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Evaluating and Comparing Systemic Risk and Market Risk of Mutual Funds in Iran Capital Market

Fereshteh Shahbazin*
*Corresponding author, Ph.D. Candidate, Department of Financial Management, Faculty of Accounting and Management, Islamic Azad University, Qazvin, Iran (Email: f_shahbazin@yahoo.com)

Hasan Ghalibaf Asl
Prof., Department of Finance and Insurance, Faculty of Management, Alzahra University, Tehran, Iran. (Email: h.ghalibafasl@alzahra.ac.ir)

Mohsen Seighali
Assistant Prof., Faculty of Accounting and Management, Islamic Azad University, Qazvin, Iran. (Email: seighali@ut.ac.ir)

Moslem Peymani Foroushani
Assistant Prof., Faculty of Finance and Banking, Allameh Tabatabaei University, Tehran, Iran. (Email: m.peymani@atu.ac.ir)

Abstract

Mutual funds are one of the most paramount investment mechanisms in financial markets. By playing a financial intermediary role, they give nonprofessionals access to professionally managed portfolios of securities and provide numerous benefits for both the capital market and investors simultaneously. This study evaluated and investigated the systemic risk of mutual funds in the Iran capital market by adopting a Conditional Value at Risk (CoVaR) approach and employing quantile regression. In the finance literature, systemic risk is the probability of a downfall in the financial system when a segment or an individual component gets in distress. This risk can trigger instability or shock in financial markets and the real part of the economy. The results revealed that stock (equity) mutual funds were systemically more important than other funds, including fixed-income and balanced mutual funds, due to the high volatility in their return, which makes them riskier. To compare systemic risk and market risk among mutual funds, funds classified into five different groups based on their systemic risk. According to this categorization, analysis of variance illuminated that the market risk of mutual funds had a direct relationship with their systemic risk, such that a higher systemic risk of a fund stood for higher market risk.

Keywords: Conditional Value at Risk, Mutual Funds, Quantile Regression, Systemic Risk

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Introduction

With the enlargement of the capital market, its operational and regulatory structure should inevitably change, and the coordination among its components has to increase. In the development process of the capital market, the mere enlargement of its components does not suffice, since it decreases the efficiency of the entire system in the long run. Constant development and growth of a system entail the gradual modification, extension, or empowerment of system components, including institutions, mechanisms, and processes. A reflection on the recent financial crisis doctrine highlights the need for the empowerment and modification of regulatory structures, along with attention to the systemic risk in financial markets.

Systemic risk in finance literature means the likelihood of a downfall in the whole financial system. This risk can trigger instability or distress in financial markets. One of the important issues in the systemic risk is a contagion, which is the spreading probability of significant economic changes in a sector or an institution to another. The banking crises of the previous decades, and the 2007-2009 financial crises at their top, made the systemic risk debate in the financial markets to be noticed by macroeconomic policy-makers.

Mutual funds are among active financial institutions in the capital market and professionally invest the accumulated money of different individuals in varying markets. As an effective instrument, mutual funds can play a foremost role in economy management by collecting capitals and leading them to the industrial sectors of the economy. Mutual funds in developed and developing countries are continuously growing and increasingly penetrating different sectors of societies. Statistics show that the movement of the public wealth towards funds has been recently begun in Iran. Thus, with the ever-increasing growth of under-management assets, funds roles in the economy, particularly in the capital market of Iran, have been noticeably valued. Adopting efficient strategies in cash inflow and outflow management through forming security portfolios, fund managers have highlighted the status of these institutions in impacting the prosperity and stability of the capital market indices and other mutual funds. This spread and development pave the way for the emergence of systemic risk if it is not accompanied by planning, controlling, and surveillance.

The joint nature of assets and investment strategies is one of the important reasons for the investigation of systemic risk in securities mutual funds. Iran securities mutual funds fall into three categories, including stock, fixed-income, and balanced mutual funds. The portfolio composition of these institutions is stocks, fixed-income securities, and bank deposits and each one's proportion of investment is varying with concern to the fund type. The prominent growth of mutual funds and their heightened weights in the Iran capital market necessitate the systemic risk examination of these financial intermediaries. In addition, the interconnectivity of mutual funds and their joint investment nature will cause price changes, derived from the trading behavior of market activists and the economic conditions of Iran, to influence fund portfolios. This may bring a shock in the mutual funds, and interconnections among them, along with an impact on the financial market.

This study specifically pays more attention to the identification of financial institutions (mutual funds), which more contribute to the emergence of systemic risk. These institutions are known as systemically important financial institutions (SIFI). Financial Stability Board (FSB) defines SIFI as "the financial institutions whose disorderly failure, because of their size, complexity, and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity". When these institutions are reckoned as a serious threat to the system, the surveillants and policy-makers throughout the world ask for the application of more strict supervisions, including obligations for the excess capital requirement and liquidity constraints, for such institutions.

This study aims to evaluate and compare the systemic risk and market risk of mutual funds in Iran. To this end, it first investigates and measures the systemic risk of Iran mutual funds by the Conditional Value at Risk (CoVaR) measure and quantile regression approach. Thus, by determining the systemic risk of each fund, it can identify the mutual funds with higher contribution to the emergence of systemic risk. The recognition of such financial institutions can assist surveillants and policy-makers with the exertion of prudential supervision. After calculating the systemic risk, the funds are categorized into five classes, and the relationship between systemic risk and market risk is evaluated by examining diverse variables and employing the analysis of variance.

In the following and the next section, previous studies conducted on the modeling and evaluation of systemic risk are reviewed, and the mathematical model employed in this paper for systemic risk estimation in mutual funds is described. Then, results are analyzed investigating the relationship between systemic risk and market risk and discovering systemically important funds.

Literature Review

To become more acquainted with the problem of the study, systemic risk, and measurement methods, some previous studies in this field are outlined.

Adrian and Brunnermeier (2011) were the pioneers who presented a method known as the Conditional Value at Risk (CoVaR) method for systemic risk measurement. CoVaR is the same as the Value at Risk (VaR) of a financial system when financial institutions are under emergency and distressful conditions. They defined a publicly-traded financial institution's contribution to systemic risk as the difference between CoVaR conditional on the institution being under distress and the CoVaR in the median state of the institution (Adrian & Brunnermeier, CoVaR, 2011). Girardi and Ergün modified the definition of financial distress in Adrian and Brunnermeier CoVaR to estimate the systemic risk in the financial industries including depository institutions, non-depository institutions, insurances, and brokerages, as well as the link between institutions' contribution to systemic risk contagion. They found that the leverage, size, and equity beta are important in explaining the contagion of systemic risk among financial institutions (Girardi & Ergün, 2013). White, and et.al. used the vector autoregressive extension to quantile models in order to estimate systemic risk and analyze spillovers in the Values at Risk between a market index and financial institutions. The results showed that the long-run risk of the largest and most leveraged financial institutions is very sensitive to market-wide shocks in situations of financial distress (White, Kim, & Manganelli, 2015). Giglio, and et.al. studied the impacts of the 19 varying measures of the systemic risk and financial market distress on the transference of shock to the real economy. They used dimension reduction estimators for constructing systemic risk composite index such that it predicted information out-of-sample for the lower tail of future macroeconomic shocks (Giglio, Kelly, & Pruitt, 2016). Kleinow, and et.al. compared the empirical results of the four conventional and commonly used systemic risk measures, including marginal expected shortfall, codependence risk, delta conditional value at risk, and lower tail dependence. Their results indicated that the different criteria of systemic risk could result in varying risk assessments of various financial institutions and proposed that the risk assessment of financial institutions should be carried out accurately and cautiously based on a single risk metric (Kleinow, Moreira, & Strobl, 2017).

Compared to financial institutions, banks, listed companies in exchanges, and the real economy, few studies have addressed systemic risk in mutual funds. Klaus and Rzepkowski employed the Logit model to investigate the spillover effect among hedge funds (Klaus & Rzepkowski, 2009). In a chapter of the econophysics of systemic risk and network dynamics (Abergel, Chakrabarti, Chakraborti, & Ghosh, 2012), Abergel, and et.al. adopted a microscopic network approach to assess the systemic risk of mutual funds. They found that fund managers could control the systemic risk by prudential epidemic spread-prevention strategies. Jin and Simone combined marginal probabilities of distress estimated with the consistent information multivariate density optimization (CIMDO) methodology and the generalized dynamic factor model (GDFM) to evaluate systemic risk evaluation in mutual funds (Jin & Simone, 2014). Pelegrini, and et.al. Calculated the systemic risk of the money market funds of the UK by the CoVaR approach. The results showed that liquidity mismatch increased systemic risk in mutual funds (Pellegrini, Meoli, & Urga, 2017).

Systemic risk measurement does not have a long history in Iran. However, Sadeghi provided a systemic risk report published by the Research, Development and Islamic Studies Center of Securities and Exchange Organization. He theoretically investigated systemic risk in the financial institutions of the capital market and did not measure systemic risk practically (Sadeghi, 2012). Ahmadi and Farhanian measured systemic risk by using the quantile regression approach in 20 listing companies of Tehran Securities Exchange and considered the interconnectivity among them as a network (Ahmadi & Farhanian, 2015). Shirmohammadi, and et.al. Investigated systemic risk among money, insurance, and capital markets and demonstrated a significant difference between the systemic risk and summation of risk in each market. Finally, according to the results of the Friedman test, they claimed that the insurance industry and banking systems had the maximum and minimum contributions in systemic risk (Shirmohammadi, Chavoshi, & Feshari, 2015). Moradmand, and et.al. Utilized Delta CoVaR (ΔCoVaR) to measure systemic risk in 24 firms accepted in the Tehran Securities Exchange. Then, they employed the Kolmogorov-Smirnov test to rank the stocks of financial firms based on systemic risk (Moradmand Jalali & Hasanlou, 2016). In their course of study, Noralidokht and Dadashi-Arani determined the rate of default contagion in the mass trading network of the capital market. According to their results, institutions with a maximum impact on the financial network's instability had greater relationships with the financial network members or enjoyed remarkably concentrated associations (Noralidokht & Dadashi Arani, 2015). By selecting the firms that enjoyed the maximum value of the entire market and outnumbered trading days, Azari-Gharelar and Rastegar measured systemic risks by using Delta Conditional Value at Risk, expected shortfall;

component expected shortfall, and systemic expected shortfall. They showed that different measures had similar performances (Azari Gharelar & Rastegar, 2015). Mohammadiaghdam, and et.al. Assessed that systemic risk originated from foreign exchange shocks on financial markets by the Conditional Value at Risk measure and quantile regression approach (Mohammadiaghdam, Ghavam, & Fallahshams, 2017). Farzinvash and his colleagues measured systemic risk at 17 banks of the banking network by using the delta CoVaR measure (Farzinvash, Elahi, Gilanipour, & Mahdavi, 2018). Hekmatifarid, and et.al. Measured systemic risk in financial markets based on Delta CoVaR (Hekmatifarid, Rezazadeh, & Malek, 2018).

Rahimi-Baghi, and et.al. Exploited the granger causality network method to evaluate systemic risk in the financial system of Iran, including banks, investment firms, and insurances, in the 2011-2017 period. Their results revealed that the banking and insurance sectors enjoyed the highest and lowest rates of systemic risk, respectively. Likewise, it became illuminated that the rate of systemic risk among financial institutions changed over time. The validation of their research findings demonstrated that the extracted results were sufficiently valid (Rahimi Baghi, Arabsalehi, & Vaez Barzani, 2019).

Ebadi and his co-authors explored the effect of foreign exchange shock on the mutual funds systemic risk index by using the multivariate GARCH (M-GARCH) models and daily net asset value of Iran mutual. The results indicated that the contagion coefficients of exchange shocks were significant for the mere return of some funds; however, the presence of contagion among funds would lead to the spread of the direct effects of exchange shocks through the transitivity channel of return volatility among funds and increase the funds' systemic risk index and systemic risk potentiality (Ebadi, Elahi, & Houshmand Gohar, 2019).

Abrishami, and et.al. analyzed and measured systemic risk in the banking sector of Iran and examined their influential factors based on three criteria, including MES, ΔCoVaR, and SRISK, for the listing banks in the stock market. Their results implied that the Value at Risk of each bank had a positive relationship to the ΔCoVaR and MES as systemic risk measures. Unlike the banking literature, not only large banks pose systemic risk, but also small ones contribute to the genesis and spread of the risk (Abrishami, Mehrara, & Rahmani, 2019).

Research Methodology

This paper employed the CoVaR measure introduced by Adrian and

Brunnemeier (Adrian & Brunnermeier, CoVaR: Dataset, 2016) to assess the systemic risk of mutual funds in the Iran Capital Market. As the reader is informed, VaR is the most prevalent risk measure used by financial institutions, which focuses on the risk of an individual institution. In other words, $q\% - VaR$ is the maximum amount (value) of loss in an event at a confidence level of q per cent. $q\% - VaR$ for an institution is defined as below:

$$Prob\left(X^i \leq VaR_q^i\right) = q\% \tag{1}$$

Where X^i is the total return of the fund *i*. The reason for selecting the total return is that it consists of both fund's asset price changes and cash dividends or interest income. The mathematical form of the total return is

$$X_t^i = \frac{NAV_{i,t} - NAV_{i,(t-1)} + I_t}{NAV_{i,(t-1)}} \tag{2}$$

Where X_t^i is the total return of mutual fund *i* at time *t*, $NAV_{i,t}$ and $NAV_{i,(t-1)}$ are the net asset value of fund *i* per a unit at times t and t – 1, respectively, and I_t is the interest income or cash dividends for a unit of fund *i* at time *t*.

The CoVaR is defined as a Value at Risk of the financial system (here a portfolio of selected funds) conditional on an event $C_i(X)$ in institution *i*. $CoVaR^{systrm|C(X^i)}$ is defined as q-quantile of the conditional probability distribution.

$$Prob\left(X^{system}\middle|C\left(X^i\right) \leq CoVaR_q^{systrm|C(X^i)}\right) = q\% \tag{3}$$

Where $X^i$is the total return of fund *i*, and $X^{system}$is the system total return which is explained as the average of $X^i s$ weighted by the net asset value of funds involved in a given portfolio. More precisely,

$$X^{system} = \sum_{i=1}^{N} w_i X^i \tag{4}$$

In which w_i is the weight of fund *i* among N funds that are present in a system or portfolio.

There are two different definitions of Conditional Value at Risk (CoVaR) in various references based on their condition ($C(X^i)$). The $CoVaR_{q,t}^{=}$ symbol is the main initial definition introduced by (Adrian & Brunnermeier, CoVaR, 2011), and displays q-quantile of the system return (X^{system}) conditional on$X^i = VaR_{\alpha,t}^i$, while $CoVaR_{q,t}^{\leq}$ is a newer CoVaR definition introduced by Girardi and Ergun (2013), in which the conditional term is$X^i \leq VaR_{\alpha,t}^i$. Generally, $CoVaR_{q,t}^{\leq}$ and $CoVaR_{q,t}^{=}$ are defined as the q-quantile of the following conditional distributions:

$$Prob(X_t^{system} \leq CoVaR_{q,t}^{=} | X_t^i = VaR_{\alpha,t}^i) = q \tag{5}$$

$$Prob(X_t^{system} \leq CoVaR_{q,t}^{\leq} | X_t^i \leq VaR_{\alpha,t}^i) = q \tag{6}$$

It should be noted that the values α and q, as the confidence levels of the fund and system can vary; however, in this paper, we consider both of them equal to 5 per cent. Since this study used the method of Adrian and Brunnermeier (2011), calculations were carried out based on Eq. (5).

(Adrian & Brunnermeier, CoVaR, 2011) Measured the contribution of each financial institution to the systemic risk by $\Delta CoVaR$ - i.e., the difference between $CoVaR$ - provided that an institution had a distress condition, and $CoVaR$ in the median or normal conditions of the institution.

$$\begin{aligned} \Delta CoVaR_{it}(q) = \; & CoVaR_t^{system|X^{i,t}=VaR_{it}(\alpha)} \\ & - CoVaR_t^{system|X^{i,t}=Median(X^{i,t})} \end{aligned} \tag{7}$$

Quantile Regression

As observed in Eq. (5), the calculation of CoVaR requires the estimation of the VaR for each fund and the portfolio of funds. Despite various methods that have been proposed for VaR estimation, quantile regression was employed in this paper.

Let $Z_t = (1, X_{1t}, X_{2t}, \dots, X_{nt})'$ be a vector of state variables. Then, quantile regression is defined as

$$X_t^i = Z_{t-1}'\beta + u_{\alpha,t} \; ; \qquad t = 2, \dots, T \tag{8}$$

Where the residual term $u_{\alpha,t}$ satisfies in $Q(u_{\alpha,t} | Z_{t-1}) = 0$. $Q(.)$ is the conditional quantile function.

By estimating the coefficient vector (β) of Eq. (8), the VaR can be estimated for fund i (or system) with a confidence level of α as

$$VaR_{\alpha,t}^{i} = Z_{t-1}'\hat{\beta} \tag{9}$$

In the next step, CoVaR is calculated by quantile regression and rewritten similar to Eq. (8) as

$$X_t^{system} = Z_{t-1}'\beta_q + \delta_q X_t^i + u_{q,t} \tag{10}$$

Using the estimated value of $X^i = VaR_{\alpha,t}^{i}$, $CoVaR_q^i$ can be estimated. Particularly, $CoVaR_q^i$ can be estimated by employing quantile regression as

$$CoVaR_q^{=,i} = VaR_q^{system|X^i=VaR_q^i} = Z_{t-1}'\hat{\beta}_q + \hat{\delta}_q VaR_{\alpha,t}^{i} \tag{11}$$

Hence, $\Delta CoVaR_q^{=,i}$ is calculated as

$$\Delta CoVaR_q^{=,i} = CoVaR_q^{=,i} - CoVaR_{50}^{=,i} \tag{12}$$

Where $CoVaR_q^{=,i}$ is the maximum loss of a system with confidence level q *per cent* when the fund i encounters a loss of a per cent, and $\Delta CoVaR_q^i$ reveals fund declination when institute i moves from the median state to the worst scenario of q per cent. For the time estimation of VaR, these measures will be defined in the forms of time-varying measures.

Results

The present study employed the library and documentary methods for data collection. For this purpose, Persian and English electronic resources were exploited. The requisite data for the study variables were collected from the Rasam System, Part Financial Data Processing Co., and Tehran Securities Exchange. Finally, statistical techniques were applied for the examination of the research hypotheses.

The data included the weekly data of all mutual funds and exchange-traded funds (i.e., stock, fixed-income, and balanced funds) licensed by the Iran Securities and Exchange Organization (SEO) that they were active from early March 2017 to late September 2019 and enjoyed the information in 75 per cent of the period. The data consisted of the weekly net asset values and total returns of funds. Moreover, the data obtained from the Tehran Stock Exchange total return index (TEDPIX) and Iran Farabourse yield to maturity of the Islamic treasury bills were considered as state variables.

The total number of mutual funds was 193 throughout this period. With respect to the conducted refinement, 41 funds were excluded, and 152 remained. Table 1 shows the number of mutual funds separated by the fund type.

Table 1. Number of Understudy Mutual Funds Separated by Fund Type

Type of fund	Fixed-income	Stock	Balanced	Total
before filtration	79	93	21	193
after filtration	70	64	18	152

Table 2 provides the descriptive statistics of the variables employed in the study. This study used the weighted return of the net asset value as the system return ($r_{s,t}$), while the variations in TEDPIX and yield to maturity of the treasury bills were considered as the state variables.

Table 2. Descriptive Statistics of Variables

	Mean on funds' total return	Mean on Weighted return	TEDPIX return	YTM variation	Mean of NAV (Billion IRR)
average	0.64	0.29	1.15	-0.07	9,443
standard error	0.12	0.01	0.27	0.28	47
standard deviation	1.38	0.11	3.08	3.2	548
median	0.53	0.27	0.65	-0.19	9,408
minimum	-3.03	-0.01	-9.61	-9.34	8,319
maximum	7.05	0.87	13.81	15.48	10,771
range	10.08	0.89	23.42	24.82	2,451
number of observation	131	131	131	131	131

The simple mean of the weekly returns of 152 understudy funds was 0.64 per cent during 131 weeks ending up with late September 2019 (i.e., a period of two years and six months). However, the net asset value-weighted average return of the funds was 0.29 per cent. In this period, the weekly return mean of TEDPIX was 1.15 per cent, and its minimum and maximum rates were -9.61

per cent and 13.81 per cent, respectively. The yield to the maturity of treasury bills had an average variation of -0.07 per cent, and its variation range was 24.82 per cent during the period. The net asset value mean of the funds was 9,443 billion IRR.

Figure 1 illustrates the graphs of the variations in the weekly return of the fund's system, the weekly return of TEDPIX, the weekly yield to the maturity of treasury bills, and the net asset value mean of the mutual funds refined during 131 weeks ending up with late September 2019.

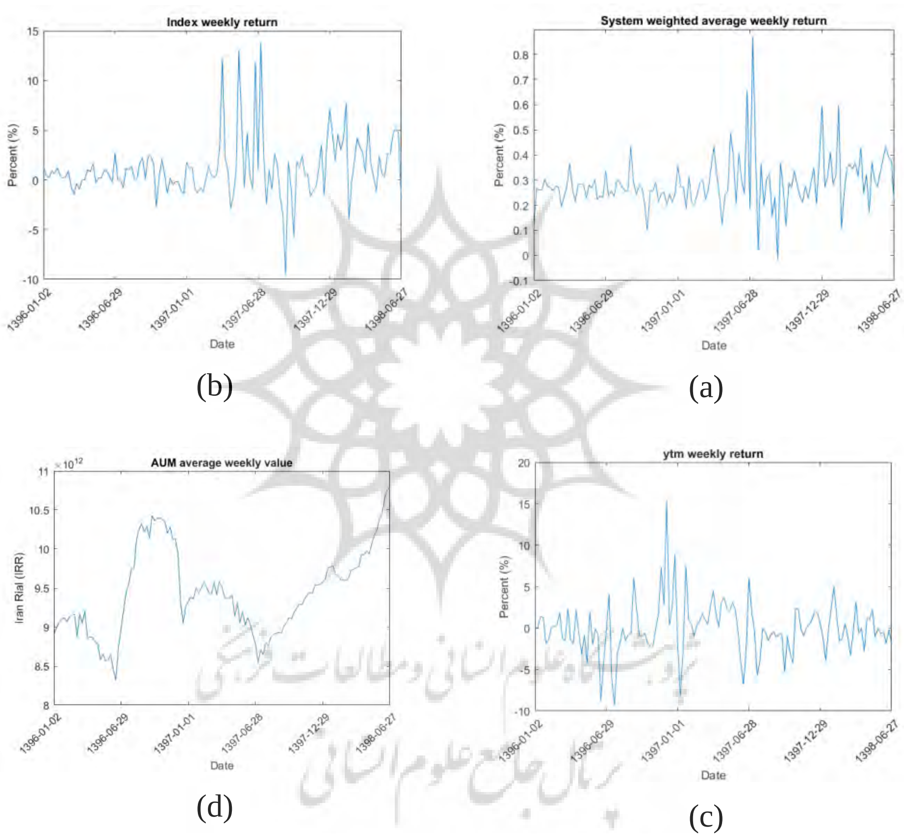


Figure 1. The Graphs of a) Mean Variations in Weekly Return of System, b) Weekly Return TEDPIX, c) Weekly Variation Yield to Maturity of Treasury Bills, and d) Net Asset Value Mean of Mutual Funds

The results derived from the quantile regression approach shows that Asemen Yekom and Armaghan Iranian mutual funds were systemically important in late September 2019. During the year ending up with the same date, Bourseiran and Gohar Nafis mutual fund were systemically important. Tables 3 and 4 provide the list of top five systemically important mutual funds in late September 2019, the year ending up with the same date.

Table 3. Five Systemically Important Funds in the Late September 2019

Rank	**Fund Name**	**Fund Type**
1	Aseman Yekom	stock
2	Armaghan Iranian	fixed-income
3	Bazr Omid Afarin	stock
4	Yekom Iranian	fixed-income
5	Etemad Meli Bank	fixed-income

As can be seen in Table 3, stock funds Aseman Yekom and Bazr Omid Afarin and fixed-income funds Armaghan Iranian, Yekom Iranian, and Etemad Meli Bank were identified as systemically important funds in late September 2019.

Table 4. Five Systemically Important Funds in the Year Leading to Late September 2019

Rank	**Fund Name**	**Fund Type**
1	Bourseiran	stock
2	Gohar Nafis Tamadon	balanced
3	Ofogh Mellat	stock
4	Dey Bank	stock
5	Tajrobe Iranian	balanced

Bourseiran, Gohar Nafis Tamadon, and Ofogh Mellat mutual funds were three important funds in the year ending up with late September 2019. In other words, the system experienced the maximum CoVaR when the funds were distressed, i.e. the fund return was less than its VaR.

Tables 5 and 6 report the quantile regression results for the Value at Risk of Aseman Yekom mutual fund and the Conditional Value at Risk of the same fund in distress conditions in late September 2019, respectively.

It should be noted that in every phase (131 weeks) and for every fund (152 funds), four regressions are fitted for the Conditional Value at Risk (CoVaR).

Table 5. Quantile Regression Results for Value at Risk of Aseman Yekom Mutual Fund in Late September 2019

	coefficients	**t-stats**	**standard error**	**p-value**
Constant	-8.84	-4.26	2.07	0.00
TRI volatility	0.36	0.78	0.46	0.44
YTM volatility	1.78	1.46	1.22	0.15

Table 6. Quantile Regression Results for Conditional Value at Risk of System in Late September 2019 When Aseman Yekom Mutual Fund is in stress

	coefficients	t-stats	standard error	p-value
constant	-0.02	-0.4	0.06	0.69
Fund's return	0.01	0.51	0.01	0.61
TRI volatility	0	0.16	0.02	0.87
YTM volatility	0.05	1.8	0.03	0.08

Figure 2 demonstrates the over-time trend of the quantile regression coefficients for CoVaR calculation when the Aseman Yekom mutual fund is distressed.

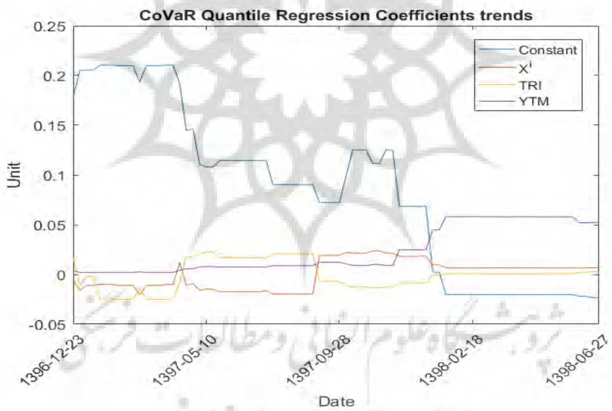
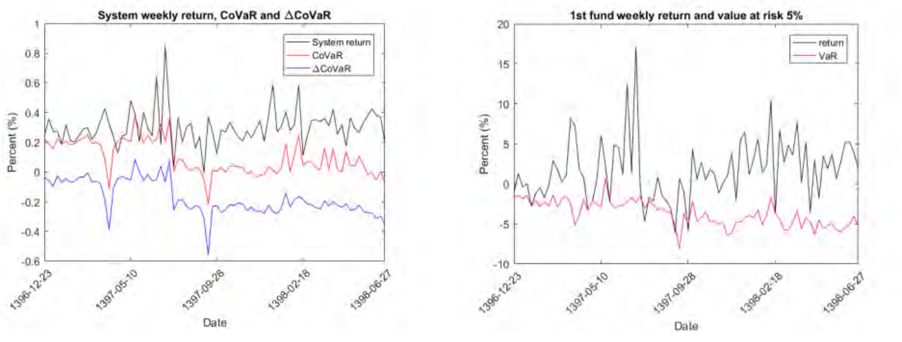


Figure 2. Over-Time Trend of Quantile Regression Coefficient

As can be seen, the changes in the constant-coefficient were sensible over time, changing from positive values at the beginning of the period to negative ones in late September 2019. The changing behavior of the total return index (TRI) and fund return (X^i) coefficients is noticeable; an increase in one coefficient reduces another.

To develop a better prospect from quantile regression estimation in VaR and CoVaR calculations, Figure 3 illustrates the weekly return of Burseiran mutual fund, its VaR, and the systemic effect of the fund on the entire system.

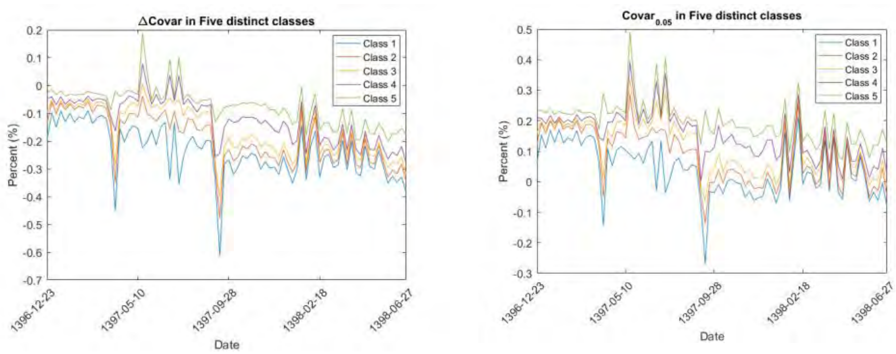


(b) (a)

Figure 3. The Graphs of a) Weekly Return and VaR of Bourseiran Mutual Fund, b) Weekly System return, CoVaR, and ΔCoVaR from Early March 2017 to Late September 2019

This paper has so far evaluated the systemic risk of mutual funds in the Iran Capital Market and estimated the VaRs of the funds as a measure of market risk. To compare the systemic risk and market risk of mutual funds, the next phase assigns the funds to five rank-ordered categories'; the funds falling into the first group are the most systemically important, while the funds in the fifth group are the least systemically important. This categorization was carried out weekly, and some variables, including total return, net asset value, VaR, beta coefficient of systematic risk, CoVaR, and ΔCoVaR, were investigated in each fund group.

The purpose of this categorization was to examine the relationships between the systemic risk of mutual funds and each one of the above-mentioned variables. Since the funds were rank-ordered based on ΔCoVaR, the mutual funds in the first-class apparently enjoyed higher CoVaR and ΔCoVaR values than the others. Figure 4 depicts the graphs of the variables in each class.



(b) (a)

Figure 4. The Graphs of a) Mean CoVaR in the Five Groups, and b) Mean ΔCoVaR in the Five Groups from Early March 2017 to Late September 2019

Figure 5 demonstrates the mean number of mutual funds separated by the fund type in each class. As can be seen, the number of mutual funds, including stock and fixed-income funds, has a reverse trend, such that the stock funds in classes with higher systemic risk outnumber the fixed-income funds, and vice versa. The number of mutual funds in every class is nearly 30.

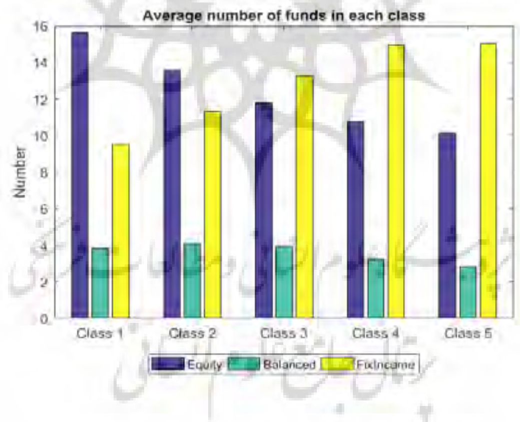
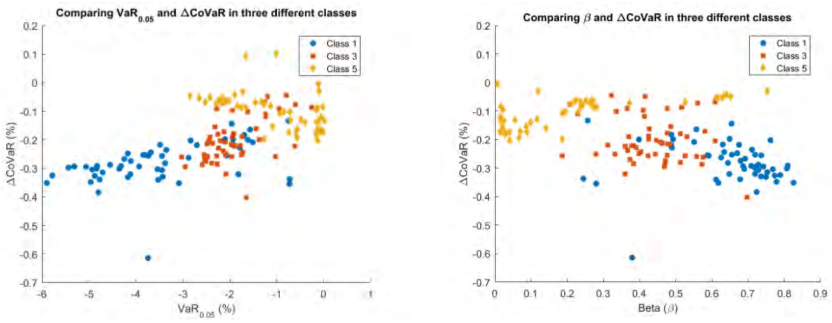


Figure 5. Mean Number of Mutual Funds Separated by Fund Type in Each Class

Concerning the above results, the behavior of the parameters present in each class is expected to be dependent on the behavior of their included funds. For example, the beta coefficient and VaR of the high-class funds are expected to be larger than those of low-class funds. Figure 6 shows the beta coefficient and VaR scatter plots for classes 1, 3, and 5 compared to CoVaR.



(b) (a)

Figure 6. The Scatter Plots of a) Beta Coefficient and ΔCoVaR and b) VaR and ΔCoVaR for Classes 1, 3, and 5

Figure 6a shows the scatter plot of the beta coefficient relative to $\Delta CoVaR$. In class 1, which is depicted in blue, the ΔCoVaR shows more negative values, and the beta coefficient, implying systematic risk, is larger. In class 5, shown in yellow, the beta coefficients are smaller than other classes, and the $\Delta CoVaR$ approach zero.

A similar behavior is observed in Figure 6b, which depicts the VaR scatter plot versus with $\Delta CoVaR$.

Table 7 summarizes the mean parameters within the classes to obtain more accurate analyses concerning the behavior of the classes.

Table 7. Mean Parameters of Funds in the Classes

	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Net Asset Value Mean (Billion IRR)	5752	7091	10193	10681	15132
Delta CoVaR	-0.28	-0.24	-0.20	-0.16	-0.10
VaR	-3.48	-2.81	-1.93	-1.31	-1.04
Beta	0.64	0.59	0.44	0.30	0.23

The net asset value mean has an uptrend form in Class 1 compared to Class 5 due to the presence of many fixed-income funds in less systemically important classes. As can be seen, there is intuitively a significant relationship between the classes with varying systemic risk and other individual risk parameters such as VaR and beta; the funds with riskier VaR and beta coefficient fall into a more systemically important fund class.

For the more meticulous investigation of the relationships between the parameters in different classes, the one-way analysis of variance (ANOVA) was employed to discover whether there were significant relationships between the mean values of more than three independent groups. The null hypothesis of this test is

$H_0: \mu_1 = \mu_2 = \cdots = \mu_k$,

Where μ is the group's mean, and k is the number of groups, which was 5 in this study. If the one-way analysis of variance offers statistically significant results, the alternative hypothesis will be accepted – i.e., there are minimally two groups with significantly different means.

It is worth noting that the one-way analysis of variance is a one-way test and cannot discern which group's mean value differs. To this end, it is required to test both groups simultaneously. The MATLAB machine learning toolbox was employed for this purpose.

Figure 7 shows the graph of beta coefficient variations in the classes. As can be seen, the beta mean has a downtrend in the classes.

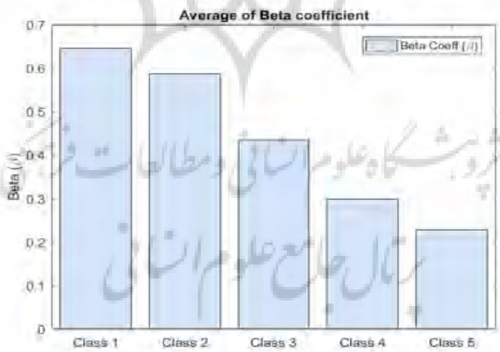


Figure 7. The Bar Chart of Beta Coefficient Mean in Five Classes

The results of the one-way analysis on the beta coefficient parameter in five classes show the presence of minimally two different classes with distinct means. Table 8 outlines the test results.

Table 8. One-Way Analysis of Variance for Beta Coefficient Variable

Source of variation	Sum of Squares (SS)	Degree of Freedom (df)	Mean Squares (MS)	F-Stats	Prob >F
columns	6.812827	4	1.703207	38.105	4E-25
error	11.62155	260	0.044698		
sum	18.43438	264			

The F-statistic and its p-value imply the presence of minimally two classes with distinct means. Table 9 summarizes the analysis of variance test for the two distinct classes. As can be seen, the means of Classes 1 and 2 and those of Classes 4 and 5 were not different at a confidence level of 95%, while the means of other classes were significantly different, which confirms the claim concerning the presence of significant relationships between the beta coefficients of the groups. This indicates that there is a significant relationship between systemic risk and the beta coefficient as a market risk variable of funds.

Table 9. One-Way ANOVA of Beta Coefficient Mean in Pairwise Classes

First Group	Second Group	95 % confidence interval for Mean		Mean Difference	p-Value
		bound Lower	Upper bound		
1	2	-0.054	0.058	0.170	0.620
1	3	0.096	0.208	0.320	0.000
1	4	0.234	0.346	0.458	0.000
1	5	0.305	0.417	0.529	0.000
2	3	0.038	0.150	0.262	0.002
2	4	0.176	0.288	0.400	0.000
2	5	0.247	0.359	0.471	0.000
3	4	0.026	0.138	0.250	0.007
3	5	0.097	0.209	0.321	0.000
4	5	-0.041	0.071	0.183	0.421

Figure 8 displays the boxplot of beta coefficient variations in the five classes.

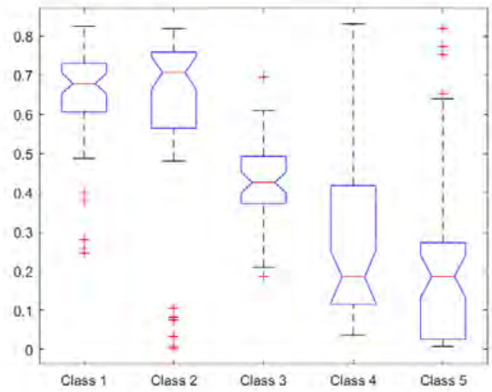


Figure 8. Boxplot of Beta Coefficient Variations in Five Classes

The central line of the boxplot (red line) represents the median, the box's edges indicate the 25%and 75% quantiles, and the separated lines display extreme values, which are not reckoned as outlier data. The remaining outlier points were drawn separately at the line ends. In Figure 8, the deviation of data in every class can be observed.

Figure 9 displays the graph of changes in VaR for the classes. As can be seen, the VaR mean has an uptrend in each class.

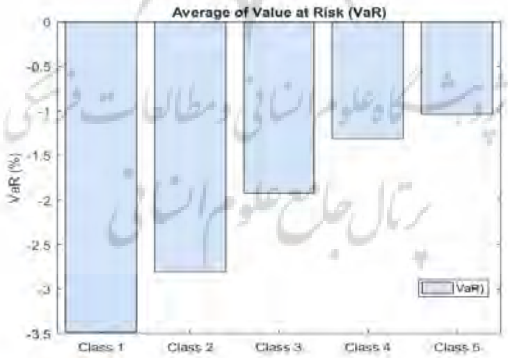


Figure 9. The Bar Chart of Value at Risk Mean in Five Different Classes

The results of the one-way analysis of variance of the VaR in the five classes imply the presence of minimally two different classes with distinct means. Table 10 outlines the results of this test.

Table 10. One-Way Analysis of Variance of Value at Risk

Source of variation	Sum of Squares (SS)	Degree of Freedom (df)	Mean Squares (MS)	F-Stats	Prob >F
columns	220.87310	4	55.21828	43.52778	6.08E-28
error	329.82963	260	1.268575		
sum	550.70273	264			

The F-statistic and its p-value indicate the presence of minimally two classes with distinct means. Table 11 summarizes the analysis of variance test for each pair of classes. As can be seen, the means of Classes 4 and 5 do not differ at a confidence level of 95%, while the means of other classes are significantly different.

Table 11. One-Way Analysis of Variance of Value at Risk in Pairwise Classes

First Group	Second Group	95 % confidence interval for Mean		Mean Difference	p-Value
		bound Lower	Upper bound		
1	2	-1.267	-0.671	-0.074	0.019
1	3	-2.149	-1.552	-0.956	0.000
1	4	-2.760	-2.164	-1.567	0.000
1	5	-3.034	-2.437	-1.840	0.000
2	3	-1.479	-0.882	-0.285	0.001
2	4	-2.090	-1.493	-0.896	0.000
2	5	-2.363	-1.767	-1.170	0.000
3	4	-1.208	-0.611	-0.014	0.042
3	5	-1.481	-0.885	-0.288	0.001
4	5	-0.870	-0.274	0.323	0.722

Figure 10 displays the boxplot of Value at Risk in the five classes.

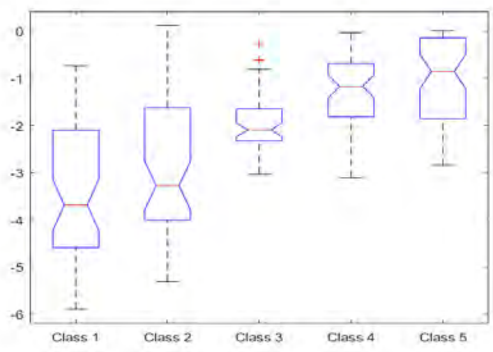


Figure 10. Boxplot of Value at Risk in Five Different Classes.

Conclusion and Suggestions

The quantile regression approach is a conventional market-value based method to calculate Conditional Value at risk (CoVaR) as a systemic risk measure. By making use of this method, the present study endeavored to measure the systemic risk of mutual funds industry, and by categorizing them into different classes, it investigated the behavior of different funds in every class and compared its relationship with the market risk. The numerical results indicated that stock mutual funds were systemically more important than the other funds, including fixed-income and balanced funds, due to their high return volatility, which makes them riskier. The categorization and analysis of variance test determined that the beta coefficient mean and Value at Risk (VaR), as the indicators of funds' market risk, had direct relationships with the funds' systemic risk; a higher the systemic risk of a fund stood for a higher beta coefficient and VaR. In other words, the results of variance analysis verified the significant relationship between the systemic risk and market risk of a fund (beta systematic risk and VaR). This result approves of the result of Abrishami, and et.al work (Abrishami, Mehrara, & Rahmani, 2019) that found a positive (direct) relationship between VaR and Delta CoVaR. Concerning the results, it is suggested that researchers evaluate the systemic risk of funds by other conventional measures and compare the results to discover systemically important mutual funds.

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