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Original Article

On the edge: The impacts of cash flow at risk on the shareholders' equity of public companies in Brazil

Bruno Meirelles Salotti[1]
https://orcid.org/0000-0002-2735-7048
Email: brunofea@usp.br

João Vinícius de França Carvalho[1]
https://orcid.org/0000-0002-1076-662X
Email: jvfcarvalho@usp.br

[1] Universidade de São Paulo, Faculdade de Economia, Administração, Contabilidade e Atuária, Departamento de Contabilidade e Atuária, São Paulo, SP, Brazil

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ABSTRACT

The objective of this article was to measure the cash flow at risk (CFaR) of non-financial companies in the Brazilian capital market and compare it to shareholders' equity in order to assess the risk of insolvency. Unlike banks and insurance companies, which have strong capital requirements, the current regulation of non-financial institutions in Brazil does not provide for the calculation or maintenance of a minimum shareholders' equity. This study fills a gap in the literature by relating CFaR to the shareholders' equity of entities, providing a measure of insolvency risk. Monitoring insolvency risk (*i.e.*, the possibility of negative shareholders' equity) is critical for any entity, regardless of its industry, market, or size. The results of the CFaR measurement show that companies in different sectors can be exposed to insufficient resources in the event of operational problems. It is hoped that this will help regulators in different sectors to assess minimum capital requirements. CFaR was measured using Ebit and Ebitda (quarterly and annual). The panel consisted of 186 companies listed on the B³ between 2010 and 2022, totaling 4,897 company-quarters. The companies were divided into eight subgroups based on their characteristics. The results showed that non-financial listed companies in the Brazilian market may be undercapitalized, as 18% of the 169 entities that currently have positive shareholders' equity would become negative at a 1% risk level. CFaRs were also re-estimated during the pandemic and did not show a clear pattern compared to other periods.

Keywords: insolvency risk, capital requirement, cash flow at risk, ruin probability.

Correspondence address

Bruno Meirelles Salotti
Universidade de São Paulo, Faculdade de Economia, Administração, Contabilidade e Atuária, Departamento de Contabilidade e Atuária
Avenida Professor Luciano Gualberto, 908 – CEP: 05508-010
Butantã – São Paulo – SP – Brazil

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No limite: impactos do fluxo de caixa em risco sobre o patrimônio líquido de empresas de capital aberto no Brasil

RESUMO

O objetivo deste artigo foi mensurar o fluxo de caixa sob risco (CFaR) de companhias não financeiras do mercado de capitais brasileiro e compará-lo ao patrimônio líquido, avaliando o risco de insolvência. Diferentemente de bancos e seguradoras, que possuem fortes exigências de capital, a regulação atual de instituições não financeiras no Brasil não prevê o cálculo nem a manutenção de um patrimônio líquido mínimo. Este estudo preenche uma lacuna da literatura ao relacionar o CFaR com o Patrimônio Líquido das entidades, fornecendo uma medida de risco de insolvência. Monitorar o risco de insolvência (i.e., possibilidade de o patrimônio líquido tornar-se negativo) é vital para qualquer entidade, independentemente do setor de atuação, mercado ou porte. Os resultados da mensuração do CFaR mostram que empresas de diversos setores econômicos podem estar expostas à insuficiência de recursos em caso de problemas operacionais. Espera-se fornecer subsídios a órgãos reguladores de diversos setores, para avaliarem as exigências de capital mínimo. O CFaR foi medido utilizando o Ebit e o Ebitda (trimestrais e anuais). O painel foi composto por 186 empresas listadas na B³, entre 2010-2022, totalizando 4.897 empresas-trimestres. Segregaram-se as empresas em oito subgrupos, baseados em suas características. Como resultado, descobriu-se que as companhias abertas não financeiras do mercado brasileiro podem estar com baixa capitalização, pois 18% das 169 entidades que atualmente possuem patrimônio líquido positivo passariam a tê-lo negativo ao nível de risco de 1%. Também foram reestimados os CFaR durante a pandemia, não apresentando padrão distinto em relação aos demais períodos.

Palavras-chave: *risco de insolvência, requerimento de capital, fluxo de caixa sob risco, probabilidade de ruína.*

1. INTRODUCTION

In all types of entities, regardless of their legal nature, segment or size, there is the presence of risks and, consequently, the need to measure and manage them (Cowell et al., 2007). However, risk measurement and management techniques have been developed and improved in a more intensive and sophisticated way in the financial industry, particularly in insurance companies and banking institutions (Andrieș et al., 2022; Moratis & Sakellaris, 2021).

It is no coincidence that the rules imposed by banking and insurance regulators require a minimum amount of capital for entities to be able to operate in the market, addressing the different risks to which they are exposed and thus minimizing the likelihood of insolvency (Areias & Carvalho, 2021; Ramsden & Papaioannou, 2019), which is damaging both to shareholders and to the health of the financial system (Harrington, 2009). In Brazil, for example, banks must follow the determinations of the Central Bank, which are based on the "Basel III" pillars (Oliveira & Ferreira, 2019). Insurers, on the other hand, must follow the rules of the Superintendence of Private Insurance (Susep), which establishes the minimum required capital, *i.e.*, the minimum amount of capital that insurers must maintain in order to operate (Carvalho & Cardoso, 2021; Euphasio Junior & Carvalho, 2022; Macohon et al., 2017).

However, for non-financial institutions, although similar risk management and measurement techniques apply, the regulation for such entities in Brazil (under the jurisdiction of the Brazilian Securities and Exchange Commission [CVM]) does not currently require the calculation and maintenance of a minimum shareholders' equity.

Several researchers have worked on developing models to measure risks in non-financial institutions. One of the pioneering works was RiskMetrics (1999), a technical paper published by JP Morgan in collaboration with the RiskMetrics Group, which proposed an adaptation of the traditional value at risk (VaR). VaR is typically used in financial institutions to measure the potential expected loss in market value of portfolios, and it was adapted by RiskMetrics (1999) to measure potential cash flow losses in non-financial institutions. This gave rise to cash flow at risk (CFaR).

Stein et al. (2001) proposed an alternative method for measuring CFaR. According to the authors, directly adapting the bottom-up methodology used for VaR to calculate CFaR implies identifying and measuring each type of risk exposure in a company, which can lead to highly inaccurate CFaR estimates. Faced with this difficulty, the authors developed the top-down methodology by constructing an empirical distribution of cash flow at risk based on historical cash flow data. However, since the amount of data from one company is too small to allow such estimates, all the companies in the market are aggregated so that later, based on the specific characteristics of each entity, it is possible to identify the corresponding empirical distribution of CFaR.

Following the development of the first models for measuring risk in non-financial entities, several studies have applied these models to real data, both in Brazil (Bego, 2007; Januzzi et al., 2012; Perobelli et al., 2007, 2011; Perobelli & Securato, 2005) and abroad (Jang et al., 2011; Oral & CenkAkkaya, 2015; Özvural, 2004; Xu, 2019; Yan et al., 2014). However, in none of these studies did the authors relate the measurement of the risk of non-financial institutions to the demand for equity capital that might be needed to cover this risk and, consequently, minimize the probability of failure of these firms.

An option available to companies under Brazilian corporate law is the creation of a contingency reserve (Article 195 of Law 6,404/1976). According to this law, the shareholders' meeting can set aside part of net income to create this reserve, with the purpose of compensating, in a future financial year, for a loss considered probable. However, apart from being an option, there is no specific guideline for measuring this possible reserve. Therefore, it is not possible to claim that the creation of this contingency reserve is fulfilling the role of retaining the shareholders' equity necessary to minimize the probability of company failure.

The objective of this study is to measure the cash flow at risk (CFaR) of non-financial companies in the Brazilian capital market and compare it to the shareholders' equity of these institutions. Therefore, it proposes an actuarial model for measuring the insolvency risk of non-financial entities based on their financial information published in the Brazilian capital market.

2. THEORETICAL AND EMPIRICAL FOUNDATIONS

2.1 Insolvency Risk and Capital Requirements

Insolvency risk can be defined as the possibility of an entity not having enough assets to pay its liabilities, *i.e.* the risk of its shareholders' equity becoming negative. Monitoring insolvency risk is therefore essential for any entity, regardless of its sector, market or size. It is no coincidence that this topic has been on the agenda of several researchers for decades (Altman, 1968; Beaver, 1966; Horobet et al., 2021).

However, the monitoring of this risk is more acute in the financial sector (e.g. banks and insurance companies), where the bankruptcy of one entity generates high systemic risk due to the contagion that it generates in the rest (Harrington, 2009; Moratis & Sakellaris, 2021).

To mitigate this risk, regulators of financial and insurance institutions set capital requirements using sophisticated risk measurement and management models. These requirements are derived from international agreements known as "Basel III" for financial institutions (Andrieş et al., 2022; Oliveira & Ferreira, 2019) and "Solvency II" for insurance companies (Carvalho & Cardoso, 2021; Chen & Yuan, 2017; Macohon et al., 2017). In essence, regulations based on these agreements require institutions to assess their risks and, based on this, to maintain a minimum amount of capital to minimize the risk of insolvency (Euphasio Junior & Carvalho, 2022; Gupta & Liang, 2005; Ramsden & Papaioannou, 2019).

As for non-financial institutions, although they are also subject to insolvency risk, there is currently no minimum capital requirement. The research over the past 25 years has been based on adapting the traditional value at risk (VaR) model to measure potential losses in cash flows (Artzner et al., 1999), giving rise to the measure cash flow at risk (CFaR).

2.2 Cash Flow at Risk

One of the first conceptual formalizations of CFaR was developed by RiskMetrics (1999). It is defined as the maximum expected shock to net cash generated relative to a specific objective that could result from the impact of market risk on a limited set of exposures, for a given disclosure period and confidence level. Although the concept of the CFaR measure was introduced in this technical paper, the measurement of the measure using a technique similar to VaR would be done by applying a bottom-up approach, which would imply identifying the components of the cash flow exposed to market risk.

Appropriating the concept of CFaR proposed by RiskMetrics (1999), Stein et al. (2001) presented another proposal for measuring CFaR, which the authors called the top-down approach. This methodology focuses on the variability of a company's historical cash flows. Stein et al. (2001) argue that this strategy has the advantage of summarizing the combined effect of all of an entity's relevant risks, because if a company's CFaR is high, it should be reflected in a high volatility of its historical cash flows.

The methodology used by Stein et al. (2001) – detailed in the "Methodology" section of this article – evaluates the volatility of a firm's cash flows by aggregating it with other firms that are comparable in terms of their characteristics. This provides a non-parametric distribution of possible shocks to its cash flows, and a specific percentile of the tail of that distribution. On the other hand, this method has disadvantages, as Andren et al. (2005) point out: a firm that is part of a cash flow distribution may be very different from the average firm in the sample. Furthermore, the top-down approach does not provide an estimate of CFaR conditional on market risk.

Therefore, Andren et al. (2005) proposed a third approach called "exposure-based CFaR". Measurement using this methodology is based on the estimation of a set of exposure coefficients (deltas) that provide information on how the various macroeconomic and market variables are expected to affect a firm's cash flows. These coefficients are estimated using multiple regression, allowing a company's risk exposures to be used to calculate CFaR. This approach is more managerial in nature and allows management to assess the factors that explain the variability of cash flows as a result of the various risks to which the entity is exposed.

In addition to these approaches, there are others, such as those proposed by Maurer (2015) or LaRocque et al. (2003). Each method has its advantages and disadvantages. The development of different models for measuring CFaR demonstrates its relevance and the enormous potential of these studies to contribute to the development of risk management models for non-financial companies.

The empirical application of these models has been developed both in Brazil (Bego, 2007; Januzzi et al., 2012; Perobelli et al., 2007, 2011; Perobelli & Securato, 2005) and abroad (Jang et al., 2011; Oral & CenkAkkaya, 2015; Özvural, 2004; Xu, 2019; Yan et al., 2014). Each study analyzes different markets, time periods, and activity segments, and each uses different methodological choices. Therefore, it is not possible to directly compare the results. However, it should be noted that none of these studies correlates the calculated CFaR with the shareholders' equity of the evaluated entities in order to assess the risk of insolvency. This is the gap that this study aims to explore.

2.3 Cash Flow Measures Used to Calculate CFaR

The operating cash flow measure used by Stein et al. (2001) to operationalize the CFaR model was earnings before interest, taxes, depreciation and amortization (Ebitda). In addition, the authors note that their model can be built using other metrics, such as Ebit.

Stumpp et al. (2000) identify ten failings of Ebitda in fulfilling its role as the principal determinant of cash flow. These include the fact that Ebitda ignores changes in working capital (and therefore overstates cash flow in periods of working capital growth) and ignores reinvestment needs, especially for firms with assets with short useful lives. This is because in these cases the value of depreciation will tend to be significantly high, and therefore Ebitda will be high. However, just as depreciation is relatively high, so is the demand for new long-term investments, *i.e.* Ebitda is not free cash flow. In this respect, Ebit might be more appropriate, assuming that depreciation can be used as an estimate of reinvestment.

Another serious problem with Ebitda and Ebit is that they are non-GAAP measures. Therefore, they are susceptible to discretionary adjustments made by managers to artificially inflate investors' future expectations (Barsky & Catanach, 2014). For this reason, the manner in which non-GAAP measures are disclosed has been a matter of concern for regulators around the world (Black et al., 2018).

3. METHODOLOGY

To measure the companies' CFaR, we chose to adapt the top-down methodology developed by Stein et al. (2001), which consists of measuring CFaR based on historical cash flow forecast errors using time series models. The advantage of this type of model is that it preserves the historical and idiosyncratic characteristics of companies. The methodology used is described below.

3.1 Modeling for the Construction of CFaR

3.1.1 Step 1: Defining the operating cash flow measure

Stein et al. (2001) used Ebitda as a measure of cash flow to operationalize the CFaR model. In this study, we also used Ebitda. However, in order to assess the robustness and to minimize any issues arising from the use of Ebitda, as highlighted in the "Theoretical and Empirical Foundations" section, all the tests were re-run using Ebit.

3.1.2 Step 2: Time series models to forecast estimated quarterly cash flow

In order to measure how much cash flow deviates from expectations, it is first necessary to forecast expected cash flow (both on a quarterly and annual basis). Therefore, an autoregressive time series model of order 4 with exogenous variables – ARX(4) – was used for each company in order to capture the dynamics of a full fiscal year. Time dummies were included to control for possible periodic effects.

$$CF_t = \phi_1 CF_{t-1} + \phi_2 CF_{t-2} + \phi_3 CF_{t-3} + \phi_4 CF_{t-4} + \sum_{j=1}^{3} \beta_j D_j + \varepsilon_t \quad \boxed{1}$$

where CF_t is cash flow measured in the t-th quarter, divided by total assets on date $t-1$; D_j are the quarter dummies; ϕ_j, β_j, $j = 1, \ldots, 3$ are the parameters to be estimated; and ε_t represents the random shocks of period t.

The Box-Jenkins methodology implemented in the R software was used to estimate the models for each company, with the parameters adjusted using the maximum likelihood method. For all quarters, the model was adjusted using the last five years of data, following the methodology of Stein et al. (2001).

3.1.3 Step 3: Time series models to forecast estimated annual cash flow

The forecast uses the same explanatory variables as Equation 1 (as well as the dummies). However, the variables are on an annual basis because they represent the sum of the cash flow for quarters t, $t-1$, $t-2$, and $t-3$, divided by total assets in period $t-4$, so that the companies can be compared. Equation 2 is specified as follows:

$$CF_t = \phi_1 CF_{t-1} + \phi_2 CF_{t-2} + \phi_3 CF_{t-3} + \phi_4 CF_{t-4} + \sum_{j=1}^{3} \beta_j D_j + \varepsilon_t \quad \boxed{2}$$

where CF_t represents the sum of the forecasts for the four consecutive quarters (t, $t-1$, $t-2$, and $t-3$), *i.e.*, the annual forecasted cash flow, divided by total assets on date $t-4$; ϕ_j, β_j, $j = 1, \ldots, 3$ are the parameters to be estimated; and ε_t represents the random shocks in t.

According to Stein et al. (2001), the goal of such forecasts is not necessarily to obtain (quarterly or annual) forecasts that are more accurate than those produced by market experts or well-informed participants. Rather, this procedure is fundamental for estimating cash flow forecast errors and their underlying probability distribution (*i.e.*, the deviations of actual flows from the forecasted ones), especially with respect to the tails of this distribution, as this is critical information for risk management (Chen & Yuan, 2017; Daníelsson et al., 2013; McNeil, 1997).

Once the cash flow forecast models (quarterly and annual) have been defined, the time series models are adjusted for each company and, based on this model, each company's cash flow for the next period is estimated. This estimate is then compared to the actual cash flow, generating an estimation error. This procedure is repeated for each company/quarter, resulting in a base of 4,897 observations obtained from the difference between the actual cash flow and the cash flow estimated by the 4,897 models. In addition, the procedure was performed for quarterly and annual bases using Ebit and Ebitda. The R software was used for all modeling.

It is important to note that the choice of the ARX(4) model was preceded by a check of the stationarity assumptions, in particular whether there were any relevant trends, using the augmented Dickey-Fuller test (Dickey & Fuller, 1979). In general, the series did not show any relevant trends, so it was not necessary to take any differences. However, the main concern was whether the residuals of the estimated models were white noise. Although some of them had non-significant coefficients, the estimated models showed residuals without any pattern. Thus, it was possible not only to use the Box-Jenkins methodology, but also to closely follow the methodology of Stein et al. (2001), who used an ARX(4), and compare the results.

As an example, Table 1 shows the parameter estimates of Ambev's adjusted ARX(4) models to obtain both Ebit/Assets and Ebitda/Assets for the first quarter of 2015, based on data from 2010 to 2014.

Table 1
Results of predictive modeling using an ARX(4) for Ambev's Ebit and Ebitda

Panel A: Ebit/Assets				
	1 quarter	**2 quarters**	**3 quarters**	**4 quarters**
Using quarterly data				
Coefficient	0.229	–0.086	–0.132	0.273
t statistic	1.076	0.416	0.633	0.953
R^2 = 0,818855, log-likelihood = 68.93, AIC = –119.86, BIC = –110.90				
Using annualized data				
Coefficient	1.0765***	0.0649	–0.8764***	0.5623***
t statistic	3.9854	0.2429	2.7932	2.3745
R^2 = 0,6999119, log-likelihood = 53.70, AIC = –89.41, BIC = –80.45				
Panel B: EBITDA/Assets				
	1 quarter	**2 quarters**	**3 quarters**	**4 quarters**
Using quarterly data				
Coefficient	0.259	–0.072	–0.170	0.299
t statistic	1.232	0.353	0.826	1.100
R^2 = 0,831203, log-likelihood = 68.80, AIC = –119.60, BIC = –110.64				
Using annualized data				
Coefficient	1.0765***	0.0649	–0.8764***	0.5623***
t statistic	3.9854	0.2429	2.7932	2.3745
R^2 = 0,7029205, log-likelihood = 52.04, AIC = –86.08, BIC = –77.12				

Note: ** Significant at 10%, ** significant at 5%, *** significant at 1%. All series were estimated with dummies as exogenous variables, which were omitted from the presentation.*
Source: *Prepared by the authors.*

All the models have a high quality of fit. In addition, the coefficients from the immediately preceding quarter are generally, although not uniformly, more relevant.

3.1.4 Step 4: Segregation of forecast errors based on company characteristics

The database used contains information on companies with different characteristics (e.g. industry, size). In order to make them comparable, the observations had to be separated into subgroups of companies with similar characteristics so that an empirical cash flow probability distribution could be adjusted. In this way, the CFaR of any company with similar characteristics can be estimated.

After conducting several experiments, Stein et al. (2001) found four characteristics that were most strongly associated with the volatility patterns of forecast errors: (1) market capitalization; (2) profitability; (3) stock price volatility; and (4) segment cash flow volatility. Following a similar methodology, the first three characteristics proposed by Stein et al. (2001) were used, using the measures Ebitda and Ebit. It was not possible to use the same breakdown as Stein et al. (2001) due to the significantly smaller size of the error base (here with just under 5,000 data items, compared to over 80,000 data items for the authors).

The characteristics used were:

- X_1: market capitalization, number of shares outstanding times the share price;
- X_2: profitability, annual Ebitda divided by total assets at the beginning of the period;
- X_3: share price volatility, standard deviation of daily share prices over a three-month period.

Each characteristic divided the sample into two halves. For example, the companies were first divided into those with the highest market capitalization (top half of the data) and those with the lowest market capitalization (bottom half of the data). The other characteristics are used in the same way, separating the sample into 2^3 partitions, resulting in eight different relatively homogeneous subgroups of companies segregated according to their characteristics.

3.1.5 Step 5: Construction of CFaR

Based on the forecast error data broken down into eight subgroups, it is possible to empirically access the cash flow at risk (CFaR) for each company.

The procedure is to determine, for each company whose CFaR we want to evaluate, which of the eight subgroups it belongs to, based on its characteristics. From this, the quantile defined for the risk measure (let's say 5%) is calculated and this value (Ebitda relative to total initial assets) refers to the maximum shock to the chosen cash flow measure, given the 5% risk scenario. Multiplying this value by the total specific assets of the selected company gives the Ebitda value in monetary units.

3.2 Comparison of CFaR with Shareholders' Equity

After determining the risk measure for the entities' cash flow using the methodology proposed by Stein et al. (2001), we compared the CFaR with the companies' book value of shareholders' equity. The purpose of this comparison is to verify the impact that an adverse cash flow could have on the entity's equity. Assuming that negative shareholders' equity represents a situation of technical insolvency (as it indicates that the company does not have enough assets to pay its liabilities), we assessed how many entities in the sample became insolvent assuming the occurrence of CFaR.

3.3 The Data

The data were obtained from the Economática database. Consolidated quarterly data were collected from all public companies in the Brazilian capital market from December 2010 to June 2022. Data prior to 2010 were not used because the Brazilian accounting standards were not fully aligned with international standards until 2009 (Salotti & Carvalho, 2015), and there is empirical evidence that the quality of accounting information increases after the International Financial Reporting Standards (IFRS) (Eng et al., 2019; Lourenço & Braunbeck, 2019; Silva & Nardi, 2017).

In addition, both Ebitda and Ebit were divided by total assets at the start of the respective period in order to ensure comparability between companies. Therefore, if the cash flow measure is quarterly, the cash flow was divided by the total assets of the previous quarter. In the case of annual cash flow, the twelve-month cash flow was divided by total assets at the end of the previous year.

Market capitalization data (as of August 31, 2022), daily stock price volatility over the last three months (between March and June 2022), and the total consolidated equity of the companies as of June 30, 2022 were also collected from the same database. On August 31, 2022, a total of 692 companies were listed as active in the Economática database. However, a number of exclusions had to be made (Table 2), and as a result, the final sample of companies consisted of 186 companies, with the aforementioned base of 4,897 data items.

Table 2
Sample used in the research

Total number of public companies active on 08/31/2022	**692**
(–) Banks and insurers	–83
Subtotal (1)	609
(–) Companies with data as of 06/30/2017	–176
Subtotal (2)	433
(–) Companies without volatility (over 3 months with daily data)	–233
Subtotal (3)	200
(–) Companies with missing depreciation data	–14
Final sample of companies used in the study	186

Source: *Prepared by the authors.*

The data were segregated into eight subgroups, as described in the section "Modeling for the Construction of CFaR," in order to follow the criteria established by Stein et al. (2001). In this way, it is possible to ensure direct comparability with the results obtained from a sample segregated using similar methods, albeit from another country (*i.e.* the USA).

First, the errors were divided into two subgroups according to characteristic X_1 (market capitalization). Smaller companies were placed in group 1 and larger ones in group 2. The next step was to divide the two previous subgroups into four smaller ones according to characteristic X_2 (profitability). Less profitable companies were placed in group 1 and more profitable companies in group 2. The final step was to subdivide the four previous subgroups into eight smaller ones according to characteristic X_3 (share price volatility), noting that the most volatile companies were placed in group 1 and the least volatile in group 2. Table 3 describes the amount of data and the companies placed in each group.

Table 3
Companies and data segregated into eight subgroups

Subgroup	Code	Quantity of data	Quantity of companies
Smaller, less profitable and more volatile	111	622	23
Smaller, less profitable and less volatile	112	596	22
Smaller, more profitable and more volatile	121	635	26
Smaller, more profitable and less volatile	122	590	23
Bigger, less profitable and more volatile	211	626	26
Bigger, less profitable and less volatile	212	591	22
Bigger, more profitable and more volatile	221	644	24
Bigger, more profitable and less volatile	222	593	20
	Totals	4,897	186

Source: *Prepared by the authors.*

For each of the eight subgroups, CFaRs were calculated for different risk levels (5%, 1%, 0.5% and 0.03%) using Ebit and Ebitda (with quarterly and annual data). These levels are considered from a one-tailed perspective to the left, as the probability of losses is taken into account. Subsequently, the CFaR of each company was recorded as a loss within equity, allowing the technical solvency of the entities to be assessed in the event of a shock to their cash flow in the following quarter (and year).

4. ANALYSIS OF THE RESULTS

According to Stein et al. (2001), the procedures described in the "Methodology" section provide a very powerful non-parametric way of assessing the CFaR for any company in the sample. All that is needed is to determine which of the eight subgroups the company belongs to, based on its respective characteristics: market capitalization, profitability and stock volatility. The 600 or so forecast errors of the subgroup can then be evaluated as a description of the empirical distribution of that company's CFaR.

4.1 Analysis of the General Model

Figure 1 shows the histograms representing the non-parametric distribution of each of the eight subgroups described in Table 3.

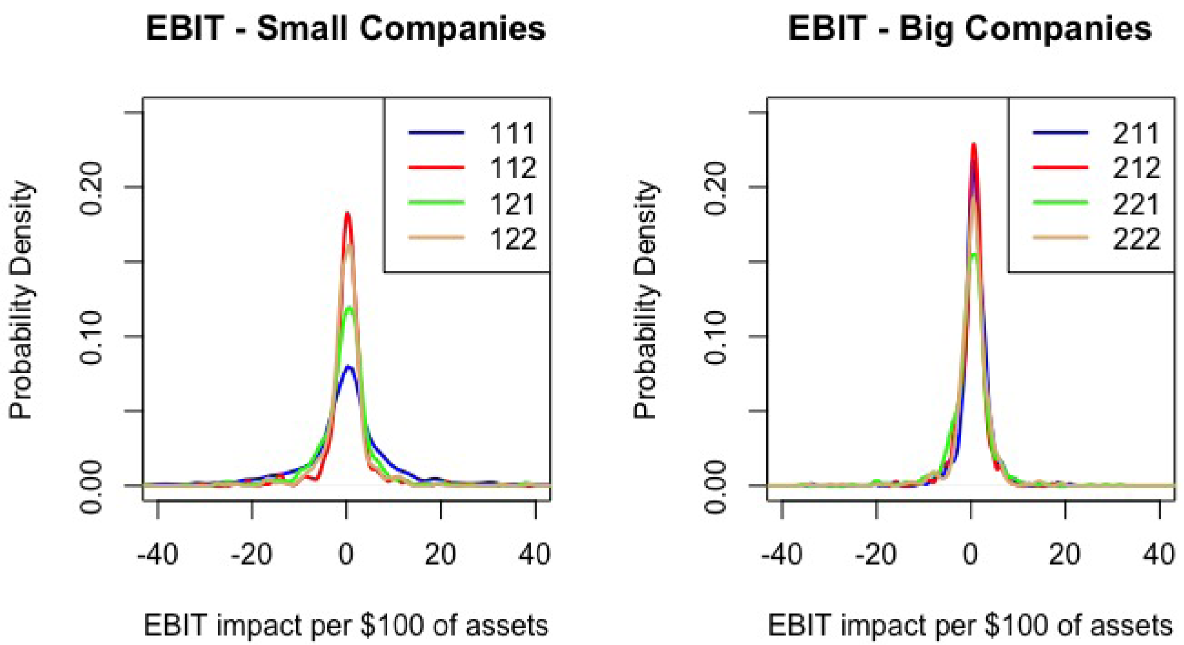

Figure 1 *Empirical distributions of CFaR for the eight sample subgroups*
Source: *Prepared by the authors.*

The distributions in Figure 1 suggest the existence of different patterns of cash flow risk for each subgroup, depending on its characteristics. Group 111, which represents the companies with the worst characteristics (smaller size, lower profitability and higher stock volatility), has a distribution with a heavier tail, greater data dispersion and, consequently, a higher risk of a negative cash flow shock. Groups 212 and 222, on the other hand, have more concentrated distributions between ±R$5, indicating a lower risk of a more severe shock to their cash flows.

Tables 4 and 5 show all the CFaRs calculated for the four measures used (Ebit and Ebitda, quarterly and annual) and for all the risk scenarios evaluated.

First, it is important to highlight the interpretation of each of these measures. The CFaR value at the 5% risk level, using quarterly Ebit, for companies belonging to group 222 (larger size, higher profitability and lower volatility of their shares) was calculated at -R$ 4.91, meaning that there is a 5% probability of an entity in this group experiencing a shock of R$ 4.91 in its Ebit for the next quarter, for every R$ 100 recorded in its assets.

The CFaR calculated for the worst subgroups (e.g. 111 and 121) tends to be more severe than for the best subgroups (e.g. 212 and 222) in all the scenarios evaluated, which is consistent and expected given the characteristics of each subgroup.

In addition, the annual measures provide a test of the robustness of the quarterly measures, since, with different criteria and bases, the shock to the next quarter is very similar using the annualized basis, compared to the quarterly basis. This is because although the basis for forecasting cash flows is annual, the uncertainties associated with those cash flows relate to the next quarter, since the twelve-month annualized cash flow already includes nine months of actual cash flow.

Another robustness test relates to the calculation of CFaR using Ebit and Ebitda. As can be seen from the values shown in tables 4 and 5, the CFaRs using Ebit and Ebitda are very close at the different risk levels. One possible interpretation of this is that there is little risk associated with the difference between the measures, which is precisely the amount of depreciation and amortization for the period. This interpretation is quite plausible given that the vast majority of companies tend to use depreciation models based on relatively stable criteria.

Table 4
CFaR for every R$ 100 of assets, using Ebit/Assets and Ebitda/Assets, on a quarterly and annual basis, at 5% and 1% levels

			5.00%					**5.00%**	
			Profitability					Profitability	
Ebit/Assets-quarterly		Size	1	2	**EBITDA/Assets-quarterly**		Size	1	2
Volatility	1	1	−21.33	−11.76	Volatility	1	1	−21.85	−12.32
		2	−4.20	−7.16			2	−4.94	−8.22
	2	1	−7.32	−7.33		2	1	−7.24	−7.86
		2	−4.56	−4.91			2	−5.35	−6.15
Profitability			**5.00%**					**5.00%**	
			Profitability					Profitability	
Ebit/Assets-annual		Size	1	2	**Ebitda/Assets-annual**		Size	1	2
Volatility	1	1	−23.01	−12.84	Volatility	1	1	−23.09	−11.89
		2	−2.78	−6.68			2	−2.07	−6.29
	2	1	−8.61	−7.98		2	1	−7.16	−7.34
		2	−4.13	−2.99			2	−4.40	−4.30
			1.00%					**1.00%**	
			Profitability					Profitability	
Ebit/Assets-quarterly		Size	1	2	**Ebitda/Assets-quarterly**		Size	1	2
Volatility	1	1	−69.20	−39.69	Volatility	1	1	−67.77	−35.31
		2	−8.65	−19.94			2	−9.52	−22.01
	2	1	−20.84	−18.12		2	1	−19.01	−19.07
		2	−9.32	−14.52			2	−9.88	−17.44
			1.00%					**1.00%**	
			Profitability					Profitability	
Ebit/Assets-annual		Size	1	2	**Ebitda/Assets-annual**		Size	1	2
Volatility	1	1	−74.63	−36.00	Volatility	1	1	−77.01	−31.21
		2	−10.27	−21.87			2	−7.22	−29.29
	2	1	−25.77	−27.11		2	1	−24.56	−30.05
		2	−12.30	−21.91			2	−12.01	−20.98

Source: *Prepared by the authors.*

Table 5
CFaR for every R$ 100 of assets, using Ebit/Assets and Ebitda/Assets, on a quarterly and annual basis, at the 0.5% and 0.03% levels

			0.50%					**0.50%**	
			Profitability					Profitability	
Ebit/Assets-quarterly		Size	1	2	**Ebitda/Assets-quarterly**		Size	1	2
Volatility	1	1	−100.86	−53.29	Volatility	1	1	−102.96	−49.33
		2	−15.26	−33.50			2	−16.63	−32.41
	2	1	−23.91	−27.14		2	1	−23.06	−27.60
		2	−10.56	−27.47			2	−10.96	−29.76
			0.50%					**0.50%**	
			Profitability					Profitability	
Ebit/Assets-annual		Size	1	2	**Ebitda/Assets-annual**		Size	1	2
Volatility	1	1	−127.28	−55.93	Volatility	1	1	−121.28	−55.72
		2	−14.72	−32.88			2	−9.96	−33.45
	2	1	−45.28	−44.65		2	1	−44.17	−44.10
		2	−16.14	−34.19			2	−15.32	−34.17
			0.03%					**0.03%**	
			Profitability					Profitability	
Ebit/Assets-quarterly		Size	1	2	**Ebitda/ Assets-quarterly**		Size	1	2
Volatility	1	1	−251.96	−128.25	Volatility	1	1	−251.21	−121.17
		2	−31.31	−72.81			2	−34.36	−67.81
	2	1	−76.60	−56.24		2	1	−73.13	−51.78
		2	−16.01	−77.54			2	−15.95	−77.55
			0.03%					**0.03%**	
			Profitability					Profitability	
Ebit/Assets-annual		Size	1	2	**Ebitda/Assets-annual**		Size	1	2
Volatility	1	1	−320.17	−99.14	Volatility	1	1	−317.32	−94.52
		2	−27.01	−168.56			2	−30.14	−172.05
	2	1	−73.23	−80.98		2	1	−73.14	−80.79
		2	−21.36	−73.39			2	−25.66	−73.12

Source: *Prepared by the authors.*

The results can also be viewed and interpreted graphically. Since the Ebit and Ebitda results on a quarterly and annual basis are relatively similar, figures 2 and 3 show the histograms of the CFaR calculated for each of the eight subgroups, using only quarterly Ebit as a reference.

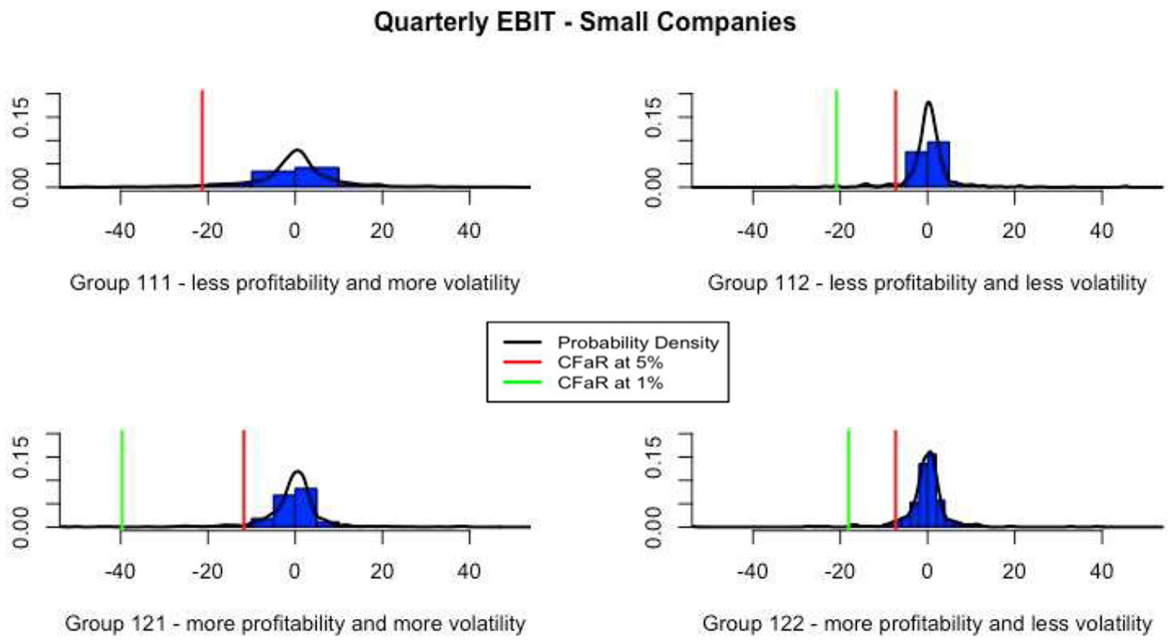

Figure 2 *Empirical distributions of the CFaR of small companies*
Source: *Prepared by the authors.*

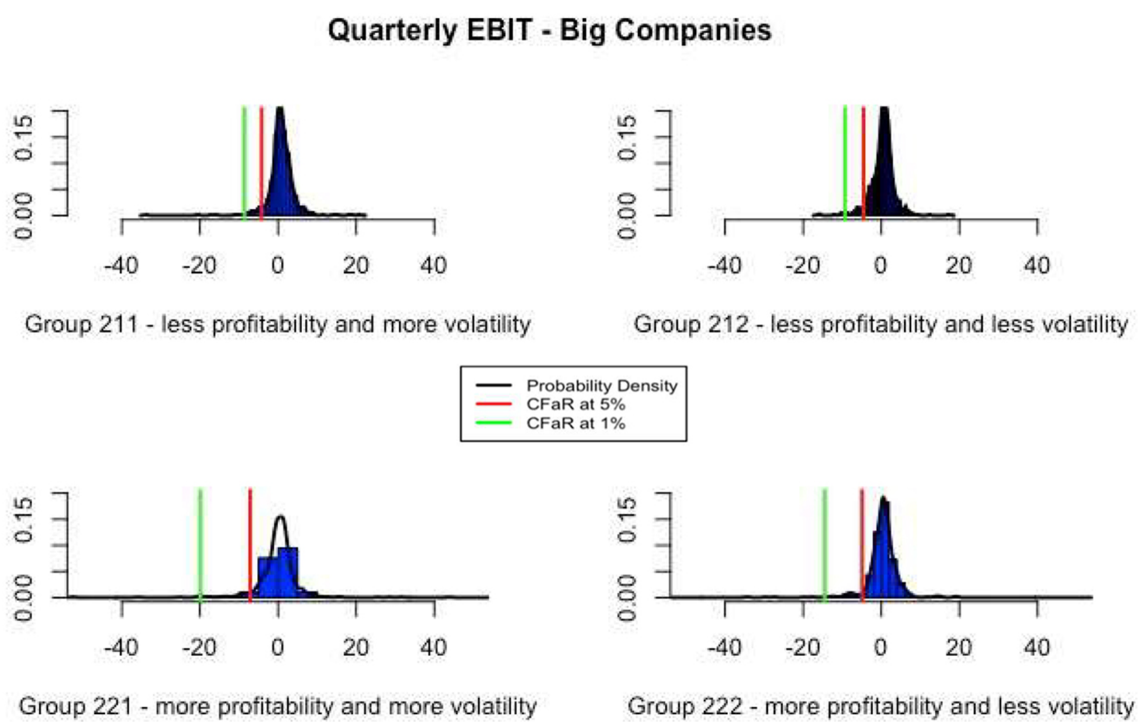

Figure 3 *Empirical distributions of the CFaR of large companies*
Source: *Prepared by the authors.*

Figures 2 and 3 show the quarterly Ebit CFaR values already presented in Table 4, for the 5% and 1% risk levels. It is interesting to note how the cash flows are more risky for subgroup 111, including the CFaR value at the 1% level, calculated at -R$ 69.20, which does not even appear because the scale was limited to the value of -R$ 40.00.

It is also possible to see that in the subgroups of large companies, the less profitable entities (211 and 212) are less at risk than the others with higher profitability (221 and 222). A possible interpretation of this could be the fact that, although the entities in subgroups 211 and 212 have lower profitability (compared to those in subgroups 221 and 222), the level of oscillation in their cash flows is relatively lower, generating greater stability for their forecasts.

4.2 Analysis in an Extreme Scenario: What Happened during the Pandemic?

A very important time frame is the period of the pandemic, an extreme, unpredictable event that began in March 2020 and whose effects continue to this day.

In order to assess the impact of the pandemic on the CFaR of the entities analyzed, the CFaR values were recalculated using the forecast errors only for the period affected by the pandemic (first quarter of 2020 to second quarter of 2022). The results are shown in figures 4 and 5.

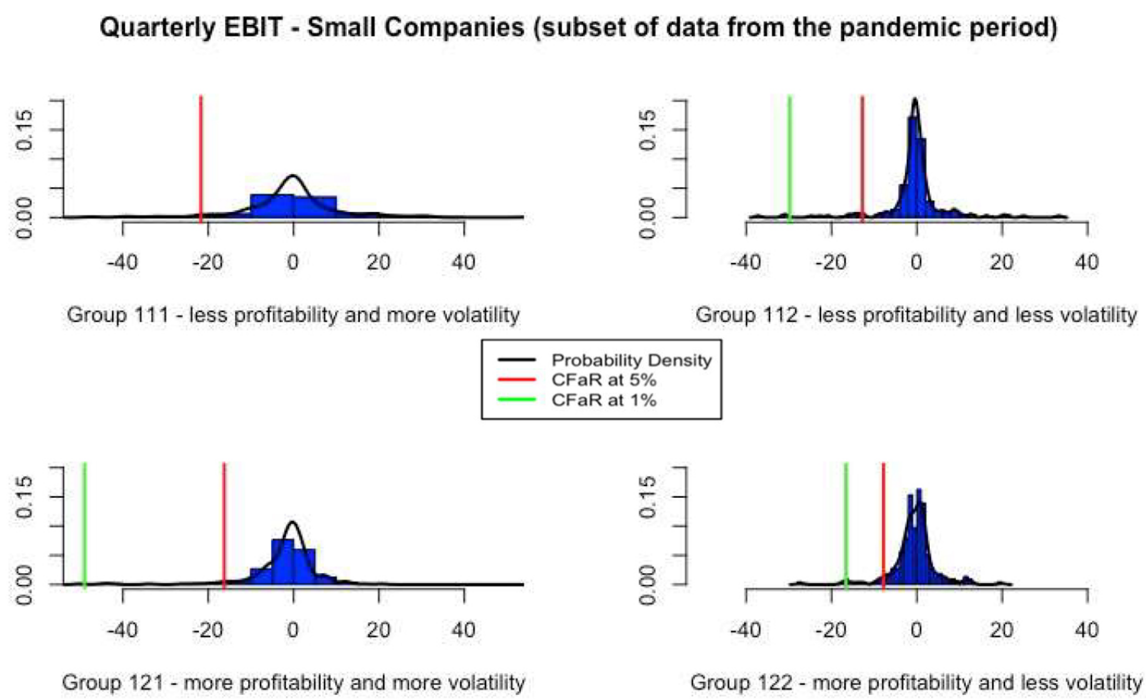

Figure 4 *Empirical distributions of the CFaR of small businesses during the pandemic*
Source: *Prepared by the authors.*

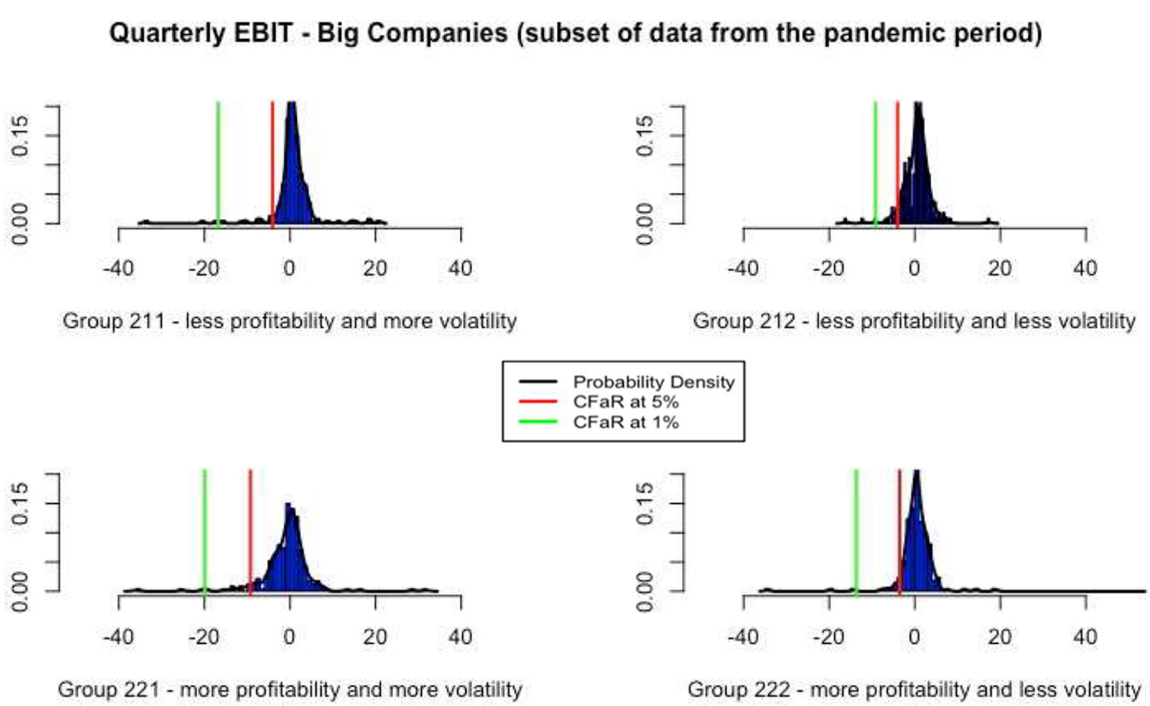

Figure 5 *Empirical distributions of the CFaR of large companies during the pandemic*
Source: *Prepared by the authors.*

It can be seen that although the cash flows at risk were higher, the pattern of CFaR values observed for the subgroups was essentially the same. This suggests that although the pandemic had a significant impact on companies' results and cash flows, it was not enough to change the pattern of CFaR behavior.

4.3 Results Segregated by Sector

Another cut was the segregation of new subgroups by sector. Using the Economática sector classification, it was found that the sectors with the largest number of entities in the sample were commerce (15), construction (20) and electricity (21). The errors were therefore regrouped into these three subgroups. Figure 6 shows the results.

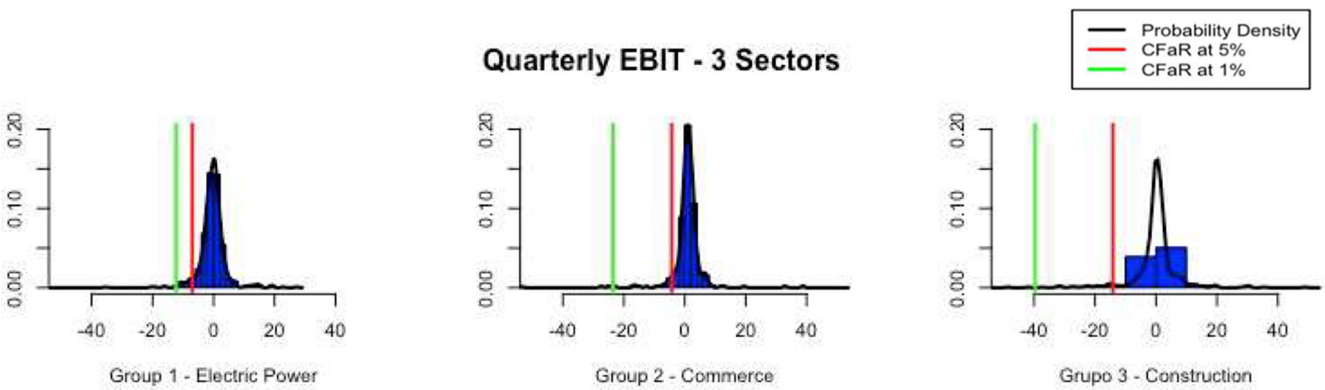

Figure 6 *Empirical distributions of the CFaR of companies belonging to the electricity, commerce and construction sectors*
Source: *Prepared by the authors.*

These results are interesting because they are related to the economic characteristics of the three sectors presented. The electricity sector, in addition to being highly regulated by the state, has more stable and predictable results (Dichev & Tang, 2009) and consequently generates less risk. The construction sector, on the other hand, is more volatile (Renault & Agumba, 2016; Shibani et al., 2022) and generates a greater risk that a shock to results and cash flows will be unfavorable to the entities. The commerce sector can be considered as intermediate risk, *i.e.*, not as stable as the electricity sector, but not as volatile as the construction sector.

4.4 Technical Insolvency Risk Analysis

The results obtained for CFaR (using Ebit on a quarterly basis) were compared to the shareholders' equity of the sample companies. As described in the section "Comparison of CFaR with Shareholders' Equity," the aim of this analysis is to assess the impact that an adverse cash flow could have on the company's equity. The results are shown in Table 6.

Table 6
Application of CFaR (Ebit) to Shareholders' Equity

Group	**111**	**112**	**121**	**122**	**211**	**212**	**221**	**222**	**Total**
Quantity of companies	23	22	26	23	26	22	24	20	186
Negative NE	10	1	3	1	2	0	0	0	17
Positive NE	13	21	23	22	24	22	24	20	169
Companies with positive equity that becomes negative after the CFaR scenario									
5%	2	0	0	0	1	0	1	0	4
1%	13	1	11	0	1	0	3	1	30
0.5%	13	1	18	1	3	0	10	6	52
0.03%	13	20	23	14	10	0	22	20	122

Table 6
Cont.

Group	111	112	121	122	211	212	221	222	Total
Percentage of companies with positive equity that becomes negative after the CFaR scenario									
5%	15.4%	0%	0%	0%	4.2%	0%	4.2%	0%	2.4%
1%	100%	4.8%	47.8%	0%	4.2%	0%	12.5%	5.0%	17.8%
0.5%	100%	4.8%	78.3%	4.5%	12.5%	0%	41.7%	30.0%	30.8%
0.03%	100%	95.2%	100%	63.6%	41.7%	0%	91.7%	100%	72.2%

Source: *Prepared by the authors.*

The first rows of Table 6 show the number of companies per subgroup, divided into negative and positive equity, before applying the CFaR to equity. Here, there are a significant number of companies that already have negative equity, especially in group 111, which, not coincidentally, includes the companies with the worst characteristics (smaller size, lower profitability and higher stock volatility).

The result of applying CFaR to equity is relevant and very worrying. Considering that negative equity represents a situation of technical insolvency, these results indicate a lack of capitalization of non-financial public companies in the Brazilian market, since around 18% of the 169 entities that currently have positive equity would have negative equity at a risk level of 1%. Considering this level of risk, 30 entities would have to strengthen their capital, given the risk of obtaining an adverse cash flow in the future.

Looking at each subgroup individually, group 111 is the most affected by CFaR, which was to be expected. The only subgroup that does not see companies going bankrupt in the face of adverse fluctuations in their cash flows is group 212. Curiously, this subgroup is heavily composed of companies in the electricity sector (7 of the 21 companies in this sector are in this subgroup), as highlighted earlier.

4.5 Results Using a Balanced Panel

Another variation used for the CFaR forecast was the use of a balanced panel, *i.e.* using only data from companies that had data for the entire period (2010-2022). Obviously, there is a survival bias in this cut, as only the most robust companies become active. As a result, the CFaR values were lower than those calculated using the full base, and the risk of insolvency was also reduced (Table 7).

Table 7
Application of CFaR (Ebit) to Shareholders' Equity: Balanced Panel

Group	111	112	121	122	211	212	221	222	Total
Quantity of companies	13	13	14	13	14	13	14	13	107
Negative NE	2	1	0	0	0	0	0	0	3
Positive NE	11	12	14	13	14	13	14	13	104
Companies with positive equity that becomes negative after the CFaR scenario									
5%	1	0	0	0	0	0	0	0	1
1%	3	0	0	0	1	0	1	1	6
0.5%	8	0	2	0	1	0	1	1	13
0.03%	11	0	2	1	1	0	3	13	31
Percentage of companies with positive equity that becomes negative after the CFaR scenario									
5%	9.1%	0%	0%	0%	0%	0%	0%	0%	1.0%
1%	27.3%	0%	0%	0%	7.1%	0%	7.1%	7.7%	5.8%
0.5%	72.7%	0%	14.3%	0%	7.1%	0%	7.1%	7.7%	12.5%
0.03%	100%	0%	14.3%	7.7%	7.1%	0%	21.4%	100%	29.8%

Source: *Prepared by the authors.*

Out of 104 companies in this group, only 1 (1.0%) would become technically insolvent under the 5% risk scenario. Group 111 continues to be the most susceptible to insolvency, which is in line with what was expected for this group, since it represents the companies with the worst characteristics, *i.e.* with the highest risk of bankruptcy.

Comparing tables 6 and 7, there is a very significant reduction in the propensity to be undercapitalized. Therefore, it seems that companies that went public after 2010 have less robust equity to withstand extreme shocks. This reinforces the call for a minimum capital requirement, as is already the case for financial entities regulated by the Brazilian Central Bank and Susep.

5. CONCLUDING REMARKS

The objective of this study was to propose an actuarial model to assess the risks of non-financial entities, extending the model of Stein et al. (2001) to Brazilian listed companies, using Ebit and Ebitda. This made it possible to measure cash flow at risk (CFaR). CFaR represents an adverse shock to an entity's future cash flows, the repercussions of which could consume the shareholders' equity of these institutions, creating a risk of bankruptcy.

The results of the CFaR measurement proved to be relatively coherent and consistent with the results presented by Stein et al. (2001), as well as those of other authors who have used this model, such as Jang et al. (2011) and Özvural (2004). In addition, entities classified in group 111 were more susceptible to extreme adverse events, a result also obtained by the aforementioned studies. In an extension of this study, it was found that this risk is lower for older companies.

It should be noted that the small sample size (almost 5,000 data items, according to Table 3) compared to Stein et al. (2001) naturally reduces the reliability of the results. However, this is an inherent limitation of the study and is directly related to the Brazilian market, which is much smaller than the North American market used. Future studies could use other criteria and techniques for clustering companies by similarity, in addition to the one used in this study. It is also suggested that future studies change the memory order of the time series model used to see if other past terms provide different estimates. They could also use non-parametric resampling methods (e.g. bootstrap or jackknife) to empirically construct the probability distributions of CFaR. In this way, it would be possible to measure the sensitivity of the measures obtained as a function of different statistical techniques.

The results of other researchers who have evaluated the CFaR of non-financial companies are not directly comparable to the results presented here, as they have used other models to measure CFaR, such as that of RiskMetrics (1999), Andren et al. (2005), or even their own model. However, the general conclusion supported by this research highlights the viability and relevance of measuring cash flow at risk for non-financial entities.

We hope to have contributed to providing support to regulators of non-financial entities to assess the possibility of implementing minimum capital requirements, as is already the case for banks and insurance companies. In both segments, there are studies that show the benefits of adopting a minimum capital requirement (Brooke et al., 2015; Carvalho & Cardoso, 2021; Firestone et al., 2017; Lorson et al., 2012; Wang, 2013), such as reducing the likelihood of firms going under and also the likelihood of financial crises occurring (as a result). Therefore, it is suggested that a minimum capital requirement for non-financial firms can generate benefits for both the companies and the markets in which they operate.

REFERENCES

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*(4), 589. https://doi.org/10.2307/2978933

Andren, N., Jankensgard, H., & Oxelheim, L. (2005). Exposure-based Cash-Flow-at-Risk: An Alternative to VaR for industria companies. *Journal of Applied Corporate Finance*, *17*(3), 76-86 https://doi.org/10.1111/j.1745-6622.2005.00046.x

Andrieş, A. M., Ongena, S., Sprincean, N., & Tunaru, R. (2022). Risk spillovers and interconnectedness between systemically important institutions. *Journal of Financial Stability*, *58*, 100963. https://doi.org/10.1016/j.jfs.2021.100963

Areias, C. A. C., & Carvalho, J. V. F. (2021). Reinsurance in the supplementary health: A counterfactual study on the impacts of reinsurance treaties adoption by healthcare plans operators in Brazil. *Brazilian Business Review*, *18*(2), 217-235. https://doi.org/10.15728/bbr.2021.18.2.6

Artzner, P., Delbaen, F., Eber, J.-M., & Heath, D. (1999). Coherent measures of risk. *Mathematical Finance*, *9*(3), 203-228. https://doi.org/10.1111/1467-9965.00068

Barsky, N. P., & Catanach, A. J. (2014). Non-GAAP nonsense: Fixing the problem once and for all. *Strategic Finance*, *96*(10), 47-51.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, *4*, 71. https://doi.org/10.2307/2490171

Bego, M. da S. (2007). *Cash-Flow-at-Risk: Análise e aplicação em uma empresa de energia*. Universidade Federal de Pernambuco.

Black, D. E., Christensen, T. E., Ciesielski, J. T., & Whipple, B. C. (2018). Non-GAAP reporting: Evidence from academia and current practice. *Journal of Business Finance & Accounting*, *45*(3-4), 259-294. https://doi.org/10.1111/jbfa.12298

Brooke, M., Bush, O., Edwards, R., Ellis, J., Francis, B., Harimohan, R., Neiss, K., & Siegert, C. (2015). *Measuring the macroeconomic costs and benefits of higher UK bank capital requirements*. Bank of England.

Carvalho, J. V. F., & Cardoso, L. (2021). Os impactos da rentabilização do estoque de capital sobre a probabilidade de ruína e o capital de solvência para seguradoras. *Revista Evidenciação Contábil & Finanças*, *9*(3), 9-29. https://doi.org/10.22478/ufpb.2318-1001.2021v9n3.54420

Chen, Y., & Yuan, Z. (2017). A revisit to ruin probabilities in the presence of heavy-tailed insurance and financial risks. *Insurance: Mathematics and Economics*, *73*, 75-81. https://doi.org/10.1016/j.insmatheco.2017.01.005

Cowell, R. G., Verrall, R. J., & Yoon, Y. K. (2007). Modeling operational risk with bayesian networks. *Journal of Risk and Insurance*, *74*(4), 795-827. https://doi.org/10.1111/j.1539-6975.2007.00235.x

Daníelsson, J., Jorgensen, B. N., Samorodnitsky, G., Sarma, M., & De Vries, C. G. (2013). Fat tails, VaR and subadditivity. *Journal of Econometrics*, *172*(2), 283-291. https://doi.org/10.1016/j.jeconom.2012.08.011

Dichev, I. D., & Tang, V. W. (2009). Earnings volatility and earnings predictability. *Journal of Accounting and Economics*, *47*(1-2), 160-181. https://doi.org/10.1016/j.jacceco.2008.09.005

Dickey, D. A., & Fuller, W. A. F. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366), 427-431.

Eng, L. L., Lin, J., & Figueiredo, J. N. (2019). International Financial Reporting Standards adoption and information quality: Evidence from Brazil. *Journal of International Financial Management & Accounting*, *30*(1), 5-29. https://doi.org/10.1111/jifm.12092

Euphasio Junior, J. W., & Carvalho, J. V. F. (2022). Reinsurance and solvency capital: Mitigating insurance companies' ruin probability. *Revista de Administração Contemporânea*, *26*(1). https://doi.org/10.1590/1982-7849rac2022200191.en

Firestone, S., Lorenc, A., & Ranish, B. (2017). An empirical economic assessment of the costs and benefits of Bank Capital in the US. *Finance and Economics Discussion Series*, *2017*(034). https://doi.org/10.17016/FEDS.2017.034

Gupta, A., & Liang, B. (2005). Do hedge funds have enough capital? A Value-at-Risk approach. *Journal of Financial Economics*, *77*(1), 219-253. https://doi.org/10.1016/j.jfineco.2004.06.005

Harrington, S. E. (2009). The financial crisis, systemic risk, and the future of insurance regulation. *Journal of Risk and Insurance*, *76*(4). https://doi.org/10.1111/j.1539-6975.2009.01330.x

Horobet, A., Curea, S. C., Smedoiu Popoviciu, A., Botoroga, C.-A., Belascu, L., & Dumitrescu, D. G. (2021). Solvency risk and corporate performance: A case study on European retailers. *Journal of Risk and Financial Management*, *14*(11), 536. https://doi.org/10.3390/jrfm14110536

Jang, S. (Shawn), Park, K., & Lee, J. (2011). Estimating Cashflow-at-Risk (CFaR). *Cornell Hospitality Quarterly*, *52*(3), 232-240. https://doi.org/10.1177/1938965510395746

Januzzi, F. V., Perobelli, F. F. C., & Bressan, A. A. (2012). Aplicação do CF@R e de cenários de stress no gerenciamento de riscos corporativos. *Estudos Econômicos (São Paulo)*, *42*(3), 545-579. https://doi.org/10.1590/S0101-41612012000300005

LaRocque, E. C., Lowenkron, A., Amadeo, E., & Jensen, J. P. (2003). *Cenários probabilísticos: Conjugando análise de riscos e projeções macroeconômicas*. RiskControl Serviços Ltda e Tendências Consultoria Integrada.

Lorson, J., Schmeiser, H., & Wagner, J. (2012). Evaluation of benefits and costs of insurance regulation – A conceptual model for Solvency II. *Journal of Insurance Regulation*, *31*(1), 125-156.

Lourenço, I., & Braunbeck, G. (2019). IFRS adoption in Brazil. In P. Weetman & I. Tsalavoutas (Eds.), *The Routledge Companion to Accounting in Emerging Economies*. Routledge Companions, 15-27.

Macohon, E. R., Petry, J. F., & Fernandes, F. C. (2017). Elaboração do panorama do mercado segurador brasileiro em relação à regulamentação internacional de solvência. *Revista Contemporânea de Contabilidade*, *14*(31), 127. https://doi.org/10.5007/2175-8069.2017v14n31p127

Maurer, F. (2015). How much cash is at risk in U.S. non-financial firms? A VaR-type measurement. *Journal of Applied Business Research (JABR)*, *31*(4), 1579. https://doi.org/10.19030/jabr.v31i4.9338

McNeil, A. J. (1997). Estimating the tails of loss severity distributions using extreme value theory. *ASTIN Bulletin*, *27*(01), 117-137. https://doi.org/10.2143/AST.27.1.563210

Moratis, G., & Sakellaris, P. (2021). Measuring the systemic importance of banks. *Journal of Financial Stability*, *54*(4), 100878. https://doi.org/10.1016/j.jfs.2021.100878

Oliveira, G. C., & Ferreira, A. N. (2019). Basileia III – Concepção e implementação no Brasil. *Revista Tempo do Mundo*, *4*(1), 115-146.

Oral, C., & CenkAkkaya, G. (2015). Cash flow at risk: A tool for financial planning. *Procedia Economics and Finance*, *23*, 262-266. https://doi.org/10.1016/S2212-5671(15)00358-5

Özvural, Ö. (2004). *Cashflow-at-Risk in publicly traded non-financial firms in Turkey: An application in defense companies*. Bilkent University.

Perobelli, F. F. C., & Securato, J. R. (2005). Modelo para mediação do fluxo de caixa em risco: Aplicação a distribuidoras de energia elétrica. *Revista de Administração de Empresas*, *45*(4), 50-65. https://doi.org/10.1590/S0034-75902005000400005

Perobelli, F. F. C., Januzzi, F. V., Berbert, L. J. S., & Medeiros, D. S. P. de. (2007). Fluxo de Caixa em risco: Diferentes métodos de estimação testados no setor siderúrgico brasileiro. *Revista Brasileira de Finanças*, *5*(2), 165-204.

Perobelli, F. F. C., Januzzi, F. V., Berbert, L. J. S., Medeiros, D. S. P. de, & Probst, L. G. da S. (2011). Testando o "Cash-Flow-at-Risk" em empresas têxteis. *Nova Economia*, *21*(2), 225-261. https://doi.org/10.1590/S0103-63512011000200003

Ramsden, L., & Papaioannou, A. D. (2019). Ruin probabilities under capital constraints. *Insurance: Mathematics and Economics*, *88*, 273-282. https://doi.org/10.1016/j.insmatheco.2018.11.002

Renault, B. Y., & Agumba, J. N. (2016). Risk management in the construction industry: A new literature review. *MATEC Web of Conferences*, *66*, 00008. https://doi.org/10.1051/matecconf/20166600008

RiskMetrics. (1999). *CorporateMetrics Technical Document*. RiskMetrics Group.

Salotti, B. M., & Carvalho, L. N. (2015). Convergence of accounting standards towards IFRS in Brazil. In I. Lourenço & M. Major (Eds.), *Standardization of Financial Reporting and Accounting in Latin American Countries* (pp. 79-102). IGI Global.

Shibani, A., Hasan, D., Saaifan, J., Sabboubeh, H., Eltaip, M., Saidani, M., & Gherbal, N. (2022). Financial risk management in the construction projects. *Journal of King Saud University – Engineering Sciences*. https://doi.org/10.1016/j.jksues.2022.05.001

Silva, R. L. M., & Nardi, P. C. C. (2017). Full adoption of IFRSs in Brazil: Earnings quality and the cost of equity capital. *Research in International Business and Finance*, *42*. https://doi.org/10.1016/j.ribaf.2017.07.041

Stein, J. C., Usher, S. E., LaGattuta, D., & Youngen, J. (2001). A comparables approach to measuring Cashflow-at-Risk for non-financial firms. *Journal of Applied Corporate Finance*, *13*(4), 100-109. https://doi.org/10.1111/j.1745-6622.2001.tb00430.x

Stumpp, P. M., Marshella, T., Rowan, M., McCreary, R., & Coppola, M. (2000, June). Putting Ebitda in perspective ten critical failings of Ebitda as the principal determinant of cash flow. *Moody's Investor Service*, 1-24.

Wang, L. (2013). *The implications of solvency II to insurance companies*. University of South Carolina.

Xu, B. Y. (2019). *Application of the CorporateMetrics Methodology in Heineken Company*. VSB – TECHNICAL UNIVERSITY OF OSTRAVA.

Yan, M., Hall, M. J. B., & Turner, P. (2014). Estimating liquidity risk using the exposure-based Cash-Flow-at-Risk approach: An application to the UK banking sector. *International Journal of Finance & Economics*, *19*(3), 225-238. https://doi.org/10.1002/ijfe.1495