SFS CAVALCADE
NORTH AMERICA 2020

Tortured Data

Campbell R. Harvey
Duke University and NBER

The Man

"If you torture the data long enough, it will confess."

Ronald Coase, Nobel ‘91

Outline

- Strategic data selection
- Delegation of responsibility (relying on others' data analysis) and the Garden of Forking Paths
- Multiplicity of methods
- Strategic manipulation of data
- Truth
- Implications for investors

Strategic Data Selection 1

White Paper | MARCH 2019

NEUBERGER | BERMAN

Strategic Data Selection 1

Strategic Data Selection 1

| White Paper | MARCH 2019

NEUBERGER | BERMAN

The Overlooked Persistence of Active Outperformance

- When performance is examined through a lens that better reflects investor experience, active managers have been much more successful over the past decade than is commonly realized.

Strategic Data Selection 1

White Paper | MARCH 2019

NEUBERGER BERMAN

The Overlooked Persistence of Active Outperformance

- Instead of comparing the performance of an index against an entire universe of active strategies, it's more appropriate to reframe the conversation to include only those managers in the top three quartiles of performance and thus eliminate a small cohort of poorly performing funds unlikely to attract significant investment flows. This comparison finds that approximately 84% of U.S. equity active managers[1] have beaten the S&P 500 net of fees over the 20-year period ended December 2018.

Strategic Data Selection 1

White Paper | MARCH 2019

NEUBERGER BERMAN

The Overlooked Persistence of Active Outperformance

- Instead of comparing the performance of an index against an entire universe of active strategies, it's more appropriate to reframe the conversation to include only those managers in the top three quartiles of performance and thus eliminate a small cohort of poorly performing funds unlikely to attract significant investment flows. This comparison finds that approximately 84% of U.S. equity active managers[1] have beaten the S&P 500 net of fees over the 20-year period ended December 2018.

Strategic Data Selection 1

White Paper | MARCH 2019

NEUBERGER BERMAN

The Overlooked Persistence of Active Outperformance

- Instead of comparing the performance of an index against an entire universe of active strategies, it's more appropriate to reframe the conversation to include only those managers in the top three quartiles of performance and thus eliminate a small cohort of poorly performing funds unlikely to attract significant investment flows. This comparison finds that approximately 84% of U.S. equity active managers[1] have beaten the S&P 500 net of fees over the 20-year period ended December 2018.

Strategic Data Selection 1

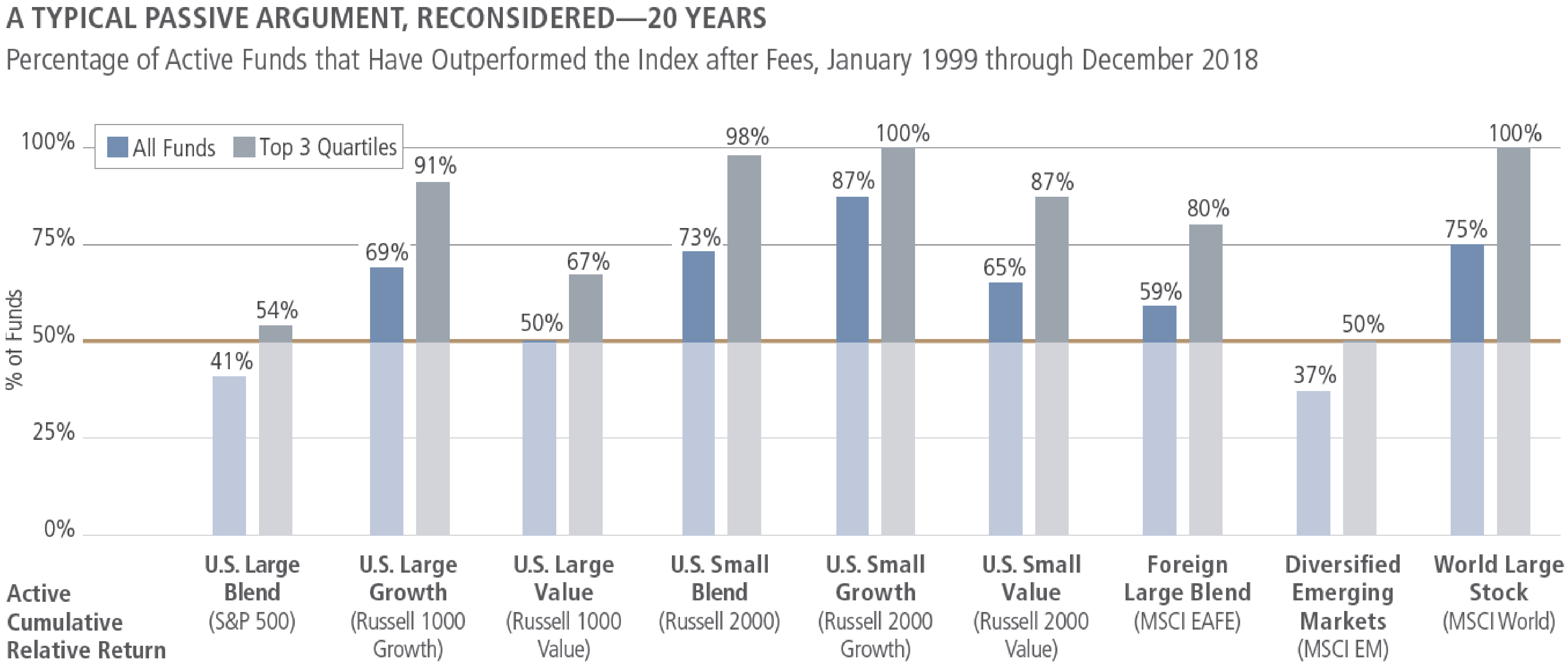
| White Paper | MARCH 2019

NEUBERGER | BERMAN

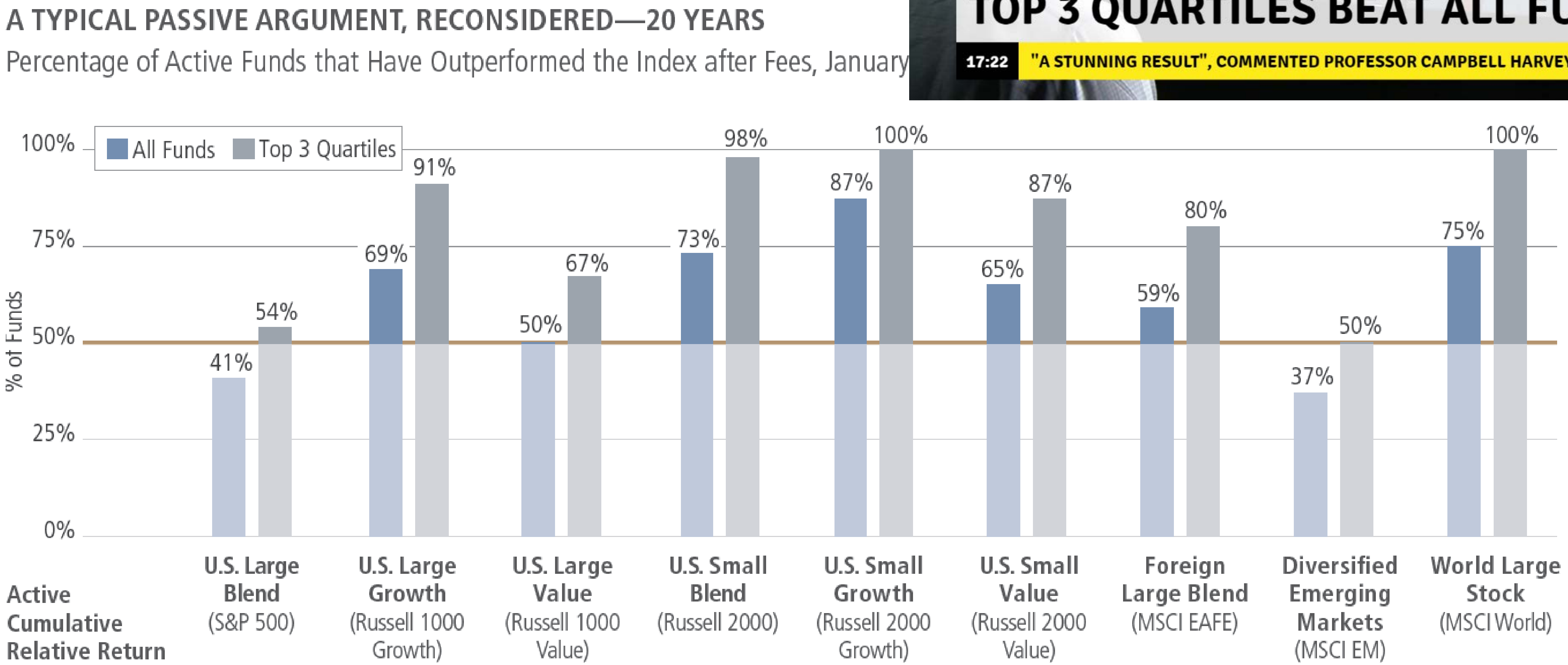
The Overlooked Persistence of Active Outperformance

- Instead of comparing the performance of an index against an entire universe of active strategies, it's more appropriate to reframe the conversation to include only those managers in the top three quartiles of performance and thus eliminate a small cohort of poorly performing funds unlikely to attract significant investment flows. This comparison finds that approximately 84% of U.S. equity active managers[1] have beaten the S&P 500 net of fees over the 20-year period ended December 2018.

Strategic Data Selection 1



Strategic Data Selection 1



Strategic Data Selection 1

Implication

- 100% of active managers beat the S&P …

Strategic Data Selection 1

Implication

- 100% of active managers beat the S&P … if you censor all managers that underperformed.

https://breakyourownnews.com/

Strategic Data Selection 2

Influential 2014 paper:

Review of the Active Management of the Norwegian Government Pension Fund Global

20 January, 2014

Andrew Ang
Ann F. Kaplan Professor of Business
Columbia Business School

Michael W. Brandt
Kalman J. Cohen Professor of Business Administration,
Fuqua School of Business, Duke University

David F. Denison
Former President and CEO of the Canada Pension Plan Investment Board

Strategic Data Selection 2

2014 Report to Norges:

- “Abstracting from the financial crisis, we conclude that active management of both equity and fixed income has significantly contributed to the returns of the fund.”

Strategic Data Selection 2

2014 Report to Norges:

- "Abstracting from the financial crisis, we conclude that active management of both equity and fixed income has significantly contributed to the returns of the fund."

Strategic Data Selection 2

Implication

- The model works …

Strategic Data Selection 2

Implication

- The model works … if you exclude the single most important economic episode -- the global financial crisis.

Delegation of Data Analysis

Early in my career, I get a telephone call my office line at about 9pm.

- The number is the familiar Goldman Sachs telephone number

Delegation of Data Analysis

Early in my career, I get a telephone call my office line at about 9pm.

- The number is the familiar Goldman Sachs telephone number
- To my shock, it is Fischer Black
- He has a problem with a table in my paper in the *Journal of Financial Economics*

Delegation

Black tells me he does not believe my Table 2

- He says that this is an example of "data mining"
- He argues that the predictability of stock returns I document is implausible and likely overfit

ELSEVIER

Journal of Financial Economics

Volume 24, Issue 2, 1989, Pages 289-317

Time-varying conditional covariances in tests of asset pricing models

Campbell R. Harvey *

Table 2

Regressions of excess returns[a] for all NYSE common stocks (ranked by firm size) on the instrumental variables[b] based on monthly data from September 1941 to December 1987 (554 observations).

$$r_{j,t} = \delta_0 + \delta_1 xew_{t-1} + \delta_2 jan_t + \delta_3 xh3_{t-1} + \delta_4 junk_{t-1} + \delta_5 xdiv_{t-1} + \epsilon_t.$$

Portfolio	δ_0	δ_1	δ_2	δ_3	δ_4	δ_5	In-sample $\bar{R}^2$	Out-of-sample $\bar{R}^{2c}$
Decile 1	−0.024	0.142	0.091	6.746	31.035	5.316	0.179	0.120
	(0.009)	(0.081)	(0.018)	(2.742)	(12.167)	(1.539)		
Decile 2	−0.018	0.114	0.064	7.692	24.429	4.333	0.149	0.108
	(0.007)	(0.055)	(0.013)	(2.456)	(8.688)	(1.124)		
Decile 3	−0.017	0.104	0.052	7.561	23.307	4.237	0.131	0.100
	(0.006)	(0.050)	(0.011)	(2.393)	(7.971)	(1.031)		
Decile 4	−0.014	0.100	0.038	8.251	19.880	3.926	0.110	0.079
	(0.006)	(0.046)	(0.010)	(2.365)	(7.344)	(0.945)		
Decile 5	−0.014	0.072	0.034	9.008	18.600	4.018	0.107	0.082
	(0.006)	(0.043)	(0.009)	(2.338)	(6.802)	(0.898)		
Decile 6	−0.014	0.059	0.027	(8.310)	(20.041)	(4.057)	0.094	0.068
	(0.005)	(0.042)	(0.009)	(2.289)	(6.437)	(0.876)		
Decile 7	−0.013	0.046	0.018	8.554	18.696	4.086	0.084	0.059
	(0.005)	(0.041)	(0.008)	(2.370)	(6.536)	(0.851)		
Decile 8	−0.011	0.019	0.016	8.818	15.731	3.750	0.075	0.047
	(0.005)	(0.040)	(0.008)	(2.324)	(6.143)	(0.798)		
Decile 9	−0.009	0.010	0.010	9.059	14.339	3.997	0.080	0.052
	(0.005)	(0.039)	(0.007)	(2.482)	(6.060)	(0.787)		
Decile 10	−0.007	0.005	0.000	7.749	11.001	3.562	0.067	0.032
	(0.004)	(0.039)	(0.007)	(2.534)	(5.487)	(0.665)		
Val. weight	−0.009	0.017	0.007	8.234	12.797	3.690	0.075	0.044
	(0.004)	(0.038)	(0.007)	(2.436)	(5.608)	(0.703)		

Delegation

Table 2 tries to predict one-month ahead US stock returns using lagged information

- He argues the R^2 is too high at 7.5%

Table 2

Regressions of excess returns[a] for all NYSE common stocks (ranked by firm size) on the instrumental variables[b] based on monthly data from September 1941 to December 1987 (554 observations).

$$r_{j,t} = \delta_0 + \delta_1 xew_{t-1} + \delta_2 jan_t + \delta_3 xh3_{t-1} + \delta_4 junk_{t-1} + \delta_5 xdiv_{t-1} + \epsilon_t .$$

Portfolio	δ_0	δ_1	δ_2	δ_3	δ_4	δ_5	In-sample $\bar{R}^2$	Out-of-sample $\bar{R}^{2c}$
Val. weight	−0.009 (0.004)	0.017 (0.038)	0.007 (0.007)	8.234 (2.436)	12.797 (5.608)	3.690 (0.703)	0.075	0.044

Delegation

Table 2

Regressions of excess returns[a] for all NYSE common stocks (ranked by firm size) on the instrumental variables[b] based on monthly data from September 1941 to December 1987 (554 observations).

$$r_{j,t} = \delta_0 + \delta_1 xew_{t-1} + \delta_2 jan_t + \delta_3 xh3_{t-1} + \delta_4 junk_{t-1} + \delta_5 xdiv_{t-1} + \epsilon_t.$$

Portfolio	δ_0	δ_1	δ_2	δ_3	δ_4	δ_5	In-sample $\bar{R}^2$	Out-of-sample $\bar{R}^{2c}$
Val. weight	−0.009 (0.004)	0.017 (0.038)	0.007 (0.007)	8.234 (2.436)	12.797 (5.608)	3.690 (0.703)	0.075	0.044

I argue he is wrong.

- There was no data mining. I report a single test based on past published research.
- I did not try to maximize the fit.

Delegation

Looking back in time, this telephone call is ironic given my research agenda is to improve research practices in finance and to call out the data miners.

- I decide to replicate and test my model (in a true) out of sample

Delegation: Market timing replication

Table 5: Time Series Regression Coefficients, Original Data

	Cons	EW NYSE	Jan	Term Prem	Junk Spread	Div Spread	IS R^2	OOS R^2
Val. weight	-0.006	0.034	-0.010	6.477	13.400	3.250	0.076	0.033

Original sample to 1987 replicates well

- R^2 about the same

Delegation: Market timing validation

Table 5: Time Series Regression Coefficients, Original Data

	Cons	EW NYSE	Jan	Term Prem	Junk Spread	Div Spread	IS R^2	OOS R^2
Val. weight	-0.006	0.034	-0.010	6.477	13.400	3.250	0.076	0.033
1988-2018 Data								
Val. weight	0.012	0.067	-0.004	5.920	-7.510	1.344	0.012	-0.052

Out of sample 1988-2018 fails

- R^2 now only 1.2% and not significant
- One-step ahead R^2 now effectively zero

Delegation: Market timing validation

Table 5: Time Series Regression Coefficients, Original Data

	Cons	EW NYSE	Jan	Term Prem	Junk Spread	Div Spread	IS R^2	OOS R^2
Val. weight	-0.006	0.034	-0.010	6.477	13.400	3.250	0.076	0.033

1988-2018 Data

	Cons	EW NYSE	Jan	Term Prem	Junk Spread	Div Spread	IS R^2	OOS R^2
Val. weight	0.012	0.067	-0.004	5.920	-7.510	1.344	0.012	-0.052

Out of sample 1988-2018 fails

- R^2 now only 1.2% and not significant
- One-step ahead R^2 now effectively zero
- Coefficients unstable

Delegation: Market timing validation

Table 5: Time Series Regression Coefficients, Original Data

	Cons	EW NYSE	Jan	Term Prem	Junk Spread	Div Spread	IS R^2	OOS R^2
Val. weight	-0.006	0.034	-0.010	6.477	13.400	3.250	0.076	0.033

1988-2018 Data

	Cons	EW NYSE	Jan	Term Prem	Junk Spread	Div Spread	IS R^2	OOS R^2
Val. weight	0.012	0.067	-0.004	5.920	-7.510	1.344	0.012	-0.052

Out of sample 1988-2018 fails

- R^2 now only 1.2% and not significant
- One-step ahead R^2 now effectively zero
- Coefficients unstable

Delegation: Market timing validation

Implication

- You might not have tortured the data …

Delegation

Implication

- You might not have tortured the data … however, relying on others who have tortured the data causes the same problems.

Garden of Forking Paths

It is even more complex

- Beware of the parallel universe problem

http://www.stat.columbia.edu/~gelman/research/unpublished/p_hacking.pdf

Garden of Forking Paths

- A researcher compiles a list of 20 variables to test for trading strategy. The first one “works”. The researcher stops and claims no overfitting.
- However, in a parallel universe, the researcher might start with #20 and only hit #1 after 20 tests. The finding could be just “lucky”.
- Both findings need to be treated equally.

http://www.stat.columbia.edu/~gelman/research/unpublished/p_hacking.pdf

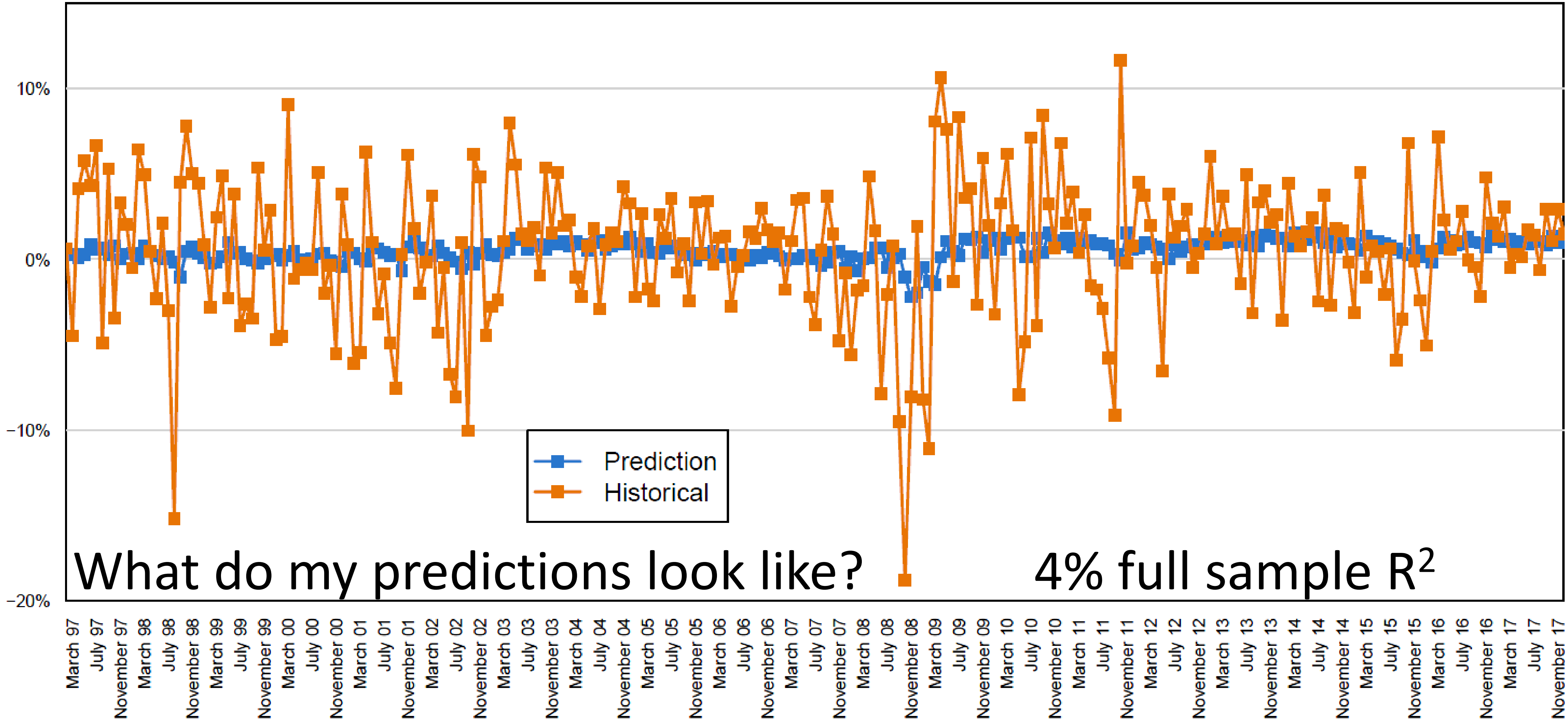
Multiplicity of Methods

I am approached by a high-profile organization to assess their one-month ahead global equity forecasting model (call it “GF”)

- First, for context, let’s return to my Fischer Black inspired example

Multiplicity of Methods

Variance of my predictions (blue) is 4% of the variance of the actual returns (orange)



Multiplicity of Methods

How the model works

- "…our model generates one-month-ahead forecasts on a strictly monthly basis. All forecasts are of MSCI indexes priced in USD."
- "59 regional MSCI indexes. These cover all developed, emerging, and frontier markets, excepting only the following: Argentina, Bangladesh, Mauritius, Sri Lanka, Kuwait, Lebanon, Oman, Serbia, and UAE."

Multiplicity of Methods

How the model was built

- The “model is the product of over two years of intensive data collection and statistical research.”
- “We have gathered and tested roughly 200 monthly variables for each market going back to the 1990s. These variables (some of them highly proprietary) cover market, economic, demographic, and political trends.”
- “All told, the model trains on over 3 million data points.”
- “Our statistical analysis is multi-stage and uses the most advanced machine learning algorithms.”

Multiplicity of Methods

How the model was built

- The “model is the product of over two years of intensive data collection and statistical research.”
- “We have gathered and tested roughly 200 monthly variables for each market going back to the 1990s. These variables (some of them highly proprietary) cover market, economic, demographic, and political trends.”
- “All told, the model trains on over 3 million data points.”
- “Our statistical analysis is multi-stage and uses the **most advanced machine learning algorithms**.”

Multiplicity of Methods

There are hundreds of ML techniques

https://www.dreamstime.com/stock-photo-kid-candy-store-child-stands-front-display-case-curiously-looking-image70922855

Multiplicity of Methods

How accurate is the model?

- “Our accuracy is impressive”
- For “the ‘Big 25’ economies, our R^2 is 0.96”
- For “the total world (all 59 economies), our R^2 is 0.98”

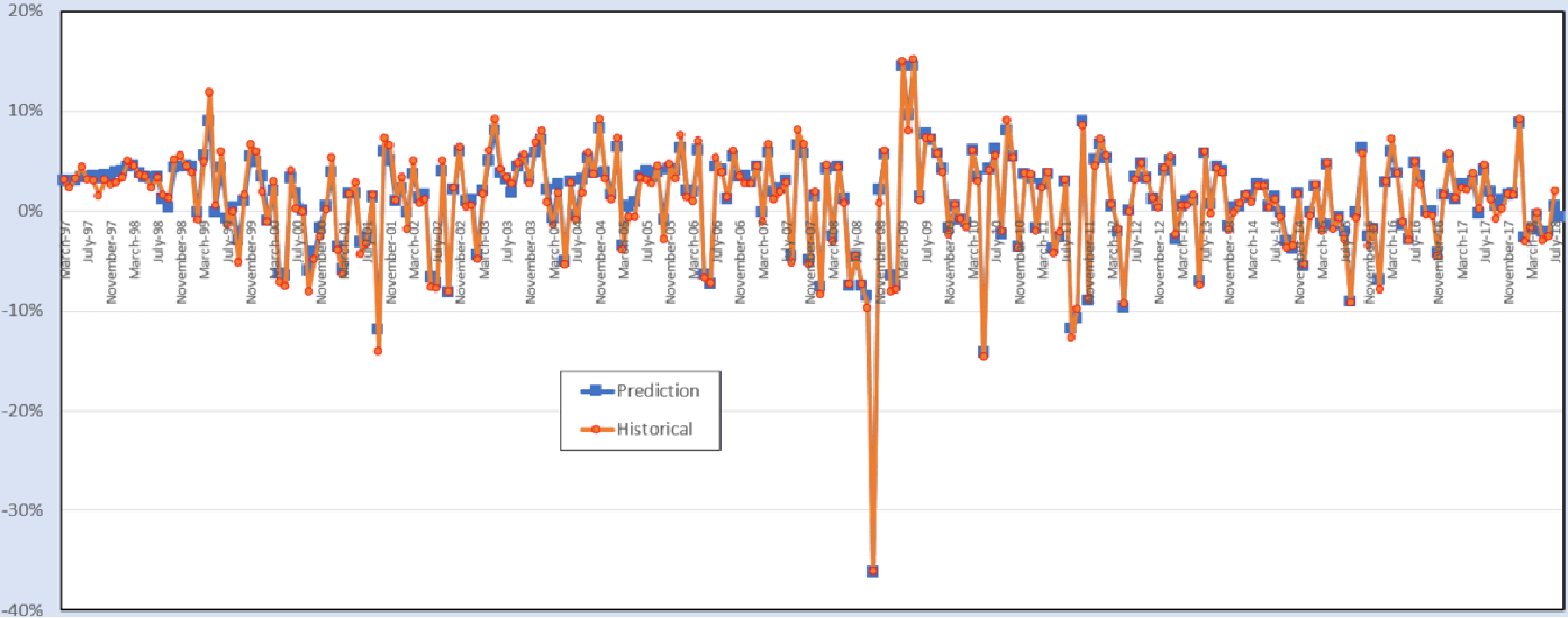
Multiplicity of Methods

How accurate is the model?

- "Our accuracy is impressive"
- For "the 'Big 25' economies, our R^2 is 0.96"
- For "the total world (all 59 economies), our R^2 is 0.98"

Maybe this is a typo and they mean 0.98%
which would be consistent with my results of 1% R^2

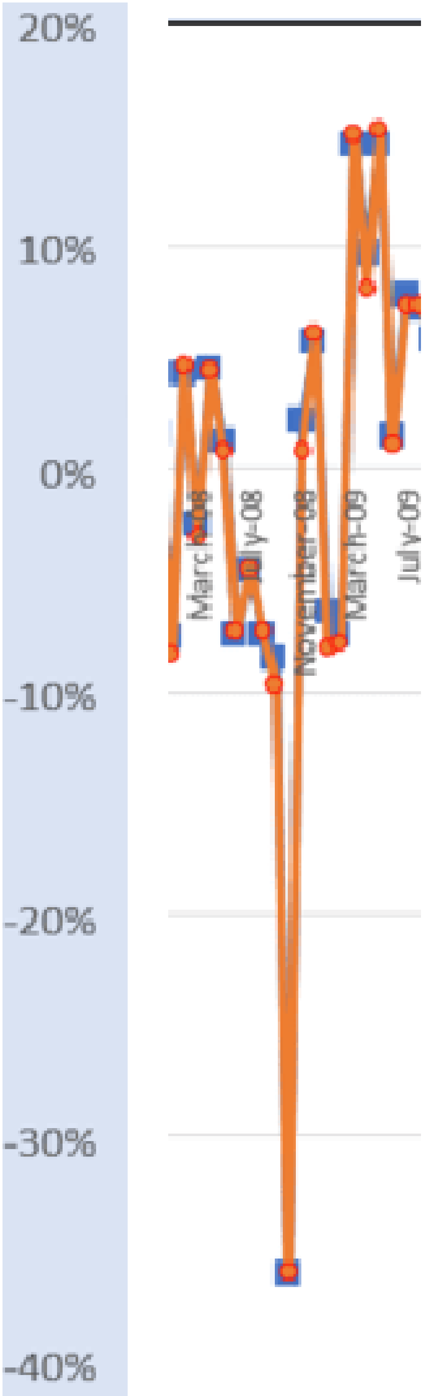
Multiplicity of Methods



Multiplicity of Methods

How accurate is the model?

- Worst month of the global financial crisis had a -35% return (October 2008)
- Blue square is the prediction; Red dot the realized return
- Forecast (made in September 2008) was -35%!



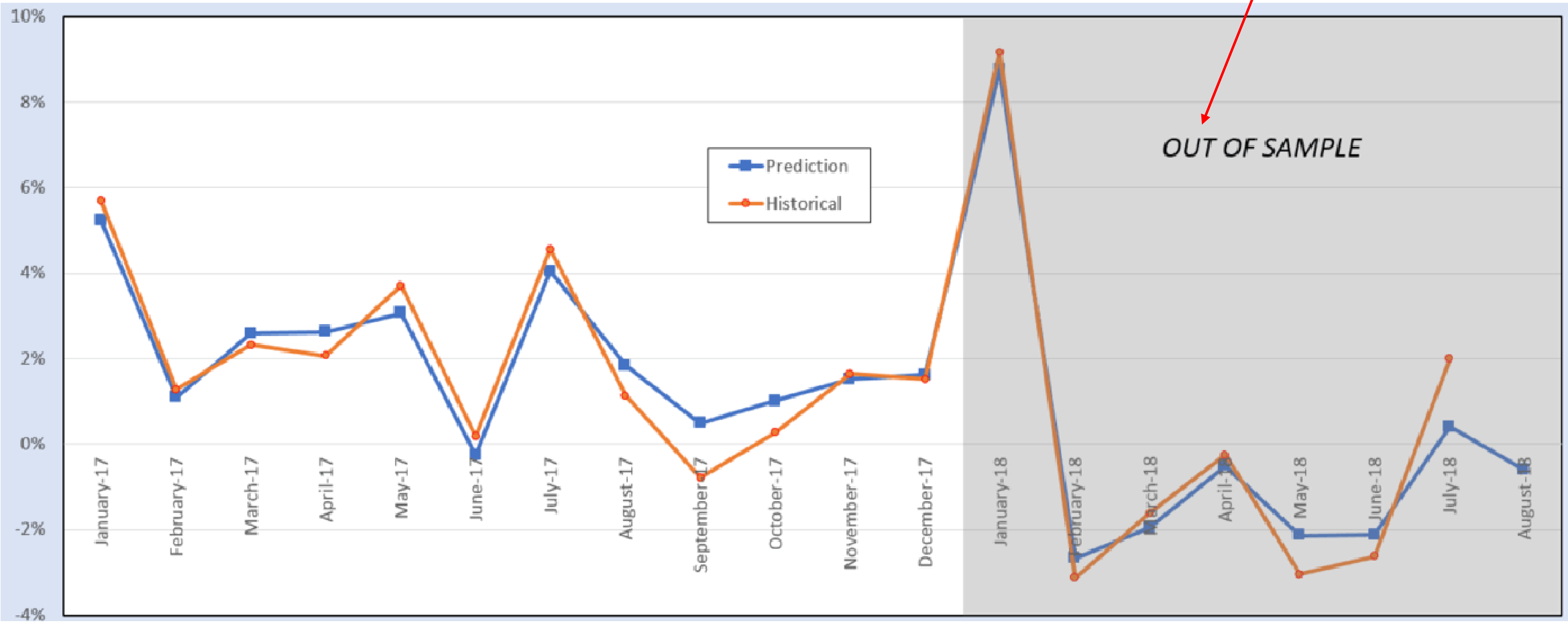
Multiplicity of Methods

GF model R^2=0.98

Harvey model R^2=0.04

Multiplicity of Methods

True out of sample??



Multiplicity of Methods

Further development of the model

- … “run alternative independent variables”
- … “generate ‘now-cast’ forecasts at any time of the month”
- “These and other improvements are in store”

Multiplicity of Methods

The Bright Side of Unionization: The Case of Stock Price Crash Risk

Posted: 11 Jun 2019

Jeong-Bon Kim
City University of Hong Kong

Eliza Xia Zhang
University of Washington Tacoma

Kai Zhong
University of International Business and Economics (UIBE)

Abstract

This study examines whether and how labor unionization influences stock price crash risk. Using a regression discontinuity design that employs union elections as an exogenous shock yielding local variation in unionization, we find that unionization leads to a significant decline in stock price crash risk. We further explore the underlying

Multiplicity of Methods

"Regression Discontinuity Design"
RDD

The Bright Side of Unionization: The Case of Stock Price Crash Risk

Posted: 11 Jun 2019

Jeong-Bon Kim
City University of Hong Kong

Eliza Xia Zhang
University of Washington Tacoma

Kai Zhong
University of International Business and Economics (UIBE)

Abstract

This study examines whether and how labor unionization influences stock price crash risk. Using a regression discontinuity design that employs union elections as an exogenous shock yielding local variation in unionization, we find that unionization leads to a significant decline in stock price crash risk. We further explore the underlying

2.21 Stock Price Crash Risk

(NASBA Field of Study: Accounting)

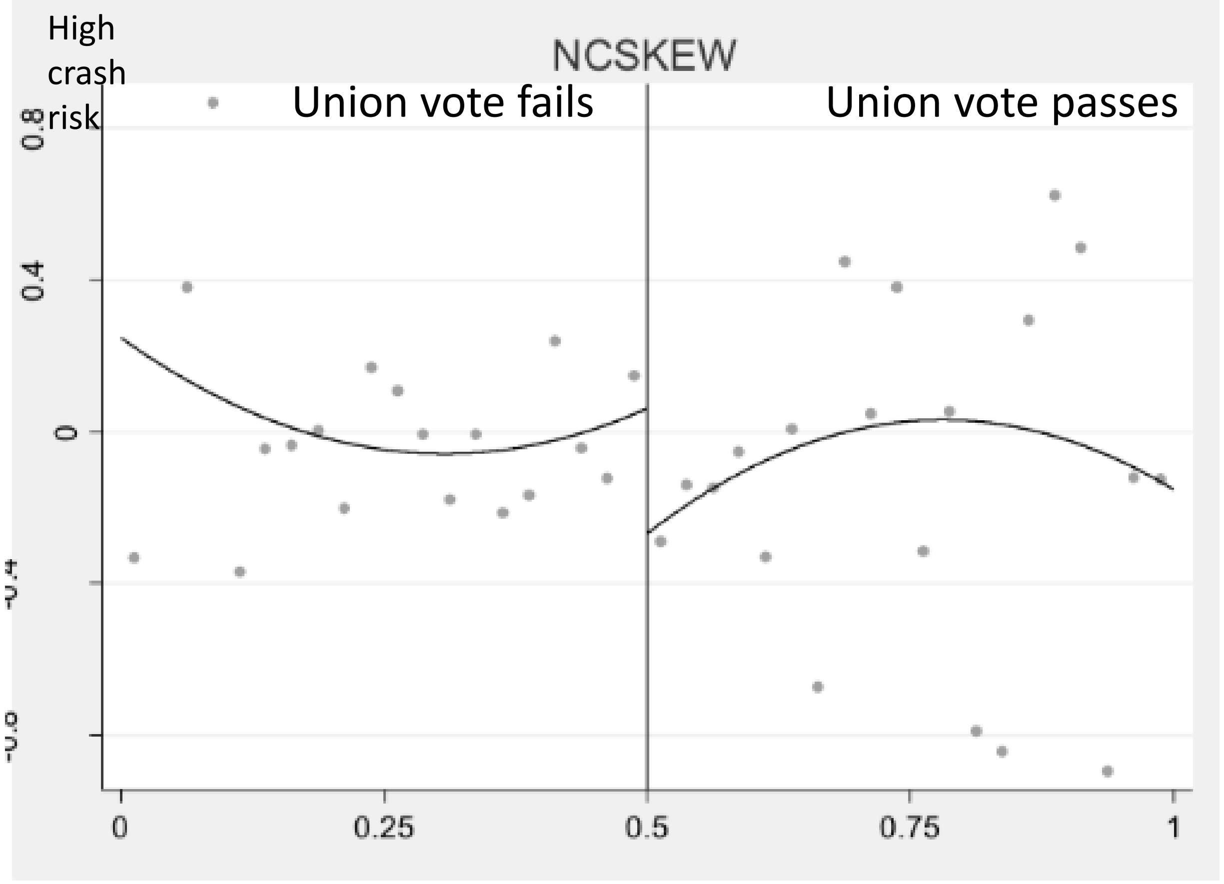
Moderator: Jean Zeng, University of California, Berkeley

American Accounting Association | Thought Leaders in Accounting

August 12, 2019

The Bright Side of Unionization: The Case of Stock Price Crash Risk.

Jeong-Bon Kim, City University of Hong Kong; Eliza Xia Zhang, University of Washington, Tacoma; Kai Zhong, University of International Business and Economics



https://www2.aaahq.org/AM/abstract.cfm?submissionID=2537

2.21 Stock Price Crash Risk

(NASBA Field of Study: Accounting)

Moderator: Jean Zeng, University of California, Berkeley

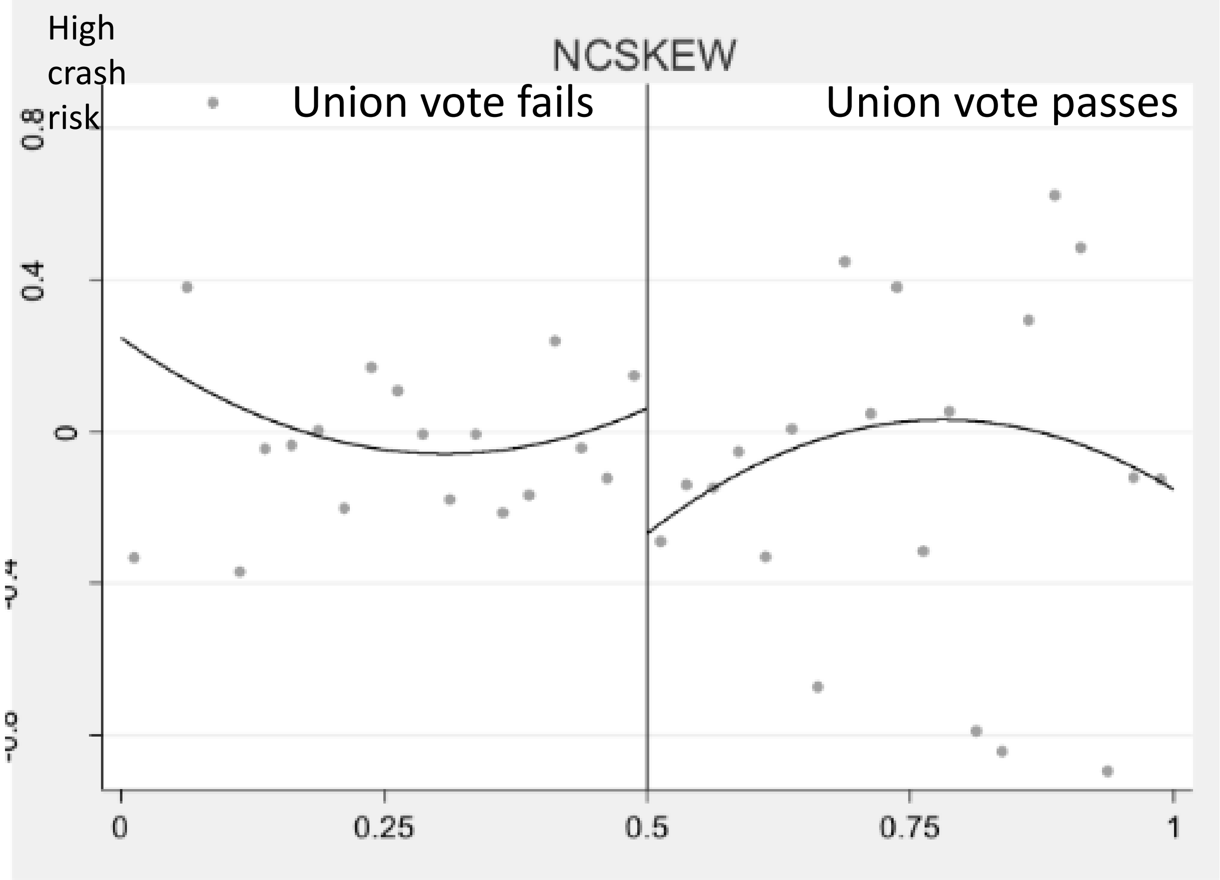
American Accounting Association | Thought Leaders in Accounting

August 12, 2019

The Bright Side of Unionization: The Case of Stock Price Crash Risk.

Jeong-Bon Kim, City University of Hong Kong; Eliza Xia Zhang, University of Washington, Tacoma; Kai Zhong, University of International Business and Economics

"We initially estimate…using the polynomial order of 1, 2, 3, and 4 respectively. …we find that the results using the polynomial order of 2 are the strongest."



https://www2.aaahq.org/AM/abstract.cfm?submissionID=2537

Multiplicity of Methods

Lead author has 15 papers trying to "explain" crash risk!

- Foreign Investors, External Monitoring, and Stock Price Crash Risk
- XBRL adoption and expected crash risk
- Analyst Coverage and Expected Crash Risk: Evidence from Exogenous Changes in Analyst Coverage
- China's Closed Pyramidal Managerial Labor Market and the Stock Price Crash Risk
- Divergence of Cash Flow and Voting Rights, Opacity, and Stock Price Crash Risk: International Evidence
- Stock price crash risk and internal control weakness: presence vs. disclosure effect
- Earnings smoothing: Does it exacerbate or constrain stock price crash risk?
- Accounting Conservatism and Stock Price Crash Risk: Firm-level Evidence
- Financial Reporting Opacity and Expected Crash Risk: Evidence from Implied Volatility Smirks
- Corporate tax avoidance and stock price crash risk: Firm-level analysis
- CEO Overconfidence and Stock Price Crash Risk
- Financial statement comparability and expected crash risk
- Dividend Payments and Stock Price Crash Risk
- Insider Trading and Stock Price Crash Risk
- The Bright Side of Unionization: The Case of Stock Price Crash Risk

Multiplicity of Methods

Lead author has 15 papers trying to "explain" crash risk!

- Foreign Investors, External Monitoring, and Stock Price Crash Risk
- XBRL adoption and expected crash risk
- Analyst Coverage and Expected Crash Risk: Evidence from Exogenous Changes in Analyst Coverage
- China's Closed Pyramidal Managerial Labor Market and the Stock Price Crash Risk
- Divergence of Cash Flow and Voting Rights, Opacity, and Stock Price Crash Risk: International Evidence
- Stock price crash risk and internal control weakness: presence vs. disclosure effect
- Earnings smoothing: Does it exacerbate or constrain stock price crash risk?
- Accounting Conservatism and Stock Price Crash Risk: Firm-level Evidence
- Financial Reporting Opacity and Expected Crash Risk: Evidence from Implied Volatility Smirks
- Corporate tax avoidance and stock price crash risk: Firm-level analysis
- CEO Overconfidence and Stock Price Crash Risk
- Financial statement comparability and expected crash risk
- Dividend Payments and Stock Price Crash Risk
- Insider Trading and Stock Price Crash Risk
- The Bright Side of Unionization: The Case of Stock Price Crash Risk

Strategic Manipulation of Data

Professor Brian Wansink, Cornell:

If apples have an Elmo sticker on them, children more likely to eat the apple than a cookie

Wansink, Just and Payne, *JAMA Pediatrics* 2012

208 students aged 8-11

Strategic Manipulation of Data

Preliminary research in 2008 was inconclusive. But then there was a “breakthrough”.

https://www.buzzfeednews.com/article/stephaniemlee/brian-wansink-cornell-p-hacking

Strategic Manipulation of Data

Payne email to Wansink: September 2008:

"I have attached some initial results of the kid study to this message for your report. Do not despair. It looks like stickers on fruit may work (with a bit more wizardry)."

https://www.buzzfeednews.com/article/stephaniemlee/brian-wansink-cornell-p-hacking

Strategic Manipulation of Data

Wansink, January 7, 2012:

One sticking point is that although the stickers increase apple selection by 71%, for some reason this is a p value of .06. It seems to me it should be lower. Do you want to take a look at it and see what you think. If you can get the data, and it needs some tweeking, it would be good to get that one value below .05.

Best,

Brian

https://www.buzzfeednews.com/article/stephaniemlee/brian-wansink-cornell-p-hacking

Strategic Manipulation of Data

Published with the p-value of 0.06 in *JAMA Pediatrics*

https://jamanetwork.com/journals/jamapediatrics/fullarticle/2654849

Strategic Manipulation of Data

Published with the p-value of 0.06 in *JAMA Pediatrics*

- Retracted and Replaced: September 17, 2017 with a p-value of 0.02

https://jamanetwork.com/journals/jamapediatrics/fullarticle/2654849

Strategic Manipulation of Data

Published with the p-value of 0.06 in *JAMA Pediatrics*

- Retracted and Replaced: September 17, 2017 with a p-value of 0.02
- Fully Retracted: December 2017.

https://jamanetwork.com/journals/jamapediatrics/fullarticle/2654849
https://jamanetwork.com/journals/jamapediatrics/fullarticle/2659568

Strategic Manipulation of Data

Published with the p-value of 0.06

- Retracted and Replaced September 17, 2017 with a p-value of 0.02
- Fully retracted December 2017. Cornell investigated…

Strategic Manipulation of Data

Professor Brian Wansink, Cornell:

…P-hacking shouldn't be confused with deep data dives – with figuring out why our results don't look as perfect as we want.

https://web.archive.org/web/20170312041524/http:/www.brianwansink.com/phd-advice/the-grad-student-who-never-said-no

Strategic Manipulation of Data

Professor Brian Wansink, Cornell:

With field studies, hypotheses usually don't "come out" on the first data run. But instead of dropping the study, a person contributes more to science by figuring out when the hypo worked and when it didn't. This is Plan B. Perhaps your hypo worked during lunches but not dinners, or with small groups but not large groups. You don't change your hypothesis, but you figure out where it worked and where it didn't. Cool data contains cool discoveries. "

https://web.archive.org/web/20170312041524/http:/www.brianwansink.com/phd-advice/the-grad-student-who-never-said-no

Strategic Manipulation of Data

Professor Brian Wansink, Cornell:

With field studies, hypotheses usually don't "come out" on the first data run. But instead of dropping the study, a person contributes more to science by figuring out when the hypo worked and when it didn't. This is Plan B. Perhaps your hypo worked during lunches but not dinners, or with small groups but not large groups. You don't change your hypothesis, but you figure out where it worked and where it didn't. Cool data contains cool discoveries. "

https://web.archive.org/web/20170312041524/http:/www.brianwansink.com/phd-advice/the-grad-student-who-never-said-no

Strategic Manipulation of Data

Professor Brian Wansink, Cornell:

With field studies, hypotheses usually don't "come out" on the first data run. But instead of dropping the study, a person contributes more to science by figuring out when the hypo worked and when it didn't. This is Plan B. Perhaps your hypo worked during lunches but not dinners, or with small groups but not large groups. You don't change your hypothesis, but you figure out where it worked and where it didn't. Cool data contains cool discoveries. "

https://web.archive.org/web/20170312041524/http:/www.brianwansink.com/phd-advice/the-grad-student-who-never-said-no

Strategic Manipulation of Data

Published with the p-value of 0.06

- Retracted and Replaced September 17, 2017 with a p-value of 0.02
- Fully retracted December 2017. Sample not 8-11 year olds.

The Washington Post

Democracy Dies in Darkness

To Your Health

This Ivy League food scientist was a media darling. He just submitted his resignation, the school says.

https://www.washingtonpost.com/health/2018/09/20/this-ivy-league-food-scientist-was-media-darling-now-his-studies-are-being-retracted/?utm_term=.17c9c9964d2d

The Truth

Rudy Giuliani, August 19, 2018

- *“Truth isn’t truth”*
- *“The truth is relative”*
- Investigators *“may have different versions of the truth”*

The Truth

Rudy Giuliani, August 19, 2018

- *"Truth isn't truth"*
- *"The truth is relative"*
- Investigators *"may have different versions of the truth"*

The Truth

Rudy Giuliani, August 19, 2018

- *"Truth isn't truth"*
- *"The truth is relative"*
- Investigators *"may have different versions of the truth"*

The Truth

Even philosophers can’t agree on what truth is

- *Correspondence theory*
- *Coherence theory*
- *Constructivist theory*
- *Consensus theory*
- *Pragmatic theory*
- *Performative theory*
- *Redundancy theory*
- *Pluralist theory*
- *Truth in mathematics*
- *Truth in logic*
- *Semantic theory of truth*
- *Revision theory of truth*

The Truth

Why does fake news go viral?
Answer: Short attention spans

Nature Human Behaviour **volume 1**, Article number: 0132 (2017)

nature
human behaviour

Limited individual attention and online virality of low-quality information

Xiaoyan Qiu[1,2*], Diego F. M. Oliveira[2*], Alireza Sahami Shirazi[3], Alessandro Flammini[2,4], Filippo Menczer[2,3,4]

[1] *School of Economics and Management - Shanghai Institute of Technology*
[2] *Center for Complex Networks and Systems Research- School of Informatics and Computing - Indiana University*
[3] *Yahoo Research*
[4] *Indiana University Network Science Institute*

Abstract

Social media are massive marketplaces where ideas and news compete for our attention [1]. Previous studies have shown that quality is not a necessary condition for online virality [2] and that knowledge about peer choices can distort the relationship between quality and popularity [3].

The Truth

Why does fake news go viral?
Answer: Short attention spans

Paper goes viral, 99th percentile of media coverage

Nature Human Behaviour **volume 1**, Article number: 0132 (2017)

nature
human behaviour

Limited individual attention and online virality of low-quality information

Xiaoyan Qiu[1,2*], Diego F. M. Oliveira[2*], Alireza Sahami Shirazi[3], Alessandro Flammini[2,4], Filippo Menczer[2,3,4]

[1] *School of Economics and Management - Shanghai Institute of Technology*
[2] *Center for Complex Networks and Systems Research- School of Informatics and Computing - Indiana University*
[3] *Yahoo Research*
[4] *Indiana University Network Science Institute*

Abstract

Social media are massive marketplaces where ideas and news compete for our attention [1]. Previous studies have shown that quality is not a necessary condition for online virality [2] and that knowledge about peer choices can distort the relationship between quality and popularity [3].

Online attention

Altmetric score (what's this?)

- Tweeted by **243**
- Blogged by **5**
- On **13** Facebook pages
- Mentioned in **7** Google+ posts
- Picked up by **66** news outlets

Show more

The Truth

Why does fake news go viral?
Answer: Short attention spans

Nature Human Behaviour **volume 1**, Article number: 0132 (2017)

nature
human behaviour

Limited individual attention and online virality of low-quality information

Xiaoyan Qiu[1,2*], Diego F. M. Oliveira[2*], Alireza Sahami Shirazi[3], Alessandro Flammini[2,4], Filippo Menczer[2,3,4]

[1] *School of Economics and Management - Shanghai Institute of Technology*
[2] *Center for Complex Networks and Systems Research- School of Informatics and Computing - Indiana University*
[3] *Yahoo Research*
[4] *Indiana University Network Science Institute*

Abstract

Social media are massive marketplaces where ideas and news compete for our attention [1]. Previous studies have shown that quality is not a necessary condition for online virality [2] and that knowledge about peer choices can distort the relationship between quality and popularity [3].

SCIENTIFIC AMERICAN®

How Fake News Goes Viral— Here's the Math

The Truth

Why does fake news go viral?

Answer: ~~Short attention spans~~

Nature Human Behaviour **volume 1**, Article number: 0132 (2017)

nature
human behaviour

Limited individual attention and online virality of low-quality information

Xiaoyan Qiu[1,2*], Diego F. M. Oliveira[2*], Alireza Sahami Shirazi[3], Alessandro Flammini[2,4], Filippo Menczer[2,3,4]

[1] *School of Economics and Management - Shanghai Institute of Technology*
[2] *Center for Complex Networks and Systems Research- School of Informatics and Computing - Indiana University*
[3] *Yahoo Research*
[4] *Indiana University Network Science Institute*

Abstract

Social media are massive marketplaces where ideas and news compete for our attention [1]. Previous studies have shown that quality is not a necessary condition for online virality [2] and that knowledge about peer choices can distort the relationship between quality and popularity [3].

⚠ This article was retracted on 07 January 2019

Conclusions

- We have all heard: "*Let the data speak*"
- Data do not speak
- The interpreter of the data speaks – often with an agenda and with a set of tools that can shape the narrative
- Investors need to be especially vigilant in this era of big data, large number of predictors, a plethora of methods, and the incentives to strategically manipulate the data to uncover a convenient "truth".

False (and Missed) Discoveries in Financial Economics

Campbell R. Harvey

Duke University, Durham, NC 27708 USA
National Bureau of Economic Research, Cambridge, MA 02138 USA

Yan Liu*

Texas A&M University, College Station, TX 77843 USA

https://ssrn.com/abstract=3073799

Contact

http://linkedin.com/in/camharvey

cam.harvey@duke.edu

@camharvey

SSRN: http://ssrn.com/author=16198

PGP: E004 4F24 1FBC 6A4A CF31 D520 0F43 AE4D D2B8 4EF4

Recommended

https://statmodeling.stat.columbia.edu/