1. FINANCIAL RISK METER FOR THE ROMANIAN STOCK MARKET

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Abstract

This article aims to estimate the systemic risk of the Romanian stock market, using the FRM (Financial Risk Meter) methodology. This research contribution is about applying a novel systemic risk index to the Romanian financial system (FRM@RO), to identify potential sources of systemic risk, and to understand network interconnections, thus increasing risk awareness of both managers and regulators. By using data for companies listed at the Bucharest Stock Exchange (BSE), our article highlights several aspects of the systemic risk of the Romanian stock market. First, our study reveals that the main driver of systemic risk, especially during financial crises, is the volatility index, VIX. However, local factors, such as ROBOR interest rate and sectorial indices for financial investment companies, in general, and energy sector companies, in particular, are extremely important in triggering systemic risk. Second, the system risk indicator for the Romanian stock market, FRM@RO, may capture both investor sentiment, measured via the Google Trends Search Volume Index, and stock market volatility. Third, FRM@RO can act as an early warning indicator for economic turmoil, being able to predict periods of technical recession one quarter in advance. Fourth, by using network analysis, we can identify, daily, the level of market interconnectedness and highlight the main companies triggering tail co-movements. Fifth, we emphasize the need for an integrated early warning system for financial crises.

Keywords: systemic risk; spillover effect; Romania; FRM@RO; financial risk meter

JEL Classification Codes: E44, C11, C32

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1. Introduction

The concept of systemic risk emerged in the mid-nineties of the twentieth century and was studied in detail after the 2008 global financial crisis. It can manifest between the real economy and the financial system, resulting in a serious economic downturn due to different reasons, such as herding behavior, information disruptions, asset bubbles and macroeconomic imbalances (Smaga, 2014). To capture the complex nature of systemic risk, there are many types of measures, such as institutional-level measures and aggregate market-level measures. Using data from the USA and Europe interbank rates, credit derivatives and stock price from 2004 – 2009, it was concluded that the best results are given by a measure based on Credit Default Swap (aggregate market measure) (Rodríguez-Moreno and Peña, 2013). The scope of the risk analysis is to identify the institutions that have the greatest impact on the overall risk of the system, named IFIS (Systemically Significant Financial Institutions). To this end, some of the main systemic risk measures used are: Systemic Expected Shortfall (SES), Marginal Expected Shortfall (MES), Delta Conditional Value-at-Risk (ΔCoVaR) and Systemic Risk Measure (SRISK), although they cannot capture the whole complex nature of systemic risk (Benoit et al., 2013).

Brownlees et al. (2020) evaluated the performance of CoVaR and SRISK, two popular measures, for the eighth financial crises that occurred before 1933. They used data from New York banks between 1866 and 1933 and concluded that the two measures provide information that could allow regulators to recognize SIFIs. CoVaR and SRISK help identify systemic institutions in times of panic, but they are not similarly good at predicting the next crisis.

ΔCoVaR is used by Borri et al. (2014) to measure systemic risk for Italian banks in 2000-2011, starting from the original research of Adrian and Brunnermeier (2016).

Another approach to systemic risk is introduced by Lai and Hu (2021). They used the Granger complex network to find the transmission direction of the Covid-19 crisis and the risk volatility spillover effect using stock market data from 20 countries. Their main finding is that financial crises can be identified using a topological network structure. They propose a way to measure systemic risk based on the Granger complex network.

Transfer entropy is another popular method used to analyze the connectedness of the stock market. Gong et al. (2019) show that level of network connectedness increases with the likelihood of a financial crisis.

The systemic risk and spillover effect can also be measured using the quantile LASSO regression method. Härdle et al. (2016), developed the Tail Event NETwork (TENET) risk approach, using network structure to identify systemically important financial institutions. TENET evolved into a novel risk predictor, the Financial Risk Meter (FRM), which compresses the high-dimensional tail risk into a single indicator (Yu et al., 2019; Mihoci et al., 2020). The FRM is based on the LASSO quantile regression, which is used to study the tail co-movements of financial securities. FRM has been shown to be efficient in quantifying systemic risk for markets such as the USA, Europe (Mihoci et al., 2020; Yu et al., 2019; Ren et al., 2022) emerging markets (Ben Amor et al., 2022), and China (Wang et al., 2021).

In this article, we use the FRM methodology to estimate systemic risk for the Romanian stock exchange. Romania is positioned as an emerging market economy, one of the most important in the Southeast area of the European Union and in the Balkans. After almost half a century of communist regime (1945-1989), Romania joined NATO in 2003 and became member of the European Union in 2007. Romania has strategic geopolitical importance because of its location on the Black Sea coast, being at the intersection of the orthodox, Turkish, and Western civilizations and cultures (Lewandowski, 2022). The Bucharest Stock Exchange (BSE) was established in 1882 (BSE, 2022), closed in 1948, during the communist regime, and reestablished in 1995. The Bucharest Stock Exchange was promoted in 2020 by FTSE Russell from a Frontier market, to a Secondary Emerging market, and bigger institutional foreign players are expected to enter the Romanian market in the following years (Tudor, 2021).

In this context, an instrument to measure systemic risk for Romanian stock market may be useful both to investors and market regulators. Using data for companies listed at the first category of the Bucharest Stock Exchange, between 2005 and 2022, we estimate the systemic risk over time and find its main drivers among international, regional and national macroeconomic risk factors.

Our research adds value to the existing literature by highlighting several features of the Romanian stock market, as a frontier country.

First, our study reveals that the main driver of systemic risk, especially during financial crisis, is the volatility index, VIX. However, local factors, such as ROBOR interest rate and sectorial indices for financial investment companies and energy sector are extremely important in triggering systemic risk.

Second, the system risk indicator for the Romanian stock market, FRM@RO, can capture both investors' sentiment, measured via the Google Trends Search Volume Index, and stock market volatility.

Third, FRM@RO can act as an early warning indicator for economic turmoil, being able to predict the periods of technical recession one quarter in advance.

Fourth, by using network analysis, we can identify, on daily basis, the level of market interconnectedness and highlight the main companies triggering tail co-movements; an increased level of tail co-movements between companies may indicate an increased likelihood of a systemic risk.

Fifth, we emphasize the need for an integrated early warning system for financial crisis.

The rest of the paper is organized as follows. Section 2 details the methodology, Section 3 illustrates the empirical application, Section 4 discuss policy and market implications, and Section 5 concludes. Appendix A presents the list of companies used for the analysis, and Appendix B presents some complementary results available in the online version of the paper. Data, code, and periodic updates are available at https://danpele.github.io/frm_ro/ and https://quantlet.com/.

2. Methodology

The methodology section consists of five parts. In the first subsection, we construct a FRM model based on the macro-features and the daily returns of selected companies listed on the Bucharest Stock Exchange and estimate the FRM@RO, the systemic risk indicator for the Romanian stock market. In the second subsection, we analyze the network connectedness and depict system risk triggers. In the third subsection, we analyze the contribution of macro-features. In the fourth subsection, we define the risk levels and introduce the color code used to characterize the risk. In the final subsection, we back test FRM@RO in relation to stock market volatility, Google Trends Search Volume Index, and the macroeconomic technical recession indicator.

2.1. Financial Risk Meter for the Romanian Stock Market (FRM@RO)

To estimate the systemic risk for the Romanian Stock Market, we follow the classical approach of the Financial Risk Meter Index (FRM) (Mihoci *et al*., 2020); FRM indices for various markets are reported on http://frm.wiwi.hu-berlin.de (FRM, 2022).

As a first initiative of this kind for Romania, Financial Risk Meter Index (*FRM@RO*) is estimated by capturing the interdependencies of selected securities using LASSO quantile regression applied to series of stock returns of shares and macroeconomic variables, used as control factors.

We use the following notations: M is the number of macroeconomic variables, J is the number of companies selected for analysis, $p = J + M - 1$ denotes the number of covariates, $t = \{1, \ldots, T\}$ is the time index, where T denotes the total number of daily observations; s is the index of time windows, where $s \in \{1, \ldots, (T-(n-1))\}$ and n is the length of window size.

The linear quantile LASSO regression for the return series X is defined as follows:

$$X^{s}_{j,t} = \alpha^{s}_{j} + A^{s\bullet}_{j,t}\beta^{s}_{j} + \varepsilon^{s}_{j,t}, \tag{1}$$

where: $A^{s\bullet}_{j,t} = \left[M^{s}_{t-1} X^{s}_{-j,t}\right]$, M^{s}_{t-1} is the M dimensional vector of macro variables, $X^{s}_{-j,t}$ is the $p-M$ dimensional vector of log-returns of all other companies except the company j at time t and in the moving window s, β^{s}_{j} is a $p \times 1$ vector defined for the moving window s and α^{s}_{i} is a constant term.

The regression is performed using a L_1-norm penalization (Tibshirani,1996) given a parameter λ_j, defined as the Least absolute shrinkage and selection operator (LASSO).

According to Ben Amor *et al*. (2022) and Mihoci *et al*. (2020), the current companies' λ_j are estimated by a modification of LASSO in a quantile regression, where the optimization is solved as follows:

$$\min_{\alpha^{s}_{j},\beta^{s}_{j}} \left\{ n^{-1} \sum_{t=s}^{s+(n-1)} \rho_{\tau}\left(X^{s}_{j,t} - \alpha^{s}_{j} - A^{s\bullet}_{j,t}\beta^{s}_{j} \right) + \lambda^{s}_{j} \left\| \beta^{s}_{j} \right\|_{1} \right\}, \tag{2}$$

with L_1-norm penalization LASSO parameters λ_s, the quantile loss function ρ for a given tail risk τ is defined as follows:

$$\rho_{\tau}(u) = |u|^{c} \left| \tau - \mathrm{I}_{\{u<0\}} \right|, \tag{3}$$

where: *c=1* corresponds to quantile regression. In equation (3), τ stands for the probability of tail events:

$$\tau = \Pr\left(X^{s}_{j,t} \le q^{s}_{\tau,j} \right), \tag{4}$$

where: $q^s_{\tau,j}$ is the quantile for the company *j* at the tail risk level *τ* for the rolling window *s.*

λ^s_j are selected using the generalized approximate cross-validation criterion (GACV), as proposed in Yuan (2006):

$$\min \mathrm{GACV}\left(\lambda^s_j\right) = \min \sum_{t=s}^{s+(n-1)} \rho_\tau\left(X^s_{j,t} - \alpha^s_j - A^{s,\top}_{j,t}\,\beta^s_j\right) \Big/ (n - \mathrm{df})\,, \tag{5}$$

where: df stands for the number of coefficients of the fitted model. For further details, see Wang *et al*. (2021), Mihoci *et al*. (2020), and Ben Amor *et al*. (2022).

FRM@RO is estimated using a regression analysis as explained above and select the λj for each company *j* using GACV. The distribution of λ_j in a moving window gives important information on the network dependencies among the financial nodes. FRM@RO is defined as the average of λ_j over the set of *J* companies for all windows:

$$FRM@RO_s = \frac{\sum_{j=1}^{J} \lambda^s_j}{J}, \text{ for } s \in \{1, \ldots, (T-(n-1))\}. \tag{6}$$

Companies with high λ_j exhibits common joint tail risk, therefore, the *FRM@RO* can be used a tool to identify market regimes with high level of interconnectedness of listed companies. These market regimes, with abnormal degree of interconnectedness and therefore high systemic risk, can increase the likelihood of financial crisis or high volatility periods (see, for example, Blundell-Wignall *et al*., 2012, Song *et al*., 2021).

2.2. Network Dynamics and Influence of Macro Variables

The FRM framework can also be used to identify the dynamics of the network that reflects the dependency structure among the nodes of the financial network, which is important because as financial markets become increasingly interconnected, the probability of a financial crisis may become significant.

The quantile LASSO regression coefficients from equation (1), for *k* companies, can be arranged into an adjacency matrix $A_k = \left(\beta_{ij}\right)_{i,j=\overline{1..k}}$, to identify the interaction between companies. To assess the influence of the macro variables used in the analysis, we use the adjacency matrix; thus, for day *t,* we estimate the adjacency matrix:

$$A^t_N = \begin{pmatrix} 0 \quad \beta^t_{12} \ldots \beta^t_{1J} \ldots \beta^t_{1N} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \beta^t_{J1}\ \beta^t_{J2} \ldots 0 \ldots\ldots \beta^t_{1N} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \beta^t_{N1}\ \beta^t_{N2} \ldots \beta^t_{NJ} \ldots 0 \end{pmatrix}, \tag{7}$$

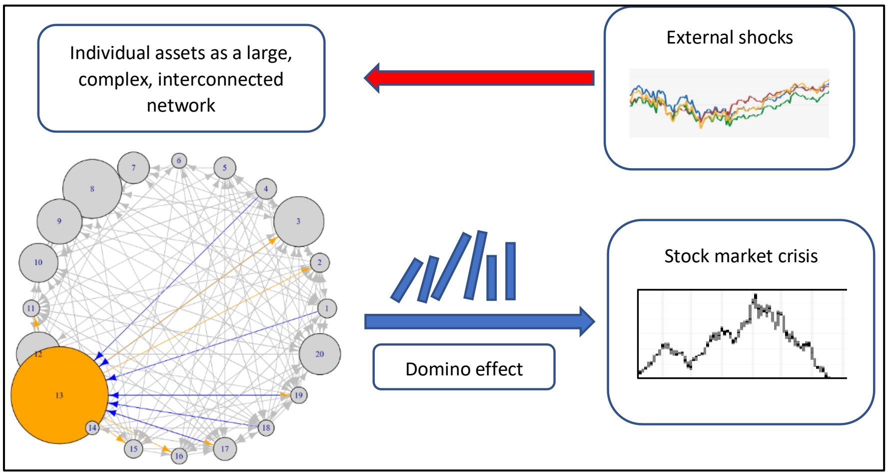
with $N = J + M$ the number of companies and macro variables.

Then, for each macro variable *j*, on day *t*, we can define its influence indicator on the selected market companies as: $Inf_j^t = \frac{card\{\beta_{ij}^t \in A_N^t \mid \beta_{ij}^t \neq 0\}}{J}$. (8)

The influence indicator can help us identify the main macro-economic factors with the highest impact on the return dynamics of the stock market.

The conceptual framework of FRM is depicted in Figure 1; thus, if the stock market is organized as a large, complex, interconnected network, the influence of external shocks can produce large tail co-movements, leading, via the domino effect (Markwat *et al*., 2009), to a market failure.

Figure 1. The Conceptual Framework of FRM



2.3. Risk Levels

Based on the daily time series of *FRM@RO*, we can estimate the level of systemic risk, following the approach of Yu *et al*. (2019). Thus, for the *FRM@RO* value estimated at a certain moment, we divide the past distribution of *FRM@RO* into quantiles, and we define five levels of risk.

If *F* is the cumulative distribution function of *FRM@RO*, estimated for the time period $[1,T]$ and $F^{-1}(q) = \inf\{x : q \leq F(x)\}$ is the *q*-quantile, for $q \in [0,1]$, then the risk level for $FRM@RO_{T+1}$ can be estimated as shown in Table 1.

The color code follows the color scheme of the US homeland security office and can be used as an early warning indicator if the information is available to the public via a website or an online application.

Table 1. Risk Levels for *FRM@RO*

Color	Risk level	Description	Condition
Green	Low risk of a crisis in the financial market.	The incidence of a crisis is less likely than usual.	$FRM\ @\ RO_{T+1} < F^{-1}(0.2)$
Blue	General risk of a crisis in the financial market.	There is no specific risk of a crisis.	$F^{-1}(0.2) \leq FRM\ @\ RO_{T+1} < F^{-1}(0.4)$
Yellow	Elevated risk of a crisis in the financial market.	The incidence of a crisis is somewhat higher than usual.	$F^{-1}(0.4) \leq FRM\ @\ RO_{T+1} < F^{-1}(0.6)$
Orange	High risk of a crisis in the financial market.	A crisis might come very soon.	$F^{-1}(0.6) \leq FRM\ @\ RO_{T+1} < F^{-1}(0.8)$
Red	Severe risk of a crisis in the financial market.	A financial crisis is imminent or is happening right now.	$F^{-1}(0.8) \leq FRM\ @\ RO_{T+1}$

Source: Adaptation from Yu et al. (2019).

2.4. Backtesting FRM@RO

To back test the ability of *FRM@RO* to capture systemic risk and the stock market volatility, we use a series of methods validated in the literature.

2.4.1. FRM@RO and Volatility Measures

Literature in the field shows that high volatility in the stock market is associated with higher systemic risk (Mieg, 2020). Granger causality and cointegration analysis has previously been applied to study the relationship between FRM and various volatility measures. For example, Yu *et al*. (2019) test the existence of a Granger causality between the FRM for the US stock market and other measures of systemic risk, such as VIX, SRISK, and Google Trends searches for the keyword ‘financial crisis’. Their results show the existence of a bivariate Granger causality between FRM and these systemic risk measures.

In this paper, we use Granger causality twofold. First, we analyze the relationship between *FRM@RO* and BET Index volatility, estimated using a GARCH(1,1) model.

Second, we analyze the relationship between *FRM@RO* and the Google Trends search index for the keyword ‘crisis’ (in Romanian, ‘criză’).

2.4.2. Binary Logistic Regression

As shown in Mihoci *et al*. (2020), FRM can be used as a predictor of financial and economic crises. This result is documented both for US and Eurozone economies, using National Bureau of Economic Research (NBER) and European Central Bank (ECB) recession indicators as dependent variables.

Because in the Romanian case there is no official recession indicator, calculated with monthly frequency, in this article we use the binary logistic regression model from Mihoci *et al*. (2020) by defining the dependent variable as:

$$Y_t = \begin{cases} 1, & if \ \ GDP_t < GDP_{t-1} < GDP_{t-2} \\ 0, & otherwise \end{cases} . \quad (9)$$

So, in this case, the recession indicator will refer to what is called technical recession, which is defined as two consecutive quarters of quarter-on-quarter GDP contraction. In formula (9), the real GDP is used, with quarterly data and seasonally adjusted, as provided by the Romanian National Institute of Statistics.

The model used to assess the relationship between the *FRM@RO* and the technical recession indicator for the Romanian economy is the following:

$$\log \frac{\mathrm{P}\left(Y_t = 1 | \ x_{t-k}; \theta\right)}{\mathrm{P}\left(Y_t = 0 | \ x_{t-k}; \theta\right)} = \theta_{0,k} + \theta_{1,k} x_{t-k}, \ k = 1, \ldots, 3, \quad (10)$$

where: x_{t-k} is *FRM@RO* at time *t-k*, obtained by averaging the daily FRM within the *t-k* quarter, and Y_t is the quarterly recession indicator defined in formula (9). The performance of estimated models is evaluated using the pseudo R-Squared (Nagelkerke 1991):

$$\tilde{R}^2 = \left(1 - \left\{L(\mathbf{0}) / L(\boldsymbol{\theta})\right\}^{\frac{2}{n}}\right) \Bigg/ \left(1 - \{L(\mathbf{0})\}^{\frac{2}{n}}\right), \quad (11)$$

where: $L(\mathbf{0})$ is the maximum likelihood of the intercept-only model, $L(\boldsymbol{\theta})$ is the maximum likelihood of the full model, and $\boldsymbol{\theta}$ is the vector of estimated parameters.

3. Data and Empirical Results

3.1. Data and Variables Description

For the quantile linear regression model, the data set consists of daily returns of selected companies and macroeconomic risk factors. The dataset used in this paper has two layers.

The first layer consists of daily data (closing price and market capitalization, in RON) for 61 companies traded on the Bucharest Stock Exchange, from the following market segments: Premium, Financial Investment Funds, Standard and Foreign, summarized in Appendix A, Table A1.

The second layer consists of 14 macroeconomic variables, summarized in Appendix A, Table A2. As macro-economic variables, we included the major indices from Bucharest Stock Exchange (BET, BET-FI, BET-NG, ROTX), two global stock market indices (from the US market – S&P500 and from the Euro area – EURO STOXX 50), the volatility index (VIX), the S&P US Treasury Bill Index, Romania, and Euro area interest rates (ROBOR and EURIBOR), the German and French stock market indices (DAX 30 and CAC 40).

The rationale behind choosing the macroeconomic variables follows the classical FRM approach for emerging markets (Ben Amor *et al*., 2022). For the particular case of Romania, we need to take into account the contagion effect, extensively documented in literature; therefore, there is a clear financial market contagion effect from the Western European countries to the Eastern European countries (Cărăuşu *et al*., 2018) and in case of Romania, there is a spillover effect from the German market (Harkmann, 2014) and the French market (Paskaleva and Stoykova, 2021).

This dataset contains daily data for the period 01/03/2005-12/13/2022 (4498 transaction days), extracted from Refinitiv Eikon.

The LASSO regression model was estimated using daily log-returns of selected companies and macroeconomic factors, using the formula $r_t = \log(P_t) - \log(P_{t-1})$, where P_t is the closing price for day *t*.

For the EURIBOR and ROBOR interest rates, the daily log-return was computed as $r_t = IR_t - IR_{t-1}$, where IR_t denotes the respective interest rate on day *t*.

3.2. Financial Risk Meter for the Romanian Stock Market (FRM@RO)

The Financial Risk Meter for the Romanian Stock Market (FRM@RO) was estimated for the period 03/01/2005-12/13/2022 (4498 transaction days), using 25 iterations and a rolling window of 63 days (approximately three trading months. Every day, only the top 20 companies are selected to estimate FRM@RO, the ones with the highest market capitalization. Following Ben Amor et al. (2022) and Mihoci et al. (2020), to measure the systemic risk for Romanian Stock Market, we estimate FRM@RO with $\tau = 0.05$ (tail level) and J=20 (number of companies).

Figure 2 shows the evolution of FRM@RO, during 2005-2022; in this graph, we observe the peaks at the most important dates in the recent history of the Bucharest Stock Exchange.

First, the Romanian stock market was the most affected in the Central and East European region by the 2008 financial crisis (see, for example, Tudor, 2011 and Pele and Mazurencu-Marinescu, 2012), both in terms of returns and volatility.

Second, the Romanian economy was severely affected by the 2008 financial crisis, and in June 2010 the Romanian Government cut wages in the public sector by 25% and imposed severe budgetary restrictions (Vasile, 2013; Voinea et al., 2018); this moment is also captured by FRM@RO, as shown in Figure 3.

Third, the Covid-19 pandemic had a significant impact on the Romanian Stock Market (Hatmanu and Cautisanu, 2021; Gherghina et al., 2021); thus, in the first quarter of 2020, the volatility of BET index increased to a level very close to that recorded during the global financial crisis of 2007–2009 (Gherghina et al., 2021).

Fourth, the economic paradigm at the beginning of 2022 is dominated by the Ukraine crisis, because of the devastating war started by the Russian Federation; the negative effect of this crisis has started to impact the neighboring economies, such as Romania, Poland and Bulgaria.

Figure 2. FRM@RO Daily Time Series, for τ=0.05

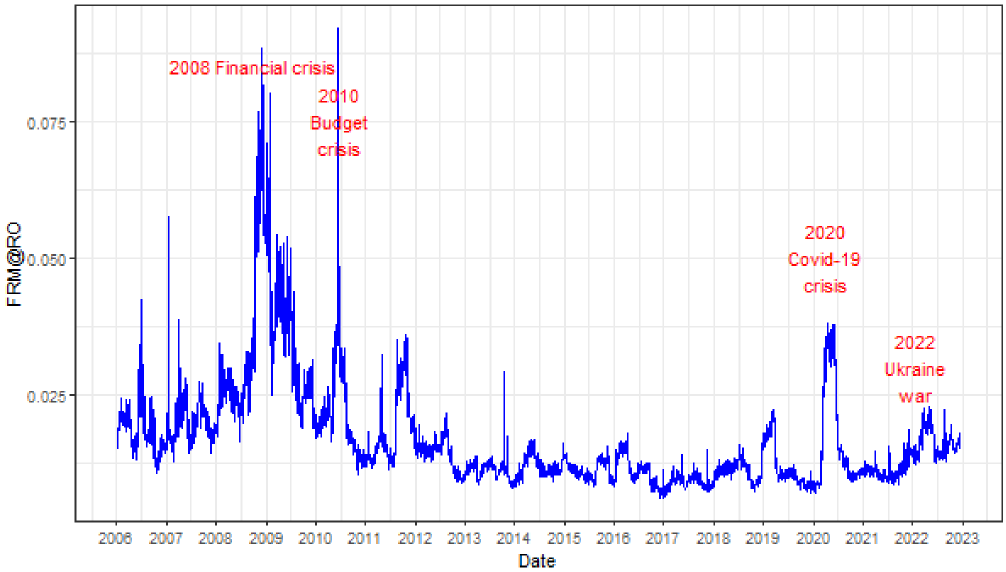


Figure 3. BET Index Daily Time Series

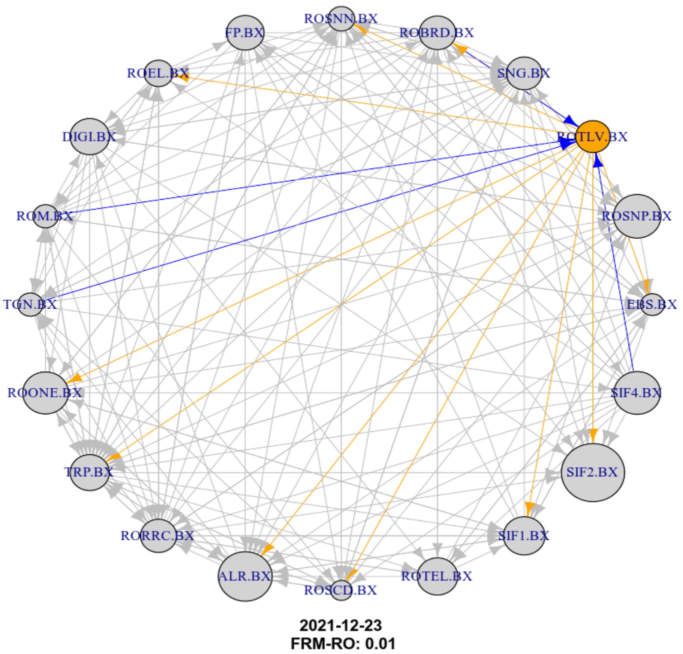
3.3. Network Dynamics

Using the adjacency matrix, we can describe the network behavior and co-movements between the companies listed at BSE.

Figure 4 shows a network graph with edges between the 20 largest companies, in terms of market capitalization, estimated at τ= 0.05 on December 23, 2021. We highlight one of the most important banks in Romania, Transylvania Bank (*Rom*. Banca Transilvania), and its edges are deduced from the adjacency matrix.

In Figure 4, the size of the circles is proportional to the individual λ of each company, the in-degree edges are represented in blue, while the out-degree edges are represented in yellow. As one may see, Banca Transilvania has a significant influence on most of the companies in the top 20, and it is influenced by companies from the energy sector, such as SNG (ROMGAZ, one of the largest producers and main suppliers of natural gas in Romania) and TGN (TRANSGAZ, the technical operator of the National Gas Transmission System, which ensures the transmission of more than 90% of the natural gas consumed in Romania).

Figure 4. Network Example on 2021/12/23 with BANCA TRANSILVANIA S.A. (ROTLV.BX) as the Central Node, and Its In-degree and Out-degree Edges



A similar network example is shown in Figure B4 (Appendix B), with BIOFARM, one of the most important producers in the pharmaceutical industry, as the central node.

Figure B1 (Appendix B) shows the adjacency matrix estimated on March 9, 2022. The columns express the marginal contribution of the company j to the remaining firms. The rows reflect the return contribution from the remaining companies.

The spillover effect is illustrated in Figure B2 (Appendix B), showing co-movements between two companies. Figures B1 and B2 have color scales from blue (negative) to red (positive), unfolding the spillover effect between companies and highlighting with companies have a higher contribution to FRM@RO.

3.4. Influence of the Macro Variables

Table 2 shows descriptive statistics for the influence indicator defined by formula (8).

Table 2. Influence Indicator for the Macro Variables

Macro variable	Mean	Median	Minimum	Maximum
VIX	80.87%	83.33%	0.00%	100.00%
RORON3MD=	66.82%	72.22%	0.00%	100.00%
BETFI	22.09%	20.00%	0.00%	85.00%
BETNG	21.04%	20.00%	0.00%	81.25%
GDAXI	14.92%	15.00%	0.00%	60.00%
ROTX	13.29%	10.53%	0.00%	55.56%
BETI	13.10%	5.26%	0.00%	88.89%
CACT	11.14%	10.00%	0.00%	45.00%
RON=	7.33%	5.00%	0.00%	50.00%
STOXX50	6.70%	5.00%	0.00%	45.00%
EURIBOR3MD=	5.63%	0.00%	0.00%	66.67%
SPX	4.71%	0.00%	0.00%	55.00%
EURRON=	0.32%	0.00%	0.00%	20.00%

The Volatility Index (VIX) is the dominant driver, followed by the ROBOR rate with a maturity of 3 months, BETFI, BETNG and the German stock market index DAX.

As VIX is the most influential factor in terms of impact on the companies listed on the Bucharest Stock Exchange, we may see this as a sign of financial contagion – the spread of major market shocks from the more developed stock markets (such as the USA) to the Romanian stock market (as documented in Horváth et al., 2018; and Albu et al., 2015).

The ROBOR rate has been used previously to estimate financial systemic stress for Romania (see, for example, Draghia and Ștefoni, 2020, and Nagy et al., 2016). An interesting finding is the presence in the top 5 of two sectorial indices, BETFI and BETNG. BETFI is a sectorial index that reflects price changes in financial investment companies (SIFs) and other assimilated entities, while BETNG is a sectorial index that reflects price changes of all companies listed on the BSE regulated market, including those in energy and related public services sector.

Previous research has shown that BETFI has a significant influence on the overall market dynamic, being a leader index for the general market index BET (Pop et al., 2013).

Furthermore, the presence in the top 5 of the integration of the DAX index confirms the stock market documented in Central and Eastern European stock markets (Tilfani et al., 2020), especially through the German stock market.

Figure B3 (Appendix B) shows the smoothed influence indicator (rolling seven-day mean) for top macroeconomic risk factors; VIX and ROBOR interest rates with 3 months maturity are the main risk drivers.

3.5. FRM@RO Risk Levels

Using the quantile approach described in Section 2.3, we can assess the level of risk for each trading day, as shown in Figure B5 (Appendix B).

Figure B4 shows the evolution of FRM@RO, in terms of risk levels: the highest risk was recorded during 2008-2012, when the effects of global financial crisis were severely felt by the Romanian Stock Market. Another period with severe risk was during the Covid-19 pandemic, starting March 2020.

The evolution of FRM@RO and the updated risk level can be found at the website https://danpele.github.io/frm_ro/.

3.6. Back Testing and Robustness Check

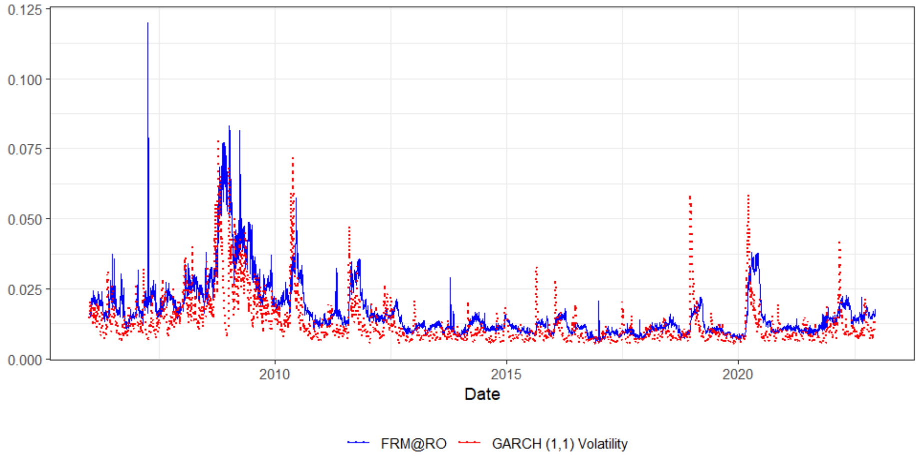
3.6.1. Granger Causality between FRM@RO and BET Index Volatility

The following GARCH(1,1) model was used to estimate the conditional volatility of the BET index:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (12)$$

where $\varepsilon_t = \sigma_t z_t$, with $z_t \sim N(0,1)$ i.i.d.

Figure 5. *FRM@RO* Time Series and Volatility of the BET Index



The evolution of *FRM@RO (τ=0.05)* and the estimated volatility of the BET Index is shown in Figure 5 (dotted line represents BET Index volatility; the same chart for τ=0.01, is presented in Figure B7, Appendix B). Table 3 summarizes the results of the Granger causality test.

Table 3. Granger Causality Test between FRM@RO and BET Index Volatility

	τ=0.05		***τ=0.01***	
Null hypothesis	**F test**	**P-value**	**F test**	**P-value**
Volatility do not Granger-cause *FRM@RO*	20.68	<0.001	14.84	<0.001
FRM@RO do not Granger-cause Volatility	12.35	<0.001	7.67	<0.001

Note: The maximum lag used is k=5.

As shown in Table 3, there is a bivariate causality between the volatility of the *FRM@RO* and the volatility of the BET index, indicating the validity of the *FRM@RO* as a systemic risk measure for the Romanian Stock Market.

3.6.2. Granger Causality between FRM@RO and Google Trends Search Volume Index

To evaluate the ability of *FRM@RO* to capture the measure of market sentiment via Google searches, we use monthly data for Google Trends Search Volume Index (SVI) for the Romanian word 'criza' ('crisis' in English), during the period January 2005-November 2022.

Figure 6, which shows the evolution of *FRM@RO (τ=0.05)* and SVI (dotted line), normalized in the interval [0,1], provides a clear correlation between the two time series (the same chart for *τ=0.01*, is presented in Figure B7, Appendix B).

Figure 6. Normalized Time Series of *FRM@RO* and SVI

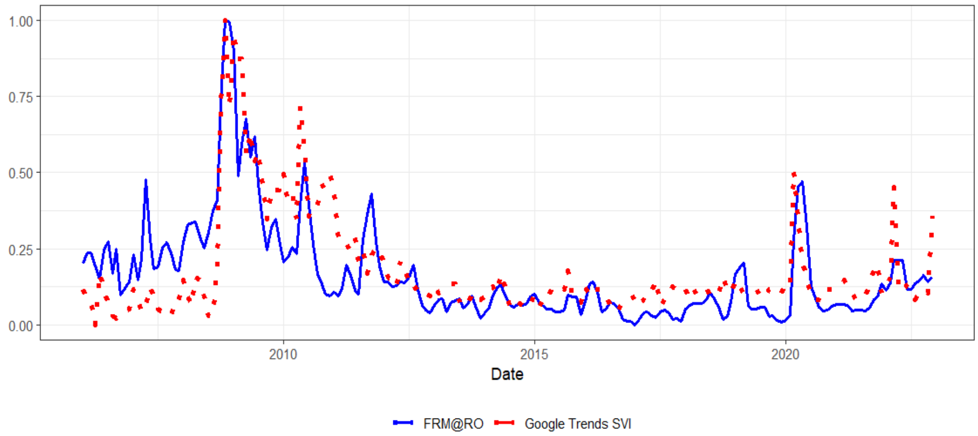


Table 4. Granger Causality Test between *FRM@RO* and Google Trends SVI for "Crisis"

	τ=0.05		*τ=0.01*	
Null hypothesis	**F test**	**P-value**	**F test**	**P-value**
SVI do not Granger-cause *FRM@RO*	5.58	<0.001	3.53	0.003
FRM@RO do not Granger-cause SVI	1.89	0.095	5.90	<0.001

Note: The maximum lag used is k=5.

As shown in Table 4, there is a univariate causality between FRM@RO and Google Trends SVI for the keyword 'crisis' (from FRM@RO to Google Trends SVI), so FRM@RO can capture the sentiment of the stock market, measured by Google searches. This result is in line with the one obtained by Yu et al. (2019), for the estimated FRM for the US stock market and complements the findings from Bui and Nguyen (2019), who documented a strong correlation between SVI and the indicators of the stock market (trade volume, volatility), for a developing economy, Vietnam.

3.6.3. Binary Logistic Regression: FRM@RO and Technical Recession Indicator

To assess the relationship between the *FRM@RO* (*τ=0.05*) and the technical recession indicator for the Romanian economy, model (10) was estimated, using quarterly data, and the results are presented in Table 5.

Table 5. Estimates of Binary Logistic Regression

Quarterly lag	Estimate	Pseudo R^2
1	168.537*** (59.324)	0.482
2	118.578*** (44.141)	0.318
3	97.115** (39.115)	0.234

*Note: Standard errors are in parentheses; *** denotes significance at 99% confidence level, ** denotes significance at the 95% confidence level.*

As shown in Table 5, the most important influence of *FRM@RO* on the technical recession indicator can be captured one quarter in advance.

Figure 7. Time Series of Recession Indicator and Predicted Probability of Recession

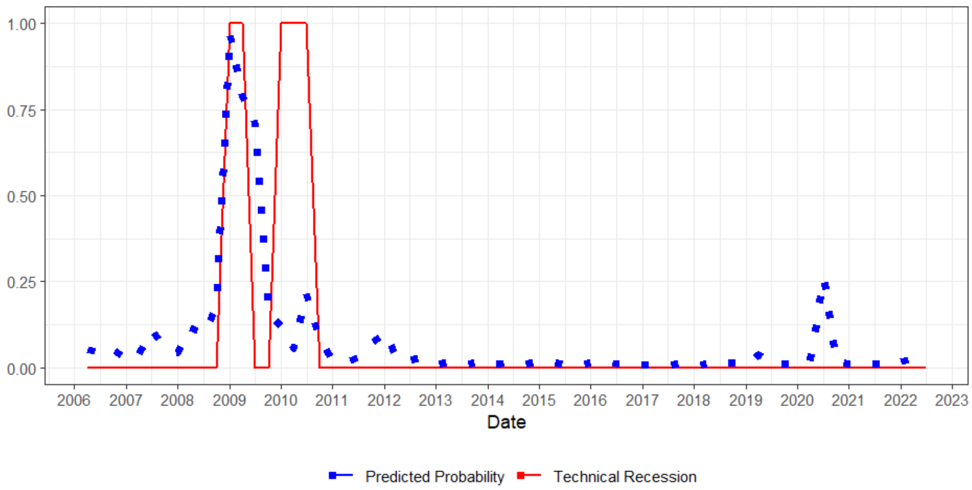


Figure 7 shows the evolution of the recession indicator and the predicted probability of recession, estimated using model (10), with an average quarterly FRM@RO, lagged for one quarter. The model can properly predict the technical recession between 2009Q1-2009Q2 and 2010Q3, as shown by high values of estimated probabilities.

Furthermore, the model gives a signal of potential risk to the economy in 2020Q2 when the Romanian real quarterly GDP (seasonally adjusted) decreased by 11.17%. Although it was not a case of technical recession (two consecutive quarters of quarter-on-quarter GDP contraction), the value of FRM@RO in the first quarter of 2020 can be seen as an early warning indicator of economic contraction in the second quarter of 2020, due to the Covid-19 pandemic.

4. Policy and Market Implications

FRM@RO is not just a new aggregate measure of the financial risk on the Romanian stock market, but it may become a powerful instrument in the toolbox of different stakeholders. Harnessing its full power could be useful for public level decision makers, for the top management of the stock exchange, for investors and for the macroprudential policy of Romania. Therefore, *FRM@RO* could be included by all these stakeholders in their analysis and decision-making processes. In the following lines, different possibilities will be presented, but one should bear in mind that more in-depth analysis is necessary for having a true understanding of *FRM@RO* in the case of each stakeholder.

This tool could be of interest for the decision makers (central government, National Bank of Romania, Financial Supervision Authority, etc.) because it is useful in assessing the economic/financial cycles and therefore it can be added in the early warning system. *FRM@RO* does even more, and it could be used as a tool for identifying which are the companies and therefore sectors which place a major risk. The possibilities opened by the *FRM@RO* go even further since it gives a perspective for the spill-over pathways and identifies connected nodes. By having this type of information at hand the decision makers could develop alternative scenarios for mitigating the systemic risk or for increasing the resilience of the entire economy.

FRM@RO could be an even stronger policy making tool for the decision makers because it could help them identify contagion patterns and could trigger therefore different actions and safety mechanisms. Thus, the decision makers can intervene fast enough to mitigate and even control the diffusion of a crisis in the entire national economy. In this regard, the power of *FRM@RO* depends on the size of the market, meaning the number of companies active on the stock exchange. Therefore, it might be a solution to also try to use *FRM@RO* as a tool for stimulating the development of the market.

FRM@RO could be extended to include the smallest companies (lowest quarter) on the main market and the entire AeRO market or only the highest companies (highest quarter from the AeRO market) to identify interdependencies and contagion patterns between these two markets. Based on such an approach, the interested stakeholders could identify the contagion patterns between the established companies (main market) and the emerging (potential future leaders in their sectors) actors of the Romanian economy. This type of information would be extremely useful for the top management of the stock exchange since they might use it to identify typologies of companies that they might encourage to take a closer look at the AeRO market. This mechanism of diversification might contribute to the resilience of the stock exchange and might offer investment opportunities to new actors.

The management of the Bucharest Stock Exchange might use *FRM@RO* as a tool for pitching to Romanian decision makers by encouraging both private and public companies to go on the stock exchange might be a good solution not only for increasing the resilience of the economy, but also for having a higher predictability of future contagions/crises since interdependencies between companies active on the stock exchange could be monitored with the *FRM@RO*. Moreover, if important companies from a certain sector are brought on the stock exchange, the *FRM@RO* might become a very powerful tool for assessing the stability and the risks of the entire sector (provided that companies listed from that sector are covering a significant part of it).

For the investors, *FRM@RO* could bring very interesting insights for their investment strategies and portfolio creation strategies by helping them to better understand the interdependencies between different companies and by helping them identify contagion pathways and directions. By employing the *FRM@RO* and its entire ecosystem (adjacency matrixes), managers can create tailored portfolios for maximizing their desired KPIs. Consequently, by using *FRM@RO*, portfolio managers could tailor more suitable portfolios for the risk aversion of their clients.

Finally, the *FRM@RO* could also be used by individual companies active on the stock market to understand where they are positioned in contagion pathways. Thus, they will be able to understand which actors have an impact on them and therefore understand how to develop mechanism that might help them increase their resilience in face of potential crises. They could also use the *FRM@RO* to identify downstream which are the actors that could be affected by them through contagion and better understand their positioning in the ecosystem.

Other directions might be further explored but only based on these six it becomes clear that the *FRM@RO* should be carefully analyzed by a large variety of stakeholders ranging from: macro level decision makers, top management of the stock exchange, investors, portfolio managers and listed companies.

5. Conclusions and Further Research

In this paper, we propose a new financial market risk meter for Romania, *FRM@RO*, which estimates the level of systemic risk, and details potential spillover paths derived from co-movements of companies listed at the Bucharest Stock Exchange in tail-event scenarios.

FRM for the Romanian Stock Market is a useful tool for stakeholders, as it can effectively manage systemic risks and acts as an early warning indicator for financial crises. We show that *FRM@RO* is sensitive to financial and economic crises, being able to predict the periods of technical recession one quarter in advance. Based on *FRM@RO* dynamics, we were able to properly predict the technical recession between 2009Q1-2009Q2 and 2010Q3, and the impact of Covid-19 pandemic on the Romanian economy. *FRM@RO* can also capture exogenous shocks as the one induced by the war in Ukraine, starting February 24, 2022.

Our study reveals that the main driver of systemic risk for the Romanian Stock Market, especially during financial crisis, is the global volatility index, VIX. However, local factors, such as the ROBOR interest rate and sectorial indices for financial investment companies and energy sector are extremely important in triggering systemic risk.

As further research, we emphasize the need for an integrated early warning system for financial crises for the Romanian Stock Market, by using a multidimensional approach, including among exogenous factors key macro-economic indicators such as unemployment rate, exchange rate, quarterly GDP etc., to contextualize even further the FRM methodology for the Romanian economy.

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