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Measuring Banks' Antifragility via Fuzzy Logic

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***Abstract*—**Analysing the world banking sector, we realize that traditional risk measurement methodologies no longer reflect the actual scenario with uncertainty and leave out events that can change the dynamics of markets. Considering this, regulators and financial institutions began to search more realistic models. The aim is to include external influences and interdependencies between agents, to describe and measure the operationalization of these complex systems and their risks in a more coherent and credible way. Within this context, X-Events are more frequent than assumed and, with uncertainties and constant changes, the concept of antifragility starts to gain great prominence in comparison to others methodologies of risk management. It is very useful to analyse whether a system succumbs (fragile), resists (robust) or gets benefits (antifragile) from disorder and stress. Thus, this work proposes the creation of the Banking Antifragility Index (BAI), which is based on the calculation of a triangular fuzzy number – to "quantify" qualitative criteria linked to antifragility.

***Keywords*—**Complex adaptive systems, X-events, risk management, antifragility, banking antifragility index, triangular fuzzy number.

I. Introduction

TODAY, faced with the emergence of complexity that permeates the uncertainties scenarios linked to markets, the traditional method of risk management and its risk matrix are no longer satisfactory for the efficient management of organizations.

Organizations, such as a Complex Adaptive System, interact with the external environment and with other agents, which can result in unpredictable and often unprecedented scenarios. In this context, X-Events begin to occur with considerable frequency and it is no longer cautious to exclude them from the roll of risks that make up the business management plan. However, since the prediction of their incidence tends to be impossible, companies should seek skills (learning, self-organization, flexibility, …) that will allow them to survive and benefit from any event of disorder and chaos, developing and stimulating the emergence of its antifragility – ability of gaining from disorder [1]. Thus, in this work, focused on the financial sector, we seek to provide information that enables companies in this sector to improve the development of their antifragility. Through the creation of what are known as the BAI, we aim to demonstrate the main variables linked to the development of the antifragility of financial institutions.

In our analysis, we tried to cover the most diverse fields linked to the development of organizations, using a more holistic view of these, in line with the complexity that permeates them.

For BAI measurement, we chose 18 variables that we linked to each one of the 6 criteria of antifragility analysis (redundancy, emergence, requisite variety, stress starvation, non-monotonicity and absorption). Through the Triangular Fuzzy Number method, we manipulate and standardize the values of each of these variables, reaching a final value that corresponds to the BAI of each institution.

Our sample is made up of 42 financial institutions, of the world's most diverse regions, of which JP Morgan is the one with the highest BAI, 0.68, and Banco do Brasil S.A. that presents the lowest BAI, 0.46.

The article is divided in 5 sections. In addition to this Introduction, in Section II we have the bibliographic review of the subjects that make up this work. In Section III, we present the methodology. Then in Section IV we present the results. And finally, in Section V we have the present of our concluding remarks.

II. State of art

A. Complex Adaptive System and How They Behave

Nowadays, it is already a consensus that we can describe a complex system as a collection of interconnected parts (agents) whose relationships result in new properties [2]. For the most part, such systems are adaptive, being able to learning, interacting, collecting information and feedback that allow them to make internal adjustments in response to or anticipating changes [3]-[6].

Among the most important features of CAS, Chiva et al. [7] highlight its ability to learn through the operationalization and constant interaction between its agents is highlighted, which allows him to glimpse and analyse various scenarios, always seeking for the best way to adapt to them [8]-[10].

Parker & Stacey [11] still point out that we are surrounded by Complex Adaptive Systems (CAS) with markets, institutions and other agents being some of their examples [12].

Hole [6] also corroborates the idea that the world is full of CAS, with ICT (Information and Communication Technology) and the economic system being examples of so many others. In Fig. 1 we have the present of how the interaction between agents and the environment occurs. Cognitive processes and tools enable a continuous process of practice and learning that composes the database for decision-making against the action of stressors [1].

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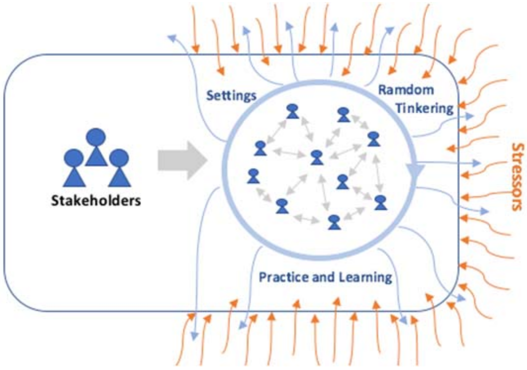

Fig. 1 The interaction between the agents leads to the formation of a CAS that interacts with the environment, in a continuous feedback process that allows its adaptation to the stimuli

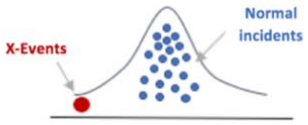

Fig. 2 Probability density function of possible events, where in the middle are the routine events and in the left tail occur the events of extremely harmful effects

Danchin et al. [13], when studying living systems, emphasize that small doses of stress are healthy for the evolution of these; because they stimulate the emergence of unexpected properties, among them antifragility, that allows the CAS to find solutions to the adversities.

Each system (re)acts in a way. However, the likely behaviors are portrayed by a continuous random variable that follows a normal distribution of the probability density function [6]. In Fig. 2, we have the representation of this distribution, where in the middle are the most routine events and in the tails the extreme events – on the left side those of negative effect and on the right side the positive ones – named by Casti [14] of X-Events.

Also called Black Swans [15], X-Events tend to be rather scarce, making it impossible to predict its incidence with any accuracy, with only a retrospective prediction possible after the event has already occurred [2]. In addition, in the short term they tend to be extremely negative, but in the long run they can aid in the evolution of systems, propelling progress by decimating fragile structures and enhancing resistant and antifragile [14].

Antifragile systems are more than robust - as well as tolerant, they still improve under stress - and opposed to fragile ones - that "break" in the face of disorder [1]. According to Hole [6], we can glimpse the fragility, robustness and antifragility through a spectrum (Fig. 3), each stage being an improvement of the previous one. In addition, it is possible to observe that antifragile systems have a 'positive' convexity against increasing volatility, while fragile systems have a 'negative' concavity and the robust ones are indifferent [1]. However, the positive impact of stress is not continuous, there is a moment (tipping point) where the disorder becomes harmful to the system and puts it in a fragile condition against the threat [2], [16], [17]. Thus, realizing the sensitivity of a system to X-Events becomes more useful for managing organizations than trying to predict risks [18]. This is because most traditional risk management models discard events (of negligible probability) and ignore interactions between agents and systems, ultimately delivering divergent results from reality [17], [19].

Fig. 3 Spectrum from fragile to antifragile

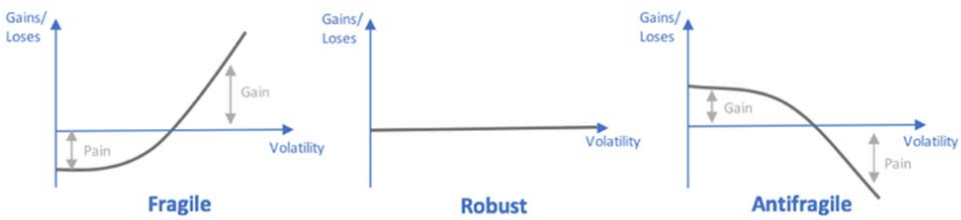

Fig. 4 Behavior of systems when volatility increase

B. Risk Management

Based on mathematical theories of Bachelier, Fama, Markowitz among others, traditional risk management is shown to be massively structured in stochastic models that result in an underestimation of the risks associated with the economic scenarios analysed [6], [19], [20].

Traditionally estimated according to triplet (e_i, p_i, c_i), where e_i is the i^{th} event, p_i is the probability of occurrence of this event and c_i is its consequence (with i = 1,2 ... n), the risks of low probability, and mild consequences are eventually discarded from the roll of risks to be managed, as they can be seen in the risk matrix (Fig. 5), they do not appear as high risk or extreme risk. However, since risk is a consequence of system dependence [21], it is incoherent to discard the events at the extremities, since there tend to be more and more interconnected and complex systems, which leads to an improvement of the CAS against the recurring events, at the same time the incidence of non-recurring events (X-Events or Black Swan) increases [6].

		Consequence				
		Negligible	Minor	Moderate	Significant	Severe
Probability	Almost Certain	Low Risk	Moderate Risk	High Risk	Extreme Risk	Extreme Risk
	Likely	Minimun Risk	Low Risk	Moderate Risk	High Risk	Extreme Risk
	Moderate	Minimun Risk	Low Risk	Moderate Risk	High Risk	High Risk
	Unlikely	Minimun Risk	Low Risk	Low Risk	Moderate Risk	High Risk
	Rare	Minimun Risk	Minimun Risk	Low Risk	Moderate Risk	X-Events

Fig. 5 The Risk Matrix and how X-Events are underestimated

The direct relationship between systems' resilience and their degree of interconnection is also highlighted by Allen & Gale [22] and Acemoglu et al. [23] while Markose et al. [24] present the lack of public information for the correct analysis of interbank relationships, which lead risk management models to simplifications and errors that can be fatal to the markets [25]-[28].

As Adrian & Brunnermeier [29] had already attempted, individual and micro-prudential instruments should be replaced by models that cover systemic risk and allow a macro-prudential approach [30], [31]. In this context, the Basel Committee [32], [33] launches as baseline indicators for the new risk management methodologies to be adopted by financial institutions: size; interconnections with other institutions; interjurisdictional activities; substitutability of its services; complexity. In addition, robustness proves to be insufficient for the development of systems, as internal and external changes over time eventually fragment them and make them increasingly vulnerable to extreme events. Therefore, it is paramount to measure the sensitivity of the systems to the unknown, as this will dictate the decisions to be taken in order to improve the search for antifragility [6].

Unlike the classical approach, in the analysis of complex systems we cannot analyze its components separately or adopt linearity and causality as means for their understanding [34]. On the other hand, the emergence becomes constant before the interaction and influence between the systems and the environment [35], and the unpredictability present in this process can no longer be neglected by the instruments of risk analysis [36], [37]. Thus, robust approaches emerge. Its basis is non-linear mechanisms and precautionary measures, control and improvement of systems, rather than acting on probabilities of future occurrences and forecasting attempts [20], [34]. In this regard, we highlight Resilience Engineering, whose proposal is to find ways to improve the resilience of systems, making them more adaptive, so as to better absorb and adapt to volatility and stress [36].

Righi et al. [38] and Bergström et al. [39], also emphasize the importance of resilience engineering in risk assessment and risk management processes, since it encompasses the complexity present in the current scenario and uses thought-forms that relate risk to performance and improvement processes over time of time [40].

The pre-Holling idea of resilience, which holds that a resilient system is one that remains in equilibrium and retreats to early stages when under stress, is left out. Instead, equilibrium is seen as something damaging (which leads to stagnation) and resilience as an emergent property of CAS, which allows them to cushion the effects of disturbances and adapt to changes, no longer retreating to early stages, but by launching them at more advanced stages [34], [41].

Accordingly, the concept of antifragility proposed by Taleb [1] comes to extend the concept of resilience (pre-Hollinger) when affirming that a certain level of uncertainties and stress, over time, is beneficial and necessary for the best performance of the systems. The focus on system vulnerabilities is no longer the basis of risk management methodologies, but the system potentials are exalted [42].

Trying to predict the future has already proved inefficient in the face of the existing complexity [20], [34]. It is necessary to stop trying to predict the future, accept the unpredictability and adopt methods, which provide means and information that contribute to the adjustment of systems [1], [43]. Thus, measuring the sensitivity of systems to future variations and understanding how they will respond to X-Events becomes a necessary precondition for the process of improving systems [1], [18], [44], [45].

C. Measurement of Antifragility

After the conceptualization of antifragility, Taleb [46] also highlighted the inefficiency of traditional risk management methods for complex systems. Alternatively, they proposed to measure the antifragility of CAS, because when we glimpsed how fragile or antifragile a system is, we will have a sense of how it will face future changes and uncertainties and can improve it if necessary.

Taleb [46] used heuristics - strategic decision-making rules, similar to natural cognitive processes and based on past experiences, which omit some information available to make quick decisions [47], [48] - and comparisons between observed stages and the "optimal stage" to transpose system sensitivity to variations of the elements that make up the "measurement function". However, the authors themselves point out that this method does not provide an accurate measure of (anti)fragility, serving only to guide whether a system is more fragile than antifragile.

Based on the assumption that antifragility is the improved resilience [49], it is important to highlight the characteristics that improve resilience in order to measure antifragility. In this line, De Florio firstly defines Antifragility as an associate of resilience, elasticity and machine learning [50]. After, De Florio [41] proposes that resilience - as an emergent property resulting from the interaction between systems and environment - can be seen as the product of internal behaviours. In its turn, such behaviours are linked to "resilient organs", which the author associates with the MAPE-K loop of autonomic computation, where each element corresponds to the following capacity:

- M = to perceive the changes;
- A = to perceive the consequences of the changes;
- P = to plan against threats;

- E = to execute the planned;
- K = to learn and thereby improve the skills M, A, P and E, improving the system [51].

Such a methodology makes it possible to compare any two resilient systems, p1 and p2, through their behavioral classes β_1 and β_2, where to say that $\beta_1 < \beta_2$ is the same as saying that p_1 demonstrates a systemically inferior resilience to that presented by p_2 [41]. However, it still does not provide an exact measure of antifragility, but it demonstrates which features of the system dictate its resilience and consequently its antifragility. This is in contrast to previous work by the author, where antifragility is the product of increased elasticity resilience and machine learning [50]. In addition, Verhulsta [52] introduces the ARRL (Assured Reliability and Resilience Level) where he argues that for the emergence of the antifragilidade of the complex systems, it is necessary: 1) Openness, where all information must be shared and accessible to all; 2) constant feedbacks, among all agents involved; 3) independent regulatory agents; 4) fault tolerance, possible by redundancy; 5) existence of stress, factor that encourages the development; 6) knowledge, acquired through learning with mistakes and failures; 7) constant reconfiguration capability.

Rafi et al. [43], when addressing the Islamic financial system highlights as characteristic that make it antifragile: 1) Prohibition of asymmetric information and speculation; 2) Collaborative and collective behavior; 3) Bottom-up management and adjustments; 4) Redundant agents; 5) Creative destruction, where through feedback and learning, failures and mistakes aid in the process of system improvement;

In search of a more accurate measure, Johnson & Gheorghe [2], aiming to measure the antifragilidade of the electrical network of the USA, list some analytical criteria of antifragility observed by them in the work of Casti [14], Taleb [1] and Jackson & Ferris [53]. These criteria are:

1) *Entropy*: increasing complexity over time. It leads to the increase of uncertainties and unpredictability, leading to the emergence of X-Events;
2) *Emergence*: The relationship between agents results in unforeseeable outputs that cannot be explained by the individual analysis of the parts;
3) *Efficiency Vs. Risk*: the higher the risk protection the lower the system efficiency;
4) *Balancing Constraints Vs. Freedom*: The ideal is to have a balance, without too many restrictions or freedom. The greater the degree of freedom, the greater the exposure of the system to X-Events;
5) *Coupling (Loose/Tight):* The more interconnected (coupled) agents are, the more fragile the system tends to be;
6) *Requisite Variety*: The need for regulatory agents to monitor and control outcomes and behaviors of agents and systems. Without proper regulation, the trend of occurrence of X-Events is greater;
7) *Stress Starvation*: Stress retention and quest for constant balance tends to make systems fragile. Small doses of stress and disorder increase the resilience/antifragility of systems;
8) *Redundancy*: Presence of agents with the same functionality. It generates excessive capacity and prevents faults. From a certain point, it can plaster the system and make it fragile.
9) *Non-Monotonicity*: Errors and failures along with new information are elements of learning to the system, which can lead to the improvement of old processes or the generation of new practices and approaches.
10) *Absorption*: Ability to absorb stress and shocks while remaining in the planned state. The higher the absorption capacity, the stronger the system tends to be. It is a prerequisite for antifragility.

Each criterion encompasses important organizational characteristics related to stakeholders, such as strategy, policy, processes, etc. Based on these criteria and characteristics, questions arise whose answers support the understanding of how the system tends to respond to stress. Through a set of responses – based on the 5-point Likert scale, which can range from (1) Strongly disagree to (5) Strongly agree or (1) Significantly degrade to (5) Significantly improve – the authors can obtain easy-to-measure responses, which take a quantitative form, the antifragility of each organization being represented by its average of the criteria values [2].

By adopting this same methodology, Ghasemi & Alizeradeh [18] select 7 out of 10 antifragility analytical criteria and request that collaborators of the analyzed organization respond to the elaborated questionnaire. Subsequently, linguistic responses were transformed into quantitative variables through the use of triangular fuzzy numbers and, in the end; it was possible to attribute an exact measure of antifragility to the organization.

In Table I, we highlight 6 criteria that we consider important for the antifragility measurement process. In it, it is possible to observe that, even with different forms or names, some of the analytical characteristics of the antifragility are redundant among the analyzed works. Thus, we can assume that these characteristics are the most important for the emersion and improvement of the antifragility.

III. Methodology

In this section we will discuss the steps and methods used throughout this work. Each process revolves around the measurement of the degree of Antifragility, represented here by the BAI, of each one of the 42 financial organizations analysed.

We chose to use a questionnaire, composed of 18 questions related to the 6 analytical criteria of Antifragility - redundancy, emergence, requisite variety, stress starvation, non-monotonicity and absorption - chosen for the IAB calculation. Through the choice of variables linked to the most diverse fields, we seek to provide a more comprehensive analysis of the company, through a more holistic view, consistent with the complexity that torments them and that is becoming more and more present in our day to day. Each question will be answered through a five-point Likert scale, ranging from the weakest (1) to the strongest (5).

TABLE I
ANTIFRAGILITY ANALYTICAL CRITERIA

Johnson & Gheorghe [2]	De Florio [50]	De Florio [41]	Verhulsta [52]	Rafi et al. [43]
Antifragility Analytical Criteria	Antifragility Equation	"Resilient Organs" (loop MAPE-K)	ARRL Classes	Islamic Finance System
Redundancy			Fault Tolerance; Defences against risks	Redundant Agents
Emergence	Elasticity; Machine Learning		Knowledge; Constant reconfiguration capability	Bottom-up
Requisite Variety		M	Opening; Independent regulatory agents	Prohibition of asymmetric information and speculation
Stress Starvation	Elasticity	A and M	Fault Tolerance; Existence of stress	
Non-Monotonicity	Machine Learning	P, E and K	Constant Feedback; Knowledge; Constant reconfiguration capability	Collaborative and collective behavior; Creative destruction
Absorption	Resilience		Fault Tolerance	

In order to avoid distortions and biases that could be caused by the collection of responses from employees of organizations, it was decided to use public data from such organizations (or related to them) to respond to the questionnaire. The variables on which the answers were based on were chosen after extensive analysis and debate among some financial professionals. In Table II we can see the variables chosen and to which criterion they are related.

TABLE II
ANTIFRAGILITY ANALYTICAL CRITERIA AND THEIR MEASUREMENT VARIABLES

Antifragility Analytical Criteria	**Synthesis**	**Variables**
Redundancy	Fault Tolerance Defences against risks	Numbers of employee Shareholder other banks
Emergence	Knowledge and innovation Bottom-up movements	Brand Value Corporate University Research Institute Startup Accelerator R&D centers
Requisite Variety	Information sharing Regulation and audit	Developed Portal Rating
Stress Starvation	Fault tolerance	Government agency Beta (β) Capital ratio Basel AML Index Probability of default (PD)
Non-Monotonicity	Ability to learn and improve Constant feedback	% Revenue Growth Δ Brand value
Absorption	Resilience Ability of adaptation	ESG Rating EBITDA margin

When transcribing the answers through the Likert scale, a standardization of the measurement units is carried out. However, for correct manipulation and analysis of the variables it is necessary to impute numerical values, which represent them with their corresponding degrees, and for this we opted for the use of the triangular fuzzy number (TFN).

The TFN is usually represented by A = (l, m, u), where l and u respectively correspond to the lower and upper limit and m to the mean value. Its function of pertinence, encompasses all possible values that a specific variable can assume and is represented by $\mu_A(x) : X \rightarrow [0,1]$. Its triangular shape can be described as:

$$\mu_A(x) = \begin{cases} \frac{x-l}{m-l}, & l < x < m \\ 1, & x = m \\ \frac{u-x}{u-m}, & m < x < l \\ 0, & x < u \; or \; x > l \end{cases}$$

In Fig. 5, we have the graphical representation of the degree of pertinence of the set, where it is possible to glimpse that m assumes the highest value.

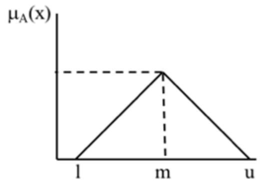

Fig. 6 TFN

In order to transform the qualitative terms, represented by the 5 degrees of Likert scale (strongly disagree, neutral, agree and strongly agree), into TFN, we chose the simple division of the interval [0,1], as we can see in Table III.

TABLE III
RESPONSE INTERVAL

Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
(0.0, 0.1, 0.2)	(0.2, 0.3, 0.4)	(0.4, 0.5, 0.6)	(0.6, 0.7, 0.8)	(0.8, 0.9, 1.0)

For each criterion in the Antifragility measurement equation a weight should be assigned. Our first idea was to use the Shannon entropy method (as used by Ghasemi & Alizeradeh [18]), which, for being objective, obtains the weights through mathematical models and does not undergo any influence of the preferences of the decision maker. However, since there is no set of answers but only one answer – based on predetermined parameters on the institutions – for each question, the use of Shannon entropy method to calculate the weights of each criterion is invalidated. Given this, after discussing the importance of each criterion, we chose to define the same weight for all.

In Table IV it is possible to see the mean of the answers of each criterion.

TABLE IV
VALUES OF EACH ANTIFRAGILITY ANALYTICAL CRITERION

Org.	Redundancy	Emergence	Requisite Variety	Stress Starvation	Non-Monotonicity	Absorption
HSBC	(0.2, 0.3, 0.4)	(0.68, 0.78, 0.88)	(0.7, 0.8, 0.9)	(0.44, 0.54, 0.64)	(0.3, 0.4, 0.5)	(0.4, 0.5, 0.6)
UBS	(0.2, 0.3, 0.4)	(0.44, 0.54, 0.64)	(0.6, 0.7, 0.8)	(0.40, 0.50, 0.60)	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)
Goldman Sachs	(0.0, 0.1, 0.2)	(0.32, 0.42, 0.52)	(0.6, 0.7, 0.8)	(0.32, 0.42, 0.52)	(0.7, 0.8, 0.9)	(0.4, 0.5, 0.6)
Bank of America	(0.2, 0.3, 0.4)	(0.64, 0.74, 0.84)	(0.6, 0.7, 0.8)	(0.36, 0.46, 0.56)	(0.7, 0.8, 0.9)	(0.4, 0.5, 0.6)
Citigroup	(0.2, 0.3, 0.4)	(0.64, 0.74, 0.84)	(0.7, 0.8, 0.9)	(0.32, 0.42, 0.52)	(0.7, 0.8, 0.9)	(0.4, 0.5, 0.6)
Credit Suisse	(0.0, 0.1, 0.2)	(0.52, 0.62, 0.72)	(0.6, 0.7, 0.8)	(0.32, 0.42, 0.52)	(0.5, 0.6, 0.7)	(0.5, 0.6, 0.7)
JPMorgan	(0.5, 0.6, 0.7)	(0.56, 0.66, 0.76)	(0.6, 0.7, 0.8)	(0.40, 0.50, 0.60)	(0.8, 0.9, 1.0)	(0.6, 0.7, 0.8)
Morgan Stanley	(0.0, 0.1, 0.2)	(0.48, 0.58, 0.68)	(0.6, 0.7, 0.8)	(0.36, 0.46, 0.56)	(0.7, 0.8, 0.9)	(0.4, 0.5, 0.6)
RBS	(0.0, 0.1, 0.2)	(0.40, 0.50, 0.60)	(0.6, 0.7, 0.8)	(0.64, 0.74, 0.84)	(0.2, 0.3, 0.4)	(0.5, 0.6, 0.7)
Barclays	(0.0, 0.1, 0.2)	(0.48, 0.58, 0.68)	(0.7, 0.8, 0.9)	(0.44, 0.54, 0.64)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)
Wells Fargo	(0.2, 0.3, 0.4)	(0.64, 0.74, 0.84)	(0.7, 0.8, 0.9)	(0.32, 0.42, 0.52)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
Santander	(0.2, 0.3, 0.4)	(0.40, 0.50, 0.60)	(0.6, 0.7, 0.8)	(0.36, 0.46, 0.56)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
Deutsche Bank	(0.2, 0.3, 0.4)	(0.52, 0.62, 0.72)	(0.7, 0.8, 0.9)	(0.28, 0.38, 0.48)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
Credit Agricole	(0.0, 0.1, 0.2)	(0.40, 0.50, 0.60)	(0.6, 0.7, 0.8)	(0.36, 0.46, 0.56)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)
BNP Paribas	(0.3, 0.4, 0.5)	(0.52, 0.62, 0.72)	(0.7, 0.8, 0.9)	(0.36, 0.46, 0.56)	(0.5, 0.6, 0.7)	(0.5, 0.6, 0.7)
Mitsubishi UFJ FG	(0.4, 0.5, 0.6)	(0.48, 0.58, 0.68)	(0.6, 0.7, 0.8)	(0.32, 0.42, 0.52)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
Bank of China	(0.3, 0.4, 0.5)	(0.56, 0.66, 0.76)	(0.6, 0.7, 0.8)	(0.44, 0.54, 0.64)	(0.7, 0.8, 0.9)	(0.4, 0.5, 0.6)
Mizuho FG	(0.0, 0.1, 0.2)	(0.44, 0.54, 0.64)	(0.6, 0.7, 0.8)	(0.40, 0.50, 0.60)	(0.5, 0.6, 0.7)	(0.5, 0.6, 0.7)
Societe Generale	(0.1, 0.2, 0.3)	(0.52, 0.62, 0.72)	(0.6, 0.7, 0.8)	(0.32, 0.42, 0.52)	(0.6, 0.7, 0.8)	(0.3, 0.4, 0.5)
ING Bank	(0.0, 0.1, 0.2)	(0.44, 0.54, 0.64)	(0.7, 0.8, 0.9)	(0.44, 0.54, 0.64)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)
Sumitomo Mitsui FG	(0.2, 0.3, 0.4)	(0.44, 0.54, 0.64)	(0.6, 0.7, 0.8)	(0.40, 0.50, 0.60)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
Unicredit Group	(0.0, 0.1, 0.2)	(0.40, 0.50, 0.60)	(0.7, 0.8, 0.9)	(0.28, 0.38, 0.48)	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)
Nordea Bank	(0.0, 0.1, 0.2)	(0.32, 0.42, 0.52)	(0.7, 0.8, 0.9)	(0.40, 0.50, 0.60)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)
BBVA	(0.1, 0.2, 0.3)	(0.52, 0.62, 0.72)	(0.7, 0.8, 0.9)	(0.36, 0.46, 0.56)	(0.7, 0.8, 0.9)	(0.4, 0.5, 0.6)
Standard Chartered	(0.0, 0.1, 0.2)	(0.36, 0.46, 0.56)	(0.7, 0.8, 0.9)	(0.32, 0.42, 0.52)	(0.8, 0.9, 1.0)	(0.4, 0.5, 0.6)
Bank of NY Mellon	(0.2, 0.3, 0.4)	(0.48, 0.58, 0.68)	(0.6, 0.7, 0.8)	(0.40, 0.50, 0.60)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
State Street	(0.4, 0.5, 0.6)	(0.44, 0.54, 0.64)	(0.6, 0.7, 0.8)	(0.40, 0.50, 0.60)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)
CCB	(0.3, 0.4, 0.5)	(0.48, 0.58, 0.68)	(0.6, 0.7, 0.8)	(0.44, 0.54, 0.64)	(0.7, 0.8, 0.9)	(0.5, 0.6, 0.7)
ABC	(0.4, 0.5, 0.6)	(0.44, 0.54, 0.64)	(0.6, 0.7, 0.8)	(0.48, 0.58, 0.68)	(0.7, 0.8, 0.9)	(0.3, 0.4, 0.5)
Bank of Commun.	(0.2, 0.3, 0.4)	(0.36, 0.46, 0.56)	(0.6, 0.7, 0.8)	(0.52, 0.62, 0.72)	(0.7, 0.8, 0.9)	(0.5, 0.6, 0.7)
China Merchants	(0.2, 0.3, 0.4)	(0.44, 0.54, 0.64)	(0.6, 0.7, 0.8)	(0.36, 0.46, 0.56)	(0.8, 0.9, 1.0)	(0.5, 0.6, 0.7)
RBC	(0.0, 0.1, 0.2)	(0.52, 0.62, 0.72)	(0.7, 0.8, 0.9)	(0.48, 0.58, 0.68)	(0.7, 0.8, 0.9)	(0.5, 0.6, 0.7)
Commonwealth Bank	(0.0, 0.1, 0.2)	(0.32, 0.42, 0.52)	(0.7, 0.8, 0.9)	(0.44, 0.54, 0.64)	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)
Itau Unibanco	(0.3, 0.4, 0.5)	(0.32, 0.42, 0.52)	(0.5, 0.6, 0.7)	(0.40, 0.50, 0.60)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)
ICBC	(0.4, 0.5, 0.6)	(0.64, 0.74, 0.84)	(0.6, 0.7, 0.8)	(0.48, 0.58, 0.68)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
Lloyds Banking	(0.0, 0.1, 0.2)	(0.32, 0.42, 0.52)	(0.7, 0.8, 0.9)	(0.52, 0.62, 0.72)	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)
Citic Limited	(0.2, 0.3, 0.4)	(0.44, 0.54, 0.64)	(0.6, 0.7, 0.8)	(0.36, 0.46, 0.56)	(0.6, 0.7, 0.8)	(0.3, 0.4, 0.5)
Commerzbank AG	(0.0, 0.1, 0.2)	(0.32, 0.42, 0.52)	(0.6, 0.7, 0.8)	(0.36, 0.46, 0.56)	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)
Intesa Sanpaolo	(0.0, 0.1, 0.2)	(0.32, 0.42, 0.52)	(0.6, 0.7, 0.8)	(0.40, 0.50, 0.60)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6)
Bradesco	(0.2, 0.3, 0.4)	(0.40, 0.50, 0.60)	(0.5, 0.6, 0.7)	(0.36, 0.46, 0.56)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)
Banco do Brasil	(0.0, 0.1, 0.2)	(0.44, 0.54, 0.64)	(0.6, 0.7, 0.8)	(0.44, 0.54, 0.64)	(0.3, 0.4, 0.5)	(0.4, 0.5, 0.6)
Westpac Banking	(0.0, 0.1, 0.2)	(0.40, 0.50, 0.60)	(0.6, 0.7, 0.8)	(0.40, 0.50, 0.60)	(0.4, 0.5, 0.6)	(0.5, 0.6, 0.7)

IV. RESULTS

From the results found for each analysis criterion of antifragility of the institutions, we were able to identify the BAI for each of the 42 financial institutions analysed by us.

In Table V it is possible to see the BAI of each institution.

The values are in a range of 0 to 1, where the higher the value, the more antifragile the organization tends to be. In addition, to facilitate the framing and comparison of results found, the median value (m) of the set is used to represent the BAI of each organization. Thus, in the sample of financial institutions analysed, JP Morgan is the one that shows the highest value, 0.68, and Banco do Brasil S.A., the lowest, 0.46.

V. CONCLUDING REMARKS

After a bibliographical review, an extensive analysis of the studies and existing methods related to the measurement of corporate antifragility was made and we chose the use of fuzzy logic, since it was the one that best suited our needs and demands. In conjunction with the use of antifragility analytical criteria, previously highlighted by Ghasemi & Alizadeh [18], and with the choice of pre-established variables to represent and measure it, it was possible to avoid bias in the answers given to the questionnaire created.

Through the transcription of Likert scale responses to numerical values, we were able to find satisfactory results - easy to analyse and compare - for the measurement of the BAI of each institution. The use of variables from the most diverse areas allowed a more holistic view/analysis of the organizations, like CAS, which are permeated and surrounded by complexity.

TABLE V
VALUES OF BAI

Financial Organization	BAI	Financial Organization	BAI	Financial Organization	BAI
JPMorgan	(0.58, 0.68, 0.78)	BBVA	(0.46, 0.56, 0.66)	Credit Agricole S.A.	(0.41, 0.51, 0.61)
ICBC	(0.52, 0.62, 0.72)	UBS	(0.46, 0.56, 0.66)	Mizuho FG	(0.41, 0.51, 0.61)
Bank of China	(0.50, 0.60, 0.70)	HSBC	(0.45, 0.55, 0.65)	Societe Generale	(0.41, 0.51, 0.61)
China Construction Bank	(0.50, 0.60, 0.70)	Deutsche Bank	(0.45, 0.55, 0.65)	Lloyds Banking Group	(0.41, 0.51, 0.61)
Citigroup	(0.49, 0.59, 0.69)	ING Bank	(0.45, 0.55, 0.65)	Credit Suisse	(0.41, 0.51, 0.61)
State Street	(0.49, 0.59, 0.69)	Bank of NY Mellon Co.	(0.45, 0.55, 0.65)	Itau Unibanco Holding	(0.40, 0.50, 0.60)
ABC	(0.49, 0.59, 0.69)	Sumitomo Mitsui FG	(0.44, 0.54, 0.64)	Commerzbank AG	(0.40, 0.50, 0.60)
Bank of America	(0.48, 0.58, 0.68)	Santander	(0.43, 0.53, 0.63)	Goldman Sachs	(0.39, 0.49, 0.59)
Wells Fargo	(0.48, 0.58, 0.68)	Standard Chartered	(0.43, 0.53, 0.63)	Royal Bank of Scotland	(0.39, 0.49, 0.59)
BNP Paribas S.A	(0.48, 0.58, 0.68)	Commonwealth Bank	(0.43, 0.53, 0.63)	Intesa Sanpaolo	(0.39, 0.49, 0.59)
Bank of Communications Co.	(0.48, 0.58, 0.68)	Morgan Stanley	(0.42, 0.52, 0.62)	Bradesco S.A.	(0.39, 0.49, 0.59)
China Merchants Bank	(0.48, 0.58, 0.68)	Barclays	(0.42, 0.52, 0.62)	Westpac Banking Co.	(0.38, 0.48, 0.58)
Royal Bank of Canada	(0.48, 0.58, 0.68)	Nordea Bank	(0.42, 0.52, 0.62)	Unicredit Group	(0.36, 0.46, 0.56)
Mitsubishi UFJ FG	(0.47, 0.57, 0.67)	Citic Limited	(0.42, 0.52, 0.62)	Banco do Brasil S.A.	(0.36, 0.46, 0.56)

From the results presented, it can be seen that banks with higher BAIs have positive changes in their brand value in the last year and increase their annual profit. This fact, from our view, is intrinsically linked to most of these institutions possessing excellent levels of investments and actions in innovation and education, through Labs and R&D Centers, Research Institutes, Startup Accelerator Partnership and Corporate University and/or partnerships with universities.

Taking into account the analysis of the data collected and the results presented, we can see that the present study presents some limitations due to the lack of data availability of some institutions. This limitation hinders a more comprehensive analysis of the activities of institutions that, according to the expertise of some professionals in the industry, would be linked to the development of corporate antifragility.

It should be noted that each branch of business tends to have its own set of variables linked to the development of the antifragility of its companies. In future works, it would be important to incorporate more variables into the antifragility measurement set of organizations. The more variables – confined to the different antifragility analytical criteria – make up the measurement process, more comprehensive and consistent with the corporate capacity to survive X-Events and to benefit from disorder and chaos tend to be the indexes found.

Finally, we would like to point out that even though there are still points to improve, our work shows a good progress in relation to previous analyses. Our analysis is based on data, not employee perceptions or opinions, which reduces or eliminates the noise present in the results. In addition, we are not limited to measuring the antifragility of a single company. Through BAI, it is possible to analyse a sample of institutions and compare their levels of antifragility, which provides important information for organizations to improve the development of their antifragility.

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