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RESEARCH ARTICLE

INVESTIGATING THE FINANCIAL DISTRESS RISK PUZZLE WITHIN THE HEDGE FUND INDUSTRY

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Abstract

This study investigates the conventional wisdom that financial assets with higher risk levels should yield higher returns, a concept known as the risk-return trade-off. However, empirical research indicates that financially distressed assets tend to yield lower returns. Although several potential explanations have been proposed, there remains a lack of consensus in the literature regarding the underlying causes. Motivated by this puzzle, this study aims to ascertain whether distress risk is present in the hedge fund industry. To this end, this study empirically analyzes hedge funds' monthly returns over a fourteen-year period from January 2000 to August 2016 and research is based upon a sample of 7151 hedge funds. The data were further segmented to capture both bull and bear market conditions and various hedge fund strategies. The results demonstrate that the distress risk puzzle is evident in the hedge fund industry. The findings suggest that hedge funds with a high probability of default do not yield higher returns, whereas those with a low probability of default yield higher returns. This study indicates that hedge funds with a high probability of default are riskier, and investors are not adequately compensated for investing in these funds.

Introduction:-

The hedge fund industry can easily be considered as one of the most significant players in the global financial market. The increased attention towards the HF industry during the last years has resulted in an influx of new stakeholders to the HF industry. From a regulatory point of view, no U.S. authority has so far issued a formal hdirective; owever, the Alternative Investment Fund Managers Directive 2011/61/EU captures HFs under the definition of an Alternative Investment Fund. According to the January 2019 Eurekahedge Report, the assets under management of the HF industry reached \$2.34 trillion in December 2018 (Eurekahedge, 2019). This level of Alternative Investment Fund is managed by more than 11,000 HFs globally. The Eurekahedge report also stated that throughout 2018, the global hedge fund industry saw its assets decline by USD 154.4 billion, down 6.3% from its 2017 year-end figure. This drop was the largest yearly percentage drop since 2008 and it has contributed to global

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trade tension and aggressive Federal Reserve rate hikes which caused elevated market volatility through the better part of the year. During 2018, investors redeemed USD 93.4 billion and performance losses of USD 61 billion were recorded.

Over the past decade, the hedge fund industry has been impacted by varying market conditions, with periods registering growth and other periods registering stress and rebound. In the years preceding the 2008 financial crisis, optimism in hedge funds was seen by the aggressive growth in the Alternative Investment Fund and the number of hedge funds established. The industry's strength has been deeply affected by the financial crisis of 2008, with the global hedge fund industry registering half a trillion of losses. Despite the losses, from 2010 onwards HFs managed to achieve excellent performance-based gains despite the Eurozone crisis and, as at the end 2018, it is still going strong. One way to understand HFs is to describe their activities. The most widespread HF investment techniques are to invest in both long and short-term diverse type of securities[1] as well as the use of leverage[2] to exploit mispricing opportunities. Also, it is not common for HFs to disclose information about their portfolio holdings[3], making investing in HFs riskier than investing in plain vanilla securities. HFs as collective investment vehicles which can generally be distinguished from other types of investment funds by the following characteristics: Focus on delivery of absolute returns even in the context of declining markets through the use of hedging and flexible investment strategies. These investment strategies typically translate into a relatively high and systematic use of leverage – through borrowing, short selling and derivative positions. Traditionally, the hedge fund investor has been confined to institutional or other sophisticated investors which has led regulators to exempt hedge funds from many investment protection and disclosure requirements. However, the extent to which hedge funds are exempt from regulatory requirements defers across countries.

As at June 2018, the United Stated dominates with the largest hedge fund population in the world. Britain's HF population has been slightly decreasing in the last few years due to Brexit negotiations uncertainties which continue to loom over the industry. On the other hand, the United States and the Cayman Islands continue to be the top two choices for HF domicile due to their advantageous tax benefits. Offering proximity to the largest pool of investors in the world, the tax cuts recently introduced in the United States might potentially be able to lure hedge fund managers to launch their firm in the country. Among offshore jurisdictions, the Cayman Islands remained as the most popular choice for hedge fund domicile. Under stable market conditions, HFs provide markets and investors significant benefits such as more liquidity, efficient pricing of securities, facilitate distribution of risk and promote a more global interaction of the financial markets. However, during distress periods, HFs correlation to the markets may magnify the turmoil.

Investing in HFs provides a platform for risk diversification; HFs invests in traditional assets portfolios such as equities and fixed income, leads to better risk-return trade off, as HF strive to generate returns irrespective of the market conditions and thus the HF industry is often uncorrelated to the broader market. Conventional wisdom suggests that financial assets with high levels of risk should have a higher level of returns. This is known as the risk-return tradeoff. Fama and French (1992) claim that higher premium result is expected from distressed risk.However, recent empirical studies such as those by Griffin and Lemmon (2002), Campbell, Hilscher, and Szilagyi (2008) and Dichev (1998) and contradict this risk-based theory. They concluded that distressed financial assets have lower returns. Additionally, the excess returns of the majority of the distressed financial assets are negative (Campbell et al, 2008). This is the distressed risk puzzle. There is still no agreement in the literature as to what drives this anomaly, and although a few potential explanations have been suggested, it continues to be a challenge to rationale asset pricing. Deepening the puzzle, distressed firms have higher market betas[4] than healthy firms. Hence, risk and return do not go hand in hand in the financial distress cross-section. To date, there is little to no literature on whether HFs also suffers from the distress risk puzzle. Against this backdrop, it is important to understand and analyse if HFs' returns suffer the same faith as the traditional financial assets. The rationale behind this study is therefore to fill this gap in existing literature and examine if the HF industry also suffers from the distress risk puzzle which is currently only linked to equities.

This research is also important from a practical point of view as it provides a better basis for understanding the returns and defaults of HFs when the HF has a higher probability of default. Investors and fund management companies may apply this study to better manage their asset allocation and risk-return optimization. The empirical analysis within this Research paper is based on a selection of HFs with various characteristics. To this end, the period under investigation covers January 2000 to August 2016, reporting monthly data. In the research undertaken, this period has been further divided into sub-samples of different investment strategies as well as sub-samples of different economic cycles to distinctly capture if HFs are affected by the so-called distress risk puzzle.

Therefore, the objective of this thesis is to address the following main research questions:
- Do hedge funds with high default risk deliver higher returns if the fund survives?
- Did the economic cycle impact the returns of hedge funds that have a high probability of default?
- Is there a difference in returns between HFs with different styles and having the same probability of default?

The possibility of the distress risk puzzle being also exhibited in the hedge fund industry has not very studied in the present literature. To this end, this study will analyse the return characteristics of HFs with different levels of probability of default and evaluate the relationship between the PD and its return.

Literature Review:-

Several studies have empirically shown that HF returns are far from being Gaussian and exhibit low skewness and high kurtosis (see Agarwal and Naik, 2004; Burton and Saha 2005: and Brooks and Kat 2001). After every financial crisis, there is always a debate on the impact and role of hedge funds. Inevitably, there are differing views whether this industry did play a role in the crises of the last decades. it is believed that HFs have a significant impact on the markets due to their leverage trading strategies. Then again, (Stromqvist., 2009) and (IOSCO report., 2009) suggest that HFs lessen the probability and occurrence of asset bubbles by going long on undervalued assets, short on overvalued assets, and, more importantly, by maximising the impact of available investment capital. The main criticism of the HFs is that they cause further market instability in times of crises by investing in the price adjustment of incorrectly valued assets, also known as arbitrage strategies. However, it would be unreasonable for expect hedge funds to behave differently in crises given their ethos is to exploit such scenarios. The role and impact of HFs in economic crises has been in the spotlight in recent years due to the substantial increase of AuM and the fact that the HF industry is not under strict regulation.

As reported by (IOSCO ., 2009) there are various views on the role of HFs in the 2008 credit crisis. One of these views is that through the activities of HFs, the consequences of the crisis may have been amplified. This is because HFs require liquidity and hence may need to quickly liquidate positions due to liquidity deadlines in meeting margin calls or investor's request for redemption. With regards to investor protection, market integrity and systemic issues, multiple concerns have been raised. (Stromqvist, 2009). On the other hand, the in-depth analyses of (Brown et al.,1999 and 2003), and (IOSCO.,2006 and 2009), (Stromqvist.,2009) and (Fung and Hsieh., 2000) showed that the action of HFs does not justify the broad negative discussion around them as HFs also present a series of advantages which could positively affect the financial markets as well as the economy in general. One of the main advantages is that since HFs are traders of financial products, they offer liquidity to the market, especially to the less traditional ones. Furthermore, several HFs' strategy is to achieve return by exploiting market inefficiencies, which leads to a reduction between sale and purchase price, thus to more efficient prices for the financial instruments.

Although many authors suggest that HFs are not to blame for the financial crisis, market participants have put the blame on HFs for their role in the economic crisis's. Is this the case? There are still some debates on this argument. The role of HFs in crises and their impact on macroeconomic imbalances has been studied on numerous occasions by several scholars. **(**Fung and Hsieh, 2000; Fung and Hsieh, 2008; Ineichen, 2001; Palaskas, Stoforos and Drakatos, 2013; Stromqvist, 2009).reported that during the last two decades, HFs are not to blame for the financial crisis. HFs may have in some cases augmented inevitable developments but as (Stromqvist.,2009) noted, "the 2007 crisis has impacted hedge funds more than they have affected the crisis". This has been proven by (Dichev, 1998; Griffin and Lemmon, 2002; Campbell, Hilscher and Szilagyi, 2008). Where they suggest that the distress puzzle may be attributable to market mispricing of these stocks.

Despite the increased popularity of hedge funds, there is still no common consensus on their definition. However, one can distinguish a HF from a traditional financial instrument by its characteristics, such as the use of high leverage and the use of short selling. These characteristics inherently lead to an increased risk level and thus highly variable returns, which in turn makes traditional performance measures unsuitable. (Agarwal and Naik 2004 ; Burton and Saha 2005 ; Brooks and Kat 2001) all reported that HF returns are not normal distributed but exhibit low skewness and high kurtosis. One of the reasons of the increased popularity of hedge funds is due to their absolute return and low correlation with the traditional asset classes. This emanates from the unregulated and opaque investment strategies that hedge fund managers use. Although the hedge fund industry saw an influx of investors, the level of closure of such hedge funds have been quite high. In fact, in recent years the number of closures is higher than the number of funds launches. Variables affecting fund closures can be size, age, past performance, fund flows, fee structure, share restriction, investment strategies, liquidity and macroeconomic factors.

It is also worth pointing out that a failed fund is not always a fund that has been liquidated. Gregoriou (2002) defined a failed fund as a fund that stops to report the data. The recent closures of hedge funds are linked to the financial crisis and the role of HFs in crisis has been studied on numerous occasions, (Fung and Hsieh 2000 ;Stromqvist 2009) are amongst others that concluded that HFs are not to blame for the financial crisis. When the economy is going through a period of financial distress, investors demand higher premium for holdings stock with high level of risk. However, several studies have shown that there is a negative relationship between returns and risks, leading to the creation of the so-called distress puzzle. Understanding the behaviour of distress stocks has proved something of a challenge for financial economists. To date there is little to no literature on whether hedge funds exhibit the same pattern. This research will present new ideas to current literature, principally whether the distress risk puzzle is present in the hedge fund industry i.e. to study if hedge funds with high probability of default deliver higher returns if they survive. Another research area for this study is to look at the relationship between different hedge fund strategies and different financial cycles and analyzing their risk and return relationship.

Methodology:-

The hedge funds with high default risk can on average deliver higher returns if they survive. This part commences with a description of the data and the process for the data cleaning. Following that is the description of the methodology used for the analysis. Subsequently the model design employed is discussed, including the description of control variables used, pre-regression analysis, and presentation of their results. Data on HFs have been obtained from the extended database used in (Kolokolova et al., 2018). This database provides information on inter alia monthly returns, AuM, investment style, domicile, currency, hurdle rate, high water mark, share restriction, and lock-up period. The database includes a total of 21,811 funds, both alive and defunct, covering the period April 1994 to August 2016. An HF is considered defunct[5] once it is liquidated, restricted, merged with other HFs or stops reporting; in such cases, the fund return history is transferred from the live database into the defunct database. For a meaningful analysis of the HFs, the sample period taken ranges from 2000 to August 2016, covering approximately 17 years of data.

Following the removal of HFs as per the conditions set, 7151 HFs remained in the analysis. In general, fund databases suffer from different types of data biases arising from the difference between the HFs in a database and those in a population. The three most prominent are: back-fill bias, selection bias and survivorship bias. The magnitude and effect of such biases are normally immeasurable, yet there are ways how researchers can control for such effects. The **first** hypothesis examines whether HFs having a high probability of default report higher returns during distress periods.

This null hypothesis is tested against the following alternative hypothesis:

H_{A1}= Hedge funds with high probability of default yield higher returns

The second hypothesis examines whether the economic cycle impacts the returns of HFs having a high probability of default ("PD"). In order to examine this hypothesis, the sample data was divided into three sub samples. These sub samples illustrate the three different periods around the financial crisis. The first period contains HFs data between 2000 till 2006, the period preceding the crisis. The second period is the financial crisis period between 2007 till 2009 where the industry saw a high number of HFs closing down. The third period, from 2010 till 2016, is the period after the financial crisis where the industry started to regain strength. Period 2 provides for the majority of the sample size with 40.16%, whilst period 1 and period 3 make up 33.07% and 26.77% respectively.

This null hypothesis is tested against the following alternative hypothesis:

$\mathbf{H_{A1}}$= The economy cycle did not affect the HFs returns of period one

$\mathbf{H_{A2}}$= The economy cycle did not affect the HFs returns of period two

$\mathbf{H_{A3}}$= The economy cycle did not affect the HFs returns of period three

The second hypothesis follows a similar hypothesis by Liang and Kat (2001) where they argued that hedge funds were impacted by the economic crisis in 1998 but concluded that this does not mean that HFs did not contribute as a trigger to the crisis. Moreover, for the financial crisis of 2008, Stromqvist (2009) did not find any evidence of HFs having a bigger impact on the crisis than other funds in the financial industry. The **third** hypothesis examines whether different investment styles generate higher return based on their level of probability of default. The three investment strategies are Long/Short Equity strategy, Fixed Income strategy and Multi-Strategy. Long/short equities strategy make up 34% of the HFs, Fixed Income strategy 10% and Multi-Strategy 7%. Together, the three strategies make up 52% of the total population of HFs under analysis. This hypothesis follows a similar hypothesis that by Baba and Goko (2006) used in their study.

This null hypothesis is tested against the following alternative hypothesis:

H_{A1}= Based on their level of probability of default, long short equities strategies did not perform better than fixed income strategy

H_{A1}= Based on their level of probability of default, long short equities strategies did not perform better than multi strategy

H_{A1}= Based on their level of probability of default, fixed income strategies did not perform better than multi strategy

The Logit Analysis:-

A logit analysis has been chosen to estimate the probability of default of hedge funds on the likelihood of liquidation. The logit model is a well-known model that has been widely used in literature, such as in (Chan et al.,2005) to examine the influence of several HF characteristics on the likelihood of liquidation. Logit model can be viewed as a generalization of the linear regression model to situations where the dependent variable takes on only a finite number of discrete values.

In a binomial logistic regression model, the dependent variable (Y) has only two distinct outcomes:

$$Y \epsilon \{0,1\}$$

The outcome can be seen either as a failure or as a success, {0,1}. The model can be expressed in the following form with an unobserved continuous dependent variable and observed independent variables X' (latent process): $Y^*_{it} = X'_{it}\beta + \epsilon_{it}$

X'_{it} and β are vectors of covariates and unknown parameters respectively, and ϵ_{it} is assumed to follow a logistic distribution with mean zero and variance $\sigma^2_\epsilon = \frac{\pi^2}{3}$. Although Y^*_{it} is unobserved, it is related to an observable discrete random variable Y whose values are determined by Y^*.

Y can be viewed as an indicator function for Y^* that takes a value of 1, indicating that a HF is dropped from the live database (liquidated) as at the end of the year whenever $Y^*_{it} > 0$, and a value of 0 indicating the HF is still alive at the end of the year, whenever $Y^*_{it} \leq 0$.

$$Y = \{0 \quad if Y^*_{it} = X'_{it}\beta + \epsilon_{it} \leq 0 1 \quad if Y^*_{it} = X'_{it}\beta + \epsilon_{it} > 0$$

Following this, probability to be estimated:

$$Pr(Y_{i,t} = 1)$$

Liquidation probability:

$$Pr\ Pr\big(Y_{i,t} = 1\big) = Pr\ Pr\ (Y^*_{i,t} \geq 0 |\ X_{i,t}) = Pr\ Pr\ (X'_{i,t},, \beta + \eta_{i,t} \geq 0\ |\ X_{i,t})$$
$$= Pr\ Pr\ (\eta_{i,t} \geq -X'_{i,t}\beta |\ X_{i,t} = 1 - Pr\ Pr\ (\eta_{i,t} < -X'_{i,t}\beta |\ X_{i,t})$$
$$= 1 - F\big(-X'_{i,t}\beta\big) = F(X'_{i,t}\beta)$$
$$= \frac{1}{1+\exp(-X'_{i,t}\beta)}$$

Equation 1: Liquidation probability equation for a logit model

Following this, the model used in this regression is:

$$\mathbf{Y_{i,t} = x + FundPerformance\beta_1 + FundSize\beta_2 + FundFlow\beta_3 + FundRisk\beta_4 + ManagementFee\beta_5 + PerformanceFee\beta_6 + HighWaterMark\beta_7 + RedemptionFrequency\beta_8 + LockupPeriod\beta_9 + \varepsilon_{i,t}}$$

In order to empirically investigate the hypothesis in question, the dependent variable and a set of explanatory[7] variables are included in the analysis. As explained in 3.5, in a logit analysis the dependent variable is an indicator variable Y that takes the value of 1 if the HF stopped reporting during a given year or a value of 0 if the HF survived during the year. This process was performed manually to determine the dependent indicator variable of every HF for each year under analysis.The variables used to control for liquidation effects are inter alia (i) fund return, (ii) fund size (iii) fund flow, and (iv) fund risk. The motivation for fund return and fund size variables is clear; funds with a higher performance and with larger and more stable AuM are less probable to be liquidated. The impact of the fund flow on the liquidation is that the higher the fund flow, the higher the survival probability of the fund. There exists a negative correlation between fund risk and liquidation probability; the higher the fund risk, the more likely the fund is to be liquidated. Fund performance and fund size are computed as the average performance and size of the HF of the previous year in analysis whilst fund risk is calculated as the return standard deviation over the previous year of analysis. Current literature on fund flow (see: Agarwal, Daniel, and Naik (2004), Goetzmann, Ingersoll and Ross (2003), and Baquero and Verbeek (2009)) shows a strong, positive correlation between investor flows and performance of HFs. To calculate fund flow, the following formula by Ding et al (2009) was used. Ding et al (2009) define investor flows as the percentage in the assets of a fund between two points in time, adjusted for the return attained during that period.

$$\mathbf{Flow_{i,t}} = \frac{\mathbf{Assets_{i,t}} - \{\mathbf{Assets_{i,t-1}}(\mathbf{1} + \mathbf{r_{i,t)}}\}}{\mathbf{Assets_{i,t-1}}}$$

Equation 2: Investor Flow:-

Where and represent the reported assets under management of HF i and is the return achieved by the HF during period i. The flow is calculated monthly and then the average fund flow during the year was computed.Secondly, management fee, performance fee and the existence of high-water mark dummy are used to capture the effects of incentive structure on liquidation probabilities of hedge funds. The feature of a performance fee is very common in the hedge fund industry. Investors comment that such presence is correlated with more risk-taking by portfolio managers given the managers have a higher incentive to take more risk. Another growing tendency in the hedge fund industry is that performance fee is commonly accompanied by a high-water mark provision that conditions the payment of high performance to the fund managers upon exceeding the highest achieved share value. The incentive structure of HF can be highly nonlinear because the majority of funds implement the high-water mark provision, which fund managers are required to compensate any losses before the incentive fee can be collected. The combination of the incentive fee and the HWM provision makes hedge fund managers' compensation look like a call option.

The management fee and performance fee variables were taken as the actual % reported by the fund, whilst for the HWM a dummy taking a value of 0 if the HF does not have a HWM is used and 1 if it has a HWM feature. Thirdly, two more variables related with cancellation policy of the hedge funds are used to capture the liquidity constraints for HFs investors. These two variables are redemption frequency and lockup period. Redemption frequency is how often an investor in a HF can withdrawing money and lockup period is the amount of time investors are required to keep their investment in the fund before any shares can be redeemed. Investors cannot access their money during this time period.Hedge fund managers claim that restrictions on flows are imposed for several reasons. It is typical for hedge funds to engage in strategies that significant losses may be incurred in the short term before any profit is produced. It also allows them to invest in relatively illiquid and complex assets over long time horizons. In either case, outflow restrictions avert a forced liquidation of fund assets.

The longer is the redemption frequency, i.e. low redemption frequency variable, the lower is the liquidity. Lower liquidity generates a more stable performance of hedge funds as portfolio managers can mitigate the likelihood of abrupt outflows which has the possibility to destabilize fund management. On the other hand, investors dislike lower liquidity and hence it is more difficult for funds with an inflexible cancellation policy to attract enough funds from investors.The variable redemption frequency is expressed in days, implying that the higher the value of the variable, the less frequent is the redemption of the fund. Similarly, the variable lockup period is expressed in days, implying that the higher the value of the variable, the more days the investor is restricted to redeem his/her invested money.

In the below table, one can find a summary of the variables considered.

Table 3.1: Definition of Explanatory Variables	
Return	Average performance over the previous year
Size	Average size over the previous year
Flow	Average monthly flow over the year

Risk	Return standard deviation of the previous year
Fees: Incentive Scheme	
Management fee	Annual fixed percentage fee payable to the hedge fund manager
Performance Fee	Annual performance fee, usually distributed as proportion of the profits to the hedge fund manager.
High Water Mark	Dummy variable representing the presence of a HWM in the fund. It takes a value of 1 if the option is present, and zero otherwise.
Liquidity: Cancellation Policy	
Redemption Frequency	Frequency at which investors can redeem their investment. The variable is denominated in days, so that a higher value means a lower frequency.
Lockup period	Minimum holding period before investors can redeem back the investment. It is denominated in days, so that a higher value means a longer lockup period

Source: authors' calculation

Model Design:-

Literature suggests that the standard approach in measuring HF performance is to regress the returns on a set of risk factors. Such risk factors would represent the risk exposure of the respective HF strategy (Agarwal, Bakshi, and Huij 2009; Bali, Brown, and Caglayan 2011; Bollen and Whaley, 2009; Fung and Hsieh, 2004). In order to evaluate the HFs return comparable to their probability of default, it was decided to utilize the t-test for mean difference and Fung and Hsieh (2004) seven-factor model. It is an approach for benchmarking HFs returns by using a model of hedge fund risk. This approach is based on a simple observation that HFs managers usually conduct in the same markets as traditional portfolio managers. However, evidence shows that HFs returns have different characteristics than those of traditional fund managers (Fung and Hsieh 2004).

t-Test for the mean difference:-

An independent mean t-test will be performed in order to check whether the differences between hedge funds with low PD and high PD is statistically significant. The null hypothesis for the t-test would be that that there is no significance difference between hedge funds returns and different levels of probability of default so different levels of PD will not impact the returns of a HF. The alternative hypothesis would be that there is difference in returns between funds having different percentage of default probabilities.

Fung and Hsieh (2004) Seven-Factor Model Performance Analysis:-

The seven risk-factor model is designed to assess the exposure of a diversified portfolio of hedge funds and can measure the amount of systematic risk of a hedge fund using conventional securities prices. The seven factors are risk factors that explain a large proportion of the returns of HFs.Thus far, research identified seven risk factors. These factors are categorized into equity factors, bond factors and trend-following factors (TFF). Long/Short equity hedge funds are exposed to two equity risk factors, fixed income HFs are exposed to two interest rate-related risk factors and TFF funds are exposed to three portfolios of option.

Different factors included in the model are:

- SP500 – the monthly return on the Standard and Poor's 500 index
- SC-LC – the difference between the Russell 2000 index monthly and the Standard and Poor's 500 monthly total returns
- Bond Factor - the monthly change in the US Federal Reserve 10 year constant maturity yield
- Credit Spread – the monthly change in the difference between Moody's Baa yield and the US Federal Reserve 10 year constant maturity yield
- PTFSBD – the return of a portfolio of lookback straddles on bonds
- PTFSFX - the return of a portfolio of lookback straddles on currency
- PTFSCOM - the return of a portfolio of lookback straddles on commodity futures

Analysis of Results:-

Hedge funds have gained more visibility in the financial industry in the last two decades and are becoming more popular as an investment vehicle, but whether they offer better returns than traditional financial assets is still unclear. In a rational market, the returns should commensurate with the risk taken, but this is not corroborated by literature which suggests that the distress risk is related negatively to stock returns (Dichev (1998; Griffin and Lemmon 2002; Campbell, Hilscher and Szilagyi 2008). This study extends this theory to the hedge fund industry and seeks to provide insight as to whether an investor is rewarded when investing in hedge funds with higher risk. The main goal of this research is therefore to examine the performance of the hedge funds returns and its characteristics and evaluate if the surviving hedge funds with high probability of default deliver higher returns.

t-Test for mean difference:-

The results attained from the two-sample t-Tests undertaken on the results of HF with high PD and low PD are provided in table 4.1. The null hypothesis is that there is no difference in returns between high PD HF and low PD HF. The null hypothesis is rejected at all levels of significance for the 14-year period and also for the Long/Short Equity strategy and the Multi strategy. In the case of Fixed Income strategy, the null hypothesis is rejected at 10% level of significance. This signifies that there exists a difference in returns between HFs with high PD and HFs with low PD.Comparing the strategies, it can be concluded that the Long/Short Equity strategy is the most rewarding strategy for investors. HF managers capture most of the upside whilst limiting the downside. On the other hand, fixed income strategy proved to be the least rewarding. Between the different three sub-periods, the null hypothesis is also rejected at all levels of significance for sub-period 1 and 2 and rejected at the 10% significance for sub-period 3. For 2008, the peak of the financial crisis, the returns were insignificant excluding for Multi Strategy HFs, implying that in 2008, there was no difference in returns between High and Low PD funds. Prior to the financial crisis (2002-2007) the majority of returns are statistically significant whilst during the financial crisis (2007-2009), the results are rather ambiguous. As previously stated, at the peak of the financial crisis (2008), the investors were not being compensated for investing in high PD funds. However, a year prior and after, results indicate that investors were being compensated enough for their risk taken in their investments. This trend continued in the period after the financial crisis (2010-2016), where the investors were being well compensated for investing in high risk HFs.

Table 4.1 – t-Test between Low PD returns and High PD returns

Year	All Hedge Funds	Fixed Income	L/S Equities	M.S	Sub-period 1	Sub-period 2	Sub-period 3
2002-2016	3.2E-09***	-	-	-			
2005-2015	-	0.0719*	1.8E-05***	5.94E-08***			
2002-2006					0.0001***		
2007-2009						0.004***	
2010-2016							0.069*
2002	0.0079***	-	-	-			
2003	0.0033***	-	-	-			
2004	0.0145**	-	-	-			
2005	0.0279**	0.9809	0.0560*	0.0147**			
2006	0.0139**	0.0628*	0.0378**	0.8500			
2007	0.0072***	0.3834	0.0667*	0.0796*			
2008	0.4636	0.6532	0.9784	0.0057***			
2009	0.0036***	0.0516*	0.0156**	0.0025***			
2010	0.0516*	0.3433	0.0846*	0.0335**			
2011	0.9816	0.1432	0.3814	0.7279			
2012	0.0167**	0.1469	0.0650*	0.6858			
2013	0.0013***	0.0626*	0.0021***	0.0135**			

2014	0.0107**	0.8608	0.0913*	0.5223			
2015	0.1557	0.5147	0.5876	0.4257			
2016	0.0490**	1.0000	0.4168	0.4415			
This table provides the t-test results between the returns of Low PD portfolios and High PD portfolios. The asterisks *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively							

Source: authors’ calculationigh PD returns

Fung and Hsieh (2004) Seven-Factor Model Performance Analysis:-

The seven-factor model concludes that, generally speaking, the null hypothesis that HFs with high PD yield lower returns may be accepted. An in-depth analysis of the performance of the funds follows. Alpha for the Low PD portfolio is positive whilst for the High PD and the High-Low PD portfolio it’s negative. This implies that investing in High PD funds is not adequately rewarding enough for the risk taken, whilst investing in low PD funds generates adequate returns. Additionally, the portfolio managers for the Low PD funds outperformed the market whilst for the high PD did not. All the portfolios experienced statistically significant exposure to the SandP500; both low and high PD portfolios were more volatile than the general equity market (coefficient of 45.44 and 11.22 respectively, statistically significant at the 1% level). This increased exposure could help explain the rationale why both portfolios did not exhibit a significant exposure to the bond market. Moreover, all three portfolios have a statistically significant exposure to Credit Spread, suggesting that the portfolios followed a strategy of buying risky bonds compared to higher grade bonds as evidenced by the negative coefficients.

Table 4.2 – Fung Hsieh (2004) seven-factor model – 14 year period (January 2002-August 2016)			
	Low PD	High PD	High PD - Low PD
α_p	1.0544***	-0.2022***	-1.2567***
	-7.4666	(-2.8269)	(-8.5866)
Bond Factor	-1001.134	-621.7935	379.3404
	(-1.1599)	(-1.4221)	-0.4241
Credit Spread	-4529.9690***	-1729.0240***	2800.9450***
	(-4.8638)	(-3.6647)	-2.9019
PTFSBD	-0.374	-0.5958	-0.2218
	(-0.3368)	(-1.0590)	(-0.1927)
PTFSCOM	1.0871)	-0.4011	-1.4882
	-1.0977	(-0.7995)	(-1.4500)
PTFSFX	1.9856**	1.0001**	-0.9855
	-2.4091	-2.3953	(-1.1538)
SC_LC	8.8133	4.5929	-4.2203
	-1.5866	-1.6322	(-0.7331)
SP500	45.4393***	11.2265***	-34.2127***

	-11.9776	-5.8417	(-8.7021)
The asterisks **,*** indicate statistical significance at the 5% and 1% level respectively			

Source: authors' calculation

Performance Analysis for the Fixed Income Portfolio:-

For both the Low PD portfolio and High PD Portfolio, the alpha value is positive implying that the fund managers applying the fixed income strategy to their portfolio, beat the market (Low PD 0.41 and High PD 0.21, both statistically significant at the 1% level). On the other hand, High-Low PD portfolio experienced a negative and significant alpha. This means that Low PD portfolios are beating the market more and thus investors are better off investing in these portfolios given that with low risk they can earn better returns.In terms of styles, it is worth noting that all portfolios have significant exposure to the SP500, which Fung and Hsieh (2004) consider as an equity risk factor. The Low PD portfolio also has a significant exposure to the Bond Factor and to Credit Spread whilst the High PD portfolio has a significant exposure to Credit Spread. This is usually because the fixed income funds invest in bonds that have lower credit rating and/or also less liquidity and then hedge the interest rate risk by shorting treasuries that

Table 4.3 - Fung Hsieh (2004) seven-factor model – Fixed Income Strategy

	Low PD	High PD	High PD - Low PD
α_p	0.4122***	0.2063***	-0.2059**
	-4.9807	-3.7531	(-2.2606)
Bond Factor	-2551.2770***	-436.1455	2115.1320***
	(-4.7248)	(-1.2159)	-3.5595
Credit Spread	-2883.9630***	-2832.1900***	51.7726
	(-5.5150)	(-8.1533)	-0.09
PTFSBD	0.0719	-0.8091*	-0.881
	-0.1102	(-1.8667)	(-1.2270)
PTFSCOM	-0.6076	-0.3713	0.2363
	(-1.0807)	(-0.9943)	-0.3819
PTFSFX	-0.3068	-0.1191	0.1877
	(-0.6011)	(-0.3513)	-0.3342
SC_LC	1.7953	-3.3881	-5.1834
	0.5043)	(-1.4327)	(-1.3231)
SP500	20.7769***	9.8243***	-10.9526***
	-8.9458	-6.3679	(-4.2853)
The asterisks *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively			

have a higher credit rating and more liquidity. (Fung and Hsieh (2004)). Source: authors' calculation Hsieh (2004) seven-factor model – Fixed Income Strateg

Performance Analysis for the Long/Short Equity Portfolio:-
Only the Low PD portfolio generated statistically positive alpha (1.04). In contrast to the Fixed Income Portfolio, High PD portfolio generated statistically negative alpha (-0.34) which indicates how once again the Low PD portfolios beat the market and the High PD portfolios did not. The High-Low PD portfolio confirms this result (alpha value -1.38, statistically significant at the 1% level). As expected, all portfolios have significant exposure to the equity factor SP500 whilst the Low and High PD portfolios also have a statistically significant negative exposure to the credit spread. Over the past few years, the Long/Short equity has been moderately correlated to US stocks and bond market. This is a desirable situation in a portfolio were interest rates to rise, or were equity markets to fall. The negative exposure to the credit spread in theory implies that the funds moved away from the safe haven of government bonds and gained exposure to high yield bonds or corporate bonds. Both the Low PD portfolio and the High-Low PD portfolio are significant (at the 5% level) to PTFSFX the currency trend-following factor. This could potentially indicate that the portfolio uses a foreign exchange for hedging purposes rather than for investment purposes.

Table 4.4 - Fung Hsieh (2004) seven-factor model – Long/Short Equity Strategy			
	Low PD	High PD	High PD - Low PD
	1.0402***	-0.3399***	-1.3801***
	(5.3210)	(-2.9582)	(-6.3849)
Bond Factor	2561.6740**	-303.7175	-2865.3910**
	(2.0085)	(-0.4051)	(-2.0318)
Credit Spread	-2414.4960*	-1801.5890**	612.9078
	(-1.9548)	(-2.4815)	(0.4488)
PTFSBD	-0.7773	-0.5016	0.2757
	(-0.5044)	(-0.5537)	(0.1618)
PTFSCOM	-0.4261	-0.5584	-0.1323
	(-0.3209)	(-0.7154)	(-0.0901)
PTFSFX	2.5922**	-0.2462	-2.8384**
	(2.1505)	(-0.3476)	(-2.1296)
SC_LC	11.7569	2.1649	-9.5919
	(1.3982)	(0.4380)	(-1.0317)
SP500	61.4881***	23.7770***	-37.7111***
	(11.2083)	(7.3737)	(-6.2170)
The asterisks *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively			

T**Source: authors' calculation**uity Strategy

Performance Analysis for the Multi Strategy Portfolio:-
Similar to the Long/Short Equity portfolios, only the Low PD portfolio exhibit a positive statistically significant alpha (1.00) whilst the High PD portfolio and the High-Low PD portfolio exhibit a negative statistically significant alpha (-0.22 and -1.22 respectively, both significant at the 1% level). This suggests that investing in High PD portfolios is not worth it as the investors are not being compensated enough. The Low PD portfolios beat the market indicating that HF managers outperform the market.The Low PD portfolio is exposed to the equity factor SP500 and the currency trend-following factor, whilst the High PD portfolio is also exposed to the equity factor and to the credit spread. This means that different portfolios use different weighting in their strategy but both portfolios invest

in equities, with the Low PD portfolio investing more heavily in stocks and less in bonds compared to the High PD portfolio.

Table 4.5 - Fung Hsieh (2004) seven-factor model – Multi Strategy			
	Low PD	High PD	High PD - Low PD
	0.9999***	-0.2233**	-1.2232***
	(6.8901)	(-2.1407)	(-6.6787)
Bond Factor	1432.8330	-1123.9750	-2556.8090**
	(1.5133)	(-1.6517)	(-2.1398)
Credit Spread	-1115.1690	-3125.0400***	-2009.8710*
	(-1.2162)	(-4.7420)	(-1.7369)
PTFSBD	-1.6285	-0.8567	0.7718
	(-1.4235)	(-1.0419)	(0.5345)
PTFSCOM	0.6433	-0.2853	-0.9286
	(0.6526)	(-0.4026)	(-0.7464)
PTFSFX	1.7647*	0.0927	-1.6720
	(1.9721)	(0.1442)	(-1.4806)
SC_LC	5.1417	-5.3401	-10.4818
	(0.8237)	(-1.1903)	(-1.3306)
SP500	25.7976***	19.0397***	-6.7580
	(6.3346)	(6.5050)	(-1.3149)
The asterisks *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively			

Source: authors' calculation

Performance Analysis for the different period under analysis:-

Preceding the financial crisis, Low PD portfolio displays a positive alpha (0.98, statistically significant at the 1% level) and is significantly exposed to multiple sectors such as the equity market, bond market, currency and futures market. Similarly, the High PD portfolio has significant exposure to both equity factors, bond market and to the currency trend-following factor (PTFSFX). The High PD portfolio also presents a positive alpha whilst on the other hand the High-Low PD portfolio presents a negative alpha, indicating that the Low PD portfolio has a higher alpha than the High PD portfolio. This result means that investors are not being compensated enough for investing in riskier portfolios. Throughout the financial crisis, both Low and High PD portfolios has a significant loading to the SP500 with the Low PD having a higher loading. Moreover, the Low PD portfolio beat the market whilst the High PD portfolio did not. Compared to the years preceding the financial crisis, both portfolios decreased their exposure to different sectors and only have a negative significant loading to the Credit Spread and positive significant loading to the SP500 implying that the portfolios changed their investment strategy to follow the current events of the market. Post the financial crisis, the fund managers of the High PD portfolios managed to beat the market (alpha value 0.09 not statistically significant) but still not as much as the Low PD portfolio (alpha value 0.19, statistically significant at the 1% level). The low PD portfolio still has a significant exposure to the equity factor SP500 but lower than the period during the financial crisis. Post crisis, it increased the portfolio exposure to the Currency Factor, Credit Spread whilst decreasing the exposure to the Bond Factor. This shows an increased level of diversification in the portfolio. In contrast, the High PD portfolio has a negative loading to the SP500 and only has a significant exposure to the lookback options on bonds.

Table 4.6 - Fung Hsieh (2004) seven-factor model – Sub-period 1 (January 2002-December 2006)

	Low PD	High PD	High PD - Low PD
α_p	0.9781***	0.2146***	-0.7636***
	-6.673	-3.4079	(-6.6999)
Bond Factor	-1938.7210**	-965.7927**	972.9281
	(-2.2285)	(-2.5846)	-1.4384
Credit Spread	-668.5485	-806.3044	-137.7559
	(-0.3767)	(-1.0577)	(-0.0998)
PTFSBD	-0.8564	0.6409	1.4973
	(-0.7034)	-1.2255	-1.5817
PTFSCOM	2.4646**	0.3929	-2.0717**
	-2.4152	-0.8965	(-2.6111)
PTFSFX	1.3693*	1.2519***	-0.1174
	-1.8859	-4.0144	(-0.2079)
SC_LC	12.7224**	13.4138***	0.6915
	-2.5886	-6.3542	-0.1809
SP500	18.9480***	19.4317***	0.4837
	-4.763	-11.3721	-0.1564
The asterisks *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively			

Source: authors' calculation

Table 4.7 - Fung Hsieh (2004) seven-factor model – Sub-period 2 (January 2007-December 2009)

	Low PD	High PD	High PD - Low PD
α_p	1.4895***	-0.1711	-1.6606***
	-4.9172	(-1.1017)	(-6.5873)
Bond Factor	181.4747	751.4838	570.0091
	-0.1142	-0.9219	-0.4309
Credit Spread	-2272.0610*	-1634.6440**	637.4175

	(-1.8784)	(-2.6355)	-0.6332
PTFSBD	1.5376	0.2135	-1.3241
	-0.5714	-0.1547	(-0.5913)
PTFSCOM	3.0383	0.859	-2.1793
	-1.1204	-0.6177	(-0.9656)
PTFSFX	-0.822	-1.2123	-0.3903
	(-0.4170)	(-1.1995)	(-0.2380)
SC_LC	-11.1275	-6.5401	4.5875
	(-0.9474)	(-1.0858)	-0.4693
SP500	34.4483***	21.3150***	-13.1333**
	-5.6069	-6.7657	(-2.5686)
The asterisks *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively			

Source: authors' calculation- Fung Hsieh (2004) seven-factor model – Sub-period 2 (January

Table 4.8 – Fung Hsieh (2004) seven-factor model – Sub-period 3 (January 2010-December 2016)			
	Low PD	High PD	High PD - Low PD
α_p	0.1854***	0.0897	-0.0958
	-3.8698	-0.6703	(-0.6964)
Bond Factor	-1109.9560***	-45.645	1064.311
	(-2.9647)	(-0.0437)	-0.9905
Credit Spread	-1231.2350**	1885.564	3116.7980**
	(-2.4314)	-1.334	-2.1446
PTFSBD	-0.1209	-2.2694**	-2.1485**
	(-0.3380)	(-2.2726)	(-2.0924)
PTFSCOM	-0.3967	-0.244	0.1528
	(-1.2988)	(-0.2861)	-0.1743
PTFSFX	0.7037**	0.6589	-0.0449
	-2.3278	-0.7808	(-0.0517)
SC_LC	0.4993	9.1236	8.6243
	-0.2271	-1.4869	-1.3669

SP500	21.3829***	-3.0672	-24.4501***
	-13.9047	(-0.7146)	(-5.5399)
The asterisks **,*** indicate statistical significance at the 5% and 1% level respectively			

Source: authors' calculation

As for the 14-years period under analysis, the t-test result shows that there is a significant difference at the 1% level between returns of High and Low PD HFs. Analyzing the individual years, all years also are significant difference except for the year 2008, 2011 and 2015. For all three HFs strategies, the result shows significance difference, with Fixed Income strategy showing a weaker significance and Long/Short Equity strategy the strongest significance. Moreover, there also exists a significance difference in returns between High and Low PD funds between the three different period, pre, during and post financial crisis. The significance difference for all portfolios represent that there is a significance in returns between high and low PD HFs. Across all portfolios and different strategies and periods, alpha of the Low PD portfolio is always positive and statistically significant at the 1% level whilst alpha of the High PD Portfolio is negative and statistically significant at the 1% level except for the Fixed Income strategy, Grp 1 and Grp 3 where the alpha is positive (Grp 1 and Grp 3 alphas' not significant). This leads to the conclusion that HFs with high PD portfolios get lower returns. Therefore, such funds are riskier than the low PD funds and obtain lower returns. Moreover, the alpha indicates that portfolio managers for high PD funds rarely beat the market compared to portfolio managers for low PD funds which in every scenario managed to beat the market.

Conclusions and Policy Recommendations:-

The hedge fund industry, as an alternative investment sector, has grown rapidly in recent years. Data reported by (Eurekahedge.,2019) calculated the global value of AuM of the HF industry amounted to USD 2.34 trillion as at December 2018. As shown by Casey, Quirk and Acito and Bank of New York 2004, 20 years ago, the main players in the hedge funds industry were mainly wealthy investors. Currently however, HFs are a main investment vehicle for institutional investors, pension funds, endowments and high net worth individuals. Their main reason to invest in HFs lies in the absolute return and low correlation with traditional asset classes. In view of the increase attention in HFs, it makes this study related to their risk and return both interesting and important. The question analysed is then how well hedge funds with high default risk deliver on average higher returns. To be able to address this question, a logit analysis has been applied on the data to estimate the probability of default of various HFs and their characteristics on the likelihood of liquidation as well the (Fung and Hsieh., 2004) seven-factor model to evaluate if high PD funds achieve lower returns. Another aspect that this study investigated was the performance of HF in relation to the financial crises, given that HF receive a lot of negative publicity during turbulent times due to the nature of their investment strategies.

Findings of Research:-

This research is based upon a sample of 7151 hedge funds. To be able to undertake a meaningful analysis, the hedge funds were carefully selected based on three criteria. Funds that (i) do not report monthly net returns in US Dollars, (ii) funds of funds and (iii) funds with less than 24 months of data were excluded from the analysis. The entire sample was then split into three portfolios namely, Fixed Income strategy, Long/Short Equity strategy and Multi Strategy. To evaluate the returns of HFs with high default probability during different economic conditions the sixteen (14) year period between 2002 and 2016, was further divided into three shorter periods representing the time preceding, during and after the financial crisis. The hedge fund's return comparable to their probability of default was evaluated using logit regression before moving on to the t-test for mean difference and the regression-based methodology (Fung and Hsieh.,2004) seven-factor model.

The findings show that:

Funds with higher return and AuM have higher survival probabilities. This result is as expected since investors tend to be more attracted to funds that have a history of good performance. Having a track record of high return to investments created a snowball effect that attracts the attention of more investors which in turn leads to an increase in the AuM. This is also as per the study by (Liang 1999; Koh et al.,2002). Funds with high risk and high flow tend to have a lower survival probability. As per literature, since the fund is riskier, it is more prone to having a higher probability of default leading to a lower survival rate. Along the same vein, funds with high flow tend to have a higher survival rate as investors are more willing to invests in funds that already have a wide base of AuM. The performance fee is directly correlated to the liquidation probability. This result is in line with the study done by

(Ackermann et al.,1999; Liang 1999; Caglayan et al.,2001) which report a statistically significant positive association between the two. Interestingly enough, the findings show that prior to the financial crisis the higher management fee the lower the liquidation probability, which leads up to conclude that investors placed significant trust in management. This was true up until the financial crisis, after which the funds that have a high management fee tend to have also a high liquidation probability. This is also confirmed by the analysis of the three different periods, where in sub-period 1 and sub-period 2 the relation is negative and in sub-period 3 the relation is positive.
Moreover, findings show that funds that have a HWM provision is also important for hedge fund survival. This is also confirmed by study of (Baba and Goko., 2006) in which they conclude that HFs with a HWM have higher survival probabilities. Funds with a longer lockup period tend to have a higher survival rate whilst funds with a higher redemption frequency tend to have on average a lower survival rate.

In addition, the use of the t-test confirms that there is a significance difference in returns between High and Low PD HFs. This significance difference is present in respect of the 14-year period, the three strategies and also present in the sub-periods under analysis. Looking at the result in more detail, for year 2008, only the Multi strategy proved to be significant. This can be that given the fund is much more diversified that the stricter investment strategies employed by Fixed Income and Long/Short Equity strategy. Moreover, as from 2007, the Fixed Income strategy did not prove to be any difference in returns between High and Low PD portfolios (except for 2009 and 2013, both significant at the 10% level). Moreover, through the results obtained, it is clear that there is difference in returns in the different economic conditions.

The study utilises the (Fund and Hsieh.,2004) seven-factor model, which according to the research done has never been used in previous literature to evaluate if high default hedge funds deliver on average higher returns. Across all portfolios under analysis, the Low PD portfolios beat the market in every different scenario whilst the High PD portfolios only beat the market in the period preceding and post the financial crisis and for funds following a fixed income strategy. However, it should be noted that still Low PD funds beat the market higher than the High PD funds. This confirms the study by (Cappocci, Corhay and Hubner.,2005) that noted hedge funds significantly outperform the market during the bullish period without significant underperformance during the bear period.
For the remaining portfolios, the High PD portfolios registered a negative alpha.

The negative alpha represents that High PD portfolios are getting lower returns i.e. the investors are not being compensated for investing in high PD funds. Thus, the investors are investing in riskier funds and receiving lower funds. This determines that High PD funds are riskier and low returns funds Tosummarise, it may be concluded that, on average, hedge funds with high default risk do not deliver higher returns. Moreover, one can conclude that there is a statistical difference in return between different trading strategies with the Fixed Income strategy proved to be the best trading strategy out of the three analysed. It can also be concluded that the economic cycle did impact the returns of hedge funds. All in all, one can say that the distress risk puzzle is also present in the hedge fund industry.

Originality and Limitations:-
Conventional wisdom suggests that financial assets with high levels of risk should have a higher level of returns. This study fills the gap in the literature by studying if the distress risk puzzle is also present in the hedge fund industry. Furthermore, this research has overcome a number of limitations by covering an extensive period of time from January 2002 to August 2016, by focusing on different hedge funds strategies as well as considering how the financial crisis shaped the returns of the hedge funds. Notwithstanding this, there is always scope for further research on the subject matter especially since the literature on this topic isn't vast.Hedge funds used in this research are funds reporting their returns in U.S. Dollars, the study can be extended to include HFs whose based currency is not the U.S Dollars and study how other based currency HFs returns are impacted by higher probability of default. Additionally, the list of HFs characteristics is not exhaustive, the nine independent variables used in the study can be extended to include more features of the HFs. Such variables can include (i) minimum investment to a HF (ii) leverage of the HF (iii) notice period of a redemption and (iv) liquidity of the fund.Another interesting topic that was not addressed in this research is the application of the models on individual funds. The portfolio approach applied used a time series analysis which provides an overall analysis of the fund's performance; however, it may be the case that this approach did not distinguish funds which may have consistently generated positive alpha. Inevitably, these highlighted limitations create some interest avenues for future research on the subject matter.

Scope for further studies:-
Primarily, it may be interesting to study the size effect of different levels of hedge funds probability of default. Secondly, it would be interesting to note the flow of a high probability of default fund and examine whether investors still continue to invest in that fund whilst controlling for other determinants of HF flows such as fees, returns and probability of default. Thirdly, it is worth investigating whether any new regulations imposed on the hedge fund industry after the aftermath of the crisis, has any effect on high probability of defaults of the hedge funds. Lastly, this empirical study has distinguished HFs according to nine different independent variables. Accordingly, a further suggestion would be to assess the returns of high PD HF across different trading strategies and more independent variables such as leverage, notice periods and minimum investments.

Implications:-
This research concluded that hedge funds with high default risk do not deliver higher returns. Investors, therefore, should knowingly start investing in low PD funds as it is proven that investing in riskier hedge funds does not imply higher returns. Moreover, investors should delve into which strategy the portfolio managers are using to obtain higher returns. Different strategies lead to different returns. The fixed income strategy, is the only strategy in this research that showed that High PD HFs beat the market. Ultimately, any investor can spend hours trying to find the perfect hedge fund but as the economist Burton Malkiel says that “a blindfolded monkey throwing darts at a newspaper’s financial pages could select a portfolio that would do just as well as one carefully selected by experts.” However, being armed with the knowledge provided by this study an investor would be able to make a more informed decision.

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