Effects of Coronavirus Pandemic on U.S Economy: D-Vine Regression Copula Approach

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Abstract

The rapid spread of Covid-19 since January 2020 has dramatically affected financial markets and economies worldwide, especially in the United States. This paper aims to utilize the regression model of D-Vine Copula introduced by Kraus to investigate the effects of each of three input variables (number of Corona cases, number of deaths, and news). We analyze the influence of those inputs on our three response variables, which are three famous indices in the U.S(S&P 500, NASDAQ100, Dow Jones). First, we examine the impact of the unemployment rate on financial markets and the economy using jobless claims reported by the department of labor during the first five months of the outbreak in the United States. Findings demonstrate that the fitted quantile curves of all input variables suggest that variable death has the most negative effect on S&P500, Dow Jones. In addition, variable news has the most negative influence on NASDAQ100, and we conclude that variable D (GDP news) has the most effect on all mentioned indices.

Keywords: pandemic; Covid-19; GDP; indices; D-Vine copula; Kendall's tau

1. Introduction

Everything started in December 2019. The Coronavirus, also known as COVID-19, was first reported in Wuhan, China. Not only this virus, with a mortality rate of 3%, has affected families adversely in over 120 countries, but it has also slowed the global monetary and financial markets. The virus has been spread almost everywhere on earth and infected over 100000 people. Many lost their jobs, and businesses have been in recession. This pandemic has shaken the economies of the countries. There are several examples of business losses worldwide, which we mention as follows.

CNN (Cable news network) announced the bankruptcy of British airline Flybe due to a sharp decline in passengers following the corona outbreak. OPEC (Organization of the petroleum exporting countries) proposed reducing oil production by 1.5 million barrels per day to reduce corona's negative impact. IMF (International monetary fund) said corona is slowing global economic growth[1]. The head of the IMF warned that corona is a serious threat to the growth of the global economy and this growth will decline compared to the past year[2]. Even sports officials have announced the possibility of postponing the Tokyo 2020 Olympics. In the export sector, the Director of international trade and commerce of the united nation declared that the virus would damage $50 billion worldwide in export products due to the closure of industrial sectors in China, and the total export will fall by 2 percent[3]. On February 28th, the London stock exchange also fell 3 percent, and the stock market in Germany and France also fell by almost the same amount. Japan's Nikkei also declined for several consecutive days. A similar trend prevailed in other Asian markets[4].

On the other hand, several large companies worldwide have warned that the supply chain of their production needs may be disrupted due to the disclosure of the industrial plants in China. In addition, the volatility of markets in Shenzhen and Hong Kong rose due to the pandemic[5]. The spread of the virus worried the investors that the impact of the disease on the global economy was more significant than we thought[6]. Because of this, the U.S. approved $8.45 billion in funding to fight the virus in different sectors, and President Trump signed it. Figure (1) is the detailed budget allocated to this topic for each section.

Governments have also taken other measures to prevent the spread of this virus. On May 11th, president trump announced the suspension of all travel from Europe, excluding the United Kingdom, to the United States for the next 30 days. Three of the top Wall Street indices, the S&P 500, NASDAQ 100, and Dow Jones, fell more than 9 percent in just one day. Black Thursday, March 12th, was marked as the worst day of the stock exchange market in the 21st century. Some other governments implement different subsidy policies based on economic and social progress[7]. In addition, the U.S dropped to 10^{th} place in a ranking of the most competitive world economies by IMD (International Institute for Management and Development, a business school in Lausanne, Switzerland), which its rank was 3^{th} in the previous year. On April 25th, President Trump signed a $484B small business coronavirus relief bill into law as the fourth bailout to fight this outbreak's detrimental effect on the U.S economy [8].

Vine Copula model and its classes have a variety of functions and have long been used in determining the independent data for multivariate data structures. This class of flexible copula models has become very well known in recent years for many applications in various fields, such as finance and engineering. The popularity of vines copulas is because it allows tail asymmetries and separate multivariate component modeling in addition to separating margins and dependence by the copula approach. In 2010, Joe et al. described tail dependence, conditional tail dependence, and its probabilities. They showed that the extremal dependence of a copula, defined by its extreme value copulas, will be determined entirely by its tail dependence functions. He and his colleagues also investigated the influence of tail dependence of bivariate linking copulas on a vine copula[9]. After that, Nikoloulopoulos et al., 2012, published a paper about Vine Copulas with symmetric tail dependence and their applications to financial return data. They have manifested that vine copulas constructed from bivariate t copulas can properly fit multivariate financial asset return data. It is proved that Vine copula models with suitable choices of bivariate reflection asymmetric linking copulas will be used to evaluate such tail asymmetries. They also compared different vine copulas regarding likelihood fit and forecasting of extreme quantiles[10]. Two years later, in 2014, So and Yeung wrote a paper, "Vine-Copula GARCH model with dynamic conditional dependence." They developed a generic approach to specifying dynamic conditional dependence using any dependence measures. They performed Simulation experiments and studied five Hong Kong blue-chip stock data from January 2004 to December 2011. They utilized t and two Archimedean copulas, which revealed that Kendall's tau and linear correlation of the stock returns vary over time[11]. Finally, Kraus and Czado, 2016, Researched D-Vine copula-based quantile regression. In that study, they introduced a new semiparametric quantile regression method. As a subclass of regular vine copulas, D-vines enable the modeling of multivariate copulas in terms of bivariate building blocks, a so-called pair-copula construction (PCC). A simulation study indicated that they improved the approach's accuracy and reduced computation time compared to established quantile regression methods. They assessed the usefulness of the technique by financial application to international credit default swap (CDS) data, including stress testing and value at risk prediction (VaR)[12].

On the other hand, some studies have been done regarding the pandemic's effect on financial markets. In 2020, Corbet et al. indicated that the volatility relationship between the main Chinese stock markets and Bitcoin evolved significantly during the epidemic. They provide several observations as to why this situation happened. Their results demonstrate that some characteristics expected during a "flight to safety" were present during the period analyzed[13]. Later in the same year, Zhang et al. presented a paper that maps the general pattern of country-specific risks and systematic risks in the financial market. Their study also analyzes the potential consequence of making some new policies, such as the U.S decision to implement a zero-percent interest rate and unlimited quantitative easing, and how these interventions may result in more uncertainties in global financial markets[14]. Then again, in 2020, Ali et al. published a paper that investigated the reaction of financial markets globally in terms of their decline and volatility as the Coronavirus epicenter moved from China to Europe and then to the United States. Their results recommend that China's earlier epicenter has stabilized while the global markets have gone into a freefall, particularly in the later spread phase. Even the relatively safer commodities have suffered as the pandemic moves into the U.S.[15]. In 2021, Pandey and Kumari studied the impacts of covid-19 on the world's stock market. They considered 23 developed and 26 emerging market indices using the methodology published by Warner in 1980. Their empirical results inferred that markets had shown a different behavior in various events. They demonstrated that the market reaction differs in the case of the first Covid-19 cases detected; however, on the other hand, the market reaction is thoroughly the same in the case of the first Covid-19 deaths. The events have negatively and tremendously influenced the global stock markets, forecasting more severity in the future[8]. In 2022, Rokhsari et al. investigated the financial market performance due to covid-19 using EGARCH. They examined the relationship between studied capital markets and commodities and the number of cases of Covid-19 in the world using the bivariate regression model. Their findings indicated that some countries had the best policies to contain the virus. Several others have taken measures and initiatives to support the businesses and their markets to alleviate the outbreak's negative influence on their economy[2].

This paper is organized as follows. Chapter 2 is devoted to discussing GDP and the unemployment rate during the pandemic in the United States. GDP is reported for the first quarter of 2020 by the Bureau of Economic Analysis (BEA) and forecasted by Goldman Sachs until the end of the year. Jobless claims are reported by the Bureau of Labor Statistics (BLS). In section 3, we explain how and where we achieved the data and used them in analyzing the situation of the three popular indices. Section 4 is dedicated to explaining Vine Copula models, which we use for our analysis in the next section. Section 5 investigates the effect of all inputs on response variables: three indices (S&P 500, NASDAQ 10, and Dow Jones). Also, it is about finding the representative of news and checking out which news has the most impact on indices' volatilities among all by using the dependence coefficient of Kendall's tau. Finally, the last section, section 6, has to do with the discussion and conclusion of the paper.

2. GDP and Unemployment rate

The Coronavirus outbreak has substantially affected all the world's economies, including the greatest one, which belongs to the United States. Some measures, like the gross domestic product, represent the value of economic activity within a country and are the sum of the market values, or prices, of all final goods and services produced in an economy during a period. GDP is a number that expresses the worth of the output of a country in local currency which is calculated as follows:

$$GDP = C + I + G + (X - M) \tag{1}$$

Where C is all private consumption, I, gross investment by businesses, G, all government spending, X, exports, and M, is imports.

With millions of Americans out of work, it is no surprise that the economy has taken a hit. People have less money to spend, so there will be no growth for some consecutive seasons. In a period of recession, GDP drops, and the economy shrinks. NBER (National Bureau of Economic Research) declares that the longest U.S economic expansion, which lasted for over ten years, ended in February, and the recession began, it may end up in one of the deepest ones. The covid-19 hit us hard, but economists think we will make a turnaround by the end of the year[16].

Figure 2 shows what Goldman predicted and then revised the GDP forecast for 2020 quarterly. However, experts say that the analysts in Goldman Sachs predicted too optimistically for the third and fourth quarters.

No related finance news more than the unemployment rate will hit the economy. According to the U.S department of labor, by the end of May 30th, 42.7 million jobless claims were filed amid the Coronavirus outbreak.

In figure 3, the number of jobless claims that people filed during the pandemic in the United States is indicated weekly. In April unemployment rate plummeted to a record 14.7%. Still, after injecting some money and financial aid from the government, the U.S unemployment rate fell to 13.13% in May and 11.1% by the end of June, and another 4.8 million jobs were added to the economy. These are the sound effects of the stimulus and bailouts, especially to the private sector, to keep their businesses going, and the money has found its way into the economy.

3. Data

We would like to investigate the effects of Coronavirus regarding the number of cases and related financial news on three indices from the beginning of the year 2020 until the end of May. We have two sets of data. Economic news is released at a specific time on the most popular websites, and coronavirus cases in the United States from the moment the first case was reported. Data sets are from January 1st to the end of May (we collected data for five months). Using text mining, we acquired data on cases from the website of Worldometers and financial news from finance-related websites such as Yahoo Finance, Bloomberg, Harvard Business Review, Department of the treasury, and Bureau of Economic Analysis. We used Google search API (Application Programming Interface) for the extraction of information from those websites. We presumed that financial news, which contains one of the keywords "S&P 500, NASDAQ 100, Dow Jones, Coronavirus, economy, bailout, Recession, Financial crisis and Jobless claim", may affect the decisions of the traders. Also, the positions they had taken in the financial market tomorrow when the news was released, published on those websites. We searched those keywords and collected the first 1000 results for each keyword from January 1st to May 31st. We corrected the results by filtering only those reporting a publication date between that period and removing duplicate results to obtain a more robust dataset. It gave us a total number of 397 web pages from those websites.

In figure 4, the number of cases in the United States reported by each state to the U.S Department of Health and Human Services (HHS) and Centers for Disease Control and Prevention is indicated from mid-February to the end of May.

As we can see in figure 5, the influence of the pandemic and financial crisis and volatility of those three indices have almost the same pattern as expected (we scaled the values of indices to a range of [0,100]). Since many of the stocks within these indices are identical or have the exact correlation regarding the fact that they are from a similar industry, however, it is evident that the indices started to plummet altogether from February 20th and reached their minimum points in 2020 on March 23rd. This issue should not be surprising since the first considerable cases were reported in mid-February, regarding figure 4. On the other hand, in section 2, figure 3, we have observed that almost 6.9 million jobless claims were filed in the week ending March 28th, which is the highest figure during the pandemic. This kind of news could hit the economy and financial markets the most and unsettle the composure of the traders casting uncertainty on the future of the market and companies.

4. Vine Copula Models

We now recall the definition of a copula, Sklar (1959). Let $X = \left(X_1, ..., X_n\right)$ be a vector of random variables, with joint distribution F and marginal distributions $F_1, ..., F_n$ Then there exists a function C – called copula – mapping the Individual distribution to the joint distribution[17]:

$$F\left(x_1,...,x_n\right)=C\left(F_1(x_1),...,F_n(x_n)\right) \tag{2}$$

When the variables are continuous, Sklar's theorem shows that any multivariate probability distribution function can be represented with a marginal distribution and a dependent structure, which is derived below:

$$F\left(x_1,...,x_n\right)=\frac{\partial F\left(x_1,...,x_n\right)}{\partial x_1,...,\partial x_n}=\frac{\partial C\left(u_1,...,u_n\right)}{\partial u_1,...,\partial u_n}\times\prod_i f_i\left(x_i\right) \tag{3}$$

Here, $f_i;i-1,...,n$ is the density function of $F_i;i=1,...n$ and $u_i=F_i\left(x_i\right);i=1,...n$. If all the margins are continuous, then the copula is unique and generally otherwise determined uniquely by the ranges of the marginal distribution functions.
The n-dimensional vine copulas are built via mixing from n(n- 1)/2 bivariate linking copulas on trees and their copula density functions. Two boundary cases are D-vines and C-vines. (see Bedford and Cooke (2002, 2001)[18][19], Kurowicka and Cooke (2006)[20] and Section 4.5 of Joe (1997)[21]). For the d-dimensional D-vine, the pairs at level 1 are $i,i+1$, for $i=1,...,n-1$, and for level k, $(2\le k\prec n)$, the (conditional) pairs are $i,i+k|i+1,...,i+k-1$ for $i=1,...,n-k$. For the n-dimensional C-vine, the pairs at level 1 , are 1, i, for $i=2,...,n$, and for level k, $(2\le k\prec n)$, the (conditional) pairs are $k,i|1,...,k-1$ for $i=k+1,...,n$. For the D-vine, conditional copulas are specified for variables i and i+l given the variables indexed in between. For the C-vine, conditional copulas are specified for variables l, and i gave those indexed as 1 to k-1. For C-vines and D-vines, the densities are respectively as equations 4 and 5 (Aas et al. (2009)[22]),

$$f\left(x_1,...,x_n\right)=\prod_{k=1}^{n} f_k(x_k)\prod_{j=1}^{n-1}\prod_{i=1}^{n-j} c_{i,i+j|i+1,...,i+j-1}(F_{i|i+j,...,i+j-1},F_{i+j|I=1,...,I+j-1}) \tag{4}$$

$$f\left(x_1,...,x_n\right)=\prod_{k=1}^{n} f_k(x_k)\prod_{j=1}^{n-1}\prod_{i=1}^{n-j} c_{j,j+i|1,...,j-1}(F_{j|1,...,j-1},F_{j+i|1,...,j-1}) \tag{5}$$

Index j denotes the tree/level, while i runs over the edges of each tree. Figures 6 and 7 depict a C-vine and a D-vine with five variables and four trees/levels. The densities are decomposed by multiplying the nodes of the nested set of trees, as indicated below for the D-vine,

$$\begin{aligned} f = {} & f_1 f_2 f_3 f_4 f_5\times C_{12}(F_1,F_2)C_{23}(F_2,F_3)C_{34}(F_3,F_4)C_{45}(F_4,F_5)\\ & \times C_{13|2}(F_{1|2},F_{3|2})C_{24|3}(F_{2|3},F_{4|3})C_{35|4}(F_{3|4},F_{5|4})\\ & \times C_{14|23}(F_{1|23},F_{4|23})C_{25|34}(F_{2|34},F_{5|34})\\ & \times C_{15|234}(F_{1|234},F_{5|234}) \end{aligned} \tag{6}$$

And for C-Vine,

$$
\begin{aligned}
f = {} & f_1 f_2 f_3 f_4 f_5 \times C_{12}(F_1, F_2) C_{13}(F_1, F_3) C_{14}(F_1, F_4) C_{15}(F_1, F_5) \\
& \times C_{23|1}(F_{2|1}, F_{3|1}) C_{24|1}(F_{2|1}, F_{4|1}) C_{25|1}(F_{2|1}, F_{5|1}) \\
& \times C_{34|21}(F_{3|21}, F_{4|21}) C_{35|12}(F_{3|12}, F_{5|12}) \\
& \times C_{45|123}(F_{4|123}, F_{5|123})
\end{aligned} \tag{7}
$$

For more general regular vines in dimension n, there are n-1 pairs at level 1, n-2 pairs in level 2 where each pair has one element in common, and for k=2, …,n-1, there are n-k pairs in level k where each pair has k-1 elements in common.

Figures 6 and 7 represent the tree structure of equations 6 and 7, respectively. As it is evident, in a tree structure, the nodes are variables, and the edges are the index of copulas assigned to the two corresponding variables, and also each edge in each tree is a node in the next tree. In the C-Vine structure (figure 7), one variable is considered a root in each tree, and other nodes are connected. While in the D-Vine network (figure 6), the variables are connected sequentially in each tree.

4.1 The d-vine-based quantile regression model

The primary purpose of D-vine copula-based quantile regression is to predict the quantile of a response variable Y given the outcome of some predictor variables $X_1, ..., X_n$, where $Y \sim F_y$ and $X_j \sim F_j; j = 1, ..., n$. Hence, the focus of interest lies on the joint modeling of Y and X and, in particular, on the conditional quantile function for $\alpha \in (0,1)$;

$$
q_\alpha = (X_1, ..., X_n) = F^{-1}_{Y|x_1,...,x_n}(\alpha | x_1, ..., x_n) \tag{8}
$$

Using the integral probability transforms $V = F_Y(Y)$ and $U_j = F_j(X_j)$ with corresponding PIT values $v = F_Y(y)$ and $u_j = F_j(x_j)$, it follows that:

$$
\begin{aligned}
& F_{Y|x_1,...,x_n}(y | x_1, ..., x_n) = p(Y \leq y | x_1 = x_1, ..., X_n = x_n) \\
& = p(F_Y(Y) \leq v | F_1(x_1) = u_1, ..., F_n(x_n) = u_n) \\
& = C_{v|u_1,...u_n}(v | u_1, ...u_n)
\end{aligned} \tag{9}
$$

Therefore, inversion yields:

$$
F^{-1}_{Y|x_1,...,x_n}(\alpha | x_1, ..., x_n) = F^{-1}_Y(C^{-1}_{v|u_1,...,u_n}(\alpha | u_1, ..., u_n)) \tag{10}
$$

Now, we can obtain an estimate of the conditional quantile function by estimating the marginal F_y and $F_j; j = 1, ..., n$. as well as the copula $C_{V|u_1,...,u_n}$ and plugging them into the bellow Equation (11):

$$
q_\alpha(X_1, ..., X_n) = F^{-1}_{Y|x_1,...,x_n}(C^{-1}_{V|u_1,...,u_n}(\alpha | u_1, ..., u_n)) \tag{11}
$$

For more details, see [7].

5. Analysis

For investigating the effect of three input data_ number of cases, the number of deaths, and news relating to Coronavirus and economics in the United States_ on three well-known indices_ S&P 500, NASDAQ 100, and Dow Jones_ the regression model of D-Vine Copula introduced by Kraus and Czado[12] is implemented. First, we must remove the serial dependence present in each component for time series data. This will be accomplished using standard univariate financial time series models such as the class of GARCH models. We fit a GARCH(1,1) model with standardized student's t-distribution innovation for each variable. A GARCH(1,1) model for a time series $Y_t, t = 1,...,T$ is defined using the conditional variance $\sigma_t = Var\left(Y_t \middle| Y_1,...,Y_{t-1}\right)$ and innovation variables $Z_t, t = 1,...,T$ where:

$$Y_t = \sigma_t Z_t \tag{12}$$

$$\sigma_t = W + \alpha Y_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{13}$$

For our data, we assumed the distribution of Y_t as standardized student's t-distribution[23]. A standardized Student's t-distribution is a scaled one with zero mean and unit variance. As validation that the resulting standardized innovation's estimates are a random sample from the standardized student's t-distribution, we use a two-sided Kolmogorov–Smirnov test (Massey Jr 1951). The resulting p-values are given in table 1.

Table 1 shows that the assumption of a standardized Student's t-distribution cannot be rejected almost for all variables. Therefore, we use the cumulative distribution function of the standardized student's t-distribution to define the copula data as a probability integral transform, i.e., we determine:

$$u_{it} = F\left(\frac{y_{it}}{\sigma_{it}}; \vartheta_1\right) \tag{14}$$

Where $F(0;\vartheta_1)$ is the distribution function of the innovation distribution with an estimated degree of freedom ϑ_1 and estimated conditional variance σ_{1t}^2 for three stocks and input variables (cases and deaths) $i = 1,...,5$ at time $t = 1,...,T$.

First, before fitting the D-vine copula, we investigate the pairwise dependencies among the representatives of each variable in Figure 8.

From the contour shapes, we observe evidence of a negative correlation between news and three indices of U.S exchange markets and a high positive correlation between three indices of U.S exchange markets. Also, a very low correlation exists between financial news and the number of deaths.

We investigated three D-vine regression specifications. In each model, the response variable is one of three indices of U.S exchange markets (S&P 500, NASDAQ 100, Dow Jones), and predictor variables are the number of cases, deaths, and financial news. Parameters are estimated using the sequential estimation method. Step by step, the algorithm adds covariates to the regression model to maximize a conditional likelihood, i.e., the likelihood of the predictor model of the response given the covariates. On the other hand, an automatic variable selection is incorporated. The algorithm will stop adding covariates to the model as soon as none of the remaining covariates can significantly increase the model's conditional likelihood[12].

Table 2 demonstrates the selected covariates and their ranking order in the D-vine, the copula families associated with each tree, sequential parameter estimates, and implied Kendall's tau (allowing for all implemented pair copula families), and log-likelihood values for each model.
As you can see, all the predictor variables are included in the D-Vine regression model, meaning that all three input variables are influential on response variables (three indices). In figures 9, 10, and 11, the Contour plot of fitted pair copula of D-vine regression betwee n three inputs and each response variable is shown as follows.

The contour plots in those figures confirm the fitted copula family of each tree in the D-vine structure is defined in Table 2. For example, some non-symmetry is visible in contour shapes in some trees, such as (cases, deaths), (cases, news), so standard or T-Copula methods are inappropriate for this purpose. While (S&P 500, deaths), (Dow Jon es, deaths), (NASDAQ 100, deaths, news), and (news, cases, deaths) are Symmetric, so t-Copula can give us a great fit and be considered a suitable method.
To examine the effect of the individual variables, we will plot the predicted quantiles against each of the response variables (S&P 500, NASDAQ 100, and Dow Jones) that are evaluated from Equation (11). For each index, we consider three levels by three quantiles, i.e., quantile 0.1 is low, 0.5 is medium, and 0.9 is the high level of each response variable. We add a smoothed line for each quantile level to visualize the relationship clearly. This gives an estimate of the expected effect of a variable. Figures 12, 13, and 14 illustrate the plot of predicted quantiles of three indices against each variable. The fitted quantile curve suggests a non-linear effect on all three response variables.

Figure 12 shows conditional quantiles of variable S&P500 on each predictor variable death, case, and news separately. Variable "case" has a fixed trend in each index level. Except that high values of this variable have a minimal downward effect on all levels of the S&P500. Variable "news" also has a trend similar to the last variable on this index. Except that in the medium and high levels, high values of news have a very slight upward effect on S&P500. The non-linear trend of variable "death" at all index levels represents the most effective predictor variable. For low values of S&P500 (0.1 quantiles) variable "death" has an increasing effect, but by increasing the values of death, it has a downward influence. For high values of S&P500 $(\alpha = 0.9)$, at first, it has a low effect, but gradually the trend is fixed when the growth of the value of this variable occurs.

Figure 13 indicates the effect of variables "cases," "death," and news on NASDAQ100 separately. As you can see, not much change occurs by changing the variables "case" and "death." However, variable "news" when its values increase (for quantile levels of 0.1 and 0,5), the NASDAQ100 index falls. Therefore, it can be inferred that the variable "news" has the most significant impact on this index.

Figure 14 represents the influence of those three variables on the Dow Jones index. This variable can be considered the most effective from the non-linear trend of the variable "death" in all three index levels. Regarding the other two variables, it can be said that the trend is constant in all three levels of quantiles of the index. But similar to the previous analysis, very high values of these two predictor variables have a low impact on this financial index.

5.1 Finding the representative of news (effective news)

First, we coded each related financial news as follows. Earlier, we assumed that this news may have affected the indices as they have been released regarding the situation in this pandemic.

A:Economy; B:Recession; C:Financial crisis ; D:GDP; E:S&P500; F:paycheck; G:corona virus+Dow Jones

We illustrate the dependencies within news through pairs of plots and normalized contour plots. The corresponding plots for each of the seven news categories for each index are contained in Figures 15, 16, and 17.
As shown in figure 15, variable D is most dependent on two variables, F and B, and the experimental Kendall's tau coefficient varies from 0 to 0.31. The lowest dependence is between variables B and C. intuitively, it can be seen that variable D (GDP) is the most influential news on S&P 500.
It is evident in figure 16 that variable D is most dependent on variable F. the coefficient of experimental Kendall's tau varies from 0.22 to 0.42. The lowest dependence is between variables F and G. it can be observed that variable D (GDP) is the most influential news on NASDAQ 100
Finally, variable D is the most dependent on variables B and F in figure 17. The experimental Kendall's tau coefficient varies from 0 to 0.29. The lowest dependence is between variables F and E. Obviously, variable D (GDP) is the most effective news on the Dow Jones index during the period.
C-vine tree structures are ideal when we are interested in ranking the nodes according to the strength of the dependence as measured by Kendall's tau. We use this property to find representative categories of news. Figure 18 shows the first tree of each index (S&P 500, NASDAQ 100, Dow Jones) of fitted C-vine copula to types of news. We choose as representative of news the root node that is D, as it could be seen in pair plots. Ultimately, after variable D (GDP), the most influential financial news among all are variables B (Recession) and F (Paycheck) based on the dependence coefficient of Kendall's tau.

6. Discussion

This pandemic threatens economic slowdown as well as a health crisis. OECD (Organization of economic cooperation and development) expects global growth this year to be its slowest since the 2008 financial crisis. For battling against the virus, the World Bank provided $12 billion and IMF $50 billion available. The United States Congress allocated $8.45 billion of funding specific to Coronavirus. Bloomberg Economics estimates that the virus could cost $2.7 trillion to the global economy, which is equivalent to the entire GDP of the United Kingdom. The virus was reported as a pandemic issue by WHO on March 12th. Asian development bank anticipated that the virus cost $4.1 trillion to the world economy, approximately 5% of the world's GDP, depending on the spread of the virus in Europe, the United States, and other major economies.

(GDP) decreased by 4.8 percent in the first quarter and 32.9 percent in the second quarter of 2020 in the United States. NBER declares that the longest U.S economic expansion, which lasted for over ten years, ended in February, and the downturn commenced. At the end of May 30th, 42.7 million jobless claims were filed amid the Coronavirus outbreak, according to the U.S department of labor, which led to a great recession, and GDP declined in the second quarter of 2020, the worst contraction since the 1940s. Table 2 shows that all the predictor variables are included in the D-Vine regression model, which implies that all three input variables are influential on response variables (three indices). According to figures 12 to 14, the findings indicate that the fitted quantile curves of all input variables suggest that number of death has the most negative effect on S&P500. Dow Jones and the variable news have the most negative influence on NASDAQ100. Also, intuitively, it can be concluded that variables D (GDP news) and B (recession), then F (paycheck), have the most effect on all mentioned indices, respectively.

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Appendices

<u>Figure and table captions:</u>

Figure 1	The diagram of the budget allocated by the United States Congress to fight the virus
Figure 2	2020 quarterly GDP growth based on Goldman Sachs forecast
Figure 3	Jobless claims filed amid Coronavirus outbreak
Figure 4	Number of cases of Coronavirus in the U.S
Figure 5	2020 Stock Market Crash and Rebound amid Coronavirus
Figure 6	5-dimensional D-vine with four trees
Figure 7	5-dimensional C-vine with four trees
Table 1	Coefficients of GARCH (1,1) models and p-values of K.S tests of the variables.
Figure 8	pairs plot of correlation between variables
Table 2	selected covariates, implied Kendall's tau and log-likelihood values for each model
Figure 9	Contour plot of fitted pair copula of D-vine regression (S&P500| cases, deaths, news)
Figure 10	Contour plot of fitted pair copula of D-vine regression (NASDAQ 100| cases, deaths, news)
Figure 11	Contour plot of fitted pair copula of D-vine regression (Dow Jones| cases, deaths, news)
Figure 12	the plot of predicted quantiles of the S&P 500 against each of the variables (news-deaths-cases)
Figure 13	the plot of predicted quantiles of NASDAQ 100 against each of the variables (news-deaths-cases)
Figure 14	the plot of predicted quantiles of Dow Jones against each of the variables (news -deaths-cases)
Figure 15	Pairs plots and normalized contour plots of all seven categories of news for the S&P 500
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Figure 17	Pairs plots and normalized contour plots of all seven categories of news for Dow Jones
Figure 18	the first tree of each index (from left to right: S&P 500, NASDAQ 100, Dow Jones) of fitted C-vine copula

Figures and tables:

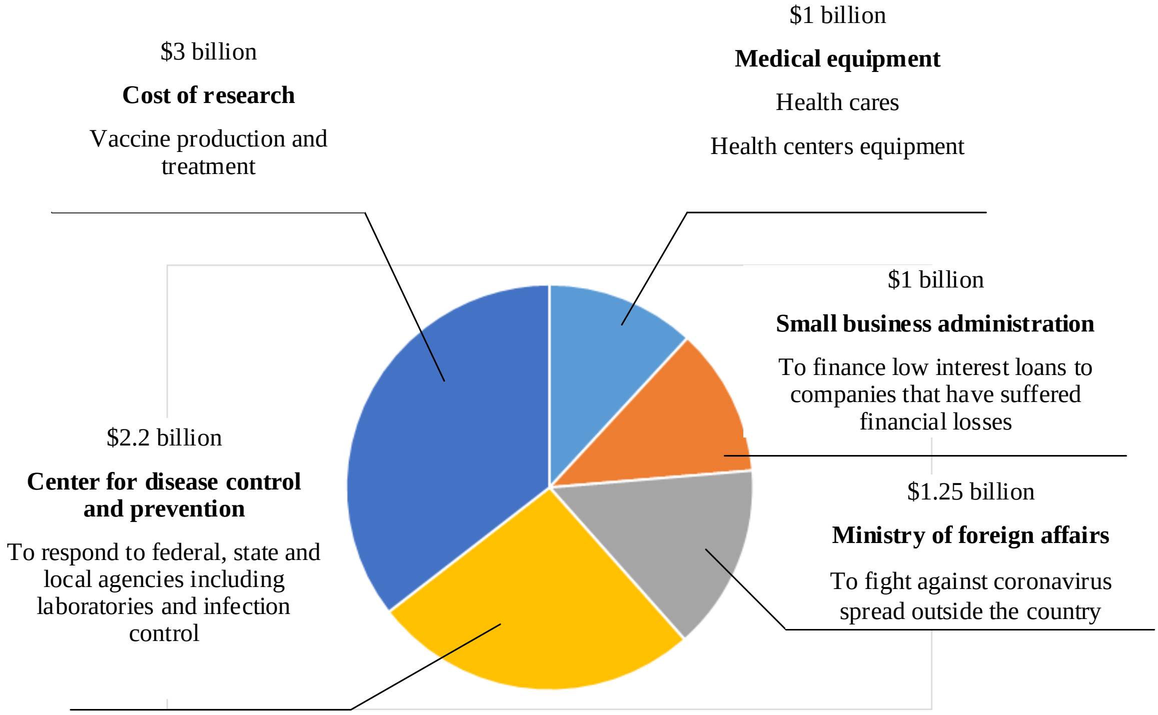


Figure 1

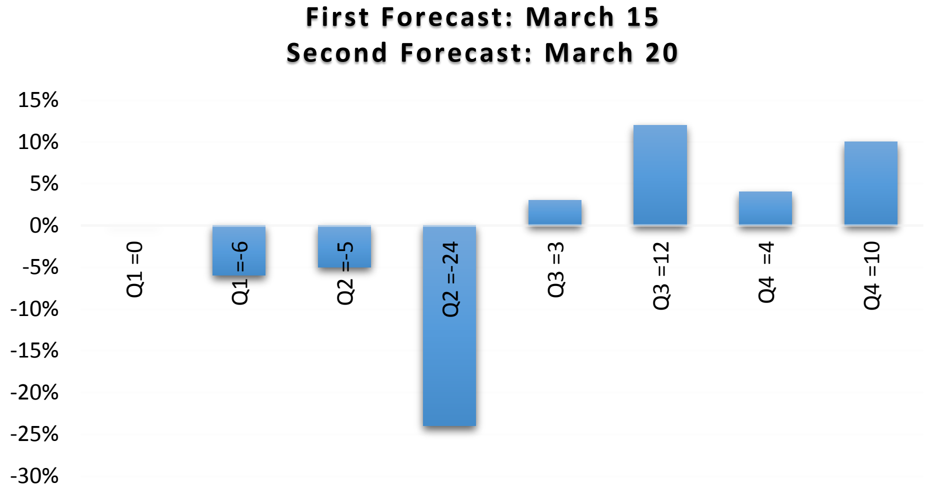


Figure 2

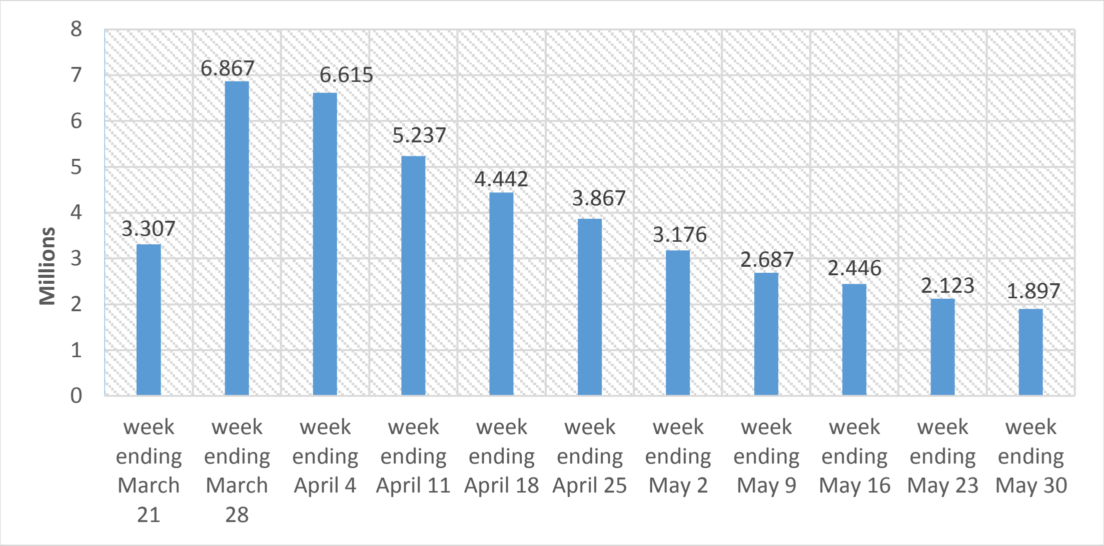
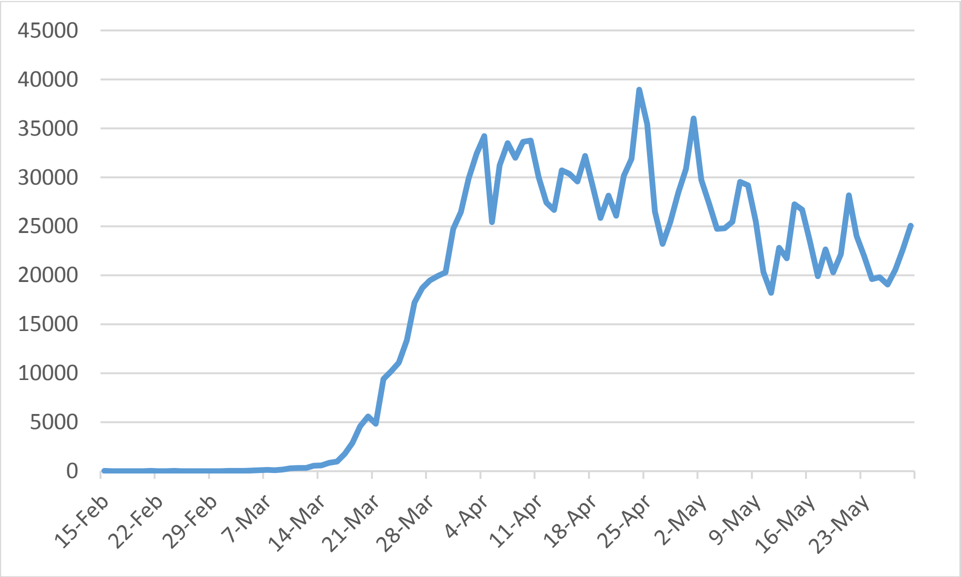


Figure 3



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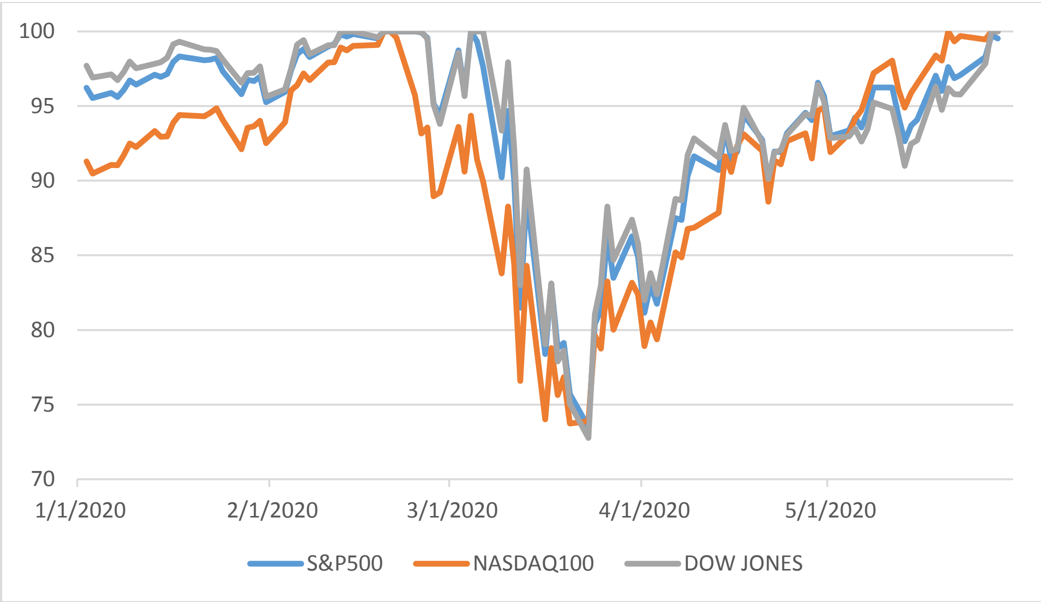

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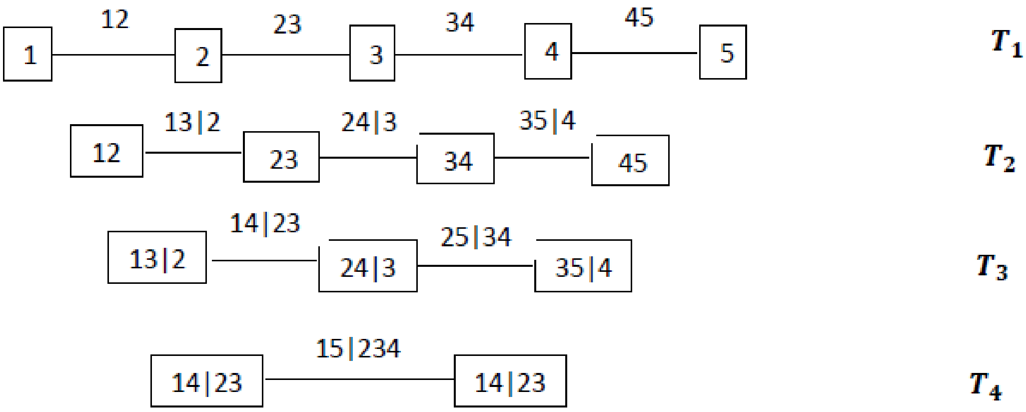


Figure 6

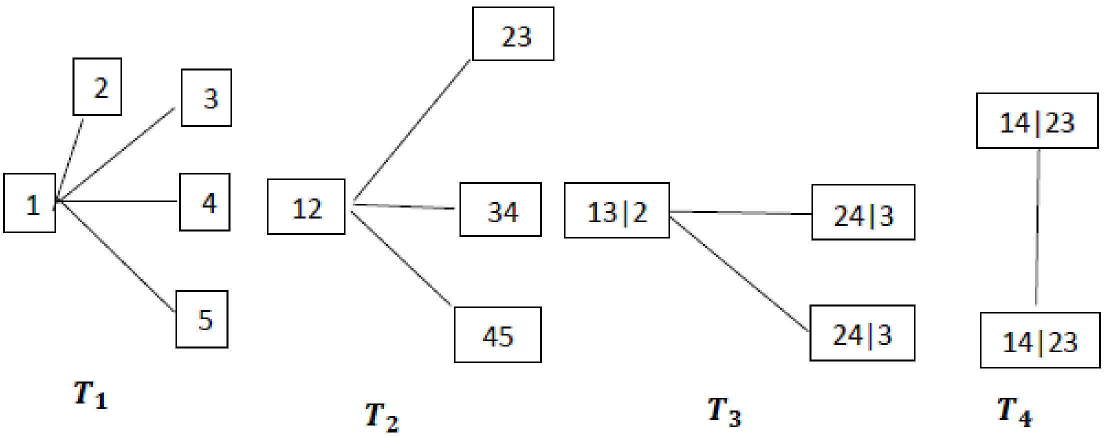


Figure 7

Variables	Coefficient(s)					Log-Likelihood	K.S test P-values
	mu	omega	alpha1	beta1	shape		
cases	6.304	97.835	1.000	0.362	3.818	-863.836	0.056*
death	0.288	1.933	1.000	0.247	3.060	-631.167	0.065*
S&P500	6.196	139.460	0.504	0.566	10.000	-554.838	0.740*
Dow Jones	25.966	15733	0.422	0.621	6.599	-779.681	0.934*
NASDAQ100	24.215	1257.7	0.461	0.599	10.000	-669.451	0.827*

*p>0.05

Table 1

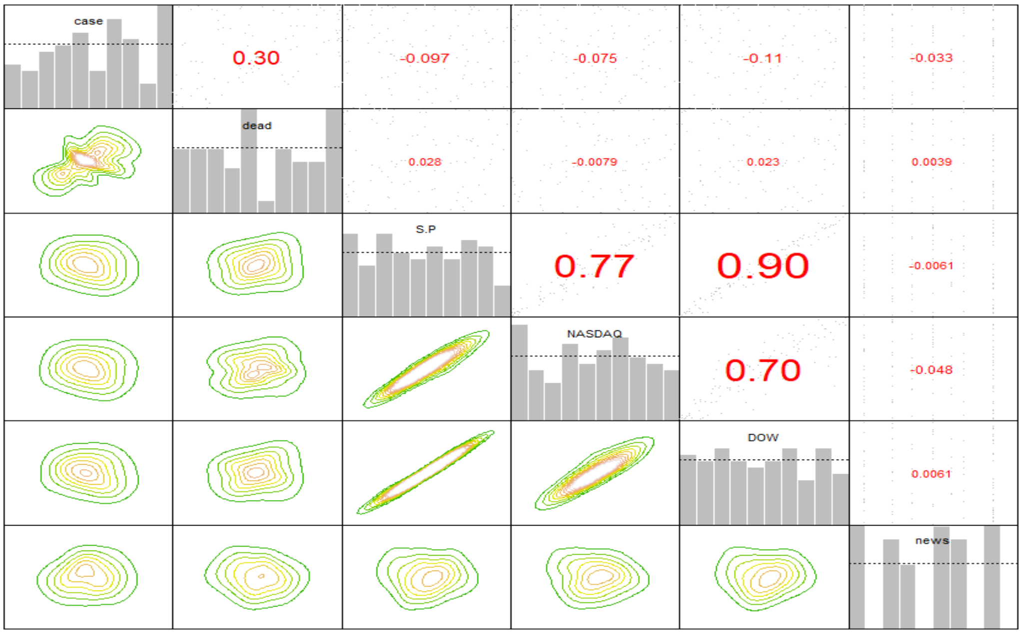


Figure 8

D-vine order: S&P500| death, cases, news

1-->S&P500 , 2-->case , 3-->death , 4-->news

tree	edge	copula	par	par2	tau	log-likelihood
1	**1,3**	**t**	**0.026**	**3.077**	**0.017**	**1.57**
1	**3,2**	**bb6**	**1.5**	**1.1**	**0.278**	**14.18**
1	**2,4**	**bb8**	**1.12**	**0.99**	**-0.058**	**0.78**
2	**1,2:3**	**bb8**	**7.22**	**0.16**	**-0.122**	**2.01**
2	**3,4;2**	**bb8**	**1.1**	**1.0**	**-0.046**	**0.88**
3	**1,4;2,3**	**bb8**	**1.11**	**0.99**	**-0.053**	**0.73**

Log-lik= -2.49, Aic = 24.21, Bic = 49.37

D-vine order: NASDAQ100| news, death, cases

1-->NASDAQ100, 2-->case , 3-->death , 4-->news

tree	edge	copula	par	par2	tau	log-likelihood
1	**1,4**	**bb8**	**1.2**	**1.0**	**-0.078**	**1.60**
1	**4,3**	**joe**	**1**	**0.014**	**0.05**	
1	**3,2**	**bb6**	**1.5**	**1.1**	**0.278**	**14.18**
2	**1,3:4**	**t**	**-0.019**	**3.631**	**-0.012**	**0.77**
2	**2,4;3**	**t**	**-0.017**	**3.543**	**-0.011**	**1.55**
3	**1,2;3,4**	**bb8**	**1.79**	**0.61**	**-0.094**	**1.14**

Log-lik = -4.65, Aic = 28.43, Bic = 53.46

D-vine order: Dow Jones | death, cases, news						
1-->Dow Jones, 2-->case , 3-->death , 4-->news						
tree	**edge**	**copula**	**par**	**par2**	**tau**	**log-lik**
1	**1,3**	**t**	**0.017**	**2.869**	**0.011**	**1.80**
1	**3,2**	**bb6**	**1.5**	**1.1**	**0.278**	**14.18**
1	**2,4**	**bb8**	**1.12**	**0.99**	**-0.058**	**0.78**
2	**1,2:3**	**bb8**	**3.47**	**0.37**	**-0.134**	**2.46**
2	**3,4;2**	**bb8**	**1.1**	**1.0**	**-0.046**	**0.88**
3	**1,4;2,3**	**bb8**	**1**	**1**	**0.020**	**0.15**
Log-lik=-2.62, Aic = 24.04, Bic = 48.61						

Table 2

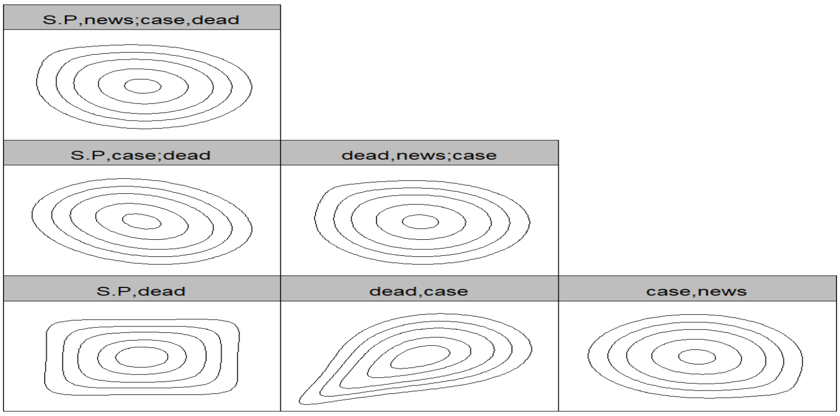
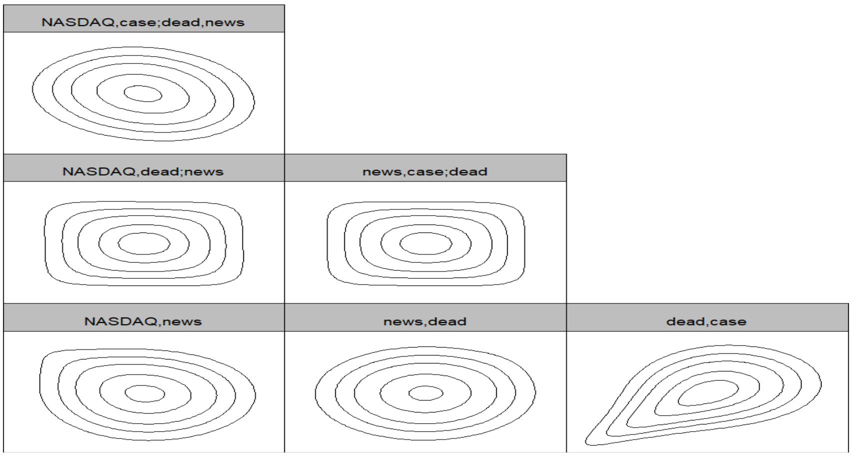


Figure 9



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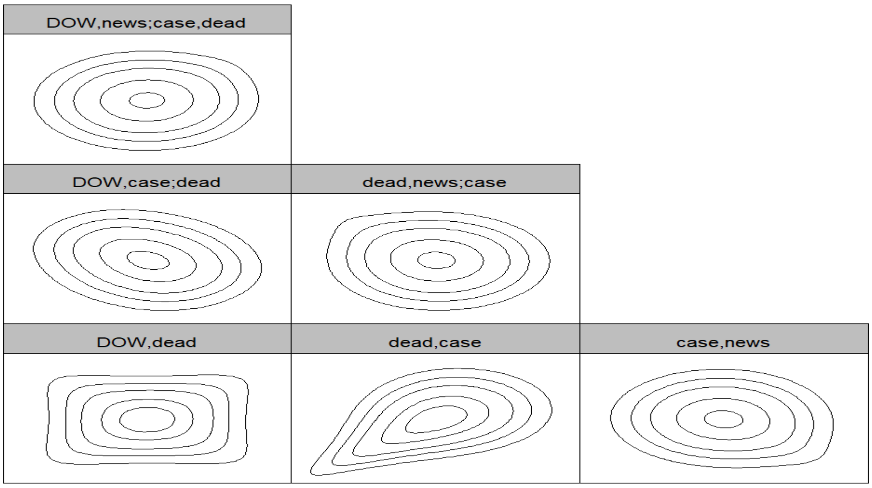

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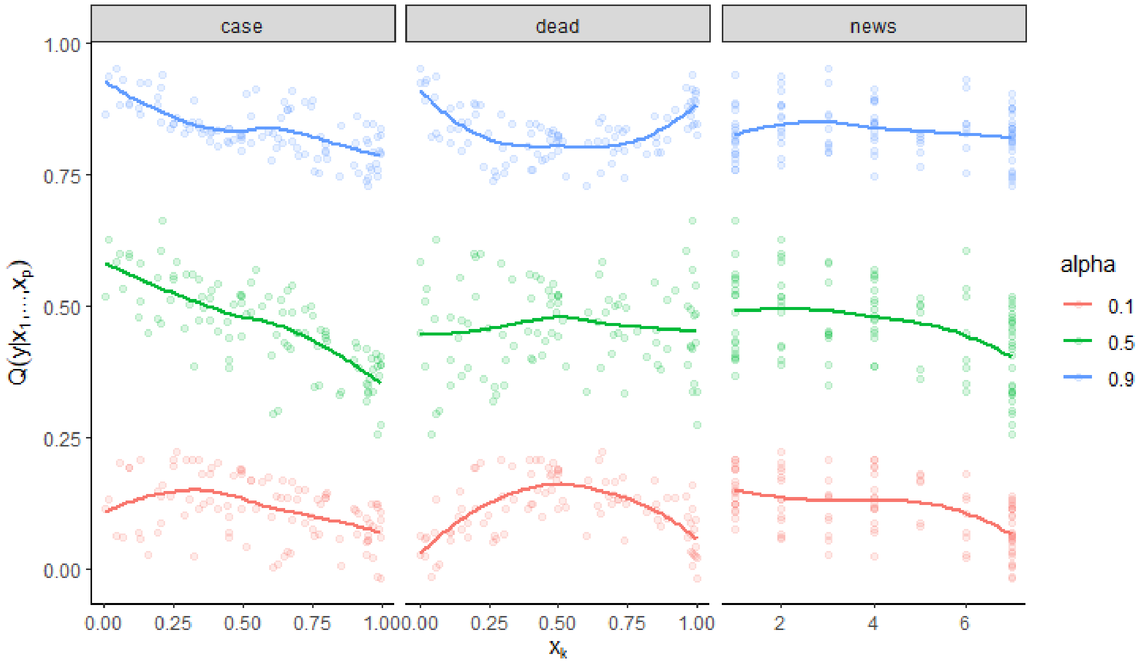

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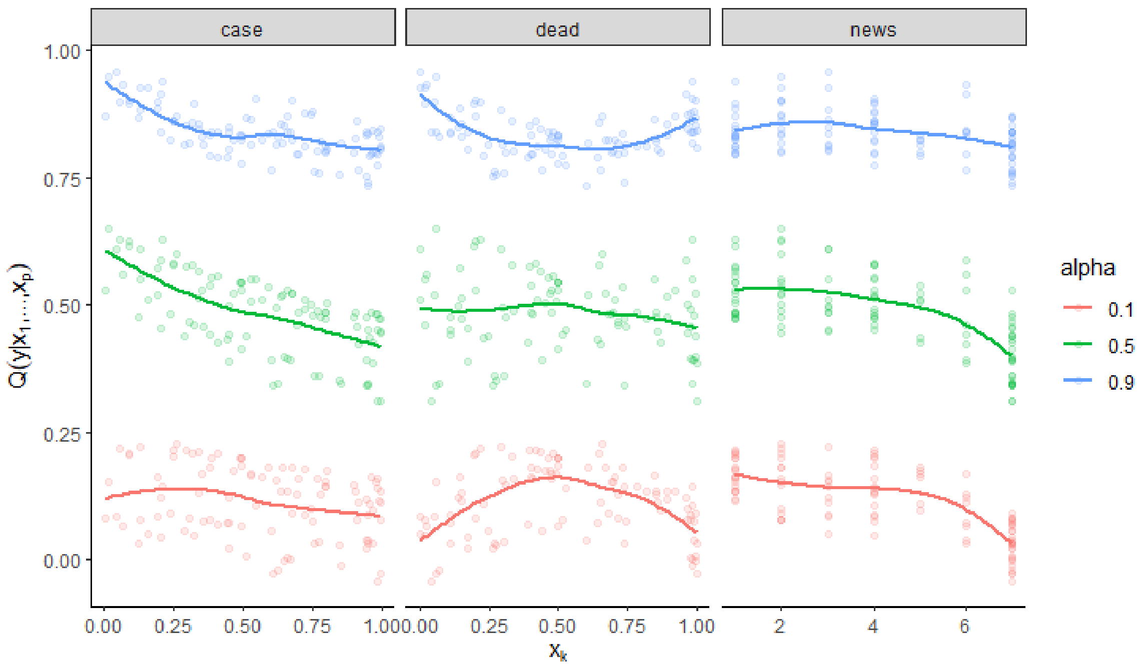
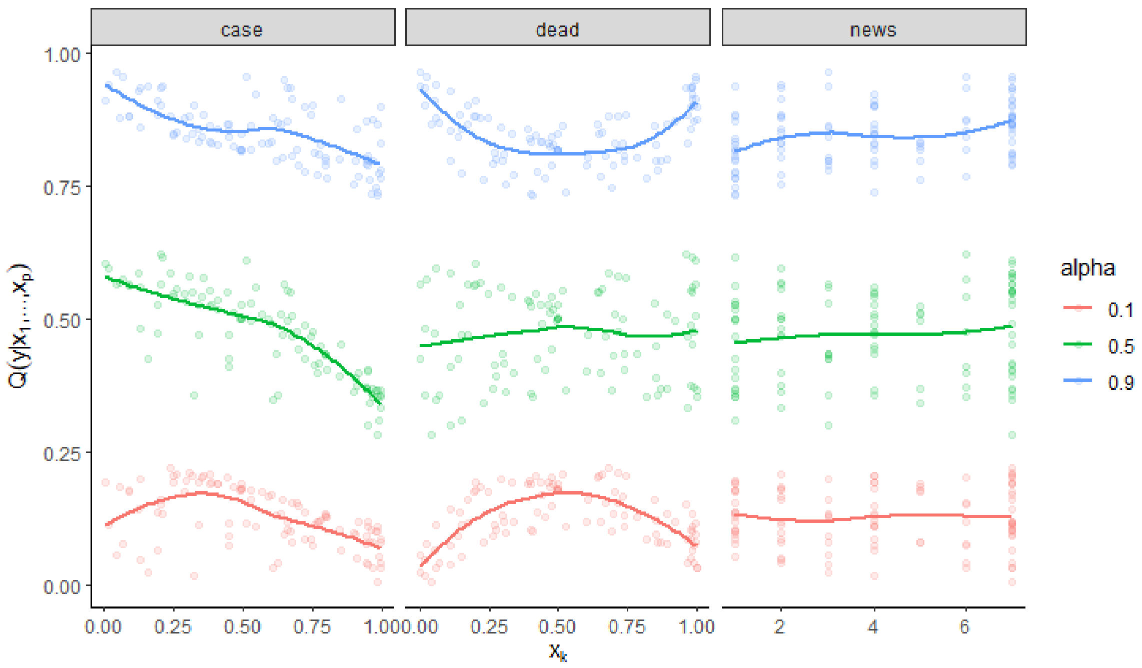


Figure 13



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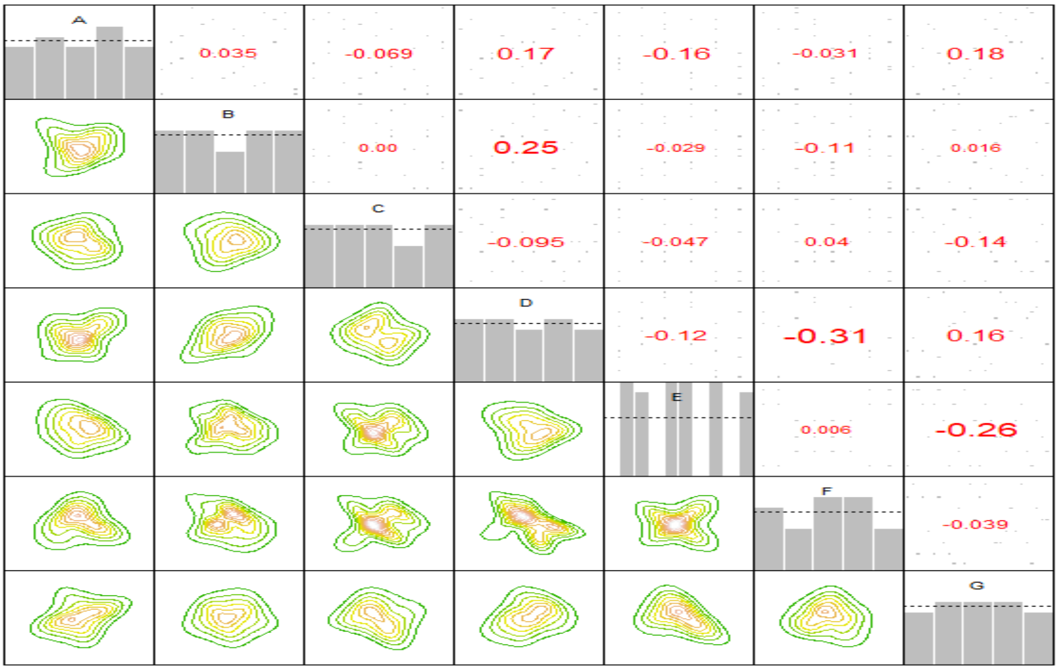

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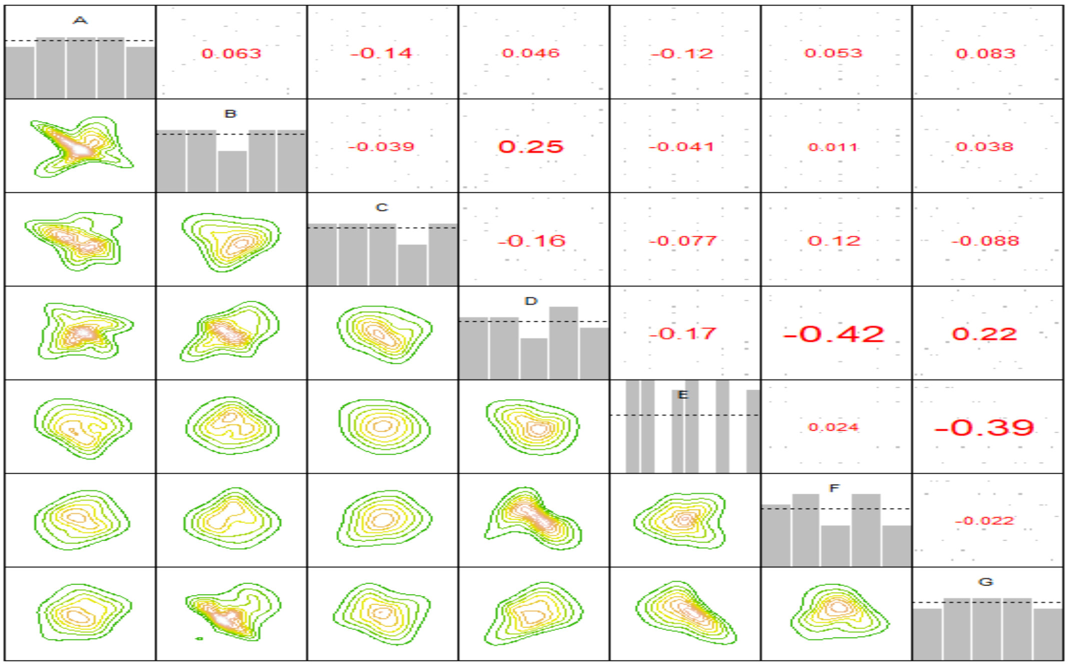

Figure 16

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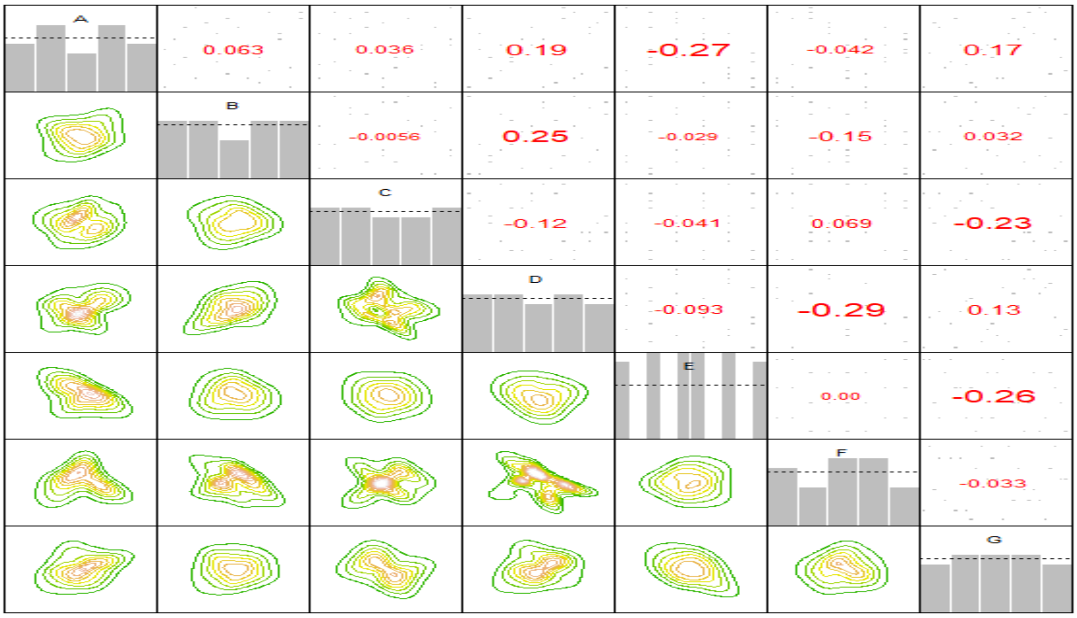

Figure 17

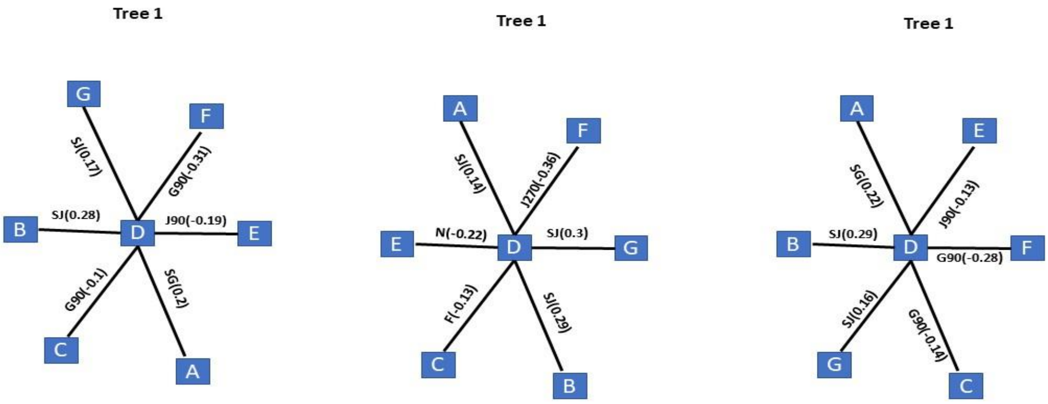

Figure 18

<u>Biographical notes:</u>

Alireza Rokhsari received his Master's in Electrical Engineering at the Amirkabir University of Technology –Master's in Financial Management at the Sharif University of Technology. His specialties are behavioral finance, corporate finance, and security valuation. He is also a CFA (Chartered Financial Analyst) level 2 candidate and obtained the FMVA®, CBCA®, CMSA®, ESG, and other professional certifications from the CFI (Corporate Finance Institute).

Neda Doodman received her Ph.D. in Statistics at Ferdowsi University. She is currently working at the Department of Mathematics, Ferdowsi University of Mashhad. She is conducting research in different methods in statistics. Her current project is the 'times series copulas.' Her specialties are statistical modeling, statistical analysis, applied statistics, and data analysis.

Hassan Tanha is an Adjunct Fellow at Victoria University Business School, Melbourne, Australia. He received his Ph.D. in Finance at Monash Business School and is researching Derivative contracts, mainly options. He published some papers in Finance in renowned international journals in recent years.