FINANCIAL STABILITY INDICATOR FOR NON-BANKING MARKETS

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Abstract

A mixed frequency indicator is designed to incorporate and extract information from time-series data that are available at different frequencies: daily, monthly, quarterly, etc.

Currently, the non-banking financial markets in Romania are supervised by the Financial Supervisory Authority and are composed of three distinct markets: the capital market, insurance, and private pension funds. Due to the mutual exposure between them, facilitated by the financial instruments held in their investment portfolios, there are common risk factors that influence their dynamics. Although a financial shock can affect all three sectors at the same time, the impact can be measured at a different frequency and with a different lag. Surveillance data for capital markets and pension funds are available every month, with a gap of one month, while for insurance the data are available quarterly, but with a gap of two months, similar to GDP data.

If a sudden financial event disrupts financial markets or a change in the macroeconomic environment changes the medium-term outlook, what is the impact on non-bank financial intermediation?

The stability indicator for non-banking financial markets is a monthly indicator estimated from mixed frequency data. The indicator is designed to provide a signal of financial instability in non-banking financial markets, to the extent that all three markets are disrupted at once.

Keywords: *financial stability indicator, non-bank financial markets, state-space model*

JEL Classification: E17; C32; E32

Introduction

Financial markets are influenced by various factors. The contagion between financial markets can have a rapid effect on financial intermediation, which cannot be rationally anticipated based on a model base. It can lead to market distress and increases in the instability of the investment portfolios.

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Financial institutions use sets of indicators to monitor risk factors. A short-term fluctuation of a risk, e.g. currency risk, is available at a daily frequency and can therefore be included in a mixed frequency indicator if, by incorporating exchange rate volatility in the indicator, the indicator is designed to be more sensitive to daily events.

Although a financial shock can affect all three sectors at the same time, the impact of a financial shock can be measured with a different frequency and with a certain lag. Surveillance data for capital markets and pension funds are available monthly, with a gap of one month, and for the insurance sector the data are available quarterly, but with a gap of two months (similar to GDP).

In a scenario where an unexpected financial event or a change in macroeconomic expectations or short/medium-term macroeconomic forecasts leads to a rapid decline in financial markets, what is the impact on non-bank financial intermediation? We intend to quantify the impact on non-bank financial intermediation using a mixed frequency macro-financial indicator.

On the other hand, if the indicator is designed to monitor the financial stability of non-banking financial intermediation, we will also need lower frequency data, such as monthly or quarterly macroeconomic data which contain information on the structure of the economy and are generally less sensitive to daily fluctuations. The indicator is constructed to be moderately sensitive, as its purpose is to provide an overview of the financial stability of non-banking financial markets, whilst providing an early warning signal.

The indicator can be modified to include a series of financial data describing the European business cycle, insofar as they provide information on the changing trends of the European economy, especially if we assume that there are side effects in the European economy.

1. Literature review

Financial data are available at high-frequency (daily frequency data) or very high frequency (data available every 5 seconds or even less), while macroeconomic data is available at monthly, quarterly and/or annual frequency. As a result, there is a lot of academic literature on mixing different frequency data, especially in analyses that exploit the links between macroeconomic series (GDP, inflation, unemployment, etc.) and financial series (stock market returns, volatility, interest rate structure, etc.).

Evans's (2005) paper on the estimation of monthly GDP opened a new chapter in the real-time estimation of GDP at high frequencies. He modeled the evolution of GDP similarly to that of the business conditions and used a state-space model to estimate GDP growth. Evans used monthly and quarterly data in his paper.

Anderson and Gascon (2009) used a state-space model to estimate GDP for the U.S. economy using all available data sets, including data revisions.

The estimation of the current state of the economy and the provision of nowcasts was also made by Giannone et al, 2008, Camacho and Perez-Quiros, 2008, Banbura and Runstler, 2007.

Albu (2008) was the first to estimate a composite index of Romanian economic activity based on monthly data.

Aruoba, Diebold, and Scotti (2009) estimated an economic activity index based on four observable indicators sampled daily, weekly, monthly, and quarterly. The authors included daily data in the model for the first time, while other models had used monthly and quarterly data with daily data transformed in monthly frequencies.

An alternative to single-equation bridge models is the Mixed Frequency-VAR model. Originally proposed by Zadrony (1990), the model considers that all variables are generated but not observed at a high frequency and can be used to make predictions at a high frequency. Variables at a lower frequency, such as quarterly data, are represented in a model in the state space where the state equations are given by a high-frequency VAR and the measurement equations, which link the observed data with the unobserved variables at the lower frequency, are represented in the state vector.

An MF-VAR model with four monthly indicators and a lag of two requires the estimation of 70 parameters. If the autocorrelations between the variables are very small, then the elements located outside the diagonal of the matrix are considered zero. Such models are computationally intense and require many data points.

To overcome this issue, there is another approach, namely the use of Bayesian methods for finding parameters (Diebold et al, 2011).

The analysis "Real-time forecasts of Economic activity for Latin American Economies" of Liu and Troy Matheson (2011) makes a comparison of model performance based on forecasts. The authors used the autoregressive quarterly model as a reference basis for the performance of the other models, namely a model with bridge equations, a VAR model with monthly-interpolated GDP, a Bayesian VAR model, and a dynamic factorial model (DFM) with nine monthly indicators. The BVAR model has the biggest errors, while the DFM model has the best results, although they use the same indicators. Regarding the combination of models, the results obtained using an equal share of the predictions obtained are reasonable but have higher errors than DFM.

Because state-space models had better results in integrating mixed frequency data, we have used the methodology proposed by Brave and Butters (2019) to design a mixed frequency indicator.

The model proposed by Brave and Butters (2019) incorporates the mixed frequency data accumulator by Mariano and Murasawa (2003), which is used to transform time series with different frequencies.

Mariano and Murasawa (2003) showed that the average of monthly observations in the quarter can be approximated by the geometric mean, which leads to the idea that quarterly growth rates can be broken down into weighted averages of monthly growth rates, which are not observed. Thus, the quarterly growth rate is approximated by the weighted average of five monthly growth rates:

$$y_t = \frac{1}{3} y_t^m + \frac{2}{3} y_{t-1}^m + y_{t-2}^m + \frac{2}{3} y_{t-3}^m + \frac{1}{3} y_{t-4}^m \qquad (1)$$

2. Methods

The mixed frequency indicator for non-banking markets is designed to take into account the dynamics of capital markets, insurance, and private pension funds to identify a possible hidden vulnerability in the data series that is available at different frequencies and gaps.

The proposed indicator uses the following data:

- for the capital market, we used the closing prices of the index for the financial sector according to the Refinitiv methodology. We have chosen a financial sector index and not the capital market index because it reacts faster to changes in external financial markets;

- for the private pension sector, we have computed an equally weighted monthly return index for all private pension funds. The data are taken from the website of the Romanian Financial Supervision Authority (ASF);

- for the insurance sector, we selected the damage indicator which represents the ratio between the total losses (paid and reserved) in receivables, to which the adjustment expenses (divided by the total premiums collected) were added. Insurance data are quarterly and they should show any registered widespread loss in the market segment;

- Robor data are the monthly interbank interest rate data series (12 months) and they reflect the interbank tightening condition;

- the overall risk aversion indicator is calculated as the difference between the yields of the BAAA and AAA corporate bonds. Data are monthly and are provided by the Federal Reserve Bank of St.Louis.

3. Results and discussion

The data used to calculate the stability indicator for non-banking financial markets have been seasonally adjusted, normalized, and standardized. Monthly pension, capital market, and interest rate data are expressed as deviations from the trend. The trend was estimated with a univariate Hodrick-Preston filter.

The data and results of this paper are also described and reported in the Financial Stability Report no.1 / 2020, available on the ASF website. The analyses of Financial Stability Report no.1 / 2020 are based on the financial reports of the entities supervised by the FSA until the reference date 31 March 2020.

The purpose of the indicator is to record the response of non-bank financial markets to economic shocks.

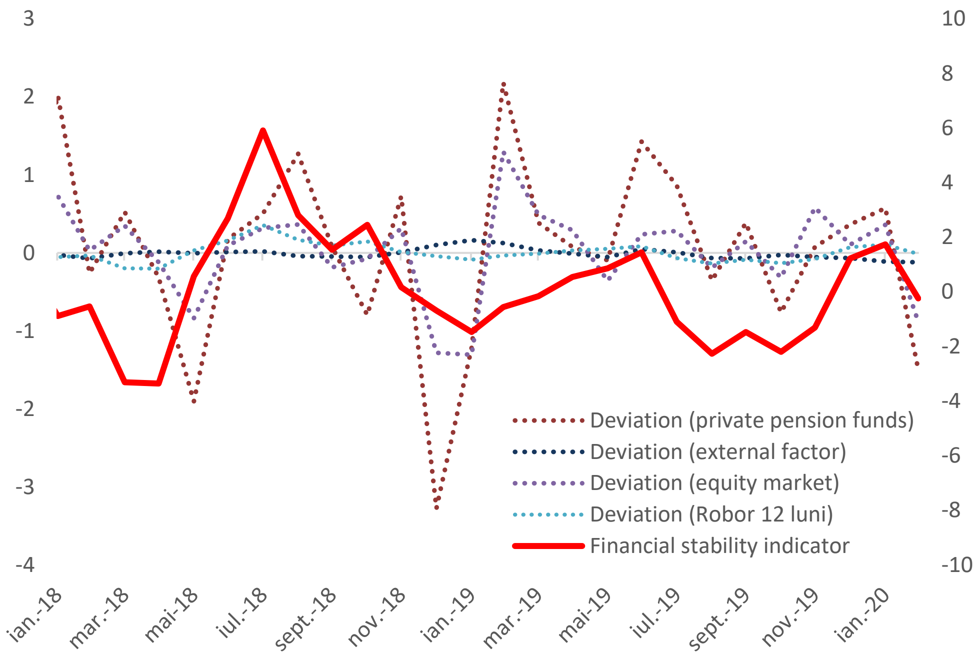

Figure no. 1. Financial stability indicator for non-banking financial markets

Source: Refinitiv, own calculations

The results show that the indicator can capture some important events of financial stress, with the last episode recorded being in December 2019.

The financial stability indicator has been calculated at a monthly frequency and is useful for studying the current evolution of non-banking financial intermediation, taking into account the dependency between the three sectors. When the indicator takes negative values, it indicates financial stress, instability, or vulnerability of the financial markets, taken together or in part, when only one or two of the non-banking sectors are affected.

The indicator was calculated with data up to the 30th of March 2020 and shows deterioration in financial stability. The indicator is useful for assessing the evolution of non-banking financial intermediation, as it may take into account the non-linear dependencies between the three sectors, which cannot be captured by methods based on linear dependencies, such as the correlation between the three sectors.

Some authors (Alvarez, Camacho, and Perez-Quiros, 2012) have shown that smaller models produce better results in out-of-sample predictions than large models with many variables. Finding the optimal number and the best series to obtain an indicator sensitive to changing economic conditions, but without being too "noisy", remains a challenge for academic research. From this point of view, the challenge for the financial stability indicator estimated for Romanian non-banking markets remains to be re-estimation of the model with other monthly data series.

Conclusion

With the help of a model in the state space proposed by Brave and Butters (2019), we have designed an early warning indicator for the financial stability of nonbanking market stability.

The indicator is based on time series with monthly and quarterly frequency, characteristic for the non-banking financial markets in Romania. This indicator can provide a signal of financial instability, as the three markets are disrupted and shocks cross the structure of non-banking financial markets through contagion and affect investment portfolios overseen by the FSA. The indicator showed a deterioration in financial stability between January and February 2020.

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