POLITIK EKONOMIK KURAM

Research Article

Time Series Chain Graphical Models in the Inference of Economic Data: A Case Study from S&P 500

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Abstract Main purpose of this study is the investigation of the relationships between economic and financial variables. This subject is well documented in the literature for both emerging and developed markets but, the contribution of this study to the literature is that the direction of the relationships is investigated by using a different method. In this study, the time series chain graphical model is utilized to examine the relationship between selected economic and financial variables over time. Time Series Chain Graphical Model enables to explore the conditional dependence among variables that are repeatedly measured at different time points. Our research validates the accuracy of the proposed model by segmenting the data by year. Additionally, graphical models are employed for precision and autocorrelation matrix analysis. We use the USA dataset, which can be found in the study of Gloyal and Welch (2021), there exist 16 variables that exhibit occasional conditional dependence and infrequent temporal dependence. This analysis, which is important in showing policy makers whether there is a relationship between variables, can also be applied to Turkish data at later stages.

Keywords: S&P500, Time Series Chain Graphical Model, Investment, Financial Markets
Jel Codes: G15, F65, C13, C19

Ekonomik Verilerin Analizinde Zaman Serisi Zinciri Grafik Modelleri: S&P500 Üzerine Bir Vaka Çalışması

Öz: Bu çalışmanın amacı, ekonomik ve finansal değişkenler arasındaki ilişkilerin araştırılmasıdır. Bu konu hem gelişmekte olan hem de gelişmiş ülke piyasaları için literatürde çokça tartışılmıştır ancak bu çalışmanın literatüre katkısı, ilişkilerin yönünün farklı bir yöntem kullanılarak araştırılmasıdır. Yapılmış çalışmalarda seçili farklı finansal ve ekonomik değişkenler arası ilişkiler araştırılırken regresyon, var analizi ve Granger nedensellik gibi doğrusal modellerin kullanıldığı görülmektedir. Bu çalışmada, zaman serisi zinciri grafik modeli, seçilen ekonomik ve finansal değişkenler arasındaki ilişkiyi zaman içinde incelemek için kullanılmıştır. Zaman serisi zinciri grafik modeli, farklı zaman noktalarında tekrar tekrar ölçülen değişkenler arasındaki koşullu bağımlılığın keşfedilmesini sağlamakta ve verileri yıla göre segmentlere ayırarak analiz edildiğinde de önerilen modelin doğruluğu ortaya koyulmuş olmaktadır. Ek olarak, grafik modeller hassasiyet ve otokorelasyon matrisi analizi için kullanılmıştır. Gloyal ve Welch'in (2021) çalışmasındaki Amerika Birleşik Devletleri'ne ait veri setindeki aralıklı koşullu bağımlılık ve seyrek zamansal bağımlılık gösteren 16 değişken için uyguladığımız bu çalışma, politika yapıcılara değişkenler arası ilişkinin var olup olmadığını göstermesi açısından önemlidir ve daha sonraki aşamalarda Türkiye verilerine de uygulanabilir.

Anahtar Kelimeler: S&P500, Zaman Serisi Zinciri Grafik Modeli, Yatırım, Finansal Piyasalar
Jel Kodları: G15, F65, C13, C19

Atıf: Farnoudkia, H.; Ak, A. (2024). Time Series Chain Graphical Models in the Inference of Economic Data: A Case Study from S&P 500, *Politik Ekonomik Kuram, 8*(3), 893-905. https://doi.org/10.30586/pek.1531696

Geliş Tarihi: 11.08.2024
Kabul Tarihi: 20.09.2024

1. Introduction

The significance of time series data in economic analysis has grown remarkably in recent years. Understanding the intricate relationships between different variables within time series data is crucial for making informed inferences in the field of economics. In this context, the application of Time Series Chain Graphical Models (TSCGM) has emerged as a powerful tool, enabling the simultaneous estimation of precision and autocorrelation matrices. This capability provides a comprehensive understanding of the underlying data dynamics and enhances the accuracy of economic inference.

As Mishkin (2018, p.208) mentioned the financial system is complex in structure and function throughout the world. It includes many different types of institutions, banks, insurance companies, mutual funds, stock and bond markets. The financial system channels trillions of dollars per year from savers to people with productive investment opportunities. Therefore, no matter how much time passes, the investigation of the relationships between economic variables will remain an ageless subject and will continue to be researched. One of these relationships is between macroeconomic variables and the stock market is a topic that is widely discussed in the literature.

The seminal study by Abegaz and Wit (2013, p.587) laid the groundwork for the utilization of TSCGM in economic data inference, marking a pivotal moment in the exploration of this methodology's potential. Subsequent studies conducted after 2013 have further expanded upon the application of TSCGM in analyzing economic time series data, demonstrating its efficacy in capturing complex relationships and dynamics within economic variables. TSCGM have gained significant attention in various domains for their utility in analyzing complex temporal relationships within data. The Gaussian graphical model (GGM) is one such model that has been extensively discussed for its ability to represent an undirected network of partial correlation coefficients. Epskampa, Waldorpa, Mõttusb, and Borsbooma (2018, p.468) elaborate on the GGM's potential as an exploratory data analysis tool, showcasing its effectiveness in revealing intricate dependencies among variables in cross-sectional and time-series data.

2. Literature Review

Depending on the complexity of the financial markets; no matter how much time passes, the investigation of the relationships between economic variables will remain an ageless subject and will continue to be researched. One of these relationships is between macroeconomic variables and the stock market is a topic that is widely discussed in the literature. Stock market returns and economic activities relationship is well documented and modeled by a fair sum of studies. (Chen, 1991 p. 529; Fama, 1990 p.1089; Huang and Kracaw, 1984 p.267; Wei and Wong, 1992, p.77; Kwon, 1999, p.71). There are various studies in the literature investigating different models on this subject. literature provides evidence of strong linkages between fundamental economic activities and stock market returns in both developed countries and emerging markets. However, no study has been conducted to investigate potential relations between the S&P stock market index and related variables by using sparse data analysis.

In the context of causal inference, Runge, Nowack, Kretschmer, Flaxman, and Sejdinovic (2019, p. 4) address the detection and quantification of causal associations in large nonlinear time series datasets. They emphasize the representation of time series variables in a graphical model, highlighting the significance of uncovering causal relationships and dependencies within complex temporal data. Moreover, Su, Zhao, Niu, Liu, Sun, and Pei (2019, p. 2831) introduce a robust anomaly detection method for multivariate time series using a stochastic recurrent neural network, where a chain of invertible mappings is employed within a graphical model to capture complex distributions of time series data. This demonstrates the applicability of graphical models in capturing intricate dependencies for anomaly detection in multivariate time series.

In a survey conducted by Nascimento, Pinto-Orellana, Leite, Edwards, Louzada, and Santos (2020, p. 5), the authors examine the susceptibility of sparse dynamic models, particularly the Time Series Chain Graphical Model (TSCGM), to manipulation within the context of brain experimentation. This research underscores the significance of TSCGM in neurobiological settings, where comprehending the dynamics of brain connectivity is essential. The findings indicate that TSCGM is capable of effectively modeling brain networks, thereby providing critical insights into their temporal behaviors. Furthermore, Farnoudkia (2020, p: 31-39) presents TSCGM as a generalized form of Gaussian graphical models, situating it within the broader category of graphical models utilized for biological network inference. This research demonstrates how TSCGM can derive meaningful connections between variables in complex biological datasets, thereby facilitating a more nuanced understanding of genetic interactions. Building on this foundation, Xu, Wang, Wu, Zhao, Zhang, and Wang (2021, p. 713) introduce a behavioral model based on TSCGM designed for detecting semantic attacks in SCADA systems. This application illustrates the adaptability of TSCGM in the field of cybersecurity, showcasing its potential for modeling complex interactions within critical infrastructure. Furthermore, Kapita (2022, p: 1-7) explores the application of TSCGM in studying time-varying genetic networks. This research emphasizes the model's capability to analyze multivariate time series data, thereby enhancing the understanding of dynamic relationships within biological systems. The TSCGM framework enables researchers to capture temporal dependencies and interactions among genes, yielding insights into underlying biological processes. Finally, Van der Tuin, Balafas, Oldehinkel, Wit, Booij, and Wigman (2022, p. 97) apply Sparse Time Series Chain Graphical Models to analyze dynamic symptom networks across various at-risk stages of psychosis. Their work exemplifies the versatility of TSCGM in clinical psychology, aiding in the identification of contemporaneous and temporal correlations among symptoms. This application highlights the model's potential to advance diagnostic and therapeutic strategies in mental health.within

3. Method

This section will begin with the copula Gaussian graphical model which is the single case of TSCGM. Then, TSCGM will be explained in detail.

This model has a $(n \times p)$-dimensional data set where n is the sample size and p is the number of variables. To explore the association among variables in a multivariate context, the multivariate linear regression serves as a valuable model for expressing each variable in terms of another variable, given the remaining variables, using the following formula.

$$Y_i = \alpha + \beta Y_{j|s-\{i,j\}} + e \tag{1}$$

For $s = \{1,2,\ldots,p\}$. Here, β signifies the measure of the conditional dependence between Y_i and Y_j. The estimation of these coefficients is achievable by utilizing the components of the precision matrix, which is the inverse of the covariance matrix. The zero components of the precision matrix correspond to the conditional independence of two entire variables.

Dobra and Lenkoski (2011, p.976) introduced a three-step reversible jump Markov chain Monte Carlo (RJMCMC) approach for estimating the precision matrix to construct the undirected graph of a sparse network. Within this graph, the variables are denoted by nodes, and an undirected edge represents the conditional dependence between entire nodes.

In this methodology, the assumption of normality is imperative for employing a G-Wishart prior distribution for the precision matrix. To ensure this, a Gaussian copula can be applied to the data to maintain the normality assumption. This is why the approach is referred to as the copula Gaussian Graphical Method. Further details can be found in Dobra and Lenkoski's (2011, p.971) study.

TSCGM is the generalized version of CGGM in which the data are repeated at different times T. So the data set is a $(n \times p \times T)$-dimensional. The vector autoregressive with lag 1 VAR(1) equation of this model is

$$X_t = \Gamma X_{t-1} + \epsilon_t \qquad (2)$$

Where Γ is a non-symmetric autoregressive matrix that represents the relationship of the variables with all variables (including itself) during the time. Furthermore, $\epsilon_t \sim N(0, \Omega)$, where the inverse of Ω is the precision matrix which is explained in the previous part.

So, in this model, two matrices will be estimated: a) the non-symmetric autoregressive matrix which represents the first-degree autoregressive coefficients of the variables, and b) the symmetric precision matrix which is related to the conditional dependence between the variables. The graphical model will consist of two networks: a) the network with directed graphs which shows the relationship during the time, and b) the undirected network which explains the conditional relationship between the nodes. Abegaz and Wit (2013, p.588) smoothly clipped absolute deviation (SCAD) penalized likelihood estimation for the precision and autoregressive coefficient matrices tested in terms of the precision for the real data and simulated data set in the same study.

In this section, we will elucidate the characteristics of the extensive monthly real dataset meticulously curated by Welch and Goyal (2008, p.1457-1461). Subsequently, we will expound upon the application of the TSCGM to analyze and derive insights from this substantial dataset

Data

The dataset utilized in this study comprises monthly data spanning from 1961 to 2021, focusing on the S&P 500 index and several associated variables, the details of which will be outlined in Table 1.

Table 1. The description of the names of the variables in the data set.

Name	Explanation
D12	Dividends are the 12-month moving sum of dividends paid on the index.
E12	Earnings are a 12-month moving sum of earnings on the S&P interpolation of quarterly earnings by the S&P Corporation.
b/m	Investment of Capital Ratio is the ratio of aggregate investment to aggregate capital for the whole economy.
tbl	treasury bill rates from 1920 to 1933 are the US yield on short-term United States securities.
AAA	AAA-rated bonds are considered the highest quality, indicating a very low risk of default
BAA	BAA-rated bonds are lower in quality and carry slightly higher risk compared to AAA-rated bonds.
lty	Long-term government bond.
ntis	The ratio of twelve-month moving sums of net issues by NYSE-listed stocks divided by the total market capitalization of NYSE stocks.
Rfree	The risk-free that is 005 is the Treasury bill rate.
infl	Inflation is the Consumer Price Index (All Urban Consumers.)
ltr	Long-term government bond returns.
corpr	Corporate Issue activity: ntis and percent equity issuing.
svar	Stock Variance is computed as the sum of squared daily returns on the S&P 500.
csp	The cross-sectional beta premium measures the relative valuations of high- and low-beta stocks.
CRSP_SPvw	value-weighted return obtained from the Center of resource in security press (CRSP)
CRSP_SPvwx	Extended (Adjusted) value-weighted return obtained from CRSP.

More details about the data and their resources can be found in the study of Welch and Goyal (2008). In this dataset, there exist 16 variables that exhibit occasional conditional dependence and infrequent temporal dependence.

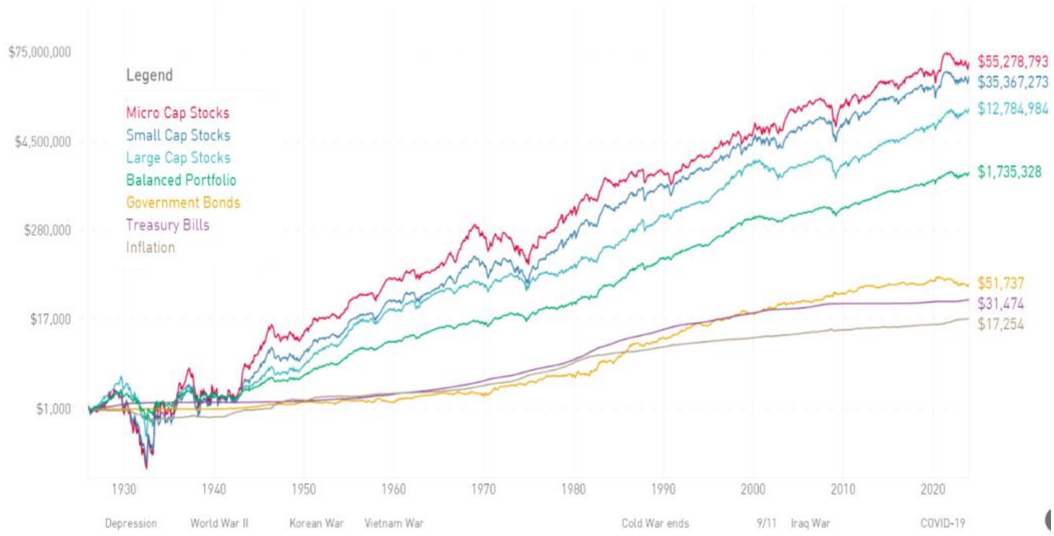

Figure 1. CRSP: https://www.investmentsillustrated.com/clients/crsp/bp/graph.html

It is seen form Figure 1 that in the 1930s, stock returns remained below inflation and gave negative real returns, and then turned into positive real returns in line with risk levels. While treasury bills, which represent risk-free rates, acted equivalent to inflation until the 1980s, they exceeded inflation after 1980 and turned into a positive real return. Similarly, government bonds started to give positive real returns after the mid-80s. While returns above inflation represent real returns, returns above treasury bills, which represent risk free rates, represent risk premium. Consistent with expectations, an increase in return is observed in every financial asset in line with the increasing risk premium.

4. Results and Discussion

Table 2 shows the estimated precision matrix where the zero elements of this matrix imply the conditional independence between the corresponding variables. Note that the precison matrix in a symmetric one and mosltly is represented as upper or lower triangular matrix. The sign of the coefficients shows the type and the value shows the strength of the relationship.

Table 2. The estimated precision matrix of the data set with 100000 runs and the first 20000 as bur-in period.

	D12	E12	b.m	tbl	AAA	BAA	lty	ntis	Rfree	infl	ltr	corpr	svar	csp	CRSP_SPvw	CRSP_SPvwx
D12	3.515	-1.559	0.092	0	-0.151	-0.101	-0.074	0	0	0	0	0	0	0.340	0	0
E12	0	3.315	0	0	-0.181	-0.032	-0.192	0.025	0	0	0	0	0	0.066	0	0
b.m	0	0	1.277	-0.092	0	-0.202	0	0	-0.041	-0.088	0	0	0	0	0	0
tbl	0	0	0	3.758	-0.562	-0.305	-0.653	0	-1.913	0	0	0	0	0.055	0	0
AAA	0	0	0	0	4.524	-1.559	-1.406	0	-0.558	0	0	0	0	0.154	0	0
BAA	0	0	0	0	0	3.947	-1.359	0.100	-0.342	0	0	-0.034	0	0	0	0
lty	0	0	0	0	0	0	4.425	0	-0.540	0	0	0	0	0.290	0	0
ntis	0	0	0	0	0	0	0	1.014	0	0	0	0	0	0	0	0
Rfree	0	0	0	0	0	0	0	0	3.679	0	0	0	0	0.086	0	0
infl	0	0	0	0	0	0	0	0	0	1.086	0	0	0	0	0	0
ltr	0	0	0	0	0	0	0	0	0	0	2.039	-1.466	0	0	0	0
corpr	0	0	0	0	0	0	0	0	0	0	0	2.106	0	0	-0.090	-0.094
svar	0	0	0	0	0	0	0	0	0	0	0	0	1.124	0	0.081	0.060
csp	0	0	0	0	0	0	0	0	0	0	0	0	0	1.438	0	0
CRSP_SPvw	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.225	-2.715
CRSP_SPvwx	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.247

The greatest coefficient is -2.715 indicating the strong dependence between CRSP_SPvw and CRSP_SPvwx that is completely reasonable because CRSP_SPvwx is an adjusted version of CRSP_SPvw.

Figure 2 would help us to see all edges of the network in a nutshell.

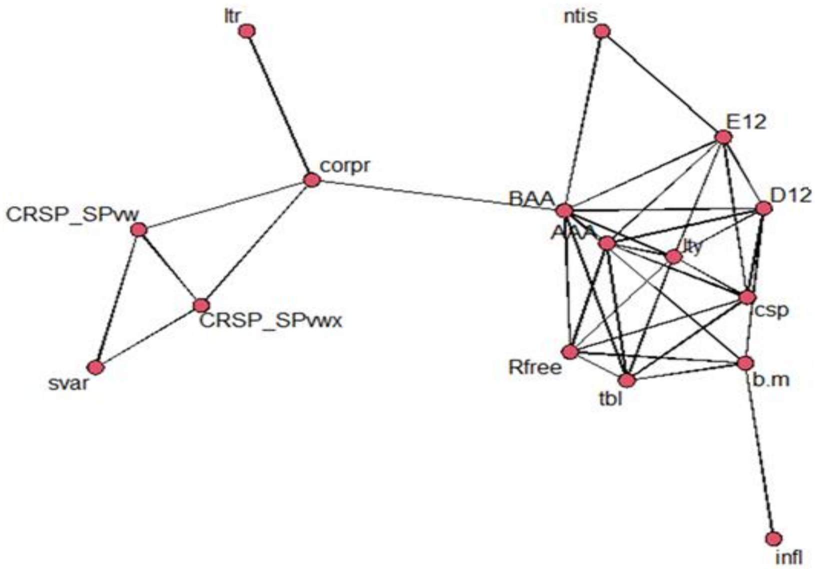

Figure 2. The estimated precision graph

Notably, when considering all time points collectively, no temporal dependencies were observed.

Based on Figure 1, to calculate the sparsity rate of a network with 40 edges among 16 nodes, the Number of Possible Edges is $\frac{p(p-1)}{2} = 120$. So the sparsity Rate = 73 / 120 ≈ 0.61 indicates that a relatively high proportion of all possible connections between the nodes are present in the network. This level of sparsity suggests that the network is densely connected, with a significant number of missing edges compared to the total possible connections. Such a sparse network structure may imply specific patterns or characteristics in the relationships between the nodes, highlighting potential areas of interest for further analysis and interpretation.

The number of edges for each node is represented as a bar chart in Figure 3.

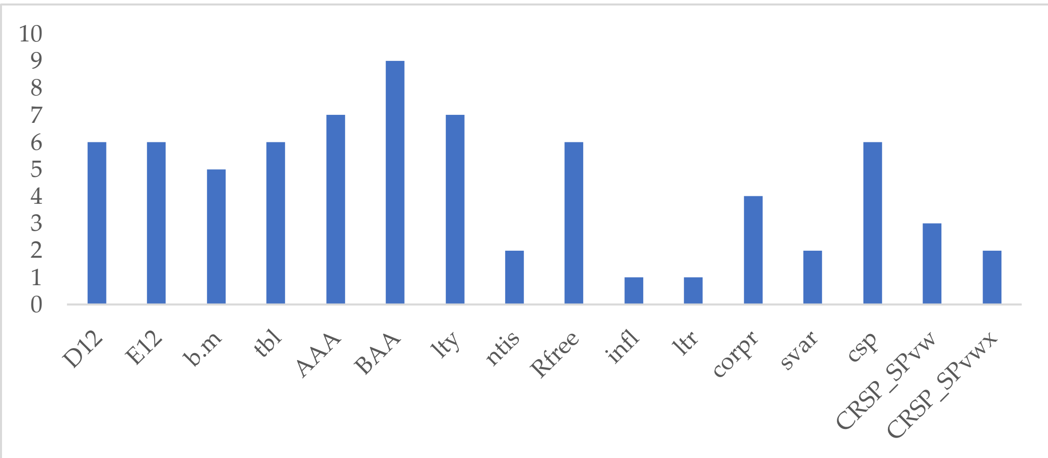

Figure 3. The bar chart of the number of the edges(connections) of each node (variable).

Based on the bar chart, it can be seen that BAA is the most connected variable with 9 edges followed by AAA and lty with 7 connected edges. On the other hand, infl and Itr are the variables with only one connected edge.

Given the null autoregressive matrix across all time points, the 61-year dataset was partitioned into six distinct periods: five 10-year segments and a final 11-year segment as presented in Table 3:

Table 3. The start and end of each six-time section.

Period	From	To
1	1961	1970
2	1971	1980
3	1981	1990
4	1991	2000
5	2001	2010
6	2011	2021

The periodic mean of the variables is represented in Table 4.

Table 4: The mean of all variables in each period.

Var \ Period	1	2	3	4	5	6
D12	2.627	4.105	8.325	14.191	21.377	43.931
E12	4.730	9.547	17.075	32.391	50.486	106.689
b.m	0.555	0.855	0.660	0.267	0.271	0.292
tbl	0.043	0.068	0.084	0.047	0.021	0.005
AAA	0.054	0.086	0.111	0.076	0.057	0.037
BAA	0.060	0.098	0.125	0.083	0.069	0.046
lty	0.049	0.080	0.104	0.068	0.048	0.025
ntis	0.022	0.023	-0.002	0.023	-0.001	-0.007
Rfree	0.003	0.005	0.007	0.004	0.002	0.000
infl	0.002	0.006	0.004	0.002	0.002	0.002
ltr	0.001	0.004	0.011	0.008	0.006	0.005
corpr	0.002	0.004	0.012	0.007	0.007	0.006
svar	0.001	0.002	0.002	0.002	0.004	0.002
csp	0.000	0.000	-0.002	-0.001	-0.002	*
CRSP_SPvw	0.007	0.008	0.012	0.014	0.002	0.013
CRSP_SPvwx	0.005	0.004	0.009	0.013	0.001	0.011

It can be seen that the increase in D12 and E12 was smooth and parallel over time as presented in Figure 4 where the time series plot shows how they both increased over time.

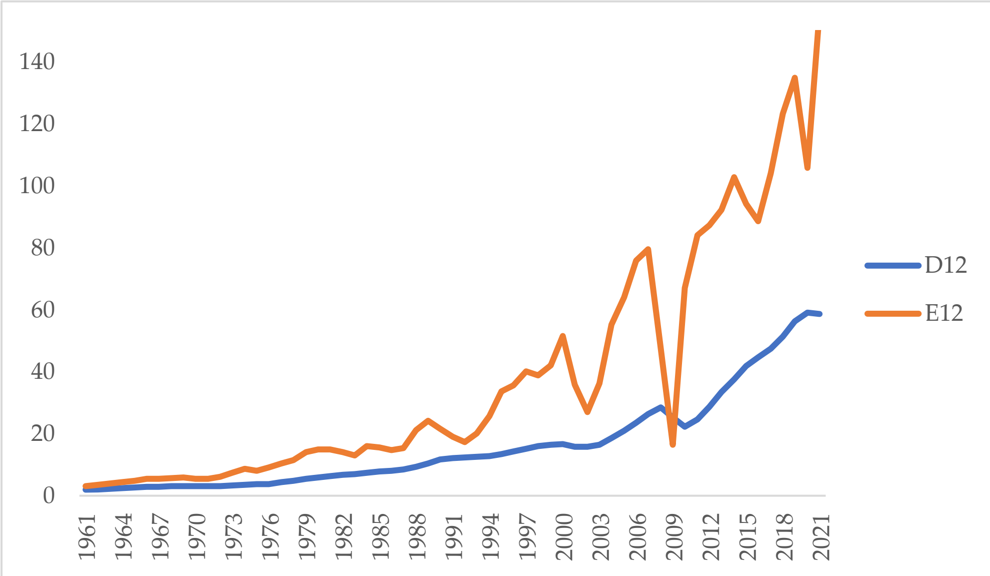

Figure 4. The time series plot of D12 and E12.

However, for some variables such as b.m, infl and csp, the greatest mean is related to the second period as plotted in Figure 5.

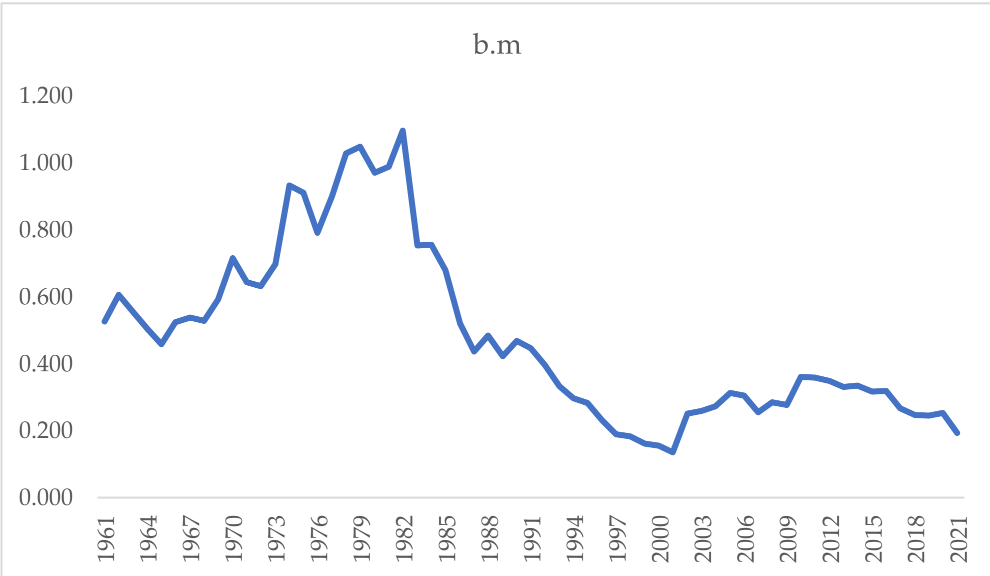

Figure 5. The time series plot of b.m.

Generally, it can be concluded that the third period 1981-1990 is the summit for most of the variables. To see the trend of change in some of these variables, the following time series plot can help.

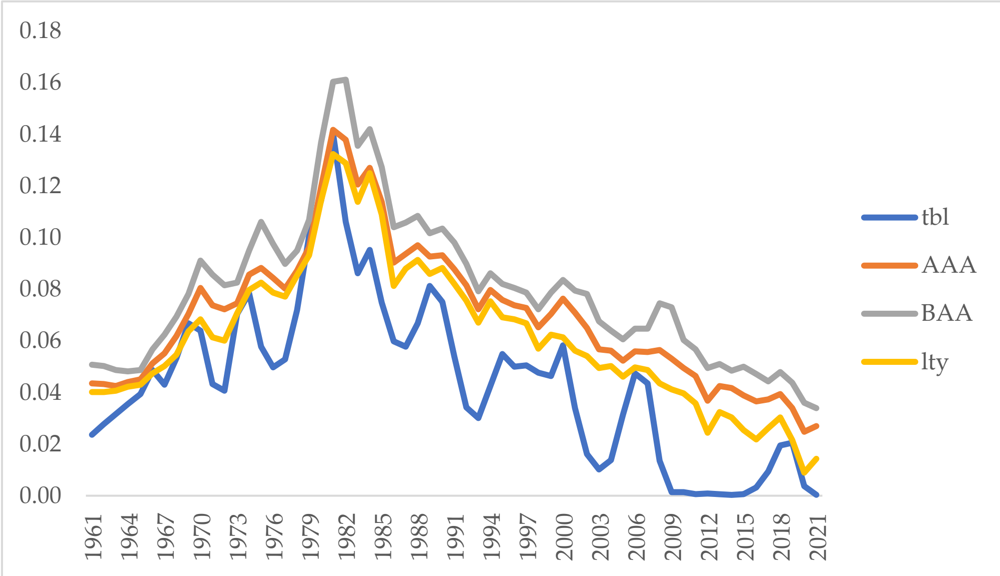

Figure 6. The time series plot of tbl, AAA, BAA and lty.

Figure 6 provides a clear indication of the risk premium; although the movement continues together as the risk levels of the variables increase, a risk premium is added to them.

Subsequently, the precision matrices were estimated for each of these individual periods separately and the results will be compared with the 61 years. The concentration will be on the autoregressive coefficient matrix which was null when considering all times.

In the first period i.e., 1961-1970 the estimated autocorrelation matrix which is a non-symmetric one, is as below and it can be seen that there are some non-zero coefficients.

Table 5. First Period Autocorrelation Matrix

	D12	E12	b.m	tbl	AAA	BAA	lty	ntis	Rfree	infl	ltr	corpr	svar	csp	CRSP_SPvw	CRSP_SPvwx
D12	0	0	0	0	0	0	0	0	0	-0.032	0	0	0	0	0	0
E12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
b.m	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tbl	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AAA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BAA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lty	0	0	0	0	0	0	0	0	0	-0.118	0	0	0	0	0	0
ntis	0	0	0	0	0	0	0	0	0	0	0	0	-0.036	0	0	0
Rfree	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
infl	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ltr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
corpr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
svar	0	0	0	0	0	0	0	0	0	0	0	0.020	0	0	0	0
csp	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CRSP_SPvw	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CRSP_SPvwx	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

In can be concluded that in the first 10 years, there is a negative connection between the first lag of D12 and inf and another negative connection from the first lag of lty to inf. Figure 7 shows the relationship between the variables over time in the first period.

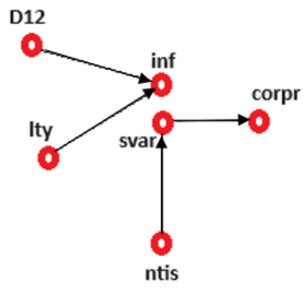

Figure 7. The estimated autocorrelation matrix in the first perid i.e., 1961-1970.

Similarly, during the fifth period (2001 to 2010), a temporal relationship was identified from 'corpr' to 'csp' with a coefficient of -0.045 that is represented in Figure 8.

Figure 8. The estimated autocorrelation matrix in the fifth period i.e., 2001-2010.

In the subsequent 11-year period from 2011 to 2021, notable time dependencies were observed from 'b.m' to 'svar' with a coefficient of -0.73.

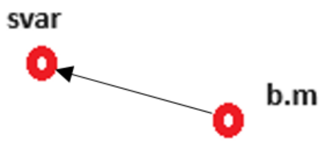

Figure 9. The autocorrelation matrix in the last period i.e., 2011-2021.

Furthermore, an investigation was conducted on the estimation of the precision matrix across the six distinct time sections. It was established that variables exhibiting connections 3 times or more within the six-time sections were consistent with those identified as related in the original 61-year dataset. Employing this criterion, a confusion matrix was constructed, where True Positives (TP) represent variables connected in the overall graph and in more than 3 instances within the segmented time graphs. False Negatives (FN) denote variables linked in the comprehensive timeline from 1960 to 2021 but exhibit connections in 0, 1, or 2 cases only. Utilizing these values, the confusion matrix was computed accordingly.

Table 6. Confusion Matrix

	1	0
1	TP=35	FN=4
0	FP=2	TN=79

Two different overall accuracy measures $F_1 - score$ and Mathew Correlation Coefficient (MCC) can compare the consistency between the divided times with the original one as below.

$$F_1 = \frac{2TP}{2TP+FP+FN} = 0.92 \quad (3)$$

For $F_1 - score$, a value of 1 represents perfect precision and recall, while a score of 0 signifies poor performance. In this context, the F1 Score of 0.92 suggests a strong overall performance in correctly identifying positive instances while minimizing false positives and false negatives.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \approx 0.885 \quad (4)$$

Similarly, for this measure the value of 1 signifies a perfect prediction, 0 indicates no better than a random prediction, and -1 represents total disagreement between prediction and observation. In this scenario, an MCC of 0.885 suggests a high level of agreement between the predicted and actual classifications, reflecting a robust model performance in capturing both true positives and true negatives while accounting for false positives and false negatives.

The FP pairs ntis-E12, BAA-corpr which are related in the general network represented for 61-year but connected only in two-time sections, and similarly, the FN pairs are E12-Rfree, b.m-csp, ltr-CRSP_vw, and ltr-CRSP_vwx those are not connected in the general case but are recognized connected in three or more cases within six-time sections.

5. Conclusion

TSCGM was employed in the study to capture the dynamic behavior of the variables and provide more information about the linkages between them. Literature provides evidence of strong linkages between fundamental economic activities and stock market returns in both developed countries and emerging markets. Mainly different economic activities are production rates, productivity, growth rate of gross national product, unemployment, yield spread, interest rates, inflation, dividend yields, and so forth. One of the earliest studies; Fama (1990, p.1089) revealed that there is a strong positive relationship between stock returns and real economic activities such as industrial production, and capital expenditures, and GNP. Bhunia (2013, p.8) analyzed crude oil prices, local gold prices, and exchange rates using daily data. Anlaş (2012, p.34), examined the relationship between TL, CHF/TL, USD/TL, CAD/TL, SA/TL) and ISE100. According to the results of the study, changes in the US dollar and Canadian dollar ISE100 Dritsaki (2005, p.45), Greek stock market index and inflation, industrial production, and interest rate. Humpe and Macmillan (2009p.111, investigate Japan and US stocks in their study on the market, they found a same-directional relationship between stock prices and industrial production for the USA and an inverse relationship between the consumer price index and long-term interest rate. Additionally, there is a positive but insignificant interaction with the money supply. According to Japanese data, a positive effect was revealed on the stock market index and industrial production, and a negative effect on the money supply. Kwon and Shin (1999, p71) investigate whether economic activities can explain current stock market returns in Korea based on the response of stock prices to macroeconomic fluctuations. Kwon finds that; the model shows that stock prices are cointegrated with several macroeconomic variables; exchange rates, trade balance, production level, S and money supply. The cointegration relationship shows direct long-term and equilibrium relationships with them.

It is seen that similar studies have been conducted for different countries with different methods. In this study, where the TSGM method was used with similar macroeconomic and financial variables, it was revealed that the data were divided into two groups and the link between them was provided by corporate issue activity and BAA bonds. An interesting point in this study conducted for the US data is that long-term government bond returns are only related to corporate issue activity. Another data that stands out in the relationship network is inflation. It was expected that inflation data would be related to all other macroeconomic and financial variables due to its effect on return rates, but it is seen that it is separated from the others and is only connected to the system with the investment of capital ratio. Contrarily, as expected, the risk-free rate, which represents the treasury bill rate, is shown to be closely correlated with AAA and BAA rated bonds.

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Conflict of Interest: None.
Funding: None.
Ethical Approval : None.
Author Contributions: Hajar FARNOUDKIA (50%), Ayşegül AK (50%)

Çıkar Çatışması: Yoktur.
Finansal Destek: Yoktur.
Etik Onay: Yoktur.
Yazar Katkısı: Hajar FARNOUDKIA (%50), Ayşegül AK (%50)