

Reflexivity in Financial Market Forecasting

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“You are not going to get the
alpha anyway”

Nassim Taleb on the Importance of Probability

May 12, 2016, Bloomberg TV

“Not only causalities but also associations are hard in social sciences”

Spyros Makridakis, @spyrosmakrid,
August 17, 2018

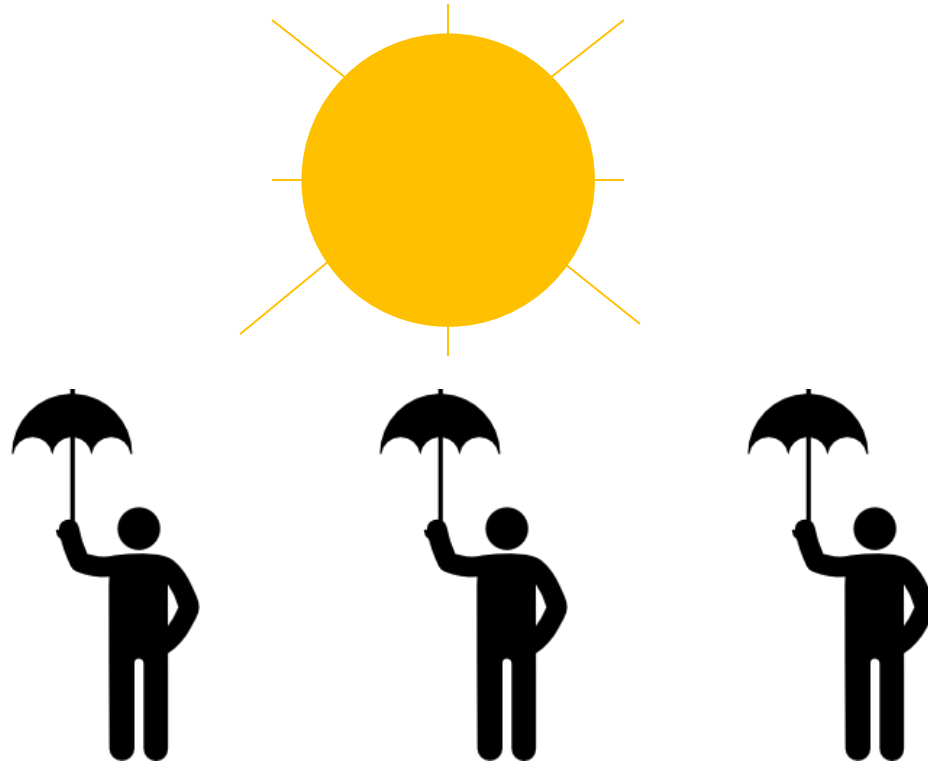
Reflexivity in Financial Market Forecasting

Presentation outline

- Brief introduction to reflexivity
- Examples from financial markets
- A practitioner's approach

Reflexivity in Financial Market Forecasting

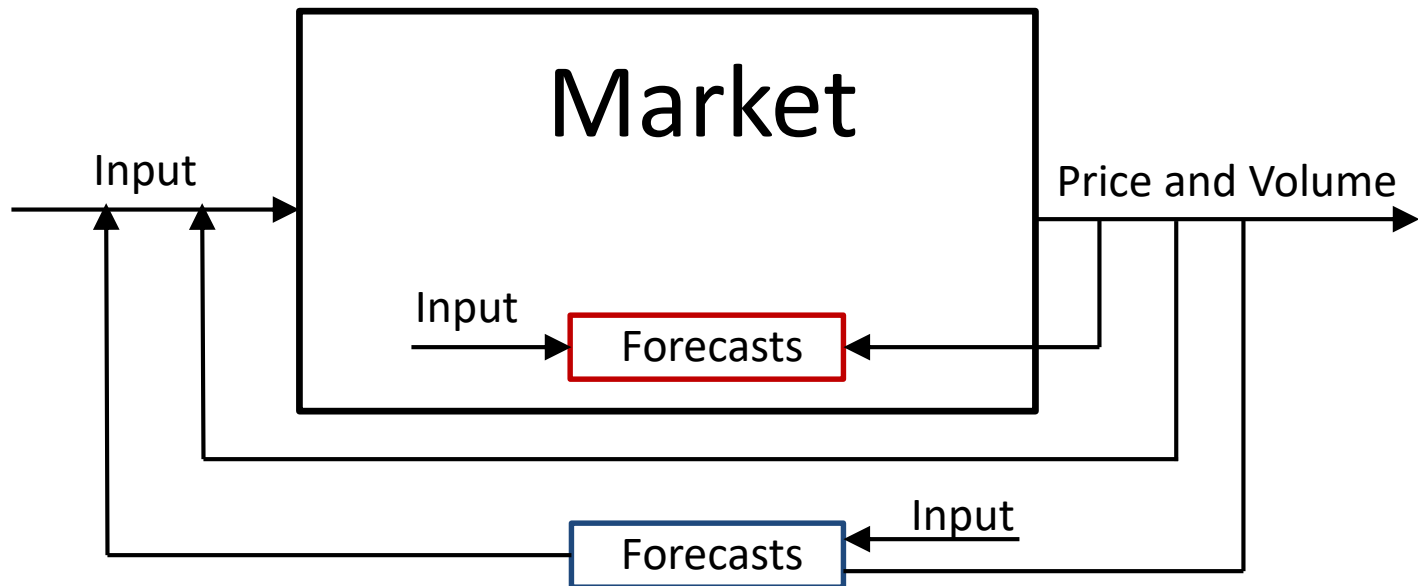
Weather Forecasting



Forecasters and users of forecasts cannot affect the weather since they are not part of the process that determines weather conditions.

Reflexivity in Financial Market Forecasting

Reflexivity in financial markets leads to highly complex non-linear stochastic systems



Reflexivity in Financial Market Forecasting

Reflexivity may be described as follows:

Forecasts influence prices and in turn prices influence forecasts

Reflexivity causes

- **Indeterminacy**
- Degraded forecasting accuracy
- Boom and bust cycles
- High complexity

Ref. Eric D. Beinhocker (2013) Reflexivity, complexity, and the nature of social science, *Journal of Economic Methodology*, 20:4, 330-342, DOI: 10.1080/1350178X.2013.859403

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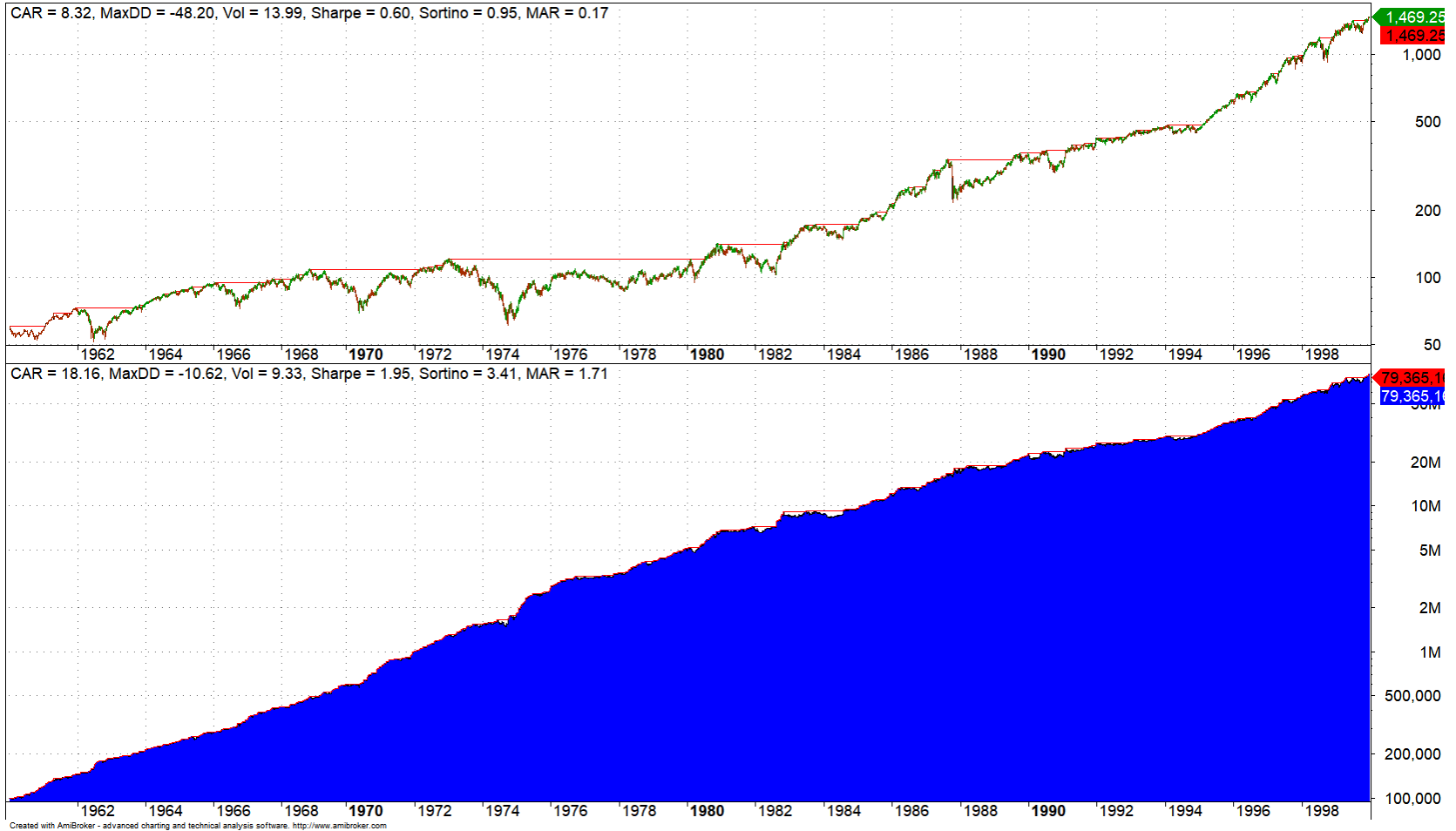
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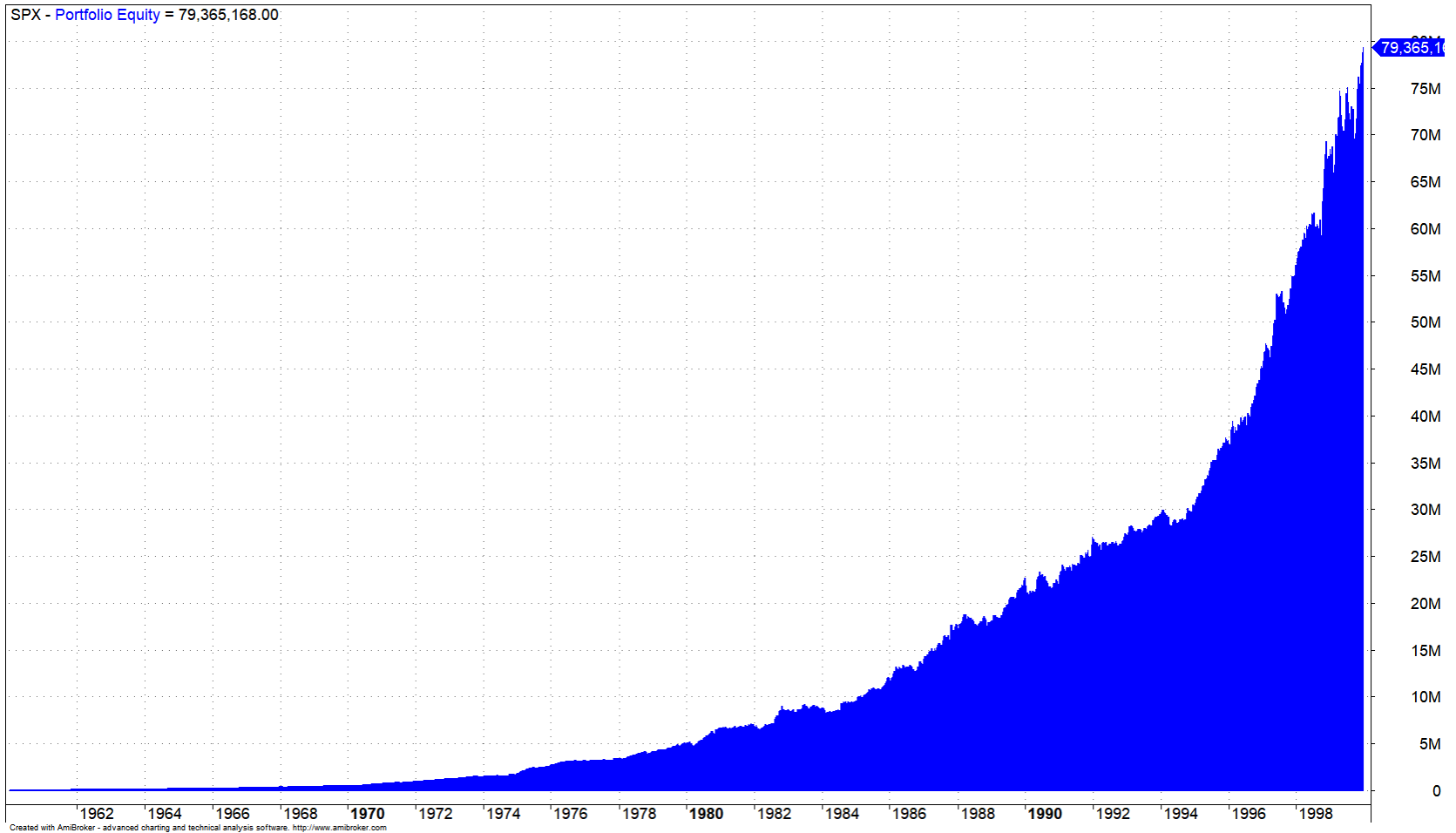
Example: S&P 500 Index 1960 -1999



Buy: $P_{t+1} > P_t \Leftrightarrow (P_{t+1}/P_t) - 1 > 0 \Leftrightarrow P_{t+1} > (P_{t+1}+P_t)/2$

Sell: $P_{t+1} < P_t \Leftrightarrow (P_{t+1}/P_t) - 1 < 0 \Leftrightarrow P_{t+1} < (P_{t+1}+P_t)/2$

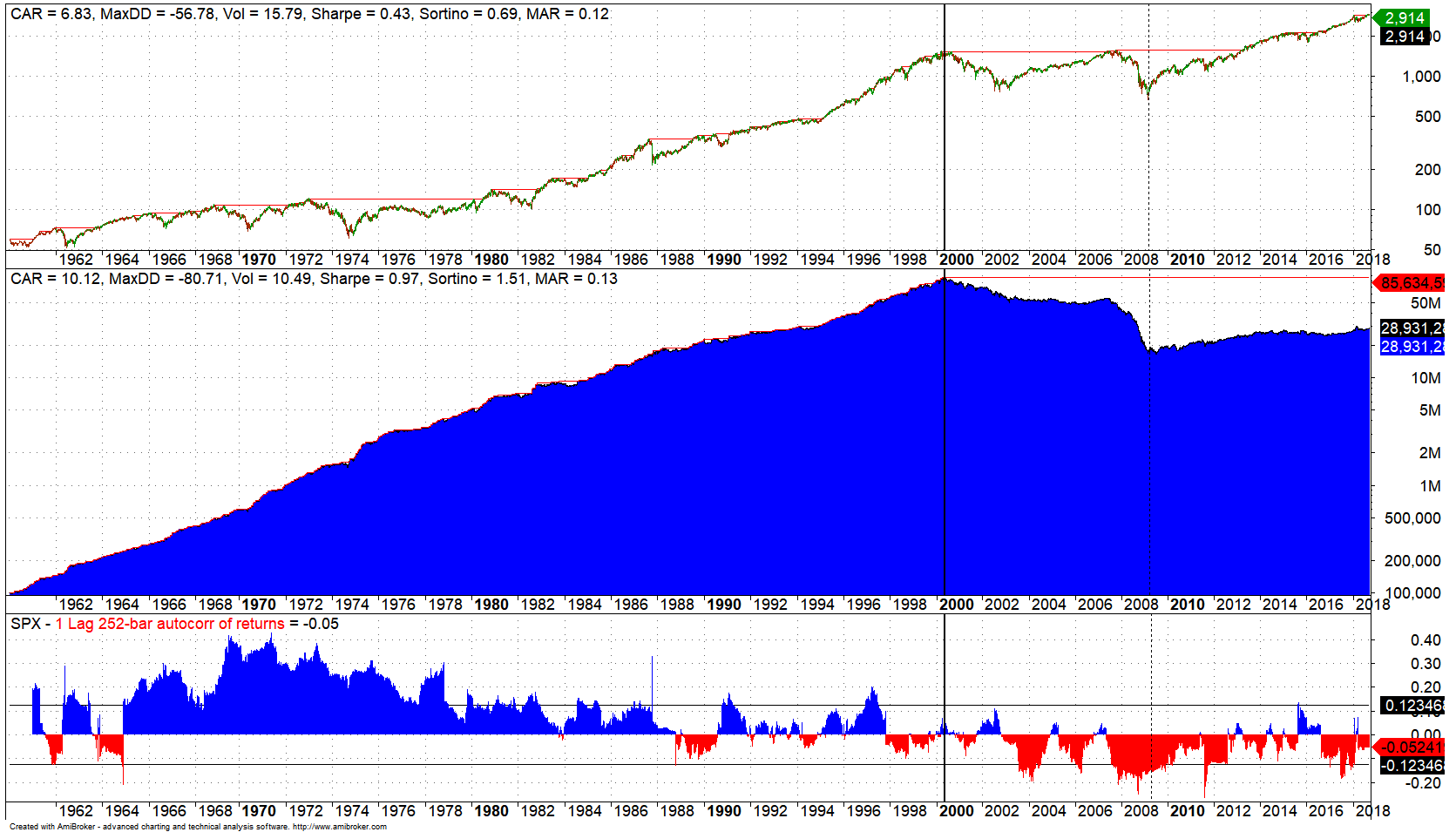
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S&P 500 Index: 1950 -1997

Period m	Annualized Return	Annualized Std Dev	Worst Drawdown	Annualized Sharpe ($R_f = 0$)	Sharpe Rank	T-stat
2	0.169	0.089	0.114	1.90	1	13.1635
3	0.148	0.088	0.142	1.68	2	11.6393
4	0.129	0.088	0.257	1.46	4	10.1151
5	0.125	0.089	0.165	1.41	6	9.76876
6	0.133	0.088	0.160	1.52	3	10.5308
7	0.126	0.087	0.145	1.45	5	10.0458
8	0.125	0.089	0.182	1.38	7	9.5609
9	0.108	0.087	0.204	1.25	9	8.6602
10	0.110	0.086	0.169	1.28	8	8.8681
11	0.106	0.087	0.185	1.23	10	8.5216
12	0.094	0.086	0.230	1.09	15	7.5517
13	0.099	0.086	0.244	1.14	11	7.8981
14	0.099	0.087	0.175	1.14	12	7.8981
15	0.095	0.087	0.192	1.10	13	7.6210
16	0.092	0.087	0.193	1.06	16	7.3438
17	0.096	0.087	0.210	1.10	14	7.6210
18	0.092	0.087	0.186	1.05	17	7.2746
19	0.091	0.087	0.202	1.05	18	7.2746
20	0.089	0.087	0.185	1.02	19	7.0667
Buy & hold	0.083	0.132	0.482	0.67	-	-

Buy if $P_t - MA_t(m) > 0$

Sell if $P_t - MA_t(m) \leq 0$

Sharpe ratio of strategy is higher than buy and hold Sharpe ratio for all moving average periods from 2 to 20.

Ref. Harris, Michael, Limitations of Quantitative Claims About Trading Strategy Evaluation (July 15, 2016). Available at SSRN: <https://ssrn.com/abstract=2810170> or <http://dx.doi.org/10.2139/ssrn.2810170>

S&P 500 - Regime Change

- **Forecasts for higher prices drove prices higher and in turn higher prices resulted in forecasts for higher prices (reflexivity)**
- An unstable mode was triggered in stock markets
- The crowded trade continued until it became unsustainable
- Markets became (more) mean-reverting
- Central Banks had to intervene to prevent collapse

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Some Misconceptions Caused by Reflexivity

- **Market participants attributed success to models, or skill, when in fact it was due to specific market regime – monkeys throwing darts could profit**
- They thought over-optimized models work better in forward samples
- They underestimated fat tails and associated risks
- After the regime change they thought more complex models must be able to generate better predictions (Machine Learning)

Some or all of the above misconception are still prevalent among practitioners and can even be found in academic papers (for example momentum studies.)

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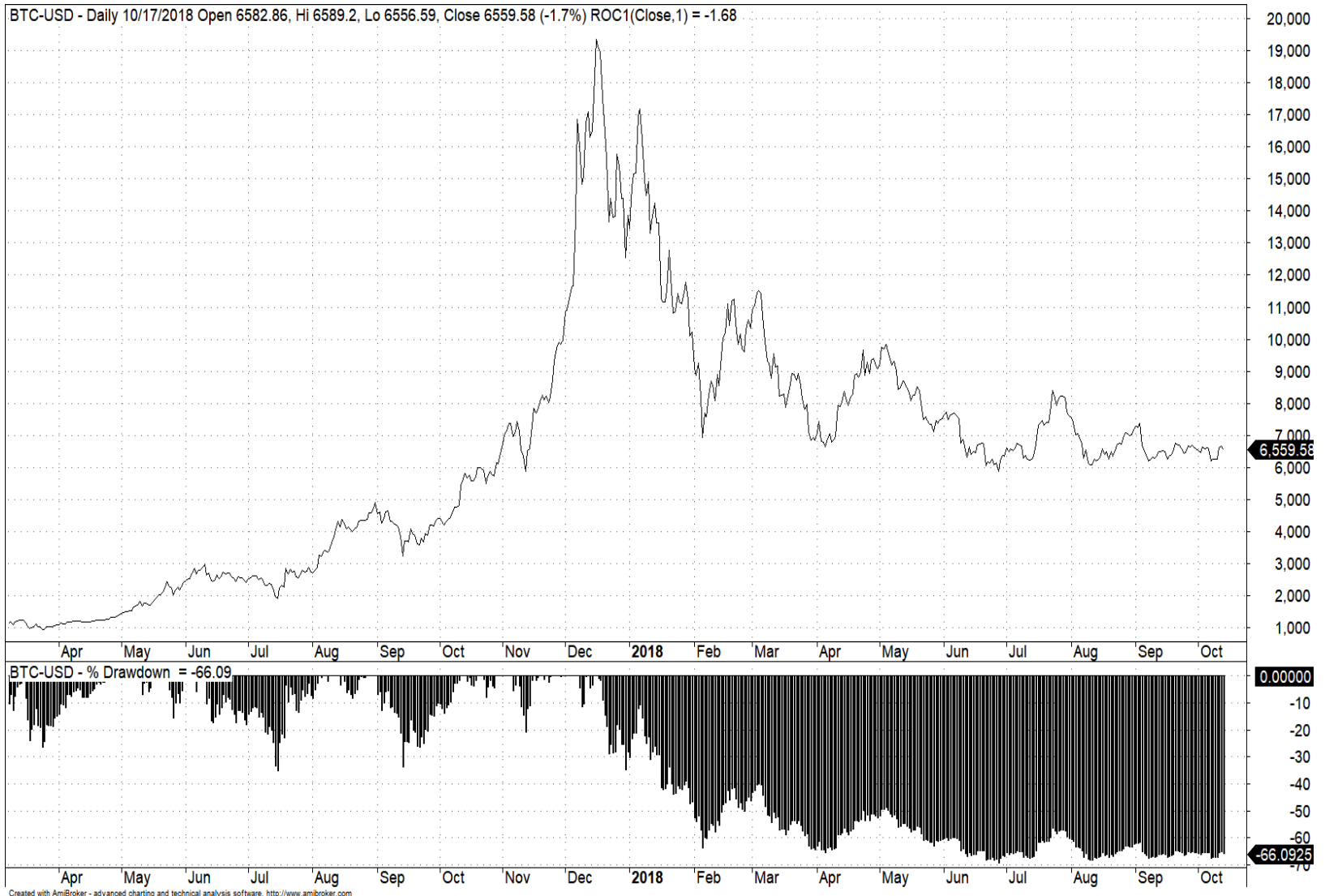
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BOOM AND BUST EXAMPLE: BITCOIN

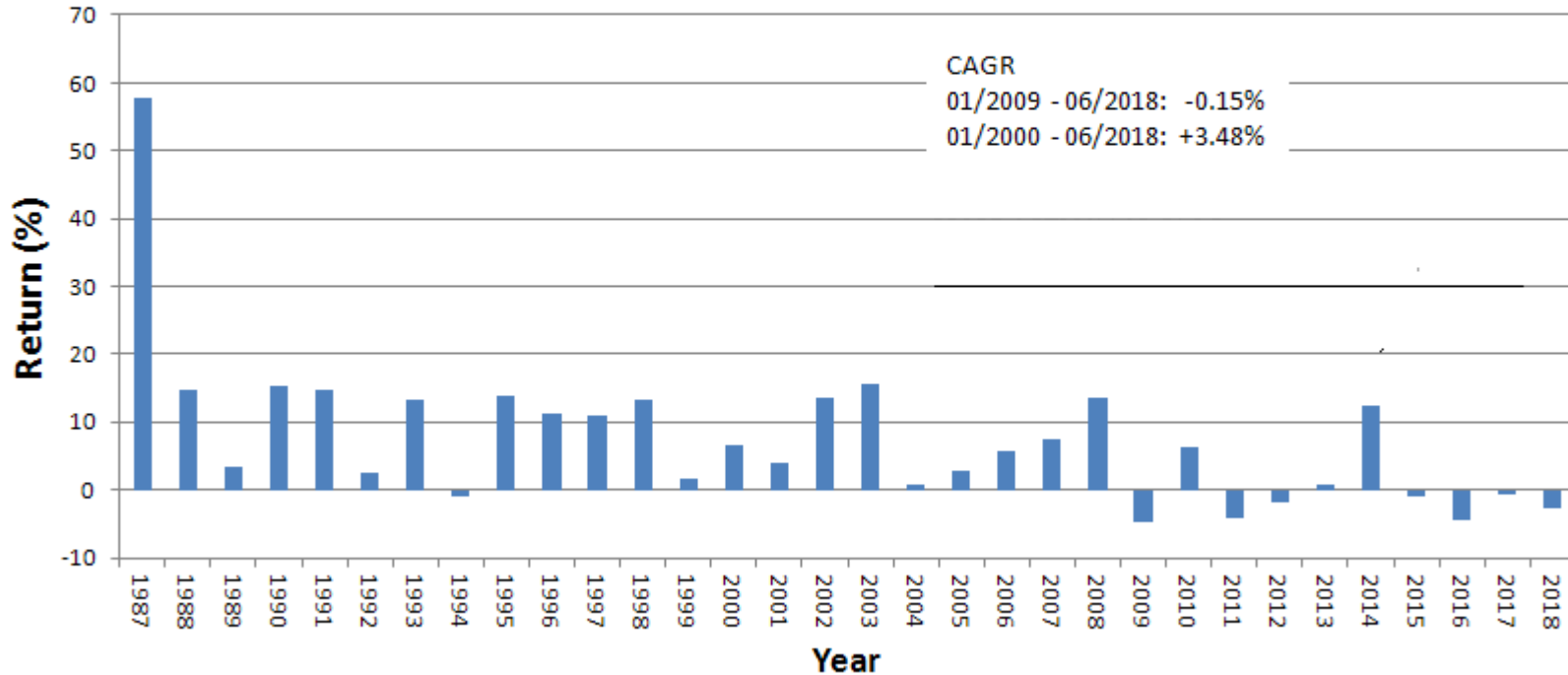


CTA Performance

CTA Performance BTOP50

01/1987 - 06/2018*

*YTD - Source: Barclayhedge



CTA performance has declined significantly although trends form in the markets. Trends necessary for trend-following but not sufficient.

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Reflexivity in Financial Market Forecasting

Complexity and the Curse of Dimensionality

Consider x_n input variables to a system with $n \geq 4$. We define the n -hypersphere as the set of n -tuples of points (x_1, x_2, \dots, x_n) such that

$$x_1^2 + x_2^2 + \dots + x_n^2 = R^2$$

The content V_n of the n -hypersphere of radius R and surface S_n is given by

$$V_n = \frac{R^n S_n}{n}$$

Ref. <http://mathworld.wolfram.com/Hypersphere.html>

Reflexivity in Financial Market Forecasting

Complexity and Peaking Phenomena

Let x_n be normalized in $[-1,1]$

The hyper-surface area S_n of the unit n -hypersphere reaches a maximum for $n = 7.257$ and then asymptotically shrinks to 0 as n increases.

For $n > 20$ all possible solutions are **extreme**.

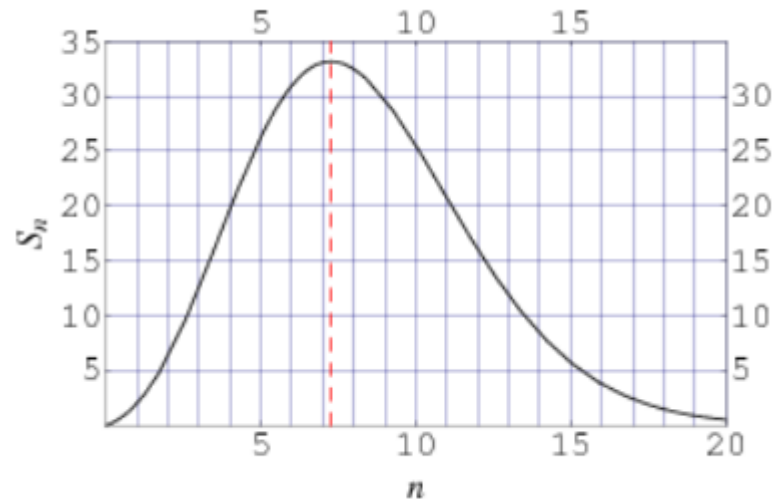


Chart from <http://mathworld.wolfram.com/Hypersphere.html>

Reflexivity in Financial Market Forecasting

Complexity ramifications

The bad news

Any centrally controlled multivariate system that attempts to juggle too many variables at once is doomed to fail due to inevitable extreme choices.

Recent example: Soviet Union. Next: EU, China and down the road USA.

- **Economic forecasting generates random results under complexity**
- There are unstable modes (2008 financial crisis)
- There may also be catastrophic modes
- Ruin is certain in the long-term

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Complexity ramifications

Some good news

Certain problems in finance involve selection/ranking. Examples:

Portfolio construction (+1 = include security, -1 = exclude security)

Trading (+1 = buy/cover, -1 = sell/short)

Main problem is discovering the signal in the noise (feature construction)

Supervised machine learning is useful as an added layer

Challenge: bias-variance tradeoff (under-fitting vs. over-fitting)

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Feature construction: Complex versus simple facts

“...the most interesting facts are those which may serve many times; these are the facts which have a chance of coming up again... Which then are the facts likely to reappear? They are first the simple facts... But are there any simple facts? And if there are, how recognize them?”

H. POINCARÉ , SCIENCE AND HYPOTHESIS (1913)

Available at: <http://www.gutenberg.org/files/39713/39713-h/39713-h.htm>

Reflexivity in Financial Market Forecasting

Feature Construction for long/short equity trading

$i = 1, 2, \dots, n$ securities, $j = 1, 2, \dots, m$ price action anomalies (simple rules)

T_{ij} = number of past occurrences (trades) of j rule in i security

PL_{ij} = win fraction of j rule in i security for long positions

PS_{ij} = win fraction of j rule in i security for short positions

At every time step t calculate the following for n securities and m rules:

$$\bar{P}L_i = \frac{\sum_{j=1}^m PL_{ij} T_{ij}}{\sum_{j=1}^m T_{ij}} \quad \bar{P}S_i = \frac{\sum_{j=1}^m PS_{ij} T_{ij}}{\sum_{j=1}^m T_{ij}}$$

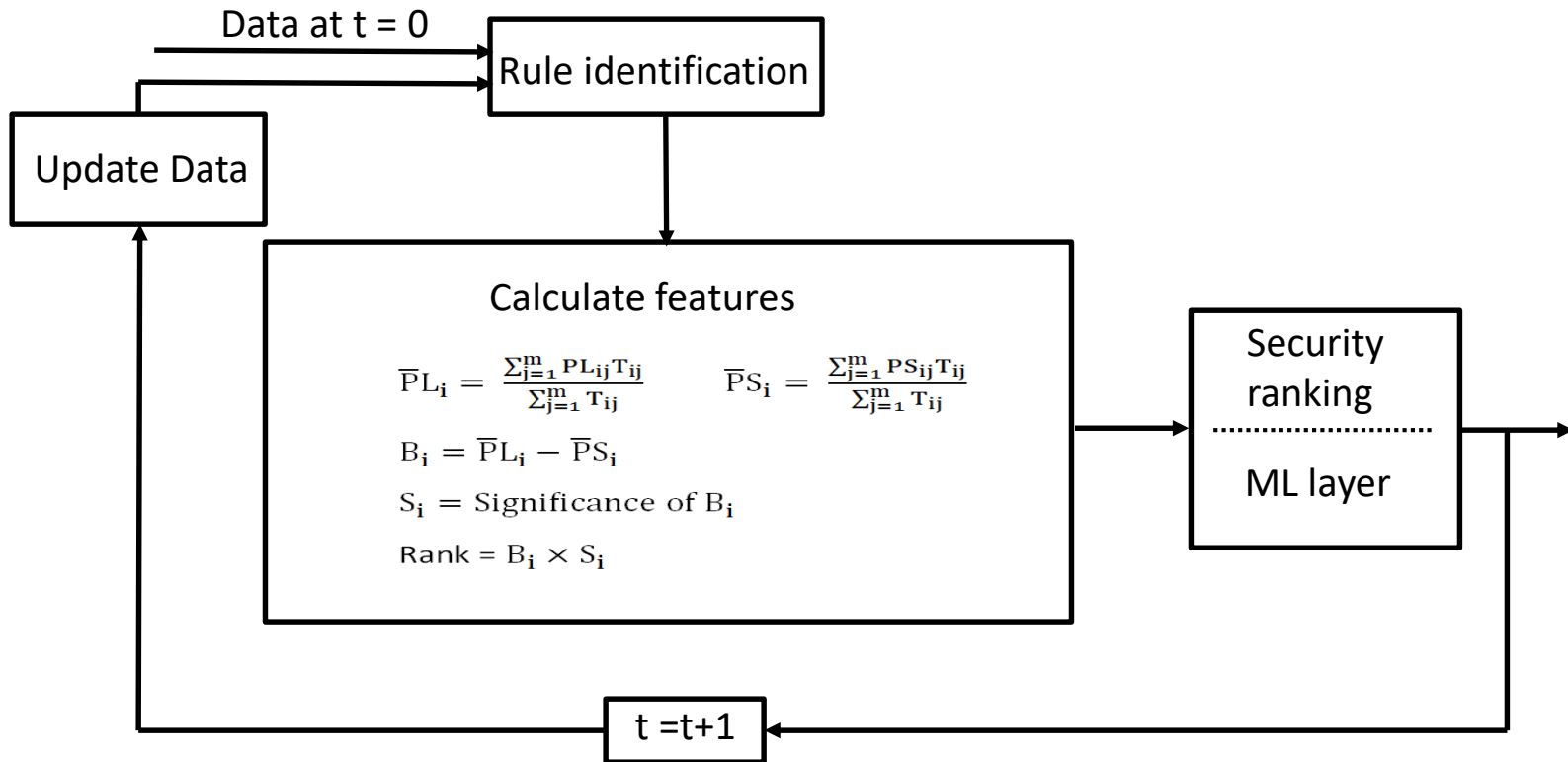
$$B_i = \bar{P}L_i - \bar{P}S_i$$

S_i = Significance of B_i

$$\text{Rank} = B_i \times S_i$$

Reflexivity in Financial Market Forecasting

Long/short equity trading



Reflexivity in Financial Market Forecasting

Long/short equity trading

Issues:

- **We are working in ensemble domain**
- Risk-of-ruin is small but still finite
- Only true validation is skin-in-the-game
- We are pursuing this route as long as it generates alpha

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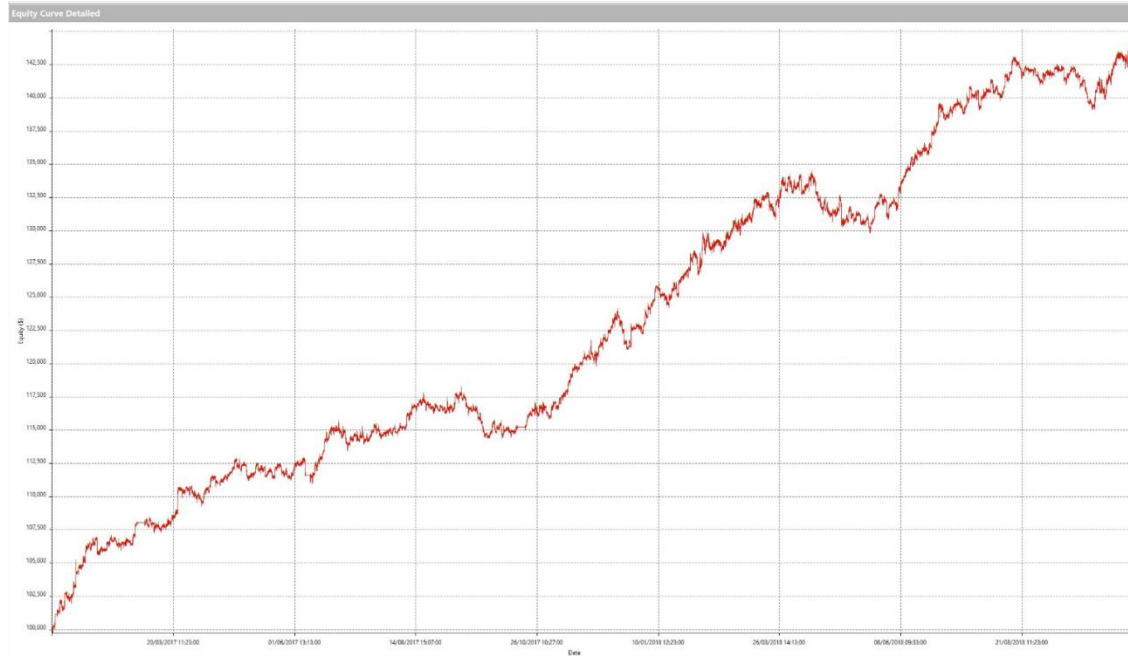
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Shown with permission

Actual fund performance from 01/2017 to 10/2018 net of commissions

Return: 45.1%, 19.7% long trades - 25.4% short trades.

Total trades = 1677, long: 911, short: 766

Win rate = 53.5%

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