

THE EFFECT OF COVID-19 SHOCKS ON THE RETURN AND VOLATILITY STRUCTURES OF BIST TECHNOLOGY COMPANIES: AN EXAMINATION WITH THE TVP-VAR MODEL

COVID-19 Şoklarının BİST Teknoloji Şirketlerinin Getiri ve Volatilite Yapılarına Etkisi: TVP-VAR Modeliyle Bir İnceleme

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ABSTRACT

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This study examines the effects of the COVID-19 pandemic on the return and volatility dynamics of companies included in the Borsa İstanbul Technology Index (XUTEK). Using weekly stock data for ten firms (ASELS, KAREL, LINK, KRONTE, NETAS, ALCTL, ARENA, DESPC, PKART, INDES) over the period January 2015–May 2025, we implement a Time-Varying Parameter Vector Autoregression (TVP-VAR) model. The TVP-VAR methodology is preferred due to its sensitivity to structural breaks, sudden shocks, and regime shifts that are frequently observed in financial markets. The findings indicate that NETAS, INDES, and ALCTL act as “shock transmitters” in the system, with high positive net spillover values, whereas LINK, PKART, and KRONTE display “shock receiver” characteristics, with negative net spillover values. In addition, ASELS and KAREL appear to exert substantial control over their own volatilities, exhibiting greater resilience to crises. A comparative analysis of the pre- and post-COVID-19 periods reveals a general decline in returns across all firms; notably, LINK and KRONTE experience the largest losses, whereas NETAS emerges as the least affected firm. The study offers important implications for both investors and policymakers. For investors, it underscores that portfolio diversification and allocating capital to firms with strong corporate structures can mitigate risks during crises; for policymakers, it highlights the critical need to safeguard financial stability, enhance information transparency, and adopt measures that bolster market confidence.

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Bu çalışma, COVID-19 pandemisinin Borsa İstanbul Teknoloji Endeksi (XUTEK) kapsamındaki şirketlerin getiri ve volatilite dinamikleri üzerindeki etkilerini incelemeyi amaçlamaktadır. Ocak 2015-Mayıs 2025 dönemini kapsayan on firmanın (ASELS, KAREL, LINK, KRONTE, NETAS, ALCTL, ARENA, DESPC, PKART, INDES) haftalık hisse senedi verileri kullanılarak Zamanla Değişen Parametrelili Vektör Otoregresyon (TVP-VAR) modeli uygulanmıştır. TVP-VAR metodolojisi, finansal piyasalarda sıkça görülen yapısal kırılmalar, ani şoklar ve rejim değişimlerine duyarlılığı nedeniyle tercih edilmiştir. Bulgular, NETAS, INDES ve ALCTL şirketlerinin yüksek pozitif net değerleriyle sistemde “şok yayıcı” konumunda olduğunu; LINK, PKART ve KRONTE firmalarının ise negatif net değerleriyle “şok alıcı” niteliği taşıdığını göstermektedir. Ayrıca ASELS ve KAREL firmalarının kendi oynaklıklarını büyük ölçüde kontrol ederek krizlere karşı daha dirençli bir yapı sergilediği belirlenmiştir. COVID-19 öncesi ve sonrası dönemlerin karşılaştırmalı analizi, genel olarak tüm firmalarda getirilerin düştüğünü, özellikle LINK ve KRONTE’nin en yüksek kayıpları yaşarken NETAS’ın en az etkilenen firma olduğunu ortaya koymaktadır. Çalışma hem yatırımcılar hem de politika yapıcılar için önemli çıkarımlar sunmaktadır. Yatırımcılar açısından portföy çeşitlendirmesinin ve güçlü kurumsal yapıya sahip firmalara yönelmenin kriz dönemlerinde riskleri azaltabileceği vurgulanırken; politika yapıcılar için ise finansal istikrarı korumak, bilgi şeffaflığını artırmak ve piyasa güvenini destekleyecek önlemler almak kritik bir gereklilik olarak öne çıkmaktadır.

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1. INTRODUCTION

As of July 2020, COVID-19—an illness for which no vaccine was yet available and which emerged in Wuhan, China before being declared a pandemic by the World Health Organization (WHO) in March 2020—posed a threat to global public health and gave rise to economic concerns due to the uncertain effects of the mandated “shutdown” of the economy on firms, the financial sector, and households (Gormsen & Koijsen, 2020; Sanchez-Duque et al., 2020; Le & Lam, 2021). Initially perceived merely as a health issue, it rapidly evolved into a global crisis with pronounced economic and financial dimensions (Akan & Ustalar, 2021). The pandemic has secured a place in the literature as a unique, worldwide crisis that profoundly disrupted the operational dynamics of international financial markets (Balci et al., 2022). Business closures stemming from disruptions in demand and supply chains directly affected human life; consequently, the pandemic emerged not only as a health problem but also as a socio-economic challenge that impeded the global sustainable development goals (Le & Lam, 2021). It led to losses amounting to trillions of dollars in the global economy (Sanchez-Duque et al., 2020). While this crisis impacted all industries, its effect on the technology sector was uniquely dualistic, acting simultaneously as a catalyst for unprecedented growth in areas like digital services and e-commerce, while also creating significant instability for hardware-focused firms reliant on global supply chains. This complex interplay makes the technology sector a critical area for in-depth analysis.

Although Turkey is an open, large economy—an exemplary emerging market in which foreign participants hold significant shares and international developments play a decisive role—Borsa Istanbul stands as a standard-bearer among emerging markets with its implementation of the closing call auction (Inci & Ozenbas, 2017). Turkey’s first official exchange, established in 1873 under the name Dersaadet Bond Exchange, is Borsa Istanbul, which marked its 150th anniversary in 2023. Accompanied by information technologies employed by the world’s most prestigious markets, its governance has enabled investors to evaluate their investments on a fair footing (Gülay & Aydoğmuş, 2023). It exhibits partial integration with the global market index, and this integration becomes more pronounced during periods of negative returns (Yildiz & Erzurumlu, 2018). As Borsa Istanbul advances in global integration and regulatory modernization, it has become a center of attraction for international investors thanks to short-term high-yield opportunities (Arsoy, 2017). Borsa Istanbul hosts numerous indices. BIST 50 (Code: XU050; ISIN: TRAIMKB00036) is among the indices with the highest trading volume on Borsa Istanbul. In other words, it is known as the index comprising the top 50 companies with the most actively traded shares in the market, where trading activity underpins price movements (Huseynli, 2022). As for BIST TECHNOLOGY (Code: XUTEK; ISIN: TRAIMKB00259), the index start date is 30.06.2000 and the initial index value is 144.6612 (Borsa Istanbul, 2025). This particular index is of critical interest for this study as it comprises a heterogeneous mix of firms—from software developers poised to benefit from accelerated digitalization to hardware distributors vulnerable to global disruptions—making it a perfect case study for analyzing the differentiated impacts of the pandemic. Examining the top 10 constituents as of the 08.04.2025 close (see Table 1), together with sectoral distributions (see Figure 1), reveals that the Information Technologies sector dominates the ranking, despite accounting for only 35.6% on a sectoral basis.

Corporate scandals and market manipulation—coupled with emerging economies’ efforts to attract foreign investment—have made corporate governance a salient issue at both global and local levels (Caliskan & Icke, 2015). In this context, market manipulation is undoubtedly another topic warranting attention. Since the late 1990s/early 2000s, Borsa Istanbul has been actively combating manipulation attempts in cooperation with the Capital Markets Board of Turkey (CMB). Call auction sessions and the use of unique client identifiers are key components of this effort (Kadioğlu et al., 2015). Despite such financial stability measures, Turkey experienced a

historic contraction of 5.8% in 2001, underscoring once again the importance of market oversight (Armagan, 2023). Similarly, the COVID-19 pandemic, which emerged in December 2019 and spread globally, profoundly affected not only economic and social life but also financial markets; it induced panic among investors and significantly shaped their decision-making processes (Tan, 2021). However, while the literature has extensively documented the market-wide volatility caused by the pandemic, a significant gap remains in understanding the dynamic, firm-level connectedness *within* a critical and internally diverse sector like technology. Most studies do not differentiate between firms that act as systemic “shock transmitters” and those that are “shock receivers”, nor do they capture how these roles evolve over the course of a crisis. This study aims to fill this void by providing a granular analysis of the time-varying return and volatility spillover networks among BIST Technology companies, offering nuanced insights that go beyond aggregate market analyses.

2. LITERATURE

The impact of the COVID-19 pandemic on financial markets—particularly its effects on stock returns and volatility—has been examined in numerous studies (Gormsen & Koijen, 2020; Thorbecke, 2020; Sanchez-Duque et al., 2020; Tan, 2021; Kışla et al., 2022; Xu et al., 2022). Tan (2021) shows that the effect of COVID-19 news on Borsa Istanbul varies markedly with the prevailing market trend. Balcı et al. (2022) demonstrate that changes in the fractal dimensions of stocks serve as an effective indicator for price prediction during the pandemic. Can Ergün et al. (2023) argue that the risk appetite of foreign and professional investors on Borsa Istanbul has long-run effects on the behavior of domestic investors and that the influence of global volatility on these risk appetite indices increased post-COVID-19. Le & Lam (2021) highlight that the pandemic led to significant negative consequences for key indicators in the Vietnamese economy—such as growth, foreign trade, tourism, unemployment, and business activity. Furthermore, Karaömer & Kakilli Acaravcı (2022) find that the impact of COVID-19 differed across sectors: while banking and transportation were adversely affected, telecommunications and food-and-beverage benefited, with banking identified as the most negatively impacted sector.

Numerous social and managerial issues concerning Borsa Istanbul have been examined in the literature. For example, Çimen (2019) reports that companies included in the Borsa Istanbul Sustainability Index deliver high returns in line with investor expectations and that investors behave emotionally rather than rationally. Caliskan & Icke (2015) emphasize that corporate governance practices have improved among firms listed on the BIST 50 index, while noting that further enhancements are needed in areas such as board independence. In addition, Arioğlu & Arioğlu Kaya (2015) find that the quality of advisory services is higher in companies whose boards are predominantly composed of busy directors; however, Sagim & Reis (2020) show that independent audit report announcements have no statistically significant effect on stock returns within a daily event window.

There is also a body of work examining price formation, sectoral indices, anomaly effects, and the influence of external factors. Temel & Eryiğit (2021) show that energy prices have short-run and generally positive effects on Borsa Istanbul’s sectoral indices, with oil prices being particularly decisive for certain indices. Kadioğlu et al. (2015) find that statistically significant closing-price manipulation existed on Borsa Istanbul prior to the implementation of closing call auctions and that this mechanism significantly reduced manipulation, thereby improving the price-formation process. Bash & Al-Awadhi (2023) demonstrate that political interventions affecting central bank independence can lead to abnormal returns on Borsa Istanbul, whereas Aksoy & Ulusoy (2015) identify that calendar anomalies and abnormal returns affect the returns and volatility of the BIST Real Estate Investment Trusts Index (XGMYO) and the BIST 100 Index

(XU100), and that a strong relationship exists between these two indices. Furthermore, Arsoy (2017) reports that share buyback announcements on Borsa Istanbul between 2010 and 2015 did not generate abnormal returns and notes the market's lack of semi-strong-form efficiency. Similarly, Özkan & Kayalı (2015) reveal that loss-making firms obscure the accrual anomaly in the aggregate sample, whereas for profitable firms, strategies based on accrual components yield significant returns, concluding that Borsa Istanbul is not efficient in the semi-strong form.

Studies dedicated to trend analysis and market prediction models have also been conducted. For example, Armagan (2023) finds that the predictive power of a CNNM model for the Borsa Istanbul Banking Index (XBANK) surpasses that of ARIMA and FPM models, while Aliyev (2019) shows that Borsa Istanbul returns are predictable with a STAR model and that the market does not satisfy weak-form efficiency. Furthermore, Özkan (2019) emphasizes the importance of factors such as investment and profitability in investors' decisions on Borsa Istanbul, suggesting that the q-factor model can serve as an alternative explanatory framework. Trending topics have likewise been addressed: Kılıç & Çütcü (2018) find that, although there is no medium- or long-term cointegration relationship, there exists a unidirectional causality running from Borsa Istanbul to Bitcoin prices.

3. METHODOLOGY

This study examines ten companies included in the Borsa Istanbul Technology Index (XUTEK) for which weekly stock closing price data are available for the period January 2015–May 2025: ASELS, KAREL, LINK, KRONTE, NETAS, ALCTL, ARENA, DESPC, PKART, and INDES. The objective is to analyze the time-varying interaction structure among these firms and to explain their return dynamics. To this end, we employ a Time-Varying Parameter Vector Autoregression (TVP-VAR) model. The TVP-VAR framework offers notable advantages over traditional approaches—such as fixed-parameter or threshold-based models—owing to its sensitivity to sudden shocks, structural breaks, and regime shifts frequently observed in financial markets (Koop et al., 2009; Primiceri, 2005; Erdoğan, 2023). First, unlike threshold-based models, it does not require a transition variable to identify regime changes. Second, by allowing parameters to evolve over time, it can capture gradual transformations in inter-variable relationships. Third, the effects of unexpected external shocks can be incorporated via the time-varying variance–covariance matrix of the error terms. Within a state-space framework and under a Bayesian estimation approach, this model enables the joint analysis of short-term fluctuations and longer-run structural changes by modeling state-specific relationship structures (Caporale et al., 2021; Nakajima, 2011).

The TVP-VAR methodology allows for time-varying variances by utilizing the Kalman filter with forgetting factors, as proposed by Koop & Korobilis (2014), thereby extending the connectedness approach introduced by Diebold & Yılmaz (2009, 2012, 2014). By eliminating the parameter instability and data loss that arise from arbitrarily chosen rolling-window lengths, it enables sound dynamic connectedness analyses to be performed on data with low frequency and limited time series (Antonakakis et al., 2017). The TVP-VAR model:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t \quad \varepsilon_t | F_{t-1} \sim N(0, S_t) \quad (1)$$

$$\beta_t = \beta_{t-1} + \nu_t \quad \nu_t | F_{t-1} \sim N(0, R_t) \quad (2)$$

Here, Y_t denotes the $N \times 1$ vector of observed variables. β_t is an $N \times N_p$ matrix of time-varying coefficients. ε_t represents a zero-mean error term with a time-varying variance–covariance matrix (S_t). F_{t-1} denotes the information set available up to period $t-1$. This structure characterizes

the evolution of the time-varying coefficients β_t via a random-walk process and the dynamic changes over time in the variance–covariance matrix of the parameters R_t .

The time-varying coefficients and error covariances are used to estimate the Diebold & Yılmaz (2014) connectedness framework based on GIRFs and GFEVDs. For these computations, the VAR model is transformed into its VMA representation under Wold's theorem (Antonakakis et al., 2017).

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t \quad (3)$$

$$Y_t = A_t \varepsilon_t \quad (4)$$

$$A_{0,t} = I \quad (5)$$

$$A_{i,t} = \beta_{1,t} A_{i-1,t} + \dots + \beta_{p,t} A_{i-p,t} \quad (6)$$

Here, $\beta_t = [\beta_{1,t}, \beta_{2,t}, \dots, \beta_{p,t}]'$ ve $A_t = [A_{1,t}, A_{2,t}, \dots, A_{p,t}]'$ are defined accordingly; therefore, each $\beta_{i,t}$ and $A_{i,t}$ is an $N \times N$ parameter matrix.

Generalized impulse response functions (GIRFs) display the responses of all variables to a shock in variable i . In the absence of a structural model, one computes the difference between the J -step-ahead forecasts in the cases where variable i is shocked versus not shocked. This difference is attributable to the shock to variable i , and the corresponding response is computed as follows:

$$GIRF_{j,t} = (h\delta W) = E[Y_{t+h} | \varepsilon_{j,t} = \delta, W_{t-1}] - E[Y_{t+h} | W_{t-1}] \quad (7)$$

Here, h denotes the forecast horizon (number of steps ahead), δ is the magnitude of the shock to variable j , and W_{t-1} represents the information set up to period $t-1$. The GIRF computation enables dynamic impulse–response analysis without requiring structural assumptions about the model.

In conjunction with this approach, the generalized forecast error variance decomposition (GFEVD) measures the relative effects of shocks to each variable on the other variables without requiring structural restrictions. Owing to the use of time-varying coefficients proposed by Koop & Korobilis (2014), this variance decomposition evolves over time. The generalized FEVD is given by:

$$\theta_{ij,t}^{(H)} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_{h,t} \Sigma_t e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_{h,t} \Sigma_t A_{h,t}' e_i)} \quad (8)$$

Here, Σ_t denotes the error covariance matrix at time t ; $A_{h,t}$ represents the impulse response coefficients computed under the VMA representation; e_i is the i -th unit selection vector; and H denotes the forecast horizon. Because the rows of this matrix do not sum to one, the connectedness measures are obtained by normalizing it, as proposed by Diebold & Yılmaz (2012, 2014):

$$\tilde{\theta}_{ij,t}^{(H)} = \frac{\tilde{\theta}_{ij,t}^{(H)}}{\sum_{j=1}^N \tilde{\theta}_{ij,t}^{(H)}} \quad (9)$$

Using these normalized values, one can compute the Total Connectedness Index (TCI), as well as each variable's received spillovers (FROM), transmitted spillovers (TO), and net effect (NET):

$$TCI_t = \frac{1}{N} \sum_{i=1}^N \sum_{j=1, j \neq i}^N \tilde{\theta}_{ij,t}^{(H)} \times 100 \quad (10)$$

$$FROM_i^t = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ij,t}^{(H)} \times 100 \quad (11)$$

$$TO_i^t = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ij,t}^{(H)} \times 100 \quad (12)$$

$$NET_i^t = TO_i^t - FROM_i^t \quad (13)$$

4. RESULTS

Descriptions of the variables used in the study are presented in Table 1. Next, we report the descriptive statistics for these variables in Table 2.

Table 1. Variables Employed in the Study

<i>Constituent</i>			
Code	Name	Sector	Case
ALCTL	ALCATEL LUCENT TELETAS	Electronic Technology	✓
ARENA	ARENA BILGISAYAR	Distribution Services	✓
ASELS	ASELSAN	Electronic Technology	✓
DESPC	DESPEC BILGISAYAR	Distribution Services	✓
INDES	INDEKS BILGISAYAR	Distribution Services	✓
KAREL	KAREL ELEKTRONIK	Electronic Technology	✓
KRONT	KRON TEKNOLOJI	Communications	✓
LINK	LINK BILGISAYAR	Technology Services	✓
NETAS	NETAS TELEKOM	Technology Services	✓
PKART	PLASTIKKART	Commercial Services	✓

Table 2. Descriptive Statistics

//	ALCTL	ARENA	ASELS	DESPC	INDES
Mean	2.73520	2.70201	3.69199	-2.48319	2.56873
Median	1.29838	0.47847	2.66905	-0.85107	2.82704
Std. Dev.	16.45465	16.03718	10.15184	12.18964	13.60098
Skewness	0.85545	0.67728	0.61443	-0.58265	0.18567
Kurtosis	4.69412	3.36096	4.03461	3.51515	3.46191
Jarque-Bera	30.19372	10.23505	13.44027	8.45469	1.82946
Probability	0.00000	0.00599	0.00121	0.01459	0.00401
Observations	125	125	125	125	125
//	KAREL	KRONT	LINK	NETAS	PKART
Mean	-2.921434	2.498145	4.539225	1.231229	2.613458
Median	-2.405853	1.801851	0.775799	-0.340716	2.071671
Std. Dev.	16.20392	19.36206	17.78552	15.05601	14.25368
Skewness	-0.208798	-0.20535	1.204574	0.736608	0.890919
Kurtosis	6.470726	4.100794	4.237954	4.432301	4.71733
Jarque-Bera	63.64754	7.189694	38.21106	21.98882	31.89669
Probability	0.00000	0.02747	0.00000	0.00002	0.00000
Observations	125	125	125	125	125

Examining the mean and median values indicates that DESPC and KAREL have negative means and thus exhibit negative returns. The differences between the mean and the median are large for ARENA, LINK, and NETAS, suggesting high volatility in these series. Although the skewness values of DESPC, KAREL, and KRONT are close to zero (symmetry), they are negatively skewed, whereas ASELS, LINK, NETAS, ALCTL, ARENA, PKART, and INDES are positively skewed. The kurtosis values of the variables under review generally lie between 3 and 5,

indicating leptokurtic (peaked) distributions; among them, KAREL is the most peaked series, with a kurtosis of 6.47.

The price series for the variables were transformed into logarithmic return series, and the ADF test results based on these transformed series indicate that all are stationary. The ADF test results are presented in Table 3.

Table 3. ADF Unit Root Test Results

//	With Constant		With Constant & Trend		With Constant & Trend	
	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
ALCTL	-23.7257	0.00000***	-23.7057	0.00000***	-23.5821	0.00000***
ARENA	-22.2287	0.00000***	-22.2151	0.00000***	-22.0824	0.00000***
ASELS	-22.6456	0.00000***	-22.6855	0.00000***	-5.2481	0.00000***
DESPC	-17.9906	0.00000***	-17.9913	0.00000***	-17.7451	0.00000***
INDES	-21.8659	0.00000***	-21.849	0.00000***	-21.6975	0.00000***
KAREL	-9.8831	0.00000***	-9.8861	0.00000***	-9.6211	0.00000***
KRONT	-20.8084	0.00000***	-20.8512	0.00000***	-20.6247	0.00000***
LINK	-22.4061	0.00000***	-22.4384	0.00000***	-22.1308	0.00000***
NETAS	-22.4092	0.00000***	-22.3885	0.00000***	-15.0663	0.00000***
PKART	-22.6629	0.00000***	-22.6775	0.00000***	-22.527	0.00000***

Notes: ***, *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

According to the ADF (Augmented Dickey–Fuller) test results reported in Table 3, all variables under investigation (ALCTL, ARENA, ASELS, DESPC, INDES, KAREL, KRONT, LINK, NETAS, and PKART) are stationary at the 1% significance level across the constant, constant-and-trend, and no-constant/no-trend specifications. Consistent with these findings, the series do not contain unit roots and are stationary in levels. Therefore, these variables can be included in econometric models in levels without the need for differencing.

Table 4. Zivot–Andrews Unit Root Test Results

Variables	t-Statistic	Prob.	Break Point	Critical Value		
				1%	5%	10%
ALCTL	-23.91941	0.03221**	5/27/2019	-5.34	-4.93	-4.58
ARENA	-22.53763	0.00387***	5/27/2020	-5.34	-4.93	-4.58
ASELS	-23.17314	0.00082***	11/13/2017	-5.34	-4.93	-4.58
DESPC	-18.10460	0.09332*	9/02/2019	-5.34	-4.93	-4.58
INDES	-22.13698	0.00690***	3/23/2020	-5.34	-4.93	-4.58
KAREL	-10.17830	0.06681*	10/23/2023	-5.34	-4.93	-4.58
KRONT	-21.00527	0.05222*	11/04/2019	-5.34	-4.93	-4.58
LINK	-22.52529	0.09134*	5/22/2023	-5.34	-4.93	-4.58
NETAS	-15.26761	0.05269*	5/27/2019	-5.34	-4.93	-4.58
PKART	-22.80615	0.06790*	10/29/2018	-5.34	-4.93	-4.58
ALCTL	-23.91941	0.03221**	5/27/2019	-5.34	-4.93	-4.58

Notes: ***, *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 reports the results of the Zivot–Andrews unit root test with structural breaks. The results indicate that all series are stationary under structural breaks at the 1% significance level. This suggests that the variables under investigation are sensitive to episodes of elevated volatility. Although the break dates differ across variables, they broadly point to the uncertainty associated with the COVID-19 pandemic and appear to cluster around mid-2021. This period corresponds to a bull market characterized by sharp price movements. Table 5 reports the appropriate lag lengths for the VAR model constructed to examine the time-varying interaction structure and to

explain the return dynamics of the ten firms (ALCTL, ARENA, ASELS, DESPC, INDES, KAREL, KRONT, LINK, NETAS, and PKART) included in the Borsa Istanbul Technology Index (XUTEK).

Table 5. Lag Length Selection Criteria for the VAR Model

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	-17126.34	NA	3.99e+15	64.30146	64.38173	64.33287
1	-15717.37	2759.784	2.94e+13*	59.38975*	60.27275*	59.73528*
2	-15649.53	130.3377	3.31e+13	59.51042	61.19614	60.17007
3	-15594.06	104.4754	3.92e+13	59.67753	62.16598	60.65131
4	-15527.1	123.6217	4.45e+13	59.80151	63.09268	61.08941
5	-15450.75	138.0998*	4.87e+13	59.89023	63.98412	61.49225
6	-15384.84	116.7183	5.56e+13	60.01818	64.91480	61.93432
7	-15326.6	100.9774	6.54e+13	60.17484	65.87419	62.40511
8	-15260.23	112.5601	7.48e+13	60.30105	66.80312	62.84544
9	-15198.57	102.2645	8.73e+13	60.44492	67.74971	63.30343
10	-15138.7	97.04413	1.03e+14	60.59551	68.70303	63.76814

As shown in Table 5, based on the Final Prediction Error (FPE), Schwarz Information Criterion (SIC), Akaike Information Criterion (AIC), and Hannan–Quinn Information Criterion (HQ), the optimal lag length is determined to be 1. The TVP-VAR results computed with a lag order of 1 are reported in Table 6.

Table 6. TVP-VAR Results

//	ASELS	KAREL	LINK	KRONT	NETAS	ALCTL	ARENA	DESPC	PKART	INDES
ASELS	45.02	7.88	3.44	3.68	9.85	6.11	4.58	6.66	4.61	8.17
KAREL	7.6	44.02	3.16	4.28	6.97	7.39	5.88	4.67	5.99	10.05
LINK	3.66	3.59	50.16	5.39	8.38	5.03	6.75	6.9	3.79	6.35
KRONT	3.86	4.72	5.13	49.33	8.71	7.45	4.5	6.01	3.46	6.82
NETAS	7.93	5.78	6.04	6.4	36.92	9.95	5.38	9	4.61	7.98
ALCTL	5.31	6.97	3.99	6.11	11.16	42.11	4.5	6.87	5.29	7.7
ARENA	5.08	6.23	6.36	4.47	7	5.11	46.25	7	5.95	6.57
DESPC	6.03	4.68	5.78	5.04	10.12	6.96	6.23	41.39	4.21	9.56
PKART	4.98	6.89	3.93	3.75	6.31	6.28	6.4	5.35	50.27	5.84
INDES	7.19	8.31	4.92	5.61	8.47	7.3	5.49	8.54	4.54	39.62
TO	51.63	55.05	42.75	44.74	76.95	61.59	49.71	61	42.45	69.04
FROM	54.98	55.98	49.84	50.67	63.08	57.89	53.75	58.61	49.73	60.38
NET	-3.35	-0.93	-7.09	-5.93	13.88	3.7	-4.04	2.39	-7.28	8.66
Inc.Own	96.65	99.07	92.91	94.07	113.88	103.7	95.96	102.39	92.72	108.66
NPT	4	6	1	2	9	7	3	5	0	8

The generalized forecast error variance decomposition (GFEVD) results obtained from the TVP VAR model are presented in Table 6. These results show the extent to which the variances of the series for the ten firms included in the Borsa Istanbul Technology Index (XUTEK)—ASELS, KAREL, LINK, KRONT, NETAS, ALCTL, ARENA, DESPC, PKART, and INDES—are explained by idiosyncratic shocks and by shocks originating from other variables. Among the variables analyzed, the three with the highest total spillovers (TO) are NETAS (76.95%), INDES

(69.04%), and ALCTL (61.59%). Systemically, these firms exert strong influence over the others and possess substantial volatility transmission capacity, playing an active role in propagating shocks within the technology index. Among the variables examined, those with the highest FROM values—LINK (49.84) and PKART (49.73)—exhibit the largest received volatility transfers. This indicates that LINK and PKART are the most affected by price shocks originating from other firms in the sector. Considering NET values, NETAS (+13.88%) and INDES (+8.66%) assume net shock transmitter roles with high positive values. These companies play a significant role in transmitting sectoral developments to other firms; notably, NETAS's high positive NET value indicates a leadership position in the propagation of within market information and price movements. By contrast, firms such as LINK (−7.09%), PKART (−7.28%), and Kront (−5.93%) exhibit negative NET values and are therefore net shock receivers, implying that their price movements are more strongly determined by the broader sector and that they are highly susceptible to external influences. The firms that best control their own volatility (Inc.Own) are ASELS (96.65) and KAREL (99.07). The firms generating the greatest net pairwise tension (NPT) in the sector are NETAS and INDES, whereas PKART and LINK generate the least tension. Figure 1 presents the total connectedness index.

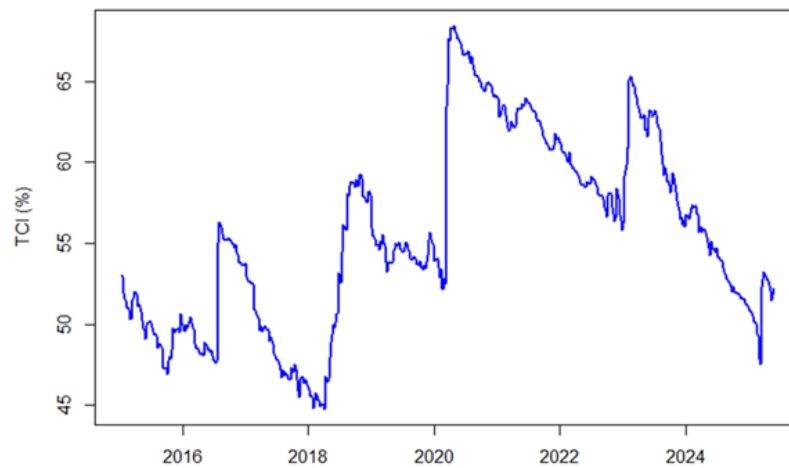


Figure 1. Total Connectedness Index (TVP-VAR)

This figure (see Figure 1) illustrates the evolution of the Total Connectedness Index (TCI), constructed from the TVP-VAR model, for the ten firms in the BIST Technology Index over 2016–2025. The index rose markedly to around 60% during the 2018 episode of exchange-rate shocks and political uncertainty, and it peaked at about 65% in 2020 due to the impact of the COVID-19 pandemic. Although a partial decline occurred in 2021, it climbed back to roughly 60% in 2022 amid the Russia–Ukraine war and shifts in monetary policy. In mid-2025, it rose again—albeit modestly—amid Iran–Israel tensions. The net spillover index by variable presented in Figure 2.

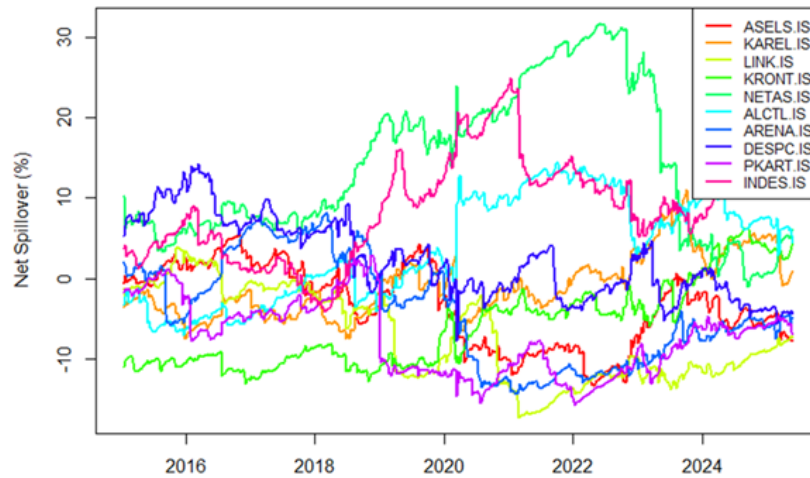


Figure 2. Net Spillover Index by Variable

This figure (see Figure 2) depicts the net volatility spillovers (net spillover index) of the sectoral constituents over the 2016–2025 period. ASELS and KAREL generally post positive values and stand out as net transmitters of volatility to the system, whereas LINK and PKART register negative values and act as net receivers. Net spillovers increase across all firms during the 2018 exchange-rate shock episode and the 2020 pandemic period, indicating heightened systemic risk. After 2022, a marked rise is evident in the net spillovers of NETAS and INDES, while the other firms exhibit a more stable pattern. These dynamics reveal the asymmetric roles of technology firms in volatility transmission and their heterogeneous responses to external shocks. Returns before and after the COVID-19 pandemic—the period with the most pronounced shock in the sample—are examined and presented in Figure 3.

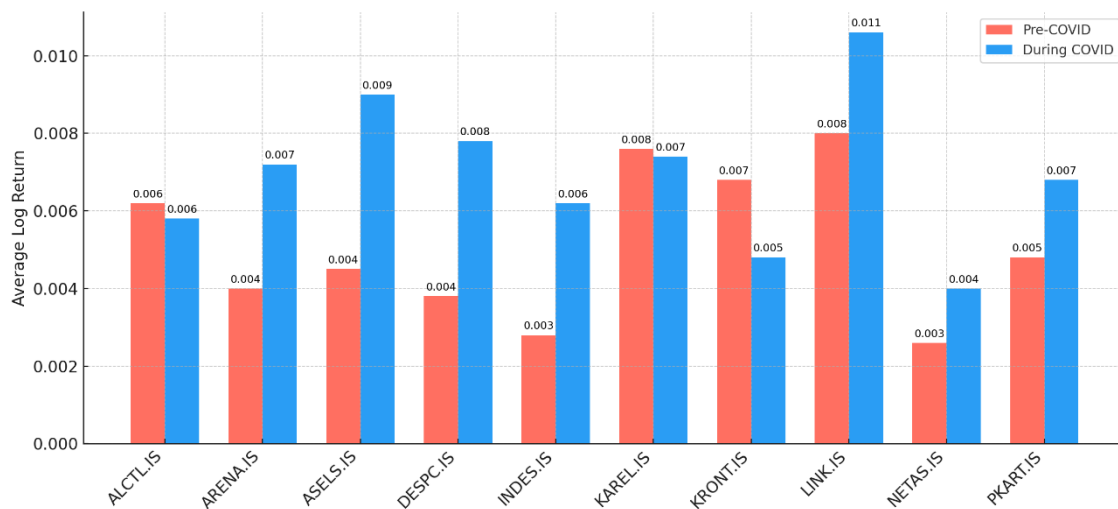


Figure 3. Average Returns Before and After COVID

This figure (see Figure 3) shows the change in average returns for the ten technology-sector firms before and after the COVID 19 pandemic, denoted as 0 (pre COVID 19) and 1 (post COVID 19). Overall, returns trend downward across all firms in the post pandemic period. LINK and KRONT experience the largest declines in average returns after the pandemic, whereas NETAS exhibits

the smallest loss. ASELS and KAREL appear relatively resilient to return losses compared with the other firms. It is evident that the COVID 19 pandemic had adverse effects on these ten firms in the technology index: large cap companies such as ASELS and KAREL were less affected, while LINK and KRONT were more severely impacted.

5. DISCUSSION, CONCLUSIONS & RECOMMENDATIONS

It has become evident that an event with globally adverse and not fully predictable effects—such as the COVID 19 pandemic—raised risk levels by undermining the functionality of the existing system within the sector, thereby revealing the technology sector’s sensitivity to macroeconomic risks (Tan et al., 2022). The findings indicate that NETAS, INDES, and ALCTL, with high positive net values, act as shock transmitters, whereas LINK, PKART, and KRONT, with negative net values, act as shock receivers. This clear differentiation in roles can be attributed to the firms’ distinct positions within the technology ecosystem. For instance, the role of NETAS as a major shock transmitter is likely linked to its central position in Turkey’s telecommunication infrastructure, where any disruption or development in its operations has a cascading effect on the broader digital economy. Similarly, INDES, as a major distributor, acts as a conduit for shocks between hardware markets and the rest of the sector. Following the COVID 19 pandemic, a substantial decline in average returns was observed across all firms traded on XUTEK. This decline was more pronounced for LINK and KRONT, while it was relatively limited for ASELS and KAREL. This clearly underscores the critical role of firm characteristics—such as scale, capital structure, and institutional capacity—in determining resilience to crises. The remarkable resilience of ASELS, for example, can be explained by its status as a defense industry giant with long-term, stable government contracts, insulating it from short-term market panic. In contrast, the vulnerability of “shock receiver” firms like LINK and KRONT may stem from their smaller scale or more specialized business models, making them more susceptible to downturns in the general economic climate. Our findings are consistent with studies reporting increased market volatility due to COVID 19 (Balci et al., 2022; Tan, 2021; Karaömer & Kakilli Acaravcı, 2022) and align with studies assessing the pandemic’s effects on financial markets using the TVP VAR methodology (Adekoya et al., 2021; Belaid et al., 2021; Tao, 2021; Tan et al., 2022; Ha & Nham, 2022; Mishra et al., 2023). However, this study contributes beyond merely confirming increased volatility by identifying the specific, time-varying network of spillovers at the firm level, thus providing a granular map of systemic risk transmission within the BIST Technology Index.

In light of the findings, several recommendations can be made for policymakers and investors. For policymakers, rising systemic risk during crises necessitates strengthening financial stability. Specifically, our identification of key “shock transmitters” suggests that regulators should pay closer attention to the financial health and operational stability of these systemically important firms to mitigate contagion risk. As uncertainty influences investor behavior, enhancing information transparency becomes crucial. Given that firms with larger scale and stronger institutional structures are more resilient, mechanisms that support firm growth and capacity expansion in the technology sector should be developed. In addition, circuit breakers, liquidity support, and policies that bolster investor confidence can strengthen crisis management and help contain market volatility. For investors, the increase in inter-firm dependence during crises makes portfolio diversification essential; rather than concentrating on a few firms, allocating investments across different sectors and companies is important for hedging against systemic risk. Our results further refine this advice: investors can strategically construct portfolios by understanding the roles of different firms. For example, the performance of “shock transmitters” like NETAS could serve as a leading indicator for sectoral trends. The resilient performance of firms with strong corporate structures—such as ASELS and KAREL—indicates that fundamental indicators such as scale, capital structure, and business model diversification should be taken into account in

investment decisions. Moreover, the pronounced return losses observed in shock-receiver firms such as LINK and KRONT underscore the importance of risk-management strategies during crises (e.g., hedging, increasing cash holdings). Given that pandemics, exchange-rate shocks, and geopolitical developments can directly affect corporate performance, it is critical for investors to closely monitor global macroeconomic and political risks. Future research that investigates cross-sector connectedness and the cascading effects of global shocks on markets will yield more comprehensive insights. Finally, this study has limitations, such as its focus on ten specific firms and the use of weekly data. Future research that investigates cross-sector connectedness and the cascading effects of global shocks on markets will yield more comprehensive insights. Additionally, future studies could incorporate firm-level financial data (e.g., leverage, liquidity ratios) to quantitatively explain why certain firms become net shock transmitters or receivers, thereby building upon the foundation laid by this analysis.

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