Entropy as a Measure of Risk or a Source of Information to Mitigate Risk: A Comparison Across Various Financial Assets

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Abstract
Since the application of entropy in financial economics has been growing extensively as a measure of volatility, in portfolio selection and to detect anomalies in markets. It's really complicated to establish that increase in entropy is a source of the useful information for the financial markets that tantamount to mitigate risk, or it is in fact an indicator of disorder reflecting the growing risk scenario in the financial market. To explore the more effective application of entropy in the field of financial economics, this study evaluates entropy in both contexts, as a source of information to mitigate risk and as an indicator of disorder reflecting volatility. Twelve years daily data of 29 financial assets have been used to measure the intrinsic entropy in addition to other eight volatility estimators and three GARCH models-based volatilities. Various assessment techniques are used to test the role of entropy in both contexts including, Run Test, Mean, Variance and Coefficients of Variation, Mean Squared Errors, Proportional Bias and Efficiency Estimator, in addition to spearman rank-order correlation. Results emphasis that entropy is more suitable as a volatility measure rather a source of information in the financial market.

Keywords: Financial Markets, Information Entropy, Volatility Estimators, GARCH Models.

Introduction

Volatility in financial assets reflects the level of risk that needs to be mitigated for a potential investment opportunity. Low volatility in any financial assets with potentially high returns would be the most desirable strategy for an investor. However, there are various techniques to calculate volatility and there is a possibility that variation in the measured volatility may exist for a given asset due to the capability of an estimator to capture the dynamic behavior of a given series. Measurement of volatility in financial assets is always considered a core concern for all financial institutions, consultants, and investors to assess the magnitude of risk in financial assets. Although the ARCH/GARCH models have been developed to measure the volatility, but their credibility became doubtful after the financial crises of 2008/9. It necessitates to explore other possible volatility measures because given measures may not effectively serve the purpose. Consequently,

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this study has been inspired by (Vinte et al., 2021) who have considered the intrinsic entropy as an effective tool to measure volatility.

Since entropy is also considered as a measure of 'information content' of the given message that may reduce uncertainty and risk factor in the financial markets, it may be expected that with increased entropy volatility should be mitigated. While volatility is referred as a 'measure of risk', consequently once a new information receives in the financial market where financial assets are already very sensitive to information, this will at least reduce the overall uncertainty about the potential returns. However, the problem is that the '*information*' content of a 'news' component may also cause high 'uncertainty' if such 'news' delivers that information undergoing some element of chaos. Consequently, there is need to test the hypothesis such as more the information a message conveys, the less volatile the market would be. If this hypothesis doesn't stand, it will imply that information content by itself does not warranty the reduction in uncertainty but its impact on the market will determine its nature, which may be observed through the pace of returns, lower volatility levels, or increased market efficiency.

Now the question is how 'entropy' is relevant in this regard? Since Rudolf Clausius has introduced the concept of entropy in early 1850s based on thermodynamics process by observing some of the functional energy loss that cannot be converted into useful work, so named it '*entropy*'. Later in 1948, Claude Shannon has quantified the amount of 'lost information' in phone line signals and named it as 'information entropy' (Nanda & Chowdhury, 2019) Although the concept information couldn't be quantified properly before the introduction of Claud Elwood Shannon entropy measure (Yin, 2019). Who has depicted the relationship between information redundancy and the probability through a mathematical framework. Shannon has described the entropy as tool to measure information, uncertainty and choice (Olbry´s & Ostrowski, 2021) as it may extract the information content through probability distribution of data belongs to any complex system. It has been observed while conducting studies on thermodynamics that the economic system seems not only 'mechanism' like in physics but instead follows a thermodynamic behavior as well. Since capturing the recent economic phenomenon through 'mechanism' devised by both Keynesian and the Monetarists remained ineffective due to the skipped entropy factors that hold strong influence over equilibrium and economic change just like they do in thermodynamics (Jaynes, 1991).

The objective of this study is to evaluate whether emerging techniques of measuring information through entropy are either more successful in minimizing the risk (volatility) for financial assets or reflecting such risk more effectively due their endowed property of disorder. The information related to prices, trade volume and daily returns of six sets of financial assets have been analyzed to prove this proposition that includes, stock-exchanges, company stocks, physical currencies, crypto-assets, commodity indices, and bond markets.

The main entropy measures consulted in this study is Shannon Entropy, however, it doesn't incorporate trade volumes which is one of the relevant factors to determine the equilibrium prices of any product as per demand theory in the field of economics. Therefore, intrinsic entropy has been considered a more appropriate measure because it incorporates the trade volume in addition to prices, provides a more reflective measure of entropy with respect to economic theory. In the same chain of argument intrinsic entropy-based volatility measures may prove more effective to estimate the magnitude of risk in the financial assets as well because no doubt trading in financial markets is influenced by the determinants of 'consumer behavior' together with 'risk behavior'. Further most of the studies have assumed that (Shannon) entropy based on information theory is another way to capture the volatility (Ghosh & Nisha, 2018).

In a nutshell, this study aims to evaluate the effectiveness of the intrinsic entropy model by comparing it with other standard volatility measures. Since the flow of news is a continuous process that delivers the information in the financial markets. To determine whether a particular news is relevant either to the few stocks or entire stock market or some other financial assets, first the information content needs to be 'captured and calculated' afterwards its relationship with financial assets can be estimated. Hence the concept of 'Entropy' based on information theory has been applied in this study to capture the 'information' content of a given 'news' item, which is truly borrowed from the field of thermodynamics in physics and effectively be used by various machine learning research to quantify information. Cumulative entropy is considered more relevant because information has historical context and pieces of information accumulate to create knowledge that can be used productively for an effective decision making.

Literature Review

As literature review reveals that entropy has become extensively focused area for research especially in the field of financial markets where variety of entropy measures have not only been applied but even originated into some new forms and evolved to grasp the more complex and highly turbulent behaviors.

In a working paper (Backus, 2011) entropy is applied on asset pricing model considering time dependance, where enormous amount of entropy is found as an outcome of disasters and jumps. However, there is a tradeoff found between a 'rise in entropy' due to recursive preferences and habits of a representative agent, and the 'rise in time dependence', because entropy varies over different time horizons. The main challenge they have identified is how to make sure that enough entropy is generated without excessive time dependence. The volatility during the financial crises of 2008-9 has been evaluated by (Ghosh & Nisha, 2018) based on GARCH (1,1) and entropy measure by using data in two time frames: 2007-11 and 2012-16, to assess the capability of Shannon's entropy as an econophysics tool to capture the volatility of these targeted time frames. GARCH method shows higher volatility in first period whereas a relatively more volatility in second period has been predicted by entropy method. A study (Datta, 2023) has focused on the measurement of volatility for oil price returns by applying sample entropy to compare it with simple standard deviation. It provides evidence that sample entropy proved to be more efficient especially during financial crises, having potential to work as an effective 'risk assessment tool'.

In the dissertation, (Stosic, 2016) has mentioned the new term 'econophysics' by referring interaction of statistical tools by the physicists and computer scientists on the economics and financial phenomenon, such as price fluctuations, risk and portfolio management. Entropy is one of the most prominent tools of econophysics that helps to quantify the uncertainty and disorder usually present in the prices movements across a variety of financial assets. Hence it has been applied in the foreign exchange market mainly to capture the impact of financial crises. In their paper (Stosic, Stosic, Ludermir, Oliveirab, & Stosicb, 2016) based on block entropy the authors prove that exchange rate entropy increases with financial crises. Entropy has also been employed to develop portfolios to achieve high optimization that has performed better than expectation-variance-models in selection of portfolios (Yin, 2019). Considering one of the three main dimensions of market liquidity including resiliency, tightness and depth, the market depth has been gauged through an entropy-based estimator where Shannon information entropy provides a new indicator as one of the liquidity dimensions in the stock market. The evidence suggested that Entropy-based-Market-Depth indicator has advantage to measure the liquidity consistent with the intuition of investor regarding its highest and lowest values within possible range from '0' to '1'

(Olbry´s & Ostrowski, 2021). Another study conducted by Kralingen et al. (2021) evaluates market clustering to measure how much trade is performed similarly by a group of investors. They consider the price adjustments is the investors' reaction to the new information in addition to the price dynamics of a given market. The maximum-entropy based model for real networks of investors, companies and stocks has been developed containing features present in real life stock markets by assuming that such clustering are not purely outcomes of random behaviors of the network nodes. In their study Liao et al. (2021) employ the structural entropy to depict monitoring and risk management in addition to the complex network of the financial system.

Whereas for evaluating the importance of bitcoin a study conducted by (Bedowska et al., 2021) has tried to measure the direction of information flow through mutual information between liquidity and the volatility across seven highest capitalization based selected cryptocurrencies. The conclusions show that cryptocurrencies have strong associations in terms of volatility and respective prices but weak in terms of liquidity. A positive information transfer from Bitcoin to Litecoin has been observed, whereas the value of Ripple remains highest in the case of transfer entropy that reflects liquidity. They have found relatively low information transfer but very high mutual information across selected cryptocurrencies. Where (Karkowska & Urjasz, 2022) have employed the mutual information and the transfer entropy to make a comparison across European Stock markets. They have observed low entropy transfer from US equity markets to European stock markets before Covid-19 crisis but higher during the crises. Another entropy technique referred as Renyi's transfer entropy measure has been considered in (Jizba & Tabachová, 2022) to establish a relationship with data driven causal inference. They have proved that in the case of Gaussian process, the Renyi's transfer entropy and Granger Causality are equivalent.

The impact of monetary policy shock on Dow John Industrial (DJI) Average has been evaluated through Von Neumann entropy and singular value decomposition entropy in (Caraiani & Lazarec, 2021) who provide the evidence that entropy declines with a positive monetary policy shock because lowering interest signaling more stability in financial market. (Olbry´s & Majewska, 2022) have tested the hypothesis that during turbulence periods, there is decrease in entropy in equity market index. By failing to reject this hypothesis the study provides evidence that during turbulence, stock market index returns become more predictable and regular. Financial risk has also been measured through Shannon's entropy by (Mahmouda & Naouib, 2017) as an alternative to standard deviation because of its similar behavior and even better performance in case of non-Gaussian distribution of returns. Same with 'Sharpe Ratio' with single index-model because entropy can assess more effectively both specific and systematic risks pertained to financial asset pricing. In their study (Wang et al., 2022) have found that entropy contains more explanatory power to calculate the risk compared to the beta measure of capital asset pricing model. They have evaluated both Renyi's and Shannon entropies to conclude that they performed best to evaluate risk in stocks. So, investors become better off by adding stocks to their portfolios that belong to those enterprises offering high returns with minimum risk, measured through techniques based on entropy.

Since anomaly detection in time series helps to detect those signals which contained relatively large uncertainty because of more noise and chaotic characteristics. This purpose cannot be achieved with the application of dynamic Shannon entropy, but its improved extension 'Deng Entropy' helps to detect time series anomalies more successfully (Wang et al., 2023). A Graph Neural Network approach has been applied by (Costa, 2023) to detect possible anomalies in the global financial markets by using 'nonextensive entropy' to prove that during crisis structural complexity of highly correlated assets mitigated significantly.

The intrinsic entropy model has been introduced by (Vinte et al., 2019) that scales the investors' level of interest considering exchange-traded security. Intrinsic entropy measure without engaging any exogenous factor provides signals for decision to buy or sell a given security. Although intrinsic entropy model uses intraday trading, it is reasonably effective in case when built over through consecutive trading days if number of transactions per day on average are few.
A literature survey conducted by (Nanda & Chowdhury, 2019) has provided an extensive list of 106 studies conducted covering variety of entropy applications in the field of statistics, reliability and information sciences from 1948 to 2018 covering the maximum possible literature on entropy after (Wiener, 1948) and (Shannon, 1948) and observed that although Shannon has developed the entropy formula that have been forked into various kinds of entropy measures to accommodate the dynamic behavior of the natural modification in the set of postulates initially followed by Shannon. Many other application of the Shannon entropy has been found in the literature including to record the information related to temperature and climate change (Twarong, 2023), to measure employment diversity across and amongst industrial region (Attaran & Zwick, 1987).

Methodology

Since in recent era generalized autoregressive conditional heteroskedasticity (GARCH) model and its respective versions have become dominant to measure the volatility, however, their efficacy become questionable especially when they have found incapable to predict about potential financial crises.
This study covers these aspects regarding volatility measurement: (a) ARCH or GARCH models are still effective in capturing the volatility in prices and returns of financial assets; (b) all other volatility estimators are good measures of volatility but may not replace the GARCH models, unless proved otherwise through extensive research; (c) Volatility estimates the level of risk effectively rather than forecast it. The presence of extensive literature that either proves or disproves the forecast-abilities of ARCH (GARCH) volatility measures could not play a significant role in avoiding the financial crisis of 2008-9. Therefore, reduction in volatility may be a more desirable outcome by using the given measures whereas improved information flow (enhanced entropy) may help to curtail the level of such volatility significantly.
The main objective of this paper is to explore how entropy helps to reduce the potential risk in financial assets especially focusing on the 'returns' by considering that the expected forecast about returns through these models will be more effective to catch the trends (rather variation) when entropy is incorporated into the estimation process.

Volatility Measurement Estimators: Structural Models

These volatility estimators have been extensively discussed by (Garman & Klass, 1980), (Yang & Zhang, 2000), (Floros, 2009), (Vinte, Smeureanu, Furtuna, & Ausloos, 2019), (Vinte, Ausloos, & Furtuna, 2021). However, a brief but needed description is reproduced here because the purpose of this study is sufficiently achieved with the reported descriptions, consequently remaining details and extensions are left for other researchers if they are intended to probe it in details.

Close-to-Close (CC) Classical Volatility Estimator (CCCVE)

As it is referred to as 'standard deviation of log returns after adjusting with dividends' however dividends are considered zero here to allow its application across those types of financial assets where there are no direct dividends available.

Now let 'w' is the magnitude of daily returns $w_i = \ln(c_t/c_{(t-1)})$, with mean of the log returns (drift shown by eta) 'η' the resultant volatility estimator takes opening price volatility into account:

CCCVE = $\sqrt{1/n \sum_{i=1}^{n} ((o_i + c_i - \eta))^2}$

Now the issue is that if distribution of log returns is not normal, application of third moment (skewness) and fourth moment (kurtosis) will provide the better estimates of risk. Consequently, based on the distribution of sample data CCCVE may be adjusted accordingly.

Garman & Klass (GK) Volatility Estimator (GKVE)

The more suitable structural model for volatility measurement is referred by (Garman & Klass, 1980) where the estimation procedure for regularly reported public data about financial assets usually covering historical series daily prices including only opening, closing, high and low values. Financial assets follow this diffusion process with 'P(t)' as daily price, 'D(t)' as diffusion process by considering *dD= σdz* as its differential representation 'dz' is assumed to be a standard Gauss-Wiener Process with 'σ' which is unknow constant that needs to be estimated (Garman & Klass, 1980, p. 68) :

$P(t) = \Omega(D(t)) \dots\dots\dots (i)$

However, price series are transformed into logarithmic formation for each cryptocurrency series where D = Ω^{-1}P, the volatility is reflected by the 'variance of the logarithm of the original prices'. Hence parameter σ^2 as an estimator of the variance of D(t) is mainly focused. The model has been applied with all due limitations as mentioned by (Garman & Klass, 1980, p. 68). The variance of the volatility as a fourth moment has been considered based on equation (ii) and (iii) but efficiency of $\hat{\sigma}_1^2$ has been found at least 50% larger than $\hat{\sigma}_0^2$. Now model formation follows as:

$\hat{\sigma}_0^2 = C_1 - C_0 \dots\dots\dots (ii)$

$\hat{\sigma}_1^2 = ((O_1 - C_0))^2/2f + ((C_1 - O_1))^2/2(1-f) \dots\dots\dots (iii)$

$subject\ to\ 0 < f < 1$

Since low and high prices are major reflections of the volatile behavior, that has been adjusted in equation (iii) by Parkinson (1976) provided in (Garman & Klass, 1980, p. 71), assuming $(H_1 - L_1)^2/4\ln2 = (u - d)^2/4\ln2$

$\hat{\sigma}_1^2 = a\ ((O_1 - C_0))^2/f + (1-a)\ ((u-d))^2/((1-f)4ln2) \dots\dots\dots (iv)$

Whereas

$\hat{\sigma}_0^2 = volatility\ of\ prices$

$f = fraction\ of\ the\ day\ used\ in\ trading\ (assumed\ 8\ working\ hours\ out\ of\ 24\ hours)$
$= 8/24$

$C_0 = log\ of\ closing\ price\ of\ last\ working\ day$

$C_i = log\ of\ closing\ price\ of\ currecnt\ working\ day$

$O_i = log\ of\ open\ price\ of\ currecnt\ working\ day$

$H_i = log\ of\ highest\ price\ of\ current\ working\ day$

$L_i = log\ of\ lowest\ price\ of\ currecnt\ working\ day$

$o = O_i - C_0\ \ as\ a\ normalised\ opening\ price$

$c = C_i - O_i\ \ as\ a\ normalised\ closing\ price$

$u = H_i - 0_i\ \ as\ a\ normalised\ high\ price$

$d = L_i - 0_i\ \ as\ a\ normalised\ low\ price$

$a = proportion\ of\ the\ volatility\ contributed\ by\ opening\ and\ closing\ price\ difference$

$1 - a$
$= proportion\ of\ the\ volatility\ contributed\ by\ highest\ and\ lowest\ price\ difference$

k = represents the weights, measured as [0.34/1.34+(n+1)/n-1)] so that *k* will never become exactly zero or one.
By assuming eight working hours per day, let $f = 8/24$ and $a = 0.3$ (lower weight is assigned to opening and closing price difference viz. 30% compared to highest-lowest price difference, however its floating and through hit and trial or model training the optimum value of '*a*' can also be obtained). The reduced form is:

$$GKVE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\left[\frac{1}{2}(u_i - d_i)\right]^2 - (2\ln 2 - 1)\, c^2\right]}$$

Parkinson Volatility Estimator (PVE)
PVE considers only extreme prices are relevant such a low and high price in a day probably overestimate the volatility:

$$PVE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\left(\frac{1}{4\ln 2}\right)(u_i - d_i)\right]^2}$$

Rogers-Satchell Volatility Estimator (RSVE)
RSVE includes drift (average trend with all four range of prices)

$$RSVE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[u_i\,(u_i - c_i) + d_i\,(d_i - c_i)\right]}$$

Yang & Zhang Volatility Estimator (YZVE)
YZVE establishes that a multiple period-based estimator may consider both opening price jumps and drift-independence to get an unbiased variance estimator:

$$YZVE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[(o)_i - \frac{1}{n}\sum_{i=1}^{n} o_i\right]^2 + \frac{1}{n}\sum_{i=1}^{n}\left[(c)_i - \frac{1}{n}\sum_{i=1}^{n} c_i\right]^2 + [1-k] * RSVE}$$

Volatility Measurement: ARCH/GARCH (1,1) and GJR-GARCH Models

Autoregressive Conditional Heteroskedasticity ARCH(T) some weights are assigned to the long run variance. Let V_L as long-term volatility, R_t as current returns, and σ_T^2 as current estimates of volatility, the ARCH (p,q) will become:

$$\sigma_t^2 = \delta V_L + \sum_{t=1}^{T} \theta_t R_t^2 \quad \dots\dots\dots (v)$$

$$Where,\ \delta + \sum_{t=1}^{T} \theta_t = 1$$

and in Generalized Autoregressive Conditional Heteroskedasticity [GARCH (p, q)] model, previous variance estimates will have some additional weights to capture the volatility clustering phenomena i.e., periods of high volatility cause high volatility and vice versa.

$$\sigma_t^2 = \varphi + \sum_{i=1}^{p} \theta_i R_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad \dots\dots\dots (vi)$$

$$Where,\quad \varphi = \delta V_L$$

To consider the time-varying component of volatility, the asymmetrical effect of shocks needs to be considered as well because especially in case of financial returns, the impact of negative shock is more relevant and perhaps one of the main factors behind excessive risk. Consequently, Golsten-Jagannathan-Runkle (GJR)-GARCH model has also been used to estimate volatility. Since Exponential (EGARCH) model has ability to capture the asymmetric (leverage) effects in financial returns and volatility clustering so it is also considered.

Shannon (Intrinsic) Entropy Measurement:
The comprehensive literature survey by (Nanda & Chowdhury, 2019) has provided a very brief perspective regarding the derivation of Shannon's Entropy. A detailed introduction and the

mathematical derivation primarily established by (Shannon, 1948) in his article '*A Mathematical Theory of Communication*' may further be consulted for detals. Shannon has successfully linked the economic concept '*choices*' with uncertainty through a statistical concept of '*probability*' by injecting the concept of '*information*' which is further leading towards the evolution of a new field of study called, 'information sciences'. The intrinsic volatility formula accommodates the volume of trading in addition to the returns of the financial assets. According to (Claudiu Vint, Smeureanu, Furtuna, & Ausloos, 2019) and (Vinte, Ausloos, & Furtuna, 2021), The Shannon entropy formula has been phrased as:

$$H_t^S = -\sum_{n=1}^{N} \left(\frac{P_n}{P_{n-1}} - 1\right) \frac{q_n}{Q_t} \ln_2 \left(\frac{q_n}{Q_t}\right) \ldots\ldots\ldots (vii)$$

where,

H_t^S – shows intrinsic Shannon entropy for a given financial asset 'S' in a sampled period 't',

N – total number of trades executed in current trading session within a day for 'S' financial asset,

q_n – trade volume, i.e., number of shares of trade 'n' for symbol 'S'

Q_t – total traded volume for sampled period of symbol 'S', measured by summation of q_k trade volume for sampled period 't', consequently satisfying this condition: $\sum_n^t q_n / Q_t = 1$

P_n –adjusted closing current prices of trade 'n' for symbol 'S'

In equation (vi), the fraction of traded quantities (q_n/Q_t) has been proxied as the probabilities for various financial assets with $(P_n/P_{n-1} - 1)$ weights assigned to such probabilities by assuming that returns are the main reason for trading and proportion of trading needs to be adjusted with it. When returns are higher 'biding' sets in while 'asking' follows the decline in returns. The entropy values have been calculated through histogram-based density estimation function as these techniques has some support from literature as well, such as (Wang et al., 2022).

Evaluation Techniques: Run Test

There are variety of techniques to measure the randomness in the returns of various financial assets. The 'Run-Test' as a linear statistical technique is applied to measure the level of randomness in each series and to test the efficient market hypothesis with mean, standard deviation and coefficient of variations. Since the run test has been considered one of the most relevant tests to measure the weak-from efficiency in the stock market (Aumeboonsuke & Dryver, 2014). This test captures the same characteristics across a series through uninterrupted sequence of a given length, effectively applicable on a binomial variable (Herger, 2024) Herger has further evaluated the statistical distribution of run test by using various probabilities. This study has calculated the 'direction' of returns i.e., increasing (+1 or 1) and decreasing (-1 or 0) as a binomial variable to measure the randomness of the series. However, the run test also helps to assess whether a given financial asset has weak form efficient or otherwise (Elbarghouthi et al., 2012).

Evaluation Techniques: Mean Squared Errors, Proportional Bias & Efficiency Estimator

The ranking of volatility estimators and other measure is performed based on Mean Squared Error (MSE) which is a standardized tool for comparison; Proportional Bias (PB) that identifies the comparative suitability and relatively better performance of one technique over the other; and Efficiency Estimator (EE) which identifies that a specific technique is more (less) efficient than the other one. These techniques have successfully applied by Vinte et al. (2021) which is one of the core studies that has inspired the present study.

Evaluation Techniques: Spearman Rank-Order Correlation

Since financial data is full of nonlinearities and sometime with outliers as well, the application of spearman rank order correlation has potential to provide robust outcome in the presence of such nonlinearities and outliers.

Sampling and Data Specification

There are a variety of financial assets where investors may choose a bunch to make an efficient portfolio. A variety of stock indices have become attractive due to high risk in a single financial asset. New types of businesses and companies have emerged as well. In addition, investment in cryptocurrencies is becoming the most attractive option for experienced investors generally but for immature young people especially. Consequently, in this study to evaluate the levels of profits, risks, and the nature of instabilities amongst the prices of various financial assets, most of the dimensions of these assets have been addressed by selecting twenty-nine assets. The sample consists of six major dimensions of these assets including:

i. *Stocks Exchanges*: NASDAQ; NIKKEI225; Shenzhen (SZ399001); Shanghai (SS000001); Performance index (DAX); CAC40 French Index (FCHI); Hand Seng Index (HSI); and Chicago (Rusell2000).
ii. *Commodity Indices*: DJI: Crude Oil; and Gold.
iii. *Crypto-Assets (cryptocurrencies)*: USDT as stable coin and DOGE, based on stability; Ripple (XRP), Ethereum Classic (ETC), Litecoin (LTC), Ethereum (ETH), Bitcoin (BTC) with long history of existence and CMC200 (Crypto Exchange). The cryptocurrencies selected for evaluation here are chosen on the basis of two criteria: (i) market capitalization (ii) long run sustainability (in years) of such currencies.
iv. *Bonds Market*: Global X MSCI Pakistan Exchange Traded Fund (PAK); SPDR S&P500 ETF Trust (SPY); PIMCO Active Bond ETF (BOND).
v. *Individual Stocks* of international companies: Apple (AAPL); Advance Micro Devices (AMD); Facebook (META); Microsoft (MSFT) and Amazon (AMZN)
vi. *Physical Currencies*: Exchange rates US dollar per Euro (USD_EUR); per British Pound (USD_GBP); Chinese Yuan per US dollar (CHY_USD) and US dollar per Japanese Yen (USD_JPY)

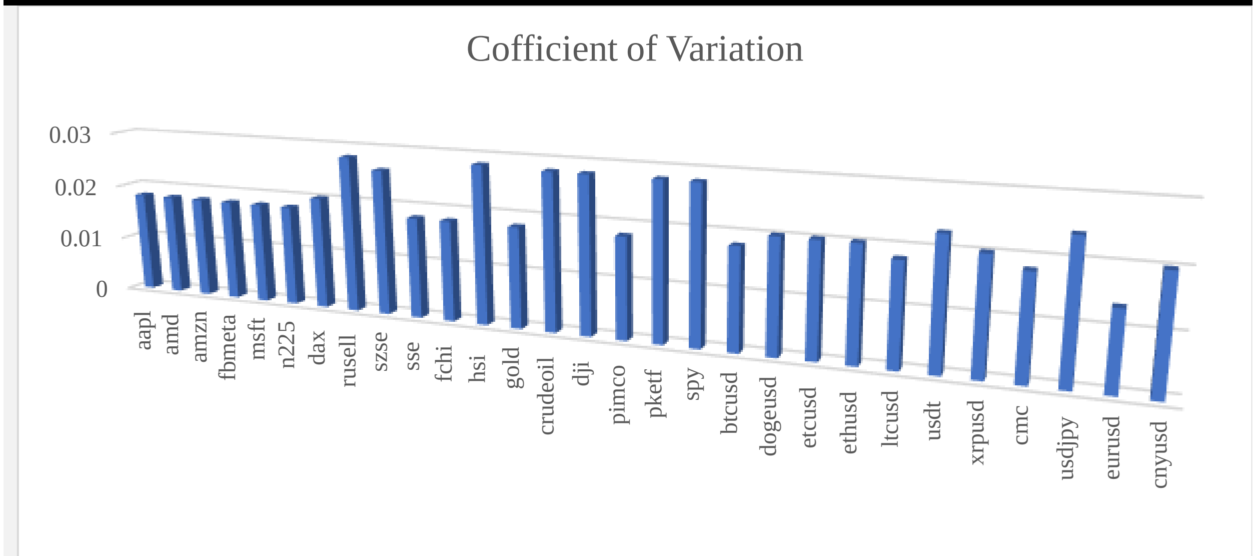
The main source of data collection is yahoo finance. The data with 'daily' frequency ranges from last five to 15 years or even more in some cases. Mostly the data period covers recent values up to July 2024 however till July 2023 in few cases due to non-availability of a latest series. : NASDAQ have to drop due data limitation as many values are 'null' in their series.

Results, Analysis and Discussion

Initially, returns are measured for all 29 financial assets which are further categorized into six main groups to observe how these types of financial instruments behave especially in the context of entropy and volatility. The purpose of categorization of these financial assets is to observe how entropy and volatility affect different segments of financial markets.

The strategy followed to measure the entropy is based on (Vinte, Ausloos, & Furtuna, 2021) where intrinsic entropy measurement has been calculated by using not only the closing prices, but the volume traded as well. The intrinsic entropy measure may be considered as an improved version of Shannon entropy. Since there is no unique way found to evaluate the impact of entropy on financial returns, consequently different strategies have been employed to capture the association and to measure the impact of entropy on stock returns and their respective volatilities in terms of two hypotheses.

Figure 1: Comparison across selected financial assets (*risk per unit of return*)



As in figure 01, the proportionally large risk is found in case of stock exchanges like Rusell, Shenzhen, and Hang Seng; commodities like crude oil and Dow Johns; Bonds including Pakistan ETF and S&P500 ETF Trust; however marginally in case of USTD crypto asset and physical currency like USD-JPY respectively. All other assets risk is justifiable with their respective mean returns.

The figure 02, shows the how all these financial assets are correlated with various volatility measures and estimators. Although a consistent pattern is found in terms of nature of correlation across all 29 assets for most of the volatility indicators except when volatility measure is based on third moment (skewness) and fourth moment (Kurtosis). Especially in case of skewness-based volatility, very high and negative correlation in most of the cases has been observed. Generally, a significant but relatively high negative correlation is found with volatility in case of LTC_USD, Gold, BTC_USD and Shenzhen. This means the returns in these assets increases with reduction in volatility or vice versa.

There are two situations formulated into respective hypotheses: First, refers that entropy measures the disorder in the field of physics and the financial data is generated through the physical activity of trading hence entropy is considered as a source of disorder measured through randomness in the field of finance. Second, it is assumed that 'entropy' in information theory, which is measurable through probability, is playing vital role in the field of finance due to the information contents of a message generated by some economic or financial variable or even caused by some random variable, when the amount of information inside such message arrives in financial markets, it should mitigate the potential 'risk'. The reason is that any new information content is considered as 'news' in the financial market that will either lead to make such market bullish or bearish depending on the way such 'news' item is perceived. Consequently, entropy helps to collect the pieces of information that accumulates and become source of knowledge for effective decision making and leads to lower down the potential magnitude of 'risk'.

H1: entropy is a source of randomness

First, 'run test' has been applied to identify whether financial returns are random or not, because in case of randomness market will be considered weak efficient and potentials for abnormal returns may not be available in the specific financial asset group. The results reported in table 1, reveals that Microsoft and Facebook stocks are more efficient compared to Apple, AMD and Amazon where probability of excess return exists.

Table 1: Application of run test

			Conclusions of run test H_0:Data is Random H_1:Data has Pattern				Weak form Efficient Market Hypothesis
	MEAN	**STD**	**CV**	**Z-SCORE**	**RT_SERIES (5% sig. level)**	**Comparative Entropy Ranks**	**EMH**
aapl	1523.099	27.56086	0.018095	1.084906	Pattern	10	Prob. Abnormal Returns
amd	1525.496	27.60427	0.018095	1.793349*	Pattern	16	Prob. Abnormal Returns
amzn	1522.24	27.54529	0.018095	-0.33544	Pattern	8	Prob. Abnormal Returns
fbmeta	1527.25	27.59083	0.018066	2.020584**	Randomness	20	Market is Efficient
msft	1522.01	27.53662	0.018092	2.396427**	Randomness	1	Market is Efficient
n225	1518.199	27.4721	0.018095	0.939168	Pattern	12	Prob. Abnormal Returns
dax	1220.88	24.68563	0.02022	2.192353**	Randomness	3	Market is Efficient
rusell	629.0064	17.69907	0.028138	1.129644	Pattern	6	Prob. Abnormal Returns
szse	726.1247	19.02957	0.026207	0.256194	Pattern	14	Prob. Abnormal Returns
sse	1523.144	27.55714	0.018092	1.700336*	Pattern	19	Prob. Abnormal Returns
fchi	1520.329	27.50616	0.018092	1.696764*	Pattern	25	Prob. Abnormal Returns
hsi	617.3536	17.54575	0.028421	-0.13414	Pattern	5	Prob. Abnormal Returns
gold	1525.138	27.59778	0.018095	1.879218*	Pattern	4	Prob. Abnormal Returns
crudeoil	625.1908	17.59145	0.028138	0.728151	Pattern	22	Prob. Abnormal Returns
dji	627.1955	17.64799	0.028138	0.838875	Pattern	13	Prob. Abnormal Returns
pimco	1524.142	27.57975	0.018095	-0.18644	Pattern	17	Prob. Abnormal Returns
pketf	625.3641	17.59633	0.028138	0.49078	Pattern	2	Prob. Abnormal Returns
spy	624.6518	17.57624	0.028138	0.531864	Pattern	9	Prob. Abnormal Returns
btcusd	1518.569	27.48331	0.018098	2.962929**	Randomness	15	Market is Efficient
dogeusd	1217.923	24.6561	0.020244	3.775001**	Randomness	24	Market is Efficient
etcusd	1218.327	24.66429	0.020244	3.554641**	Randomness	23	Market is Efficient
ethusd	1217.879	24.6552	0.020244	3.776937**	Randomness	7	Market is Efficient
ltcusd	1525.976	27.60845	0.018092	3.40561**	Randomness	26	Market is Efficient
usdt	270.5621	6.174322	0.02282	0.070922	Pattern	18	Prob. Abnormal Returns
xrpusd	1073.482	21.72391	0.020237	2.647685**	Randomness	21	Market is Efficient
cmc	1525.48	27.60399	0.018095	0.924498	Pattern	11	Probable Ab. Returns
usdjpy	847.7645	20.51286	0.024196	1.961475**	Randomness	28	Market is Efficient
eurusd	1926.337	26.24968	0.013627	5.320549**	Randomness	27	Market is Efficient
cnyusd	1245.281	24.93554	0.020024	1.753271*	Pattern	29	Prob. Abnormal Returns

Note: More randomness should reflect higher entropy but ranking shows otherwise.

In contrast, all sampled cryptocurrencies and physical currencies have followed the randomness hypothesis of 'run test' and found weakly efficient with exception of a stable coin USDT, crypto-exchange CMC and Chinese Yuan per US dollar. The coefficient of variation is marginally higher in case of Rusell, Shenzhen, HSI, Crudeoil, DJI, PKETF and SPY reflecting higher risk per unit of returns, compared to other selected financial assets.

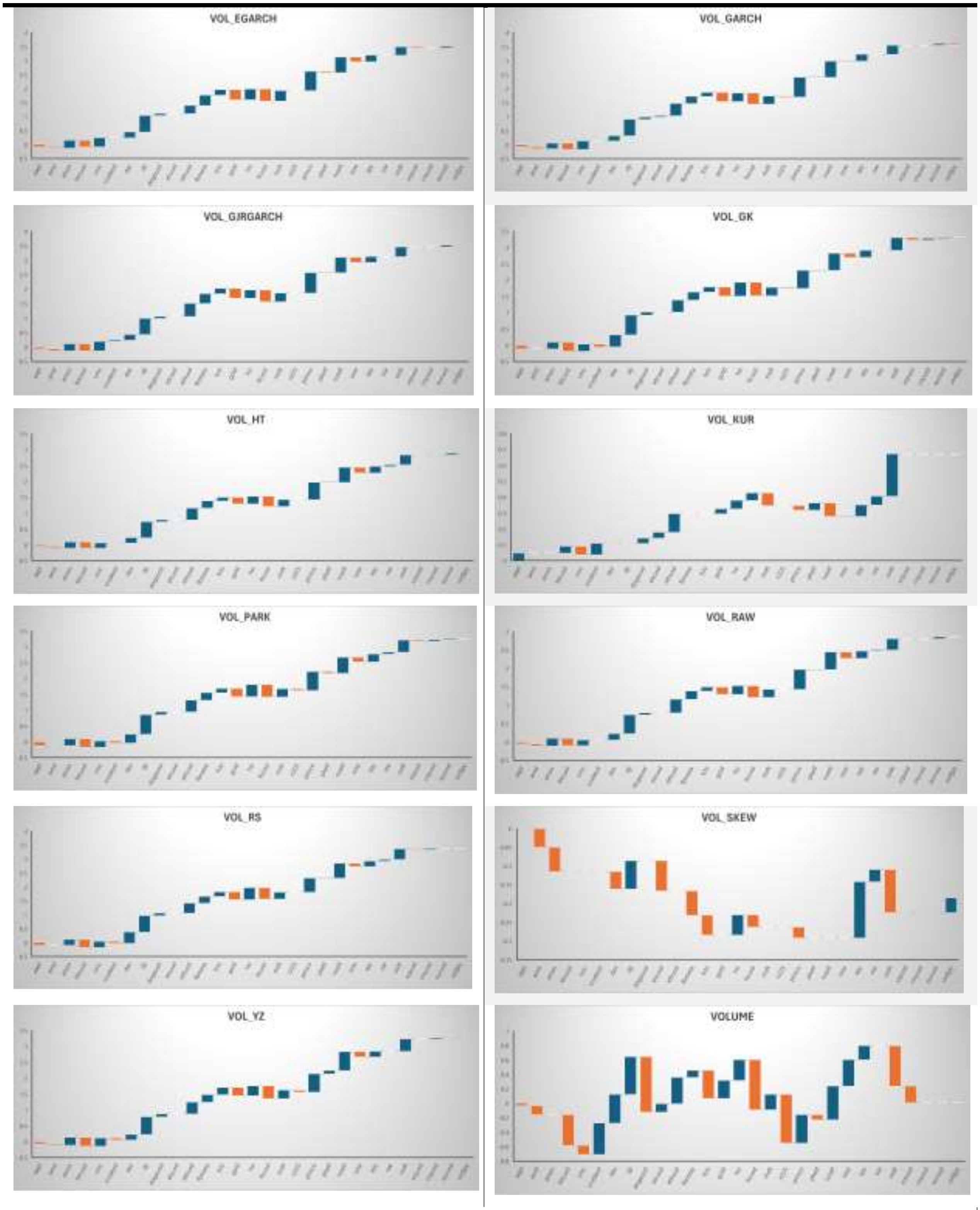
The *comparative entropy ranks* help to make another possible comparative analysis based on results provided in table 1, where ranking through the levels of entropy measure using intrinsic entropy approach have been reported. Considering that entropy is the measure of randomness, the assumption is that the more the entropy more the randomness, hence randomness should follow the level of entropy. Highest rank is 1 and the lowest rank is 29. Although the comparison may be crude but confirms one aspect of financial assets that in this sample, entropy ranks are not consistent with the level of randomness expressed by the run test. Most of the financial assets with significant randomness take comparatively low entropy ranks. So, the hypothesis that entropy reflects randomness becomes asset specific and cannot be applied on all sampled assets generally. Entropy ranks also convey that comparatively Microsoft (stock) , PKETF (Bond), DAX (Stock Exchange) have large number of possible return outcomes, but physical currencies have very small number of such possibilities. To probe this hypothesis further, future studies may apply other measures of randomness such as spectral analysis or surrogate data analysis.

H2: accumulated entropy is a source of information to mitigate risk

The results mentioned in figure 2 show the spearman rank-order correlation between entropy and all volatilities measured through eight estimates and three Grach based models. The assumption here is that if entropy is measuring the volatility in financial assets then there should be positive and direct association between entropy and the corresponding volatility measure otherwise in case of inverse association it may be considered as a source of information that mitigate risk.

Only eight financial assets show strong negative correlation with accumulated entropy supporting the given hypothesis, five assets have either insignificant correlation or very few correlations with volatility measures, while fifteen assets have positive significant correlation with given volatilities. Consequently, based on majority evidence it can be declared straightforwardly that accumulated entropy is not a source of information to mitigate the risk in case of selected sample of this study. So, the hypothesis that entropy may lead to reduced risk doesn't have majority vote to prove valid. Although, it is not proved that entropy can play a role to mitigate risk as a source of information but 30% of the sampled assets validate that entropy can be helpful to mitigate risk in some asset returns. Based on the results it can be concluded that entropy is more suitable as a measure of volatility rather than a source to reduce volatility. Since the case for entropy as a volatility measure is getting more support from the hypotheses tested through various statistical tools in this study. It is imperative to make a comparison of entropy with all other volatility measurement techniques to further explore its potential role.

Figure 2: Spearman Rank Correlation across assets for all volatility variables



Legend: Blue bars reflect positve and Oring bars negative correlation respectively.
Only significant corrlation is reported, at 1% and very few at 5% or 10% level of significance.

In table 2, very low values of the mean and variance of entropy variables compared to all other volatility measurement techniques have been observed in the case of all the financial assets except physical currencies. However, the coefficient of variation is large reflecting more volatility than the expected returns i.e., returns may not justify the level of potential risk. In table 3, mean squared error, proportional bias and efficiency estimators values have been provided. In most cases mean squared error is minimal in the case of entropy compared to all other volatility measures with only one exception Litecoin(LTCUSD). It means entropy as measure of volatility provides more precise estimates compared to other selected volatility measures. Proportion bias is either 1 or close to 1 for all financial assets for entropy except for HSI where it is positive but excessively large, Litecoin where it is again positive and more than 2, but less than 1 for Ripple (XRPUSD) and USDT with negative sign. In comparison, entropy has proved the best measure of volatility again based on proportional bias with minimum possible bias across all assets including USDT. For HSI and LTCUSD the better measure of volatility estimates is not the intrinsic entropy but Hodges Tompkins (HT) and for XRPUSD it is Skewness-based volatility measures. Efficiency estimator has been found very high in case of entropy compared to all other volatility measures except in case of both FCHI and LTCUSD where Garman Klass (GK) perform most efficiently to measure their volatilities. However, in physical currencies entropy is not relevant because absence of volume traded couldn’t allow to apply intrinsic entropy measure in these cases.

Conclusion

Since the role of entropy in the field of economics and finance pivot around mostly as a measure of volatility in returns, selection of optimized portfolios and to detect anomalies in markets. The literature emphasis on first two applications more than the third one. The main objective of this paper is to evaluate the more precise role of entropy either as an information measure that helps to minimize the riskiness of financial assets or another measure of risk (volatility) due to its intrinsic capacity that helps to measure disorder. Application of run test, variance ratio, correlation analysis along other evaluation criteria tested with two hypotheses in accordance with the objective, support intrinsic entropy as a measure of volatility with majority of evidence. Therefore, it is suggested that in future intrinsic entropy technique need to be preferred when and where volatility estimation is the major concern.

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Annexure A

Table 2 : Comparison across various volatility measures through mean, variance (var) and coefficient of variation (CV)

		ENTROPY	ACU_ENTROPY	vol_gk	vol_ht	vol_rs	vol_yz	vol_park	vol_raw	vol_kur	vol_skew	vol_garch	vol_egarch	vol_gjrgarch
aapl	Mean	1.48306E-06	0.00559732	0.199197727	0.241099772	0.199143111	0.286097402	0.199289595	0.240989967	0.170886357	0.070618114	2.141557864	9.84298778	2.128030341
	Var	6.70359E-09	2.0267E-06	0.007700988	0.023920617	0.008220885	0.025343326	0.007739554	0.023898834	4.006786199	0.890380894	0.400649167	59.04061713	0.436872153
	CV	55.13024375	0.25367584	0.440432471	0.641409115	0.45526482	0.556484276	0.441241145	0.641409115	11.71547276	13.3609385	0.295550084	0.780714959	0.310604808
amd	Mean	2.30483E-07	0.00187506	0.423327438	0.482762927	0.423085307	0.572361322	0.423559469	0.482546764	0.217587085	0.048597638	3.531744139	12.46735956	3.529765312
	Var	3.07481E-08	2.0784E-06	0.021340194	0.090677087	0.02191223	0.065433978	0.024292531	0.090595901	4.24508488	0.953580003	0.622054357	31.69977812	0.617105591
	CV	760.9223083	0.76876985	0.345126166	0.623857852	0.349921635	0.446991375	0.36802527	0.623857852	9.464270682	20.0830439	0.223329963	0.451645715	0.222563593
amzn	Mean	2.51083E-06	0.00415801	0.229051867	0.270656891	0.228872543	0.324599946	0.228432885	0.270458654	0.118770794	0.081881155	2.043655696	4.618602731	2.050374302
	Var	8.70451E-09	9.0666E-06	0.00944262	0.030858337	0.009642513	0.035352234	0.009630381	0.030813151	4.216323407	0.913516032	0.332838177	11.85380809	0.40998271
	CV	37.16259236	0.72404958	0.424298627	0.649140108	0.429101785	0.579335593	0.429657361	0.649140108	17.28987367	11.67417662	0.282294056	0.745570047	0.312322799
fbmeta	Mean	-9.56817E-07	-0.001663	0.267556079	0.325334882	0.267767039	0.385185866	0.266206114	0.324802524	0.158529454	0.056184818	2.347766882	6.04038217	2.358076952
	Var	1.39481E-08	1.0095E-06	0.013957492	0.05860622	0.014627066	0.07006298	0.013989685	0.058414577	4.226671818	0.915112787	0.74402665	26.46719458	0.973475318
	CV	-123.4323137	-0.6041666	0.441559129	0.744116997	0.451670256	0.687185455	0.444309844	0.744116997	12.96848666	17.02622351	0.367400103	0.851705669	0.418412354
msft	Mean	0.000271311	-0.0245541	0.188005837	0.223465738	0.188514582	0.264781232	0.186848855	0.223350067	0.147874366	0.072683036	1.627979267	2.941734931	1.633408046

	Var	0.000224525	1.77940345	0.006826167	0.023268391	0.007163153	0.021051035	0.006865762	0.023244308	4.152430957	0.90705433	0.412660189	9.641670274	0.442198914
	CV	55.22869339	-54.326743	0.439457747	0.68260934	0.448959501	0.547960843	0.443459463	0.68260934	13.78028867	13.10338763	0.394591219	1.055534907	0.407112226
n225	Mean	9.00743E-07	0.00210851	0.112629962	0.174297604	0.110971485	0.188629489	0.115985478	0.174127012	0.073490982	0.048997797	1.223918079	1.6464908	1.216855965
	Var	2.85704E-09	1.282E-06	0.003185553	0.01058273	0.003113622	0.005987798	0.003736465	0.010562025	4.059310266	0.868032936	0.171342304	1.842970281	0.203106486
	CV	59.34128292	0.53700382	0.501116231	0.590211201	0.502830413	0.410226764	0.527019676	0.590211201	27.41524144	19.01479049	0.338204944	0.824517462	0.370358845
dax	Mean	4.70371E-06	0.00995773	0.094391885	0.183587733	0.092549776	0.217582175	0.101491866	0.183211158	0.153622525	-0.050367705	1.284788234	1.834407485	1.287995749
	Var	6.40856E-09	6.9442E-06	0.004356496	0.014209794	0.004989215	0.019382562	0.004115864	0.01415156	4.107782757	0.89870184	0.271797879	3.75245627	0.332917405
	CV	17.01923171	0.264637	0.699252485	0.649307228	0.763204142	0.639856047	0.632119643	0.649307228	13.1931602	-18.82156148	0.405780788	1.055995351	0.447975044
rusell	Mean	4.3006E-06	0.00356395	0.170282567	0.227620262	0.168016641	0.209482613	0.182462289	0.226713121	-0.169661444	0.000372444	1.550041702	2.949729523	1.561078598
	Var	2.59164E-08	3.5614E-06	0.007454207	0.026624165	0.007201736	0.012917172	0.009363483	0.026412376	3.572881327	0.713676043	0.694597211	25.5849521	0.89745524
	CV	37.43335028	0.52951755	0.507026355	0.716848002	0.505087136	0.542544961	0.530329258	0.716848002	-11.14105037	2268.24032	0.537679075	1.714786711	0.606850381
szse	Mean	6.92036E-07	0.00089512	0.160716199	0.199761446	0.157614542	0.211252933	0.168048038	0.199072399	0.083947792	0.064863869	-0.012801034	1.965280166	1.372026937
	Var	7.55416E-09	3.1918E-07	0.003480111	0.010465291	0.00373577	0.009164409	0.003906665	0.010393014	4.021929362	0.851934758	0.997595794	0.958355156	0.124455034
	CV	125.5927196	0.63115411	0.367059843	0.512110851	0.38778747	0.453157814	0.371937231	0.512105809	23.88954846	14.22984995	-78.02472819	0.498125496	0.25712458

sse	Mean	-8.6219E-07	-0.001469	0.140098336	0.163926752	0.13866119	0.179830371	0.144577812	0.163764178	0.248739008	0.002676772	1.197739637	1.691442287	1.201266604
	Var	1.68129E-10	7.2678E-07	0.006618069	0.012763351	0.007008136	0.013523751	0.006926125	0.012738047	4.381868606	0.950007561	0.286104199	3.817538637	0.292632974
	CV	-15.03897902	-0.5803396	0.580674383	0.689179761	0.603734986	0.646674204	0.575630144	0.689179761	8.415613429	364.1264052	0.446580437	1.155139771	0.450321028
fchi	Mean	-0.005092236	0.00187886	0.125331815	0.153930227	0.125673719	0.178997796	0.125865289	0.153777959	0.11519126	0.016710345	1.097143126	1.435558241	1.098122923
	Var	0.079104025	1.051E-05	0.003960221	0.010595565	0.004357524	0.01087888	0.003929	0.010574614	4.188176166	0.891544592	0.237937005	3.922487027	0.334396714
	CV	-55.23200436	1.72543601	0.502109434	0.668710527	0.525261355	0.582699178	0.498006547	0.668710527	17.76613436	56.50490066	0.444598209	1.379621461	0.526599016
hsi	Mean	4.50391E-06	0.00330265	0.160939663	0.21465136	0.160326867	0.246848021	0.161996703	0.213778511	0.112855372	0.017630778	1.471693091	2.21389367	1.452556536
	Var	1.43544E-08	6.2132E-06	0.003301369	0.012446105	0.003284377	0.01023161	0.003536466	0.012345091	3.788402309	0.850033538	0.11859066	1.117780157	0.121058926
	CV	26.60130955	0.75473496	0.357012917	0.519736349	0.357454054	0.409772066	0.367095103	0.519736349	17.24669204	52.29335943	0.233995763	0.477552848	0.239533005
gold	Mean	4.6137E-06	0.00960707	0.306715417	0.350814414	0.305395703	0.420792297	0.305862101	0.350637657	0.270794957	-0.01713479	2.449556844	6.568070862	2.451220473
	Var	1.37422E-08	1.2828E-05	0.017660235	0.037761726	0.017149196	0.034581468	0.018518702	0.037723683	4.365853404	0.982517703	0.423890777	14.47572383	0.425633068
	CV	25.40851913	0.37280704	0.433274005	0.553921842	0.428804135	0.441930453	0.444917615	0.553921842	7.716031694	-57.84840668	0.265790505	0.579271704	0.266155414
crude oil	Mean	-2.48208E-05	0.34864119	0.423045365	0.399777546	0.423755601	0.495241881	0.414261617	0.398181758	-0.055281885	-0.165406616	2.790902571	9.60213158	2.775367488
	Var	1.20318E-06	0.00029833	0.090889707	0.12398271	0.089687248	0.140613769	0.08882999	0.122994884	4.099929014	0.794083517	3.111225691	227.9451147	2.817279491

	CV	-44.19253178	0.04954191	0.712640351	0.880769293	0.706724093	0.757175511	0.719457443	0.880769293	-36.62733556	-5.387412294	0.632005827	1.572343724	0.604775892
dji	Mean	7.94973E-07	0.00105707	0.128126119	0.170364328	0.127498564	0.175414774	0.130655421	0.16968537	-0.016277928	-0.006016048	1.170013234	1.840188945	1.190388073
	Var	1.11739E-08	4.8427E-07	0.006239676	0.021181892	0.006213175	0.014292712	0.006600769	0.021013395	3.828022809	0.774150461	0.601723652	12.45220179	0.704195005
	CV	132.9690825	0.65832249	0.616514601	0.854286839	0.618232005	0.681539693	0.621827379	0.854286839	-120.1954766	-146.251862	0.662991205	1.917611642	0.704949332
pimco	Mean	3.85017E-08	4.7369E-05	0.030315247	0.038999256	0.030699343	0.048750944	0.030286638	0.038936548	0.023820415	-0.084668681	0.269295477	0.086890022	0.270982978
	Var	2.94243E-10	3.211E-08	0.000352791	0.000807206	0.000353381	0.000796234	0.000409481	0.000804612	3.902850985	0.813986476	0.018539848	0.012818436	0.019590488
	CV	445.5258028	3.78293753	0.619580599	0.7285107	0.612339957	0.578811839	0.668137619	0.7285107	82.93572724	-10.65579359	0.505619746	1.303009598	0.516512234
pketf	Mean	1.44367E-05	0.0123308	0.16617924	0.217684491	0.1757626	0.28613079	0.162038112	0.216816948	0.257148364	-0.018944075	1.55567012	2.617017954	1.546781484
	Var	4.19801E-08	3.3251E-05	0.01251189	0.019498444	0.015380134	0.028807639	0.010348826	0.019343338	4.021789557	0.955287072	0.280418657	5.565621454	0.333629241
	CV	14.19236665	0.46763975	0.673107899	0.641464297	0.705591916	0.593183746	0.627810208	0.641464297	7.798766269	-51.59332821	0.340397171	0.901467617	0.373424742
spy	Mean	2.43165E-06	0.00229259	0.132450559	0.165237525	0.133351326	0.194245323	0.13159599	0.164578999	-0.072858068	0.020442623	1.124083094	1.692176668	1.142916984
	Var	1.61854E-08	1.4625E-06	0.007788563	0.019192136	0.008654675	0.022571212	0.007027595	0.019039467	3.717109773	0.759593397	0.516576406	10.52063235	0.615837635
	CV	52.31925265	0.5274934	0.666307749	0.838403295	0.69763463	0.773440426	0.63703119	0.838403295	-26.46214496	42.63379226	0.639394457	1.916793021	0.686623126

btcusd	Mean	5.96916E-07	-0.0001481	0.460124684	0.481683253	0.454850135	0.518672348	0.472803779	0.481010623	0.459909585	0.023252139	3.592194308	21.99624036	3.565895604
	Var	5.78707E-08	1.2915E-05	0.089277825	0.114189136	0.096769958	0.117867353	0.089889555	0.113870448	4.415287253	1.054403632	2.422368498	430.1789898	2.307360756
	CV	-2.348241438	1.97455386	0.559174987	0.763295758	0.548828287	0.559039138	0.601281274	0.763295759	1.343740724	-0.792777985	0.503017561	1.586002364	0.527765223
dogeusd	Mean	-7.0924E-05	-0.0653043	0.811208217	0.761476447	0.816098573	0.916930207	0.807706808	0.759910655	0.295917782	0.007203318	5.747798654	1053.108864	5.807328451
	Var	5.03815E-06	0.00431703	0.506211518	0.697985774	0.498018857	0.647334402	0.545103813	0.695118247	4.261051601	0.961192077	23.90292706	1023698007	26.209933
	CV	-31.64770652	-1.0061225	0.877068817	1.097152029	0.864729501	0.877461487	0.914083493	1.097152028	6.975692599	136.1045051	0.850597294	30.38174126	0.881569519
etcusd	Mean	-2.6094E-05	-0.0288421	0.771098442	0.748054983	0.773995479	0.870265449	0.772447016	0.746516789	0.397940322	-0.136240699	6.048181484	46.99699957	5.992983669
	Var	1.30507E-06	0.00080591	0.253935726	0.311449701	0.272097549	0.334656186	0.257236898	0.310170175	4.12693584	0.986028432	7.519942851	2384.544846	7.777189605
	CV	-43.78001758	-0.9842725	0.653509758	0.746037123	0.673944123	0.664733685	0.656595546	0.746037123	5.105001942	-7.288494949	0.453400981	1.039040833	0.465337711
ethusd	Mean	2.70432E-06	0.00520933	0.596628258	0.626919473	0.590482846	0.672628293	0.61268046	0.625630365	0.273560952	0.028763757	4.785521045	26.19124937	4.759884787
	Var	1.56904E-07	5.0662E-05	0.125247093	0.163308006	0.138931081	0.168723226	0.126817649	0.16263709	4.114244082	0.940478274	3.150044886	367.7838113	3.0322585
	CV	146.4735636	1.36634333	0.593171134	0.64460249	0.631236964	0.610678041	0.581240435	0.64460249	7.414654507	33.71543527	0.37087635	0.732217474	0.365836194
ltcusd	Mean	-0.100992152	-0.0064615	0.654601509	0.678671645	0.648908242	0.737181312	0.667925424	0.677724203	0.321685946	-0.034913684	5.031107822	44.98150029	5.036368897
	Var	31.09789325	0.00724312	0.183742988	0.244669067	0.194155167	0.240694637	0.191519034	0.243986416	4.375169953	1.009447352	5.718659054	3518.955253	6.029755294

	CV	-55.21764206	-13.171359	0.654829725	0.728836021	0.679033477	0.665516596	0.655206197	0.728836021	6.502275654	-28.77704257	0.475317142	1.318781772	0.487564762
usdt	Mean	-7.26335E-08	-3.921E-05	0.124853181	0.04505924	0.139640484	0.151160294	0.110235407	0.04494045	-1.415200836	-0.014617656	0.380010712	263691.9426	0.378574579
	Var	5.07936E-10	2.1192E-09	0.020689267	0.005633655	0.024223363	0.027922551	0.015865055	0.005603991	7.013358884	0.480862446	0.115134	2.17906E+11	0.116064764
	CV	-310.2896175	-1.1740264	1.15205426	1.665755582	1.114566205	1.105451824	1.142614359	1.665755582	-1.871306625	-47.43869048	0.892906445	1.77026315	0.899909317
xrpusd	Mean	-4.46891E-06	-0.0093596	0.707160169	0.731353241	0.731132955	0.832265164	0.723156807	0.729850008	0.528698489	-0.029540923	5.923973463	69.74150593	5.916428907
	Var	8.94733E-07	1.6245E-05	0.326074005	0.383944441	0.343733567	0.417770703	0.327161863	0.382367734	5.679995357	1.144414549	10.2955333	10764.96492	10.09229932
	CV	-211.6631181	-0.4306311	0.807495848	0.847241073	0.801889659	0.776617681	0.790949685	0.847241073	4.507813307	-36.21325999	0.541640736	1.487698718	0.536951934
cmc	Mean	1.30757E-06	0.00169619	0.311723757	0.329295482	0.314368819	0.41148725	0.306860103	0.329148035	0.09697631	0.011862213	2.288948289	5.864600045	2.298242527
	Var	1.16287E-08	4.4145E-06	0.013259084	0.034728683	0.014522854	0.031167311	0.012180317	0.034697589	3.98108273	0.864048181	0.509926513	19.19307203	0.577510894
	CV	82.4825842	1.2387619	0.3694251	0.565990456	0.383341514	0.429096093	0.359699502	0.565990456	20.57810018	78.37354778	0.312022737	0.747144203	0.330715801
usdjpy	Mean	-3107.105563	720.957224	0.075270042	0.070637377	0.091527535	0.128984419	0.063945103	0.070429571	0.177990416	-0.026088382	0.49861615	0.274173497	0.498047603
	Var	567449648.1	1353007317	0.001481977	0.00185956	0.002305573	0.004608604	0.001069504	0.001848635	4.172462488	0.912240488	0.02859588	0.039808955	0.030660115
	CV	-7.666685657	51.0200142	0.511444634	0.61047876	0.524611348	0.52631704	0.511427329	0.61047876	11.47623949	-36.61065756	0.33914498	0.727721021	0.351573423

eurusd	Mean	-150.5051567	-922.28625	0.103946735	0.10193966	0.134763635	0.181489788	0.094932173	0.101844007	0.689172175	-0.021973355	0.76591683	7.026543892	0.76671352
	Var	22750.45101	252347134	0.237713067	0.006857029	0.470949157	0.523557802	0.171277853	0.006844167	8.801089332	1.450970611	0.124905003	126.0603551	0.122477982
	CV	-1.00217514	-17.223978	4.69046259	0.812315642	5.092303663	3.986852106	4.359505044	0.812315643	4.304676108	-54.81923168	0.461432632	1.597892284	0.456452815
cnyusd	Mean	-2747608.933	28196.0868	0.04527168	0.039427726	0.056531297	0.077538035	0.038917158	0.039348413	0.447527501	0.030092534	0.271371632	0.207790185	0.272993654
	Var	6.35176E+14	1.4079E+12	0.000798178	0.001050806	0.001244979	0.003163969	0.000750115	0.001046583	4.718411719	1.056925784	0.023479134	0.042745016	0.022621485
	CV	-9.172593639	42.0827419	0.624055402	0.822166152	0.624154507	0.725439734	0.703757239	0.822166153	4.853758776	34.16358833	0.564646433	0.994987704	0.550944697

Annexure B

Table 3 : Comparison across variuos volatility measures through mean squared error (mse), proportionality bias (pb) and efficiency estimator (ee) by using cccve as a proxy for unobserved volatility

		ENTROPY	vol_gk	vol_ht	vol_rs	vol_yz	vol_park	vol_raw	vol_kur	vol_skew	vol_garch	vol_egarch	vol_gjrgarch
aapl	MSE	0.08198597	0.12936783	0.16404665	0.1298627	0.18916818	0.12944719	0.16397193	4.11535671	0.97686339	5.06889352	155.97792	5.0472739
	PB	1.000002959	0.33053857	0.00045564	0.35357024	0.42171233	0.30063864	0	9.62054841	4.31842971	10.34439	44.83868972	10.2091859
	EE	3565078.328	3.10334629	0.99908934	2.9070876	0.94300305	3.08788259	1	0.00596459	0.02684114	0.05965028	0.000404786	0.05470441
amd	MSE	0.323388737	0.52392162	0.64706721	0.52428878	0.71637765	0.52706816	0.64677741	4.61635917	1.27955857	13.4183896	187.4416306	13.3994745
	PB	0.999999882	0.36458374	0.00044796	0.39810882	0.47720833	0.31936287	0	5.01106962	2.35810638	8.78148473	31.09379852	8.77903695
	EE	2946394.198	4.24531764	0.99910467	4.13449022	1.3845391	3.72937268	1	0.02134136	0.09500608	0.14563985	0.002857935	0.14680778
amzn	MSE	0.103941425	0.16584335	0.20803526	0.1659607	0.24463569	0.16574851	0.20788283	4.33304032	1.02364895	4.61322223	33.28151603	4.71772655
	PB	1.000000282	0.31259369	0.00073297	0.33652757	0.41644631	0.28492213	0	9.05879645	3.98780346	8.90634379	18.30698386	8.83778885
	EE	3539906.006	3.26319915	0.99853568	3.19555181	0.87160406	3.19957759	1	0.00730806	0.03373028	0.09257697	0.002599431	0.0751572
fbmeta	MSE	0.163892175	0.24943135	0.32832201	0.25021363	0.38230039	0.24874297	0.32778432	4.41431385	1.08186253	6.41968492	63.10865126	6.69757616
	PB	1.000008574	0.32466075	0.00163902	0.35311067	0.4167923	0.28846783	0	7.96247718	3.56027469	8.5963804	19.83596772	8.48193366
	EE	4187986.665	4.18517727	0.99673	3.99359503	0.83374384	4.17554642	1	0.01382047	0.0638332	0.0785114	0.002207056	0.06000622
msft	MSE	0.073346391	0.11529206	0.14631964	0.11582049	0.16427517	0.11489795	0.14624388	4.24605827	0.9851617	3.13596332	18.36543542	3.18319772

	PB	1.000466915	0.34338618	0.00051789	0.36931609	0.44597622	0.30936658	0	10.9465886	4.9345379	8.30483686	13.26561808	8.2758695
	EE	103.5267056	3.40517717	0.99896503	3.2449828	1.1041884	3.38553958	1	0.00559776	0.02562615	0.05632796	0.002410818	0.05256528
n225	MSE	0.04087878	0.05674879	0.08183769	0.05630605	0.0824457	0.05806665	0.08175755	4.10425861	0.9110278	1.71014035	4.594176562	1.72465709
	PB	1.00000453	0.37994146	0.0009797	0.39318579	0.36574602	0.36126467	0	13.7373902	6.0644217	7.70623359	8.926138583	7.56020037
	EE	3696846.23	3.31560185	0.99804347	3.39219899	1.76392465	2.82674278	1	0.00260193	0.01216777	0.06164283	0.00573098	0.0520024
dax	MSE	0.047712097	0.06097663	0.09562052	0.06126472	0.11442872	0.06212687	0.09542418	4.1774119	0.94858267	1.97007943	7.16368192	2.03942616
	PB	0.999984306	0.47798106	0.00205541	0.50121605	0.36997752	0.44249541	0	12.8350149	5.87507714	7.61109492	9.467662461	7.54943096
	EE	2208227.695	3.248381	0.99590181	2.83643041	0.73011813	3.43829605	1	0.00344506	0.01574667	0.05206648	0.003771279	0.04250772
rusell	MSE	0.077790245	0.11423465	0.1562042	0.11321582	0.13458009	0.12043875	0.15558044	3.67661642	0.79089909	3.17446456	34.34330877	3.41149845
	PB	0.999996498	0.30912101	0.00400127	0.34238847	0.29677242	0.25469907	0	9.97981602	4.31701854	7.06105843	10.72139892	6.98330227
	EE	1019136.275	3.54328448	0.99204523	3.66750112	2.04474913	2.82078545	1	0.00739246	0.03700891	0.03802546	0.00103234	0.0294303
szse	MSE	0.050015679	0.07932308	0.10037838	0.07859121	0.10380157	0.08215979	0.10003134	4.07622043	0.90557061	1.04708781	4.870036479	2.05684285
	PB	1.000015607	0.31398871	0.00345914	0.34617292	0.33738788	0.2695498	0	10.5374194	4.68905087	4.34076384	10.00948357	7.18873614
	EE	1375799.214	2.98640326	0.99309364	2.78202731	1.13406269	2.66032871	1	0.00258409	0.01219931	0.01041806	0.010844637	0.08350818
sse	MSE	0.039552577	0.06579602	0.07918372	0.06578534	0.08541086	0.06737918	0.07910515	4.4818556	0.98925582	1.76014321	6.716816572	1.77513106
	PB	1.000006206	0.31764369	0.00099273	0.35347596	0.37683026	0.27045074	0	15.2064479	6.6100531	7.83313733	9.347861418	7.84980876

	EE	75763496.74	1.92473775	0.99801749	1.81760838	0.94190195	1.83913029	1	0.00290699	0.01340836	0.04452241	0.003336717	0.04352909
fchi	MSE	0.113296883	0.05388579	0.06850541	0.05436879	0.07713433	0.05398859	0.06843761	4.23429083	0.92575033	1.47580084	6.016247235	1.57437984
	PB	1.012846974	0.33744291	0.00099018	0.36198733	0.43817398	0.3055808	0	16.8879649	7.3308021	7.92258771	8.062244151	7.63111359
	EE	0.133679842	2.67020795	0.99802258	2.42674796	0.97203148	2.69142602	1	0.00252487	0.011861	0.04444291	0.002695895	0.03162296
hsi	MSE	0.02941176	0.04420992	0.05906417	0.04410154	0.06547295	0.04450195	0.05882351	1.95420236	0.46000139	1.18709133	3.079325072	1.15998165
	PB	1867187517	0.23261842	0.00206076	0.24709101	0.1213127	0.21825463	0	-0.1492414	-0.1675612	0.43470796	0.455080523	0.43371051
	EE	860022.0811	3.73938555	0.99188382	3.75873072	1.20656377	3.49079824	1	0.00325865	0.01452306	0.10409834	0.011044292	0.10197588
gold	MSE	0.160658091	0.27238687	0.32147817	0.27106818	0.37229436	0.27272233	0.32131615	4.59840949	1.14314714	6.58473856	57.77118906	6.59463336
	PB	0.999983087	0.3282461	0.0005041	0.35535867	0.46177322	0.29278534	0	6.73725846	3.13020606	7.66932624	20.10188145	7.67494981
	EE	2745090.81	2.13608047	0.99899256	2.19973475	1.09086415	2.03705875	1	0.00864062	0.03839491	0.08899388	0.002605996	0.08862959
crude oil	MSE	0.281447029	1.09059648	11.1815959	320.234034	10.9034712	0.26037207	0.28144583	4.09972602	0.82081164	10.8978897	319.9648492	10.5177047
	PB	0.9999873	0.37234451	0.00400769	0.41105646	0.49609668	0.30657224	0	6.35695315	2.93514894	7.4698827	21.22401413	7.43278517
	EE	102225.0619	1.35323227	0.99203255	1.37137539	0.87470015	1.38460991	1	0.02999927	0.1548891	0.03953261	0.000539581	0.04365732
dji	MSE	0.049789827	0.79622229	2.02036536	15.8510628	2.16571069	0.02366636	0.04978982	3.82524484	0.77357127	1.9701763	15.82859873	2.120659
	PB	1.000021072	0.32143051	0.00400127	0.34570645	0.33331658	0.2876274	0	14.6619159	6.79534828	7.30768023	8.209653644	7.31942254

	EE	1880573.929	3.3677059	0.99204523	3.38207064	1.4702175	3.18347678	1	0.00548936	0.02714381	0.034922	0.001687524	0.02984031
pimco	MSE	0.002320404	0.00359209	0.00464829	0.00361612	0.00549303	0.00364703	0.00464081	3.90445876	0.8232087	0.09337422	0.022684511	0.09533624
	PB	1.000008172	0.37047502	0.00161051	0.39070708	0.51002705	0.34472658	0	62.0898419	27.4952776	7.45416852	1.244461883	7.47608448
	EE	2734518.323	2.28070408	0.99678674	2.27689719	1.0105223	1.96495585	1	0.00020616	0.00098848	0.04339909	0.062769942	0.04107159
pketf	MSE	0.066337593	0.10645503	0.13320703	0.11259795	0.17699312	0.1029345	0.1326751	4.15105542	1.02122413	2.76664282	12.47631779	2.79223455
	PB	0.999923848	0.44315136	0.00400127	0.47982473	0.57368017	0.40970987	0	10.9983349	5.11248049	8.18623197	12.60459494	8.12895807
	EE	460773.9943	1.54599655	0.99204523	1.25768332	0.67146558	1.86913357	1	0.00480963	0.02024872	0.06898021	0.003475504	0.05797855
spy	MSE	0.046110596	0.0714361	0.0925909	0.07254095	0.10639509	0.07045009	0.09222116	3.76557387	0.80551807	1.82583915	13.42184183	1.96771791
	PB	1.000001875	0.2951838	0.00400127	0.31363912	0.39039148	0.27955212	0	14.4271367	6.58560689	7.25538885	7.830679017	7.25258117
	EE	1176333.218	2.44454179	0.99204523	2.19990561	0.84352879	2.70924377	1	0.00512212	0.02506534	0.03685702	0.001809726	0.03091637
btcusd	MSE	0.345204366	0.64616757	0.69137474	0.64883116	0.732054	0.65860779	0.69040862	4.9705598	1.39980267	15.670638	914.2176495	15.3674195
	PB	1.00000765	0.34760051	0.00139837	0.402621	0.40527506	0.27037067	0	6.0646515	2.91560752	8.91501791	46.45865533	8.85590729
	EE	1967670.971	1.27546171	0.99720912	1.1767128	0.96608981	1.26678175	1	0.02579004	0.10799512	0.0470079	0.000264705	0.04935095
dogeusd	MSE	1.272302022	2.43635938	2.54984249	2.43612819	2.76012654	2.46956722	2.54459396	5.619166	2.23314621	58.202597	1024386637	61.1965299
	PB	1.000021511	0.43756011	0.0020605	0.50528823	0.55714246	0.3447817	0	4.36392557	2.17695359	8.9829095	160.8784791	9.03934085
	EE	137970.8394	1.37317746	0.99589171	1.39576692	1.07381632	1.27520342	1	0.16313303	0.7231835	0.02908088	6.79027E-10	0.02652118

etcusd	MSE	0.867331417	1.71575436	1.73823816	1.73838492	1.95921081	1.72113576	1.73466022	5.15092761	1.87151513	44.964684	4593.150866	44.5571791
	PB	1.000016949	0.37725174	0.0020605	0.43280966	0.47438776	0.29685103	0	3.56510977	2.00507599	9.8009301	65.82062824	9.69628844
	EE	237665.7726	1.22145151	0.99589171	1.13992271	0.92683234	1.20577638	1	0.0751575	0.31456514	0.04124635	0.000130075	0.03988204
ethusd	MSE	0.553983809	1.03514459	1.11025262	1.04152767	1.17506641	1.05612657	1.1079673	4.7413737	1.49490305	26.6039466	1054.168298	26.2415001
	PB	1.0000095	0.32905659	0.0020605	0.37811418	0.38432466	0.25744361	0	4.09262193	2.04120477	8.90730578	45.56938829	8.86755615
	EE	1036535.736	1.29852986	0.99589171	1.17063143	0.96392829	1.28244839	1	0.03953025	0.17293019	0.05163009	0.000442208	0.05363563
ltcusd	MSE	31.79091378	1.3154024	1.40840056	1.31838993	1.48726852	1.34079713	1.40643303	5.18043383	1.71355187	31.7320465	5541.840082	32.0960065
	PB	2.06678887	0.33467049	0.00139798	0.38756101	0.40080465	0.26194862	0	4.43415249	2.22756381	8.89891344	66.23498376	8.87463429
	EE	0.007845754	1.3278679	0.9972099	1.25665683	1.01367616	1.27395388	1	0.05576616	0.24170296	0.04266497	6.93349E-05	0.04046373
usdt	MSE	9.012461048	9.04872774	9.02012207	9.05617113	9.06321834	9.0404696	9.02008173	18.0249221	9.49328408	9.27194259	2.87325E+11	9.27178344
	PB	-0.528421373	-0.6051025	-0.5663049	-0.6119477	-0.6190994	-0.5973701	-0.566205	0	-0.521478	-0.7446234	-64156.39061	-0.7440478
	EE	13807567984	338.98538	1244.90378	289.528706	251.171851	442.063329	1251.4937	1	14.5849586	60.9147505	3.21852E-11	60.4262537
xrpusd	MSE	5.957186654	6.78320141	6.87585015	6.83533362	7.06745027	6.80716909	6.87207756	11.9143715	7.10200318	51.3419542	15630.38064	51.0494731
	PB	0.062150891	-0.6139025	-0.7199569	-0.6211975	-0.7085801	-0.6558321	-0.7187599	0	0.03288096	-3.2408071	-22.25517876	-3.2466925
	EE	6348253.862	17.4193443	14.793795	16.5244128	13.5959638	17.3614226	14.8547978	1	4.96323239	0.55169511	0.000527637	0.56280488

cmc	MSE	0.143015414	0.25344026	0.28615896	0.25636155	0.34348572	0.24935296	0.2860308	4.13131186	1.00677732	5.89189627	53.71708357	6.00206874
	PB	0.999993396	0.37804614	0.00044796	0.41194568	0.5381518	0.33089991	0	6.78064761	3.12730882	7.5637936	19.01422483	7.55980399
	EE	2983801.838	2.61689178	0.99910467	2.38917158	1.11326862	2.84866055	1	0.00871562	0.04015701	0.06804429	0.001807818	0.06008127
usdjpy	MSE	576770547.1	0.01395456	0.01365598	0.01748938	0.02805075	0.01196573	0.01361575	4.20850088	0.9191933	0.28400503	0.12176456	0.2855014
	PB	91546.19248	0.36229401	0.00295055	0.52700532	1.0102716	0.30753101	0	34.5998731	15.0788075	7.87179576	3.228081399	7.82168704
	EE	3.2578E-12	1.24741119	0.99412492	0.80181156	0.40112695	1.72849749	1	0.00044306	0.00202648	0.0646469	0.04643767	0.06029446
eurusd	MSE	45398.03981	0.26116364	0.03382169	0.49809639	0.56294632	0.19427006	0.03378994	9.11882473	1.44108989	0.72840534	175.4261292	0.7271998
	PB	1520.577676	0.46128593	0.00085836	0.62671214	0.88717303	0.42135748	0	30.0164113	11.3199131	6.49324259	59.18857578	6.50099294
	EE	3.00837E-07	0.02879171	0.99812422	0.01453271	0.01307242	0.03995944	1	0.00077765	0.00471696	0.05479498	5.42928E-05	0.05588079
cnyusd	MSE	6.4247E+14	4.91964197	4.91940181	4.92123358	4.92597172	4.91906124	4.91939134	9.83359375	5.97420358	5.01390914	5.002701481	5.01393481
	PB	-1218813.228	0.06240089	0.07122718	0.05076176	0.03007349	0.06999983	0.07131747	0	0.31644037	-0.0597207	-0.066125873	-0.0620389
	EE	7.42851E-15	5911.48135	4490.27762	3789.95205	1491.29505	6290.24911	4508.39743	1	4.46427913	200.961916	110.3850721	208.580987