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Systemic risk and systematic trading: how much can we know?

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Since the Global Financial Crisis we have witnessed a number of sudden market “corrections” or “dislocations”. These have cast a spotlight on the supply and demand of liquidity in financial markets. The analysis of these events has brought attention on market participants that react in a systematic way to price movements. In the financial press a question has been asked for CTAs and risk-parity funds: do they induce positive feedback which might amplify market movements? There is no objective data available to answer this question, and so in this paper we make order-of-magnitude estimates of the response of these two types of market participants to a shock. Under normal conditions, their estimated price impact is small, but under extreme circumstances, we estimate that they could have a discernible impact.

Systemic risk and positive feedback: pumping up the tulips

Positive feedback has been a feature of financial markets since their beginning. In asset price bubbles, rising prices feed confidence and attract more buyers, who further increase the price (sometimes intentionally, ‘pumping up the tulips’ [1]). From the South Sea Bubble to the 2008 financial crisis, traders have seen a falling price as a signal to sell in order to avoid further losses [2]. Selling drives the price down further, leading to a spiral of positive feedback and a market crash. Systematic trading strategies can suffer the same problem. An example is portfolio insurance, blamed for the stock market crash of October 1987 [3].

Two groups of systematic trading strategies have seen large growth in assets recently: trend-following strategies employed by CTAs (Commodity Trading Advisors) and risk parity. Trend following aims to profit from trends by buying as the price rises and selling as it falls. The potential for positive feedback is obvious. Risk-parity funds aim to maintain a fixed level of risk in a particular asset. A large price movement will increase the fund manager’s estimate of the volatility, and so lead to selling as the fund attempts to maintain a fixed level of total risk. Again, selling may lead to further price moves. Recent articles in the financial press and blogs have suggested that these two classes of funds may cause or exacerbate financial crises [4] [5] [6] [7] [8] [9].

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In this paper, we estimate how important these effects might be. We concentrate on a single futures market: CBOT ten-year US treasury futures. This is the most active bond futures market and is one of the largest components in the portfolio of a typical CTA or risk parity fund.

There are three steps in the calculation. We first estimate the assets managed by CTAs and risk parity funds. We then model their trading in response to a large price movement. Finally, we estimate the price impact: how much would they move the markets?

At every step, there are uncertainties. This paper describes 'back-of-the-envelope' calculations. We aim to understand the order of magnitude of possible effects using limited information. There is a long tradition of such calculations in science. In a famous example, Enrico Fermi watched as scraps of paper were displaced by the shock wave from the first atomic explosion in the New Mexico desert in 1945 [10]. Using this limited information, he estimated the energy released. He was wrong by a factor of two, but obtained a quick answer with the information available. Similarly, we believe that an approximate calculation, combined with honesty about the unknowns, is preferable to no calculation at all.

Assets under management

A 2014 Winton working paper estimated the assets managed by CTAs [11], and we recently published updated figures [12]. There is some uncertainty because of CTA-like strategies managed in-house by pension and endowment funds, but we estimate the assets in CTA strategies in 2015 are approximately $230B.

Risk parity funds are more difficult to track. The largest risk parity fund is Bridgewater's All-Weather Fund, with approximately $75B under management. We can identify several other funds, of which the largest are AQR, Invesco, Salient and Putnam. Their assets add up to perhaps half the All-Weather total [13]. However, we believe that assets managed in-house by sovereign, endowment and pension funds and by investment banks form a larger fraction of the total for risk parity than for CTAs. This agrees with published estimates of $400-$500B for total risk parity funds [9] [14].

Models of trading strategies

We will not attempt to construct a detailed model of the combined behaviour of all CTA and risk parity funds. Instead, we make a simple estimate of the risk allocated to a single futures market.

Risk targets, volatility and leverage

For both types of fund, it is useful to work with 'risk targets' expressed as annualised volatilities in dollars. This allows us to speak about different types of investment on equal terms.

For example, suppose we have a hundred-million-dollar investment in the S&P 500 and a hundred-million dollar investment in two-year US treasury bonds. Both the equity and the bond position might be held in the assets themselves, or in an exchange-traded fund, or as long positions in futures contracts. In any case, the notional value of the equity and bond investments are the same, but their contributions to the portfolio performance are quite different.

Because the annual volatility of the S&P 500 is about 15%, and the annual volatility of the treasury bonds is about 0.8%, changes in stock prices are likely to have a much stronger influence on the portfolio value than bond movements. To put it another way, the 'risk' (measured as dollar annual volatility) of the stock position is $15M, while the 'risk' of the bond position is only $0.8M. We place 'risk' in inverted commas because we know that volatility is only one measure of risk.

Both risk parity funds and CTAs use leverage and tend to allocate capital using measures of risk rather than by notional value. In both cases, the algorithms used to form a portfolio are more complex than the back-of-the-envelope estimates we give here and vary from fund to fund, but we can get a rough estimate of likely positions with a simple calculation.

A risk parity industry model

For risk parity funds, we assume an annual volatility target of 8% of the assets under management (AUM), with this volatility shared equally between four asset classes. The annual volatility target for a single asset class, such as government bonds, is then 4% of AUM (not 2%, because for uncorrelated assets we must sum the variances to get the portfolio variance). We assume that trading in this asset class is shared equally between four highly correlated assets, one of which is ten-year US treasury futures[1]. The annual volatility target for our positions in this market is then 1% of AUM.

The trading rule for our risk-parity model is very simple. We make a backward-looking estimate of the market volatility over one year, and our position is scaled inversely to this volatility, to target an annual volatility of 1% of the $400B total assets (in this case, annual volatility of $4B). To achieve this volatility, we need a position of around $75B in the futures contract, since the annual volatility of the futures prices is about 5.4%.

To check whether this model was realistic, we examined public material released by the largest risk parity funds, and in most cases found figures which allowed us to estimate the size of positions in this futures market. In all cases where we could make an estimate, it was equivalent to a position with annualised volatility between 0.3% and 1.5% of assets.

A CTA industry model

For CTAs, our method is similar. We estimate the total trend-following positions in ten-year US treasury futures. We assume a total volatility target for an average CTA of 12% and risk shared equally between eight uncorrelated asset class/strategy combinations. For example, these might be trend-following on the six asset classes of equities, bonds, short-term interest rates, currencies, energy and other commodities, and two other strategy groups such as carry or seasonal systems. This leads to annualised volatility of 4% of AUM in trend-following on bonds. As for risk parity, we share the positions equally between four highly correlated markets, so that the annual volatility target for positions in ten-year treasury futures is again 1% of the total AUM. This would correspond to a position of $43B (nominal value) for a $230B fund, again using the 5.4% volatility of futures prices. But while the risk parity fund aims to maintain a constant level of risk, the trend-following algorithm allocates more risk to a market when trends are detected and less when no trend is present.

We combine trend-following trading systems with a range of timescales from a few days up to a year, choosing weights concentrated at intermediate speeds to reflect what we believe is the balance of activity in the industry. The model uses a moving-average crossover system, modulating its position using a backward-looking 60-day volatility. The average holding period is around 4 weeks. The average risk is 1% of AUM. In this case the assets are $230B. Again, we can check the accuracy of our model by comparing with public material from CTAs (and with our own private information). The position taken is sensitive to both the trend over the last few weeks and the backward-looking volatility, so the strongest signal for a reduction in position occurs when the price drops suddenly after a sustained positive trend.

Comparison

Figure 1 shows the positions taken by these two models over the last fifteen years. We are interested in the behaviour of the current industry's strategies, so the assets managed have not been scaled down as we go back in time.

The two models behave very differently. The risk-parity model scales up its position as volatility decreases (as in the quiet period leading up to the financial crisis of 2007-8), aiming to maintain constant risk. The trend-following model takes its largest positions after a sustained upwards or downwards trend, and swings from positive

[1] One of these four assets, for example, might be a group of cash bonds, or another high-capacity bond futures market such as German Bunds or US five-year treasury futures.

to negative according to the direction of market movements. For the CTA model, peak positions are up to three times the average level of $43B.

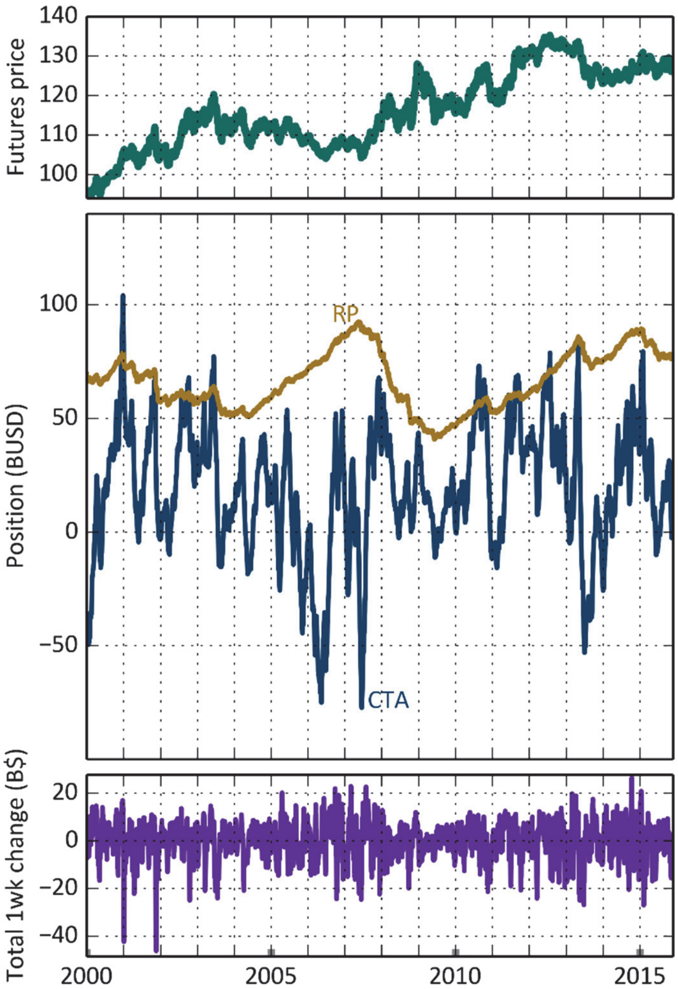

Figure 1: Positions taken by simple models of all CTAs and all risk-parity funds in ten-year US treasury futures. The upper plot shows the price of the nearest-to-expiry futures contract, the middle plot shows positions (nominal value) of the risk parity and CTA models, and the lower plot shows the one-week change in combined position. Assets under management are fixed at 2015 estimates throughout.

The busiest week for our combined model was in November 2001, when 46 billion dollars of nominal value were sold. This was the week of Enron's collapse. The company was forced to liquidate a large position in interest-rate futures as its financial position deteriorated [15]. This, together with changing market opinion on future interest rates, caused large swings in the prices of fixed-income assets. Both models sold: risk parity funds in response to an increase in volatility, and CTAs in response to a downward price movement against the previous trend.

Assets managed by both CTAs and risk parity funds were smaller than in our models in 2001, so this is not a realistic picture of market activity at that time. But this is an example of the type of event that we want to study.

Sell-offs: a worst-case scenario

We would like to know how risk parity and CTA funds would respond in the worst case. Looking back over the history of ten large global bond futures markets, the largest increase in (one-year) volatility σ in the space of a single week was 23%. This happened in Japanese bond futures, when quantitative easing was announced in 2013.

We will take this largest volatility change as the worst case. If a risk parity fund scales its position by σ^{-1}, then a 23% increase in σ leads to a 19% reduction in the position. Our model has average position $43B, so this is a sale of $14B of nominal value. We have assumed no limits are set on the amount of trading. This is almost certainly untrue, as we discuss below.

Similarly, we can run our CTA model across the history of the same ten markets. We find that the largest sell-off in one week occurs, again in Japanese bond futures, during the 'VaR shock' of 2003. The amount of selling is equivalent to three times the annual risk target. In ten-year treasury futures, this would mean sales of $129B of nominal value.

Added to the $14B figure for risk parity funds, this gives the total amount of one-week selling in our worst-case scenario. The total is $143B of nominal value in this futures market in one week. We should compare this with the typical volume of trading, which is about $150B per *day*. Before looking at the impact of this selling, we stop to wonder whether this level of trading is realistic.

Volatility updates and trading caps: a more realistic scenario

After the stock market turmoil of August 2015, there has been discussion in the financial press of the role of risk parity funds in market crashes [4] [5] [8] [9]. Calculations similar to the one above were proposed. Several sources then suggested that the true level of trading would be smaller. For example, according to a a *Financial Times* blog article [16], Bridgewater's risk levels do not change in response to short-term volatility estimates, and other material released by Bridgewater seems to agree [17]. Salient released a note indicating that daily changes are limited to 1% of the position [18].

	CTA	Riskparity
Assets	230B$	400B$
Mean risk (1 market)	1%	1%
Peak risk (1 market)	3%	1%
Peak value (US10Y)	129B$	74B$
No trading limits:		
Est max change (1wk)	-100%	-19%
Est max sales (1wk)	**129B$**	**14B$**
With limits:		
Est. max. sales (1 wk)	**75B$**	**2B$**

Table 1: Worst-case scenarios for sell-offs in 10Y us treasury futures. For models of all CTAs and all risk-parity funds, we estimate positions in this futures market. Trading in response to a volatility shock is estimated with no limits on trading and with daily limits. Risk figures are the annualised volatility of positions in a single market as a fraction of the assets under management.

With this information in mind, we assume that half of risk-parity funds do not respond to short-term changes, and the other half limit changes to 1% per day. This would imply a maximum total change of 2.5% of the $74B risk parity position in a week.

CTAs also limit their daily trading. Winton's limits are confidential and depend on the capacity of individual markets. We do not know the limits applied by other CTAs, but we suspect that our limits are more severe than most others. A conservative estimate is that the CTA industry as a whole limits its activity to 10% of the market volume each day: this would allow selling of $75B in the space of a week.

Taking these limits into account, we again estimate the total sales that CTAs and risk-parity funds might make in a week, in response to a sudden decrease in prices. The amount is $77B. We believe that the trading limits leading to this figure are probably more severe than the true levels, so it is likely that the real level of trading in a 'worst-case' crisis would be between $77B and $143B. A larger amount of trading is possible if we assume larger assets managed. The largest part of the selling (in either case) is from CTAs.

Price impact

We would like to know how much these sales move the price. Again, there are large uncertainties, but we take the view that an approximate calculation, with an honest assessment of the sources of error, is better than no calculation at all.

Normal trading conditions

The average price impact of many small trades, in equity or futures markets, can be predicted with some accuracy [19] [20] [21] [22]: it is typically modelled as proportional to $(T/V)^{\gamma}$, where T is the trade size, V is a measure of the volume in the market and γ is an exponent with value around 0.5. Because of the large random movement of prices during trading, it is necessary to average over many similar trades to validate a model. It is difficult to estimate the impact of large trades because financial institutions avoid large trades as much as possible.

For our estimates, we use a model implied by the work of Tóth *et al* [20]. For half a million trades across many futures markets they found that, on average,

$$\delta p \sim 0.7\sigma \left(\frac{T}{V}\right)^{1/2},$$

where σ is the daily volatility and V the daily volume in the market. This power law is an excellent fit to the data across three orders of magnitude (T/V from 10^{-5} to

10^{-2}). To use it for our problem, we must extrapolate another order of magnitude, to $T/V \sim 0.1$.

We must also make the distinction between trading cost and price impact. The trading cost δp in the equation above is the difference between the futures price before trading starts and the average price obtained during execution. Published work (for example, [22]) and our own investigations suggest that the residual price impact remaining after trading is typically about two-thirds of this immediate impact.

There is one more adjustment we should make. A large movement in ten-year treasury futures is not likely to take place without similar movements in other bond futures markets. In a crisis, CTAs and risk parity funds may make similar trades across all bond futures, and there is likely to be cross-market price influence which increases the impact. It is difficult to estimate the size of this effect, but we know that it is present (see [23] and [24] for studies of linkages between these markets). We simply estimate that cross-market effects amplify impact by a factor 3/2, equivalent to ignoring the difference between trading cost and price impact, so that we can use the equation above without modification.

Using these ideas, we can estimate the price impact of trading in a crisis. If \$77B is shared over five business days, with \$15B of trading in each day, in a market with mean daily volume \$150B, then each day's trading has price impact $0.7\sigma\left(\frac{15}{150}\right)^{1/2} = 0.22\sigma$. The total impact over five days is 1.1σ. Our own price impact models, constructed using the eighteen-year records of Winton futures trading, have a different functional form but give similar results.

To arrive at this estimate, we used a combination of rough calculations, extrapolation and guesswork. But there are reasons to believe that the method might give an answer with the correct order of magnitude.

The first reason is the square-root form of the impact law. This means that the result depends weakly on the size of assets managed or the trading speed. Multiplying the size of daily trades by four results in a price impact only twice as large. Similarly, using our first estimate of CTA and risk parity crisis trading, which does not include limits on trading speed, leads to only a small increase in impact: an estimate of 1.5σ instead of 1.1σ.

The second reason is an empirical one. Applying this type of impact estimate to the few large trades in our records gives results which are of the same order as the historically recorded impact.

Liquidity droughts

Over five days, a total price impact similar to the daily volatility is not enough to cause worry about the stability of financial markets. But we should not feel complacent, because the price impact models describe average behaviour, under *normal conditions*. They were fitted using thousands of small trades executed in the course of normal trading. This is true of the published work and our own models.

The crises which we are seeking to understand (by definition) are not *normal conditions*. Extreme movements are often accompanied by a withdrawal of liquidity. Short-term traders normally place limit orders in the exchange's order book, signalling their willingness to trade. In response to higher volatility, these traders reduce their activity. This is because, like risk-parity funds, they have a limited appetite for risk. High volatility makes each trade more risky, so short-term traders trade less and demand a higher premium, retreating from the top levels of the order book.

This effect can be extreme, particularly when unusual price movements occur, making traders uncertain about the level of risk. An example from October 2014 [25] is shown in Figure 2.

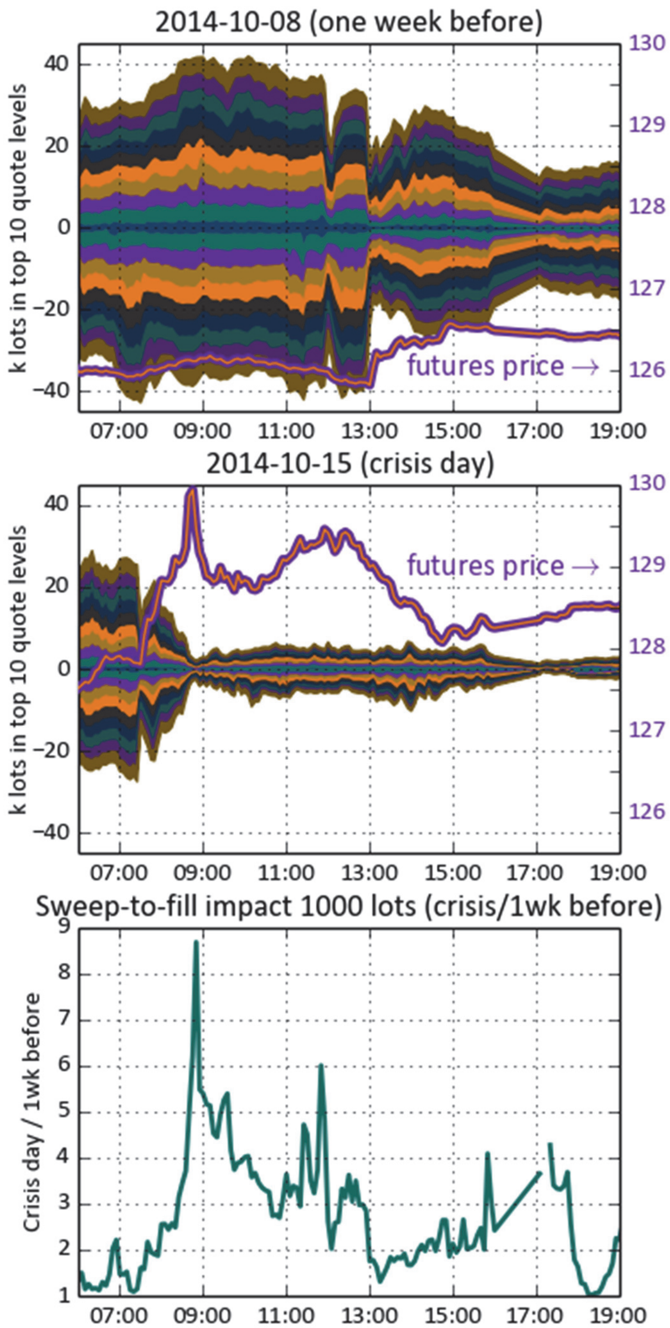

Figure 2: Lots available for trading in top 10 price levels in 10Y treasury futures. 8 October 2014 was an ordinary trading day, but large price movements on 15 October 2014 led to withdrawal of liquidity. Lots available to buy are shown above the x-axis: those available to sell are below. The price of the nearest-to-expiry futures contract is also shown. The lower chart shows the sweep-to-fill impact (STFI) of a 1000-lot order executed on the crisis day, divided by the STFI at the same time one week earlier. Times are EST.

October 8 was an ordinary day, with 40 000 lots available on each side of the order book at 09:30 EST. Each lot had nominal value $126 000, so this is more than $10 billion. One week later, there were large intraday price movements and liquidity providers withdrew. At 09:30 there was less than $1 billion displayed.

We can estimate the effect of this withdrawal on price impact by calculating the sweep-to-fill impact (STFI) of a 1000-lot purchase. This is the change in the top price level which would result if we bought 1000 lots instantaneously, starting at the best available price and proceeding upwards through the order book until our demand was satisfied. The STFI tends to overestimate the true price impact [20], but by seeing how it changes in the liquidity drought, we can estimate how the drought affects price impact generally.

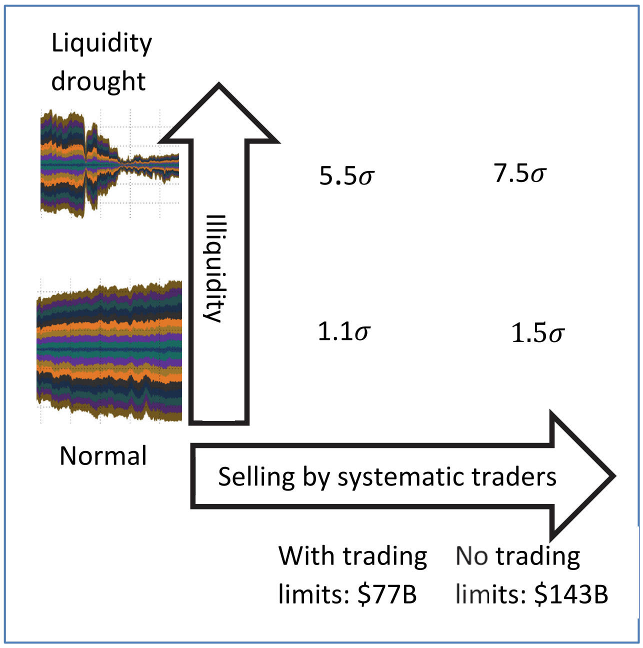

Figure 3: Order-of-magnitude estimates of the Impact of CTA and risk parity trading in four scenarios. Estimates given as multiples of the daily volatility $\boldsymbol{\sigma}$. Estimated price impact depends more strongly on liquidity supply than on assets managed or trading activity. Impacts estimated are in addition to the (large) price movements needed to trigger crisis selling.

During the part of the crisis day when most orders were traded, the price impact was between three and eight times larger than on a normal day. For an hour after the largest price movement, the STFI was more than five times its value a week earlier. We use this factor in our worst-case scenario assuming that a liquidity drought can increase price impact by a factor of five.

We summarise our conclusions in Figure 3 and Figure 4. There are two important variables: the amount of selling by systematic funds and the liquidity available in the market. The level of market liquidity makes a much larger difference to our estimates than the assets managed or trading limits. This agrees with the conclusions of other researchers on the causes of crises [26].

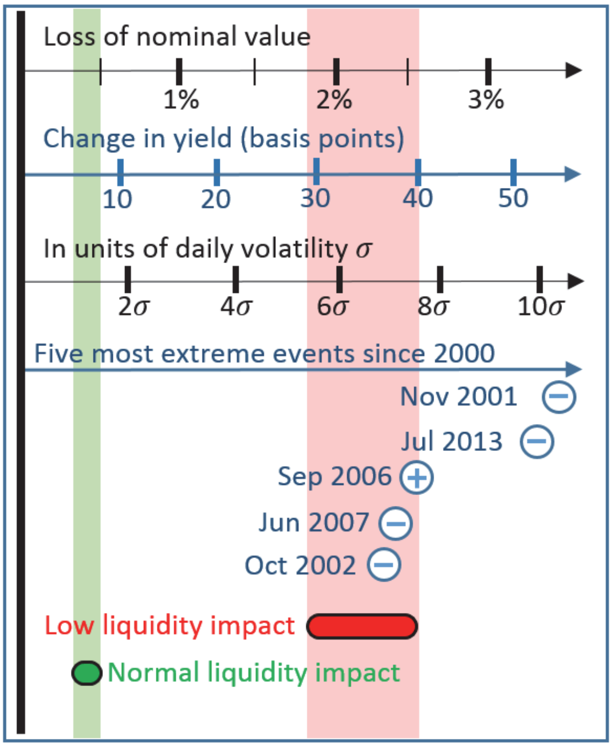

Figure 4: Estimates of price impact, measured in terms of loss of nominal value, yield changes and in units of futures daily volatility, compared to the five largest five-business-day price movements in this futures market since 2000. Of the five largest movements, only the 2006 move was positive.

Figure 4 provides four different ways to assess the scale of the estimated price movements. For example, price impact in the range estimated for low-liquidity conditions would correspond to a loss of ~2% of nominal value for the holder of a long position in a futures contract, or equivalently a 2% loss for the holder of a cash bond. It is also equivalent to a change in yield of about 0.3-0.4% and is as large as the fifth largest five-day price movement since 2000.

We should remember that the possible price impact we have estimated is in addition to price movements due to other causes. It is only likely to occur after a large price movement (perhaps itself $\sim 4\sigma$). So we might conclude that in low-liquidity conditions, the response of systematic traders to an unusual price movement would be enough to transform it into an exceptional one. In other words, we might see a bond portfolio lose 5% of its value, where only 2% would have been lost in the absence of systematic trading. This is our estimate for the worst possible case: we need the triggering price movement to occur at a time when CTAs have a strong positive position, and market-makers must also withdraw liquidity in an extreme way and over a period longer than we have seen in the history of this market.

Other market participants: mutual funds, discretionary hedge funds

Assets in mutual funds exceed 30 trillion dollars [27], dwarfing CTA and risk parity funds. If their investors withdraw quickly, mutual funds sell. In the US, the Investment Company Institute collects data on the flow of money into and out of equity and bond mutual funds [28]. The bond fund data are shown in Figure 5.

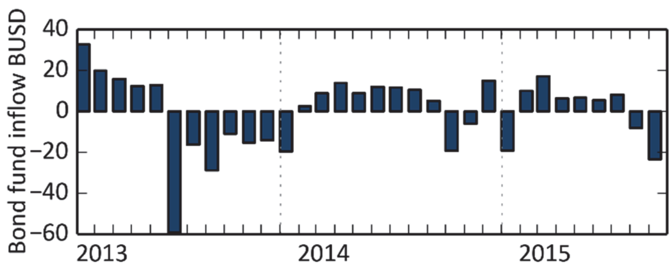

Figure 5: Monthly investment flows into US bond mutual funds (ICI).

The largest recorded movement in a single month was a \$60B outflow, at the time of the 'taper tantrum' in the summer of 2013. This provides a rough estimate of the scale of response of mutual funds in a crisis. Mutual fund investment is shared across corporate and government bonds and across a range of maturities, so there is no reason to expect the impact to be concentrated in one market. We might guess that the impact would be equivalent to $15B of selling in ten-year treasury futures, considerably smaller than the CTA total.

Discretionary hedge funds are probably more influential. The assets managed by hedge funds are more than $4 trillion [29]. Discretionary funds may reasess risk levels and use human judgement to withdraw from their positions for the same reasons that automated traders are programmed to do so.

Shleifer and Vishny give a general review of this effect [30], and Brunnemeier has described how it contributed to the 2008 financial crisis [31]. Other research details how margin requirements and redemptions lead to large sales of stocks and bonds by hedge funds [32] [33]. Ben-David *et al* [32] show that although they managed a much smaller pool of assets, hedge fund sales of US stocks far outweighed mutual fund stock sales during the financial crisis.

Conclusion: what makes a market unstable?

In response to a sudden downwards price movement, we estimate that systematic traders might sell up to ~$100B of US treasury futures in one week. Under *normal trading conditions*, the price impact of this selling would be of the same order as the daily volatility and therefore would not cause market disruption.

There is uncertainty in this conclusion, but most of it does not come from assumptions about assets managed or trading limits. The largest uncertainty is in the phrase '*normal trading conditions*'. Liquidity in financial markets often evaporates in a crisis. If a liquidity drought is severe and prolonged, then the impact of systematic trading may be significant. We can make similar estimates in other futures markets, and the qualitative conclusions are the same.

This paper presents approximate calculations with large uncertainty. Many of the ingredients are unknown or difficult to estimate. We would not be surprised if the figures turn out to be wrong by a factor of two or three. But they suggest that there are some circumstances where trading by systematic funds could transform a large price movement into an exceptional one. The response of liquidity providers in the market is a more important factor than the amount of trading by systematic funds. It is also important to realise that discretionary traders managing risk or following trends may react to market events, perhaps trading in larger volumes than systematic traders.

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