Financial Market Simulation `rebooted`

THE FOLLOWING OUTLINES THE TRANSCRIPT OF A PRESENTATION DELIVERED BY
ROBERT HILLMAN - CIO, NEURON ADVISERS.

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Disclaimer

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

The study does not represent actual results and models may not behave like this in reality.

Charts are for illustration only. All data is simulated and purely for expositional purposes. Source: Neuron

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- Motivations from the LQG..
- Some history
- Simulation rebooted - a new wave of interest
- What is making simulation so attractive & viable?
- What are the challenges?
- Some ideas about risk & investment management

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- LQG Debate 12/12/2017
- This house believes that low volatility, low trading volumes and positive returns across assets are "the new normal" and are here to stay...

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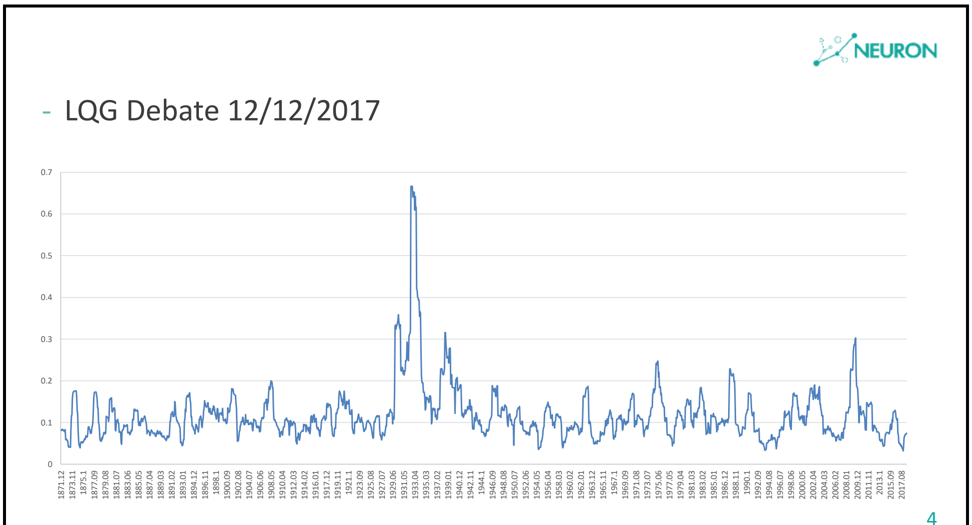
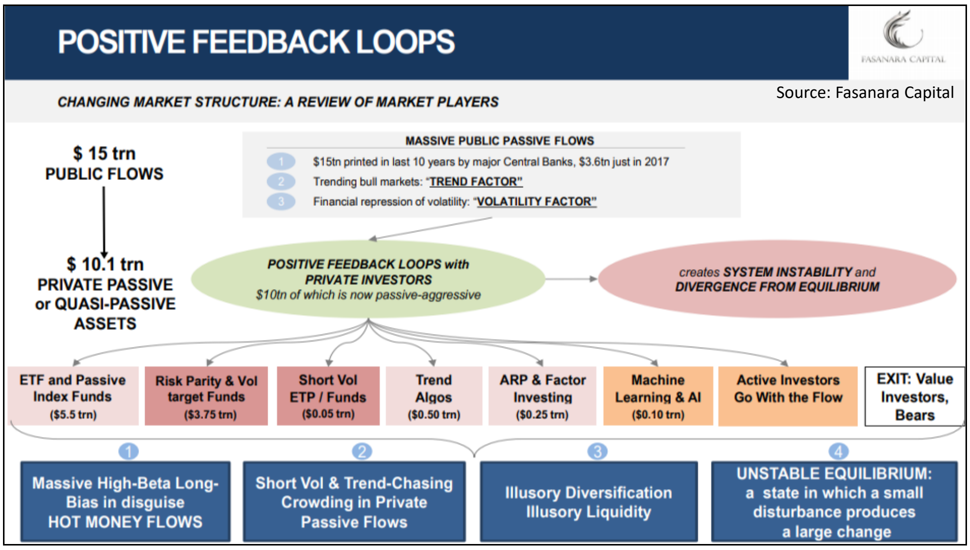
In December 2017, almost at the low in terms of recent volatility, the London Quant Group debated the motion “This house believes that low volatility, low trading volumes and positive returns across assets are "the new normal" and are here to stay...”.

As I recall, Ed Fishwick, for the motion, made a simple but compelling case. He looked back over decades and pointed out that volatility is either in one of two states, low or high. It is in a low state more than high, and when it is low it is more likely to be low tomorrow than high. States persist. Francesco Filia, opposing the motion said that sort of thinking was risky. For him, it is precisely when volatility is low and has been for a while, that markets are most vulnerable. He described a number of structural and cyclical trends in markets, like QE, the rise of procyclical strategies and institutional selling of volatility, that for him suggested that an exit from low volatility could be particularly brutal. The vote was close and required several recounts. I think Ed may have won.



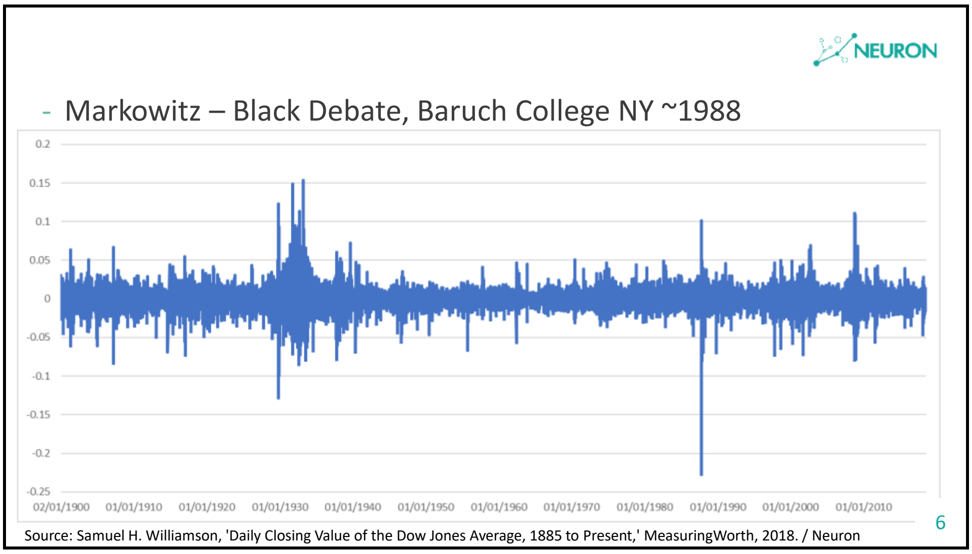
Source: Shiller - http://www.econ.yale.edu/~shiller/data.htm

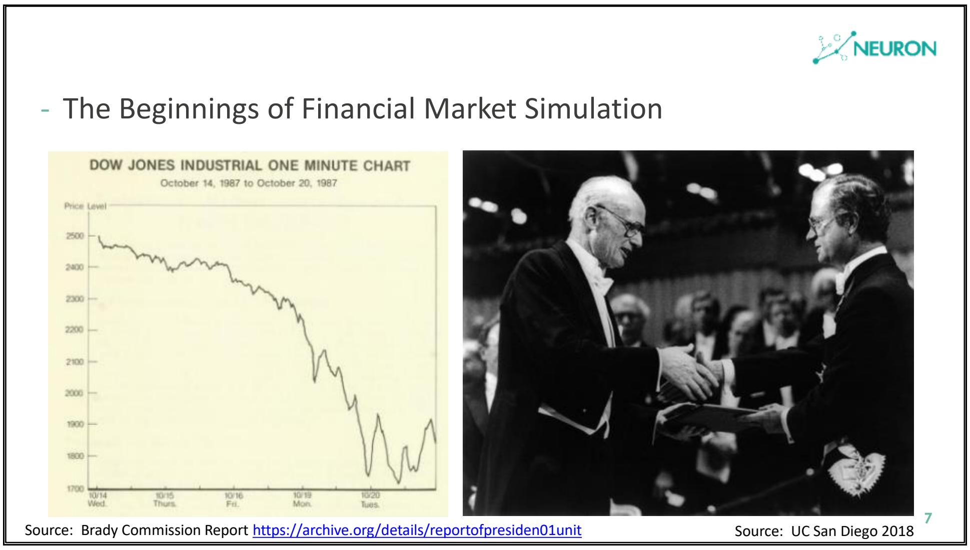
In retrospect the timing of the LQG debate was prescient. S&P 500 30-day historical volatility has not been lower since, and a few weeks into the new year we had the biggest ever jump (in percent terms) in implied volatility. The VIX jumped from 16% to 33% in the space of one day, as the inverse-VIX complex (that Francesco had specifically warned about) blew up in spectacular fashion.



Source: Fasanara Capital

Another debate took place almost exactly 30 years earlier.





In the immediate wake of the 1987 crash Fischer Black argued to Harry Markowitz (HM) that portfolio insurers (PI) can't be too destabilising as long as there are at least as many portfolio rebalancers[1]. The rebalancers orders would outweigh the PI guys. Black had a dog in the race, he been working at Goldman Sachs a while and was involved in helping them compete in the PI space.

HM decided the best way to explore this was via simulation. Although HM is best known for modern portfolio theory he was in fact the creator of the first commercial simulation language, something he returned to at General Electric after publishing the portfolio work that made his name. I suspect he went down the mean-variance analytical route because computers didn't support the simulation approach which would have been his natural go-to. These days (in his 90s) he is writing four volumes revisiting his earlier work. Much of the second volume (known as 'Volume 2') is devoted to explaining how best to implement a simulation program,

[1] Markowitz, Harry (2016) Risk-Return Analysis, Volume 2, McGraw Hill

and how to think about portfolio choice decisions in terms of dynamic games that can be designed and tested within a simulation environment. This is far from academic speculating. HM has been involved in consulting and commercial ventures for a long time, such as GuidedChoice. I find it interesting also that Bill Sharpe (another Nobel Prize winning economist from a similar cohort) has been heavily involved in simulation approaches, decision support systems and commercial enterprises like Financial Engines. Sharpe's recent book, though not explicitly tackling dynamic problems, uses simulation explicitly to deal with the complexity that investor heterogeneity brings to portfolio decisions. Maybe it's just me but I find the fact these guys clearly embrace heterogeneity and dynamic games, and use simulation as the way to approach problem solving interesting. I suspect quite a lot of people associate them primarily, if not solely, with a much narrower, and a frequently disparaged, representative-agent-rational-expectations-mean-variance orthodoxy.

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- The Kim & Markowitz 1989 Model

- Discrete Event
- Asynchronous Random Trading

- Two assets (stock and cash)
- Limit Order Book
- Margins

- Two-types of manager (rebalancer, portfolio insurer)
- Investors (pension funds or investment companies)
- Random withdrawals & deposits

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The K&M model had the following features:

- Discrete Event
- Asynchronous Random Trading
- Two assets (stock and cash)
- Two-types of manager (rebalancer, portfolio insurer)
- Many different instances of each type (e.g. up to 150 different managers interacting)
- Investors (pension funds or investment companies)
- Random withdrawals & deposits
- Limit Order Book
- Margins

The model was in many ways completely contrary to the orthodox approach of the day, a single representative agent, operating in continuous time. K&M also included practical constraints like leverage and margin. They also deliberately kick-started the model in a situation of disequilibrium because their explicit focus was on how markets behave out of equilibrium. These days economists are often ridiculed for not having taken factors like these into account before the financial crisis. It seems a shame in retrospect perhaps that this line of work that started with K&M didn't gain more traction. Bruce Jacobs and others did follow through with a number of papers (the 'JLM' simulator, described nicely in Lindsey & Schachter's book 'How I became a quant'). But I think it is fair to say this work has not yet gone mainstream.

What K&M found was that, contrary to Black's assertion, it was relatively easy for procyclical strategies to overwhelm theoretically stabilising strategies like portfolio rebalancing. Partly this is due to the potential for temporal liquidity mismatches. It doesn't matter how much AUM is following rebalancing. If the rebalancers are not active when the portfolio insurers want to trade then PIs will drive the market and demand and supply will be heavily skewed one way or the other. You don't really need to do a simulation to argue this point, but the sim does allow you to explore the issue quantitatively. Recently we have seen a shift towards trade volume clustering towards the beginning and end of the day. It would be interesting to think about the cause and implications of this. The K&M framework, or something like it seems useful. More subtly, the K&M model helped shine a light on the role of leverage and margin. They found that when margin is introduced the price dynamics can become explosive, and market drops of the size of 1987 could be commonplace.

- 2,000 miles west... The Santa Fe Institute

- Heterogeneity
- Nonlinearities
- Emergence
- Reflexivity

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Meanwhile 2,000 miles west a different group was embracing complexity theory and applying it to finance and economics. In some ways their agenda was purer. They thought they could explain market phenomena like booms and crashes by modelling the economy at an atomic level (individuals=agents). They tried to start these agents off with little or no prior knowledge and see if (artificial) evolution principles would lead them to learn to trade as we observe in the real world. Many of the researchers were physicists.

"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."

Toward Agent-Based models for Investment, Doyne Farmer, Association for Investment Management and Research, 2001

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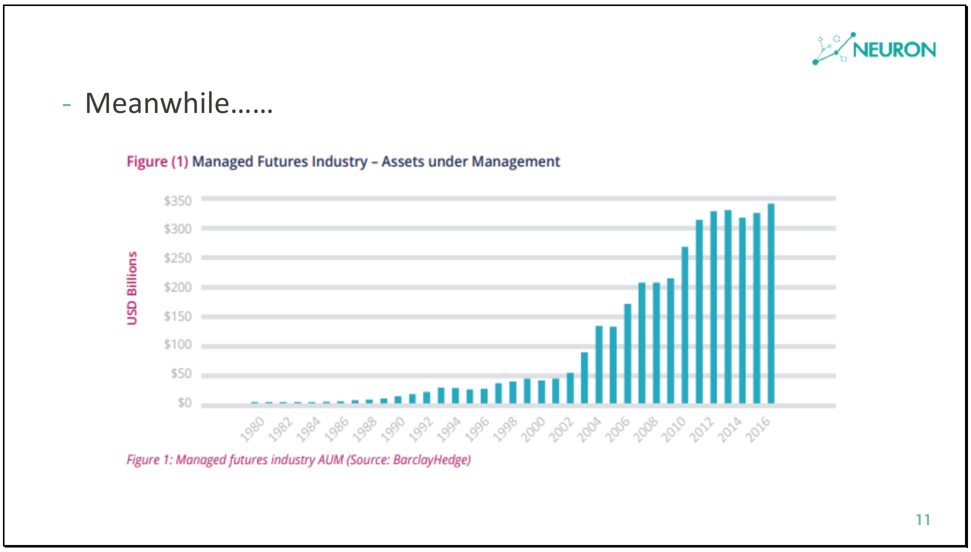
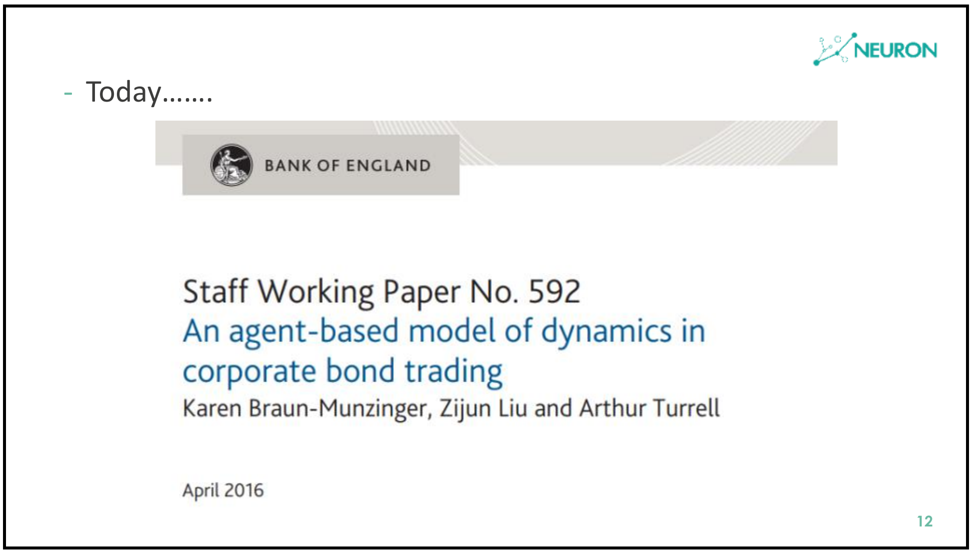
By 2006 they were getting quite excited and one of their founding and most influential members suggested that this approach (broadly labelled agent-based modelling) was about to take-off. Like K&M and the JLM simulator, it didn't.

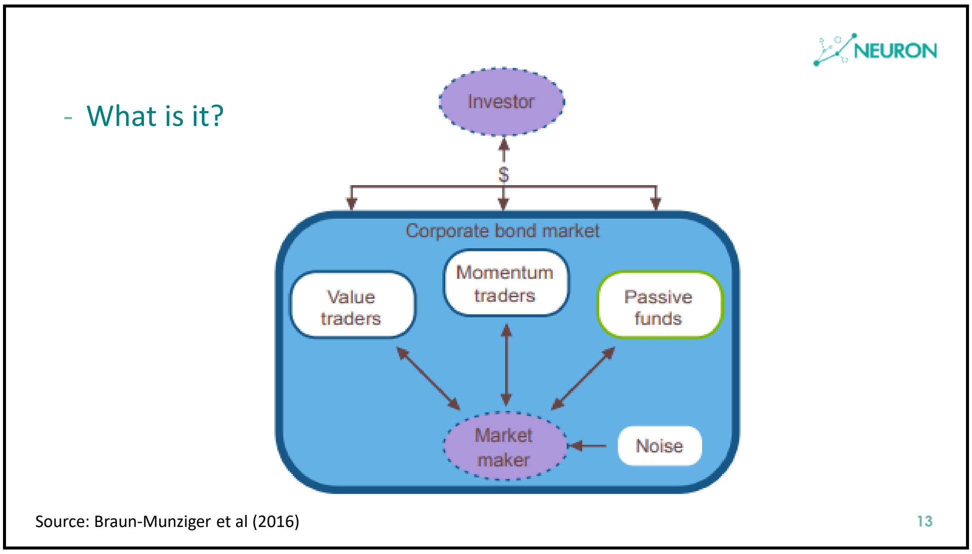


One of the reasons the Santa Fe programme may have failed to persuade people could be that it was accused of assuming (or allowing) behaviour by individuals that economists considered daft, such as trend-following. But paradoxically, right before a critic's eyes there was an industry beginning to boom labelled 'managed futures' that largely consisted of trend-following firms. Most of these firms were trading across a wide range of markets, hoping that at any point at least some markets would be trending, offsetting losses from those markets that might be chopping around. It is perhaps a fair criticism that many economists, in endeavouring to build a foundation for models based on rational individual behaviour, did not pay enough attention to what institutions were actually doing. It is hard to conceive of individuals behaving irrationally, but it is arguably easier to think less highly of institutions, especially hedge funds. Had the focus been more on what institutions were actually doing, and less on what individuals ought to be doing, perhaps things would have developed differently.



But 15 years (not 5) after Farmer's speculation there are now signs that ABMs are being used in anger, applied to real-world problems. The use-cases are driven by policy makers not investors.

My view is that the global financial crisis had a major effect in pushing people to exploring these models. It became immediately apparent that financial markets and structures (institutions, regulations, risk-management, derivatives) matter, and that single agent models were hamstrung. The single path of historical data was also recognised to offer scant information about potential market dynamics. In 2016 researchers from the Bank of England published a paper that I suspect may mark the start of the rebooting of financial market simulation. Interestingly they seem to draw more on the Santa Fe tradition than K&M (with no reference to K&M), but this is not unusual. The K&M and Jacobs/Levy work does not often feature in today's references to ABMs. One honourable exception is Samidou et al (2007).



The BoE's model ('BLT' after the author's surnames) looked at the US corporate bond market. In structure it is much closer to K&M than the Santa Fe ABMs. It is calibrated to real world data, its agents are tangible objects – mutual funds. Its behavioural rules were calibrated from empirical data on fund flows. There are three modelled strategy types, value, momentum and passive. Within each strategy type the model can have many funds. The market microstructure is different to K&M. K&M used a limit order book, but BLT used a construct drawn more from the Santa Fe tradition, the concept of a market-maker (Farmer and Joshi, 2002). Someone who collects the orders from the funds and adjusts prices according to the net demand or supply.

The BLT model allows analysis of things like the role of passive trading, and allows policy experiments such as what is the impact of shortened redemption terms. This is a good thing to study. It is my perception that redemption notice periods have shortened in recent years, and that hedge-funds (and other products) have introduced less liquid markets and strategies into their portfolios without lengthening notice periods to compensate for the potential risk of a liquidity mismatch between the market and investors.

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- What is it?
- A simulation model of hundreds of funds
- Calibrated to institutional data (e.g. AUM distributions)
- and empirical behaviour data
- Estimated via simulated method of moments

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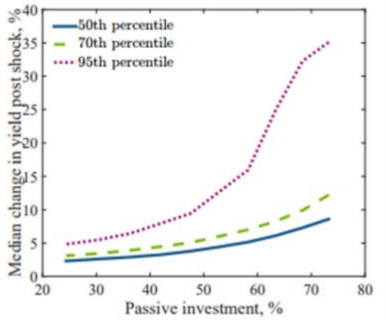
- What can we learn?



"We also explore the impact of the growth in passive investment, and find that it increases the tail risk of big yield dislocations after shocks, though, on average, volatility may be reduced."

Source: Braun-Munzinger, Liu, and Turrell (2016)

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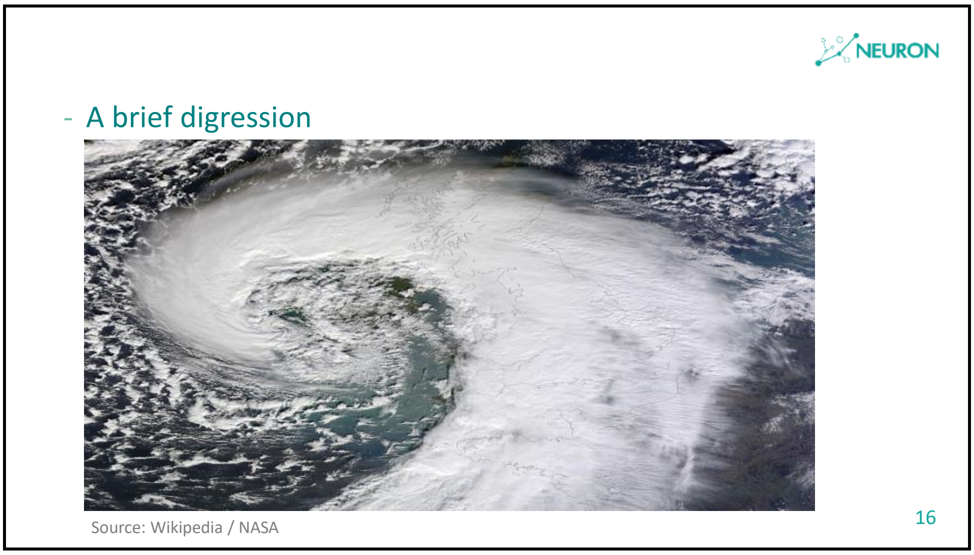
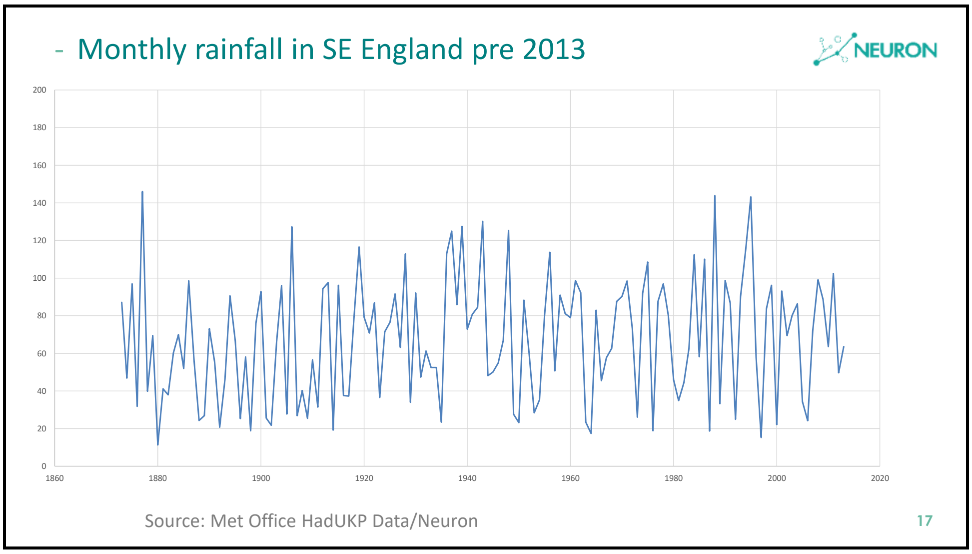
One of the results from the BLT model suggested that as passive trading increases, average volatility might drop, but the market could be more vulnerable to dislocations after shocks. This seems plausible to me. It also coincides with the worries some people have about the rise of high-frequency trading and electronic market-making, and the decline of prop-desk and market-maker risk-taking across banks.

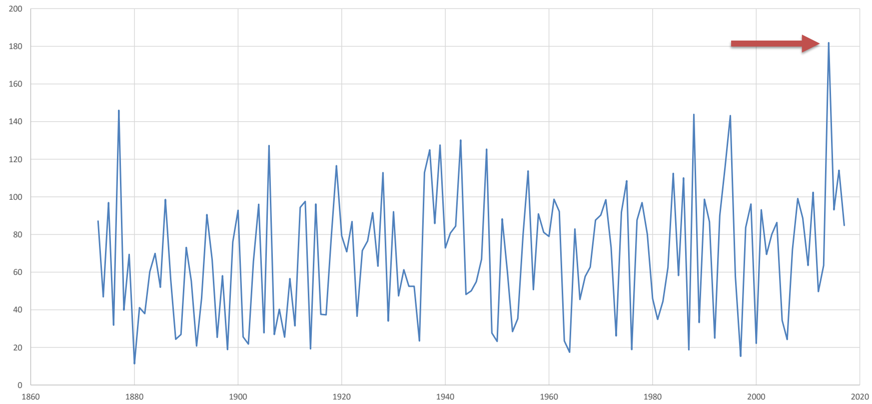


What factors have combined to make this new type of ABM practically useful?

To understand why it is only recently that ABMs have started making an impact in policy circles, it is helpful to consider developments in a completely different field, weather forecasting. In the winter of 2013/2014 there were extreme floods in the UK. Extreme in the sense that they were well outside the historical record. Furthermore, forecasters had good reason to believe that the record was less relevant. What I've called the dual problem of relevancy and sufficiency, Hillman (2017).



- Monthly rainfall in SE England to 2017



Source: Met Office HadUKP Data/Neuron

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- Why are these approaches becoming useful ? - Environment

Source: Met Office

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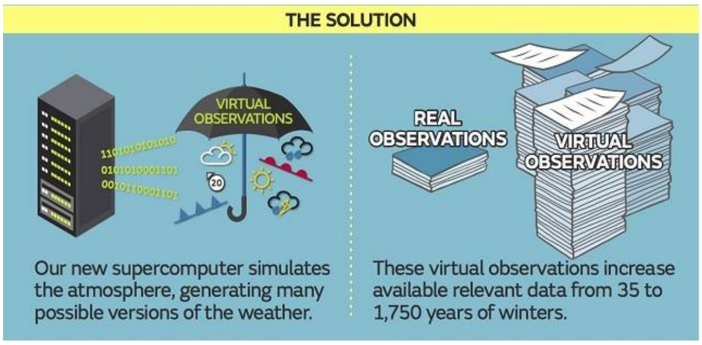
- Why are these approaches becoming useful ? - Technology



Source: Met Office

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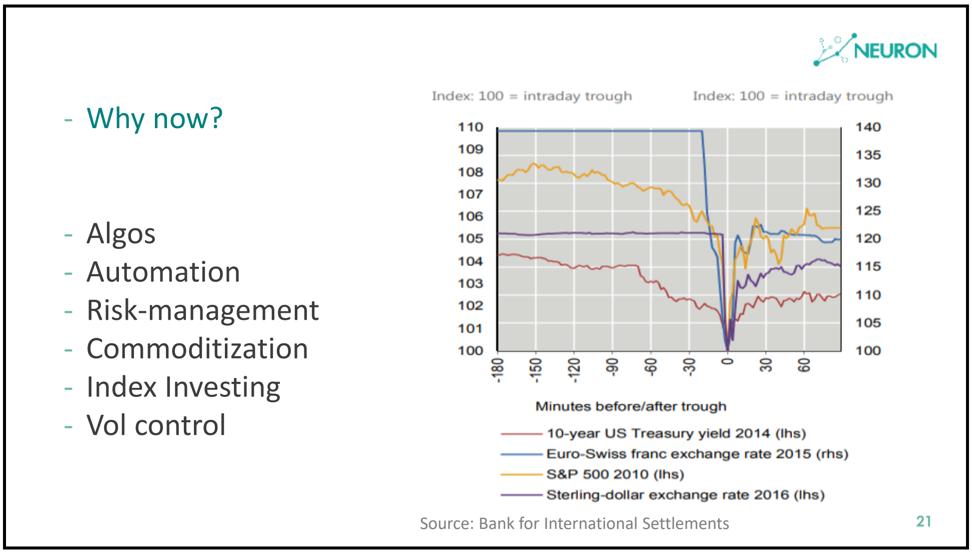
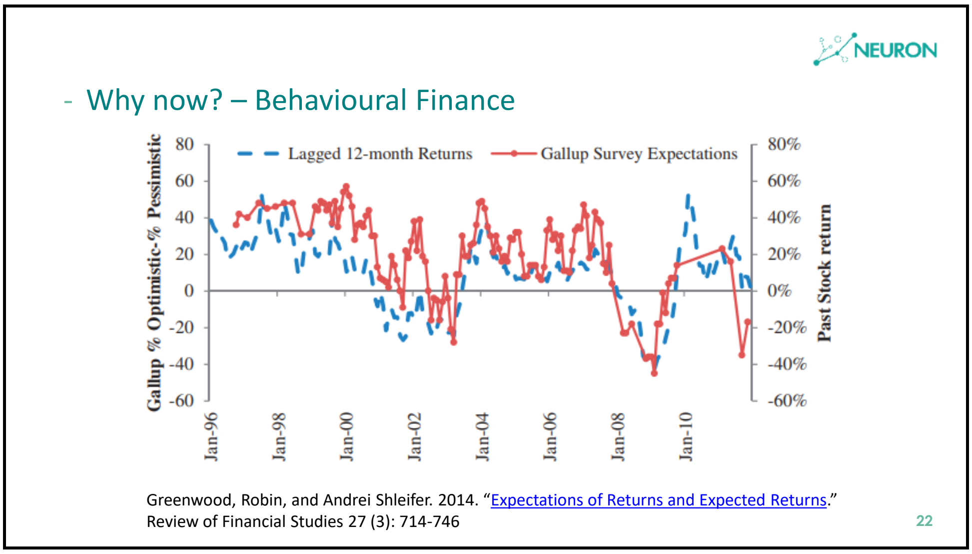
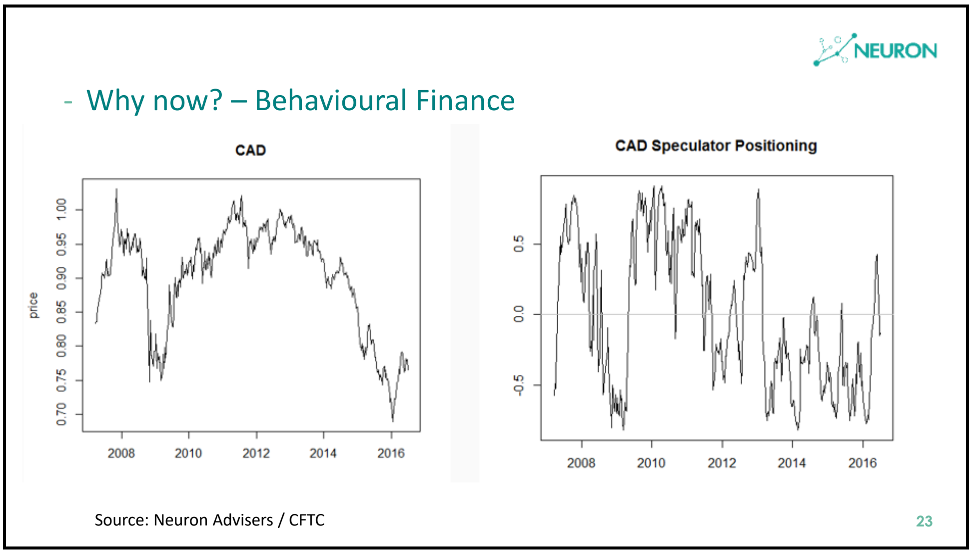
To tackle these problems the Met Office has invested in a much more powerful computer to simulate the atmosphere. It enables them to simulate thousands of alternative virtual weather observations. It isn't just sheer computing power enabling faster brute force simulation. Perhaps more importantly, innovations in data management and coding tricks are playing a crucial role. I am thinking more generally here of things like MapReduce and parallelization. Many of these innovations are spin-offs from progress in other fields like image recognition and more broadly big data and AI.



Turning back to finance, another reason the ABM approach has become more attractive is that underlying markets themselves have evolved to be more computer like. As investors and institutions have embraced algorithms, oddly the real-world has evolved to resemble the virtual computer markets conceived of by K&M and the Santa Fe programme. And we have also started seeing things like 'flash crashes' which are widely thought to be a product of this technology. Regulators are naturally pushing for ways to enhance our understanding of these phenomena.



We have also learnt (or come to terms with the fact) that actually people do often behave like trend followers. There is much survey evidence to support this, a bi-product to some extent of the behavioural finance field. For example, work by Greenwood and Shleifer (2018) looks at survey data and shows investors' expectations are often little more than extrapolations of past returns. Researchers like Nick Barberis have explored potential causes and implications of these findings within more theoretical finance models (see Greenwood refs).



In my own work looking at speculator (as classified by the CFTC) positioning data, I have found strong support that speculators form positions based on simple moving average cross over models – a common construct within the early ABM models, and one that was regularly derided as irrational by economists.

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- Why now? – Behavioural Finance

- $\mathrm{N(t)} = \frac{L(t)-S(t)}{L(t)+S(t)}$ net speculator position

- $r(t) = \frac{p(t)-p(t-1)}{\sigma(t)}$ volatility-adjusted returns

- $N(t) = a + \sum_{i=0}^{\mathrm{T}} b_i \, r(t-i) + \mathrm{e(t)}$

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Regressing the net speculator position on the lhs versus lags of volatility-adjusted returns on the rhs gives a profile of coefficients that looks like a nonlinear distributed lag model. For example, in foreign exchange markets I fund that a simple weighted combination of a fast and slow exponentially weighted moving average crossover signal fits the empirical data well. I believe such combinations of signals are commonplace within the trend-following community. The bottom line of the empirical expectations work is that it is hard to object to ABMs because they allow or assume strong extrapolative expectations mechanisms (as many of them have done over the years).

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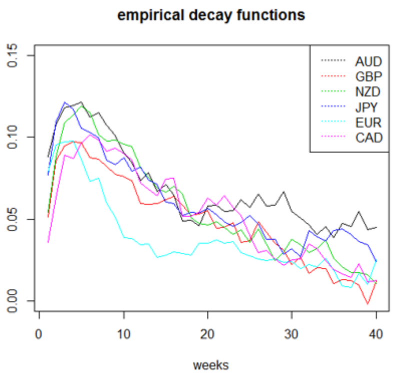
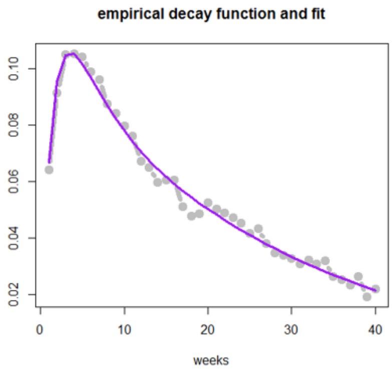
- Why now? – Behavioural Finance





Source: Neuron Advisers

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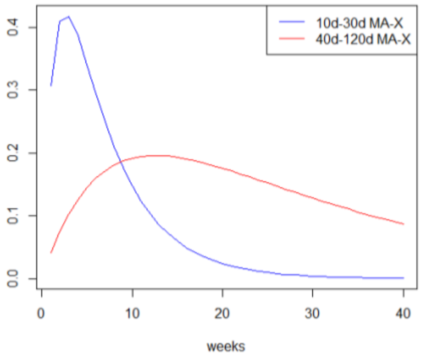
- Why now? – Behavioural Finance



The best 2-frequency fit suggests

35% 'fast' traders who extrapolate from the last 3 weeks

65% 'slow' traders who extrapolate from the last 3 months

Source: Neuron Advisers

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- What has changed? – Uncertainty Awareness/Acceptance

- Known Unknowns etc
- Radical Uncertainty
- Model uncertainty

Source: shutterstock

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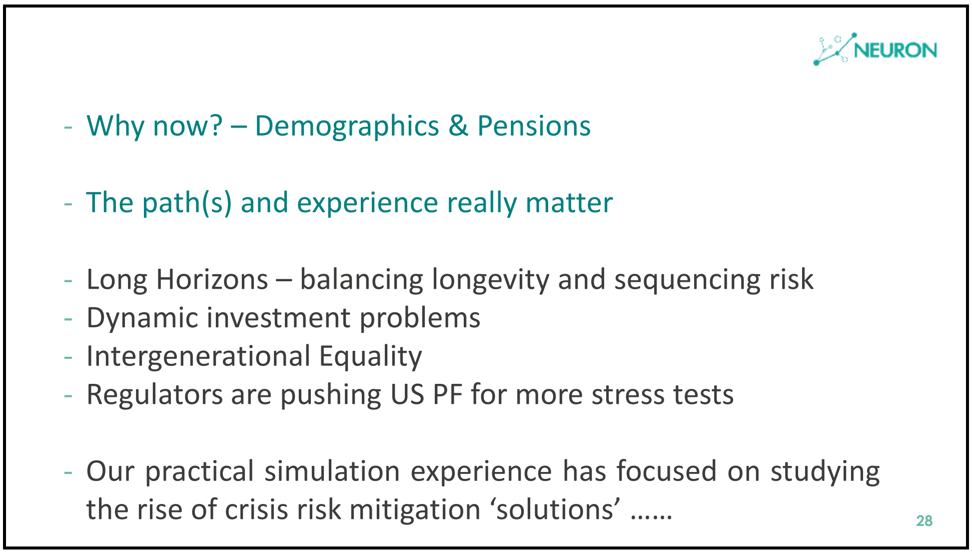
Next, people have become more open to the idea "risk" is not the same as "uncertainty". Donald Rumsfeld famously articulated it quite well[2]. As it happens within stats, econometrics and ML this idea can be seen in many places. People now talk about model uncertainty and even 'radical uncertainty'. In some sense these concerns are hardly new. We can trace back these concepts at least a hundred years ago, to economists like Frank Knight[3] and Keynes[4] who both discussed wider notions of uncertainty. But it does seem to me that in the last ten years or so we have seen a paradigm shift in the sense that people have begun to formalise such uncertainty within both theoretical and empirical economics. An interesting adopter of these ideas relevant to the ABM research agenda is Rick Bookstaber. He discussed the risks of financial market participants ignoring wider uncertainty in his 2007 book 'A Demon of Our Own Design'. He has since become one of the most prominent ABM evangelists himself. His 2017 book 'The End of Theory' eloquently describes his journey.



A final reason why these generative/simulation models are becoming attractive is because longer term horizons are becoming important. Seeing life as a series of one-shot games is falling out of favour as people try to consider portfolio planning over multiple decades. The pensions arena is central to this shift, boosted by the shift towards individuals taking responsibility for their own pension pot. Remember it is precisely these types of problems that Markowitz's 'Volume 2' addresses.

Our own experience with ABMs has been focused around related issues, specifically on the rise of risk-mitigation products. We have seen a rise in the use of trend-following to offset losses that would occur if equity markets fall. The use of trend-following, alongside more direct methods of portfolio insurance is well underway in the US and beginning to grow in Europe in the DC market and elsewhere.

[2] US Department of Defense news briefing on February 12, 2002
http://archive.defense.gov/Transcripts/Transcript.aspx?TranscriptID=2636
[3] Knight, F. H. (1921) Risk, Uncertainty, and Profit. Boston, MA: Hart, Schaffner & Marx; Houghton Mifflin Company
[4] Keynes, J.M. (1921), A Treatise on Probability, The Collected Writings of John Maynard Keynes, Vol. VIII, London. Keynes, J.M. (1936), The General Theory of Employment, Interest and Money, The Collected Writings of John Maynard Keynes, Vol. VII, London. Keynes, J.M. (1937), "The General Theory of Employment", reprinted in The Collected Writings of John Maynard Keynes, Vol. XIV, pp. 109-124

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Regulators say: "Low Volatility, Financial Leverage, and Liquidity Mismatches Could Amplify a Market Shock"

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?

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Aware of this shift in investor demand, regulators are getting concerned. A recent example is the IMF in their October 2017 Global Stability Report. They highlighted CTAs (a term for manages futures firms who as stated are typically heavily trend-following driven) as well as variable annuity hedging and risk parity funds as presenting some risks. The idea that trend-followers may be destabilising and therefore a risky solution as a hedge for pension funds is controversial even within the trend industry itself. One of the most prominent characters in the space, David Harding has not minced his words in describing his views of the idea (Harding, 2016).

Our proposal:

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Build an ABM that includes CTAs, variable annuity funds, risk-parity funds, portfolio rebalancers and 'other' participants who bring order flow into the market

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 CTAs

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Our solution to addressing this issue is via an ABM methodology. We build an ABM that includes CTAs, variable annuity funds, risk-parity funds, portfolio rebalancers and 'other' participants who bring order flow into the market.

We calibrate the behaviour and size of participants we can think we can proxy with data, and estimate the remaining parameters so as to produce realistic data (price dynamics, volumes). We simulate to explore the impact of changing key parameters of choice i.e. the AUM of risk-mitigating CTAs.

- Each fund type's orders are specified separately

- j=1,2,3,4,5 fund types

- $order(t, 1) \sim trend\ (\text{'fast'}..)$
- $order(t, 2) \sim trend\ (\text{'slow'}..)$
- $order(t, 3) \sim risk\ parity\ (..)$
- $order(t, 4) \sim variable\ annuity(..)$
- $order(t, 5) \sim rebalancer\ (..)$

- $\text{noise}(t) \sim \text{N}(0, \text{eta})$ represents orders from all other participants not explicitly modelled

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- Each fund has a simple nonlinear representation (~ANN)

- $\text{order(t)} = lots(t) - lots(t-1)$

- $\text{lots(t)} = \text{gearing(t)} \sum_{h=1}^{H} w_h\, f\left(\sum b_{i,h} r_{t-i}\right)$

- $r(t) = \frac{p(t)-p(t-1)}{\sigma(t)}$
- $\sum b_{i,h} r_{t-i}$: weighted sum of past returns (e.g. EWMA)
- $f(.)$: squashing function e.g. cdf of a normal dist (~ANN)
- w_h : weights of each signal decay e.g. if combining 'lookbacks'
- gearing(t) ~ function of AUM, vol target, market vol

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- The market-maker concept reduces price dynamics to

- $\ln P(t+1) = \lambda\ \left(\sum order_j(t)\ + noise(t)\right) + \ln P(t)$

- $\ln P(t+1) - \ln P(t) = \lambda\ \ \sum order_j(t)\ + \lambda\, noise(t)$

- $r(t+1) = \ \lambda \sum order_j(t)\ +\ \lambda\ \ noise(t)$

- Without orders the price is a martingale
- Without the noise term it is a nonlinear deterministic model
- (and as a nonlinear system may exhibit endogenous dynamics)

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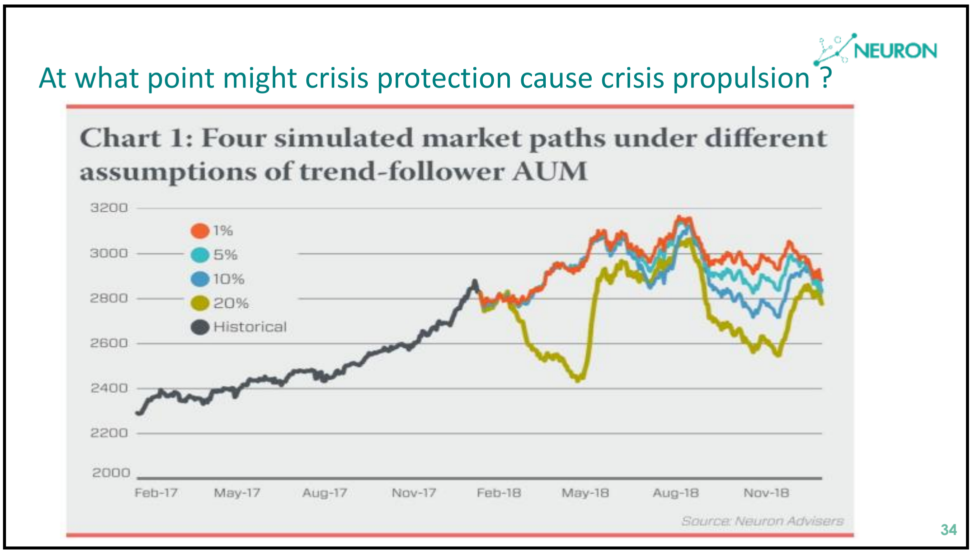
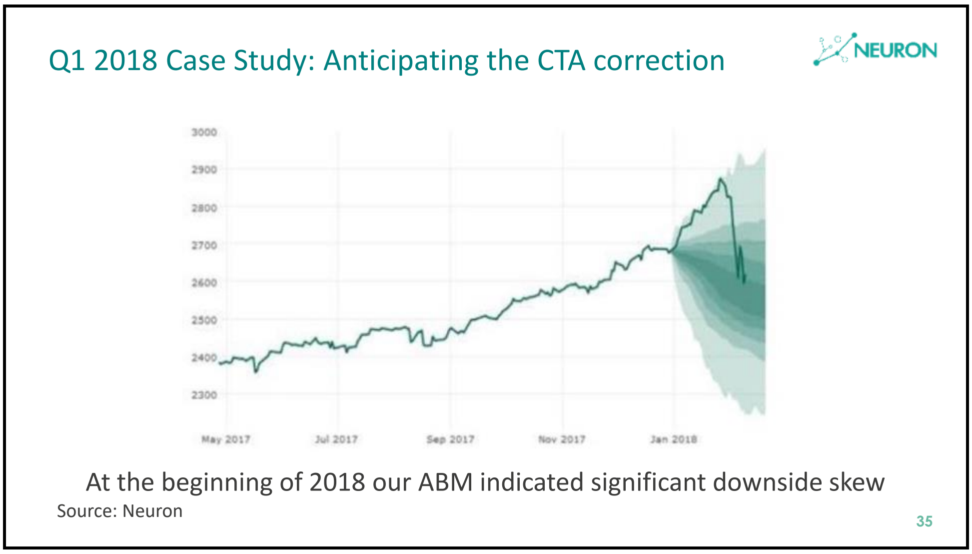


We found that for current levels of AUM in trend the impact of CTAs was slight but as we pushed up the AUM the dynamics would start to change. We found beyond a certain point the dynamics would shift, typical of the phase-transitions common in complex dynamic systems. In the context of our model, if we believe we have calibrated the current influence of trend-followers sensibly, then we would need the AUM in trend to be at least 10 times higher than it is today to significantly change the dynamics. But we are very unconfident we have calibrated the model well, much more work is needed.



Despite our weak confidence in the model calibration we do use our favoured calibration to give us insights. Each day we forecast 1,000s of possible paths. The distribution of future paths is wide but that’s life. We see that the conditional distributions vary over time depending on the positioning of the participants. Towards the end of 2017 our model suggested many CTAs and other vol targeters would be “limit long” and vulnerable to a reversal. This fitted with market commentary at the time.

Q1 2018 Case Study: Anticipating the CTA correction

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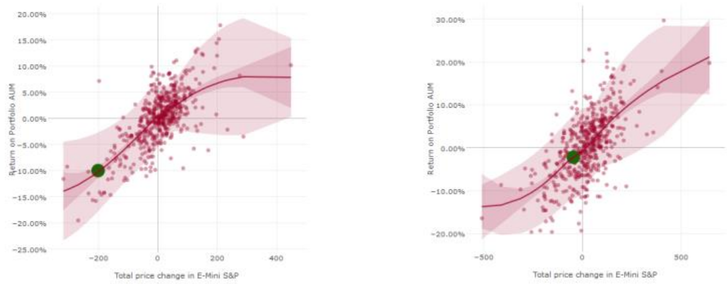
Validation support at a disaggregate level, but you need ‘extreme’ events



The view point from Jan 31 2018 - CTAs contained a lot of equity beta

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Source: Neuron

A problem with validating the model is that although it may occasionally forecast a skewed distribution, only occasionally will that skew be realised. However, perhaps there was some sign of positive feedback in February 2018 when markets were shocked by inflation data, this triggered a feedback spiral among some derivatives and some de-risking by CTAs and others as volatility increased. It is hard to know how much was endogenous but we did get some validation that at least or modelling of the CTA part of our artificial market was reasonably accurate. We had forecast that the CTAs had significant conditional equity beta.

Q1 2018 Case Study: Anticipating the CTA correction

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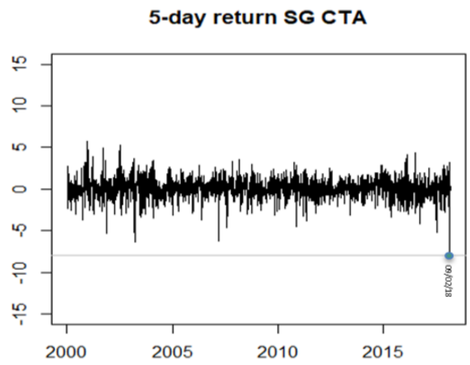

In February 2018 CTAs had a (predictable) “disaster”

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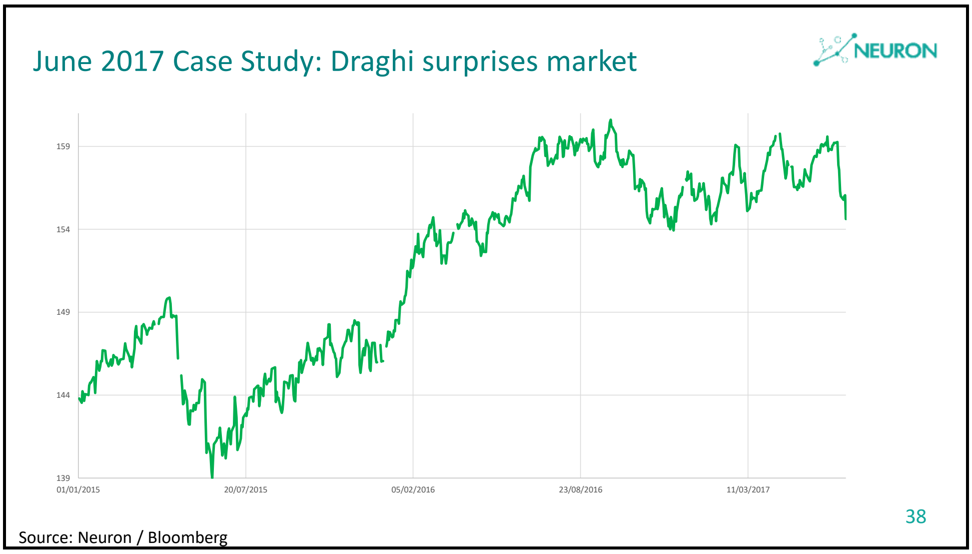
Source: Neuron / Soc Gen

In early February these CTAs had their “worst ever 5 days” as judged by industry indices like the Soc Gen CTA Index. Several commentators expressed shock and drama. It was reported JP Morgan said it could be an ‘extinction event’ for CTAs. Maybe it will prove to be, but it should not be if it was a surprise.

Within our ABM world the CTA return was entirely to be expected, and in fact the risk of this had been flagged as heightened towards the end of 2017/early 2018. To tie it back to Markowitz and Black, because the equity market had such a strong run in 2017, in January portfolio rebalancers were more likely to be selling in February as the shock hit, therefore not providing the offsetting flow Black had suggested.



Source: Neuron / Bloomberg

We had used a similar approach (retrospectively in this case) to explore a shock to the German fixed income market in late June 2017. Mario Draghi had mentioned that reflationary forces were now more of a focus than deflationary ones[5]. An initial price drop (causing a jump in yields of 13 basis points on the 27th June was followed by a further 36 basis points rise before the yield began falling back again. Like February 2018 CTAs suffered a sudden loss at the same time. The question we asked was to what extent the subsequent 36 bp move was an amplification of the initial news shock. We calibrated a small-scale simulation model (like our equity one) to the German bund market, once again modelling the trading dynamics of players like trend-followers, rebalancers, risk-parity and other volatility targetters. Armed with the model we carried out an experiment in which we subjected the simulated market to a 1% exogenous negative price shock. This was roughly the same amount the bund price dropped between the initial Draghi announcement and the close the next day (28th).

By the nature of their trading styles and risk-management rules the participants in our simulated market were then forced to react. Our model suggested that after a 1% shock the follow-through could vary from between 20 bps to 45 bps, and that this amplification effect varied over time depending on the state of the market (and by implication the positioning of the market participants). By carrying out this experiment each day for the previous few years we discovered that our simulated bund market was particularly vulnerable to a shock in June 2017. This was largely because recent volatility had been very low, and thus leverage higher than usual. Note that this follow-through is in terms of price return, so roughly speaking within our simulated model a 1% price drop could lead to a further 0.45% price fall, or mapping back to yield terms the initial 13 bps jump in yields might have induced a further 6 basis points rise in yields. While our experiments were only indicative, we believe they help articulate the problem and offer some quantitative information about endogenous market risks.

[5] https://www.ecb.europa.eu/press/key/date/2017/html/ecb.sp170627.en.html

June 2017 Case Study: Draghi surprises market

Source: Neuron

Amplification t+3 after a 1% exogenous shock

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- Specific Challenges for Us
- What to calibrate to?
  - Volatility ? Vol-of-vol? Persistence? Serial Correlation? Tails? This is still something of an art. Domain Expertise.
- Is it safe to consider 1 market in isolation? Should we include stock-index arb? Other products (e.g. VIX ETPs)?

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Building our ABMs we have faced several challenges, many of which are not resolved!

- Common Challenges – GIGO – Model Fidelity
- Parameter Calibration vs Estimation
- Back-Testing
- The Lucas Critique

Source: University of Chicago Photographic Archive

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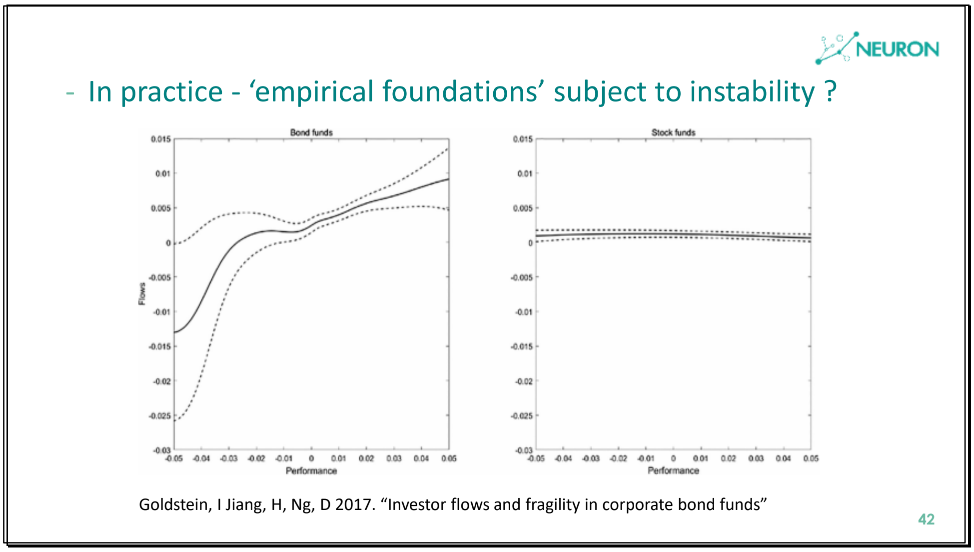
Beside our specific problems, we see three main challenges in operationalising ABMs. The first one is that there are many parameters and not much data with which to fit the models. On the other hand because the models (unlike a neural network for example) have a structural interpretation it means some parameters can be 'set' by the researcher. In our work we have tried to fix as many parameters as we could e.g. fixing the parameters that determine how CTAs, portfolio balancers and portfolio insurers trade. I will return to this in more detail later.

The second problem is back-testing. By definition we want to use these types of models precisely because they are capable of generating behaviour we may not have seen in the past. Back-testing is therefore somewhat awkward to say the least. A related problem is that ABMs are naturally all about forecasting a range of possibilities. Often the forward forecast distribution is wide. So we are really into the problem of evaluating forecast densities. There are ways and means to do this, but demands on data are high.



Finally, we are also subject to the Lucas critique (another Nobel economist)[6]. This idea is particularly easy to explain in the context of an ABM. For example, in the BLT model the researchers 'plugged-in' an equation that determined how much investors withdraw or deposit in an index fund (passive investing) as a function of past performance of the index. Not surprisingly this function is upward sloping. When corporate bonds rise more money flows in. But the function also suggests nonlinearity. If past performance was negative but modest, investors appear willing to stay invested. But beyond a point, around 2% a month, they withdraw funds, and much quicker than had added (the 'beta' is about double on the downside).

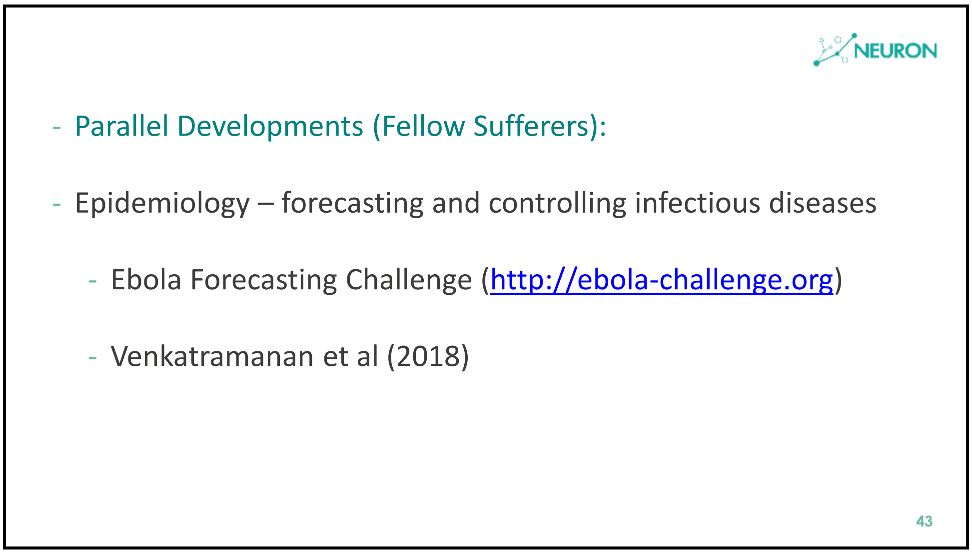
Where the Lucas critique comes in is if we want to do policy experiments with the model. BLT did do just this. They explored altering fund redemption policies. Instead of paying out immediately (and thereby needing to close positions immediately to accommodate the redemption) they explored what happens if funds are able to spread the redemption payment over a number of days. They found that when funds could spread their redemptions out it reduced the potential dislocation risk after a shock. Perhaps not a surprising result, but experiments were able to shed insight into the potential quantitative impact of this policy. For example, they found that spreading over more than 15 days has a very marginal impact. The problem with this experiment is that it relies on the stability of the nonlinear investor flow function they had plugged-in. Lucas pointed out

[6] Lucas, Robert, (1976), Econometric policy evaluation: A critique, Carnegie-Rochester Conference Series on Public Policy, 1, issue 1, p. 19-46.

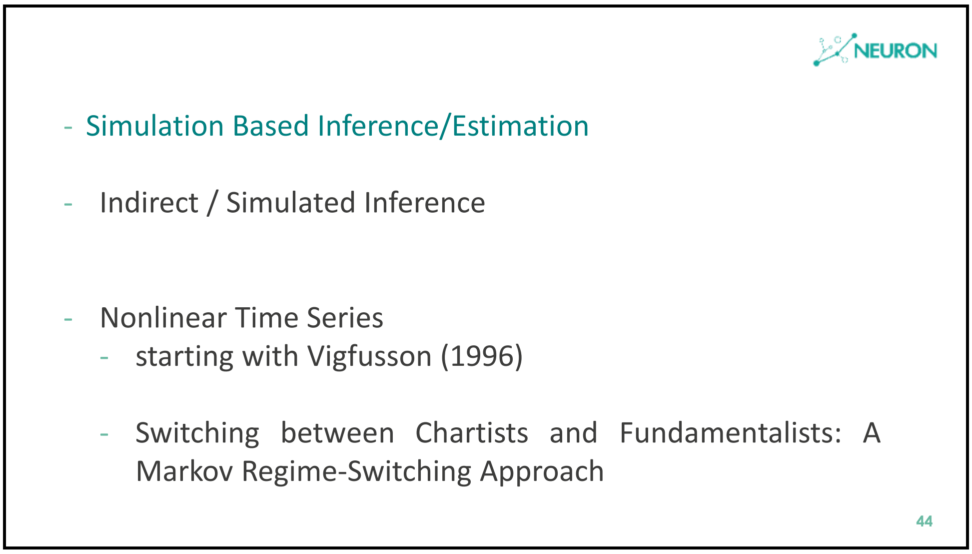
that in practice people change their behaviour when policies like this change. In the context of the BLT model it means it might not be safe to assume that investors would only start redeeming if monthly performance is worse than 2%. For example, it is plausible to think that if investors might not get their money back for a few weeks they might have less tolerance for losses.

This observation highlights one of the fundamental differences between ABMs and DSGE models (dynamic stochastic general equilibrium models). The main point of DSGE modelling is that it is grounded in behavioural micro-foundations. At the heart of these models the agent's behaviour is deduced (from a set of axioms), not imposed. In principle it means DSGE models are more immune to the Lucas critique. If our ABM contained agents who were constantly updating their behavioural in response to changes in policies, then the ABM could be immunised to the Lucas critique too.

In fact the idea of ABMs containing agents who are learning and updating their behaviour was at the heart of the early Santa Fe ABMs. All be it in those models agents were deemed to be learning in an attempt to maximise some objective function (like wealth). They were not so much continuously reoptimizing with respect to, or constrained by, some set of underlying axioms. Nevertheless, it feels to me that ABM and DSGE modelling is likely to move closer together. DSGE modellers are liable to relax some of their assumptions about perfect foresight and rationality, and introduce more heterogeneity. ABM modellers are likely to start endogenizing the behavioural parts of their model. One thing they can do already of course is explore as to whether any experimental results they obtain are sensitive to changes in these behavioural assumptions. That is one of the beauties of an ABM framework. It encourages sensitivity analysis.



That said it is not just us in finance and economics who face these issues. Developments in using ABMS are well underway in other fields. One application I have found particularly interesting is epidemiology. Recent work around the 'Ebola forecasting challenge' resonates strongly with issues we experience in developing ABMs in finance (Venkatramanan, 2018). They too suffer from the Lucas critique. They often want to test the impact of a health policy (for example forced vaccinations etc), but like us, they need to be careful that other assumptions in their model about how people behave will remain stable.



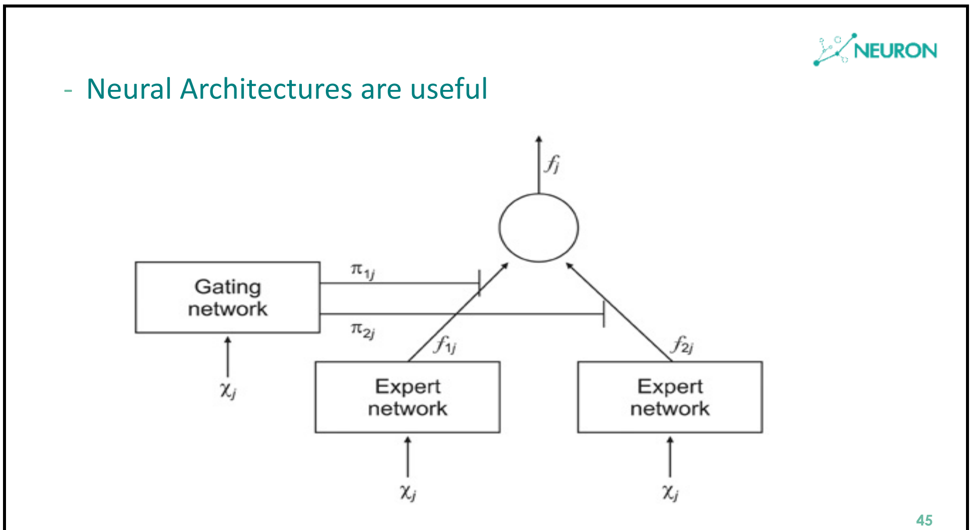
The first challenge facing ABM researchers that I mentioned was estimation and inference. It is hard, but there have been some interesting developments in the last few years that is helping researchers operationalise ABMs. One of the first attempts was by Robert Vigfusson in the 90s. He explored a simple two-agent model and approached the problem like a regime-switching mode (Vigfusson 1996). I mention this paper as it encouraged me 20 years ago to try a similar approach where I modelled each fund type (trend and mean-reversion strategies) as a simple neural network, and used a mixture of experts (Jacobs 1990) gating mechanism to govern the switching between them. More recently Hommes and others have estimated small (n-type) models by exploiting their similar representation to nonlinear regression models (Hommes 2013).

A key step has been the development of indirect inference techniques to help estimate and validate models. These sorts of methods have been used for a couple of decades for various intractable models in economics. The idea is pretty simple. What we want to do is produce an ABM that is able to generate data that is as plausible as possible. This doesn't necessarily mean we need the same model we use today to be able to reproduce past data. The weather example makes that clear. If we think that it is changes in background effects like greenhouse gases that has led to more extreme weather, then we might well expect the model we think relevant today might predict too many extremes than occurred in the historical record. So we need to find a balance between a model that is plausible, but also capable of producing data we haven't yet seen.

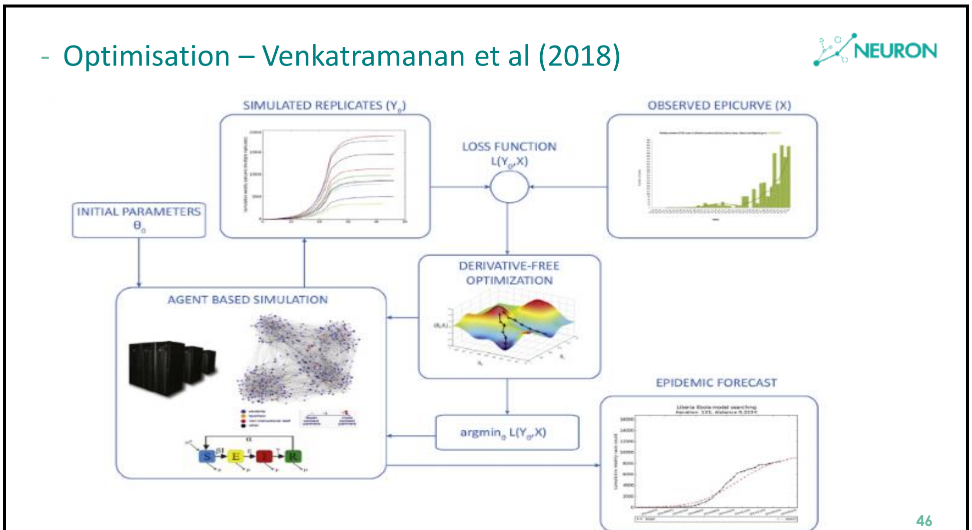
Indirect inference techniques are useful. A simple example is provided by the BLT paper. They impose some parameters based on judgement (like the fraction of value traders versus the momentum traders), and some based on empirical research (such as the response of investors to performance). But others they need to estimate, like the sensitivity of the market maker's price adjustment function (how much they adjust prices in response to excess demand). To do this they select a bunch of characteristics on observed data they would like their model to generate. For example, they want price returns to have small negative autocorrelation, volatility to be around 15% on average, and volatility to be persistent (as measured by the autocorrelation function on absolute returns). Given some base parameters they generate thousands of paths of data and calculate the ensemble averages. They then use a derivative-free numerical optimisation algorithm to adjust the free parameters to try and minimise the distance between the generated characteristics and the observed ones. When the characteristics are just moments of the data (like the mean, standard deviation, skewness and kurtosis etc) this method is called the simulated method of moments. This same type of method has seen application in both the epidemiology and climate model examples.

All these approaches, as is often the case with numerical optimisation, are often as much art as science. In our cases we have to make a judgement about what properties of the data we want to emphasise, and how to weight them. Do we care more about accuracy of the average level volatility of the series, or about the persistence of volatility for example? Once again however, we can explore the possible numerical trade-offs over these choices via simulation. But there is no doubt that while automated processes might be used, at this stage of development of techniques the researcher will be extremely hands on guiding the research. Domain expertise will also no doubt be highly valuable. I expect the very same need for interaction and domain expertise is mirrored in recent advances in machine learning and AI.

In fact, some of the most exciting research in this space is taking place at the intersection of ABMs and AI. On a practical level some researchers are exploring using ML within the ABM specification and estimation process (Lamperti et al, 2017). In my own work I have long favoured representing both trading models (the funds in my ABMs) as artificial-neural-network inspired architectures, and so this resonates strongly with my own thinking. More speculatively I suspect that as ABM modellers begin to endogenize more of the behavioural components of their model by including learning, the models will become more dynamic and contain elements of ML, shifting away in time from the currently predominantly mechanistic models we see policy makers using.

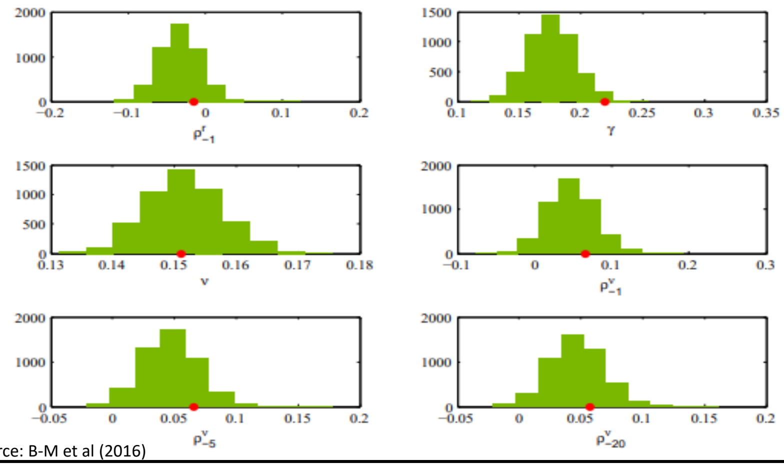


Source: Neuron



Source: Venkatramanan et al (2018)

- Simulation Based Inference Example (B-M et al 2016)



Source: B-M et al (2016)

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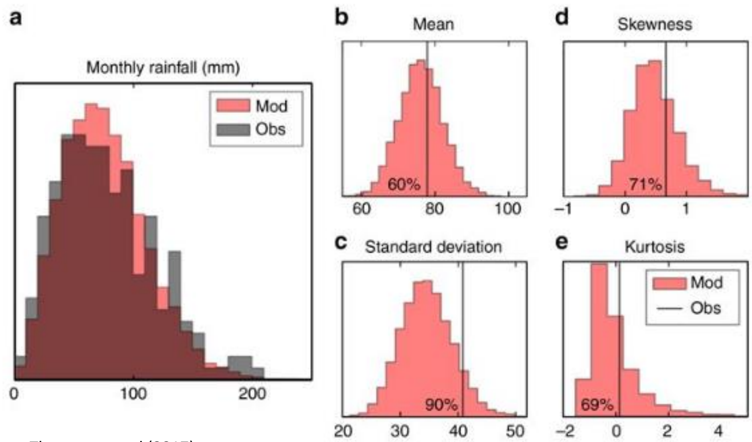
- Simulation Based Inference Example (Thompson et al 2017)



Source: Thompson et al (2017)

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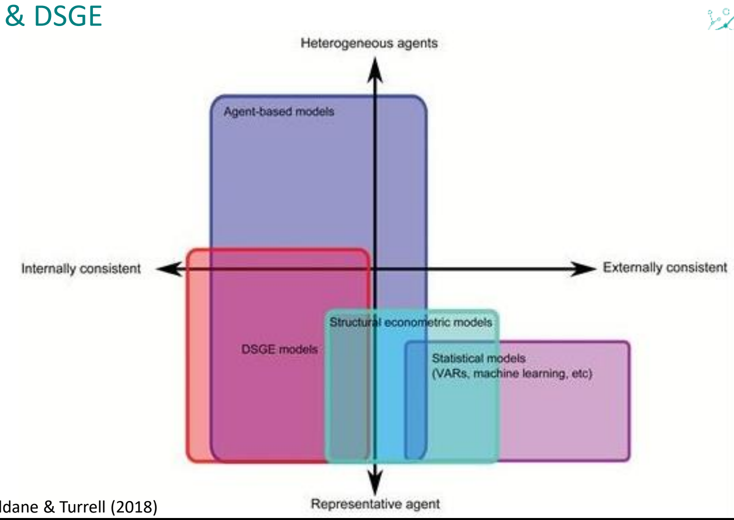
- ABM & DSGE



Source Haldane & Turrell (2018)

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- ABM & DSGE

  - ABMs like DSGE 10 years ago?
  - Linearisation/rescaling/detrending
    - Most ABMs have focused on price level generation
    - So could potentially learn from DSGE
  - Flat likelihoods, curse of dimensionality, p >> N

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Two other quick comments on the links between ABMs and DSGE. Haldane and Turrell (2018) recently produced a chart that tries to place ABMs in relation to DSGEs and more statistical approaches. The take-away for me is that ABMs and DSGE models are similarly internally consistent. To me this really means they are designed to theoretically hang together. At the other extreme a purely black-box neural network mapping past prices to future prices for example has no immediate theoretical interpretation. On the other hand black-box approaches might, in principle be more externally consistent i.e. they can fit the data better unencumbered by internal consistency constraints. There is a view that the constraints that DSGE models impose (driven by their deductive axiomatic nature) may mean they are potentially less able to fit the data better than ABMs. Haldane and Turrell's chart suggests this. But I am not certain these need necessarily be the case. Constraints can be extremely useful in avoiding overfitting and improving the generalisation potential of models. After all, the best black-box models (take neural network architectures) often employ all sorts of heuristic techniques to constrain their potential power, e.g. regularization techniques like pruning and drop-one-out cross validation etc.

A second comment is that DSGE and ABM modellers can most certainly learn from each other. Many of these ideas were expressed in a recent paper by Grazzini and Richiardo (2013). One thing they pick up on is that historically DSGE models have tended to be linearised in order to facilitate analysis. So even though they may contain nonlinearity and therefore behave in interesting ways outside of equilibrium, it is not obvious how to see this. Also in order to estimate them they are fitted in terms of detrended series. This is mainly to ensure stationarity, a necessary condition for estimation. In the ABM world, by focusing on simulated method of moments there has been less emphasis on these issues. Finally both classes of model suffer from similar problems related to their high numbers of parameters and short data sets, such as flat likelihood surfaces and so on. ABM and DSGE modellers probably have a lot more to talk about than might at first meet the eye.

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- New Directions

Empirical Validation of Agent-Based Models (Lux, Zwinkels, 2017)

Agent-Based Model Calibration using Machine Learning Surrogates (Lamperti et al, 2017)

Consistent Estimation of Agent-Based Models by Simulated Distance (Grazzini, Richiardi, 2013)

Bayesian Estimation of Agent-Based Models (Grazzini, Richiardi, Tsionas, 2015)

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- Some ideas of opportunities available today for …

- Risk Managers

- Better / complimentary risk models e.g. (Neuron's hybrid ABM-Crisp Conditioning Approach)

- Univariate model as an alternative, or complement to Monte Carlo or historical simulation

- Address volatility-paradox
- Endogenize liquidity

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- Generating Scenarios – Crisp Conditioning (Meucci 2008)

- Use the ABM to create distribution of potential paths in key market(s)

- Draw from an unconstrained block bootstrap distribution to be consistent with the ABM terminal distribution

- We retain the cross market correlations
- Simulate events that have never happened..
- ..but may be intuitively plausible and come with a narrative

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- Advisors
- Planning & risk communication / war games etc
- Traders / Managers
- Escaping the backtest
- Rule-based managers can give investors greater transparency
- Opportunistic Liquidity Provision (e.g. SWF)
- Identifying (regulation driven) opportunities, UK QE Exit?

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Some Applications

Advisors might use a simulation platform for demonstrating risk, comparing alternatives and playing through scenarios. Getting clients to try and imagine the experience in advance. Perhaps to help develop protocols that might be helpful to keep the investor calm in the future, mitigating the risk of rash decisions.

Traders might use simulation models as a compliment to back-testing. By supplying a richer set of alternative scenarios the trader can anticipate (and perhaps design robustness toward) and get a more genuine distribution of outcomes. Managers should use these forward scenarios to enhance their risk reporting.

Finally, from an "alpha" perspective traders might be able to identify distortions in pricing due to certain participants, for example in the yield curve due to the persistent hedging demands of certain players. An ABM may help test how resilient those distortions might be to other factors. Anyone with a keen interest in the UK corporate bond market may want to put themselves in the BoE/Treasuries shoes to imagine how they might be thinking about unwinding QE. Others with deeper pockets and patient capital may want to try and model the short-term distortions that might arise from a liquidity shock that could affect certain markets products differently, in effect creating a fair price model to be used as fire-sales play out.

- New Directions
  - Calibrating to micro data sets & non-price e.g. volume
  - Multi-variate & multi-product models (e.g. VIX/XIV)
  - Incorporating learning / experimental work
  - Microstructure (where asynchronicity matters)

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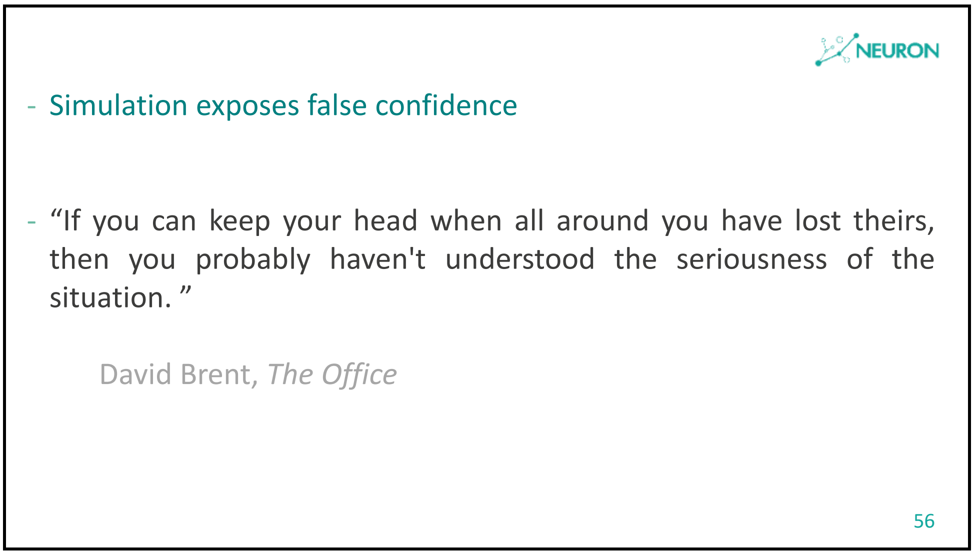
There are three other directions in which I suspect progress will be made.

More use of micro data sets, and non-price data should help propel financial ABMs. We are getting more data on individual and institutional behaviour all the time, partly as a response of regulators requiring it.

We will see the development of multi-variate ABMs, modelling more than one or two assets simultaneously, and different products linked to the same underlying asset simultaneously. This may facilitate potential relative value trading opportunities. An open challenge crying out to be modelled is the February inverse-VIX blow up.

Finally I expect to see richer microstructures enter the model. The market-maker approach (BLT) leads to a nice and interpretable price generating equation, but it is limited. In reality we would want to consider the asynchronicity that Markowitz modelled 30 years ago. We may well also want to reflect the reality of different trading venues, and different exchange types. Some ABM micro-structure models already exist (to study things like exchange rules), and it would be nice to see them tied up with lower frequency questions.

Overall it feels to me that the Markowitz institutional realism will combine with the Santa Fe learning and evolutionary emphasis to produce a new breed of ABM. We are also likely to see a blurring between DSGE and ABM within economics, not a bad thing either.



To end, one of the criticisms of financial simulation models is that you can do anything and so the uncertainty around any output is so wide as to be meaningless. I would flip this on its head. If your model of choice gives you confidence because it has tight confidence bounds and seems much more certain than what a simulation approach offers, you might want to revisit your model. I can't put it more eloquently than David Brent "If you can keep your head when all around you have lost theirs, then you probably haven't understood the seriousness of the situation. "

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