Publication Bias and the Cross-Section of Stock Returns

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Disclaimer: The views expressed herein are those of the author and do not necessarily reflect the position of the Board of Governors of the Federal Reserve or the Federal Reserve System
“The Lord of the p-value”
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The Cross-Sectional Asset Pricing Lit
“The Lord of the p-value”

p-hacking

• data-mining, data-snooping
• suspicion and ambition
• collective re-use of data

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Journal Review
- robustness tests
- theoretical motivations
- supporting results
- a scientific, ethical culture

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The Cross-Sectional Asset Pricing Lit

Our Question: Which Side is Winning?
This Paper: A Focused, Structured Estimate of Who’s Winning
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(1) Focus: replications of 172 published cross-sectional predictors

- Excludes non-predictive and aggregate factors in Harvey, Liu, Zhu 2016
- Excludes un-published predictors in Chordia, Goyal, Saretto 2017

Result: ▶ Journal review dominates. Nearly all predictors were real!!
- Consistent w/ McLean-Pontiff 2016, Jacobs-Müller 2016, Yan-Zheng 2017
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(2) **Structure:** estimated model of biased publication
   - Allows for **p-hacking** effects *and* journal review
   - Unlike Hou, Xue, Zhang’s 2017 informal approach
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Nearly all predictors were real!!

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Standard logic (Bonferroni, Benjamini-Hochberg 1995) – After looking at 172+ predictors, many in-sample returns will be large by pure chance ⇒ many predictors were fairy tales

Our more structured logic (James-Stein 1961, Efron-Morris 1973) – 172 predictors tell us about the nature of the publication process – They tell us that journal review dominates p-hacking ⇒ nearly all predictors were real.
Nearly all predictors were real!!

How can this be true??
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Replications of 172 Published Predictors
Data: Replications of 172 Published Predictors

(1) Replicate McLean and Pontiff’s (2016) 97 published cross-sectional predictors

(2) Replicate 75 additional variables that were
   – shown to predict cross-sectional returns
   – published in “top-tier” journals

Data available at sites.google.com/site/chenandrewy/
Distribution of Replicated t-stats

- Sharp left shoulder $\Rightarrow$ strongly suggestive of p-hacking
- But what explains the long right tail?
Sharp left shoulder ⇒ strongly suggestive of \textbf{p-hacking}

But what explains the long right tail? ⇒ \textbf{need model}
Model and Estimation
Motivating Story:

1. Anything that might be published is submitted to journals
   - Allows for p-hacking

2. Only portfolios with “narratives” are considered for publication
   - Allows for journal review: robustness tests, supporting results, ...

3. Only narratives with high t-stats are published
   - Another p-hacking effect
A Statistical Model of Publication 1/2

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⇒ statistical model of publication similar to Harvey, Liu, and Zhu’s (2016) model with correlations
Key equations

- If portfolio $i$ has a narrative,

  $$\mu_i \sim \text{scaled student's t with } \sigma_\mu, \nu_\mu$$

- dispersion of true returns $\sigma_\mu$ measures power of journal review
  - large $\sigma_\mu \Rightarrow$ narratives find variation in true returns
Key equations

- If portfolio $i$ has a narrative,

  \[
  \text{true return } \mu_i \sim \text{scaled student’s t with } \sigma_{\mu}, \nu_{\mu}
  \]

- dispersion of true returns $\sigma_{\mu}$ measures power of journal review
  - large $\sigma_{\mu} \Rightarrow$ narratives find variation in true returns

- In-sample returns are noisy and biased signals of $\mu_i$

  \[
  r_i = \mu_i + \epsilon_i
  \]
Maximum Likelihood Estimation

- Choose 7 parameters to maximize likelihood of replicated data
  - 172 in-sample returns and standard errors
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- Identification of $\sigma_\mu$ comes from dispersion of t-stats
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$$\sigma_\mu = 0.10$$

![Histogram of t-stats](chart.png)
Maximum Likelihood Estimation

- Choose 7 parameters to maximize likelihood of replicated data
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\[
\sigma_\mu = 0.10
\]

Log Like = -371.90
Maximum Likelihood Estimation

- Choose 7 parameters to maximize likelihood of replicated data
  - 172 in-sample returns and standard errors

- Identification of $\sigma_\mu$ comes from dispersion of t-stats

\[ \sigma_\mu = 0.10 \]
\[ \sigma_\mu = 0.20 \]

Log Like = -371.90
Log Like = -250.19

Data vs. Model for different values of $\sigma_\mu$.
Maximum Likelihood Estimation

- Choose 7 parameters to maximize likelihood of replicated data
  - 172 in-sample returns and standard errors
- Identification of $\sigma_\mu$ comes from dispersion of t-stats

- $\sigma_\mu = 0.10$
  - Log Like = -371.90
- $\sigma_\mu = 0.20$
  - Log Like = -250.19
- Estimated: $\hat{\sigma}_\mu = 0.45$
  - Log Like = -197.69
We focus on **Shrinkage** defined by

\[
[Bias-Adjusted \ Return]_i = (1 - \text{Shrinkage}_i)[\text{In-Sample \ Return}]_i
\]

- 100% Shrinkage ⇒ **p-hacking** dominates, bias-adjusted return = 0
- 0% Shrinkage ⇒ **journal review** works, bias-adjusted = in-sample
Bias Adjustment and Shrinkage

- We focus on **Shrinkage** defined by

  \[ ([\text{Bias-Adjusted Return}]_i = (1 - \text{Shrinkage}_i) [\text{In-Sample Return}]_i) \]

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- **Bayesian logic gives a shrinkage formula**
  (Dawid 1994, Senn 2008, Efron 2011, 2012)

  \[
  \text{Shrinkage}_i \approx \frac{[\text{Standard Error}]^2_i}{\hat{\sigma}^2_\mu + [\text{Standard Error}]^2_i}
  \]

  \[
  \hat{\sigma}^2_\mu = \text{Estimated Dispersion of True Returns}
  \]
Results
Main Result 1/2: Bias Adjustments are Modest
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\[ [\text{Bias-Adjusted Return}]_i = (1 - \text{Shrinkage}_i)[\text{In-Sample Return}]_i \]
Main Result 1/2: Bias Adjustments are Modest

\[ \text{[Bias-Adjusted Return]}_i = (1 - \text{Shrinkage}_i) \times \text{[In-Sample Return]}_i \]

\[\begin{array}{c}
\text{AbnAccr} \\
\text{BPEBM} \\
\text{ChForeca} \\
\text{ChInv} \\
\text{ChInvIA} \\
\text{ChNAAnaly} \\
\text{ChNCOA} \\
\text{ChNWC} \\
\text{ChPM} \\
\text{ChTax} \\
\text{Composit} \\
\text{ConvDebt} \\
\text{DebtIssu} \\
\text{DebBread} \\
\text{DeiCOA} \\
\text{DeiCOL} \\
\text{DeiFINL} \\
\text{DeiLTI} \\
\text{DivOmit} \\
\text{DownFore} \\
\text{EBM} \\
\text{EarnCons} \\
\text{EarnSurp} \\
\text{EntMulti} \\
\text{ExclExp} \\
\text{FirmAge} \\
\text{GrAdExp} \\
\text{GrLTNOA} \\
\text{GrSaleTo} \\
\text{Herf} \\
\text{IndRetBi} \\
\text{Investme} \\
\text{KZ} \\
\text{Mom1m} \\
\text{NOA} \\
\text{NetDebtF} \\
\text{NumEarnI} \\
\text{PriceDel} \\
\text{Profittab} \\
\text{RevenueS} \\
\text{ShareRep} \\
\text{UpForeca} \\
\text{gcapx} \\
\text{hire} \\
\text{invest} \\
\text{realesta} \\
\text{roaq} \\
\end{array}\]

\[\text{<-- 47 predictors (out of 172) have tiny shrinkage}\]
Main Result 1/2: Bias Adjustments are Modest

\[ \text{Bias-Adjusted Return}_{i} = (1 - \text{Shrinkage}_{i}) \times [\text{In-Sample Return}]_{i} \]
Main Result 1/2: Bias Adjustments are Modest

[Bias-Adjusted Return]_i = (1 − Shrinkage_i)[In-Sample Return]_i

--- 94 predictors (out of 172) have small shrinkage
Main Result 1/2: Bias Adjustments are Modest

$$[\text{Bias-Adjusted Return}]_i = (1 - \text{Shrinkage}_i)[\text{In-Sample Return}]_i$$
Main Result 1/2: Bias Adjustments are Modest

\[ \text{Bias-Adjusted Return} \, i = (1 - \text{Shrinkage}_i) \times \text{In-Sample Return}_i \]

The other half are skewed right, but nearly all are < 40%
Main Result 1/2: Bias Adjustments are Modest

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Main Result 1/2: Bias Adjustments are Modest

$$[\text{Bias-Adjusted Return}]_i = (1 - \text{Shrinkage}_i) [\text{In-Sample Return}]_i$$

| Count | Feature 1 | Feature 2 | Feature 3 | Feature 4 | Feature 5 | Feature 6 | Feature 7 | Feature 8 | Feature 9 | Feature 10 | Feature 11 | Feature 12 | Feature 13 | Feature 14 | Feature 15 | Feature 16 | Feature 17 | Feature 18 | Feature 19 |
|-------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|
| 50    | AbnAccr    | AOP        | Accruals   | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 45    | BPEBM      | Accruals   | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 40    | ChForeca   | AOP        | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 35    | ChInv      | AOP        | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 30    | ChInvIA    | AOP        | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 25    | ChNAH      | AOP        | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 20    | ChNCOA     | AOP        | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 15    | ChNWC      | AOP        | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 10    | ChPM       | AOP        | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 5     | ChTax      | AOP        | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |
| 0     | Composit   | AOP        | AdExp      | AnalystV   | AssetGro   | BetaTail   | ChAssetT   | ChEQ       | Changein   | CompEqul   | Coskownee  | DelEqu     | DivInd     | EarningsNcr | EarnSupB   | EarnCu     | EarnCu     | GrSaleTo   |

High volatility => high shrinkage
More noise => higher chance of p-hacking
Main Result 1/2: Bias Adjustments are Modest

\[ \text{Bias-Adjusted Return} \_{i} = (1 - \text{Shrinkage}_{i}) \times \text{In-Sample Return} \_{i} \]

But even IndIPO (48% shrinkage) has a good bias-adjusted return

\[
\text{bias-adjusted return} = 1.04 \times (1 - 0.48) = 0.54\% \text{ monthly}
\]
Main Result 1/2: Bias Adjustments are Modest

Bias-Adjusted Return \( i = (1 - \text{Shrinkage}_i) \times [\text{In-Sample Return}]_i \)

Summary: shrinkage is modest, journal review dominates
Consistent with McLean-Pontiff 2016
Main Result 2/2: Nearly All Anomalies were Real
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We can estimate the false discovery rate (FDR) (à la HLZ 2016)

- Simulate true returns and t-stats using estimated parameters
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- Define false discoveries: true returns \( \leq 0 \) (equivalent to HLZ)
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- Calculate false discovery rate (FDR) for a given t-stat hurdle
- Naive hurdle (1.96) implies a tiny FDR of 0.6%
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We can estimate the false discovery rate (FDR) (à la HLZ 2016)

- Calculate false discovery rate (FDR) for a given t-stat hurdle
- Naive hurdle (1.96) implies a tiny FDR of 0.6%
- Nearly all anomalies were real (in-sample)
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How can this be true???
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Standard t-stat hurdles can actually be **lowered!!!**

**How can this be true??**

- Standard multiple-testing logic (Bonferroni, Benjamini-Hochberg 1995)
  - After running 172+ tests, **the null will be rejected by pure chance**
  ⇒ t-stat hurdles should be raised
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- Other multiple testing studies find most results are false
  - Harvey, Liu, Zhu (2016); Chordia, Goyal, Saretto (2017)
- Difference: focus on cross-sectional predictors in top-tier journals
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| Variable Counts                          | Harvey-Liu-Zhu | Chordia-Goyal-Saretto | Our Paper |
|-----------------------------------------|----------------|-----------------------|-----------|
| Aggregate Risk Factor                   | 113            | 0                     | 0         |
| X-Sectional Predictor                   | 202            | 2,100,000             | 172       |
| X-Sectional & Top Tier Pub              | 146            | <500                  | 151       |
| Total                                   | 315            | 2,100,000             | 172       |
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- Suggests p-hacking much worse among aggregate risk factors and outside top journals
Conclusion
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- A structured, focused estimation finds
  - Journal review has triumphed over p-hacking*
    *in top-tier pubs predicting cross-sectional stock returns, for now
  Consistent w/ McLean-Pontiff 2016, Jacobs-Müller 2016, Yan-Zheng 2017
Conclusion

- A structured, focused estimation finds
  - Journal review has triumphed over \textit{p-hacking}\textsuperscript{*}\textsuperscript{1} in top-tier pubs predicting cross-sectional stock returns, \textit{for now}
    Consistent w/ McLean-Pontiff 2016, Jacobs-Müller 2016, Yan-Zheng 2017

- Suggests a \textit{complete accounting for the typical anomaly return}
  - 13\% publication bias (this paper)
  - 35\% mispricing that can be traded away (McLean and Pontiff 2016)
  - 52\% trading costs (Chen and Velikov 2017)