Research Question:- “Does the trend towards indexation cause market instability?

If yes, can you design a trading strategy to benefit from it?”

Abstract:-

“The next crash risk is hiding in plain sight-Sometimes the ticking time bomb is in corners of the system that seem dull and safe”-,by Gillian Tett.

# Sometimes,market shocks and bubble occur because of risky bets like LTCM crisis,Lehmann brother bankruptcy filling in 2008 and may more crisis which lead to a massive expodus of most of the clients, devaluation of asset and so on so forth.Today western banks are well capitalized ,basel regulation, and the system is so flush with the cash and seemingly calm -there is sense of security, but this calmness will not only lead to danger of clearly risky bets but about the pearls of safe assets too. “ETFs are the new Investment Trusts (similar vehicles in 1920’s) that led to the Great Crash and will lead to the next crash”.This sector has recently exploded in size with more than $4 bn in asset under management , in which $3bn in the US. Passive and quantative investor have cover more than 60% of the AUM, up from under 30% a decade ago.This inclination towards passive investment is due to higher fees charged by the Active manager and they have underperformed in past decades. Therefore in order to maintain balance in the economy and outperform in the market Active fund managers fight back against ‘Darwinian cull’Stockpickers turn to strategies that are difficult to replicate in a passive format. In this paper the a strategy to benefit from the tail risk which emanates from crowding which is not adequately priced, can help active manager to outperform.Research findings will be used by all the other active managers in the industry to scientifically justify their business model

Introduction:

Passive funds have made a big chunk of overall assets under management in Asian and US equities and a smaller - but rising - proportion in areas such as US bonds.

Over time, active management, underperforms passive across all major geographies, developed and emerging. Active managements higher fees and trading friction also drive investors’ costs higher.As long as corporate governance improves to developed-market standards, passive is likely to grow overseas at a rate similar to US market.

In the US the majority of pension funds have equity exposure which is indexed (in total 11 trn. USD). However mechanically investing in an index that is 100% invested in the equity market requires the pensioner to take on far more risk that he most likely wants. Two massive bear markets over the last decade have made investors lost something far more valuable than money – the time that was needed to reach their retirement goals. From a regulatory perspective it is therefore interesting to understand what impact the trend towards indexation has for social welfare.

A crowded trade generally grows around what started to be a good idea. Portfolio insurance was just such a good idea. It was such a good idea most  large pension funds used it. A good idea leads to successful business model. Copycats learn to enter into the space, capital flows into the strategy, leading to even more success for those already there, until at one point, the pendulum swings and the music stops. The only difference, the index crowds is bigger now than portfolio insurance was pre-1987. Indexing imposes a non-linearity that drives the most overpriced stocks to become even more overpriced. That is precisely why the lofty valuations on the FAANGs just keep getting loftier. ETFs trade shares robotically with zero cash buffer. The first hint of trouble causes cash inflows to dry up and buying to stop. Redemptions by drawdown-sensitive (active) investors cause instantaneous selling. Passive buying will give way to active selling. The unwind should also be the mirror image of the ramp: FAANGs will lead the way down owing to their high market caps. Once again, selling begets selling, and the virtuous cycle quickly turns vicious.

Disaffection with underperforming fund managers can push institutional investors towards ‘passive’ management of their assets. Indeed, the UK’s Department for Communities and Local Government has recently suggested that as much as £85 billion of defined benefit pension fund assets managed for UK local authorities could be moved from active to passive management. The rationale for the suggestion is that the average returns from active management may not justify its higher cost(by Schroders).

Moreover passive indices have both concentration risk and unwelcome biases, and lead to the systemic risk .The main concern is that the ascent of the passive investments will lead market more chaotic ,unpredictable and brittle many inverstors claim that the the shift from active to passive mostly]y in ETF .The increased ownership of TF are detracting from the stock market efficiency. Some fund manager and analyst can detect the warning sign of bubbles in passive investment, also passive tide is affecting the accountability.

“A cure-all. This is what passive investing represents to its growing band of proponents. Equity tracker funds, we’re told, will rid the financial market of toxic elements and restore it to full health.

At first glance, it’s a persuasive argument. Poorly performing and expensive active managers have lingered in the system for too long, eroding returns for investors.

Yet on deeper reflection, index-tracking products are no miracle remedy. They’re more like antibiotics: valuable when deployed in moderation, but likely to do more harm than good should their use become widespread”(by Renaud de Planta the chairman of Pictet Asset Management, an active investment manager).

He claims passive investing erodes competitive forces, because companies in the same sector end up with the same investor base, which is probably where he’s on the strongest ground. But he also argues that if passive funds monopolised investment flows, pricing mechanisms in the stock market would break down. The price of a stock would no longer reflect a company’s actual performance, because their shares would be bought simply as a result of their inclusion in an index, he suggests.

( https://ftalphaville.ft.com/2017/05/30/2189496/passive-investing-is-worse-than-the-misuse-of-antibiotics/).

In order to mitigate this risk Active management should efficiently allocate the capital within the market .Also the active manager can use quantative strategy which uses the new data ,and despite of using standard accounting data, apply significant computational ability to outperform the Passive funds. Moreover if the active investor formulate a strategy to benefit from the tail risk which emanates from crowding which is not adequately priced, can help active manager to outperform.

Our approach:

In order to solve the problem statement, first we create a model which simulates the trading behavior of the individuals in the market. To model the behavior, we can make use of various computational models. In this thesis, we developed Statistical Agent based model (SABM) for our problem. In chapter 2, implementation and use of SABM model is well explained. Next, using historical data and back-testing, we calculate decisions (to hold or not to hold) and compute performance i.e. annual return and volatility, for the model created. Using these computations, we try to calibrate our model to mimic the market behavior. The details of methods used for calibration are explained in chapter 3. After calibration, we are able to predict the returns and volatility for the future dates. In chapter 4, we analyze the future data to identify possibility of crash or financial bubbles in the market. The results obtained are shown in chapter 5. The thesis ends with the chapter 6 containing conclusion and discussion.

Models:

Computer modeling is the process by which a computer is used to develop a mathematical model of a complex system or process. Computer modeling is an efficient way to take into account many different factors and to simplify and organize real-world processes. Models can be designed to better explain or understand historical data, to predict future behavior or perform virtual experiments, or to make decisions about courses of action based on the likelihood of expected outcomes(<http://www.epimodels.org/10_Midas_Docs/infoMaterials/MIDAS_101_Model_Types_flyer_web.pdf>)

The various computational models which can be used in quantitative analysis are:- Compartmental Models, Agent-Based Models, Decision-Analytic Models, Decision-Analytic Models. Although these methods are very efficient but for our research which is focused more on the behavior of system over time, agent model is more relevant.

Agent based Models:-

It is used to simulate the behavior of the system over time. It uses the bottom up or individual level approach, means how the behavior of individuals can effect the overall behavior of the system. It shows how the virtual person might behave in the simulated community. Moreover it is low cost ,flexible ,provide the natural description. The agents make trading decisions based on the history of price

change directions .It has limited memory of length m, which is the same for all agent Each agent has the same number s of trading strategies, but different agents have in general different trading strategies. The decisions is made by learning from the historical performance of their trading strategies. They asses the performance of trading strategy and choose the best strategy.

Its drawbacks:

1. Results are uncertain means, variability of results obtained depending on the internal structure of the model for the same set of parameters when the model is repeated several times (<https://www.cairn-int.info/article-E_RFS_554_0653--the-potential-and-limitations-of.htm>)

### 2.Results are dependent on the input values and internal structure a lot.

, but it does not do reverse engineering and simulation Therefore we develop Statistical agent based model, which uses the approach of the agent based model ,in order calibrate bubbles ,crashes and change of regime.

Statistical agent-based model

It is a kind of computational modelling. It is an efficient way to take into account different factors, calibrate and and finally optimize it to generate the result which can be useful for the real time problem. It is designed to understand the historical data and predict the future behavior or performance of the market..It is relatively easier to reproduce some stylised facts of asset returns in stock markets, such as fat-tail distributed returns, absence of autocorrelation in returns, volatility clustering, and so on, but it is

more difficult to reproduce/calibrate bubbles, crashes and the change of regimes. we propose a Statistical agent based Models(SABM)) which could overcome these difficulties, and it is also relatively straightforward and easy to calibrate.

There are two classes of agents in the SABM, as all other ABMs do:

1.Fundamentalists

2.Chartists

The fundamentalists:- buy and hold a stock when it is cheap and will sell it and hold cash when the stock is expensive. They use the P/E ratio to determine if the stock is under-valued or over-valued.

The chartists :- use a fast MA and a slow MA of prices to identify trends. If the fast MA is higher than the slow MA they will buy and hold; otherwise they will close positions and hold cash.

All agents use stop-loss to manage risks.

Though the SABM looks to be simple, it can generate rich dynamics. In a random-walk market phase and the P/E ratio is moderate, the market is in equilibrium: fundamentalists will buy and sell with the

same probability and the price trend is not obvious so the chartists will also buy and sell with the same probability. The random-walk phase will continue.

When some stochastic positive price jumps occur, a trend will emerge in the market. A positive feedback loop will make more and more chartists enter the market, as long as the P/E ratio is not extremely

high and the trend is not totally destroyed by the fundamentalists selling their shares. Hence, a bull market is formed and continues.

When the bull market continues, the P/E ratio will increase until it reaches a critical point: some fundamentalists will start to sell and cause some price drops. There could be some oscillations because of the oscillations of the P/E ratio. If there is a big random price drop, both fundamentalists and chartists will sell out their stocks to stop loss and they will create a positive feedback loop to cause a crash

before a bear market.

When the bear market goes on until the P/E ratio is low enough, the fundamentalists will enter to buy and hold shares to stop the bear market.

In order to work with this model we use following notation and strategy:-

1.Let S be the total number of shares outstanding of the stock.

2.Let the total number of fundamentalists be Nf , and that of the

chartists be Nc .

Both them will 100% in the market or 100% out.

3.If one decides to enter, her capacity of buying and holding shares is ni , related to her wealth and knowledge and so on.

4.We assume it is stationary, distributed with some mean u and variance \_2.

5.Agents learn from the history with a window length wi1 (in-sample window 1) to find the best trading strategy to use. Of course fundamentalists and the chartists have different styles of strategies.

At any time, the fundamentalists try to find a good P/E ratio denoted by x to enter or exit, and a good stop-loss ratio h to manage their risks. The chartists use a fast MA, denoted by MAf , and a slow

MA, denoted by MAs to enter or exit, and they need also a good stop-loss raito h to manage risks. So the fundamentalists look at the pairs such as (x; h), while chartists look at triplets such as (MAf ;MAs ; h), to make decisions.

6 With any pair (x; h) or triplet (MAf ;MAs ; h) one can get back-test results in wi1 . We assume the agents pick trading strategies with mean-variance preferences. Let rk (t) and \_k (t) be the average return

and the standard deviation of returns of the back-test with parameter pair k (for fundamentalists) or triplet k (for chartists), at time t.

7.Denote by \_ the risk aversion of agents. The expected utility gained by the trading strategy k at time t will be a function of rk (t) 􀀀 \_vk (t).

8.For convenience we assume the probability of choosing the trading strategy k is proportional to e

rk (t)􀀀\_vk (t) T , where T is a temperature determining how sophisticated the traders are and how intensive the

traders are coupled.

9.We assume the risk aversion \_ is exponentially distributed with a parameter \_ .

10. we can get the probability of any trading strategy being picked, which is denoted by

P(k; t) = P(rk (t); vk (t);T; \_ ),

where rk (t) and vk (t) can be extracted from historic data and T and \_ are model parameters to

calibrate.

At any time t, a trading strategy will tell agents to hold or not to hold the stock. Let Y (k; t) be the output of trading strategy at time t according to the price context at t, which can be 0 (not to hold) or

1 (to hold).

11.Df denote the demand of fundamentalists. We thus have

E(Df ) = Nf \_XkP(k; t)Y (k; t) (1), and

VAR(Df ) = Nf \_2(XkP(k; t)Y 2(k; t) 􀀀 (Xk(k; t)Y (k; t))2) (2)

12. Denote by Dc the demand of chartists. We thus have similarly

E(Dc ) = Nc\_XkP(k; t)Y (k; t) (3) and

VAR(Dc ) = Nc\_2(XkP(k; t)Y 2(k; t) 􀀀 (XkP(k; t)Y (k; t))2) (4)

Note: fundamentalists and chartists have different P(k; t)'s and Y (k; t)'s.

13.Demand of agent is calculated as:

D = Df + Dc the total demands. Therefore,

E(D) = Nf \_XkP(k; t)Y (k; t) + Nc\_Xk0P0(k0; t)Y 0(k0; t) (5), and

VAR(D) = Nf \_2(XkP(k; t)Y 2(k; t) 􀀀 (XkP(k; t)Y (k; t))2)+Nc\_2(Xk0P0(k0; t)Y 02(k0; t) 􀀀 (Xk0P0(k0; t)Y 0(k0; t))2) (6)

14.Price discovery process is calculated as :

Denote the stock price at t by X(t), then

DX(t) = SX(t + 1) (7)

, so the return of the stock at time t + 1 is

rt+1 =DS􀀀 1 (8) , therefore,

E(rt+1) =NfS\_XkP(k; t)Y (k; t) +NcS\_XkP0(k0; t)Y 0(k0; t) 􀀀 1

VAR(rt+1) =

magnitudes of Nf and Nc , and is big enough.

It is thus obvious that we can use the MLE to calibrate the SABM to

According to the Central Limit Theorem, rt+1 is approximately normally distributed, when the shares outstanding S is of the same the real returns, within an in-sample window 2, whose length is wi2 .

There are 5 parameters to calibrate, which are T, \_ , Nf \_ S , Nc\_S , and Nf \_2S2 .

The calibrating of this SABM is much more e\_cient than the GA approach, because we need to analyse with P/E ratio based trading strategies and trend following trading strategies just once. After storing the P(k; t)'s and Y (k; t)'s, the calibration is nothing but a normal numerical optimization problem.

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