An Alternative Model of Risk in Non-financial Companies Applied to the Brazilian Pulp and Paper Industry

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Abstract

Earnings at Risk (EaR) is a financial risk measure that can be applied to non-financial companies, similarly to *Cash Flow at Risk* (CFaR). It is based on a relation that can be quantified using a multiple linear regression model, where the dependent variable is the change on the company's results and the independent variables are changes in distinct risk factors. The presence of correlation between explanatory factors (multicollinearity) in this kind of model may cause problems when calculating EaR and CFaR. In this paper, we indicate some possible consequences of these problems when calculating EaR, and propose a method to solve it based on Principal Component Analysis technique. To test the model, we choose the Brazilian agriculture-business industry, more specifically the paper and pulp sectors. We will show that, on the absence of significant correlation between variables, the proposed model has equivalent performance to usual multiple linear regression models. We find evidence that when correlation appears, the model here proposed yields more accurate and reliable forecasts.

Keywords**:** risk management; PCR model; international finance; earning at risk.

JEL codes: G32; M16.

Resumo

O Earnings at Risk (EaR) é uma medida de risco financeiro aplicável a empresas não financeiras, assim como o *Cash Flow at Risk* (CFaR). Esta medida se baseia numa relação que pode ser quantificada através de modelos de regressão linear múltipla, nos quais a variável resposta é a variação do resultado da empresa, e as variáveis explicativas são variações nos diversos fatores de risco. A presença de correlação entre variáveis explicativas (multicolinearidade) neste modelo pode provocar problemas nos cálculos do EaR e do CfaR. Nesse trabalho, apontaremos algumas possíveis consequências deste problema no processo de cálculo do EaR, e apresentaremos uma proposta para contorná-lo baseada na técnica de

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Análise de Componentes Principais. Escolhemos para análise o setor de agronegócio, especificamente o ramo de papel e celulose. Mostraremos que, na ausência de correlação significativa entre as variáveis, o modelo proposto tem desempenho equivalente ao da regressão linear múltipla usual. Na presença de correlação, encontramos evidências de que o modelo aqui proposto produz previsões mais confiáveis e precisas.

Palavras-chave: gestão de riscos; método econometrico; finanças internacionais.

1. Introduction

Brazilian agriculture industry currently represents around 33% of Gross Domestic Product (GDP), 42% of exports and 37% of jobs created in the country. These data were obtained from a Brazilian organization named Portal do Agronegócio – directed for research, development, planning and business management in the agribusiness field – and show the importance of the sector to Brazil's economy (`http://www.portaldoagronegocio.com.br/`).

Features inherent to this industry include harvest shock and shortage risk, price variation from the initial planting decision until physical delivery, products seasonality, currency exchange risk and over supply in global markets. Therefore, a sound risk management policy is essential for the industry to succeed in domestic and global markets; this paper thus addresses on how to measure the risk exposure of non-financial firms in this sector.

The methodology for measuring corporate risk through Earnings at Risk (EaR) allows the company to evaluate the impact of market risk factors on the firm's results and it was first proposed by RiskMetrics Group on the technical document Corporate Metrics (1999). EaR adapts Value at Risk (VaR) for non-financial companies and estimates the worst variation in earnings of the company, for a fixed time horizon and with a pre-established confidence level, and this forecast is based on the values of specific risk factors, which influence the firm's operational and financial results. Table 1 compares some features of EaR and VaR.

Table 1
VaR and EaR comparison

	VaR	EaR
Analysis period	Daily/Weekly	Quarterly/Annually
Analysis value	Assets´ Present Value	EBITDA
Risk exposure	Assets in Portfolio	Earnings
Applies to	Market assets with liquidity	Market assets without liquidity
Methodology	Bottom up	Top Down / Bottom up

EaR belongs to the group of financial risk measures, and another measure that is widely used is Cash Flow at Risk (CFaR); the two methodologies are similar, differing on how the company's results are measured. EaR is based directly on the firm's results, measured for example by the EBITDA (Earnings Before Interest, Taxes, Depreciation and Amortization), while CFaR analyses variations of forecasted cash flows.

Many researches have already proven the efficiency of EaR as well as CFaR to estimate risk exposure of non-financial firms. A previous work by Stein et al. (2001) applied CFaR to a portfolio of American firms in many industries. Another work (Andrén et al., 2005) performed a test using only an American mining conglomerate. The methodology to estimate CFaR has been discussed in Brazil, where it was first analyzed by Werlang and La Rocque (2002), then adapted to electric power industry (Securato and Perobelli, 2005) and consumer goods industry (Berbert and Perobelli, 2007).

The relation between risk factors and the company's results can be estimated with multiple regression models, where the explanatory variables are changes in distinct risk factors and the dependent variable is the change on the firm's results. The presence of correlation among the risk factors can affect the forecast reliability of the fitted models, so this topic needs further investigation and discussion. This kind of problem commonly appears when the models are applied on agribusiness firms, which can sell either the raw materials or the transformed products from this same raw material. It means sales price of finish good could be highly correlated with cost of raw material. Correlation among commodities prices and macroeconomic indicators may also show up. Therefore, a careful data analysis demands a model that takes in account these correlations.

The objective of this paper is to propose a model that takes in account these correlations and then to use this new model to estimate EaR. This paper develops an alternative model to measure each risk factor impact, complements previous researches and also contributes to broaden literature related with risk exposure measurement of non-financial firms.

In the theoretical reference section, we will describe the standard process to measure the firm's EaR, and how this process should be adapted when the correlation problem between the risk factors appears. Next, we collect a sample of firms from the paper and pulp industry to empirically test this potential problem and to compare performance of the proposed solution with the usual regression models. The results are discussed in empirical analysis section. The last section presents final considerations.

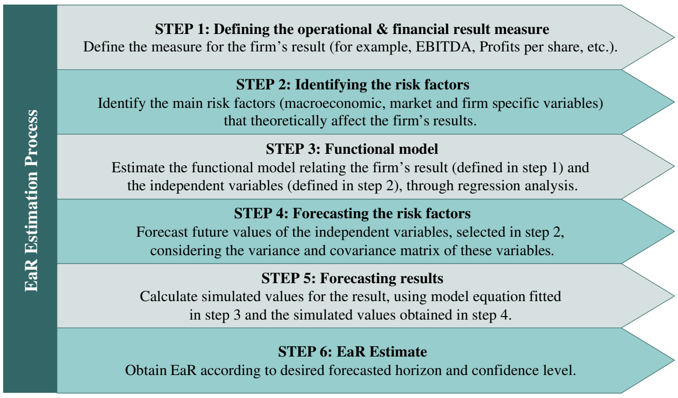
2. Theoretical Approach

2.1 EaR estimation process

EaR is a risk metric that informs the maximum loss value of a specific future result or group of future results, of payment or income, within a fixed time horizon and with a pre-defined confidence level. The calculation is based on the market and / or operational values that affect the firm's results and, according to the definition of Corporate Metrics (1999), assumes that the relation among the risk factors (commodities prices, exchange rate, etc.) and the company's results is fixed and described by a deterministic function given a priori.

Recent literature, however, tries to estimate this functional relation between result and risk factors directly from data, through a multiple linear regression model and herein, we adopt this approach. This approach is motivated mainly by the impossibility of knowing the deterministic relation between the company's results and the risk factors, specially when working outside the companies; this deterministic relations are informations of great strategic relevance, and so are usually confidential. The steps to EaR calculation according to this methodology are summarized in Figure 1. This same procedure can also applied to estimate Cash Flow at Risk (CFaR) using cash flows, instead of the firm's results.

The model selection to fit the relation among risk factors and aggregate company's results (STEP 3) is the critical part of the process, because all other steps depend on a good model specification.



Source: elaborated by authors

Figure 1
EaR calculation process

Most studies in this area use multiple linear regression models as the functional model that measures the impact of each risk factor on the results or cash flows. Previous works (Andrén et al., 2005) applied this methodology on the energy market and a regression model was estimated, using EBITDA variation as dependent variable and variation in risk factors as the independent variables. To forecast EaR, the authors assume that the risk factors are jointly distributed according to a Multivariate Normal Distribution (MVN), with mean and covariance matrix estimated from data, and thus simulate the future risk factors values. Applying these values in the regression equation, they are able to determine the simulated future values of EBITDA, and from these, the EaR value.

In the Brazilian study (Berbert and Perobelli, 2007), any distributions were fitted to the sample risk factors and the Cholesky decomposition was applied to simulate correlated risk factor values based on the sample correlation structure. The sample was obtained from a retail chain of stores, Lojas Americanas S.A., and the analysis investigated the impact of distinct Brazilian macroeconomic factors on the adjusted cash flows. Also there are some studies (Securato and Perobelli, 2005, Varanda Neto, 2004) that focus on Brazilian electrical power industry; the chart below shows the independent variables used as risk factors in each of these studies.

Table 2
Variables of previous studies

	Berbert and Perobelli (2007)	Securato and Perobelli (2005)	Varanda Neto (2004)
Industry	Retail Chain	Electrical Power	Electrical Power
Risk measure	CFaR	CFaR	CFaR
Independent Variables	IPCA (measure of inflation) BRL/USD Selic (Interest Rate) T-note Gross Domestic Product Family Consuming Nominal and real wages Unemployment rate	IGP-M (measure of inflation) BRL/USD Selic C-bond (country risk) Production index	IGP-M and IPCA BRL/USD CDI and TR (Interest Rate) Energy Price

VIF for VCP and Suzano

Variable	R^2	VIF
Δ Pulp	0,112	1,126
Δ Paper	0,620	2,629
Δ A4	0,252	1,337
Δ PTAX	0,535	2,152
Δ IPCA	0,538	2,164
Δ Selic	0,031	1,032

VIF for Aracruz

Variable	R^2	VIF
Δ Pulp	0,080	1,087
Δ PTAX	0,055	1,059
Δ IPCA	0,119	1,135
Δ Selic	0,012	1,012

2.2 Multicollinearity problem and alternative model

All researches discussed in the prior section assume that the independent variables are jointly distributed according to a MVN, and the information contained on the covariance matrix is used explicitly in the simulation of future values. On the other hand, statistical theory for regression analysis assumes that the independent variables are not correlated (Montgomery et al., 2006). When this assumption is violated, the multicollinearity problem appears and affects the reliability of the model forecasts. An alternative to cope with this problem is to use the technique of Principal Components Analysis (PCA).

The objective of the PCA technique is to transform a group of correlated variables in a group of jointly orthogonal (i.e. uncorrelated) components where each component is a linear combination of one or more original variables. The coefficients of these components are calculated based on the spectral decomposition of the correlation or covariance matrix (Johnson, 2001).

The method of principal components and its application in regression analysis has been discussed widely in the literature. It was used, for instance, to obtain forecasts for the Portuguese GDP (Melro, 1996) and to estimate the impact of socioeconomic factors and family planning on fertility indexes in emerging countries (Sufian, 2005). In both studies, there are explicit mentions to the multicollinearity problem, and the solution adopted is the Principal Components Regression (PCR) method, in both cases.

The PCR method consists of a regression of the company's results on the orthogonal factors obtained with PCA. All factors may be used or only those that represent a larger portion of the original variability (i.e., larger eigenvalues). The components obtained by PCA are independent, or orthogonal, so the multicollinearity problem is eliminated.

3. Sample and Methodology

3.1 Sample

The paper and pulp industry was selected for this research, because this sector is consolidated in Brazil and historical data is available. EBITDA was used as a measure for the firms' results. Data for EBITDA were obtained for three companies in the industry listed on Brazilian Stock Market Bovespa Index: Suzano, Votorantim Papel e Celulose (VCP) and Aracruz. Data for product prices were obtained from annual reports: average paper price in domestic market, short fiber pulp price, paper A4 exports price. Data for currency exchange rate PTAX, extended consumer price index IPCA (measure of inflation) and interest rate Selic (special clearance & custody system) were obtained from Bloomberg system. The period analyzed includes quarterly data for 8 years, from 2000 until 2007, totaling 32 quarters. All commodities prices are dollar denominated.

The data were divided in test sample (from 2000 until 2006) and validation sample (2007) to test the quality of the estimated models. The original data were transformed to log-returns – so that we analyze the effect of (log) variation of risk factors on (log) variation of EBITDA. To test for the presence of multicollinearity, we analyzed the relation between the macroeconomic independent variables using the sample correlation matrix (Figure 2).

	ΔPulp	ΔPaper	ΔA4	ΔPTAX	ΔIPCA	ΔSelic
ΔPulp	1					
ΔPaper	-0,1138	1				
ΔA4	0,2327	0,1149	1			
ΔPTAX	0,0459	-0,4666	0,1464	1		
ΔIPCA	0,2586	-0,4475	0,1477	-0,2066	1	
ΔSelic	0,0760	-0,1393	0,0603	0,0357	0,0805	1

Figure 2
Correlation matrix of log-returns: pulp short fiber price, paper A4 price, currency exchange PTAX, price index IPCA, interest rate Selic

This matrix shows high correlations between returns of domestic market paper price and, currency exchange PTAX and price index IPCA, and also some correlation between returns of pulp price, paper A4 price and IPCA. Thus, there are evidences for presence of multicollinearity in these variables.

To evaluate if the correlations between macroeconomic variables are jointly different from zero (and, as consequence, if there is multicolinearity), the Bartlett's sphericity test was used. The null hypothesis for the test states that the sample correlation matrix is equal to the identity matrix, and thus that the variables are mutually uncorrelated. Applying this test on the above correlation matrix, we obtain a p-value of 0.0235, which indicates that there are statistically significant correlations in this matrix (using 5% significance level). This means that, when using all these independent variables to calculate EaR for Suzano and VCP, there will be multicollinearity problems. On the other hand, for the correlation matrix of variables used to analyze Aracruz – returns from pulp price, currency exchange PTAX, interest rate Selic and price index IPCA – the p-value of the Bartlett's sphericity test was 0.7779, which indicates that on this case there are not statistically significant correlations in the sample correlation matrix (using again a 5% significance level). This indicates that, theoretically, the regression model used to forecast EBITDA for Aracruz will not have multicollinearity problems.

As to confirm the sphericity test, the Variance Inflation Factors (VIF) were also calculated, and its values are shown in the tables below. It can be noted that some of the variables (Paper, PTAX and IPCA) presented a VIF greater than 2, which is a signal for the presence of colinearity; for the variables used in the analysis of Aracruz, however, all the factors presented small values, and thus the results of the VIF analysis are in accordance with those obtained via the sphericity test.

3.2 Methodology

As discussed before in the theoretical approach section, the PCR model is an alternative to cope with correlations problems between explanatory variables, preventing the reliability of the regression model from being affected.

The model fitting starts with the decomposition of correlation matrix in principal components. A vector and a real positive number – respectively, eigenvector and eigenvalue, represent each component. The eigenvalues quantify the proportion of original total variability “explained” by that component and the eigenvector brings the component coefficients.

In this case, the general term of the first component developed to analyze Votorantim and Suzano is the equation below:

$$\begin{aligned} C_{1,i} &= v_{1,1} \cdot \Delta Celulose_i + v_{1,2} \cdot \Delta Papel_i + v_{1,3} \cdot \Delta A4_i \\ &+ v_{1,4} \cdot \Delta PTAX_i + v_{1,5} \cdot \Delta IPCA_i + v_{1,6} \cdot \Delta Selic_i \end{aligned} \quad (1)$$

in which v_{ij} is the j-th eigenvector coefficient of the component i, with $i, j = 1, 2, ..., 6$.

The term of the first component developed to analyze Aracruz is similar, except for the absence of Paper and Paper A4 factors.
Following, the calculated components become independent variables for a multiple linear regression model (equation 2).

$$\Delta E_i = \alpha + B_1 \cdot C_{1,i} + B_2 \cdot C_{2,i} + B_3 \cdot C_{3,i} + B_4 \cdot C_{1,4} + B_5 \cdot C_{5,i} + B_6 \cdot C_{6,i} + e_i \quad (2)$$

where e_i is the random error, which we assume as being normally distributed.

For comparison with the proposed model, we also are going to fit the usual multiple linear regression models (equation 3), which they are more commonly used in recent studies.

$$\begin{aligned} \Delta E_i &= a + B_1 \cdot \Delta Celullose_i + B_2 \cdot \Delta Paper_i + B_3 \cdot \Delta A4_i \\ &+ B_4 \cdot \Delta PTAX_i + B_5 \cdot \Delta IPCA_i + B_6 \cdot \Delta Selic_i + E_i \end{aligned} \quad (3)$$

The Backward Analysis procedure (Montgomery et al., 2006) was used for selecting variables in the multiple linear regression models and PCR models of the three companies. According to this procedure, the first model to be fitted is the full model, with all the independent variables. In the next step, the variable whose coefficient has the largest p-value (i.e., the coefficient which presents the largest p-value for the hypothesis of being equal to 0) is taken out and the model is re-estimated. This procedure goes on until all independent variables have significant coefficients (the cutting point was the usual 5% significance level).

For calculating EaR, the future values of independent variables were forecasted assuming joint normal distribution for these variables – this was made using both the usual regression models and the PCR models. The simulation was carried on by the Cholesky decomposition of the covariance matrix (Conte, 1965). At last, applying the simulated values of independent variables on the regression models, the simulated values of EBITDA were obtained for the desired time horizon (in our case, one quarter).

A backtest procedure was performed to compare the results obtained for all the fitted models with the observed EBITDA values for the 2007 year period (validation sample), in order to analyze the models fit to real data.

4. Empirical Results

4.1 Multiple regression models

First, the best fitted linear regression model for EBITDA of each of the three firms was chosen, according to the Backward procedure for variable selection, described before. The models obtained through this procedure for the three companies are presented on the equations 4, 5 e 6 below and the fitted multiple linear regression models for the three companies are presented on Table 3.

The fitted model for Suzano is

$$\Delta E_i^{suzano} = 0.01008 + 0.74752 \cdot \Delta Paper_i + 0.72649 \cdot \Delta PTAX_i \tag{4}$$

The fitted model for VCP is

$$\begin{aligned} \Delta E_i^{vcp} &= 0.02151 + 0.65092 \cdot \Delta Paper_i + 0.37987 \cdot \Delta Celullose_i \\ &+ 0.37987 \cdot \Delta PTAX_i \end{aligned} \tag{5}$$

The fitted model for Aracruz is

$$\Delta E_i^{aracruz} = 0.02382 + 0.67769 \cdot \Delta Celullose_i + 1.1602 \cdot \Delta PTAX_i \tag{6}$$

Table 3
Fitted multiple linear regression models for each firm

Firm	Variables	Coefficients	Standard-error	T-Statistics	P-value
Suzano	Δ Paper	0,74752	0,27910	26,790	0,013100
	Δ PTAX	0,72649	0,26600	27,310	0,011600
VCP	Δ Paper	0,65092	0,19342	33,650	0,002670
	Δ Pulp	0,37987	0,17613	21,570	0,041710
	Δ PTAX	0,53972	0,18340	29,430	0,007290
Aracruz	Δ Pulp	0,67769	0,31732	21,360	0,043113
	Δ PTAX	11,60200	0,29410	39,450	0,000605

The diagnostic analysis of the models didn't present any problems, so they can be considered well adjusted with respect to the usual assumptions of regression modelling.

It can be verified that the currency exchange factor (Δ PTAX) had an important influence on the variations of the EBITDA of the three firms. The variations of domestic market paper price were found important for variations of Suzano and VCP's EBITDA. On the other hand, the effect of variations in pulp price was significant only on the models for VCP and Aracruz's EBITDA. The absence of pulp price variation effects in the model for Suzano seems strange, considering that on the company's annual report is mentioned that pulp price is an influent factor on the firm's results.

One of the possible explanations for the exclusion of pulp prices from this model could be multicollinearity. On the other hand, this variable didn't present high correlation with any of the other variables used in the model (currency exchange PTAX and paper). Anyhow, the PCR model guarantees the incorporation of variations values for pulp paper, through the principal components.

4.2 PCR models

The principal component coefficients obtained for Votorantin and Suzano (Table 4) and for Aracruz (Table 6) don't suggest any immediate interpretation of the components.

The analysis for Votorantin and Suzano's component coefficients showed that the variables with larger weight in each component are, respectively, domestic market paper, currency exchange PTAX, paper A4, interest rate Selic, pulp, and again, domestic market paper. The analysis for Aracruz indicated that the most important variables for each component are, respectively, price index IPCA, currency exchange PTAX, interest rate Selic and again price index IPCA. The variations in pulp price have the most important effect on component 1 (inversely proportional due to negative correlation).

The proportion of total variance explained by each of the components estimated is presented on Table 5 for Suzano and VCP and on Table 7 for Aracruz.

Table 4
Principal component coefficients for VCP and Suzano

	C_1	C_2	C_3	C_4	C_5	C_6
ΔPulp	0,3975	-0,3923	0,254	-0,1351	0,7772	0,0367
ΔPaper	-0,6057	-0,3763	0,3046	0,1123	0,069	-0,6175
ΔA4	0,2244	-0,3458	0,689	-0,0341	-0,5329	0,2649
ΔPTAX	0,3341	0,6466	0,4303	-0,0968	0,0229	-0,5246
ΔIPCA	0,4998	-0,4075	-0,4275	-0,1624	-0,3253	-0,5188
ΔSelic	0,2516	-0,0271	-0,0043	0,9655	0,0295	-0,0535

Table 5
Total variability proportion explained by components for VCP e Suzano

Component	Proportion	Cumulative
C_1	28,61%	28,61%
C_2	21,57%	50,18%
C_3	18,93%	69,11%
C_4	15,90%	85,01%
C_5	12,10%	97,12%
C_6	2,88%	100,00%

Table 6
Principal coefficient component for Aracruz

	C'_1	C'_2	C'_3	C'_4
ΔPulp	-0,5639	0,3932	0,4847	0,5409
ΔPTAX	0,3332	0,7528	0,3086	-0,4764
ΔIPCA	-0,7081	-0,1478	0,0634	-0,6876
ΔSelic	-0,2639	0,5068	-0,8160	0,0876

Table 7
Total variability proportion explained by components for Aracruz

Component	Proportion	Cumulative
C'_1	33,33%	33,33%
C'_2	27,21%	60,54%
C'_3	23,38%	83,92%
C'_4	16,08%	100,00%

After the principal components were calculated, the regression models using them as independent variables were estimated again through the Backward procedure for variable selection. The fitted PCR model for each company is presented on equations 7, 8 and 9 and on Table 8.

The fitted PCR model for Suzano is,

$$\Delta E_i^{suzano} = 0.01703 - 6.15573 \cdot C_{1,i} + 1.03675 \cdot C_{2,i} - 22.42608 \cdot C_{4,i} \quad (7)$$

The fitted PCR model for Votorantin is,

$$\Delta E_i^{vcp} = 0.02519 - 3.2657 \cdot C_{1,i} - 13.63768 \cdot C_{4,i} \quad (8)$$

Fitted PCR model for Aracruz is,

$$\Delta E_i^{aracruz} = 0.02382 - 10.74368 \cdot C^*_{1,i} - 9.94849 \cdot C^*_{4,i} \quad (9)$$

Table 8
Fitted PCR model for each company

Firm	Component	Coefficients	Standard-error	T-Statistics	P-value
Suzano	C_1	-6,15573	1,80679	-3,407	0,00242
	C_2	1,03675	0,36591	2,833	0,00942
	C_4	-22,42608	6,83380	-3,282	0,00327
VCP	C_1	-3,26570	1,03775	-3,147	0,00437
	C_4	-13,63768	4,20240	-3,245	0,00344
Aracruz	C_1^*	-10,74368	2,42374	-4,433	0,00018
	C_4^*	-9,94849	0,21770	-4,570	0,00012

Again, the diagnostic analysis of PCR models didn't present any problems, so they can be considered well adjusted.

On the final EBITDA model for Suzano, a major influence of the forth component can be noted. The main variable for this component is interest rate Selic, which it wasn't significant on the multiple regression model. Since the interest rate Selic's returns (calculated over unit prices) has a magnitude considerably smaller than the others (exception for price index IPCA), it's expected that the correspondent coefficient would compensate for this difference.

On the other models, the effects of the coefficients were more homogeneous. Considering Aracruz's model, the first and fourth components had similar influence. With VCP's model, the fourth component again has a larger coefficient; the interpretation is similar to that for Suzano's case.

4.3 EaR forecast

In this section, we compare results for EaR forecast on both methodologies. The EAR forecast from the estimated regression models, starts from the simulation of future values of independent variables.

To perform this simulation, we used the usual procedure according to literature: assumption of jointly normal distribution and simulation through Cholesky decomposition of the covariance matrix. Herein, we simulate the log-returns of pulp prices, domestic market paper prices, paper A4, as well as log-returns for currency exchange PTAX, price index IPCA and interest rate Selic for four consecutive quarters, summing a year. The total number of simulated points was 10.000. The log-returns for price index IPCA and interest rate Selic were calculated from unit prices.

Thus, 10.000 simulated points were obtained for EBITDA's annual log-return for each company. From these values, an empirical probability distribution was obtained and then the EaR, on a time horizon of one year, can be estimated for any desired confidence level.

According to Corporate Metrics technical document, in EaR calculations, the loss is defined over a target future EBITDA. Since we lack a prior-defined target, we will calculate EaR as potential loss over the last effective EBITDA value released (last quarter 2006). The forecasted EaR values obtained (in R$ millions) are presented on Table 9.

Table 9
Forecasted EaR values (in million R$)

(Millions R$)	Suzano		VCP		Aracruz	
Confidence level	Regression	PCR	Regression	PCR	Regression	PCR
80%	25,14	21,06	15,43	1,08	35,75	35,74
90%	43,13	40,74	41,83	24,7	63,3	63,27
95%	57,91	55,28	62,12	44	84,64	84,65
99%	80,7	81,64	96,69	72,7	118,75	118,7
99,90%	105,45	104,5	127,01	95,7	149,42	149,4

The first important point to mention is that the two methodologies had equivalent results for Aracruz. According to the sphericity test calculated on section 3.1, the data for this company didn't present significant multicollinearity problems. This shows that on the absence of colinearity, the PCR method is equivalent to the usual multiple linear regression methods.

On the other hand, for Suzano and VCP, the PCR method resulted in smaller EaR values for almost all confidence levels, indicating that when ignoring multicollinearity between independent variables, the firm's risk may be over-estimated.

The actual EBITDA values for the last quarter of 2006 and 2007 for the three companies are displayed on Table 10, where we can see that the losses taken by each company are coherent with the forecasted values (on Table 11, the positive values indicate loss and the negative values indicate profit).

Table 10
Actual EBITDA values for the three companies on last quarters of 2006 and 2007

(Millions R$)	EBITDA Dec/06	EBITDA Dec/07	Effective Loss
Suzano	299,11	325,76	-26,65
Aracruz	279,00	184,00	95,00
VCP	454,50	428,80	25,70

Source: elaborated by authors.

Taking for example the adjusted PCR model for VCP data, the end of period loss (last quarter 2006) with 95% probability should be smaller than R$43.88 millions (see Table 9); comparing with the multiple linear regression model, the last quarter 2006 loss should be smaller or equal to R$62.12 millions. The observed actual loss, of R$25,70 millions, matches both intervals; however, the interval obtained through PCR method is much more efficient than the one obtained through the usual regression model.

5. Conclusion

The EaR values for annual horizon forecast obtained through PCR models were smaller than those obtained through multiple linear regression for almost all confidence intervals, indicating that ignoring multicollinearity on econometric models can lead to an over-estimation of risk. In the absence of colinearity, the PCR models showed equivalent results to the usual multiple linear regression models.

Generally, the multiple linear regression model has simpler implementation and interpretation. But since it doesn't take into account possible correlations among the independent variables and it may produce risk estimates that are both biased and subject to instability. On the other hand, the PCR model explicitly eliminates multicollinearity, but has more complex implementation and interpretation. Therefore, the methodologies here presented should be considered as complementary to each other.

A sound risk management policy should contemplate the analysis and comparison of the two techniques' results, thus leading to a more reliable and less exposed to faults financial risk dimensioning process.

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