Pension Funds and Risk Mitigation

Crisis Protection or Crisis Propulsion?

The Best Way to Predict the Future is to Create It, Alan Kay[1]

Robert Hillman[2]

22 December 2017, London

Just as pension funds have begun allocating to trend-following as a hopeful source of tail protection[3], regulators are beginning to voice concerns over whether trend-following and other algorithmic risk-management strategies can amplify market downturns[4]. Might a pension fund's attempts to mitigate their risks be self-defeating?

As one trend-following pioneer put it when reflecting on the similarities of today's developments with the rise of portfolio insurance in 1987:

"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. " (Harding, 2016).

To put some rough numbers on it a conservative estimate of the AUM in trend-following is 220bn[5]. US Pension funds collective AUM is 22,000bn[6]. If each pension fund allocated 10% to trend-following as part of a risk-mitigation strategy, that would be an extra 2,200bn in trend AUM, 10 times the existing industry AUM.

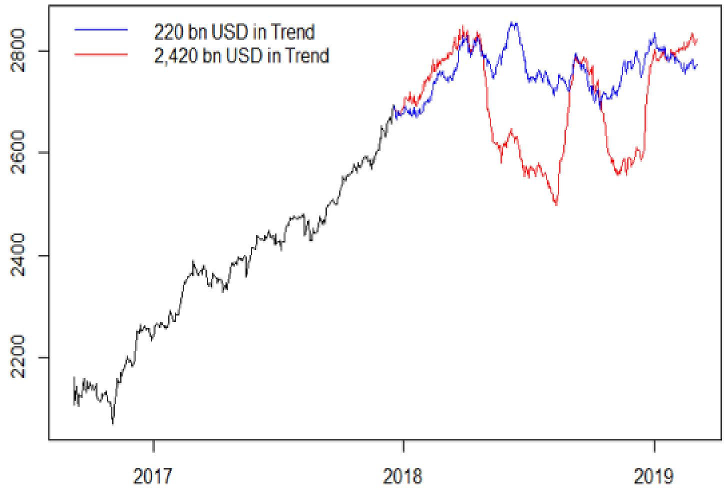

Chart 1. Two possible future paths for a simulated hypothetical equity index, with varying influence of trend followers.
Note: In these two paths the simulated index rises over the next year but they could just as

[1] I have hijacked this quote from a completely different context because I like it. https://en.wikiquote.org/wiki/Alan_Kay
[2] Robert is CIO of Neuron Advisers LLP.
[3] See P&I (2016, 2017) and Wigglesworth (2017).
[4] Most recently see IMF (2017). Others like the Office for Financial Research set up in the wake of the crisis, and the Bank of England have been warning about these issues for some time for example OFR (2013) and Bank of England (2014).
[5] See IMF (2017).
[6] Willis Towers Watson (2017).

easily fall. The point of the chart is to convey that whatever the terminal price, in a world in which trend-followers are more influential the path is likely to exhibit greater swings and sudden reversals. See rest of the text for explanation. Source Neuron Advisers.

As a preview of what is to come Chart 1 shows a hypothetical equity index over the last year and two simulated future paths. The blue path is one where trend-followers have little influence on the market they trade (it uses the 220bn AUM estimate). The red path represents a world in which trend-followers have become influential (using the 2,420bn AUM). Perhaps not surprisingly, the red path exhibits greater swings and sudden crashes and recoveries. In my illustration both paths end up rising by the end of the simulation period but just like any real-world equity index they could just as easily fall. The point of the chart is to convey that whatever the terminal price, in a world in which trend-followers are more influential the market is likely to exhibit greater swings and sudden reversals.

I produced these charts by building a small-scale simulation of an equity market. It is my belief that simulation methods are critical to analysing these 'what-if' scenarios. Historical data analysis is of little use. For example, since 1950 there have been only seven separate periods in which the S&P dropped more than 20%[7]. And markets change over time - the crux of regulator concern is that today's algorithmic strategies and risk-management are new and untested.

The problem has parallels with why meteorologists cannot rely on historical records to estimate the risk and scale of extreme weather[8]. Data sets are too short to contain the full range of possibilities and changing background factors such as greenhouse gases make older data less relevant. In the last few years meteorologists have turned to forward looking computer simulations of the climate for help. Economists are beginning to do the same.

In this note I describe some of my research using small-scale simulations to explore how vulnerable the equity market might be to a rise in trend-following. The approach belongs to a tradition of modelling best described as agent-based, or heterogenous agent models[9].

A simple model

I model an equity index price as determined by the trading demands of a variety of market participants or 'agents'. Because many of today's participants explicitly rely on algorithms it is natural to model them with algorithms. Other agents like corporates or discretionary hedge-funds are less predictable and I model their orders as random. I model each fund type with a single representative fund.

The time-step of my simulation is daily. Every day each fund calculates their order as the difference between their desired portfolio holding and their existing holding[10]. I use the fiction of market-maker who nets off buy and sell orders across funds and adjusts price in response to the remaining order. If say the

[7] Source Bloomberg/Neuron Advisers.

[8] I present and discuss these parallels in my 'Extreme Weather and Extreme Markets' paper.

[9] For recent surveys and arguments for why these models are beginning to see a resurgence of interest see Haldane, Turrell (2017) for a macroeconomic perspective; Bookstaber (2017) from an institutional risk-management perspective; and Hillman (2016) from a trading/algo perspective.

[10] It is trivial to introduce adjustment friction into this process, for example forcing each fund to only move x% toward their desired holding, or to imagine they have a more sophisticated optimal adjustment algorithm as for example explored in Garleanu and Pederson (2013).

trend-funds want to buy x and the portfolio-rebalancers want to sell x and no other funds generate orders there is no price impact. But if the trend-funds want to buy and there are no sellers the market-maker adjusts prices up by an amount that is a constant multiplier of the net order[11].

For the purposes of this exercise I do not model the impact of longer term allocation decisions (e.g. if pensions de-risk by switching out of equities into bonds) or flows of capital between funds (e.g. if institutional investors switch from medium to slow trend, or from trend to risk-parity)[12]. This allows me to focus exclusively on the mechanical trading behaviour of funds.

I have five main types of fund. I split trend-followers into two types: medium and slow trend-followers with average holding periods of approximately 2 and 4 months respectively. I split the benchmark 220bn trend AUM equally across the two types of trend fund. I also model risk-parity and variable-annuity funds, portfolio-rebalancers and 'other'. Table 1 gives some high-level characteristics and benchmark settings for each fund type. The notional assets-under-management (AUM) I give each fund type are somewhat arbitrary and hard to pin down.

Fund Type	Characteristic	Benchmark AUM (bn)
Medium Trend	Trend & Vol Target	110
Slow Trend	Trend & Vol Target	110
Core-Trend	Medium & Slow Trend & Vol Target	0
Risk-Parity	Allocation Vol target	175
Variable Annuity	Portfolio Insurer	440
Portfolio Rebalancer	60% Allocation Value target	22,000
Other	Random Orders	27,000

Table 1. Fund Types and Key Characteristics Modelled

I have chosen numbers from the IMF October 2017 Global Financial Stability Report to get me started. As I discussed in an earlier article there is no end of controversy about the absolute and relative size of these strategies

[11] This approach was introduced by Farmer and Joshi (2002). One way to make this more sophisticated is to allow the market maker to adjust prices more when volatility is higher, thereby introducing a simple form of risk-aversion, see for example Baranova et al (2016). This introduces another source of positive feedback from volatility to further price movements.

[12] In the earlier wave of ABMs agents themselves were often modelled as flexible in their strategy choice and would switch between strategies over time based on reinforcement learning or evolutionary principles, see Hommes (2013). Although this was sufficient to enable ABMs to generate many of the stylized facts we observe in markets (like bubbles and crashes and clustered volatility) it is a bit at odds with the real world. Most capital is managed by institutions who are generally slow to change their approach. A simple modelling solution is to introduce investors who can shift their capital into and out of different funds. With the increasing commoditization of investment strategies this mechanism may be becoming more potent (for instance ETFs mimicking factors, or risk-parity, risk-premia and trend-following UCITs and mutual funds). A live example of this mechanism at play is the apparent shift from active to passive investing. I suspect this is part structural (perception that active rarely outperforms passive) and part cyclical (return-chasing).

but I sense the numbers I use here are not controversially high[13].

How do my simulated funds behave?

The trend-followers are usually, but not always, destabilising because generally their trading is procyclical. If they are long equities to begin with as the market falls they will generate selling pressure, potentially amplifying the move. But there may also be a situation in which a trend-follower can buy into a falling market, potentially dampening a move[14]. This could happen if the trend fund is limit short. If market volatility increases as the market falls further it could end up buying to reduce its short exposure in order to try and meet its longer-term volatility target.

The risk-parity and variable-annuity funds are both driven by volatility. The risk-parity funds have a volatility target and reduce (increase) long exposure as their forecast of volatility rises (falls). I model the variable-annuity funds as following a form of portfolio insurance. They want to hedge the value of their equity portfolio dropping below a certain level and so they react to both price movements (as the price falls they need to sell equity futures) and volatility (which they estimate with historical volatility)[15].

The portfolio-rebalancers are a stabilising force in the market. When the market falls, other things being equal, they need to buy to offset the drop in the value of their holdings as a proportion of their broader portfolio. This rebalancing behaviour can be profitable if markets are mean-reverting and the fund finds itself buying-low and selling-high. But when markets move persistently downward the manager may find themselves consistently buying high[16] and facing what some have called 'wrong-way risk'[17].

The 'other' category represents the market agents I cannot simulate so easily. Examples would be value-driven hedge funds who might have disperse views on fair value, or funds pursuing multi-asset strategies that might be trading for reasons not directly related directly to the equity index itself. In the context of my virtual market model if these traders were the only ones the price would follow a random walk.

It is important to note that all of my funds have constraints on their exposures. A risk-parity fund will not keep buying equities if volatility keeps falling because they will hit leverage or risk caps. This fund level risk management is an important driver of some of the effects we will observe at the market level in simulations.

Calibrating and running the model

I use historical S&P data to calibrate each fund's position at the start of the simulations.

[13] My benchmark AUM numbers each assume a volatility target of around 15%. The IMF's variable annuity estimate of 440bn was for a vol target of 8-12% but I suspect the 440bn is a little low. According to the Insured Retirement Institute there is nearly 2 trillion USD in Variable Annuity net assets and 39% of that is in equity. http://irionline.org/newsroom/newsroom-detail-view/iri-issues-first-quarter-2017-annuity-sales-report

[14] This could also (and likely often does) happen if the trend model has a sense of trend 'overextension'; 'take-profit'; or long-term mean reversion – the funds we simulate here do not have these features built in because we want to focus in on a pure trend case.

[15] Variable-annuity (and other insurance like product) sellers may choose to hedge a variety of risks (e.g. directional, volatility, interest-rate etc). They are a diverse bunch as well but for simplicity I use a representative fund to model their trading demands.

[16] One established trend follower manager has proposed institutional portfolios could use trend-following to offset these rebalancing costs, Granger et al (2014).

[17] See Edleson (2013) how this and other factors lead to institutional portfolios suffering disproportionately badly as equities fall. A fancy term for this is negative-convexity.

As the simulation steps forward fictional prices are created one day at a time. The model can generate an infinite number of potential paths but I only focus in a few that help illustrate how the market dynamics can be qualitatively different under different modelling assumptions. It is important to emphasise that these forward simulations should not be seen as a forecast of the S&P, that is not the purpose of this exercise[18].

I need to calibrate the average random order size and the market-maker sensitivity factor. To begin with I calibrate the random order size so that the algo funds represent a small part of the market. It is easy to visualize this in Chart 1 which shows the orders for each fund type over a 100-day window. The market-maker sensitivity factor is determined so that the daily return volatility of forward simulations matches recent history[19].

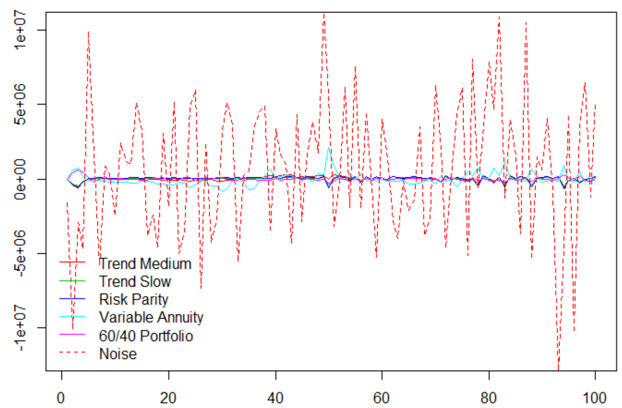

Chart 2. Simulated fund trading orders in Benchmark Case.

Note: The noise orders swamp the fund orders. Source Neuron Advisers.

Experiment 1 – what happens as more money flows into trend?

In my benchmark settings the size of the trend funds (and other fund types) are small relative to the noise orders as can be seen in Chart 2. To explore how pension fund allocations to trend-following could become influential I take US pension fund AUM as 22 trillion USD. To keep things simple I look at two possible allocations to trend-following (that might be part of a broader crisis-risk offset or risk-mitigation strategy), either 5% or 10% to trend. These assumptions are in line with some recently published reports from various sources, summarised in Table 2.

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%

Table 2. Some typical allocations to trend-following for risk-mitigation purposes.

Notes: Target column shows the publicised target allocation (of total AUM) to be allocated to risk-mitigation. The '% in Trend' indicates how much

[18] That said, if I did want to forecast with this kind of agent-based model it is perfectly possible. In my experience this is not widely understood. Most people I've come across think ABMs are interesting for exploring how systems might behave, but they have no predictive ability. This is not true. It might help to think of an ABM as an alternative or compliment to Monte Carlo simulation. Alternatively, you can frame an ABM like the one I use here as a nonlinear model. Hommes (2013) book contains examples that directly compare ABMs to nonlinear econometric models like smooth-transition autoregressive models. Once you make this connection it opens the door to bridging ABMs with statistical models and inference techniques which will in turn resolve some of the scepticism surrounding ABMS.

[19] Note this is quite a loose requirement. If average volatility (as measured as the sample standard deviation of daily returns) was 15% then all I require is my forward simulations on average produce 15%. It does not say anything more about the return distribution and does not preclude effects like clustered volatility and excess kurtosis. It is in the spirit of simulated method-of-moments approaches as I discussed in my Extreme Weather paper.

of that is allocated to trend, and the final column gives the implied trend allocation as a proportion of total AUM. Source: various, see footnotes.[20]

Chart 1 showed two typical simulation runs, beginning 18th December 2017. The blue line is under the benchmark settings. There is 220 bn 'in' trend-following strategies but in my benchmark model they are a small part of the overall market. As Chart 2 indicates (from the same settings) their daily orders are barely visible compared to the size of the random orders. The red line in Chart 1 is a simulation where our pension funds have allocated 10% to trend-following, bringing the overall AUM to 2.4 tn (I retain the 50/50 split across the two speed of fund). In other words, it represents a world in which there is an additional allocation to trend that is 10 times the benchmark allocation of 220 bn. Now we see big swings in price.

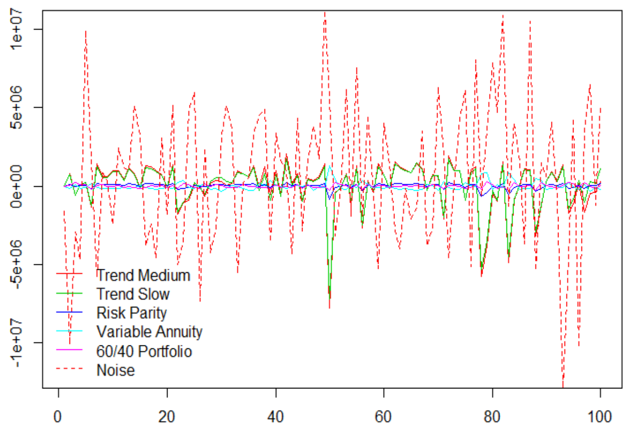

Chart 3. Simulated fund trading orders when Pension Funds allocate 10% to trend. Note: A lot of the time the noise orders swamp the fund orders but occasionally the trend orders become large. Source Neuron Advisers.

Chart 3 shows the trading orders when trend AUM is 2.4 tn. It is apparent that at times the trend orders can become large. The impact trend followers have at any point in time depends on what else is going on. If by chance the rest of the market produces offsetting orders it will dampen their influence. But, if their sell (or buy) orders happen to coincide with sell orders from other constituents they can amplify trends in either direction.

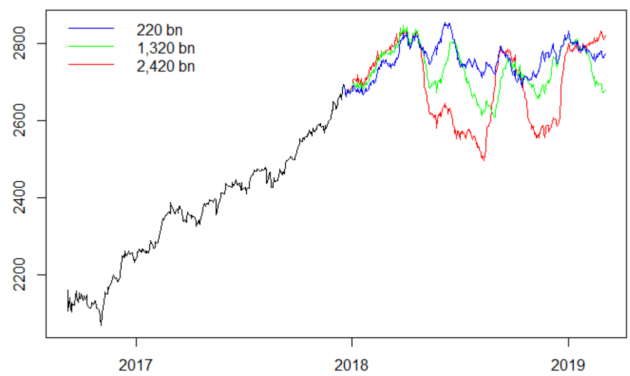

Chart 4. Three possible future paths for the S&P under three different assumptions of trend follower AUM. Source Neuron Advisers.

Chart 4 adds the 5% allocation case. At first glance it appears to lie somewhere in between the 0% and 10% cases. But in fact moving from 5% to 10% is more significant than moving from 0% to 5%. To see this more clearly I run another experiment.

Experiment 2 - Do trend followers amplify shocks?

I now consider that an external hit shocks today's market and causes three days in a row where the price drops 1% a day. I then let the model run as before. Chart 5 shows three

[20] These numbers come from the P&I articles (2016, 2017a), Wigglesworth (2017) and PCA (2017) and SJCERA (2015).

simulated paths. In each path the simulated market experiences the exact same random orders, the only thing that is different is the AUM of the trend followers.

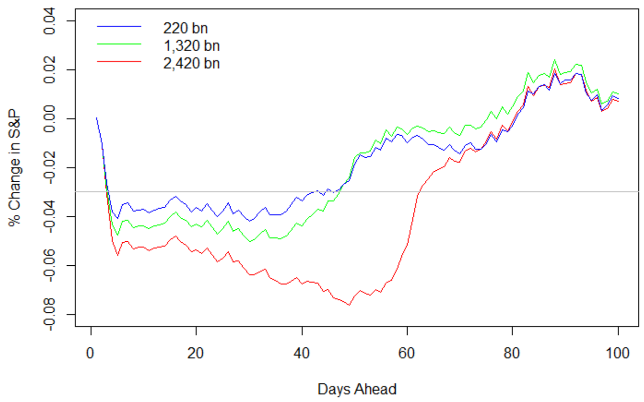

Chart 5. Response to a shock for a hypothetical equity index.

Note beginning the 18th December 2017 the simulated market experiences three down days of 1% a day. The three paths show simulations under different AUM assumptions in trend-following. Source Neuron Advisers.

What Chart 5 shows is that the simulated market response to a shock is quite similar if there is 220bn or 1,320bn AUM in trend. There is a little bit more follow through initially with the higher AUM but nothing striking. The situation changes when we endow the trend followers with 2,420bn, associated with the scenario in which pension funds allocate 10% to trend. We see a slightly greater initial follow-through but then we see a marked divergence between 20 and 50 days forward during which the market price keeps falling. After 50 days the funds are mainly limit short and at this point they are much more vulnerable to a positive shock. The rebound is extremely rapid. By day 100 the market price is almost identical and daily moves are highly correlated across all 3 scenarios. This is a function of the fact each path uses the same underlying sequence of random orders. Towards the end of the 100 day window each fund happens to be in a similar state and generating relatively small orders compared to the wider market.

The rebound scenario is consistent with investor interest in the positioning of speculators as evidenced in the widespread practise of analysing the CFTC commitment-of-trader reports. It is also consistent with the increasingly common reporting and discussion of trend-follower positioning. Often discretionary macro traders show an interest in how CTAs are positioned as part of their process of building up a qualitative picture of the risks embedded in the market[21].

Concluding thoughts

In this note I have attempted to shed some light on the potential influence of a growing trend-follower industry. The idea that trend-following, or risk-management, can end up affecting the underlying market is an old one and the modelling concepts I use here are not new. What is perhaps new, and pressing, is how widespread the use of algorithms is becoming. The potential that pension funds, and others, in seeking to mitigate their own risks might be inadvertently contributing to systemic risk is one worthy of more consideration.

My analysis shows, within the context of a small-scale computer simulation, that being able to anticipate the scale of this risk is hard. If you are prepared to take the model seriously, a simple take-away would be that at current allocations trend-following is not big enough to seriously destabilise markets. But that conclusion comes with a caveat, supported by the model, that there may well be a tipping point where market dynamics

[21] For an example see Childs et al (2016)

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can suddenly change as the influence of these traders become significant. This kind of tipping point is often observed within nonlinear complex adaptive systems, indeed it is a defining characteristic of such systems.

As markets become more algorithmically driven it has a positive side effect of making the modelling of those markets more credible. I predict that in a short space of time not using agent-based and related computer simulation models to understand modern markets will look as odd as trying to design an aircraft without a simulation environment and computer aided design.

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