Snapback risk in government bond markets

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22 August 2018, London

On the 27th June 2017 Mr Draghi surprised the market by shifting expectations about the timing of monetary policy withdrawal. It evidently caught the market off guard as judged by the sudden price reaction. Yields then continued to move higher over the next few hours and days. In this note we consider how we might go about analysing whether the reaction of the market was related to the growing use of algorithms in the market. We frame our narrative around an agent-based-model, a type of computer simulation of the market.

ON the morning of the 27th June 2017 Mr Draghi said that deflationary forces had been replaced by reflationary ones. Yields jumped across Europe. The yield on Euribor contracts for September 2018 moved 6 basis points (bps) higher, ones on contracts a year further out rose by 10 bps. The ten-year German government bond yield rose by about 13 bps on the day, and has subsequently continued to rise breaking above the range in which it has traded so far this year. At the time of writing (the 12th July 2018) it is some 30 bps higher[2]. Chart 1 shows the price of the bund future.

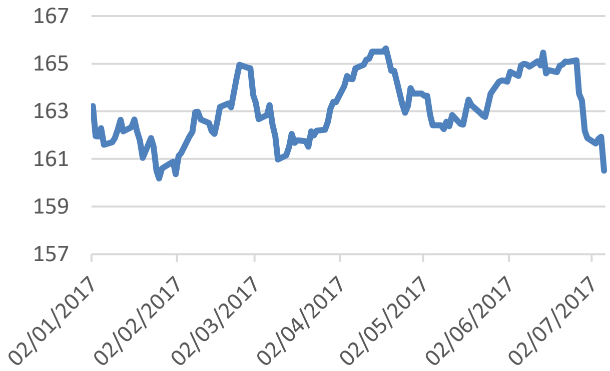

Chart 1. The German Bund Future Price
Data: 1 Jan to 6 July 2017
Source: Bloomberg/Neuron

A policy maker says something. Expectations adjust. Prices change. So what?

The 'so what' is that there is a growing narrative in the market that markets are becoming increasingly unstable because of the rise in the use of algorithms. It is possible that some price moves we observe are the result of algorithmic portfolio and risk management and not pure expectations.

Snapback Risk

The Bank for International Settlements (BIS) recently suggested this phenomenon could pose a risk in government bond markets. They brought attention to what they have termed 'snapback risk' (Shin, 2017). They focused on the potential dynamics created by insurance company trading of long-dated bonds. At the heart of the issue is the

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[1] Robert is CIO of Neuron Advisers LLP. An earlier version of this article was originally published for our clients only (in July 2017) with the title 'Towards a new framework for today's markets'. This version is slightly updated to reflect subsequent attention drawn to related issues by policy makers such as the Bank for International Settlement, as explained in the text.

[2] Source: Bloomberg.

observation that insurers hold long-dated bonds as assets, while at the same time use the yields of long-dated bonds to measure their liabilities. When bond prices rise, yield fall and insurer liabilities rise. Asset-liability-management (ALM) programmes (implemented as an algorithm) would determine they need to buy bonds. Other thing being equal, this puts upward pressure on price, thus creating a positive feedback. What concerns the BIS today is how this process might work in reverse. Specifically, they consider the risks associated with the end of quantitative easing, when central banks slow their asset purchases, yields may rise and kick-off a selling spiral. Small initial changes in quantities (bond supply) may end up causing large amplified price effects.

Rising concerns

These types of concern are not restricted to fixed income. In fact, far more focus to date has centred around equity markets. There are two particularly popular refrains. First, that the rise in passive trading is zombifying the market, delinking stocks from any rational or even vague sense of relative valuation. Second, and our focus here, is that the use of risk management procedures designed to control portfolio volatility might lead to a deleveraging death-spiral[3].

Journalists smell a story. Quant strategists sense a chance to call the next Big Short. And high-profile fund managers have been baited into defending their approaches[4].

These questions are not just of interest to regulators and policy-makers. Some of the exact type of funds that the death-spiral protagonists have in their sights have themselves suffered some of their worst losses for years in June 2017, see Chart 2. Evidently it is in their self-interest (and ours too) to find ways of addressing these questions.

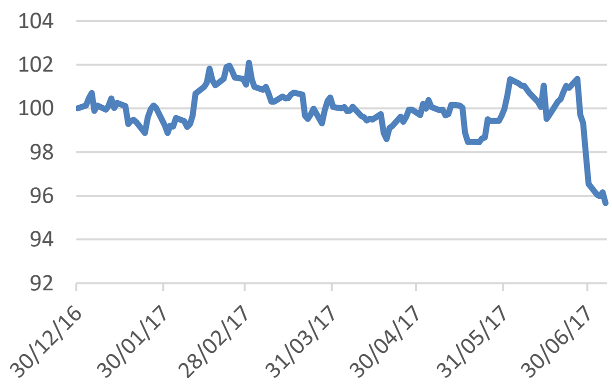

Chart 2. The SG CTA Index
Data: 1 Jan – 6 July 2017
Source: Societe Generale. See notes[5]

When history can't help - turn to simulation

History is of little help in considering the impact of algorithms. We can't look back and say, this is like 1987. Well, we can, but the truth is it isn't just like 1987[6]. History tends to rhyme but not repeat.

If history cannot help we need to look to other ideas. Our proposal is to build computer simulations of *today's* market. We see these simulations, which are just a

[3] For a nice example of today's confidence in volatility control methods see Andrew Lo's comments in a recent roundtable moderated by Leibowitz (2016). He was challenged that vol control sounded a lot like portfolio insurance.

[4] Perhaps tensions, and the fund manager response, are best exemplified by AQR in their article 'Dog Bites Man'. This was written in 2015 but if anything the debate has since intensified. Zero Hedge supplies a streaming, and often screaming aggregation of third-party analyses of the issues.

[5] The CTA Index comprises 20 of the largest CTAs and is designed to be representative of the managed futures space. The index history goes back to Jan 2000. There have been only 3 separate periods of comparable duration during which the index fell more: Nov 2001, Mar 2003 and Mar 2007. https://cib.societegenerale.com/en/prime-services-indices/

[6] We discussed some similarities in Hillman (2015).

computer program fed with data, as a type of model. If we can build up a reasonably accurate model of how today's market works, its players, their behaviour and the institutional network in which they interact, then we can simulate it to see what kind of behaviour emerges. It is possible to use these models to run experiments, for example varying exchange rules like speed-bumps and circuit-breakers, or altering fund redemption policies. We can explore what the effect of an increase in the use of passive trading might be. This is not idle speculation. Policymakers have been doing precisely these sorts of things recently[7].

Snapback risk from risk management?

In our own work – as a hedge fund manager trying to get insights into shifting market dynamics - we have built research models that attempt to reflect some of today's institutional realities[8]. We consider a market that is primarily driven by different fund trading strategies. We model various categories of these fund strategies such as 60/40 types, passive index trackers, trend-followers, risk-parity and value traders. We model end-investors as following intuitive and empirically founded heuristics, such as return-chasing. This allows capital to shift away from losing strategies towards winning ones. Note in this paper we did not include insurance companies (the focus of recent BIS concern) but hopefully it is obvious this would be an easy extension.

We accept there are many market participants that are harder to model like corporates and hedge-funds pursuing complex multi-asset strategies[9]. We also know that random things happen. News breaks. Brexit happens and Trump gets elected. We reflect this less predictable activity as random shocks in our computer simulations.

Our simulated funds trade with each other via a simple synthetic market mechanism. In order to operationalise the model we need to make certain assumptions, such as the relative amounts of capital following different trading strategies, and the behaviour of the strategies themselves. For example, we need to plug in how much money follows trend-following, how much is in passive and so on. Industry estimates vary on these inputs. However, and in our opinion one of the strengths of this approach, is that within the context of our simulations we can explore sensitivity to these assumptions.

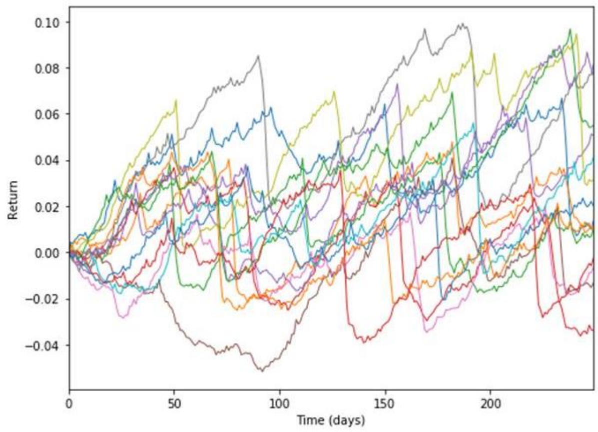

Chart 3. Some typical bund futures path runs from a computer simulation
Source: Neuron. See text for details

A pattern we observe is shown in Chart 3. It shows a few typical runs of a simulated market, in this case calibrated to the bund

[7] We discussed and provided several references in our 'Science Fiction Becomes Fact' note, Hillman (2016).

[8] The research model we designed to explore the issues is a kind of hybrid between the Hommes (2013) n-type models, and the corporate bond market model in Braun-Munziger et al (2016).

[9] Although many hedge-fund strategies have recently become commoditized and widely available. For example, in mutual fund or exchange-traded fund format.

future[10]. Each path is optically different but they all exhibit an irregular and strongly asymmetric cycle. Prices tend to rise gradually at first, gaining momentum, before levelling off. At some point thereafter they fall sharply, yields snapback, and then the pattern repeats.

What drives the pattern in our computer simulation is the systematic risk management process embedded in the trading strategies of the various funds. There are two key features. First, they calculate the risk of their positions (size their trades) based on historical volatility. Secondly, they have a notion of position saturation (risk limits). Trend-followers are induced into buying as prices begin to rise. During this period volatility is falling as the shock of the previous price collapse decays into the past. Other things being equal risk-parity and other volatility-control types tend to buy more[11].

In our simulation model as funds build their positions they edge ever closer to being limit long. In doing so their activity declines. In the absence of significant news or shocks to the market, volatility continues to fall. As this process continues the market gets more unstable. Positioning gets to extremes, at which point it is much 'easier' for funds to sell than to buy. A single piece of news can have a very asymmetric effect on prices. An external shock raising volatility will generate selling via the volatility control channel. Even a large positive news shock can lead to net selling if the volatility control pressure to sell outweighs any trend strengthening that may cause buying pressure[12]. In the absence of stabilising buying as the price falls, trend follower signals weaken, adding to the selling. As our simulations indicate this process can accelerate and force prices down very quickly[13].

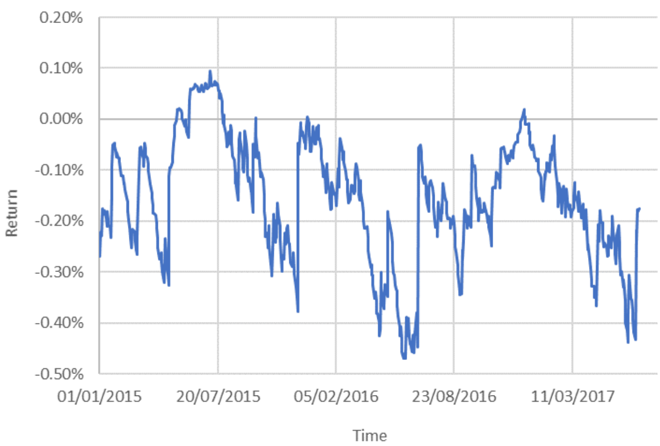

Chart 4. The vulnerability of our simulated market over time. Source: Neuron. See text

This approach can also help suggest when our simulated market is more or less vulnerable to an external shock. Chart 4 shows an example of how we may look at it. We show how far our computer simulation price moves 3 days after a 1% exogenous shock hits the market[14]. In doing this exercise

[10] We have calibrated this model so that our active traders (the 'funds') generate orders that are on average the same size as the random orders. One of the characteristics of these types of models is that 'average' market statistics can be misleading. At times, even in the absence of large external shocks, we see our active traders contributing much more than average and it is at these times market dynamics become temporarily predictable.

[11] We accept there are many ways of implementing risk-parity type strategies. Not all emphasise smoothing portfolio volatility over time, and the ones that do will vary in their aggressiveness, which will often be constrained by their size. More granular models can allow for heterogeneity within the fund strategy type.

[12] Many trend followers look at measures of risk-adjusted trend like the Sharpe ratio of past returns. Due to the construction of the Sharpe ratio an extremely large positive return could reduce the Sharpe ratio if the denominator (volatility) rises by more than the numerator (average return).

[13] These sorts of asymmetric dynamics have been demonstrated many times elsewhere. Three prominent and useful examples are Thurner et al (2012); Hommes (2013) and Bookstaber (2017).

[14] These numbers are averages over many simulations. Each point on the chart refers to a 3-day forward (t+3) out-of-sample forecast made using only market data known up to the time of forecast (t), conditional on a shock occurring at time t. The forecast is made by simulating the model forward many times under different future shock paths. This process produces a

we have lowered the influence of our active traders so the ratio of noise orders to our fund orders is 5:1. Even then we see interesting effects. Within the context of our simulation, our artificial market is at times more vulnerable to a shock that at others. During June 2017 the follow-through to an external shock was estimated to be at the highest for a year. Subsequent to the actual shock on the 27th our simulated active traders reduced risk, reducing the vulnerability to a subsequent shock back to more typical levels[15].

Using these models for real-time forecasting of risk is novel and there are no examples we are aware of[16]. But there is nothing magical about it. If anything, it would be intuitive to a discretionary macro trader, particularly ones experienced in implementing contingent trades with options when the future path matters. When building positions, macro traders have long taken factors like market positioning, skews, and stop-loss levels into account. Not surprisingly macro managers often demonstrate a keen interest in how systematic funds are positioned. It is all part of building a dynamic picture of the market.

Appropriately calibrated computer simulation models offer the prospect of systematically projecting the risks from these kinds of factors and updating them in real-time as the actual market path evolves.

Whether and to what extent the market follow-through to Draghi in June 2017 was influenced by these internal market dynamics is hard to say definitively. It is possible that prolonged price movements simply reflect a gradual shift in expectations about the future level of interest rates, what behavioural finance calls an information-diffusion effect (Hong & Stein, 1999). These theories make nice empirical predictions like the idea that momentum effects should be greater in markets populated by less sophisticated investors or where costs of trading are higher.

But our experiments indicate to us at least that these potential internal market dynamics should not be ignored. Computer simulations of markets appear to offer a promising framework to explore these issues.

distribution of future prices at each point in the future. We report the mean of the forecast density 3-days ahead, but in practice the full distribution is likely to be much more meaningful from a trading perspective.

[15] The size of the follow-through we show is empirically small, on average around 20bps and increasing to 45bps. When positions are light there may be little, or even small positive impact. We would caution against over interpretation of these numbers but focus instead on their relative variation. As stated above we applied an assumption here that our active funds are outweighed by random noise trading in a ratio of 5:1. If we change this to 1:1 then we see much larger effects. The follow-through can be as much as 3.5%. Further inspection also reveals that while the average follow-through increases moderately, the generation of extreme moves ('fatter tails') increases. This result is consistent with findings in Braun-Munziger (2016).

[16] Hommes (2013) contains a retrospective forecast of the US equity market contrasting a linear regression model with a 2-type heterogeneous agent model.

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