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The Bank of Italy's systemic risk dashboard for the Italian financial system: a technical note on the aggregation of risk indicators

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Overview

The Bank of Italy's risk dashboard (RD) is a set of indicators providing a general overview of systemic risks to the Italian financial system. It is one of the tools used by the Bank to measure and assess financial stability risks. The RD is currently comprised of more than 80 indicators. In this note we describe the methodology used to aggregate these indicators in nine broader categories of risk.

1. Introduction

The risk dashboard (RD) is an analytical framework developed by the Bank of Italy to measure and assess systemic risks to the Italian financial system and to indicate possible sources of vulnerability.[1] The RD is not designed to forecast future levels of systemic risks.

Since the global financial crisis, several institutions have developed risk dashboards to monitor risks to financial stability. For instance, the European Systemic Risk Board

[1] Venditti F., Columba F., Sorrentino A. M. (2018), 'A risk dashboard for the Italian economy', Banca d'Italia, Questioni di Economia e Finanza (Occasional Papers), 425, Bank of Italy.

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(ESRB) publishes, on a quarterly basis, a set of quantitative and qualitative indicators of systemic risk in the EU financial system.

The Bank of Italy's RD is based on more than 80 indicators of risks to financial stability and their development over time. These indicators are organized into nine main categories of risk: *interlinkages* (specifically, contagion risk in the banking sector), *credit*, *macroeconomic*, *funding*, *market*, *profitability and solvency of banks* and *of insurance companies*, *asset management industry*, and *market infrastructures* (specifically, central counterparties). For each of these main categories we calculate an aggregate indicator providing a snapshot of the level of the risks and recent developments. Aggregate indicators have two main purposes: to deliver concise information on the current level of each category of risk, and to guide the discussion around the potential sources of these risks, their channels of transmission, and possible amplification mechanisms stemming from their interaction.

This note describes the methodology developed to calculate aggregate risk indicators.

2. The methodology to calculate aggregate risk indicators

Individual indicators may have different characteristics, such as frequency or unit of measurement, and different interpretations in terms of the risks to financial stability (some variables entail, according to some predetermined metrics, risks for high values, others for low values, and others for both low and high values).[2] Thus, the aggregation of individual indicators requires several methodological choices.

A first problem is that the time series have to be defined in a common frequency of observation. In our approach, the series are transformed in order to have a monthly frequency. This is done by linearly interpolating the quarterly series and by calculating the monthly averages of those with daily frequency.

Indicators also differ in terms of unit of measurement, the range of values that they can take with positive probability (support), and other characteristics of their historical distributions. We therefore map each series into the [0,1] interval by means of a non-parametric estimation of the empirical distribution and by using the probability integral transform (PIT). In particular, for each risk indicator we estimate the empirical cumulative distribution function $F(X)$ by means of a normal kernel smoother estimator.[3] Then the PIT implies that the random variable $Y = F(X)$ has a standard uniform distribution $Y \sim U(0,1)$.

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[2] Thresholds defining high and low values are discussed below in detail.

[3] Bowman, A. W., Azzalini A. (1997), *Applied Smoothing Techniques for Data Analysis*, New York: Oxford University Press Inc.

While earlier studies rely on parametric assumptions and focus on the distribution's location and scale,[4] our non-parametric approach allows us to preserve differences between the indicators' distributions in terms of symmetry and kurtosis. These characteristics are of particular interest for the assessment of risks to financial stability and the likelihood of tail events.

A second problem is that some indicators point to the existence of risk when their value is above a given threshold (so called 'right-tail' risk), while others do so when their value is below a threshold ('left-tail' risk). There are also indicators that point to a risk when their value is outside a given range ('two-tails' risk). For instance, the public debt-to-GDP ratio is of the right-tail type, with higher debt implying higher risks to financial stability. The GDP growth rate is of the left-tail type, since lower values entail higher risks to financial stability due to reduced debt sustainability. The year-on-year change in consumer price inflation is a two-tails risk: both high and low inflation increase risk to financial stability.

The thresholds, in all types of variables, are determined either by the choice of the percentiles of the indicators' historical distribution or by specific (fixed) values that are clearly grounded in economic theory or justified by other sources of external knowledge; in both cases, some expert judgment has also to be applied. The first approach, based on percentiles, implies that unusually high or low values are by themselves signalling some risk. Overall, in the risk dashboard for the Italian economy about one third of the thresholds are defined using historical distributions. The second method, based on specific fixed values, is especially useful when thresholds have a clear economic meaning or identify specific targets. For instance, the thresholds for the year-on-year change in consumer price inflation identify ranges of values around the ECB's price stability target (2 per cent), regardless of the historical distribution of the variable. This second approach can be useful when the available data do not permit the identification of a well-behaved distribution (e.g. because the time series is too short or strongly non-stationary).

A third problem is that the aggregate risk indicators should be calculated in a way that meaningfully puts together right-tail, left-tail, and two-tails variables, with thresholds based on the historical distribution or on specific values. To do so, we define a function $Risk(x)$ mapping each series from the [0,1] interval into a value on the interval [0,3], where 0 stands for no risk and 3 for maximum risk. The function $Risk(x)$ is monotone, with kinks at $Risk(x) = 1$ and $Risk(x) = 2$, respectively identifying the thresholds between low and medium risk and between medium and high risk. Analytically, the risk function takes three different forms for the three types of individual indicators (right-tail, left-tail and two-tails). The risk function $Risk_{LR}(x)$ of a two-tails variable $X \sim F(\cdot)$ is defined as:

[4] Bedford P., Bloor C. (2009), 'A cobweb model of financial stability in New Zealand', Reserve Bank of New Zealand. Discussion Paper DP 2009/11; Zalkinder H., 2012, 'Measuring stress and risks to the financial system in Israel on a radar chart', Bank of Israel Discussion Paper 2012-15; Miglietta A., Venditti F. (2019), 'An indicator of macro-financial stress for Italy', Questioni di Economia e Finanza (Occasional Papers), 497, Bank of Italy.

$$
Risk_{LR}(x) = \begin{cases} 3 - F(x) \, / \, F(R_L), & 0 < F(x) \leq F(R_L) \\ 2 - \big(F(x) - F(R_L)\big)/(F(Y_L) - F(R_L)), & F(R_L) < F(x) \leq F(Y_L) \\ 1 - (F(x) - F(Y_L))/(F(M) - F(Y_L)), & F(Y_L) < F(x) \leq F(M) \\ 0 + \big(F(x) - F(M)\big)/\big(F(Y_R) - F(M)\big), & F(M) < F(x) \leq F(Y_R) \\ 1 + (F(x) - F(Y_R))/\big(F(R_R) - F(Y_R)\big), & F(Y_R) < F(x) \leq F(R_R) \\ 2 + (F(x) - F(R_R))/(1 - F(R_R)), & F(R_R) < F(x) \leq 1 \end{cases} \qquad (1)
$$

where F is the estimated empirical CDF, $\{R_L, Y_L, Y_R, R_R\}$ is the vector of thresholds[5] and $M = (Y_L + Y_R)/2$ represents the midpoint between the lower and upper thresholds that delimit the low risk range.

For a left-tailed variable the risk function is:

$$
Risk_L(x) = \begin{cases} 3 - F(x) \, / \, F(R_L), & 0 < F(x) \leq F(R_L) \\ 2 - (F(x) - F(R_L))/(F(Y_L) \ - F(R_L)), & F(R_L) < F(x) \leq F(Y_L) \\ 1 - (F(x) - F(Y_L))/(1 - F(Y_L)), & F(Y_L) < F(x) \leq 1 \end{cases} \qquad (2)
$$

Similarly, for a right-tailed variable we have:

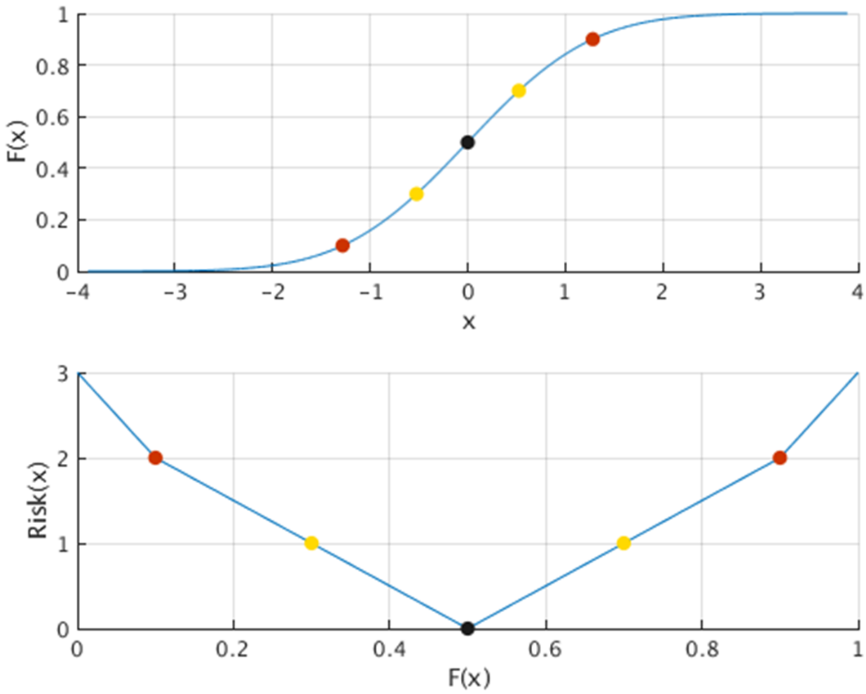
$$
Risk_R(x) = \begin{cases} 0 + F(x) \, / \, F(Y_R) \, , & 0 < F(x) \leq F(Y_R) \\ 1 + (F(x) - F(Y_R))/(F(R_R) \ - F(Y_R)), & F(Y_R) < F(x) \leq F(R_R) \\ 2 + (F(x) - F(R_R))/(1 - F(R_R)), & F(R_R) < F(x) \leq 1 \end{cases} \qquad (3)
$$

Figure 1 below provides a graphical representation of the risk function for a two-tails variable. The top panel shows the cumulative distribution function of the underlying individual indicator X. The bottom panel shows how the function *F(x)* is mapped into the interval [0,3] by means of the risk function $Risk(x)$.

Once all the series have been transformed through the risk function, it is possible to aggregate them and to build a measure of risk for each of the abovementioned nine categories. A classical approach for aggregating the transformed series is to calculate a

[5] For a two-tails risk variable, R_L represents the lower (left) threshold between high and medium risks; Y_L is the left threshold between medium and low risks; Y_R is the right threshold between low and medium risks; R_R is the upper (right) threshold between medium and high risks.

Figure 1 – An example of a *Risk* function for a two-tails risk variable



weighted average that makes use of the correlation matrix of individual risk indicators.[6] For the risk dashboard for the Italian financial system, Venditti et al. (2018)[7] show that exploiting the correlation matrix provides very little additional information on aggregate indicators. In addition, since for some series there is insufficient recorded history, the estimation of the correlation matrix would be inaccurate, and the estimated time-varying parameters could be quite unstable. We therefore take an alternative approach, assigning higher weights to those variables that signal high risks in a given period, irrespective of their historical distribution. This choice reduces the probability of overlooking conditions of high risk at the cost of increasing the occurrence of false positives, consistent with the greater negative consequences that may follow from errors of the first kind. This approach is also coherent with the primary use of the risk dashboard, which is to stimulate a prompt and thorough discussion of systemic risks. Therefore, the aggregate indicators are calculated through averaging with time-specific weights. In particular, for each data point, the series are assigned a weight equal to 1, 2, or 3 when they are in the low-, medium- or high-risk range respectively.

[6] Holló, Kremer, Lo Duca (2012), 'CISS - a composite indicator of systemic stress in the financial system', ECB Working Papers, 1426; Garcia-de-Andoain C., Kremer M. (2018), 'Beyond spreads - measuring sovereign market stress in the euro area', ECB Working Papers, 2185.

[7] See footnote 1.

Analytically, the aggregate risk indicator G at time t is:

$$AggregateRisk_{G,t} = \sum_{i \in G} Risk(x_{i,t}) \cdot w_{i,t} \quad (4)$$

$$w_{i,t} = \frac{1 + \mathbb{I}_{\{Risk(x_{i,t})>2\}} + \mathbb{I}_{\{Risk(x_{i,t})>3\}}}{\sum_{i \in G} 1 + \mathbb{I}_{\{Risk(x_{i,t})>2\}} + \mathbb{I}_{\{Risk(x_{i,t})>3\}}}$$

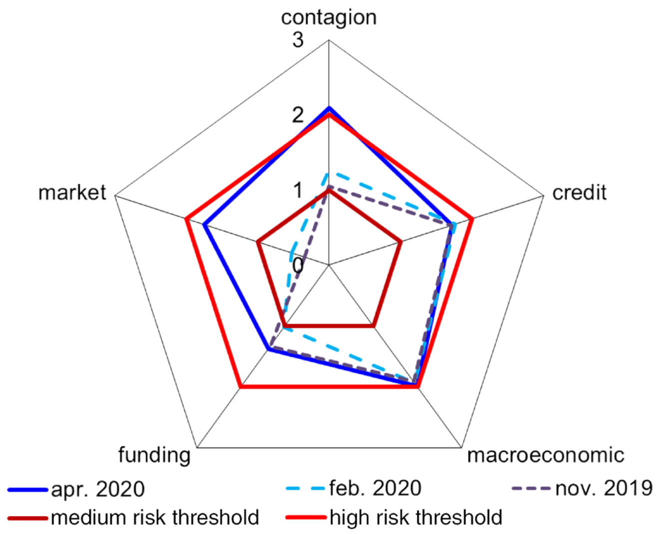
where $\mathbb{I}\{c\}$ is the indicator function equal to 1 if condition c is satisfied and 0 otherwise, and $\{i \in G\}$ is the set of indicators used to calculate the aggregate indicator G.

This approach implies that the values of aggregate risk indicators are more sensitive to changes in those variables in the high-risk range of values.

3. An example

A subset of the aggregate risk indicators have been published since November 2019 in the Bank of Italy's twice-yearly Financial Stability Reports.[8] By means of a radar chart (Figure 2), three different dates for five cross-sectoral risks (out of nine) are shown. In the April 2020 *Financial Stability Report*, four out of five of these risks were in the medium level range (between 1 and 2), with *macroeconomic* risk reaching the upper-medium threshold; contagion risk was above 2, i.e. in the high-risk range. It is interesting to observe that aggregate indicators quickly increased to capture the effects of the COVID-19 pandemic on risks to financial stability.

Figure 2 – Radar chart of aggregate risk indicators (1)



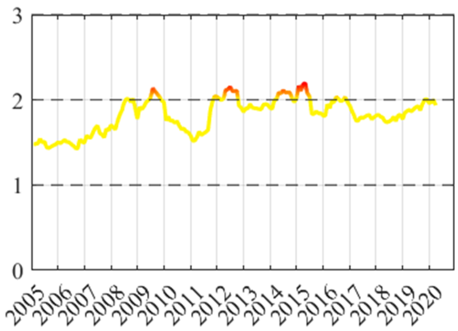
(1) Source: Banca d'Italia, *Financial Stability Report, April 2020*.

[8] Aggregate indicators on the profitability and solvency of banks and of insurance companies, the asset management industry, and market infrastructures, are not currently being published.

Overall, the aggregate indicators are capable of reflecting high-stress events in the financial system. For instance, Figure 3 shows the level of *macroeconomic* and *market* risk over the longer data span available. *Macroeconomic* risk, whose underlying components tend to be quite persistent over time, has been consistently around 2, the high-level threshold, since the sovereign crisis of 2011-12. *Market* risk reached levels above 2 (entering the high-risk range) at that time, and then remained at a relatively low level up to the COVID-19 crisis.

Figure 3 – Aggregate risk indicators

Macroeconomic risk



Market risk