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Economic Uncertainty on Social Media: The Impact of X Posts on Economic and Financial Indicators

Sosyal Medyada Ekonomik Belirsizlik: X Gönderilerinin Ekonomik ve Finansal Göstergeler Üzerindeki Etkisi

Muhammed Fatih YÜRÜK
Asst. Prof. Dr., Dicle University
mfyuruk@gmail.com
https://orcid.org/0000-0001-7429-2278

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ABSTRACT

This study explores the influence of posts on the social media platform X (formerly Twitter) concerning economic uncertainty on key economic and financial indicators, including GDP, commercial bank loans, and the New York Stock Exchange (NYSE). The analysis focuses on the United States due to its pivotal role in global financial markets and the significant presence of U.S. users, who account for 50% of English-speaking X users, offering a rich dataset for studying social media-driven economic sentiment. Variables such as the USA Gross Domestic Product Index, Commercial Bank Loans, New York Stock Exchange Composite, and X-based Economic Uncertainty Index (TEU) were analyzed using monthly data from June 2011 to April 2023. Employing a Vector Autoregressive (VAR) model, the study finds that fluctuations in commercial bank loans and the NYSE Composite significantly impact GDP, while posts reflecting economic uncertainty, as captured by the TEU, primarily respond to changes in bank loans. The results reveal a bidirectional relationship between GDP and commercial bank loans, where loans can drive economic growth through increased consumer spending and investment, though excessive borrowing may lead to instability and crises. Furthermore, the TEU is influenced solely by variations in commercial bank loans, highlighting social media sentiment's sensitivity to credit dynamics in the U.S. economy.

Anahtar Kelimeler:
Ekonomik Belirsizlik,
Sosyal Medya,
X,
GSYİH,
VAR
Jel Kodları:
D81, E01, E32

ÖZET

Bu çalışma, X (eski adıyla Twitter) sosyal medya platformunda ekonomik belirsizliğe dair paylaşımların, GSYİH, ticari banka kredileri ve New York Borsası (NYSE) gibi ekonomik ve finansal göstergeler üzerindeki etkisini incelemektedir. Analiz, ABD'ye odaklanmıştır çünkü ülke, küresel finansal piyasalardaki lider konumu ve İngilizce X kullanıcılarının %50'sini oluşturan geniş kullanıcı kitlesiyle, sosyal medya kaynaklı ekonomik duyarlılık çalışmalar için ideal bir örnek teşkil etmektedir. Çalışmada, USA Gross Domestic Product Index, Commercial Bank Loans, New York Stock Exchange Composite ve X tabanlı Ekonomik Belirsizlik Endeksi (TEU) değişkenleri, Haziran 2011 - Nisan 2023 dönemine ait aylık verilerle analiz edilmiştir. Vektör Otoregresif (VAR) model yapılan araştırmada, ticari banka kredileri ve NYSE'deki değişimlerin GSYİH'yi önemli ölçüde etkilediği, TEU ile ölçülen ekonomik belirsizlik paylaşımlarının ise esasen banka kredilerindeki dalgalanmalara tepki verdiği bulunmuştur. Bulgular, GSYİH ile ticari banka kredileri arasında çift yönlü bir ilişki olduğunu göstermektedir; krediler, tüketici harcamaları ve yatırımlar yoluyla büyümeyi teşvik edebilirken, aşırı borçlanma istikrarsızlık ve krizlere yol açabilir. Ayrıca, TEU'nun yalnızca banka kredilerindeki değişimlerden etkilenmesi, sosyal medya duyarlılığının ABD ekonomisindeki kredi dinamiklerine özel bir hassasiyet gösterdiğini ortaya koymaktadır.

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1. INTRODUCTION

Nowadays, people are more connected to technology. As technology has evolved, investors' sources of information have shifted. The desire for rapid access to information and the pursuit of quick profits drive investors to social media platforms like X (formerly Twitter). For economic managers and decision-makers, social media can serve as a tool to predict investors' economic tendencies within a country. It also provides insights into changes and sensitivities in consumer behavior, which can inform financial and economic decisions such as investments, interest rates, and loans. Economic crises may be signaled by shifts in consumer and investor attitudes, enabling policymakers to devise strategies to anticipate future crises.

Investors' emotions can be analyzed through X posts. Research has identified significant relationships between financial markets and X posts, highlighting their influence on equilibria such as stock markets, gross domestic product, inflation, interest rates, and bank credit volumes. Behavioral and mood shifts in X posts demonstrate sensitivity across domains like health, communication, information, and technology. Increased pessimism on social media correlates with heightened trading activity, and negative sentiment in X posts often leads to more aggressive trading behavior in financial markets (Zeitun et al., 2023). X has emerged as a key platform for business and finance discussions.

Social media platforms have transformed how individuals acquire information, communicate, and share ideas. Their impact on economic and financial markets is growing, with investors, consumers, and policymakers increasingly turning to social media data to gauge market sentiment, consumer behavior, and economic expectations. However, the use of social media data to measure economic uncertainty and its effects on macroeconomic variables remains underexplored. Traditional methods—such as surveys, news texts, or market volatility—dominate the literature but often fail to capture the real-time, direct sentiment analysis offered by social media. This study addresses this gap by examining economic uncertainty through X discourse and its impact on macroeconomic variables, focusing on the United States. The U.S. was selected due to its dominant role in global financial markets, the prominence of the NYSE, and the substantial engagement of U.S. users on X, who represent 50% of the platform's English-speaking population (Baker et al., 2021). Additionally, the U.S.'s reliance on credit markets, a key driver of consumer spending and economic growth, makes it an ideal case for exploring the interplay between social media sentiment and real economic activity. While traditional measures provide valuable insights, this study offers a novel, real-time measure via X, capturing instantaneous investor and consumer sentiments.

Communication dynamics on X are influenced by an attention economy in which users interact with trending hashtags and mentions to expand their reach and influence within the platform (Shultz, 2023). Discussions on X also extend to topics such as the circular economy, with stakeholders prioritizing economic benefits, environmental impacts and resource scarcity in their conversations, and highlighting the platform's role in fostering dialogues on sustainability and resource management (Grover & Kar, 2020). The relationships built on X go beyond mere interactions, as users build meaningful connections and relationships through the platform, highlighting its role in fostering interpersonal communication and relationship building (Bertapelle & Ballard-Reisch, 2015). These relationships can be classified as either informational, such as sharing news, or social, e.g. interactions with friends and followers (Alshammari et al., 2019). In the financial context, access to finance and financial literacy have been identified as critical factors affecting the growth of small and medium-sized enterprises (SMEs) in developing countries, highlighting the interface between financial access and economic development (Bongomin et al., 2017).

In the political sphere, X serves as a platform for political discussions, with users engaging in conversations that reflect their interests and affiliations, highlighting the role of social media in shaping political discourse among users (Choi et al., 2014). Personality traits have also been linked to social media usage patterns, with platforms such as X and Facebook serving as tools for individuals to express themselves, connect with others, and share information based on their personality traits (Hughes et al., 2012). Furthermore, the role of X as a social network and news medium has been examined and its evolution into a powerful information- sharing platform with extensive user engagement and diverse content distribution has been demonstrated (Kwak et al., 2010).

Social media platforms have fundamentally changed the way individuals acquire information, communicate, and share their ideas today. The impact of these platforms on economic and financial markets is also increasing.

Investors, consumers, and policymakers are increasingly interested in social media data to understand the market sentiment, consumer behavior, and economic expectations. However, the issue of how social media data can be used to measure economic uncertainty and analyze its impact on macroeconomic variables is still under-researched. The existing literature generally measures economic uncertainty using traditional methods such as surveys, news texts, or market volatility. While these methods provide important information, they are insufficient in capturing the real-time and direct sentiment analysis offered by social media. In this context, this study contributes significantly to the literature by examining the measurement of economic uncertainty through social media discourse and its impact on macroeconomic variables. While existing literature predominantly relies on traditional measures of economic uncertainty, such as surveys, news sentiment, and market volatility, this research offers a novel, real-time, and direct measure derived from social media platforms, specifically Twitter (now X). This approach captures the instantaneous sentiments and expectations of investors and consumers, providing insights beyond those offered by conventional methods. This study's findings reveal a significant negative relationship between the Twitter-based Economic Uncertainty Index (TEU) and commercial bank lending. This suggests that adverse economic narratives on social media can amplify perceived uncertainty in credit markets, influencing both credit demand and supply, and consequently exerting substantial effects on the real economy. This dynamic, often overlooked in the existing literature, underscores the evolving role of social media in contemporary economies. Moreover, the conditional/time-varying relationship observed between the TEU and other macroeconomic indicators, including GDP and the NYSE, highlights the context-dependent nature of social media's impact, a dimension previously unexplored in the literature.

2. LITERATURE REVIEW

Researchers are studying the connection between social media activity and market prices to improve investment strategies (Ahmed & Watters, 2018). Studies have shown that X discussions can influence economic uncertainty, with non-fossil fuel energy indices showing strong coherence with economic uncertainty on X for short- and medium-term investment horizons (Durani, 2024). Additionally, X has been used to study the stock market through trust networks between users, offering insights into how platform interactions impact market dynamics (Ruan et al., 2015). In hotel management, X's role as a facilitator of electronic word-of-mouth (eWOM) and customer relationship management has been recognized, highlighting its influence across industries (Kim & Chae, 2018). During the COVID-19 pandemic, X users expressed concerns about the economy and employment, demonstrating the platform's utility in reflecting public sentiment and capturing socioeconomic discussions (Deng & Yang, 2021). Research has also examined X's role in crowdfunding networks, showing how social media and crowdsourcing attract external funding and early-stage customers for entrepreneurs (Lynn et al., 2020).

To explore X users' relationship with business and finance, particularly in the context of economic uncertainty, several studies provide valuable insights. Kılınç et al. (2023) estimated the Baltic Dry Index using a NARX neural network model, incorporating the X-based Economic Uncertainty Index (TEU) and Market Uncertainty Index (TMU), emphasizing X data's integration into economic analysis. Yeşiltaş et al. (2022) developed a high-frequency Economic Policy Uncertainty (TEPU) index based on expert opinions on X, highlighting the platform's influence on financial market dynamics. Nazir et al. (2023) examined the impact of various uncertainty sources, including X-based uncertainty, on stock prices in emerging markets, underscoring social media's role in shaping market sentiments. Wu et al. (2021) analyzed economic policy uncertainty's effect on cryptocurrency markets using X-based measures, demonstrating X data's relevance across financial domains.

Moreover, early studies like Gilbert & Karahalios (2010) demonstrated that widespread worry expressed on social media correlates with stock market declines, suggesting that collective sentiment can serve as an economic indicator. Bollen et al. (2011) further advanced this field by showing that X mood can predict stock market movements, providing a foundation for real-time sentiment analysis in financial research. Similarly, Sprenger et al. (2014) found that X posts contain valuable information for stock trading, with specific sentiments linked to market returns. These studies primarily focus on stock markets, leaving the relationship between social media sentiment and real economy variables like commercial bank lending underexplored. This study addresses this gap by examining the TEU's connection to credit markets, offering a novel perspective on how X-based uncertainty influences macroeconomic dynamics beyond financial markets. Researchers have also investigated various applications of VAR models. For instance, Lu (2001) used VAR models for dynamic analysis of geographic processes, while Bringmann et al. (2018) developed a time-varying VAR (TV-VAR) model to capture temporal dependencies. Bayesian methods have improved VAR model efficiency (Yang et al., 2021), and algorithms for recursive identification of large VAR models have enhanced their adaptability (Monchen et al., 2019).

3. METHODOLOGY AND DATA

The Vector Autoregressive (VAR) model was employed in this study due to its ability to simultaneously estimate relationships among multiple variables and capture their dynamic dependencies over time (Ibrahim et al., 2020; Souza et al., 2017). This feature is particularly valuable when analyzing systems in which variables influence each other, making VAR models a suitable choice for studying complex phenomena such as economic dynamics, climate trends, and disease patterns.

VAR models are preferred because of their flexibility in dealing with multivariate time series data. They can take exogenous variables into account and provide a comprehensive framework for incorporating additional factors that may affect the variables of interest (Yasin et al., 2018; Haslbeck et al., 2020). This flexibility improves the model's ability to capture the full range of influences on the system under study, resulting in more accurate forecasts and insightful analyses. In addition, VAR models are versatile and are widely used in various disciplines such as economics, finance and statistics. They are used to analyze trends, predict future outcomes and conduct policy assessments (Rusman et al.,2019; Gunarto et al., 2023).

VAR models provide a structured framework for conducting hypothesis testing, forecasting, and policy analysis (Pripoaie et al., 2022). The Vector Autoregressive (VAR) model was preferred in the analysis of this study due to its flexibility in analyzing multivariate data, its effectiveness in interpreting data in finance and its structured approach to forecasting, as well as its ability to identify complex relationships between variables. Additionally, vector autoregressive (VAR) models are gaining popularity in various fields due to their ability to capture dynamic relationships between multiple time series variables. These models predict each variable based on its own past values as well as the past values of other variables in the system (Dablander et al., 2020; Bulteel et al., 2016; Bulteel et al., 2018). VAR models are particularly useful for analyzing multivariate time series data because they can effectively capture the temporal dynamics of lead-lag (Bai et al., 2021; Bashir & Wei, 2018).

The study utilized the EViews software for statistical and econometric calculations. It examined the association between economic uncertainty expressed on the X platform in the United States and various economic and financial variables, using monthly data from June 2011 to April 2023. Details of the variables are presented in Table 1.

Table 1. Variables Used in the Study

No	Variable	Code	Reference
1	USA Gross Domestic Product Index	GDP	spglobal.com
2	Commercial Bank Loans	LOAN	fred.stlouisfed.org
3	New York Stock Exchange Composite	NYSE	tr.investing.com
4	Twitter (X)-Based Economic Uncertainty Index	TEU	policyuncertainty.com

The TEU variable, developed by Thomas Renault (University of Paris 1 Panthéon-Sorbonne) in collaboration with Scott R. Baker (Northwestern), Nicholas Bloom (Stanford), and Steve Davis (University of Chicago), was derived from all X posts in the U.S. since June 2011 containing keywords related to uncertainty and economics. U.S. users constitute 50% of the English-speaking X population (Baker et al., 2021).

4. RESULTS

The continuity of the series was tested before establishing the VAR model. For series stationarity, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were used.

Table 2. Stationary Test Results

	Variables	ADF	PP
I(0)	LNGDP	-0.856955 (0.7991)	-0.748062 (0.8300)
	LNLOAN	0.3028218 (0.9777)	0.4874012 (0.9858)
	LNNYSE	-1.2298955 (0.6605)	-1.038487 (0.7384)
	LNTEU	-3.7617090 (0.0041)	-1,116220 (0.0154)
I(1)	LNGDP	-10.829535 (0.0000)	-13.78817 (0.0000)
	LNLOAN	-6.6087214 (0.0000)	-5.787855 (0.0000)
	LNNYSE	-13.526455 (0.0000)	-13.86655 (0.0000)
	LNTEU	-16.471948 (0.0000)	-26.08785 (0.0000)
	Critical Value %1	-3.477143	-3,474567
	Critical Value %5	-2.881977	-2,880853
	Critical Value %10	-2.577747	-2,577147

In unit root tests, the null hypothesis (H_0) indicates that the series are not stationary. The aim is to reject the H_0 hypothesis. The logarithms of the series were taken before the stationarity tests. The stationary test results are shown in Table 2. The ADF test used the Akaike Information Criterion, commonly applied in financial series. The estimation method for the PP test was Bartlett Kernel, while Newey-West Bandwidth was used for bandwidth selection. According to the stationarity tests, the series become stationary at the first difference in both the ADF and PP tests. Therefore, the null hypothesis H_0, “the series have a unit root,” was rejected. The next step of the study examined the lag length.

Table 3. VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	458.03776921	NA	1.41e-08	-6.726485	-6.640403	-6.691504
1	1216.2692756	1460.298	2.36e-13	-17.72251	-17.29210	-17.54760
2	1269.5743989	99.50290	1.36e-13	-18.27518	-17.50044*	-17.96034
3	1298.0225851	51.41746	1.13e-13*	-18.45959*	-17.34053	-18.00484*
4	1304.6236123	11.53957	1.31e-13	-18.32035	-16.85695	-17.72567
5	1315.5487813	18.45140	1.41e-13	-18.24517	-16.43744	-17.51056
6	1323.7725184	13.40165	1.60e-13	-18.12996	-15.97791	-17.25543
7	1346.6583652	35.93926*	1.46e-13	-18.23198	-15.73559	-17.21752
8	1354.5536644	11.93067	1.67e-13	-18.11191	-15.27119	-16.95752

As shown in Table 3, an analysis was performed to determine the lag length of the VAR model. To determine the lag length, the lag with the asterisk (*) was selected. The table shows an accumulation of stars at the third lag. Consequently, three lags were chosen, and the model was established.

In the established VAR model, we need to test whether the process is stationary using another method to determine whether it contains a unit root. The stationarity of the model is related to its eigenvalues (Hendry & Juselius, 2001):

$$\binom{x_t}{x_{t-1}} = \begin{pmatrix} \Pi_1 & \Pi_2 \\ \mathrm{I}_p & 0 \end{pmatrix} \binom{x_{t-1}}{x_{t-2}} + \binom{\epsilon_t}{0} \qquad (1)$$

a) if all the eigenvalues of the complementary matrix are in the unit circle, then { x_t } is the constant;

b) if all the eigenvalues are in or above the unit circle, { x_t } is not constant;

c) if any of the eigenvalues is outside of the unit circle, { x_t } is the expansive.

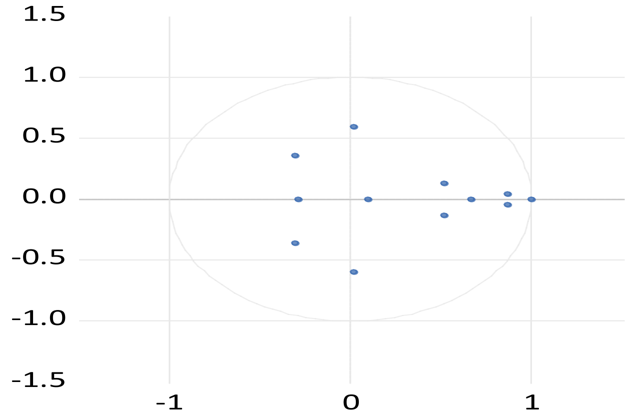

Figure 1. Inverse Roots of AR Characteristic Polynomial

For this purpose, the unit circle position of the inverse roots of the AR characteristic polynomial is analyzed in Figure 1. As can be seen in the figure, all eigenvalues of the coefficient matrix lie within or on the unit circle. This indicates that our VAR model is stationary. The positions of the unit roots, graphically analyzed in Figure 1, within the unit circle are shown in Table 4. Since all values are less than 1, there is no unit root, meaning the model is stationary.

Table 4. Unit Roots of the Coefficient Matrix and Their Positions in the Unit Circle

Root	Modulus
0.999182	0.999181622
0.867345 - 0.044947i	0.868508586
0.867345 + 0.044947i	0.868508586
0.666392	0.666392010
0.016552 - 0.590742i	0.590974080
0.016552 + 0.590742i	0.590974080
0.512364 - 0.130303i	0.528673741
0.512364 + 0.130303i	0.528673741
-0.305736 - 0.356907i	0.469954784
-0.305736 + 0.356907i	0.469954784
-0.290578	0.290578487
0.098329	0.09832942

The LM test is used to test whether the model exhibits autocorrelation. In the LM test, the null hypothesis H_0 is that there is no autocorrelation. To accept the hypothesis H_0, a p-value > 0.05 is required. As can be seen in Table 5, the hypothesis is accepted as the p-values are > 0.05. In other words, there is no autocorrelation in our model.

Table 5. VAR Residual Serial Correlation LM Tests

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	20.4514	16	0.2005	1.289210	(16, 367.2)	0.2007
2	21.1152	16	0.1741	1.332247	(16, 367.2)	0.1742
3	17.3269	16	0.3647	1.087662	(16, 367.2)	0.3649

4.1. Impulse-Response Function Graphical Results

Impulse-response functions were used to examine the response of the variables of interest to a one standard deviation (SD) shock to GDP, LOAN, NYSE, and TEU variables. The impulse-response functions in the 4-variable VAR model are plotted in Figure 2 over 10 periods. When analyzing the relationship between the TEU variable and other variables in the graphs, it is observed that GDP does not respond to a 1 SD shock applied to the TEU variable. Despite a 1 SD shock applied to the TEU variable, the LOAN variable shows a slight increase before stabilizing after the third period. Despite a 1 SD shock applied to the TEU variable, the NYSE variable shows no response after the second period. In response to a 1 SD shock applied to TEU, TEU itself responds with a rapid increase followed by a decrease, and by the end of the 10th period, its effect approaches zero. GDP can be influenced by its own lagged values and shocks.

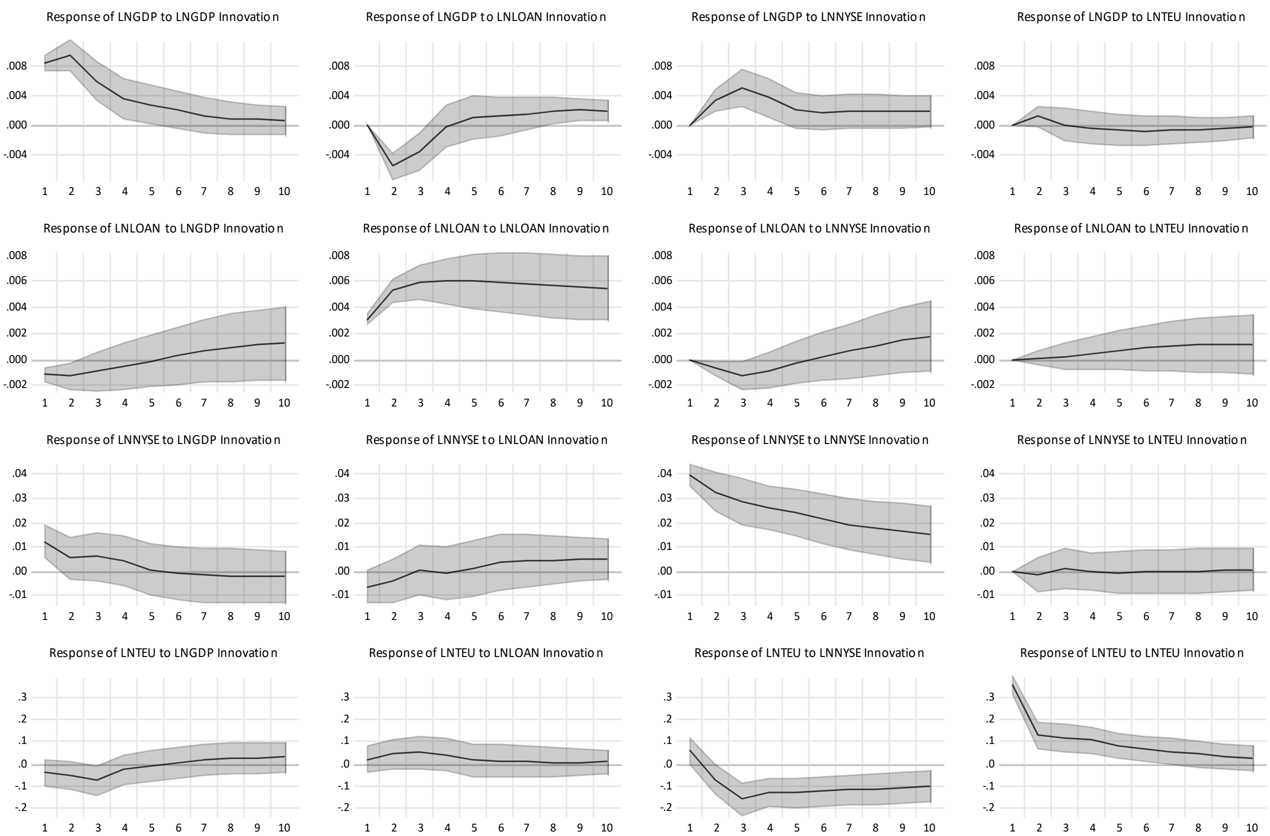

Figure 2. Response to Cholesky One S.D. (d.f. adjusted) Innovations

4.2. Results of Variance Decomposition

Variance decomposition offers a method to observe the movements of the established VAR model in detail. In the established model, the proportion of movements in the dependent variables is attributed to shocks from other variables, in addition to shocks from the same variable. For example, a shock applied to one variable will directly affect that variable, but importantly, the shock will also propagate to all other variables in the model structure. Variance decomposition measures how much of the forecast error variance of a given variable is explained by the innovations in each explanatory variable for i=1,2,3 (Sarıkovanlık et al., 2020).

Table 6. Variance Decomposition

Variance Decomposition of LNGDP:					
Period	**S.E.**	**LNGDP**	**LNLOAN**	**LNNYSE**	**LNTEU**
1	0.009327	100	0	0	0
2	0.013833	83.44557	7.909523	8.143257	0.501645
3	0.016120	71.58195	14.52368	13.37183	0.522523
4	0.017118	65.65912	16.77198	16.84101	0.727875
5	0.017511	63.02310	16.78595	19.27282	0.918117
6	0.017701	61.68228	16.42893	20.87730	1.011487
7	0.017865	60.56066	16.54090	21.86502	1.033403
8	0.018045	59.36186	17.14719	22.46840	1.022528
9	0.018236	58.12745	17.99113	22.87897	1.002427
10	0.018425	56.94369	18.86049	23.21388	0.981922
Variance Decomposition of LNLOAN:					
Period	**S.E.**	**LNGDP**	**LNLOAN**	**LNNYSE**	**LNTEU**
1	0.003332	12.07354	87.92645	0	0
2	0.006387	7.280231	91.58140	1.058601	0.079766
3	0.008970	4.571294	94.06899	1.116308	0.243396
4	0.011027	3.125336	95.65011	0.890271	0.334279
5	0.012660	2.372518	96.57889	0.677609	0.370977
6	0.013992	1.991601	97.02425	0.612022	0.372120
7	0.015124	1.796587	97.10820	0.740111	0.355091
8	0.016130	1.687565	96.92363	1.057745	0.331051
9	0.017057	1.616450	96.54119	1.536463	0.305889
10	0.017934	1.562810	96.01403	2.140995	0.282155
Variance Decomposition of LNNYSE:					
Period	**S.E.**	**LNGDP**	**LNLOAN**	**LNNYSE**	**LNTEU**
1	0.042381	4.875689	2.808296	92.31601	0
2	0.054482	3.615368	2.398511	93.59255	0.393569
3	0.062167	3.048282	1.899765	94.66254	0.389406
4	0.067671	2.726726	1.606617	95.29388	0.372774
5	0.071829	2.540728	1.473259	95.63760	0.348408
6	0.075092	2.433287	1.432844	95.80724	0.326617
7	0.077709	2.372700	1.441979	95.87648	0.308834
8	0.079840	2.339176	1.478871	95.88719	0.294757
9	0.081596	2.320467	1.534666	95.86122	0.283644
10	0.083054	2.309431	1.606509	95.80926	0.274793
Variance Decomposition of LNTEU:					
Period	**S.E.**	**LNGDP**	**LNLOAN**	**LNNYSE**	**LNTEU**
1	0.372807	1.481761	0.932534	1.018070	96.56763
2	0.419500	4.254512	2.207735	3.844734	89.69301
3	0.468641	4.066774	4.272650	10.39533	81.26524
4	0.504419	3.598828	5.173628	16.78393	74.44360
5	0.532223	3.236507	5.367420	22.41217	68.98389
6	0.554147	2.985472	5.280771	27.10423	64.62951
7	0.571991	2.802598	5.133541	30.93759	61.12626
8	0.586817	2.667596	5.004808	34.03189	58.29569
9	0.599263	2.570711	4.917624	36.50645	56.00520
10	0.609719	2.503240	4.874894	38.46781	54.15405

Table 6 shows the results of the 10-period variance decomposition of the variables. According to the results, in the 10th period, about 57% of the error variance in the GDP variable is explained by itself, while the remaining approximately 43% is explained by the LOAN and NYSE variables. The results of the 10-period variance decomposition of the LOAN variables are presented in Table 6. According to the results, a significant part of the error variance in the LOAN and NYSE variables is explained by themselves, while the remaining part is explained by other variables. For the TEU variable, about 54.15% of its variance in the final period is explained by itself, approximately 39% by the NYSE variable, and approximately 5% by LOAN.

4.3. Granger Causality Test Results

The Granger causality test was performed to determine the relationship between variables. The Granger causality test is used to assess the direction of causality in the lagged relationship between the variables analyzed as a function of time. According to Granger (1969), A is the Granger cause of B if the prediction of B is more successful when A's past values are used than when A's past values are not used (Sarıkovanlık et al., 2020).

Table 7. VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: LNGDP			
Excluded	Chi-sq	df	Prob.
LNLOAN	37.86858	2	0.0000
LNNYSE	29.17402	2	0.0000
LNTEU	2.802127	2	0.2463
All	94.72243	6	0.0000
Dependent variable: LNLOAN			
Excluded	Chi-sq	df	Prob.
LNGDP	10.12201	2	0.0063
LNNYSE	5.921556	2	0.0517
LNTEU	0.417331	2	0.8116
All	22.44935	6	0.001
Dependent variable: LNNYSE			
Excluded	Chi-sq	df	Prob.
LNGDP	0.750964	2	0.6869
LNLOAN	3.380836	2	0.18444
LNTEU	0.992576	2	0.60878
All	8.436135	6	0.2078
Dependent variable: LNTEU			
Excluded	Chi-sq	df	Prob.
LNGDP	2.356065	2	0.3078
LNLOAN	10.61641	2	0.0049
LNNYSE	23.03027	2	0.9779
All	37.610335	6	0.0000

Table 7 shows the results of the Granger causality test. Changes in LOAN and NYSE are the Granger causes of changes in GDP. Changes in GDP and NYSE are the Granger causes of changes in LOAN. Only changes in LOAN are found to be the Granger cause of changes in TEU. Changes in the NYSE affect GDP, while changes in GDP do not affect NYSE. Another finding is that changes in the TEU do not affect other variables. The only variable that affects the TEU variable is LOAN.

The relationships between commercial bank loans, stock market fluctuations (specifically the NYSE), and GDP changes have been explored in various studies, revealing insights that align with the findings of this study. The literature indicates that economic policy uncertainty and the credit supply from banks significantly influence economic growth and market dynamics. Bordo et al. (2016) highlight that economic policy uncertainty is closely linked to slower loan growth, suggesting that banks adjust their lending practices in response to uncertainty, which in turn can affect broader economic indicators like GDP. This aligns with our finding that changes in commercial bank loans are a Granger cause of changes in economic uncertainty. Similarly, Valencia (2013) discusses how aggregate uncertainty is countercyclical, leading to reduced bank lending during periods of weak economic activity, reinforcing the notion that economic conditions and bank lending are interdependent. Moreover, Ashraf (2021) provides evidence that heightened economic uncertainty leads banks to increase loan pricing, which can further restrict lending and impact economic growth. This supports our assertion that changes in commercial bank loans can influence economic uncertainty, as banks may react to perceived risks by tightening credit availability. Raunig et al. (2016) also find that banks are likely to lend less during uncertain times, which could explain the cyclical nature of our findings regarding the relationship between NYSE changes and GDP. Several authors further examine the interplay between GDP and the NYSE. While this study posits that changes in GDP do not affect the NYSE, other research suggests that stock market performance can reflect underlying economic conditions. Ghosh (2016) notes that regional economic indicators significantly influence real estate lending, which is often tied to broader economic performance, suggesting that while GDP may not directly impact stock prices, it does play a role in shaping the economic environment that affects market performance. Additionally, the findings of Morina and Özen (2020) indicate a positive relationship between commercial bank lending and economic growth, which supports our conclusion that commercial bank loans can drive changes in GDP. This is consistent with the notion that banks play a crucial role in financing economic activities, thereby influencing overall economic performance. In summary, the literature provides a robust framework that supports our findings regarding the causal relationships among commercial bank loans, the NYSE, and GDP. The studies collectively emphasize the significance of economic uncertainty and bank lending dynamics in shaping economic outcomes.

5. CONCLUSION

This study examines the relationship between the X-based Economic Uncertainty Index (TEU) and the GDP, LOAN, and NYSE variables, while also exploring the interactions among all variables in general. It investigates whether posts by X users in the United States containing words related to economic uncertainty influence or are influenced by the country's economic and financial variables. This question is addressed in the study. The study first tested the stationarity of the series and then established the VAR model. The relationship between the series was observed using the Granger causality test, performed after the model assumptions were met. As a result of the test, changes in LOAN and NYSE are observed to affect GDP. The amount of credit provided by commercial banks can have both negative and positive effects on GDP. Individuals can purchase more goods and services by obtaining loans from banks. This increases consumer spending, which contributes to GDP growth. Companies finance their investments by taking out loans. The increase in productive capacity through investments and the resulting increase in employment contribute to GDP growth. Proper and efficient utilization of credit provided by banks can positively contribute to economic growth, which leads to an increase in GDP in the long run. On the other hand, credit utilization can also have a negative impact on GDP. Excessive borrowing by individuals and businesses can create the risk of non-repayment. This situation can lead to an economic crisis, economic instability, and a decline in GDP. Increasing credit volume can lead to an increase in inflation as demand rises. High inflation can threaten economic stability, and the accompanying crises will have a negative impact on GDP. In short, as noted in the study, changes in LOAN impact GDP. Changes in the NYSE can affect GDP. Changes in major stock market indices such as the NYSE can affect GDP through various channels, such as consumer and business behavior, wealth effects, confidence, and financial crises. This multidirectional effect can impact the economy and thus lead to changes in GDP.

When LOAN is the dependent variable in the study, only changes in GDP are observed to affect LOAN. As already explained, there is a bidirectional relationship between GDP and LOAN. When TEU is the dependent variable, it is observed that only changes in LOAN cause a change in TEU. Changes in the amount of credit provided by banks can directly affect levels of economic uncertainty. While an increase in lending generally indicates greater economic confidence and support for growth, a decrease in lending can indicate heightened uncertainty and risk perception. Changes in the other two variables have no impact on TEU. This could indicate that X users in the U.S. are more sensitive to interest rates, particularly the amount of loans provided by banks. Using credit has become a common behavior in the United States. American citizens often meet their financial needs by using loans for both personal and business purposes. The creditworthiness of individuals in the U.S. is crucial. With this rating, they can secure credit loans. Therefore, American citizens value creditworthiness. The U.S. economy is closely tied to consumer spending. Consumers usually cover their needs with loans from banks.

This spending is linked to economic growth. In short, the use of credit by U.S. citizens has become a part of their life and culture. Loans such as home loans and student loans are particularly important for U.S. citizens. For this reason, it is natural that changes related to creditworthiness will be reflected in the posts of X users. By tracking X posts, economists and policymakers are able to anticipate economic uncertainties in the U.S. and take measures in advance to mitigate financial crises that may occur.

This finding is novel in the literature, as it demonstrates a direct link between real economic activity in the credit markets and social media discourse. While previous studies have examined the relationship between social media sentiment and financial market variables (Bollen et al., 2011; Loughran & McDonald, 2011; Ranco et al., 2015), this study extends the literature by focusing on the connection between social media discourse on economic uncertainty and commercial bank lending, a critical component of the real economy. This highlights the potential of social media data to provide timely insights into credit market dynamics.

This study has several limitations. First, it relies solely on data from X, which may not be representative of the entire population. Second, the TEU is constructed based on a predefined set of keywords, which may not capture all nuances of economic uncertainty. Third, the study focuses specifically on the U.S. economy. Future research could incorporate data from other social media platforms and employ more sophisticated text analysis techniques, as well as examine similar relationships in other countries.

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The entire research is written by the author.

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