

# Trading Strategies That Are Designed Not Fitted

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FXCM London Quant Conference  
Friday 15<sup>th</sup> June

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# How most people think systematic trading design should work...

Data

Magic box

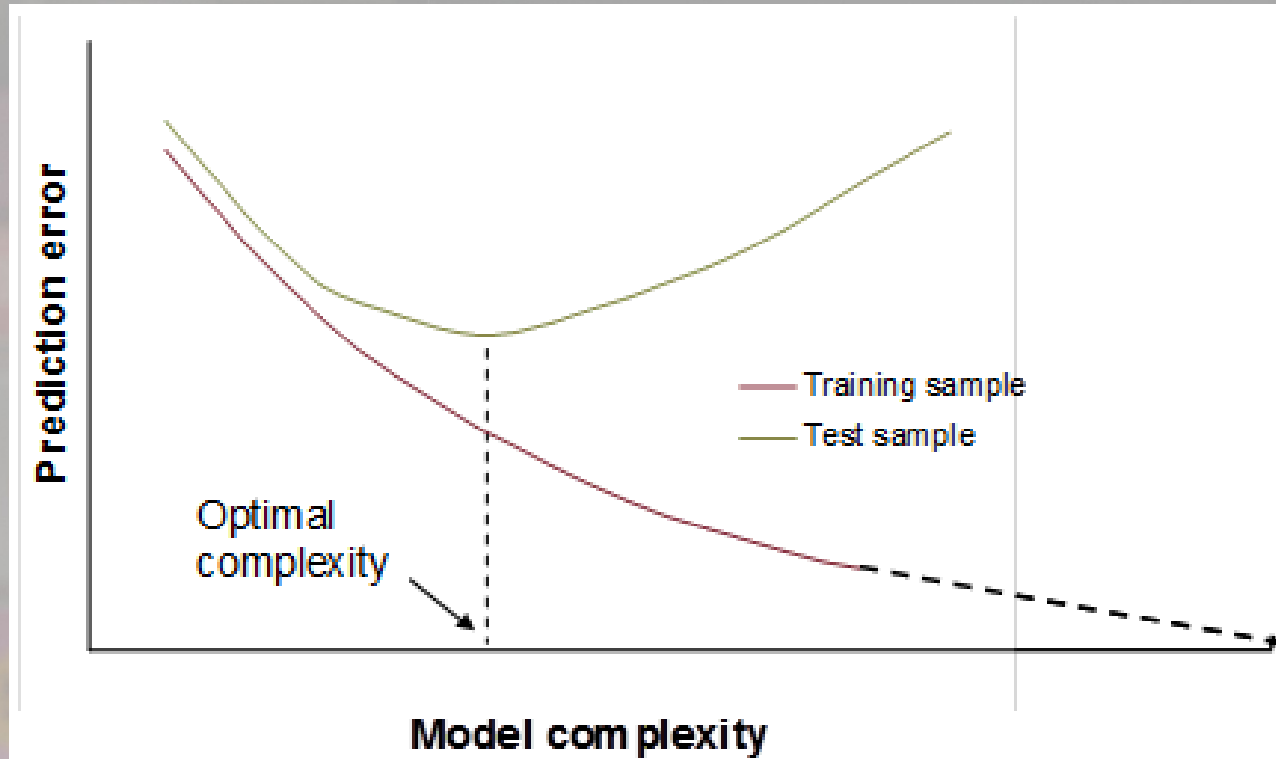
Trading strategy

Algo + Parameters

Data first

# Why is fitting bad....

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*"The elements of statistical learning" by Hastie et al fig 2.11*

# The three types of fitting...

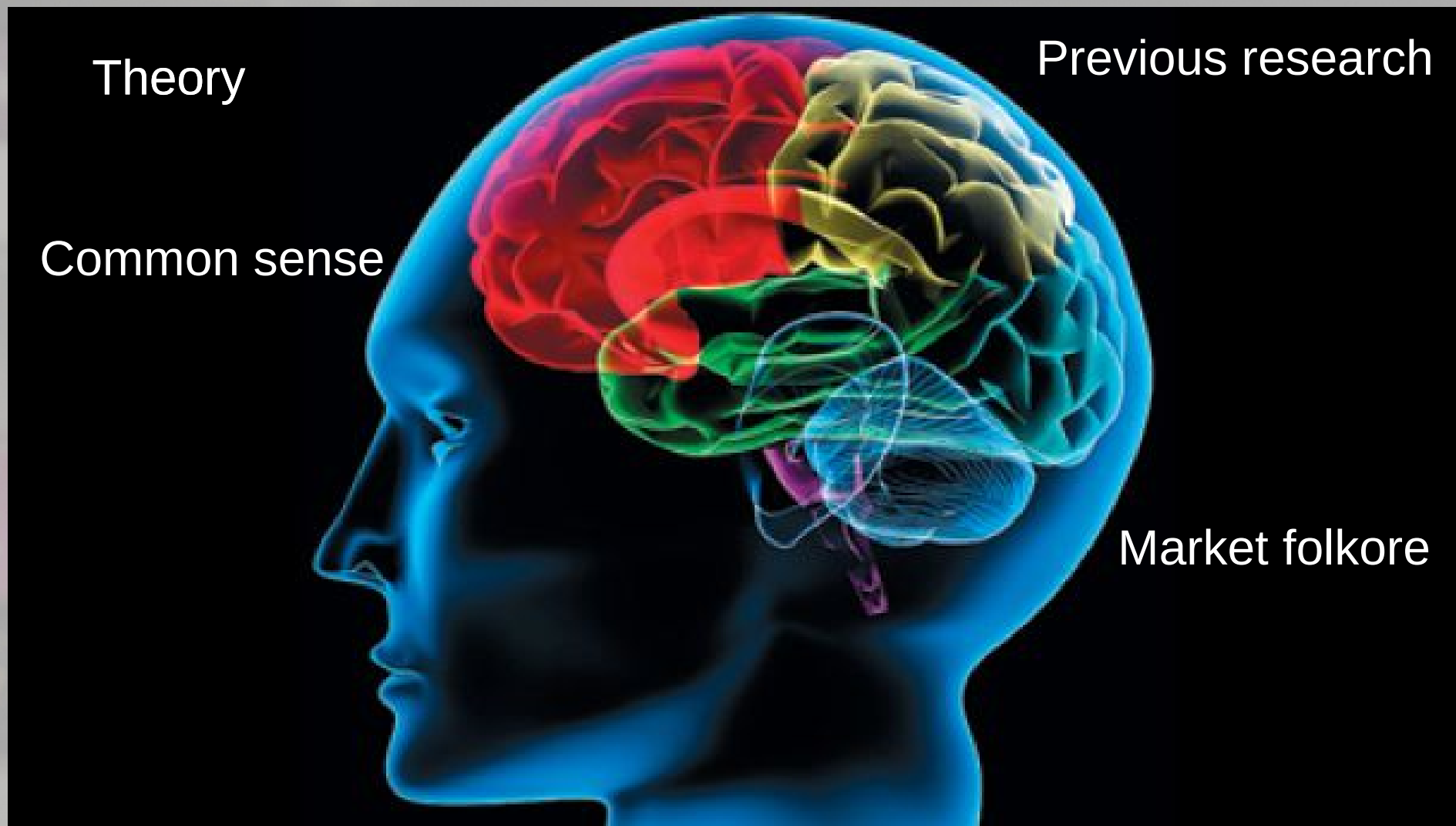
Explicit

Implicit

Tacit

# Tacit financial market knowledge

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## How do we **design** rather than **fit**?

- Acknowledge and embrace tacit knowledge
- Avoid implicit fitting
- Do the minimum amount of explicit fitting, and do it right.

Start with **ideas** not **data**

# How I design trading strategies...

Tactit knowledge

Ideas first

Design process

Fake data

Real  
Data

Trading strategy  
Algo + Parameters

# How I design trading strategies...

Theory

Market folklore

Previous research

Common sense

Fake data

Design process

Real  
Data

# How do people design real products...

Theory

Market research

Previous products

Personal taste

Focus group

Prototypes

Design process



# Tacit knowledge: Trend following

- Market folklore:
  - “Cut your losers and let your winners run”
  - “Don’t fight the tape”
  - Turtle Traders
  - US CTA tradition (Campbell, Chesapeake, Dunn), UK CTA tradition (AHL, Winton, Aspect), Europeans (Transtrend, Systematica)
- Previous empirical research:
  - Levy 1960
  - Jegadeesh and Titman 1993
  - Carhart “fourth factor” 1997
- Theory:
  - Prospect theory (Kahneman and Tversky 1992),
  - Herding, Confirmation bias, under reaction.
  - Behaviour of other participants (eg risk parity funds)

# Unanswered questions

- What period of time do trends last for?
  - When should we enter trends?
  - When should we exit trends?
  - Should we have a stop loss rule? What is it?
  - How do we identify markets that are, or aren't "trend friendly"?
  - How do we identify how strong the trend is?
  - What size should our positions be?
- 
- What is our algo?
  - What are it's parameters?

Data first

Possible algos

Data

Possible parameters

Magic box

Strategy = Best Algo +  
Best parameters

What is best strategy? Data first answer:

## **Best return versus risk in dataset**

Assuming leverage is possible and risk is Gaussian:

**Highest Sharpe Ratio**

(Other measures are available...)

**Single metric of 'best': Performance**

**Single source of information: Past data**



What is best strategy? Ideas first answer:

## **Best designed strategy**

### **Multi-faceted metrics:**

Performance, turnover, behaviour in given scenarios...

### **Multi-faceted sources of information:**

Common sense, Theoretical principles, Fake data, (Limited amounts of) Real Data

# Designing a trading strategy – 6 steps:

- Start with a sound framework which imposes some conditions
- Come up with the idea
- Use some random data or single scenario of real data plus theory / common sense to develop algo
- Use fake data to “fit” algo
- Real data for parameter sensitivity check / sense check
- Fit *allocation* using real data (out of sample, robust optimisation)

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# Start with a sound framework

Trading rule 1

Trading rule 2

Trading rule 3

SP500

EDOLLAR

CORN

Combine forecasts from trading rules

Risk targeting

Position sizing

Portfolio: Weight instrument positions



# Start with a sound framework: Conditions

- Trading rules make forecasts of risk adjusted price changes
- Forecasts are continuous, not discrete entry + exit conditions
- Forecasts are scaled in an instrument / temporal independent way (no “magic numbers”)
- Forecast is proportional to  $E(\text{Sharpe Ratio } \mu / \sigma)$   
[Position is proportional to Forecast /  $\sigma$  hence position is proportional to  $\mu / \sigma^2$  ]
- $E(\text{abs}(\text{forecast})) = 10.0$
- In principal all forecasts used on all markets (portfolio optimisation stage will become later)
- Use multiple variations of the same trading rule to capture different time frames (as many as possible, not too highly correlated)
- Costs are the most important thing. The second most important thing is costs. Costs are predictable – returns are not. Throw away very expensive systems.
- Throw away very slow systems (LAM)

# Start with a sound framework

## ... remember these questions?

- What period of time do trends last for?
- When should we enter trends?
- When should we exit trends?
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- How do we identify how strong the trend is?
- What size should our positions be?

# Start with a sound framework ... remember these questions?

- ~~What period of time do trends last for?~~
- ~~When should we enter trends?~~
- ~~When should we exit trends?~~
- ~~Should we have a stop loss rule? What is it?~~
- ~~How do we identify markets that are, or aren't "trend friendly"?~~
- **How do we identify how strong the trend is?**
- ~~What size should our positions be?~~

Fewer open questions:

Fewer parameters to "fit" or design



# Designing a trading strategy – 6 steps:

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# Come up with the idea: What are trends?



# Come up with the idea

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Linear regression price against time, using Ordinary Least Squares:

$$y = \alpha + \beta x + \varepsilon \quad \text{minimise } \sum \varepsilon^2$$

with  $y$  = price, and  $x$  = some measure of time (eg years)

$\beta > 0$  price in uptrend

$\beta < 0$  price in downtrend

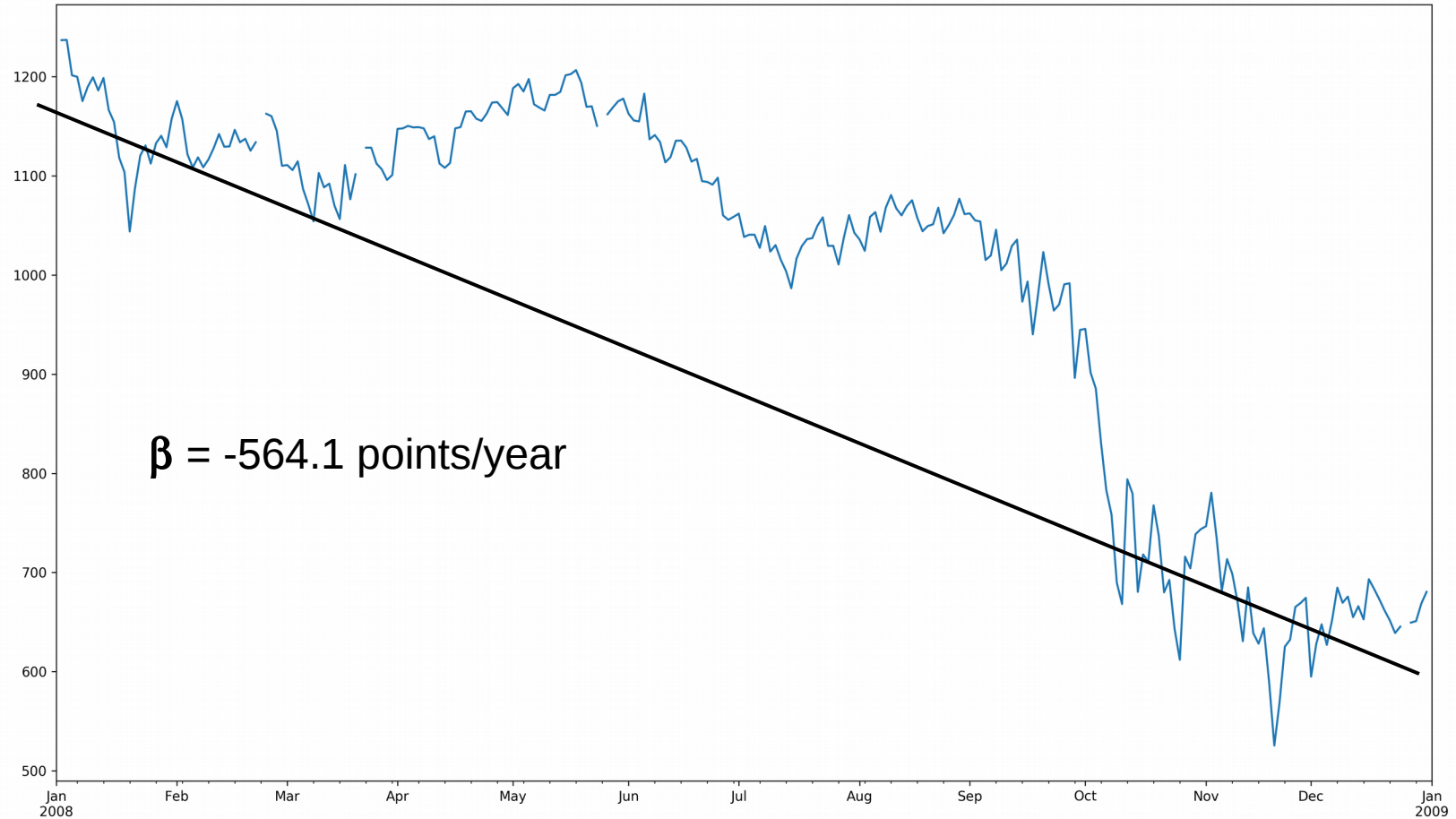
We use a rolling regression over the last  $N$  weekdays to capture different length trends.

Single parameter: **window\_size**

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# Develop algo: Real scenario... 2008





# Conditions (reminder)

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- Throw away very slow systems (LAM)

# Develop algo: Evaluate design

Does this scale well? No...

(No need to look at data! **Common sense!**)

Forecast is proportional to  $E(\text{Sharpe Ratio} = \mu / \sigma)$

[Position is proportional to Forecast /  $\sigma$  hence position is proportional to  $\mu / \sigma^2$  ]

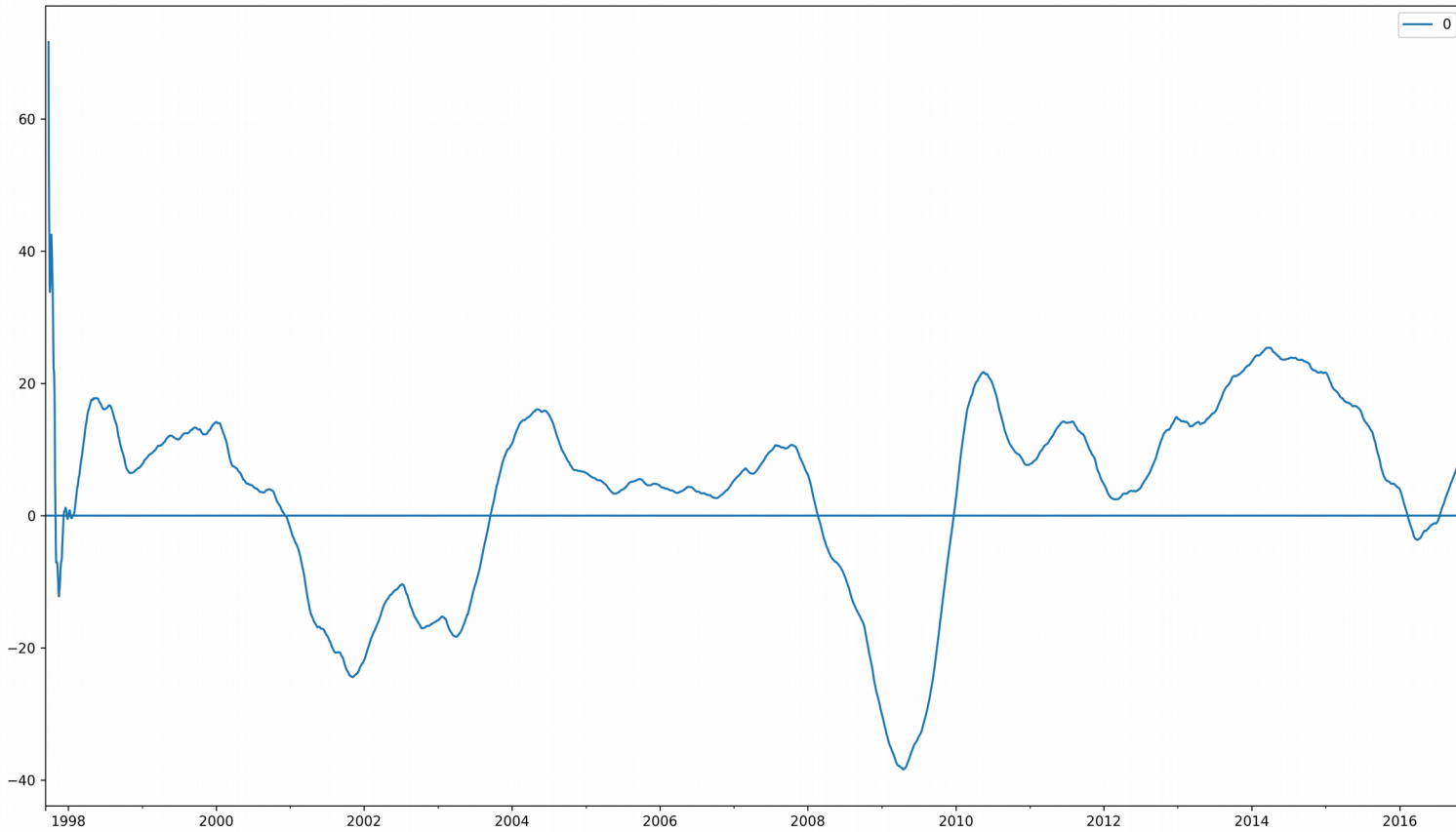
$\beta$  in units of  $\Delta(\text{price})$  so:

$$\text{Forecast} = \beta / \sigma$$

Where  $\sigma$  is measured is annual standard deviation of  $\Delta(\text{price})$

(No need to look at data! **Theory**)

# Develop algo: 2<sup>nd</sup> iteration





# Develop algo: Evaluate design

Does this scale well? Yes.

Does behaviour make sense? Yes.

Bullish in bull markets, bearish in bear markets

How about the trading speed? Seems reasonable given the length of trends involved

Anything weird? Yes

Need to set initial `min_periods` to a higher value (eg ***window\_size* / 4 : Common sense!**)

Too slow? Probably  $N=256$  is the slowest we'd go (LAM)



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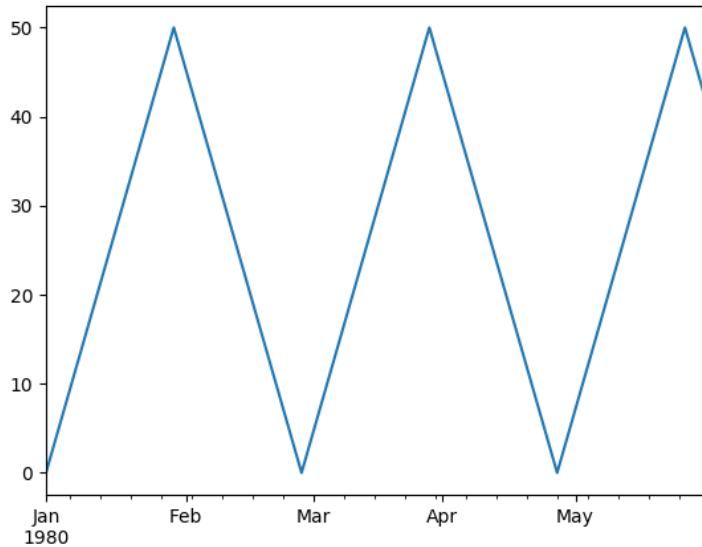
# Use fake data to “fit” algo: method

What value(s) should we use for *window\_size*?

- 1) Get an understanding of how trend length relates to profitability of *window\_size*
- 2) Get an idea of how fast different *window\_size* will trade
- 3) Prune any *window\_size* that are likely to be too expensive
- 4) Prune any *window\_size* that are likely to be too slow
- 5) Understand correlation structure to work out best *window\_size* pattern

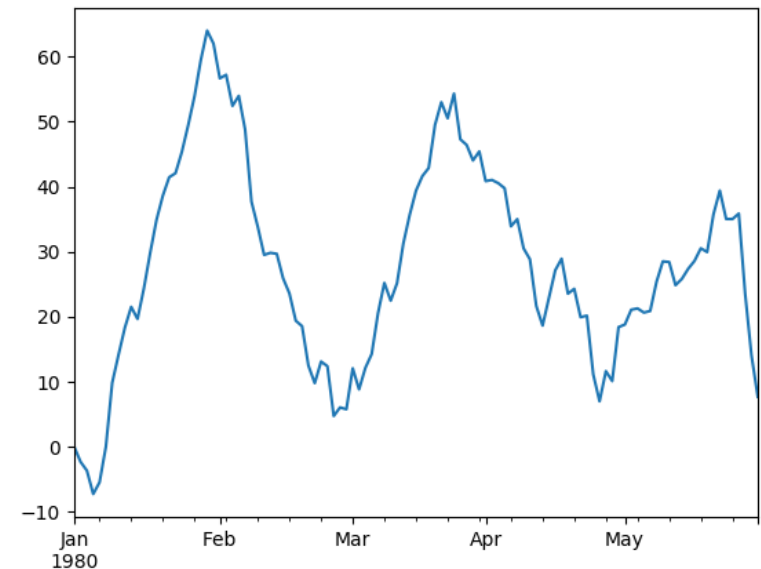


# Use fake data to “fit” algo: Generating data



+  $N(0, \sigma)$

=



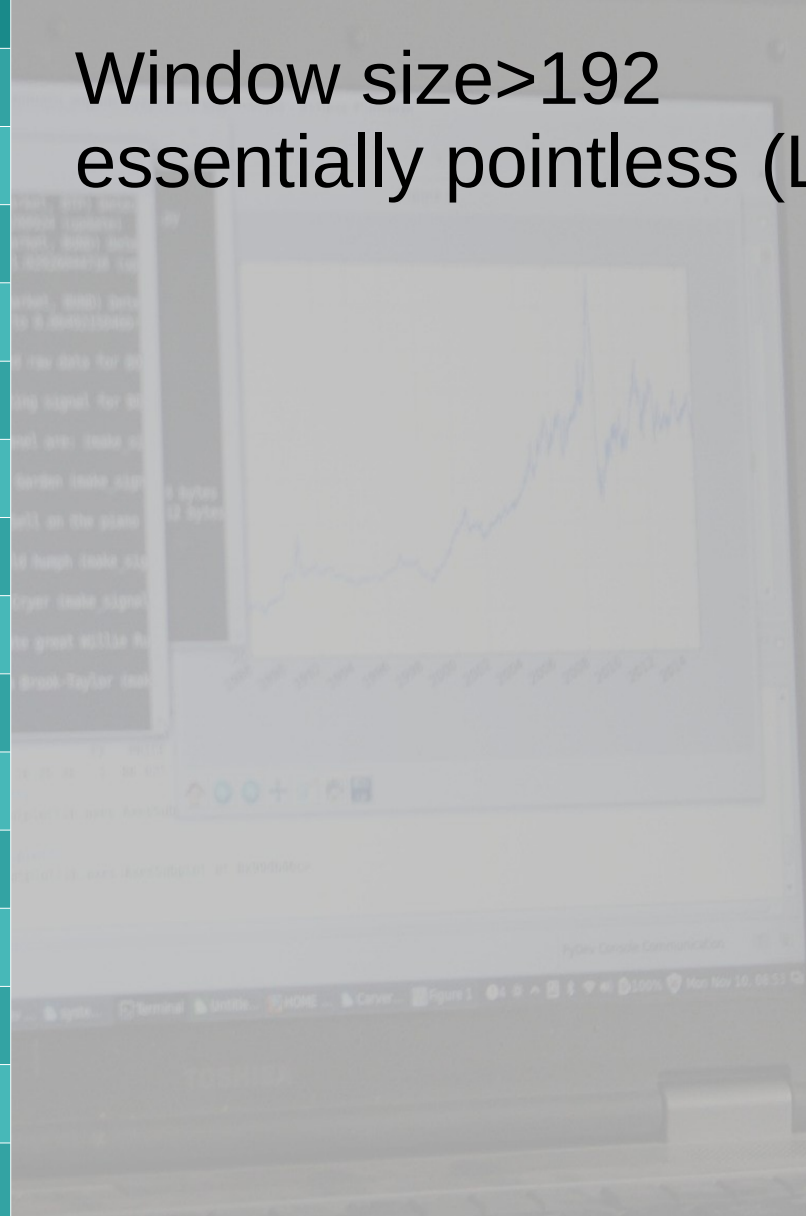


# Use fake data to “fit” algo:

## Trend length & window\_size: pre-cost SR

		21	64	128	192	256
5	1 week	<b>6.4</b>	2.1	0.3	0.2	0
10	2 weeks	<b>4.5</b>	<b>2.6</b>	0.6	0.2	0
15	3 weeks	1.6	<b>2.9</b>	0.8	0.2	0
21	1 month	<b>-2.0</b>	<b>2.9</b>	<b>1.1</b>	0.2	0.1
42	2 months	<b>-11</b>	1.6	<b>1.4</b>	0.4	0.1
64	3 months	<b>-0.4</b>	<b>-0.1</b>	<b>1.1</b>	<b>0.5</b>	0.1
85	4 months	<b>-5.0</b>	<b>-1.8</b>	0.8	<b>0.5</b>	0.1
107	5 months	<b>-0.1</b>	<b>-3.0</b>	0.4	<b>0.5</b>	0.1
128	6 months		<b>-3.0</b>	0	<b>0.5</b>	<b>0.1</b>
150	7 months		<b>-1.8</b>	<b>-0.5</b>	0.3	<b>0.1</b>
171	8 months		<b>-0.5</b>	<b>-0.7</b>	0.3	<b>0.2</b>
192	9 months		<b>-0.1</b>	<b>-1.0</b>	0.1	<b>0.2</b>
213	10 months			<b>-1.3</b>	0	<b>0.2</b>
235	11 months			<b>-1.6</b>	<b>-0.2</b>	<b>0.2</b>
256	12 months			<b>-1.6</b>	<b>-0.3</b>	0.1

Window size > 192  
essentially pointless (LAM)



# Use fake data to “fit” algo: window\_size and trading speed

		Turnover/year
5	1 week	176
10	2 weeks	75
15	3 weeks	49
21	1 month	36
42	2 months	21
64	3 months	13
85	4 months	12
107	5 months	9.3
128	6 months	8.8
150	7 months	7.4
171	8 months	7.1
192	9 months	6.5
213	10 months	6.5
235	11 months	6.1
256	12 months	6.1

Turnover / year

So turnover = 52 implies  
holding period of one  
week

Barely any  
improvement beyond  
window\_size>191

# Use fake data to “fit” algo: window\_size and costs

		<i>Cheap eg SP500</i>	<i>Expensive eg EDOLLAR</i>
5	1 week	0.176	1.76
10	2 weeks	<b>0.075</b>	0.75
15	3 weeks	<b>0.049</b>	0.49
21	1 month	<b>0.036</b>	0.36
42	2 months	<b>0.021</b>	0.21
64	3 months	<b>0.013</b>	0.13
85	4 months	<b>0.012</b>	<b>0.12</b>
107	5 months	<b>0.0092</b>	<b>0.093</b>
128	6 months	<b>0.0088</b>	<b>0.088</b>
150	7 months	<b>0.0074</b>	<b>0.074</b>
171	8 months	<b>0.0071</b>	<b>0.071</b>
192	9 months	<b>0.0065</b>	<b>0.065</b>
213	10 months	<b>0.0065</b>	<b>0.065</b>
235	11 months	<b>0.0061</b>	<b>0.061</b>

Costs in SR units  
/year

Max allowable is 13bp

See ch.12 of my book

No point having  
window\_size =5

# Use fake data to “fit” algo: window\_size and correlation structure

It turns out that if  $\text{window\_size}_{n+1} = \text{window\_size}_n * \sqrt{2}$

Then  $\text{correlation}(\text{forecast}_{n+1}, \text{forecast}_n) \sim 0.90$

And  $\text{correlation}(\text{forecast}_{\text{another } n}, \text{forecast}_n) < 0.90$



# Use fake data to “fit” algo: Final iteration

## Summary of findings:

- Window size in  $\sqrt{2}$  steps covers the space best
- Window size  $<10$  too expensive for any instrument
- Window size  $>200$  pointlessly slow

**Window\_size = [10,14,20,28,40,57,80, 113,160]**

Should capture trends lasting for around 1 month to 18 months

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- **Real data for parameter sensitivity check / sense check**
- Fit *allocation* using real data (out of sample, robust optimisation)

NOTE: Although I’m using real data, I’m **not** going to be looking at performance.

# Real data check: consistent scaling

Window size:	10	14	20	28	40	57	80	113	160
Corn	0.14	0.17	0.20	0.22	0.26	0.29	0.32	0.37	0.42
Eurodollar	0.13	0.15	0.18	0.20	0.24	0.28	0.33	0.39	0.43
S&P 500	0.14	0.18	0.21	0.25	0.30	0.36	0.42	0.50	0.56
US 10 year bond	0.13	0.16	0.19	0.22	0.26	0.30	0.36	0.42	0.48

# FAKE: window\_size and trading speed

		Turnover/year
5	1 week	176
10	2 weeks	75
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Turnover / year

So turnover = 52 implies  
holding period of one  
week



# Real data check: turnover

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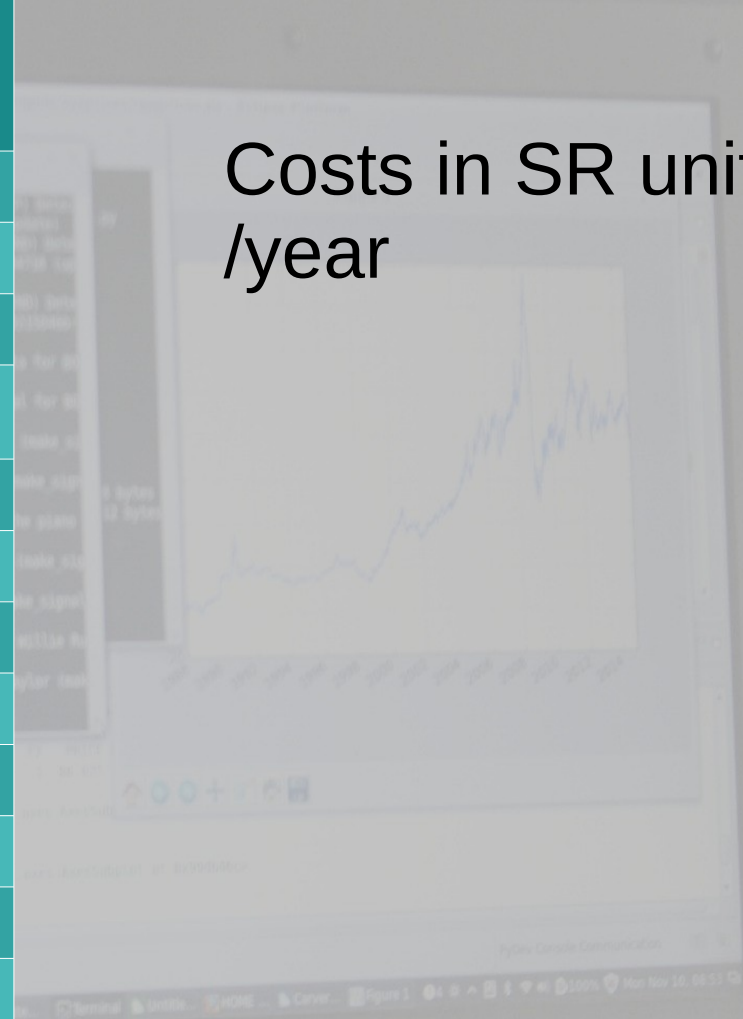
<b>window_size</b>	<b>turnover</b>
10	80.4
14	55.2
20	36.9
28	25.8
40	18.4
57	13.6
80	10.7
113	8.6
160	7.0



# FAKE DATA: window\_size and costs

		<i>Cheap eg SP500</i>	<i>Expensive eg EDOLLAR</i>
5	1 week	0.176	1.76
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235	11 months	<b>0.0061</b>	<b>0.061</b>

Costs in SR units  
/year

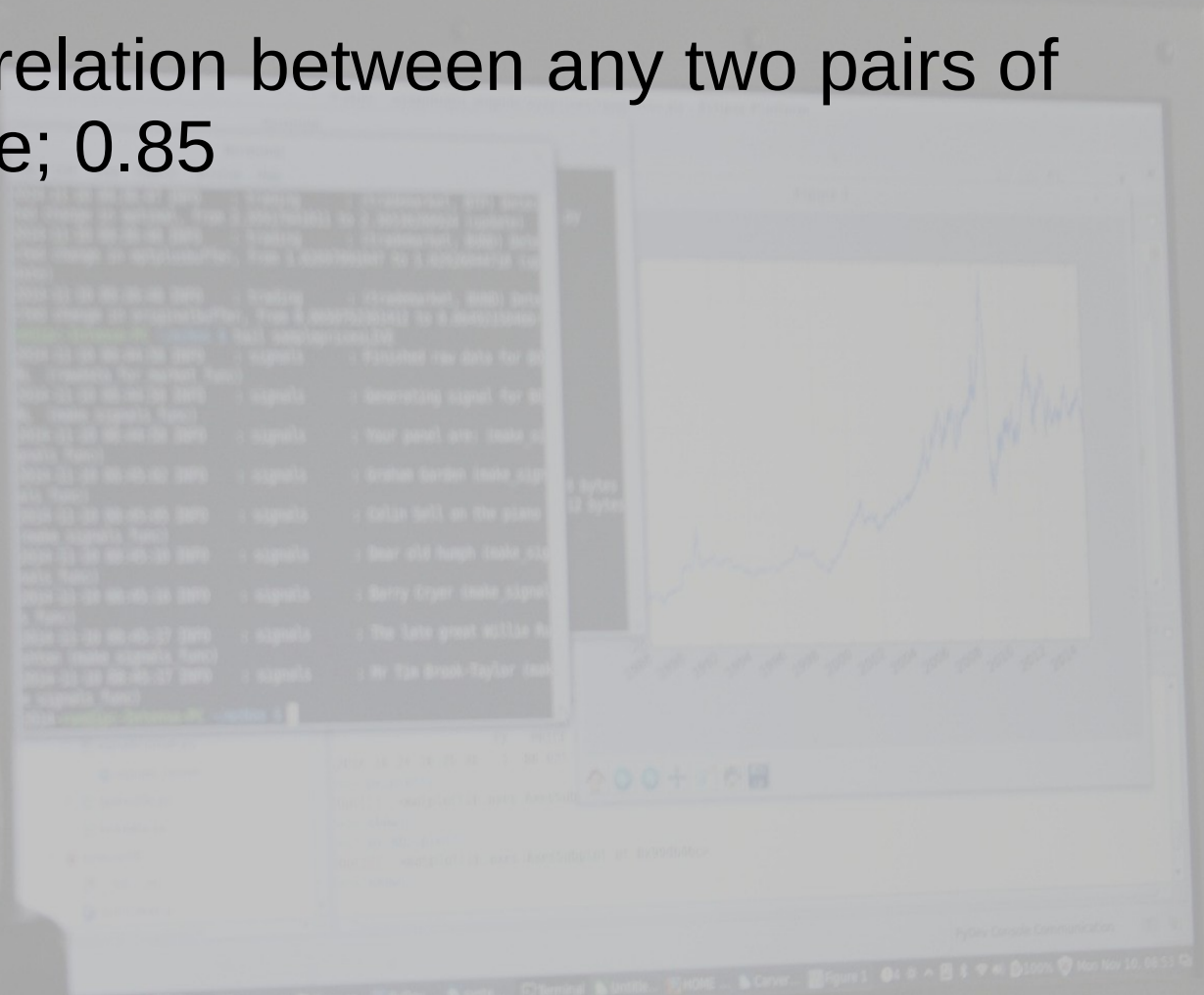


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Window size:	10	14	20	28	40	57	80	113	160
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Eurodollar	0.64	0.44	0.29	0.20	0.14	<b>0.11</b>	<b>0.08</b>	<b>0.07</b>	<b>0.05</b>
S&P 500	<b>0.10</b>	<b>0.07</b>	<b>0.05</b>	<b>0.04</b>	<b>0.03</b>	<b>0.02</b>	<b>0.02</b>	<b>0.01</b>	<b>0.01</b>
US 10 year bond	0.25	0.17	<b>0.12</b>	<b>0.08</b>	<b>0.06</b>	<b>0.04</b>	<b>0.03</b>	<b>0.03</b>	<b>0.02</b>

# Real data check: correlation structure

Highest correlation between any two pairs of window\_size; 0.85





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- **Fit *allocation* using real data (out of sample, robust optimisation)**

First and last time I will use *performance* calculated using *real data*.

# Conditions: reminder

- Trading rules make forecasts of risk adjusted price changes
- Forecasts are continuous, not discrete entry + exit conditions
- Forecasts are scaled in an instrument / temporal independent way (no “magic numbers”)
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# Fit *allocation* using real data

Combined forecast =  $w^1f^1 + w^2f^2 + w^3f^3 + \dots$

$f$  are in same vol scale so, values of  $w$  depend on:

- Pre-cost performance (different by market?)
- Costs (different by market)
- Correlation structure
- Well known portfolio optimisation problem....
- ... with well known problems (estimation error, extreme weights)
- .... and well known solutions: clustering, shrinkage, bootstrapping...
- Only line of defence against incorporating a **(statistically significantly)** loss making trading rule in our system



# Fit *allocation* using real data: Hypocrisy?

An aside, Why is fitting model parameters bad...  
... but optimising model portfolio allocations acceptable?

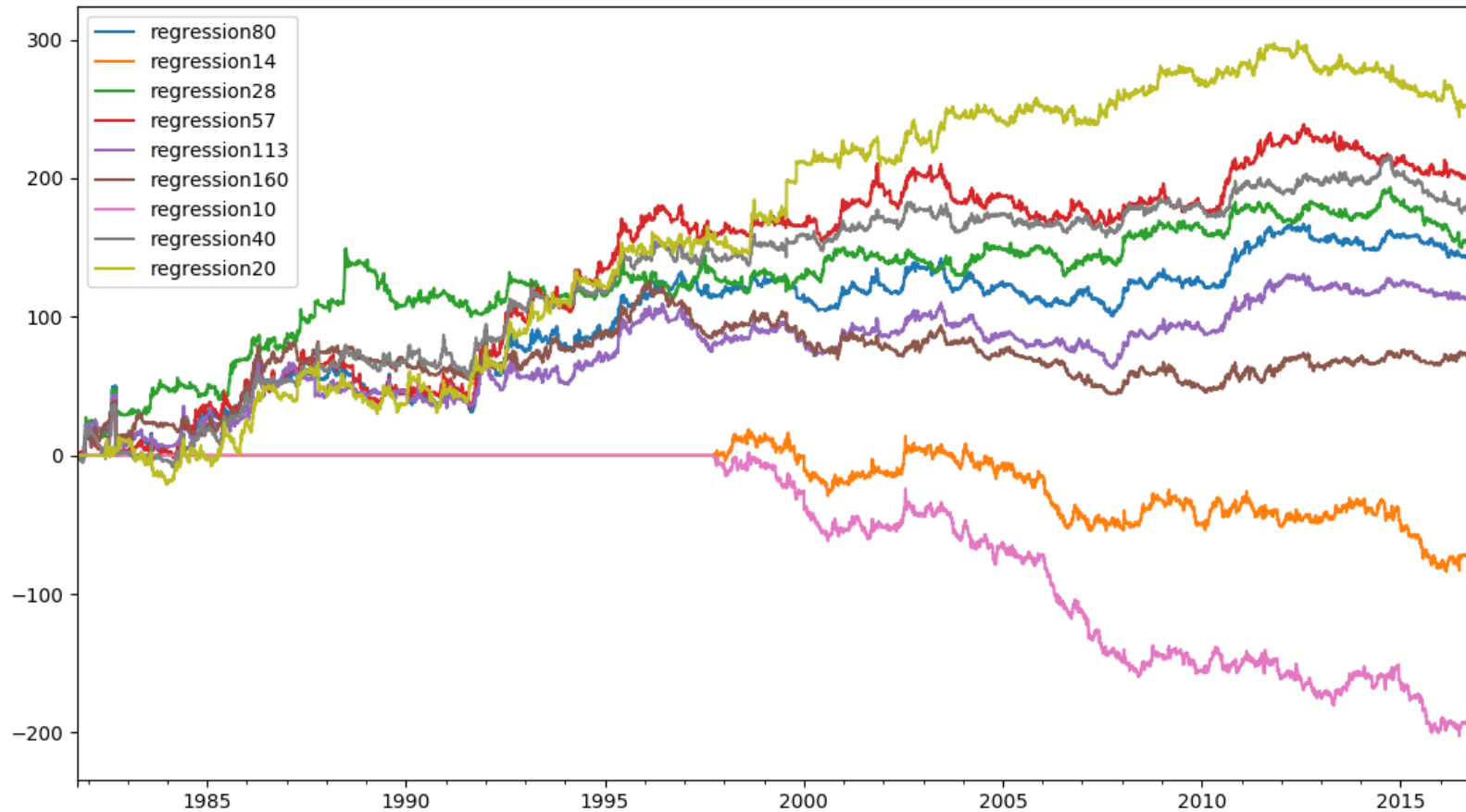
Answers:

- Parameter space much smaller
- Rolling out of sample is feasible
- Nicer surface
- Well developed techniques exist to cope with problems and use correct amount of degrees of freedom
- Much harder to do implicit fitting = much easier to resist the temptation



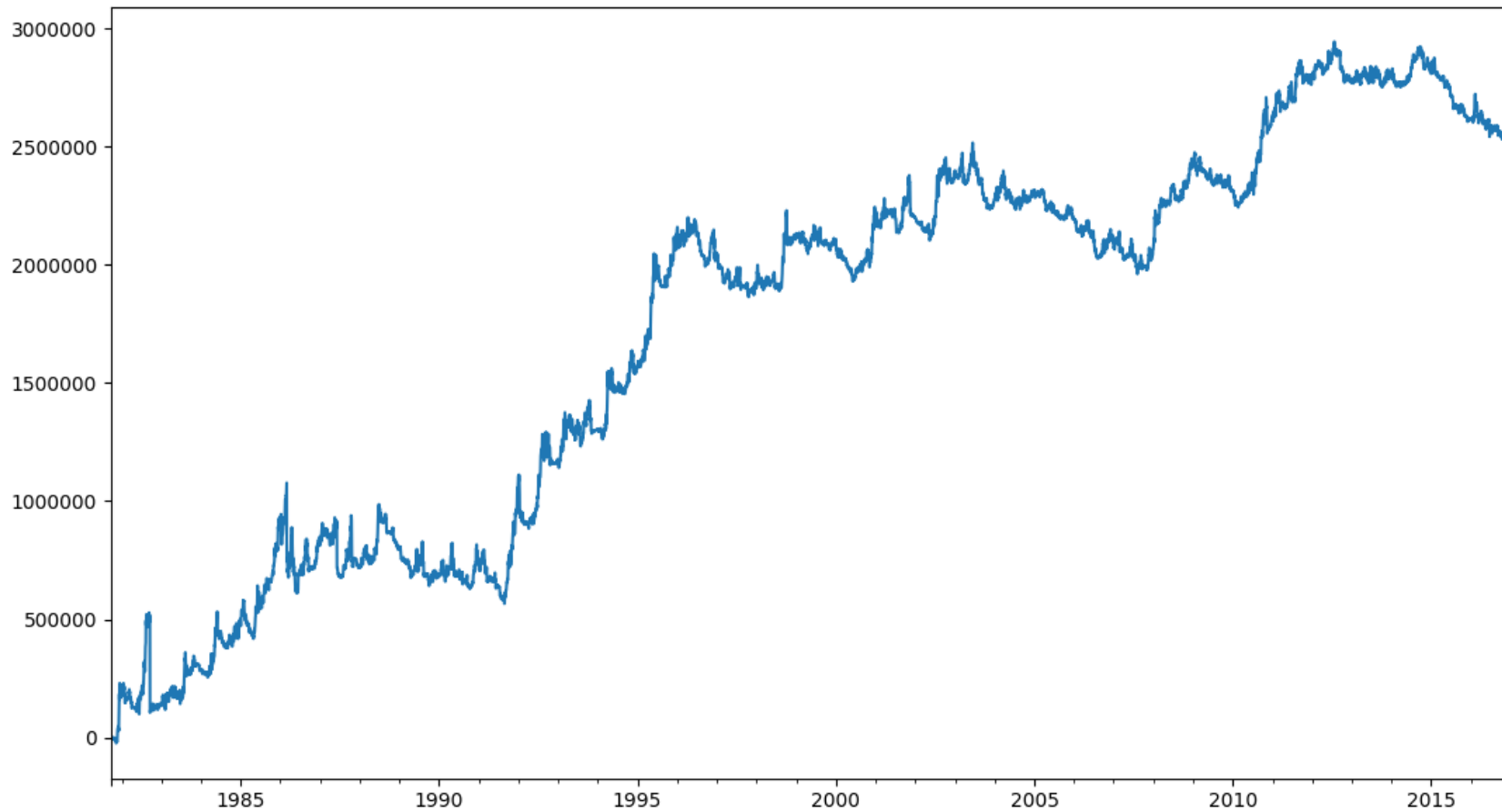
# Fit *allocation* using real data:

## Some account curves



# Fit *allocation* using real data:

## Some account curves



# Summary

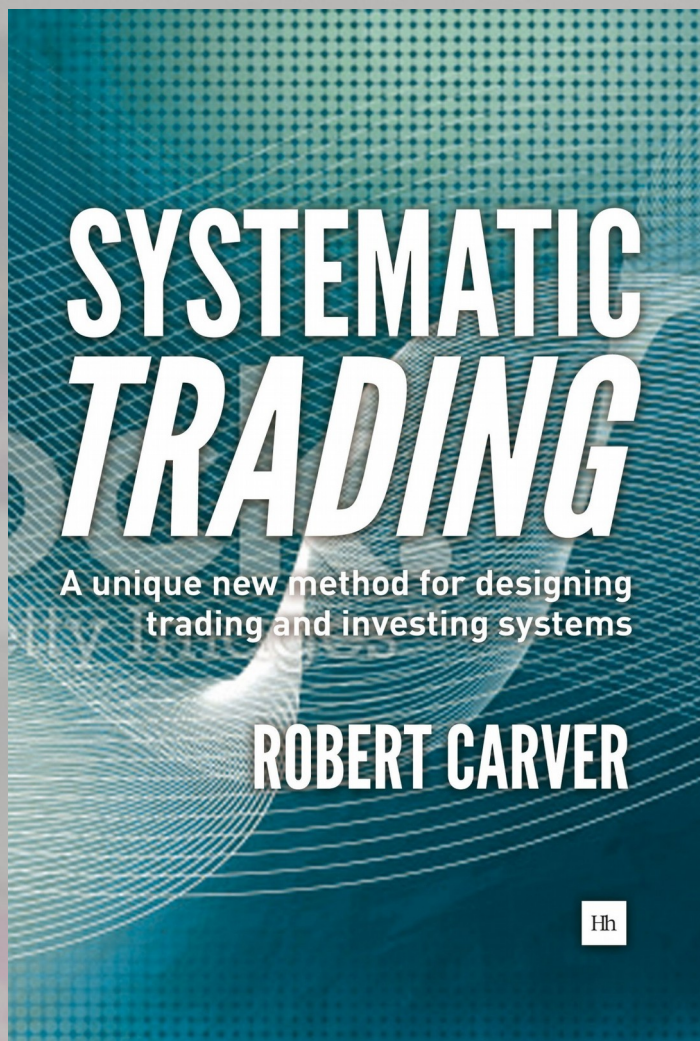
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- Three types of over fitting: tacit, implicit, explicit.
- You can't get around tacit knowledge.
- Use tacit knowledge to **design** trading strategies.

## Design process:

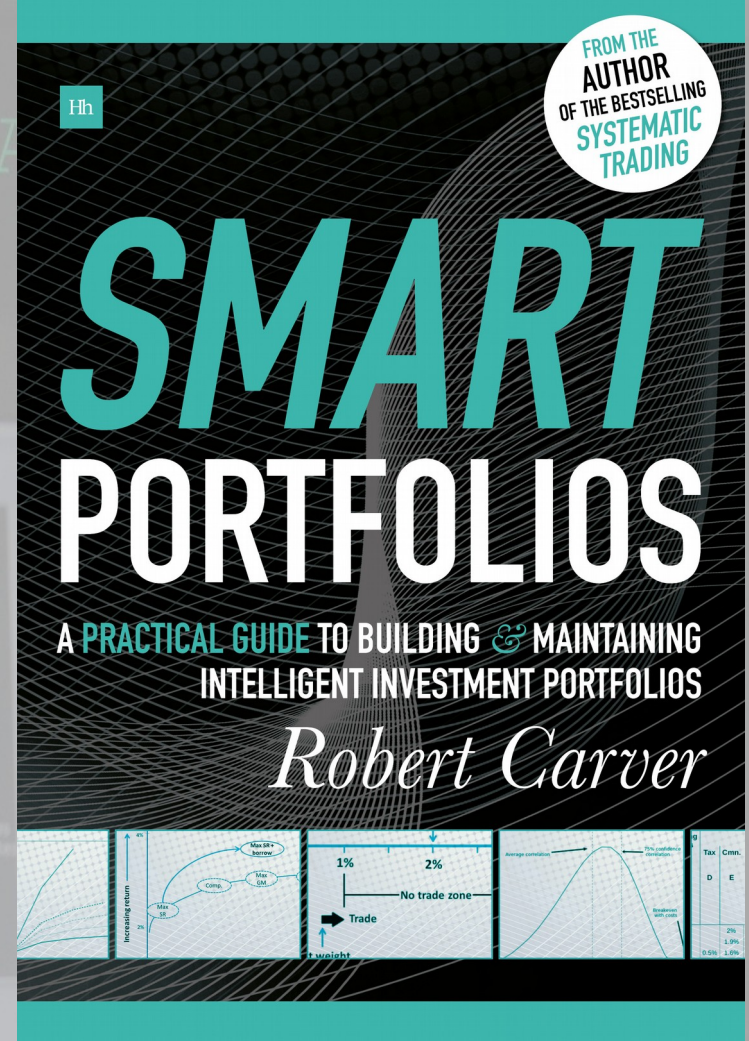
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My website:  
[systematicmoney.org](http://systematicmoney.org)

My blog:  
[qoppac.blogspot.com](http://qoppac.blogspot.com)



Some python:  
[github.com/robcarver17/](https://github.com/robcarver17/)

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# A final page of legal stuff

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