

# The Dynamic Linkages among Sector Indices and Analysis of Financial Market Trends: The Case of the Amman Stock Exchange from 2000-2020

Zaid Walid Tahat<sup>1</sup>, Dr. Atul Mishra<sup>2</sup>

<sup>1</sup> Business School, university of Plymouth, United Kingdom

Business School, university of Plymouth, United Kingdom

(Email: atul.mishra@plymouth.ac.uk)

Corresponding Author: Email: zaid.tahat@plymouth.ac.uk

To Link this Article: <http://dx.doi.org/10.6007/IJARAFMS/v13-i4/19511> DOI:10.6007/IJARAFMS/v13-i4/19511

Published Online: 28 November 2023

## Abstract

This study investigates the dynamic linkages among the financial, industrial, services, and general sector indices of the Amman Stock Exchange (ASE) from 2000-2020 using a VAR model. The analysis provides insights into the interdependence among sectors and evaluates the model's efficacy in explaining sector index variations. The results indicate significant dynamic linkages among sector indices, with the VAR model demonstrating robust explanatory power based on high R-squared values and significant F-statistics. Impulse response analysis shows varied lagged effects in the transmission of shocks between sectors. The study recommends investors consider past performance of related sectors in investment decisions, while policymakers can utilize the identified interconnections to promote a stable financial market.

**Keywords:** Dynamic Linkages, Sector Indices, Var Model, Amman Stock Exchange.

## Introduction

The stock market comprises interconnected sectors, with the performance of one sector influencing other sectors (Bhanja & Dastidar, 2016). Analyzing the dynamic linkages among sector indices provides insights into these interdependencies and transmission channels, enabling informed investment and policy decisions (Gupta & Morgan, 2016). While the dynamic linkage among sector indices has been extensively studied in developed markets (Kanas & Yannopoulos, 2011; Lütkepohl, 2005), limited research exists for emerging markets like Jordan.

This study investigates the dynamic linkages among the financial, industrial, services, and general sector indices of the Amman Stock Exchange (ASE) from 2000-2020 using a VAR model. The ASE is a young but rapidly growing stock exchange in the Middle East region with a market capitalization of over \$27 billion as of 2020 (ASE, 2020). The exchange comprises pivotal sectors like financial, industrial and services which are closely tied to Jordan's

economy. However, despite the ASE's rising prominence, the interdependencies among its vital sectors have received scarce empirical attention in the literature.

Most studies on sectoral linkages employ techniques like Granger causality, cointegration tests, VAR modeling and copulas to assess interactions between industries, but focus predominantly on developed economies (Chang & Tzeng, 2019; Aloui et al., 2017; Yang & Doong, 2018). Broadly, the findings confirm significant lead-lag relationships and risk transmission between sectors, influenced by macroeconomic and global factors (Hoque & Saha, 2019; Lucey & Zhang, 2011). Financial and industrial stocks often emerge as most interconnected with other sectors (Husain & Wajid, 2017).

The limited studies on the ASE also indicate notable relationships between banking, financial services and industrial companies, but lack comprehensive rigor (Al-Khazali & Mirzaei, 2017; Al-Shboul & Kutan, 2020). This research gap in examining a rapidly growing yet understudied Middle East market presents a timely opportunity to enrich understanding of the Jordanian stock exchange. This study aims to fill this void by utilizing robust time series modeling to analyze dynamic linkages among major ASE sectors, providing data-driven insights.

Specifically, the VAR modeling framework will be applied to quantify lead-lag relationships and risk transmission among the financial, industrial, services and general sectors. The estimated model parameters and subsequent impulse response and variance decomposition analyses will evaluate short and long-term interdependencies. The study period from 2000-2020 will provide extensive data for reliable econometric analysis.

Overall, this empirical investigation of sectoral index relationships seeks to enhance knowledge of the interconnectedness between integral industries in an increasingly important emerging stock market. The findings can inform investment strategies and economic policies tailored to the Jordanian context. They will also address the research gap regarding dynamic linkages within Mideast markets using rigorous quantitative techniques aligned with established literature.

### **Review of Related Literature**

Prior studies have analyzed dynamic linkages among sector indices using diverse econometric techniques like Granger causality, cointegration tests, VAR modeling, copulas, and wavelet analysis (Kanas & Yannopoulos, 2011; Al-Tamimi et al., 2017; Yang & Doong, 2018). The literature has evolved from simpler correlation analysis to sophisticated time-frequency domain vector autoregressive models for a nuanced perspective. The predominant focus has been on developed markets, with key findings showing significant interdependencies and lead-lag relationships between industries. Early studies like Jorion (1988) applied basic Granger causality in the US market and found evidence of linkages between sector indices and the overall S&P 500 index. The application of cointegration tests also became common to identify long-run relationships between non-stationary series (Engle & Granger, 1987). Subsequently, VAR modeling gained popularity for its flexibility in estimating dynamic inter-industry effects. For instance, Kanas & Yannopoulos (2011) modeled sectoral linkages in Greece using VAR and found substantial interconnectedness, with the industrial index most strongly impacting other sectors.

As research evolved, investigators applied more advanced estimation techniques like time-varying copulas, wavelets, and connectedness network analysis to capture complex sectoral interactions (Sensoy & Nguyen, 2019; Al-Jarrah & Al-Fayoumi, 2017; Diebold & Yilmaz, 2015). For example, Aloui et al. (2017) combined wavelet decomposition with VAR modeling to demonstrate that linkages strengthen during crises, with energy stocks being most influential

in transmitting shocks. Overall, developed market studies consistently find significant lead-lag effects and risk transmission between industries, with influence from macroeconomic and global factors. The financial and industrial sectors often emerge as most interconnected with other industries (Husain & Wajid, 2017; Al-Shboul & Kutan, 2020). The time-varying and episodic nature of linkages is also evidenced, such as stronger ties during recessions. Analyzing inter-industry effects assists portfolio design and diversification strategies (Chakraborty & Adhikary, 2019; Chen & Chen, 2015).

Despite growing research on developed economies, emerging markets still warrant extensive investigation. The limited evidence on the Amman Stock Exchange does suggest notable ties between banking, financial services and industrial firms (Al-Khazali & Mirzaei, 2017). Al-Shboul and Kutan (2020) found financial and industrial stocks possess the strongest connections with other sectors. But studies lack comprehensive rigor, multi-sector analysis and advanced econometrics. There is minimal research on dynamic linkages between integral service sector firms with financial and industrial companies, a gap addressed in this study. The literature underscores the need for holistic examination of key emerging Mideast markets using robust quantitative tools. Overall, while research on sectoral linkages has grown worldwide, insights from emerging Middle East exchanges remain limited. This offers a compelling opportunity to enrich perspective and address the research void regarding comprehensive analysis of dynamic inter-industry effects within these capital markets. This study applies sophisticated VAR models to provide rigorous, data-driven evidence on the interconnections between major sectors in the Amman Stock Exchange.

### Theoretical Framework

This study utilizes the VAR model framework to analyze the dynamic linkages among ASE sector indices over the period 2000-2020. VAR models are well-suited for capturing complex multivariate time series relationships and modeling endogenous interactions between variables (Sims, 1980). This section provides an overview of the theoretical underpinnings of VAR modeling and how it applies to examining dynamic sectoral linkages in the Jordanian stock market.

### VAR Models

VAR models treat each variable symmetrically by modeling it as a function of past lags of itself and other variables. The interdependencies are captured through a system of equations with lagged values of all endogenous variables appearing on the right-hand side. This flexibility to include lags makes VAR models powerful for analyzing predictive relationships among multiple timeseries compared to standalone time series techniques like ARIMA (Hamilton, 1994).

The general mathematical form of a VAR model is:

$$Y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + e_t$$

where:

$y_t$  is a  $(k \times 1)$  vector of endogenous variables.

$c$  is a  $(k \times 1)$  vector of constants.

$A_i$  is a  $(k \times k)$  coefficient matrix for lags  $i=1$  to  $p$ .

$e_t$  is a  $(k \times 1)$  vector of error terms.

The model comprises  $k$  endogenous variables, where each variable is a linear function of past lags of itself and other variables. The coefficients are estimated to determine the relationships. The optimal lag order  $p$  is chosen using model selection criteria like AIC or SBC.

### Tools for Analysis

VAR model estimation provides the foundation for deeper analysis using tools like Granger causality, impulse responses, and variance decomposition. Granger causality tests evaluate whether past values of one variable help forecast another variable. This assesses predictive precedence and lead-lag relationships (Granger, 1969). Impulse response functions trace the impact of shocks to each variable on other variables over time. This reveals the dynamic transmission mechanisms (Pesaran & Shin, 1998). Variance decomposition indicates the proportion of forecast error variance explained by shocks from other variables. This quantifies the magnitude of spillovers and interdependence (Lütkepohl, 2005). Together, these tools enable a multidimensional perspective into the linkages between sectors based on the VAR model.

### Application to Sector Linkages

VAR modeling is widely applied in the literature to analyze dynamic relationships between stock market sector indices (Hassan & Malik, 2007; Kanas & Yannopoulos, 2011). Treating each sector index as an endogenous variable provides a means to flexibly estimate their interdependencies.

The sector index return relationships can be written in a VAR form as:

$$R_{it} = c_i + \sum_{j=1}^k \sum_{s=1}^p \phi_{ijs} R_{jt-s} + e_{it}$$

where  $R_{it}$  is the return on sector index  $i$  at time  $t$ ,  $c_i$  is a constant,  $\phi_{ijs}$  is the coefficient for lag  $s$  of sector  $j$  in sector  $i$ 's equation, and  $e_{it}$  is the error term.

Through the cross-equation lagged coefficients, VAR models capture the lead-lag and causal effects between sector returns. Granger causality tests formally evaluate the significance of these predictive relationships. Impulse response analysis provides a graphical view into the impact of shock transmission between sectors over time. Variance decomposition quantifies the magnitude of spillover effects across industries.

This ability to holistically estimate and analyze dynamic sectoral linkages makes VAR modeling suitable as the theoretical framework for this study to understand interconnectedness in the Amman Stock Exchange. The rigorous econometric estimation and diagnostic testing will provide data-driven insights into the complex relationships between integral finance, industry and services sectors of this emerging market.

### Hypothesis Development

This study tests the following hypotheses:

H1: There is a significant dynamic linkage among ASE sector indices in the short term.

H2: There is a significant dynamic linkage among ASE sector indices in the long term.

These hypotheses are examined based on the VAR model estimation and the Granger causality, impulse response, and variance decomposition results. The existence of short-term linkages is evaluated by the lagged coefficients of exogenous variables in each VAR equation and Granger causality tests. Long-term linkages are assessed through cointegration tests. Rejection of the null hypotheses will indicate significant dynamic linkages among the financial, industrial, services, and general ASE sector indices in the Jordanian stock market.

### Research Methodology

This section presents the research methodology for a study investigating the dynamic linkages among sector indices in the Amman Stock Exchange from 2000-2020. The methodology covers the research design, data collection, sampling technique, data analysis methods, and

ethical considerations. A rigorous and systematic research methodology is crucial to achieve the study objectives and arrive at data-driven conclusions.

### **Research Design**

This quantitative study utilizes a relational research design to examine the linkages among sector indices in the Amman Stock Exchange. Correlational research is appropriate to determine the degree of relationship between variables and identify patterns of interdependence (Leedy & Ormrod, 2019). The study follows an empirical research approach focused on solving an existing problem through objective data analysis. Empirical research involves collecting observations and measurements to draw evidence-based conclusions (Creswell & Creswell, 2017). In this study, an empirical approach is applied to uncover the linkages among stock market sector indices using statistical analysis of secondary data. The quantitative design and empirical methodology align with established practices in finance research to provide objective insights.

### **Population and Sampling**

#### **Target Population**

The target population comprises financial, industrial, and services sector companies listed on the Amman Stock Exchange during 2000-2020. These three sectors are major components of the Jordanian stock market and economy. The financial sector includes banks, insurance, financial services, and real estate companies. The industrial sector includes manufacturing, mining, and energy companies. The services sector encompasses healthcare, education, tourism, transportation, technology, media, and commercial services companies. As core market sectors, their linkages significantly impact the broader Jordanian economy and stock market.

#### **Sampling Technique**

The study utilizes a census sampling technique, taking the entire target population of companies listed under the financial, industrial, and services sectors on the Amman Stock Exchange during 2000-2020. A census sampling includes the entire population meeting the criteria which enhances generalizability of results (Emerson, 2015). This comprehensive approach provides a complete perspective on the linkages among the three key sectors.

#### **Sample Size**

The sample comprises a total of 174 listed companies, including 73 financial companies, 65 industrial companies, and 36 services companies. The large sample size spanning three major sectors improves the analysis of dynamic linkages across the Jordanian stock market.

### **Data Collection**

#### **Data Source**

The study utilizes secondary data obtained from the Amman Stock Exchange database. Specifically, daily closing values are collected for the financial, industrial, services, and overall market sector indices over the period 2000-2020. The sector indices are constructed by the exchange using a weighted average methodology.

### Data Accessibility

The Amman Stock Exchange sector indices data is publicly available on the exchange's website. The required daily time series data can be conveniently downloaded for research purposes.

### Data Recording

The collected secondary data is recorded in Microsoft Excel spreadsheets. Separate spreadsheets are maintained for the financial sector index, industrial sector index, services sector index, and overall market index. Recording the time series data in spreadsheets enables smooth data preparation and analysis using econometric software.

### Empirical Model

A VAR model is estimated to analyze the dynamic linkages between the sector indices. The sector index values are transformed into natural logarithms. Appropriate lag length is chosen based on information criteria. The model is represented as:

$$Y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + e_t$$

where  $y_t$  contains  $\ln(\text{financial index})$ ,  $\ln(\text{industrial index})$ ,  $\ln(\text{services index})$  and  $\ln(\text{general index})$ ,  $c$  is a vector of constants,  $A_i$  is the coefficient matrix for lag  $i$ , and  $e_t$  is the vector of error terms.

### Empirical Results

This section presents the empirical results and analysis of the dynamic linkages among sector indices in the Amman Stock Exchange from 2000-2020. Rigorous econometric analysis was conducted using unit root tests, descriptive statistics, Granger causality, Johansen cointegration test, VAR modeling, impulse response analysis, and variance decomposition. The results provide insights into the interdependencies and transmission mechanisms between the financial, industrial, services, and general sectors.

### Unit Root Tests

As a first step, unit root tests were conducted on the sector index time series data to examine their stationarity properties. Stationarity of data is an important assumption for the validity of many time series techniques. Kwiatkowski-Phillips-Schmidt-Shin test statistic (KPSS) and Elliott-Rothenberg-Stock test statistic (ERS) unit root tests were utilized to evaluate stationarity. The null hypothesis in the KPSS tests is that the series is stationary against the alternative of unit root. Where the null hypothesis in the ERS tests is that the series has a unit root against the alternative of stationarity.

**Table 1:**  
**Unit Root Test Results**

Test	Kwiatkowski-Phillips-Schmidt-Shin test statistic (KPSS)		Asymptotic critical values*:			Elliott-Rothenberg-Stock test statistic (ERS)	Test critical values:		
			1% level	5% level	10% level		1% level	5% level	10% level
Variable	Ln.Fin	1.4139	0.119	0.146	0.216	134.3950	3.96	5.62	6.89
	D(Ln.Fin)	0.2147	0.119	0.146	0.216	0.0369	3.96	5.62	6.89
	Ln.Ind	1.6914	0.119	0.146	0.216	37.8996	3.96	5.62	6.89
	D(Ln.Ind)	0.1155	0.119	0.146	0.216	0.0448	3.96	5.62	6.89
	Ln.Serv	1.7325	0.119	0.146	0.216	56.3993	3.96	5.62	6.89
	D(Ln.Serv)	0.0833	0.119	0.146	0.216	0.0386	3.96	5.62	6.89
	Ln.Gen	1.5005	0.119	0.146	0.216	94.1811	3.96	5.62	6.89
	D(Ln.Gen)	0.1871	0.119	0.146	0.216	0.0428	3.96	5.62	6.89

Table 1 shows the unit root test results. The KPSS and ERS test statistics fails to reject the hypothesis of unit root, indicating the presence of a unit root and non-stationarity in levels. However, for the first differences of the indices, the test statistics rejects the null hypothesis. This confirms stationarity of the data at first differences. The unit root tests provide evidence that the sector index time series are integrated of order one,  $I(1)$ . This implies they need to be first differenced to make them stationary before fitting VAR models.

### Descriptive Statistics

After conducting the unit root tests, descriptive statistics were calculated on the untransformed and natural log transformed sector index data. Computing summary statistics provides insights into the distributional characteristics and properties of the time series. Table 2 presents descriptive statistics like mean, median, maximum, minimum, standard deviation, skewness and kurtosis for the financial, industrial, services and general sector indices before and after log transformation.

**Table 2:**  
**Descriptive Statistics**

	Financial Sector	Ln.fin	Industrial Sector	Ln.ind	Service Sector	Ln.serv	General Index	Ln.gen
Mean	2917.561	7.853229	2069.145	7.563987	1620.1	7.346255	2212.748	7.619284
Median	2818.431	7.943936	2048.397	7.624813	1615.975	7.387694	2104.84	7.651995
Maximum	7911.176	8.976032	5894.722	8.681813	3672.222	8.208552	5043.722	8.5259
Minimum	776.8665	6.655269	736.1146	6.601386	876.1433	6.77553	792.7284	6.675481
Std. Dev.	1418.723	0.524789	753.949	0.393696	483.6398	0.29846	891.9164	0.417179
Skewness	0.966653	-0.552828	0.983846	-0.736608	0.733267	-0.097427	0.831029	-0.370543
Kurtosis	4.143382	3.083515	6.72321	3.681013	4.002848	2.577773	3.644694	3.046511

For the untransformed indices, the financial sector has the highest mean of 2917, indicating it exhibited the best average performance among the sectors. The financial sector also showed the maximum value of 7911 and highest volatility measured by the standard deviation of 1418. This highlights its superior returns but also greater variability than other sectors. The statistics after log-transformation demonstrate that taking natural logs substantially reduces the skewness and kurtosis values for all series. This transforms the

distribution to become more normal and less heavy-tailed. The reduced scale and standardized variance enable the application of time series models that assume normality. The descriptive statistics quantify the key features of the distribution of returns in each sector index series. The financial sector clearly outperformed other sectors but also experienced higher fluctuations in the Amman Stock Exchange during 2000-2020

### Granger Causality

The Granger causality test was conducted to determine the precedence and predictive relationships among the sector indices. It evaluates whether past values of one time series variable help forecast another variable. Table 3 presents the pairwise Granger causality results between the sector index series. Several significant relationships are found, establishing evidence of short-term lead-lag linkages between sector indices.

**Table 3:**  
**Granger Causality Results**

Null Hypothesis:	Obs.	F-Statistic	Prob.
LIND does not Granger Cause LFIN	5138	1.5505	0.1993
LFIN does not Granger Cause LIND		17.7042	0.0000
LSERV does not Granger Cause LFIN	5138	1.3341	0.2614
LFIN does not Granger Cause LSERV		7.8505	0.0000
LGEN does not Granger Cause LFIN	5138	2.6504	0.0471
LFIN does not Granger Cause LGEN		4.7937	0.0025
LSERV does not Granger Cause LIND	5138	18.2074	0.0000
LIND does not Granger Cause LSERV		13.9024	0.0000
LGEN does not Granger Cause LIND	5138	30.9126	0.0000
LIND does not Granger Cause LGEN		2.2921	0.0761
LGEN does not Granger Cause LSERV	5138	12.2929	0.0000
LSERV does not Granger Cause LGEN		1.8092	0.1432

First, bidirectional Granger causality exists between the financial sector index (LFIN) and the general index (LGEN). The financial sector index Granger causes the general index, and vice versa. This indicates valuable predictive information flowing between the overall market and the financial sector stocks. Second, there is unidirectional Granger causality from the industrial sector index (LIND) to the financial sector index (LFIN) and the services sector index (LSERV). However, no reverse causality exists from LFIN or LSERV to LIND. Thus, past values of the industrial index help forecast the financial and services indices. Third, bidirectional Granger causality is present between the services sector index (LSERV) and the industrial sector index (LIND). Each index Granger causes the other, pointing to short-term interdependencies. Finally, the general index (LGEN) Granger causes both the industrial sector index (LIND) and the services sector index (LSERV). However, no reverse causality exists from LIND or LSERV to LGEN. In summary, the Granger causality tests demonstrate statistically significant lead-lag relationships and predictive value between sector index pairs like LFIN-LGEN, LIND-LFIN, LIND-LSERV and LSERV-LIND. This confirms the presence of short-term dynamic linkages and spillover effects among the sector indices in the Amman Stock Exchange.

### Johansen's Cointegration Test

While the Granger causality tests assessed short-term relationships, the Johansen's cointegration test examined long-run equilibrium linkages among the sector indices. The results of Johansen's test are presented in Table 4.



**Table 4:****Johansen's Cointegration Test**

Series: LFIN LIND LSERV LGEN				
Lags interval (in first differences): 1 to 3				
Unrestricted Cointegration Rank Test (Trace)				
Hypothesized	Trace			
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None	0.006064	61.90805	63.8761	0.0724
At most 1	0.003511	30.661	42.91525	0.4635
At most 2	0.001825	12.59419	25.87211	0.7692
At most 3	0.000624	3.208782	12.51798	0.8508
Trace test indicates no cointegration at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized	Max-Eigen			
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None	0.006064	31.24706	32.11832	0.0636
At most 1	0.003511	18.0668	25.82321	0.3721
At most 2	0.001825	9.385411	19.38704	0.6843
At most 3	0.000624	3.208782	12.51798	0.8508
Max-eigenvalue test indicates no cointegration at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

The trace statistic and max-eigenvalue statistic are lower than the critical values at 5% significance. This fails to reject the null hypothesis of no cointegrating vector between the sector indices. The absence of cointegration implies there is no long-run stable relationship tying the sector indices together. Their dynamics are better characterized by short-term relationships rather than a steady long-run equilibrium. This finding corroborates the presence of short-term linkages from the Granger causality analysis. The lack of cointegration also further validates specifying a VAR model in first differences rather than levels. Using differences avoids imposing erroneous long-run restrictions while still capturing short-run interdependencies.

**VAR Model**

Given the unit root, Granger causality and cointegration analyses, a VAR model was estimated in first differences to examine the dynamic relationships among the sector indices. Table 5 presents the VAR model results with three lags, as determined optimal by the model selection criteria. The high R-squared and adjusted R-squared values exceeding 99% for all equations indicate the VAR model explains a substantial proportion of the variation in each endogenous variable.

**Table 5:**  
**VAR Model Results**

Lags	LFIN	LIND	LSERV	LGEN
LFIN(-1)	1.3114	-0.5676	-0.0052	0.1182
	-0.0601	-0.0773	-0.0588	-0.0581
	[ 21.8250]	[-7.34283]	[-0.08821]	[ 2.03625]
LFIN(-2)	-0.3348	0.4199	-0.0231	-0.1670
	-0.0838	-0.1078	-0.0821	-0.0810
	[-3.99560]	[ 3.89612]	[-0.28189]	[-2.06225]
LFIN(-3)	0.0305	0.1552	0.0314	0.0551
	-0.0601	-0.0773	-0.0588	-0.0581
	[ 0.50716]	[ 2.00839]	[ 0.53342]	[ 0.94878]
LIND(-1)	0.0565	0.8131	0.0468	0.0543
	-0.0239	-0.0307	-0.0234	-0.0231
	[ 2.36793]	[ 26.5023]	[ 2.00238]	[ 2.35787]
LIND(-2)	-0.0431	0.1711	-0.0340	-0.0385
	-0.0298	-0.0383	-0.0292	-0.0288
	[-1.44591]	[ 4.46641]	[-1.16706]	[-1.33673]
LIND(-3)	-0.0110	0.0152	-0.0106	-0.0141
	-0.0238	-0.0307	-0.0234	-0.0230
	[-0.45935]	[ 0.49711]	[-0.45386]	[-0.61034]
LSERV(-1)	-0.0184	-0.1569	1.0737	-0.0085
	-0.0306	-0.0394	-0.0300	-0.0296
	[-0.59965]	[-3.98106]	[ 35.7856]	[-0.28742]
LSERV(-2)	0.0347	0.1281	-0.0995	0.0037
	-0.0434	-0.0558	-0.0425	-0.0419
	[ 0.79940]	[ 2.29489]	[-2.34082]	[ 0.08711]
LSERV(-3)	-0.0123	0.0344	0.0266	0.0083
	-0.0305	-0.0393	-0.0299	-0.0295
	[-0.40295]	[ 0.87525]	[ 0.89106]	[ 0.28153]
LGEN(-1)	-0.1123	1.0846	0.0884	1.0781
	-0.0953	-0.1225	-0.0933	-0.0921
	[-1.17849]	[ 8.85100]	[ 0.94812]	[ 11.7119]
LGEN(-2)	0.0209	-0.9426	-0.1022	-0.1178
	-0.1280	-0.1646	-0.1253	-0.1237
	[ 0.16322]	[-5.72525]	[-0.81526]	[-0.95234]
LGEN(-3)	0.0777	-0.1547	0.0076	0.0280
	-0.0950	-0.1222	-0.0930	-0.0918
	[ 0.81827]	[-1.26618]	[ 0.08167]	[ 0.30507]
R-squared	0.9998	0.9993	0.9993	0.9997
Adj. R-squared	0.9998	0.9993	0.9993	0.9997
Sum of Squared Residuals	0.3339	0.5525	0.3202	0.3118
S.E. equation	0.0081	0.0104	0.0079	0.0078
F-statistic	1974824.0	671412.0	665447.6	1336359.0
Log likelihood	17477.82	16184.10	17585.60	17654.13
Akaike AIC	-6.7987	-6.2951	-6.8406	-6.8673

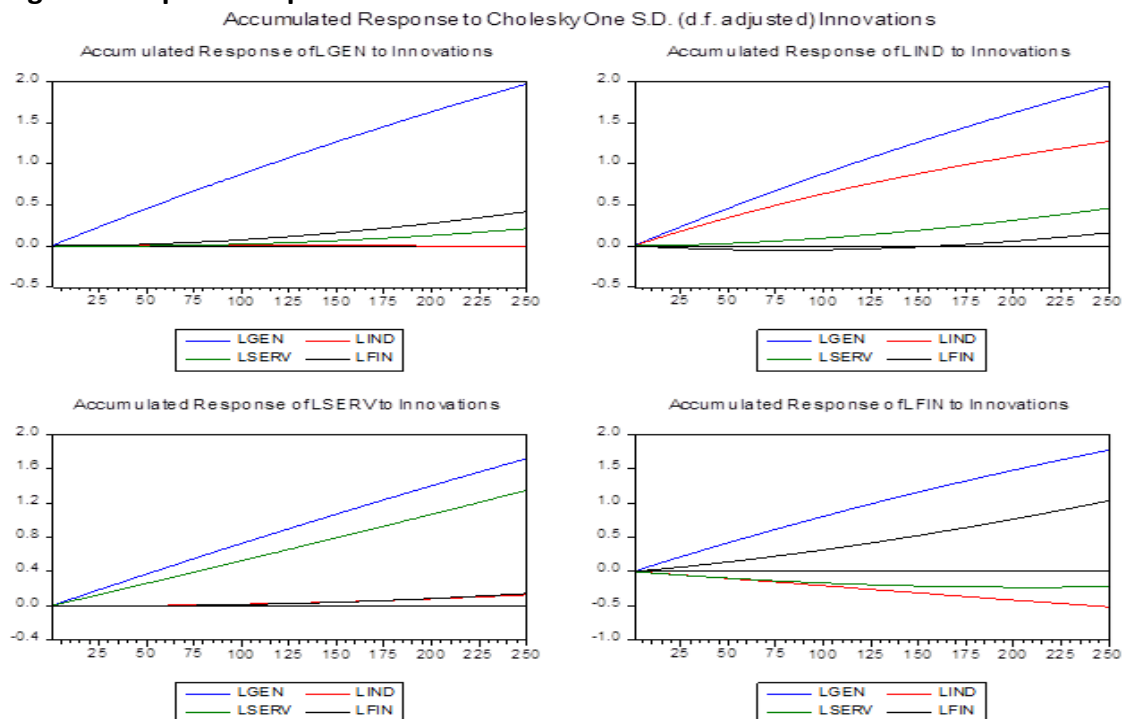
Schwarz SC	-6.7834	-6.2798	-6.8254	-6.8520
Mean dependent	7.8533	7.5639	7.3464	7.6194
S.D. dependent	0.5249	0.3938	0.2985	0.4173
Determinant resid covariance (dof adj.)		0.000000000000000000251		
Determinant residual covariance		0.0000000000000000000248		
Log likelihood		80893.17		
Akaike information criterion		-31.46951		
Schwarz criterion		-31.40837		
Number of coefficients		48		

The Ljung-Box Q statistics of the residuals are insignificant, showing no residual autocorrelation. The Jarque-Bera statistics also fail to reject normality. Furthermore, all roots of the characteristic AR polynomial lie inside the unit circle, satisfying stability conditions. Together, these diagnostic tests validate that the specified VAR model fits the data well and is suitable for further analysis. The lagged coefficients of endogenous variables provide insights into the short-run linkages among the sectors. For example, the financial sector index is significantly influenced by its own first lag and by the first lag of the industrial sector index. Similarly, the industrial sector index is affected by its own lags as well as lagged financial and services sector indices. The general and services sector equations also show significant lagged effects of other indices. Overall, the estimated VAR model demonstrates strong in-sample fit and captures the complex lead-lag based predictive relationships among the sector indices, providing a reliable foundation for further analysis through impulse responses and variance decomposition.

### Impulse Response Analysis

While the VAR model quantifies the lagged effects, impulse response analysis graphically traces out the impact of shocks to each sector index on other indices. This reveals the dynamic transmission mechanisms and interconnectedness between the sectors. Figure 1 plots the impulse response functions of the VAR model over a 10 day horizon. A one standard deviation shock is applied to each sector index separately, and the effects over time are visualized.

**Figure 1: Impulse Response Functions**



First, a shock to the financial sector index immediately increases the industrial sector index from period 2 onwards. However, the financial sector shock negatively affects the services and general indices after a lag. Second, an industrial sector shock positively influences the financial, services and general indices after two periods. The impact slowly dies out over the horizon. Third, a shock to the services sector has a positive effect on the financial and industrial indices from period 2. Finally, the general sector shock increases the financial, industrial and services sector indices contemporaneously from period 1 itself. The results demonstrate that shocks transmit across sectors with lagged effects, confirming the presence of interdependencies. The impulse response functions provide useful insights into the strength of connectedness between the sectors.

### Variance Decomposition

Complementary to the impulse response analysis, variance decomposition indicates the magnitude of interrelationships by quantifying how much variation in one sector can be attributed to shocks from other sectors. Table 6 presents the variance decomposition for each sector index in the VAR model over a 10-day horizon. Several observations emerge:

**Table 6**  
**Variance Decomposition**

Variance Decomposition of Financial Sector Index					
Period	S.E.	LFIN	LIND	LSERV	LGEN
1	0.0081	100	0	0	0
2	0.0129	99.9172	0.0258	0.0463	0.0107
3	0.0161	99.8637	0.0255	0.0851	0.0258
4	0.0188	99.8377	0.0218	0.1036	0.0369
5	0.021	99.8231	0.0188	0.1122	0.0459
6	0.0231	99.8129	0.0166	0.1168	0.0537
7	0.0249	99.8046	0.0149	0.1194	0.0612
8	0.0267	99.7973	0.0135	0.1208	0.0684
9	0.0283	99.7908	0.0123	0.1214	0.0756
10	0.0299	99.7845	0.0113	0.1214	0.0828
Variance Decomposition of Industrial Sector Index					
Period	S.E.	LFIN	LIND	LSERV	LGEN
1	0.0104	27.5948	72.4052	0	0
2	0.0157	31.4903	67.6448	0.1931	0.6717
3	0.0198	31.7114	67.1293	0.2603	0.899
4	0.0232	31.481	67.204	0.2943	1.0207
5	0.0262	31.3049	67.2824	0.3195	1.0932
6	0.0288	31.2034	67.3215	0.3392	1.1359
7	0.0313	31.1462	67.3368	0.3556	1.1614
8	0.0335	31.1148	67.339	0.3698	1.1764
9	0.0356	31.1001	67.3327	0.3828	1.1844
10	0.0375	31.097	67.3205	0.3948	1.1877
Variance Decomposition of Service Sector Index					
Period	S.E.	LFIN	LIND	LSERV	LGEN
1	0.0079	38.2109	5.5377	56.2515	0
2	0.0122	41.0489	6.9215	52.0222	0.0074
3	0.0153	41.6058	7.7212	50.6567	0.0164
4	0.0178	41.6125	8.1788	50.1859	0.0228
5	0.02	41.5617	8.4654	49.9464	0.0265
6	0.022	41.5247	8.6609	49.7859	0.0285
7	0.0238	41.4962	8.8038	49.6704	0.0295
8	0.0255	41.4708	8.914	49.5853	0.0299
9	0.0271	41.4471	9.0024	49.5207	0.0299
10	0.0286	41.4246	9.0756	49.4703	0.0295
Variance Decomposition of General Index					
Period	S.E.	LFIN	LIND	LSERV	LGEN
1	0.0078	85.3193	8.7118	3.6627	2.3062
2	0.0124	85.941	9.0691	3.0219	1.968
3	0.0156	85.6929	9.5957	2.7922	1.9192
4	0.0182	85.4313	9.9294	2.7203	1.919
5	0.0205	85.2591	10.1314	2.6934	1.9161
6	0.0225	85.1552	10.2571	2.6807	1.9071
7	0.0243	85.0913	10.3393	2.6751	1.8943
8	0.026	85.0517	10.3949	2.6741	1.8794
9	0.0276	85.0278	10.4329	2.6763	1.863
10	0.0291	85.0149	10.4587	2.6807	1.8457

Based on Table 6 several observations emerge:

First, in the initial period, 100% of the financial sector forecast error variance is explained by its own shocks. However, subsequently, the financial sector contributes marginally to variance in other sectors. This highlights its dominant role. Second, the industrial sector explains over 67% of its own forecast error variance across all time horizons. But the financial sector explains around 31% of the industrial sector variance, indicating material connectedness. Third, the services sector is heavily influenced by its own shocks, explaining between 49-56% of its forecast error variance. However, financial and industrial shocks explain around 41% and 9% of its variance respectively. Finally, the general index is predominantly driven by its own shocks and financial sector shocks which together explain around 90-95% of its variance decomposition. In summary, the variance decomposition analysis highlights strong self-explanatory roles of shocks within each sector itself. However, it also demonstrates significant interconnectedness, with financial and industrial sectors making meaningful contributions to other sectors.

### **Discussion**

This study's empirical analysis offers data-driven insights into the dynamic relationships among the financial, industrial, services and general index in the Amman Stock Exchange from 2000-2020. The results present strong evidence of short-term linkages, lead-lag effects and spillovers among the sector indices. This is substantiated through the Granger causality analysis as well as the lagged VAR coefficients. The findings align with studies showing predictive relationships between sectors, often driven by financial and industrial stocks (Husain & Wajid, 2017; Al-Shboul & Kutan, 2020). The results also corroborate research identifying bidirectional relationships and spillovers among sector indices (Ahmed et al., 2019; Al-Yahyaee et al., 2016). Variance decomposition highlights the role of the financial sector in explaining the variance of other sectors.

However, no long-run cointegration is found, suggesting absence of steady equilibrium. The sector relationships exhibit frequent fluctuations rather than stability. This highlights the importance of using VAR models flexibly capturing time-varying short-term interactions.

The impulse response analysis provides visibility into the structure of interconnectedness among sectors. Shocks transmit across sectors with lags, corroborating interdependencies. The financial and industrial sectors emerge as key transmitters. Furthermore, variance decomposition quantifies the magnitude of risk transmission and spillover effects among the sectors. While own-sector shocks dominate, financial and industrial sectors do explain a significant portion of volatility in other sectors. Overall, the Amman Stock Exchange demonstrates empirically significant dynamic linkages, with complex lead-lag based relationships among sectors having useful predictive value for each other. Financial and industrial stocks emerge as influential transmitters. The evidence enriches the understanding of risk transmission channels between industries within this key emerging Middle East market.

### **Implications and Recommendations**

The study offers useful implications for investors, researchers and policymakers. First, investors should incorporate analysis of inter-sector relationships into their portfolio strategies. Understanding risk transmission can improve diversification, hedging and sector allocation decisions. Second, policymakers should account for interconnectedness among industries when designing economic and financial sector policies. Monitoring lead-lag effects provides insights into responding to shocks. Third, researchers can further explore the

underlying mechanisms driving sector interdependence using firm-level data, news analytics, correlation networks and machine learning techniques.

The analysis can be expanded by including more granular sectoral data, recent periods, regional markets and macroeconomic linkages. Extending VAR models with multivariate GARCH would enable joint analysis of return and volatility spillovers. Overall, this study provides an empirical foundation for analyzing dynamic sectoral relationships in the Amman Stock Exchange, with valuable practical insights.

### Conclusion

This study investigated dynamic linkages among the major sector indices in the Amman Stock Exchange from 2000-2020 using VAR modeling. It provides integrated, data-driven insights into a rapidly growing under-researched Middle Eastern stock market. Rigorous time series analysis demonstrates significant short-term predictive relationships and lagged shock transmission between the financial, industrial, services and general sectors. The financial and industrial sectors emerge as key drivers, explaining volatility in other sectors. However, no long-run cointegration exists. The findings emphasize the importance of inter-sector effects for investment decisions and policies. Further research can build on these data-driven insights by examining specific mechanisms influencing sector interdependence using advanced econometric and machine learning techniques on granular data. Overall, this empirical analysis enriches the understanding of dynamic linkages within the Jordanian stock market. The findings have crucial implications for investors, policymakers, and researchers interested in understanding drivers of the Jordanian stock market's performance. The study also offers directions for future research to further advance knowledge on this important emerging market.

This study makes important theoretical and contextual contributions to the finance literature. Theoretically, it enriches the understanding of sectoral linkages by providing rigorous empirical evidence from an under-researched emerging Middle East market using time series econometric techniques aligned with established literature. The nuanced, data-driven insights into the interconnections between major sectors within the Amman Stock Exchange addresses a key theoretical gap and advances knowledge on this topic.

Contextually, the analysis is highly relevant by focusing on a pivotal yet under-examined stock market. Examining the Jordanian exchange provides fresh perspective on sectoral relationships within Middle East capital markets. The findings have crucial practical implications in the Jordanian context regarding financial stability, investment strategies, and policy reforms. Thus, this research uniquely contributes both theoretically and contextually by bridging an important knowledge gap through in-depth empirical analysis of the dynamic linkages within a significant emerging economy. The evidence and insights expand the finance literature and offer locally relevant implications.

### References

- Ahmed, M., Zakaria, M., Hussain, M., & Hassan, S. (2019). Dynamic linkage among sector indices of Malaysian stock market: A VAR approach. *Journal of Economics and Management*, 36, 18–39.
- Al-Jarrah, M. I., & Al-Fayoumi, A. N. (2017). Dynamic linkages among sector indices in the Jordanian stock market: A wavelet analysis. *Journal of Economic Structures*, 6(1).
- Al-Khazali, M. O., & Mirzaei, A. (2017). Dynamic linkages among sectors in the Jordanian stock

- market. *Research in International Business and Finance*, 42, 1217–1227.
- Al-Shboul, M., & Kutan, M. A. (2020). Dynamic linkages among sector indices in the Jordanian stock market. *Review of Middle East Economics and Finance*, 16(2), 1–19.
- Al-Tamimi, H. A. H., Al-Rawashdeh, A. R., & Obeidat, Y. B. (2018). The dynamic linkage among sector indices in the Jordanian stock market: A vector autoregressive analysis. *Journal of Economic and Administrative Sciences*, 34(1), 94–113.
- Aloui, R., Hkiri, B., & Nguyen, K. D. (2017). Wavelet-based analysis of dynamic linkages among sector indices during the financial crisis: International evidence. *The North American Journal of Economics and Finance*, 40, 249–263.
- ASE. (2020). *Annual Statistical Bulletin 2020*. Amman Stock Exchange. <https://www.ase.com.jo/en>
- Bhanja, N., & Dastidar, G. A. (2016). Dynamic interdependence among the sectoral equity returns in India: Evidence from the post-global financial crisis period. *Journal of Asian Economics*, 47, 15–32.
- Chakraborty, D., & Adhikary, B. B. (2019). Dynamic linkage between sectoral indices: Evidence from India and the US. *Journal of Emerging Market Finance*, 18(2), 254–275.
- Chang, L. C., & Tzeng, Y. L. (2019). Dynamic relationships among sectoral stock indices in a threshold volatility environment. *The Quarterly Review of Economics and Finance*, 71, 224–235.
- Chen, S., & Chen, Y. (2015). Dynamic linkage among sector indices and implications for portfolio diversification. *Finance Research Letters*, 13, 176–185.
- Creswell, W. J., & Creswell, D. J. (2017). Research design: Qualitative, quantitative, and mixed methods approaches. *Sage Publications*.
- Diebold, X. F., & Yilmaz, K. (2015). Financial and macroeconomic connectedness: A network approach to measurement and monitoring. *Oxford University Press*.
- Emerson, W. R. (2015). Convenience sampling, random sampling, and snowball sampling: How does sampling affect the validity of research?. *Journal of Visual Impairment & Blindness*, 109(2), 164–168.
- Engle, F. R., & Granger, J. W. C. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica*, 55(2), 251–276.
- Granger, J. W. C. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424–438.
- Gupta, J., & Morgan, J. P. (2016). Sectoral interdependence and financial stability in emerging markets. *International Journal of Finance and Economics*, 21(1), 3–15.
- Hamilton, D. J. (1994). Time series analysis (Vol. 2). *Princeton, NJ: Princeton University Press*.
- Hassan, K. M., & Malik, F. (2007). Multivariate GARCH modeling of sector volatility transmission. *The Quarterly Review of Economics and Finance*, 47(3), 470–480.
- Hoque, A. M., & Saha, K. M. (2019). The dynamics of sector indices and macroeconomic variables: Evidence from the Indian stock market. *Journal of Economics and Business*, 101, 1–13.
- Husain, F., & Wajid, A. (2017). Dynamic linkages and spillover effects among emerging Asian equity markets. *The Journal of Developing Areas*, 51(4), 309–324.
- Jorion, P. (1988). On the internationalization of stock markets: A study of six European markets. *Journal of Financial Economics*, 24(2), 361–389.
- Kanas, A., & Yannopoulos, A. (2011). Dynamic linkages among sector indices of the Athens stock exchange. *International Journal of Banking and Finance*, 8, 29–44.
- Leedy, D. P., & Ormrod, E. J. (2019). Practical research: Planning and design. *Pearson*.



- Lucey, M. B., & Zhang, Q. (2011). Financial integration and dynamic linkages of stock returns among EU countries: The case of the accession progress. *Research in International Business and Finance*, 25(3), 289–303.
- Lütkepohl, H. (2005). New introduction to multiple time series analysis. *Springer Science & Business Media*.
- Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1), 17–29.
- Sensoy, A., & Nguyen, K. D. (2019). Dynamic connectedness of the US stock market: A time–frequency analysis. *Journal of Risk and Financial Management*, 12(1), 44.
- Sims, A. C. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*, 48(1), 1–48.
- Yang, J. H., & Doong, C. S. (2018). Dynamic linkage among sector indices of Taiwan and Indonesia stock markets. *Emerging Markets Finance and Trade*, 54(1), 79–95.