# Applying Agent Based Models in Financial Markets

Robert Hillman

28th November 2019 – NAEC Innovation Lab Seminar, OECD

This presentation represents an example of the type of analysis we do to enhance understanding of, and expectations around, general model behaviours.

CHARTS ARE FOR ILLUSTRATION ONLY
Source: Neuron. All data is simulated and purely for expositional purposes

- This is not investment advice.

- Charts contained herein are for illustration purposes only.

- Views are those of the author only.

# Some personal background

**1989-1999 Economics:** University of Leicester; QMW London; PhD in University of Southampton, UK; visiting researcher European University Institute, Florence; post-doc teaching/research/consultancy in Financial Econometrics Research Centre, CASS

**2000-2003 Bank of England:** ‘quant’ financial market analysis

**2003-2019 Hedge funds:** Research -> Portfolio Management -> CIO, in global macro funds and systematic trading strategies

**2018 ->** Investment research, risk reporting & consultancy

# Overview

NEURON

## Some historical and current motivations for agent-based models

- An early example of an agent-based-model in finance
- Some problems facing long term investors today
- Sequencing risk and probability of paying pensions

## Practical applications

- Long-horizon market simulation
- Forecasting and scenario analysis
- Pension funds and risk mitigation
- Operational tools

## Challenges

- So why aren’t ABMs popular today?
- Evidence that things are changing…..

# A brief history of agent-based models

Early promise….

**“Agent-based modeling of markets is still in its infancy. I predict that as the models get better, they will begin to be useful for real problems”**

**“Within five years, people may be trading money with agent-based models. Time will tell.”**

Doyne Farmer, ‘Toward Agent-Based models for Investment’

Association for Investment Management and Research, **2001**

# A brief history of agent-based models
What is an agent-based model?

## First example is still (highly?) relevant today, Kim & Markowitz (1988)

- K&M implemented a computer simulation model to address a debate with Fischer Black
- How likely was it portfolio insurance had contributed to the 1987 crash?
- The crash was unprecedented and the market environment (techniques) were new

## The model – a ‘test-tube’ model

- 150 different funds, mixture of portfolio rebalancers and portfolio insurers
- Each fund traded according to their own situation, submitting orders to an exchange - asynchronously
- Strategies (rules based) and parameters were grounded in practical experience

## The insights

- Asynchronicity matters and is a source of randomness / volatility
- Relatively low numbers of portfolio insurers can destabilise the market in certain conditions
- The transition from stability to instability can be quick

# A brief history of agent-based models

## Disappointing reality, with some exceptions

**Time has told: ABMs are barely used within investing today**

**Investing:** empirical models dominate, theory or justifications (and *marketing*) often coming after the fact e.g. factor strategies like min vol, size etc. See Kahn & Lemmon (2018)

**Risk:** VaR (Risk 1.0: Monte Carlo, historical and bootstrap simulation) and stress tests & scenarios (Risk 2.0) dominate. Rick Bookstaber (2014) made a case for ‘Risk 3.0’ (generative & reflexive) but it has not been widely, if at all, implemented

**Execution:** As execution has gone almost ‘fully algo’, ABMs (& econophysics) *are* creeping in, informing market-impact modelling, algo-testing strategy design, market design.

Europe: Much work by J-P Bouchaud and others. US: Signs that microstructure literature is embracing econophysics concepts e.g. Kyle & Obizhaeva (2016)

# A new use case – based on work with Kenneth Blay*
# (1) Simulating long-horizon returns

## Investors and individuals need to plan over decades

- Shift towards defined contribution, annuities etc. Individuals have lots of choices
- Would be nice to have reliable ways of generating possible futures
- And be able to consider long term trends like persistent low bond yields

## But…

- Most simulation methods are alternative ways of reproducing history
- We want to consider long horizons but only have short histories
- And acknowledge path dependency matters

## There is a clear analogy with climate and weather forecasting – will return to this

* The next slides (up to slide 29) are based on joint work with Kenneth Blay but all views expressed herein may be attributed to Robert Hillman only.

# Long-horizon simulations
## Consumption expectations

**Following Bengen (1994) we explore a simulated drawdown strategy**

Our simulated retiree determines a withdrawal amount of 4% of their initial wealth (1,000,000) and withdraws the same amount each year, adjusting for inflation.

We assume they are 100% invested in US equities. The simulation uses Robert Shiller’s total real return series from his website, 1927 to 2018.

**We use the coverage ratio to assess outcomes for different simulation methods**

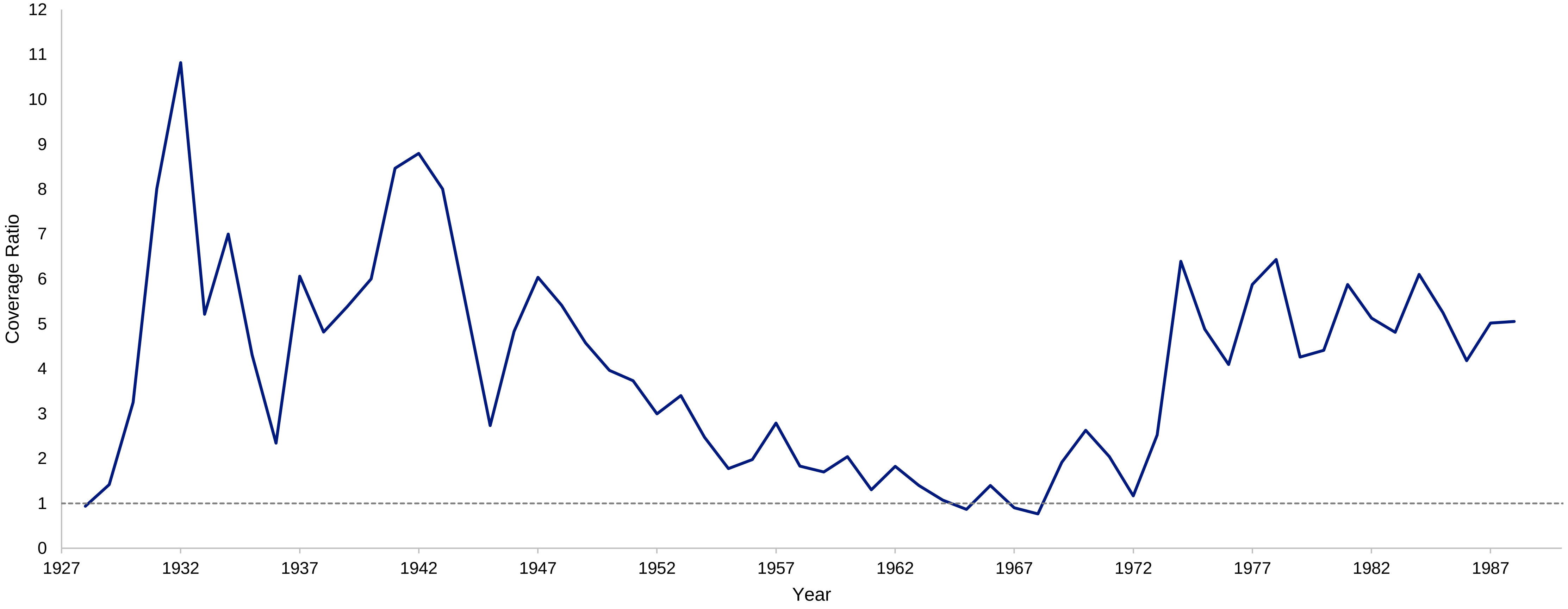
$$Coverage\ ratio = C_t = {}^{Y_t}/_{L}$$

$Y$ = the number of years of withdrawals sustained by a strategy, both during and after the retirement period

$L$ = the length of the retirement period considered

Source: Bengen, W.P. (1994) Determining Withdrawal Rates Using Historical Data. Journal of Financial Planning. Vol 7, no. 1. Pp 171-180
Estrada, Javier and Kritzman, Mark, Toward Determining the Optimal Investment Strategy for Retirement (December 14, 2018).

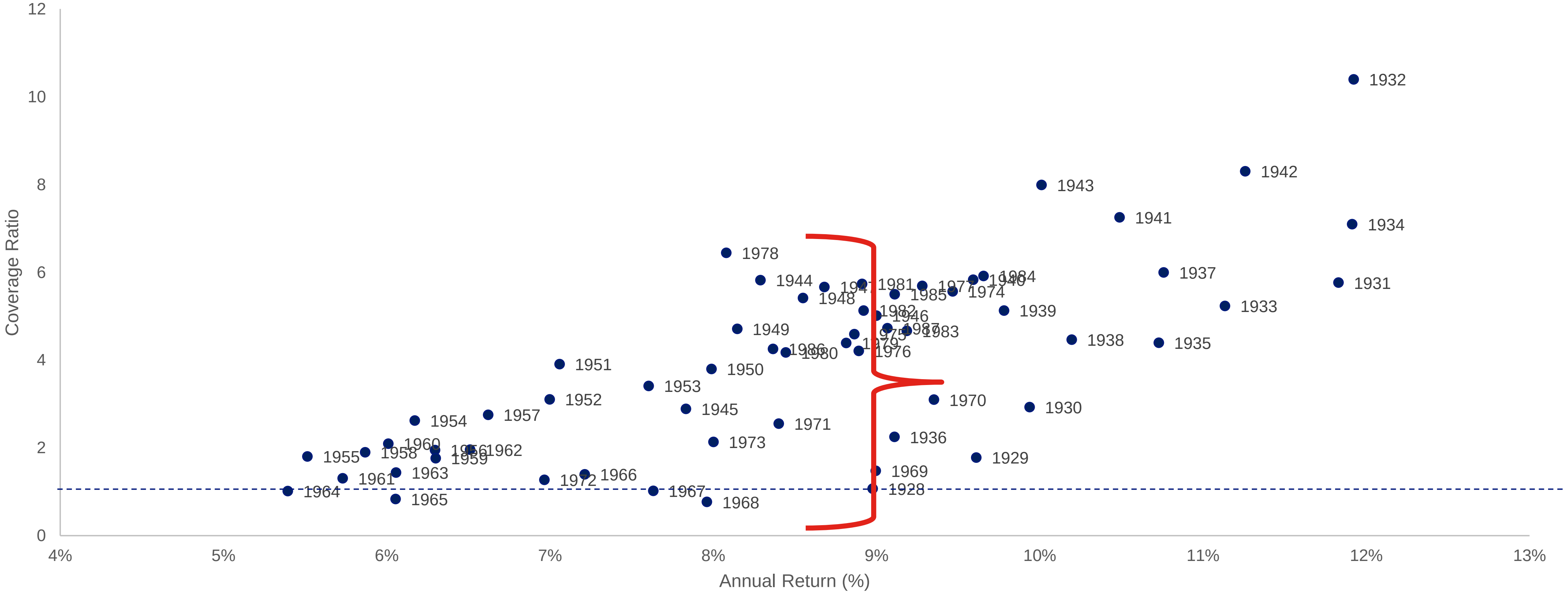
# Forward return scenarios
## Historical coverage ratios (1927-1988)




Source: Neuron Capital, Online Data - Robert Shiller. The historical coverage ratio is constructed using the log ‘Real Total Return Price Index’ from Shiller’s website. Each data point shows the coverage ratio for a 30 year retirement period beginning in the December of each year. Starting capital is $1,000; the initial withdrawal rate is 4%.

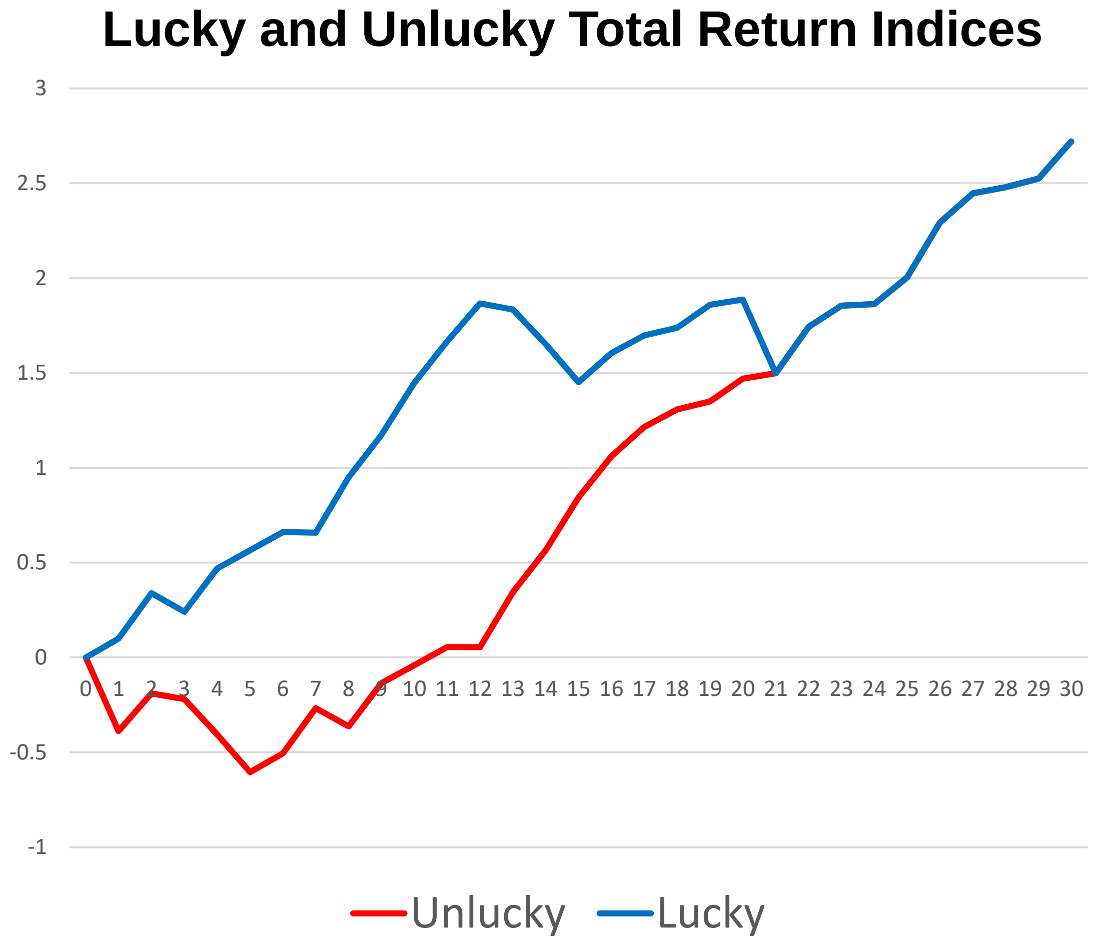
# Forward return scenarios – sequencing risk

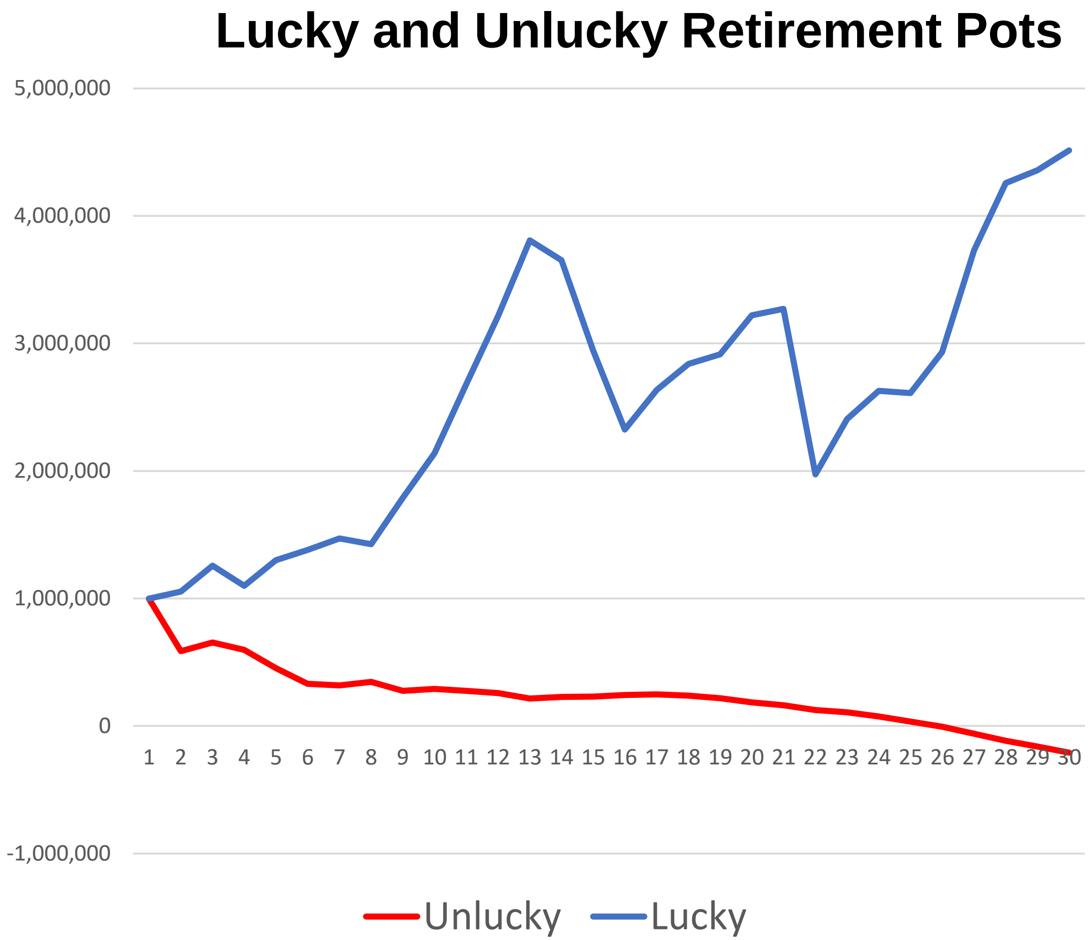
## Market returns and coverage ratios (1927-1988)




Source: Neuron Capital, Online Data - Robert Shiller. The chart shows simulated coverage ratios using the log 'Real Total Return Price Index', versus the 'Cyclically Adjusted Total Return Price Earning's Ratio' from Shiller's website. Each data point shows the coverage ratio for a 30 year retirement period beginning in the December of each year. Starting capital is $1,000; the initial withdrawal rate is 4%.

# Sequencing Risk
## …and expectations for pension withdrawal




Source: Neuron Capital, Online Data - Robert Shiller

The left chart shows in blue the cumulative returns from December 1987 for the following 30 years. The red line shows an alternative experience created by reordering the annual returns from 1987 to 2017 such that the worst returns come early on. The chart on the right shows the retirement pot under each experience. The consumption period lasts 30 years; starting capital is $1,000,000 and the initial withdrawal rate is 4%.

# Long-horizon simulations
## Common practice

**Portfolio and asset return simulations are used for a variety of purposes including:**

- Risk management
- Portfolio construction
- Multi-period portfolio (target date) evaluation
- Financial planning

However, simulation methods often represent a trade-off between ease of implementation and realism in incorporating well-known asset dynamics.

These trade-offs have implications for the practical application of these methods in providing effective decision support.

### Common simulation methods

| Simulation method | Distribution assumption | Incorporates auto correlation | Incorporates mean reversion |
|---|---|---|---|
| **Parametric** | Lognormal (most common) | No | No |
| **Bootstrapping (i.i.d)** | Empirical | No | No |
| **Block bootstrapping** | Empirical | Yes | No |

Parametric simulation requires a model to be estimated on historical data, and then data is generated from that model. Bootstrapping simulation is a means of generating possible future price or return scenarios by resampling single returns from the historical data set. Block bootstrapping resamples “blocks” of returns from the historical data set.

# Long-horizon simulations
## Short- and long-horizon risk

**We use the variance ratio to assess short- and long-horizon risk implications for different simulation methods.**

$$VR(k) = \frac{\textit{variance of k-period returns}}{k * \textit{variance of 1-period returns}}$$

The intuition is related to the common practice of scaling volatility by the square root of time ($\sigma \times \sqrt{T}$)

**Are stocks less volatile in the long run?**

An old question that has implications for equity allocations and rules for target-date funds, etc.

A variance ratio test is one way to explore this. The idea is to measure how ‘diffusive’ a time series is.

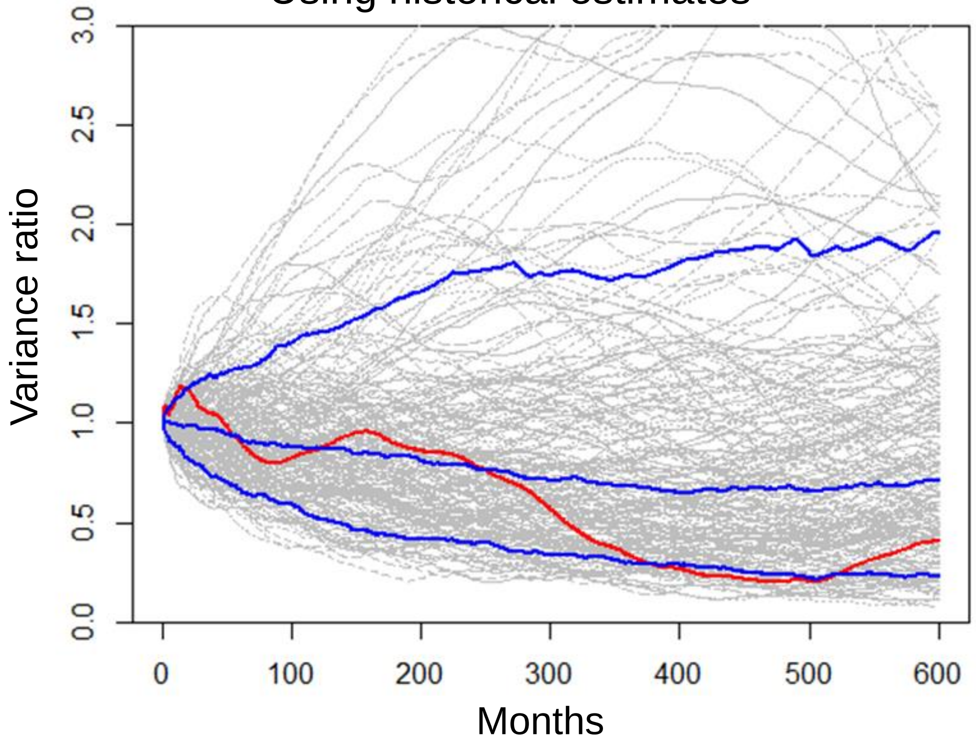
It is closely linked to the Hurst exponent and Mandlebrot’s rescaled range statistic

For a recent application see Pastor & Stambaugh (2012)

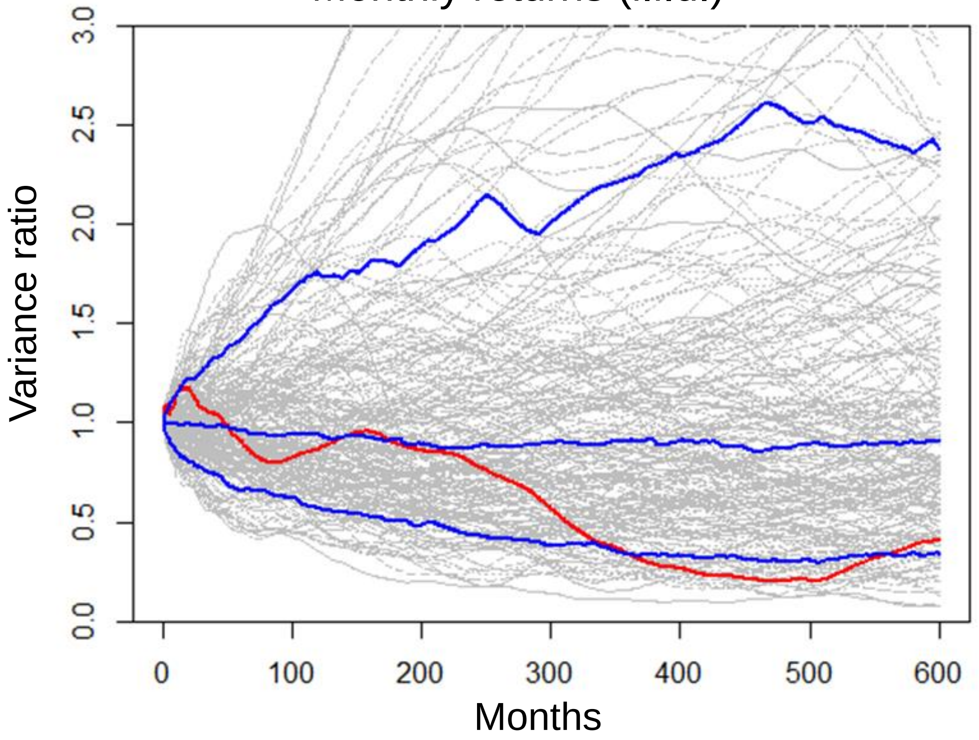
Source: Campbell, Lo, and McKinlay (1997), Pastor and Stambaugh (2012)

# Long-horizon simulations
## …and expectations for investment risk

**Parametric (lognormal)**
Using historical estimates




**Bootstrapping**
Monthly returns (i.i.d.)



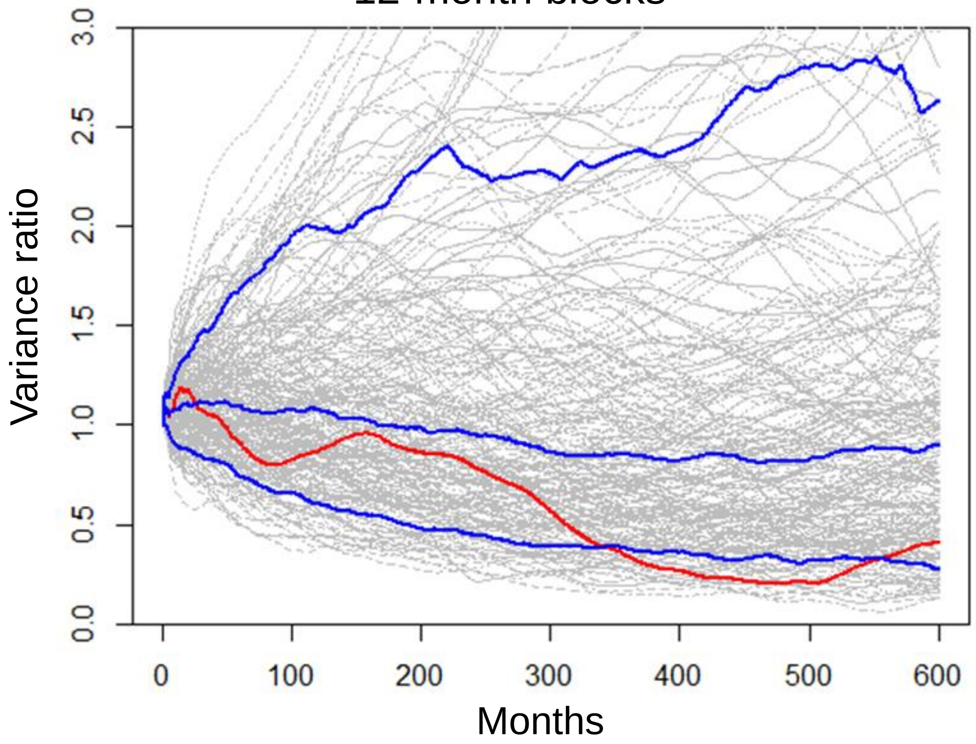

Source: Neuron Capital, Online Data - Robert Shiller
Historical estimates of average monthly (mean) return and standard deviation are 0.22% and 5.40% based on S&P 500 real equity returns for the period Dec 1927 through August 2019; bootstrapped returns are drawn from the same historical period. The blue lines indicate (simulated) 10th , 50th and 90th percentile confidence bands..

# Long-horizon simulations

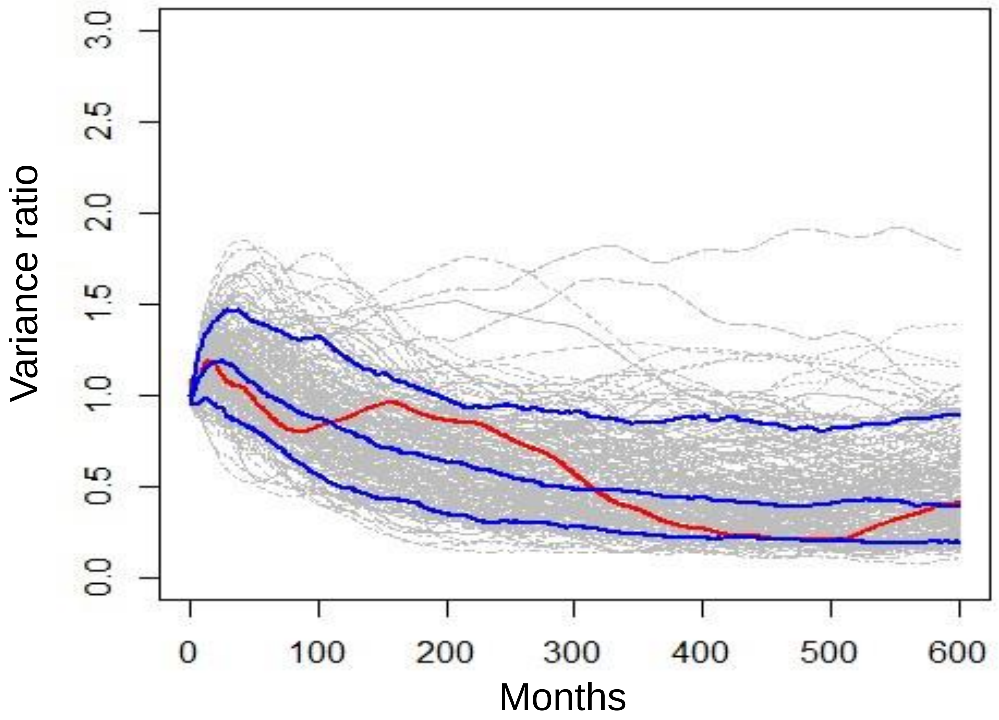
## …and expectations for investment risk

### Block bootstrapping

12-month blocks




### Heterogenous Agent Model

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# A simple model

**Following Beja and Goldman (1980) a number of models were formalized with a general form:**

$$p_{t+1} - p_t = \lambda \sum_{i=1}^{N} D(i,t) + \epsilon_t$$

$\lambda$ is similar to "Kyle's Lamba" – market impact

- The sum is over agent's demand and represents a net order imbalance
- $\epsilon$ is often interpreted as noise trader demand
- Key to the model is heterogeneity in expectations, i.e. not a representative agent – see Alan Kirman's (1992) Whom or what does the representative individual represent?

Source: Beja, A., Goldman, M.B. (1980) On the dynamic behaviour of prices in disequilibrium. The Journal of Finance. 35 (2). Pp 235-248.
Kirman, A. (1992) Whom or what does the representative individual represent? Journal of Economic Perspectives, Volume 6, Number 2—Spring 1992—Pages 117–136

# A simple model

- **Price:** $p_{t+1} - p_t = \kappa(v_t - p_t) + \beta\tanh(\gamma\, m_t) + \epsilon_t$

- **Value Traders:** $\kappa(v_t - p_t)$

  Value: $v_{t+1} = v_t + g + \eta_{t+1}$

- **Momentum*** (Extrapolators): $\beta\tanh(\gamma\, m_t)$

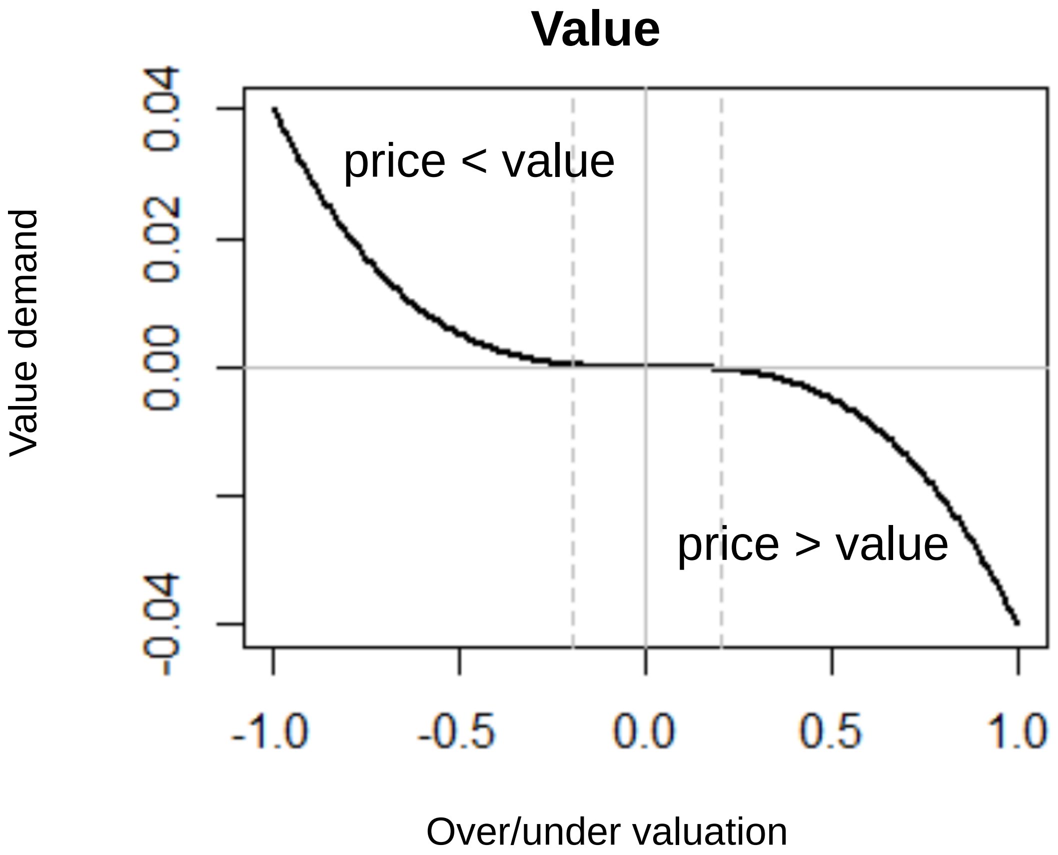
  EWMA: $m_t = (1-\alpha)\, m_{t-1} + \alpha(p_t - p_{t-1})$

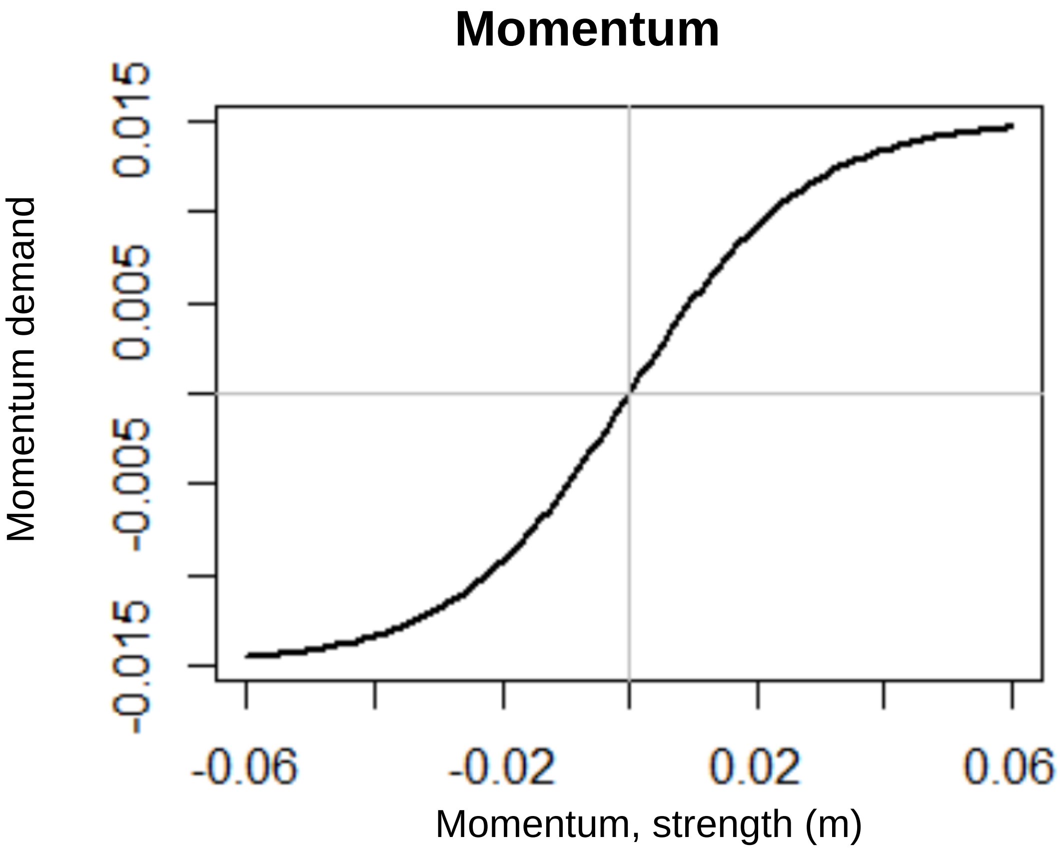
- **Noise traders:** $\epsilon_t$

In 1992 Carl Chiarella formalised the approach suggested by Beja and Goldman (1980). The set-up above follows Majewski et al (2018). But there is a problem…..the model best describes positions not orders as implied by B & G. We will return to this.

Source: Neuron Capital, Online Data - Robert Shiller
Chiarella, C. (1992) The dynamics of speculative behaviour. Annals of Operations Research. 37 (1), pp. 101-123.
* Momentum in this context refers to time-series momentum not cross-sectional momentum.

# A simple model
## Value and trend influence on prices



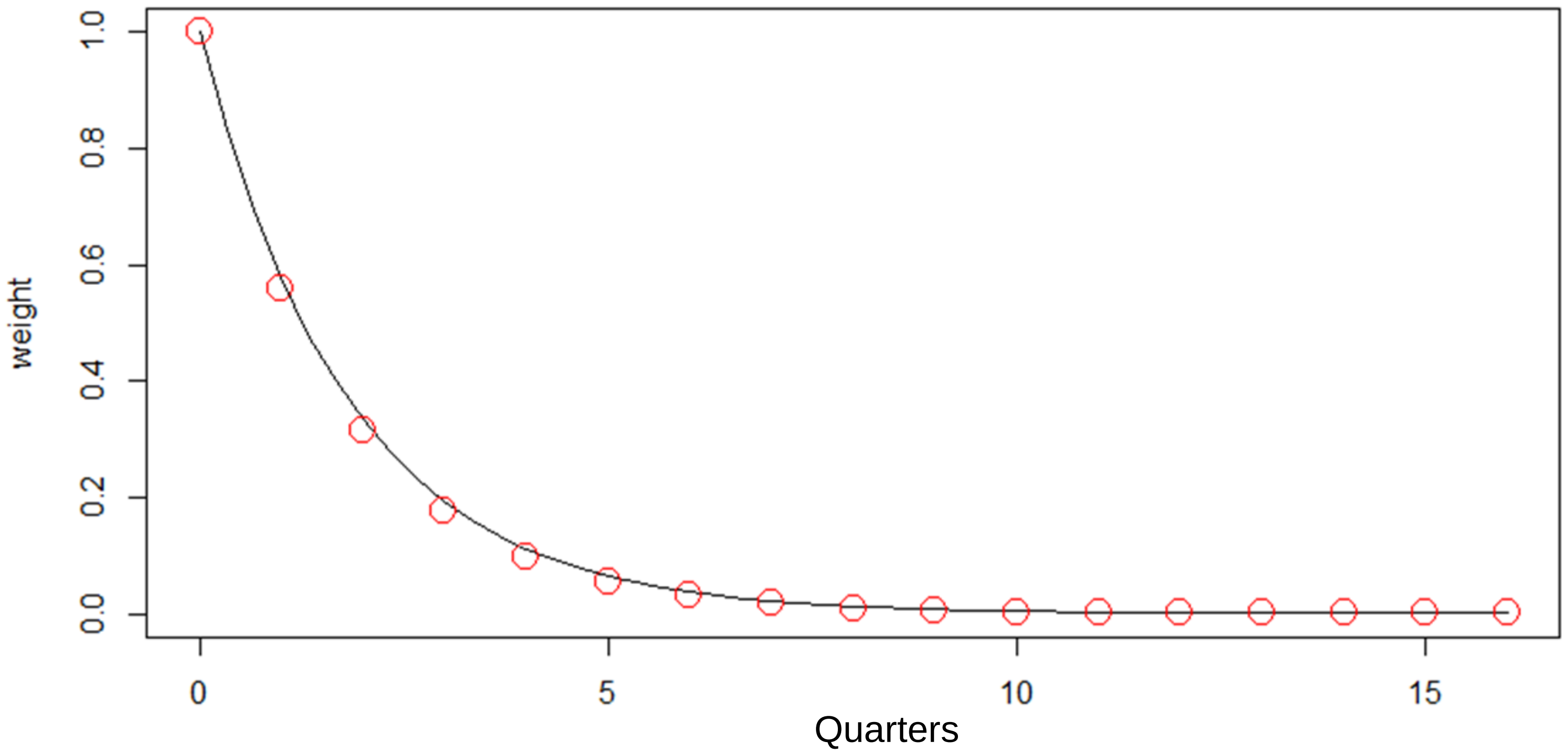




- **We use Shiller's cyclically adjusted price earnings series to construct 'fair value'**
- **Value effects kick in around +/20% and increasingly so as price deviates further**
- **Trend influence grows as the price trends more but eventually saturates**

Source: Neuron Capital, Online Data - Robert Shiller. The fair value series is constructed using the log 'Real Total Return Price Index' and the 'Cyclically Adjusted Total Return Price Earning's Ratio' from Shiller's website.

# A simple model

## Optimal extrapolator response function is consistent with surveys



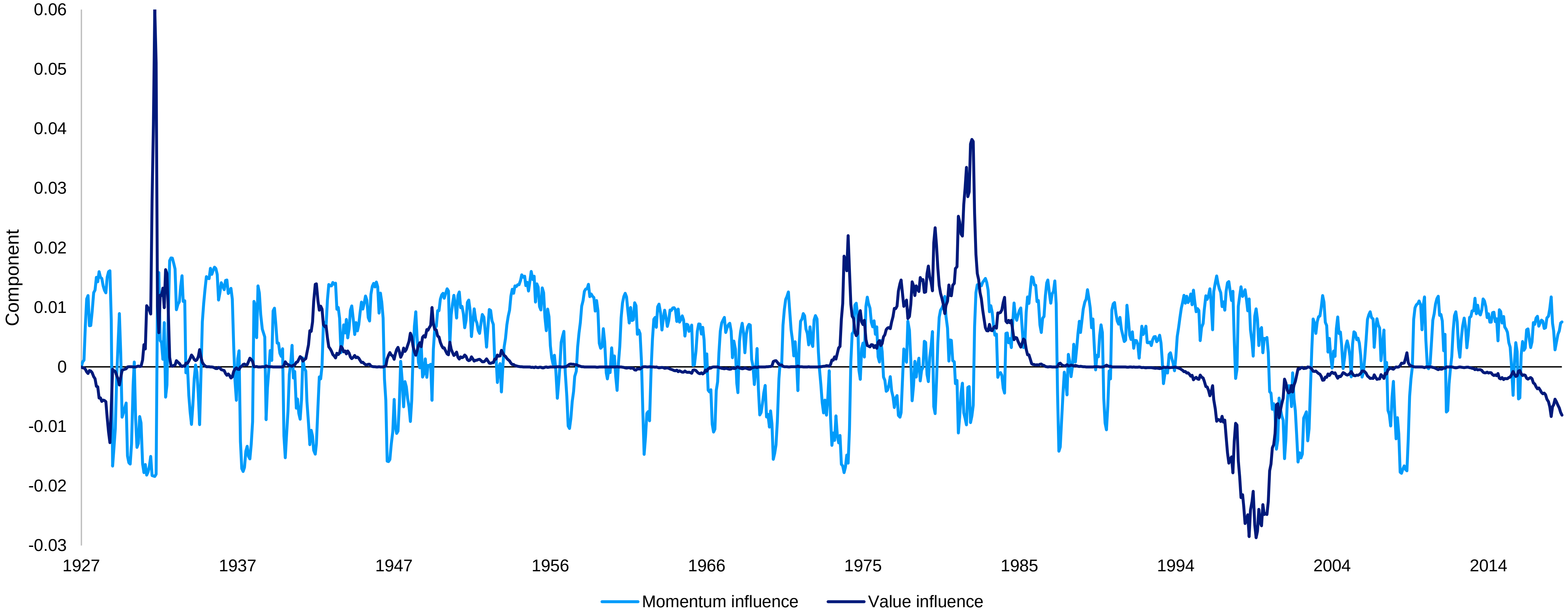

The black line shows the weights on lagged returns as estimated by the empirical model on price data

The red circles show the weights from Greenwood & Shleifer (2014) where the average alpha across 7 surveys is 0.56 on quarterly data – confession – the 0.56 is not precisely estimated sd = 0.21 but still….

Source: Neuron Capital, Online Data - Robert Shiller

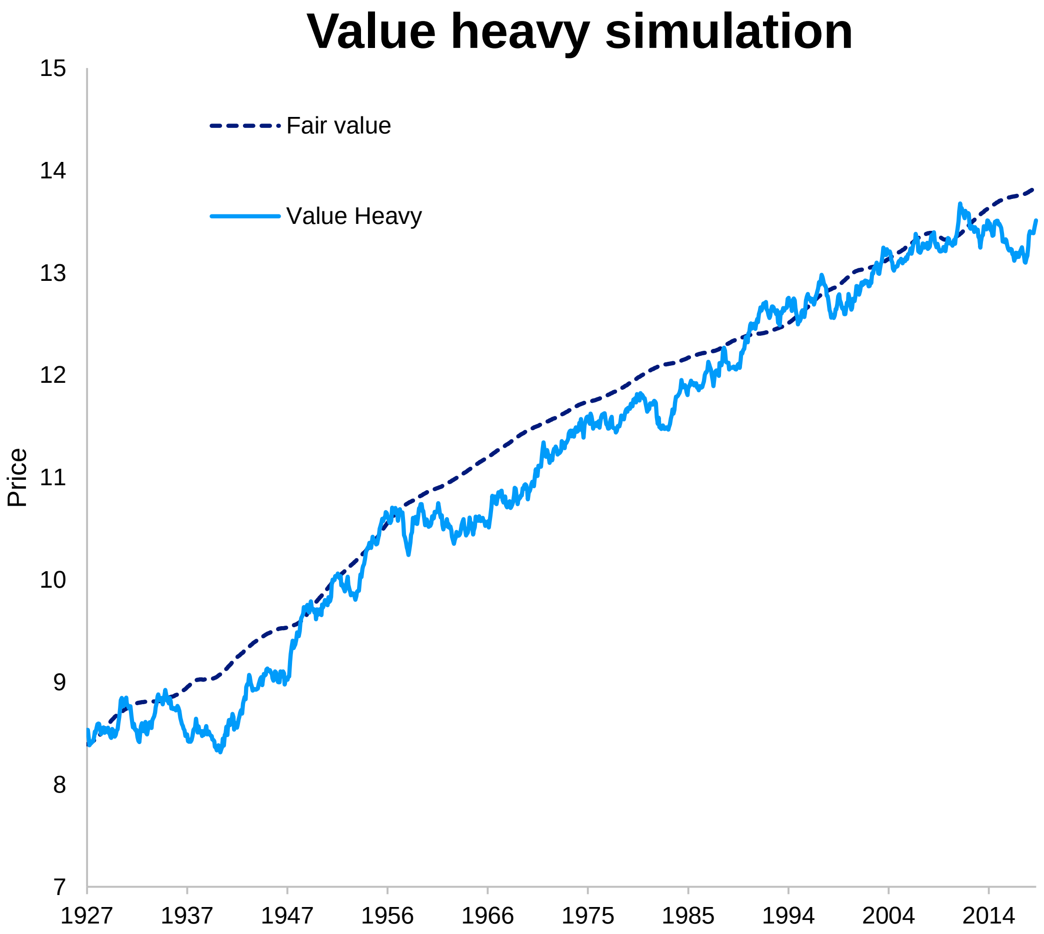
# A simple model

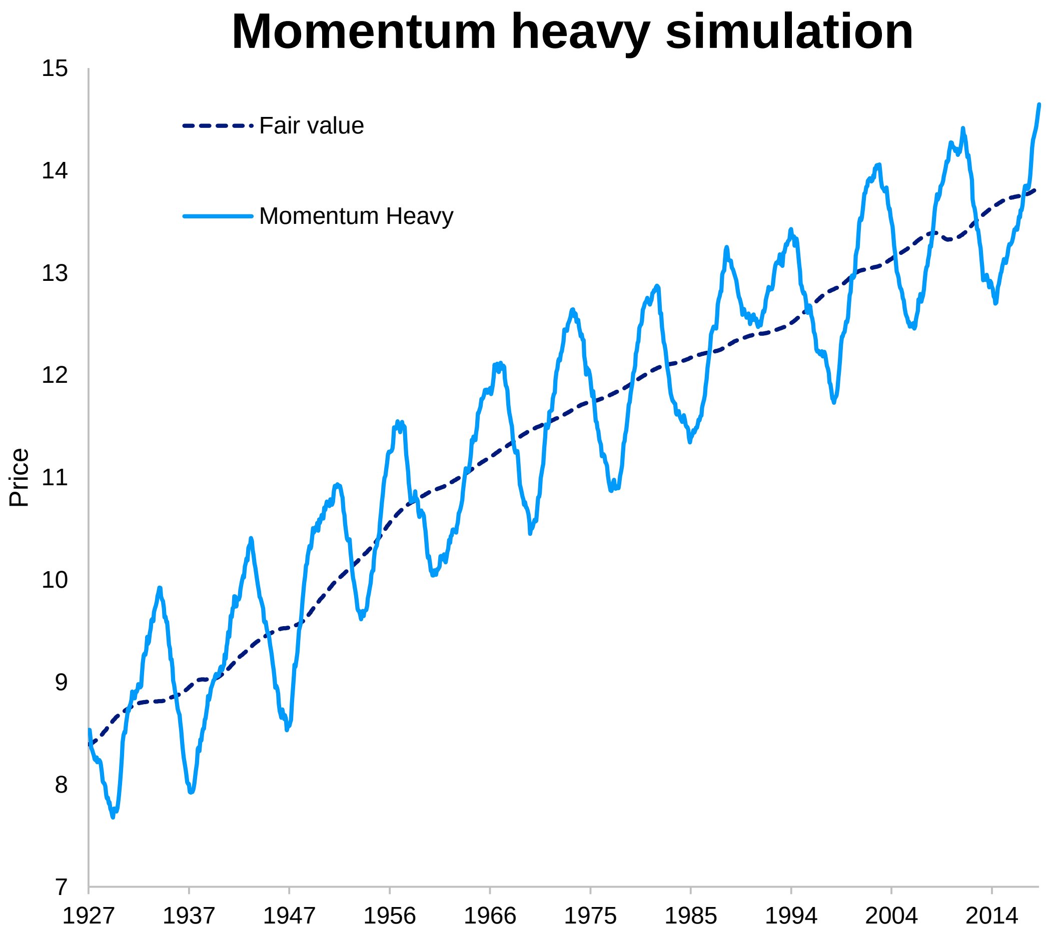
## Momentum and value influences




Source: Neuron Capital, Online Data - Robert Shiller

# A simple model
## Simulation samples

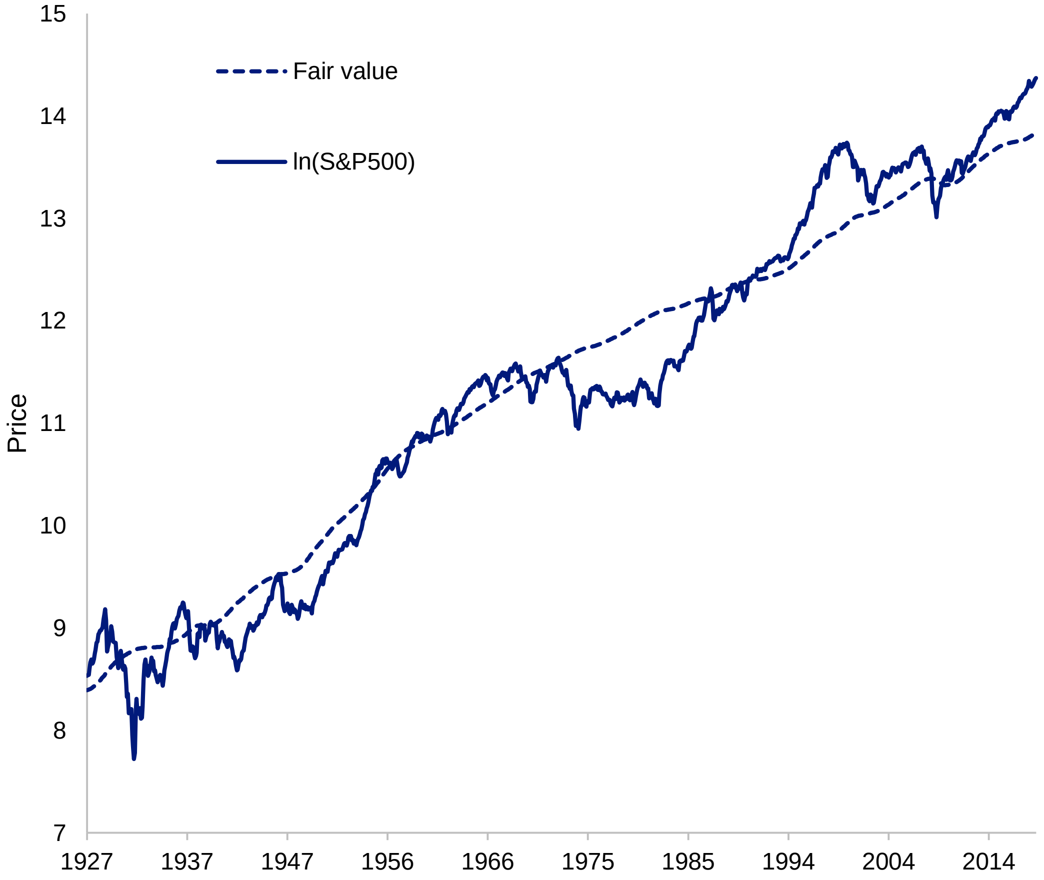


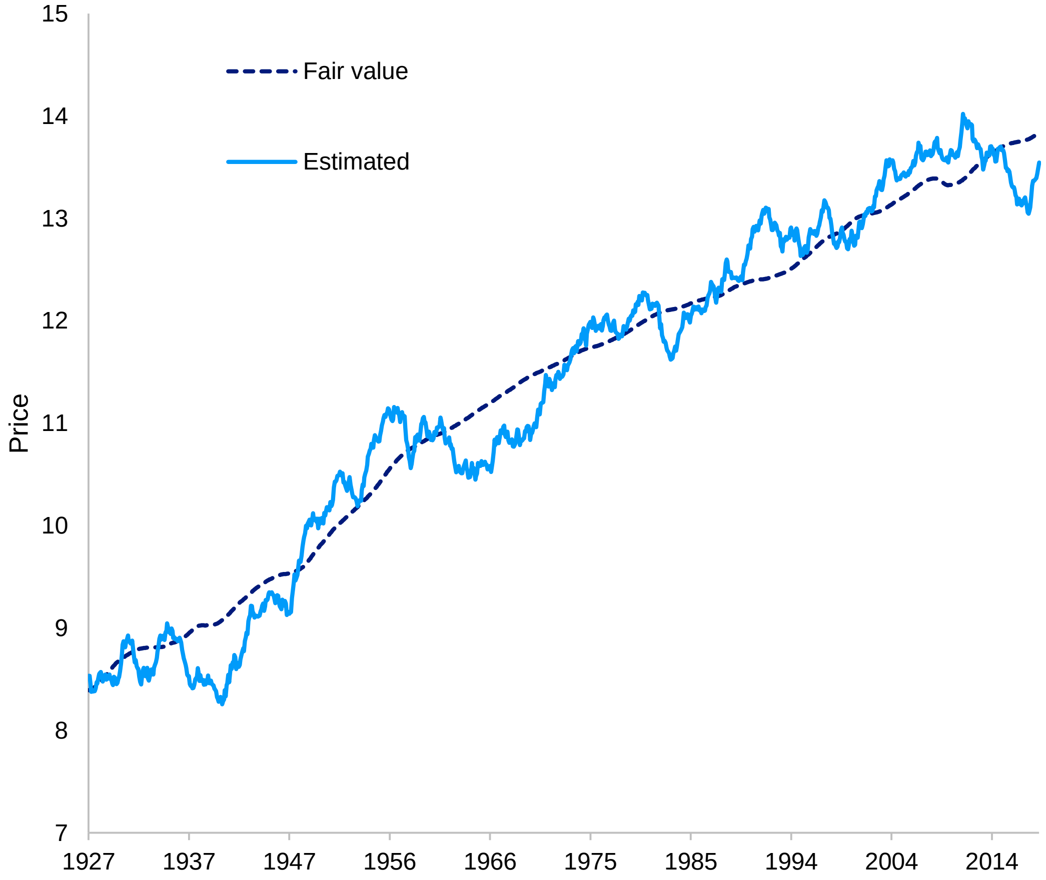

Source: Neuron Capital, Online Data - Robert Shiller. The fair value series is constructed using the log ‘Real Total Return Price Index’ and the ‘Cyclically Adjusted Total Return Price Earning’s Ratio’ from Shiller’s website. The Value Heavy and Momentum Heavy series are two runs from the simulation model.

# A simple model
## Simulation samples

### Historical returns
1972-2018



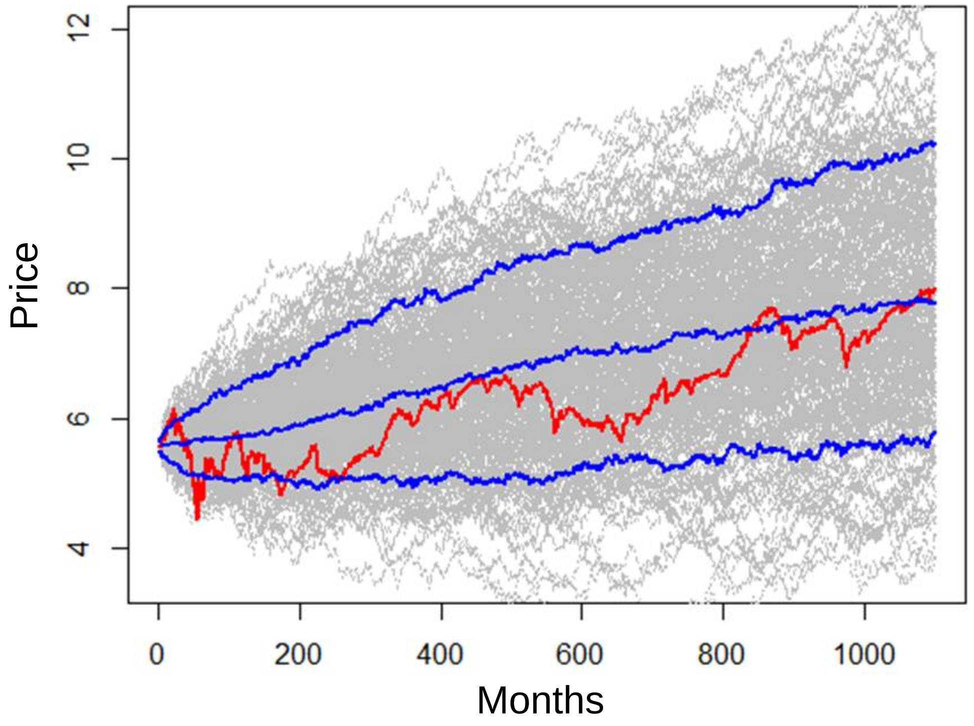

### Simulated returns



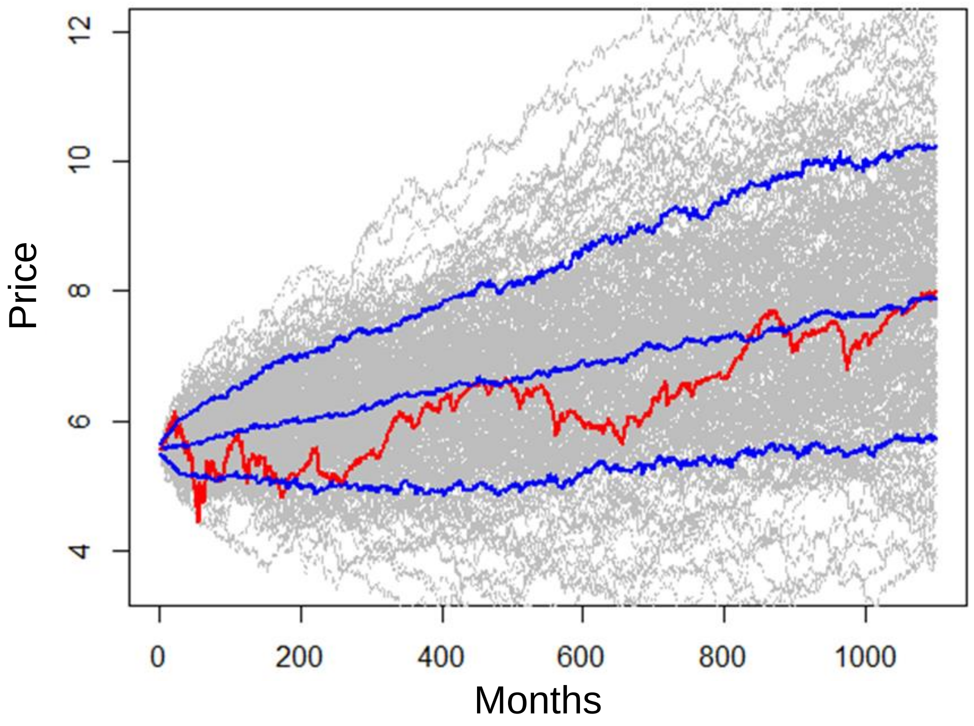

Source: Neuron Capital, Online Data - Robert Shiller. The fair value series is constructed using the log 'Real Total Return Price Index' and the 'Cyclically Adjusted Total Return Price Earning's Ratio' from Shiller's website. The Value Heavy and Momentum Heavy series are two runs from the simulation model. The actual series on the left chart is the log 'Real Total Return Price Index' from Shiller's website.

# Long-horizon simulations
## …and expectations for investment outcomes

**Parametric (lognormal)**
Using historical estimates




**Bootstrapping**
Monthly returns (i.i.d.)



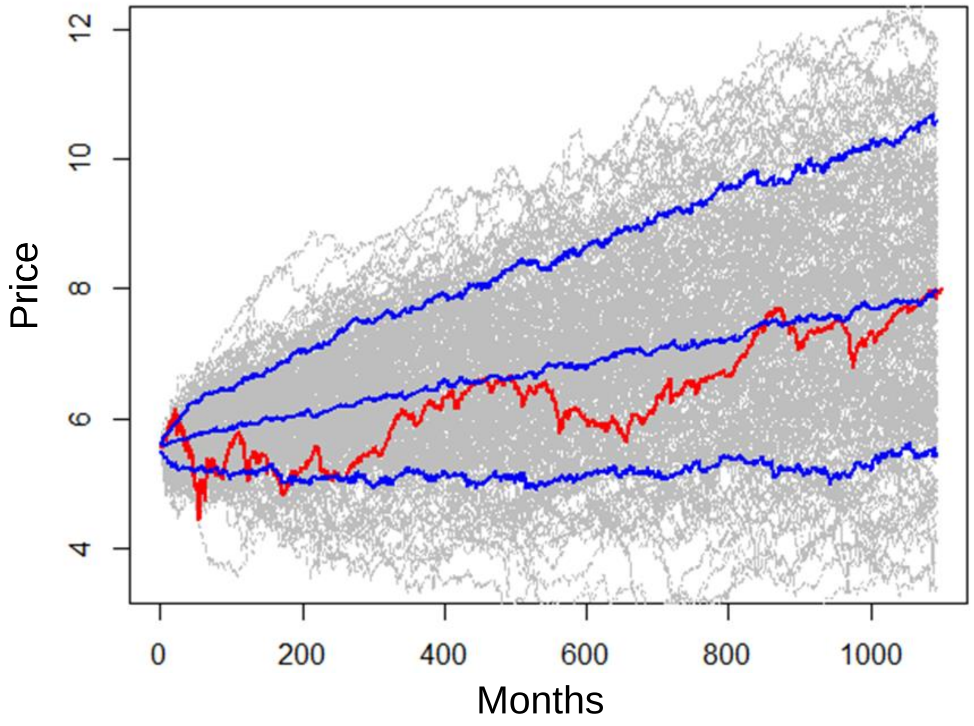

Source: Neuron Capital, Online Data - Robert Shiller
Historical estimates of average monthly (mean) return and standard deviation are 0.22% and 5.40% based on S&P 500 real equity returns for the period Dec 1927 through August 2019; bootstrapped returns are drawn from the same historical period. The blue lines indicate (simulated) 10th , 50th and 90th percentile confidence bands.

# Long-horizon simulations

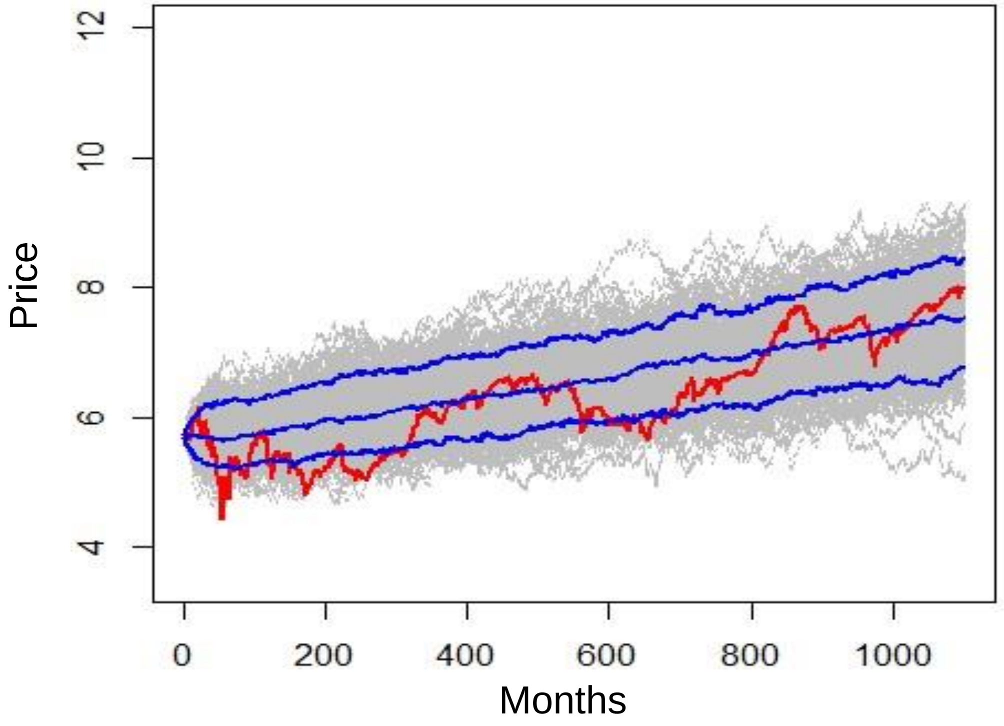
…and expectations for investment outcomes

**Block bootstrapping**

12-month blocks




**Heterogeneous Agent Model**

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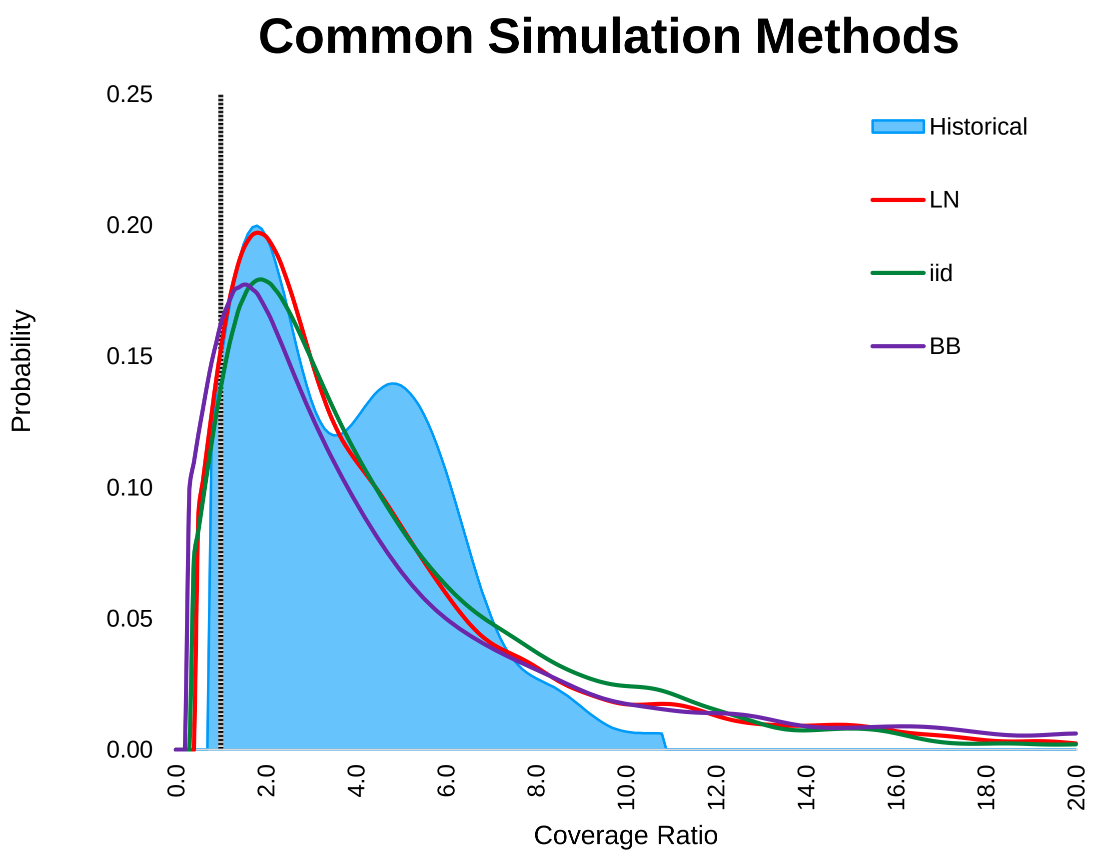
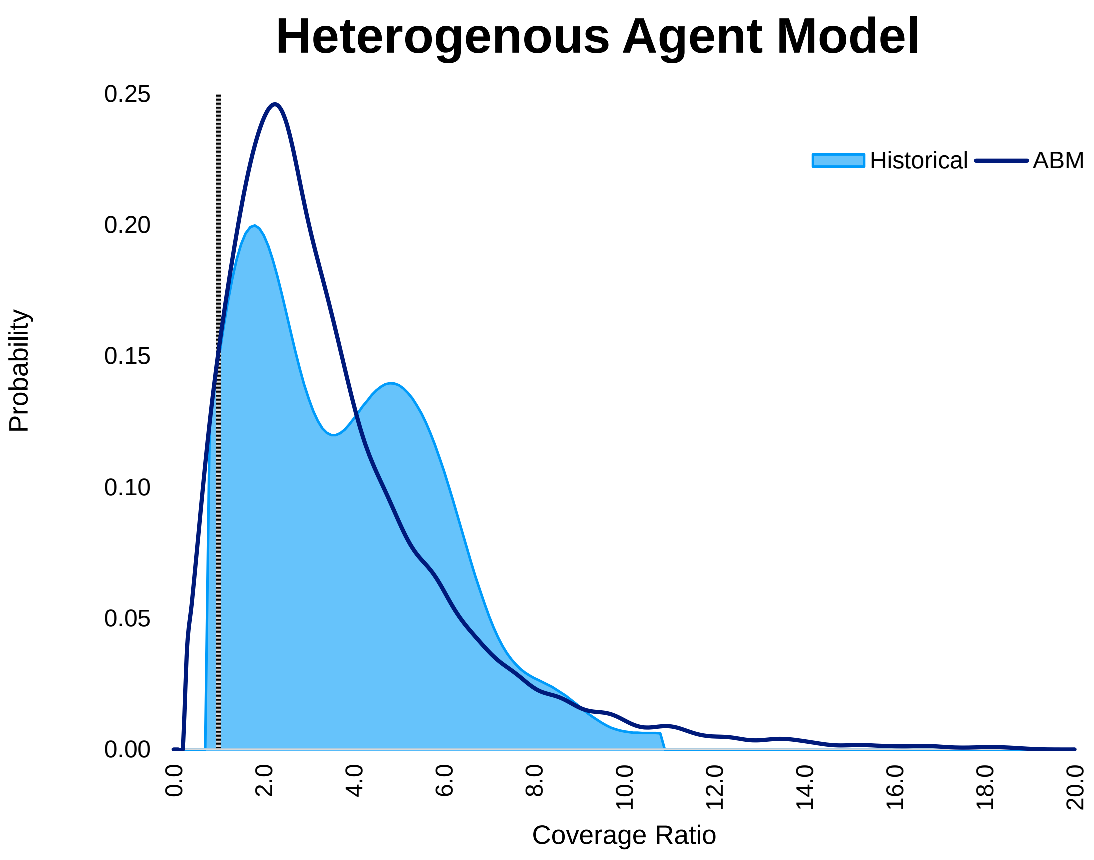
# Long-horizon simulations

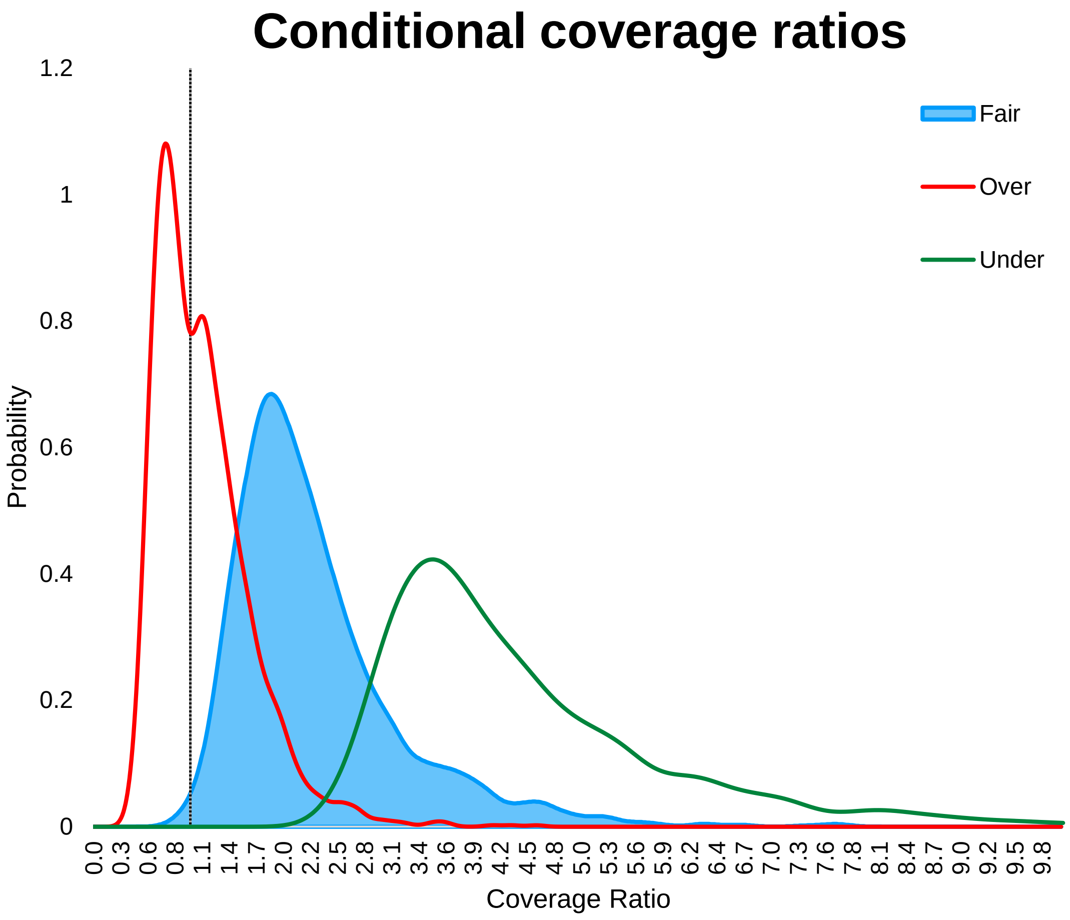
## …and expectations for investment consumption

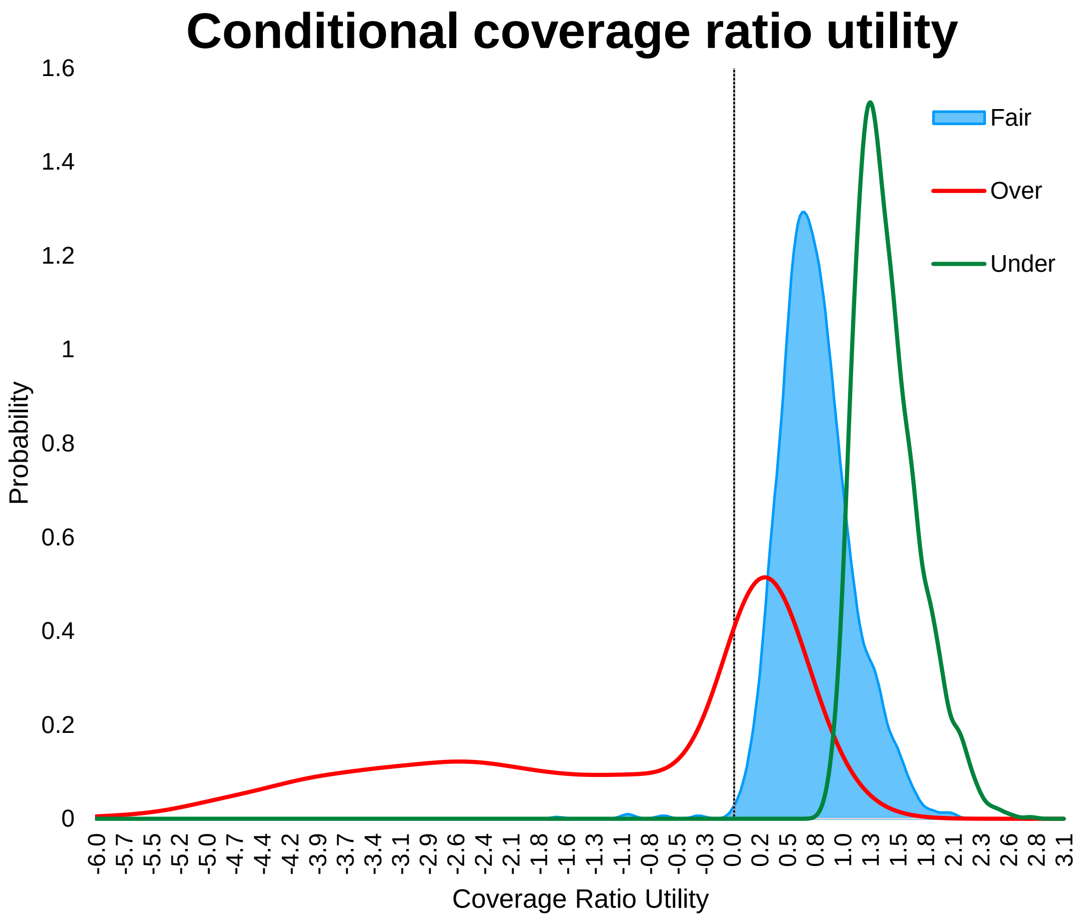



Source: Neuron Capital, Online Data - Robert Shiller
The distribution of coverage ratios are presented using 2,000 sets of simulated monthly returns over 30+ year periods; Historical estimates of average monthly (mean) return and standard deviation are 0.54% and 4.46% based on real total S&P 500 equity returns for the period Jan 1927 through August 2019; bootstrapped returns are drawn from the same historical period; starting capital is $1,000; the initial withdrawal rate is 4%.

# Conditional return forecasts
## …and expectations for investment consumption



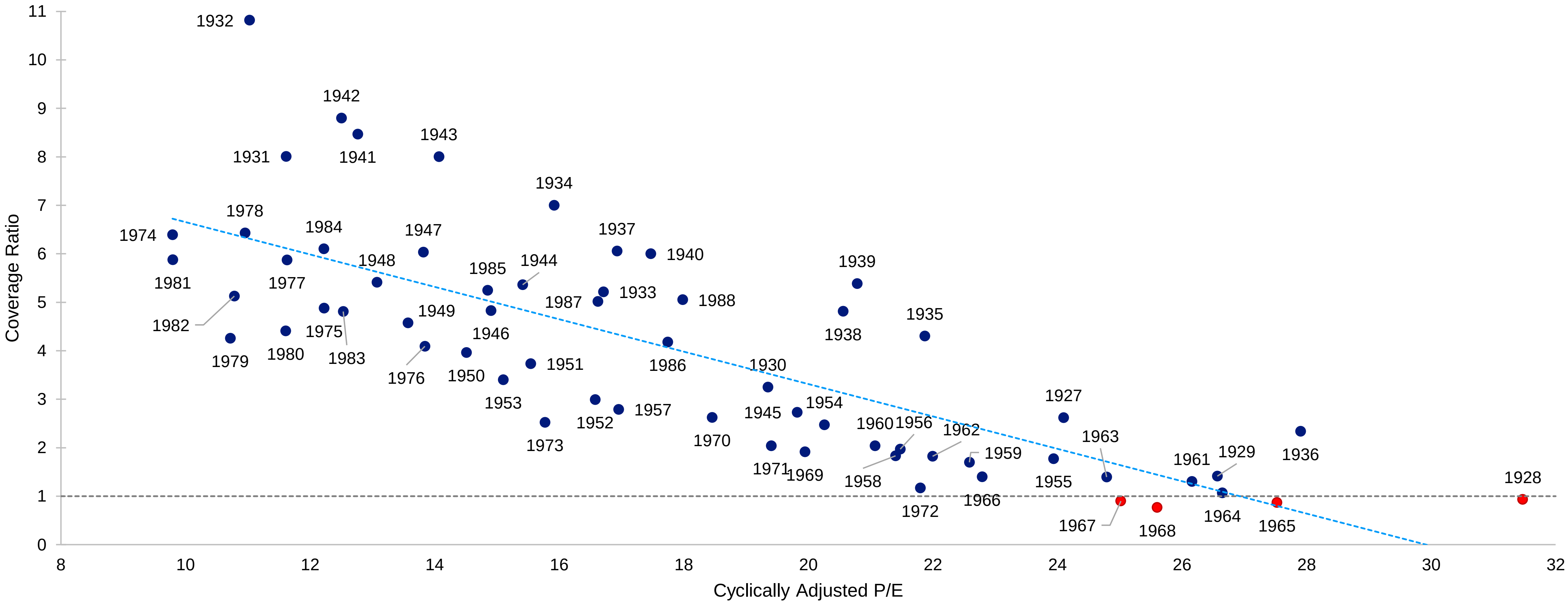




Source: Neuron Capital, Online Data - Robert Shiller

The distribution of coverage ratios and utilities are presented using 2,000 sets of simulated monthly returns over 30+ year periods; starting capital is $1,000; the initial withdrawal rate is 4%.

# Forward return scenarios

## CAPE and coverage ratios (1927-1988)




Source: , Neuron Capital, Online Data - Robert Shiller. The chart shows simulated coverage ratios using the log ‘Real Total Return Price Index’, versus the ‘Cyclically Adjusted Total Return Price Earning’s Ratio’ from Shiller’s website. Each data point shows the coverage ratio for a 30 year retirement period beginning in the December of each year. Starting capital is $1,000; the initial withdrawal rate is 4%.

# A new use case – based on work with Kenneth Blay
## (1) Simulating long-horizon returns

### Takeaways from the model

- A 2-type model is capable of reproducing some of the ‘stylized’ facts of long-horizon returns
- Popular simulation methods appear overly optimistic
- Estimated parameters are consistent with a growing body of work on extrapolation
- The model sheds (quantitative) light on the variation in experience and risks from path dependency
- The starting point matters. Suggests caution in designing policies – more work required

### But…

- The model is consistent with ABMs but is more like a reduced form econometric model
- On the plus side it can borrow from nonlinear time series model inference methods
- But it is a little vague on the link to agent behavior and interaction: see Farmer & Joshi (2001) & Franke (2009)

# A new use case
## **(2)** Pension fund risk mitigation: Crisis protection or crisis propulsion?

### Many pension funds are underfunded

- No US state plans are ‘overfunded’
- The average funding ratio is around 66%, best 99%, worst 31%
- A sudden shock to equity markets like 2008 could be fatal

### But…

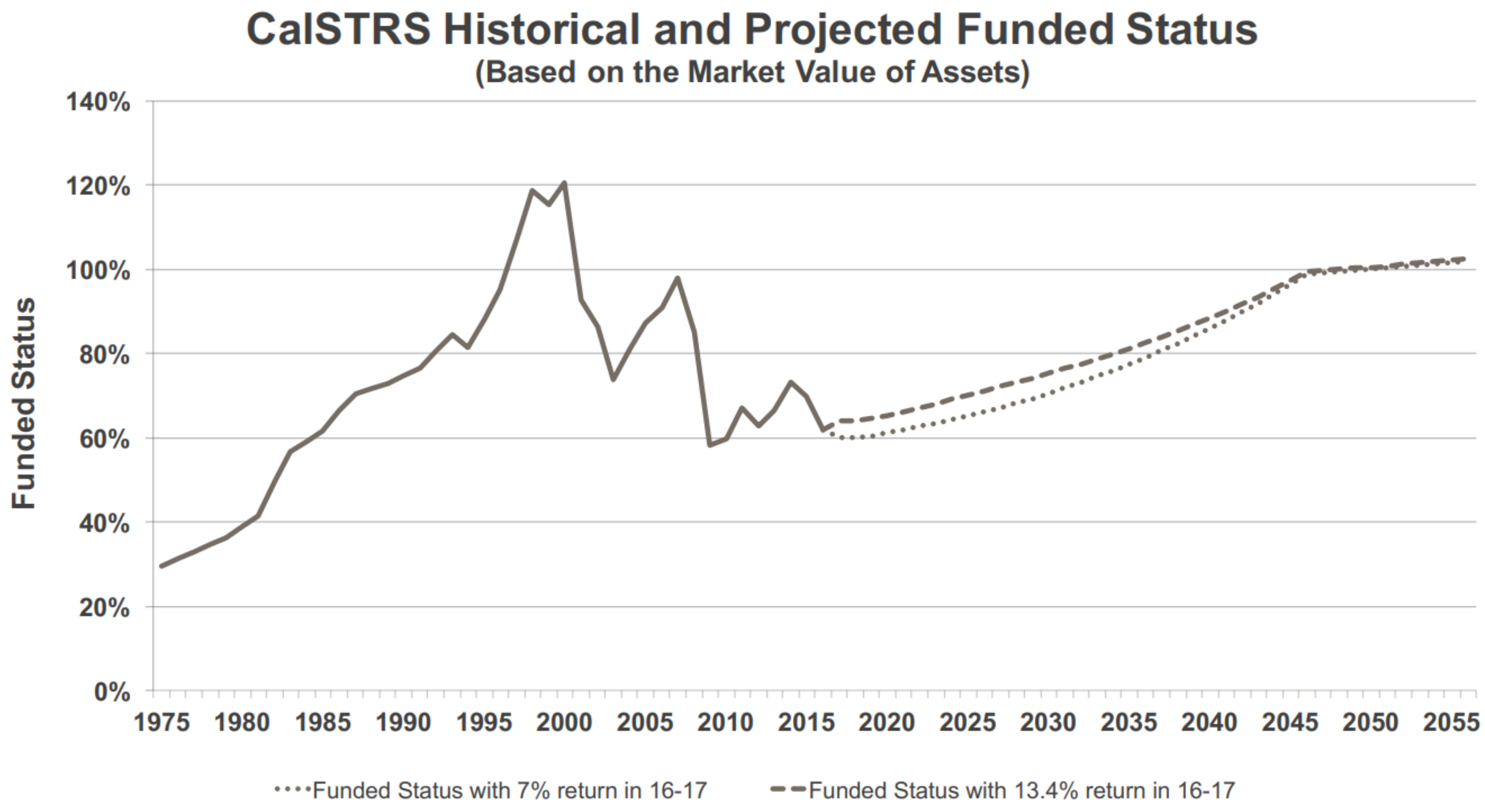
- In the face of these risks some funds have turned to portfolio insurance techniques
- Today the term portfolio insurance is often avoided, instead crisis-risk-offset or risk mitigation
- What is the risk that such techniques force prices even lower?

### The issue is remarkably similar to that studied by Kim & Markowitz in 1988



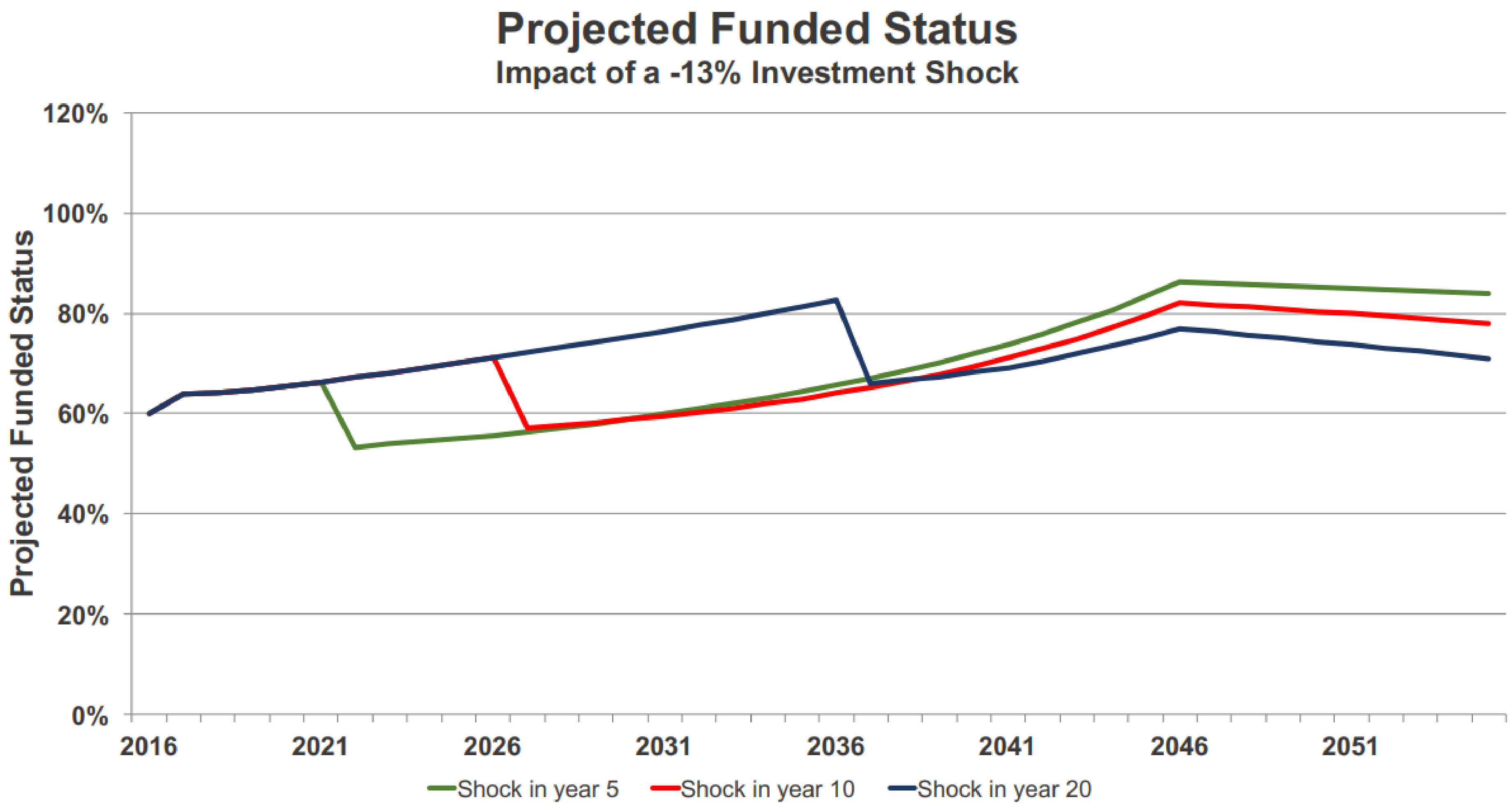
Source: Pew Foundation, e.g. https://www.pewtrusts.org/en/research-and-analysis/data-visualizations/2018/state-retirement-fiscal-health-and-funding-discipline#/indicators/state_funded_ratio?year=2016

# A new use case
## (2) Pension fund risk mitigation: Crisis protection or crisis propulsion?




Source: Calstrs (2017) Annual Funding Report. http://resources.calstrs.com/publicdocs/Page/CommonPage.aspx?PageName=DocumentDownload&Id=6a1e133d-e87d-4220-8249-a9ac28604aeb

**A new use case** – sequencing risk again
**(2)** Pension fund risk mitigation: Crisis protection or crisis propulsion?

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# A new use case
## (2) Pension fund risk mitigation: Crisis protection or crisis propulsion?

### Some sound confident..

‘Mr. Ailman likens the portfolio to an insurance policy.

"In life, you buy car and house insurance to protect yourself," Mr. Ailman said. The risk mitigation strategy is to "protect ourselves against left-hand tail events”.’

**Chris Ailman, Chief Investment Officer, CALSTRs (2018)**

### But even veteran trend followers are worried…

"If the odd institution wishes to protect itself in this way there is no contradiction, but if they all do, the risk of destabilising short-term market behaviour will again be high. "

**David Harding, Winton Capital (2017)**

Source: https://www.pionline.com/article/20181210/PRINT/181219918/calstrs-preps-for-downturn-with-risk-mitigation-strategy ; Harding, David (2016) ‘Crisis Risk Offset, Positive Convexity, Tail-Risk Hedging and Smart Beta’ ‘David’s Views’ October 2016. Winton Group.

# A new use case

## **(2)** Pension fund risk mitigation: Crisis protection or crisis propulsion?

**The IMF and others have pointed to risks from procyclical strategies more broadly:**

*"Low Volatility, Financial Leverage, and Liquidity Mismatches Could Amplify a Market Shock"* (IMF, 2017)

| Investment Strategy | AUM Mid-2017 | 3Y Growth Rate (%) |
|---|---|---|
| Variable Annuities | $440 billion | 69 |
| CTA/Systematic Trading | $220 billion | 19 |
| Risk Parity Funds | $150–175 billion | … |

Source: : IMF Global Financial Stability Report October 2017: Is Growth at Risk?

# A new use case
## (2) Pension fund risk mitigation: Crisis protection or crisis propulsion?

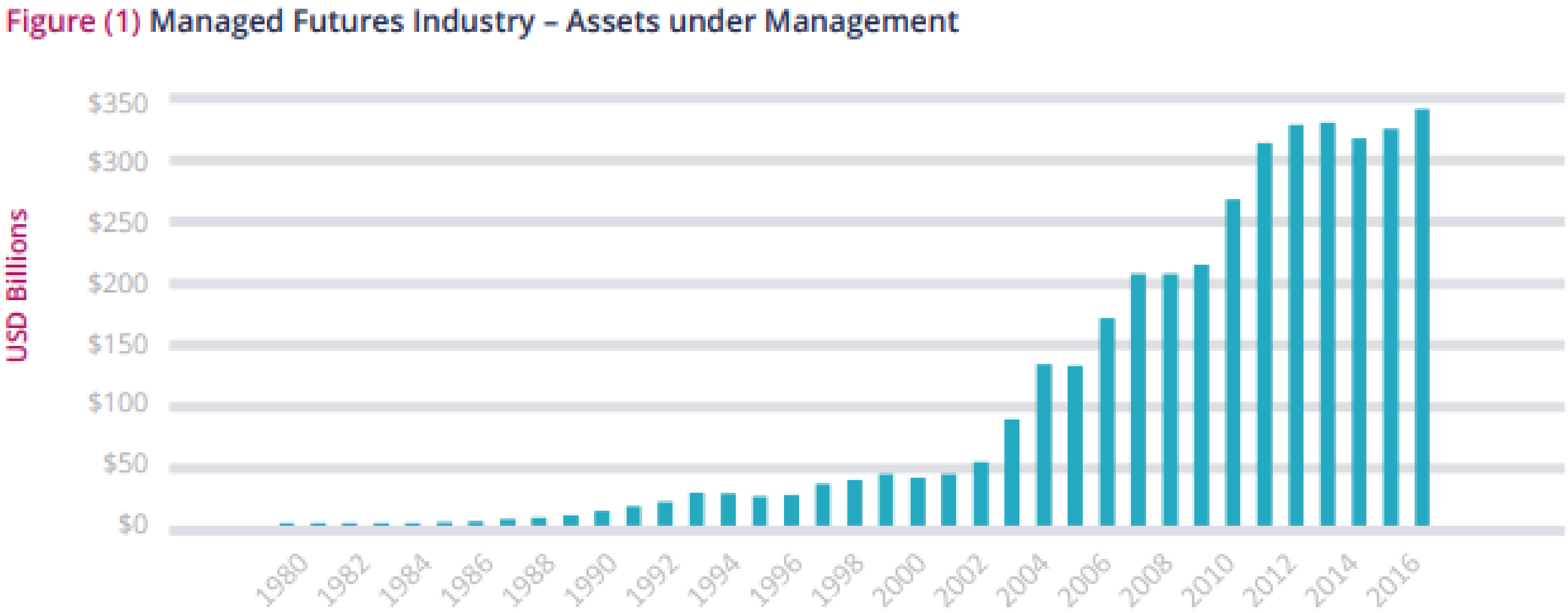



*Figure 1: Managed futures industry AUM (Source: BarclayHedge)*

Source: Calstrs (2017) Annual Funding Report. http://resources.calstrs.com/publicdocs/Page/CommonPage.aspx?PageName=DocumentDownload&Id=6a1e133d-e87d-4220-8249-a9ac28604aeb

# A new use case

**(2)** Pension fund risk mitigation: Crisis protection or crisis propulsion?

| Pension Fund | AUM | Target Risk Mitigation | % in Trend | Trend % of AUM |
|---|---|---|---|---|
| CALSTRs | 200bn | 9% | 45% | 4% |
| HAWAII | 15bn | 20% | 45% | 9% |
| RHODE ISLAND | 8bn | 8% | 50% | 4% |
| SJCERA | 2.6bn | 20% | 33% | 7% |
| Average | | | | 6% |

These numbers were collected in 2017, as of 2019 Calstrs AUM is 246bn

Source: Source: Pension Fund Risk Mitigation, Neuron Advisers 2017.

# A new use case

## (2) Pension fund risk mitigation: Crisis protection or crisis propulsion?

| Asset | Market Value (in millions) | Actual | Current Target | Difference | Range |
|---|---|---|---|---|---|
| Global Equity | 122,803 | 49.92% | 51.00% | (1.08%) | +/- 6% |
| Fixed Income | 31,066 | 12.63% | 13.00% | (0.37%) | +/- 3% |
| Real Estate | 34,192 | 13.90% | 13.00% | 0.90% | +/- 3% |
| Private Equity | 22,564 | 9.17% | 9.00% | 0.17% | +/- 3% |
| Risk Mitigating Strategies | 22,829 | 9.28% | 9.00% | 0.28% | +/- 3% |
| Inflation Sensitive | 6,576 | 2.67% | 3.00% | (0.33%) | +/- 3% |
| Cash / Liquidity | 4,922 | 2.00% | 2.00% | 0.00% | +/- 3% |
| Innovative Strategies | 1,050 | 0.43% | 0.00% | 0.43% | +/- 2.5% |
| Strategic Overlay | (2) | 0.00% | 0.00% | 0.00% | |
| **Total Investment Assets** | **246,000** | **100.00%** | **100.00%** | | |

Source: https://www.calstrs.com/current-investment-portfolio Asset allocation October 31st, 2019

# A new use case

## (2) Pension fund risk mitigation: Crisis protection or crisis propulsion?

**To explore we build** an ABM that includes CTAs, variable annuity funds, risk-parity funds, portfolio rebalancers and ‘others’

**Calibrate** the behaviour and size of participants we can think we can proxy with data, **estimate** the remaining parameters so as to produce realistic data (price dynamics, volumes)

**Simulate** to explore the impact of **changing** key parameters of choice

i.e. the AUM of risk-mitigating strategies

16 RESEARCH


Neuron Advisers investigates whether increasing allocations to trend-following could destabilise markets

assertion by Fischer Black that portfolio insurance was benign if there was at least as much AuM in portfolio rebalancing strategies

# A new use case

**(2)** Pension fund risk mitigation: Crisis protection or crisis propulsion?

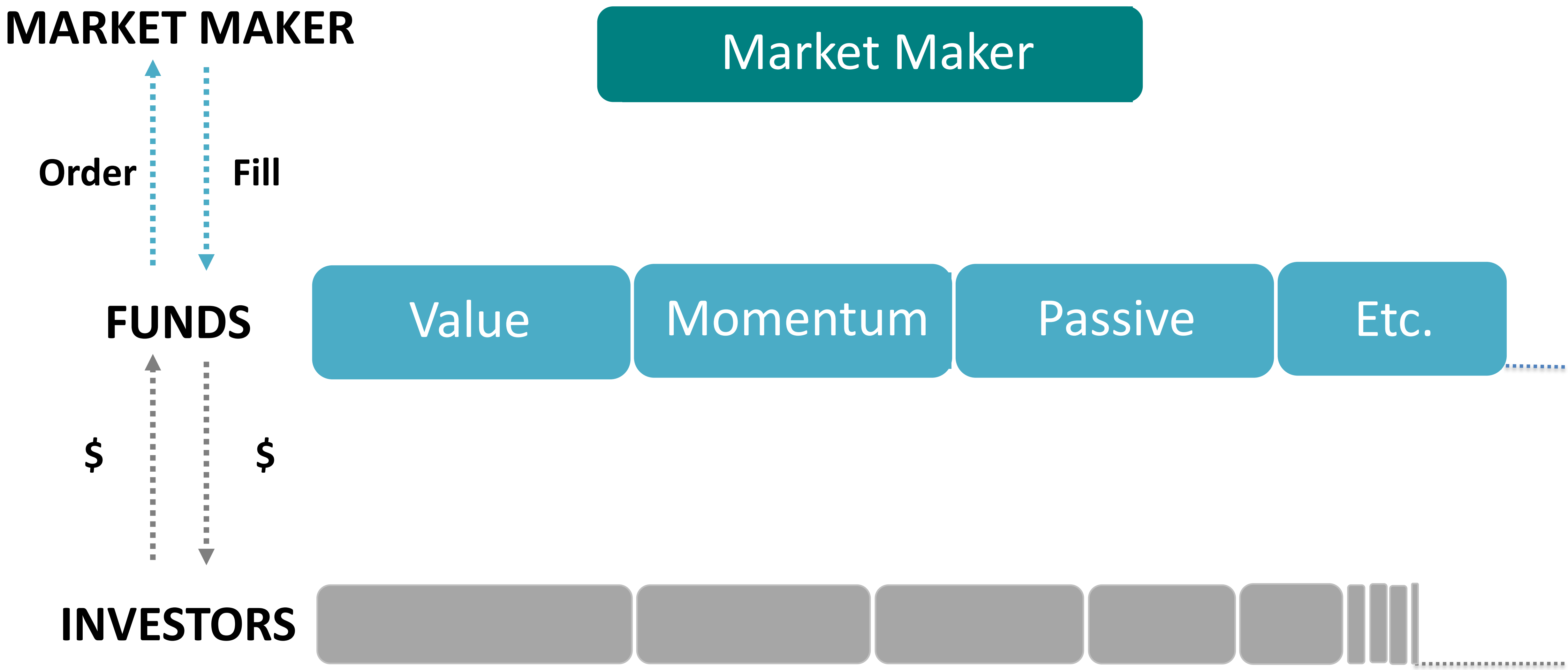
- $p_{t+1} - p_t = \lambda \sum_{i=1}^{5} order(t,i) + \epsilon_t$

- **This model is in *orders* so truer to Beja & Goldman & Santa Fe ABMs**
- $order(t,1)\sim trend\ ('\mathrm{fast}'..)$
- $order(t,2)\sim trend\ ('\mathrm{slow}'..)$
- $order(t,3)\sim risk\ parity\ (..)$
- $order(t,4)\sim variable\ annuity(..)$
- $order(t,5)\sim rebalancer\ (..)$
- $\epsilon_t\sim \mathrm{N}(0,\mathrm{eta})$ represents orders from all other participants not explicitly modelled

 Source: Hillman, R. Pension fund risk mitigation: crisis protection or crisis propulsion? (2017) CTA Intelligence

# A new use case

(2) Pension fund risk mitigation: Crisis protection or crisis propulsion?



# A new use case

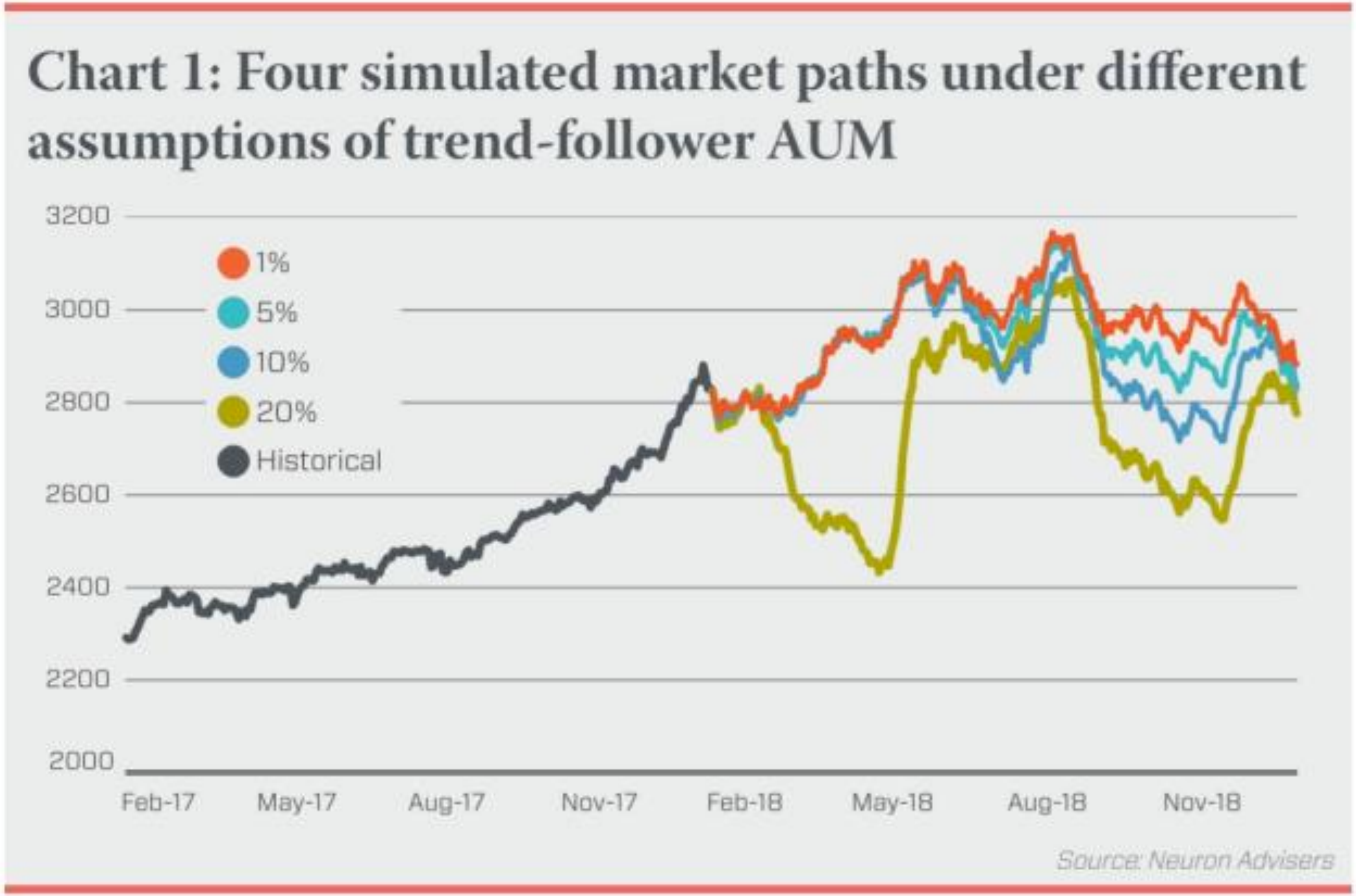
## Design choices

(mine in bold other options in grey)

| Component | Options | | |
|---|---|---|---|
| **Fund behaviour** | ▪ **Published fund data e.g. (returns, AUM, flows)**<br>▪ **Domain expertise (e.g. leverage targets)** | ▪ **Calibrated**<br>▪ Estimated<br>▪ Learning cf Santa Fe | |
| Investor behaviour | ▪ Flow data<br>▪ Surveys | ▪ Reinforcement learning | |
| **Market microstructure** | ▪ **'Market-maker'** vs exchange/order book | ▪ **Fixed lambda** vs market impact model | ▪ **Discrete Calendar Time** vs Event time |

# A new use case – exploring how much may be too much

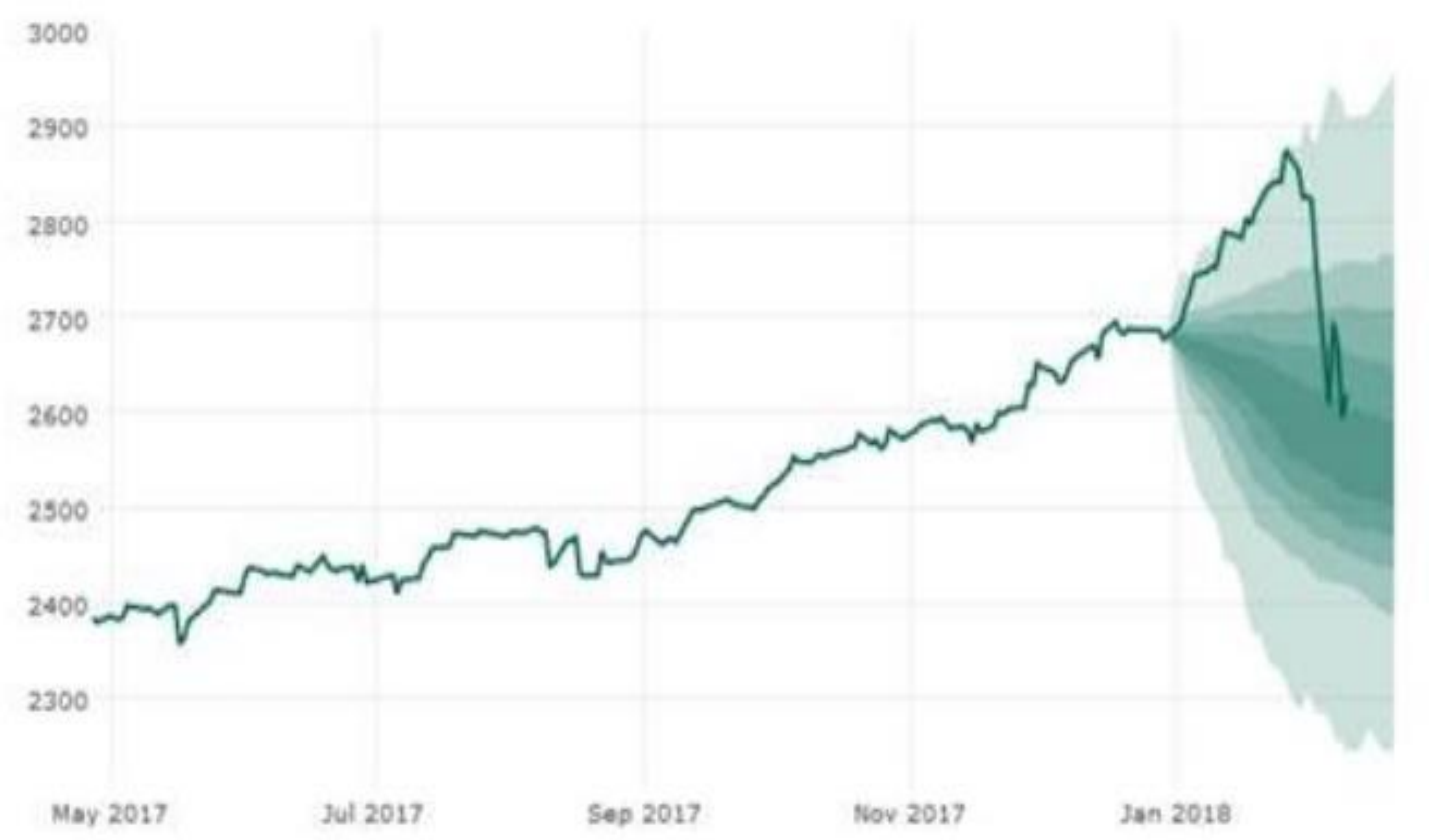
**(2)** Pension fund risk mitigation: Crisis protection or crisis propulsion?




 Source: Hillman, R. Pension fund risk mitigation: crisis protection or crisis propulsion? (2017) CTA Intelligence

# A new use case – forecasting with the model

**(2)** Pension fund risk mitigation: Crisis protection or crisis propulsion?

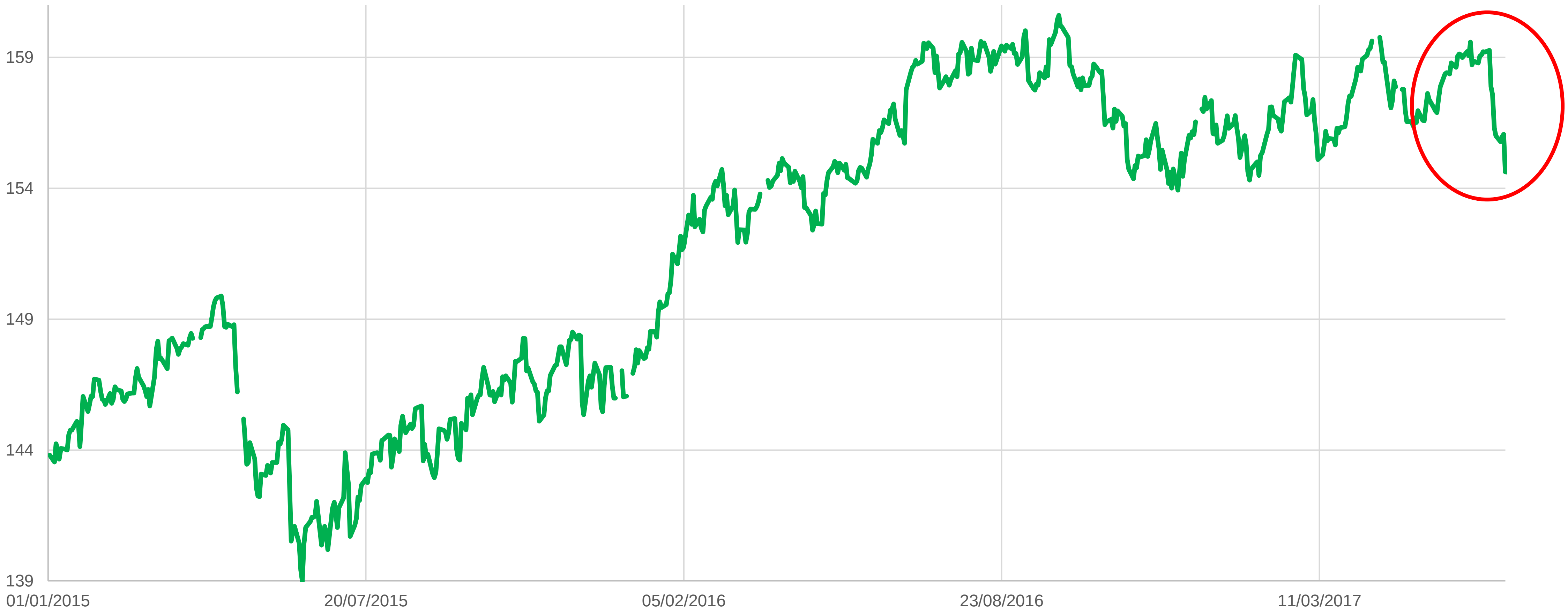



 Source: Neuron Capital

# A new use case – a risk amplification indicator

## (2) Pension fund risk mitigation: Crisis protection or crisis propulsion?

- In June 2017 Mario Draghi surprised the market, and yields rose for several days




 Source: Neuron Capital

# A new use case – a risk amplification indicator

## (2) Pension fund risk mitigation: Crisis protection or crisis propulsion?

- A shock amplification index suggested the market became vulnerable in the preceding weeks


Source: Neuron Capital

# A new use case
## **(2)** Pension fund risk mitigation: Crisis protection or crisis propulsion?

### Takeaways from the model

- An N-type model was calibrated to the S&P 500 and German bund market
- Calibrated to published fund performance and reflects domain expertise
- The model generates paths consistent with stylized facts of interest:
  - asymmetric dynamics; skewness; time-varying momentum; volatility clustering in time aggregated returns
- The model was designed to address a <u>policy</u> question but can be used to <u>forecast</u> and because it is <u>causal</u> in nature as a <u>conditional scenario generator tool</u>

### Tentative conclusion

- Some support that short term amplification effects from mechanistic strategies might be possible
- We are some distance from destabilizing effects, would need > 10% for all PFs
- But model highlights caution required: simulated behavior can be very difference between 10% and 15% allocations to trend-following. Transitions take place over small parameter ranges

# Challenges and new directions

Some parallels between financial & weather models

| Challenge | Examples | | Solutions |
|---|---|---|---|
| **Short histories** | ▪ UK daily rainfall records ~ 100 years | ▪ Financial market data ~ 100 years | ▪ Simulate more data |
| **Nonstationary background** | ▪ Greenhouse gases | ▪ Electronic trading<br>▪ Active to Passive<br>▪ Public to Private | ▪ Change 'forcing' variables |
| **Uncertainty** | ▪ Parameters<br>▪ Granularity / S.I.C. | ▪ Model<br>▪ Parameter | ▪ Ensemble<br>▪ Bayesian |
| **Model Fidelity** | ▪ Can models reproduce history?<br>▪ Overfitting / GIGO | | ▪ Backtesting<br>▪ Forecasting & ML |
| **Lucas critique** | ▪ Responses to climate policy | ▪ Will investors change behavior? | ▪ Empirical & micro foundations<br>▪ Include learning |

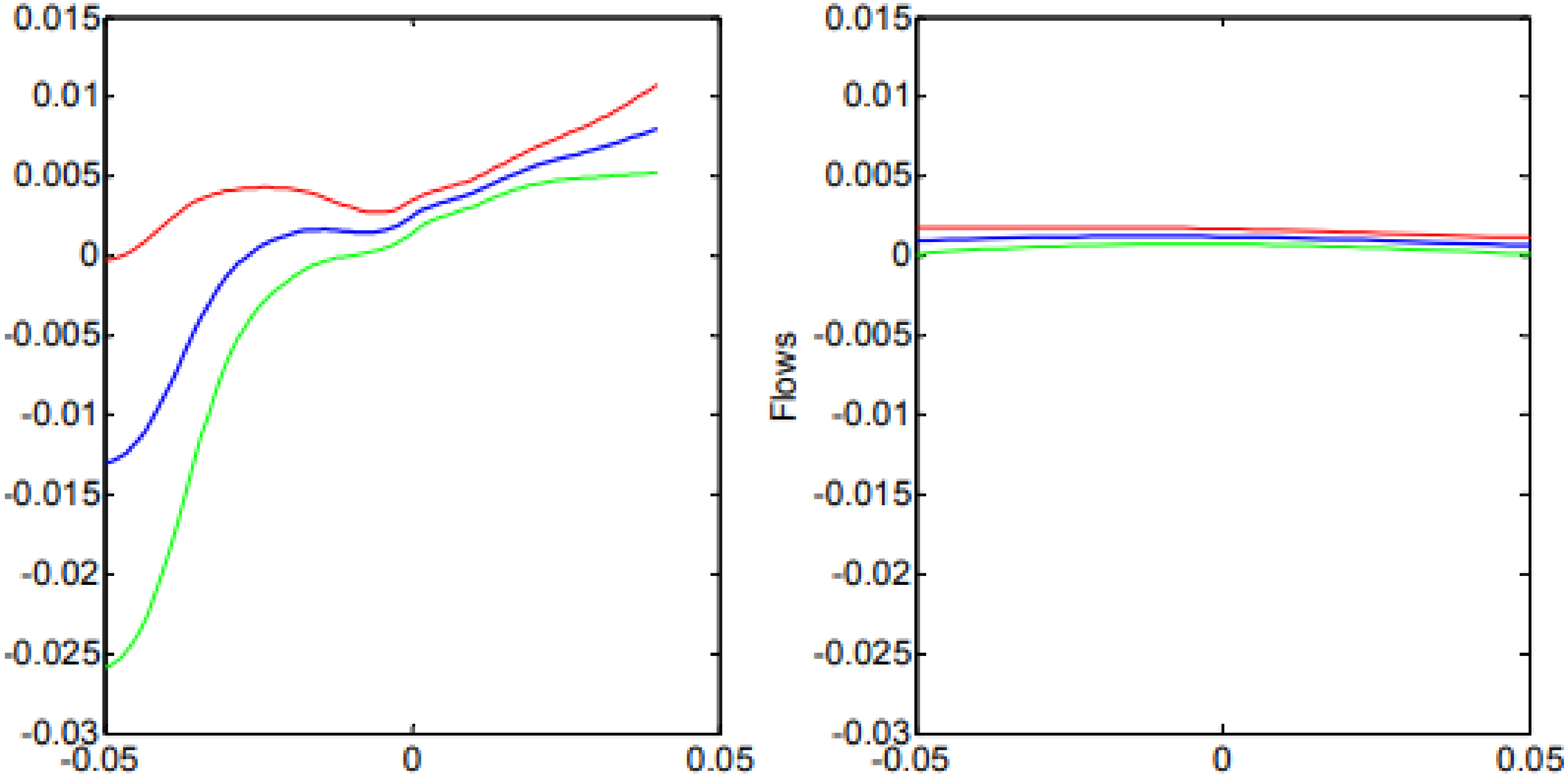


See for example Thompson et al (2017) High risk of unprecedented UK rainfall in the current climate, Nature Communications 8, 107.
Hillman, R. (2017) Extreme weather and extreme markets: Computer simulation meets machine learning.

# A new use case – Lucas critique example

## (2) Pension fund risk mitigation: Crisis protection or crisis propulsion?

- Are behavioural functions stable under parameter changes? LHS chart shows estimated bond flows versus lagged performance




Source: Braun-Munziger, K, Zijun, L, and Turrell A (2016) “An agent-based model of dynamics in corporate bond trading” Bank of England Working Paper No. 592.

# Challenges and new directions
## Developments in econometrics of ABMs

### Inference Methods – Simulation and indirect inference

- Consistent Estimation of Agent-Based Models by Simulated Distance (Grazzini, Richiardi, 2013)
- Bayesian Estimation of Agent-Based Models (Grazzini, Richiardi, Tsionas, 2015)
- Empirical Validation of Agent-Based Models (Lux, Zwinkels, 2017)
- The Problem of Calibrating an Agent-Based Model of High-Frequency Trading (Platt & Gebbie, 2017)
  - Identification problems and parameter degeneracy

### Learning – Innovations in ML/AI

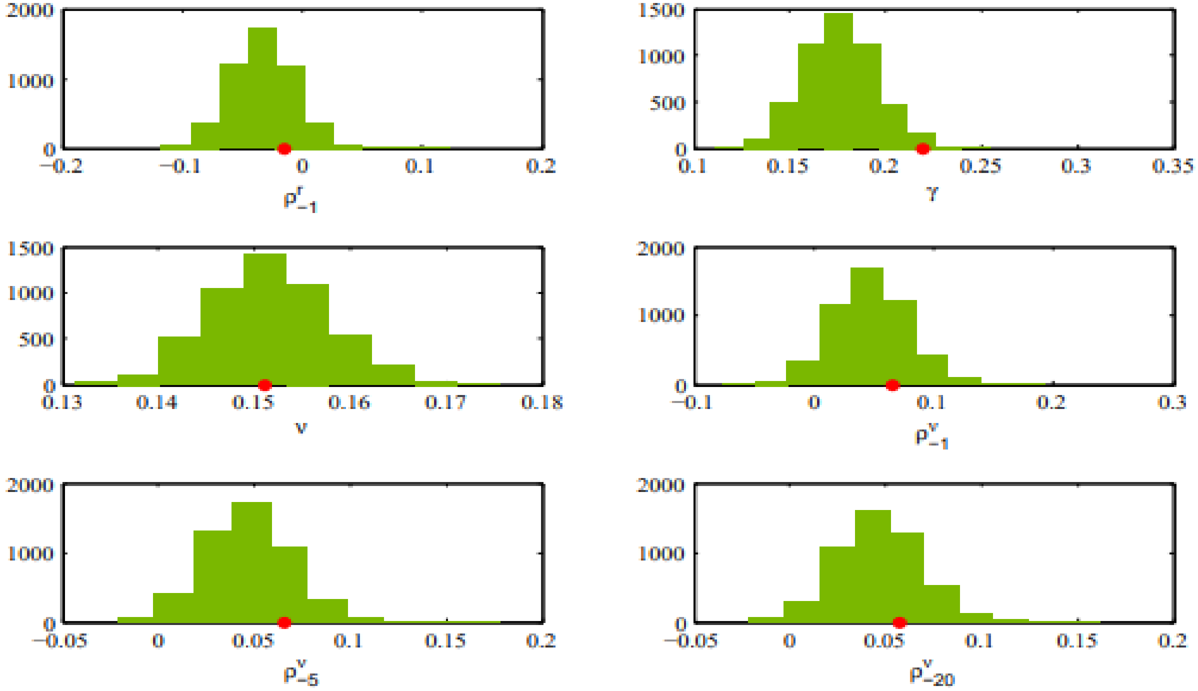
- Deep Learning in Agent-Based Models: A Prospectus (Van der Hoog, 2016)
- Agent-Based Model Calibration using Machine Learning Surrogates (Lamperti et al, 2017)
  - Neural Net models are strong on data fitting but weak on causality
  - ABM models are strong on causality (structure) but weaker on data fitting

**More progress likely as AI becomes more causal and ABMs more data focused**

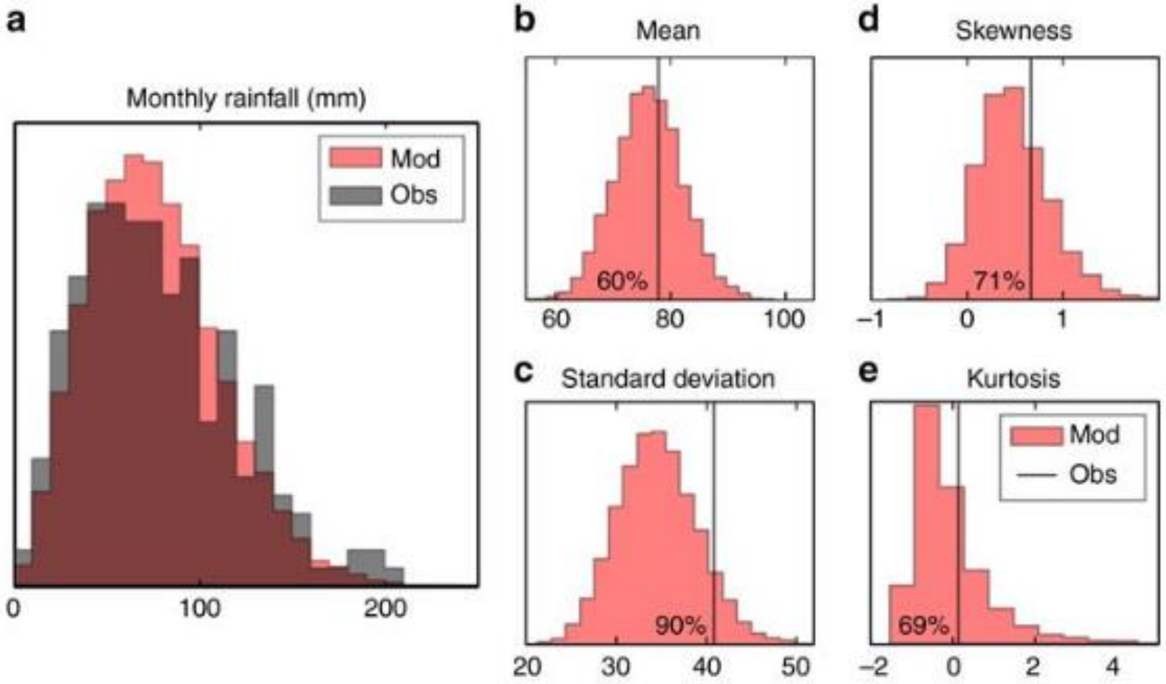
# Challenges and new directions

## Some parallels between financial & weather models

### Daily corporate bond returns (Braun-Munziger et al 2016)



### Monthly rainfall (Thompson et al 2017)




See for example Thompson et al (2017) High risk of unprecedented UK rainfall in the current climate, Nature Communications 8, 107. Braun-Munziger, K, Zijun, L, and Turrell A (2016) “An agent-based model of dynamics in corporate bond trading” Bank of England Working Paper No. 592. Both discussed in Hillman, R. (2017) Extreme weather and extreme markets: Computer simulation meets machine learning.

# Challenges and new directions
## Reflections on Farmer's 2001 "within five years" prediction

### "Why are they called agents again?"

- Sell the results first, explain the methodology later. Is a rebrand occurring? AI, and ABM may be seen as part of a broader technological shift –> AI + Big Data + Modelling (see Matt Taddy's work)

### "Death by proof-of-concept"

- Never in the history of economic research has the term "toy model" been used so much. Why is this? Until very recently little progress in "taking to data"…this does seem to be changing

### "What's this going to cost?"

- A minimum viable product might be developed in a week. An enterprise level implementation could take two years. Integration or supplanting of legacy systems, or standards (e.g. VaR) could be next to impossible…

### "All very interesting! But is it better than what I currently do?"

- There is a role for better prospective research. Look at the problems / limitations people have with existing techniques and try and *price* the value of solving those problems.

# Challenges and new directions

## My 2019 “within five years” prediction! We will see much more ABM-like modelling and simulation within investment and elsewhere

| What’s changing | Examples |
|---|---|
| World changed | Algos are everywhere. ABMs look real |
| Policy makers | Deeper in markets |
| Regulators | Demanding impact awareness |
| Systemic problems | Climate change |
| Macro crisis | DSGE & ABM blurring |
| Data | Lots more of it |
| AI & ML | Need for causality & interpretation |
| Methodological innovations | Ensembles & simulation common |
| Accessibility | Cloud + open source + commercial |
| Inter-Disciplinary platforms | e.g. NAEC Innovation Lab ! |



Note: I added the Data line after I presented at the OECD as someone quite rightly asked why it wasn’t! I discussed the impact of data in markets in a couple of former white papers “Extreme Weather and Extreme Markets” and “Managing Risk Through Human Guidance of AI” both available on the neuroncapital.com website under Research Papers

# Challenges and new directions

Reflections on Farmer’s 2001 “within five years” prediction

## Why I expect to see more ABM-like models being explored by investors within 5 years

### (1) Fiction has become Fact

Some of the earlier scepticism over ABMs in investing contexts – even from within the field e.g. Farmer and more recently Bookstaber – was about the **credibility of behavioural rules and trading models**. But investing practice has significantly shifted. Today much (most?) capital is driven by algorithmic processes. The days of secret-sauce and mystery legendary traders seem over.

### (2) The increasing presence of policy makers

Response to crisis has engaged policy-makers deeper into markets. And there is increasing recognition that **regulations and rules impact markets**. Understanding the size and risks of these effects is textbook hedge fund territory.

**The Impact of Pensions and Insurance on Global Yield Curves 2019, Greenwood & Vissing-Jorgensen**

Is this is an empirical paper crying out for simulation modelling…?

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# The End