Compositions

Your Strategy

Your Risk Management

Market Sentiment

Specific

Market Breadth

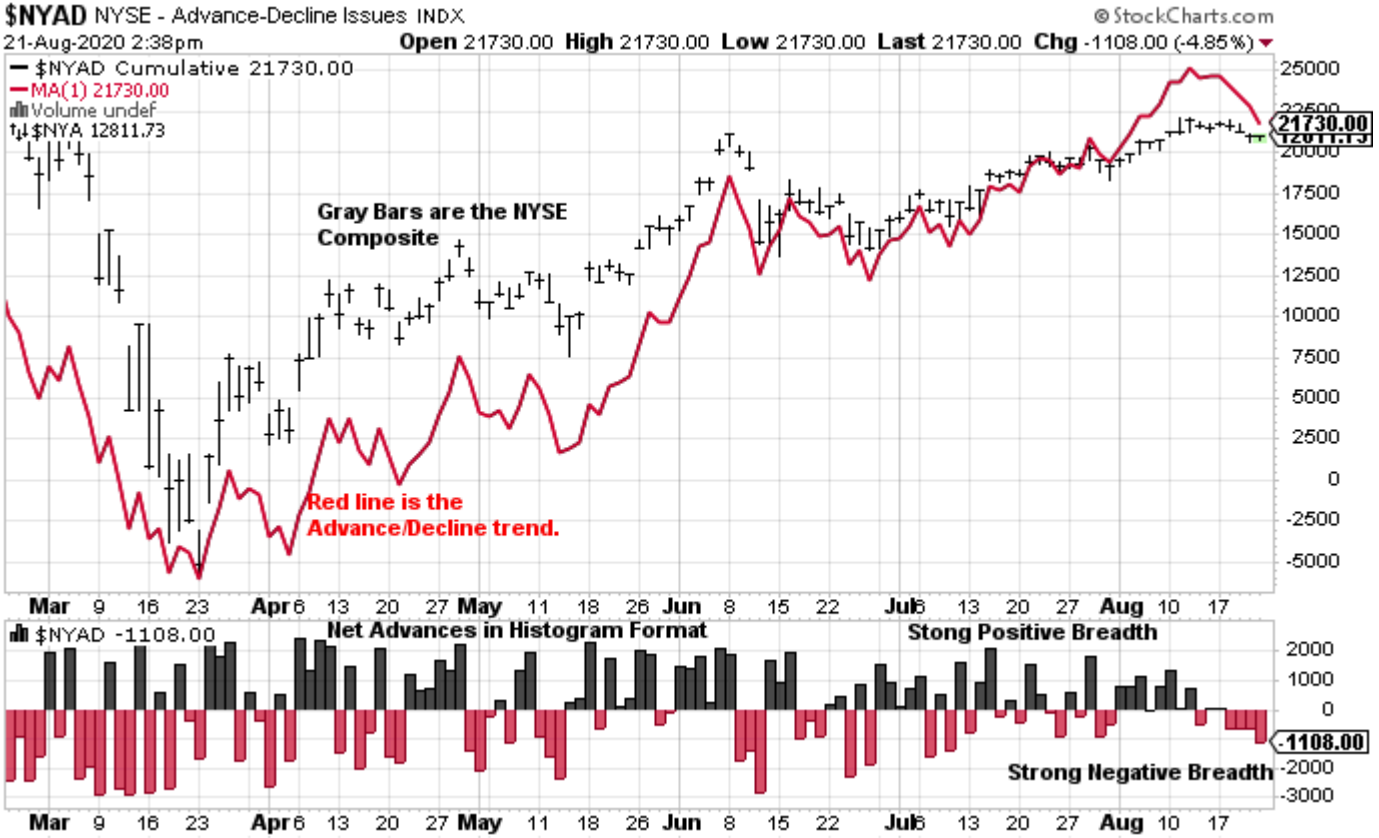
Why Use Market Breadth Indicators?

Market Sentiment – Breadth pointers can enable you to decide whether a market is inclining bullish or bearish.

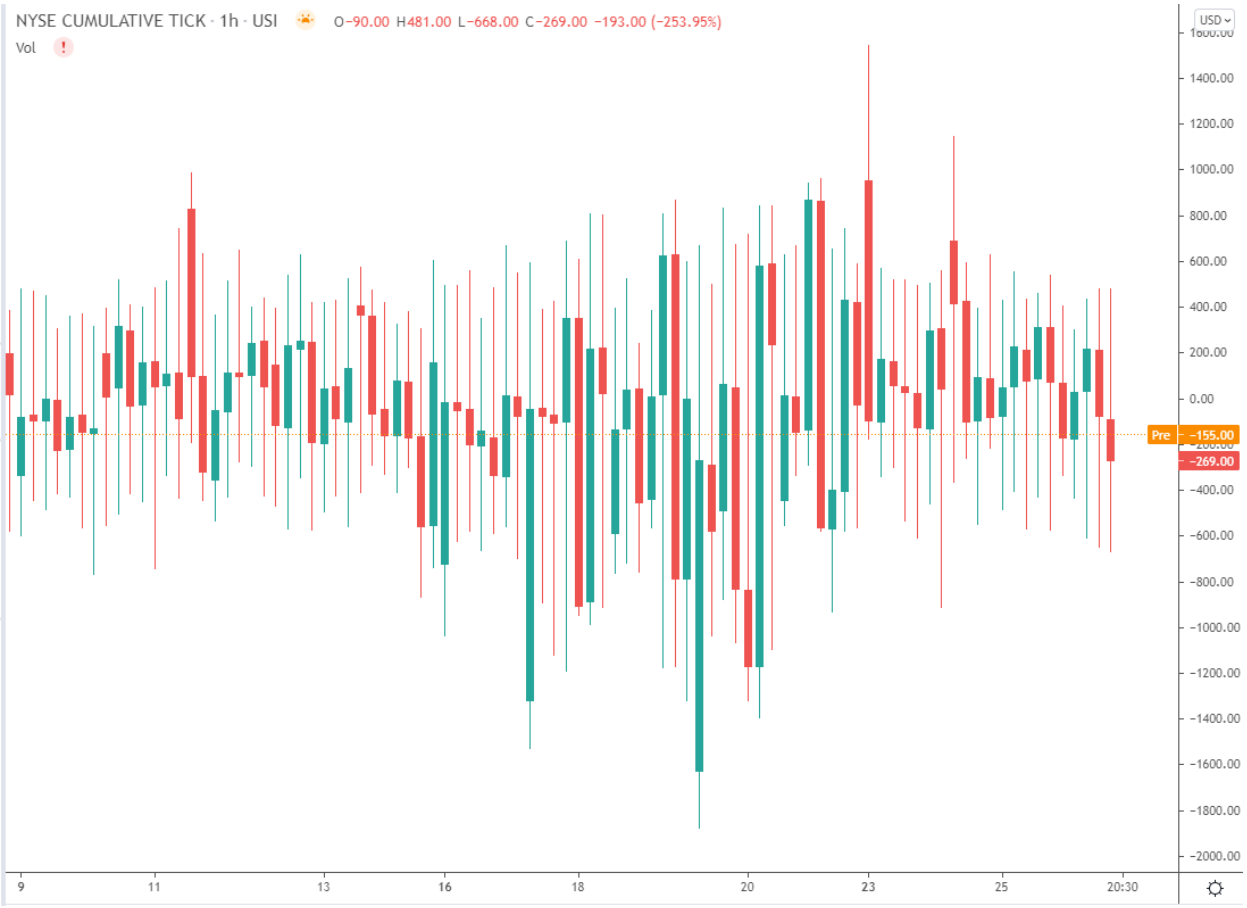
Pattern Strength – Breadth markers can enable you to decide the quality of a bullish or bearish pattern.

Advance/Decline High/Low Above/low avg

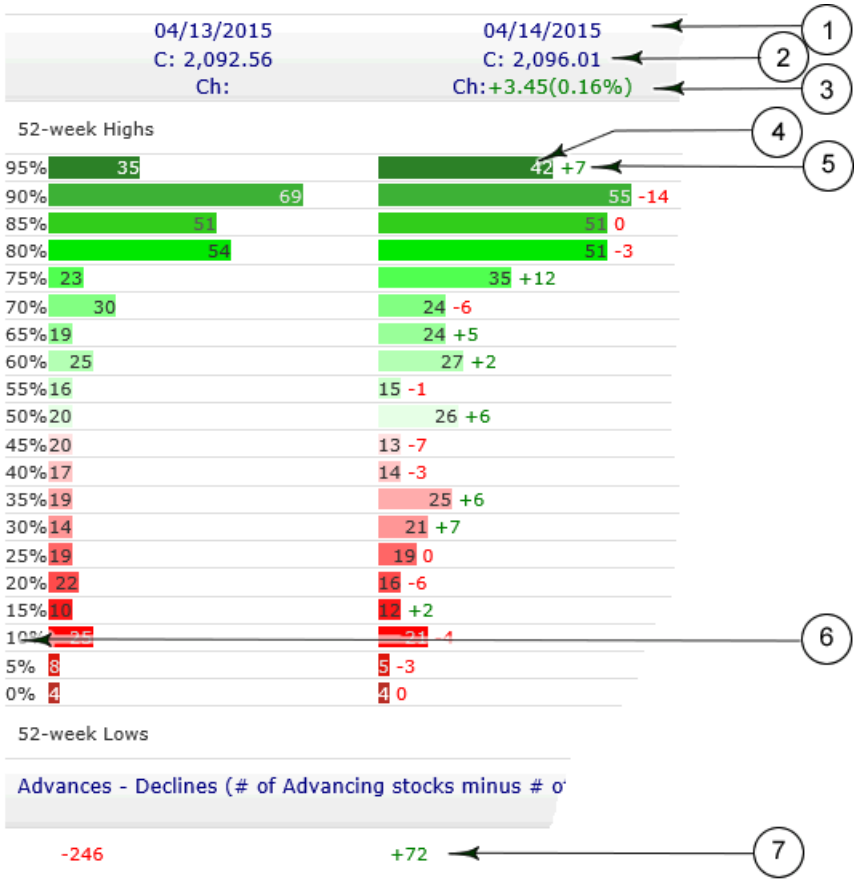
Market Breadth



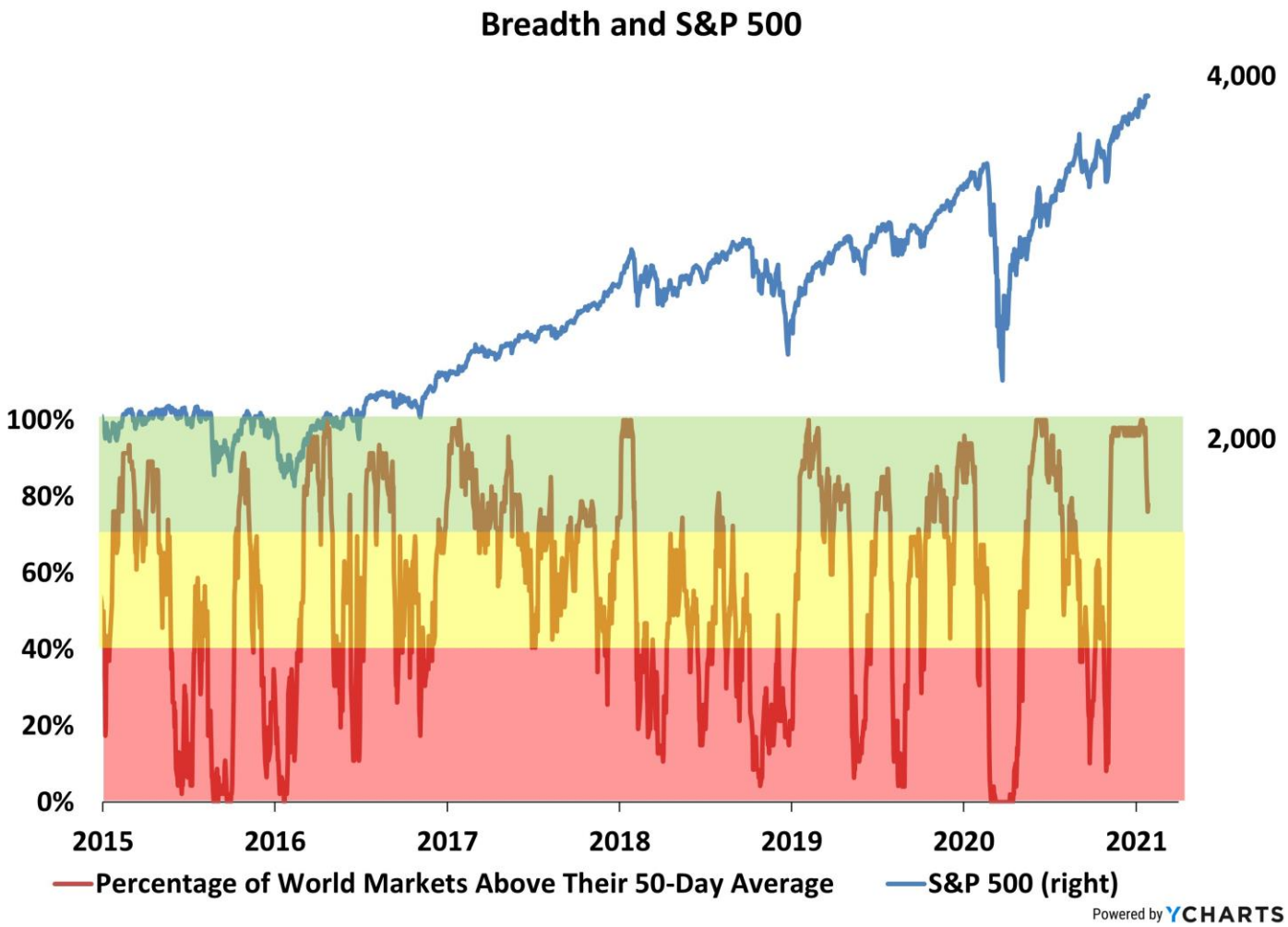
Market Breadth



Market Breadth



Market Breadth



Compositions

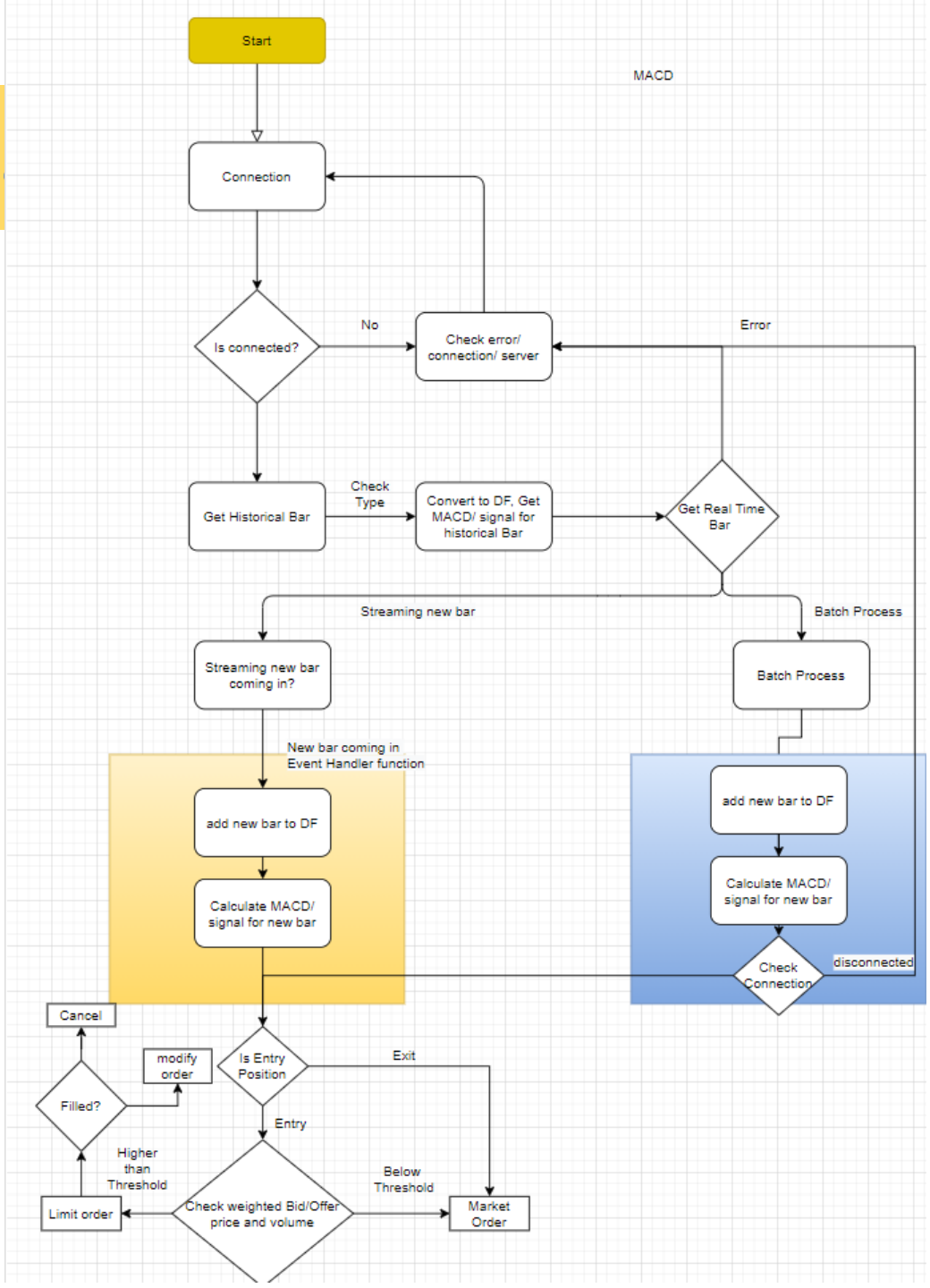
Your Strategy

Your Risk Management

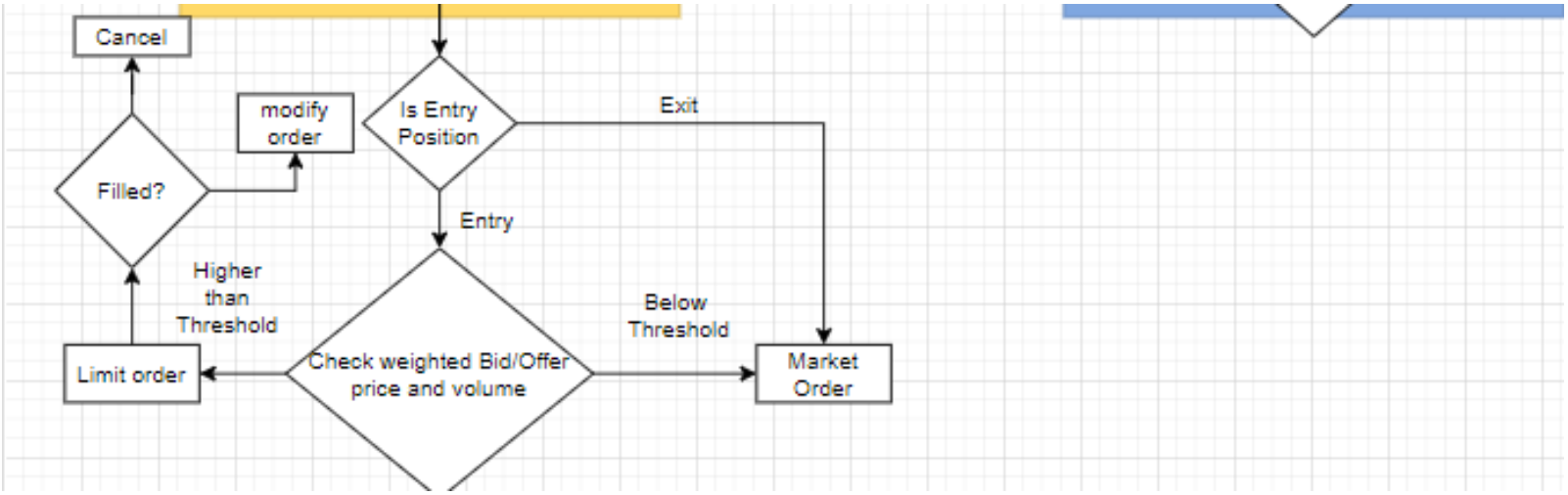
Market Sentiment

Events

What if


Start
MACD
Connection
Is connected?
No
Check error/ connection/ server
Error
Get Historical Bar
Check Type
Convert to DF, Get MACD/ signal for historical Bar
Get Real Time Bar
Streaming new bar
Batch Process
Streaming new bar coming in?
Batch Process
New bar coming in
Event Handler function
add new bar to DF
Calculate MACD/ signal for new bar
add new bar to DF
Calculate MACD/ signal for new bar
Check Connection
disconnected
Cancel
modify order
Is Entry Position
Exit
Filled?
Entry
Higher than Threshold
Below Threshold
Limit order
Check weighted Bid/Offer price and volume
Market Order

What if …


Cancel
modify order
Is Entry Position
Exit
Filled?
Entry
Higher than Threshold
Below Threshold
Limit order
Check weighted Bid/Offer price and volume
Market Order

Time to get orderbook

```
In [45]: bid_ask = binance.fetchOrderBook('BTCUSDT')

In [46]: bid_ask

Out[46]: {'symbol': 'BTCUSDT',
          'bids': [[46644.52, 1.04641],
           [46642.44, 0.11999],
           [46642.43, 0.39],
           [46642.31, 0.13649],
           [46640.59, 0.01747],
           [46640.38, 0.17399],
           [46640.37, 1.1],
```

Time to get orderbook

```
 [46588.75, 0.00085]],
'asks': [[46644.53, 0.06748],
 [46646.77, 0.06999],
 [46647.06, 0.006]
 [46728.76, 0.04179],
 [46729.03, 0.03024]],
'timestamp': None,
'datetime': None,
'nonce': 13255404501}
```

```
In [49]: bid = pd.DataFrame(bid_ask['bids'],columns =['price','volume'])
```

```
In [50]: ask = pd.DataFrame(bid_ask['asks'],columns =['price','volume'])
```

Time to get orderbook

```
In [53]: bid
```

Out[53]:

	price	volume
0	46644.52	1.04641
1	46642.44	0.11999
2	46642.43	0.39000
3	46642.31	0.13649
4	46640.59	0.01747
...	...	...
95	46589.51	0.16708
96	46589.09	0.00023
97	46589.05	0.05880
98	46588.92	0.00141
99	46588.75	0.00085

```
In [52]: ask
```

Out[52]:

	price	volume
0	46644.53	0.06748
1	46646.77	0.06999
2	46647.06	0.00600
3	46650.00	0.08627
4	46650.70	0.04497
...	...	...
95	46725.73	0.23332
96	46725.83	0.02007
97	46726.49	0.00068
98	46728.76	0.04179
99	46729.03	0.03024

Time to get orderbook

```
In [53]: bid
```

Out[53]:

	price	volume
0	46644.52	1.04641
1	46642.44	0.11999
2	46642.43	0.39000
3	46642.31	0.13649
4	46640.59	0.01747
...	...	...
95	46589.51	0.16708
96	46589.09	0.00023
97	46589.05	0.05880
98	46588.92	0.00141
99	46588.75	0.00085

0.12% diff

```
In [52]: ask
```

Out[52]:

	price	volume
0	46644.53	0.06748
1	46646.77	0.06999
2	46647.06	0.00600
3	46650.00	0.08627
4	46650.70	0.04497
...	...	...
95	46725.73	0.23332
96	46725.83	0.02007
97	46726.49	0.00068
98	46728.76	0.04179
99	46729.03	0.03024

Time to get orderbook

```
amount = 100000
```

```
ask['cum_amount'] = ask.prod(axis=1).cumsum()
```

```
bid['cum_amount'] = bid.prod(axis=1).cumsum()
```

Upper Buy Price

```
ask.loc[ask.cum_amount >amount].iloc[0]
```

```
price          46659.380000
volume             1.248000
cum_amount    152284.881765
Name: 21, dtype: float64
```

```
ask
```

	price	volume	cum_amount
0	46644.53	0.06748	3147.572884
1	46646.77	0.06999	6412.380317
2	46647.06	0.00600	6692.262677
3	46650.00	0.08627	10716.758177
4	46650.70	0.04497	12814.640156

Time to get orderbook

```
ask['cum_vol'] = ask['volume'].cumsum()
```

```
ask.loc[ask.cum_amount < amount].iloc[-1]
```

```
price          46659.000000
volume             0.080000
cum_amount     94053.975525
cum_vol            2.016020
Name: 20, dtype: float64
```

```
ask.loc[ask.cum_amount > amount].iloc[0]
```

```
price          46659.380000
volume             1.248000
cum_amount    152284.881765
cum_vol            3.264020
Name: 21, dtype: float64
```

Time to get orderbook

```
In [76]: (bid.iloc[0,0] + ask.iloc[0,0])/2
Out[76]: 46644.524999999994
```

Upper Buy Price

Mid price

```
In [78]: ask.loc[ask.cum_amount >amount].iloc[0,0] /  ((bid.iloc[0,0] + ask.iloc[0,0])/2) -1
Out[78]: 0.0003184725324141269
```

0.03%

What's your threshold?

What's if 1,000,000 not 100,000 .. Still worth MKT order?

Know when to .. Stop/Take profit on Events

Yesterday | Today | Tomorrow | **This Week** | Next Week | Filters

Current Time: **02:09** (GMT -4:00)

All data are streaming and updated automatically.

Time	Cur.	Imp.	Event	Actual	Forecast	Previous
			Monday, August 23, 2021			
10:00	USD	★★★	Existing Home Sales (Jul)	5.99M	5.83M	5.87M
			Tuesday, August 24, 2021			
10:00	USD	★★★	New Home Sales (Jul)	708K	700K	701K
			Wednesday, August 25, 2021			
08:30	USD	★★★	Core Durable Goods Orders (MoM) (Jul)	0.7%	0.5%	0.6%
10:30	USD	★★★	Crude Oil Inventories	-2.979M	-2.683M	-3.234M
			Thursday, August 26, 2021			
07:30	EUR	★★★	ECB Publishes Account of Monetary Policy Meeting			
08:30	USD	★★★	GDP (QoQ) (Q2) P	6.6%	6.7%	6.5%
08:30	USD	★★★	Initial Jobless Claims	353K	350K	349K
			Friday, August 27, 2021			
10:00	USD	★★★	Fed Chair Powell Speaks			

Compositions

Your Strategy

Your Risk Management

Market Sentiment

Specific

Relative

ETHUSDT/BTCUSDT · 1D · BINANCE
0.07 +0.00 (+0.18%)
Vol
BTC
0.08
0.07
0.07
0.06
0.05
0.04
0.03
Feb
Mar
Apr
May
Jun
Jul
Aug
23

Relative

Ethereum / Bitcoin · 1D · BINANCE
O0.065891 H0.066444 L0.065431 C0.066141 +0.000247 (+0.37%)
Vol 42.596K
BB 20 close 2 0 0.067984 0.070986 0.064983
BTC
0.085000
0.080000
0.075000
0.070000
0.066141
0.065000
0.060000
0.055000
0.050000
0.045000
0.040000
0.035000
0.030000
0.025000
Mar
Apr
May
Jun
Jul
Aug
23

Relative

Axie Infinity / USD · 1D · FTX
O72.478 H73.889 L67.167 C68.971 −3.507 (−4.84%)
Vol 1.925M
BB 20 close 2 0 66.306 87.679 44.933
USD
900.00%
800.00%
707.34%
600.00%
500.00%
400.00%
300.00%
200.00%
100.00%
0.00%
−100.00%
BTCUSD, COINBASE 46979.61 −2007.72 (−4.10%)
USD
0.00%
−10.00%
−16.85%
−20.00%
−30.00%
−40.00%
−50.00%
May
17
Jun
14
Jul
12
22
Aug
16
30

Relative

SET50/SET · 1D · SET
0.60 −0.00 (−0.22%)
Vol
0.66
0.65
0.64
0.63
0.62
0.61
0.60
0.60
RSI 14 close 55.47
80.00
70.00
60.00
50.00
40.00
30.00
20.00
Sep
Nov
2021
Mar
Apr
Jun
Jul
Sep

TFEX S50 Anomalies

Intraday

10.15, 10.30

15.00, 15.30

4.00

Daily +

Friday to Monday

Turn of the month effect

Second Half Month messed

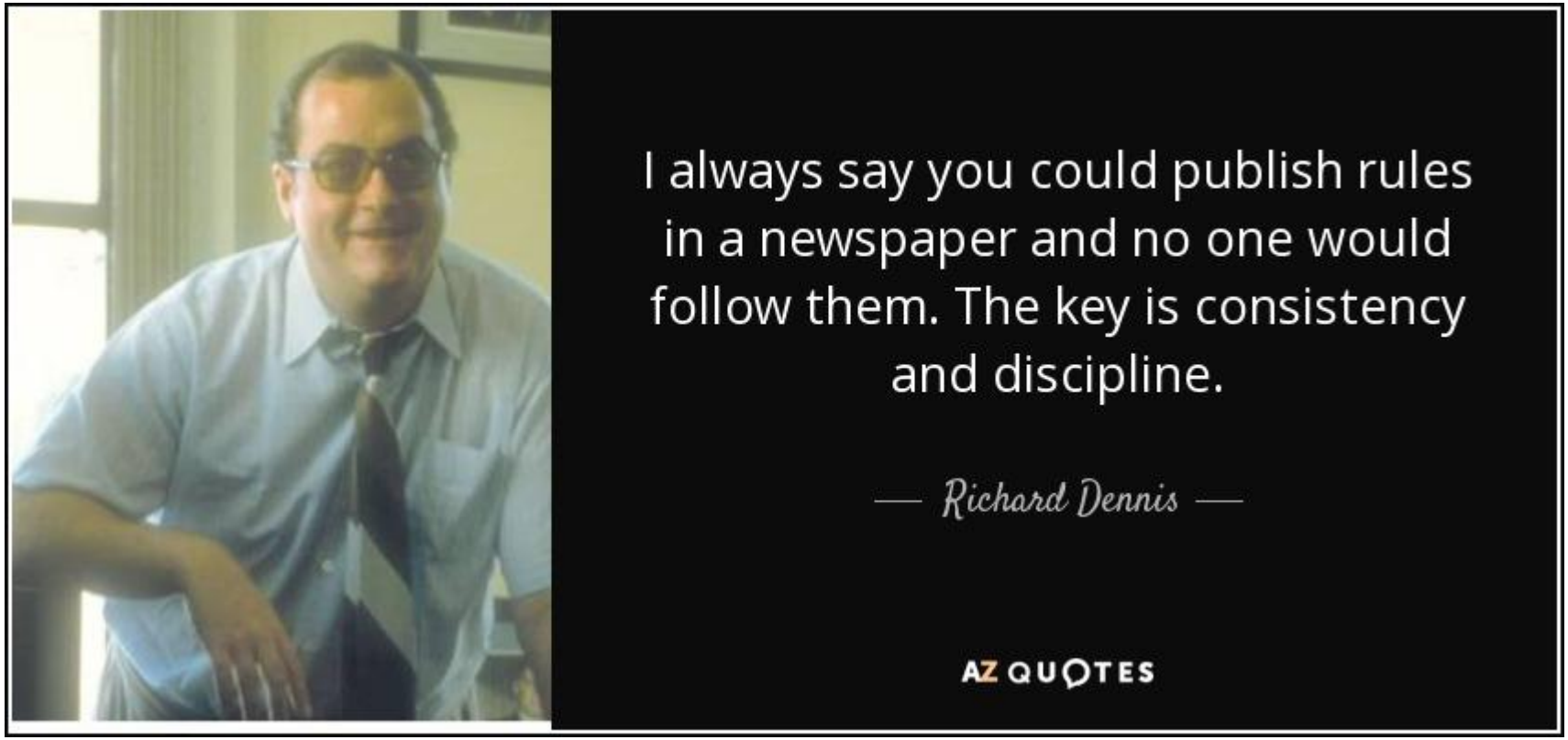
Window Dressing

January Effects

Then … what is so called ‘the best Strategy’ in history

So what is best?

40 years ago: Systematic Trend Following



So what is best?

40 years ago: Systematic Trend Following

In the 1980s, Richard Dennis and William Eckhardt developed a trend following trading system that turned **$5,000 into $100 million**

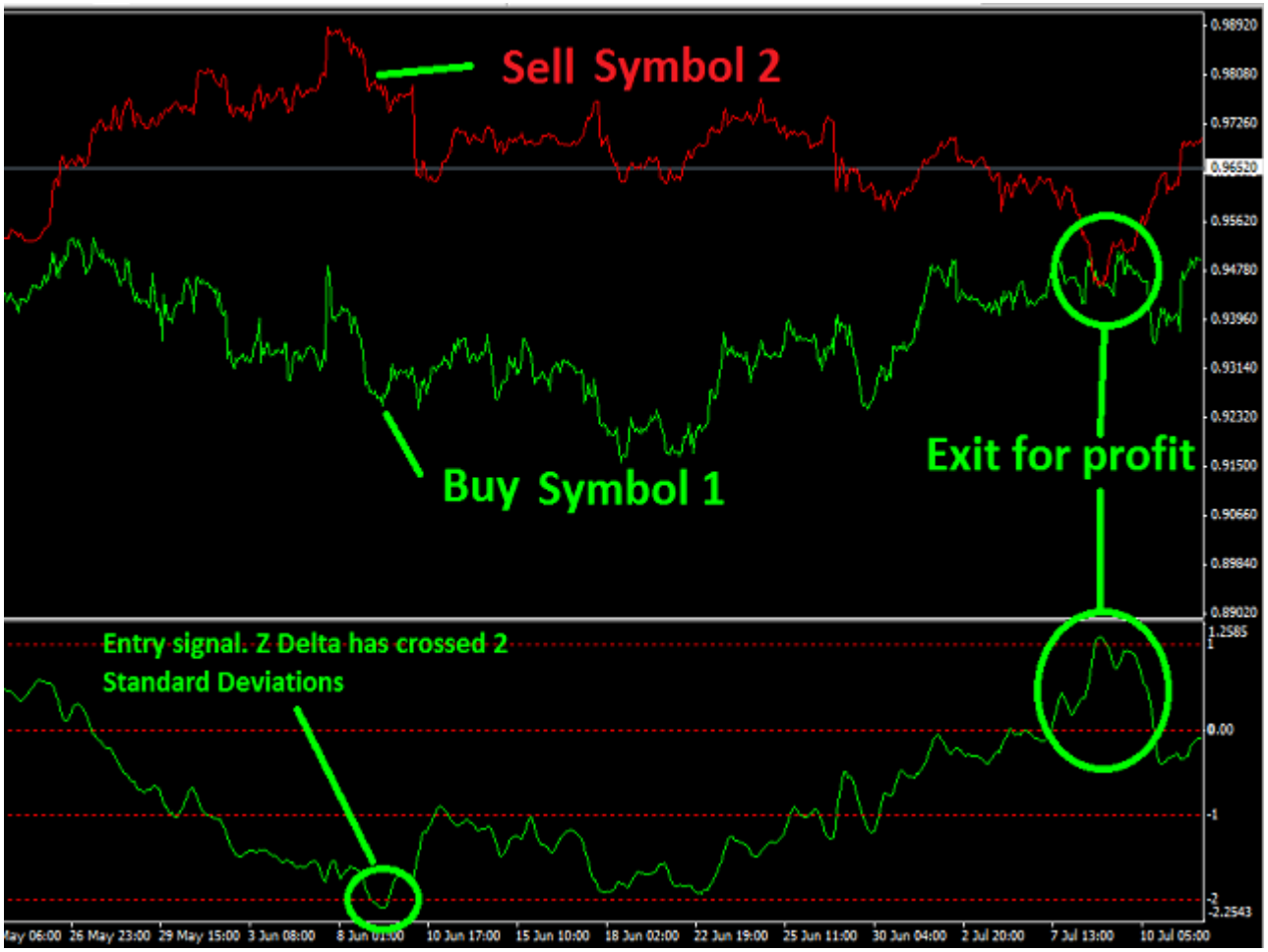
Dennis believed successful traders can be trained while Eckhardt believed they are born with a gift for trading.

Dennis picked people off the streets, interviewed them and selected a handful for the experiment. He and Eckhardt taught these traders (they were called the Turtles) how to trade for two weeks.

They gave the Turtles money to manage after the training.
The Turtles made $175 million in 5 years (that's over $400 million in today's dollars!)

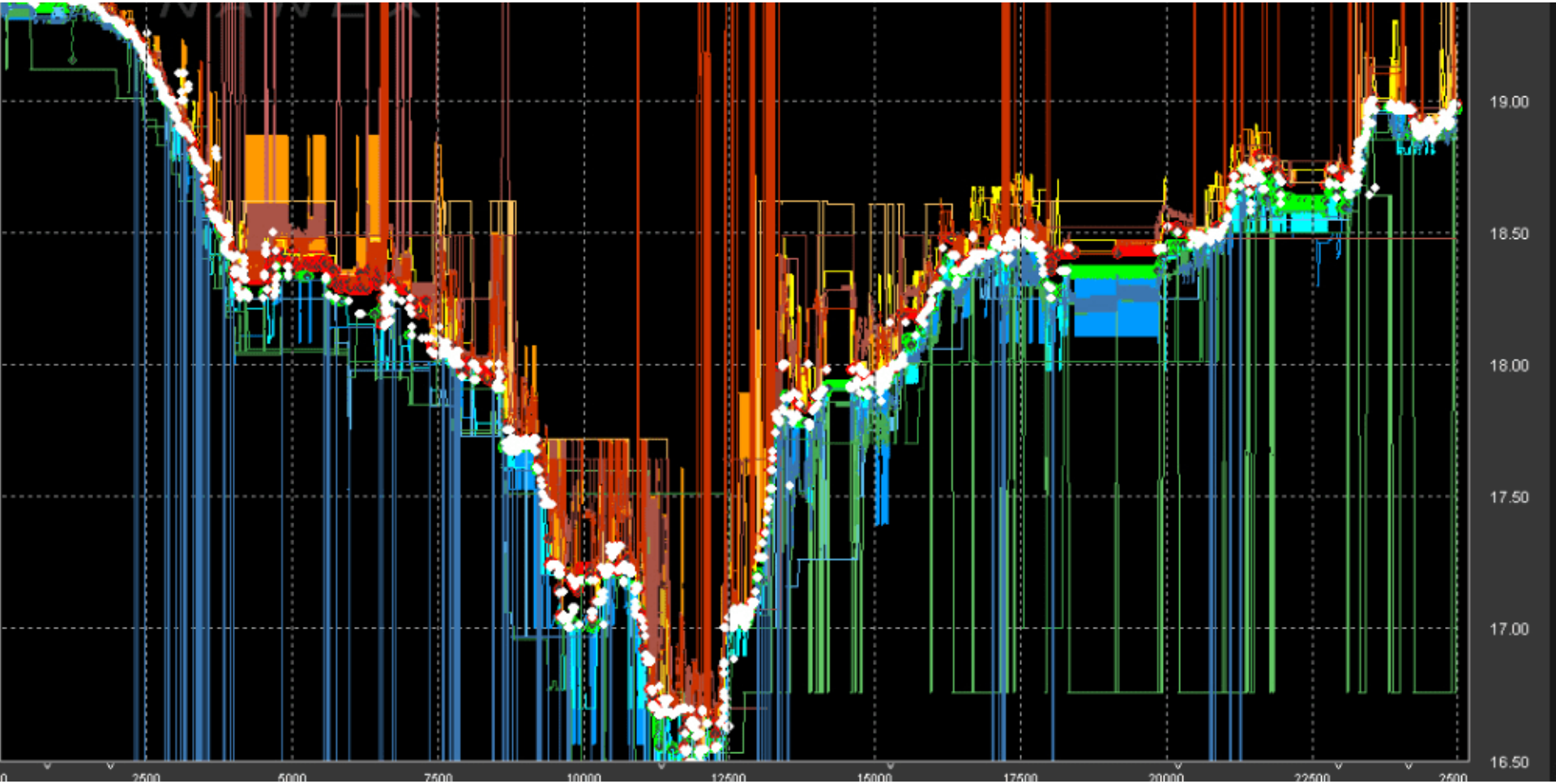
So what is best?

25 years ago: Statistical Arbitrage



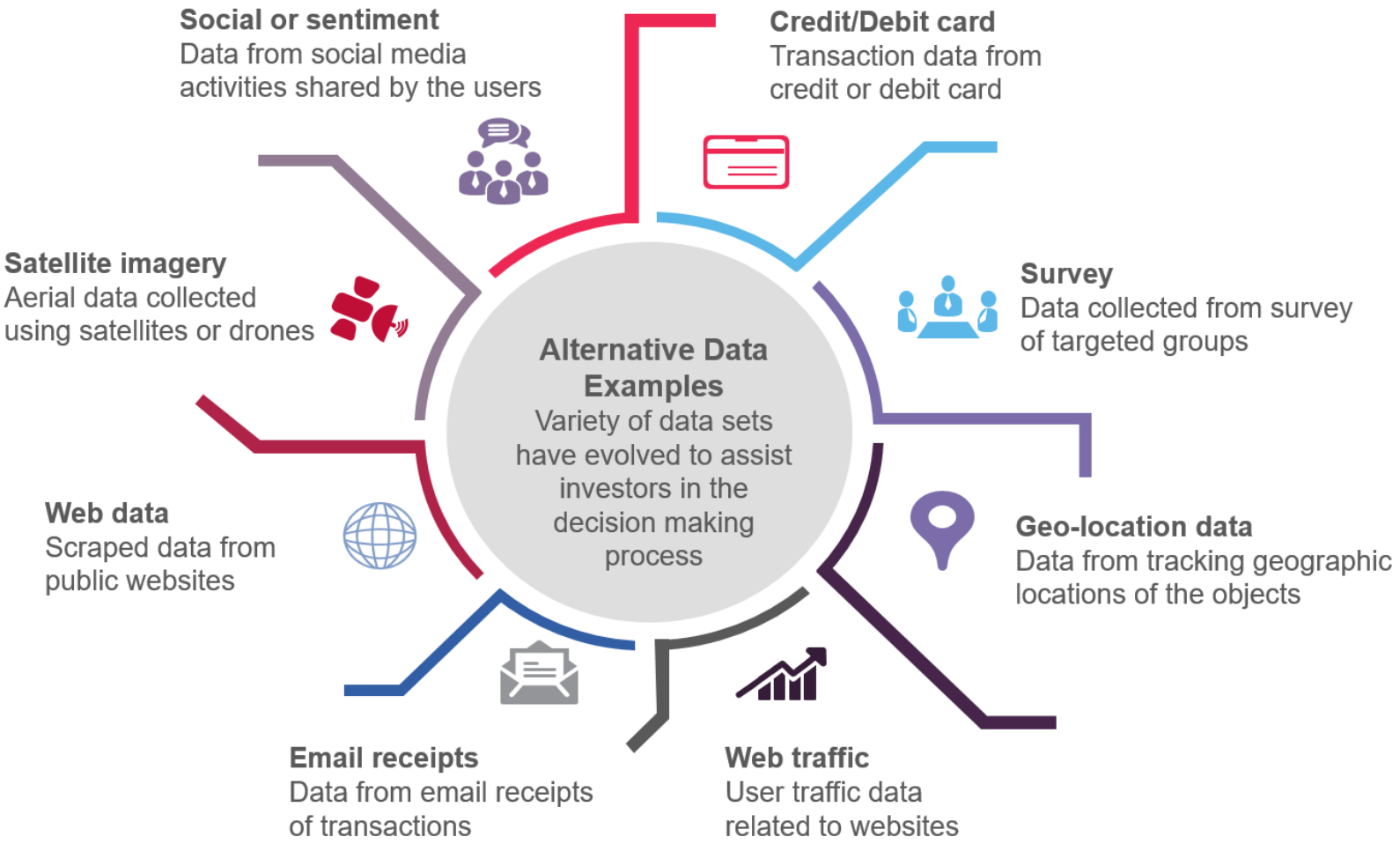
So what is best?

15 years ago: High frequency trading (HFT)



So what is best?

Today: Alternative Data Strategies

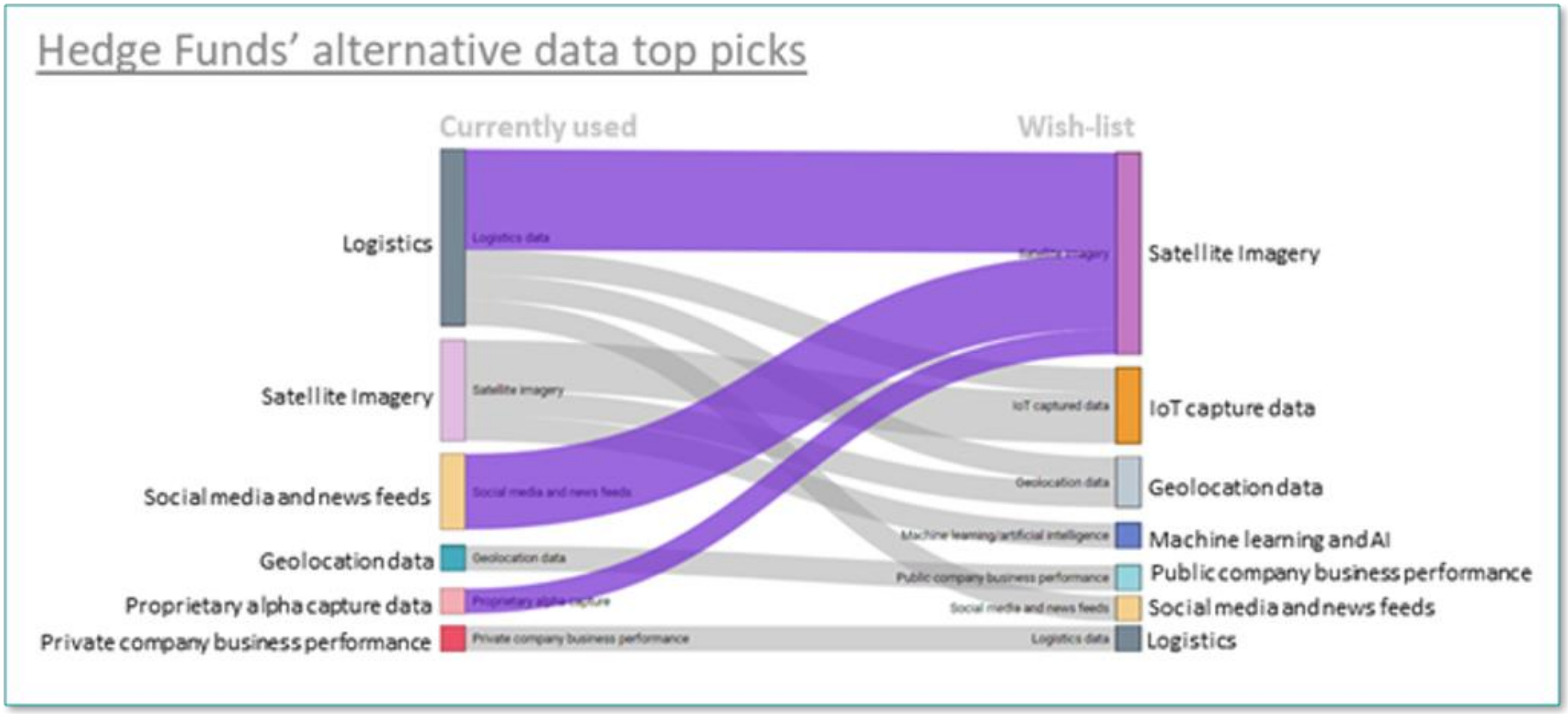


So what is best?

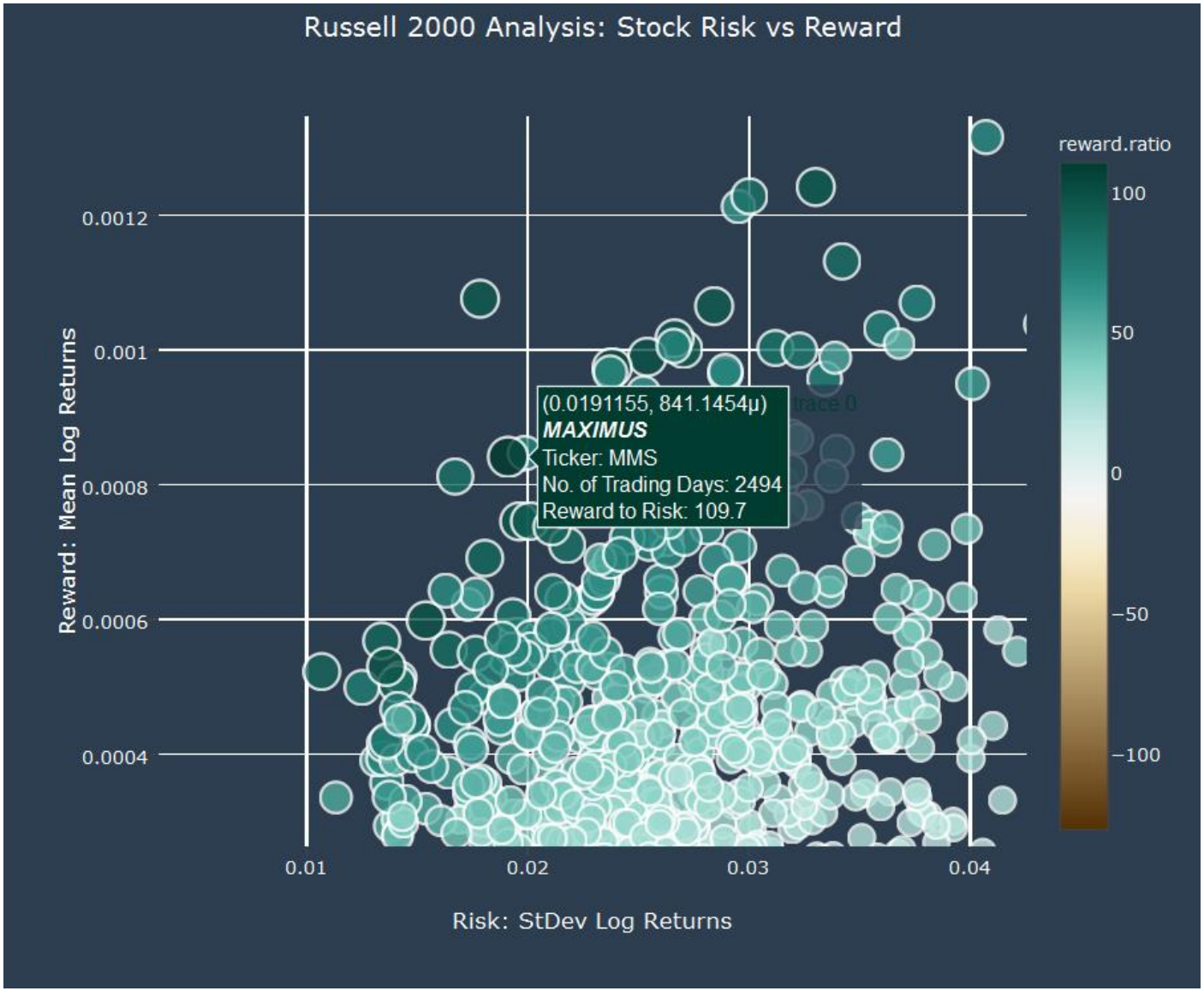
Future ???

So what is best?

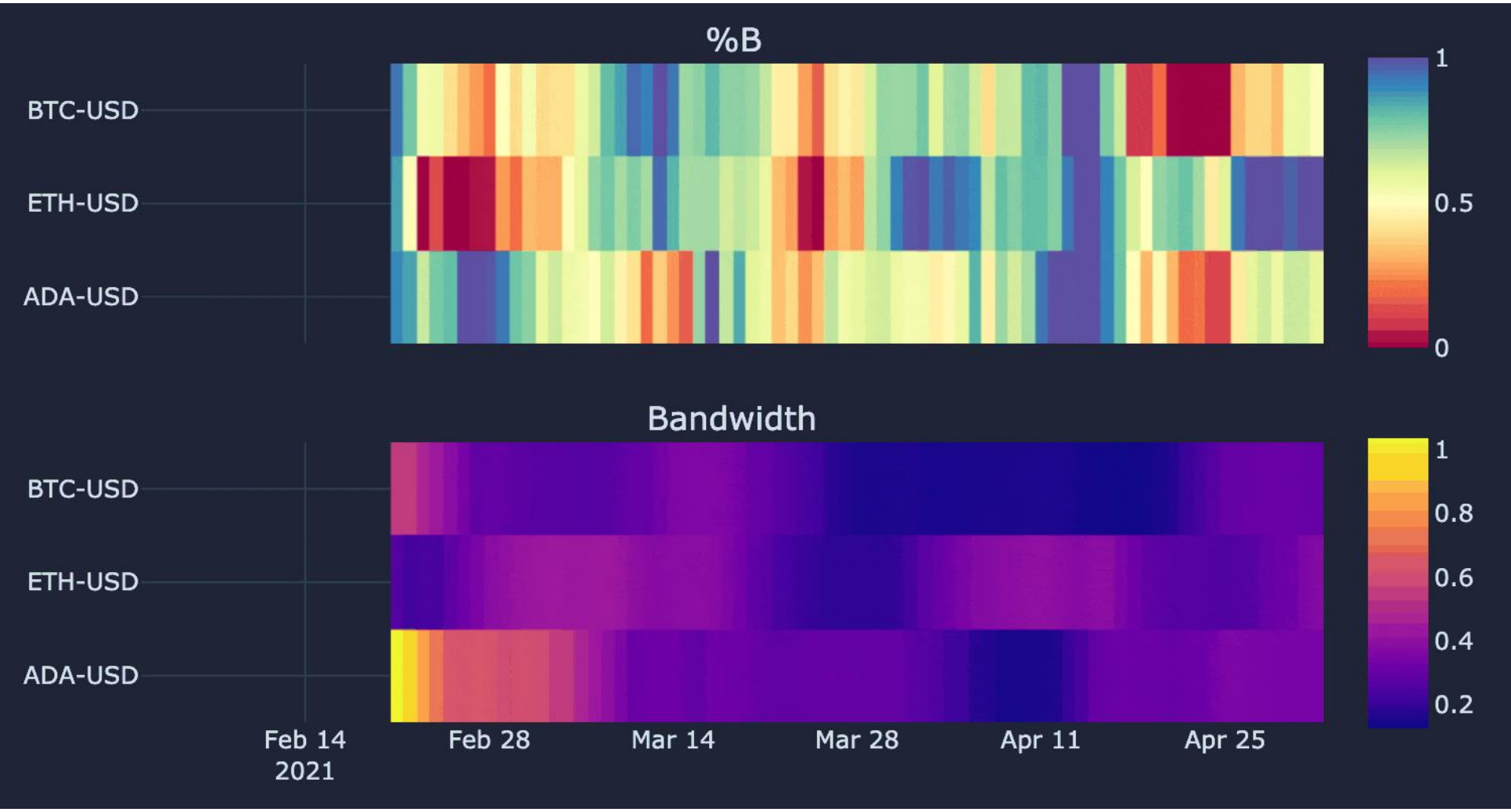
Future ???



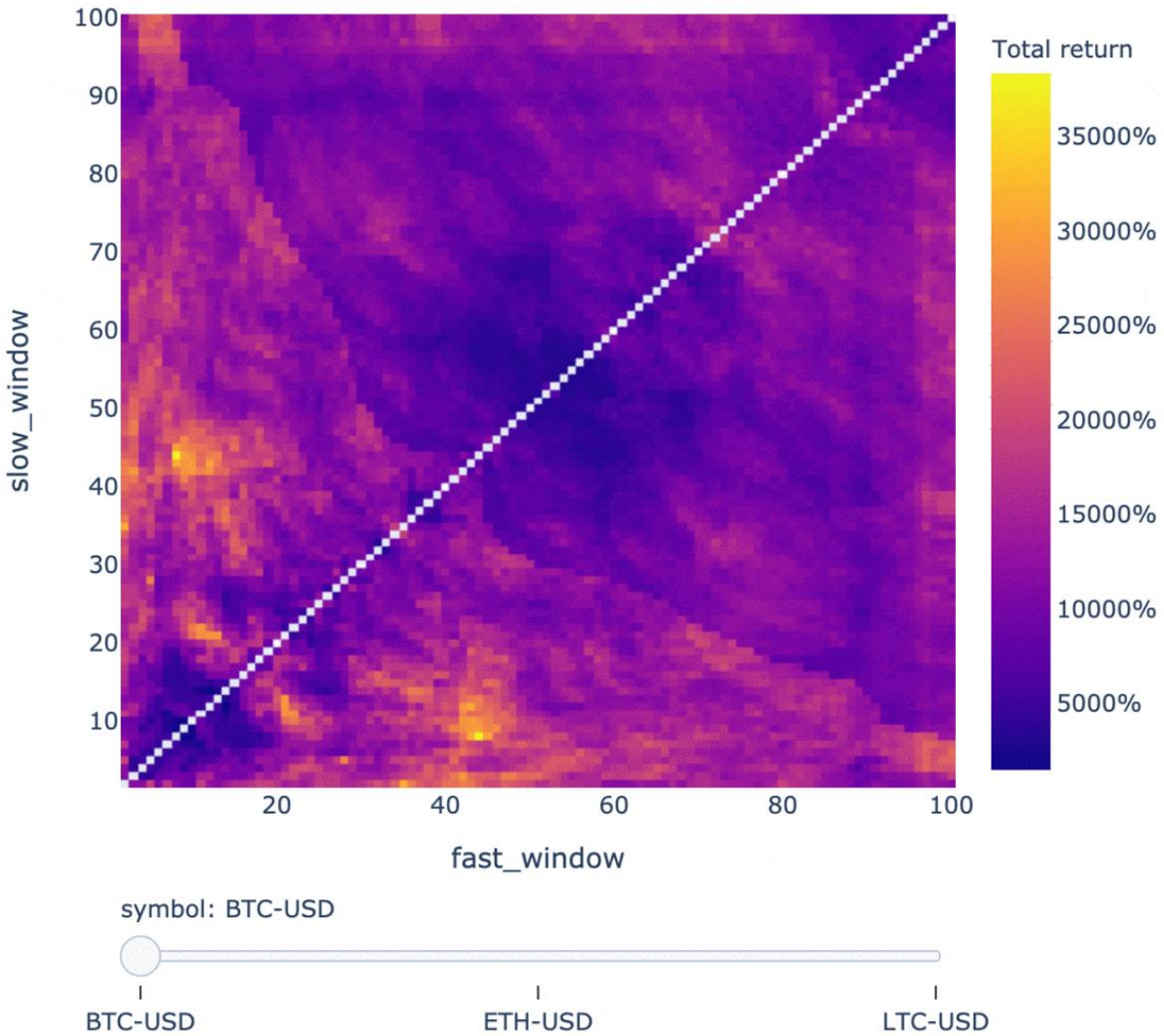
Quantitative Analysis



Quantitative Analysis



Quantitative Analysis



Quantitative Analysis

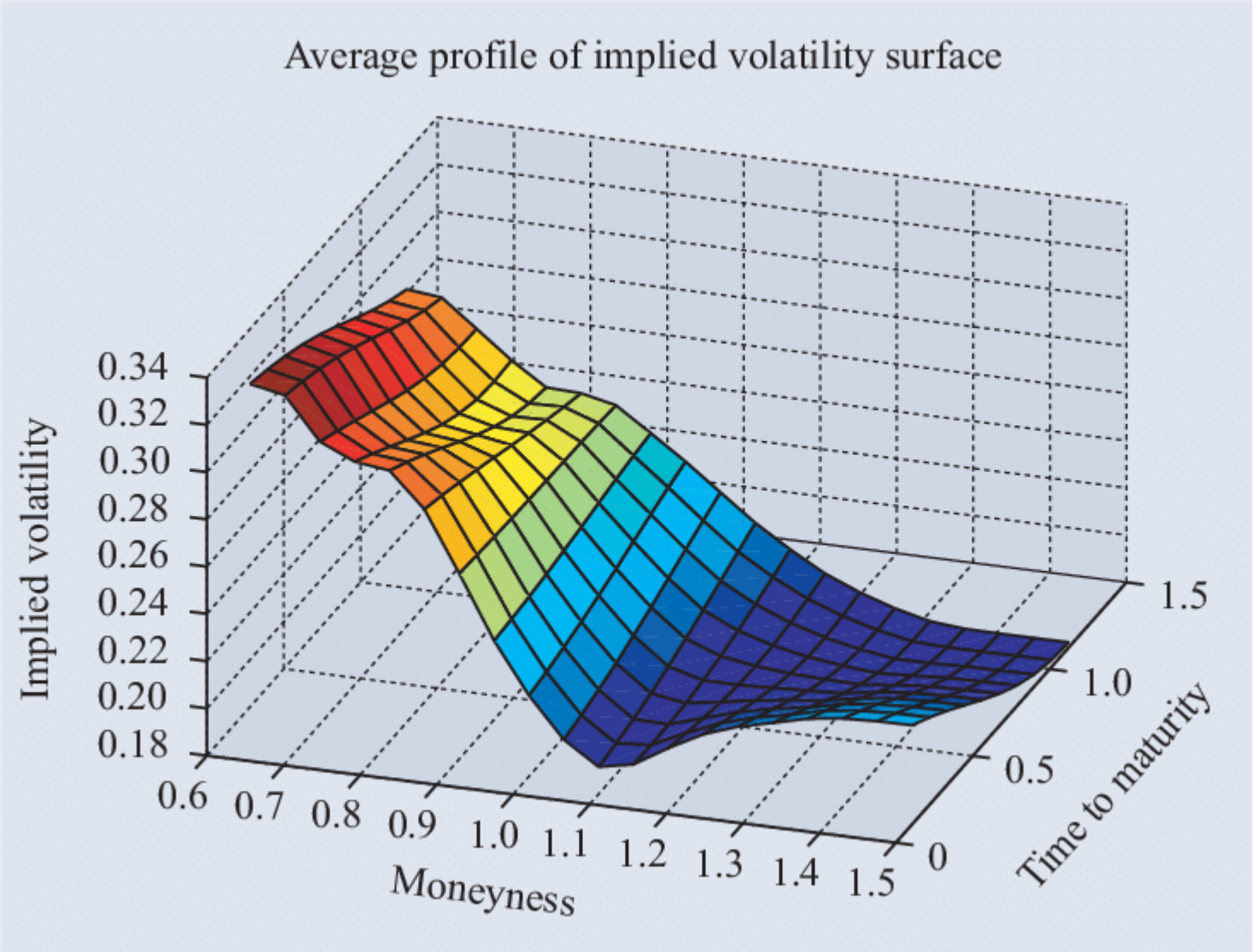
```
symbols = ["BTC-USD", "ETH-USD", "LTC-USD"]
price = vbt.YFData.download(symbols, missing_index='drop').get('Close')

windows = np.arange(2, 101)
fast_ma, slow_ma = vbt.MA.run_combs(price, window=windows, r=2, short_names=['fast', 'slow'])
entries = fast_ma.ma_above(slow_ma, crossover=True)
exits = fast_ma.ma_below(slow_ma, crossover=True)

pf_kwargs = dict(size=np.inf, fees=0.001, freq='1D')
pf = vbt.Portfolio.from_signals(price, entries, exits, **pf_kwargs)

fig = pf.total_return().vbt.heatmap(
    x_level='fast_window', y_level='slow_window', slider_level='symbol', symmetric=True,
    trace_kwargs=dict(colorbar=dict(title='Total return', tickformat='%')))
fig.show()
```

Quantitative Analysis



Quantitative Analysis

Black-Scholes Assumptions

The Black-Scholes model makes certain assumptions:

- The option is European and can only be exercised at expiration.
- No dividends are paid out during the life of the option.
- Markets are efficient (i.e., market movements cannot be predicted).
- There are no transaction costs in buying the option.
- The risk-free rate and volatility of the underlying are known and constant.
- The returns on the underlying asset are log-normally distributed.

Option Pricing Model

$$C = S_t N(d_1) - K e^{-rt} N(d_2)$$

where:

$$d_1 = \frac{ln\frac{S_t}{K} + (r + \frac{\sigma_v^2}{2})\, t}{\sigma_s \sqrt{t}}$$

and

$$d_2 = d_1 - \sigma_s \sqrt{t}$$

where:

C = Call option price

S = Current stock (or other underlying) price

K = Strike price

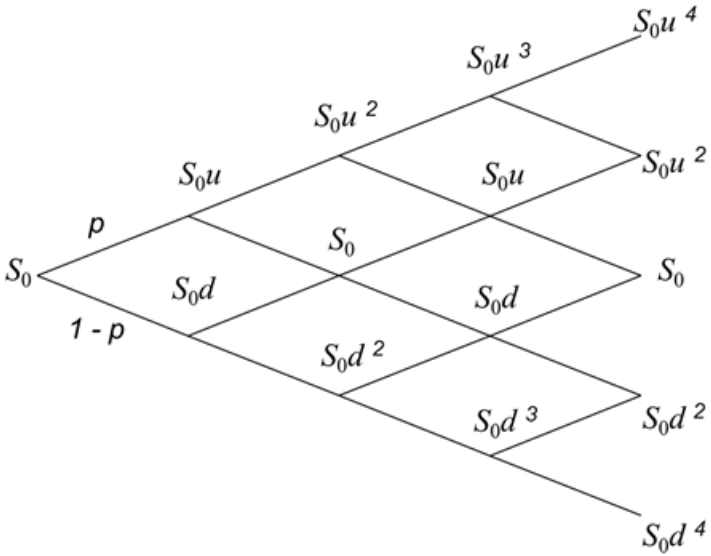
r = Risk-free interest rate

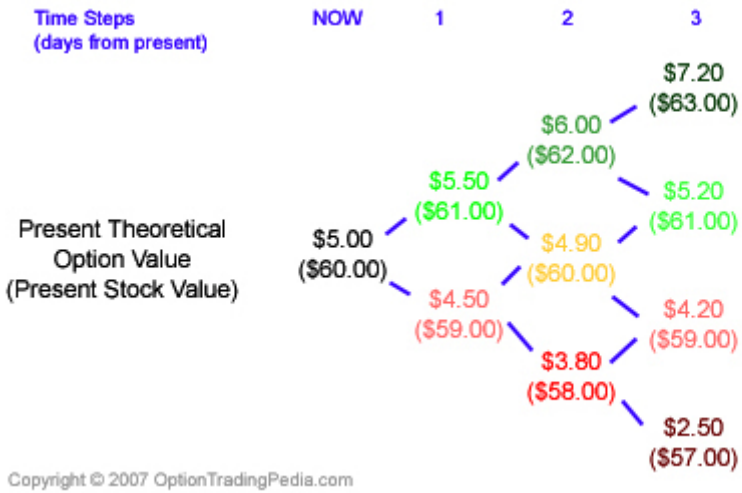
t = Time to maturity

N = A normal distribution

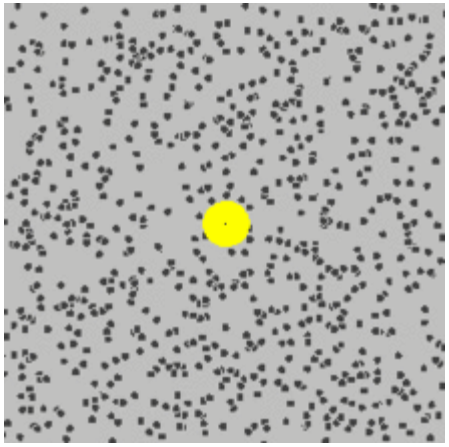
Quantitative Analysis

Option Pricing Model



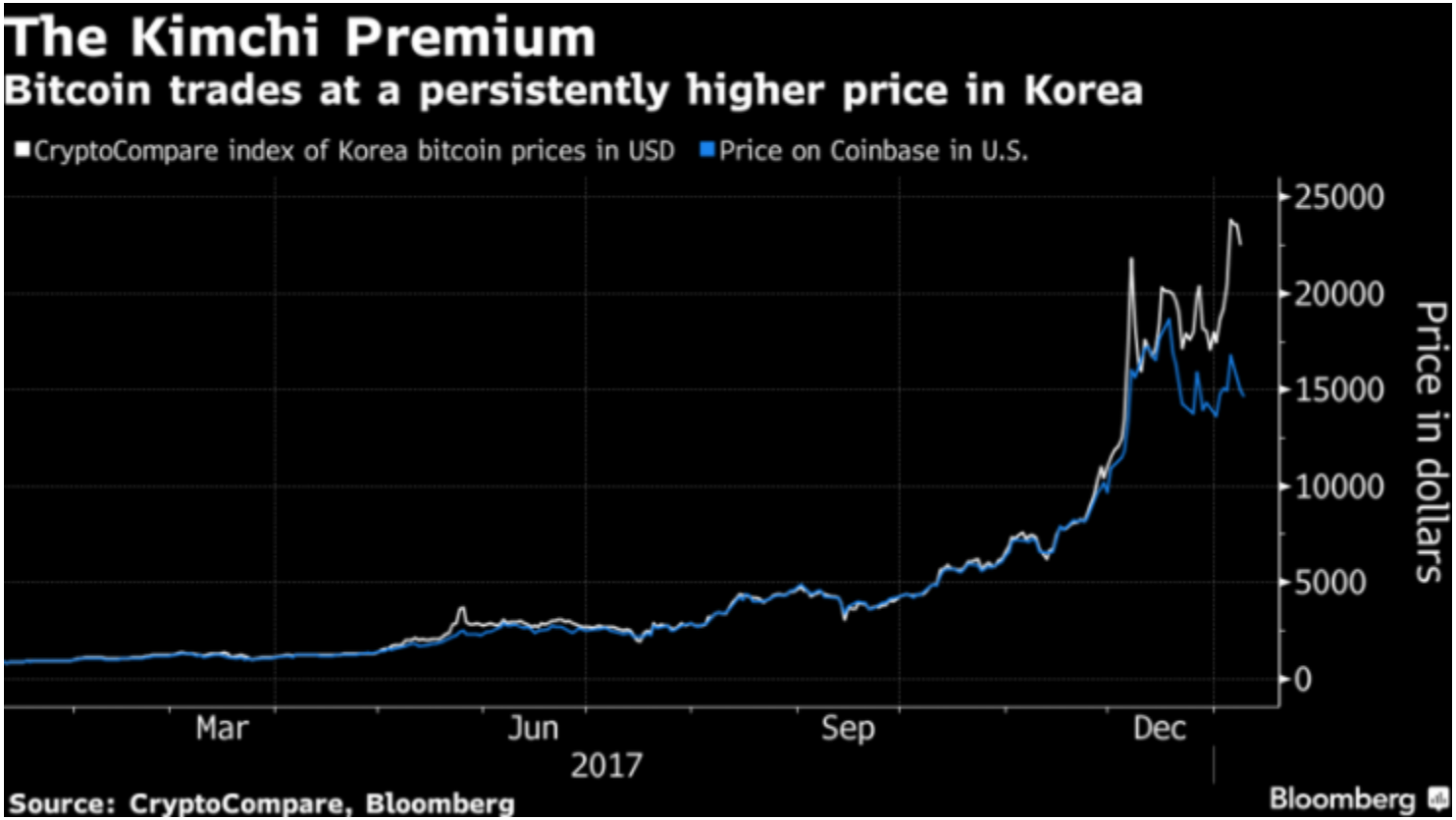


Random Walk with Drift ($Y_t = \alpha + Y_{t-1} + \varepsilon_t$)



Quantitative Analysis

Quantitative Analysis



Random Walk Theory

Random Walk Theory says that Stock Prices are not dependent on each other

WallStreetMojo

Quantitative Analysis

Distribution of US Market Returns

CRSP 1–10 Index returns by year
1926–2018

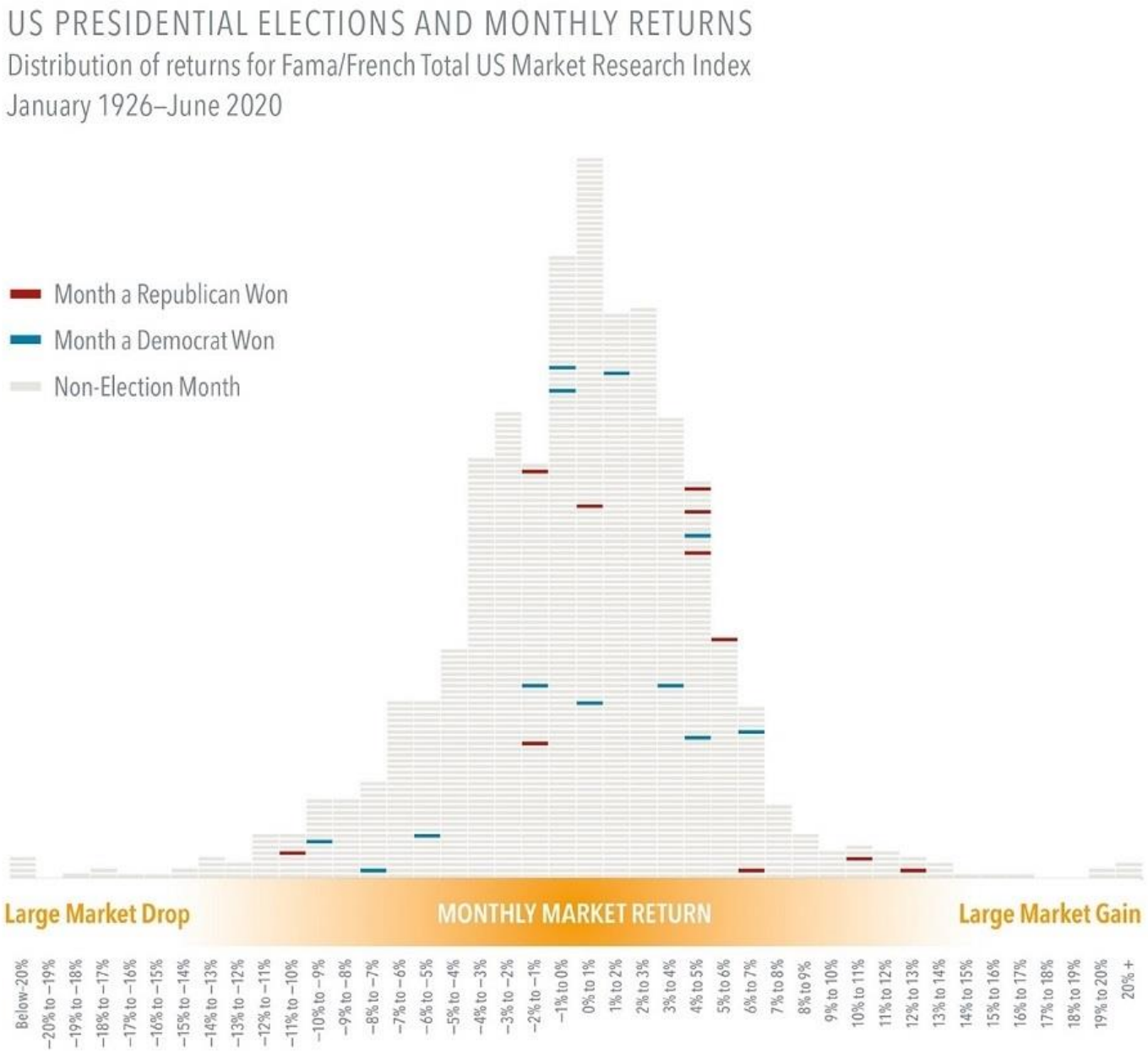
Positive Years:	**69**	**74%**
Negative Years:	**24**	**26%**

-50% to -40%	-40% to -30%	-30% to -20%	-20% to -10%	-10% to 0%	0% to 10%	10% to 20%	20% to 30%	30% to 40%	40% to 50%	50% to 60%
							1949 20.2			
							1951 20.7			
							1963 21.0			
						1993 11.1	1982 21.0			
					1970 0.0	2014 11.6	2017 21.1			
					1953 0.7	2004 12.0	1996 21.4			
					2011 0.8	1959 12.7	1944 21.5			
					1960 1.2	1952 13.4	1983 22.0			
					1987 1.7	2016 13.6	1979 22.6	1997 31.4		
					1948 2.1	1968 14.1	1998 24.3	2003 31.6		
				1966 -8.7	1939 2.8	1965 14.5	1955 25.2	1985 32.2		
				1932 -8.6	1947 3.6	2008 15.5	1999 25.2	1936 32.3		
			1973 -18.1	1940 -7.1	1934 4.1	1942 16.1	1976 26.8	1980 32.8		
			1929 -15.2	1946 -6.2	1984 4.5	1964 16.1	1961 26.9	1927 33.5		
			2000 -11.4	1990 -6.0	2007 5.8	1971 16.1	1938 28.2	1991 34.7		
			2001 -11.1	2018 -5.0	2005 6.2	2012 16.2	1943 28.4	2013 35.2		
			1969 -10.9	1977 -4.3	1978 7.5	1986 16.2	1967 28.7	1995 36.8		
		1930 -28.7	1962 -10.2	1981 -3.6	1956 8.3	1972 16.8	2009 28.8	1928 38.4	1935 44.4	
	2008 -36.7	1974 -27.0	1941 -10.1	2015 -0.5	1926 8.4	2010 17.7	1989 28.9	1945 38.5	1958 45.0	
1931 -43.5	1937 -34.7	2002 -21.1	1957 -10.0	1994 -0.1	1992 9.8	1988 18.0	1950 29.6	1975 38.8	1954 50.0	1933 56.7

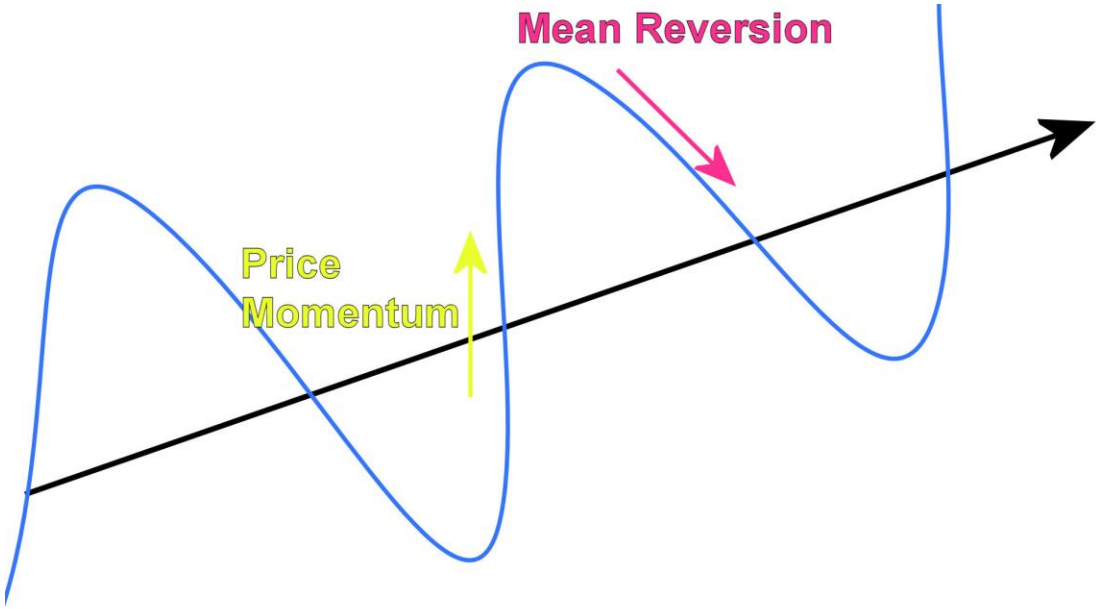
Annual Return Range

In US dollars. CRSP data provided by the Center for Research in Security Prices, University of Chicago. The CRSP 1–10 Index measures the performance of the total US stock market, which it defines as the aggregate capitalization of all securities listed on the NYSE, AMEX, and NASDAQ exchanges. Indices are not available for direct investment; therefore, their performance does not reflect the expenses associated with the management of an actual portfolio. Past performance is not a guarantee of future results.

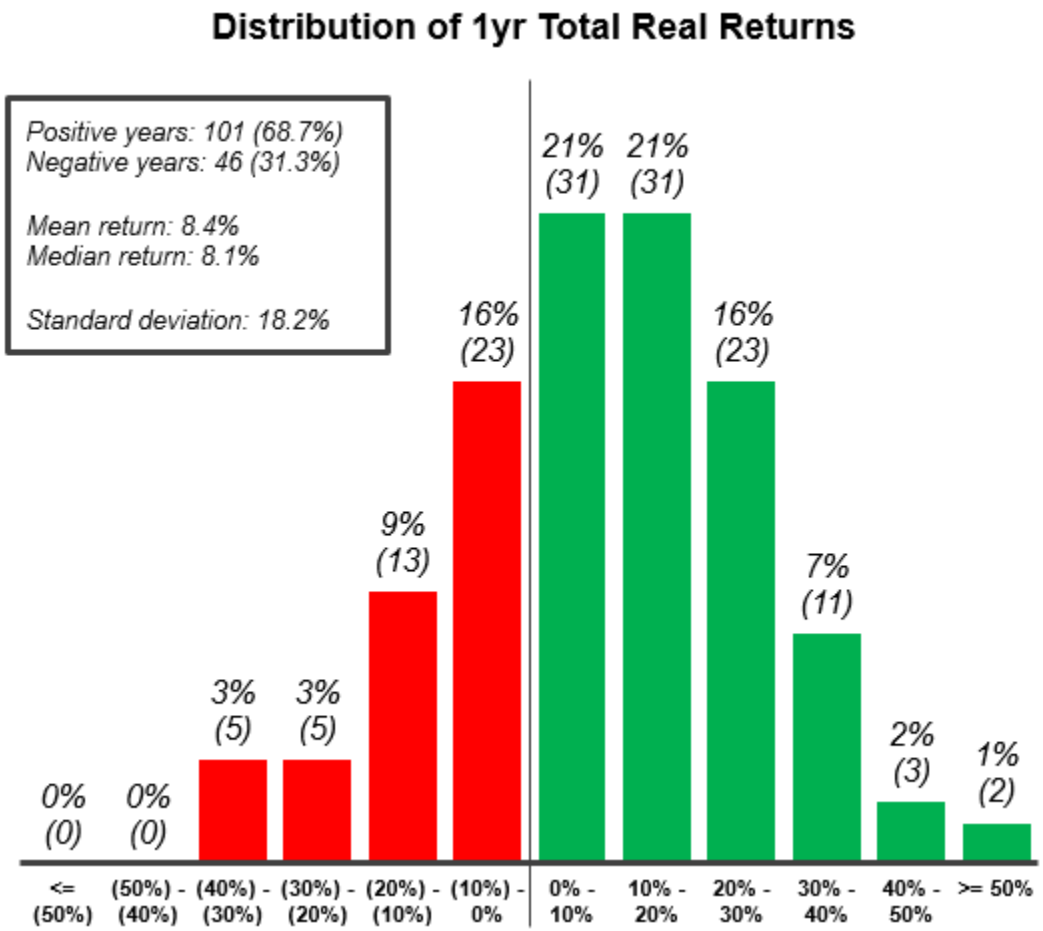
Quantitative Analysis



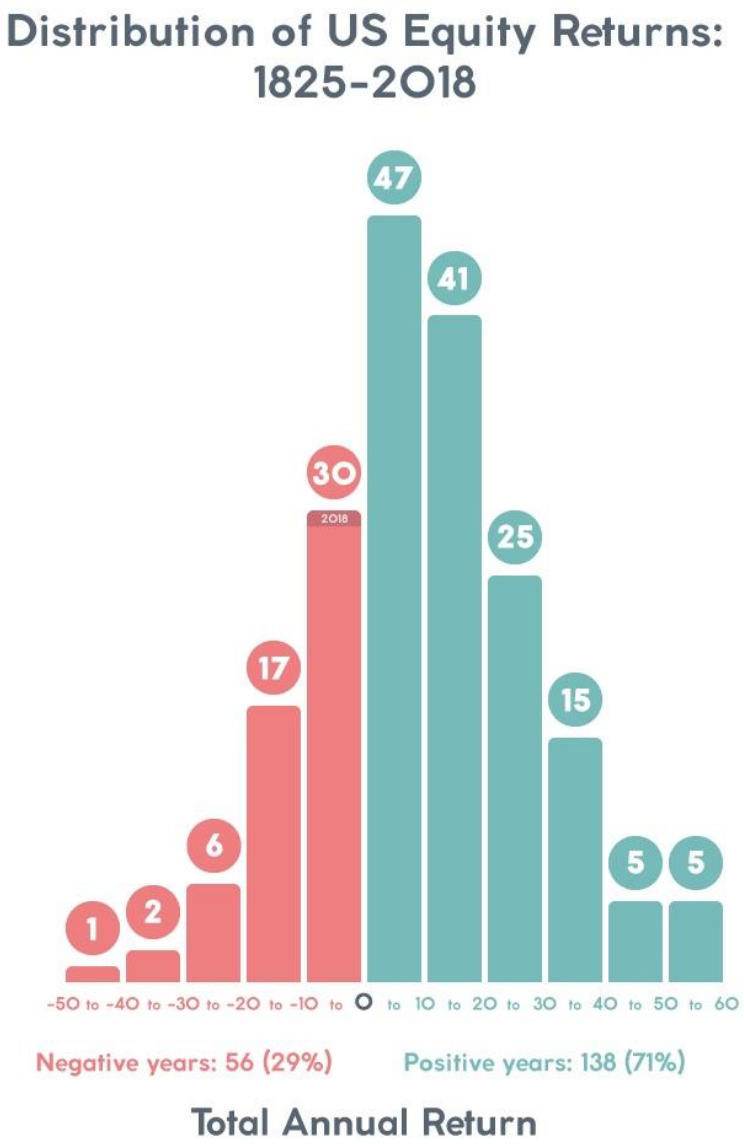
Mean Reversal?



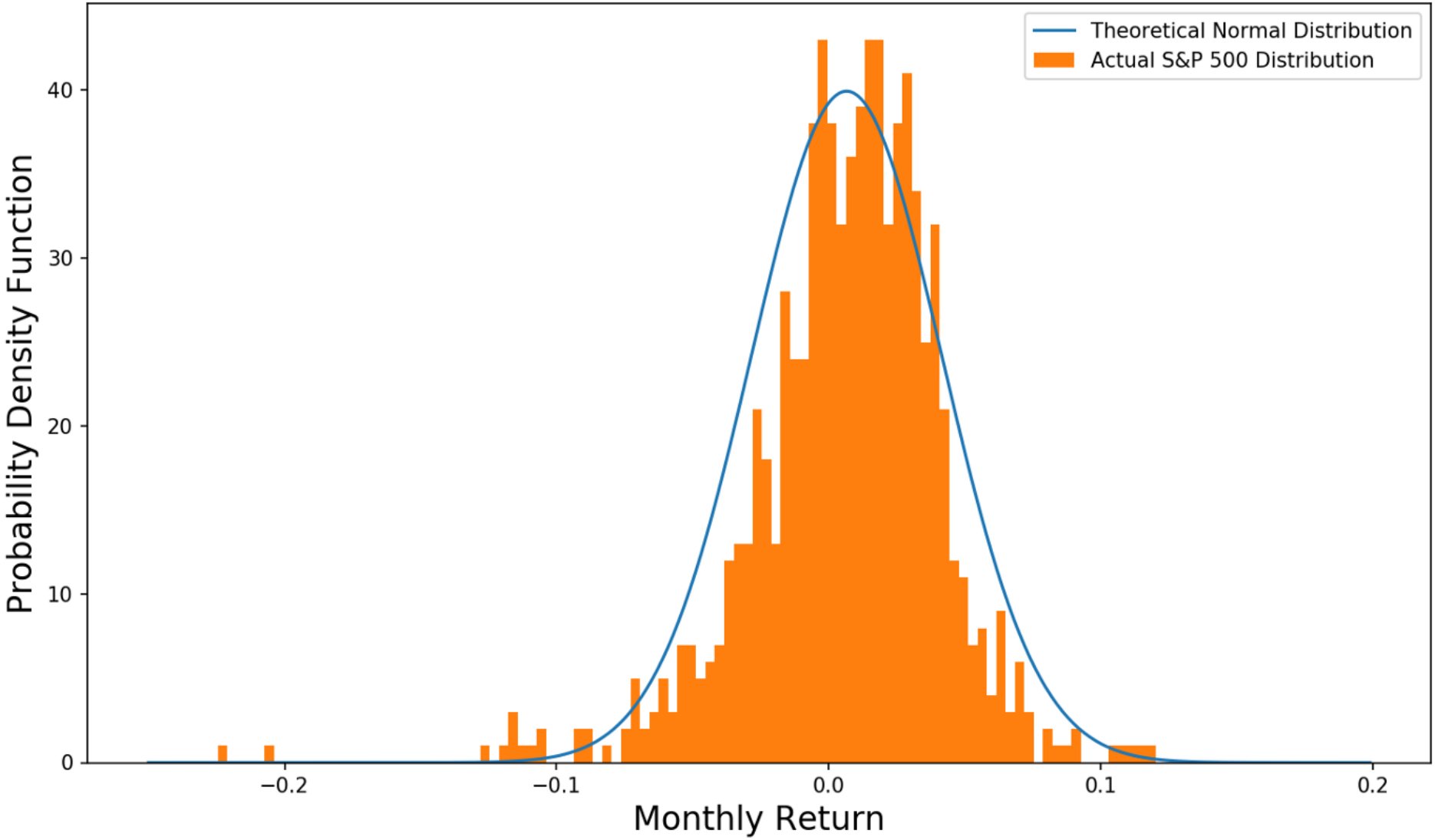
Good Year Bad Year?



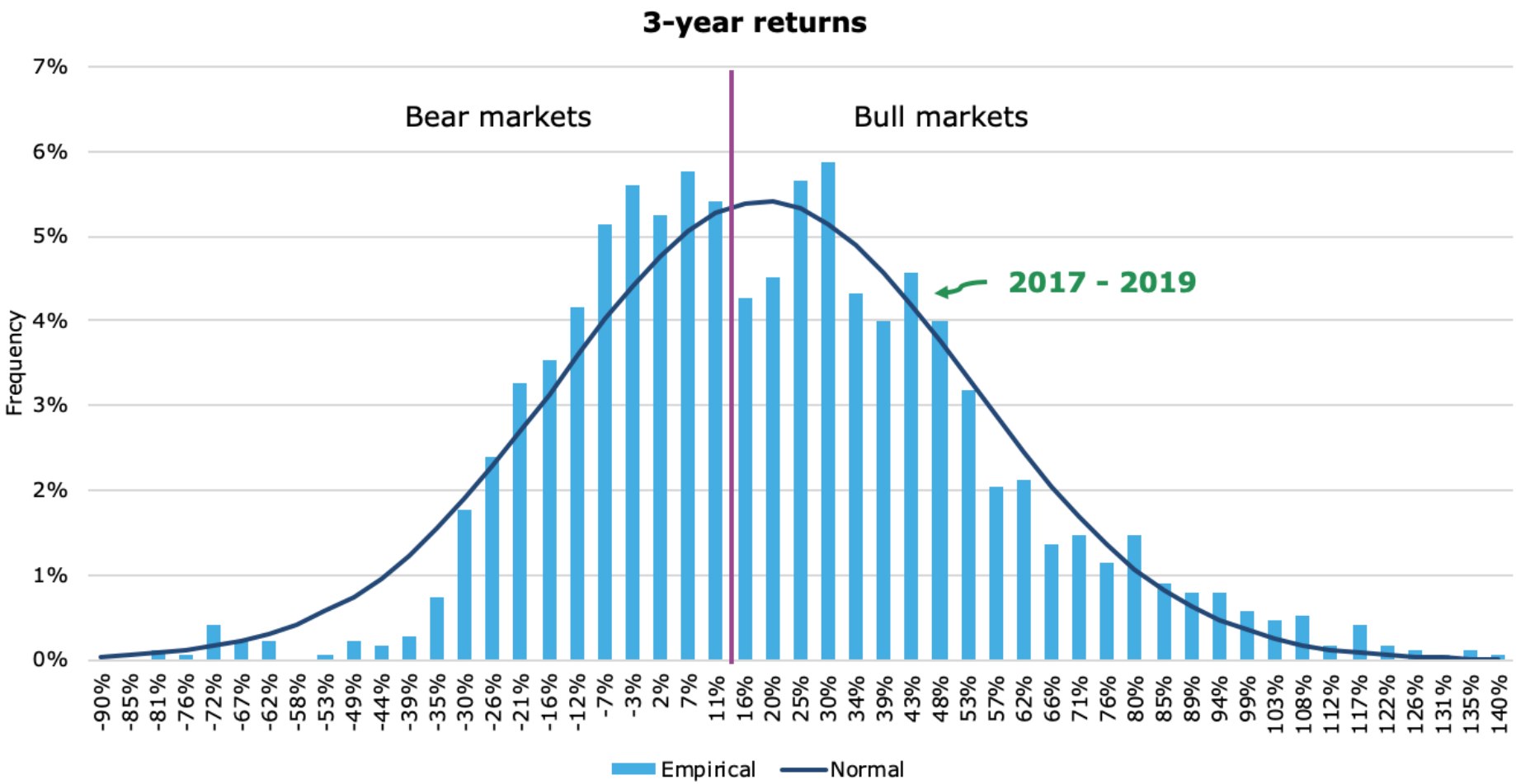
Good Year Bad Year?



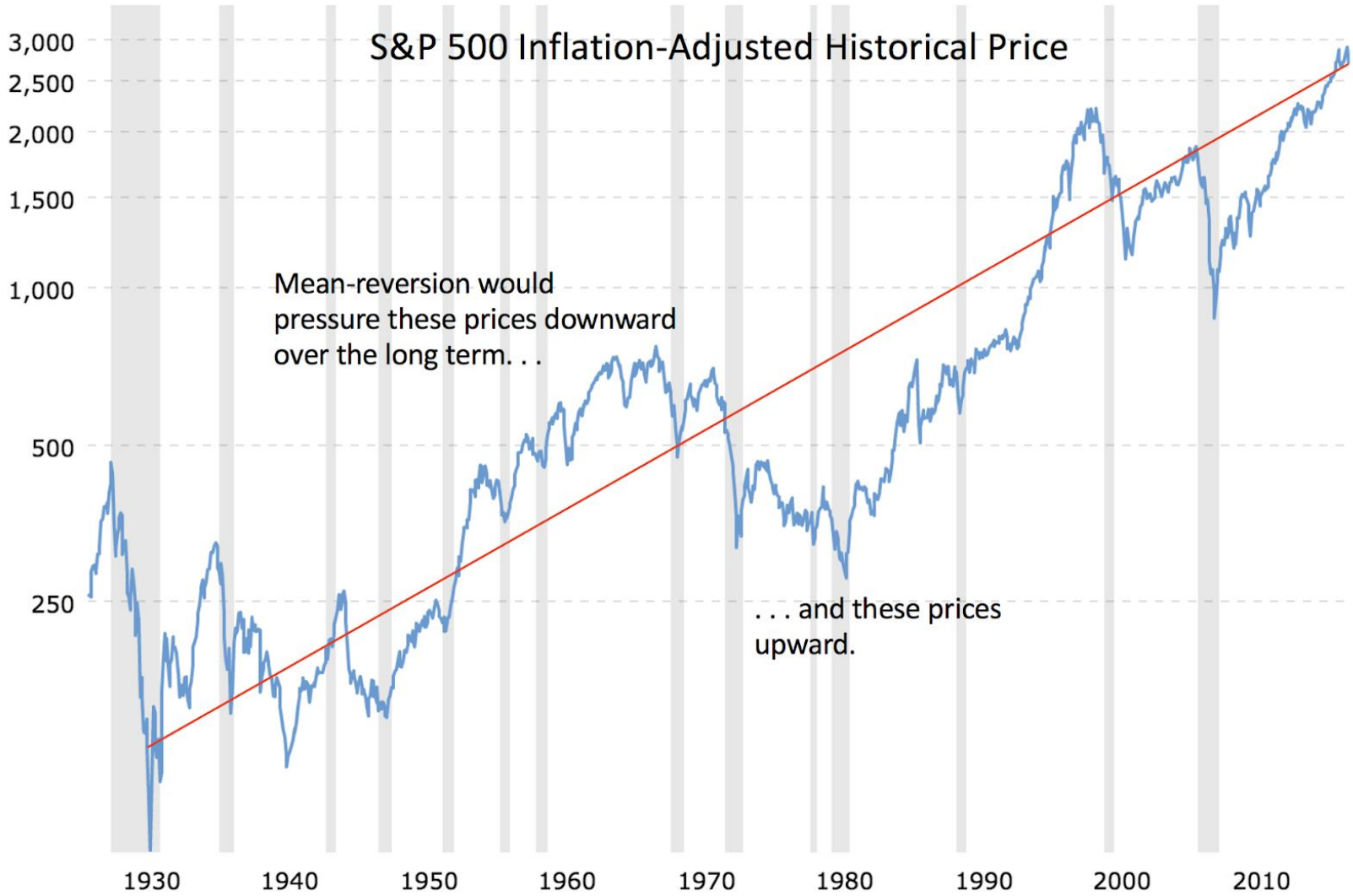
Where the messed begin



Quantitative Analysis



Mean Reversion if **long** enough and **Positive Mean**

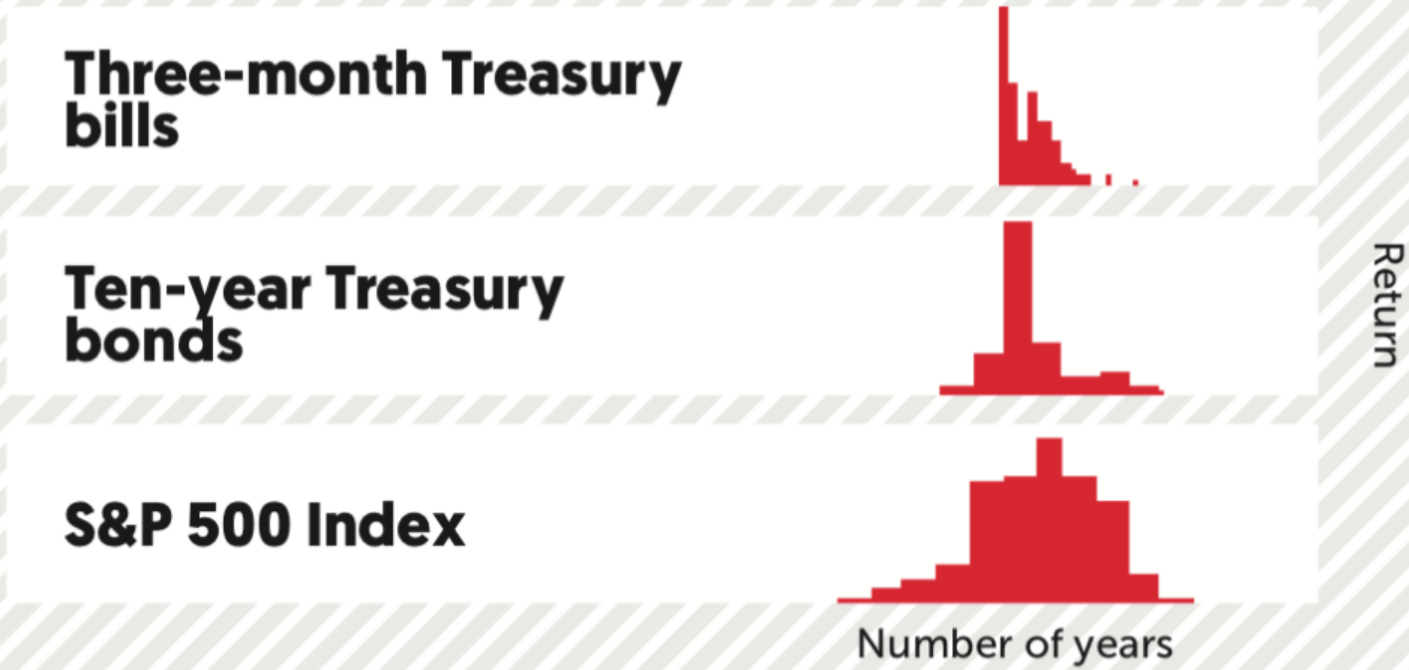


Quantitative Analysis

FIGURE 1

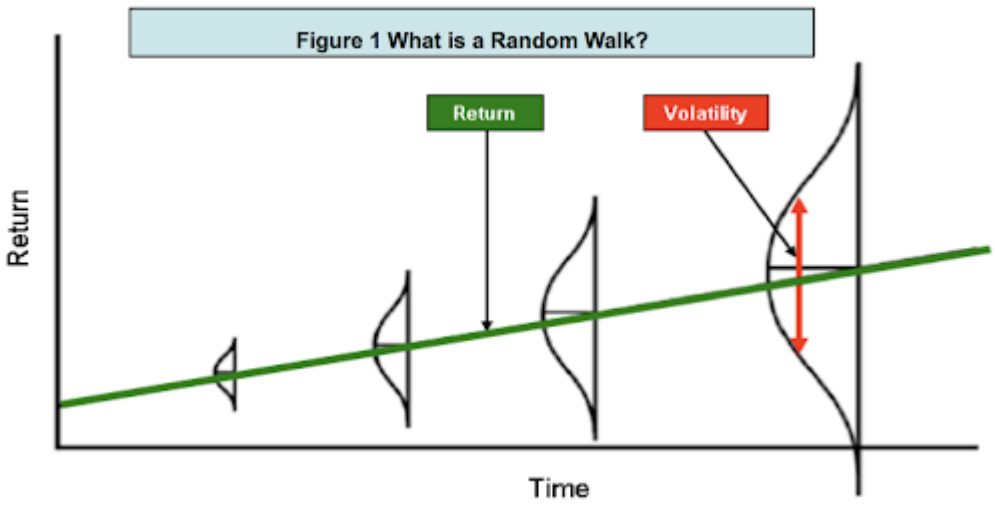
DISTRIBUTION OF ANNUAL RETURNS

Annual returns on three forms of investment, 1928-2018

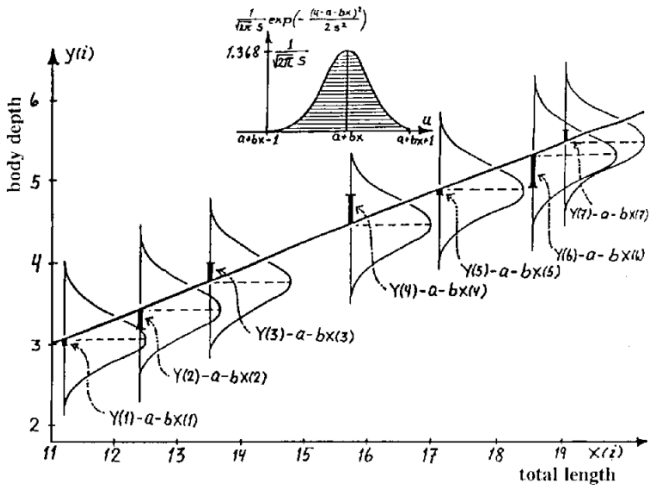


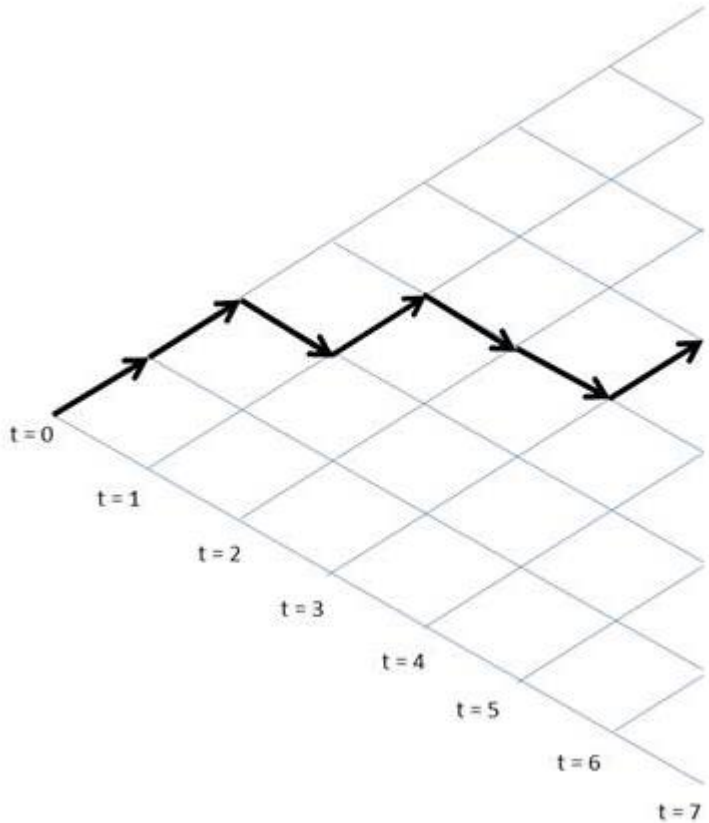
Source: NYU Stern

Quantitative Analysis

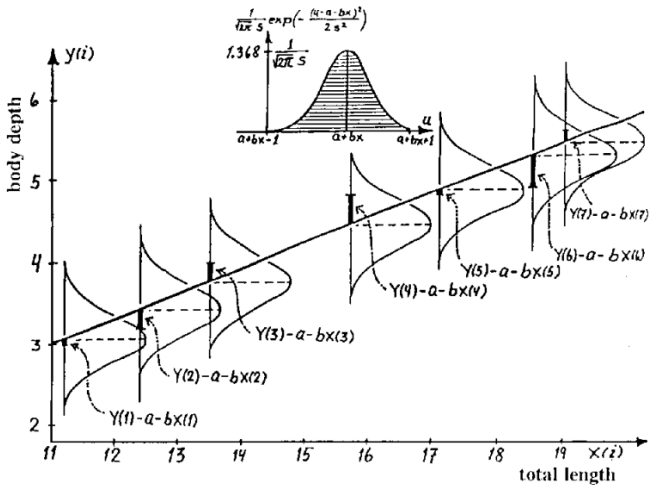


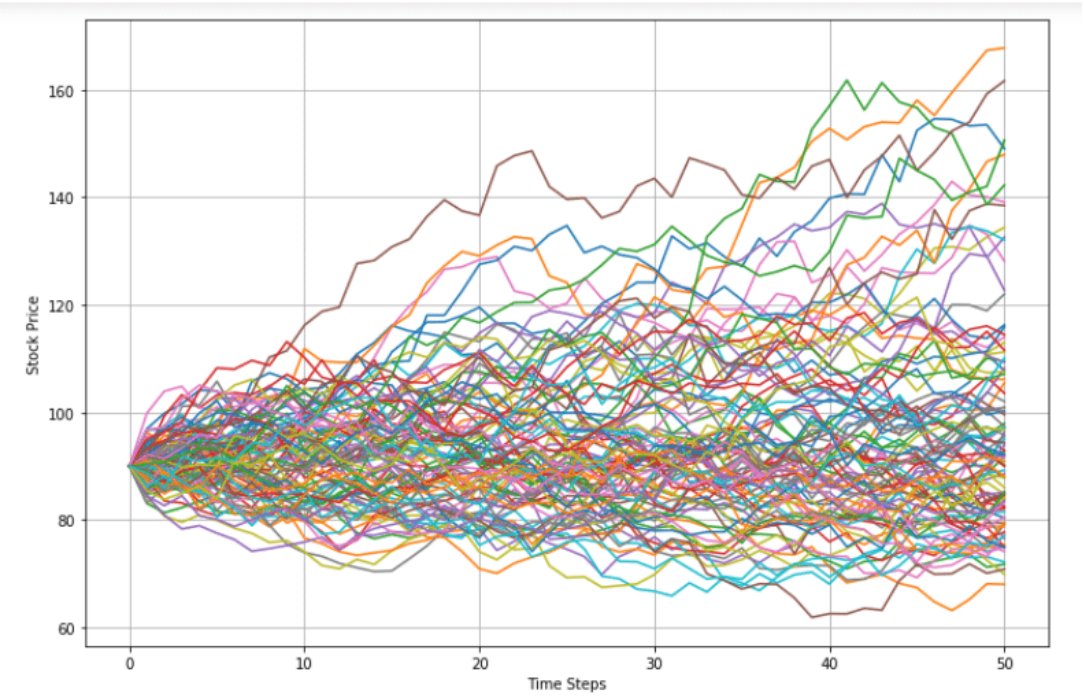
Quantitative Analysis





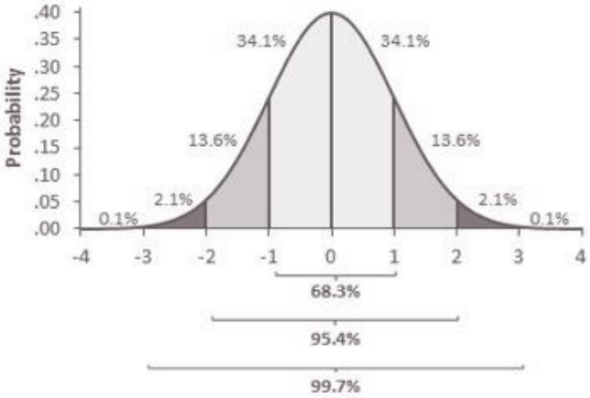
Quantitative Analysis



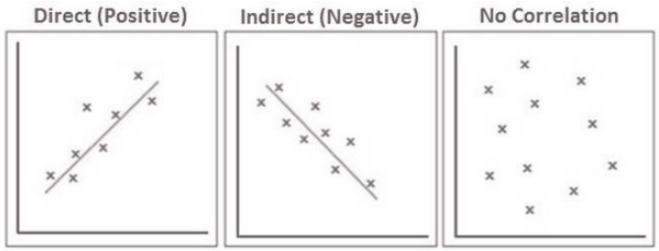


Quantitative

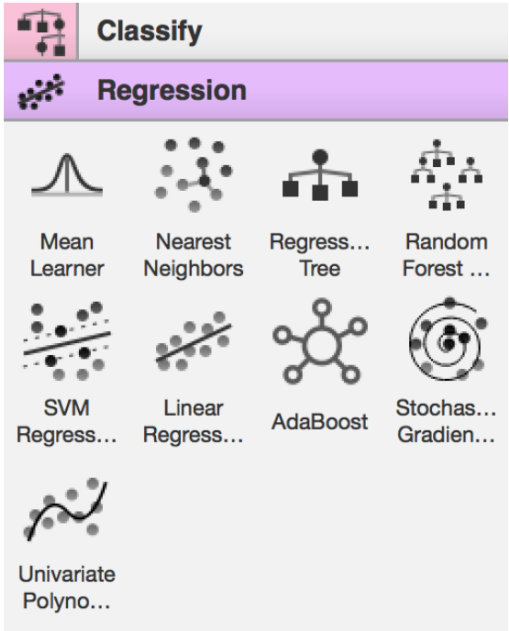
Stats & Probability



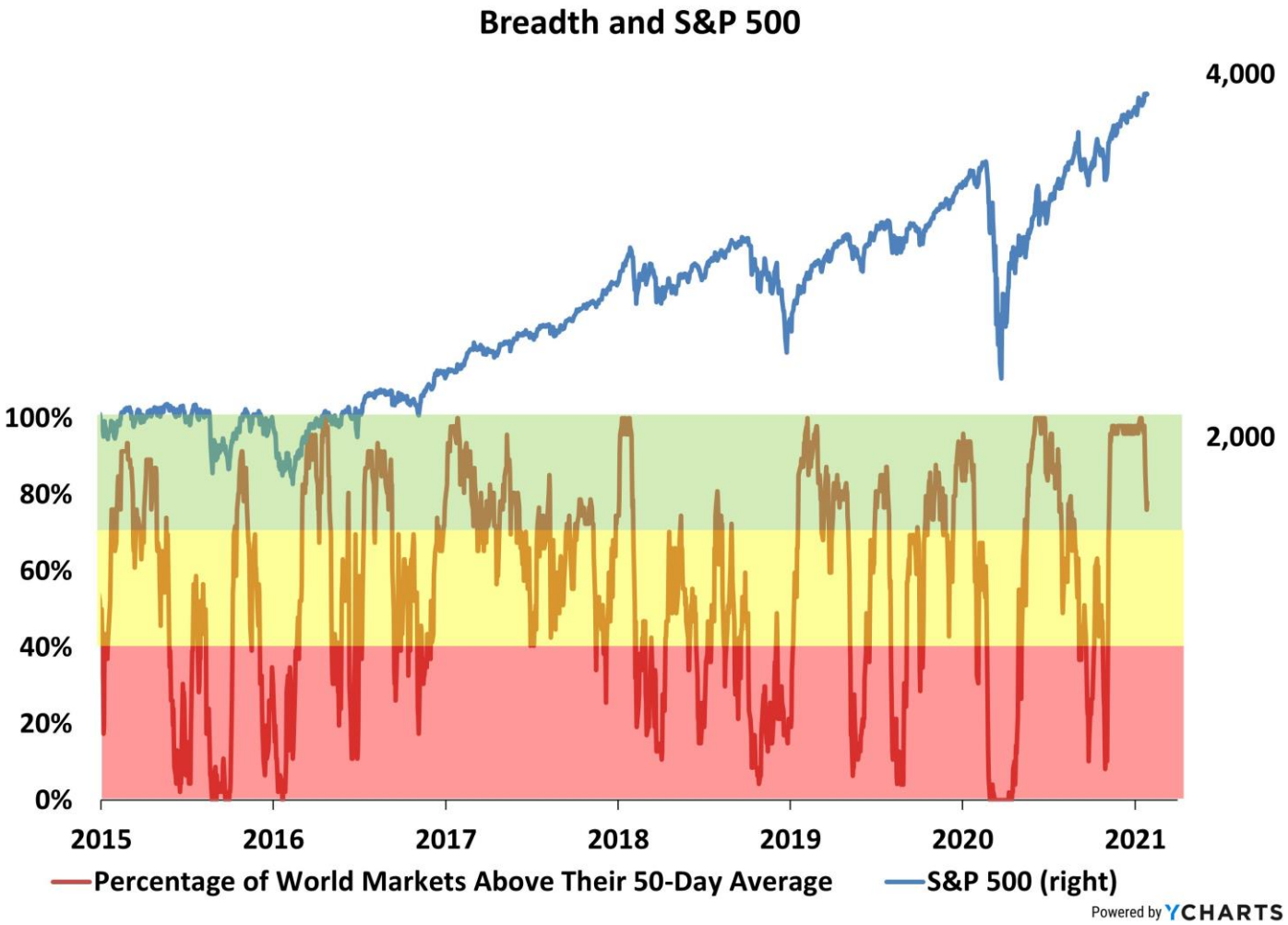
Relationship



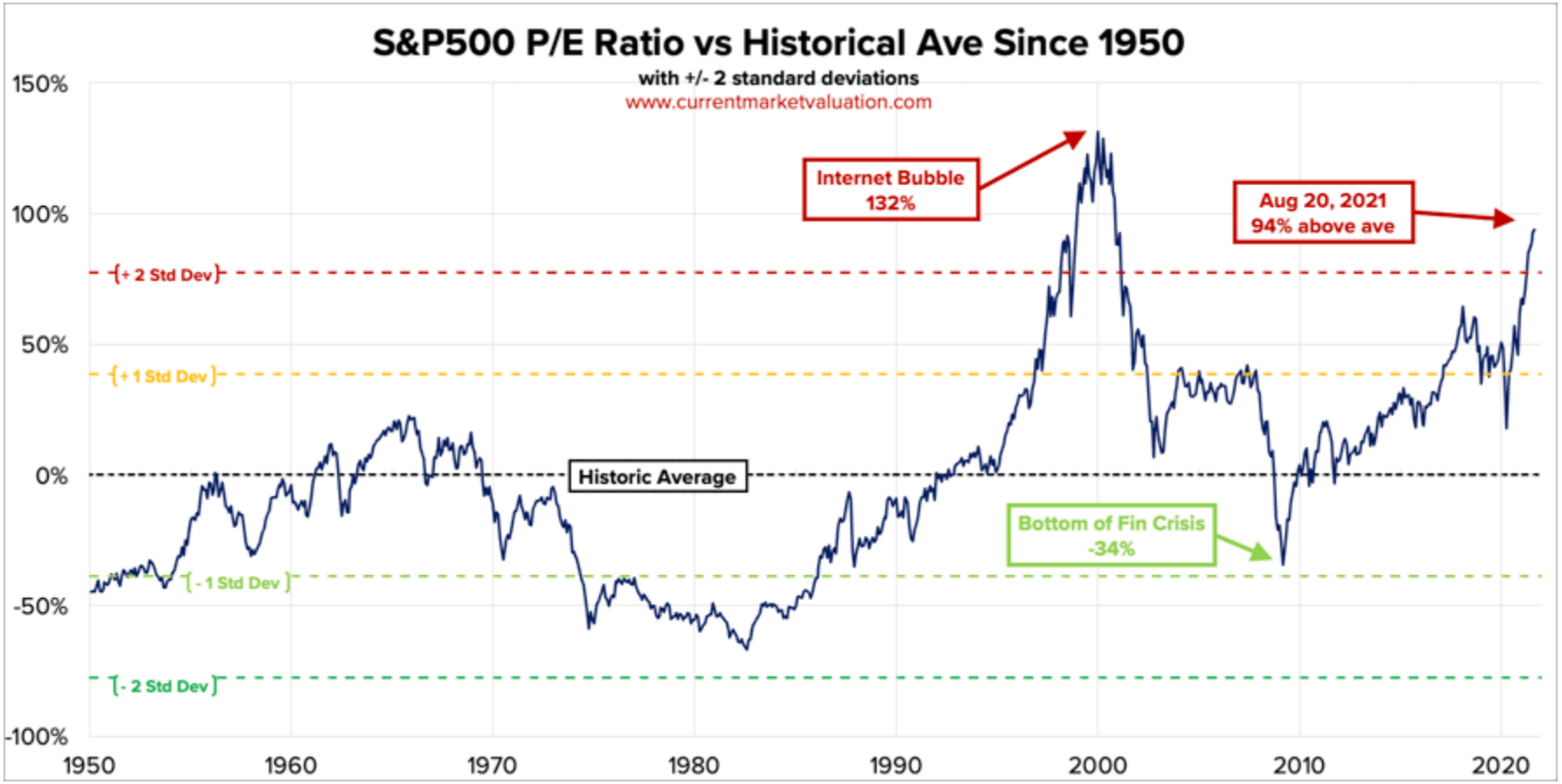
Modeling



Quantitative Analysis

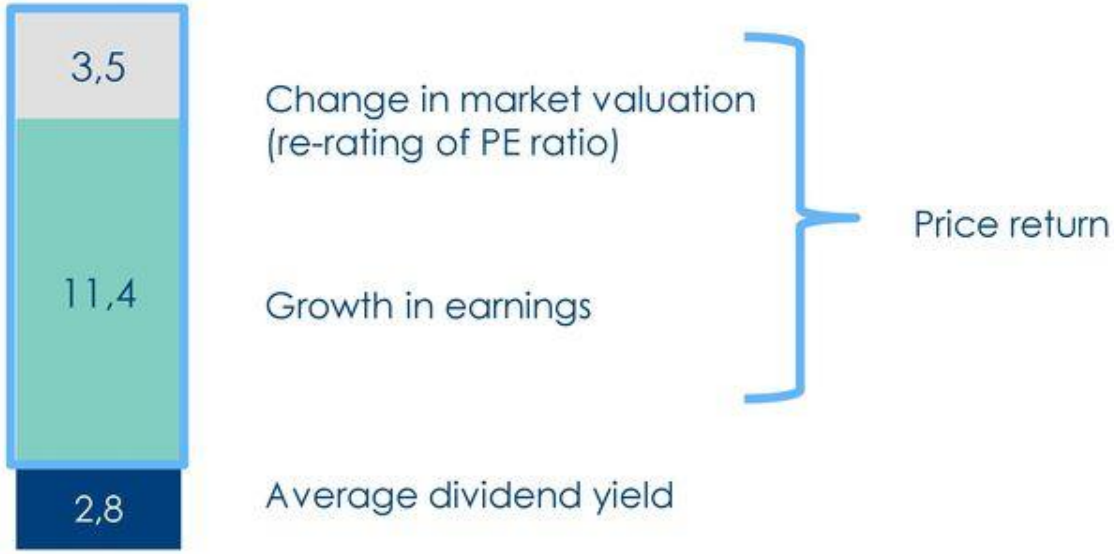


What we familiar



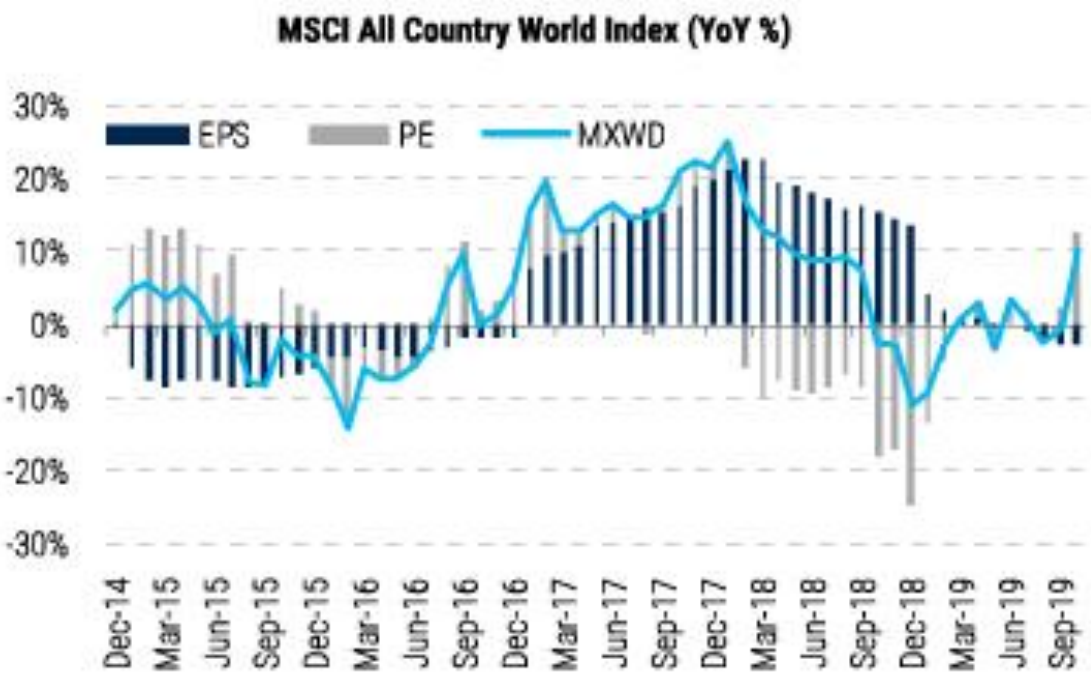
Decomposing equity total returns

Where does the return of equity come from?

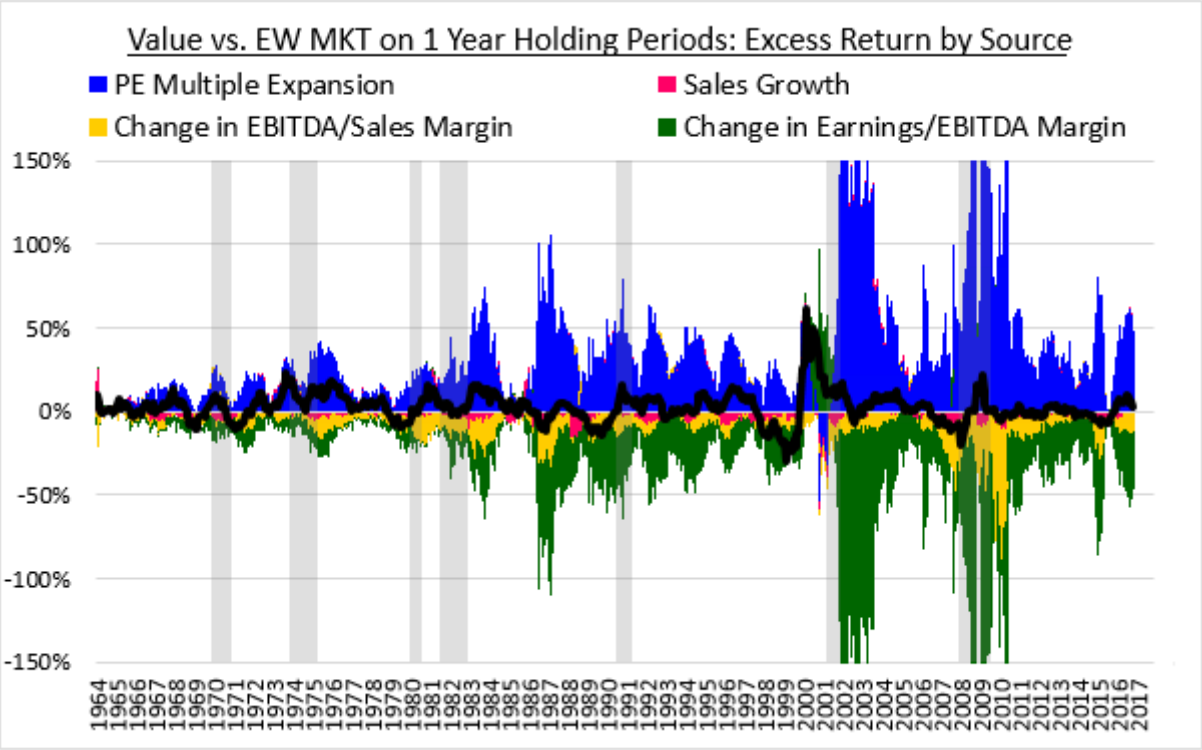


Average over rolling 12-month periods, calculated monthly from January 1996 to December 2016

Fundamental Quants

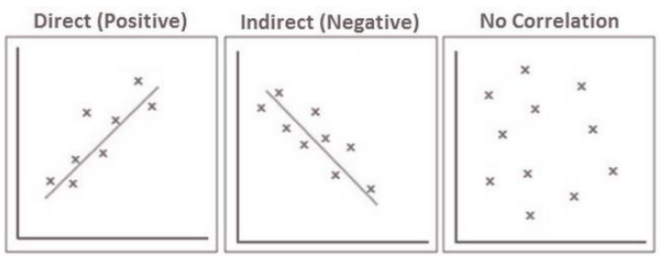


Fundamental Quants

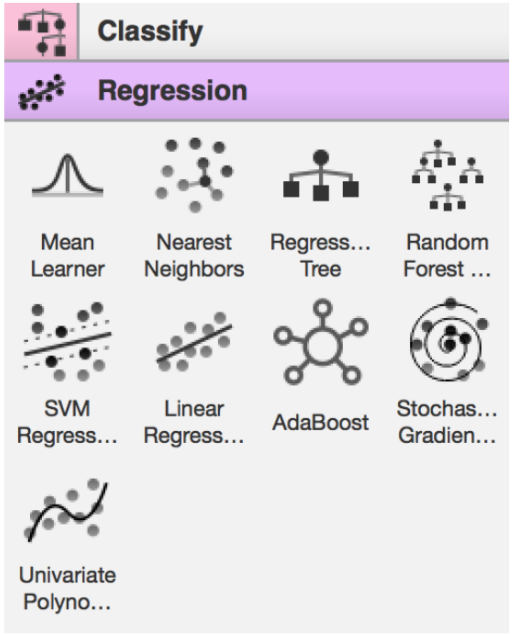


Quantitative

Relationship



Modeling



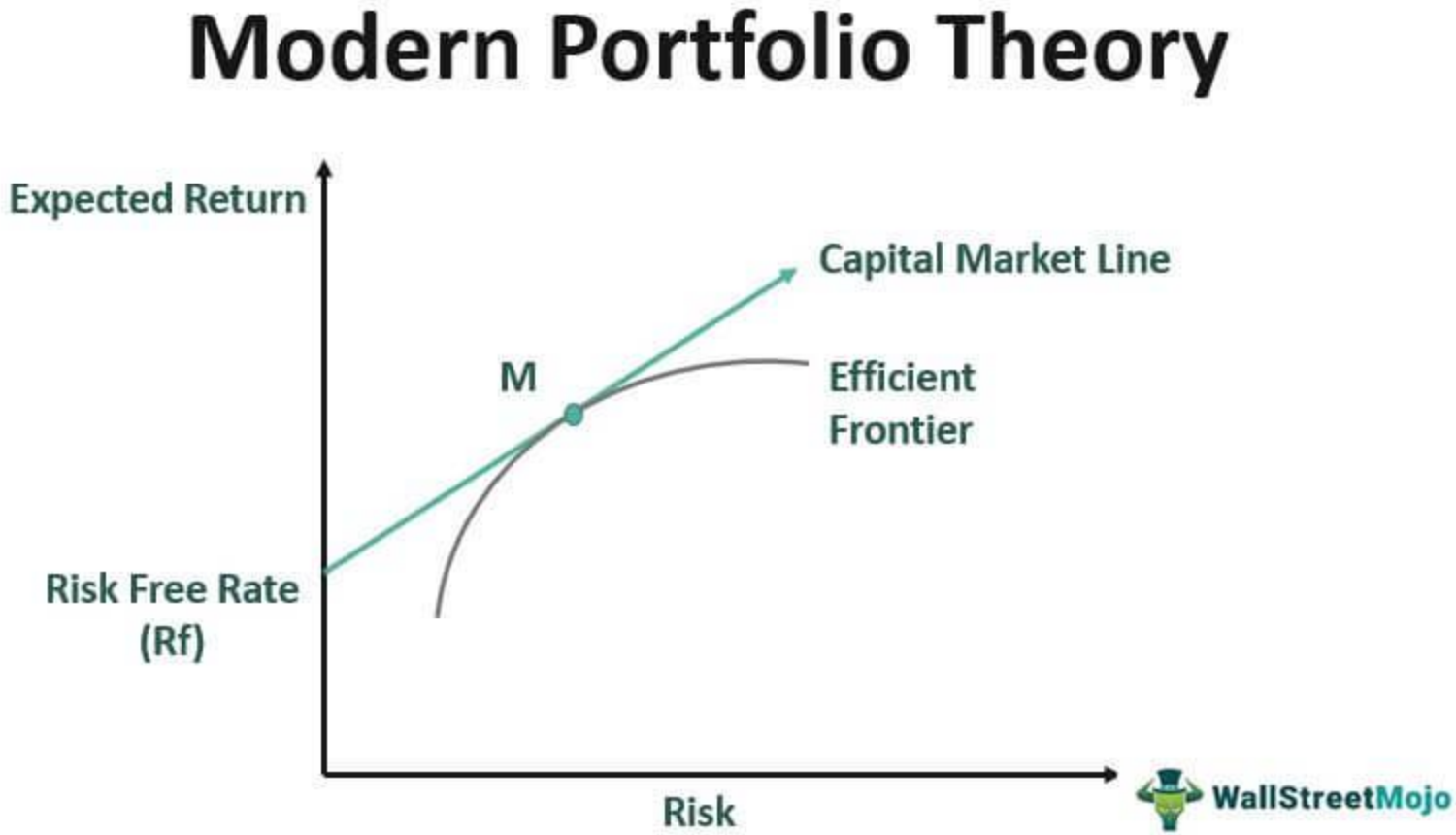
Alternative + Quants

Concept Exposures

TSLA Tesla Inc

Concept	Exposure (long-term)	Exposure (short-term)	Sentiment	Daily Change	Weekly Change	Sentiment Trend (3
Elon Musk	15.69 %	10.05 %	-0.19	45.84 %	-75.16 %	
Electric vehicle	7.65 %	5.43 %	0.07	-21.24 %	13.58 %	
Gigafactory 1	6.98 %	12.20 %	-0.19	-37.89 %	-22.29 %	
Electric car	6.32 %	5.24 %	0.23	-44.98 %	0.56 %	
Autopilot	5.58 %	3.39 %	0.14	29.37 %	11.94 %	
Vehicle	5.31 %	3.33 %	0.46	-8.16 %	38.06 %	
Pickup truck	4.12 %	-	-	-	-	
Panasonic	4.06 %	2.95 %	-0.13	2.33 %	-26.53 %	
China	4.00 %	3.20 %	0.19	29.98 %	69.32 %	
Sedan (automobile)	3.89 %	-	-	-	-	
General Motors	3.82 %	-	-	-	-	
Volkswagen	3.73 %	3.90 %	0.53	53.11 %	110.88 %	
Factory	3.56 %	3.02 %	-0.34	-31.68 %	-33.97 %	
Ford Motor Company	2.89 %	-	-	-	-	
Toyota	2.82 %	5.71 %	0.03	-0.45 %	-10.93 %	
SolarCity	2.75 %	1.82 %	0.20	-1.13 %	20.00 %	
Sport utility vehicle	2.66 %	2.47 %	-0.34	5.99 %	-49.30 %	
BMW	2.37 %	-	-	-	-	

Markowitz efficient frontier



Mandate

8% return

Drawdown < 10%

Risk averse

3y max underwater

blahblahblah

Cracking formula? For best composition?

Highest	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Annual returns, %	30.9	12.1	7.1	10.5	25.1	18.9	24.6	18.1	12.5	44.7	44.2	18.7	16.9	14.7	29.9	20.8
	24.9	10.5	5.8	9.4	21.1	13.2	23.0	17.8	10.3	13.1	21.8	17.5	8.1	14.1	23.6	19.3
	20.0	8.9	5.2	5.3	17.6	7.9	18.8	6.6	7.7	5.7	20.6	16.8	6.8	11.7	21.2	14.7
	14.1	6.3	5.1	4.1	15.7	6.6	17.3	4.9	6.2	-0.1	12.6	14.5	3.4	10.9	10.9	11.2
	6.0	1.7	3.2	-10.6	11.2	4.8	13.5	1.6	5.2	-12.8	2.2	8.9	2.9	2.8	6.0	7.6
	5.6	-0.9	-9.6	-26.0	3.8	4.7	7.9	0.6	3.7	-19.5	1.2	7.8	0.9	2.4	0.5	6.1
	-1.2	-1.9	-13.7	-26.8	2.1	3.4	7.3	-0.4	1.3	-22.5	-1.3	7.6	-6.2	0.9	-4.3	0.5
Lowest	-0.1	-7.1	-17.5	-29.6	1.3	1.8	4.8	-6.6	-5.5	-25.4	-4.6	0.7	-9.8	-0.3	-4.5	0.2

Global Equities (MSCI AC World Index)

US Equities (S&P 500 Index)

European Equities (MSCI Europe Index)

Property (IPD Index) 19.31

Global Bonds (Bank of America Merrill Lynch Global Broad Markets Index)

Global High Yield Bonds (Bank of America Merrill Lynch Global High Yield Bonds)

UK Gilts (Bank of America Merrill Lynch UK Gilts)

UK Cash (UK Interbank 3 month middle rate)

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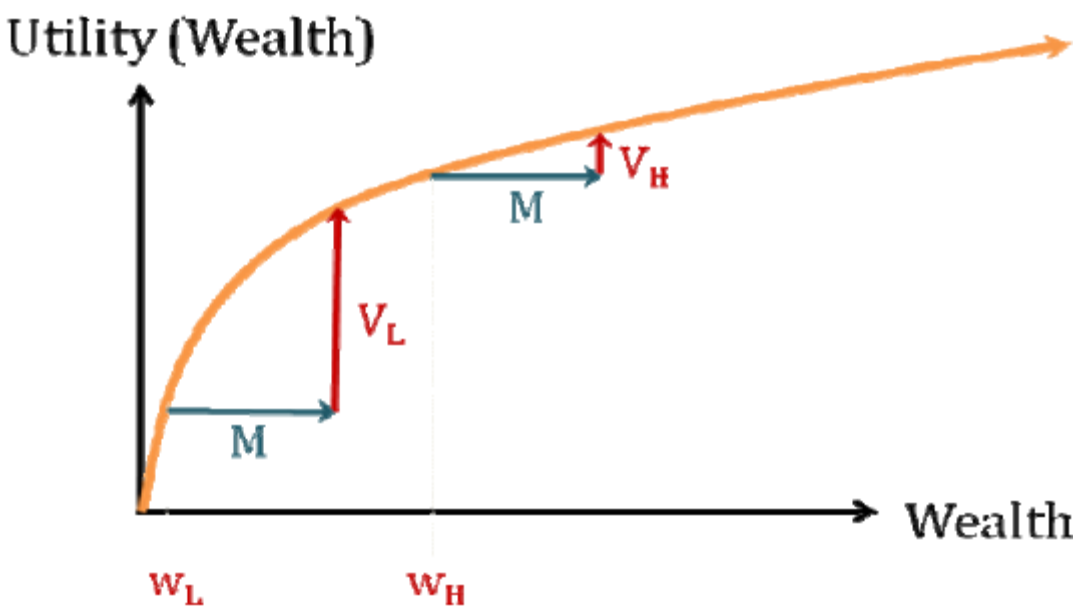
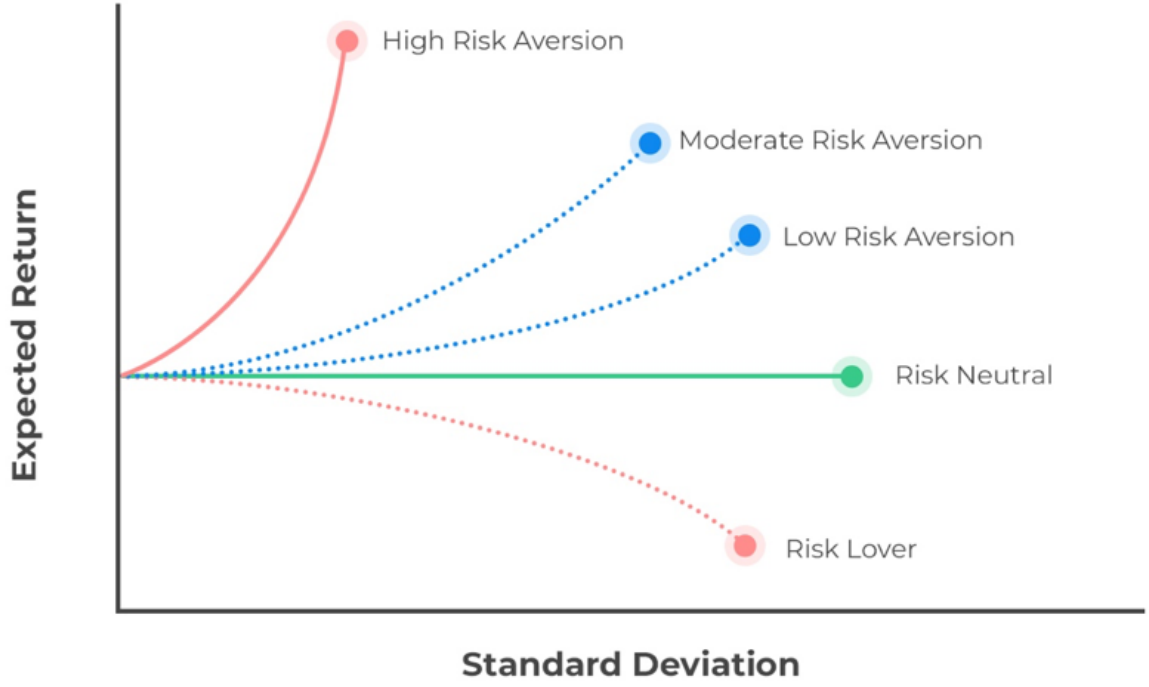
Utility Function

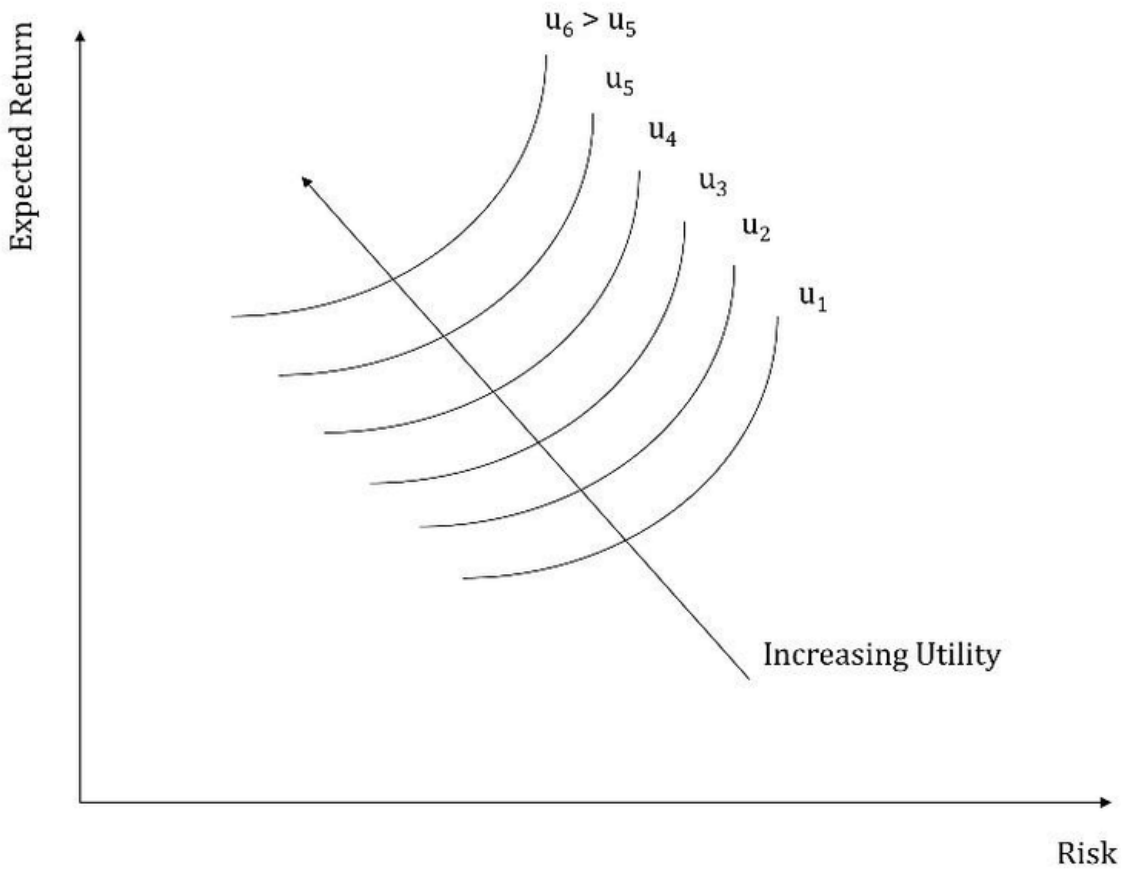


Utility function are same

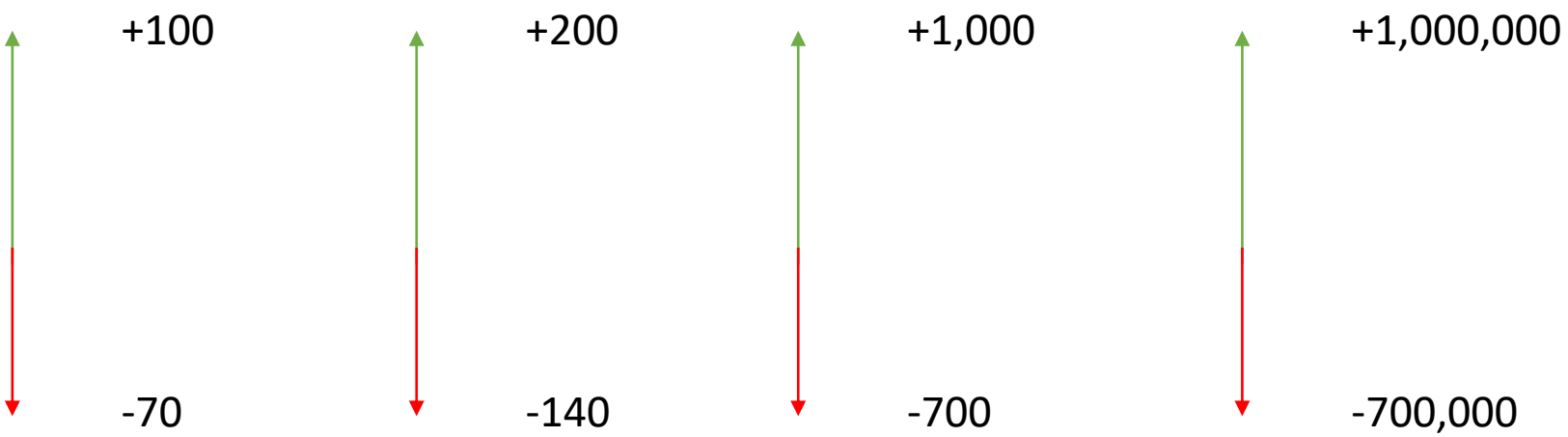
Investor is risk averse



Utility Function



Investor is risk averse



See that 2008?

Highest	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	30.9	12.1	7.1	10.5	25.1	18.9	24.6	18.1	12.5	44.7	44.2	18.7	16.9	14.7	29.9	20.8
	24.9	10.5	5.8	9.4	21.1	13.2	23.0	17.8	10.3	13.1	21.8	17.5	8.1	14.1	23.6	19.3
	20.0	8.9	5.2	5.3	17.6	7.9	18.8	6.6	7.7	5.7	20.6	16.8	6.8	11.7	21.2	14.7
	14.1	6.3	5.1	4.1	15.7	6.6	17.3	4.9	6.2	-0.1	12.6	14.5	3.4	10.9	10.9	11.2
	6.0	1.7	3.2	-10.6	11.2	4.8	13.5	1.6	5.2	-12.8	2.2	8.9	2.9	2.8	6.0	7.6
	5.6	-0.9	-9.6	-26.0	3.8	4.7	7.9	0.6	3.7	-19.5	1.2	7.8	0.9	2.4	0.5	6.1
	-1.2	-1.9	-13.7	-26.8	2.1	3.4	7.3	-0.4	1.3	-22.5	-1.3	7.6	-6.2	0.9	-4.3	0.5
Lowest	-0.1	-7.1	-17.5	-29.6	1.3	1.8	4.8	-6.6	-5.5	-25.4	-4.6	0.7	-9.8	-0.3	-4.5	0.2

Annual returns, %

- **Global Equities** (MSCI AC World Index)
- **US Equities** (S&P 500 Index)
- **European Equities** (MSCI Europe Index)
- **Property** (IPD Index) 19.31
- **Global Bonds** (Bank of America Merrill Lynch Global Broad Markets Index)
- **Global High Yield Bonds** (Bank of America Merrill Lynch Global High Yield Bonds)
- **UK Gilts** (Bank of America Merrill Lynch UK Gilts)
- **UK Cash** (UK Interbank 3 month middle rate)

© MSCI

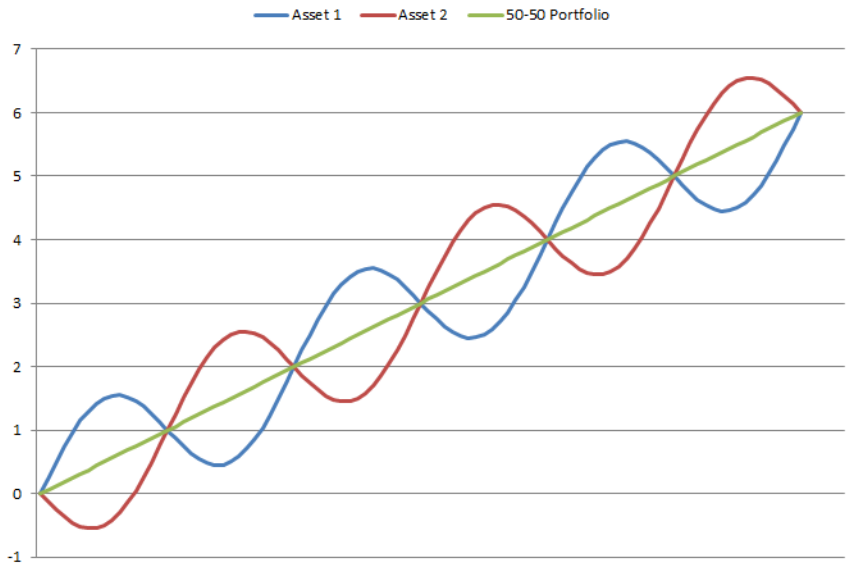
$$\rho_{X,Y} = corr(X,Y) = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$$

$$r = \frac{1}{(n-1)} \sum \frac{(X-\mu_X)(Y-\mu_Y)}{\sigma_X \sigma_Y}$$

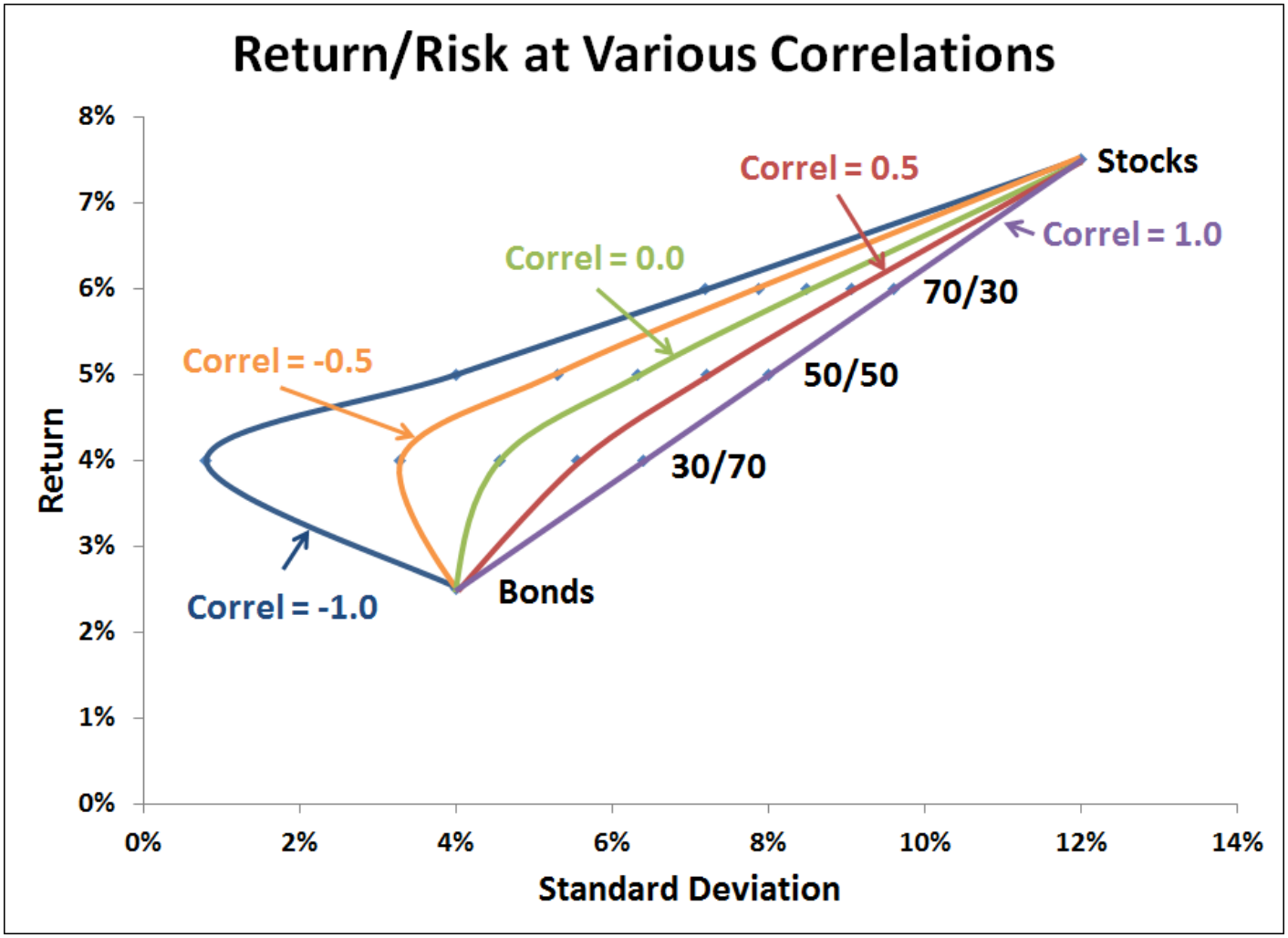
Even stock markets are correlated among themselves

Mthly Correl (Past 36M)	*S&P 500*	*Dow Jones*	*Nasdaq*	*Canada*	*Europe*	*UK*	*Australia*	*Japan*	*Hong Kong*	*Brazil*	*China*	*India*	*Russia*	*Sou Afri*
S&P 500	1.000													
Dow Jones	0.960	1.000												
Nasdaq	0.925	0.832	1.000											
Canada	0.647	0.565	0.594	1.000										
Europe	0.665	0.612	0.676	0.568	1.000									
UK	0.645	0.594	0.583	0.615	0.670	1.000								
Australia	0.622	0.559	0.602	0.617	0.597	0.564	1.000							
Japan	0.592	0.600	0.648	0.307	0.644	0.295	0.384	1.000						
Hong Kong	0.598	0.527	0.637	0.550	0.406	0.558	0.526	0.442	1.000					
Brazil	0.440	0.421	0.371	0.635	0.230	0.373	0.328	0.150	0.574	1.000				
China	0.364	0.392	0.374	0.277	0.256	0.221	0.259	0.460	0.633	0.322	1.000			
India	0.529	0.425	0.520	0.387	0.436	0.410	0.411	0.373	0.460	0.325	0.103	1.000		
Russia	0.153	0.123	0.182	0.225	0.333	0.227	0.165	0.200	0.161	0.129	(0.135)	0.185	1.000	
South Africa	0.570	0.461	0.592	0.614	0.532	0.448	0.557	0.315	0.654	0.380	0.306	0.422	0.293	1.
MSCI EM	0.641	0.585	0.598	0.645	0.429	0.573	0.451	0.307	0.849	0.782	0.444	0.606	0.180	0.
MSCI FM	0.538	0.466	0.467	0.599	0.388	0.562	0.406	0.116	0.652	0.619	0.261	0.521	0.063	0.

What if we can find such a thing



Mix is best?


Return/Risk at Various Correlations
8%
7%
6%
5%
4%
3%
2%
1%
0%
Return
0%
2%
4%
6%
8%
10%
12%
14%
Standard Deviation
Correl = 0.5
Stocks
Correl = 1.0
Correl = 0.0
70/30
Correl = -0.5
50/50
30/70
Correl = -1.0
Bonds

Adding Coca-Cola stock to portfolio, S.D. decreasing

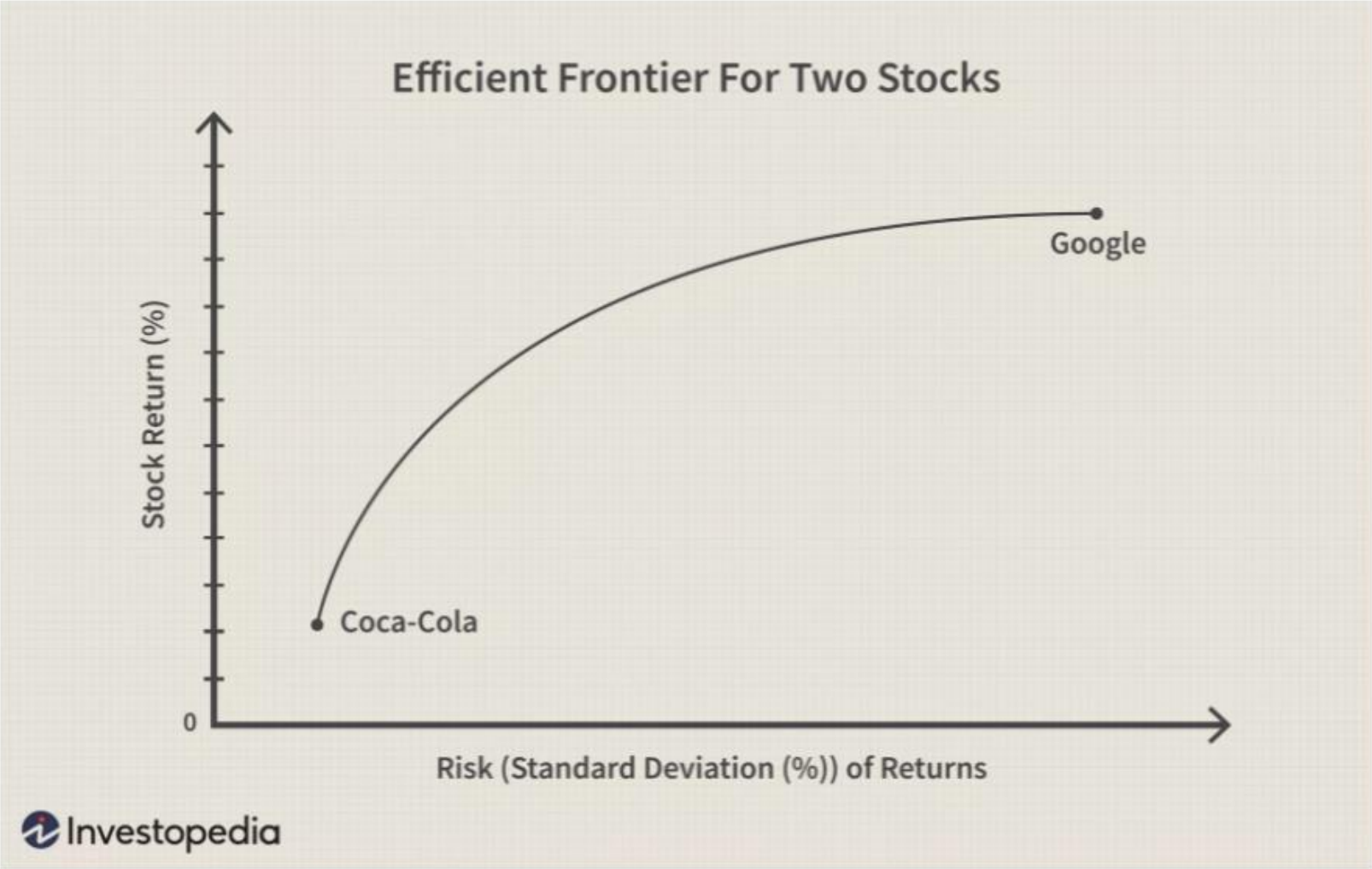
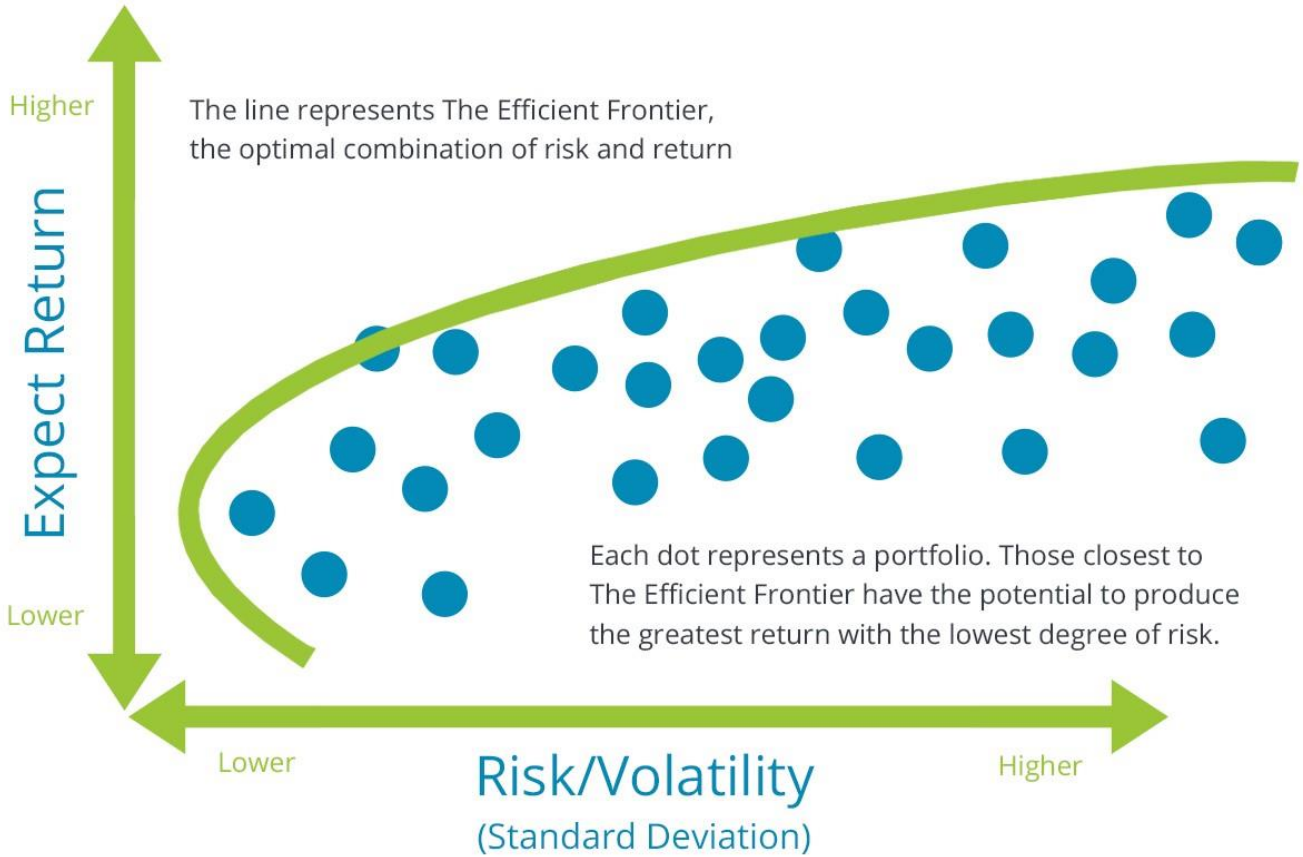


Image by Julie Bang © Investopedia 2020

Markowitz efficient frontier



Reduce unsystematic risk by increasing number of stocks

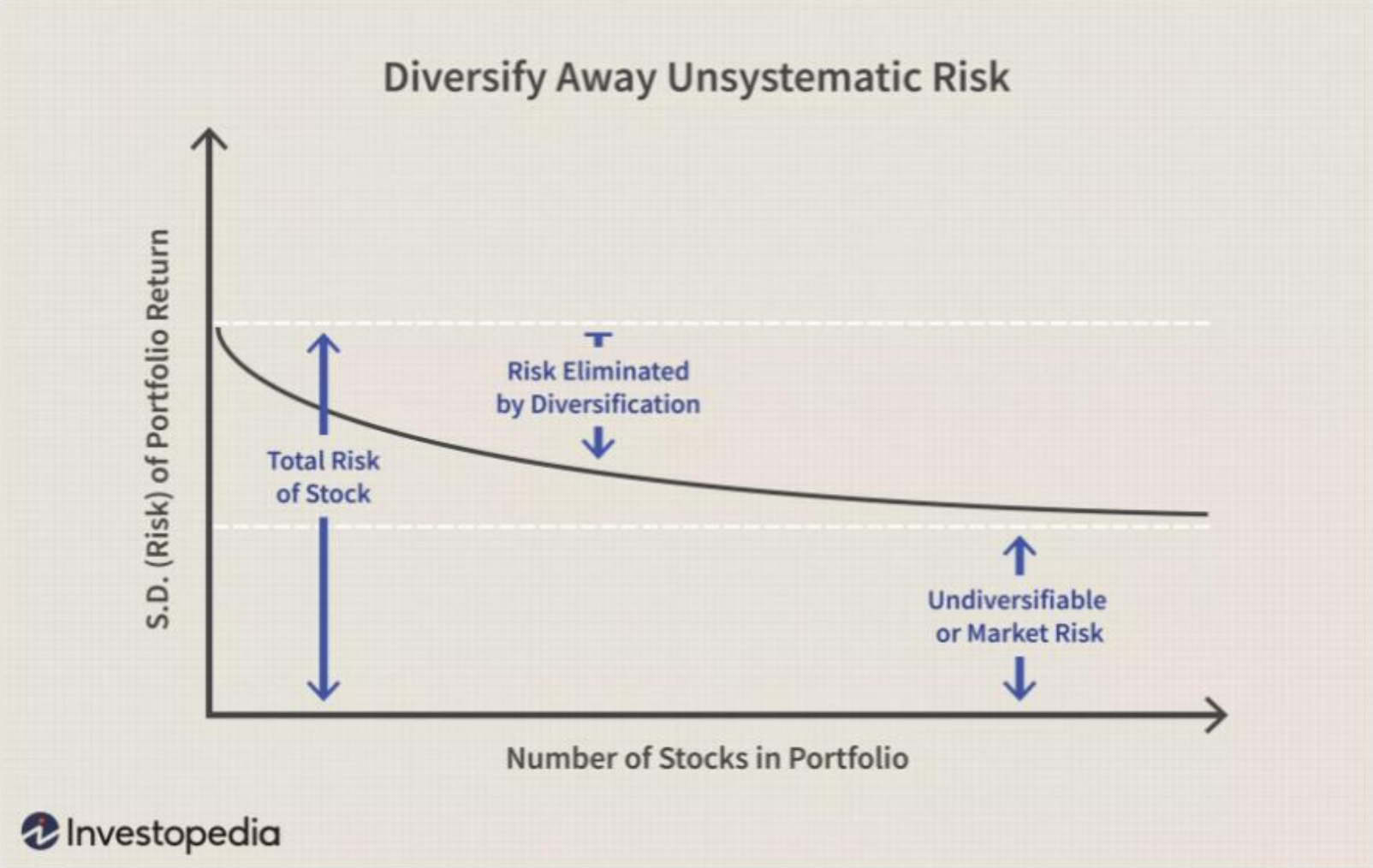


Image by Julie Bang © Investopedia 2020

Return and S.D. formulas

For a **two-asset** portfolio:

- Portfolio return: $\mathrm{E}(R_p) = w_A\,\mathrm{E}(R_A) + w_B\,\mathrm{E}(R_B) = w_A\,\mathrm{E}(R_A) + (1 - w_A)\,\mathrm{E}(R_B).$
- Portfolio variance: $\sigma_p^2 = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + 2w_A w_B \sigma_A \sigma_B \rho_{AB}$

For a **three-asset** portfolio:

- Portfolio return: $\mathrm{E}(R_p) = w_A\,\mathrm{E}(R_A) + w_B\,\mathrm{E}(R_B) + w_C\,\mathrm{E}(R_C)$
- Portfolio variance: $\sigma_p^2 = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + w_C^2\sigma_C^2 + 2w_A w_B \sigma_A \sigma_B \rho_{AB} + 2w_A w_C \sigma_A \sigma_C \rho_{AC} + 2w_B w_C \sigma_B \sigma_C \rho_{BC}$

Markowitz efficient frontier

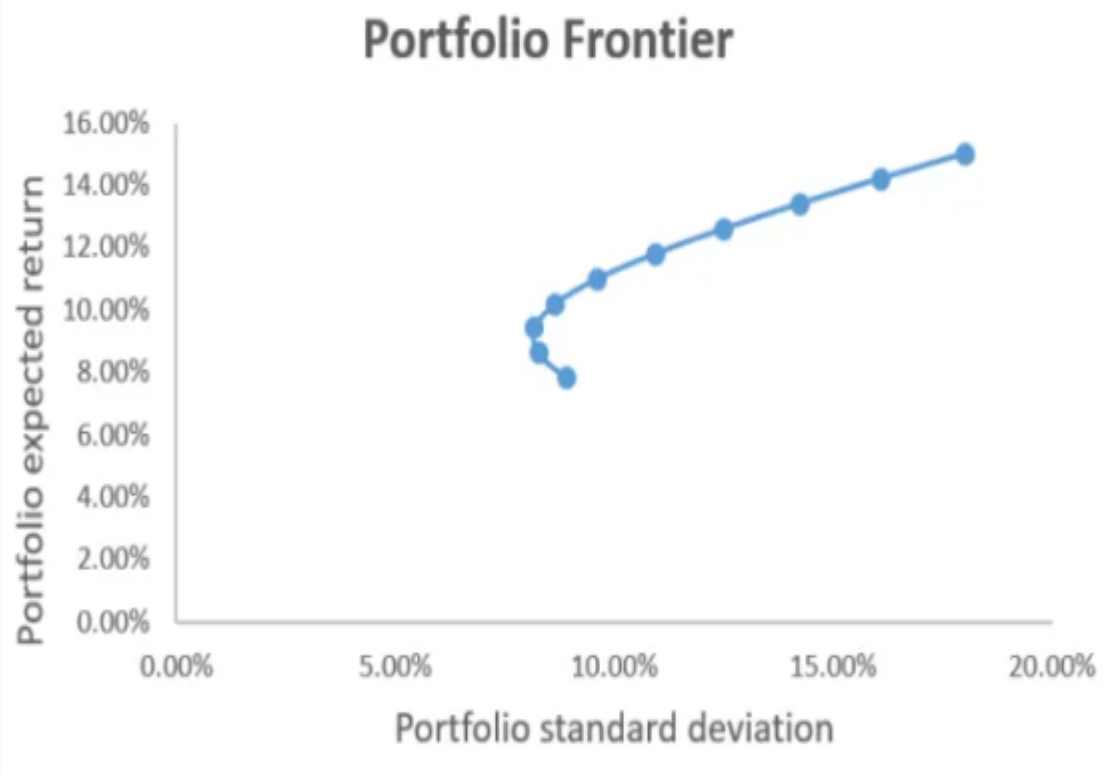
Return

Volatility

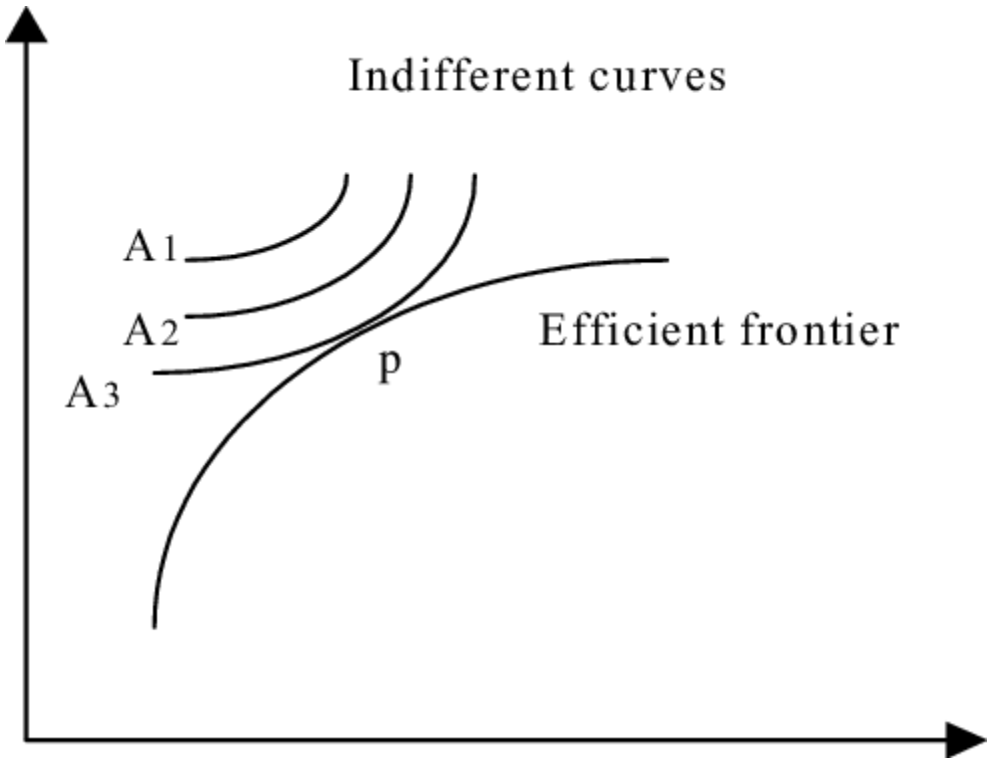
Allocation

How to create efficient frontier

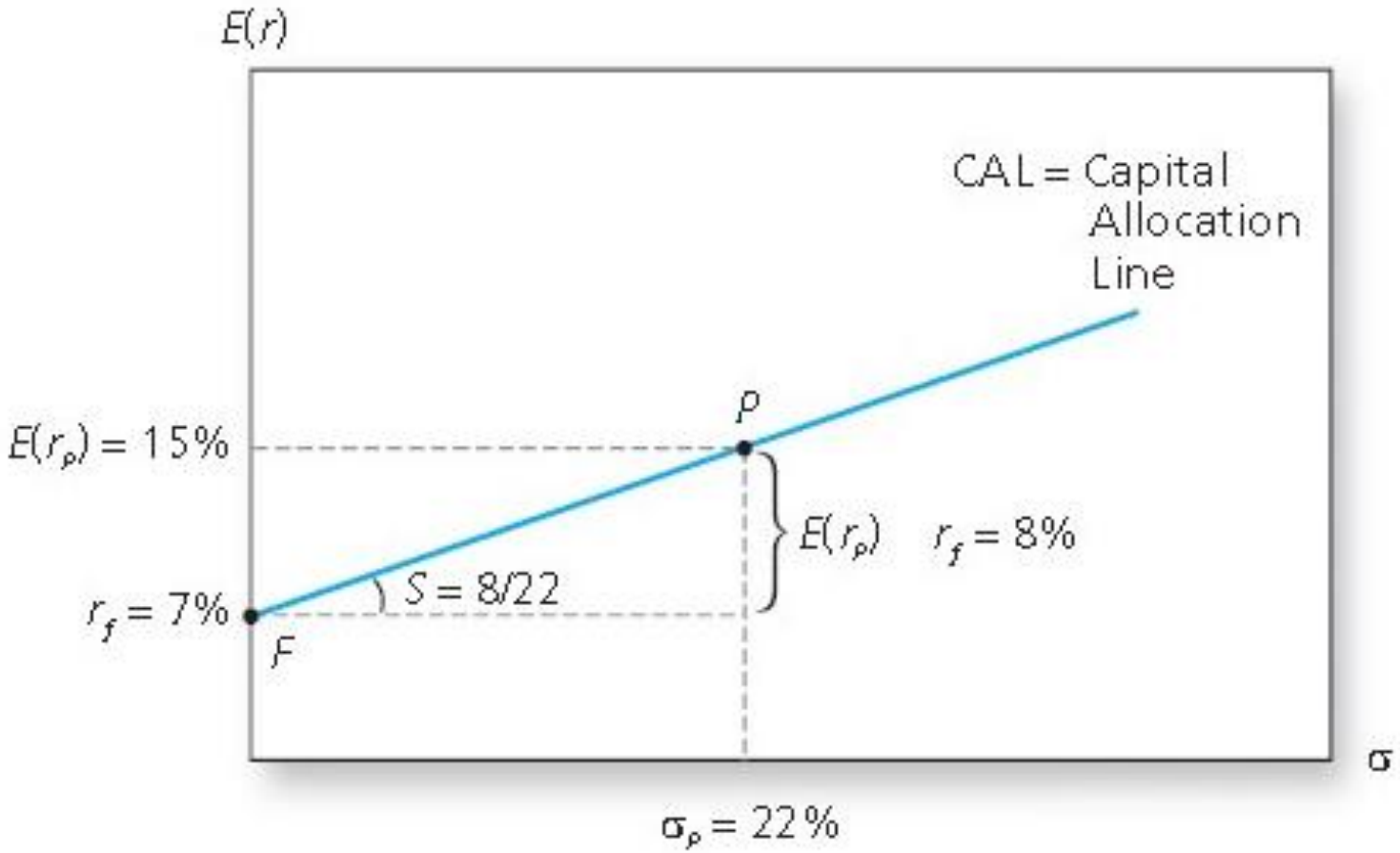
	A	B	C	D	E
1	E(R1)=	15.00%	sigma(R1)=	18%	
2	E(R2)=	7.00%	sigma(R2)=	10%	
3					
4	rho(R1,R2)= -	0.15			
5			Portfolio standard deviation	Portfolio expected return	
6	w1=	0.1	8.91%	7.80%	
7		0.2	8.27%	8.60%	
8		0.3	8.17%	9.40%	
9		0.4	8.65%	10.20%	
10		0.5	9.62%	11.00%	
11		0.6	10.94%	11.80%	
12		0.7	12.51%	12.60%	
13		0.8	14.24%	13.40%	
14		0.9	16.08%	14.20%	
15		1	18.00%	15.00%	
16					



Match your Portfolio and Utility Function



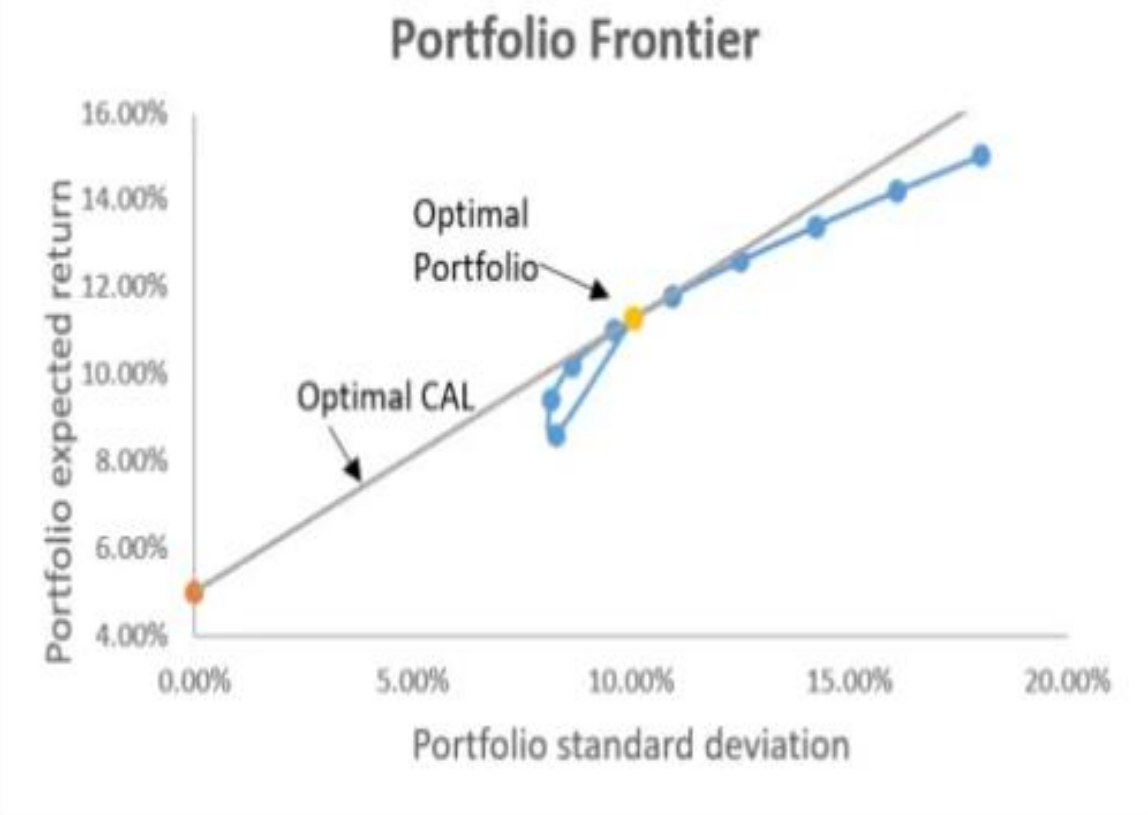
Capital Allocation Line



$E(R_p) = R_f + \text{Sharp ratio}_p \times \sigma_p$

Optimal portfolio

The optimal portfolio consists of a risk-free asset and an optimal risky asset portfolio. The optimal risky asset portfolio is at the point where the CAL is tangent to the efficient frontier. This portfolio is optimal because the slope of CAL is the highest, which means we achieve the highest returns per additional unit of risk. The graph below illustrates this:



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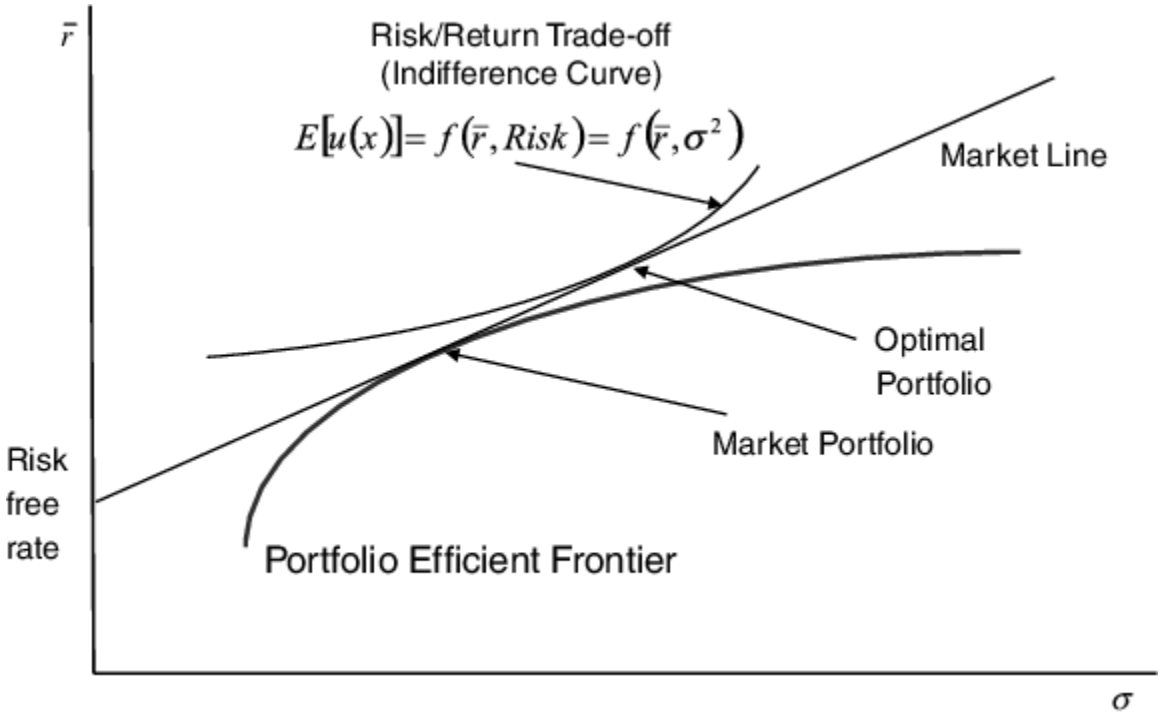
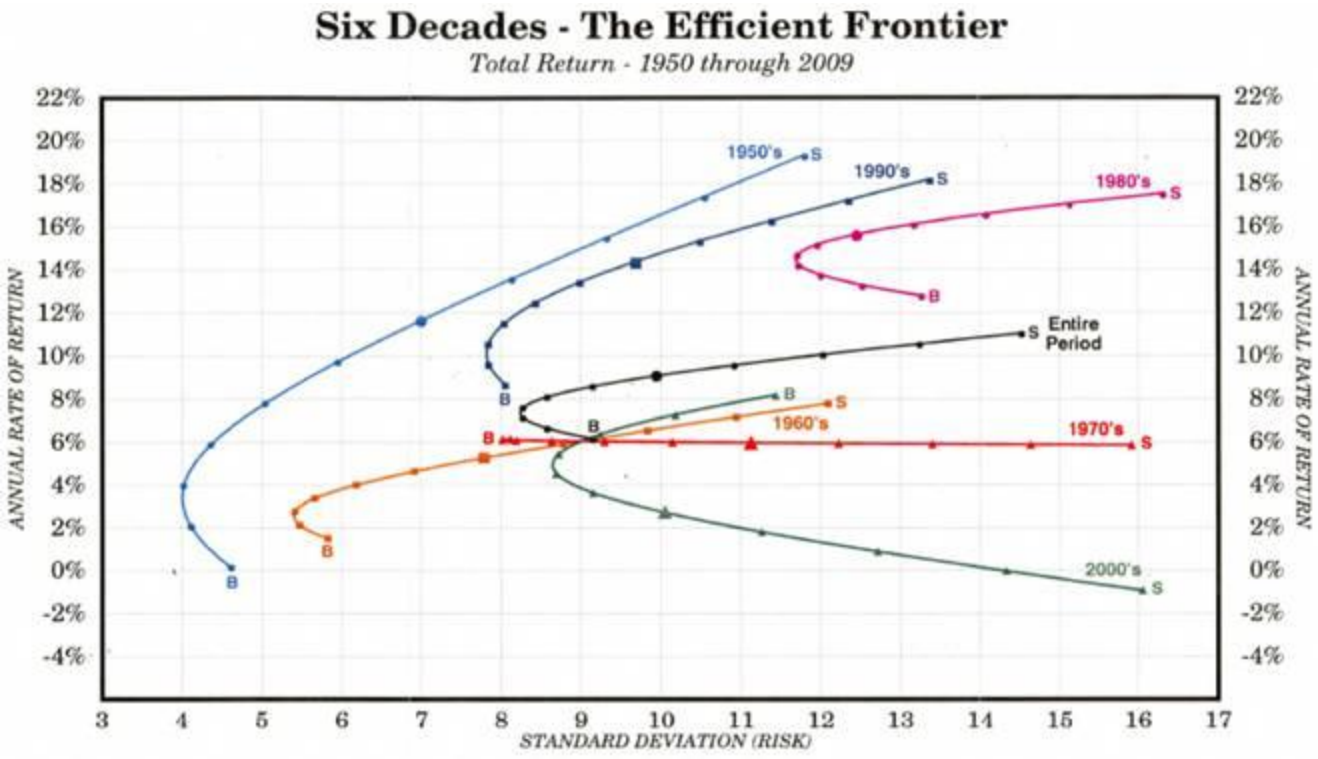
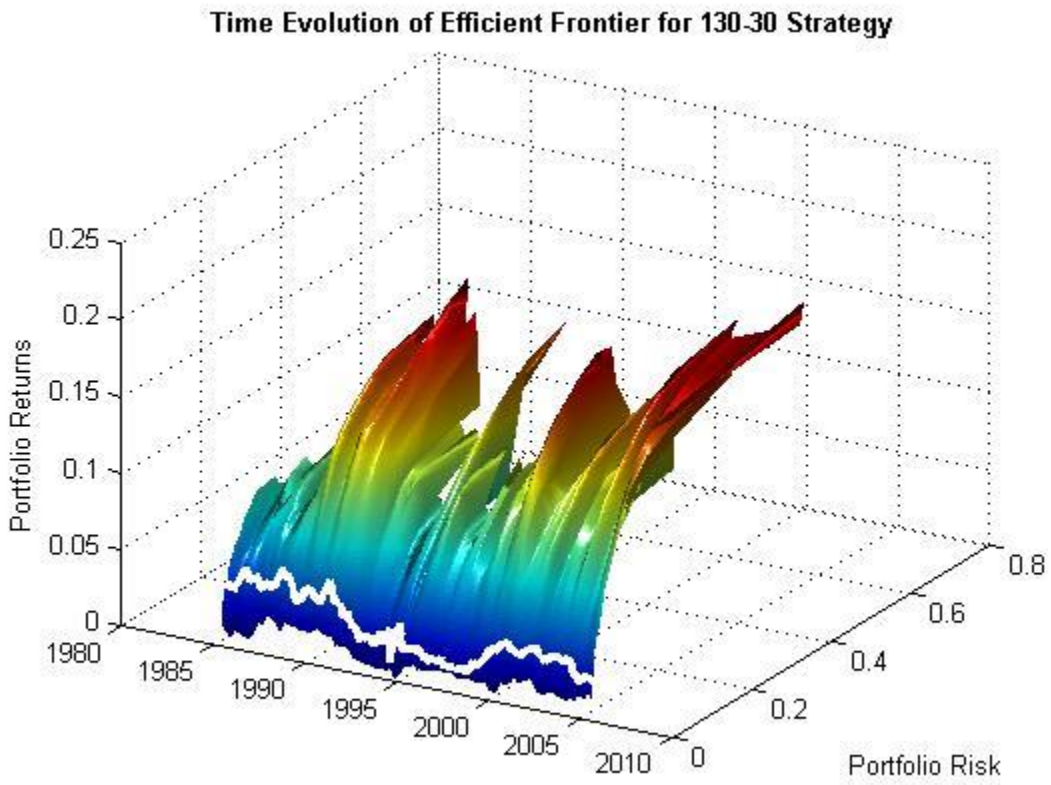
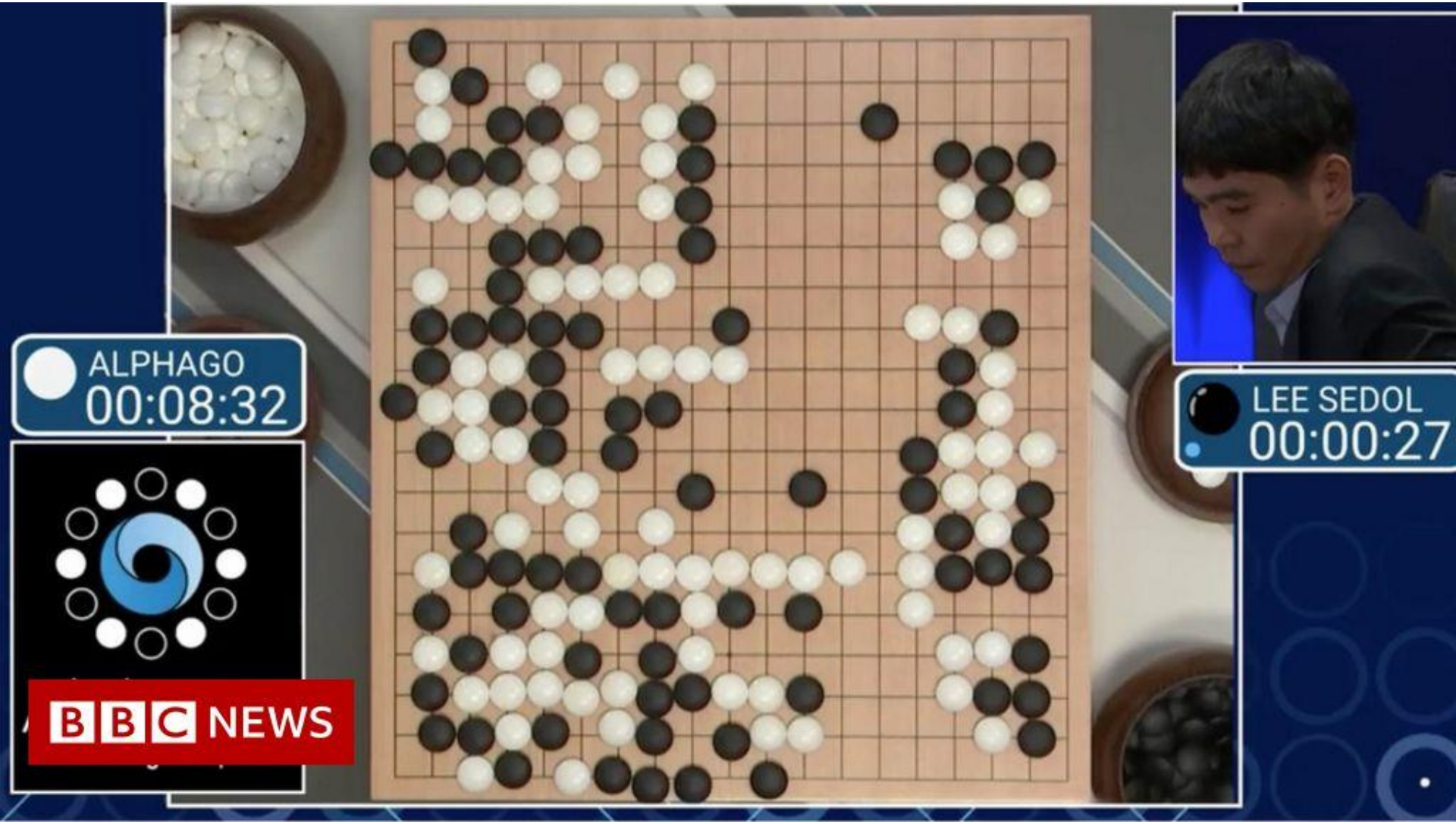
Where they meet



Markowitz efficient frontier



Markowitz efficient frontier



But in this era of A.I.?