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# GOING BEYOND GOLD: CAN EQUITIES BE SAFE-HAVEN?

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# Going Beyond Gold: Can Equities be Safe-Haven?

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## Abstract

*Popular investment choice like fixed income, gold, and real estate has generated low returns over long horizons. Equity seems to have performed much better despite its' inherent risk. Although, investors prefer safe-haven assets, they are increasingly moving to equities in search for better returns. We consider whether equity could be a safe-haven investment if chosen from quality stocks' basket. We examine the safe-haven and hedging properties of the Nifty-50 constituent stocks over the period 2008–2020. To address this, we employ copula-based framework to model the dependence structure between stocks and five indices. We distinguish between safe-haven attributes and hedging features of the individual stocks. We show that the safe-haven properties of the Nifty-50 listed stocks are not as concentrated as gold but they show much low co-movement with the market. We call them pseudo–safe-haven as they are the safe-bets for investors seeking relatively safe-haven assets with impressive returns.*

**Key words**: *Safe-haven; Hedging; Copula*
**JEL Codes:** *G11, G12, G15*

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# INTRODUCTION

The age-old wisdom of investing broadly in fixed income products (bonds, fixed deposits, pension accounts, etc.) like gold, and real estate is still the most preferred choice amongst investors especially the retail investors. These asset classes, in fact, have underperformed equity by a significant margin over the long horizon. If we consider inflation-adjusted returns, these assets often produce either very low or negative returns. Hence they do not help investors in growing their wealth but slowly destroy it. Despite that, for a country like India which has one of the highest gross domestic savings (percent of Gross Domestic Product) rate amongst other emerging countries, citizens of India hold 77 percent and 11 percent of their assets in real estate (one of the most illiquid asset class) and gold respectively with just only 5 percent in liquid financial assets as per the Housing Finance Committee in 2017. A similar pattern holds for the other emerging and even most of the developed countries with a slight difference in the choice of their assets. The main reason is that we are interested more in protecting the nominal value of our assets rather than allowing it to grow in a volatile market like equity. Intuitively, we always prefer safe-haven assets that could give capital protection.

More often than not, safe-haven assets are government securities, precious metals, oil, and certain currencies. Research on safe-haven properties of currencies (Ranaldo and Soderlind, 2010) document that Swiss Franc, Japanese Yen, and the Euro have had significant safe-haven attributes from 1993-2008. But instruments like currency and oil are neither easily available nor preferred investment options for retail investors. The oil price has generated a compound annual growth rate (CAGR) of 4.6 percent from 2008-09 to 2017-18[1] while that same for gold was a mere 1.5 percent (Nirmal, 2019), whereas the CAGR of Nifty for the last ten years was 15 percent

[1] India Brand Equity Foundation (IBEF)

(Nathan, 2019). Though we can say that gold being a store of wealth is a reliable, risk-averse investment avenue (Hoang *et. al.*, 2016) and promises feasible trades, it does not yield returns as high as equity assets in comparison. While the returns from the real-estate sector in other countries are either negative or very low, in India it is around 8 percent. However, after the 2016 demonetarization announcement, the real-estate boom has busted in India as it has generated only 2-3 percent returns in the last 4 years[2].

With continued fall of banks' deposit rate, bond yields, and underperformance of gold, investors are presently looking for a better investment avenue with a mix of safety and returns. They are willing to take some amount of risk to generate decent returns. Association of Mutual Funds in India data shows a 23 percent annual growth rate of assets under management in the equity segment in 2019. Moreover, this could be one of the best times to invest in the equity market due to a cheap valuation of stocks amidst the 2020 Coronavirus-led financial crisis. High liquidity is one of the major advantages of equity assets, unlike real-estate. However, not all stocks in equity markets generate good returns. The majority of stocks even struggle to generate positive returns over the long horizon. Further, if unlucky, an investor could even lose their whole capital in the equity market if they choose a basket of bad stocks. Therefore, the equity market portfolio needs to consist of good quality stocks which could possibly generate decent returns with minimum risk. A good (if not the best) choice of a basket of quality stocks is the available large-cap index as most of the constituent stocks are the industry leader in their respective sectors, run by good management, and with a history of generating decent returns for the investors. With this in mind, we choose a basket of possibly quality stocks (i.e. constituent stocks of the market index) and test for their safe-haven and also the hedging properties in this paper.

[2] As per the press release on All-India Household Price Index by Reserve Bank of India

Baur and Lucey (2010) refer to "safe-haven asset as having negative correlation with the stock market in the periods of extreme market declines and weak correlation on average with other asset classes offering diversification benefits." whereas Kaul and Sapp (2006) define safe-haven assets as "an ideal venue to park money during periods of uncertainty." In recent years with growing integration between global financial markets, there have been recurring incidents of financial crises of different magnitudes. They have had a prominent impact on portfolios and returns of different assets (Abuzayed, 2012). Hence, cultivating an understanding of safe-haven assets with respect to equities is further important not only for retail investors but also for institutional and international investors.

India has one of the largest and vibrant financial markets around the globe. For our analysis we pick Nifty-50 which is the benchmark based stock market index for the Indian equity market. We limit ourselves to only Nifty-50 for mainly three reasons: (i) we use it just for the representation purpose (it can be done with any other stock index of other countries) (ii) we are more aware of the Indian markets, Indian companies, and their data, hence it becomes our preferred choice; (iii) extending it for other countries in the same paper could be cumbersome as it involves extensive data work and would make the paper unnecessarily clumsy with many large tables. In fact, we could not report all the tables (available upon request) we have due to space constraint.

Nifty-50 represents the weighted average of fifty Indian companies across thirteen sectors. We try to identify those stocks which appear possibly immune (or less prone) to market fluctuations. Following suit of literature such as Genest *et. al.* (1993), Nelson (1999), Mendes (2005), Hu (2006), Patton (2009), Lai *et. al.* (2009), we identify the safe-haven and hedging properties of stocks of the companies listed under the Nifty-50 index using copulas. Though there are many empirical methods that identify dependency and co-movements like vector autoregressive model and cointegration tests; owing to the non-linear dynamics of our return series, we rely on copula based models. In our analysis, we train a copula-based approach to test dependency across 250 index-stock pairs (50 stocks and 5 indices). Nguyen *et. al.* (2016) create a new class of copula using existing ones such as Clayton, Frank, Gumbel and Joe copulas to bring about a mixed copula. Christoffersen *et. al.* (2012) discuss the dependency across stock markets for diversification purposes using an assortment of copulas. Using a similar approach, Avdulaj and Barunik, (2015) and Zhua *et. al.* (2014) explore the dependence structure of oil markets and different international stock markets. Aloui *et. al.* (2013) use copulas to measure contagion risk in transition economies. In our work, we use the Student-*t* copula across all the 250 pairs as it adequately represents the dependence structure of index return series and individual stocks return series. An appealing feature of this approach is that it allows us to model marginal distributions of the joint distributions separately while taking into account tail dependencies as well (Jondeau and Rockinger, 2006). It also observes the nonlinearities in the stock-index relationships as well as the empirical stylized facts of return distributions such as volatility clustering, fat tail behavior, and asymmetric impacts while at the same time avoiding the drawbacks of the linear measures of interdependence.

We acknowledge that for any individual investors it may be impossible to analyze and run this kind of econometric models in the process of choosing the right stocks. However, our work tries to complement the idea of choosing quality stocks explained in many popular investment books[3] with academic backing.

Our analysis shows that the safe-haven properties of the listed stocks are not as concentrated as gold or oil but they show much low

[3] Investment books like *Coffee Can Investing*, *One Up on Wall Street*, *Beating the Street*, *The Intelligent Investor*, *Value Investing and Behavioral Finance*, etc.

correlation for an asset class such as equity. We use the term *pseudo–safe-haven* to denote such properties. The contribution of this study is dual. First, this paper develops the idea of safe-haven investment (which provides decent returns with minimum risk) in an asset class like equity. Second, it adds to the literature of portfolio management by providing an academic patronage to the process of picking right stocks with one of best suited and relevant econometric models. This study renders intriguing insights of the Indian stock markets and sheds light for institutional and retail investors seeking investor-friendly safe-haven assets which could generate extraordinary profits and also safe-guard the investment during times of extremities.

## LITERATURE SURVEY

It has been long-standing now that gold is a rational choice of investment in times of extreme market upheaval. This hypothesis was formally tested by Baur and Lucey (2010) by making the clear distinction between safe-haven and hedging properties of an asset. Reboredo (2013) propounded this idea further by contributing to the implications of such work for risk management. They find benefitting evidence of diversification and downside risk reduction having gold in a currency portfolio. Dee *et. al.* (2013), Arouri *et. al.* (2015), Beckmann *et. al.* (2015), Wen and Cheng (2018), and Baur and Kuck (2019) explain extensively on the flight to gold phenomenon during turbulent markets and also against oil price fluctuations. Though taking refuge under gold during the extreme market is a behavioral bias (Baur and McDermott (2016)) stemming from the historical dimensions of gold as a currency and a store of value, Baur and Lucey (2010) find that the effect of gold as a safe-haven in a portfolio is short-lived. Hood and Malik (2014) observe Volatility Implied Index (VIX) to be a superior hedging tool and a better safe-haven choice than gold for the period from November 1995 to November 2010. This work motivates us to check for the safe-haven properties of equities which run against the conventional wisdom.

In addition to gold, investors trust currencies that are usually considered low risk whose issuing governments are stable with strong, well-functioning economies among other reasons. For the period 1993-2008, Ranaldo and Soderlind (2010) find that Swiss franc and Japanese yen appreciate against the United States (US) dollar when there are adverse movements in the US financial markets. Fatum and Yamamoto (2016) accredit that Japanese Yen as the "safest" of safe-haven currencies as it stays robust irrespective of the prevailing market conditions. Most currency safe-havens work only in developed economies, as Beck and Rahbari (2011) establish that dollars are better safe-haven for developed economies of Asia and Latin America whereas the Euro is the equivalent to European economies. Factors like net foreign asset position which Habib and Stracca (2012) posit to be an indicator of exogenous vulnerability is shown to denote if a currency is a good safe-haven or not. Even the currencies of fast-growing, emerging countries like China have not yet merited the status of safe-haven asset for their Renminbi (Fatum *et. al.* (2017)). Further panoptic works that discuss the safe-haven attributes of currencies are Kaul and Sapp (2006), Fratzscher (2009), McCauley and McGuire (2009), Kohler (2012), Hoffmann and Suter (2010), Botman *et. al.* (2013), Coudert *et. al.* (2014), De Bock and de Carvalho Filho (2015) and Grisse and Nitschka (2015).

Of late, with the advent of cryptocurrencies, investors have shown interest in digital currencies like Bitcoin, mainly for their efficiency and tractability. Since such instruments are in their incubation period, despite their weak safe-haven properties. Feng et al (2018), Wu et al (2019), Smales (2019), and Shahzad *et. al.* (2019) suggest refraining from classifying Bitcoin as a safe-haven. Inclined to such notable shortcomings of safe-haven assets like gold, currency and potentially Bitcoin, retail investors are showing increasing interest in the equity markets over the years to seek decent returns. The inherent risk in the equity market could possibly make investors lose their capital if mistakes are made while choosing the right stocks. Therefore, they need quality stocks which generate decent returns with much lower risk than common equity index. Keeping that in mind, we examine the safe-haven and hedging properties of a basket of possibly quality stocks.

Customarily, correlation analysis is performed to see the co-movement but by and large, financial data exhibits non-normality and linear correlation measures are misleading in such cases. Zhang and Wei (2010) employ cointegration tests and Granger causality to explain the co-movement in crude oil and gold markets. Dynamic conditional correlations (DCC) yield better and consistent results than the aforementioned tests. On testing gold against the US dollar using DCC, Capie *et. al.* (2005) and Joy (2011) find gold to be a poor safe-haven. Different papers employ different variants of the generalized autoregressive conditional heteroscedasticity (GARCH) model (Bollerslev (1986)) like exponential GARCH (Nelson and Cao (1992) and Hammoudeh and Yuan (2008)), Glosten-Jagannathan-Runkle GARCH (Glosten *et. al.* (1993)) and Threshold GARCH (Zakoian (1994)) to best capture the stylized facts. It was not until the late 1990s that copulas were used in finance and quantitative techniques. Copulas are widely applied in modeling asymmetric dependences (Li (2000), Fortin and Kuzmics (2002), Chollete *et. al.* (2006), Hu (2006), Patton (2009) and Lai *et. al.* (2009)). Of many advantages that copula holds against correlation analysis, the prime vantage point of it resides in the separation of dependence structure and the univariate distributions of the variables. This property gives copula functions a leeway to model dependencies for any type of distribution functions. Early works (Bouyé et al (2000), Embrechts *et. al.* (2002) and Embrechts *et. al.* (2003)) provide some holistic guide to working with copulas in finance and risk management. There is a considerable dearth of copula approach in assessing the safe-haven properties of financial assets expect Jondeau and Rockinger (2006), Lai and Tseng (2010), Zhu *et. al.* (2014), and Avdulaj and Barunik (2015) to name a few, in the literature. However, given the manifold perks of copulas, in this paper, we employ the bivariate *t*-copula as it has been shown to grasp the empirical truths of financial data the best (Cossin and Schellhorn, 2007 and Fang *et. al.* (2002).

While acknowledging the relevant contribution made by prior research, our paper supplements to the existing literature by examining the relationship between equities and major stock indices in the Indian financial market. Although we do not find any stocks with strong safe-haven properties but a handful of stocks shows minimum co-movements with market indices, we term them as pseudo–safe-haven since they can produce decent returns with an acceptable level of capital protection capability. The advantage of using pseudo–safe-haven equities is that investors can generate relatively stable, much higher returns than the other safe-haven asset classes with a very low level of volatility in the investment value.

## DATA AND METHODOLOGY:

### Data

Our data consist of the daily returns of the five indices (Nifty-50, Nifty-100, Nifty-Midcap-100, Nifty-200, and Nifty-Smallcap-100) and the daily returns of the constituent fifty companies listed under the NIFTY-50 index. We collect the data from Investing.com website for the period of January 2008 to January 2020. We chose this period considering our motive to find specific equity stocks listed under the Nifty-50 index that grew after the 2008 financial crisis and simultaneously indicated safe-haven traits in those years. The ticker symbols of the stocks follow the nomenclature adopted by Investing.com. The fifty companies predominantly fall under one or the other following industries – automobile, financial services, cement industries, cigarette manufacturers, information technology, consumer goods, engineering, metals and mining, energy, fertilizers, pharmaceuticals, shipping and cargo, and media and entertainment. 41 percent of the total composition is made up by financial service companies, followed by energy industries comprising of 16 percent and informational technology-oriented companies making up for 12 percent. The residual portion, on an average, is fairly spread across the remaining sectors.

**Modelling the Marginal Distributions**

As discussed earlier, copulas are multivariate cumulative distribution function whose marginal functions follow a uniform distribution from the interval [0, 1]. From the descriptive statistics, (see table 1) we observe that distributions are fairly symmetrical which implies that we do not need a threshold or an asymmetrical GARCH model. Hence, we estimate a marginal AR(p)-t-GARCH(p,q). The standardized errors from this model follow the t-distribution (Bollerslev, 1986). On plugging different values for the p and q lag parameters, We find the best model to be AR(1)-t-GARCH(1,1) based on the Akaike information criterion (AIC) comparison between 2, 12 and 36 lags for AR(p) and GARCH(1,2) and GARCH(2,2). The marginal model is mathematically specified as –

$$R_{i,t} = \mu_i + \sum_{j=1}^{p} \emptyset_j R_{i,\, t-j} \text{ and } \varepsilon_{i,t}$$

$$= \sigma_{i,t} v_{i,t} \text{ where } v_{i,t} \sim i.i.d\ (0,1)$$

$$\sqrt{\frac{v}{\sigma_{i,t}^2 (v-2)}} \,.\, \varepsilon_{i,t} \mid I_{t-1} \sim t(v)$$

$$\sigma_{i,t}^2 = a_i + b_i \sigma_{i,t-1}^2 + c_i \varepsilon_{i,t-1}^2$$

$R_{i,t}$ is the return on the $i^{th}$ stock and $\sigma_{i,t}^2$ is variance of $\varepsilon_{i,t}$ for the $i^{th}$ stock. We observe the estimated parameters of the AR(1)-t-GARCH(1,1) model and the AIC values for all the series. Since most return series indicate auto-regressive properties and conditional heteroscedasticity, AR(1)-t-GARCH(1,1), a parsimonious model captures the stylized facts of the stock returns impressively. The coefficient of the GARCH term (i.e. β) aptly models the conditional heteroscedasticity for all the series.

## Marginal Model- Goodness of Fit Tests

Since copulas are built on marginal distributions, it is crucial to run goodness of fit tests and check for misspecifications. Any incorrectness or misspecification in the model invalidates the empirical adequacy of copulas. We employ Lagrange Multiplier (LM) and the Box-Ljung (Q-tests) tests to examine the same estimated by the aforementioned AR(1)-t-GARCH(1,1). The LM test is a method for a testing hypothesis about the parameters based on likelihoods. The test statistic is formulated as the following: Let $L(\theta)$ be a log-likelihood function of a $k \times 1$ parameter vector θ, and let the score function and the information matrix be

$$q(\theta) = \frac{\partial L(\theta)}{\partial \theta}$$

$$I(\theta) = -E\left[\frac{\partial^2 L(\theta)}{\partial \theta \partial \theta'}\right]$$

We let $\tilde{\theta}$ be the maximum likelihood estimator (MLE) of θ subject to constraints such as an $r \times 1$ vector of $h(\theta) = 0$. The Lagrangian function would be as follows:

$$\mathcal{L} = L(\theta) - \lambda' h(\theta)$$

Where $\lambda$ is a vector of $r \times 1$ Lagrange multipliers. The first order conditions for $\tilde{\theta}$ are:

$$\frac{\partial \mathcal{L}}{\partial \theta} = q(\tilde{\theta}) - H(\tilde{\theta})\, \tilde{\lambda} = 0$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = h(\tilde{\theta}) = 0$$

Here, $H(\theta) = \frac{\partial h(\theta)'}{\partial \theta}$. Hence, the LM statistic is given by

$$LM = \tilde{q}'\tilde{I}'\tilde{q} = \tilde{\lambda}'\tilde{H}'\tilde{I}'\tilde{H}\tilde{\lambda}$$

For $\tilde{q} = q(\tilde{\theta}), \tilde{I} = I(\tilde{\theta})$ and $\tilde{H} = H(\tilde{\theta})$.

The Q-test statistics is a diagnostic tool to check the fit of the model. In our analysis, we fit AR(1)-t-GARCH(1,1) and apply the Q-test to the residuals after fitting the model. For a given series of values $X$ of length $n$, the Q-test statistic is computed as:

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{r}_k^2}{n-k}$$

Where $\hat{r}_k$ is the estimated autocorrelation of the series at lag $k$, and $m$ is the number of lags being tested.

**t-copula Model**

Before getting into the interpretation of results, it is necessary to understand what a copula is. The correlation coefficient measures how strong a relationship between the two variables is. The coefficients are significant only when the distributions of the variables are Gaussian. More often than not financial data is non-Gaussian so it is not advisable to rely on the correlation coefficient as it can be very misleading. We instead employ 'copulas' which measures the degree of dependence and the structure of dependence.

***Definition:*** An n-dimensional copula is a function $C: [0,1]^n \rightarrow [0,1]$ such that $C$ is grounded and n is increasing. Also, $C$ has margins $C_k, k = 1,2,\ldots,n$, which satisfy$C_k(u) = u \; \forall \; u \text{ in } [0,1]$.

The ***Sklar's Theorem*** (Skalar *et. al.* 1959; Durante et al, 2013) states that let $F_{XY}$be a joint distribution function where the margins are $F_X$and$F_Y$. Then there exists a copula $C$ such that$\forall \; x, y \; \in R$,

$$F_{XY}(x, y) = C(F_X(x), F_Y(y))$$

We observe $C$ to be unique if $F_X$and$F_Y$ are continuous. Conversely, we can say that if $C$ is a copula with $F_X$and$F_Y$ for cumulative distribution functions (CDFs), then the function $F_{XY}$ (also defined above) is a joint distribution function with margins $F_X$and$F_Y$ (see Joe, 1997; Nelson ,1999) for further empirical examination of copulas and measures of dependence).

This theorem indicates that joint distribution can be disintegrated to its univariate marginal distributions and a copula function which captures the dependence structure between the variables X and Y. Moreover, there are various other measures of dependence, among which Kendall's $\tau$ and Spearman's $\rho$ are usually studied with copula models. More often than not the tail dependence between X and Y, as one of the copula properties, is invariant under the strictly increasing transformation of X and Y. The lower and upper tail dependence coefficients are defined as:

$$\lambda_L = \lim_{u \to 0} \Pr(F_Y(y) \leq u | F_X(x) \leq u] = \lim_{u \to 0} \frac{C(u,u)}{u}$$

$$\lambda_U = \lim_{u \to 1} \Pr(F_Y(y) \geq u | F_X(x) \geq u] = \lim_{u \to 1} \frac{1 - 2u + C(u,u)}{1 - u}$$

Where $\lambda_L$ and $\lambda_U \in [0,1]$. Different copulas usually represent different dependence structures with the association parameters indicating the strength of the dependence. For example, Gaussian copula has zero tail dependence while Clayton copula has left tail dependence and no right tail dependence.

***Copula:*** t-copula represents an implicit dependence structure (Embrechts *et. al.*, 2001; Fang *et. al.*, 2002) in a multivariate t-distribution. Mashal and Zeevi (2002), Breymann *et. al.* (2003), Jondeau and Rockinger (2006) show that the empirical fit of a t-copula is superior to Gaussian copula - the dependence structure of the multivariate normal distribution. Further, the ability to capture the phenomenon of dependent extreme values (very often observed in financial return series) makes the t-copula a better choice.

***The Multivariate t- Distribution***

Suppose there exists a *d*-dimensional random vector $\boldsymbol{X} = (X_1, \ldots, X_d)'$ which is said to have a multivariate $t$ distribution with $\nu$ degrees of freedom, mean vector $\boldsymbol{\mu}$ and positive-definite scatter matrix $\sum$, denoted $\boldsymbol{X} \sim t_d(\nu, \boldsymbol{\mu}, \sum)$, then its density is given by

$$f(x) = \frac{\Gamma\left(\frac{\nu+d}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{(\pi\nu)^d |\sum|}} \left(1 + \frac{(x - \boldsymbol{\mu})' \sum^{-1} (x - \boldsymbol{\mu})}{\nu}\right)^{-\left(\frac{\nu+d}{2}\right)}$$

Multivariate $t$ belongs to the class of multivariate normal variance mixtures and has the representation $\boldsymbol{X} \stackrel{\text{def}}{=} \boldsymbol{\mu} + \sqrt{\mathrm{W}}\mathbf{Z}$ where $\mathbf{Z} \sim N_{\boldsymbol{d}}(\mathbf{0}, \sum)$ with W independent of Z; equivalently W has an inverse gamma distribution $W \sim \mathrm{Ig}(\nu/2, \nu/2)$.

***t-copula:*** We now extend the Sklar's Theorem (from 3.4.) to explain the multivariate $t$ copula. In this case, the copula $C$ of the joint distribution function can be evaluated as

$$C(\boldsymbol{u}) := C(u_1, \ldots, u_d) = F(F_1^{-1}(u_1), \ldots, F_d^{-1}(u_d))$$

Where $F_i^{-1}$ are the quantile functions of the msargins. The copula $C$ can be thought of as the distribution function of the probability transformed random vector $(F_1(X_1), \ldots, F_d(X_d))'$. The copula does not vary if the marginal distributions are standardized. So, the copula of a $t_d(\nu, \boldsymbol{\mu}, \sum)$ is identical to that of a $t_d(\nu, \mathbf{0}, \sum)$ distribution where *P* is the correlation matrix implied by the dispersion matrix $\sum$. The unique $t$ copula is thus given by

$$C^t_{\nu,P}(\boldsymbol{u}) = \int_{-\infty}^{t_\nu^{-1}(u_1)} \cdots \int_{-\infty}^{t_\nu^{-1}(u_d)} \frac{\Gamma\left(\frac{\nu+d}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{(\pi\nu)^d|P|}} \left(1 + \frac{x' P^{-1} x}{\nu}\right)^{-\left(\frac{\nu+d}{2}\right)} dx$$

where $t_\nu^{-1}$ is the quantile function of a standard univariate $t_\nu$ distribution. In this paper, we interchangeably use *t*-copula for unique copula of a multivariate Gaussian distribution as Gaussian copula can be thought of as a limiting case of the *t*-copula as $\nu \rightarrow \infty$.

To simulate a *t*-copula, we generate a multivariate *t* distribution random vector $\boldsymbol{X} \sim t_d(\nu, \boldsymbol{\mu}, P)$ and then return a vector $U = (t_\nu(X_1), \ldots, t_\nu(X_d))'$ where $t_\nu$ denotes the distribution function of a standard univariate *t*. The estimated *t*-copula would have the form

$$C^t_{\nu,P}(\boldsymbol{u}) = \frac{f_{\nu,P}(t_\nu^{-1}(u_1), \ldots, t_\nu^{-1}(u_d))}{\prod_{i=1}^{d} f_\nu(t_\nu^{-1}(u_i)}, \qquad \boldsymbol{u} \in (0,1)^d$$

where $f_{\nu,P}$ is the joint density of a $t_d(\nu, \mathbf{0}, P)$- distributed random vector and $f_\nu$ is the density of the univariate standard *t* distribution with $\nu$ degrees of freedom.

Our results exhibit the parameter estimates of the t-copula that is fit to a stock index and its constituent stocks' return series. The t-copula parameter *ρ* is very similar to the linear correlation coefficient of the data owing to the fact that t-copula is a member of the elliptical copula family with the elliptical margin being the t-distribution. The slight difference between the estimated *ρ*'s of different pairs and their linear correlation coefficient is the value yielded due to fat tails and extreme co-movements that often appear in financial return data, which linear correlation values fail to take into account.

The literature suggests that an asset is a safe-haven if it is uncorrelated or negatively correlated with another asset or portfolio in times of extreme market movements. It is essential that the dependence holds under extreme market movements for an asset to be classified as a safe-haven. On another note, if the assets portray a significant $\rho$ positive for the whole sample period, we can sort that the asset has 'hedging' properties. Thus, we can state our hypotheses as

$a)\ \rho_i > 0; H_0 = the\ i^{th}\ stock\ is\ not\ a\ hedge$

$b)\ \lambda_L, \lambda_U > 0;\ H_0$
$= the\ i^{th}\ stock\ is\ not\ a\ safe\ haven\ where\ \lambda_L\ is\ lower\ tail\ depence\ and\ \lambda_U\ is$
$the\ upper\ tail\ dependence\ parameter$

## EMPIRICAL RESULTS:

The sample periods for some stocks are shorter than the period mentioned above (January 2008 to January 2020) as data is not available for them. The complete dataset spans over 158,778 discrete observations for fifty individual stocks and five indices over 2,982 days. The descriptive statistics for the stocks and their corresponding sample periods are exhibited in Table 1. One can infer that the data is approximately symmetrical from the skewness measures. The kurtosis values indicate a leptokurtic distribution i.e., these distributions have a heavier and fatter tail as opposed to a normal distribution. Moreover, the Jarque-Bera test statistics rejects the Gaussian properties of all the series.

### Results from Marginal model

As discussed earlier, the marginal model employed is AR-t-GARCH (1,1). Table 2 shows that the intercept (μ) is asymptomatically zero for all the stocks and indices. The β's of the marginal model denotes large values which indicate that GARCH(1,1) adequately captures the heteroscedastic effects. The values range from 0.502 to 0.983. Furthermore, the AIC values are small enough to vouch for the robustness of the marginal models. The LM test verifies if the probability transformations are independent, identically distributed (IID). On the other hand, the Q-test checks the model fit. The p-values of the LM test and the Q-test are shown in Table 3. The large p-values suggest no serial correlation, as necessary and no autoregressive conditional heteroscedasticity in the standardized residuals. Kolmogorov-Smirnov (KS) test can also be used for diagnostic checking in lieu of Q-tests. More often than not, the standard LM test and Q-test suffices to check the fit of such marginal models. The p-values of our LM test ranges from 6 percent to 99.41 percent and the p-values of Q-test ranges from 11.21 percent to 100 percent. These results assure that the dependence structure of the return series that will further be modeled by copulas is not misspecified.

Table 1 consists of descriptive statistics. One can infer that the data is approximately symmetrical from the skewness measures. The kurtosis values indicate a leptokurtic distribution i.e., these distributions have a heavier and fatter tail as opposed to a normal distribution. Moreover, the Jarque-Bera test statistics rejects the Gaussian properties of all the series.

**Table 1: Descriptive Statistics**

| | Mean | SD | Skew | Kurt | JB | | Mean | SD | Skew | Kurt | JB |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **APSE** | 0.001 | 0.027 | 0.457 | 8.531 | 3897 | **LART** | 0.000 | 0.022 | 0.758 | 11.326 | 8901 |
| **BRTI** | 0.000 | 0.023 | 0.632 | 10.129 | 6514 | **MAHM** | 0.001 | 0.022 | 0.823 | 14.956 | 18105 |
| **ASPN** | 0.001 | 0.017 | 0.117 | 6.593 | 1611 | **MRTI** | 0.001 | 0.020 | 0.124 | 6.185 | 1268 |
| **AXBK** | 0.001 | 0.025 | 0.345 | 7.387 | 2450 | **NEST** | 0.001 | 0.014 | 0.252 | 5.744 | 967 |
| **BJFN** | 0.002 | 0.026 | 1.004 | 13.056 | 13062 | **NTPC** | 0.000 | 0.018 | 0.035 | 8.815 | 4227 |
| **BAJA** | 0.001 | 0.019 | 0.036 | 8.537 | 3683 | **ONGC** | 0.001 | 0.017 | 0.996 | 10.564 | 7600 |
| **BJFS** | 0.001 | 0.024 | 0.205 | 10.303 | 6428 | **PGRD** | 0.000 | 0.018 | - | 13.557 | 13856 |
| **BPCL** | 0.001 | 0.023 | 0.059 | 7.428 | 2439 | **REDY** | 0.001 | 0.018 | - | 7.924 | 3037 |
| **BHRI** | 0.000 | 0.023 | 0.180 | 6.234 | 769 | **RELI** | 0.001 | 0.021 | 0.211 | 11.450 | 8896 |
| **BRIT** | 0.001 | 0.017 | 0.996 | 10.564 | 7600 | **SBI** | 0.000 | 0.024 | 0.970 | 12.995 | 12875 |
| **CIPL** | 0.000 | 0.016 | 0.465 | 5.926 | 194 | **SUN** | 0.001 | 0.020 | 0.119 | 11.546 | 9084 |
| **COAL** | 0.000 | 0.018 | 0.257 | 6.408 | 1126 | **TAMO** | 0.001 | 0.028 | 0.191 | 7.717 | 2785 |
| **EICH** | 0.002 | 0.024 | 0.979 | 12.010 | 10558 | **TISC** | 0.000 | 0.027 | 0.026 | 6.695 | 1696 |
| **GAIL** | 0.000 | 0.020 | -0.056 | 7.847 | 2922 | **TCS** | 0.001 | 0.020 | 0.420 | 9.510 | 5352 |
| **GRAS** | 0.000 | 0.019 | 0.301 | 8.993 | 4507 | **TEML** | 0.001 | 0.026 | - | 61.555 | 428460 |
| **HCL** | 0.001 | 0.023 | 0.335 | 9.903 | 5979 | **TITN** | 0.001 | 0.024 | 0.361 | 9.926 | 6013 |
| **HDFC** | 0.001 | 0.022 | 0.675 | 11.282 | 8752 | **ULTC** | 0.001 | 0.020 | 0.382 | 6.818 | 1879 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **HDBK** | 0.001 | 0.017 | 0.420 | 10.242 | 6606 | **UPLL** | 0.001 | 0.027 | 0.026 | 17.643 | 26651 |
| **HROM** | 0.001 | 0.019 | 0.949 | 13.097 | 13088 | **VDAN** | 0.000 | 0.030 | 0.217 | 7.230 | 2241 |
| **HALC** | 0.000 | 0.028 | 0.231 | 6.027 | 1163 | **WIPR** | 0.000 | 0.020 | - | 15.963 | 21149 |
| **HLL** | 0.001 | 0.016 | 0.693 | 10.063 | 6424 | **YESB** | 0.001 | 0.034 | 0.335 | 17.289 | 25434 |
| **ICBK** | 0.001 | 0.026 | 0.392 | 9.900 | 5990 | **ZEE** | 0.001 | 0.026 | - | 10.942 | 7844 |
| **IOC** | 0.000 | 0.022 | 0.129 | 9.841 | 5824 | **NIFTY100** | 0.000 | 0.014 | 0.332 | 17.921 | 27762 |
| **INBK** | 0.001 | 0.026 | 0.332 | 8.751 | 4163 | **NSEI** | 0.000 | 0.014 | 0.430 | 18.778 | 31075 |
| **INFY** | 0.001 | 0.019 | -0.478 | 16.510 | 22799 | **NIFMDCP100** | 0.000 | 0.013 | - | 10.957 | 7971 |
| **ITC** | 0.001 | 0.017 | 0.047 | 7.205 | 2197 | **NIFTY200** | 0.000 | 0.017 | - | 11.191 | 8424 |
| **JSTL** | 0.001 | 0.030 | 0.817 | 12.631 | 11835 | **NIFSMCP100** | 0.000 | 0.015 | - | 9.390 | 5362 |
| **KTKM** | 0.001 | 0.024 | 0.055 | 10.615 | 7209 | | | | | | |

**Note:** All the JB test statistics have a p-value < 0.05. For some stocks data is not available from 2008. We have considered the maximum period for them.

**Table 2: Estimation of Marginal Models**

Table 2 encompasses the coefficients of the AR(1)-*t*-GARCH(1,1) model. It shows that the intercept (μ) is asymptomatically zero for all the stocks and indices. The other coefficients similarly are statistically significant. The β's of the marginal model shows large values which indicate that GARCH(1,1) adequately captures the heteroscedastic effects. The values range from 0.502 to 0.983. Furthermore, the AIC values are small enough to vouch for the robustness of the marginal models.

| | **μ** | **ϕ** | **α** | **β** | **AIC** | | **μ** | **ϕ** | **α** | **β** | **AIC** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **APSE** | 0.001 | -0.013 | 0.031* | 0.960*** | -4.533 | **LART** | 0.001 | 0.069*** | 0.066*** | 0.917** | -5.071 |
| **BRTI** | 0.001 | -0.020 | 0.087 | 0.826*** | -4.833 | **MAHM** | 0.001 | 0.017 | 0.059 | 0.931** | -5.049 |
| **ASPN** | 0.001*** | 0.019 | 0.085 | 0.845*** | -5.407 | **MRTI** | 0.001** | 0.064*** | 0.039*** | 0.950** | -5.163 |
| **AXBK** | 0.001 | 0.056 | 0.071* | 0.910*** | -4.782 | **NEST** | 0.001*** | 0.011 | 0.077 | 0.807** | -5.652 |
| **BJFN** | 0.002*** | 0.051 | 0.091 | 0.876*** | -4.663 | **NTPC** | 0.000 | -0.047 | 0.076*** | 0.890** | -5.371 |
| **BAJA** | 0.001** | 0.052 | 0.036* | 0.955*** | -5.309 | **ONGC** | 0.000 | 0.005 | 0.092*** | 0.880** | -5.063 |
| **BJFS** | 0.002*** | 0.104 | 0.083* | 0.868*** | -4.788 | **PGRD** | 0.000 | -0.050 | 0.126*** | 0.845** | -5.522 |
| **BPCL** | 0.001 | 0.024 | 0.071* | 0.894*** | -4.781 | **REDY** | 0.001* | 0.024 | 0.083*** | 0.883** | -5.269 |
| **BHRI** | 0.000 | -0.022 | 0.140* | 0.730*** | -4.847 | **RELI** | 0.001 | 0.053* | 0.060*** | 0.922** | -5.168 |
| **BRIT** | 0.001*** | 0.019 | 0.038* | 0.921*** | -5.401 | **SBI** | 0.000 | 0.071*** | 0.155 | 0.790** | -4.789 |
| **CIPL** | 0.000 | -0.059 | 0.114* | 0.770*** | -5.507 | **SUN** | 0.001** | 0.010 | 0.030*** | 0.961** | -5.036 |
| **COAL** | 0.000 | -0.001 | 0.039* | 0.935*** | - | **TAMO** | 0.001 | 0.055** | 0.068** | 0.904** | -4.469 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **EICH** | 0.002*** | 0.074 | 0.028 | 0.964*** | -4.741 | **TISC** | 0.000 | 0.021 | 0.070*** | 0.912** | -4.603 |
| **GAIL** | 0.000 | -0.030 | 0.034 | 0.954*** | -5.053 | **TCS** | 0.001*** | 0.027 | 0.076*** | 0.903** | -5.258 |
| **GRAS** | 0.001 | 0.031 | 0.056* | 0.930*** | -5.238 | **TEML** | 0.000 | 0.066 | 0.056* | 0.908** | -4.577 |
| **HCL** | 0.001*** | 0.000 | 0.068* | 0.920*** | -5.012 | **TITN** | 0.002*** | - | 0.113*** | 0.789** | -4.736 |
| **HDFC** | 0.001** | 0.017 | 0.061* | 0.923*** | -5.174 | **ULTC** | 0.001 | 0.044** | 0.021*** | 0.973** | -5.159 |
| **HDBK** | 0.001** | 0.042 | 0.043 | 0.951*** | -5.659 | **UPLL** | 0.001* | 0.021*** | 0.155*** | 0.737** | -4.559 |
| **HROM** | 0.001 | 0.048 | 0.051* | 0.933*** | -5.173 | **VDAN** | 0.000 | 0.025 | 0.059*** | 0.915** | -4.282 |
| **HALC** | 0.000 | 0.019 | 0.058* | 0.925*** | -4.445 | **WIPR** | 0.001 | -0.038 | 0.102*** | 0.821** | -5.207 |
| **HLL** | 0.001*** | -0.021 | 0.244* | 0.502*** | -5.549 | **YESB** | 0.002*** | 0.052 | 0.078*** | 0.921** | -4.269 |
| **ICBK** | 0.001** | 0.047 | 0.079* | 0.898*** | -4.762 | **ZEE** | 0.001* | -0.018 | 0.040*** | 0.953** | -4.721 |
| **IOC** | 0.000 | 0.022 | 0.165* | 0.764*** | -4.951 | **NIFTY1** | 0.001 | 0.079* | 0.088 | 0.905** | -6.233 |
| **INBK** | 0.002*** | 0.041 | 0.076* | 0.918*** | -4.857 | **NSEI** | 0.001 | 0.065*** | 0.084 | 0.911* | -6.229 |
| **INFY** | 0.001 | -0.004 | 0.010 | 0.983*** | -5.150 | **NIFMDC** | 0.001 | 0.168*** | 0.12* | 0.853** | -6.069 |
| **ITC** | 0.001 | -0.018 | 0.057* | 0.912*** | -5.420 | **NIFTY2** | 0.001* | 0.115*** | 0.113** | 0.866** | -5.652 |
| **JSTL** | 0.001** | -0.009 | 0.070* | 0.916*** | -4.500 | **NIFSMC** | 0.001 | 0.221*** | 0.145*** | 0.809** | -5.879 |
| **KTKM** | 0.001*** | -0.006 | 0.061* | 0.928*** | -5.085 | | | | | | |

**Note:** (***) denotes 1 percent level significance. Similarly, (**) and (*) show 5 percent and 10 percent level significance.

## Table 3: Goodness of Fit Tests for the Marginal Model

Table 3 presents the results for the goodness of fit tests for the AR(1)-*t*-GARCH(1,1) is as follows. Q(2) denotes Q-statistic for 2 lags, similarly Q(4) is for 4 lags. The ARCH(3), ARCH(5) and ARCH(7) indicate the p-values of the ARCH LM tests for their corresponding lags in parenthesis.

| | Q(2) | Q(4) | ARCH(3 | ARCH(5 | ARCH(7 | | Q(2) | Q(4) | ARCH(3 | ARCH(5 | ARCH(7 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **APSE** | 0.637 | 0.403 | 0.651 | 0.861 | 0.923 | **LART** | 0.25 | 0.19 | 0.263 | 0.624 | 0.632 |
| **BRTI** | 0.127 | 0.112 | 0.063 | 0.205 | 0.374 | **MAHM** | 0.99 | 0.61 | 0.870 | 0.741 | 0.882 |
| **ASPN** | 0.957 | 0.907 | 0.112 | 0.218 | 0.225 | **MRTI** | 0.98 | 0.93 | 0.848 | 0.983 | 0.950 |
| **AXBK** | 0.950 | 0.539 | 0.994 | 0.858 | 0.946 | **NEST** | 0.99 | 0.41 | 0.664 | 0.688 | 0.772 |
| **BJFN** | 0.999 | 0.984 | 0.161 | 0.294 | 0.479 | **NTPC** | 0.62 | 0.78 | 0.646 | 0.868 | 0.928 |
| **BAJA** | 1.000 | 0.729 | 0.623 | 0.854 | 0.887 | **ONGC** | 0.68 | 0.36 | 0.327 | 0.539 | 0.736 |
| **BJFS** | 0.941 | 0.390 | 0.907 | 0.944 | 0.834 | **PGRD** | 0.81 | 0.07 | 0.456 | 0.715 | 0.683 |
| **BPCL** | 0.931 | 0.819 | 0.422 | 0.692 | 0.610 | **REDY** | 0.99 | 0.94 | 0.834 | 0.837 | 0.770 |
| **BHRI** | 0.403 | 0.209 | 0.870 | 0.540 | 0.235 | **RELI** | 0.99 | 0.48 | 0.441 | 0.599 | 0.738 |
| **BRIT** | 0.999 | 0.794 | 0.537 | 0.894 | 0.963 | **SBI** | 0.91 | 0.86 | 0.379 | 0.726 | 0.866 |
| **CIPL** | 0.991 | 0.982 | 0.932 | 0.617 | 0.787 | **SUN** | 0.84 | 0.56 | 0.806 | 0.978 | 0.990 |
| **COAL** | 0.976 | 0.909 | 0.215 | 0.234 | 0.300 | **TAMO** | 0.89 | 0.77 | 0.298 | 0.686 | 0.796 |
| **EICH** | 0.896 | 0.233 | 0.135 | 0.304 | 0.482 | **TISC** | 0.90 | 0.84 | 0.184 | 0.416 | 0.221 |
| **GAIL** | 0.397 | 0.079 | 0.369 | 0.155 | 0.224 | **TCS** | 0.99 | 0.40 | 0.291 | 0.590 | 0.623 |

| | | | | | |
|---|---|---|---|---|---|
| **GRAS** | 0.568 | 0.400 | 0.899 | 0.871 | 0.901 |
| **HCL** | 0.596 | 0.038 | 0.233 | 0.609 | 0.812 |
| **HDFC** | 0.915 | 0.941 | 0.544 | 0.682 | 0.791 |
| **HDBK** | 0.750 | 0.925 | 0.655 | 0.864 | 0.964 |
| **HROM** | 0.734 | 0.180 | 0.861 | 0.924 | 0.906 |
| **HALC** | 1.000 | 0.998 | 0.584 | 0.360 | 0.486 |
| **HLL** | 0.997 | 0.949 | 0.204 | 0.487 | 0.645 |
| **ICBK** | 0.508 | 0.208 | 0.504 | 0.806 | 0.907 |
| **IOC** | 0.605 | 0.873 | 0.675 | 0.687 | 0.672 |
| **INBK** | 0.977 | 0.302 | 0.297 | 0.462 | 0.187 |
| **INFY** | 0.314 | 0.624 | 0.660 | 0.961 | 0.984 |
| **ITC** | 0.129 | 0.153 | 0.322 | 0.562 | 0.402 |
| **JSTL** | 0.861 | 0.755 | 0.624 | 0.108 | 0.201 |
| **KTKM** | 0.987 | 0.613 | 0.708 | 0.829 | 0.797 |

| | | | | | |
|---|---|---|---|---|---|
| **TEML** | 1.00 | 1.00 | 0.857 | 0.996 | 1.000 |
| **TITN** | 0.89 | 0.60 | 0.335 | 0.614 | 0.733 |
| **ULTC** | 1.00 | 0.62 | 0.103 | 0.103 | 0.140 |
| **UPLL** | 0.12 | 0.12 | 0.683 | 0.919 | 0.985 |
| **VDAN** | 0.99 | 0.99 | 0.294 | 0.531 | 0.532 |
| **WIPR** | 0.97 | 0.60 | 0.795 | 0.974 | 0.996 |
| **YESB** | 0.35 | 0.38 | 0.792 | 0.987 | 0.976 |
| **ZEE** | 0.06 | 0.01 | 0.801 | 0.985 | 0.993 |
| **NIFTY100** | 0.94 | 0.92 | 0.871 | 0.751 | 0.862 |
| **NSEI** | 0.41 | 0.17 | 0.510 | 0.807 | 0.908 |
| **NIFMDCP10** | 0.62 | 0.24 | 0.547 | 0.719 | 0.823 |
| **NIFTY200** | 0.25 | 0.34 | 0.570 | 0.777 | 0.881 |
| **NIFSMCP100** | 0.15 | 0.13 | 0.699 | 0.834 | 0.903 |

**Source:** Authors calculation

## Results from t-Copula

We can observe that (see Table 4), in most cases the dependence among the individual stocks and the Nifty-50 index lies between -3 percent and 34.5 percent. This degree of co-movement can be attributed to industry-specific risks and their composition in the index. The dependence between the Nifty-100 index and the stocks are from -3.9 percent to 36.4 percent, following a similar suit to the dependence between the same stocks and the Nifty-50 index. Likewise, the Nifty-200 index and the Nifty-Midcap-100 index show respective dependence structures: -3.626 percent to 3.659 percent and -2.075 percent to 34.92 percent. The Nifty-Smallcap index shows relatively less dependence with the copula estimates ranging from 2.98 percent to 29.25 percent. The stock that shows large co-movement with all the indices is BJFN (Bajaj Finance) and the stock with a least co-movement is CIPL (Cipla).

Regarding hedging property of these stocks, we observe 45 of them to exhibit a positive and a significant ρ against all the five indices. Whereas BAJA (Bajaj Auto), BJFS (Bajaj Finserv), CIPL (Cipla), NEST (Nestle) and REDY (Dr. Reddy's Laboratories) show zero or negative *ρ*s, thereby nullifying their hedging properties. Finally, we check the safe-haven properties. Student-*t* copulas always exhibit lower and upper tail dependence and since all the pairs modeled in our work is based on t-copulas, we determine the stocks with *ρ*s ≥ 0.2 to have a *pseudo–safe-haven* properties. Stocks such as MRTI (Maruti Suzuki), TCS (Tata Consultancy Services), HLL (Hindustan Unilever), REDY (Dr. Reddy's), HROM (Hero Motorcorp), COAL (Coal India), BAJA (Bajaj Auto), NEST (Nestle), EICH (Eicher Motors), CIPL (Cipla), BJFN (Bajaj Finance), APSE (Adani Port and Special Economic Zone), ULTC (Ultratech Cements), BHRI (Bharti Infratel), HALC (Hindalco Industries), TITN (Titan) and PGRD (Power Grid Corporation of India) show very low dependency. These findings are more or less pervasive across indices.

## Table 4: Estimation of Copula Parameters

In the following table, ρ denotes the t-copula estimate. SE, ∂l and AIC are the corresponding standard error values, log-likelihood values and AIC measures respectively.

**Table 4A:**

| | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ρ | **APSE** | 0.044 | 0.046 | 0.053 | 0.050 | 0.032 | **BRTI** | 0.220 | 0.216 | 0.174 | 0.175 | 0.022 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.018 | 0.018 | 0.019 | 0.019 | 0.019 |
| ∂l | | 3.370 | 3.890 | 6.804 | 5.928 | 7.101 | | 78.310 | 76.330 | 54.310 | 53.840 | 1.783 |
| AIC | | -2.739 | -3.780 | -9.607 | -7.857 | -10.201 | | -152.619 | -148.655 | -104.621 | -103.674 | 0.433 |
| ρ | **ASPN** | 0.108 | 0.114 | 0.142 | 0.126 | 0.073 | **AXBK** | 0.322 | 0.325 | 0.305 | 0.298 | 0.058 |
| SE | | 0.018 | 0.018 | 0.019 | 0.019 | 0.019 | | 0.017 | 0.017 | 0.017 | 0.017 | 0.019 |
| ∂l | | 17.500 | 19.710 | 34.090 | 25.150 | 9.393 | | 169.800 | 174.300 | 153.700 | 145.600 | 7.837 |
| AIC | | -30.994 | -35.410 | -64.189 | -46.292 | -14.786 | | -335.589 | -344.659 | -303.353 | -287.282 | -11.673 |
| ρ | **BJFN** | 0.355 | 0.365 | 0.366 | 0.349 | 0.293 | **BAJA** | 0.000 | -0.002 | -0.001 | 0.011 | 0.107 |
| SE | | 0.017 | 0.017 | 0.017 | 0.017 | 0.018 | | 0.019 | 0.019 | 0.019 | 0.019 | 0.020 |
| ∂l | | 213.200 | 227.700 | 232.900 | 211.400 | 141.700 | | 0.477 | 0.519 | 1.521 | 2.222 | 28.810 |
| AIC | | -422.437 | -451.488 | -461.706 | -418.762 | -279.403 | | 3.046 | 2.962 | 0.959 | -0.445 | -53.614 |
| ρ | **BJFS** | -0.014 | -0.013 | -0.001 | 0.003 | 0.011 | **BPCL** | 0.131 | 0.132 | 0.120 | 0.118 | 0.002 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 |
| ∂l | | 0.745 | 1.017 | 1.777 | 1.985 | 2.174 | | -53.079 | -54.324 | -47.043 | -44.670 | 3.832 |
| AIC | | 2.510 | 1.967 | 0.445 | 0.029 | -0.349 | | 28.540 | 29.160 | 25.520 | 24.330 | 0.084 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ρ | **BHRI** | 0.012 | 0.018 | 0.036 | 0.028 | 0.024 | **BRIT** | 0.261 | 0.275 | 0.306 | 0.284 | 0.226 |
| SE | | 0.024 | 0.024 | 0.024 | 0.024 | 0.024 | | 0.018 | 0.018 | 0.017 | 0.018 | 0.018 |
| ∂l | | 0.248 | 0.312 | 1.096 | 0.682 | 1.081 | | 109.600 | 121.900 | 158.800 | 135.200 | 88.710 |
| AIC | | 3.505 | 3.375 | 1.807 | 2.637 | 1.837 | | -215.112 | -239.787 | -313.635 | -266.496 | -173.411 |
| ρ | **CIPL** | -0.039 | -0.039 | -0.036 | -0.021 | 0.030 | **COAL** | 0.064 | 0.000 | -0.014 | -0.006 | -0.011 |
| SE | | 0.048 | 0.048 | 0.048 | 0.048 | 0.048 | | 0.019 | 0.021 | 0.021 | 0.021 | 0.021 |
| ∂l | | 1.383 | 1.433 | 0.746 | 0.907 | 0.205 | | 9.412 | 0.447 | 0.223 | 0.046 | 0.152 |
| AIC | | 1.234 | 1.134 | 2.508 | 2.187 | 3.591 | | -14.823 | 3.106 | 3.553 | 3.907 | 3.697 |
| ρ | **EICH** | 0.046 | 0.047 | 0.055 | 0.047 | 0.039 | **GAIL** | 0.223 | 0.225 | 0.203 | 0.209 | 0.058 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 |
| ∂l | | 9.005 | 8.609 | 9.469 | 8.609 | 5.974 | | 80.790 | 82.260 | 68.620 | 71.830 | 5.384 |
| AIC | | -14.009 | -13.217 | -14.938 | -13.217 | -7.948 | | -157.581 | -160.518 | -133.235 | -139.664 | -6.767 |
| ρ | **GRAS** | 0.235 | 0.233 | 0.196 | 0.200 | 0.060 | **HCL** | 0.226 | 0.222 | 0.185 | 0.189 | 0.018 |
| SE | | 0.018 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 |
| ∂l | | 94.240 | 93.110 | 69.440 | 71.540 | 6.475 | | 93.880 | 91.410 | 67.580 | 67.320 | 4.794 |
| AIC | | -184.475 | -182.219 | -134.888 | -139.081 | -8.949 | | -183.770 | -178.829 | -131.163 | -130.644 | -5.588 |

**Source:** Authors calculation

**Table 4B:**

| | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ρ | HDFC | 0.275 | 0.271 | 0.233 | 0.239 | 0.042 | HDBK | 0.287 | 0.284 | 0.250 | 0.257 | 0.063 |
| SE | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 |
| ∂l | | 135.100 | 130.800 | 92.080 | 97.900 | 4.542 | | 147.000 | 144.700 | 107.600 | 115.500 | 6.503 |
| AIC | | -266.171 | -257.635 | -180.153 | -191.796 | -5.084 | | -289.972 | -285.368 | -211.275 | -227.015 | -9.005 |
| ρ | HROM | 0.006 | 0.009 | 0.017 | 0.019 | 0.014 | HALC | 0.014 | 0.014 | 0.019 | 0.019 | 0.031 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 |
| ∂l | | 0.590 | 0.773 | 1.697 | 2.701 | 0.489 | | 2.915 | 3.330 | 4.400 | 3.697 | 2.218 |
| AIC | | 2.819 | 2.453 | 0.607 | -1.403 | 3.023 | | -1.829 | -2.659 | -4.799 | -3.394 | -0.436 |
| ρ | HLL | -0.003 | -0.006 | -0.018 | -0.016 | 0.019 | ICBK | 0.353 | 0.352 | 0.303 | 0.299 | 0.062 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 3.645 | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 |
| ∂l | | 1.075 | 1.597 | 4.728 | 4.317 | 3.645 | | 230.300 | 230.600 | 167.300 | 160.100 | 7.643 |
| AIC | | 1.849 | 0.806 | -5.455 | -4.635 | -3.291 | | -456.664 | -457.209 | -330.552 | -316.274 | -11.285 |
| ρ | IOC | 0.129 | 0.134 | 0.139 | 0.136 | 0.027 | INBK | 0.261 | 0.268 | 0.275 | 0.276 | 0.086 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 |
| ∂l | | 30.160 | 32.460 | 36.630 | 35.920 | 1.557 | | 114.800 | 122.300 | 136.500 | 136.200 | 18.020 |
| AIC | | -56.318 | -60.911 | -69.261 | -67.845 | 0.885 | | -225.622 | -240.599 | -269.038 | -268.319 | -32.040 |
| ρ | INFY | 0.272 | 0.266 | 0.208 | 0.217 | 0.005 | ITC | 0.194 | 0.189 | 0.157 | 0.158 | 0.010 |
| SE | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 |
| ∂l | | 124.100 | 118.300 | 68.880 | 75.150 | 0.962 | | 66.470 | 64.390 | 43.530 | 45.570 | 2.979 |
| AIC | | -244.270 | -232.633 | -133.762 | -146.305 | 2.076 | | -128.937 | -124.786 | -83.054 | -87.148 | -1.958 |

| | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ρ | JSTL | 0.255 | 0.260 | 0.249 | 0.265 | 0.076 | KTKM | 0.284 | 0.289 | 0.274 | 0.272 | 0.048 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 |
| ∂l | | 118.500 | 123.800 | 118.700 | 137.200 | 11.280 | | 146.700 | 153.700 | 139.100 | 135.500 | 7.013 |
| AIC | | -233.013 | -243.669 | -233.309 | -270.429 | -18.552 | | -289.396 | -303.495 | -274.282 | -267.021 | -10.027 |
| ρ | LART | 0.310 | 0.310 | 0.281 | 0.273 | 0.064 | MAHM | 0.248 | 0.247 | 0.242 | 0.238 | 0.062 |
| SE | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 |
| ∂l | | 177.800 | 179.200 | 149.800 | 139.800 | 9.412 | | 118.000 | 118.700 | 106.800 | 105.300 | 10.400 |
| AIC | | -351.693 | -354.458 | -295.627 | -275.625 | -14.823 | | -231.906 | -233.319 | -209.682 | -206.607 | -16.797 |
| ρ | MRTI | 0.005 | 0.006 | 0.008 | 0.001 | -0.004 | NEST | 0.002 | 0.002 | -0.005 | -0.009 | -0.029 |
| SE | | 0.018 | 0.018 | 0.018 | 0.019 | 0.019 | | 0.020 | 0.020 | 0.020 | 0.020 | 0.020 |
| ∂l | | 0.035 | 0.049 | 0.191 | 0.107 | 1.100 | | 0.008 | 0.016 | 0.031 | 0.084 | 1.009 |
| AIC | | 3.930 | 3.903 | 3.617 | 3.786 | 1.801 | | 3.984 | 3.968 | 3.939 | 3.832 | 1.982 |

**Source:** Authors calculation

**Table 4C:**

| | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ρ | **NTPC** | 0.264 | 0.265 | 0.228 | 0.230 | 0.056 | **ONGC** | 0.224 | 0.222 | 0.182 | 0.189 | 0.051 |
| SE | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 | | 0.018 | 0.018 | 0.019 | 0.019 | 0.019 |
| ∂l | | 119.400 | 120.300 | 89.100 | 92.200 | 5.893 | | 84.590 | 83.790 | 58.300 | 64.400 | 6.840 |
| AI | | - | - | -174.197 | - | -7.787 | | - | - | -112.608 | - | -9.679 |
| ρ | **PGRD** | 0.012 | 0.012 | 0.009 | 0.005 | 0.000 | **REDY** | -0.007 | -0.005 | 0.018 | 0.012 | 0.021 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.019 | 0.018 | 0.018 | 0.018 | 0.018 |
| ∂l | | 0.919 | 1.135 | 1.009 | 0.513 | 0.452 | | 0.137 | 0.066 | 0.450 | 0.201 | 0.664 |
| AI | | 2.162 | 1.730 | 1.982 | 2.975 | 3.097 | | 3.727 | 3.868 | 3.100 | 3.598 | 2.671 |
| ρ | **RELI** | 0.324 | 0.317 | 0.240 | 0.256 | 0.029 | **SBI** | 0.310 | 0.315 | 0.296 | 0.289 | 0.056 |
| SE | | 0.018 | 0.018 | 0.019 | 0.018 | 0.019 | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 |
| ∂l | | 190.600 | 181.900 | 104.500 | 118.100 | 1.516 | | 164.600 | 171.600 | 162.700 | 151.700 | 9.253 |
| AI | | - | - | -204.976 | - | 0.967 | | - | - | -321.401 | - | -14.507 |
| ρ | **SUN** | 0.119 | 0.119 | 0.111 | 0.111 | 0.033 | **TAMO** | 0.279 | 0.281 | 0.269 | 0.269 | 0.081 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.020 | | 0.018 | 0.019 | 0.019 | 0.019 | 0.019 |
| ∂l | | 25.310 | 25.670 | 21.030 | 22.520 | 10.360 | | 143.900 | 147.000 | 147.900 | 145.900 | 15.390 |
| AI | | -46.616 | -47.341 | -38.062 | -41.046 | -16.725 | | - | - | -291.871 | - | -26.780 |
| ρ | **TISC** | 0.316 | 0.317 | 0.284 | 0.300 | 0.070 | **TCS** | 0.006 | 0.007 | 0.001 | -0.003 | -0.002 |
| SE | | 0.018 | 0.018 | 0.018 | 0.019 | 0.020 | | 0.019 | 0.019 | 0.019 | 0.019 | 0.018 |
| ∂l | | 184.000 | 188.600 | 161.700 | 179.700 | 16.630 | | 2.266 | 1.857 | 0.410 | 1.034 | 0.007 |
| AI | | - | - | -319.352 | - | -29.259 | | -0.531 | 0.286 | 3.180 | 1.932 | 3.987 |
| ρ | **TEML** | 0.223 | 0.225 | 0.203 | 0.209 | 0.058 | **TITN** | 0.030 | 0.030 | 0.030 | 0.026 | 0.014 |
| SE | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 | | 0.018 | 0.018 | 0.018 | 0.018 | 0.018 |
| ∂l | | 80.790 | 82.260 | 68.620 | 71.830 | 5.384 | | 1.302 | 1.367 | 1.349 | 1.022 | 0.317 |
| AI | | - | - | -133.235 | - | -6.767 | | 1.397 | 1.266 | 1.301 | 1.956 | 3.366 |

| | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 | | NSEI | NIFTY-100 | NIFMDCP 100 | NIFTY-200 | NIFSMCP 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ρ | **ULTC** | 0.053 | 0.055 | 0.050 | 0.047 | 0.046 | **UPLL** | 0.193 | 0.201 | 0.220 | 0.224 | 0.106 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.018 | 0.018 | 0.019 | 0.019 | 0.019 |
| ∂I | | 7.587 | 7.383 | 4.699 | 4.010 | 5.045 | | 58.210 | 64.510 | 88.880 | 91.350 | 20.330 |
| AI | | -11.175 | -10.766 | -5.398 | -4.020 | -6.090 | | - | - | -173.755 | - | -36.659 |
| ρ | **VDAN** | 0.026 | 0.027 | 0.032 | 0.032 | 0.033 | **WIPR** | 0.253 | 0.246 | 0.198 | 0.207 | 0.014 |
| SE | | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | | 0.018 | 0.018 | 0.019 | 0.019 | 0.019 |
| ∂I | | 1.933 | 2.298 | 1.956 | 2.241 | 2.078 | | 111.100 | 105.700 | 66.940 | 73.250 | 0.576 |
| AI | | 0.133 | -0.595 | 0.089 | -0.481 | -0.156 | | - | - | -129.881 | - | 2.847 |
| ρ | **YESB** | 0.278 | 0.284 | 0.298 | 0.286 | 0.086 | **ZEE** | 0.192 | 0.197 | 0.201 | 0.192 | 0.082 |
| SE | | 0.018 | 0.018 | 0.018 | 0.018 | 0.019 | | 0.018 | 0.018 | 0.018 | 0.019 | 0.019 |
| ∂I | | 136.800 | 144.200 | 169.900 | 155.900 | 0.019 | | 57.850 | 61.000 | 68.330 | 63.870 | 11.520 |
| AIC | | -269.556 | -284.328 | -335.718 | -307.761 | -29.650 | | -111.710 | -118.009 | -132.661 | -123.745 | -19.033 |

**Source:** Authors calculation

These copula estimates for these stocks with respect to the Nifty-100 index vary from estimates as low as -0.20 percent to 5.27 percent. NIFTY-100 represents the top 100 companies based on full market capitalization from NIFTY-500. The intention of this index is to measure the performance of large market capitalization companies. It evaluates the behavior of a combined portfolio of two indices that is, NIFTY-50 and NIFTY Next 50, whereas the NIFTY-200 -index is contrived to reflect the behavior and performance of large and mid-market capitalization companies. NIFTY-200 includes all companies forming part of NIFTY-100 and NIFTY Full Midcap 100 index. The copulas estimates for the above-mentioned equities corresponding to the Nifty-200 index is from -0.11 percent to 5.47 percent. Similarly, the values with respect to Nifty-Midcap-100 solely, are ranging from 0.34 percent to 4.70 percent. We document increasing lower limits as the equivalence among the stocks and the indices reduce. Finally, we check with the Nifty-Smallcap-100 index. The values for this are bound from -0.36 percent to 4.62 percent. But we do not find the copula values that is, the dependency structure to be as modest and low as copulas calculated for gold and currencies from our literature. Owing to such disparities, we term the as *pseudo–safe-haven*. They are the possibly best bets amongst the NIFTY-50 stocks to generate which could generate extra-ordinary profits and also safeguard the investment during times of extremities. The stocks that are *pseudo–safe-haven* are mostly consumer goods oriented companies and automobile industries. Moreover, mutual funds rated five stars by CRISIL include these stocks in predominant portions for the respective fund.

## CONCLUSION

The popular investment choice like fixed income, gold, and real estate has generated low or negative real returns for the investors over long horizons. Equity, although comes with inherent risk, has performed much better. Indian investors are showing increasing interest in the equity markets over the years to seek decent returns. The recent crisis in the financial markets due to Coronavirus makes a good starting point for digging good stocks as they are available for a much cheaper price. They should be aware that the inherent risk in the equity market could possibly make investors lose their capital. Therefore, we need to look for quality stocks that are investor-friendly i.e. generates decent returns with much lower risk than a common equity index. Keeping that in mind, we examine the safe-haven and hedging properties of a basket of possibly quality stocks (Nifty-50 stocks) using a copula-based method. Capability to deal with fat tails and extreme co-movements of financial return data makes copula a better choice for our analysis.

We observe that stocks like Maruti Suzuki, Tata Consultancy, Hindustan Unilever, Dr. Reddy's, Hero Motor, Coal India, Bajaj Auto, Nestle, Eicher Motors, Cipla, Bajaj Finance, Adani Port, Ultratech Cements, Bharti Infratel, Hindalco Industries, Titan, and Power Grid act good as hedging instruments at times and also a moderate version of safe-haven assets We call them *pseudo–safe-haven*. Investors could benefit investing in them which could possibly generate decent returns with an acceptable level of capital protection. We expect our analysis to aid retail and institutional investors in making better investment decisions whilst keeping in mind that this is just a fragment that supplements to an extensive stock analysis.

Our contribution is dual. First, we develop the idea of *pseudo–safe-haven* investment (which provides decent returns with an acceptable level of capital protection) in an asset class like equity. Second, we add to the literature of portfolio management by providing academic backup to the process of picking the right stocks with one of the best suited and relevant econometric models.

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