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Volatility Spillover among Industries in the Capital Market in Iran

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Measuring the dynamic relationship between banking and industries with systemic importance has attracted much attention after the recent financial crisis. This paper examines the dynamic conditional correlations and volatility spillover using three popular multivariate GARCH models in the twelve-year period (from the beginning of 2005 to the beginning of 2016) among the fourteen systemically important industries in Iran's capital market. The purpose of this study is to understand and identify the volatility spillover between industries to predict financial fluctuations, as well as policy decisions and risk management. The results of this study confirm the spillover between "Banking" and the five industries of "Basic Metals", "Industrial Multidisciplinary", "Investments", "Computers", and "Transportation & Warehousing". There is also an asymmetric spillover between "Banking" index and the "Chemical Industry", the "Extraction of Metal Ores", "Pharmaceuticals" and "Communications Devices". The results are used for mapping fundamental analysis and risk programming.

Keywords: Volatility Spillover, Dynamic Conditional Correlation, Banking Industries.
JEL Classification: C22, C32, C58, G10

1 Introduction

Several terms related to stock market co-movements are used in literature. After recent crisis, more complicated and frequently used term is "spillover". The general meaning of the word is: "the effects of an activity which have spread further than was originally intended''. Benelli and Ganguly (2007) use the word spillover as "any types of impact on other countries financial markets". Balasubramanyan (2005) defines spillover as lagged shock in one stock market transmitted to other market. The impact of a shock can be measured in various ways but we are mainly concern with volatility spillover, under which we mean unilateral transmission of volatility from one stock market/sector to another.

In recent decades, the study of the volatility spillover among industries has been attended by many researchers and financial circles as well as

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international institutions (such as International Monetary Fund, 2016). The complexity of the financial markets and the close relationship between industries, as well as the vital need for predicting future financial and economic scenarios, have led them to discover these inter-sectorial connectedness.

The stability of the financial system can be negatively affected by systemic risk in bank-based financial structures. Systemic risk may be defined as a disruption to the flow of financial services that is (i) caused by an impairment of all of the financial system; and (ii) has the potential to have serious negative results for the real sectors. Banks can generate systemic risk for a number of reasons (Bats & Houben, 2017). First, they are highly leveraged. In leveraged institutions, fire sales amplify downturns when asset values are falling (Adrian & Shin, 2014). Also, when higher bank leverage induces stronger creditor discipline, systemic risk rises on account of contagious bank by creditors' claims (Acharya & Thakor, 2016). Second, the large asset-liability mismatches make them vulnerable to exchange rate, liquidity pressure and interest rate shocks, and finally bank run. Third, banks trade with each other through markets and systems which creates long intermediation chains, more complexity and leads them to be highly interconnected (Craig and Von Peter, 2014). Interconnectedness is a key driver of systemic importance (Tarashev & Drehmann, 2013). For settlement, liquidity and funding risk, this interconnectedness can increase losses through the financial system, as losses for one bank may cause losses for other important sectors.

The volatility spillover between systemic important industries shows the process of data transfer between them. So the reaction created in an industry can affect other industries. Meanwhile, identifying volatility spillover in various industries is important in boosting the country's financial resonance in order to make the economy more robust. It should be consider that economy system of Iran is bank-based and banks play unique roles in terms of function, the volume of assets under management and effects on other industries. In this paper banking industry is considered as a financial proxy in comparison with other industries. The main objective of this research is to identify and model the dynamics of relations and volatility in the different industries with regard to utilizing a wide range of data and choosing the most efficient model.

So the main question is: Is there volatility spillover between banking and other important industries in Iran's capital market? If this is confirmed, how is the spillovers intensity the selected industries? A clear understanding of the mechanism of volatility transmission across sectors is important for its implication on monetary policies, resource allocation, risk hedging, capital requirements and asset valuation. The outcomes of this research will be a graphical representation of a model using historical data trends, which present a steady, and persistent property. This paper is classified into the descriptive research category. The overall research method is presented as an applied study, and correlational in terms of nature and method.

The necessity of this research is due to several reasons. First, studies on volatility spillover mainly focus on developed countries such as the United States, European countries, and East Asian countries. Therefore, it is important to consider this important issue in Iran's bank-based financial system. On the other hand, the banks and financial institutions have a significant share of the total market value so its price volatility may affect the entire capital market, which shows its systemic importance. Also, the outputs of this research have the dimensions of economic policy implications and scenario analysis regarding the attention to the macro-monetary programs of the country. Finally, attention to volatility plays a key role in investment and risk management decisions of market participants and institutional stakeholders of banks and credit institutions.

The main difference between the present study and other researches is in terms of the data scope and also the method of the measurement. This paper tries to explain the concept of sectorial volatility spillover by accurately measuring the relationships with attention to the convergence of the results in conditional correlation models. So it captures spillover features in Iran's capital market.

This article consists of five sections; in the first part briefly outlines the goals and framework of the research, the basic questions and the requirement to do. After the introduction, the second part devotes to the statement of theoretical foundations and a review of relevant previous studies. The third part presents the research model. Part fourth, tests data and analyzes results. Finally, the conclusion and presentation of the research findings is in the fifth section.

2 Literature Review

The price of every stock is determined by investors' expectations about future profitability of the underlying firm (Reilly & Brown, 2000). Two factors are always present in the development of stock prices: fundamental and human. The former reflects facts, the latter reflects the behavior of investors on financial markets. Thus, causes of stock market co-movements can be divided into two basic categories: fundamental and behavioral. What both categories have in common is an intensifying trend of globalization. The fundamental causes include innovations in Information and Communication Technologies (ICT), trade and financial linkages, supranational nature of businesses, and common shocks. The behavior of investors is much harder to tackle. The industries in the capital market are considered to be rivals to each other, so investors can adjust their capital through different sectors. When the industry does not have enough attractiveness for investors, capital resources are pulled out of the industry and leading to turbulence. Volatility is interpreted as uncertainly. It becomes a key factor to many investment decisions and portfolio management because investors and portfolio managers want to mitigate levels of risk. The thing to realize is that market volatility is inevitable. It's the nature of the markets to move up and down over the short term. Public interest in market movements has intensified in the last decades more so after the global financial crisis of 2007 (Natarajan et al., 2014). Information transmission across markets might be through returns as well as through volatility (Choudhry & Jayasekera, 2014). Increasing integration between different markets has led to information and sentiment spillover from one market to another.

The concept of spillover of the volatility of asset returns is drawn from the seminal work of Engle et al., (1990). The spillover effects are economic events in one context that occur because of something else in a seemingly unrelated context. A market failure can influence the demand or supply behavior of affected participants in other markets, causing their effective demand or supply to differ from their notional conditions. The profile of spillovers depends on the network structure, including the size and location of the epicenter in the network, the number and economic characteristics of its partners, and the direction and strength of economic flows among them (Kireyev & Leonidov, 2014). In general, a number of different types of spillover distinguished in the markets are:

1) External vs. internal spillover: External spillover originates from interactions between the special area and the rest of the world. Internal spillover originates from the economic linkages between the own market.
2) Shock vs. policy induced spillover: This is particularly relevant in terms of policy action. Coordination mitigates negative consequences from policy errors and internalizes the consequences of spillover
3) Direct vs. indirect spillover: Direct spillover operates mainly through trade linkages. In addition, indirect spillover is working through the common interest rate and the exchange rate.

4) Positive vs. negative spillover: In the case of positive spillover, individual policies and events reinforce each other. In the case of negative spillover, events are mutually inconsistent and in conflict to each other.

Empirical estimations of spillover may not always confirm theoretical priors. The interactions of spillover, non-linearity and the complexity of dynamics may lead to more unknown outcomes concerning sign, size and timing of spillover (Weyerstrass et al., 2006). However, it is also empirically proven that markets that are not fully integrated show cross-market spillover mostly during a financial crisis, a phenomena which is generally termed as "financial contagion".

In the present study, the following channels of spillover are Output (trade) channel, Price (competitiveness) channel, Interest rate and exchange rate channel, Government debt channel and Structural reform channel. Theoretical foundations present "own" and "cross" type spillovers. Own-spillover states that present volatility of a market is a function of past volatility of the same market (volatility clustering). Empirically, strong evidence is found in favor of own-spillover (Engle & Susmel, 1993). On the other hand, cross-spillover (also termed as volatility transmission) states that the present volatility of a market is a function of both past volatility of the same market and past volatility from other markets (Hamao et al., 1990; Fratzscher, 2002).

A significant characteristic regarding volatility spillover is the property of asymmetry (Nelson &Foster, 1994). The spillover of volatility also exhibits asymmetry according to the type of news. Bad news seems to have severe effect on spillover (both own and cross) as compared to good news. This asymmetric property of spillover is a prime contributor to the cause of financial contagion.

The study of empirical literature presents different methodologies for similar context. Bernard and Durlauf (1996) and Aubyn (1999) suggest that one way to assess the convergence (or divergence) in prices of interdependent markets is by performing pair-wise stationarity tests on the price differences of the two series. The difference level of the price series of two stock markets should not contain any unit root to meet the convergence criteria. The Augmented Dickey Fuller (ADF) test is generally used for convergence analysis between the prices series of two stock markets. However, using stationarity property for testing of price convergence has some drawbacks. For example, the stationarity of price differentials only imply convergence and do not indicate the level of market integration. Secondly, the unit root tests lack robustness in the presence of outliers and may wrongly reject the convergence hypothesis (Zachmann, 2008).

Another way to measure market integration is the detection of cointegration relationships between two stock markets price series with direct interconnections. Johansen's cointegration test or Engle and Granger cointegration test are usually used to detect any evidence of integration. One implicit assumption of cointegration methodology is that the cointegrating vector is constant over the period of study (Barret & Li, 2002). Considering market features, it is impossible that the long-run relationship remain constant and it shifts due to any systemic change such as socio-political and economic events.

The third and most popular method for analyzing the level of integration is to measure the volatility spillover between two markets. When sectors/markets are economically integrated via trade and investments then it is expected that their cash flows move by investors' expectations. Spillover models such as ARCH, and GARCH developed by Engle (1982) and Bollerslev (1986), respectively, and their various extensions test market integration and interdependence by capturing the extent of spillover from one market to another.

In recent years, financial market integration has become a central theme in international finance literature. Harris and Pisedtasalasai (2006) investigates return and spillover effects between the FTSE100, FTSE250 and FTSE Small Cap equity. They find that volatility transmission mechanism between large and small stocks in the UK is asymmetric. Hammoudeh, Yuan and McAleer (2009) examine the dynamic volatility and volatility transmission in a multivariate setting using the VAR–GARCH model for three major sectors, namely, Service, Banking and Industrial/or Insurance, in four GCC's economies (Kuwait, Qatar, Saudi Arabia and UAE). The results suggest that past own volatilities matter more than past shocks and there are moderate volatility spillovers between the sectors within the each country, with the exception of Qatar.

Kouki et al. (2011) investigates volatility spillover for 5 sectors, including banking, financial service, industrial, real estate and oil, between international stock markets by Using VAR-BEKK model. The result supports the hypotheses of constant conditional correlation. The dynamic conditional correlation (DCC) provides evidence of cross border relationship within sectors.

Vardhan et al. (2015) examine the existence of both short-run and long-run relationships between the Indian major sector indices. The results indicate that the eight sample indices share long-run equilibrium relationship. However, no short-run Granger Causality exists between sector indices. Ahmed (2016) investigates both the long-run and short-run links among sectors of the Egyptian equity market using cointegration analysis and Granger's causality analysis. The results indicate that there exists a single cointegrating vector within the sample sector indices. The Granger's causality analysis shows that the short-run causal relationships between the sector indices are substantially limited.

The study of volatility spillover is essential for two reasons: firstly, it relates to the notion of market efficiency. The "own" aspect of spillover (heat wave phenomenon) is a direct result of the level of efficiency in the market. Higher level of spillover indicates lower level of efficiency (Bollerslev & Hodrick, 1992). Secondly, volatility spillover indicates the level of market integration. The "cross" aspect of spillover (meteor shower phenomenon) measures the extent to which markets are integrated (Engle & Susmel, 1993; Bekaert & Harvey, 2003). The higher the interdependence among markets, the higher will be the cross-market spillover and greater chances of contagions occurring in the event of a financial crisis especially in bank-based systems.

3 Methodology

The typical specification underlying the multivariate conditional mean and conditional variance in returns are given as follow:

$$y_t = E(y_t|F_{t-1}) + \varepsilon_t,\ \varepsilon_t = D_t\eta_t \tag{1}$$

where $y_t = (y_{1t}, \dots, y_{mt})'$, $\eta_t = (\eta_{1t}, \dots, \eta_{mt})'$ is a sequence of independently and identically distributed (i.i.d.) random vectors, F_t is the past information available to time t, $D_t = diag(h_1^{\frac{1}{2}}, \dots, h_m^{\frac{1}{2}})$, m is number of returns, and $t = 1, \dots, n$.

Engle (2002) proposed the Dynamic Conditional Correlation (DCC) model. The DCC model can be written as follows:

$$y_t|F_{t-1}: (0, \varrho_t), t = 1, \dots, T \tag{2}$$
$$\varrho_t = D_t\Gamma_t D_t \tag{3}$$

Where D_t =diag(h_{1t},…,h_{mt}) is a diagonal matrix of conditional variances, with m asset returns, and F_t is the information set available to time t. the conditional variance is assumed to follow a univariate GARCH model, as follows:

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_{i,k}\, \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_{i,l}\, h_{i,t-l} \tag{4}$$

When the univarate volatility models have been estimated, the standardized residuals, $\eta_{it} = y_{it}/\sqrt{h_{it}}$, are used to estimate the dynamic conditional correlations, as follows:

$$\varrho_t = (1 - \phi_1 - \phi_2)S + \phi\eta_{t-1}\eta'_{t-1} + \phi_2\varrho_{t-1} \tag{5}$$
$$\Gamma_t = \{diag(\varrho_t)^{-1/2}\}\varrho_t\{diag(\varrho_t)^{-1/2}\} \tag{6}$$

where S is the unconditional correlation matrix of the ε_t and equation (6) is used to standardize the matrix estimated in (5) to satisfy the definition of a correlation matrix. Where the $k \times k$ symmetric positive definite matrix ϱ_t is given by

$$\varrho_t = (1 - \theta_1 - \theta_2)\bar{\varrho} + \theta_1\eta_{t-1}\eta'_{t-1} + \theta_2\varrho_{t-1} \tag{7}$$

in which θ_1 and θ_2 are scalar parameters to capture the effect of previous shocks and previous dynamic conditional correlations on current dynamic conditional correlation, and α, β are non-negative scalar parameters satisfying $\alpha + \beta < 1$. As ϱ_t in is conditional on the vector of standardized residuals, (7) is conditional covariance matrix. $\bar{\varrho}$ is the k × k unconditional variance matrix of η_t.

Ling and McAleer (2003) proposed a vector autoregressive moving average (VARMA) specification of the conditional mean in (1) and the following specification for the conditional variance:

$$\Gamma_t = \{diag(\varrho_t)^{-1/2}\}\varrho_t\{diag(\varrho_t)^{-1/2}\} \tag{8}$$
$$H_t = W + \sum_{i=1}^{r} A_i\varepsilon_{t-i} + \sum_{j=1}^{s} B_jH_{t-j}$$

where $H_t = (h_{1t}, \dots, h_{mt})'$, $\varepsilon_t = (\varepsilon_{1t}^2, \dots, \varepsilon_{mt}^2)'$ and W, A_i for i=1,…,r and B_j for j=1,…,s are $m \times m$ matrices. As in the univariate GARCH model, VARMA-GARCH assumes that negative and positive shocks have identical impacts on the conditional variance. To separate the asymmetric impacts of the positive and negative shocks, McAleer, Hoti and Chan (2008) proposed the VARMA-AGARCH specification for the conditional variance, namely

$$H_t = W + \sum_{i=1}^{r} A_i\varepsilon_{t-i} + \sum_{i=1}^{r} C_iI_{t-i}\varepsilon_{t-i} + \sum_{j=1}^{s} B_jH_{t-j} \tag{9}$$

where C_i are $m \times m$ matrices for i=1,…,r ; and $I_t = diag(I_{1t}, \dots, I_{mt})$, where

$$I_t = \begin{cases} 0, & \varepsilon_{it} > 0 \\ 1, & \varepsilon_{it} \le 0 \end{cases}$$

If m=1, (8) collapse to the asymmetric GARCH, or GJR model. Moreover, VARMA-AGARCH reduces to VARMA-GARCH when $c_i = 0$ for all i. If $c_i = 0$ and A_i and B_i being diagonal matrices for all i and j then VARMA-AGARCH reduces to CCC-MGARCH. The parameters of model (1)-(9) are obtained by maximum likelihood estimation (MLE) using a joint normal density. When η_t does not follow a joint multivariate normal distribution, the appropriate estimator is defined as the Quasi-MLE (QMLE).

4 Empirical Results

The special domain of this research is the market sectors in Iran's capital market. The research period is from the beginning of 2005 to the beginning of 2016 for the twelve-year period. The stock market data is non-randomly selected because the basis for the selection is judgments. Selection of sample size is based on the highest market value, due to more relative inclusion in the total stock price index. They meet the modeling requirements and have a systemic impact on the entire market.

The frequency of the time series data is monthly, since daily data often has fluctuations such as inductance, and seasonal data may cause the volatility transition to be maximized due to cumulative effects. On the other hand, due to the existence of some systemic interventions in real data such as the existence of base volumes, free floatation, etc., it is expected that any interference in the data process will be balanced in a month (prices will go up to their actual value given). Therefore, the monthly logarithmic returns is used for the selected industry index. The indices are value-weighted and not adjusted for dividends.

The returns of stock prices i at time t in a continuous compound basis are calculated as $r_{i,t} = \log(p_{i,t}/p_{i,t-1})$, where $p_{i,t}$ and $p_{i,t-1}$ are the average prices for month t and $t-1$, respectively. Statistical analysis of the present study is done through E-views and RATS software. Table (1) shows coding of selected industries in this paper.

Table 1
Selected Industries Coding

	Industry		Industry
r 1	Chemical	r 8	Pharmaceuticals
r 2	Basic Metals	r 9	Telecommunications
r 3	Banking	r 10	Communication Devices
r 4	Oil Products	r 11	Power supply, gas and steam
r 5	Multidisciplinary Industry	r 12	Investments
r 6	Extraction of Metal Ores	r 13	Computer
r 7	Automotive and Parts	r 14	Transportation and Warehousing

The descriptive statistics of the fourteen selected industries are presented in Table 2. In all investigated industries, Kurtosis is more than 3 (Normal Distribution Kurtosis equals 3). In the major series, a small mean with high variance is observed. Therefore, beside positive kurtosis in most of the series, this shows their non-normal distribution.

Table 2
Descriptive Statistics of the Fourteen Selected Industries

	(r 1)	(r 2)	(r 3)	(r 4)	(r 5)	(r 6)	(r 7)
Mean	1.3376	1.8331	1.06310	1.39612	1.18730	2.00954	**0.83894**
median	0.0000	1.6001	-0.22507	0.29563	-0.21826	0.13339	**-0.75633**
Max	23.8633	22.0083	28.4812	25.4513	29.4380	27.4510	**45.2663**
Min	-18.0818	-27.4461	-20.7041	-37.7437	-17.6513	-30.0315	**-16.1737**
Stdev	6.7705	8.0113	7.31131	8.97902	6.8289	9.4649	**8.89670**
Skewness	0.5668	-0.1822	0.62140	-0.15970	1.07761	0.14561	**1.64000**
kurtosis	4.3821	3.9809	5.33084	5.83125	5.6949	3.81397	**7.64773**
JB	19.1735	6.5702	41.8642	48.7079	71.4467	4.48415	**194.159**
Prob.	0.00007	0.0374	0.0000	0.0000	0.0000	0.10623	**0.00000**
	(r 8)	**(r 9)**	**(r 10)**	**(r 11)**	**(r 12)**	**(r 13)**	**(r 14)**
Mean	2.12673	1.42648	0.74156	0.36070	0.85662	2.38756	**1.74521**
median	0.87119	0.0000	-5.55111	0.00000	-0.08976	1.18428	**-0.02210**
Max	30.7830	25.4681	62.2796	18.0546	31.3588	21.9138	**131.830**
Min	-8.05087	-11.3960	-29.7155	-2.62132	-11.8162	-25.2509	**-128.1787**
Stdev	5.49098	5.87872	13.6481	2.19636	5.98420	7.3535	**21.9274**
Skewness	2.01787	1.40701	1.88492	5.38730	1.68512	0.17275	**1.03980**
kurtosis	9.15086	6.26235	10.1050	37.4259	7.96820	4.88338	**22.6457**
JB	324.7222	111.3703	388.1636	7807.43	216.250	21.9991	**2341.68**
Prob.	0.00000	0.00000	0.00000	0.0000	0.0000	0.00001	**0.00000**

Source: Authors' estimations

When using White's test, the distribution of the variance of the error terms is usually not known and it is guessed. White test is very similar to that by Breusch-Pagen. White test for testing heteroscedasticity is common because it does not rely on the normality assumptions. Because of the generality of White test, it may identify the specification bias too. White test output confirms the existence of the heteroscedasticity in the initial model.

Table 3
White Heteroscedasticity Test

F-statistic	49387.40	Prob. F(17,112)	0.0000
Obs*R-squared	129.9827	Prob. Chi-Square(17)	0.0000
Scaled explained SS	254.3546	Prob. Chi-Square(17)	0.0000

Source: Authors' estimations.

The variance is not constant during the random process. The Lagrange Multiplier (LM) test is one of the key tools to detect ARCH and GARCH effects in financial data analysis. These models explain the conditional variance process according to the past information, and apply to time series that vary over time. Therefore, before using GARCH methods, the existence of conditional discrepancies is confirmed by the ARCH test.

Table 4
ARCH-LM Test

F-statistic	18.50548	Prob. F(1,127)	0.0000
Obs*R-squared	16.40630	Prob. Chi-Square(1)	0.0001

Source: Authors' estimations.

In order to model the conditional variances of returns in ARCH processes, the GARCH model (1.1) is estimated using the Box-Jenkins approach .The robust t ratios shows that the ARMA (1,1) GARCH (1,1) the specifications of all returns are statistically significant for both the conditional mean and conditional variance except r4, r5 and r13. However, the variance equations do not present the asymmetric effect of negative and positive shocks on conditional variance.

The correlation between each pair of series at a given time is created dividing conditional covariance by conditional deviations. One of the alternative approaches is modeling dynamics directly by correlation. In the fixed conditional correlation model (CCC), although conditional covariance is not constant, it is linked to constant conditional correlations.

The results of the stationarity conditional correlation model are presented in Table 5. This table shows that there is a constant conditional correlation between the banking industry (r3) with the automotive & parts industry (r7) and investments industry (r12) index. Apart from the two aforementioned industries, there is no significant correlation between the banking and other industries based on the experimental results of this section.

Table 5
Constant Conditional Correlation

Method: ML ARCH - Generalized Error Distribution (GED) (OPG - BHHH /Marquardt steps)
Covariance specification: Constant Conditional Correlation

GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))

variable	**coefficient**	**Std. Error**	**statistics - z**	**Prob**
r (7)	0.178334	0.077450	2.302565	0.0213
r (12)	0.422025	0.151311	2.789125	0.0053
Log likelihood	-365.0665			
Avg. log likelihood	-2.808204		Schwarz criteria.	6.777127
Akaike info criterion	6.093331		H-Q criteria.	6.371180
R-squared	0.517512			
Adjusted R-squared	0.463440		Mean dependent var	1.710718
S.E. of regression	5.119053		S.D. dependent var	6.988444
Durbin-Watson stat	1.451202		Sum squared resid	3039.745

Transformed Variance Coefficients

	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
M(1,1)	0.031201	0.512899	0.060832	0.0115
A1(1,1)	1.251117	2.491116	0.050117	0.0400
B1(1,1)	0.986423	0.022051	44.73328	0.0000

Source: Authors' estimations.

A dynamic conditional correlation model is estimated in two steps in which each variable in the system are first modeled as a single-variable GARCH process. The logarithm of likelihood is created for combining these steps, in which the sum of the logarithms of likelihood aggregates all univariate GARCH. Then in the second step, the conditional likelihood is presented with correlation matrix. The significance of the values of θ indicates that conditional correlations are not constant over time. Here θ_1 represents the effect of past shocks on current conditional correlations, θ_2 represents the effect of past dynamic conditional correlations, and θ_3 represents the effect of cross-sectional correlations in the GARCH (or asymmetric GARCH).

The dynamic conditional correlation analysis of the variables of the fourteen industries with the banking industry are calculated pairwise that is presented in Table 6.

Table 6

Dynamic Conditional Correlation among Industries

Industry	**type**	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Chemical(r =1)	θ(2)	0.85600	0.07713	11.09768	0.0000
basic metals(r =2)	θ(2)	0.89205	0.07464	11.95015	0.0000
	θ(3)	0.09062	0.04503	2.012405	0.04417
Oil products(r =4)	θ(1)	-0.01732	0.00832	-2.081795	0.03736
	θ(2)	0.98087	0.03360	29.18826	0.0000
multidisciplinary industry(r =5)	θ(1)	0.15406	0.07381	2.087224	0.0369
	θ(2)	0.63316	0.20042	3.159184	0.0016
Extraction of metal ores(r =6)	θ(2)	0.81590	0.24898	3.276890	0.0010
Automotive & parts(r =7)	θ(1)	0.44392	0.15448	2.873619	0.0040
	θ(3)	3.11538	0.26838	11.60771	0.00000
pharmaceuticals (r =8)	θ(1)	0.26161	0.09223	2.836467	0.0045
	θ(2)	0.63406	0.12681	4.999783	0.0000
	θ(3)	3.21745	0.29837	10.78337	0.00000
Telecommunications(r =9)	θ(1)	0.08541	0.04163	2.051712	0.0402
	θ(2)	0.88890	0.05887	15.09928	0.0000
communication devices(r =10)	θ(1)	-0.05102	0.00391	-13.03506	0.0000
	θ(3)	2.36521	0.06651	35.55754	0.0000
Power supply, gas & steam (r =11)	θ(1)	0.10548	0.01334	7.903398	0.0000
	θ(2)	0.89446	0.00665	134.4644	0.0000
Investments(r =12)	θ(1)	0.34842	2.23111	1564437.	0.0000
	θ(2)	0.28550	6.80121	419986.0	0.0000
	θ(3)	0.07474	1.23121	607058.7	0.0000
Computer(r =13)	θ(1)	0.19397	0.09035	2.146820	0.0318
	θ(2)	0.61934	0.25220	2.455760	0.0141
Transport. & Warehousing (r =14)	θ(1)	-0.01658	0.00284	-5.825813	0.0000
	θ(2)	0.86807	0.26864	3.231322	0.0012

Source: Authors' estimations.

In Figure (1), dynamic conditional correlations among fourteen industries in Iran's capital market are presented from 2005 to 2016.

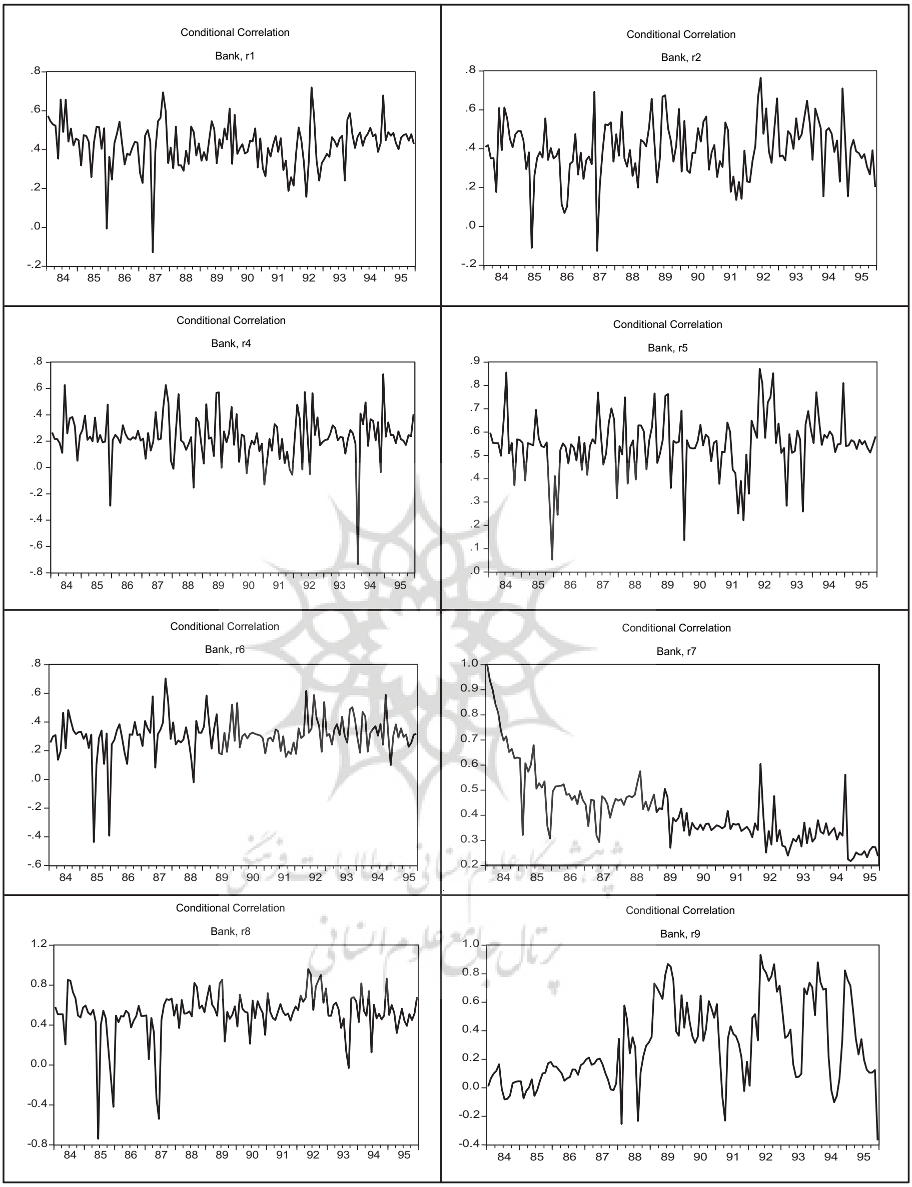

Figure 1. Dynamic conditional correlation among industries. *Source*: Research Findings.

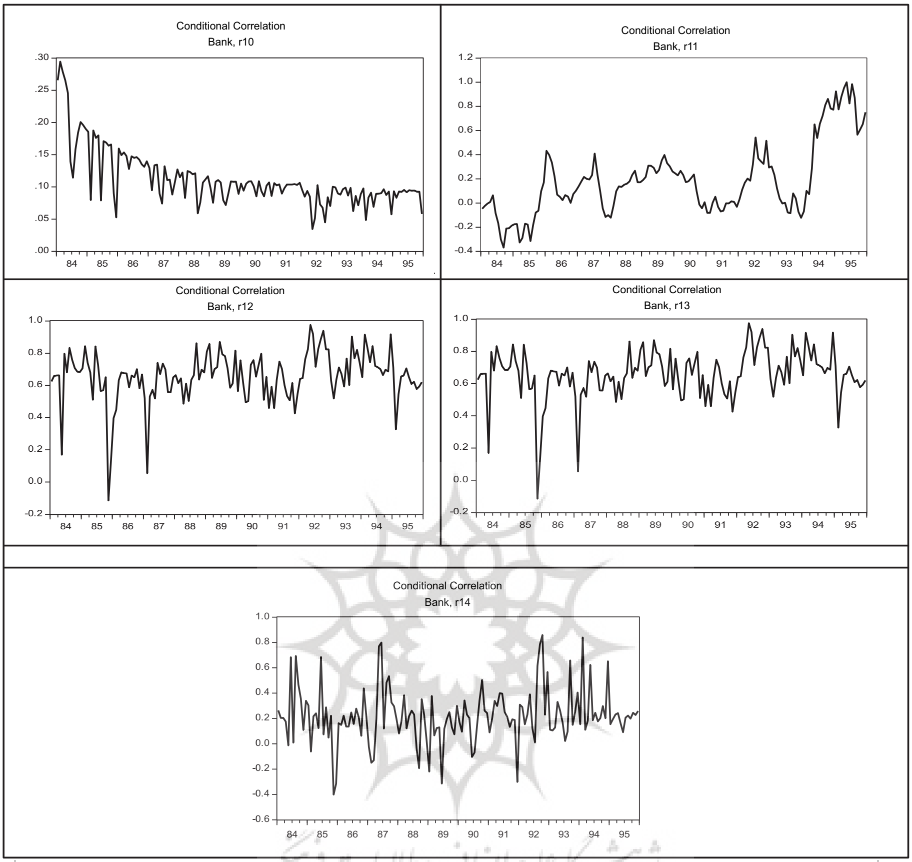

Figure 1. (continued) Dynamic conditional correlation among industries. *Source*: Research Findings.

In the next step, by using the VARMA model, an analysis of the spillover between industries is performed. The results of the three models used for the analysis of the relationships are presented in Table 7. The results of the estimation indicate that due to the significance of the coefficients in the mean equations, there is an opposite direction volatility spillover between basic metals and communication devices industries with the banking industry index. It is also asymmetrically opposed to the chemical industry, extraction of metal ores, pharmaceuticals, communication devices and power supply, gas & steam.

Table 7
Volatility Spillover among Industries

MV-GARCH, CC with Spillover Variances - Estimation by BFGS				
Variable	**coefficient**	**Std. Error**	**t-statistics**	**Signif**
Banking	0.742502	0.001554	477.6438	0.00000
r (1)	0.871311	0.002775	313.9764	0.00000
	coefficient	Std. Error	t-statistics	Signif
Banking	0.9961872	0.4883812	2.03977	0.041372
r (2)	1.618747	0.5976370	2.70858	0.0067572
	coefficient	Std. Error	t-statistics	Signif
Banking	0.361051	0.689409	0.52371	0.006004
r (4)	1.380149	0.600848	2.29700	0.021618
	coefficient	Std. Error	t-statistics	Signif
Banking	2.139027	0.015369	139.16946	0.000000
r (5)	2.1041516	0.0713796	29.47831	0.000000
	coefficient	Std. Error	t-statistics	Signif
Banking	0.741803	0.028174	26.3285	0.000000
r (6)	1.978581	0.021795	90.77824	0.000000
	coefficient	Std. Error	t-statistics	Signif
Banking	0.630615	0.438752	1.43729	0.006354
r (9)	0.006788	0.000137	49.49834	0.000000
	coefficient	Std. Error	t-statistics	Signif
Banking	1.118373	0.003745	298.568	0.000000
r (10)	-1.301738	-0.009404	138.416	0.000000
	coefficient	Std. Error	t-statistics	Signif
Banking	0.624667	0.600898	1.03956	0.029854
r (11)	-0.005714	-0.00066	8.58715	0.000000
	coefficient	Std. Error	t-statistics	Signif
Banking	-0.074668	- 0.00061	121.3051	0.00000
r (12)	-0.765711	0.068356	-11.20169	0.000000
	coefficient	Std. Error	t-statistics	Signif
Banking	0.861137	0.002973	289.5964	0.000000
r (13)	3.618639	0.039923	90.6402	0.000000
	coefficient	Std. Error	t-statistics	Signif
Banking	0.412657	0.0134832	30.60544	0.000000
r (14)	-1.52166	-0.064618	23.54832	0.000000

Source: Authors' estimations.

Table 7 also shows that the volatility spillover between banking industry and the chemical industry, basic metals, industrial multidisciplinary, extraction of metal ores, pharmaceuticals, communications, investments, computer and transportation & warehousing. This is despite the fact that the volatility spillover is not confirmed for oil products, automobiles and parts, telecommunications and power supply, gas & steam.

5 Conclusion

The selected models have convergence in the estimation of parameters, which creates a stable technique in the measurement of spillover. In response to the main question of the research, it can be argued that there are symmetric spillovers between the "Banking" industry and industries of "Basic Metals", "Industrial Multi-disciplinary", "Investments", "Computers", and "Transportation and Warehousing". There are also asymmetric spillovers between the "Banking" industry and the Industries of “Chemical”, "Extraction of Metal Ores," "Pharmaceuticals," and "Communications Devices".

In the following, using the conditional correlations calculated in the previous section, the answer to the research question on the degree of volatility spillover in the selected industries is explained as follows:

- Level 1 Priority: The largest spillover is among “Banking” and “Investments” industries.
- Level 2 Priority: volatility spillover among “Banking” and “Pharmaceutical” Industries.
- Level 3 Priority: The volatility spillover among the "Banking" and "Transportation & Warehousing" and then "Computer" and "Industrial Multi-discipline" Industries.
- Level 4 Priority: volatility spillover among "Banking" with the industries of "Communication Devices" and "Basic Metals", respectively.
- Level 5 Priority: volatility spillover among "Banking" with the "Chemical" and "Extraction of Metal Ores" industries.

The other finding of this study is the confirmation of the asymmetric phenomenon of volatility between the banking industry and the chemical, petroleum products, extraction of metal ores, pharmaceuticals, communication devices, power supply & steam, and transportation & warehousing industries. Thus, like the findings of some researchers (Nelson and Foster, 1994), volatility spillover is asymmetric for bad news, so that the impact of bad news on spillover is more than good news.

Table 8
Summary Volatility Spillover among Industries

Industry	**direction**	**type**	**spillover**
Chemical	Same	Asymmetric	accepted
basic metals	Opposition		accepted
Oil products	Same	VARMA-A	rejected
multidisciplinary industry	Same		accepted
Extraction of metal ores	Same	Asymmetric	accepted
Telecommunications	Same		rejected
communication devices	Opposition	Asymmetric	accepted
Power supply, gas & steam	Same	Asymmetric	rejected
Investments	Same		accepted
Computer	Same		accepted
Transportation & warehousing	Same	VARMA-A	accepted

Source: Research Findings.

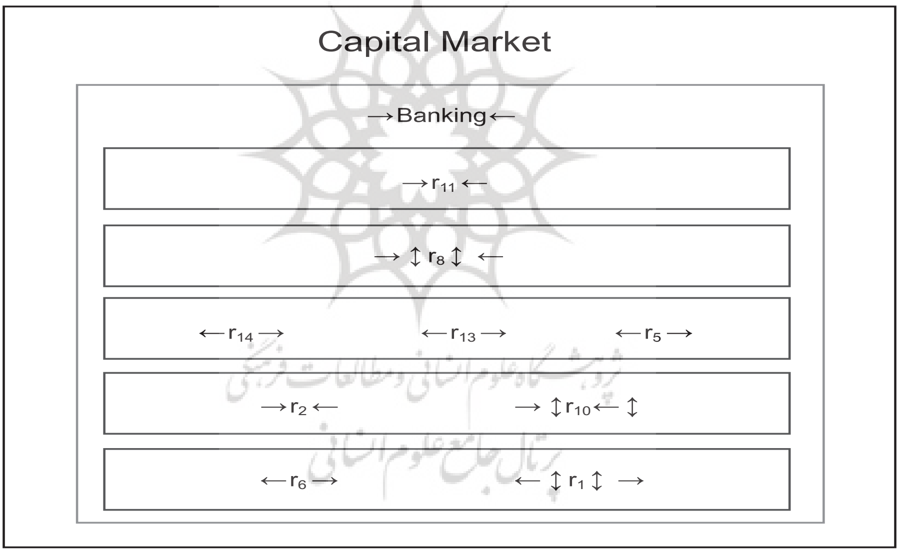

Figure 2. Conceptual summarization of volatility spillover among industries. Description: Horizontal arrows represent same or opposite spillover. Vertical arrows represent an asymmetric spillover. *Source*: Research Findings.

In addition, the leverage effect is confirmed in each industry. This means that a significant decline in the stock price of an industry is indicative of a significant increase in its market volatility. Therefore, according to Christie (1982), the decline in stock prices (negative returns) has led to an increase in the leverage effect on the capital structure of the company (the reduction of equity ownership while the debt is constant), and this leads to a more risky stock in the industry and thus increase the fluctuation in the industry's market return. Therefore, the conceptual model of the volatility spillover of banking and other systemic important industries in the capital market is presented in Figure 2.

This research also intends to model the concept of volatility spillover and its impacts on the economy in terms of systemic importance in the capital market, in order to provide a basis for the scientific increase of financial resilience and the implementation of the resistance economy dimensions.

The results are important for financial analysts and investment institutions since one of the most important components of the fundamental analysis is to examine the impact of volatility and the risk management among the industries. Also, the results of this study can be used by the capital market regulators (in order to create financial stability policies and issue permits for various types of finance) to analyze and predict possible scenarios for the relationships among sectors.

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