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The credit volume and its relations with money supply in Turkey: the Bai-Perron and Wavelet coherence analysis

Abstract

Structural breaks in credit volume refer to sudden and significant changes in the extent to which credit is extended by financial institutions. These breaks can occur for various reasons, such as changes in lending standards, shifts in economic conditions, or changes in government policies. A structural break in credit volume can have important implications for the broader economy, including impacts on economic growth, inflation, and financial stability. This study focuses on multiple structural breaks and the relationship with the money supply of the credit volume of deposit banks from 2006 to 2022 when vital economic, financial, political, and social developments were experienced in Turkey and the world. The Central Bank of the Republic of Turkey provides the data used in the analysis, including the total loans provided to economic actors by deposit banks. Bai and Perron's multiple structural break test and wavelet coherence methods were used for the data analysis. As a result of the study, five structural break dates in credit volume were determined, and the reasons for these breaks were emphasized. Furthermore, wavelet coherence analysis shows that money supply and credit volume move together in the long run.

Keywords: Credit Volume, Bai-Perron, Structural Breaks, Money Supply, Wavelet Coherence

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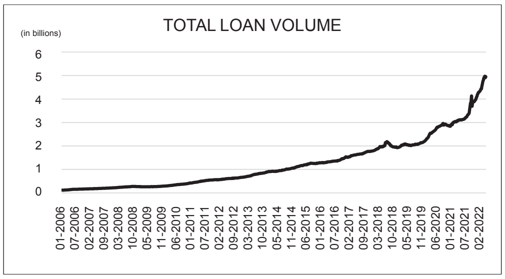
1. INTRODUCTION

The nexus between financial development and economic growth has attracted the attention of scholars and policymakers, leading to a flurry of research on the dynamics, causality, and long-term interdependence of these two factors (Omisakin & Adeniyi, 2014). Based on Schumpeter's seminal work in 1912, he argued that the reallocation of capital to innovative initiatives by financial intermediaries stimulates economic growth (Becsi and Wang, 1997). A sustainable financial system encourages savings, investment and entrepreneurship, which are important for economic development and poverty reduction and supports small and medium-sized enterprises (SMEs) and local economies (Gertrude, 2021). Some studies argue that increased bank lending encourages economic growth, while others argue that economic growth has a greater impact on the level of bank lending. Structural changes in economic indicators over time, due to political and economic considerations, require econometric tests (Önel, 2005). These structural disturbances and sudden trend discontinuities in economic time series have attracted the attention of researchers, investors and policymakers. As economies grow, credit volume increases, especially in developing countries moving into developed countries. The role of the money supply in economic growth, unemployment, inflation and interest rates has been discussed by contrasting endogenous and exogenous perspectives (Kaldor, 1970; Wray, 1992; Howells, 2009). The exogenous monetary hypothesis assumes central bank control, while the endogenous perspective emphasizes the money supply responsible for economic activity (Baştav, 2021). Factors affecting bank lending, such as transaction volume, financing conditions, and structural changes in the banking sector, also affect supply and demand, making empirical differentiation difficult (Repkova, 2010; Castro-Santos, 2010). Financial markets in Turkey underwent significant changes in the early 1980s due to foreign trade and financial liberalization policies, followed by the restructuring of the banking sector after 2001 (Ümit, 2016). Figure 1 shows weekly credit volume trends in Turkey (2006–2022). Lending has grown steadily through 2018 and has increased significantly since 2019, especially during the pandemic. Regulatory action by the Banking Regulatory Authority (BRSA) supported the real sector, bank customers and banks throughout the pandemic, particularly in housing and consumer lending under the Economic Stability Shield (Ümit, 2016).

Figure 1. Weekly credit volumes in Turkey between 2006 and 2022 (in TRY)



Source: Central Bank of the Republic of Turkey, 2022

Notes: Notes: Deposit Banks (Thousand TRY): Commercial and Personal, Agricultural, Housing

Structural breaks in the volume of credit are crucial indicators of underlying shifts or disruptions in the financial system. By identifying and understanding these structural breaks, policymakers and central banks can gain insights into the evolving dynamics of credit markets, which in turn can inform the development of more effective strategies to manage credit growth and mitigate systemic risks. Structural breaks can signal vulnerabilities in the financial system, such as unsustainable credit expansion or imbalances in lending practices. By recognizing these vulnerabilities early on, policymakers can take preemptive measures to address potential risks and prevent the buildup of systemic vulnerabilities that could lead to a credit crunch. Understanding the timing and nature of structural breaks allows policymakers to tailor their policy responses accordingly. For example, during periods of rapid credit growth, policymakers may implement measures to strengthen regulatory oversight, enhance risk management practices, or adjust monetary policy settings to maintain financial stability. Analyzing past structural breaks can also help policymakers anticipate future trends and potential challenges in the credit market. By identifying patterns or recurring themes associated with structural breaks, policymakers can develop more robust forecasting models and scenario analyses to assess the potential impact of different policy interventions on credit growth rates and overall economic stability. Structural break analysis provides valuable insights into the drivers of credit market dynamics and the factors contributing to systemic vulnerabilities. This information can inform the development of more sophisticated risk management frameworks and stress testing methodologies, enabling policymakers and central banks to better assess the resilience of the financial system to adverse shocks and external disruptions. In summary, while the specific implications of structural break analysis may not have been explicitly outlined throughout the paper, its importance lies in its ability to provide policymakers and central banks with valuable insights into the evolving dynamics of credit markets and the potential risks and vulnerabilities associated with credit growth. By incorporating structural break analysis into their policymaking frameworks, policymakers can enhance their ability to identify warning signs of a potential credit crunch and develop more effective strategies to promote financial stability and sustainable economic growth.

In this study, we aim to examine the volume of credit in Turkey, focusing on its structural characteristics and often overlooked macroeconomic variables. Understanding these changes is crucial for establishing strategies to achieve optimal credit growth rates. Identifying these changes can aid policymakers, especially central banks, in detecting warning signs of potential credit crashes with systemic economic consequences. Additionally, previous research on the interaction between credit volume and the money supply has been limited. Many studies have neglected to account for multiple structural breaks, which can significantly impact the findings. This study addresses this gap by employing methods proposed by Bai and Perron (1998, 2003) and wavelet coherence to detect structural breaks in credit volume, determine their dates, and assess their correlation with the money supply. By focusing on these often overlooked aspects, this study contributes to a more comprehensive understanding of the dynamics between credit volume, structural disruptions, and the money supply in the Turkish economic environment. The Bai and Perron methods are advantageous because of their ability to detect adjustments for multiple break times, the uncertainty of break dates, the calculation of confidence intervals, and the different distributions of pre- and post-break periods (Gurish et al., 2011). This study improves the understanding of the dynamics between credit volume, structural disruption and the money supply in the Turkish economic environment.

2. LITERATURE REVIEW

Most credit research has traditionally focused on macroeconomic indicators, particularly the relationship between economic growth, credit, and nonperforming loans. However, there are notable gaps in the research concerning the structural characteristics and trends of aggregate credit in Turkey. Moreover, limited attention has been given to understanding the correlation between the money supply and credit volume. While numerous studies have contributed to this field, a critical examination reveals several shortcomings and areas for further exploration.

For instance, Buchtkova (2001) studied the impact of microeconomic variables on aggregate credit in the Czech Republic; however, the broader applicability of these findings to other contexts remains unclear. Similarly, Paaliova and Stiller (2002) analyzed the effect of monetary policy on aggregate credit supply; however, the extent to which their conclusions can be generalized requires further investigation. Additionally, studies such as Peak et al. (2003) and Bassett et al. (2010) have examined the impact of bank supply shocks on GDP in the U.S., yet their findings may not fully capture the nuances of credit dynamics in different economic environments.

Driscoll (2004) found no significant effect of bank lending on output in the U.S., raising questions about the efficacy of traditional monetary policies in stimulating economic growth. Similarly, Repkova (2010) explored structural factors affecting aggregate credit in the Czech banking sector, but the transferability of these findings to other countries, including Turkey, warrants examination.

While some studies, such as Hoffmann (2010) and Apostoaie et al. (2014), have explored the credit cycle in specific regions, their focus on individual economies limits their broader applicability. Similarly, while Uddin et al. (2013) examined the correlation between financial development and economic growth in Kenya, the extent to which their findings apply to other emerging markets such as Turkey requires further investigation.

Moreover, while Lovreta and López (2020) and Muwanga (2020) identified structural fractures coinciding with significant societal and political events, the causal mechanisms underlying these relationships remain unclear. Additionally, studies employing Bai-Perron structural break analysis, such as Jouini and Boutahar (2003) and Bajo-Rubio et al. (2008), provide valuable insights into temporal shifts in credit dynamics; however, the broader implications of these findings for policy formulation require further exploration.

Furthermore, while recent studies such as Liu et al. (2022) and Tiryaki and Hasanov (2022) have shed light on the relationship between money supply, deposits, and credit in specific contexts, their findings may not fully capture the complexity of credit dynamics in Turkey.

While the literature has provided valuable insights into the dynamics of credit and its relationship with economic variables, there is a need for further research that addresses the limitations and gaps identified in previous studies. Future research should aim to develop more comprehensive models that account for the heterogeneity of credit dynamics across different economic environments and provide actionable insights for policymakers and practitioners in Turkey and beyond.

3. METHODOLOGY

The data used in the analyses are provided weekly and taken from the Central Bank of the Republic of Turkey's Electronic Data Distribution System covering the period of January 6, 2006 - July 8, 2022. The variables used in the study are total credit volume (TOTAL), which includes commercial and individual credit (Thousand TRY); agricultural credit (Thousand TRY); housing credit (Thousand TRY); and commercial and consumer credit (Comcon) variables, which include commercial and consumer credit. The authors chose to use the Bai-Perron test specifically for the "TOTAL" variable due to its suitability for detecting structural breaks in that particular type of data or because previous research has shown it to be effective in similar contexts. The "TOTAL" variable is of primary interest to the research question or represents a broader measure of credit volume that encompasses various types of credit, including commercial and consumer credit.

Moreover, the second set of variables consists of RAWM1, the notional amount index representing the M1 money supply (currency in circulation (outside banks) + sight deposits), and RAWM3, while the M3 money supply (M1+time deposits+repos+money market funds+ domestic banks' securities with maturity shorter than 2 years) represents the notional amount index. By considering both M1 and M3, this paper captures varying degrees of liquidity and financial depth, allowing for a comprehensive analysis of monetary dynamics. The inclusion of M1 and M3 aligns with the study's objective of examining the relationship between credit volume and macroeconomic variables. As measures of the money supply, changes in M1 and M3 can have significant implications for credit creation, lending behavior, and overall economic activity. By analyzing the dynamics of these money aggregates alongside variables such as total credit volume, including commercial, individual, agricultural, and housing credit variables, this paper aims to elucidate the interplay between monetary factors and credit dynamics, shedding light on their impact on economic growth, inflation, and financial stability. The inclusion of M1 and M3 money supplies allows for the precise tracking and analysis of changes in these monetary aggregates, enhancing the accuracy and depth of the study's findings.

The index of notional amounts (INA) is formulated as equation 1 (for detailed calculations, see https://www.tcmbblog.org):

$$INA_t^{2014=100} = INA_{t-1}^{2014=100} \times \left(1 + \frac{NetTransaction_t}{Stock_{t-1}}\right) \quad (1)$$

A decrease in the index from 100 to 90 indicates a 10% decrease between the two periods after the money supply is adjusted for the impact of the exchange rate. The base year for the Index of Notional Amounts (INA) is set at 2014 to provide a reference point for calculating exchange rate-adjusted growth rates of the money supply. The INA serves as a benchmark, allowing for the comparison of money supply movements without the influence of fluctuations in exchange rates. By anchoring the index to 2014, the calculation aims to isolate the impact of exchange rate changes on the money supply, offering a clearer understanding of the underlying trends.

Net transactions within the context of this study represent the actual changes in the stock of money supply, excluding the effects of exchange rate movements. This accounts for the alterations that would be observed in the absence of any exchange rate fluctuations. Stocks, on the other hand, denote the total amount in the money supply, encompassing both local currency (TL) and foreign currency (FX) components.

Adjustment to exchange rates is necessary due to the inclusion of FX aggregates in the money supply. Since foreign currency (FX) assets are considered close substitutes for analogous Turkish lira (TL) assets, FX aggregates are integrated into the calculation of money supply. In this process, TL items are valued based on market value, while FX items are valued using the relevant period-end exchange rate. Consequently, changes in exchange rates can impact the overall money supply, affecting the purchasing power of savers. This adjustment becomes particularly crucial during periods of high volatility in exchange rates, where the exchange rate effect can make the volatility in the money supply appear higher than it is. By calculating exchange rate-adjusted growth rates and formulating the Index of Notional Amounts, this study aims to provide a more accurate interpretation of money supply trends in the presence of a significant share of FX deposits in Turkey's money supply.

Utilizing weekly frequency enhances the evaluation of both short-term and long-term fluctuations in comparison to using monthly or annual data (Bumpass et al., 2019). In the context of our research, the utilization of weekly frequency data serves specific purposes that align with our study objectives. Weekly data granularity allows us to strike a balance between capturing short-term fluctuations while also maintaining a broader perspective to assess long-term trends. This frequency results in a practical compromise between granularity and computational feasibility, especially considering the complexities involved in our analysis methodology. Weekly data offer several advantages in our study context. First, it provides a sufficient level of detail to identify structural breaks and assess their implications for credit volume and money supply dynamics. Second, weekly frequency facilitates alignment with the reporting schedules of relevant financial institutions and regulatory bodies, ensuring consistency and accuracy in our data sources. Finally, weekly data granularity allows for more precise tracking of policy interventions and market responses, which are essential considerations in our examination of credit growth strategies and their interactions with the money supply. Therefore, the choice of weekly frequency in our study was deliberate and tailored to meet the specific objectives and requirements of our research framework.

The study employs the sequential Bai-Perron test to identify structural breaks in the loan series from deposit banks to economic actors. Distinguished by its ability to detect multiple breakpoints, this advanced method requires certain assumptions, including a maximum of 5 breaks, a 5% significance level, and a 5% clipping percentage. The methodology comprises three steps: initially examining the unit root features of time series and then applying the Bai and Perron (1998, 2003) technique to address structural discontinuities. Subsequently, ordinary least squares regression analysis incorporates break dates using dummy variables, aligning with Bai and Perron's methodology (1998, 2003) (Weideman et al., 2017). The MATLAB, R, and Eviews programs facilitated the analysis, and the results are presented independently. The Bai-Perron test can accommodate variables at either level or first difference. If a variable is not stationary in level, it is appropriate to test for stationarity in first differences. The Bai-Perron test is flexible in this regard and can be applied to both stationary and nonstationary time series data.

3.1. Unit Root Tests

The series' stationarity was first examined. Unit root tests from Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) and the Augmented Dickey-Fuller (ADF) test were applied. The inclusion of the KPSS test alongside the ADF test serves to provide a comprehensive assessment of stationarity. While the ADF test primarily focuses on identifying unit roots in a time series, the KPSS test complements this by detecting deviations from stationarity. Employing both tests enhances the robustness of the stationarity analysis, offering a more thorough evaluation of the variable under consideration, in this case, the credit volume (total loan).

The ADF test is the first technique used to examine the stationarity of a time series. We used three different models to conduct this test. The ADF test is based on the presumption that time series data follow a random walk specified by y_t:

$$y_t = \rho y_{t-1} + \varepsilon_t \cdots \cdots \cdots \quad (2)$$

substituting y(t) by the Δy(t)+y(t-1) and after regrouping, a pure random walk becomes:

$$(t) = \beta y(t-1) + \varepsilon(t) \quad (3)$$

Equation (3) on the right-hand side may include deterministic components, such as drift or linear trend, as well as additional lags of the first differences as augmented terms.

The null hypothesis is H_0:*β=0*, i.e., $\rho=1$, against the alternative given by H_1:*β<0*, i.e., $\rho<1$. The ADF test was performed at the *5%* significance level.

Another unit root test used in the study, KPSS, was developed by Kwiatkowski et al. (1992). This test runs counter to the ADF test, a stationarity test considered a complement to unit root tests. The time series is assumed to be separable into a stationary error, a random walk, and a deterministic trend for the test. This means that the time series can be represented as follows:

$$Y_t = \delta t + r_t + \varepsilon_t \quad (4)$$

δ_t is the deterministic trend, r_t is the random walk, and e_t is the zero mean stationary error. The random walk can be displayed as:

$$r_t = r_{t-1} + v_t \quad (5)$$

v_t is the point at which the equations (0, σ_v^2) and r_0 intersect. It assumes that the null hypothesis is σ_v^2 = 0. This causes the Y_t time series to be trend stationary. KPSS then tests for the unit root in r_t when δ is nonzero. The test statistic used is a one-sided Lagrange multiplier and is given as follows:

$$LM = \frac{\sum_{t=1}^{T} S_t^2}{\hat{\sigma}_e^2} \quad (6)$$

Here, S_t is the sum of the residues, and $\hat{\sigma}_e^2$ is the variance of error estimated from equation 7. This is for the trend stationary hypothesis. The only difference for the level stationary null hypothesis is that the residuals are from the equation that excludes the time trend. The test statistics are the same. The test statistic is derived under the assumption that the time series error, e_t, is *iid*; this assumption is often not met because time series are often time dependent. Therefore, the following test statistic is used for the null hypothesis of trend stationarity (τ) and level stationarity (l):

$$\eta_{\tau/l} = T^{-2} \frac{\sum_{t=1}^{T} S_t^2}{S^2(l)} \quad (7)$$

$S^2(l)$ is a consistent estimator of the long-run variance of errors. The estimator is created from residuals e_t. This is an appropriate denominator of the equation rather than an estimate of σ_e^2. The estimator is created from residuals. This is an appropriate denominator of the equation rather than an estimate. The equation is normalized to T^{-2}, where T is the number of observations (Kwiatkowski et al., 1992). For large test statistics, the null hypothesis is rejected (Müller, 2005).

Table 1 displays the outcomes of ADF and KPSS unit root testing. Table 1 shows that the total deposit bank loan volume is not stationary at the 1% and 5% probability levels. However, according to both tests, the series is stationary at the first difference. Furthermore, M1 and M3 money supply are stationary at first differences according to ADF test."

Table 1: ADF and KPSS Unit Root Test Results

TOTAL LOAN VOLUME				
	Levels		**First Differences**	
	ADF	**KPSS**	**ADF**	**KPSS**
Intercept	-0.1816	3.6763***	-5.6254***	0.1644
Intercept and Trend	-2.4273	0.6024***	-5.6020***	0.1331

ADF			
At Level			
		RAWM1	**RAWM3**
Intercept	t-Statistic	2.6833	2.7991
Intercept and Trend	t-Statistic	0.4736	2.0118
At First Difference			
		d(RAWM1)	**d(RAWM3)**
Intercept	t-Statistic	-6.1742***	-13.3830***
Intercept and Trend	t-Statistic	-7.3786***	-13.6675***
KPSS			
At Level			
		RAWM1	**RAWM3**
Intercept	t-Statistic	3.5660***	3.6094***
Intercept and Trend	t-Statistic	0.6111***	0.5841***
At First Difference			
		d(RAWM1)	**d(RAWM3)**
Intercept	t-Statistic	0.6530***	0.8783***
Intercept and Trend	t-Statistic	0.0818	0.2442***

Notes: *The variables are in natural logs. ADF is the Augmented Dickey-Fuller test and KPSS the Kwiatkowski-Phillips-Schmidt-Shin test. *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% levels, respectively. ADF Unit Root Test Null Hypothesis: the variable is not stationary. KPSS Unit Root Test Null Hypothesis: the variable is stationary. Lag Lengths based on AIC for ADF, and SIC for KPSS. Probability based on Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1) for KPSS and MacKinnon (1996) one-sided p values for ADF.*

3.2. Bai and Perron Tests

Rappoport and Reichlin (1989) and Perron (1989) challenged the prevailing unit root paradigm, contending that most economic disturbances are temporary rather than permanent. They argued that structural disruptions, unaccounted for in econometric models, can lead to erroneous rejection of the unit root hypothesis. Bai and Perron (1998) later enhanced prior tests by allowing for multiple unknown breaks. The methodology involves examining unit root characteristics, identifying break dates, segmenting the series accordingly, and using dummy variables in regression analysis to address structural breaks (Bumpass et al., 2019; Weideman, Inglesi-Lotz, and Van Heerden, 2017).

The core of Bai and Perron's (2003) analysis can be described by the following multiple linear regression with *m* break (or *m+1 regime*):

$$y_t = x_t^{'}\beta + z_t^{'}\delta_j + \mu_t \quad t = T_{j-1}+1,\ldots,T_j \quad j = 1,\ldots,m+1 \tag{8}$$

In this model, y_t is the dependent variable observed at time t, the vectors of covariates $X_t(p \times 1)$ and $Z_t(p \times 1)$, β and δ_j(j = 1, ..., m + 1) are the corresponding coefficient vectors, and μ_t is the immediate disorder at time *t* (Perron, 2006). The covariates *x* and *z* represent vectors of independent variables, while variable *d* in the equation denotes a dummy variable indicating the regime or segment to which each observation belongs.

Indices (T_1, ..., T_m) or breakpoints express unambiguously unknown breakpoints (the rule using $T_0 = 0$ and $T_{m+1} = T$). The goal is to estimate unknown regression coefficients with breakpoints when *T* observations are available on (y_t, x_t, z_t).

Modelers can anticipate internal structural breaks by using the approach put forth by Bai and Perron (1998, 2003). Stated differently, prior knowledge of the timing of breaks is not required (Perron, 2006). Beginning with the baseline, the series are split for m+1 and t = 1, 2, 3,... T m with unknown breaks. A sequence of ϕ matrices represents estimated coefficients for each partition from 1 to m+1, while other coefficients in the ρ matrix remain constant throughout all partitions, as shown by the equation. The least squares approach was used to determine the coefficients in ρ and ϕ. In essence, the parameters of the ρ and ϕ matrices are selected to reduce the total squared errors. The minimization function has the following characteristics (Adedoyin et al., 2020):

$$\left(Y - X_{\rho} - \overline{D}\phi\right)'\left(Y - X_{\rho} - \overline{D}\phi\right) = \sum_{i=1}^{m+1}\sum_{t=T}^{T_i}\left(y_t - x_t^{'}\rho - d_t^{'}\phi_i\right)^2 \quad (9)$$

Here, the total of the first squared differences is computed for all time points in a specified segment ranging from 1 to m+1. Additionally, $S_T(T_1, T_2, ..., T_m)$ represents the sum of the squared residuals in the m-section, and $(T_1, T_2, ..., T_m)$ is specific to the break dates. The equality of the function being minimized in matrix form and nonmatrix form may seem trivial and require no further elaboration.

3.3. Wavelet coherence analysis

In the second stage of the study, the comovement between the variables was examined via wavelet coherence analysis. The notional amount index was used as the money supply indicator in the present study, and the relationships between total, individual and commercial credit were examined. The wavelet analysis approach was introduced by Torrence and Compo (1998) and further refined by Torrence and Webster (1999).

There are two main types of wavelets: father Φ and mother wavelets ψ (Yang et al., 2016). $1(\int \Phi(t)dt = 1)$ represents the integration of the father wavelet, and $0(\int \psi(t)dt = 0)$ represents the integration of the mother wavelet. The mother wavelet represents the detailed and high-frequency components of the signal, whereas the father wavelet represents the flat and low-frequency sections of the signal (raw data).

By transforming any $y(t)$ function in $L^2(\mathbb{R})$ (region for square summable functions) into frequency components with a scale-appropriate resolution, the wavelet function can be built as a series of projections on the mother and father wavelets produced from Φ and ψ scaling and translation as follows: (Lee, 2004):

$$\Phi_{j,k}(t) = 2^{-j/2}\Phi(2^{-j}t - k),$$
$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k), \quad (10)$$

$j = 1,2, \cdots, j$ scaling parameter in a J-level decomposition, and k: translation parameter. We can express the wavelet representation of the signal $y(t)$ in $L^2(\mathbb{R})$ as:

$$y(t) = \sum_k S_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \quad (11)$$

in the above equations $s_{j,k} = \int y(t)\phi_{j,k}(t)dt$ and $d_{j,k} = \int y(t)\psi_{j,k}(t)dt$, J: the number of multiresolution components, $S_{J,k}$: smooth coefficients, and $d_{j,k}$ illustrates the detailed coefficients. The value of the coefficient $(S_{j,k}, d_{j,k})$ measures the contribution of the corresponding wavelet function relative to the total signal.

Under the translation parameter $2^j k$, which refers to the position parameter, the scale factor 2^j denotes the expansion factor. The scaling factor 2^j increases with the jth index. As a result, functionality becomes broader and more diffuse. As the functions $\Phi_{J,k}(t)$ and $\psi_{J,k}(t)$ increase, their translation parameters $2'k$ increase accordingly.

The decomposed signals for multiresolution decomposition are shown in the following manner:

$$S_j(t) = \sum_k^5 j_{j,k}\phi_{jk}(t),$$
$$D_j(t) = \sum_k d_{j,k}\psi_{jk}(t). \quad (12)$$

The functions $S_j(t)$ and $D_j(t)$ in Eqs. (4) and (5) are smooth and detailed signals. They represent the process of breaking down a signal into distinct and independent components that are perpendicular to each other and exist at various sizes. Thus, a signal $y(t)$ can be rewritten as:

$$y(t) = S_j(t) + D_j(t) + D_{j-1}(t) + \cdots + D_1(t) \quad (13)$$

The highest-level approximation $S_j(t)$ is the smooth signal, and the detailed signals $D_1(t)$, $D_2(t)$, ⋯, $D_1(t)$ are associated with oscillations of length 2 – 4,4 – 8, …, 2ʹ – 2^{j+1}. The discrete wavelet transform (DWT) defines a real-valued function as follows:

$$\omega = Wy, \tag{14}$$

The coefficients in the vector are arranged in ascending order from coarse scales to fine scales ∝. W and are introduced as a set of low-pass bandpass filters called filters and/. W and y are orthogonal vectors with $N \times 1$ elements. The type of mother wavelet determines the coefficients in the filter. As n is divisible by 2ʹ, ω, it can be specified as:

$$\omega = \begin{pmatrix} s_j \\ d_j \\ d_{j-1} \\ \vdots \\ d_1 \end{pmatrix} \tag{15}$$

where

$$s_j = (s_{j,1}, s_{j,2}, \cdots, s_{j,2,2})',$$

$$d_j = (d_{l,1}, d_{j,2}, \cdots, d_{j,4/22'}),$$

$$d_{J-1} = (d_{j-1,1}, d_{j-1,2}, \cdots, d_{J-1,8/2})',$$

$$d_1 = (d_{1,1}, d_{1,2}, \cdots, d_{1,1/2i})'. \tag{16}$$

Each set of coefficients s_1, d_1, $d_j - 1$, w_1', d_1 is defined as a collection of translated wavelet functions stacked on a regular lattice, for which the wavelet coefficients correspond to a crystal. The definition of the cross-wavelet power of two time series $x(t)$ and $y(t)$ is as follows (Ercan and Karahanoğlu, 2019):

$$Wxy(u, j) = Wx(u, j) \cdot Wy * (u, j). \tag{17}$$

$Wx(u, j)$ and $Wy(u, j)$ show the time series continuous wavelet transformations $x(t)$ and $y(t)$, respectively. The complex conjugate is represented by star $(*)$, the scale parameter is represented by parameter j, and a time position is assigned by parameter u. A low wavelet scale in the time series indicates a short investment horizon since it represents the high-frequency component of the data. (Torrence and Webster, 1999).

When the time series exhibits high power, the cross-wavelet power reveals specific areas in the time-frequency domain. The objective of comovement analysis is to detect instances in time-frequency-space comovement where the two-time series may not exhibit optimal performance. The wavelet method of wavelet coherence is appropriate for locating these comovements.

The square wavelet coherence coefficient is defined as follows by Torrence and Webster (1999):

$$R^2(u,j) = \frac{\left|S\left(j^{-1}Wxy(u,j)\right)\right|^2}{S\left[\left[j^{-1}\left(Wx(u,j)\right)^2\right]\right]S\left[j^{-1}\left|Wy(u,j)\right|^2\right]}. \tag{18}$$

S reflects an operator for smoothing. The coefficient $R^2(u, j)$ lies in the interval [0, 1]. The R^2 will be closer to zero if there is a weak correlation; if the values are closer to one than to zero, a stronger correlation will be observed. This means that R^2 is similar to the squared correlation coefficient in linear regression and explains the local linear correlation between two stationary time series at any scale. The phase differences are calculated using the formula below and Torrence and Webster's (1999) definition:

$$\theta_{x,y}(u,j) = \tan^{-1}\left(\frac{\mathcal{F}\left\{S\left(j^{-1}W_{xy}(u,j)\right)\right\}}{\Re\left\{S\left(j^{-1}W_{xy}(u,j)\right)\right\}}\right). \tag{19}$$

$\mathcal{F}$ is imaginary, and the black arrows in the wavelet coherence figures with significant coherence show the phase differences; $\Re$ is a fundamental part of this formulation. The arrows point to the right, indicating a positive correlation once the two time series under study move in unison on a specific scale. Conversely, if there is a negative correlation between the time series, the arrows will indicate a leftward direction. Subsequently, the arrows shift toward the left. (Yang et al., 2016).

Wavelet coherence analysis often produces a form consisting of five primary components. The black arrows have eight sides and include the following directions: left (←), right (→), up (↑), down (↓), southeast (↘), northeast (↗), southwest (↙), and northwest (↖). The image consists of two axes, each representing a different color temperature: warm and cold. The outlines are black, and there is a cone shape pointing toward the left. Arrows denote a relationship that is either in-phase or out-of-phase. The black arrows specifically represent an out-of-phase relationship or a positive correlation. The upward-pointing arrow signifies the maximum influence of the first series, while the downward-pointing arrow signifies the maximum effect of the second series. The black arrows, such as the '↘' symbol, indicate that the second time series has the most significant influence. The wavelet coherence plots show a positive in-phase or comovement relationship between the two time series. The presence of black arrows on wavelet coherence plots, specifically those pointing in the '↖' direction, signifies a negative comovement or out-of-phase relationship between two time series. These arrows represent the maximal influence of the first time series. When there was no phase difference, the two time series demonstrated synchronous progression. The wavelet coherence plots illustrate the cone of influence through a solid white bell-shaped line. The black curves in the plots indicate areas of significant coherence at the 5 percent significance level (Rubbaniy et al., 2021).

4. FINDINGS

4.1. Bai and Perron Test Results

The study used the R programming language for the Bai-Perron analysis. The data were imported and analyzed in R, revealing structural breaks. Table 2 indicates break observations: the 385th for one break and the 230th, 264th, 567th, and 620th for four breaks, with corresponding dates. Bai and Perron's sup-F type test (1998, 2003) rejects the null hypothesis of no structural change, supported by p values below the 1% and 5% thresholds in Table 2. Thus, the analysis confirms a structural break in total credit from deposit banks.

To evaluate the goodness of fit and to determine the optimal number of breakpoints m, sequential tests were used, and criteria were compared based on the Bayesian information criterion (BIC) and the sum of residual squares (RSS), which is the sum of the differences between observed and expected outcome values (Vališ et al., 2019). Table 2 shows the summary of the *BIC*, one of the criteria used in model selection, and the *RSS*, a statistical technique used to measure the amount of variance in a dataset that the regression model does not explain. The RSS and BIC values were smaller than those of the single exponential model ($p<0.001$). According to Bai and Perron (2003), the breakpoint selection process is based on the RSS and BIC. The first limitation is the maximum of five breaks. The test procedure will be designed to capture all potential breakpoints if the effective number of breaks is greater than 5, in which case a greater number of breaks will be used. In theory, a model's minimum BIC is related to the ideal number of breakpoints for that model (Gregoriou, 2009). The RSS calculation is the basis for this idea. This demonstrates that the penalty that affects the outcome of the BIC increases with the number of regression coefficients, which should be another breakpoint (Vališ et al., 2019). The results for the optimum number of breakpoints m are given in Table 2. According to the results, there are 5 breaks. The break dates are 6/27/2008, 12/31/2010, 8/23/2013, 11/18/2016, and 1/24/2020.

Figure 2 shows the BIC and RSS values extracted from the structural break test and the corresponding breaks in the series of deposit bank credits.

Practically, the variable represents the independent variable used in the regression analysis. When estimating the regression in segments, is considered the threshold at which the coefficients transition from one stable regression relationship to another. Thus, there are segments with constant regression coefficients, and the model is written as follows (Zeileis et al., 2003):

$$y_i = x_i^{\mathrm{T}}\beta_j + u_i \text{ (for } i = i_{(j-1)+1,\ldots,}\, i_{j,} \text{ where } j = 1, \ldots, m + 1) \quad (20)$$

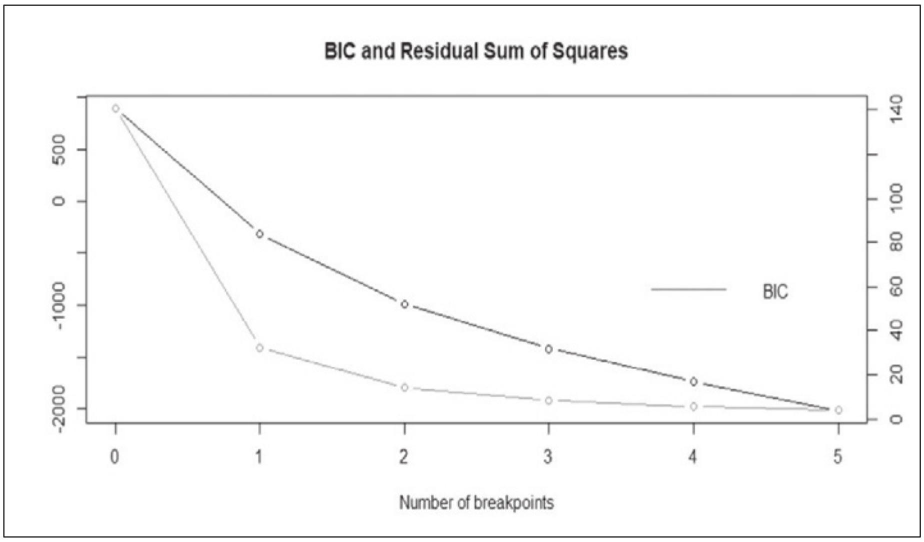
Here, j indicates the segment index, and i represents the observation index within each segment. In practice, breakpoints are rarely given exogenously but must be estimated. Breakpoint analysis involves estimating breakpoints by minimizing the sum of the squared residuals of the equation shown above.

Table 2: Bai-Perron Structural Break Analysis

Number of Fractures	Observation Values	Break Dates
1	385	5/17/2013
2	271 567	3/11/2011, 11/11/2016
3	232 399 620	6/11/2010, 8/23/2013, 11/17/2017
4	230 264 567 734	5/28/2010, 5/31/2013, 11/11/2016, 1/24/2020
5	130 260 399 568 734	6/27/2008, 12/31/2010, 8/23/2013, 11/18/2016, 1/24/2020
Goodness of Fit: **m** **0** **1** **2** **3** **4** **5** RSS : 140.975 32.359 14.194 8.360 5.606 3.970 BIC : 897.619 -314.847 -987.863 -1415.367 -1734.771 -2008.784		
sup.F = 2760.4, *p value < 2.2e-16*		

Source: Prepared by the author.

Figure 2. BIC and sum of residual squares (RSS) for models with m breakpoints



The research statistically confirmed that the series had structural breakdowns, and it was established that there were many structural fractures. Therefore, the R program checked the coefficients to determine how many structural breaks would be selected. The structural break segments are shown in Table 3 below. According to the table, the first break occurred between the first week of 2006 and the twentieth week of 2008. The last break occurred between the 34th week of 2019 and the 1st week of 2022.

Figure 3. Cusum test structural change graph

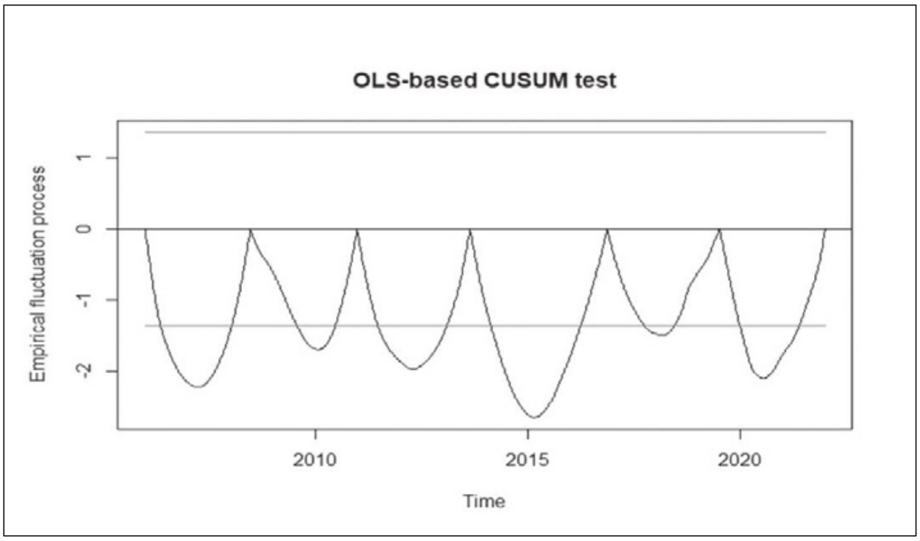


Table 3. Structural Breaks Segments

Fracture Periods	Fixed
2006(1) - 2008(20)	8.245303
2008(21) - 2010(52)	8.468472
2011(1) - 2013(34)	8.767912
2013(35) - 2016(46)	9.041610
2016(47) - 2019(33)	9.257447
2019(34) - 2022(1)	9.430127

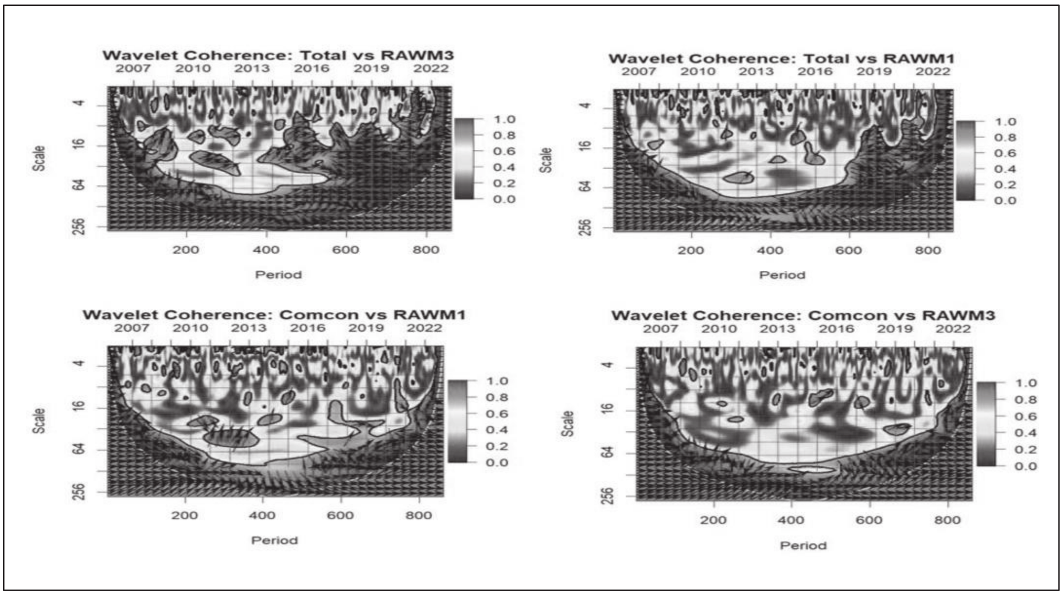
4.2. Stability Testing with CUSUM in R

CUSUM tests evaluate the stability of the β coefficients in the $y = X\beta + \varepsilon$ format multiple linear regression model. The cumulative sum of recursive residuals or OLS residuals is used to determine if there is a structural break. Under the null hypothesis, the cumulative sum of the residuals will be zero. Additionally, the CUSUM test plots the cumulative sum with confidence bands, showing whether the series behaves as predicted by the null hypothesis.

As shown in Figure 3 above, empirical fluctuations overwhelm this process. A suitable empirical fluctuation process of a particular type can be constructed using the formula that defines a linear regression model to be tested. The fact that grey lines surround the black lines of the plotted graph means that the hypothesis suggesting the existence of a structural break is rejected. However, there is a structural break in the model of the series as the graph drawn in Figure 4 is outside the boundary lines. There is evidence of structural change as the OLS-based CUSUM process appears to have crossed its boundaries (Zeileis et al., 2003). In addition, six changes (structural breaks) can be observed when looking at the lines that go beyond the process.

In Figure 5, the peaks are the parts of the time series with structural changes. Calculating the bounds and plotting the F statistics are similar to the experimental fluctuation processes introduced in the previous section. The asymptotic probability of the superiority (or average) of the F_i $(\underline{i} \le i \le \bar{i})$ statistics exceeding this limit can be calculated under the null hypothesis of no structural change (Zeileis et al., 2003). A F value exceeding the established limit indicates the occurrence of a structural change (at the level of $\alpha = 0.05$).

Figure 4. Wavelet coherence heatmaps



4.3. Wavelet coherence test results

In the second stage of the study, the relationships between commercial and individual bank credit, total credit, and the money supply were examined via wavelet coherence analysis. The wavelet coherence results are shown in Figure 6. In the figure, TOTAL calculates the total loan volume, and Comcon calculates the total commercial and consumer credits. RAWM1 is the notional amount index representing the M1 money supply (currency in circulation (outside banks) + sight deposits), and RAWM3 is the M3 money supply (M1 + time deposits + repos + money market funds + domestic banks' securities with maturity shorter than 2 years) representing the notional amount index.

Figure 4 shows the wavelet consistency heatmaps that reflect the most important of the typical movements of credit volumes and M1 and M3 money supply indexes. Figure 6 displays the analysis period on the horizontal axis daily. Wavelet coherence identifies regions in the time-frequency domain where changes occur in two time series. These regions are shown on the vertical axis, which corresponds to frequency. Lower frequencies are represented by greater scales. Colors such as dark indicate lower levels of dependency between series, while lighter colors such as grey represent regions with significant correlations. Not reliant on the series, time and frequency are represented by the cold (dark) regions outside the areas expressing meaningful relationships. The forward/lag phase relationships between the series under consideration are shown as arrows in the wavelet coherence plots. When there is no phase difference, the two time series exhibit synchronous movement on a certain scale. Arrows indicate the direction of movement: to the right for in-phase and to the left for out-of-phase. In-phase movement implies propagation in the same direction, while out-of-phase movement indicates movement in opposite directions. When one variable leads the other, arrows point left or up for the leading variable and right or down for the lagging variable (Vacha and Barunik, 2012; Goodell and Goutte, 2021).

The wavelet coherence heatmaps in Figure 6 show that the credit-money supply comovements are significant and at phase (moving together in the same direction). Generally, credit volumes follow money supplies. Considering the Comcon variable, credits followed the M1 money supply between 2007 and 2013 on a 128–256-day scale, and the relationship between them is positive and significant (warm colors and ↗). However, between 2013 and 2016, the money supply followed the loan volume. Although there is a short-term mixed relationship (between 2010-2013 and 2016-2022), as observed at 32-64 32-128-day scales, in general, the relationship between them is in phase (→), and they move together (there is a zero phase difference). Similar relationships between the Comcon variable and the M1 money supply are also observed for M3.

Substantial and significant relationships are observed on the total credit (TOTAL) front, as in the Comcon variable. Here, too, there is a phase situation in general. The relationships between variables are positive and significant. The variables move together. In addition, as in the Comcon variable between 2007 and 2013, credits follow the M1 and M3 money supply.

5. CONCLUSION

A structural break indicates a sudden and significant change in a time series or its relationship to another time series. A significant change in the average parameters or other parameters of a process occurs over time. Our focus is on data that reflect dramatic changes in lending by financial institutions, particularly identifying structural disruptions in lending volume. These disruptions may result from changes in credit standards, economic conditions, or government policies. The consequences of a structural breakdown of credit are highly significant and include affecting economic growth, inflation and financial stability. There is a relationship between the structural breakdown of credit, primarily through bank lending, and the money supply. Banks, which play a central role in credit creation, influence the money supply by lending or reducing credit. A decrease in bank lending due to a structural collapse could reduce the money supply and affect spending and investment. However, this correlation is affected by factors such as changes in monetary policy and changes in the demand for money and can have a lag effect. Understanding the complex relationship between the structural breakdown of credit and the money supply requires a careful analysis of the broader economic context and other influencing factors.

This study investigates structural break processes in Turkey's credit volume from 2006 to 2022 using the Bai-Perron multiple structural break test. The analysis identifies significant breakpoints on 6/27/2008 (during the global financial crisis) and 12/31/2010 (marked by increased competition and campaigns in the consumer loan market). Further breakpoints occurred on 8/23/2013, 11/18/2016, and 1/24/2020, each associated with specific economic conditions and interest rate reductions. These structural breaks signify changes in the levels of univariate time series. The study explores the relationship between loan volume and the money supply and reveals a positive correlation. Despite occasional comovements, bank credit generally follows the money supply. These findings suggest the need for the Central Bank of the Republic of Turkey (CBRT) to sustain expansionary monetary policies for interest rate reduction, particularly during crises. Institutions such as the Banking Regulation and Supervision Agency (BRSA) and CBRT play crucial roles in averting excessive risky credit. Overall, the study anticipates economic growth in Turkey through an expanded bank loan volume driven by expansionary monetary policies.

This study addresses the need to understand the dynamics of credit volume and its relationship with the money supply in the Turkish economic context, particularly focusing on identifying structural disruptions in lending volume. The goal of our paper is to shed light on these structural breaks and their implications for economic growth, inflation, and financial stability in Turkey. To achieve this goal, we employ the Bai–Perron multiple structural break test to analyze Turkey's credit volume. This method allows us to identify significant breakpoints that represent sudden and significant changes in lending volume. Our analysis reveals specific breakpoints on 6/27/2008 (during the global financial crisis) and 12/31/2010 (associated with increased competition and campaigns in the consumer loan market). Additionally, breakpoints occurred on 8/23/2013, 11/18/2016, and 1/24/2020, linked to distinct economic conditions and interest rate reductions. The identified structural breaks signify changes in the levels of univariate time series, indicating shifts in lending behavior influenced by various economic factors and policy interventions. Regarding the relationship between loan volume and the money supply, our analysis reveals a positive correlation, suggesting that bank credit generally follows the money supply. This finding underscores the interconnectedness between credit creation by financial institutions, particularly banks, and the money supply, which has implications for spending, investment, and overall economic activity. Our study contributes to the literature by providing insights into the dynamics of credit volume and its interaction with the money supply in Turkey. By identifying structural disruptions in lending volume and analyzing their implications, we offer valuable insights for policymakers, particularly those of the Central Bank of the Republic of Turkey (CBRT) and the Banking Regulation and Supervision Agency (BRSA), in formulating effective monetary and regulatory policies to promote economic stability and growth.

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Kreditna aktivnost i njen odnos s ponudom novca u Turskoj: Bai-Perron i valna koherencijska analiza

Sažetak

Strukturni lomovi u obujmu kredita odnose se na nagle i značajne promjene u mjeri u kojoj financijske institucije odobravaju kredite. Ovi lomovi mogu se dogoditi iz različitih razloga, kao što *su promjene u standardima kreditiranja, promjene u gospodarskim uvjetima ili promjene u vladinim politikama. Strukturni lom u kreditnoj aktivnosti može imati važne posljedice za* šire *gospodarstvo, uključujući utjecaj na gospodarski rast, inflaciju i financijsku stabilnost. Ovaj rad usredotočuje se na višestruke strukturne lomove i njihov odnos s ponudom novca u kreditnoj aktivnosti depozitnih banaka u razdoblju od 2006. do 2022. godine, kada su Turska i svijet doživjeli značajne gospodarske, financijske, političke i društvene promjene.. Podatke korištene u analizi osigurava Središnja banka Republike Turske, uključujući ukupne kredite koje depozitne banke odobravaju gospodarskim subjektima. Za analizu podataka korišteni su Bai-Perronov test višestrukih strukturnih lomova i metoda valne koherencije. Kao rezultat istraživanja, utvrđeno je pet datuma strukturnih lomova u kreditnoj aktivnosti, a naglašeni su razlozi tih lomova. Nadalje, analiza valne koherencije pokazuje da ponuda novca i kreditna aktivnost dugoročno zajedno variraju.*

Ključne riječi: Kreditna aktivnost, Bai-Perron, strukturni lomovi, ponuda novca, valna koherencija