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Tail Risk Transmission: A Study of Iran Food Industry

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Abstract

This paper extends the extreme downside correlations and hedge (EDC and EDH) methodology of Harris et al. (2019) to model the tail risk co-movement of financial assets under severe firm-level and market conditions. The model is applied to analyze both systematic and systemic exposures in the Iranian food industry. The empirical application address the following questions: 1) which food company is the safest for investors to diversify their investment, and 2) which companies are the risk "transmitters" and "receivers", especially in turbulent times. To this end, we sampled the time series of 11 manufacturing companies and proxy the market indicator with the food industry index, all of which are publicly listed on the Tehran Stock Exchange (TSE). The data covers daily close prices from October 5, 2015, to January 15, 2020. The systematic analysis reveals a positive and statistically significant relationship between the tail risk of the companies and the market index. The centrality analysis of the systemic exposures reveals Mahram Manufacturing as the safest and Behshahr Industries as the riskiest company. We also find evidence that W.Azar.Pegah is the main "transmitter" of tail risk, while Pegah.Fars.Co is the main "receiver" of risk.

Keywords: Food industry, Extreme downside hedge, Extreme downside correlation, Systematic risk, Systemic risk.

JEL: C31, C58, G01, G12

1. Introduction

Natural resources are abundant in Iran. Almost one-tenth of the world's oil and one-fifth of its natural gas reserves are located in Iran. Also, the country has large mineral deposits such as copper, lead, zinc, iron ore, and decorative stones. Among all of these resources, the role of the agricultural sector is very important to the economy as well. Over the 1990s, the agricultural sector was the fastest-growing economic sector of the country (Stads et al., 2008). Although Iran is still a major agricultural country, the capability of its land and water resources to reach the food supply of all populations is largely unknown. The reason for this is that the increasing population and consumption have raised concerns about the capability of agriculture in the provision of future food security (Mesgaran et al., 2017). In an environment with changing demands, the ability to achieve or maintain food must be considered. In most of the developing countries, the main approach is to focus on finding a way that can help the agricultural part and improve its (Shafiei Nikabadi and Aliakbari Nouri, 2017).

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To achieve the above objective, the Food and Conversion Industries is one of the most important industrial groups that play an efficient role in the expansion of developing countries such as Iran. There are, however, some challenges that must be addressed to enhance the industry play its role efficiently. One such challenge is the need to improve the financing of the sector. In other words, the lack of sufficient capital and inefficient use of available resources is one of the major challenges confronting the sector in many developing countries. With efficient use of capital resources and more efficiency of stock markets in developing countries, the capital input allocation mechanism would be more effective and the possibility of economic growth is provided (Durnev et al., 2004). Capital market indices in any economy show the performance of the macroeconomy and immediately reflect the effects of policymakers' decisions on the country's economy even before its implementation. So, the stock market as a very important tool of capital market plays a significant role in economic growth which can improve the industry or other parts of a country's economy (Amiri et al., 2009).

Although, the stock market is a market that can be useful for financing, there are many factors that directly or indirectly affect the market performance and causes uncertainty in stock price movements. One of the most important things that must be considered is "risk", either systematic and/or systemic. Estimating risks is important to achieve the best investment decisions. Typically, individuals consider a trade-off between expected return and risk in investment decisions (Bera and Kannan, 1986; Puspitaningtyas, 2018; Scott and O'Brien, 2003). There is a wide consensus that the relationship between asset returns and market risk varies, and depends on market conditions. For example, a stronger correlation could be exhibited by asset returns during volatile periods, and especially in the case of extreme market downturns (see Ang and Chen, 2002; King and Wadhwani, 1990; Longin and Solnik, 2001). So, for deciding to choose a share in the stock market, investors need some useful information that helps them. One of them is being aware of what is happening among the companies and market at crash time. One issue that is important and can be considered in decision making is systematic risk. According to Dowen (1988), security could be added to a portfolio based on its systematic risk. In other words, systematic risk is priced by the market because all non-systematic risk would be eliminated by diversification.

Another issue that can be considered is systemic risk. Because the financial crisis of 2008-2009 showed that liquidity and valuation shocks can spread through the economic system and influence financial institutions operating in different markets, without considering the size and business structure, and then causing widespread losses and effects. The concept of systemic risk lies in the transmission effect and its negative impact on the real economy. The available definitions of systemic risk focus on different aspects of the phenomenon, that is, imbalances, the collapse of confidence, correlated exposures of financial institutions, negative impact on the real economy, information asymmetry, feedback effects, price bubbles, contagion, and negative externalities: see, for a survey, Bisias et al. (2012) and Oosterloo and de Haan (2003). Widespread financial regulations, such as Basel I and Basel II, are designed to limit financial risk (market, credit, and operational risk) seen in isolation; they are not sufficiently focused on systemic risk. Many studies have worked on systematic or systemic risk but to our knowledge, no study considers these two risks as what we will use. In light of this observation, Kadan et al. (2016) generalized the concept of systematic risk to a broader class of risk measures. They proposed an equilibrium framework that generalizes the Capital Asset Pricing Model and an axiomatic approach which leads to a systematic risk measure as the unique solution to a risk allocation problem. Both approaches extend the traditional market beta to capture the multiple dimensions of risk. Systematic market factors are not the only cause of return volatilities. Especially after the recent financial crisis, researchers have understood the importance of systemic risk - the inherent vulnerability of the financial system that propagates initial shocks to leading to the failure of many institutions, whose cascading effects may endanger the whole system (see Acemoglu et al., 2015; Battiston et al., 2012; Billio et al., 2012; Diebold and Yilmaz, 2014; Elliott et al., 2014; Härdle et al., 2016; Ladley, 2013). Systemic risk can be thought of as a widespread failure of financial institutions or as a freezing up of capital markets, which can substantially reduce the supply of such critical intermediation. Failures of financial institutions or capital markets can have an important externality on the rest of the economy, and the recent financial crisis provides ample evidence of the importance of containing systemic risks.

The available definitions of systemic risk focus on different aspects of the phenomenon, such as imbalances, collapse of confidence, correlated exposures of financial institutions, negative impact on the real economy, information asymmetry, price bubbles, transmission, and negative externalities. For a comprehensive review, see Ahelegbey (2016); Bisias et al. (2012); Brunnermeier and Oehmke (2013); De Bandt and Hartmann (2000); Eijffinger and Masciandaro (2011); Oosterloo and de Haan (2003). From a regulatory viewpoint, widespread financial regulations, such as Basel I and Basel II, are designed to limit financial risk (market, credit, and operational risk) seen in isolation; they are not sufficiently focused on systemic risk. This even though the systemic risk is often the rationale provided for such regulation Acharya et al. (2017). Basel III attempts to include systemic risk, but it does so to a limited extent. This may be due to a lack of consensus in the systemic risk literature.

The limited consensus on the definition of systemic risk is reflected in a large number of measurement methods available. Among them are conditional value-at-risk (CoVaR; Adrian and Brunnermeier, 2016), marginal expected shortfall (MES; Acharya et al., 2017), distressed insurance premium (Huang et al., 2012), dynamic causality index with principal component analysis systemic risk measures (Billio et al., 2012), network connectedness measures (Diebold and Yilmaz, 2014). Other recent contributions include Wang et al. (2019), who proposed a new measure of systemic risk named CSRISK, which identifies a financial institution's capital shortfall under the worst scenario, conditional on a substantial market decline; Brunnermeier and Cheridito (2019) who developed a framework for measuring systemic risk, SystRisk, that captures the a priori cost to society for providing tail-risk insurance to the financial system; Bianchi et al. (2019) who developed a scheme in which latent states are identified based on a novel weighted eigenvector centrality measure; Brownlees and Engle (2017) who introduced SRISK, which measures the capital shortfall of a firm, conditional on a severe market decline and is a function of size, leverage, and risk of the firm itself.

Another cause of return volatilities, additional to systematic and systemic risk, is tail risk. The importance of tail risk in financial markets has been highlighted because of the turbulence of financial markets over the last years, especially in the stock market. Many studies have documented the considerable impact of this risk on expected returns, see for instance Barro (2006); Gabaix (2012); Gillman et al. (2015); Rietz (1988); Wachter (2013). From an econometric viewpoint, Harris et al. (2019) proposed two complementary measures of systematic tail risk and showed that the first measure, named extreme downside correlation (EDC), is based on the tendency of asset returns to crash at the same time as the market, while the second measure, named extreme downside hedge (EDH), measures the sensitivity of asset returns to market tail risk.

Related to this contribution, several studies have examined the relationship between tail risk and asset returns. For example, Chabi-Yo et al. (2018) proposed a systematic tail risk measure, Lower Tail Dependence (LTD), based on the estimated crash sensitivity of an individual asset to a market crash; Van Oordt and Zhou (2016) proposed a systematic tail risk measure that captures the sensitivity of asset returns to market returns, conditional on market tail events and showed that this measure is associated with future asset returns; Almeida et al. (2017) introduced a tail risk measure that is based on the risk-neutral excess expected shortfall of a cross-section of asset returns.

This study aims to investigate the level of systemic and systematic risk for each company to show how much they would be affected in crash time. in other words, 1) which companies can be considered as the safest for investors to diversify their investment, and 2) which companies are the risk "transmitters" and "receivers", especially in turbulent times. To achieve these goals, we extend the proposed systematic risk measures, EDH and EDC, taking into account not only the market (systematic) tail risk but also a systemic tail risk. In this way, we consider as potential explanations of returns volatilities: systematic risk, systemic risk, and tail risk. We thus contribute to the market risk literature with a model that combines tail risk not only with systematic risk but also with systemic risk.

We apply our proposed methodology to the return series of 11 publicly listed companies of the food industry of the Tehran Stock Exchange (TSE). We also consider the market index for the food industry. Closely related our study are (Abbasi et al., 2012; Afrooz et al., 2010; Akbari et al., 2020; Azad et al., 2013; Hajiha et al., 2011; Hosseini et al., 2012; Hosseininia and Ramezani, 2016; Naeini et al., 2019). The difference, however, is that, the above studies only focus on the Beta's as a measure of systematic risk, while we consider a model that combines extreme downside firm and market level events for systematic and systemic risk analysis.

The paper is organized as follows: Section 2 presents our proposed methodology. For our empirical application, we present a description of the data and report the results in Section 3 and a sensitivity analysis in Section 4. Section 5 concludes the paper with a brief discussion and suggestions for future research.

2. Methodology

In this section, we briefly present the background to network models. Next, we describe our extension of the extreme downside correlation (EDC) and of the extreme downside hedge (EDH) measures, aimed at modeling tail risk dependence among return series of assets.

2.1. Background: Network Models

A network model is a convenient class of multivariate analysis that uses graphs to represent statistical models (Lauritzen, 1996). They are formally represented by $(G, \theta) \in (\mathcal{G} \times \Theta)$, where G is a graph of relationships between variables, θ is the model parameter, $\mathcal{G}$ is the space of graphs and Θ is the parameter space. The graph, G, is defined by a set of vertices (nodes/variables) joined by a set of edges (links), describing the statistical relationships between a pair of variables. A typical multivariate multiple regression model is given by

$$Y = BX + U \tag{1}$$

where $X = (X_1, \ldots, X_n)$ and $Y = (Y_1, \ldots, Y_n)$ are vector of exogenous and response variables respectively, B is a coefficient matrix and U is a vector of errors. In this example, relationships between X and Y can be summarized in the form of a weighted (A^W) or unweighted adjacency matrix (A^U), where A^W_{ij} or A^U_{ij} is such that

$$\begin{array}{lllll} A^W_{ij} = 0 & \implies & A^U_{ij} = 0 & \implies & X_j \nrightarrow Y_i \\ A^W_{ij} = B_{ij} \in \mathbb{R} & \implies & A^U_{ij} = 1 & \implies & X_j \rightarrow Y_i \end{array} \tag{2}$$

where $X_j \nrightarrow Y_i$ means that X_j does not influence Y_i.

A key contribution of network models to financial contagion analysis is their usefulness in identifying important institutions in risk transmission. This can be obtained by performing an analysis of the network structure through network centrality measures. Various definitions of centrality have given rise to different measurement models in the financial networks literature (see Bonacich, 1972; Faust, 1997; Freeman, 1978). For some, centrality is expressed by the number of connected nodes (degree centrality), and for others, centrality depends on the importance of a node's neighbors (eigenvector centrality).

Degree centrality can computed as unweighted/weighted in/out-degree. Let $A = \{A^U, A^W\}$, then the in-degree of node-i, $\overleftarrow{D}_i$, and out-degree of node-j, $\overrightarrow{D}_j$, is given by

$$\overleftarrow{D}_i = \sum_j A_{ij}, \qquad \overrightarrow{D}_j = \sum_i A_{ij} \tag{3}$$

where $\overleftarrow{D}_i$ counts the number of links directed towards node-i, while $\overrightarrow{D}_j$ is the number of links going out of node-j. If A is a bi-directed (or undirected), then the in-degree of node-i is equal to its out-degree, which can be simply referred to as the degree of node-i.

Eigenvector centrality can also be computed in terms of unweighted or weighted hub/authority centrality. Following the notation, $A = \{A^U, A^W\}$, the hub and authority centrality measures assign a score to nodes by solving the following:

$$(A'A)\ h = \lambda_h h, \qquad (AA')\ a = \lambda_a a, \tag{4}$$

where h and a are the hub score and authority score eigenvectors, corresponding to λ_h and λ_a, the largest eigenvalues of $A'A$ and AA' respectively. If A is a bi-directed adjacency matrix, then $A' = A$, which means that $\lambda_h = \lambda_a$ and the hub score of the network is the same as the authority score and generally referred to as the eigenvalue centrality score.

From a financial contagion viewpoint, nodes with the highest in-degree are liable to be influenced and those with high out-degree are "influencers". However, nodes with the high hub measures indicate high "transmitters" of risk, while nodes with high authority values are "receivers" of risk. If the underlying network is undirected, then the "influencers" are also liable to be influenced, and the risk "transmitters" are also risk "receivers".

For purposes on visualizing the network structure, the nodes in the adjacency matrix can be positioned through an eigen-decomposition. Following Ahelegbey et al. (2017); Hoff (2008), we can obtain the position of the nodes in network associated with A^W via an eigen-decomposition of $\Omega = (I + A^W)'(I + A^W)$, whose ij-th entry can be parametrized as:

$$\Omega_{ij} = \ (U \Lambda U')_{ij} \tag{5}$$

where Ω_{ij} is the i-th row and the j-th column of Ω, $\Lambda = \text{diag}\ (\lambda_1, \ldots, \lambda_r)$, is a diagonal matrix of eigenvalues, U is a $n \times r$ coordinate matrix of n points in an r-dimensional system such that $U_{i,:}$ denotes the i-th row of U (that is, the coordinates of i-th node). These coordinates can provide a spatial representation of the nodes of a financial network which can be very useful for their interpretation.

2.2. Extreme Downside Correlation (EDC)

The EDC is a correlation-based technique that measures the marginal relationship between a pair of continuous variables, focusing on the tail of their joint return distributions. It is a non-parametric measure of tail risk co-movement of financial assets. Let $Y_{i,t}$ be the returns of assets i (or Y_i) at time t and denote with μ_i the historical mean of asset i. The $EDC_{\tau,ij}$ measures the tail correlation between assets i and j given by

$$EDC_{\tau,ij} = \frac{Cov(Y_{\tau,i}, Y_{\tau,j})}{\sqrt{Cov(Y_{\tau,i}, Y_{\tau,i})}\sqrt{Cov(Y_{\tau,j}, Y_{\tau,j})}} \tag{6}$$

where $Cov(Y_{\tau,i}, Y_{\tau,j})$ is the covariance between $Y_{\tau,i}$ and $Y_{\tau,j}$, $Y_{\tau,i}$ is the left-side τ-quantile of the standardized distribution on Y_i, $\tau \in (0, 1)$, and $F_X(\tau) = Pr(Y_i \leq \tau)$ is the cumulative distribution function (CDF) of Y_i. The value of τ defines the percentage confidence level, $100(1 - \tau)\%$. If $j = m$ is a market index, then $EDC_{\tau,im}$ captures the systematic relationship between asset-i and the market.

The tail of the return distribution technically corresponds to either extremely low gains (left tail) or very high returns (right tail). Following standard applications, we set our focus on the left tail to study the co-movement in returns of assets during stressful times which are usually characterized by losses. Following standard practice, we use the $\tau = 5\%$ quantile level which corresponds to a 95% confidence level in our empirical application. We also conduct robustness checks with other τ-quantile levels to validate the sensitivity of the findings.

2.3. Extreme Downside Hedge (EDH)

The extreme downside hedge (EDH) measures the sensitivity of returns to innovations in the tail risk of the market and/or of other counterparties. The variables of interest for the EDH model are the return series of the assets and a measure of innovation in the tail risk of the conditioning set of variables. Recent measures for assessing the riskiness of assets is the expected shortfall (also referred to as conditional value at risk - CoVaR or CVaR) (see Adrian and Brunnermeier, 2016; Alexander, 2009; Bali et al., 2009).

Let $Y_t = (Y_{1,t}, \ldots, Y_{n,t})$ be n-variable vector of return observations at time t, where $Y_{i,t}$ is the time series of asset-i at time t. Let $Y_{\tau,i}$ denote the left-side τ-quantile of the distribution on Y_i, for $\tau \in (0, 1)$. Following Rockafellar and Uryasev (2002) and Gaivoronski and Pflug (2005), we compute the $CVaR_\tau(Y_i)$ as a proxy for the tail risk by

$$CVaR_\tau(Y_i) \;=\; \lambda\; E\left(Y_i | Y_i < Y_{\tau,i}\right) + (1 - \lambda)Y_{\tau,i} \tag{7}$$

where $\lambda = \frac{1}{\tau}F_X(\tau)$, $F_X(\tau) = Pr(Y_i \leq Y_{\tau,i})$ is the CDF of Y_i. $CVaR_\tau(Y_i)$ calculates the weighted average of the losses that occur beyond $Y_{\tau,i}$, the value at risk point, in a distribution. We denote with $CVaR_{i,t}$ - the $CVaR_\tau(Y_i)$ at time t. We employ $\Delta CVaR$ as a proxy for the innovation in the tail risk.

Following Harris et al. (2019), we start the EDH model with the systematic tail risk of an asset as the sensitivity of returns of asset-i with respect to $\Delta CVaR$ of the market index as

$$Y_{i,t} = \alpha_i + \beta_{i|m}\; \Delta CVaR_{m,t} + \epsilon_{i,t} \tag{8}$$

where $\Delta CVaR_{m,t} = CVaR_{m,t} - CVaR_{m,t-1}$, α_i is the intercept, $\epsilon_{i,t}$ is the error term, and $\beta_{i|m}$ is the response of the asset returns to changes in market tail risk.

The EDH for systematic risk expresses the "contagion" effect of the market tail risk on asset returns. It does not, however, capture other channels such as exposure to the tail risk of other assets. This application extend the EDH to consider a "systemic" version that estimate the sensitivity of the returns of a single index to the innovation in the CVaR of other indices. More formally, we can define the single index model of the EDH systemic risk by

$$Y_{i,t} = \alpha_i + \sum_{i \neq j=1}^{n-1} \beta_{i|j}\ \Delta CVaR_{j,t} + \epsilon_{i,t} \tag{9}$$

where $\Delta CVaR_{j,t} = CVaR_{j,t} - CVaR_{j,t-1}$, $\beta_{i|j}$ is the response of the stock return of asset-i to changes in the tail risk of other assets.

A further approximation is a mixed EDH models that combines the right-hand side of (8) and (9) in the single index model. Thus, the mixed covariates model is given by

$$Y_{i,t} = \alpha_i + \sum_{i \neq j=1}^{n-1} \beta_{i|j}\ \Delta CVaR_{j,t} + \beta_{i|m}\ \Delta CVaR_{m,t} + \epsilon_{i,t} \tag{10}$$

3. Empirical Findings

We apply our proposed methodology to the return time series of 11 companies and the index for the food industry, all listed on the Tehran Stock Exchange (TSE). The data covers the period from October 5, 2015, to January 15, 2020. The choice of the food industry motivated by the fact that food and conversion industries are one of the most important industrial groups that play an efficient role in the expansion of developing countries such as Iran. Despite the essential role of the industry, it has not received much attention as compared to that of the financial sector. Due to differences in the values, plotting the original prices

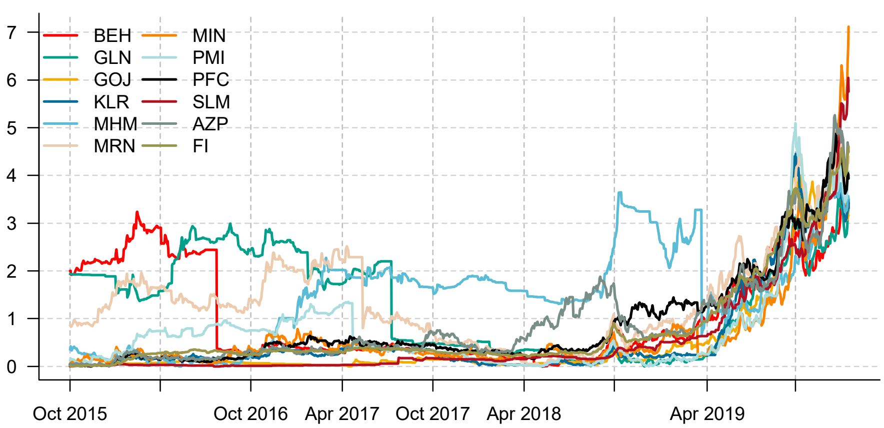


Figure 1: Time series of scaled daily log prices and their corresponding variations for Shares of Food Industrial Companies in Tehran Stock Exchange

would make it difficult to visualize some of them. To overcome this limitation, we standardize each series to a zero mean and unit variance and add the absolute minimum value of each series. This keeps the values positive and standardizes the scale of measurement for the different series.

Let $P_{i,t}$ be the daily close price of company i on trading day t. We compute the return series as the 30-day percentage changes in the closing prices, that is:

$$Y_{i,t} = 100\left(\frac{P_{i,t} - P_{i,t-30}}{P_{i,t-30}}\right)$$

Table 1 presents the summary statistics of the 30-day return series of companies. It shows that on average the 30-day returns are quite different from zero and exhibit different variability in terms of standard deviations. In particular, Behshahr.Ind recorded the highest variability, followed by Margarin, and Gorji Biscuits Co. reported the lowest variability among the companies. The skewness of the 30-day returns of the companies varies between -2.04 and 1.80, with the majority of companies exhibiting moderate skewness. The kurtosis varies from -0.27 to 8.90. Except for Pegah.Fars.Co recording a negative kurtosis, half of the companies displayed leptokurtic distribution (kurtosis > 3), while the other half exhibiting a platykurtic behavior (kurtosis < 3).

Name	Code	Mean	Sdev	Min	Max	Skew.	Kurt.
Behshahr.Ind	BEH	0.8938	25.5891	-112.4748	82.0604	-2.0393	8.9006
Glucosan	GLN	1.0053	22.6782	-87.8075	69.0898	-0.9241	4.1582
Gorji Biscuits Co.	GOJ	6.1419	16.2587	-28.7854	89.2357	1.8046	4.7277
Kalber.Dairy	KLR	6.7867	22.1965	-39.6847	114.5958	1.5405	3.2716
Mahram.Mfg	MHM	3.7692	18.6985	-80.8469	59.0031	-0.6202	3.1723
Margarin	MRN	3.5734	22.7993	-74.8406	85.4551	-0.0431	0.7512
Minoo.Co.	MIN	5.5302	18.6314	-50.0414	61.6627	0.4793	0.4014
Pars.Minoo	PMI	5.1382	22.1901	-60.5344	96.9973	0.4527	2.7284
Pegah.Fars.Co.	PFC	8.2174	19.1356	-28.9386	64.6445	0.7015	-0.2708
Salemin Factory	SLM	9.3441	16.5300	-16.3660	69.8651	1.2758	1.1279
W.Azar.Pegah	AZP	6.3855	21.0382	-56.4672	63.8704	0.1613	0.1116
Food.Industry	FI	6.2765	12.4747	-26.8253	59.3385	1.1011	1.0803

Table 1: Summary statistics of 30-day return series of the companies.

A summary of Table 1 based on the mean-variance relationship of stock returns shows that the Salemin Factory (SLM) has the highest average monthly returns (9.3441) and relatively lower risk (16.53 of returns) compared to the rest over the sample period of the data. The only stocks with a much lower risk than SLM are the food industry index (FI) and the Gorji Biscuits Co. (GOJ), however, both indices have a relatively lower average monthly returns compared to SLM. Thus, in normal times, investing in the stocks of Salemin Factory (SLM) will be a safe choice for investors seeking to diversify their exposures.

In the rest of this section, we present the results of the Extreme Downside Correlation analysis in Section 3.1 and Extreme Downside Hedging in Section 3.2.

3.1. Extreme Downside Correlation Analysis of Iran's Food Industry

We analyze the tail correlations by daily VaR via a 30-period rolling estimation of daily returns. Preliminary estimation of the VaR of some returns produced constant observations overtime. We used a Monte Carlo Sampling algorithm to draw 1000 samples of the loss vector given the mean and standard deviation of the loss distribution. This exercise is replicated 10 times to estimate the VaR series and the EDC model.

Figure 2 shows the result of the extreme downside correlation (EDC) matrix at 5%-quantile level, with correlations coefficients with lower than the 5% significance level set to zeros. A

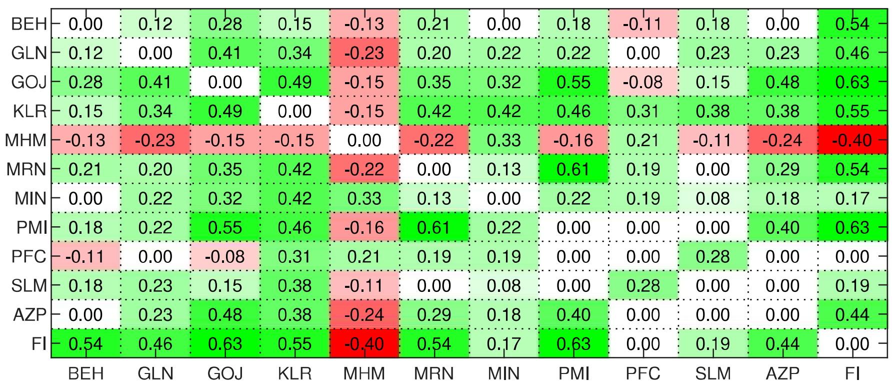


Figure 2: Weighted adjacency matrix of Extreme downside correlation (EDC) at 5%-quantile level. The light (dark) green color indicates weak (strong) positive correlations.

systematic analysis of the results focuses on the relationship between the food industry index (FI) and the rest, while the systemic analysis concentrates on the results of the figures, focusing only on the companies with the industry index.

3.1.1. Systematic EDC Analysis

From a systematic perspective, Figure 2 reveals positive co-movement between the tail risk of the market index (FI) and the companies, except MHM and PFC. More specifically, the tail risk of the market index strongly co-moves with that of GOJ and PMI, both tied at the top with correlation coefficients around 0.63, followed by KLR, MRN, and BEH. The weakly correlated companies with the market index are SLM and MIN, with correlation coefficients 0.19 and 0.17 respectively. PFC is the only company uncorrelated with the market index, and the MHM is the only one with a negative correlation.

EDC	Companies
High	AZP, GLN, BEH, MRN, KLR, GOJ, PMI
Low	MIN, SLM
Zero	PFC
Negative	MHM

Table 2: Ranking tail correlation to food industry index (FI), October 2015 to January 2020

Table 2 summarizes the systematic analysis of the EDC in Figure 2 by ranking the tail correlations between the companies and the market index over the sample period. The result suggests that to manage systematic risk (such as Iran food industry risk), an investor can choose low-correlation assets (MIN, SLM), no-correlation stocks (PFC), or negatively correlated assets (MHM). However, for purposes of hedging equity risk, it is ideal for an investor to select an asset that has a negative correlation with the market index. In this particular case, stocks of MHM presents that opportunity for investors such that, poor performance in the market can be offset by better performances in the MHM. This is in line with the results of Hosseini et al. (2017), which shows that Mahram Manufacturing company has the highest share in portfolio selection.

3.1.2. Systemic EDC Analysis

Figure 3 reports the network structure extracted from Figure 2 that pertains to the companies only. The links are color-coded to describe the sign of the statistical relationships with green for positive associations and red for co-movements. The size of the vertices corresponds to the degree of the nodes. The network in Figure 3 reveals three clusters of companies over the sample period. In one cluster is MHM alone, (PFC, SLM, and MIN) constitute another cluster, and the rest (GOJ, PMI, MRN, AZP, BEH, GLN, and KLR) form another. These three communities of companies seem to follow the pattern of correlation ranking with the market index as shown in Table 2. More specifically, stocks that are negative-correlated with

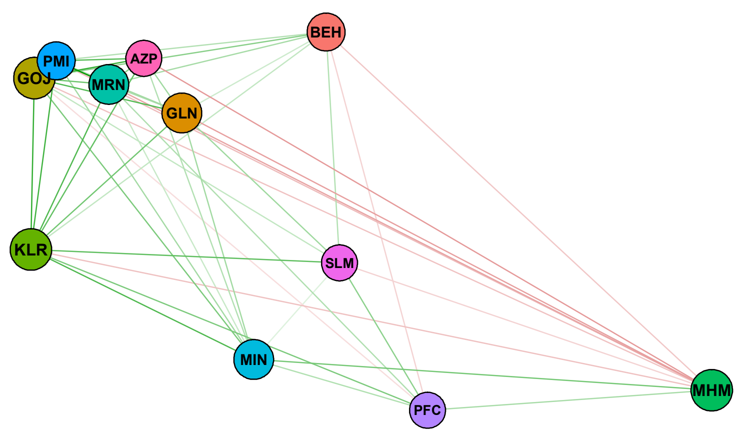


Figure 3: EDC systemic network (5%-quantile level). The links are color-coded to describe the sign of the statistical relationships with green for positive associations and red for co-movements. The size of the vertices corresponds to the node-degrees. Companies are positioned based on their latent coordinates following the eigendecomposition in (5).

the market index from one cluster, those with low-and-no correlation constitute another cluster, and the high-correlated ones form the third cluster. MHM is negatively correlated with all the companies in the third cluster. It is, however, positively correlated with (MIN, PFC) but negative with SLM in the second cluster. All the companies in the third cluster exhibit positive correlations with each other. The size of the companies in the network shows that the three clusters are centered around (MHM), (MIN) and (KLR, GOJ), respectively.

To better understand the centrality of the companies, Table 3 summarize the EDC network using standard network measures. Since the EDC is an undirected network, the in-degree and out-degree of nodes are the same for weighted and unweighted networks. The same is true for hub and authority centrality measures. The table shows that if centrality is expressed by the number of connected counterparties (degrees), then the most important companies are GOJ, alongside KLR and MHM, followed by GLN, MRN, and MIN. The least connected companies are PFC, SLM, and AZP. By weighting the connections among companies, the result identifies KLR as the most influential company in terms of connectedness. Although, MHM is highly interconnected with the rest, the weighted degree is -0.8565, which follows from the fact that it is negatively correlated with almost all the other companies. If centrality, however, depends on the importance of an individual's neighbors (eigenvector, i.e, either hub or authority), then the order of ranking of assets coincides with that of the degrees.

	Degree		Eigenvector	
	Unweighted	Weighted	Unweighted	Weighted
BEH	8	0.8899	0.2817	0.1759
GLN	9	1.7405	0.3147	0.2867
GOJ	**10**	2.7875	**0.3407**	0.4089
KLR	**10**	**3.1931**	**0.3407**	**0.4153**
MHM	**10**	-0.8568	**0.3407**	0.2305
MRN	9	2.1821	0.3147	0.3465
MIN	9	2.0935	0.3116	0.2741
PMI	8	2.4746	0.2887	0.3834
PFC	7	0.9884	0.2515	0.1594
SLM	7	1.1876	0.2515	0.1647
AZP	7	1.7094	0.2596	0.3152

Table 3: Centrality Measures for EDC network according to Degree and eigenvector score from unweighted and weighted networks. Boldface values indicate the best choice for each metric.

In summary, both systematic and systemic EDC analysis reveals a clustering behavior among the companies in our sample. Those with a high positive correlation with the market index have similar characteristics and are strongly interconnected among themselves. The companies identified in this group are (GOJ, PMI, MRN, AZP, BEH, GLN, and KLR). The second group of companies was also identified to have a low-to-no correlation with the market index, and they include (PFC, SLM, and MIN). Lastly, only MHM was identified to have a negative relationship with the market index and with almost all the other companies. The result, therefore, shows that to diversify or hedge equity risk, MHM is the ideal choice of stock for investors. The most critical stock, highly correlated with the market and other food manufacturing companies is KLR.

3.2. Extreme Downside Hedging of Iran's Food Industry

We compute the daily $CVaR$ as in (7) via a 30-day horizon rolling estimation of daily returns. As with every rolling window estimation, we acknowledge that by choosing a different and rather larger windows size might alter the daily estimates of the $CVaR$. The choice of optimal rolling window size is considered outside the scope of this work and can be explored as a further research topic. We used the Monte Carlo sampling approach to draw 1000 samples of the loss vector given the mean and standard deviation of the loss distribution. We replicate the simulation 10 times to estimate the $CVaR$ series and the EDH model. We report the EDH results for a scenario model whose covariates include the market index and the other companies a single model. The results from the calculation of the EDH systematic are presented in Figure 4.

We begin by first discussing the results of the systematic analysis of the EDH which focuses on the relationship between the food industry index (FI) and the rest. This can be seen from the last column of Figure 4. This is followed by the systemic analysis, which concentrates on the results of Figure 4 without the last column.

3.2.1. Systematic EDH Analysis

Here the analysis is focused on how the expected value of a loss in market index affects the returns of an asset. A look at the last column of Figure 4 shows that the response of

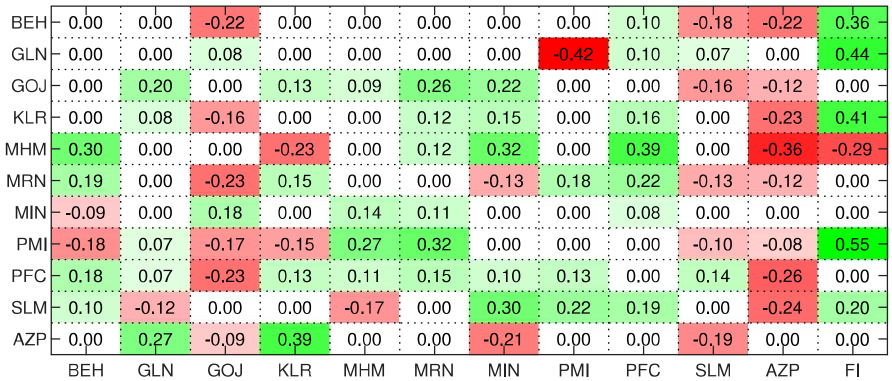


Figure 4: EDH estimates for combined systematic and systemic risk model. The light (dark) green color indicates weak (strong) positive effects, and light (dark) red color indicates weak (strong) negative sensitivity to tail risk. Column labels are $\Delta CVaR$ (Explanatory Variables) and row labels are $Y_{i,t}$ (Dependent Variables).

the company returns to the tail risk of the market index leads to three groupings of the companies. This is summarized in the Figure 4. Thus, a tail risk will have a positive effect on the returns of (SLM, BEH, KLR, GLN, and PMI), no significant effect on (GOJ, MRN, MIN, PFC, and AZP), and a negative effect on MHM. There is some agreement between

EDH Coefficients	Companies
Positive	SLM, BEH, KLR, GLN, PMI
Zero	GOJ, MRN, MIN, PFC, AZP
Negative	MHM

Table 4: Ranking of companies based on systematic EDH coefficients, October 2015 to January 2020

EDH systematic results and the EDC analysis in the sense that, they identify (MIN and PFC) as instruments for diversification, and MHM for hedging equity risk. The difference, however, is that SLM becomes positively affected when the food industry takes a hit. Also, some companies, like (GOJ, MRN, and AZP), that were identified by the EDC to be highly correlated with the market index, may be unaffected when extreme downside risk of other companies are considered in the model.

3.2.2. Systemic EDH Analysis

We now turn our attention to analyze how the returns of the companies are affected when others experience extreme downside risks. We notice from Figure 4 that the downside risk of AZP, GOJ, and SLM has negative effects on the returns of the majority of the other companies. PFC and MRN have only positive effects. The rest, however, have mixed interactions. PMI has the least effect on other companies. Figure 5 display the EDH systemic interaction network extracted from Figure 4 through the eigendecomposition in (5). The result shows a scattered placement of the companies with some close communities like (AZP), (GOJ), (GLN, KLR), (SLM, MIN, MHM), and (PFC, MRN, PMI, BEH).

The result of the most critical company to the transmission and receipt of risk is summarized in Table 5. Since the EDH is a directed network, we notice a difference in the in- and out-degrees. The out-degree shows that the GOJ and AZP are tied at the first position with 8 out-links, which indicates that the two companies are by far the ones with the highest

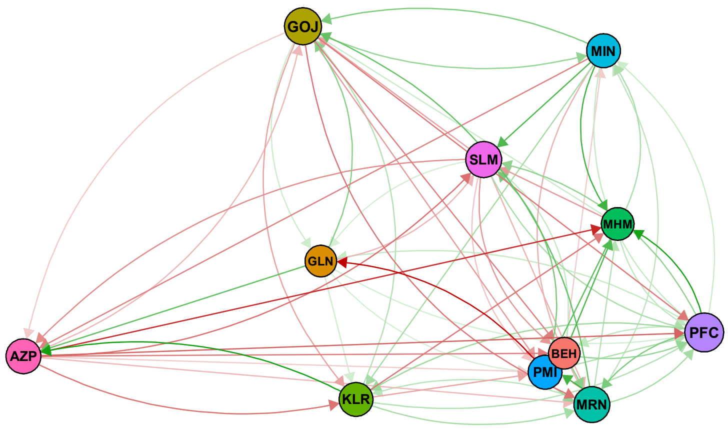


Figure 5: EDH systemic network (5%-quantile level). The links are color-coded to describe the sign of the statistical relationships with green for positive associations and red for co-movements. The size of the vertices corresponds to the node-degrees. Companies are positioned based on their latent coordinates following the eigendecomposition in (5).

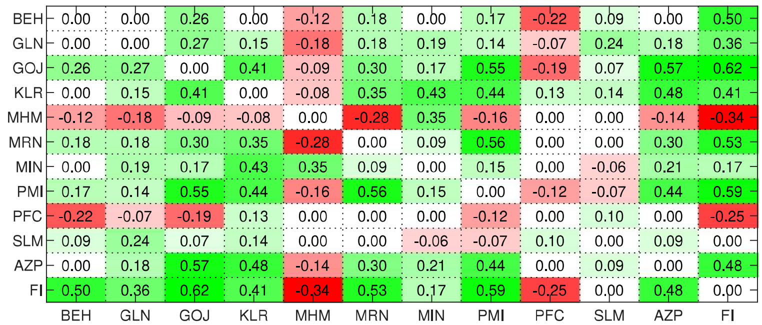
	In-Degree	Out-Degree	Hub	Authority
BEH	4	6	0.2966	0.1965
GLN	4	6	0.2946	0.1677
GOJ	7	**8**	0.3422	0.3246
KLR	6	6	0.3031	0.2867
MHM	6	5	0.2485	0.2812
MRN	8	6	0.2882	0.3651
MIN	5	7	0.3360	0.2164
PMI	8	4	0.1920	0.3699
PFC	**10**	7	0.2715	**0.4488**
SLM	7	7	0.3156	0.3027
AZP	5	**8**	**0.3851**	0.2380

Table 5: Centrality Measures for EDH systemic. Boldface values indicate the best choice for each metric.

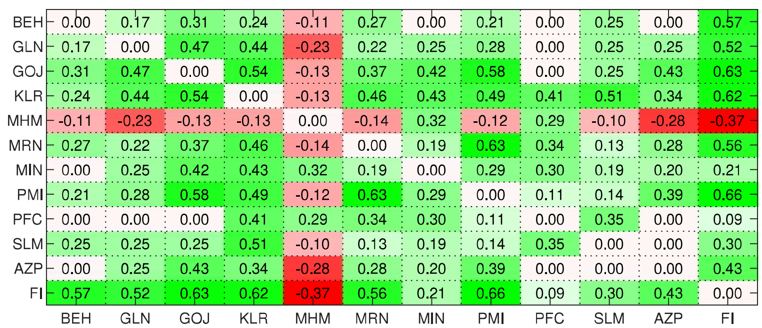
influence on 8 out of 10 companies. They are closely followed by MIN, PFC, and SLM with 7 out-links. The relative importance of the hub centrality, however, ranks AZP above GOJ, making it the top "transmitter" of downside risk. The in-degree shows PFC as the company whose return is likely to be affected the most from the extreme downside risk of all the other companies. It is followed by a tie between MRN and PMI. The authority centrality ranks PFC as the highest "receiver" of risk, followed by PMI and MRN.

4. Sensitivity Analysis

To validate the sensitivity of our empirical results, and our conclusions, we have conducted several robustness checks, as described by the following tables. The stability of the obtained results confirms the validity of our results. The result shows that the choice of different values of $\tau \in \{1\%, 10\%\}$ does not change the results significantly (see Figures 6 and 7).

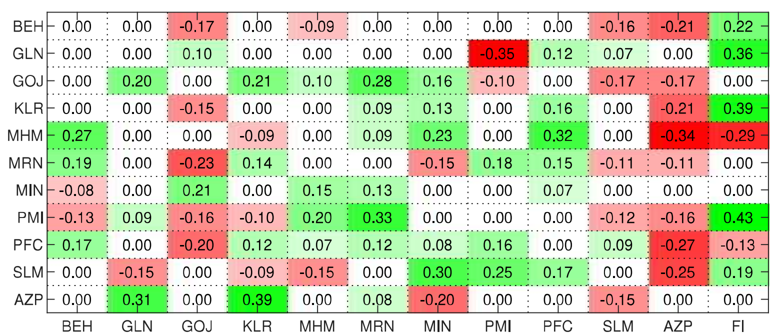


(a) **Panel A: EDC** ($\tau = 1\%$)

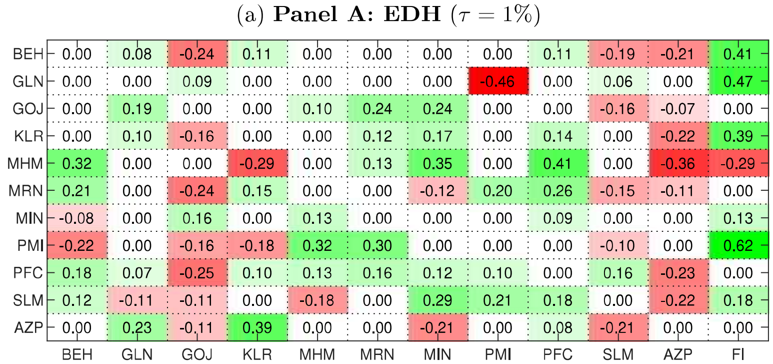


(b) **Panel B: EDC** ($\tau = 10\%$)

Figure 6: Extreme downside correlation (EDC) matrix for different τ values.



(a) **Panel A: EDH** ($\tau = 1\%$)



(b) **Panel B: EDH** ($\tau = 10\%$)

Figure 7: Extreme downside hedging (EDH) matrix for different τ values.

5. Conclusions

In the paper, we extend the extreme risk model introduced by Harris et al. (2019) to analyze the systemic and systematic exposures of financial assets under severe firm-level and market conditions. The model is applied to study the interconnectedness among food manufacturing companies in Iran. The choice of the Iranian food industry is motivated by the relevance of Iran in the Middle East and North Africa (MENA) region and its food industry widely recognized as a 'sunrise industry'. This description is due to the huge potential in the enlistment of the agricultural economy, the creation of large scale processed food manufacturing, the food chain facilities, and the generation of employment and export earnings. As a result, it can be considered as one of the largest industries in Iran. The development of this industry would also increase the demand for agricultural products in food processing and reduce the level of waste. (Afrooz et al., 2010)

We address the question of which company in the Iranian food industry is, from an investment viewpoint, the safest, or the most critical, and which companies transmit, or receive, risks from the market, particularly during crisis times.

Our result shows that Mahram Manufacturing (MHM) is the ideal stock to hedge equity risk from the market due to its negative tail correlation with the market index. Thus, we consider MHM as a haven for an investor to hedge their equity risk. This is in line with the results of Hosseini et al. (2017), which shows that Mahram Manufacturing company has the highest share in portfolio selection, thus confirming our result. On the other hand, Behshahr Industries (BEH) has the lowest average return and the highest risk, and a strong positive correlation with the market. This shows that BEH would be affected positively by a market crisis. We, therefore, classify it as the riskiest one. A study Hosseini et al. (2017) attributed a very low share of BEH in their selected portfolio, while Ghadiri and Rafiy (2010) did not even consider it in their optimal portfolio selection. These results in a way confirm our findings of BEH as the riskiest asset. We also found that W.Azar.Pegah is the main "transmitter" of tail risk among the companies, while Pegah.Fars.Co is the main "receiver" of risk.

In conclusion, our results show that the proposed extended tail risk measures are quite effective to individuate risky companies in the Iranian Food market. Future research will involve the application of the methodology to other markets and their extension into a portfolio optimization framework.

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