Cascade effects in modern concentrated financial markets

Analysing the network effects of sudden shocks in undiversified passive markets

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April 29, 2019

In these notes we present a network simulation model of the market where we stress test the impact of an idiosyncratic shock to a set of specific companies on the market as a whole. This is done by examining the cascade effect triggered by the redemption of large portions of assets from similar, mostly passive asset managers.

1 Introduction

Most asset managers have similarly distributed portfolios. This is largely due to the overwhelming prevalence of passive ETFs, and how a large proportion of the financial market's money is locked up in such funds. This is especially true in US markets, and since they matter the most, given their sheer magnitude as a percentage of broader global financial market, this matters the most for systemic risk. How dangerous to markets this is has been discussed by Fasanara at length in Fasanara Capital [2018a], and since early 2017 in Fasanara Capital [2017a] and Fasanara Capital [2017b]. In Fasanara Capital, this was further shown as an analytically defined network measure of fragility, known as the "System Resilience Indicator" (SRI), which used a purely structural measure of network fragility, the Ricci Curvature, to develop a further measure of market fragility. It shows that markets are even more fragile than they were during the dot-com bubble, although there has been no collapse yet.

In these papers, through the lens of nonlinear dynamics, the Fasanara team shed light on how such homogeneity is indicative of the markets approaching a "critical threshold" on account of the observable "critical slowing down" of market movement, as described in Fasanara Capital [2018b]. This is due to the lack of change over time in portfolios, and lack of capacity for market origination. Each is a consequence of living in the wake of market manipulation and suppression of volatility, driven by the policies of QE and Zero Interest Rates the world over.

This fact was explained in Fasanara Capital [2017c] over a year before developing the SRI. The delay in a deep adjustment in markets is a consequence of large fiscal injections in the US in 2018 and the reinstatement of QE in 2019. This is through the interruption

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of rate hikes and reinvestments of maturing treasuries, which is itself a form of QE. Artificial buffers to total collapse were reintroduced, to buy more time at the risk of deeper adjustments to come, as systemic risks further compound on the same root causes.

After a prolonged period of narcosis, provoked by QE and extreme policy interventionism, the market has lost its immune response to crisis. The buffers of resilience are no longer present, and the risk of instant liquidation has become like the sword of Damocles, dangling over the neck of an inherently fragile and illiquid market.

The highly liquid nature of ETFs and their relentless, yet relatively sudden rise highlights them as one of the weakest links in a growingly un-diversified asset management industry, together with other funds that offer daily liquidity to investors. If ETFs and other daily liquidity vehicles experience a significant amount of sudden redemptions, due to a mild market correction or other minor catalyst, the structure of the market would be unable to absorb the consequent sell off of assets without a severe adjustment to asset prices, making a market crash a probable outcome.

At present the market recognises the potential liquidity issues but appears satisfied with the risk, however if ETF volume continues growing at this pace, then this thinking may revise. The ratio of ETFs to managed funds is growing. In 2019, at the time of writing, ETF volume is at around \$5 trillion, up from less than \$700 billion before the 2008 financial crisis, and if expectations are correct, potentially reaching \$10 trillion by 2022.

As capital is redeemed, passive ETFs will automatically sell off ownerships of the assets they are invested in, in an attempt to preserve target portfolio weighting. This generates a cascade that propagates through the network of managers and assets, which if subject to a large enough shock, devalues companies market capitalisation to the point of a critical threshold.

Redemption risk is a major concern for investors, and has been analysed in Morris et al. [2017] and Grill et al. [2018]. Other papers have used agent-based models addressing inter-bank debt, as in Birch Annika and Aste [2014] and then Birch et al. [2015], or in Levy-Carciente et al. [2015]. However, less has been written on simulating redemption actions. In this paper, we describe a general model for the reaction to sudden devaluation of companies in the form of instant redemptions of shares in ETFs. Using this, we investigate how large changes in asset value can propagate through a system, causing system wide collapse. We provide a numerical simulation of such an event using a network model of the market, represented by a set of asset managers and their investments, and the associated parameters that define their relationship.

The tech sector is subject to regular, cyclical revolutions, with periods of stability and growth, volatility, and then sudden crashes, in a process defined by disruptive innovations Yu and Hang [2010]. This stable period is overrun with speculative investment in both "unicorn" companies, valued at over \$1 billion based on based on potential growth, given extremely rosy assumptions rather than hard data or past performance, and huge growth centric companies, such as Amazon. The PE Ratio of Amazon is just under 90 as of the time of writing, and its size is already greater than the total equity market cap of several of the G20 countries it is supposed to further penetrate into to support its current valuation. On account of their size and great potential for instability, we focus our analysis on these tech giants, and use NASDAQ listed stocks.

In the Section 2 we will introduce the model and the mathematics behind the update procedure. In the Section 3 we describe the results of the numerical simulation, wherein

Subsection 3.1 we perform a sensitivity analysis, followed by Subsection 3.2 which gives an analysis of a shock even on current market conditions. Finally, this paper concludes with suggestions on further ways to extend the model, both theoretically and methodologically.

2 A network model of the market

Consider a model of the market described on a two-mode network whose nodes are represented by $N + 1$ companies and M asset managers. We characterise the companies by their market capitalisation, C_n, the asset managers by their assets under management, A_i, and the asset managers' level of leverage by ℓ_i. We further denote the $M(N + 1)$ target weights for the asset managers in the network by $w_{i,n}$. The dollar amount invested by the i^{th} asset manager in the n^{th} company is represented by $Q_{i,n}$.

These represent the initial state of a dynamic network model. To introduce dynamic behaviour, we induce a shock $\delta = (\delta_1, \ldots, \delta_N)$ that hits the value of the companies, $C_0, \ldots, C_N$. To indicate that this is a change in time, we add a superscript t to all variables. We model time with discrete increments, where each increment corresponds to an indeterminate amount of clock time before which all asset managers can react to new incoming information and consequently affect the market. Using c_n to denote the initial market capitalisation of company n, we trigger a cascade reaction by inducing a shock on the value of the companies, which, for all n, is described by

$$C_n^1 = c_n(1 + \delta_n).$$

The cumulative effect of a change in the companies' market capitalisation on the assets under management of an asset manager is

$$A_i^{t+1} = A_i^t + \sum_{n=0}^{N} Q_{i,n}^t \left(\frac{C_n^{t+1}}{C_n^t} - 1 \right).$$

In the case of negative shocks, $C_n^{t+1} < C_n^t$, and so $A_i^{t+1} < A_i^t$. That is, losses in market capital correspond to losses in assets under management.

As an asset manager accumulates losses, their clients are incentivised to redeem their capital and move it to some other, better performing, manager. We denote the percentages of AUM that get redeemed as R_i and model this quantity with the function f, parametrised by the fear coefficient ρ, such that

$$f(x; \rho) = \frac{\tanh(\rho(x - \rho)) - \tanh(-\rho^2)}{\tanh(\rho(1 - \rho)) - \tanh(-\rho^2)} = a \tanh(\rho(x - \rho)) + b,$$

where a and b are defined as normalising constants such that $f(x) \in [0, 1],\ \forall x \in [0, 1]$. To compute the redemptions we plug in the change in assets under management, such that

$$R_i^t = f\left(A_i^{t+1} - A_i^t;\, \rho\right), \qquad \rho > 0.$$

The interpretation of the fear coefficient, ρ, is that as fear of losses increases, investors will redeem a greater percentage of their investment in response to worsening asset manager performance. We display in Figure 1 some examples of the redemption function for different values of the fear parameter.

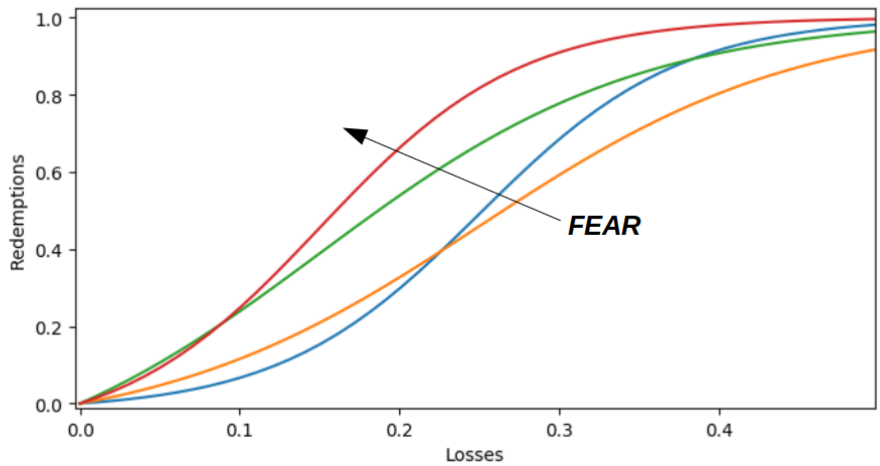


Figure 1: This shows different examples of the redemption function, each with a different fear. The arrow intuitively shows how more fear in the market affects the shape of the redemption function.

The change in AUM over time for each asset manager is finally computed as follows:

$$A_i^{t+1} = A_i^t(1 - R_i^t)^+.$$

where we denote the positive part of c with $c^+ = \max(c, 0)$. This reduction in capital further reduces the amount of cash available for holding a position in a portfolio, triggering a re-balancing, which is calculated as

$$Q_{i,n}^{t+1} = w_{i,n}\ell_i A_i^{t+1},$$

where $w_{i,n}$ represents the optimal allocation for the asset manager i, assuming this is kept fixed throughout a simulation. The liquidation of assets required to re-balance a portfolio has an impact on the valuation of the companies. We assume the latter to be proportional to the amount of shares liquidated and a specific price impact coefficient, $\alpha_n > 0$, such that

$$C_n^{t+1} = C_n^t - \alpha_n \sum_{i=1}^{M} \left(Q_{i,n}^t - Q_{i,n}^{t+1} \right),$$

which is the final step of the model before restarting the procedure at the assets under management update step. This loops until convergence or market collapse. In this initial analysis, α_n is defined in terms of λ, such that liquidity has a negative relationship with market impact. That is, $\alpha_n = 1 - \lambda_n$, which is time invariant. Market impact, however, could also be made time dependant to model the drying up of liquidity during prolonged sell offs. To capture the decay behaviour, a simple definition would be $\alpha_{n,t} = \log(t\alpha_n)$. This was not used at present, because this would make the model even more prone to cascades, starting even from very conservation market impact coefficients.

This section has described each step involved in the core update procedure. In an intuitive sense, this model tries to capture the dynamics following a considerable market correction that triggers a cascade of combined fire sell offs, redemptions in day liquidity instruments, and portfolio re-balancing.

To conclude this section, we present in Panel 1 the algorithm used to compute the update steps of the market simulation. The following section will look at applying a numerical simulation, testing our model, and providing results on liquidity risk in the market as of April 2019.

Algorithm 1 Cascade effect

initialise the system with a shock $C_n^1 = c_n(1+\delta_n)\ \forall\, n$
$t = 0$
while not converged **do**
    $A' = A_i^t + \sum_{n=0}^{N} Q_{i,n}^t \left(\frac{C_n^{t+1}}{C_n^t} - 1 \right)$
    $A_i^{t+1} = A'(1 - R_i^t)$
    $Q_{i,n}^{t+1} = w_{i,n} \ell_i A_i^{t+1}$
    $C_n^{t+1} = C_n^t \left(1 + \alpha_n \sum_{i=1}^{M} \left(Q_{i,n}^{t+1} - Q_{i,n}^t \right) \right)$
    converged : $\sum_{n=1}^{N} \left(C_n^{t+1} - C_n^t \right) < 10000$
    $t = t + 1$

3 Numerical Simulation

3.1 Sensitivity Analysis

In this section we calibrate and analyse the model introduced in Section 2 to identify possible catalysts of a cascade event which would lead to market collapse. Our aim is to show that the current market conditions, and the high portfolio concentration and homogeneity of the biggest asset managers, represent a source of risk that is often overlooked.

We trigger the market dynamics by probing the system with an idiosyncratic shock to few companies, and observe how the consequent sell-off can turn into a cascade/feedback loop of redemptions, portfolio rebalancing and companies devaluation. For the sake of these analysis we decided to test a shock to Facebook stock price of about 30%, along with a market (NASDAQ) correction of 5% and some other random market movement for the other stocks comprised in the model. Recall that the time steps used in the model do not represent uniform "clock time-steps", but rather they stagger time in equally significant, buckets of market activity.

We exploit the flexibility of the model to study how the market reaction to the aforementioned shock changes based on the market conditions and the psychology of the investors. This is done by selecting the price impact coefficient, reparametrised in terms of market liquidity coefficient as a proxy for the market liquidity, and the fear coefficient as a proxy of the general sentiment of the investment community. In Figure 2, we display a 3D representation of the market-wide correction triggered by the initial shock experienced by Facebook and the market as a whole. It can be observed that, for increasing fear and decreasing liquidity, the correction becomes increasingly severe.

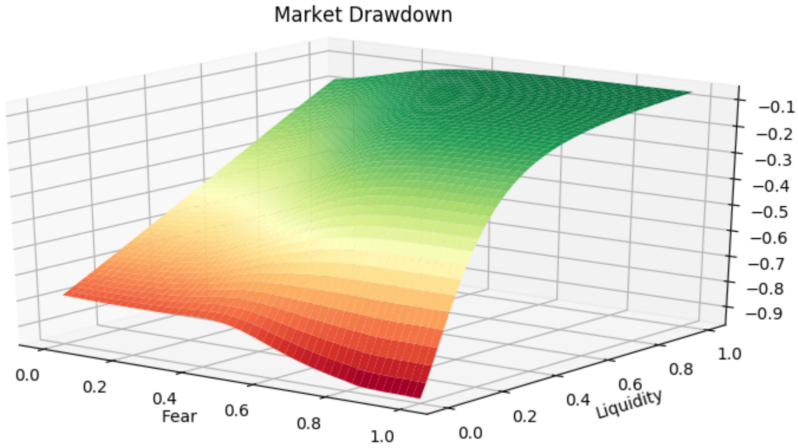


Figure 2: Market drawdown surface: we display the sensitivity of the market to investors' fear and market liquidity as encoded by the normalised redemption and price impact coefficients

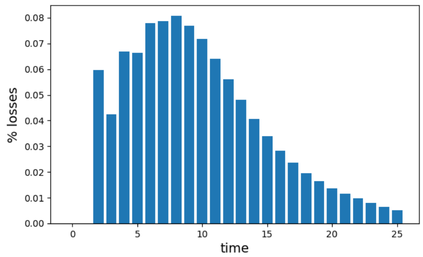
Figure 2 also allows us to assess the relative importance of both measures as triggers of a cascade event, and it can be concluded that, provided the market remains liquid, increasing fear in the investment community is not sufficient to trigger a market sell-off of noticeable magnitude. On the other hand, when liquidity dries up, even relatively low levels of fear can be sufficient to amplify the initial shock on the market ten-fold or more.

3.2 Current Market Conditions

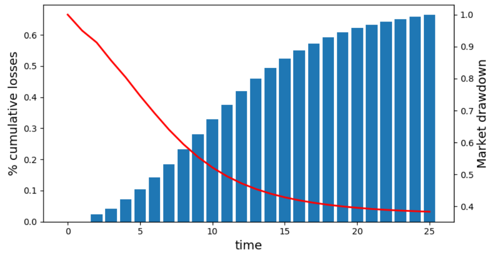
Having established the overall behaviour of the model, we aim to identify the current market conditions through the value of the two coefficients representing fear and liquidity. Through multiple simulations and cross validations against real market data, we estimate the fear coefficient to be about 60%, while the liquidity coefficient about 30%, relative to the normalised values tested in the sensitivity analysis Subsection 3.1.

Using these parameters, we compute the simple and cumulative average losses and redemptions experienced by the asset managers in the market system over time. We display these measures in Figure 3, it can be observed how a crisis spreads over time through the market, and the redemption/loss profile that an asset manager can expect in the case of such an event.

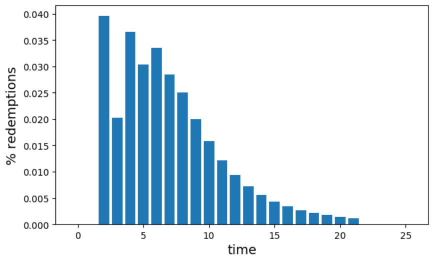
The most informative result of this experiment, however, is shown by the red curve as in Subfigures 3ii and 3iv, which shows the impact on the NASDAQ of a cascade event triggered by an idiosyncratic shock to a single stock, under the current levels of fear and liquidity. It can be noticed that such an event could result in a market-wide drawdown of up to 60%, primarily caused by repeated withdrawal of capital. This is in response to bad performance that, in turn, forces an asset manager to liquidate additional assets and put increasing pressure on prices, finally causing a market meltdown.



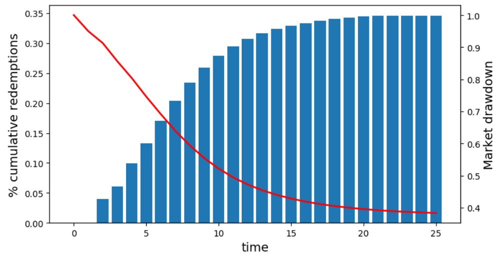
(i) Asset Managers' losses



(ii) Asset Managers' cumulative losses (as blue bars) and market drawdown (as a red curve)



(iii) Asset Managers' redemptions



(iv) Asset Managers' cumulative redemptions (as blue bars) and market drawdown (as a red curve)

Figure 3: The figures above display the losses and redemptions incurred by the Asset Managers caused by the reaction of investors to their bad performance and the market impact of their own selling of assets. Imposed on the cumulative scale is the market drawdown, as a function of time. This shows the cascade effect on the market, where, over time, the feedback loop of portfolio rebalancing and redemptions causes considerable market-wide losses.

4 Conclusion

In this research note we presented a network model of the market comprised by two different types of node - Asset Managers and Companies. After establishing the physics of the interactions among different market actors, we studied the sensitivity of the system to fear and liquidity conditions, as well as evaluated the current market conditions and presented a possible outcome of an idiosyncratic market correction. Our results suggest that, in an healthy system, these kind of events should not trigger market-wide distress. This is arrived at by observing that cascades of losses in our framework indicates that the way the market is structured, and the behaviour of its biggest players is jeopardising the stability and resilience of the system. That is, our research suggests that there is a systemic fragility in the market, and this may put it at risk of collapse.

We release these notes in their present form, intending to update this work with additional details on the calibration procedure, complement it with increasingly realistic assumptions and modelling choices, and deeper analysis into its internal structure.

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