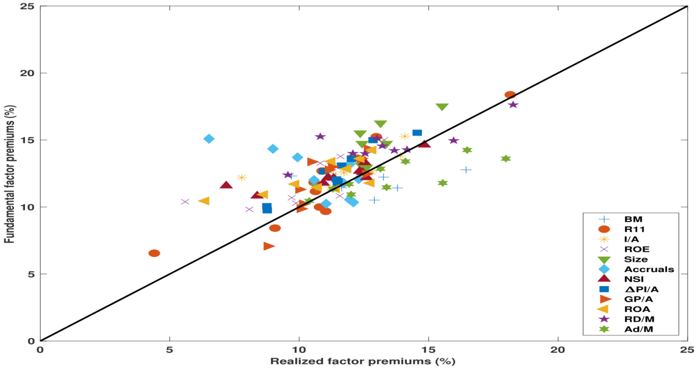
Business Equipment: a



This Paper

$$r_i^F = r^F \left(r_i^{Ba} ; w_i^B ; \frac{I_i}{K_i} ; \frac{I_i}{K_i} ; \frac{Y_i}{K_i + W_i} ; \frac{K_i}{K_i + W_i} ; \delta_i \right)$$

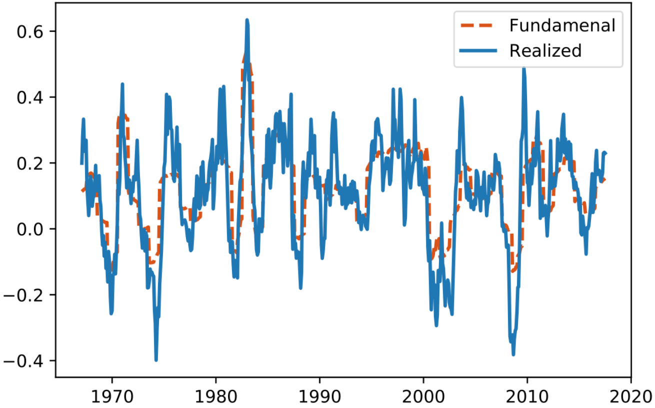
$\mathbb{E}[r]$ for 12 Anomalies



This Paper

$$r_i^F = r^F\left(r_i^{Ba}\,;\, w_i^B\,;\, \frac{I_i}{K_i}\,;\, \frac{I_i}{K_i}\,;\, \frac{Y_i}{K_i+W_i}\,;\, \frac{K_i}{K_i+W_i}\,;\, \delta_i\right)$$

Aggregate Returns



Outline

The Paper

My Comments

Final Remarks

1) Compare Bayesian and Frequentist Methods

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad with \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- $r^F_{it} = r^F(Data\,;\, \theta_{jt})$ and $\varpi_{it} = V_{it} / \sum_{i=1}^{N_{jt}} V_{it}$

- Paper explores the effect of j and t, but not of the Bayesian framework

- You can estimate θ_{jt} at each t and for each j (by NLS)

- How much does the fit improve as you change from the Frequentist (NLS) to the Bayesian (MCMC) framework?

1) Compare Bayesian and Frequentist Methods

$$r^S_{it+1} \;=\; r^F_{it+1} \;+\; \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad\qquad \textit{with} \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- $r^F_{it} = r^F(Data\,;\,\theta_{jt})$ and $\varpi_{it} = V_{it}/\Sigma_{i=1}^{N_{jt}} V_{it}$
- Paper explores the effect of j and t, but not of the Bayesian framework
- You can estimate θ_{jt} at each t and for each j (by NLS)
- How much does the fit improve as you change from the Frequentist (NLS) to the Bayesian (MCMC) framework?

1) Compare Bayesian and Frequentist Methods

$$r^{S}_{it+1} = r^{F}_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^{r}_{it+1} \qquad \textit{with} \ \ e^{r}_{it} \overset{iid}{\sim} N(0,1)$$

- $r^F_{it} = r^F(Data\,;\,\theta_{jt})$ and $\varpi_{it} = V_{it}/\Sigma_{i=1}^{N_{jt}} V_{it}$
- Paper explores the effect of j and t, but not of the Bayesian framework
- You can estimate θ_{jt} at each t and for each j (by NLS)
- How much does the fit improve as you change from the Frequentist (NLS) to the Bayesian (MCMC) framework?

1) Compare Bayesian and Frequentist Methods

$$r^S_{it+1} \; = \; r^F_{it+1} \; + \; \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad \textit{with} \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- $r^F_{it} = r^F(Data\,;\,\theta_{jt})$ and $\varpi_{it} = V_{it}/\Sigma_{i=1}^{N_{jt}} V_{it}$
- Paper explores the effect of j and t, but not of the Bayesian framework
- You can estimate θ_{jt} at each t and for each j (by NLS)
- How much does the fit improve as you change from the Frequentist (NLS) to the Bayesian (MCMC) framework?

1) Compare Bayesian and Frequentist Methods

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad \textit{with} \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- $r^F_{it} = r^F(Data\,;\,\theta_{jt})$ and $\varpi_{it} = V_{it}/\Sigma_{i=1}^{N_{jt}} V_{it}$
- Paper explores the effect of j and t, but not of the Bayesian framework
- You can estimate θ_{jt} at each t and for each j (by NLS)
- How much does the fit improve as you change from the Frequentist (NLS) to the Bayesian (MCMC) framework?

2) Check if Variation in γ_{jt} and a_{jt} is Economically Sensible

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad \textit{with} \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Variation in γ_{jt}
- (ii) Variation in a_{jt}

2) Check if Variation in γ_{jt} and a_{jt} is Economically Sensible

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad with \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Variation in γ_{jt}
  - $\Pi_{it} = \gamma \cdot Y_{it}$ (Gonçalves, Xue, and Zhang (2020))
  - Is variation in γ_{jt} in line with variation in Π_{jt}/Y_{jt}?
  - Gross profits (Sales - COGS) provides a rough estimate for Π_{jt}
- (ii) Variation in a_{jt}

2) Check if Variation in γ_{jt} and a_{jt} is Economically Sensible

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad \textit{with} \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Variation in γ_{jt}
  - $\Pi_{it} = \gamma \cdot Y_{it}$ (Gonçalves, Xue, and Zhang (2020))
  - Is variation in γ_{jt} in line with variation in Π_{jt}/Y_{jt}?
  - Gross profits (Sales - COGS) provides a rough estimate for Π_{jt}
- (ii) Variation in a_{jt}

2) Check if Variation in γ_{jt} and a_{jt} is Economically Sensible

$$r^{S}_{it+1} = r^{F}_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^{r}_{it+1} \qquad \textit{with} \;\; e^{r}_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Variation in γ_{jt}
  - $\Pi_{it} = \gamma \cdot Y_{it}$ (Gonçalves, Xue, and Zhang (2020))
  - Is variation in γ_{jt} in line with variation in Π_{jt}/Y_{jt}?
  - Gross profits (Sales - COGS) provides a rough estimate for Π_{jt}
- (ii) Variation in a_{jt}

2) Check if Variation in γ_{jt} and a_{jt} is Economically Sensible

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad \textit{with} \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Variation in γ_{jt}
  - $\Pi_{it} = \gamma \cdot Y_{it}$ (Gonçalves, Xue, and Zhang (2020))
  - Is variation in γ_{jt} in line with variation in Π_{jt}/Y_{jt}?
  - Gross profits (Sales - COGS) provides a rough estimate for Π_{jt}
- (ii) Variation in a_{jt}

2) Check if Variation in γ_{jt} and a_{jt} is Economically Sensible

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad with \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Variation in γ_{jt}
  - $\Pi_{it} = \gamma \cdot Y_{it}$ (Gonçalves, Xue, and Zhang (2020))
  - Is variation in γ_{jt} in line with variation in Π_{jt}/Y_{jt}?
  - Gross profits (Sales - COGS) provides a rough estimate for Π_{jt}
- (ii) Variation in a_{jt}
  - $(V_{it} + B_{it+1})/K_{it} = Q_{it} = (1 + a_{jt} \cdot (1 - \tau_t) \cdot I_{it}/K_{it}) + W_{it}/K_{it}$
  - Is variation in a_{jt} in line with variation in Q_{jt}?
  - Is variation in a_{jt} in line with the sensitivity of Q_{it} to I_{it}/K_{it}?

2) Check if Variation in γ_{jt} and a_{jt} is Economically Sensible

$$r^{S}_{it+1} = r^{F}_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^{r}_{it+1} \qquad \textit{with} \;\; e^{r}_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Variation in γ_{jt}
  - $\Pi_{it} = \gamma \cdot Y_{it}$ (Gonçalves, Xue, and Zhang (2020))
  - Is variation in γ_{jt} in line with variation in Π_{jt}/Y_{jt}?
  - Gross profits (Sales - COGS) provides a rough estimate for Π_{jt}
- (ii) Variation in a_{jt}
  - $(V_{it} + B_{it+1})/K_{it} = Q_{it} = (1 + a_{jt} \cdot (1 - \tau_t) \cdot I_{it}/K_{it}) + W_{it}/K_{it}$
  - Is variation in a_{jt} in line with variation in Q_{jt}?
  - Is variation in a_{jt} in line with the sensitivity of Q_{it} to I_{it}/K_{it}?

2) Check if Variation in γ_{jt} and a_{jt} is Economically Sensible

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad \textit{with } e^r_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Variation in γ_{jt}
  - $\Pi_{it} = \gamma \cdot Y_{it}$ (Gonçalves, Xue, and Zhang (2020))
  - Is variation in γ_{jt} in line with variation in Π_{jt}/Y_{jt}?
  - Gross profits (Sales - COGS) provides a rough estimate for Π_{jt}
- (ii) Variation in a_{jt}
  - $(V_{it} + B_{it+1})/K_{it} = Q_{it} = (1 + a_{jt} \cdot (1 - \tau_t) \cdot I_{it}/K_{it}) + W_{it}/K_{it}$
  - Is variation in a_{jt} in line with variation in Q_{jt}?
  - Is variation in a_{jt} in line with the sensitivity of Q_{it} to I_{it}/K_{it}?

2) Check if Variation in γ_{jt} and a_{jt} is Economically Sensible

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad \textit{with } e^r_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Variation in γ_{jt}
  - $\Pi_{it} = \gamma \cdot Y_{it}$ (Gonçalves, Xue, and Zhang (2020))
  - Is variation in γ_{jt} in line with variation in Π_{jt}/Y_{jt}?
  - Gross profits (Sales - COGS) provides a rough estimate for Π_{jt}
- (ii) Variation in a_{jt}
  - $(V_{it} + B_{it+1})/K_{it} = Q_{it} = (1 + a_{jt} \cdot (1 - \tau_t) \cdot I_{it}/K_{it}) + W_{it}/K_{it}$
  - Is variation in a_{jt} in line with variation in Q_{jt}?
  - Is variation in a_{jt} in line with the sensitivity of Q_{it} to I_{it}/K_{it}?

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad with\ \ e_{it}^r \overset{iid}{\sim} N(0,1)$$

- Impossible to perfectly align r_{it}^S and r_{it}^F
- Not relevant for prior papers as they rely on (portfolio) $\mathbb{E}[r]$
- Very relevant for this paper
- Overfitting: time-varying θ_{jt} compensates for misalignment
- This is why the specification with θ_j performs better OOS

3) Deal with Misalignment Between r_{it}^{S} and r_{it}^{F}

$$r_{it+1}^{S} = r_{it+1}^{F} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^{r} \qquad \textit{with } e_{it}^{r} \overset{iid}{\sim} N(0,1)$$

- Impossible to perfectly align r_{it}^{S} and r_{it}^{F}
- Not relevant for prior papers as they rely on (portfolio) $\mathbb{E}[r]$
- Very relevant for this paper
- Overfitting: time-varying θ_{jt} compensates for misalignment
- This is why the specification with θ_j performs better OOS

3) Deal with Misalignment Between r^S_{it} and r^F_{it}

$$r^S_{it+1} = r^F_{it+1} + {\varpi_{it}}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad \textit{with} \;\; e^r_{it} \overset{iid}{\sim} N(0,1)$$

- Impossible to perfectly align r^S_{it} and r^F_{it}
- Not relevant for prior papers as they rely on (portfolio) $\mathbb{E}[r]$
- Very relevant for this paper
- Overfitting: time-varying θ_{jt} compensates for misalignment
- This is why the specification with θ_j performs better OOS

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \text{with } e_{it}^r \overset{iid}{\sim} N(0,1)$$

- Impossible to perfectly align r_{it}^S and r_{it}^F
- Not relevant for prior papers as they rely on (portfolio) $\mathbb{E}[r]$
- Very relevant for this paper
- Overfitting: time-varying θ_{jt} compensates for misalignment
- This is why the specification with θ_j performs better OOS

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \text{with } e_{it}^r \overset{iid}{\sim} N(0,1)$$

- Impossible to perfectly align r_{it}^S and r_{it}^F
- Not relevant for prior papers as they rely on (portfolio) $\mathbb{E}[r]$
- Very relevant for this paper
- Overfitting: time-varying θ_{jt} compensates for misalignment
- This is why the specification with θ_j performs better OOS

3) Deal with Misalignment Between r_{it}^{S} and r_{it}^{F}

$$r_{it+1}^{S} = r_{it+1}^{F} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^{r} \qquad \textit{with} \;\; e_{it}^{r} \overset{iid}{\sim} N(0,1)$$

- Impossible to perfectly align r_{it}^{S} and r_{it}^{F}
- Not relevant for prior papers as they rely on (portfolio) $\mathbb{E}[r]$
- Very relevant for this paper
- Overfitting: time-varying θ_{jt} compensates for misalignment
- This is why the specification with θ_j performs better OOS

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \text{with } e_{it}^r \overset{iid}{\sim} N(0,1)$$

- (i) Autocorrelation "Solution"
  - Misalignment generates autocorrelation in observed $r_{it}^S - r_{it}^F$
  - $e_{it}^r \overset{iid}{\sim} N(0,1)$ forces θ_{jt} to be artificially autocorrelated
  - Solution: allow for autocorrelation in e_{it}^r
- (ii) Return Unsmoothing "Solution":

3) Deal with Misalignment Between r^S_{it} and r^F_{it}

$$r^S_{it+1} = r^F_{it+1} + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e^r_{it+1} \qquad \text{with } e^r_{it} \overset{iid}{\sim} N(0,1)$$

- (i) Autocorrelation "Solution"
  - Misalignment generates autocorrelation in observed $r^S_{it} - r^F_{it}$
  - $e^r_{it} \overset{iid}{\sim} N(0,1)$ forces θ_{jt} to be artificially autocorrelated
  - Solution: allow for autocorrelation in e^r_{it}
- (ii) Return Unsmoothing "Solution":

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \textit{with} \;\; e_{it}^r \overset{iid}{\sim} N(0,1)$$

- (i) Autocorrelation “Solution”
  - Misalignment generates autocorrelation in observed $r_{it}^S - r_{it}^F$
  - $e_{it}^r \overset{iid}{\sim} N(0,1)$ forces θ_{jt} to be artificially autocorrelated
  - Solution: allow for autocorrelation in e_{it}^r
- (ii) Return Unsmoothing “Solution”:

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \textit{with } e_{it}^r \overset{iid}{\sim} N(0,1)$$

- (i) Autocorrelation "Solution"
  - Misalignment generates autocorrelation in observed $r_{it}^S - r_{it}^F$
  - $e_{it}^r \overset{iid}{\sim} N(0,1)$ forces θ_{jt} to be artificially autocorrelated
  - Solution: allow for autocorrelation in e_{it}^r
- (ii) Return Unsmoothing "Solution":

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \text{with } e_{it}^r \overset{iid}{\sim} N(0,1)$$

- (i) Autocorrelation "Solution"
  - Misalignment generates autocorrelation in observed $r_{it}^S - r_{it}^F$
  - $e_{it}^r \overset{iid}{\sim} N(0,1)$ forces θ_{jt} to be artificially autocorrelated
  - Solution: allow for autocorrelation in e_{it}^r
- (ii) Return Unsmoothing "Solution":
  - Couts, Gonçalves, and Rossi (2020)
  - Observed r_{it}^F is a Moving Average of true r_{it}^F
  - MA parameters assure $r_{it}^S - r_{it}^F$ is uncorrelated
  - Recover r_{it}^F and use $r_{it+1}^S = r_{it}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r$

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \textit{with} \;\; e_{it}^r \overset{iid}{\sim} N(0,1)$$

- (i) Autocorrelation "Solution"
  - Misalignment generates autocorrelation in observed $r_{it}^S - r_{it}^F$
  - $e_{it}^r \overset{iid}{\sim} N(0,1)$ forces θ_{jt} to be artificially autocorrelated
  - Solution: allow for autocorrelation in e_{it}^r
- (ii) Return Unsmoothing "Solution":
  - Couts, Gonçalves, and Rossi (2020)
  - Observed r_{it}^F is a Moving Average of true r_{it}^F
  - MA parameters assure $r_{it}^S - r_{it}^F$ is uncorrelated
  - Recover r_{it}^F and use $r_{it+1}^S = r_{it}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r$

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \textit{with } e_{it}^r \overset{iid}{\sim} N(0,1)$$

- (i) Autocorrelation "Solution"
  - Misalignment generates autocorrelation in observed $r_{it}^S - r_{it}^F$
  - $e_{it}^r \overset{iid}{\sim} N(0,1)$ forces θ_{jt} to be artificially autocorrelated
  - Solution: allow for autocorrelation in e_{it}^r
- (ii) Return Unsmoothing "Solution":
  - Couts, Gonçalves, and Rossi (2020)
  - Observed r_{it}^F is a Moving Average of true r_{it}^F
  - MA parameters assure $r_{it}^S - r_{it}^F$ is uncorrelated
  - Recover r_{it}^F and use $r_{it+1}^S = r_{it}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r$

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \textit{with } e_{it}^r \overset{iid}{\sim} N(0,1)$$

- (i) Autocorrelation "Solution"
  - Misalignment generates autocorrelation in observed $r_{it}^S - r_{it}^F$
  - $e_{it}^r \overset{iid}{\sim} N(0,1)$ forces θ_{jt} to be artificially autocorrelated
  - Solution: allow for autocorrelation in e_{it}^r
- (ii) Return Unsmoothing "Solution":
  - Couts, Gonçalves, and Rossi (2020)
  - Observed r_{it}^F is a Moving Average of true r_{it}^F
  - MA parameters assure $r_{it}^S - r_{it}^F$ is uncorrelated
  - Recover r_{it}^F and use $r_{it+1}^S = r_{it}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r$

3) Deal with Misalignment Between r_{it}^S and r_{it}^F

$$r_{it+1}^S = r_{it+1}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r \qquad \textit{with} \;\; e_{it}^r \overset{iid}{\sim} N(0,1)$$

- (i) Autocorrelation "Solution"
  - Misalignment generates autocorrelation in observed $r_{it}^S - r_{it}^F$
  - $e_{it}^r \overset{iid}{\sim} N(0,1)$ forces θ_{jt} to be artificially autocorrelated
  - Solution: allow for autocorrelation in e_{it}^r
- (ii) Return Unsmoothing "Solution":
  - Couts, Gonçalves, and Rossi (2020)
  - Observed r_{it}^F is a Moving Average of true r_{it}^F
  - MA parameters assure $r_{it}^S - r_{it}^F$ is uncorrelated
  - Recover r_{it}^F and use $r_{it+1}^S = r_{it}^F + \varpi_{it}^{-1/2} \cdot \sigma_r \cdot e_{it+1}^r$

4) Miscellaneous Comments

- γ_{jt} and a_{jt} are random walks, but look mean reverting
- In section 5.5 (Equation 10), I suggest you also explore:

$$d^a = \frac{1}{N} \sum_{i=1}^{N} |\bar{r}_i^S - \bar{r}_i^{F(a)}| - |\bar{r}_i^S - \bar{r}_i^{F(b)}|$$

- Value premium decline (e.g., Gonçalves and Leonard (2021)):

4) Miscellaneous Comments

- γ_{jt} and a_{jt} are random walks, but look mean reverting
- In section 5.5 (Equation 10), I suggest you also explore:

$$d^a = \frac{1}{N}\sum_{i=1}^{N} |\bar{r}_i^S - \bar{r}_i^{F(a)}| - |\bar{r}_i^S - \bar{r}_i^{F(b)}|$$

- Value premium decline (e.g., Gonçalves and Leonard (2021)):

4) Miscellaneous Comments

- γ_{jt} and a_{jt} are random walks, but look mean reverting
- In section 5.5 (Equation 10), I suggest you also explore:

$$d^a = \frac{1}{N}\sum_{i=1}^{N} |\overline{r}_i^S - \overline{r}_i^{F(a)}| - |\overline{r}_i^S - \overline{r}_i^{F(b)}|$$

- Value premium decline (e.g., Gonçalves and Leonard (2021)):

4) Miscellaneous Comments

- γ_{jt} and a_{jt} are random walks, but look mean reverting
- In section 5.5 (Equation 10), I suggest you also explore:

$$d^a = \frac{1}{N}\sum_{i=1}^{N} |\bar{r}_i^S - \bar{r}_i^{F(a)}| - |\bar{r}_i^S - \bar{r}_i^{F(b)}|$$

- Value premium decline (e.g., Gonçalves and Leonard (2021)):
  - The r_t^F value premium declines by 5.3%
  - In line with the data (e.g., FF data implies 4.8% decline)
  - But the r_t^S value premium declines by less than 1% in your data
  - Why so much lower than prior papers?

4) Miscellaneous Comments

- γ_{jt} and a_{jt} are random walks, but look mean reverting
- In section 5.5 (Equation 10), I suggest you also explore:

$$d^a = \frac{1}{N}\sum_{i=1}^{N} |\overline{r}_i^S - \overline{r}_i^{F(a)}| - |\overline{r}_i^S - \overline{r}_i^{F(b)}|$$

- Value premium decline (e.g., Gonçalves and Leonard (2021)):
  - The r_t^F value premium declines by 5.3%
  - In line with the data (e.g., FF data implies 4.8% decline)
  - But the r_t^S value premium declines by less than 1% in your data
  - Why so much lower than prior papers?

4) Miscellaneous Comments

- γ_{jt} and a_{jt} are random walks, but look mean reverting
- In section 5.5 (Equation 10), I suggest you also explore:

$$d^a = \frac{1}{N}\sum_{i=1}^{N} |\overline{r}_i^S - \overline{r}_i^{F(a)}| - |\overline{r}_i^S - \overline{r}_i^{F(b)}|$$

- Value premium decline (e.g., Gonçalves and Leonard (2021)):
  - The r_t^F value premium declines by 5.3%
  - In line with the data (e.g., FF data implies 4.8% decline)
  - But the r_t^S value premium declines by less than 1% in your data
  - Why so much lower than prior papers?

4) Miscellaneous Comments

- γ_{jt} and a_{jt} are random walks, but look mean reverting
- In section 5.5 (Equation 10), I suggest you also explore:

$$d^{a} = \frac{1}{N}\sum_{i=1}^{N} |\bar{r}_i^{S} - \bar{r}_i^{F(a)}| - |\bar{r}_i^{S} - \bar{r}_i^{F(b)}|$$

- Value premium decline (e.g., Gonçalves and Leonard (2021)):
  - The r_t^F value premium declines by 5.3%
  - In line with the data (e.g., FF data implies 4.8% decline)
  - But the r_t^S value premium declines by less than 1% in your data
  - Why so much lower than prior papers?

4) Miscellaneous Comments

- γ_{jt} and a_{jt} are random walks, but look mean reverting
- In section 5.5 (Equation 10), I suggest you also explore:

$$d^a = \frac{1}{N}\sum_{i=1}^{N} |\bar{r}_i^S - \bar{r}_i^{F(a)}| - |\bar{r}_i^S - \bar{r}_i^{F(b)}|$$

- Value premium decline (e.g., Gonçalves and Leonard (2021)):
  - The r_t^F value premium declines by 5.3%
  - In line with the data (e.g., FF data implies 4.8% decline)
  - But the r_t^S value premium declines by less than 1% in your data
  - Why so much lower than prior papers?

Outline

The Paper

My Comments

Final Remarks

Final Remarks

- First paper to estimate $r_{it}^{S} = r_{it}^{F}$ at the firm level
- Strong response to the criticism that the investment model needs different parameter estimates for different anomalies
- Provides a methodological foundation for future work
- It would be useful to:
- Good luck!

Final Remarks

- First paper to estimate $r_{it}^S = r_{it}^F$ at the firm level
- Strong response to the criticism that the investment model needs different parameter estimates for different anomalies
- Provides a methodological foundation for future work
- It would be useful to:
- Good luck!

Final Remarks

- First paper to estimate $r_{it}^{S} = r_{it}^{F}$ at the firm level
- Strong response to the criticism that the investment model needs different parameter estimates for different anomalies
- Provides a methodological foundation for future work
- It would be useful to:
- Good luck!

Final Remarks

- First paper to estimate $r_{it}^{S} = r_{it}^{F}$ at the firm level
- Strong response to the criticism that the investment model needs different parameter estimates for different anomalies
- Provides a methodological foundation for future work
- It would be useful to:
  - Compare Bayesian and Frequentist methods
  - Show that variation in γ_{jt} and a_{jt} is economically sensible
  - Deal with misalignment between r_{it}^{S} and r_{it}^{F}
- Good luck!

Final Remarks

- First paper to estimate $r_{it}^{S} = r_{it}^{F}$ at the firm level
- Strong response to the criticism that the investment model needs different parameter estimates for different anomalies
- Provides a methodological foundation for future work
- It would be useful to:
  - Compare Bayesian and Frequentist methods
  - Show that variation in γ_{jt} and a_{jt} is economically sensible
  - Deal with misalignment between r_{it}^{S} and r_{it}^{F}
- Good luck!

Final Remarks

- First paper to estimate $r_{it}^{S} = r_{it}^{F}$ at the firm level
- Strong response to the criticism that the investment model needs different parameter estimates for different anomalies
- Provides a methodological foundation for future work
- It would be useful to:
  - Compare Bayesian and Frequentist methods
  - Show that variation in γ_{jt} and a_{jt} is economically sensible
  - Deal with misalignment between r_{it}^{S} and r_{it}^{F}
- Good luck!

Final Remarks

- First paper to estimate $r_{it}^{S} = r_{it}^{F}$ at the firm level
- Strong response to the criticism that the investment model needs different parameter estimates for different anomalies
- Provides a methodological foundation for future work
- It would be useful to:
  - Compare Bayesian and Frequentist methods
  - Show that variation in γ_{jt} and a_{jt} is economically sensible
  - Deal with misalignment between r_{it}^{S} and r_{it}^{F}
- Good luck!

Final Remarks

- First paper to estimate $r_{it}^S = r_{it}^F$ at the firm level
- Strong response to the criticism that the investment model needs different parameter estimates for different anomalies
- Provides a methodological foundation for future work
- It would be useful to:
  - Compare Bayesian and Frequentist methods
  - Show that variation in γ_{jt} and a_{jt} is economically sensible
  - Deal with misalignment between r_{it}^S and r_{it}^F
- Good luck!