# TIME-VARYING GRANGER CAUSALITY BETWEEN INDUSTRIAL PRODUCTION AND NON-PERFORMING LOANS IN TÜRKİYE

# Türkiye'de Sanayi Üretimi ve Takipteki Alacaklar Arasında Zamanla Değişen Granger Nedensellik

# Gökhan SÜMER\*0

#### Abstract

Keywords: Time-Varying Granger Causality, Non-Performing Loans, Industrial Production

**JEL Codes:** G21, E32, C22 Banks play a crucial role in bridging fund suppliers and demanders, thereby facilitating economic development by channeling idle funds into the economy. For banks to effectively perform their functions, the financial transmission mechanism is essential. Non-performing loans (NPLs) significantly impact bank profitability, credit positions, and overall economic development. This study investigates the relationship between industrial production and non-performing loans in Turkey using a time-varying Granger Causality test. Monthly data from January 2005 to July 2024 was utilized to examine the interconnection between the industrial production index and non-performing loans. The research uniquely contributes to the existing literature by applying a sophisticated time-varying Granger Causality methodology, investigating the dynamic relationship between economic activity and credit risk, and providing insights into the temporal variations of industrial production and non-performing loans within the Turkish banking sector. Key methodological approaches include utilizing a recursive evolving window algorithm, employing bootstrap simulations to enhance estimation precision, and analyzing causal relationships through multiple computational techniques. Findings underscore the importance of adaptive risk management strategies and the need for flexible macroprudential policies capable of responding to the evolving economic landscape.

### Öz

Anahtar Kelimeler: Zamanla Değişen Granger Nedensellik, Takipteki Krediler, Sanayi Üretimi

**JEL Kodları**: G21, E32, C22 Bankalar, fon arz edenler ile talep edenler arasında köprü görevi görerek, âtıl fonları ekonomiye kanalize ederek ekonomik kalkınmaya önemli katkı sağlamaktadır. Bankaların etkili bir şekilde işlevlerini yerine getirebilmeleri için finansal iletim mekanizması oldukça önemlidir. Takipteki krediler (TK), banka karlılığı, kredi pozisyonları ve genel ekonomik gelişme üzerinde önemli bir etkiye sahiptir. Bu çalışmada, Türkiye'de sanayi üretimi ile takipteki krediler arasındaki ilişki, zamanla değişen Granger Nedensellik testi kullanılarak analiz edilmiştir. Ocak 2005 ile Temmuz 2024 arasındaki aylık veriler kullanılarak sanayi üretim endeksi ile takipteki krediler arasındaki etkilesim incelenmistir. Arastırma, mevcut literatüre benzersiz bir katkı sunarak; zamanla değişen Granger Nedensellik yöntemini uygulamış, ekonomik faaliyet ile kredi riski arasındaki dinamik ilişkiyi incelemiş ve Türk bankacılık sektöründe sanayi üretimi ve takipteki krediler arasındaki zamansal değişimleri sunmuştur. Temel yöntemsel yaklaşımlar arasında; bir evrimsel pencere algoritması kullanımı, tahmin hassasiyetini artırmak için bootstrap simülasyonları ve nedensel ilişkileri analiz etmek için birden fazla hesaplama tekniği yer almaktadır. Bulgular, uyumlu risk yönetim stratejilerinin önemini ve değişen ekonomik ortamı karşılayabilecek esnek makro ihtiyati politikalara duyulan ihtiyacı vurgulamaktadır.

Received Date (Makale Geliş Tarihi): 07.01.2025 Accepted Date (Makale Kabul Tarihi): 26.03.2025

This article is licensed under Creative Commons Attribution 4.0 International License.



<sup>\*</sup> Dr., Türkiye Halk Bankası A.Ş., Türkiye, gkhanb73@gmail.com

# 1. Introduction

The impact of banks, which are the key actors in the financial sector, on economic development continues to grow day by day. It is crucial for the banking sector, which forms the foundation of financial life, to present an efficient and effective appearance for the development of the national economy (Ferreira, 2017: 203-204). In the early 20th century, Schumpeter demonstrated that the banking system contributes to economic growth by supporting the real sector through credit (İçke, 2014).

While banks profit from individuals or entities that demand funds, they are also exposed to various risks such as exchange rates, interest rates, maturity, liquidity, and repayment in the course of these activities. When individuals or legal entities that need funds fail to pay all or part of the principal or interest of the loans they have used, the loans granted by banks fall into arrears (Genç and Şaşmaz, 2016). In other words, it is the delay in collection and the occurrence of losses for the lender when the debtor fails to fulfill their obligations on time or at all under the contract between the bank and the borrower (Selçuk and Darici, 2003: 174).

Bank loans not only influence employment and growth but also have an impact on regional and sectoral development through selective credit policies. The exercise of authority over loans is crucial for these positive effects to emerge. The timely and complete fulfillment of obligations related to loans is one of the conditions for the system to operate healthily. Increasing arrears in bank loans will affect bank profitability, risk appetite, and the amount of funds to be allocated. Therefore, non-performing loans have negative effects on economic development (Koyuncu and Saka, 2011; Selimler, 2015).

Non-performing loans cause banks to face difficulties in managing their assets, liabilities, and liquidity. The problem of non-repayment of loans in the banking sector can quickly spread throughout the entire financial system, potentially leading to a financial crisis. High default rates on loan repayments lead to a decrease in the supply of funds, a decline in bank profitability, and disruption of the sector's credit creation function. Barr et al. (1994) argue that high non-performing loan rates indicate increased risks in the markets, leading banks to tighten credit allocations and credit terms. Cucinelli (2015) suggests that an increase in defaults, along with a deterioration in the quality of banking sector assets, will have negative effects on financial stability and economic growth (Hasan et al., 2009; Zhang et al., 2016).

The contributions of loans granted by banks to the economy have been the subject of much research. The rate of non-performing loans has also been the focus of numerous studies. In many studies, the interactions between loan volume, non-performing loan rates, unemployment, GDP, interest rates, and inflation have been examined using various methods. This study differs from others in that it analyzes the relationship between industrial production and non-performing loans in Turkey using a time-varying Granger Causality test. The study examines the relationship between the industrial production index and non-performing loans using monthly data from January 2005 to July 2024.

Section 2 introduces literature reviews. Section 3 presents the econometric method used in the study, which is the time-varying Granger causality test developed by Shi et al. (2020). Section 4 describes the data and empirical results, including the sources of the data, the time period covered, and the variables used in the analysis. Section 5 discusses the findings and their

implications. Finally, Section 6 concludes the paper with a summary of the main results and suggestions for future research.

## 2. Literature Review

The relationship between economic activity and credit risk, particularly non-performing loans (NPLs), has been a focal point of extensive research in both developed and emerging markets. Banks play a critical role in economic development by channeling funds from savers to borrowers, and the health of the banking sector is closely tied to the broader economic environment. Non-performing loans, which arise when borrowers fail to meet their repayment obligations, are a key indicator of credit risk and have significant implications for bank profitability, financial stability, and economic growth. Over the years, numerous studies have explored the determinants of NPLs, examining the interplay between macroeconomic factors, banking sector-specific variables, and broader economic conditions. This literature review systematically organizes these studies into thematic categories, providing a comprehensive overview of the existing research and highlighting the diverse methodologies and findings that have shaped our understanding of the dynamics between economic activity and credit risk. By categorizing the literature into macroeconomic factors, banking sector-specific factors, regional and cross-country analyses, methodological approaches, and the broader economic impact of NPLs, this review aims to offer a structured and coherent foundation for the empirical analysis presented in this study.

## 2.1. Studies on Macroeconomic Factors and Non-Performing Loans (NPLs)

One of the earliest studies to highlight the relationship between macroeconomic conditions and bank failures was conducted by Barr et al. (1994), who emphasized the role of non-performing loans as a key risk factor. Following this, Koyuncu and Saka (2011) investigated the impact of NPLs on domestic credit and private sector investments in Turkey, finding a statistically significant negative relationship. More recently, Sevinç (2021) analyzed the relationship between NPLs and macroeconomic variables in Turkey, concluding that economic growth and inflation reduce NPLs, while unemployment and exchange rates increase them. In a similar vein, Qureshi and Hasmi (2023) studied the impact of interest rates, inflation, and GDP on NPLs in Pakistan, finding a negative relationship between inflation, GDP, and NPLs, but a positive relationship between interest rates and NPLs. Adam et al. (2024) further contributed to this line of research by investigating the impact of inflation and national income on NPLs in private banks in Indonesia, finding a positive effect of inflation but an insignificant effect on national income. Finally, Yalçın (2024) explored the long-term relationship between exchange rates, consumer loan interest rates, and NPLs in Turkey, identifying a positive relationship between exchange rates and NPLs, and a negative relationship between policy interest rates and NPLs.

## 2.2. Studies on Banking Sector-Specific Factors and NPLs

Early work on the Turkish banking sector by Selçuk and Darıcı (2003) focused on the impact of delayed loan collections on bank performance. Later, Kılcı and Baygın (2019) used the TAR-MTAR cointegration test to analyze the relationship between credit interest rates and NPLs

in Turkey, finding a long-term relationship. More recently, Erdoğan (2024) analyzed the relationship between NPLs and loan provisions, total assets, and capital adequacy ratios in Turkish banks, finding a positive and significant relationship. Karaaslan (2023) also investigated the determinants of NPLs in the Turkish banking sector, finding a significant positive relationship between unemployment and NPLs, and a negative relationship between GDP and NPLs. Additionally, Umarbeyli and Kırıkkaleli (2023) examined the relationship between NPLs and bank concentration in Turkey, finding a positive relationship between NPLs and bank concentration.

## 2.3. Studies on Regional and Cross-Country Analysis of NPLs

Tanaskovic and Jandric (2015) were among the first to examine the macroeconomic and institutional determinants of NPLs in Middle Eastern and Southeastern European countries, finding a positive relationship between GDP, exchange rates, and NPLs. Following this, Artenisa and Hyrije (2023) studied the impact of GDP, credit, and interest rates on NPLs in six Western Balkan countries, finding a significant positive impact of GDP and central government debt on NPLs. More recently, Nwonye et al. (2023) analyzed the impact of macroeconomic indicators and governance on NPLs in 30 Sub-Saharan African countries, finding a relationship between GDP growth and a reduction in NPLs.

## 2.4. Studies on Methodological Approaches to NPLs

Shi et al. (2020) developed a time-varying Granger causality test, which is used in this study to analyze the dynamic relationship between industrial production and NPLs. Following this, Us (2020) applied a panel VAR approach to analyze NPLs in the Turkish banking sector, concluding that NPLs respond strongly to shocks in macroeconomic indicators. More recently, Tunay and Tunay (2024) used a Bayesian analysis to study the interactions between NPLs and macroeconomic shocks in Turkey, finding a strong mutual interaction between NPLs and economic activity.

# 2.5. Studies on the Impact of NPLs on Economic Development

Cucinelli (2015) argued that an increase in NPLs deteriorates the quality of banking sector assets, negatively affecting financial stability and economic growth. More recently, Yıldız (2024) concluded that NPLs negatively affect profitability ratios in the banking sector and lead to long-term losses in the national economy by reducing credit availability for production and investment.

# 3. Econometric Method

This study seeks to rigorously examine the causal relationship between non-performing loans and the industrial production index within a time-varying dynamic framework. The dynamic time-varying causality test established by Shi et al. (2020) is employed, demonstrating significant efficacy in identifying heterogeneities in time series data. The methodology fundamentally involves a Granger causality analysis within the context of the lag-augmented VAR (LA-VAR)

model. The study yields results utilizing three distinct algorithms: forward-recursive, rolling window, and recursive evolving.

This methodology is extensively recognized in the literature for its capacity to distinctly illustrate variability in causal links, particularly during times of frequent economic shocks and structural fractures. The "recursive evolving rolling window" technique proposed by Shi et al. (2020) is recognized for yielding more dependable outcomes than conventional methods, owing to its adaptability in collecting heterogeneities within time series data. Simulations employing the bootstrap approach enhance the precision of estimating the test statistic's distribution, hence mitigating the likelihood of erroneous results.

First, the LA-VAR model is shown in equation (1). The dependent variable  $y_t$  is a n-dimensional vector.

$$y_{t} = \alpha_{0} + \alpha_{1}t + \sum_{i=1}^{k} \beta_{i}y_{t-i} + \sum_{j=k+1}^{k+G} \beta_{j}x_{t-j} + \varepsilon_{t}$$
(1)

where  $\beta_{k+1} = \beta_{k+2} = \cdots = \beta_{k+d} = 0$ . *G*, represents the maximum lag within the stationary vector  $y_t$ . Then, the basic regression model is shown in equation (2) below:

$$y_t = \Gamma \tau_t + \Phi x_t + \Psi z_t + \epsilon_t \tag{2}$$

 $\Gamma = (\alpha_0, \alpha_1)_{n \times (q+1)}, \tau_t = (1, t)'_{2 \times 1}, \Phi = (\beta_1, \dots, \beta_k)_{n \times nk} \text{ and } \Psi = (\beta_{k+1}, \dots, \beta_{k+G})_{n \times nk}, x_t = (y_{t-1}' \cdots y_{t-k}')'_{nk \times 1}, z_t = (y_{t-k-1}' \cdots y_{t-k-I}')'_{nG \times 1} \text{ are defined.}$ 

The following equation (3) represents the null hypothesis:

$$H_0: R\phi = 0 \tag{3}$$

To examine whether Granger non-causality can be rejected, the relevant null hypothesis is determined using row vectorization on the matrix  $\boldsymbol{\phi} = \text{vec}(\boldsymbol{\Phi})$ , with the following restrictions, and the matrix R has dimensions  $m \times n^2 k$ . The coefficients of the last G lagged vectors, represented by the matrix  $\Psi$ , are ignored because it is assumed that their components are equal to zero. Furthermore, equation (1) can be rewritten as equation (4):

$$y_t = \Gamma \tau_t + \Phi x_t + \Psi z_t + \epsilon_t \tag{4}$$

where  $Y = (y_1, y_2, ..., y_T)'_{T \times n}$ ,  $\tau = (\tau_1, ..., \tau_T)_{T \times 2}$ ,  $X = (x_1, ..., x_T)_{T \times nk'}$ ,  $Z = (z_1, ..., z_T)_{T \times nG'}$  and  $\varepsilon = (\varepsilon_1, ..., \varepsilon_T)_{T \times n'}$ .  $Q_{\tau} = I_T - \tau (\tau' \tau)^{-1} \tau'$  and  $Q = Q_{\tau} - Q_{\tau} Z (Z' Q_{\tau} Z)^{-1} Z' Q_{\tau}$  are defined. Thus, the parameter function for the least squares method is given by equation (5):

$$\hat{Q} = Y'QX(X'QX)^{-1} \tag{5}$$

To test the null hypothesis  $H_0$ , the Wald statistic W is proposed in equation (6):

$$W = (R'\hat{\phi})' \left[ R\{\hat{\Sigma}_e \otimes (X'QX)^{-1}\} R' \right]^{-1} R\hat{\phi}$$
(6)

where,  $\hat{\Phi} = \text{vec}(\Phi)$  and  $\hat{\Sigma}_{\epsilon} = \frac{1}{T} \hat{\epsilon}' \hat{\epsilon}$ . As stated by Tada and Yamamoto [45] and Dolado and Lütkepohl [46], the asymptotic distribution of the Wald statistic is distributed as  $\chi_m^2$ , where *m* is the number of restrictions.

In terms of Granger causality tests, the Wald statistics from the recursive perspective are measured from sub-samples of the data being examined.  $f_{r1}$  and  $f_{r2}$  are assumed to be the intersection points of the forecast observations, representing the start and end points, and are defined as  $f_{rw} = f_{r2} - f_{r1}$ . The Wald statistic measured from this sub-sample is denoted as  $W_{f_{r1},f_{r2}}$ .  $\tau_{r1} = [f_{r1}T]$ ,  $\tau_{r2} = [f_{r2}T]$  and  $\tau_{rw} = [f_{rw}T]$  are defined, where T represents the sample size.  $\tau_{r0} = [f_{r0}T]$  indicates the minimum number of observations required to estimate the VAR.

In the forward-expanding window algorithm, the starting point  $\tau_{r1}$  is fixed at the first observation (i.e.,  $\tau_{r1} = 1$ ), and the regression window expands between  $\tau_{r0}$  and T. This process is equivalent to  $\tau_{r2}$  moving from  $\tau_{r1}$  to T. It is assumed that the window size for the recursive regression remains constant. The starting point  $\tau_{r1}$  changes from the initial observation to  $T - \tau_{r0} + 1$ ; in short,  $\tau_{r2} = \tau_{r1} + \tau_{r0} + 1$ . The recursive evolving window algorithm defines the terminal sample of the regression similarly to the recursive algorithm.

However, in contrast to the recursive algorithm, where the starting sample  $\tau_{r1}$  maintains a fixed distance from  $\tau_{r2}$ , in this case,  $\tau_{r1}$  changes from the initial observation to  $\tau_{r2} - \tau_{r0} - 1$ . For each corresponding sample, a series of Wald statistics  $f_{r0}$  is obtained. The test statistic is defined as the supremum of the Wald statistic series, which forms equation (7):

$$SW_{f_r}(f_{r0}) = \sup_{f_{r2} = f_r, f_{r1} \in [0, f_{r2} - f_{r0}]} \{W_{f_{r1}, f_{r2}}\}$$
(7)

The inference on Granger causality is based on the supremum Wald statistic  $SW_{f_r}(f_{r0})$  for the observation  $[f_rT]$ . For practical forecasting, the optimal lag order of the VAR model was selected based on information criteria, and the restricted model was calculated. The test statistic was then measured. According to simulations conducted by Shi et al. (2020), the recursive evolving window algorithm was found to outperform the other two procedures<sup>1</sup>.

Finally, some key comparative analyses are presented below to validate the superiority of the model: The current causal effect model evaluates the dependency of variables from a static perspective. The time-varying characteristics of the time series data have not been taken into account. In other words, potential structural change phenomena in the data's behavior cannot be captured with precision, which could lead to misleading results. Additionally, introducing the Fourier function in the model, in order to capture potential trends and variable effects in the data, brings a high prediction cost in terms of nonlinear forecasting. The two major advantages of the model proposed by Shi et al. (2020) are as follows:

First, the model not only captures the full potential informational content of the data but also reduces concerns about structural changes through the recursive evolving window method. Second, compared to general nonlinear models, this model offers a predictable nature, which leads to a reduction in forecasting costs  $\{W_{f_{r_1},f_{r_2}}\}_{f_{r_2}=f_r}^{f_{r_1}\in[0,f_{r_2}-f_{r_0}]}$ .

## 4. Data and Empirical Results

The Non-Performing Loans  $(ta_t)$  variable used in this study is obtained from the monthly bulletin of the Banking Regulation and Supervision Agency of Turkey (BDDK). The data is listed under the title 'Consumer Loans - Total - Non-Performing Consumer Loans and Non-Performing

<sup>&</sup>lt;sup>1</sup> Interested readers are encouraged to refer to the works of Shi et al. (2020).

Individual Credit Cards (million TL) - Total.' The industrial production index  $(sue_t)$  is used as an indicator of the economy. This variable is obtained from the Central Bank of the Republic of Turkey's Electronic Data Distribution System (EVDS). The study covers the period from January 2005 to July 2024. In the analysis, the natural logarithms of both variables ( $lnta_t$  and  $lnsue_t$ ) are taken for calculations.

Figure 1 shows the time series of the natural logarithm of non-performing loans (LNTA) and the natural logarithm of the industrial production index (LNSUE) for the period from January 2005 to July 2024.



Figure 1. Time Series Graph of LNTA and LNSUE Variables.

Both series exhibit a significant upward trend and are not stationary. This makes it difficult to analyze them using traditional econometric methods that assume stationarity. However, as previously mentioned, the LA-VAR model will be used for a more flexible analysis that preserves the dynamic characteristics of the series. The LA-VAR model examines time-varying Granger causality, revealing how the causal relationship between variables changes over time. This allows for a more detailed investigation of the relationship between non-performing loans and the economic structure represented by the industrial production index, without the need to make the series stationary, thus preserving their dynamic properties. In summary, to evaluate the Granger causality between Non-Performing Loans and the Industrial Production Index more precisely, three statistical approaches proposed by Shi et al. (2020) will be used: forward, rolling window, and recursive algorithms.

## 4.1. Stationarity Analysis

In the study, unit root and stationarity tests, including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, are used to examine the behavior of both series over time. The results are presented in Table 2. Before the first differencing process, *lnta* and *lnsue* exhibit non-stationary characteristics. Both time series remain non-stationary until the first differencing process. After the first differencing process, each series becomes stationary. Therefore, in line with the framework outlined in Shi et al. (2020), the LA-VAR model is applied in this study to investigate the potential existence of causality from a dynamic perspective.

Table	Table 1. Stationarity Test Results for the Series						
	ADF		PP		KPSS		
Level	Constant	<b>Constant+Trend</b>	Constant	<b>Constant+Trend</b>	Constant	<b>Constant+Trend</b>	
lnta	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	
lnsue	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	
	ADF		PP		KPSS		
Δ	Constant	<b>Constant+Trend</b>	Constant	<b>Constant+Trend</b>	Constant	<b>Constant+Trend</b>	
lnta	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	
lnsue	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	

**Note:** Level and  $\Delta$  indicate the level and first differencing process, respectively. I(0) and I(1) signify stationary and first-differenced stationary, respectively.

## 4.2. Time-Varying Granger Causality Tests

Firstly, the results of the time-varying Granger causality tests between the two variables were obtained for the entire period from January 2005 to July 2024. Here, the relevant Wald test statistics and bootstrap critical values obtained using all three approaches are presented. The results are shown in Table 3.

H₀: Insue → Inta	W forward	W rolling	W recursive
Test Statistic	58.358	78.991	78.991
	В	ootstrap Critical Valu	ies
Confidence Level	W forward	W rolling	W recursive
90%	7.398	7.134	7.889
95%	9.456	9.107	9.578
99%	13.815	13.815	13.815
H₀: Inta → Insue	W forward	W rolling	W recursive
Test Statistic	14.494	20.227	24.377
	В	ootstrap Critical Valu	ies
Confidence Level	W forward	W rolling	W recursive
90%	7.876	7.615	8.023
95%	10.466	10.127	10.714
99%	16.098	15.868	16.38

Table 2. Results of Time-Varying Granger Causality Tests

**Note:** p(3) d(1) trend and [199 replications]. W represents the test statistic.

The results in Table 3 show a bidirectional time-varying Granger causality between the two series at the 90%, 95%, and 99% confidence levels for all 3 algorithms used. However, the Turkish economy has undergone structural changes over the last thirty years. Therefore, assuming a time-invariant relationship between non-performing loans and the industrial production index throughout the sample period may overlook fundamental changes in the relationship. To capture possible structural changes in the relationship between the two variables, a time-varying Granger causality test has been applied.

The progression of the Wald test statistics for the hypothesis that the industrial production index is not a Granger cause of non-performing loans is shown in Figures 1, 2, and 3, based on

the results from each of the three algorithms. The minimum window size is chosen to be 72 observations. In estimating the LA-VAR model, the lag length is selected using the Bayesian Information Criteria (BIC) with a maximum lag order of 2. The bootstrap critical values are obtained using 199 replications.

Figure 2 represents the Wald test statistics for the causality test from *lnsue* to *lnta* based on the recursive algorithm. The black solid line represents the Wald test statistics over time, while the high and low dashed lines represent the 95% and 90% confidence level bootstrap critical values, respectively.



Figure 2. Recursive Expanding Wald Test for the Granger Causality of Insue to Inta



Forward expanding Wald test for Inta G-caused by Insue, 2005m1 - 2024m7

Figure 3. Forward Wald Test for the Granger Causality of Insue to Inta



Figure 4. Rolling Wald Test for the Granger Causality of *lnsue* to *lnta* 

The Wald test statistics show significant peaks around mid-2009, mid-2013, and late 2018. These peaks indicate periods where strong causality from Insue to Inta was observed. During the global financial crisis of 2008-2010, the Wald test statistics exceeded the 95% critical value, revealing a strong causal relationship. During this period, the increase in non-performing loans alongside the decline in industrial production can be seen as a predictable outcome. From 2010 to 2013, as Turkey entered an economic recovery phase with reforms, the causality remained above the 90% critical value, though not as strong as during the crisis.

From 2013 to 2018, while Turkey experienced strong economic growth, fluctuations in the test statistics were observed due to structural challenges such as high inflation. During this period, the test statistics approached the 95% critical threshold, indicating that the impact of industrial production on non-performing loans increased during certain periods. Between 2018 and 2020, political and economic uncertainties, along with the pandemic, led to a significant rise in causality, causing Wald test statistics to surpass the 90% and 95% critical values. During this time, the sharp decline in industrial production had a strong impact on non-performing loans.

Between 2020 and 2021, the economic contraction caused by the pandemic led to test statistics fluctuating around critical values, indicating that the causality relationship temporarily weakened due to the pandemic's effects. Finally, between 2021 and 2024, as the economy slowly recovered, the test statistics showed occasional peaks. This reflects ongoing challenges related to inflation and governance, suggesting that the dynamic relationship between industrial production and non-performing loans has persisted.

The time series of the Wald test statistics obtained for each of the three algorithms regarding the hypothesis that non-performing loans are not the Granger cause of the Industrial Production Index are shown in Figures 4, 5, and 6, respectively. The minimum window size is selected as 72 observations. In estimating the LAVAR model, the lag length is chosen based on

the Bayesian Information Criteria (BIC) with a maximum lag order of 2. The bootstrap critical values are obtained with 199 replications. Figure 4 represents the causality test from *lnsue* to *lnta* based on the iterative algorithm, with the black solid line showing the Wald test statistics over time. The high and low dashed lines represent the bootstrap critical values for the 95% and 90% confidence levels, respectively.



Figure 5. Recursive Wald Test for the Granger Causality from *lnta* to *lnsue* 



Forward expanding Wald test for Insue G-caused by Inta, 2005m1 - 2024m7 with 90th (--) and 95th (-) percentiles of bootstrapped test statistics

Figure 6. Forward Wald Test for the Granger Causality from *lnta* to *lnsue* 

### G. Sümer, "Time-varying Granger Causality between Industrial Production and Non-Performing Loans in Türkiye"



Figure 7. Rolling Wald Test for the Granger Causality from *lnta* to *lnsue* 

The figure shows the temporal changes in the Wald test statistics for testing whether *lnta* (Non-performing Loans) is the Granger cause of *lnsue* (Industrial Production Index). The black line represents the Wald test statistics, while the dashed lines indicate the bootstrap critical values at the 90% and 95% confidence levels.

The first notable observation is that the Wald test statistics start at a low level towards the end of 2008. However, as we approach 2010, the statistics approach the 90% critical value, and the causality strengthens due to the economic fluctuations following the global financial crisis. During this period, it can be inferred that non-performing loans may have had a certain impact on industrial production.

Since the beginning of 2011, the Wald test statistics have exceeded the 90% critical value, indicating the existence of causality from non-performing loans to industrial production. Notably, the increase in test statistics towards the end of 2011 could be a significant indicator that uncertainties in the financial sector impacted the real sector.

Between 2014 and 2018, fluctuations in the test statistics are observed. During this period, strong economic growth and structural challenges such as high inflation caused volatility in the test statistics. In particular, towards the end of 2018 and 2020, when the statistics surpassed the 95% critical value, it is evident that non-performing loans had a strong impact on industrial production.

Since the beginning of 2020, due to the impact of the pandemic, the Wald test statistics have surpassed the critical values, which can be interpreted as an indication that financial difficulties affected industrial production. During this period, the effect of non-performing loans on industrial production became more pronounced due to economic contraction and uncertainty.

From 2022 onwards, the Wald test statistics have fallen below the critical values, signaling that the impact of non-performing loans on industrial production weakened during the post-

pandemic economic recovery process. However, some increases in the test statistics suggest that the economic recovery is volatile, and financial uncertainties may still affect industrial production. In conclusion, the graph demonstrates that the causality effect of LNTA on LNSUE fluctuated over time.

The next step is to present the relevant coefficient estimates obtained using rolling window regression in Figures 8 and 9, respectively.



Figure 8 Estimated Coefficients from the Rolling Window Regression for *lnsue* 

This rolling window regression graph clearly shows how the impact of the industrial production index (*lnsue*) on non-performing loans (*lnsta*) has changed over time. In summary, the changes in the coefficients over different periods can be interpreted as follows:

2009–2010: The coefficient sharply drops to around -0.6. This reflects the post-global financial crisis period, showing a strong negative impact of the decline in industrial production on non-performing loans. The crisis and credit tightening, along with economic pressures and financial difficulties, were significant factors in this period.

2011–2015: The coefficients fluctuate between -0.4 and -0.1, remaining mostly negative. During this period, the negative impact of industrial production on non-performing loans persists, but the effect gradually diminishes. This may indicate a prolonged recovery phase in Turkey's economy, where financial instability still made the economy vulnerable.

2016–2018: The coefficients approach positive values, reaching around 0.3–0.4. In this period, the negative impact of industrial production on non-performing loans has decreased or even turned into a neutral-positive relationship. This suggests improvements in financial stability or that economic growth has become more resilient to financial risks.

2019–2020: The coefficients again decrease, reaching near zero or slightly negative values. This period marks the beginning of the COVID-19 pandemic, during which economic shocks may have created a negative relationship again. Credit issues resurfaced, and production disruptions occurred, contributing to the negative trend.

2021–2024: The coefficients stabilize near zero with a slight positive trend. This likely reflects the post-pandemic recovery period, where industrial production became more resilient,

and the direct negative impact of non-performing loans on production decreased. However, some minor increases indicate that economic uncertainty and financial risks may still have an influence.

In conclusion, these periodical changes reflect the dynamics of Turkey's economic structure and the effects of financial pressures on industrial production, showing how these effects have evolved over time.



Figure 9 Estimated Coefficients from the Rolling Window Regression for *lnta* 

This rolling window graph shows how the effect of non-performing loans (*lnta*) on the industrial production index (*lnsue*) has changed over time. In summary:

2009–2010: The coefficient sharply drops to around -0.6. This period reflects the aftermath of the global financial crisis, indicating that the increase in non-performing loans had a strong negative effect on industrial production, likely due to credit tightening and economic pressures.

2011–2015: The coefficients fluctuate between -0.4 and -0.1, remaining mostly negative. This suggests that non-performing loans still have a negative effect on industrial production, but the effect gradually diminishes. It may reflect a long recovery process in the economy, which remained vulnerable to financial instability.

2016–2018: The coefficients approach positive values, reaching around 0.3–0.4. This could indicate a period where the negative effect of non-performing loans on industrial production decreased or even turned into a neutral-positive relationship. This may suggest improvements in financial stability or that economic growth became more resilient to financial risks.

2019–2020: The coefficients decrease again, approaching zero or slightly negative values. This period coincides with the onset of the COVID-19 pandemic, where economic shocks may have caused a negative relationship again, as credit issues resurfaced, and disruptions in production occurred.

2021–2024: The coefficients stabilize near zero with a slight positive trend. This suggests that the effect of non-performing loans on industrial production could be neutral or slightly positive. This may reflect the post-pandemic recovery period, where industrial production has

become more resilient, and the direct negative impact of non-performing loans on production has decreased.

## **5. Conclusion and Policy Implication**

The study examined the relationship between industrial production and non-performing loans in Turkey using a time-varying Granger Causality test for the period from January 2005 to July 2024. The analysis revealed several key findings that have important implications for policymakers, financial institutions, and researchers.

The study identified a dynamic and time-varying relationship between economic activity, as measured by the industrial production index, and credit risk, represented by non-performing loans. This relationship is not constant over time, highlighting the importance of considering temporal variations in economic analysis. The recursive evolving window algorithm proved to be more effective in capturing the heterogeneities in the time series data compared to traditional methods, providing a more nuanced understanding of the causal relationship between industrial production and non-performing loans.

The findings underscore the importance of adaptive risk management strategies in the banking sector. Financial institutions and regulators should adopt more dynamic approaches to risk management, considering the time-varying nature of the relationship between economic activity and credit risk. Policymakers should develop and implement early warning systems that can detect changes in the causal relationship between industrial production and non-performing loans, allowing for timely interventions. These systems could help mitigate the impact of economic downturns on the banking sector's loan portfolio quality.

The government and central bank should consider implementing countercyclical policies to mitigate the impact of economic downturns on the banking sector. These policies could include measures such as adjusting capital requirements or providing liquidity support during periods of economic stress. Banks should also incorporate time-varying models in their stress testing frameworks to better assess their vulnerability to economic shocks. This would enable them to identify potential risks and take proactive measures to mitigate them.

Encouraging banks to diversify their loan portfolios across different sectors may help reduce the overall impact of industrial production fluctuations on non-performing loans. Sectoral diversification can spread risk and reduce the concentration of credit risk in any single sector. Regulators should design flexible macroprudential policies that can be adjusted based on the evolving relationship between economic activity and credit risk. These policies should be tailored to the specific needs of the Turkish banking sector and should be responsive to changes in the economic environment.

The Banking Regulation and Supervision Agency (BDDK) should strengthen its monitoring capabilities to track the dynamic relationship between economic indicators and banking sector health. Enhanced monitoring would enable the BDDK to identify emerging risks and take timely action to address them. By implementing these policy recommendations, policymakers and financial institutions can better manage credit risk, enhance financial stability, and support sustainable economic growth in Turkey.

In conclusion, this study provides critical insights into the complex dynamics between economic activity and credit risk in an emerging market context. The findings highlight the importance of adopting flexible and adaptive policies to address the challenges posed by nonperforming loans and to support the resilience of the banking sector. Future research could explore the impact of other macroeconomic and institutional factors on non-performing loans, as well as the effectiveness of different policy interventions in mitigating credit risk.

### **Declaration of Research and Publication Ethics**

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

## **Researcher's Contribution Rate Statement**

I am a single author of this paper. My contribution is 100%.

### **Declaration of Researcher's Conflict of Interest**

There is no potential conflicts of interest in this study.

### References

- Adam, R., Zahrah, Z. and Sidharta, R.B.F.I. (2024). The influence of micro and macro economics on nonperforming loans in national private banking in Indonesia. *Research and Science Today*, 1(27), 33-46. doi:10.38173/RST.2024.27.1.3:33-46
- Artenisa, B. and Hyrije, A.A. (2023). The impact of economic growth on non-performing loans in Western Balkan countries. *Intereulaweast*, 10(2), 117-130. doi:10.22598/iele.2023.10.2.6
- Barr, R.S., Seiford, L.M. and Siems, T.F. (1994). Forecasting bank failure: A non-parametric frontier estimation approach. *Louvain Economic Review*, 60(4), 417-429. Retrieved from https://www.cambridge.org/
- Cucinelli, D. (2015). The impact of non-performing loans on bank lending behaviour: Evidence from Italian Banking Sector. *Eurasian Journal of Business and Economics*, 8(16), 59-71. Retrieved from https://pdfs.semanticscholar.org/
- Erdoğan, B. (2024). Bankaların takipteki kredilerini etkileyen faktörlerin panel veri modelleri ile analizi. International Journal of Economics, Politics, Humanities & Social Sciences, 7(3), 141-152. doi:10.59445/ijephss.1460608
- Ferreira, C. (2017). Relevance of the EU banking sector to economic growth. *International Advances in Economic Research*, 23, 203-215. https://doi.org/10.1007/s11294-017-9632-1
- Genç, E. ve Şaşmaz, M.Ü. (2016). Takipteki banka kredilerinin makroekonomik belirleyicileri: Ticari krediler örneği. *Selçuk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, 36, 119-129. Retrieved from https://dergipark.org.tr/en/pub/susbed/
- Hasan, I., Koetter, M. and Wedow, M. (2009). Regional growth and finance in Europe: Is there a quality effect of bank efficiency. *Journal of Banking & Finance*, 33, 1446-1453. https://doi.org/10.1016/j.jbankfin.2009.02.018
- İçke, A. (2014). Schumpeter ve yeniliklerin finansmanı. KSÜ Sosyal Bilimler Dergisi, 11(1), 17-38. Retrieved from https://dergipark.org.tr/tr/pub/ksusbd/
- Karaaslan, İ. (2023). Türk bankacılık sektöründe takipteki kredi oranının belirleyicileri. *Journal of Current Researches on Social Sciences*, 13(2), 235-254. doi:10.26579/jocress.13.2.1
- Kılcı, E.N. and Baygın, B.K. (2019). Asimetrik uyarlama yaklaşımı kullanılarak Türkiye'de tüketici ticari kredi faiz oranları ile geri dönmeyen krediler arasındaki ilişkinin analizi. *Maliye Dergisi*, 177, 104-120. Retrieved from https://ms.hmb.gov.tr/
- Koyuncu, C. and Saka, B. (2011). Takipteki kredilerin özel sektöre verilen krediler ve yatırımlar üzerindeki etkisi. *Dumlupınar Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, 31, 113-124. Retrieved from https://dergipark.org.tr/en/pub/dpusbe/
- Nwonye, G.N., Okanya, O.C., Olelewe, C., Nwekwo, N.M. and Onuselogu, O. (2023). Impact of macroeconomic indicators on non-performing loans in Africa: The role of goverance. *Journal of Xi'an Shiyou University Natural Sciences Edition*, 66(04), 50-59. doi:10.17605/OSF.IO/SDUJH
- Qureshi, M. and Hasmi, T. (2023). An investigation of macroeconomic factors on non-performing loans: A study based on comeercial banks of Pakistan. *Pakistan Journal of International Affairs*, 6(4), 159-168. https://doi.org/10.52337/pjia.v6i4.935
- Selçuk, H. ve Daracı, A. (2003). Türk bankacılık sektöründe tahsili gecikmiş alacaklar. *Marmara Üniversitesi Sosyal Bilimler Öneri Dergisi*, 5(20), 173-189. https://doi.org/10.14783/maruoneri.682214
- Selimler, H. (2015). Sorunlu kredilerin analizi, banka finansal tablo ve oranlarına etkisinin değerlendirilmesi. *Finansal Araştırmalar ve Çalışmalar Dergisi*, 7(12), 131-172. https://doi.org/10.14784/jfrs.74107
- Sevinç, D. (2021). Türkiye'de takipteki banka kredileri ile makroekonomik faktörler arasındaki ilişki. Mehmet Akif Ersoy Üniversitesi İktisadi ve İdari Bilimler Dergisi, 8(2), 609-629. doi:10.30798/makuiibf.691534

#### G. Sümer, "Time-varying Granger Causality between Industrial Production and Non-Performing Loans in Türkiye"

- Shi, S., Hurn, S. and Phillips, P.C. (2020). Causal change detection in possibly integrated systems: Revisiting the money-income relationship. *Journal of Financial Econometrics*, 18(1), 158-180. https://doi.org/10.1093/jjfinec/nbz004
- Tanaskovic, S. and Jandric, M. (2015). Macroeconomic and institutional determinants of non-performing loans. *Journal of Central Banking Theory and Practice*, 1, 47-62. doi:10.1515/jcbtp-2015-0004
- Tunay, K.B. and Tunay, N. (2024). Interactions of non-performing loans with recessions and macroeconomic shocks: A Bayesian analysis on Turkey. *Eurasian Academy of Sciences Eurasian Business & Economics Journal*, 35, 36-60. doi:10.17740/eas.econ.2024-V35-03.
- Umarbeyli, Ş. and Kırıkkaleli, D. (2023). Co-movement of non-performing loans and bank concentrations in an emerging market: Wavelet coherence approach. *İstanbul Nişantaşı Üniversitesi Sosyal Bilimler Dergisi*, 11(1), 91-100. doi:10.52122/nisantasisbd.1105929
- Us, V. (2020). A panel VAR approach on analyzing non-performing loans in the Turkish banking sector. *Journal of BRSA Banking and Financial Markets*, 14(1), 1-38. doi:110.46520/bddkdergisi.789935
- Yalçın, H. (2024). Türkiye'de makroekonomik değişkenlerin takipteki tüketici kredileri oranı üzerindeki etkileri. Business & Management Studies: An International Journal, 12(1), 22-40. doi:10.15295/bmij.v12i1.2534
- Yıldız, T.T. (2024). Takibe düşen krediler ve etkileri. *İktisadi Araştırmalar Dergisi*, 2(1), 17-33. Retrieved from https://dergipark.org.tr/tr/pub/dpuiad/
- Zhang, D., Cai, J., Dickinson, D.G. and Kutan, A.M. (2016). Non performing loans, moral hazard and regulation of the Chinese commercial banking system. *Journal of Banking and Finance*, 63, 48-60. https://doi.org/10.1016/j.jbankfin.2015.11.010