ESTIMATION OF OPERATIVE RISK FOR FRAUD IN THE CAR INSURANCE INDUSTRY

Jorge Aníbal Restrepo Morales, Tecnológico De Antioquia
Santiago Medina Hurtado, Tecnológico De Antioquia

ABSTRACT

The regulatory framework for assessing and risk measurement in most companies focuses primarily on proposals of the New Capital Accord (Basel II). The Basel Committee gives importance to the concept of operational risk and requires that financial institutions cover possible loses with capital. The goal is to identify expected losses because of different events that might arise in firm management. This work develops a model to estimate the monetary loss due to car theft for Columbian insurance companies. We estimate the probability functions of monetary losses for car theft. First we estimate the distribution functions of the number of car thefts and for the monetary loss. Then, we use Monte Carlo simulation to identify the severity of expected losses. The results and conclusions will be useful for insurance firms. Using the results here, they can set up guidelines to improve risk management.

JEL: G22; C15

KEYWORDS: Insurance, Operational Risk, Simulation, Loss Distribution Aggregated.

INTRODUCTION

Is important to identify and value enterprise operational risk. Potentially, the operative faults affect all businesses. Manufacturing enterprises, commercial, financial services both large and small could experience monetary losses caused by their workers, internal and external frauds, human and technical wrongs, government policies or economic cycles. Company exposure to monetary loss may be higher or lower for several reasons. We find some conflicts between interests between rapid growth, internal changes, financial condition, weak culture control and corruption in the country or region. Not only do giants like Enron and governments have losses because of fraud but also small financial institutions and small businesses experience losses (Sivirichi, 2010). In Colombia, manufacturing companies, services and financial markets enterprises undergo constant development and transformation that dramatically increases the likelihood of adverse events. This creates an unending dynamic, marked by mergers and takeovers, internal streamlining and technical upgrading.

In addition, the complexity of transactions associated with product life cycle cause exposure to operational risk. This paper supplies a knowledge base to build an organized view of management. We quantify operational risk and measure risk events. This work is split into three parts: The first focuses on generic ideas and definitions of operational risk, based on the Basel Committee approach. In the second phase we show the present state of the insurance sector against losses because of car theft in the region. The third part shows how to use probability distribution functions to model the number of stolen cars and monetary losses - from 2004 to 2009-. Finally, we use Monte Carlo Simulation (MS) to identify the severity of expected car theft losses for 2011.

LITERATURE REVIEW

Simulation is accepted widely in both an educational and business context. It helps us to explain and predict and identify best solutions to decision problems. It also provides an in depth analysis when we want to assess events with high degree of uncertainty. In addition, the simulation provides comprehensive vision of the event under study and overcomes limits of analysis based only on historical data. It describes the behavior by a probability distribution function and therefore considers the probabilities of events happening.

Evans (1998) define simulation as the procedure of building a logical-mathematical model that represents an observable fact and allows us to experiment with it, to understand behavior and help us make decisions. It is important to identify "inputs" and their probability distribution function. We must also define interdependencies to describe behavior by means of covariance or correlation analysis to explain the expected behavior. Meanwhile, Fiorito (2006) shows how simulation is useful in problems or circumstances that involve uncertainty. The model is useless if it does not help users understand the problem. So the simulation lets us conduct experiments with models and analyze the results.

We quantify the economics loss to operative risk events by Operative Value at Risk (OpVaR). Alcántara (2010), shows how the raise on it value, depends on the number of events likely to occur and the severity of these economic losses. Several authors show that economic loss by operational risk typifies probability distribution functions known as heavy-tailed or fat tail distributions, such as Gamma and Exponential, Weibull Lognormal and Pareto generalized other distributions (Chernobai et al., 2007; Panjer, 2006; Venegas, 2008). Economic losses are able to be insured and we can use other estimations including stochastic analysis for insurance businesses (Daykin 1994).

Several authors argue that model selection depends on risk behavior. We wish to know the degree of exposure and severity of risk events faced by institutions in specific macroeconomic environments. These can be recessive or protectionist. In the same way, they depend on the overseeing regulatory institutions or the specific information recorded in historical risk events (Pathak, 2006; Moscadelli, 2004). On the other hand, when there statistical data about loss events are not available, we can estimate the probability distribution function by means of surveys (Evans, 1998, Da Costa, 2004). Alternatively, we can use more refined methods to measure the exposure to economic loss by operative risk such as "fuzzy logic" (Medina 2010).

We highlight the importance of recording each risk event that occurs in the company and build a database containing this information. The database should contain for each risk event, information on what happened and the loss estimate. However, the information systems should be integrated with enterprise risk management models (Enterprise Risk Management-ERM-). Next, we describe the research, we show how insurance companies should consider and manage external causes of car theft. The goal is to develop common strategies between insurance companies, professional associations and police institutions. The target is to control car theft and reduce economics loss.

Defining Operational Risk

This section outlines risk of fraud in car insurance companies. The operational risk is the potential loss from an unforeseen event arising from failures or shortages in information systems in internal control systems or errors in processing investment (AFIN S.A. Stock Brokerage). Castillo (2009) defines "operational risk, as the possibility of financial losses incurred by business events or performance, arising from failures or weaknesses in strategic planning, or business management, or related technology, or the information used by external events and includes legal risk. It does not refer to the possibility of losses from unexpected changes in political, economic and social development Castillo (2008). For the operational risk assessment, companies mist capture, measure and processing data efficiently. Currently government institutions have regulated and formalized the idea, including rigor in collecting and control operational risk events.

Operational risk must be included by managers in strategic planning. The Basel Committee defines it as the risk of loss from failed or inadequate processes, people and systems or from external events (Basel

Committee on Banking Supervision). Jorion (2000) define the risk as the volatility of expected results, commonly related to the value of assets or liabilities. Typically large organizations rank the four pillars or risk categories: credit risk, market risk, business or strategic risk and operational risk. Operational risk is characterized by external events displaying different levels of severity. They are inherent in all phases and events of enterprise management. Most managers face adverse events, some with unknown probability. Sometimes these adverse events are related to the complexity and variety of tasks and processes or the asymmetry of information available.

Events Associated with Insurance Management in Colombia

The insurance industry is a leading protagonist in the economy, mainly because of its presence as an institutional investor. They promote personal savings, protects assets and production capacity of enterprises from random events and severe losses. In 2008, the insurance industry reached a 2.6% share of GDP, showing its continued expansion and contribution to the country's economic growth. In Colombia, the insurance industry is represented by FASECOLDA – Colombian Federation of Insurers. This is a nonprofit professional association, which brings Columbian insurance and capitalization companies together. FASECOLDA´s strategic management aims to lead development of the insurance industry through advancing accomplishments at the national and international level. To achieve this goal, FASECOLDA collects and analyses general statistics on specific performance of the industry, produces bills for Congress consideration that can impact insurance firms. It also provides technical, legal and economic support to its partners.

A study by Fasecolda, and taken up by the National Institute for Research and Prevention of Fraud (INIF), reveals that from January to September 2010, theft was 4,333 cars with an estimated value of 117,289 million pesos (65 million USD). Different studies show how insurance fraud is considered a misdemeanor. But, since the creation of INIF in 2003, several statistics emerge about insurance fraud convictions. In 2002, the four largest insurers in the country came together for a common goal: to research prevent insurance fraud. They argue the only effective way to counter fraud is to work together. In this collaborative effort emerged INIF, an institution that brings together a group of people with the most advanced technological methods. The goal is to produce concrete results for insurers in their fight against fraud. The INIF, basic objective is to building a culture of antifraud among insurance users and give its partner companies management solutions that decrease fraud risk through internal policies, resulting in efficiency and profitability.

Cities Index and the Most Stolen Cars

Table 1 shows the percentage of stolen insured cars by city. The results show Bogota and Medellin with the highest levels of car theft at 31% and 30% respectively.

Table 1: Percentage of Stolen Insured Cars in a City

City	Percentage
Bogotá	31
Medellin	30
Cali	20
Barranquilla	3
Bucaramanga	1
Others	15

This Table shows the monthly statistics for January-September 2009 and 2010 of car theft for major cities. Data from Fasecolda

Cars, vans and heavy cars are most affected by theft. Allegations of theft are known to the INIF. The prosecution's office allowed the institute access to statistics on the most stolen cars in the country; Table 2 shows the car theft statistics.

Table 2: The Statistics by Car Thefts

Vehicle	Percentage
Cars	49
Truck and Jeeps	20
Heavy Cars	11
Bikes	19
Others	1

Table 2 shows monthly statistics for January-September 2009 and 2010 of car thefts by car type. Cars, vans and heavy car are the most affected theft. Data from Fasecolda

The use of models as taxis is important in theft, says INIF´s director. Chevrolet Spark and Hyundai Atos are the leading theft models in three cities. However, others like Mazda 323, Chevrolet Aveo, Corsa, Renault Twingo and Clio appear on the lists of 'most wanted' by thieves. Criminals frequently use the "carousel scheme" to commit the theft. This involves securing a car, committing fraud then charging the fraud to the insurance company. They recover the car and take it another insurance car in another company, where they repeat the process.

This is easy, because insurance companies often act alone against fraud. Until 2003 there was no authority to function as bridge between insurance companies and police investigators and prosecutors, to help them detect fraud. The INIF director indicates, we have 10 individuals convicted of fraud. INIF and insurance´ companies research, and alert authorities to the fraud methods. Different studies show Columbia has several kinds of fraud. The first is called "planned", and occurs when involved fake accidents to collect insurance or other profit opportunities. Another common practice is called "gemeleo" cars. This involves placing a legal car plate on a stolen car and circulating the car in a different city. In another case a car is reported as stolen to several insurance companies. Multiple claims for collection are submitted. This is call "carousel". We call the third fraud opportunistic. It occurs when the insured simulates and accident so that a third-party will benefit from the civil liability coverage. Finally, we have fraud inflated losses. In this case the loss is real, but the circumstances of claims do not match the real damage to the vehicle. The insured takes this advantage to fix a previously damaged car.

DATA AND METHODOLOGY

According to Castillo, a high percentage of companies in Colombia have a poor concept of operational risk or they are only beginning to understand it. Management carries out audit actions and internal control, to identify the sources of operational risk exposure, but not their quantification (Castillo M, 2008).

There are a set methods to quantify operational risk including MS, extreme value theory, Bayesian trees, and fuzzy logic. These techniques are used depending on the availability information about loss events. We use MS with historical data from 2004 to 2010 on car theft in Colombia, to run the simulation. We adjust the probability distributions to the frequency and severity of loss events that occurred. These adjustments allow us to estimate the loss distribution aggregated (LDA) and in turn to estimate the specific period loss provision (2011). The historical information of frequency and severity of car theft is taken from FASECOLDA.

LDA Model Assumptions

In the LDA model total loss is define as sum of different random losses:

$$S = \sum_{i=1}^{7} \sum_{j=1}^{8} Sij \qquad (1)$$

Where Sij represents total loss in (i, j) cell loss matrix. i represents the operative risk analyzed. Several risk operatives are defined by the Basel committee but each company can have its own risk matrix.
j represent the business line of the enterprise.

To calculate each loss S_{ij} in the risk matrix we complete the following computations:

$$Sij = \sum_{R=1}^{n} X_R \qquad (2)$$

Where R represents a random variable of the number of risk events in cell *(i, j)* (frequency of events). X_R represents the number of losses in cell *(i, j)* (severity of the event.) From this it follows that losses are the result of two sources of randomness: the frequency and severity The LDA model, used to estimate the appropriate operational risk exploits the following assumptions: a) R, that represent variable frequency and X_R, that represent the variable severity, are independent random variables. b)X_R, represent the severity of loss, within the same class, and is identically distributed. c)X_R, represents the severity of losses within the same class and is independent. According to Frachot et al (2004), the first assumption involves frequency and severity which are independent sources of randomness, while b) and c) symbolize the losses within the same class and are uniform, independent and identically distributed.

Modeling Severity

Now we fit different probability distribution functions to historical data series of operational losses for the car theft business line using 81 months of data from January 1, 2004 to September 30, 2010. Next we find the probability distribution function that best fits the detect data and estimate its parameters. The distribution function achieved suggests the range of loss of each event occurred. Severity of loss is a continuous variable according to the central limit theorem, when n is large. It must be demonstrated that it behaves as a normal distribution. To do this, we define the following: (X) Is the loss in cell (i, j) of the losses matrix (severity of the event). The specific variable follows a probability distribution $F_{ij}(x)$ which we define as:

$$F_{ij}(x) = P(X_{ij} \leq x) \qquad (3)$$

Modeling frequency

Frequency is a discrete random variable that incorporates the number of observed theft events in a monthly period, with a given probability of the event. Carrillo (2006) proposed the Poisson distribution to model this variable but if we have historical data, we must search for the optimal distribution function using a goodness of fit test. N_{ij} is a random variable representing the number of risk events in cell (i, j) of the array of events (frequency of events). The specific variable follows a probability distribution $P_{ij}^{(n)}$, which we define:

$$P_{ij}^{(n)} = P(N_{ij} = n) \qquad (4)$$

From the FASECOLDA historical data, it is assume that for every 100 insured cars an average of 5.15 are stolen in 2010. This means that the probability of success is small (0.0515). From the database of 81 months, λ = 474 cars month. So we postulate that the proper probability distribution for the random variable is Poisson, but we must prove that the better distribution function is Poisson.

RESULTS

To develop a frequency analysis of car theft we use @Risk. To find the best distribution to apply to car theft data the best fit is identified using a chi-square test at a 95% confidence level. The results show a binomial negative distribution (NegBin) with the largest P-Value of 0.919 as shown in Table 3. We conclude the NegBin probability function provided the best fit for the sample data. No other

Table 3: Test Results for the Frequency

	Input	NegBin	IntUniform	Poisson	Geomet
Function		463	435	447	166
Minimum	365	0	365	0	0
Maximum	586	+Infinity	586	+Infinity	+Infinity
Mean	475.839	475.839	475.5	475.839	475.839
Mode	429	473	365	475	0
Median	472	475	475	476	330
Std. Deviation	41.402	41.069	64.085	21.813	476.339
Skewness	0.290	0.148	0	0.045	2
Kurtosis	3.129	303%	1.8	3.002	9
Chi-Sq Statistic		4.536	52.598	63.429	365.83
P-Value		0.919**	0**	0**	0**

This Table shows the results for the frequency of car thefts. The P-Value of 0.919 allow us to assume that NegBin probability function fits the sample data.

Other graphics such as P-P and Q-Q plots can be used to examine the data fit to the theoretical distribution. The NegBin distribution has the expect value E (X) = 475.83, and a standard deviation of 41.06. The parameter of the binomial negative distribution are K=187 and P=0.282

<u>Analysis of Severity (Losses)</u>

To fit the parametric distributions we must update the losses using an update inflation. The procedure allows us to express the economics loss to a base year 2010. Then, the interpretation is similar to that raised by frequency analysis. Table 4- shows the fit of different distributions to the historical data on losses for each car theft. The results suggest that several distributions have good fit to the data. The best fit is the logistic distribution, which gives a higher p-value of 0.4148. We use a Chi-square test with 95% confidence, and find parameters of the logistic distribution to be α=31.146 and β=2.295.

Table 4: Test Results for the Loss of Each Event of Car Theft (Severity)

	Input	Logistic	Log Logistic	Ext Value	InvGauss	Pearson5
Function		32.983	29.099	25.085	26.655	31.127
Minimum	24.708	-Infinity	18.590	-Infinity	20.650	17.204
Maximum	63.961	+Infinity	+Infinity	+Infinity	+Infinity	+Infinity
Mean	31.469	3.146	31.548	31.459	31.469	31.434
Mode	31.498 [est]	31.146	30.068	29.506	29.030	29.298
Median	31.133	31.146	30.858	30.746	30.621	30.641
Std. Deviation	5.007	4.163	4.570	4.337	4.489	4.43
Skewness	3.392	0	2.085	1.139	1.244	1.378
Kurtosis	24.277	4.2	19.326	5.4	5.582	6.915
Chi-Sq Statistic		9.246	12.950	14.925	16.160	17.395
P-Value		0.4148**	0.1649**	0.093**	0.0636**	0.0429**

This Table shows the results for the severity. As the P-value = 0.4148, the null hypothesis is accept by the severity follows a logistic distribution

The histogram strengthens the conclusion that losses follow a logistic distribution. Using the logistic distribution we see that the histogram midpoints are reached by the continuous logistic distribution function, which reveals its setting. The Kolmogorov Smirnov test is also performed. The results are presented in Table 5. As shown the p-values are higher than the logistic distribution.

Table 5: The Kolmogorov Smirnov Test

Estimated Kolmogorov statistic DPLUS	**0.0732**
Estimated Kolmogorov statistic DMINUS	0.0493
Estimated overalls statistic DN	0.0732
Near P-Value	0.7845**

This table shows the Kolmogorov test results for the severity of car theft. As the P-value = 0.7845, the null hypothesis is accept by the severity follows a logistic distribution

Test of Goodness of Fit

Next, we want to test the hypothesis that the parametric distribution fits the data, given a confidence level (1-α) express as follows:

$H_{o:}$ the loss data (severity) follows a logistic distribution

$H_{1:}$ the severity does not follow a logistic distribution

If the P-value <= α, we reject $H_{o.}$ With a confidence 95%, α = 0.05. As the p-value of 0.7845 is greater than α = 0.05, the null hypothesis is accepted. Thus, the severity follows a logistic distribution

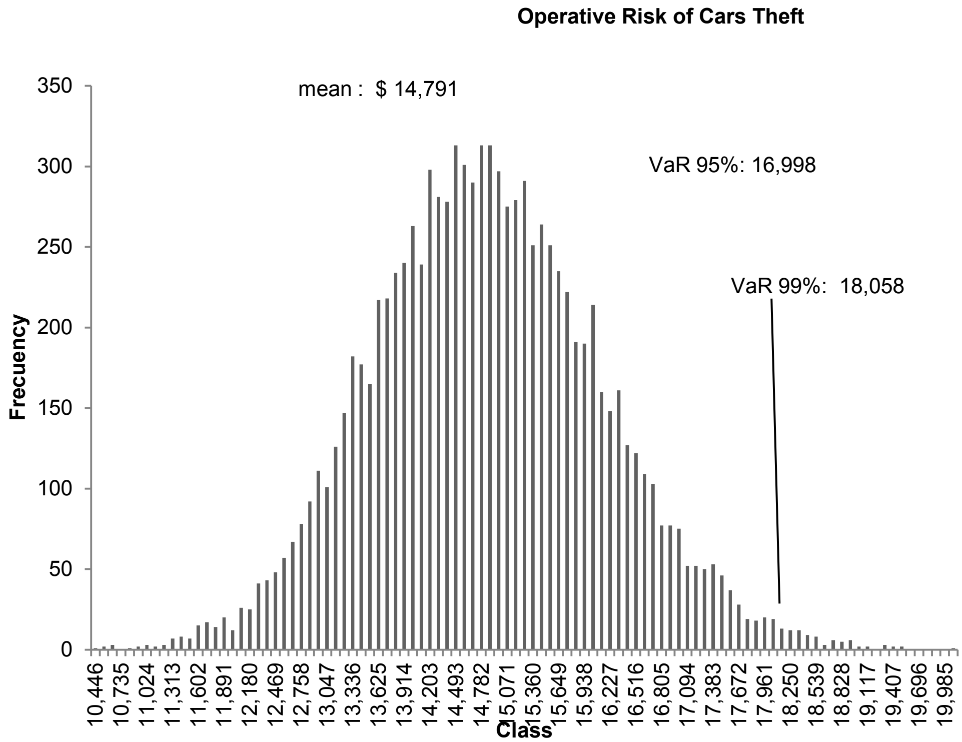
Estimating the Loss Distribution Aggregated (LDA)

To estimate loss for operational risk it is necessary to combine the discrete variables (frequency) with continuous variables (severity), so the aggregate loss is an uncertain variable with a nonlinear relation. This complicates loss estimates by analytical methods. However, the MS, being a simple and flexible analytical method, allows convolution of the distributions of thefts and losses to produce the aggregate loss distribution. The results were obtained using MS with data frequency and severity of theft simulated using the probability distribution. The results are show in Figure 1. The expected values for 10,000 iterations of the convolution between the frequency and severity distributions are reported using the NegBin-logisitic combination for each risk event.

After performing the MS we get a distribution of aggregate losses associated with car theft in Colombia by aggregating distributions of frequency and severity. The results are presented in Figure 3. As shown in the figure the average value of monthly losses total $14,791 million pesos ($8.2 million USD). The operational VaR at 95% and 99% is $16,998 and $18,058 millions pesos ($10 millions USD) respectively, These values should be covered by insurance companies through reinsurance or another means of coverage. The following Table 6 shows some statistical measures of the simulation. In general, standard deviation, Skewness and kurtosis of the aggregate loss distribution approaches a normal distribution.

The simulation gives a countrywide expected loss for the year 2011 of nearly $157,219 million pesos as shown in Table 7. This represents the theft of around 5,494 cars.

Figure 3: The Operative Risk of Cars Theft



This Figure shows the results of the 10.000 repetitions of the convolution between the frequency and severity distributions, taking NegBin-logisitic combination for each risk event.

Table 6: The Statistical Measures of the Simulation

Operative Risk of Car theft.	
Mean	14,791
tipic error	12.87
Median	14,753
Tipic Desviation	1,287
Variance	1,656,034
Curtosis	0.0976
Skewness	0.1609
Rang	9,635
Mín.	10,446
Max	20,081
Iterations	10,000
perc 90%	16,516
perc 95%	16,998
perc 99%	18,058

This table shows the main statistical measures of the simulation

Table 7: Countrywide Expected Loss for the Year 2011

Month	*Random Number*	*Thefts Expected*	*Random Number*	*Expected Loss*
January	0.29	452.54	0.86	15,051.16
February	0.29	451.89	0.04	9,446.14
March	0.51	475.68	0.86	15,019.41
April	0.19	440.09	0.68	13,830.55
May	0.91	531.27	0.10	10,401.19
June	0.04	408.49	0.92	15,668.24
July	0.29	452.38	0.23	11,479.12
August	0.50	475.12	0.54	13,117.57
September	0.76	504.16	0.09	10,342.79
October	0.06	413.68	0.55	13,178.87
November	0.64	489.73	0.59	13,355.24
December.	0.02	398.65	0.96	16,328.78
Accumulated		*5,493.67*		*157,219.04*

This table shows the simulation results for countrywide expected losses for the year 2011. The estimate is $ 157,219 million pesos, representing the theft of around 5,494 cars.

CONCLUSIONS

Methods to estimate the Operative Risk exist including MS, Extreme Value Theory, Bayesian Trees and Fuzzy Logic. These techniques are used depending upon the historical data of loss events. We used MS because we have historical data of car theft in Colombia from 2004 to 2010. To carry out the simulation; we adjust probability distribution function of frequency and severity of loss on the thefts that occurred. These adjustments allow us to use a Loss Distribution Aggregated (LDA) to estimate provision for expected losses. These estimates are necessary to plan for the specific period (2011). The historical data of frequency and severity of car theft is taken from FASECOLDA.

After performing the MS, we get an LDA associated with car theft in Colombia from aggregation frequency and severity. The probability distribution function aggregate is not a fat tailed distribution. It has parameters similar to normal distribution (Kurtosis and Skewness). The loss distribution has a low volatility (1,287 mills) and variation coefficient of 8.72%, suggesting losses are centered on the average. It is convenient to work with a 95% confidence level. The average value of monthly losses totaled $ 14,791 million. The simulation gives a countrywide expected loss for the year 2011 of nearly $ 157,219 million pesos (87.3 million USD), representing the theft of around 5,494 cars.

The works objectives were estimate economic expected losses for inclusion in pricing car theft insurance policies, as well as the estimate of unexpected losses “Value at Risk". Through this we can calculate the potential capital to absorption losses. The operational VaR at 95% and 99% is $ 16,998 and $ 18,058 million respectively. These values should be covered by insurance companies through reinsurance or another means of coverage. In general, Operational Risk for car theft is greater as the number of issued insurance policies increase and it is more likely to occur in the cities of Bogota and Medellin. The rest of the country also shows a rising trend with the passage time. As December approaches theft increases. To start a process of risk management firms should have a strategy approved by management. The principles should be to identify, measure, control, check and moderate operational risk. They should develop their own approach and method for risk management, according to geographical position, underwriting volume and complexity of operations. The system must consider all stages of risk management.

We suggest future research that studies city, car´s marking and color to set boundaries that allow development of different rates by city, car and color. This model can be run by city, region or department to identify the influence on successful financial companies and allow them to lower risk by increasing premiums, reinsurance, and abandonment of the business line in some cities. Alternatively firms might design insurance policies exclusively for high performing volume customers. In the same way, if the insurance company needs estimations of economic capital needs, we recommend applying statistical and mathematical techniques identified in this article using historical data to measure Operational Risk. Analysts should note the model obtained is not static. Rather it changes overtime because companies take actions to moderate risk and control plans. The main limit of the study was the lack of systematic data. The data in this study extends back only to 2004. In addition, insurance companies are just developing a culture for risk measurement because of difficulty obtaining reliable qualitative information. It is important that once risks are identified and quantified the insurance companies manage them through policies, procedures, systems and controls. Companies that have not yet started the process of risk management are isolate efforts and have a long way to go. The risk measurement methods recommended by Basel II are applicable to insurance markets, which behave in lineal way for the severity of the loss.

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Abbreviations

AMA Advanced Measurement Methods / Advanced Measurement Approaches
ANPR: Notice of Proposed Rulemaking / Advance Notice of Proposed Rulemaking

BIOGRAPHY

Jorge Anibal Restrepo Morales, PhD., is an associated professor of management at Tecnológico de Antioquia. He can be contact by email: jrestrepo@tdea.edu.co.

Santiago Medina Hurtado, PhD., is an associated professor on Management Engineering School of Minas Faculty. National University of Colombia. He can be contact by email: smedina@unal.edu.co