

MGMT MFE 431-3

Statistical Arbitrage

Lecture 10: Final Lessons

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Plan

1. Data-Snooping Biases
2. August 2007 Quant Meltdown
3. Does this stuff still work?

Ed Leamer



- Chauncey J. Medberry Chair in Management / Professor in Economics & Statistics
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Specification Searches

“Data mining,” “fishing,” “grubbing,” “number crunching.” These are the value-laden terms we use to disparage each other’s empirical work with the linear regression model. A less provocative description would be “specification searching,” and a catch-all definition is “the data-dependent process of selecting a statistical model.” This definition encompasses both the estima-

6 Types of Specification Searches

1. Hypothesis testing search: choose a “true model”
2. Interpretative search: interpret multidimensional evidence
3. Simplification search: construct a “fruitful model”
4. Proxy search: find a quantitative facsimile
5. Data-selection search: select a dataset
6. Post-data model construction: improve an existing model

Executive Summary

- If you torture the data long enough, Nature will confess.
- Econometricians, like artists, tend to fall in love with their models.
- There are two things you are better off not watching in the making: sausages and econometric estimates.

Data-Snooping Biases

- Andrew Lo and Craig MacKinlay, *Review of Financial Studies* (1990)
- Family of test statistics $T(a)$ whose null distribution is known for fixed a , but where you use the test statistic $T = T(a)$ for some a chosen using the data.
- Example: the size effect... There's no theory!

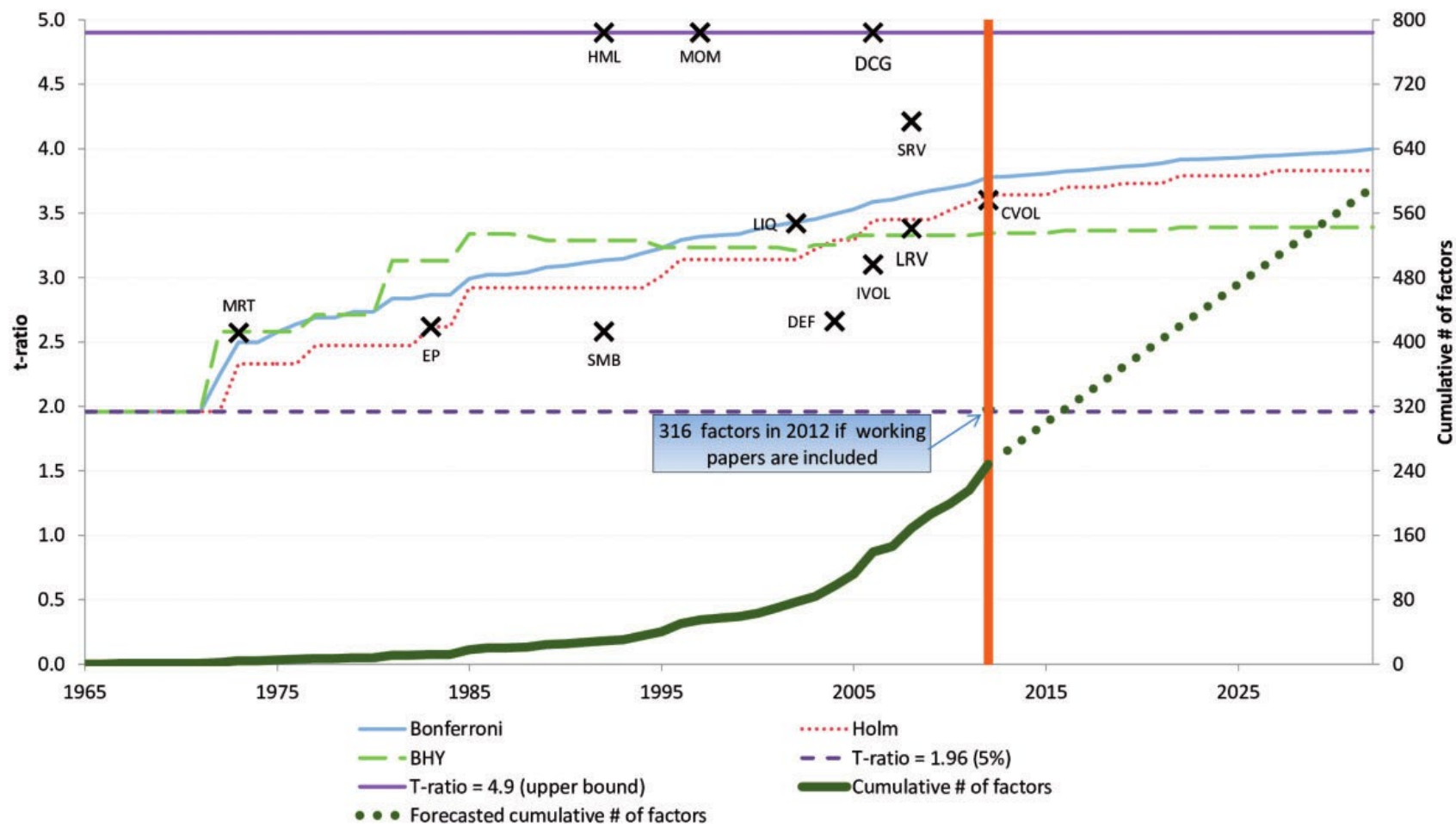
Paper's Conclusions

- Human nature focuses, often disproportionately so, on the unusual.
- This induces severe bias: out-of-sample performance never as good as backtest.
- There needs to be some economic model for why the alpha works.

... and the Cross-Section of Expected Returns

- Campbell R. Harvey, Yan Liu and Heqing Zhu, *Review of Financial Studies* (2016)
- Given extensive data mining, t-stat of 2.0 should not be significance criterion.
- Multiple testing problem.
- New factor needs to clear a much higher hurdle: $t\text{-stat} > 3.0$.
- Most claimed research findings in financial economics are *likely false*.

Threshold as Function of # Factors



Technical Trading Rules

- Data-Snooping, Technical Trading Rule Performance, and the Bootstrap: Ryan Sullivan, Allan Timmermann, and Halbert White - Journal of Finance (1999)
- Revisit 26 technical trading rules that are deemed to “work”
- Say they are drawn from universe of 7,846 trading rules.

Conclusions of the Paper

- Use Hal White's "Reality Check" bootstrap
- Best technical trading rules were statistically significant prior to 1986
- Not after 1986 (if account for data snooping)
- Markets have become more efficient
 - Cheaper computing power
 - Lower transaction costs
 - Increased liquidity in the stock market

Overall Lessons

- Data snooping is real and dangerous
- Require economic reason why alpha works
- Keep few degrees of freedom
- If you fit complex model: use regularization
- Keep out-of-sample data clean
- Divide backtest Sharpe ratio by 2
- Test on multiple geographies

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The Facts

1 week: Monday Aug. 6 → Friday Aug. 10, 2007

Long-short quant equity strategies around the world experienced substantial losses

Bounced back afterwards

No significant news

Nobody else got affected

Market level was stable

WSJ – September 7, 2007

AUGUST AMBUSH

How Market Turmoil Waylaid the 'Quants'

*Morgan Stanley Star Is
Among Those Battered;
No Time for Music Now*

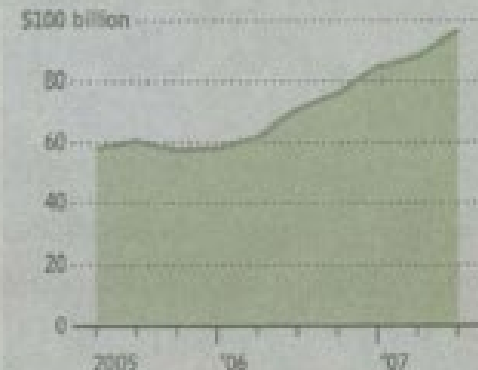
By SCOTT PATTERSON
And ANITA RAGHAVAN

Peter Muller, a 43-year-old trader at Morgan Stanley, is used to markets behaving more or less as he expects. But in late July, some unusual patterns perplexed him. Certain investing strategies that historically had posted steady gains started faltering for no evident reason.

Soon, the unusual trading spread from U.S. to Japanese and European

Adding Up

Estimated assets in quant hedge funds using two common strategies, 'market neutral' and 'statistical arbitrage'; quarterly data



Source: Hedgefund.net

Whose Fault?



Mark Carhart



USC Finance
Professor
1995-1997

4-Factor Model

Goldman Sachs'
Global Alpha
1997-2009

Unwind Hypothesis

- Global Alpha fund was huge
- Not doing well
- Liquidated positions brutally early August
- Impacted people who had strategies in the same space
- They had to reduce their exposure

Andrew Lo Presentation @ NY Fed

AUM in TASS Equity Hedge Funds and
the Profitability of the Contrarian Trading Strategy
1995 to 2007

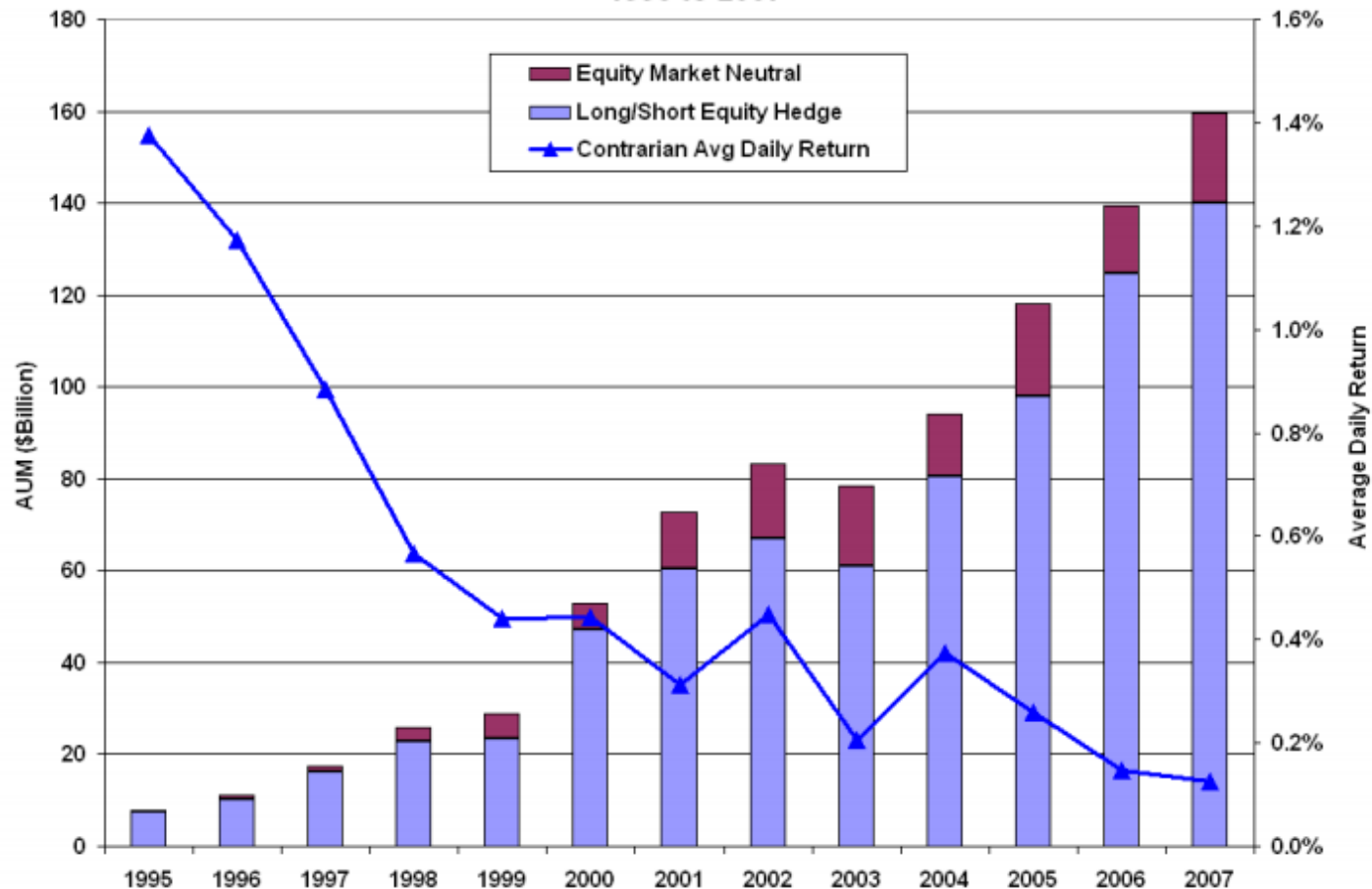
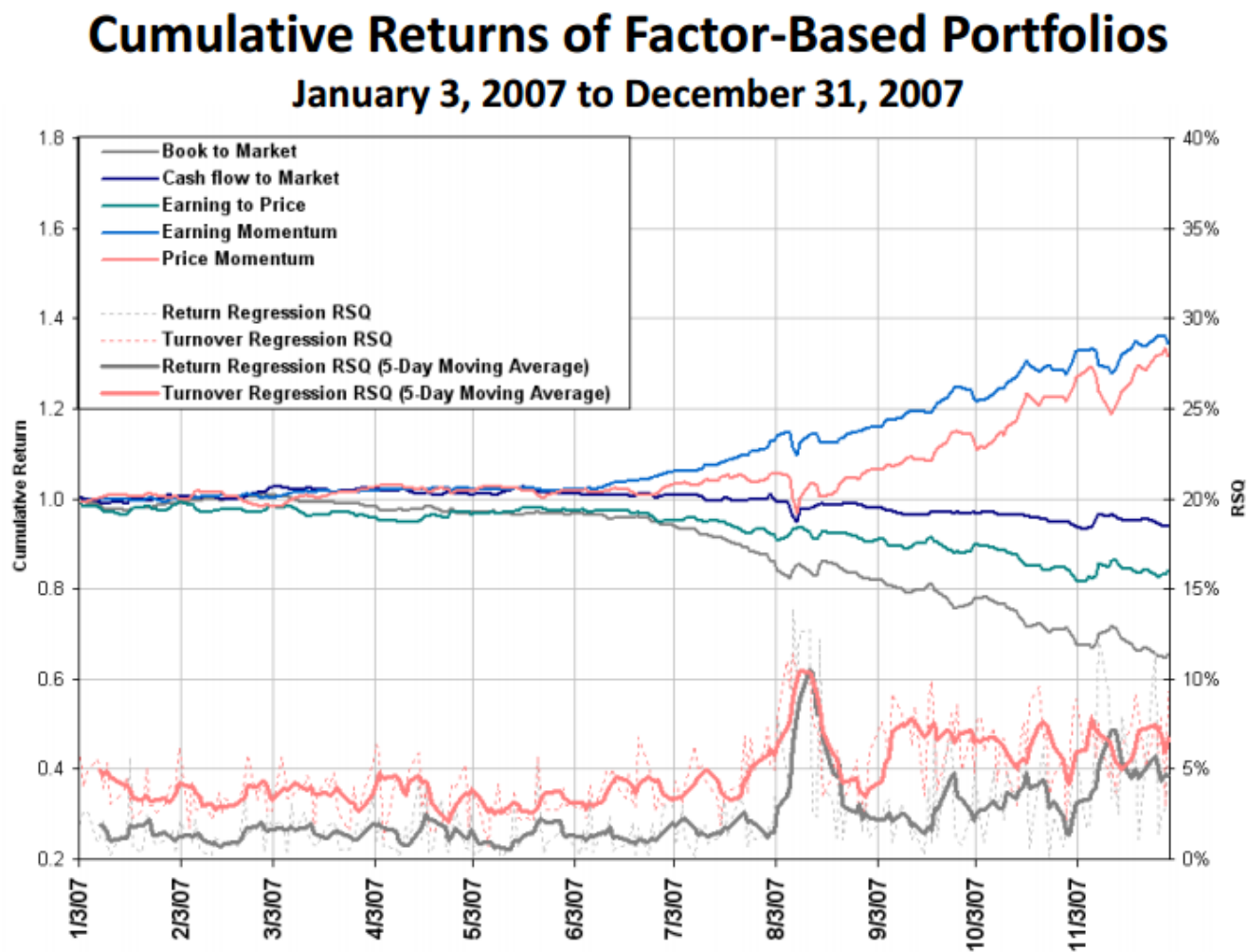


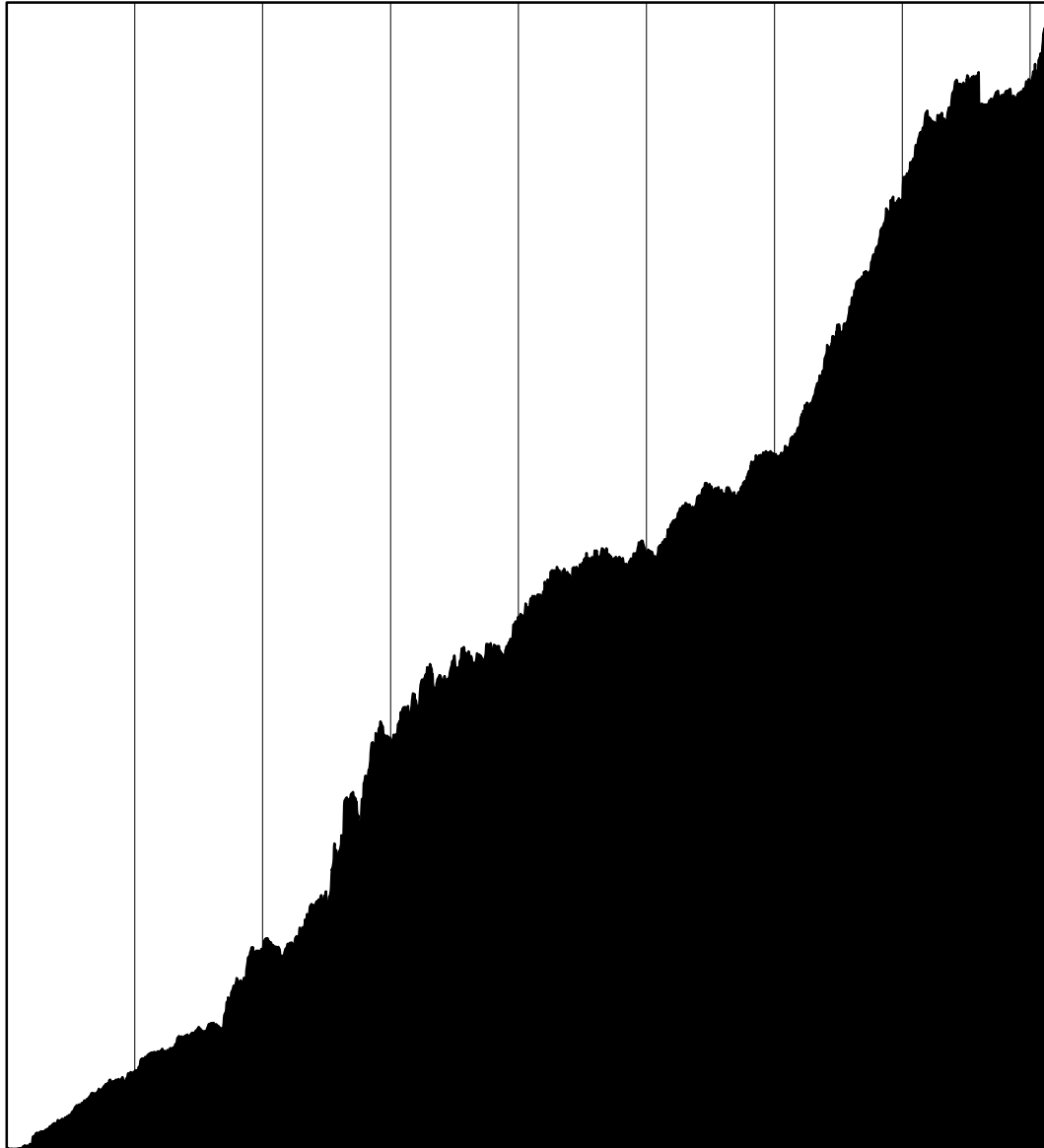
Fig. 2 of Khandani & Lo (2011)



Carhart Speech at Columbia

- Global Alpha rescued by \$3 Billion injection
- Without the injection: no rebound...
- Goldman Sachs was pleased with the Quant Meltdown
- GS saw first hand in 2007 how liquidity in the markets can dry up in an instant
- So they had ample time to prepare for the bigger crisis in 2008, which catapulted them to the top of the financial world

Impact on my P&L



Final Lessons: Plan

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The Cross Section of Expected Stock Returns

- Subrahmanyam (2010) lists > 50 anomalies
- 4 categories:
 - Informal **Wall Street** wisdom (such as “value-investing”)
 - **Theoretical** motivation based on risk-return model
 - **Behavioural** biases or misreaction by cognitively challenged investors
 - **Frictions** such as illiquidity or arbitrage constraints

JP Morgan US Factor Reference Book

- 17 Valuation Factors
- 7 Quality Factors
- 8 Sentiment Factors
- 12 Technical Factors
- 6 Growth Factors

- Total: 50 Factors

62 Factors

Journal of Financial Econometrics, 2018, 1–42

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OXFORD

Efficient Sorting: A More Powerful Test for Cross-Sectional Anomalies

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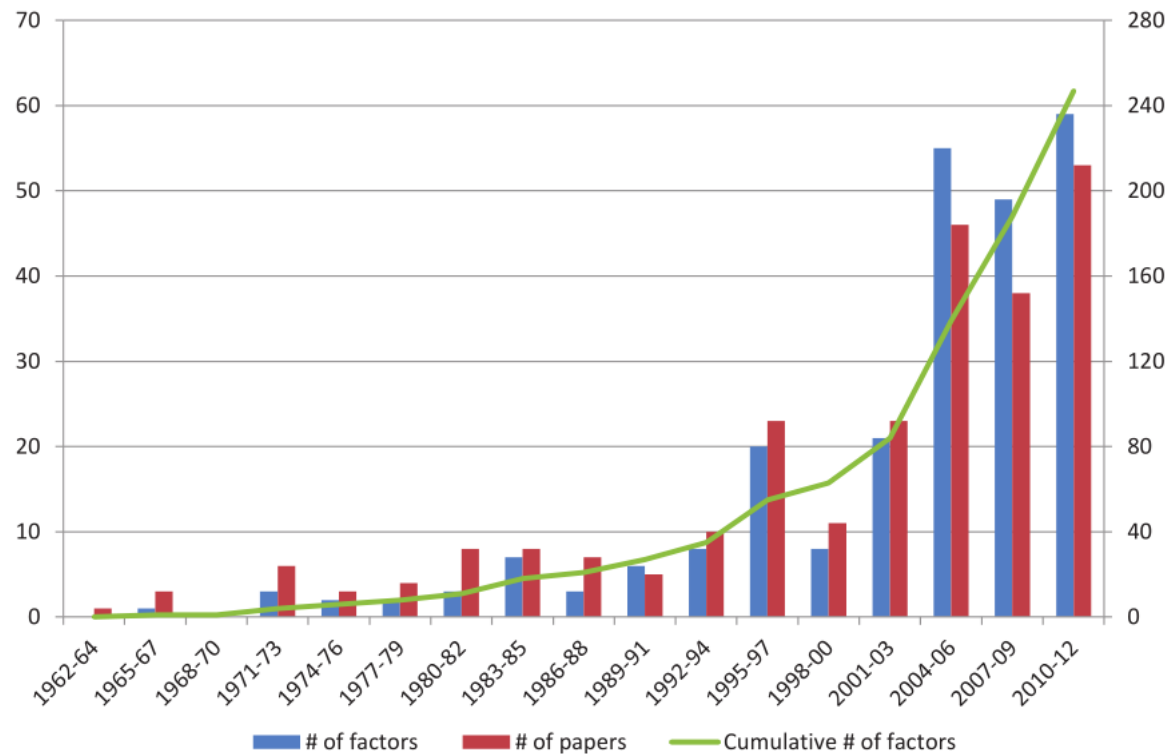
Received July 5, 2017; revised May 21, 2018; editorial decision May 22, 2018; accepted May 28, 2018

Abstract

Many researchers seek factors that predict the cross-section of stock returns. The

Harvey, Liu and Zhu (2013)

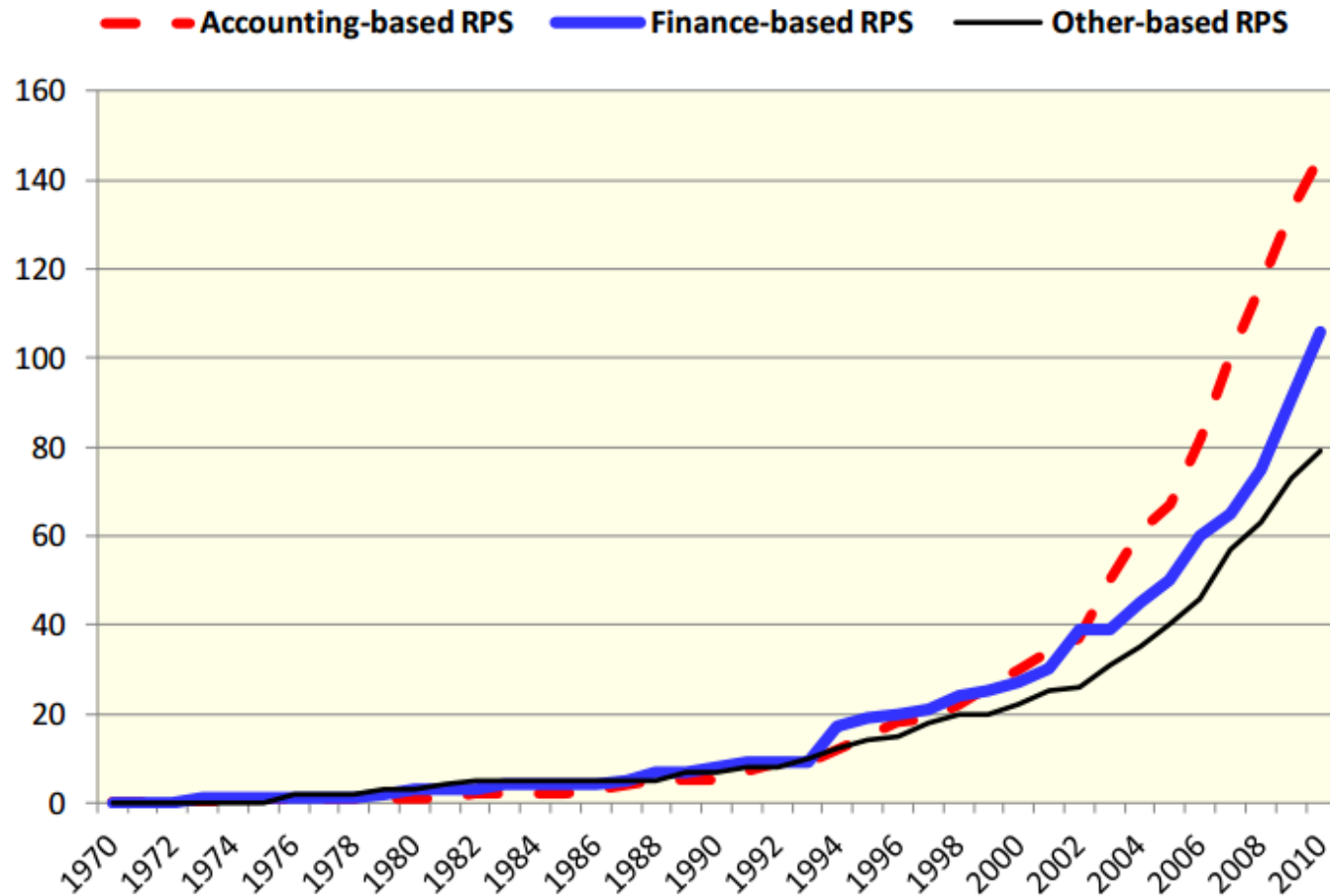
Figure 2: Factors and Publications



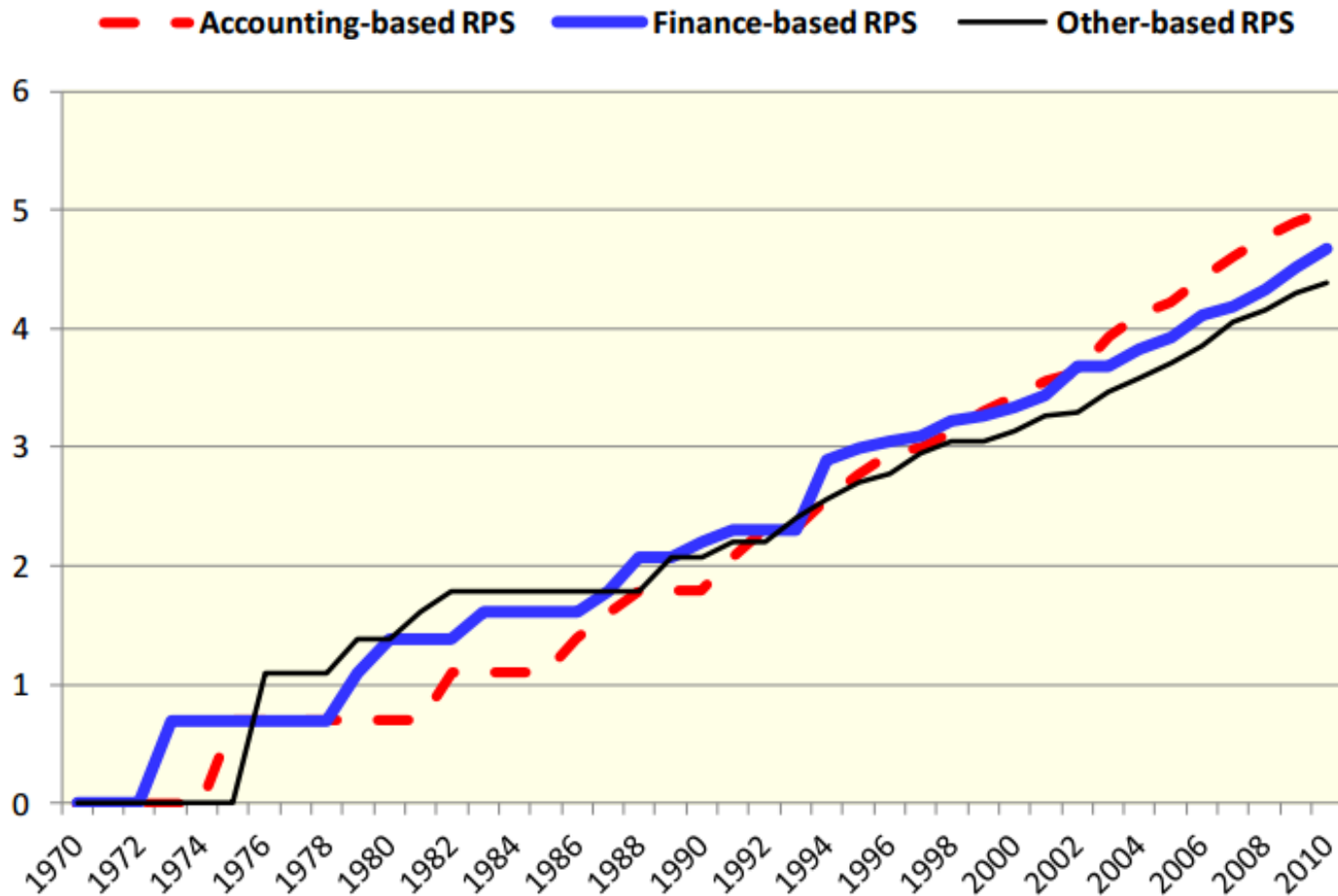
Green, Hand & Zhang (2012)

- “The Supraview of Return Predictive Signals”
- 333 Return Predictive Signals (RPS = Alpha)
- From 1970 to 2010

Cumulative Number of RPS



Log(cumulative # of RPS)



Extract Subset of 33 Signals

- Easily replicable using CRSP, Compustat & I/B/E/S
 - They give the list of the 33 signals
 - Average cross-correlation between RPS returns **only 6%**
- ⇒ Combining them is very beneficial!

McLean and Pontiff (JoF2015)

- “Does Academic Research Destroy Stock Return Predictability?”
- 80 academic studies
- 97 sources of alpha
- Published between 1972 and 2011
- Search for articles in finance and accounting journals in [Econlit](#) with keywords such as “cross-section”

Results on Table 3

<i>Post Sample</i>	-0.097 (0.112) [0.386]	-0.102 (0.119) [0.389]
<i>Post Publication</i>	-0.369 (0.093) [0.000]	
<i>Post SSRN</i>		-0.343 (0.079) [0.000]
<i>Constant</i>	0.982 (0.070) [0.000]	0.961 (0.062) [0.000]

Recommended Reading

