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Abstract

The reputation of an institution refers to its public image in terms of competence, integrity and trustworthiness, which results from the awareness of its stakeholders. The related risk, *i.e.* "Reputational Risk", is defined as the current or prospective risk of a decline in profits or capital resulting from a negative perception of the financial institution image by clients, counterparties, shareholders, investors or supervisory authorities. In this scenario, the reputation and the assessment of the associated risk component represent a decisive factor for ensuring long-lasting profitability.

In recent years, the importance of managing and monitoring Reputational Risk is growing in importance with supervisory authorities, but nevertheless, there are no specific guidelines yet that the institutions can follow. The lack of a precise orientation means that the risk component is still considered discretionary, subjective and highly prone to interpretation.

Considering that in the economic literature there is not a universally accepted approach, the aim of the paper is to provide a quantitative and objective methodology, a Quantitative Model, to assess the Reputational Risk in order to overcome the limits of a qualitative approach, by using exclusively numerical and objective analysis drivers, and to meet the increasing attention of the supervisory authorities on the issue.

The Quantitative Model structure allows firms to study and to monitor the phenomenon from a managerial point of view. This approach provides financial institutions, in particular the Risk Management Department, a model to evaluate the reputational risk arising from economic magnitudes that characterise the business model of the financial institution. This means that the Quantitative Model enables financial institutions to steering possible negative situations and promptly intervening with any corrective measures or actions deemed appropriate.

Keywords

Reputational Risk, Quantitative Model, Financial Institutions, Reputational Risk Synthetic Index, Stakeholder, Risk Factor, Risk Indicator, Risk Phenomena, Cross-Monitoring, Managerial Approach

1. Introduction

1.1 Literature Review

Since corporate reputation is an elusive concept in economic literature, there is not a unique definition of "reputation" but rather a multitude of interpretations. Reputation can be generally defined as "the ultimate intangible" meaning that it is nothing more than the organisation perception by a variety of people (Low and Cohen Kalafut, 2002). Reputation takes time to create, cannot be bought and is easily damaged (Scott and Walsham, 2005). In particular, corporate reputation can be defined as a perceptual representation of a company past actions and future prospects that describes the firm overall appeal to all of its key constituents when compared with other leading rivals (Fombrun, 1996). Analysing corporate reputation requires one to consider a firm intrinsic nature: a legal fiction representing a nexus of a set of contracting relationships, stakeholder interactions with the institution (Jensen and Meckling, 1976). Therefore, it is of the utmost importance to take into consideration the distinction between the stakeholder groups. In this regard, reputation can be then described as a collective assessment of a company attractiveness to a specific group of stakeholders (Fombrun, 2012). Consequently, when defining corporate reputation, one of the major questions is whether corporate reputation is singular or plural (Helm, 2007). In this concern, there is consensus that the corporate reputation is a multidimensional construct (Gatzert, 2015), meaning that different groups of stakeholders can have different perceptions (Burke, 2011). In that respect, some authors had argued that corporate reputation could be the aggregation of all perceptions (Fombrun, 1996), but others had assigned to the company as many different reputations as there are stakeholders (Bromley, 2002). In addition, it is relevant to highlight that some definitions set differences depending on the relevance of the stakeholder group. Indeed, according to some definitions, corporate reputation is only based on the perceptions of external stakeholders (Barnett et al., 2006), in contrast to other definitions, where the corporate reputation is based on the perceptions of all stakeholders, including internal ones (Fombrun and Van Riel, 1997). In this regard, reputation is connected to the company competence, integrity and trustworthiness, which result from the perception of all the group of stakeholders as customers, shareholders, business partners, employees, but also competitors, government and regulatory authorities. Consequently, it is possible to define the reputation of an organisation as the blend of all expectations, perceptions and opinions developed over time by customers, employees, suppliers, investors and the wider public concerning the organisation quality, features and behaviours that result from their personal experience, hearsay or observation of the organisation past actions (Bennett and Kottasz, 2000). It is also important to point out that the conceptualisations of reputation concern both an economic/strategic perspective that views reputation as a resource, and a sociologically perspective that sees reputation as the outcome of shared socially constructed impressions of a firm – as mentioned above. From an economic perspective, reputation can be considered a strategic intangible asset that produces tangible benefits: premium prices for products, lower costs for capital and labour, improved loyalty from employees, greater latitude in decision making and a cushion of goodwill when crises hit (Fombrun, 1996).

Hence, aiming for a positive corporate reputation is crucial and companies should take measures to build a positive corporate reputation in the long term (Eckert, 2017). In this direction, the first step is to define corporate reputational risk and then to measure it (Gatzert and Schmit, 2015). Reputational risk can be defined as an uncertain change in corporate reputation. Some of the obstacles in controlling reputation are its high dynamism, complexity and causal ambiguity (Talantsev 2015). Any past, current or future business decision, activity or behaviour (business action) induces potential changes. The management of reputational risk is then challenging, as it is generally considered to be a risk of risks (Scott Walsham, 2005). Indeed, it should generally be managed in an integrated way by considering the underlying risks along with their effects on reputation. Moreover, it is important to consider that the term "reputation risk" is generally used to describe potential threats or actual damage to the standing of an organisation. In this regard, the necessity of building capabilities for managing and therefore, measuring reputational risks are especially pronounced in the banking and insurance industry, whose business model is based on trust (Fiordelisi et all, 2014).

Part of academic studies analyse corporate reputation via rankings and qualitative indexes. Hence, there is no uncontroversial measurement method; however, several different methods are available since there are a multitude of definitions for "corporate reputation" (Gatzert et al., 2016). Among the other methods, some authors have developed models to measure reputation through questionnaires and interviews, based on selected items or attributes divided into pre-defined dimensions. Each dimension could be possibly associated with a score and then weighted, according to its importance to specific external stakeholder groups - Harris-Fombrun Reputation Quotient - (Fombrun et al., 2000) and/or internal stakeholder groups - Fortune's AMAC/GMAC Model[1] - (Schwaiger, 2004). Since different stakeholders have different expectations of the company behaviour, the measurement of reputation and the related risk could be based on the gap between expectations and performance - Honey Model - (Honey, 2009). These models could represent an important tool by which the firm improves its relationship with heterogeneous stakeholder groups. This is particularly evident in the case of the SPIRIT model (MacMillan et al, 2004), where the SPIRIT acronym stands for "Stakeholder Performance Indicator Relationship Improvement". Needless to say, none of these approaches purports to provide a monetary measure of reputation or reputational risk.

In order to make available this monetary measure part of the literature, especially practitioner-oriented, has prioritised the correlation between reputation risk and shareholder value (Veysey, 2001), in particular considering the markets reaction to an unexpected event able to alter the perception of an institution (Kaiser, 2014). In this respect, some authors also have focused their attention on how to manage the risk to repair the reputation after a crisis event (Rhee and Valdez, 2009). Others have centred their researches on events connected with financial institution operating activities. This also because the reputational loss could be defined as the financial loss, caused by an underlying operational risk event, which exceeds the actual operational loss of the underlying event. Indeed, the market value loss exceeding an actual operational loss represents a reliable measure of the financial reputational losses (Eckert and Gatzert, 2016; Biell and Muller, 2013). Even if, the average expected loss arising from a reputational risk event can be estimated in broad terms through the loss given event rate, the related exposure indicator and the probability of the event (Gabbi, 2004; Anolli and Rajola, 2010), there are only few papers on the empirical quantification of reputational losses resulting from operational losses (Cannas et al., 2009; Fiordelisi et al., 2013, 2014). However, part of recent literature (Eckert and Gatzert, 2016) has focused on the extension of existing models for operational risk by taking into account reputational losses. For this reason, some authors argued that reputation risk, also due to its aforementioned specific structure, requires a special role in risk management and should not be managed separately but in an integrated way together with the underlying risks - such as operational risk - (Tonello, 2007; Regan, 2008). While recognising the relevance of these studies the aim of the following paper is not to link the reputational risk notion to the valuation of related possible losses, but rather allowing the financial institution to study and monitoring the phenomenon from a managerial point of view.

Furthermore, it is of the utmost important underling that there is a limited literature dealing with proactive reputation risk management approaches (Scott and Walsham, 2002) - such as embedding the reputation risk in a holistic enterprise risk management framework (Gatzert and Schmit, 2015) -, even if reputation risk management does create value for firms. The quantification of reputation risk is extremely difficult as there is no universally accepted methodology. Indeed, despite its great relevance, the academic debate on a reputational risk management quantitative model is still at a preliminary stage. Moreover, there is no evidence of models that are able to schematise accurately the risk component associated with the reputation so far.

1.2 Regulatory Environment

A regulatory definition of reputational risk is ascribable to the Board of Governors of the Federal Reserve System (1995)[2]: "Reputational risk is the potential that negative publicity regarding an institution business practices, whether true or not, will cause a decline in the client base, costly litigation, or revenue reductions."

All major risks, such as credit, market, and operational risk, eventually affect the economic value of an institution and reputational risk is no different. A specific event can impact the public image that the stakeholders have towards the institution. If stakeholders subsequently choose to change their behaviour, it may ultimately impact, future revenues losses and/or higher costs and consequently the final market value of the institution.

The following two examples demonstrate the importance of the public image. The first example is related to Wells Fargo[3]: "From 2002 to 2016, employees used fraud to meet impossible sales goals. They opened millions of accounts in clients' names without their knowledge, signed unwitting account holders up for credit cards and bill payment programs, created fake personal identification numbers, forged signatures and even secretly transferred clients' money. Wells Fargo has agreed to pay $3 billion to settle criminal charges and a civil action stemming from its widespread mistreatment of clients in its community bank over a 14-year

[1] Fortune. World's Most Admired Companies: https://fortune.com/worlds-most-admired-companies/

[2] Board of Governors of the Federal Reserve System, Division of Banking Supervision and Regulation: SR95-51 (SUP), November 14, 1995

[3] Flitter E. (2020). The Price of Wells Fargo's Fake Account Scandal Grows by $3 Billion. New York Times, 21 February 2020

period." The second example, instead, involved 15 major banks[4]: "A U.S. judge on Thursday 28th May 2020 said institutional investors, including BlackRock Inc. and Allianz SE's Pacific Investment Management Co, can pursue much of their lawsuit accusing 15 major banks of rigging prices in the $6.6 trillion-a-day foreign exchange market. U.S. District Judge Lorna Schofield in Manhattan said the nearly 1,300 plaintiffs, including many mutual funds and exchange-traded funds, plausibly alleged that the banks conspired to rig currency benchmarks from 2003 to 2013 and profit at their expense. The banks, which sometimes controlled more than 90% of the market, included Bank of America, Barclays, BNP Paribas, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Royal Bank of Canada, Royal Bank of Scotland, Societe Generale, Standard Chartered and UBS or various affiliates."

In the last few years, Regulators have placed greater focus on the measurement and assessment of the reputational risk.

Basel Committee on Banking Supervision defined reputational risk in 2009 as[5]: "The risk arising from negative perception on the part of clients, counterparties, shareholders, investors, debt-holders, market analysts, other relevant parties or regulators that can adversely affect a bank ability to maintain existing, or establish new, business relationships and continued access to sources of funding (e.g. through the interbank or securitisation markets)."

Within the Basel II framework[4], Pillar 2 guidance on reputational risk is also included, and requires implicit support: "Reputational risk can lead to the provision of implicit support, which may give rise to credit, liquidity, market and legal risk – all of which can have a negative impact on a bank's earnings, liquidity and capital position. A bank should identify potential sources of reputational risk to which it is exposed. These include the bank business lines, liabilities, affiliated operations, off-balance sheet vehicles and the markets in which it operates. The risks that arise should be incorporated into the bank risk management processes and appropriately addressed in its ICAAP and liquidity contingency plan."

The European Banking Authority (EBA) defined the meaning of reputational risk as[4]: "The current or prospective risk to the institution's earnings, own funds or liquidity arising from damage to the institution reputation."

Following the EBA point of view, during the assessment of the operational risk, competent authorities should also consider reputational risk[6] - in this case reputational risk is included under operational risk because of the strong links between the two. However, the outcome of reputational risk assessment should not be reflected in the scoring of operational risk but, where relevant, should be considered as part of the business model analysis and/or the liquidity risk assessment. This is because the main effects it can have are a reduction in earnings and loss of confidence and/or disaffection with the institution by investors, depositors or interbank-market participants.

According to this view, competent authorities need to conduct an assessment of the reputational risk to which the institution is exposed, leveraging their understanding of the institution governance, its business model, its products and the environment in which it operates. Competent authorities should also assess whether the institution has implemented adequate arrangements, strategies, processes and mechanisms to manage reputational risk.

On the contrary, within the Basel Framework, operational risk is considered separately, and its definition explicitly excludes reputational risk[7]: "Operational risk is defined as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk but excludes strategic and reputational risk."

In the next sections, the main focus will be placed on the development of the Quantitative Model for the assessment of reputation, with the ability to provide a picture of how the market perceives the financial institutions. With this model, a basis for the inclusion of reputational risk in the comprehensive controlling cycle of a financial institution can be developed.

1.3 Problem Statement

The aforementioned reputation is one of the most important assets for financial institutions. Protecting it from events that could undermine its solidity is a priority for firms to pursue in order to hedge the financial institution value from potential negative impacts. Reputation is the litmus paper of the stakeholders perception of the financial institution and it is closely correlated and dependent on its value.

For this reason, it is fundamental to be able to identify and to manage the elements that can put the reputation at risk and to also be aware of how much, from a quantitative point of view, that image can be influenced by the actions that the stakeholders put in place.

The current market standard for reputational risk management certainly offers valid ideas for identifying specific nesting points but discretion represents one of the main limits of the traditional models, as this affects how the risk is managed.

Within the current management perimeter, the reliance on human sensitivity for risk management cannot find an effective counterproof in the financial institution numbers, as it leads to discretion, which can only be overcome with the approach to quantitative models.

To deepen and extend the perimeter of evaluation as well as to remove discretion, it is essential to leverage on the Stakeholder that can be considered the main driver of the Quantitative Model.

A model based on real financial institution data offers a starting point for objective analysis which, therefore, can be verified and monitored over time.

In the light of these statements, the proposed model has a twofold purpose: it is aimed, on one hand, at proposing a quantitative approach to assess Reputational Risk and, on the other hand, at making intelligible all the information for steering possible negative situations that may occur in the future.

The main objective is to provide a measure of the Reputational Risk that, thanks to its model structure, allows firms to study and to monitor the phenomenon from a managerial point of view.

The case study presented in this paper applies the quantitative approach to a large private Italian bank (hereinafter simply "the Bank") to obtain the numerical component necessary to provide a reference as objective as possible for the quantification of Reputational Risk.

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[4] Stempel J. (2020). U.S. judge orders 15 banks to face big investors' currency rigging lawsuit. Reuters, 29 May 2020.
[5] BCBS, Enhancements to the Basel II framework, July 2009, paragraph 47 - 48
[6] EBA (2014). Guidelines on common procedures and methodologies for the supervisory review and evaluation process (SREP). Paragraph 6.4 Assessment of operational risk.
[7] BCBS, Principles for the Sound Management of Operational Risk, June 2011

2. The quantitative model

This section describes how the Reputational Risk Synthetic Index is able to group the trend of tens of risk phenomena and provide a picture of how the market perceives the financial institution.

Reputational Risk Synthetic Index (or simply Synthetic Index) is defined as the number that represents the overall risk exposure of the financial institution, calculated by weighting the magnitude of each component (*i.e.* Stakeholders, Risk Factors or Risk Indicators, depending on the required detail of analysis) that can contribute to the reputational risk, by a specific load factor deriving from the applied business model and its related peculiarities. In order to explain the meaning of the Synthetic Index, it is essential to define the different components that feed it.

In particular, the Stakeholders (listed in Fig. 3 in the following) are the entities that can incorporate reputational risk or be impacted by reputational consequences, hence contributing to the reputational risk of the financial institution actively or passively, respectively.

Each Stakeholder is linked to a set of Risk Factors representing any potential source of risk that may have repercussions in reputational terms on the financial institution.

Each Risk Factor can in turn be identified through one or more Risk Indicators, which are any potential analysis view that can contribute to correctly and completely define the Risk Factor *per se*, *i.e.* any possible measure that can intercept a risk phenomenon.

The framework described above can be represented with a pyramid-shaped scheme divided by six levels, as depicted in the figure below.

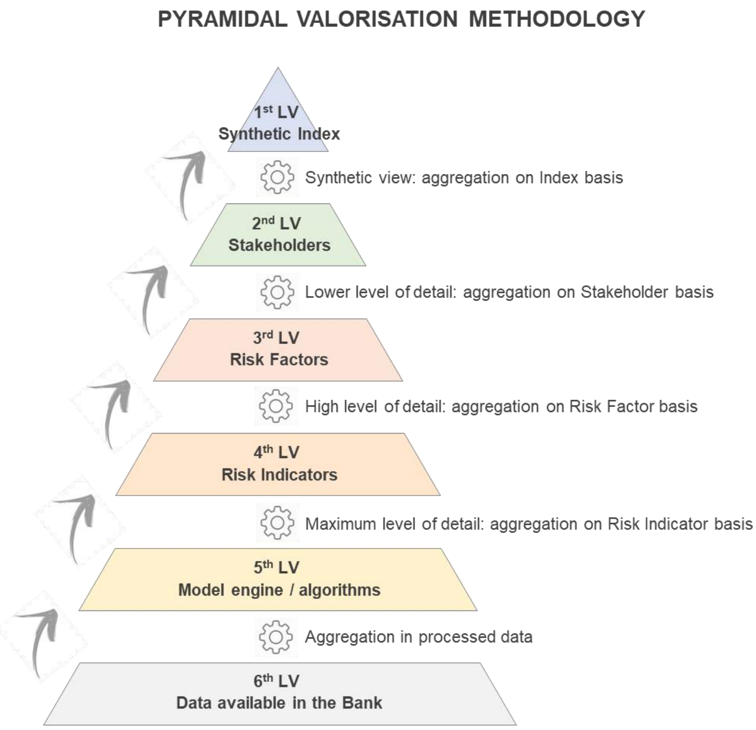

Fig. 1 - Pyramidal valorisation methodology: inputs & outputs

More specifically, the value of the Reputational Risk Synthetic Index is represented by the top of the pyramid (1st level) and it may vary from 0% to 100%: in the first case, the financial institution has no exposure in terms of reputational risk; in the second case, the financial institution fully incorporates all the different risky components thus maximising its exposure to reputational risk; in all other cases, where the Synthetic Index assumes intermediate values (between 0% and 100%, range boundaries excluded), the financial institution might partially include a portion of risky components commensurate with the level that the Synthetic Index represents.

The Synthetic Index is calculated by weighting the contributions of the Stakeholders (2nd level), who in turn are based on the underlying Risk Factors (3rd level), each consisting of one or more Risk Indicators (4th level), as explained above. The levels from the 2nd to the 4th represent the components that determine, on the basis of the assumed values, the contribution to the exposure of the financial institution in terms of reputational risk.

With specific reference to the 4th level, the Risk Indicators are variables that are a function of (i) the risk phenomena (such as, for example, clients portfolios illiquidity, grey/black list products concentration and numerousness of clients complaints) and of (ii) the data source available in the financial institution: those functions constitute the engine of the model and give a numeric output to the Risk Indicators.

Therefore, the Risk Indicators have the intrinsic ability to intercept basic risk phenomena. This statement enables firms to assert that there is a one-to-one correspondence between each Risk Indicator and each risk phenomenon, making them interchangeable. In light of the fact that all the Quantitative Model components are strictly linked through the pyramid mechanism, it is possible to also conclude that each Quantitative Model component (*i.e.* Reputational Risk Synthetic Index, Stakeholders and Risk Factors) has a bi-univocal relation with risk phenomena.

From an operational point of view, in order to understand the model construction logic, it is easier to interpret the pyramid according to a bottom-up approach (following the direction of the arrows in Fig. 1): the raw data available in the Bank (6th level) are processed thanks to the model engine (5th level) with the aim, through successive aggregations, to give rise to the different components (Risk Indicators, Risk Factors and Stakeholders).
From a mathematical point of view, the adopted approach can be summarised by the following formula:

$$R = \sum_{x=1}^{n_s} \sum_{y=1}^{n_x} \sum_{z=1}^{n_y} I_z w_z \quad (1)$$

with: $R = \sum_{x=1}^{n_s} S_x w_x$ $\quad S_x = \sum_{y=1}^{n_x} \frac{F_y w_y}{FMAX_y}$ $\quad F_y = \sum_{z=1}^{n_y} I_z w_z$ $\quad I_z = f(X, D)$

Where:

- Component R (1st level)
- Reputational Risk Synthetic Index, output of the 1st level
- Component S (2nd level)
- S_x: x-th Stakeholder contribution, output of the 2nd level
- w_x: weight of x-th Stakeholder, underlying the Reputational Risk Synthetic Index
- n_s: number of Stakeholders underlying the Reputational Risk Synthetic Index
- Component F (3rd level)
- F_y: y-th Risk Factor of each Stakeholder, whose score is the output of the 3rd level. Each Risk Factor can be composed of one or more Risk Indicators (I_z)
- $FMAX_y$: maximum score associated with the variable F_y
- w_y: weight of y-th Risk Factor, underlying the x-th Stakeholder
- n_x: number of Risk Factors underlying the x-th Stakeholder
- Component I (4th level)
- I_z: z-th Risk Indicator of each Risk Factor, that represents the variable as function - the engine of the model - of the risk phenomena (X) and of the financial institution data source (D); the Risk Indicator score is the output of the 4th level
- w_z: weight of z-th Risk Indicator, underlying the y-th Risk Factor
- n_y: number of Risk Indicators underlying the y-th Risk Factor.

The picture below shows the association between the pyramid-shaped scheme and the formulas:

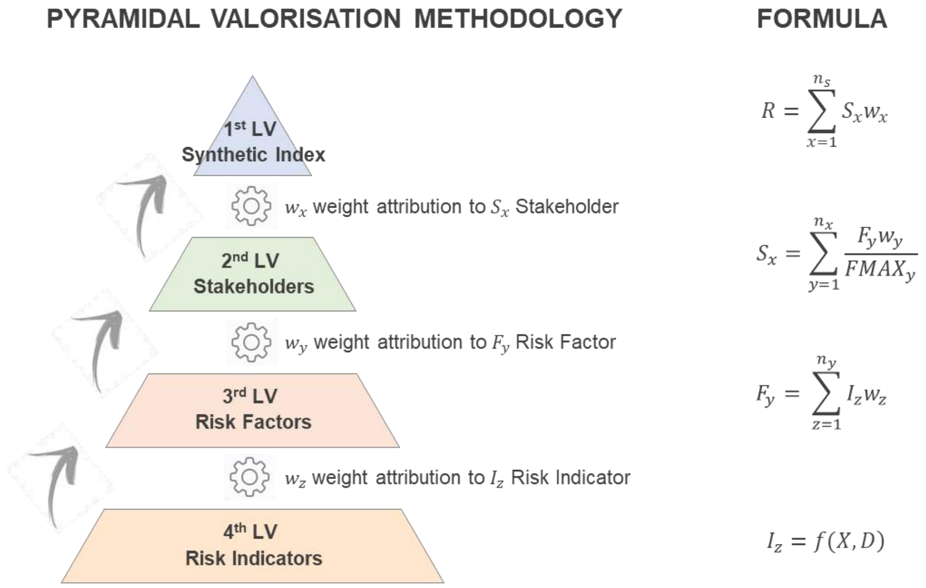

Fig. 2 - Association between pyramidal valorisation methodology and formulas

The figure below shows a theoretical association between Stakeholders and Risk Factors, where the latter imply one or more underlying Risk Indicators, each of which analyses a specific risk phenomenon.
The image also shows the vastness of the analysis conducted, which can count about 100 Risk Factors identified at the Bank involved in the development of the model, and about 120 underlying Risk Indicators, which offer about as many monitored risk phenomena.

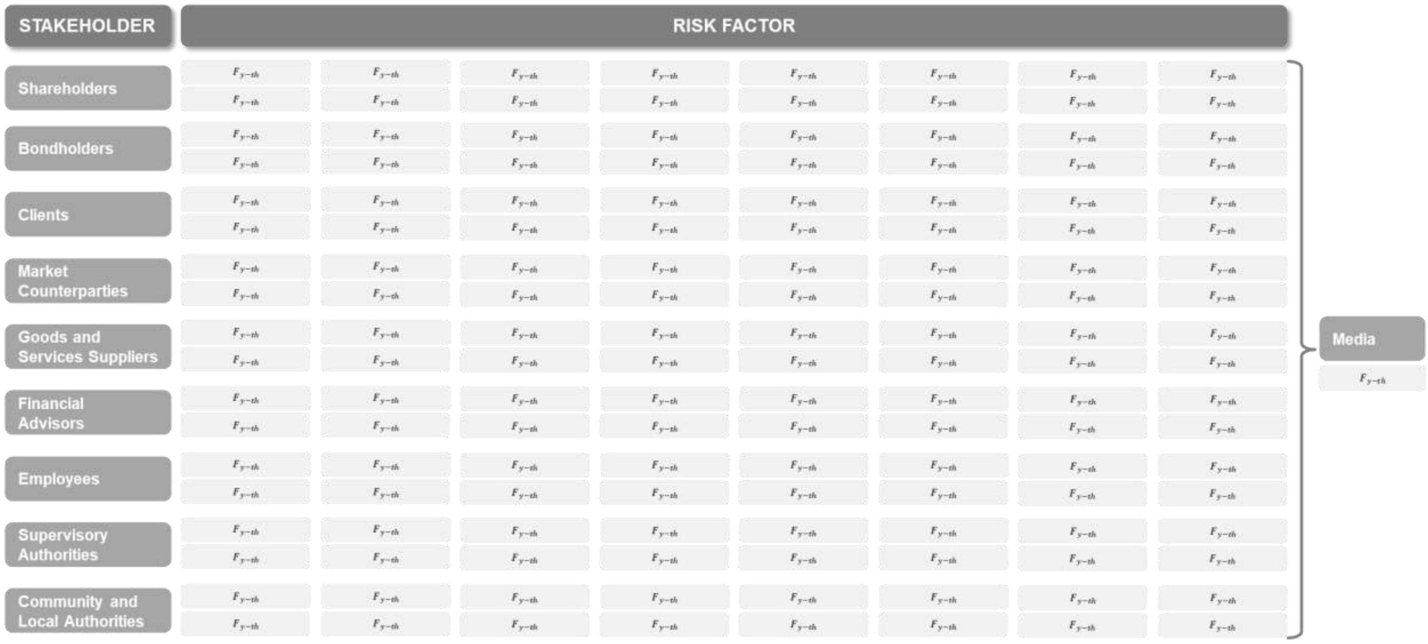

Fig. 3 - The model vastness: Stakeholders and Risk Factors

Particular attention should be paid to the Stakeholder "Media" since it is a cross-entity where its Risk Factor acts as an amplifier of the Reputational Risk Synthetic Index. In particular, in the case of negative ads that regard the institution, the Media effect increases the Synthetic Index value and the related institution reputational risk.
In conclusion, by exploring the connection between Risk Indicators, and in general, each component of the Quantitative Model and risk phenomena, it is possible to analyse events that may affect financial institution stability.
Eventually, it is possible to consider the complement of the Reputational Risk Synthetic Index, which provides an evaluation for the other side of the coin, the Trust and Reputation Synthetic Index: in this case, the final score varies from 0%, in the case of a total absence of Trust and Reputation, to 100%, in case of maximum Trust and Reputation towards the financial institution. However, hereinafter, the representation of the model will focus on the side of the Reputational Risk Synthetic Index.
Notwithstanding the way the Synthetic Index is presented a dedicated process can be designed and set up to properly warn and eventually react to specific signals raised by pre-determined Index values. Below an illustrative representation.

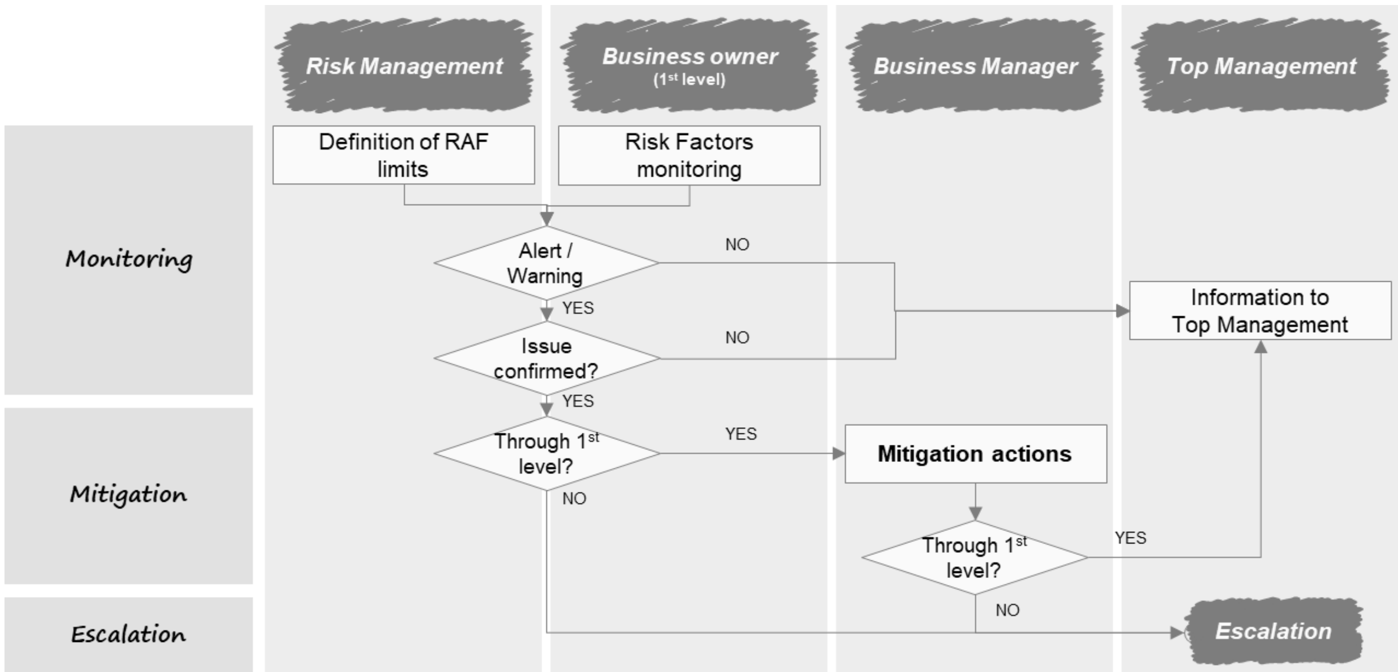

Fig 4 – Dedicated process to monitor specific signals raised by pre-determined Index values

Some examples of the mitigation actions that can be put in place are the following: high transparency and disclosure of risk profile evolution in time, clients portfolio diversification, risk appetite on illiquid/complex financial products concentration, periodical monitoring of market counterparties reputational profile, exclusion of financial product types or market counterparties from the proposed investing universe, update of the risk profile of financial products involved, timely communication to the clients,…

2.1 The Chance to Create a Quantitative Model without Losing Sight of Risk Phenomena Analysis

As anticipated, the Quantitative Model offers the Reputational Risk Synthetic Index as the output. This value leads inside several risk phenomena that have been grouped under entities, the Stakeholders, which represent the quantitative drivers of the model.
Three steps link the risk phenomena to the Stakeholders and initialise the process that leads to the calculation of the Synthetic Index starting from raw data:

1. Risk phenomena detection;
2. Association between risk phenomena and Stakeholders;
3. Data source identification.

The first step refers to risk phenomena detection. As anticipated, each risk phenomenon is intercepted by the Risk Indicator, which in turn contributes to the precise definition of any potential source of risk (Risk Factors): based on the characteristics of each individual financial institution - such as business model, service model, internal organisation and governance, products offered to the clients, core business and market context where it operates - the potential risk phenomena can vary and can therefore find expression in a dynamic perimeter of Risk Indicators that does not necessarily contribute to define the same clusters of Risk Factors. This does not alter the significance of the identified components, at any level (from risk phenomenon to Risk Factor), but instead it allows for the design of a model that perfectly suits the financial institution profile (an example of risk phenomenon that can be monitored is illustrated in paragraph 4.2).
Risk phenomena optimisation has further consolidated the perimeter, offering a way to divide the associated Risk Indicators into two clusters based on their nature: “current” and “forward-looking”.
The *current* phenomena, or associated Risk Indicators, allow firms to analyse risks already present in the financial institution, on which countermeasures should be implemented to contain them.
The *forward-looking* phenomena, or associated Risk Indicators, are instead able to analyse risks not yet emerged within the financial institution, but which could emerge and, as such, it is necessary to implement procedures aimed at anticipating contingencies.
The second step foresees the association between risk phenomena and Stakeholders to address the way in which the first affects the second. The Stakeholders that have been identified include Shareholders, Bondholders, Clients, Market Counterparties, Suppliers of Goods and Services, Employees, Financial Advisors, Supervisory Authorities, Community and Local Authorities and Media. This offers the opportunity to grasp the vastness of the analysis conducted, which can boast several identified Risk Factors, Risk Indicators and, thus, risk phenomena.
The last step is related to the data source identification, on which each risk phenomenon should be based, and linked to the Risk Indicators.
The model basis is quantitative with numeric data as the only input of the model engine: the numbers should be elaborated to produce Risk Indicators in line with the related risk phenomena.

2.1.1 Thresholds Score System

As explained in the last paragraph, every risk phenomenon, which contributes individually to the overall picture through the various drivers mentioned above, is linked to a specific Risk Indicator underlying the Risk Factor and the related Stakeholder.
The mechanism that allows firms to link all of the different drivers together is represented by the thresholds score system, structured on the following components:

- Thresholds (min/max), identified by the user and to be compared with the calculated value of Risk Indicator or Risk Factor;
- Risk Indicator or Risk Factor values, a result of the Quantitative Model, to be compared with the thresholds;
- Scores assigned to the Risk Factor or Risk Indicator, depending on the reputational risk concentration. In more detail, the scores of Risk Indicators, Risk Factors and Stakeholders could be weighted differently based on the need to be intercepted, *i.e.* focus on the main aspects connected to the phenomenon, on the main phenomena for each Stakeholder and on the main Stakeholders, respectively.

To better explain the logic behind the thresholds score system, that allows firms to calibrate the model, it is useful to reference the analogy represented by the pricing methods. “Mark-to-model” is the pricing method for a specific investment position or portfolio based on financial models in the light of the fact that assets in question don't have a regular market that could provide accurate pricing or have evaluations that rely on a complex set of reference variables and timeframes.
This contrasts with the traditional “mark-to-market” approach, in which market prices are used to calculate values as well as the losses or gains on positions. Assets that must be marked-to-model either don't have a regular market that provides accurate pricing or have valuations that rely on a complex set of reference variables and timeframes.
More in detail, assets can be categorised in three groups: i) assets that are valued according to observable market prices, ii) assets that are valued based on quoted prices in inactive markets and/or indirectly rely on observable inputs such as interest rates, default rates and yield curves and iii) assets that are valued with internal models.
Following the method described above, the thresholds score system of the reputational risk model can be managed through three different approaches: i) evaluation of the peers positioning and the curve composed by the limit set and/or the moral suasion exercised by the supervisory authorities, that enables one to appropriately fit the model ii) evaluation of the peers positioning only, that allows one to tailor the thresholds score system to evaluate the deviation between the peers and the Bank under analysis and iii) evaluation of the competent structures of the Bank who make use of the experience in the field to suggest the more appropriate weight, taking into account the presence of any potential historical data.

The application of the thresholds score system, in the three possible scenarios represented above according to the information and references available from time to time, to an increasing number of cases will allow a firm, over time, to start a process of continuous and supervised learning within the model thus allowing it to self-calibrate.
Referring to the Risk Indicators, Risk Factors and Stakeholders weighting, the model provides for the attribution of supplementary load factors to an initially flat distribution, with the aim of giving greater weight to the components that have emerged as the most relevant from the analysis of objective drivers.
The process provides for the identification of objective drivers to apply, for each level (Risk Indicators, Risk Factors and Stakeholders), a weight adjustment according to the characteristics of each component. Each level has specific and objective peculiarities, such as the public or private availability of the data used for the calculation of a Risk Indicator, that can be translated into quantitative drivers then associated with parameters.
As soon as all the drivers for each level have been identified, it is necessary to attribute a load factor to the possible values of the driver, depending on the financial institution business model, its operations and the financial institution ability to produce corrective actions in the short term.
Given the flat distribution initially attributed to each component, the next step foresees the calibration process through the parametrisation coefficients, taking into account that the weights are peculiar of each specific component.
A normalisation of the weights in percentage scale concludes the rebalancing activity for Risk Indicators, Risk Factors and Stakeholders.

2.2 How the Model Works: The Case Study

In this section, the Reputational Risk Quantitative Model is analysed on a specific Risk Factor “High-Risk AML Concentration”, belonging to the Stakeholder “Clients”, that has been identified during the collaboration with a large private Italian bank.
The explanation follows a step-by-step approach, from the bottom to the top of the pyramid, to get to the reputational risk evaluation as a whole [Fig. 1].
More in details, in the case study - for the sake of simplicity - “High-Risk AML Concentration” and “Clients” are the only Risk Factor and Stakeholder, respectively, of the model that has been illustrated from the 6th to the 3rd level; in the 2nd level, the score of the Risk Factor is Stakeholder-based weighted to detect the Stakeholder contribution to reputational risk. To conclude the evaluation, in the 1st level, the Stakeholder contribution is Index-based weighted and the add-on of the Stakeholder “Media” is applied to calculate the Reputational Risk Synthetic Index value.

2.2.1 Pyramid 6th, 5th, 4th and 3rd Levels – Risk Factors & Risk Indicators

This paragraph offers an in-depth analysis conducted on the Risk Factor “High-Risk AML Concentration” of the Stakeholder “Clients”, offering an overview of the levels of the pyramid ranging from 6th to 3rd.
For this Risk Factor, the following levels are analysed:

- 6th level: large amounts of raw data are selected and then aggregated into processed data,
- 5th level: the engine works on processed data to calculate Risk Indicators values and feed the upper level of the pyramid,
- 4th level: Risk Indicators values and the thresholds score system are compared in order to attribute scores to Risk Indicators,
- 3rd level: Risk Indicators, underlying each Risk Factor, awarded scores are collected and weighted to attribute Risk Factors global scores.

As previously mentioned, the Risk Factor represents any potential source of risk that may have repercussions in reputational terms on the financial institution. In this case, the Risk Factor under observation studies the concentration of clients that present a high-risk AML profile (Anti Money Laundering), which helps to understand if there may be reputational impacts due to the analysed phenomenon.
The analysis focuses on both aspects of clients number and portfolios wealth concentrations in the Bank, which are represented by the Risk Indicators underlying the Risk Factor, in order to track the frequency and the magnitude of potential risk phenomena.
This Risk Factor offers valid analysis insights into the consideration of some fines imposed on financial institutions for deficiencies relating to AML aspects. For example, 46 fines were imposed by the Bank of Italy between April 2017 and February 2020. These shortcomings have cost institutions operating in Italy 35.8 mln euros in fines, even considering the events with positive media coverage.
Two representative examples regarding the Italian market can be summarised by the fines imposed on ING and Banca Monte dei Paschi di Siena. For the first case, ING was fined by two Authorities: the first one is the Milan Prosecutor Office, which fined ING 30 mln euros for online scams and money laundering committed between 2014 and 2019; the second one is the Bank of Italy which fined ING by 3.5 mln euro for deficiencies in customer due diligence obligations.
Regarding the second case, the Bank of Italy imposed on Banca Monte dei Paschi di Siena a fine of 1.3 mln euros for deficiencies in the obligations of customer due diligence, identification of the effective owner and active collaboration.
In the international market, it is useful to remember the fines imposed on HSBC and UBS.
In the first case, HSBC was fined by the United States Department of Justice 1.9 bln US dollars for money laundering of Mexican drug traffickers.
In the second case, the Swiss banking group UBS was sentenced to pay a fine of 3.7 bln euros for tax fraud aggravated by money laundering.
Having understood the relevance of potential negative impacts related to AML data treatment, here follows a way to intercept the risk phenomenon through the pyramid approach.
In the 6th level, large amounts of raw data are selected and then aggregated into processed data. Referring to this Risk Factor, raw data regarding clients portfolios and transactions and clients declaration on the AML form allows to classify the clients risk profile: the $Client_{ID}$ column includes this information.

The institute, therefore, as prefixed by AML regulation, classified the $i-th\,Client_{ID}$ into the AML_{z-th} risk range, where $z = 1, 2, 3, 4$. As the variable z increases, the risk coefficient increases:

- AML_1 risk range: the $i-th\ Client_{ID}$ is at AML risk not present or impact not relevant;
- AML_2 risk range: the $i-th\ Client_{ID}$ is a low risk AML profile;
- AML_3 risk range: the $i-th\ Client_{ID}$ is a medium risk AML profile;
- AML_4 risk range: the $i-th\ Client_{ID}$ is a high risk AML profile.

The third information needed to properly evaluate the bank global risk refers to the clients' assets. Considering that the $i-th\ Client_{ID}$ will hold a position on a given financial product in his portfolio, the $y-th\ Value_{ID_i}$, it is possible to calculate the total value of the client's portfolio as:

$$Tot\_Value_{ID_i} = \sum_{y=1}^{n} Value|ID = i \quad (2)$$

The $Tot\_Value_{ID_i}$ should be expressed in institute reference currency.
In the 5th level, the engine works on processed data to calculate Risk Indicators values and feed the upper level of the pyramid. Referring to this Risk Factor, to investigate the high-risk AML profiles concentration in the Bank in terms of portfolios values and clients amount, the clients to be monitored are identified and the Risk Indicators values are calculated.
It is possible to aggregate the information by the AML_{z-th} risk profile in order to split the clients volume. In particular, the total number of clients that belong to a AML_{z-th} risk profile range is determined by the following:

$$Tot\_Clients_{AML_{z-th}} = \sum_{i=1}^{m} Client_{ID_i}|\,AML_{z-th} \quad (3)$$

The client's total assets values are the second information to refer to the AML_{z-th} risk profile range:

$$Tot\_AuM_{AML_{z-th}} = \sum_{i=1}^{m} Tot\_Value_{ID_i}|\,AML_{z-th} \quad (4)$$

It is possible to divide the client perimeter into 4 risk profile ranges, focusing on the AML_4 risk range that is the relevant one for the purposes of reputational risk.
The Risk Indicators, which represent any potential analysis view that can contribute to correctly and completely define the Risk Factor, can finally be calculated, having all the necessary data available.
The first Risk Indicator, the *AML High-Risk Concentration on Total by Asset under Management (AuM)*, is then calculated by comparing the total amount of high-risk AML profile clients portfolios to the total amount of all the clients portfolios.

$$Conc_{AML4_{AuM}} = \frac{Tot\_AuM_{AML_4}}{\sum_{z=1}^{4} Tot\_AuM_{AML_z}} = \frac{27.015.035}{2.395.482.590} = 1{,}13\% \quad (5)$$

The second Risk Indicator, the *AML High-Risk Concentration on Total by Clients Number*, evaluates the high-risk AML clients against the total number of clients.

$$Conc_{AML4_{Cl}} = \frac{Tot\_Clients_{AML_4}}{\sum_{z=1}^{4} Tot\_Clients_{AML_z}} = \frac{3.031}{162.049} = 1{,}87\% \quad (6)$$

This means that the concentration of AML high-risk profile can be viewed both in terms of AuM (1,13%) and number of clients (1,87%).
In the 4th level, a comparison between the values calculated for Risk Indicators and the thresholds score system is made in order to attribute scores, defined as I_z, to Risk Indicators.
The values of the two Risk Indicators, underlying the *High Risk AML Concentration* Risk Factor, are then compared to the related thresholds score system tables.
The thresholds score system has 4 bands, each of which has a minimum band value, $Band_{MIN}$, and a maximum band value, $Band_{MAX}$.
A reputational risk score is then awarded to each band. When considering the first Risk Indicator, the Risk Indicator score, I_z, is the one related to the satisfied band, under the assumption that the values $Band_{MIN}$ and $Band_{MAX}$ are specific for each Risk Indicator.

$$I_z = Score|[Band_{MIN} \leq Risk\ Indicator\ value \leq Band_{MAX}] \quad (7)$$

i.e. for the first Risk Indicator $I_{z=1}$:

$$I_{Conc_{AML4_{AuM}}} = Score|[Band_{MIN} \leq Conc_{AML4_{AuM}} \leq Band_{MAX}] \quad (8)$$

In the table below, the thresholds score system for both Risk Indicators is shown.

Risk Indicator Value Band	$Conc_{AML4_{AuM}}$ **AML High Risk Concentration on Total by Amount: 1,13%** Band Description	$Conc_{AML4_{Cl}}$ **AML High Risk Concentration on Total by Clients Number: 1,87%** Band Description	Score
x ≤ 1,10%	The clients portfolios value, invested by clients with AML high risk evaluation, is low	The clients amount, with AML high risk evaluation, is very low	0,00
1,10% < x ≤ 1,18%	**The clients portfolios value, invested by clients with AML high risk evaluation, is medium**	The clients amount, with AML high risk evaluation, is low	**1,00**
1,18% < x ≤ 1,25%	The clients portfolios value, invested by clients with AML high risk evaluation, is high	The clients amount, with AML high risk evaluation, is medium	2,00
x >1,25%	The clients portfolios value, invested by clients with AML high risk evaluation, is very high	**The clients amount, with AML high risk evaluation, is high**	**3,00**

Fig. 5 - 4th level – Risk Indicators: calculated values and score attribution for the first and second Indicator

In the 3rd level, Risk Indicators, underlying each Risk Factor, awarded scores are collected and weighted to attribute Risk Factors global scores. Regarding this Risk Factor, the Risk Indicator linked to the frequency of the potential risk phenomenon has the same weight as the Risk Indicator linked to the magnitude of the potential event.
The Risk Factor Score calculation formula to an $y-th$ Risk Factor, defined as F_y, with $n-th$ underlying Risk Indicators with related w_z weights and I_z scores is equal to:

$$F_y = \sum_{z=1}^{n_y} I_z w_z \quad (9)$$

i.e. given the previously calculated $I_{Conc_{AML4_{AuM}}}$ and $I_{Conc_{AML4_{Cl}}}$, setting $w_{Conc_{AML4_{AuM}}}$ as the weight of the first Risk Indicator value and $w_{Conc_{AML4_{Cl}}}$ as the weight of the second Risk Indicator value, the Risk Factor global score is calculated as:

$$F_{y=1} = F_{Conc_{AML4}} = w_{Conc_{AML4_{AuM}}} \times I_{Conc_{AML4_{AuM}}} + w_{Conc_{AML4_{Cl}}} \times I_{Conc_{AML4_{Cl}}} \quad (10)$$

The *High-Risk AML Concentration* Risk Factor is equal to 2,00 out of a maximum score of 3,00. In the table below, the steps to calculate it are presented.

Risk Factor *High Risk AML Concentration*	w_z	I_z	*Max Score*
$I_{Conc_{AML4_{AuM}}}$	50,00%	**1,00**	3,00
$I_{Conc_{AML4_{Cl}}}$	50,00%	**3,00**	3,00
$\boldsymbol{F_{Conc_{AML4}}}$		**2,00**	3,00

Fig. 6 - 3rd level – Risk Factors: score attribution

2.2.2 Pyramid 2nd Level – Stakeholders

In the 2nd level, the scores of the Risk Factors underlying each Stakeholder are Stakeholder-based weighted to detect the Stakeholder contribution to reputational risk. The Risk Factors scores are Stakeholder-based weighted and the Stakeholder evaluation is the output at the 2nd level.
Consider $y-th$ Risk Factors underlying a Stakeholder, each of which characterised by a weight w_y, a score F_y, and a maximum score $FMAX_y$, it is possible to calculate each Risk Factor contribution, $Contribution_{F_y}$, as:

$$Contribution_{F_y} = \frac{F_y w_y}{FMAX_y} \quad (11)$$

The Not-weighted $x-th$ Stakeholder Total Contribution to the Reputational Risk Synthetic Index, S_x, is equal to:

$$S_x = \sum_{y=1}^{n_x} Contribution_{F_y} = \sum_{y=1}^{n_x} \frac{F_y w_y}{FMAX_y} \quad (12)$$

In the table below, the case study Risk Factors contribution to Clients Stakeholder and the Not-weighted Clients Stakeholder Total Contribution to the Reputational Risk Synthetic Index are calculated; here the Stakeholder represents the entity that incorporates reputational risk hence it actively contributes to the reputational risk of the financial institution.

Stakeholder
Clients

$Risk\ Factor$	w_y	F_y	$FMAX_y$	$Contribution_{F_y}$
High Risk AML Concentration	5,00%	**2,00**	3,00	3,33%
$y-th$ Risk Factor	…	…	…	…
$S_{Clients}$	100,00%			**14,31%**

Fig. 7 - 2nd level – Stakeholders: contribution to Reputational Risk Synthetic Index

2.2.3 Pyramid 1st Level – Reputational Risk Synthetic Index

In the 1st level, the Stakeholders contributions are Index-based weighted and the Media Stakeholder add-on is applied to calculate the Reputational Risk Synthetic Index value. The Reputational Risk Synthetic Index value is calculated by weighting the Stakeholders evaluations to the relative weights.
Consider $x-th$ Stakeholder, each of which characterised by a weight w_x and a contribution S_x, it is possible to calculate each Stakeholder weighted contribution, $Wgt\_Contribution_{S_x}$, as:

$$Wgt\_Contribution_{S_x} = S_x w_x \quad (13)$$

All the Stakeholders, with the exception of the Media one, fall within the scope of contributions to the Index. The Stakeholder “Media” acts as an amplifier of the Index considering the nature of the Stakeholder and that of the underlying Risk Factors which will be analysed below.
The Reputational Risk Synthetic Index calculated without Media Stakeholder contribution, No_Media_RRSI, is equal to:

$$No_{Media_R} = \sum_{x=1}^{n_s} Wgt_{Contribution_{S_x}} = \sum_{x=1}^{n_s} S_x w_x = 23{,}79\% \quad (14)$$

In a quantitative model for reputational risk, the Media Stakeholder analysis is fundamental to detect negative ads and the related media coverage, as news, albeit niche, risks being distorted by the media potentially damaging an institution reputation.
With reference to the previous paragraphs which deal with sanctions imposed by the Regulator on financial institutions, the effect of media can move within a range of scenarios defined based on the relevance, *i.e.* the importance, and the resonance, in terms of the private confinement of the news relating to the sanction.
More in detail, media coverage, linked to the announcement severity, the number of advertisements published by the media and the stature of the media themselves, represents the driver that affects the public image of the financial institution and makes the quantification of the potential damage possible.
As mentioned previously, the Risk Factor underneath the Stakeholder “Media” acts as an adjustment that affects the Reputational Risk Synthetic Index. In particular, in the case of negative ads that regard the institution, the Risk Factor increases the Synthetic Index value, while it has no impact on positive ads.
Assigning a value to the underneath Risk Factor $Ads\ Amount$ of the Stakeholder “Media”, which is based on the number of negative or potentially negative news spread by the media regarding the financial institution, the Reputational Risk Synthetic Index $RRSI$ is equal to:

$$R = Ads\ Amount + No_{Media_R} = Ads\ Amount + \sum_{i=1}^{n} Wgt_{Contribution_{S_x}} =$$

$$= Ads\ Amount + \sum_{x=1}^{n_s} S_x w_x = 3{,}00\% + 23{,}79\% = 26{,}79\% \quad (15)$$

In the table below, the Reputational Risk Synthetic Index is calculated.

Reputational Risk Synthetic Index

$Stakeholder$	w_x	S_x	$Wgt\_Contribution_{S_x}$
Clients	15,00%	**14,31%**	2,15%
$x-th$ Stakeholder	…	**…**	…
No_Media_R	100,00%		**23,79%**
Stakeholder Media – Ads Amount			3,00%
R			**26,79%**

Fig. 8 - 1st level – Reputational Risk Synthetic Index: final output

The picture below shows the association between the pyramid-shaped scheme, the formulas and the case study:

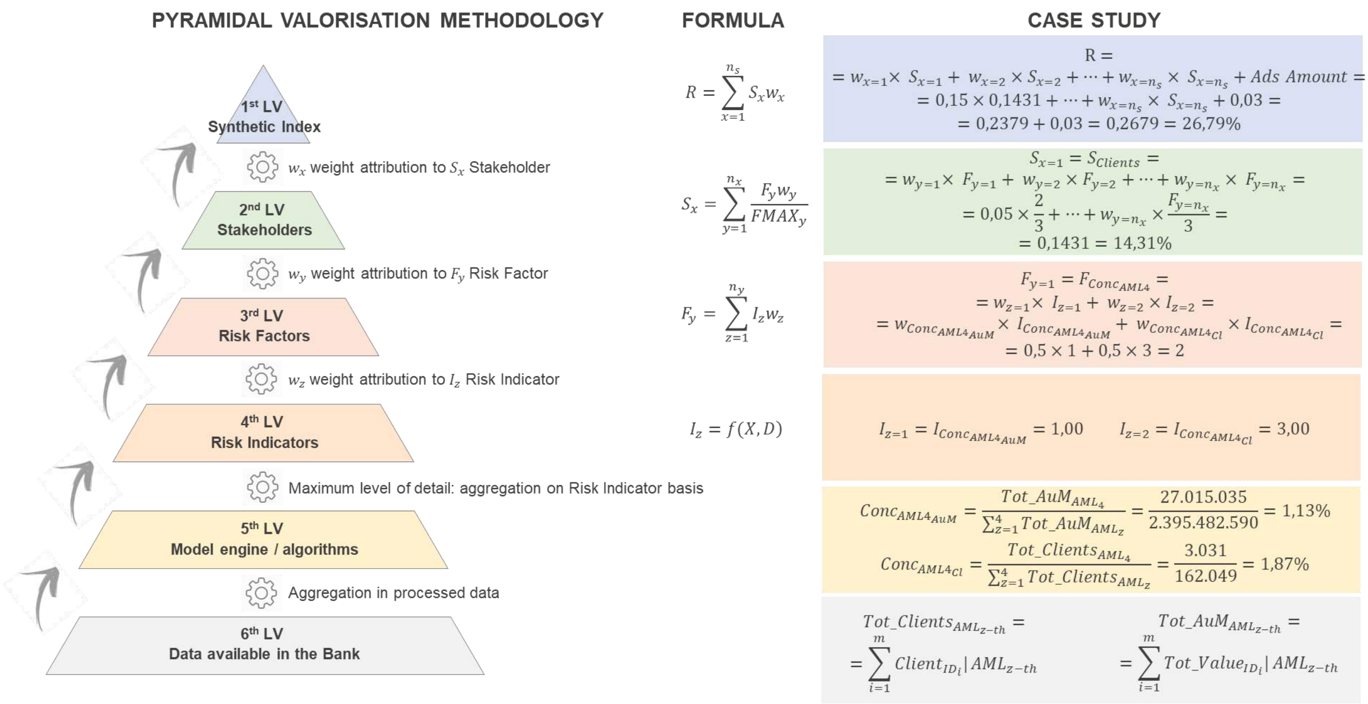

Fig. 9 - Pyramidal valorisation methodology: case study results

Figure 10 represents the historical trend of the Reputational Risk Synthetic Index during the year. In particular, the latest evaluation shows the effect that the *Ads Amount* had on the Synthetic Index: without the penalty, the Synthetic Index would have been in the Low-Risk range, but given the penalty represented by the mentioned Risk Factor, the Synthetic Index is now on the Medium-Risk range.

2.2.4 Case Study Outcome

To fully understand and properly read the outcome of the model, it is essential to attribute a definition to the risk ranges for *R* as follows:

- Low risk range, where the financial institution faces very few components - if present at all - that might expose it to reputational risk (*e.g.* only some Risk Indicators belonging to a specific Risk Factor and/or only minor Risk Factors belonging to a less significant Stakeholder);
- Medium risk range, where the critical components that the financial institution has to manage can put it at a moderate reputational risk or, alternatively, where some specific risky components have exceeded the predetermined level of attention;
- High risk range, where there are several and severe components that lead the financial institution to a high and strong exposure in terms of reputational risk.

Having defined the different ranges, the *R* can be read in both absolute and relative terms. In the first case, the Synthetic Index is representing the overall company position in terms of reputational risk that can be compared against other competitors provided that all the players are adopting the same parameterisation schema (*i.e.* bands, ranges,…); in the second case, the Synthetic Index is

analysed in performance terms allowing to appreciate the status trend over time, highlighting the progressive greater or lesser exposure to reputational risk.
In the case study explained above, given the business model of the financial institution and the historical analysis carried out, it is possible to state that there is a moderate exposure to reputational risk, due to the presence of potentially risky components, but without reaching significant levels of concern. More in detail - and therefore evaluating not only the *R*, but also the different levels of analysis that the model provides (2nd, 3rd and 4th levels of the pyramid) - it is however considered appropriate to monitor specific risk phenomena that can potentially become critical, such as, for example, in the context of clients (Stakeholder level analysis), a high risk in terms of AML (Risk Factor level analysis) due to the presence of a number of subjects with high AML risk (Risk Indicator level analysis).

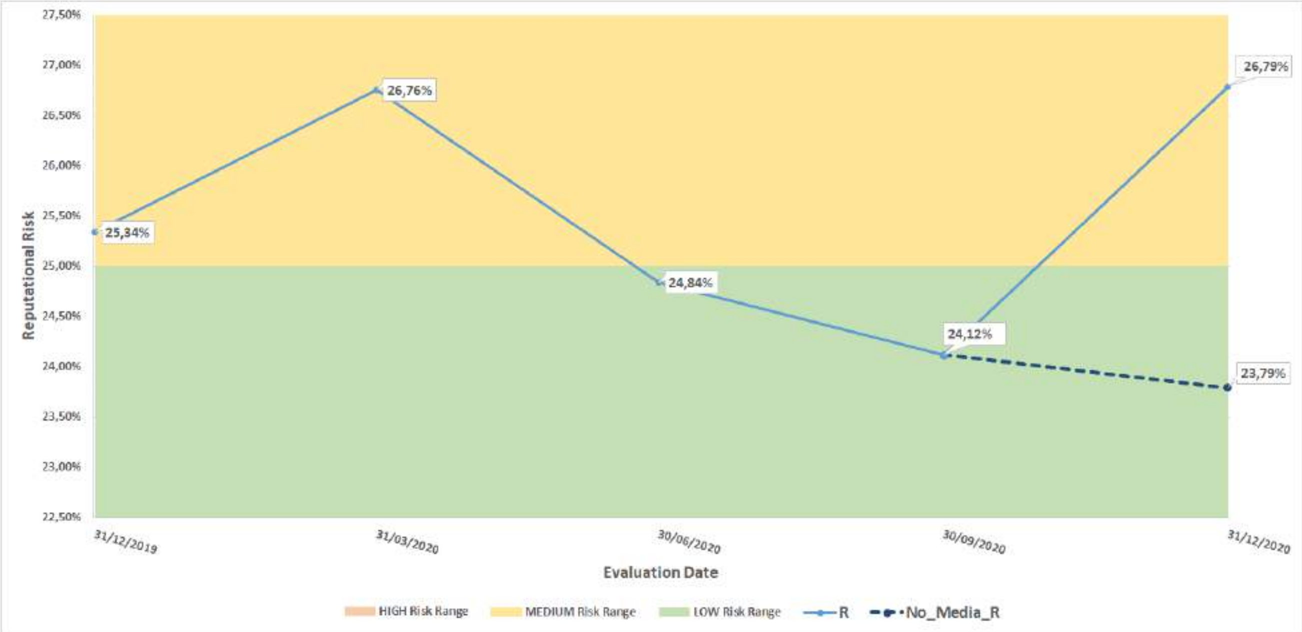

Fig. 10 - 1st level – Reputational Risk Synthetic Index: final output after ads amount

2.3 Quantitative Model Strengths
The Quantitative Reputational Risk Model has several strengths that make it able to provide a global overview as well as a very detailed level of analysis, surpassing the solutions currently used by the market for the management of this risk. This 360° analysis offers the ability to define many attributes to the model: modularity, flexibility, scalability, customisation, ability to evolve with the business, ability to identify business opportunities and pitfalls boundaries.
The model modularity allows firms to divide the phenomena analysed into different drivers (Stakeholders, entity, type of impact,...) and, thanks to its flexibility, different parametrisations of risk sustainability levels can be set.
In addition, each Risk Indicator requires a limited volume of data which provides the opportunity to focus on the model perimeter sub-sections upon specifics needs. This scalability is just one of model characteristics, as the possible customisations are nearly limitless and linked to how the users concatenate data and phenomena.
All these capabilities add up to two aspects with high added value in term of business:

- The model is able to evolve linearly with the business, offering ideas for new risk nesting points management and optimising processes and procedures that could damage the financial institution;

- Certain trends in the Risk Indicators related to risk phenomena make it possible to identify business opportunities and pitfalls boundaries.

2.3.1 Risk Measurement Framework Expansion
The Quantitative Model is number-based and auditable; the output is an analysis that is less discretionary than market standards and, thanks to real data input, offers an expansion of the risk measurement framework proportional to data availability.
The risk measurement framework of the quantitative model integrates and extends risk analysis offered by the qualitative approach, thanks to measurable elements: scores and contributions.
The main advantage of measurable elements is the possible handling that allows cross-data analysis through aggregation by Stakeholder.
This possibility allows Risk Factors to be studied also through aggregation by thematic areas. The Risk Factors calculation relies on several attributes: financial institution, financial products, clients, financial advisors/distribution network, sustainability and proprietary portfolio. It offers a view to find Reputational Risk nesting points and target areas for further exploration.

2.3.2 Risk phenomena Monitoring
The Quantitative Model offers the possibility to monitor a multiplicity of risk phenomena through the Risk Factors underlying the Stakeholders. Risk phenomena represent a tool for the Bank for tracing the nesting points of Reputational Risk; and therefore, with an adequate level of detail of the Risk Factors, it is possible to identify current phenomena and forward-looking ones. As previously explained, they allow firms to intercept risks already present and to anticipate potential future risks.

2.3.3 Cross Monitoring

As stated, the model offers the possibility to analyse specific topics from many different points of view.

Illiquidity is an aggregation factor underlying the portfolios of clients, portfolios of financial advisors and the proprietary portfolio of the financial institution, but it also represents the reading key to understand the adherence to regulatory fulfilments, as discussed in paragraph III of this chapter.

More specifically, client portfolios are just a part of the global phenomenon which involves, for example, the financial institution counterparties illiquidity or the product types concentration in financial advisors portfolios.

The risk phenomena monitored through the specific Risk Indicators can be cross-analysed to allow for focus on dynamics which, taken individually, offer views on certain risks, but collectively reveal situations on possible global shortcomings in the monitoring processes that need to be implemented.

2.3.3.1 Possible Views

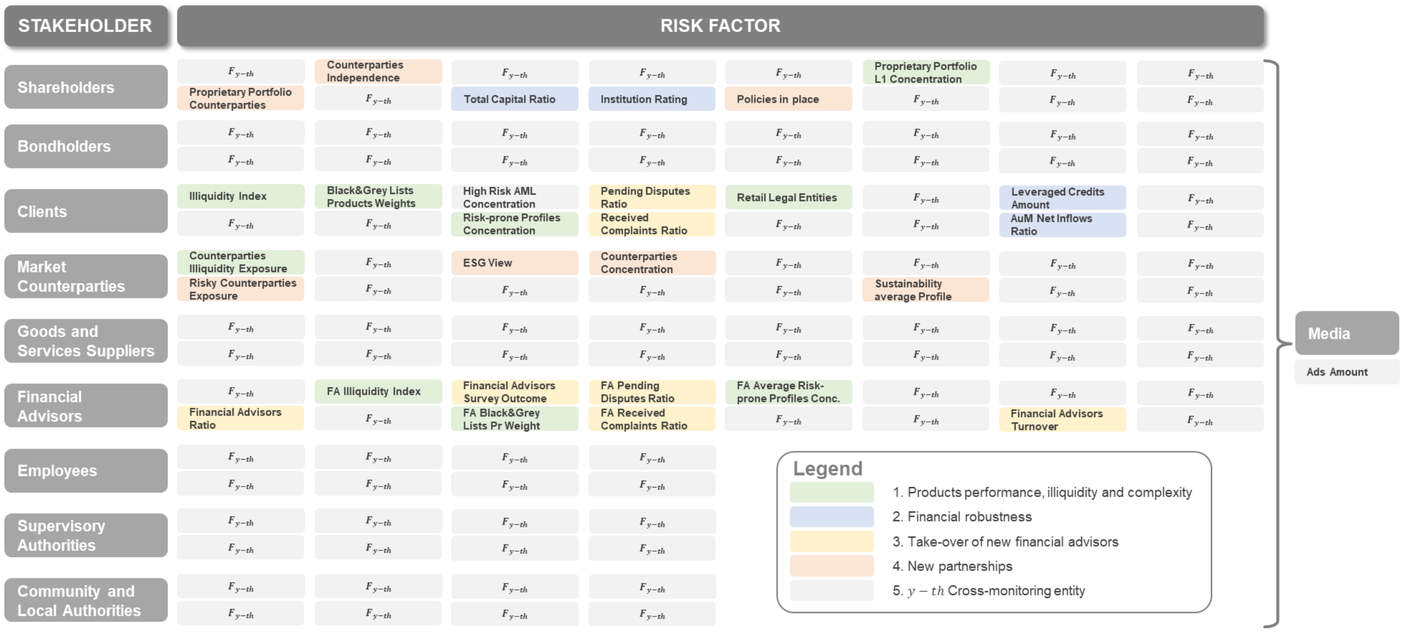

Fig. 11 - Possible cross-monitoring entities

1. Product performance, illiquidity and complexity: when dealing with the characteristics of particular financial products that may bring a higher concentration of some specific risks (mainly related to illiquidity and complexity) as main drivers for the return of the portfolio, the right tool to target the proper risk/reward trade-off might be what we identified as "cross-monitoring analysis". This could be conducted by blending the impacts on portfolios of clients, financial advisors, counterparties and institution. Analysing the trend of the Risk Factors related to portfolios illiquidity (for clients, financials advisors and counterparties), product types concentration, with a focus on grey/blacklist products, and MiFID suitability profile (for clients and financial advisors), joined with risk exposure for the same Stakeholders, offers a specific view on the cross-monitoring phenomenon. If sanctions imposed by the Regulator for any shortcomings are added, the full picture is available.

2. Financial robustness: an analysis of the solidity of the financial institution, combined with the net deposits among clients and the loyalty of the same, offers insights into the credit area of the institution. As in the previous case, additional Risk Factors were developed to complete the scope of analysis; the negative gross collection or the leveraged credit amounts offer illustrative ideas.

3. Take-over of new financial advisors: studying the ways of acquiring new recruits, the survey outcomes and the pending disputes and complaints help to contextualise this cross-monitoring phenomenon that involves the financial advisors. Possible repercussions could affect the Clients Stakeholder, considering the deep bond that relates financial advisors to clients.

4. New partnerships: the market counterparties with which the financial institution interfaces are certainly one of the most delicate points, as the reputation of the institution is also reflected in the subjects with whom it communicates on a daily basis. Shareholders confidence is largely based on commercial alliances that are built and the monitoring of any risk concentrations towards specific counterparties. In the same way, the attention of the institute towards sustainability issues is nowadays one of the pillars to discuss and face the policies in place that allow firms to protect the view that counterparties have of the institute.

The four cross-monitoring entities represent aggregation scenario examples between the global range of scenarios already identified and structured. These scenarios have the peculiarity of evolving because of market context or business models changes.

The cross-monitoring entities proposed in the graph show the Risk-Prone Profiles Concentration, Illiquidity Index and Pending Disputes Ratio Risk Factors underlying the ClientsStakeholder. On the other hand, the Risk Factor “High Risk AML Concentration” of the same Stakeholder and the Ads Amount of the Media Stakeholder belong to other cross-monitoring entities already identified, even though not shown.

3 Back-end cloud-based solution

The rationale and logical construction of the proposed solution could be supported by a technical architecture that, in the light of its intrinsic characteristics described below, enables the full availability of all existing and potential features brought by the quantitative model. The answer to this need could be provided by the Cloud Computing that nowadays has become a pervasive element that backs infrastructures at any level and scale. For this purpose, this section gives a thorough overview of how the power of Cloud Computing services can bring into view capabilities that allow this model to seamlessly perform at scale making use of the so-called "serverless" paradigm[8].

The Cloud fuels newer ways of users demands offering a rich and smooth experience in their daily operations without taking care of provisioning any hardware upfront. Two key elements may be considered as a baseline for any cloud provider: scalability and elasticity[9].

Scalability is referred to as the ability of a cloud environment to quickly handle a growing amount of load by adding more capacity to the system. Elasticity is the ability to autonomously adapt the provisioned capacity over time based on real needs. By bringing these elements together, it becomes clear that the concept of efficiency is one of the biggest leverage strengths that cloud platforms could leverage.

With efficiency defined as the effective utilisation of resources when they are required, it can lead to a decrease in costs from optimal resource utilisation as well as economies of scale the cloud provider can draw on.

Having provided such a distributed network, it is also possible to choose where elements geographically reside, depending on the related availabilities of the specific provider. This helps to comply with National regulations that sometimes might be a breakthrough in the choice of a cloud provider for another. These concepts might be applied to both traditional infrastructures, where components are configured and governed by customers, and to the newer cloud paradigm named serverless.

In this paradigm, components are run in a transparent way to end-users, allowing them to concentrate only on the quantitative model logic implementation. With the advent of such a model, operational procedures and the infrastructure components deployment is even more simplified. Operations are decreased since there is no longer a need to provision any hardware resources, giving the tough task of keeping the elements always updated and protected to the provider as well as hosting the solution whilst using the Infrastructure as Code paradigm[10] every infrastructural resource might be defined and deployed using replicable templates, which is not doable in regular customers data centres.

Under these circumstances, the proposed solution is backed by pure serverless components which might commonly be found in every relevant cloud provider. Following the drawing containing the reference architecture of the solution:

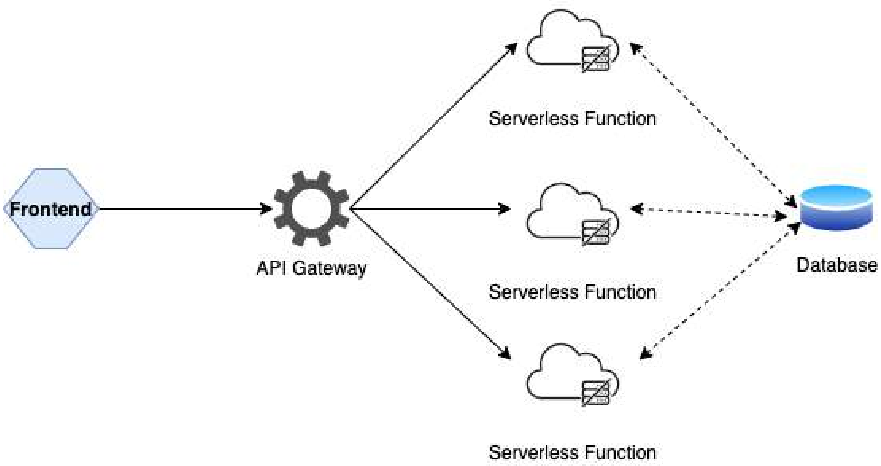

Fig. 12 - Cloud back-end solution

where the front end component is run across multiple containers to balance ingress traffic as well as high availability purposes while the API Gateway and serverless functions are a Platform as a Service (PaaS) element of the cloud provider.

Making such infrastructure, every component is freed up to scale independently based on need since the state is not kept in the dynamic components but in a separate one. This kind of infrastructure is commonly known as stateless.

4 Conclusion

The Quantitative Model lays the groundwork for the assessment of reputational risk in an objective way, summarising an institution reputation solidity in a single number - the Reputational Risk Synthetic Index - and finds its strength in several consolidated notions.

Through historical trend analysis, it is possible to study how the different phenomena affect the Synthetic Index and vice versa.

The model can be broken down into parts and aggregated into new entities, allowing monitoring to be aligned with the financial institution needs.

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[8] Lynn T.G. Emeakaroha V.C. Rosati P. (2017). A Preliminary Review of Enterprise Serverless Cloud Computing (Function-as-a-Service) Platforms. IEEE 9th International Conference on Cloud Computing Technology and Science.

[9] Lehring S. Eikerling H. Becker S. (2015). Scalability, Elasticity, and Efficiency in Cloud Computing: a Systematic Literature Review of Definitions and Metrics. 11th International ACM SIGSOFT Conference on the Quality of Software Architectures.

[10] Artac M. Borovssak T. et al. (2017). DevOps: Introducing Infrastructure-as-Code. IEEE/ACM 39th International Conference on Software Engineering Companion.

Model modularity, flexibility and scalability allow for its adjustment and calibration according to different parameters, risk management views and business evolution, lending itself to be applied, verified and monitored in a wider financial services context. These model features help, step-by-step, to improve some key aspects, that are: i) the phenomena identification, that needs to know about the financial services field, ii) the data identification to perform analysis and collection properly and iii) the data optimisation for ensuring the model toughness.
It is possible to enclose the various facets that characterise the model by distinguishing two souls. The first one is represented by the pure reputational risk quantification associated with the observable phenomena at each financial institution, while the second one refers to the evaluation and calibration of such phenomena relevant to the institution respectively through the thresholds score system and the weights rebalancing.
While the first soul can rely on the aforementioned consolidated notions, the second one requires refinement, since the starting point of this optimisation is identifiable within the learning process hypothesised for the thresholds score system. Through the model application in several financial institutions, the model will acquire a more solid base to provide a better global context view.

4.1 Lessons Learned

Nevertheless, the model development brought out several issues that need to be managed, starting from the awareness of the management, through the involvement of the structures of the Institution and the identification of risk phenomena, up to the analysis, collection and optimisation of data.

A list of the main ones is shown:

- Bringing the Institution to the awareness of the importance of using the model in day-to-day management is certainly the main aspect to manage: an awareness campaign should be conducted to explain that one of the most important assets for the financial institution is its reputation. This is directly linked to the perception of the financial institution by the different Stakeholders and how the Institution can manage the possible risks that could emerge during daily operation.

- The components evaluated within the model allow one to understand and intercept phenomena regarding all the financial institution departments. Therefore, it is fundamental to properly handle the departments onboarding and to assure their active contribution. Below, the tested process that allows firms to comply with all of the preparatory steps for the Risk Factors implementation and the scoring system thresholds for each Risk Factor.

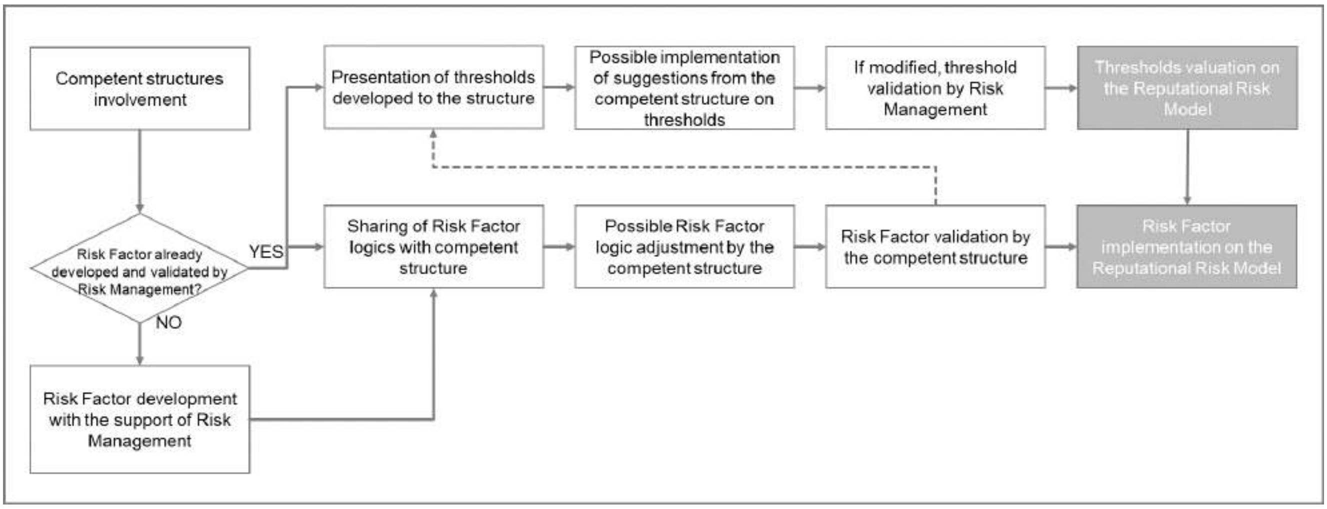

Fig. 13 - Departments Onboarding: the Tested Process

- Data analysis and collection is one of the most time-consuming issues: pre-analysis of what is needed to create the different Risk Factors foreseen in the model and identification of the financial institution departments in charge of the data provision allowed to promptly and appropriately address the requests and to effectively manage the problem.

- The last main issue regards the data optimisation: detecting data already available in the right format, data already available but to be fixed for feeding the model and data to be retrieved, ensuring the non-proliferation of potentially useless requests are the "keys to solve the puzzle".

These aspects, together with the features of the technological solution outlined previously in chapter 5, will be taken into consideration for future and further implementation of the quantitative model at other financial institutions.

4.2 Future and further implementations

The following observations can be made from the above discussion and may also serve as starting points for future development. In particular, further research should pick up three main issues:

- First of all, considering the model that has been implemented in a large private Italian bank, it would be interesting to expand and test the model on other banking business models, characterised by a greater heterogeneity of core activities. Looking further ahead, the quantitative model could also be adapted to the insurance industry; this represents an extremely tough challenge due to the sector peculiarity and, therefore, the need to revise the Risk Indicators as well as Risk Factors.

- Second, the aforementioned importance of data as a strategic asset suggests for further development of the model. The increasing amount of data – especially real-time and instant ones – allows firms to move to a dynamic quantitative model where the Reputational Risk Synthetic Index is calculated simultaneously to the data feed.

- Third, to promote a constructive debate on this subject, it will be crucial to analyse the effectiveness of the model on Reputational Risk Management and on the Institution performance. This paper is a useful first step in exploring in greater depth a quantitative approach to evaluate the exposure to reputational risk. Therefore, academic research should focus on validating the higher level of advantages coming from a quantitative model compared to a qualitative one.

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