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MODELLING THE INTERCONNECTIONS BETWEEN THE FINANCIAL STRESS AND THE REAL ECONOMY: EVIDENCE FROM EX-COMMUNIST EUROPEAN COUNTRIES

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Abstract. This study investigates the interconnections between the financial system and the real economy using Vector Autoregressive (VAR) models and their advanced variants. Analyzing data from five Ex-Communist European countries (Romania, Czech Republic, Poland, Slovakia, and Hungary), the Country-Level Index of Financial Stress (CLIFS) is employed, alongside Industrial Production Index and GDP, as proxies for financial and real economic activity. Findings reveal bidirectional causal relationships in some countries and unidirectional relationships in others, with financial stress having significant negative short-term impacts on industrial production. Using Simple Switching VAR and Markov-Switching VAR models, distinct crisis periods were identified, thus demonstrating that financial system disturbances precede real economy downturns.

1. Introduction

The global financial crisis that began in 2007 illustrated the strong relationship existing between the financial system and the real economy. Financial market instability rapidly transmitted to the real economy, contributing to the Great Recession. Although these effects are most visible during crisis periods, financial conditions also influence economic activity during normal economic cycles (Ankargren et al., 2017).

The importance of financial systems in economic development has been widely debated. Some economists argue that financial development stimulates economic growth, while others view it as a consequence of real economic expansion. Empirical evidence supporting the finance-led growth hypothesis emerged prominently in the World Bank's World Development Report (1989). King and Levine (1993) provide strong empirical support for this perspective, demonstrating that financial development indicators are positively associated with long-term GDP growth. Their findings reinforce Schumpeter's earlier argument that financial intermediaries play a key role in fostering technological innovation and economic development.

The aim of this paper is to explore the interconnections between the financial system and the real economy through classical Vector Autoregressive (VAR) models and two more complex variants: Simple Switching VAR and Markov-Switching VAR. The primary objective is to develop models capable of identifying crisis periods that simultaneously impact both the real economy and the financial system. The study focuses on five East European countries: Romania, Czech Republic, Poland, Slovakia, and Hungary. Countries were selected based on two key criteria: all are current European Union members with available Country-Level Index of Financial Stress (CLIFS) data, and all share a similar historical background as former

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members of the communist bloc. Considering all this, the present study fills a gap in the literature by providing new empirical evidence on financial stress and real economy linkages in under-researched Eastern European economies using advanced econometric methods.

Section 2 provides a review of the theoretical and empirical literature concerning the interconnections between the financial system and the real economy, with particular emphasis on financial stress indicators and VAR-based methodologies. Section 3 outlines the data selection process and presents the methodological framework employed in the empirical analysis, including the specification of the VAR, Simple Switching VAR, and Markov-Switching VAR models. Section 4 discusses the empirical findings and interprets the estimated relationships and regime dynamics identified across the analyzed economies. The last section concludes by summarizing the main results, highlighting their economic implications, and outlining directions for future research.

2. Literature Review

A financial system that is functioning accordingly is essential for a country's development, as well as for assuring the well-being of its population. However, with the recognition and acceptance of the neoclassical theory of economic growth, this conventional view of the financial system begins to be overlooked in academic circles, according to Schmidt and Tyrell (2003). Thus economists have divided into two sides: those who consider perceiving the financial system as a trigger for economic growth to be correct and those who believe it is more appropriate to be seen as a consequence of real economic development.

This debate on the role and importance of the financial system was brought back into discussions by the report published in 1989 by the World Bank, entitled "The World Development Report". Here, the first evidence emerged regarding the fact that the financial system indeed matters when discussing development and economic growth. It also illustrated a causal connection that starts from the financial system towards economic growth. Thus, articles such as "Schumpeter might be right" by King and Levine (1993) appeared. The article presents evidence using a panel that includes eighty countries, regarding the vision that Joseph Schumpeter presented to the world in 1911: the services provided by financial intermediaries are essential for technological innovation and economic development. The authors discover that various measures capturing the level of development in the financial system are strongly associated with increases in real gross domestic product and improvements that enhance the efficiency of an economy (King and Levine, 1993).

It can be concluded that the financial system plays a fundamental role in the development and growth of the economy, as it adjusts according to changes that occur in the real economy, just as the economy, in turn, responds when changes take place within the financial sector.

Financial stress refers to moments of disruption in the normal functioning of the financial system (Hakkio and Keeton, 2009). Thus, although it is difficult to generalize such episodes as "financial stress", a consensus has been reached regarding the events included in this definition, which are: uncertainty regarding investor behavior, a high level of information asymmetry and the avoidance of holding high-risk assets and illiquid assets.

The real economy refers to that part of a country's economy that produces goods and services and does not include the part that deals with financial activities, such as banks or the stock market. Therefore, it can be said that the real economy includes sectors such as industry, commerce, agriculture, and construction. Pirounakis (1997) argues that the real economy is and will always be a fundamental part of the economy. It plays a very important role in determining the standard of living in a country, as well as the welfare of the population in that particular state. Brender et al. (2015) argue that the changes made by a central bank to monetary policies affect the real economy through the impact these policies have on the returns of all financial investments and the loans offered by the financial system. Gabrovski et al. (2025) illustrate how high inflation levels have an impact on the real economy.

This topic is approached through various methods by authors from around the world, ultimately reflecting the same conclusion: there is a connection between the financial system and the real economy. It is important to note that the strong connection between the financial system and the real economy is not highlighted only in times of crisis; it is also present in normal economic circumstances, but with less drastic effects (Ankargren et al., 2017). There are research papers such as the one written in 2014 by Christiano, Motto, and Rostagno, as well as Bloom's from 2012 and 2009, which attempt to understand how financial shocks affect the real economy through structural dynamic stochastic general equilibrium (DSGE) models.

In addition to the DSGE model approach, analyses have been conducted to identify the link between the real economy and the financial system using vector autoregressive (VAR) models. The Bayesian VAR model has been successfully used by Ankargren et al. (2017), Österholm (2012), and Jarocinski and Smets (2008) to determine whether the financial system truly matters for the development of the real economy. To examine how the financial system affects the real economy through transmission channels, Bjellerup and Shahnazarian (2012) utilize the VAR model, concluding that GDP can be explained by the VAR model that utilizes the variables proposed by the authors to cover the four transmission channels.

The VAR model is also used by Duprey et al. (2017) to explain the relationship between the two systems that constitute the subject of this study. They present two models that successfully describe the interconnections between the real economy and the financial system: the Markov-switching vector autoregressive (MS-VAR) model and the Bayesian threshold vector autoregressive (TVAR) model. For the financial system, they use CLIFS (Country-level Index of Financial Stress), which was developed in the first part of their study. The results obtained from applying the two different models led to the conclusion that, in general, events defined as the repercussions of financial stress exhibit a recurrent pattern. During periods of increased financial turbulence, recessions tend to last on average more than seven months, and it has been observed that in most cases, financial stress events appear first, preceding events that disrupt the real economy.

The Markov-Switching VAR algorithm appears to identify most accurately the data that marks the beginning and end of a systemic financial crisis since it separately analyzes episodes in the financial market and those in the real economy. MS-VAR models have the capacity of combining gradual movements with sudden regime changes (Kole & van Dijk, 2023). As a result, negative market developments that often occur prior to the negative impact on the economy can be captured more efficiently (Duprey et al., 2017). The authors point out that the TVAR approach can capture early increases in the financial system indicator only if they are sufficiently large, compared to the MS-VAR model. A TVAR model is used by Yildirim & Sanyal (2023) to illustrate that the economy behaves differently depending on whether the financial stress is above or below an estimated threshold. The TVAR approach is extended in the study ran by Wichmann, Cordeiro & Caldeira (2024) that shows how financial stress interacts not only with real activity but also with policy transmission mechanisms. In other words, complex models like TVAR and MSVAR primarily signal the peak of the systemic stress period, as that is when the common dynamics are most pronounced.

Quan Yonghui and Miao Wenlong (2025) have a valuable contribution to the macro-financial contagion literature by linking commodity price risks with financial sector instability in China. Using rolling regressions and a generalized VAR spillover framework, the authors show that risk transmission between the real economy and financial markets is highly asymmetric, especially during crisis periods. One of the paper's main strengths is its use of commodity price indices as proxies for real-economy stress, which, according to the authors, offers a more direct measure of economic activity than stock-sector indices commonly used in earlier studies.

Although the literature on the relationship between financial stress and real economic activity has grown considerably in recent years, several gaps remain. Most existing studies concentrate on advanced economies or treat the euro area as a single unit of analysis, with relatively little attention paid to the individual dynamics of Central and Eastern European post-communist economies. Additionally, while methodological approaches such as DSGE models, TVAR, and MS-VAR have been widely used in the literature, their application to country-level analysis of EU member states that underwent post-communist transition is still limited. This study aims to fill these gaps by providing empirical evidence on the transmission of financial stress to real economic activity in five ex-communist bloc EU member states: Romania, the Czech Republic, Poland, Slovakia, and Hungary. Using VAR, Simple Switching VAR, and Markov-Switching VAR models on data covering the period 2002–2023, the study contributes to the existing literature in two main ways. First, by taking a country-level approach, it provides a more detailed perspective on the finance–growth nexus than aggregate euro-area studies, allowing for a direct assessment of cross-country differences in the strength and persistence of financial stress transmission. Second, by applying regime-switching methodologies to economies that share a common historical and institutional background, the study extends the application of these techniques to a region that remains underrepresented in the empirical literature on financial–real interactions within the European Union.

3. Data and Methodology

The aim of this research is to investigate the impact of financial stress on real economic activity in five ex-communist EU member states: Romania, the Czech Republic, Poland, Slovakia, and Hungary, over the period 2002–2023. To this end, the empirical analysis is structured around three main hypotheses. First, it is expected that financial stress, measured by the Country-Level Index of Financial Stress (CLIFS), has a significant negative effect on real economic activity, proxied by both the Industrial Production Index (IPI) and Gross Domestic Product (GDP). This expectation is grounded in the well-documented transmission channel through which financial instability reduces investment and consumption, ultimately leading to lower output. Second, it is assumed that this relationship is not symmetric across different economic conditions: the negative impact of financial stress on the real economy is expected to be stronger and more persistent during periods of high financial stress than during more stable periods. Lastly, the study expects that episodes of financial stress tend to precede downturns in real economic activity, rather than the other way around, in line with the finance-led transmission found in the literature for euro-area economies. These hypotheses are tested using VAR, Simple Switching VAR, and Markov-Switching VAR models, as described in the methodological framework below.

3.1. **Variable Selection and Data Description.** To analyze the impact of financial stress on the real economy, the following variables are employed, covering the period from 2002 to 2023: CLIFS (published at a monthly frequency by the European Central Bank), GDP (available at a quarterly frequency from Eurostat) & IPI (provided at a monthly frequency from Eurostat). Given these differences in data frequency, harmonization procedures were applied to ensure comparability across variables within each model specification, as detailed in the variable descriptions below.

Country-Level Index of Financial Stress (CLIFS): Financial cycles reflect cumulative interactions between asset valuations, risk perceptions, and financing constraints, typically resulting in expansionary periods followed by sudden contractions (Borio, 2014). To capture financial system dynamics, this study employs the Country-Level Index of Financial Stress (CLIFS), introduced in Dating Systemic Financial Stress Episodes in the EU Countries (Duprey et al., 2017). The indicator builds on the methodology proposed by Hollo, Kremer, and Lo Duca (2012) for the Composite Indicator of Systemic Stress (CISS), but differs by providing country-specific measurements rather than a euro-area aggregate. CLIFS measures financial pressure at the level of individual EU member states using information from three financial market segments: capital market (stock price index), bond market (10-year government bond yield) and foreign exchange market (real effective exchange rate). The real exchange rate is computed as the geometric mean of bilateral exchange rates weighted by trade flows. Due to data limitations, the indicator does not include banking-sector or real estate market variables. Database was extracted from European Central Bank's website, where monthly data for CLIFS indicator is available. Selected time horizon is 2002–2023.

Gross Domestic Product (GDP): Gross Domestic Product is another commonly used measure of economic activity. In this study, GDP serves as an alternative indicator of the real economy. Because GDP data are available at a quarterly frequency on Eurostat, CLIFS values are converted into quarterly observations by averaging the corresponding monthly values within each quarter. GDP data are seasonally and calendar adjusted and transformed into logarithmic quarter-to-quarter growth rates (g_GDP). The temporal aggregation of monthly CLIFS values into quarterly observations follows the simple arithmetic mean approach, whereby the three monthly observations within each calendar quarter (Q1: January–March; Q2: April–June; Q3: July–September; Q4: October–December) are averaged to produce a single quarterly value. This method is consistent with standard practice in the empirical macroeconomic literature for converting high-frequency financial indicators to lower frequencies (Silvestrini & Veredas, 2008; Marcellino, 1999), and has been applied in analogous contexts by Duprey et al. (2017).

Industrial Production Index (IPI): The industrial production index is widely used as a proxy for real economic activity in business cycle studies. It provides a high-frequency measure of economic fluctuations and is therefore suitable for analyzing short-term interactions between the financial system and the real economy. According to the National Institute of Statistics, "the industrial production index is a volume index and measures the evolution of the results of industrial activities from one period to another" (National Institute of Statistics Press Release No. 114, 2023). In processing the monthly dataset provided by Eurostat, a seasonal adjustment of the index was performed. Furthermore, in order for the index to be used in the model presented below, it was necessary to calculate its growth rate, following the same procedure applied in the case of gross domestic product (g_IPI). When IPI is used alongside CLIFS in the monthly-frequency model, no temporal aggregation of CLIFS is required, as both variables are already available at monthly frequency. The monthly CLIFS series is used directly as published by the European Central Bank, without further transformation. IPI will also follow a temporal aggregation from monthly into quarterly values following the simple arithmetic mean approach explained for CLIFS, following standard practice in the empirical macroeconomic literature for converting a high-frequency financial indicator into lower frequencies (Silvestrini & Veredas, 2008; Marcellino, 1999), and has been applied in analogous contexts by Duprey et al. (2017).

Ex-communist countries: As CLIFS indicator is available for all EU member states, along Romania, four other countries were selected alongside: Czech Republic, Poland, Slovakia, and Hungary. The countries were selected primarily due to their current membership in the European Union, but also considering the historical context, particularly their past within the communist bloc, which had a significant impact on them. A similar period spent behind the Iron Curtain is observed, a reality that has an impact on the economic development that followed after 1989. Of the five countries mentioned above, only two are currently members of the eurozone (Slovakia and Hungary), with the other three preparing to take the same step, as documented by the European Union. The percentage indicating the share of the industrial sector in the totality of sectors present in the economy of the five mentioned countries is taken from the official page of the European Union, with the last update of data relating to these being made in 2020. This percentage is indicated from the beginning to observe that, from a percentage perspective, the industrial sector represents approximately 24% of the total economic sectors, with the largest share being found in the case of the Czech Republic, and the smallest percentage being attributed to Romania with 21.7% in 2020. The use of the production index within the models is therefore justified, viewing from this perspective.

The descriptive statistics table (Table 1) showcases notable differences in the behavior of the three variables across the five economies of the ex-communist countries block. CLIFS indicator reflects low average values illustrating low levels of financial stress. The positive skewness and high kurtosis indicate that stress episodes are extreme when occurring, despite not being so frequent. This condition can be especially observed in the Czech Republic and Hungary. In contrast, the industrial production index (IPI) shows relatively stable central tendencies, with mean and median values closely aligned, suggesting near-symmetric distributions. Skewness values close to zero and kurtosis below three indicate a platykurtic distribution and a moderate volatility. This is not the case for Hungary and Slovakia where a higher dispersion can be identified. GDP mean and median values are similar across countries, indicating relatively symmetric distributions. Higher standard deviations reflect greater variability over time, especially in Poland, Romania and Slovakia. Skewness coefficients for GDP are generally close to zero, while kurtosis values suggest mostly platykurtic distributions, with slight deviations in the Czech Republic and Hungary. Overall, while GDP and IPI display relatively stable and symmetric dynamics, CLIFS stands out for its asymmetric and heavy-tailed distribution, capturing the episodic nature of financial instability in the Eastern European region that is analyzed in this study.

Table 1. Descriptive statistics

Variable	Statistic	Romania	Czech Rep.	Hungary	Poland	Slovakia
CLIFS	Mean	0.10	0.13	0.14	0.11	0.10
	Median	0.09	0.09	0.08	0.07	0.08
	Maximum	0.46	0.81	0.91	0.48	0.52
	Minimum	0.01	0.02	0.01	0.02	0.02
	Std. Dev.	0.09	0.12	0.16	0.10	0.08
	Skewness	1.29	2.24	2.32	1.38	1.94
	Kurtosis	5.23	9.78	8.75	4.37	7.75
IPI	Mean	92.50	90.52	90.74	87.14	83.12
	Median	92.65	88.55	89.85	84.45	86.80
	Maximum	117.80	127.80	154.40	120.90	121.40
	Minimum	58.50	53.70	44.70	58.00	38.20
	Std. Dev.	16.34	19.60	30.58	19.86	25.41
	Skewness	(0.19)	0.08	0.37	0.11	(0.25)
	Kurtosis	1.94	2.00	2.27	1.55	1.74
GDP	Mean	90.70	90.60	94.23	87.91	84.46
	Median	91.30	92.92	92.45	85.50	88.65
	Maximum	135.33	122.07	127.66	144.17	121.67
	Minimum	53.97	61.11	65.28	44.31	45.79
	Std. Dev.	26.55	19.71	20.46	29.27	24.82
	Skewness	(0.01)	(0.50)	(0.34)	0.18	(0.25)
	Kurtosis	2.33	3.77	4.08	2.17	2.15

Source: author's computations.

3.2. **Fundamentals of Research Methodology.** For the purpose of the study several methodological approaches are employed, as described below.

3.2.1. *Vector Autoregressive Model.* The Vector Autoregressive (VAR) model is used to simultaneously estimate equations equal in number to the existing variables, thus expanding the basic model of Ordinary Least Squares (OLS) analysis.

$$\begin{aligned} X_t &= \beta_{10} + \beta_{11} X_{t-1} + \beta_{12} X_{t-2} + \cdots + \beta_{1l} X_{t-l} + \gamma_{11} Y_{t-1} + \cdots + \gamma_{1l} Y_{t-l} + \varepsilon_{1t} \\ Y_t &= \beta_{20} + \beta_{21} Y_{t-1} + \beta_{22} Y_{t-2} + \cdots + \beta_{2l} Y_{t-l} + \gamma_{21} X_{t-1} + \cdots + \gamma_{2l} X_{t-l} + \varepsilon_{2t} \end{aligned} \tag{1}$$

This model is first constructed for the set of variables CLIFS and GDP, which have a quarterly frequency. Furthermore, the relationship between CLIFS and IPI, with a monthly frequency, will also be analyzed. These two variables are preferred for testing the interconnection between the financial system and the real economy by the authors who established the CLIFS indicator. The selection of the lag order was performed using the Lag-length Criteria, considering three criteria: Akaike, Schwartz, and Hannan-Quinn. The most suitable criterion to follow in this case is Akaike. Both time series are stationary, as verified by the VAR Stability Condition Check. Therefore, if all the modulus of the inverse roots of the characteristic AR polynomial are less than one, we can conclude that the estimated VAR is stable.

The results obtained for both situations confirm the validity of the test for the monthly and quarterly data series specific to each country analyzed in this study. By using Granger causality will be examined whether the lagged values of variable Y help predict the other variable in the model. According to this test, causality can be explained as the predictive power relationship that exists between the analyzed variables, as stated by Stock & Watson (2009, p. 547–548).

H₀: Variable Y do not Granger cause variable X, precisely

$$\gamma_{11} = \gamma_{12} = \gamma_{13} = \cdots = \gamma_{1l} = 0 \tag{2}$$

H₁: Variable Y does Granger cause variable X, respectively

$$\gamma_{11} \neq 0 \text{ and/or } \gamma_{12} \neq 0 \text{ and/or } \gamma_{13} \neq \cdots \neq \gamma_{1l} \neq 0 \tag{3}$$

Table 2 displays the interconnections between financial pressure, represented by the variable CLIFS, and the industrial production index (IPI) through a VAR model. At the beginning of each row, the independent variable for each lag is indicated within the parentheses. The columns exemplify the equations showing the variation of the two variables included in the model, CLIFS and IPI. The results shown within parentheses represent the associated standard deviation. To consider a coefficient significant, a significance level of 5% is applied (indicated in bold). Observing the value obtained for the coefficient of determination (adjusted R^2), for all five countries, it can be stated that the VAR model is suitable for explaining the relationships existing between the two variables. For Romania, the Czech Republic, and Hungary, the estimated equation explaining financial pressure is more appropriate compared to the value obtained in the case of industrial production index growth. An opposite situation is observed for Poland and Slovakia.

The table illustrates that when, in Romania, g_IPI increases by one point, a rather small increase of only 0.0039 points in CLIFS can be observed in the following month, ceteris paribus. However, a one-point increase in CLIFS has a much more significant impact on the growth of the industrial production index, causing a decrease of 1.38 points in the immediately following month, while at the same time generating an almost proportional increase in the second period. This rather insignificant impact that a one-point increase in the industrial production index has on CLIFS is observed in all the countries analyzed.

Table 3 presents the situation where the real economy is illustrated using the GDP. In this case, the VAR model is applied to quarterly data, considering that the real economy is represented by gross domestic product (GDP). An interesting situation can be observed. The equation explaining the economy is not estimated accurately, as indicated by the values obtained for the coefficient of determination (adjusted R^2). This issue could be explained by the relatively small size of the data sample. Thus, the results show that, during the first period, the real economy has a negative impact on the financial system, while in subsequent periods the impact becomes positive for Romania, the Czech Republic, and Slovakia. In Poland, GDP will increase by 5 points in the first quarter if CLIFS increases by one point, with this value remaining nearly identical in the second quarter as well.

Table 2. VAR model for analyzing the interconnections between CLIFS and IPI

	Romania		**Czechia**		**Hungary**		**Poland**		**Slovakia**	
	CLIFS	g_IPI	CLIFS	g_IPI	CLIFS	g_IPI	CLIFS	g_IPI	CLIFS	g_IPI
CLIFS(-1)	0.6688	0.0039	0.6716	0.0052	0.6424	0.0003	0.4819	0.0063	0.7496	0.0023
	(0.0632)	(0.0048)	**(0.0597)**	(0.0029)	**(0.0604)**	(0.0031)	**(0.0581)**	(0.0063)	**(0.0608)**	(0.0028)
CLIFS(-2)	0.1509	0.0039	0.0276	-0.0017	0.1938	0.0009	0.2938	0.0002	-0.0209	-0.0003
	(0.0638)	(0.0049)	**(0.0727)**	(0.0035)	**(0.0601)**	(0.0031)	(0.0584)	(0.0063)	**(0.0748)**	(0.0035)
CLIFS(-3)			0.1733	-0.0007					0.2551	0.0009
			(0.0598)	(0.0029)					**(0.0742)**	(0.0034)
CLIFS(-4)									-0.1154	-0.0002
									(0.0597)	(0.0027)
g_IPI(-1)	-1.3806	0.6953	-2.7556	0.9312	-2.5969	0.8952	0.1117	0.8153	0.4741	0.9106
	(0.0841)	**(0.0645)**	**(1.2759)**	**(0.0613)**	**(1.2043)**	**(0.0609)**	**(0.5657)**	**(0.0611)**	**(1.3669)**	**(0.0634)**
g_IPI(-2)	1.0098	0.0641	3.1419	-0.2623	0.7021	-0.0454	-0.2423	0.0047	-3.8966	-0.0839
	(0.8331)	**(0.0638)**	**(1.7569)**	**(0.0845)**	**(1.2239)**	**(0.0619)**	**(0.5675)**	**(0.0613)**	**(1.8266)**	**(0.0847)**
g_IPI(-3)			-2.8068	0.1929					2.8822	-0.0149
			(1.2886)	**(0.0619)**					**(1.8794)**	**(0.0872)**
g_IPI(-4)									-3.1232	0.0498
									(1.4252)	**(0.0662)**
C	0.0245	-0.0005	0.0229	-0.0001	0.0274	0.0005	0.0209	0.0047	0.0326	-2.4E-05
	(0.0065)	(0.0005)	(0.0065)	(0.0003)	(0.0066)	(0.7237)	(0.5675)	(0.0613)	(0.0074)	(0.0004)
R^2	0.6234	0.5785	0.7244	0.7109	0.6994	0.7277	0.5161	0.6809	0.8069	0.7065
R^2 adj.	0.6173	0.5716	0.7183	0.7044	0.6949	0.7237	0.5089	0.6761	0.8010	0.7079

Source: author's computations.

Table 3. VAR model for analyzing the interconnections between CLIFS and GDP

	Romania		**Czechia**		**Hungary**		**Poland**		**Slovakia**	
	CLIFS	g_GDP	CLIFS	g_GDP	CLIFS	g_GDP	CLIFS	g_GDP	CLIFS	g_GDP
CLIFS(-1)	0.8153	-0.0127	0.7729	-0.0027	1.0509	-0.0052	0.5891	0.0018	0.7471	-0.0096
	(0.1104)	(0.0032)	**(0.0747)**	(0.0011)	**(0.1027)**	(0.0023)	**(0.0843)**	(0.0043)	**(0.0831)**	(0.0023)
CLIFS(-2)	-0.2305	0.0079			-0.2862	0.0009				
	(0.1468)	(0.0043)			**(0.1099)**	(0.0025)				
CLIFS(-3)	0.3129	-0.0058								
	(0.1169)	(0.0034)								
g_GDP(-1)	-0.8347	-0.0517	-0.8606	-0.0128	5.7363	-0.3409	-4.1761	-0.0898	0.5546	-0.0983
	(3.9779)	**(0.1157)**	**(7.9240)**	**(0.1113)**	**(4.9248)**	**(0.1102)**	**(2.1730)**	**(0.1095)**	**(4.0554)**	**(0.1113)**
g_GDP(-2)	6.2712	-0.0643			5.7911	0.0697				
	(3.9571)	**(0.1151)**			**(4.9297)**	**(0.1103)**				
g_GDP(-3)	10.1759	-0.0563								
	(3.9096)	**(0.1137)**								
C	0.0035	0.0023	0.0322	0.0008	0.0199	0.0014	0.0413	0.0008	0.0332	0.0021
	(0.0185)	(0.0005)	(0.0141)	(0.0002)	(0.0124)	(0.0003)	(0.0094)	(0.0005)	(0.0138)	(0.0004)
R^2	0.6159	0.23368	0.5917	0.0775	0.6829	0.1969	0.4154	0.0121	0.5496	0.1910
R^2 adj.	0.5847	0.1749	0.5825	0.0565	0.6679	0.1587	0.4019	-0.0107	0.5383	0.1708

Source: author's computations.

One-point changes in GDP generate only minor changes in the financial system indicator, although they follow the same pattern observed previously, namely a negative effect in the immediately following quarter and a positive effect in subsequent periods. The small magnitude of these changes indicates that a variation occurring in the real economy will not produce substantial effects on the financial system. This situation can also be observed in the case of monthly data, where the equation explains the model much more significantly. What can be inferred from these results is that the economy, in general, is affected by changes occurring within the financial system; however, this relationship is not bilateral.

3.2.2. *Switching VAR and Markov Switching VAR Models.* Considering Krolzig (1997) the Equation 4 will be modified to allow for regime switching, so that X_t and Y_t follow a VAR process that depends on the value of a discrete state variable s_t. It will be considered that m represents the number of regimes, where $m \in [1, M]$ and it will be assumed that in period t, the model is in regime m if $s_t = m$.

$$X_t = A_{11}X_{t-1} + A_{12}X_{t-2} + \cdots + A_{1l}X_{t-l} + \mu_{1t} + \varepsilon_{1t} \tag{4a}$$

$$Y_t = A_{21}Y_{t-1} + A_{22}Y_{t-2} + \cdots + A_{2l}Y_{t-l} + \mu_{2t} + \varepsilon_{2t} \tag{4b}$$

Where,

- $X_t = (X_{1t}, X_{2t}, \cdots, X_{kt})'$ is the first vector that contains endogenous variables, with the dimension $k \times 1$;
- $Y_t = (Y_{1t}, Y_{2t}, \cdots, Y_{kt})'$ is the second vector that contains endogenous variables, with the dimension $k \times 1$;
- $A_{11}, \cdots, A_{1l}$ and $A_{21}, \cdots, A_{2l}$ represent matrixes with the dimension $k \times k$ of lagged coefficients that will be estimated;
- μ_{1t} and μ_{2t} are the vectors with the dimension $k \times 1$ of the intercept series;
- $\varepsilon_{1t} = (\varepsilon_{11t}, \varepsilon_{12t}, \cdots, \varepsilon_{1kt})'$ and $\varepsilon_{2t} = (\varepsilon_{21t}, \varepsilon_{22t}, \cdots, \varepsilon_{2kt})'$ are "white noise" processes with the dimension $k \times 1$, where $E(\varepsilon_t) = 0$, $E(\varepsilon_t \varepsilon_t') = \sum \varepsilon$ and $E(\varepsilon_t \varepsilon_s') = 0$, where $t \neq s$.

According to Krolzig (1997), Equations 4a and 4b will be modified to allow regime changing, so as X_t and Y_t follow a VAR process that depends on the value of a discrete variable with state s_t. A number of m regimes can be considered, where $m \in [1, M]$, assuming that in period t the model is in regime m if and only if $s_t = m$.

The dependence of VAR regime will take one of the following two forms:

- *SI ("switching intercept")*

$$X_t = \sum_{j=1}^{l} A_j(s_t) X_{t-1} + \mu_t(s_t) + \varepsilon_t \tag{5}$$

- *SM ("switching mean")*

$$X_t - \mu_t(s_t) = \sum_{j=1}^{l} A_j(s_t) \left[X_{t-j} - \mu_{t-j}(s_{t-j}) \right] + \varepsilon_t \tag{6}$$

The presented model will use a regime-switching of the SI type (Equation 5), as in this case, the model produces linear changes within the time series, unlike the SM (Equation 6), case where there is a sudden jump in the mean, thus not being suitable for highlighting the regime change in the series of data considered in this thesis. Additionally, the model does not consider other exogenous variables; instead, a probability regressor is considered: IPI (in the first model) and GDP (second model). This type of regressor determines the unconditional probabilities of the regime. For both models that will be further explained, according to Duprey et al. (2017), two regimes will be considered. The first regime represents a period characterized by low financial system stress, while the second regime represents the opposite situation, where the financial stress experienced is high. According to the authors, the second regime exhibits greater pressure and increased uncertainty. The "Smoothed regimes probability" graphs, as well as the Impulse-Response Function are extremely important to observe the Switching VAR model.

Within the model the errors are normally distributed, $\varepsilon_t \sim N(0, \sum_\varepsilon(s_t))$, where $S_t = 1, \ldots, M$. Density function is as follows:

$$f(\varepsilon \mid \Sigma) = \frac{1}{(2\pi)^{k/2} |\Sigma|^{1/2}} e^{\left(\frac{-1}{2} \varepsilon' \Sigma^{-1} \varepsilon\right)} \tag{7}$$

Σ parameters represent the variances parameters of errors. "Log-likelihood" function for "switching intercept", where $S_t = s_t = m$ is:

$$L_t(\mu, A, \Sigma, \delta) = \sum_{m=1}^{M} f(\varepsilon \mid S_t = m) \times P(S_t = m \mid \lambda_{t-1}) \tag{8}$$

where $\varepsilon_t(m) = (\varepsilon \mid S_t = m)$ for the SI regime specification.

Log-likelihood could be rewritten as:

$$l(\mu, A, \Sigma, \delta) = \sum_{t=1}^{T} \log \sum_{m=1}^{M} \left[(2\pi)^{k/2} |\Sigma(m)|^{1/2}\right]^{-1} \times P(S_t = m \mid \lambda_{t-1}, \delta) \tag{9}$$

VAR parameters are:

- $\mu = (\mu_1, \cdots, \mu_M)$
- $A = (A_{11}, \cdots, A_{1l}, \ldots, A_{lM})$
- $\Sigma = (\Sigma_1, \cdots, \Sigma_M)$

For both, Simple Switching VAR and Markov Switching VAR will be considered two regimes, following Duprey, Klaus and Peltonen (2017). The first regime showcases a period that is subject to a reduced financial system turbulence, whereas the second regime illustrates high financial stress.

The Simple Switching VAR model considers independent regime probabilities that do not depend on previous state (Equation 10).

$$P(S_t = j \mid S_{t-1} = i, S_{t-2} = k, \ldots) = P(S_t = j) = p_j(t) \tag{10}$$

The foundation on which the Markov Switch model, also known as MS-VAR in the literature, is based, states that the probability of the model being in a certain regime depends only on the previous state. Therefore, the equation presented in the Simple Switching VAR model becomes Equation 11.

$$P(S_t = j \mid S_{t-1} = i, S_{t-2} = k, \ldots) = P(S_t = j \mid S_{t-1} = i) = p_{ij}(t) \tag{11}$$

The presented model is implemented in Python for both cases where the real economy is represented by the GDP variable and the IPI variable. For the latter, both monthly and quarterly frequency datasets are modeled. It is observed that for all five countries analyzed in this study, the only valid model for the Markov Switching VAR is the one with monthly frequency data and the real economy represented by the industrial production index. This situation is predictable based on the results obtained by Duprey, Klaus, and Peltonen (2017). The results obtained in all three situations for each country will be presented, even though a stable VAR structure for quarterly data was not successfully identified in every case.

- For modelling IPI and CLIFS (monthly and quarterly data) the applied system is:

$$g\_IPI\_s_t = \mu_1^{S_t} + \sum_{l=1}^{n} \left(\beta_{1,1,l}^{S_t} g\_IPI\_s_{t-1} + \beta_{1,2,l}^{S_t} CLIFS_{t-l}\right) + \varepsilon_{t,1} \tag{12}$$

$$CLIFS_t = \mu_1^{S_t} + \sum_{l=1}^{n} \left(\beta_{2,1,l}^{S_t} CLIFS_{t-1} + \beta_{2,2,l}^{S_t} g\_IPI\_s_{t-l}\right) + \varepsilon_{t,2} \tag{13}$$

- For modelling GDP and CLIFS (quarterly) the system is as follows:

$$g\_ln\_PIB_t = \mu_1^{S_t} + \sum_{l=1}^{n} \left(\beta_{1,1,l}^{S_t} g\_ln\_PIB_{t-1} + \beta_{1,2,l}^{S_t} CLIFS_{t-l}\right) + \varepsilon_{t,1} \tag{14}$$

$$CLIFS_t = \mu_1^{S_t} + \sum_{l=1}^{n} \left(\beta_{2,1,l}^{S_t} CLIFS_{t-1} + \beta_{2,2,l}^{S_t} g\_ln\_PIB_{t-l}\right) + \varepsilon_{t,2} \tag{15}$$

4. Research Results

4.1. **Vector Autoregressive Model Results.** After selecting the optimal lag length using the Akaike criterion, the Granger causality test was applied to determine the direction of influence between the financial system and the real economy.

Table 4. Granger test results: CLIFS and IPI

H₀: CLIFS does not Granger cause IPI.		**p-value**
Romania	Null hypothesis is not rejected.	0.2598
Czechia	Null hypothesis is rejected.	0.0037
Poland	Null hypothesis is rejected.	0.0069
Slovakia	Null hypothesis is not rejected.	0.8806
Hungary	Null hypothesis is rejected.	0.0001
H₀: **IPI does not Granger cause CLIFS.**		**p-value**
Romania	Null hypothesis is rejected.	0.0480
Czechia	Null hypothesis is not rejected.	0.1674
Poland	Null hypothesis is not rejected.	0.8238
Slovakia	Null hypothesis is not rejected.	0.3716
Hungary	Null hypothesis is rejected.	0.0421

Source: author's computations.

For the monthly dataset (CLIFS and IPI), a bidirectional Granger causality relationship is identified only in the case of Hungary, with a probability of 99.99% that CLIFS Granger-causes IPI and 95.79% that IPI Granger-causes CLIFS. This reveals a strong feedback mechanism between the real economy and the financial system, indicating a vulnerability in crisis periods, as financial system shocks reinforce shocks in real economy and vice versa. In the remaining countries, the relationship is generally unidirectional toward the industrial production index, indicating that financial stress helps predict changes in real economic activity. Periods with increased financial stress negatively impact economic output, as it decreases companies access to financing and it increases borrowing costs. Romania represents an exception, where a probability of 95.20% suggests that IPI Granger-causes CLIFS.

Table 5. Granger test results: CLIFS and GDP

H₀: CLIFS does not Granger cause GDP.		**p-value**
Romania	Null hypothesis is rejected.	0.0080
Czechia	Null hypothesis is not rejected.	0.9135
Poland	Null hypothesis is not rejected.	0.3670
Slovakia	Null hypothesis is rejected.	0.0546
Hungary	Null hypothesis is not rejected.	0.8912
H₀: **GDP does not Granger cause CLIFS.**		**p-value**
Romania	Null hypothesis is rejected.	0.0000
Czechia	Null hypothesis is rejected.	0.0109
Poland	Null hypothesis is rejected.	0.0068
Slovakia	Null hypothesis is not rejected.	0.6750
Hungary	Null hypothesis is rejected.	0.0000

Source: author's computations.

When the analysis is performed using the quarterly dataset (CLIFS and GDP), the results differ. A bidirectional relationship is found only in Romania, showcasing an interdependence between the financial sector stability and the macroeconomic performance. The other countries display unidirectional causality. The results for the Czech Republic, Hungary, and Poland indicate stronger predictive power from GDP to CLIFS, whereas in Slovakia the opposite relationship is observed.

4.2. **Simple Switching VAR Model Results.** For Romania, the results illustrated in Table 6 indicate a strong tendency to remain in the second regime, corresponding to periods of elevated financial stress. The estimated time-varying expected durations suggest that the economy remains in this regime for approximately 14 quarters, compared with only one quarter in the low-stress regime. Slovakia shows a pattern similar to Romania. In the Czech Republic, the model does not precisely estimate regime duration; however, the probability of remaining in both regimes appears relatively balanced. Hungary

Table 6. Transition results (CLIFS & IPI)

Regime		**Romania**		**Czechia**		**Slovakia**		**Hungary**	
		1	*2*	*1*	*2*	*1*	*2*	*1*	*2*
Mean	*1*	0.0609	0.9391	0.7778	0.2222	0.0227	0.9777	0.9431	0.0569
	2	0.0609	0.9391	0.7778	0.2222	0.0227	0.9777	0.9431	0.0569
Std. Dev.	*1*	0.0007	0.0007	0.4181	0.4181	0.0881	0.0881	0.0059	0.0059
	2	0.0007	0.0007	0.4181	0.4181	0.0881	0.0881	0.0059	0.0059
Time-varying	*1*	1.0648	16.428	**NA**	**NA**	1.0455	1072.8	17.752	1.0604
exp. durations	*2*	0.0008	0.1813	**NA**	**NA**	0.2661	2813.4	1.7437	0.0066

Source: author's computations.

exhibits the opposite pattern compared with Romania, associated with low financial stress, with an expected duration of approximately 18 quarters, compared with only one quarter in the high-stress regime. Poland is an exception, as the model does not converge due to the inability to identify regime transition moments.

The smoothed regime probability graphs illustrated in Figure 1 help identify major transition periods. In Slovakia, two significant regime switches are observed: one around the country's accession to the European Union in 2005 and another during the COVID-19 crisis (2019–2021). The pandemic generated regime changes in all analyzed countries, reflecting the severe impact of lockdown measures on industrial production across Europe. For Romania, regime changes are clearly associated with the global financial crisis of 2008–2009 and the COVID-19 crisis. The Great Recession led to a sharp decline in exports and industrial production, producing a regime shift that persisted for nearly one year. Similar regime transitions associated with the financial crisis are observed in Hungary and the Czech Republic, although the duration differs. Hungary exhibits regime persistence of approximately six months, while the Czech Republic experiences a longer adjustment period of roughly two years. Slovakia does not display a strong regime shift during the global financial crisis, which may be explained by the country's exchange-rate stability and convergence policies during that period (Dąborowski, 2009).

Table 7. Transition results (CLIFS & GDP)

Regime		Romania		Czechia		Slovakia	
		1	*2*	*1*	*2*	*1*	*2*
Mean	*1*	0.8415	0.1585	0.9663	0.0337	0.0333	0.9667
	2	0.8415	0.1585	0.9663	0.0337	0.0333	0.9667
Std. Dev.	*1*	0.3675	0.3675	0.3675	0.3675	0.1805	0.1805
	2	0.3675	0.3675	0.3675	0.3675	0.1805	0.1805
Time-varying	*1*	**NA**	**NA**	44.518	1.0429	**NA**	**NA**
exp. durations	*2*	**NA**	**NA**	41.550	0.1342	**NA**	**NA**

Source: author's computations.

Impulse-response analysis indicates that a financial stress shock generally produces a strong reaction in industrial production, although the direction and persistence vary across countries. In Romania, the response of industrial production to financial stress initially increases before gradually declining and stabilizing after several quarters. Similar patterns are observed in the Czech Republic and Hungary. In Slovakia, however, the response is initially negative, followed by gradual recovery toward equilibrium.

When shocks originate from the industrial production index, the financial stress indicator typically exhibits oscillating adjustments, suggesting a slower and less direct transmission from the real economy to the financial system. The impulse-response analysis has important economic implications. The relatively faster stabilization observed in some countries suggests that industrial sectors gradually adapt to financial shocks.

The model is also estimated using quarterly data with GDP as the real economy indicator. In this specification, the model does not successfully estimate regime persistence for Romania and Slovakia, as

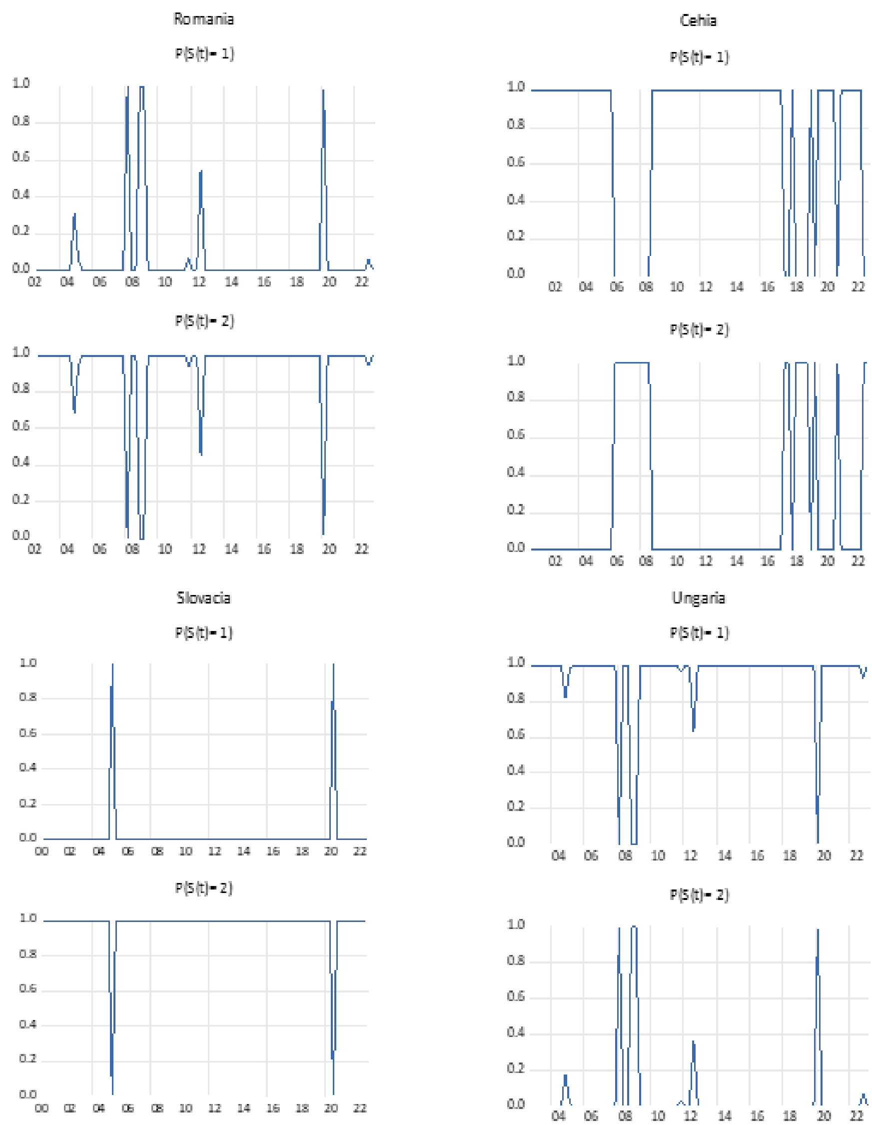

Figure 1. Smoothed Regime Probabilities Graphs (CLIFS & IPI)

Source: author's computations.

seen in Table 7. Romania shows higher stability in the first regime (probability 0.84), while Slovakia displays a stronger tendency toward the second regime.

The regime-switching graphs showcased in Figure 2 reveal that the global financial crisis represents a major transition point for the Czech Republic and Romania. In Romania, the crisis triggered a prolonged regime shift lasting nearly two years, reflecting the slowdown in economic growth, declining exports, and increasing public debt that led to the country's 2009 agreement with the International Monetary Fund. Impulse-response functions for the quarterly model show that a financial stress shock produces a short-term negative impact on GDP, with stabilization occurring within approximately one to two years. For the Czech Republic and Slovakia, the responses differ in magnitude but follow a similar adjustment pattern.

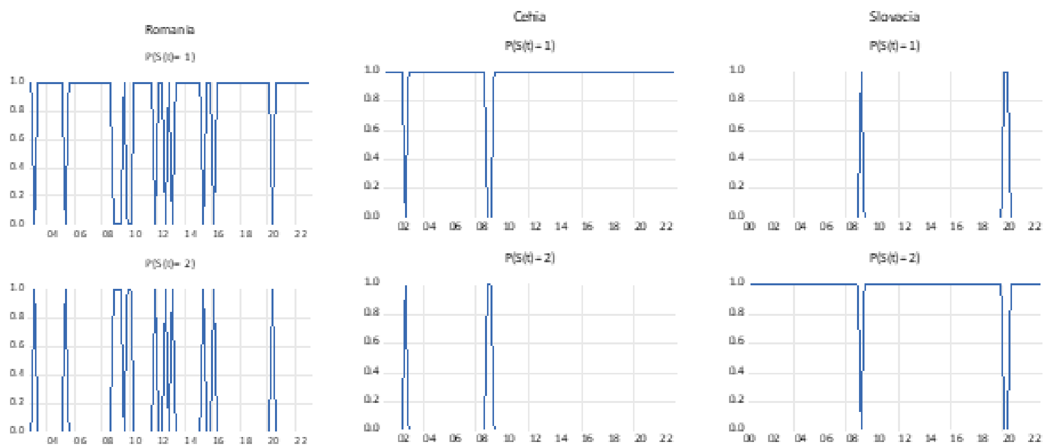

Figure 2. Smoothed Regime Probabilities Graphs (CLIFS & GDP)

Source: author's computations.

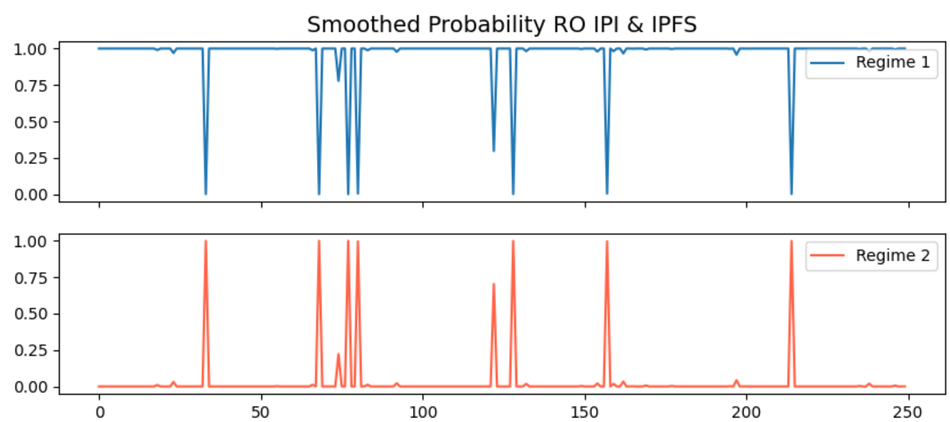

Figure 3. Smoothed Regime Probabilities Romania (monthly IPI & CLIFS)

Source: author's computations.

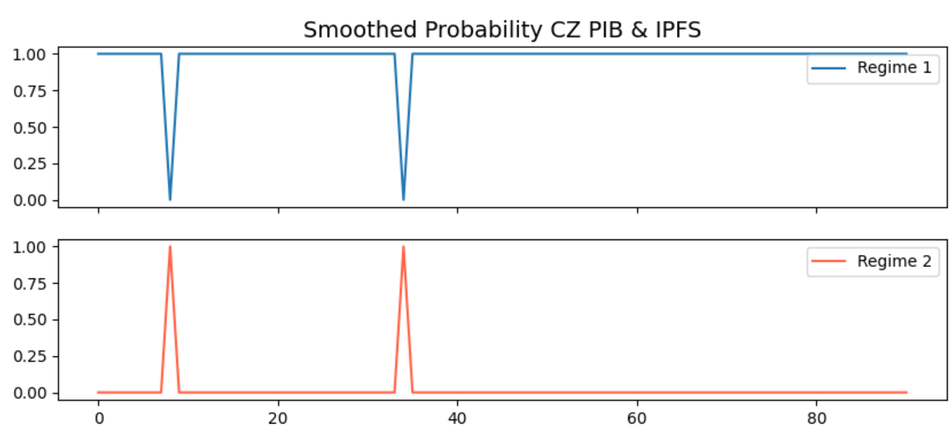

Figure 4. Smoothed Regime Probabilities Czech Republic (quarterly GDP & CLIFS)

Source: author's computations.

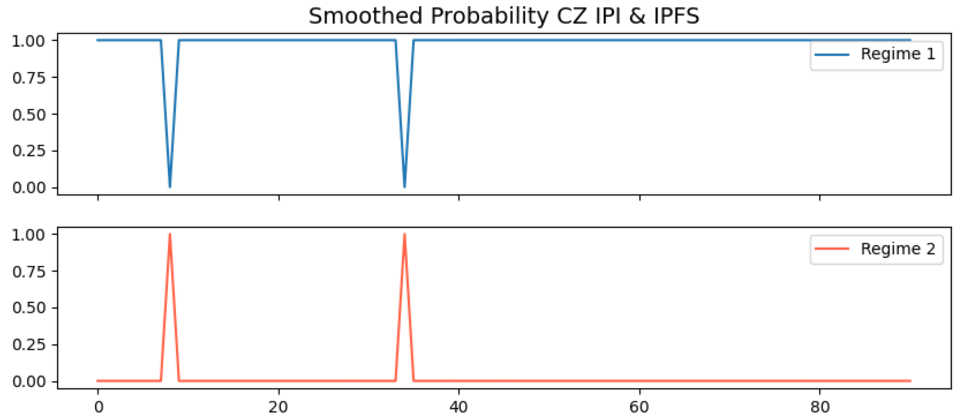

FIGURE 5. Smoothed Regime Probabilities Czech Republic (quarterly IPI & CLIFS)

Source: author's computations.

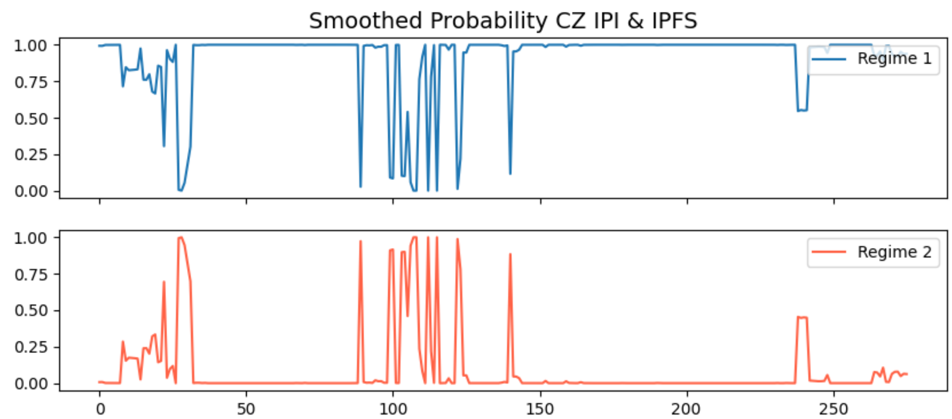

FIGURE 6. Smoothed Regime Probabilities Czech Republic (monthly IPI & CLIFS)

Source: author's computations.

4.3. **Markov Switching VAR Model Results.** In Figure 3 can be observed the graph obtained by modeling the data with monthly frequency (IPI and CLIFS) for Romania, that successfully captures regime changes. We observe the presence of impulses that are caused by important moments that have had an impact on both the economy and the financial system, such as the global financial crisis in 2008, the political crisis in 2012, the impact of COVID-19, as well as the deflationary period in 2014. However, although the model shows these significant moments from the past twenty years, there are no periods of time where the regime change is maintained. According to the results, the probability of maintaining the regime with low financial stress is 0.97, and the probability of transitioning back to it from the second regime is one. Repeated regime changes illustrate a high sensitivity of the Romanian economy to political uncertainty and international financial conditions.

For the Czech Republic, the probability of maintaining the regime indicating low financial stress is high, at 0.96, as seen in Figures 4, 5 and 6, showcasing a relatively stable financial environment. However, once it transitions to the second regime of high stress, the probability of returning to the initial regime is only 0.42. The figures illustrate this trend, as can be observed by analyzing the frequency of "switch" moments during the 2007–2010 period, where the economic crisis had a significant impact.

In the case of Poland (Figure 7), these regime changes are clearly correlated with crisis moments during the analyzed period. Additionally, there was a constitutional crisis in Poland from 2015 to 2016 when the Parliament appointed judges to the Constitutional Court, threatening democracy, state

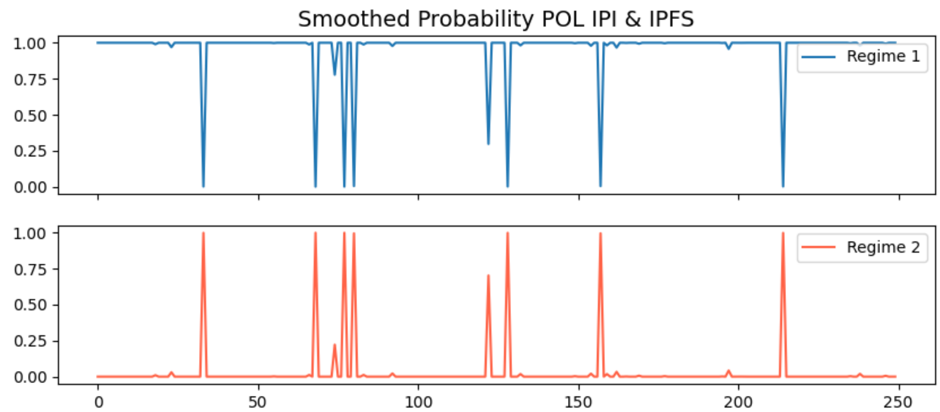

FIGURE 7. Smoothed Regime Probabilities Poland (monthly IPI & CLIFS)

Source: author's computations.

balance, and human rights. This indicates how political uncertainty may also contribute to severe regime changes, even in the absence of a financial crisis.

The Markov Switch VAR model reveals numerous regime changes for Slovakia (Figure 8), none of them being maintained for an extended period, revealing that the economy recovers relatively fast after an external shock. One reason may be that Slovakia is a eurozone member state and so external turbulences have a much more direct impact on the economy. The probability of returning to the initial regime is 0.99.

Duprey, Klaus, and Peltonen (2017) mention that a regime change occurs whenever a threshold of 0.5 is exceeded. Therefore, transitional moments between regimes are considered for Hungary (Figure 9), and the crisis generated in 2022 by the military conflict between Russia and Ukraine. The refugee crisis in 2015 also generated a significant impulse, which persisted for two quarters. This reveals that external political events have an impact on the financial stability.

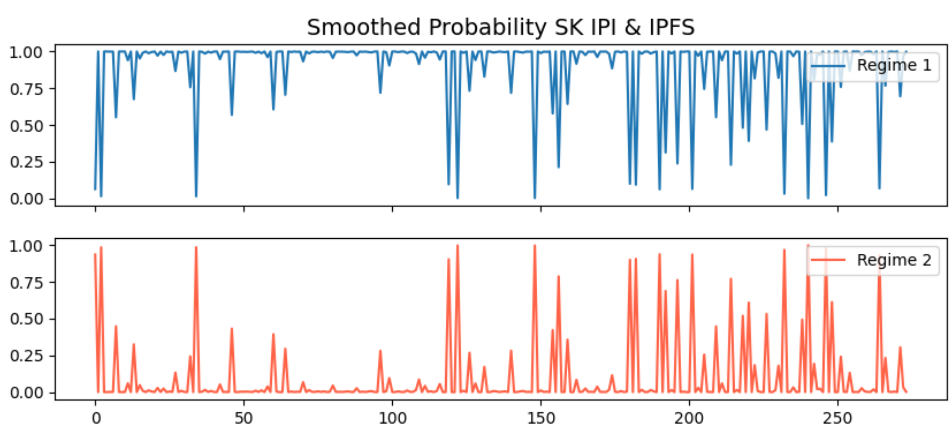

FIGURE 8. Smoothed Regime Probabilities Slovakia (monthly IPI & CLIFS)

Source: author's computations.

5. CONCLUSIONS

This study examined the interaction between the financial system and the real economy in five ex-communist European Union countries: Romania, the Czech Republic, Poland, Slovakia, and Hungary over the period 2002–2023. By employing VAR, Simple Switching VAR, and Markov-Switching VAR

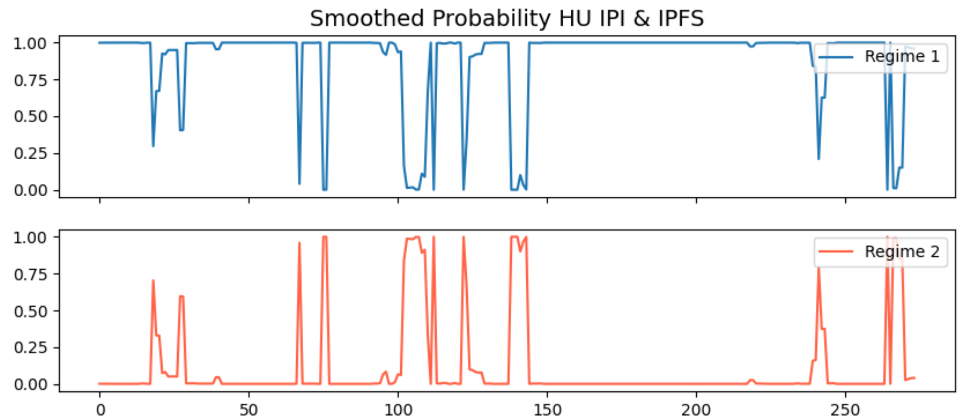

Figure 9. Smoothed Regime Probabilities Hungary (monthly IPI & CLIFS)

Source: author's computations.

models, and using the Country-Level Index of Financial Stress (CLIFS) alongside GDP and the Industrial Production Index (IPI), the study aimed to capture both the linear and nonlinear dimensions of the financial stress transmission mechanism at country level.

The empirical results point to several consistent patterns across the five countries. In all cases, the VAR estimates indicate a negative and statistically significant relationship between financial stress and the real economic activity, with impulse response functions showing that a positive shock to CLIFS leads to a contraction in both GDP and IPI. The Markov-Switching VAR models identify two distinct regimes in each country: a high-stress regime, in which the impact on output is more persistent, and a low-stress regime, in which the transmission is considerably weaker. This finding supports the hypothesis that the relationship between financial stress and real economic activity is asymmetric across economic conditions, and suggests that linear models may underestimate the true impact of financial stress during crisis periods. The Granger causality results further indicate that, in most of the countries analyzed, changes in financial stress tend to precede downturns in real activity. In terms of cross-country differences, Romania and the Czech Republic display somewhat sharper and more prolonged output responses to financial stress shocks compared to Slovakia and Hungary. This pattern may reflect differences in financial market development, institutional frameworks, and eurozone membership status.

These findings connect to several strands of the existing literature. The negative and asymmetric impact of financial stress on output is broadly consistent with the financial accelerator mechanism described by Bernanke, Gertler, and Gilchrist (1999), which highlights how deteriorating financial conditions amplify economic downturns through tighter credit constraints and declining collateral values. The identification of distinct high- and low-stress regimes supports the argument made in the nonlinear modelling literature that standard linear VAR models are not well-suited to capture the full dynamics of linkages between the financial stress and the real economy. At the same time, the cross-country heterogeneity in the results suggests that structural and institutional differences, such as the degree of financial market integration and the exchange rate regime, are important for how financial stress transmits to the real economy.

From a policy perspective, the results underline the importance of timely and proactive macroprudential surveillance. Policymakers should pay close attention to developments in capital, bond, and foreign exchange markets, as these appear to be the key segments through which financial stress propagates to the real economy. The implementation of early-warning systems based on composite financial stress indicators such as CLIFS could help identify the build-up of stress at an early stage and support more timely policy responses. Given the evidence that the effects of financial stress are considerably stronger during high-stress regimes, tools such as capital buffers, liquidity support mechanisms and coordinated fiscal and monetary responses should be activated early, before stress episodes escalate into broader economic downturns.

As with any empirical study, the findings should be interpreted in light of several limitations. First, the CLIFS indicator covers only three market segments: capital markets, bond markets and foreign exchange markets. It does not include banking sector or real estate market variables that may also play an important role in the transmission of financial stress, particularly in the bank-dominated financial systems of Eastern Europe. Second, the sample period of approximately two decades, while covering two major financial crises, may not be sufficient for reliable regime identification in the Markov-switching models, especially in the quarterly specifications. Lastly, the bivariate structure of the models does not account for other macroeconomic variables such as interest rates or inflation, that may influence both financial stress and the real activity.

Several directions for future research emerge from this study, such as extending the empirical framework to include additional macroeconomic and financial variables. This would help to identify better the specific channels through which financial stress impacts the real economic activity. A more flexible and informative characterization of regime dynamics could be provided by the use of multivariate Markov-switching models with time-varying transition probabilities. In addition, broadening the country coverage to include other ex-communist EU member states, such as Bulgaria or Croatia, would allow for a more complete regional picture. Finally, the use of higher-frequency data and more recent methods for regime detection, including machine learning approaches, could improve both the accuracy and the policy relevance of financial stress monitoring frameworks.

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