REPUTATIONAL EFFECTS OF OPERATIONAL RISK EVENTS FOR FINANCIAL INSTITUTIONS

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ABSTRACT
This paper aims at measuring reputational effects for financial institutions by examining a firm's stock price reaction to the announcement of particular operational loss events such as internal frauds. We conduct at this purpose an event study analysis of the impact of operational loss events on the market values of banks and insurance companies, using the OpVar database (OpData® dataset supplied by OpVantage®). This analysis concerns some publicly reported banking and insurance operational risk events affecting publicly traded US or European institutions from 2000 to 2006 that caused operational losses of at least $20 million – a total of 20 bank and insurance company events. We estimate for these institutions the cumulative abnormal return. It turns out the evidence that stock prices react negatively to announcements of operational losses due to internal frauds. We conclude our analysis by estimating the Reputational Value at Risk at a given confidence level, which represents the economic capital needed to cover reputational losses over a specified holding period.

KEYWORDS
Operational risk, internal fraud, event study, abnormal return, market model, Monte Carlo simulation, Value at risk, Economic capital.

1. INTRODUCTION

Financial institutions have faced increasingly operational risk events during these last years, but the attention devoted to managing operational risk is very recent (while market and credit risk management is more consolidated). At this purpose, both the new regulatory framework in the banking sector (Basel II) and the project for the new solvency regime in the insurance sector (Solvency II) recognize the importance of operational risk and require explicit treatment through allocations of specific capital.

For what concerns "famous" operational risk events, in the banking sector we can remind bankruptcy of Barings bank (1995) which was triggered by a $1.3 billion loss due to a rogue trader and the Allied Irish Bank's loss of $750 million (2002) due to unauthorized trading. Some famous operational loss events in the insurance sector include Prudential Insurance Company of America which paid $2 billion to settle allegations of sales abuses (1990) and State Farm Insurance which paid $1.2 billion to auto insurance policyholders as the result of a breach of contract lawsuit in 1999 due to the use of inferior quality generic replacement parts for damaged cars. These examples show that operational events can produce very severe losses.

Operational risk is a pure risk category (unlike market and credit risk). This means that operational events lead exclusively to negative losses. Furthermore, the impact of operational risk on financial institutions has been scarcely studied.

The main objective of this paper is to investigate the impact of operational loss events in financial institutions. At this purpose, we analyzed operational events gathered in the OpVar database developed by OpVantage, a subsidiary of Fitch Risk. OpVar consists of operational loss events from the late 1970s to 2006 coming from publicly available data sources. More precisely, we aim at analyzing the impact of operational loss events on the stock price performance of the affected financial institutions. Actually, we want to show that operational events (especially internal fraud events) can produce reputational effects on the financial institution which cause an abnormal depreciation of stock prices.

Reputational risk represents a more elusive risk category with respect to market, credit and operational risk, because of the difficulty in quantifying its effects and above all in understanding of the mechanisms that generate it. The first definition of reputational risk is due to the Board of Governors of the Federal Reserve System (2004): "*Reputational risk is the potential that negative publicity regarding an institution's business practices, whether true or not, will cause a decline in the customer base, costly litigation, or revenue reductions*". In general a reputational risk is any risk that can potentially damage the standing or estimate of an organization in the eyes of third-parties. It may also happen that a firm's reputation depreciation emerges gradually. Nevertheless, it is evident that equity markets react progressively to the reputational damages caused by some negative operational event.

Indeed, a firm's stock price can be set as the present discounted expected value of the cash flows generated. Any reputational event will entail present or future expected cash flows and consequently the equity value of the firm will depreciate. We can assume that a loss announcement may be interpreted as the fact that the firm has a scarce control management. In this situation, Shareholders are likely to sell stocks if they suspect that future losses are about to happen. We can thus assume that a reputational effect can be indirectly measured through the impact of a loss announcement on a firm's equity value.

Such an event study analysis has been performed by de Fontnouvelle et al. (2005), and Cummins et al (2004). Both papers measure the impact of operational losses thanks to the estimation of the cumulative abnormal return. Cummins consider the three factor model to estimate stock returns while de Fontnouvelle uses the one factor market model.

The main results of these authors are the following.
Cummins shows that a strong, statistically significant negative stock price reaction to announcements of operational loss events occurs. Besides, the market value response is larger for insurers than for banks. Finally, he shows that the market value loss significantly exceeds the amount of the operational loss reported. This implies that such losses have a negative impact about future cash flows. Finally, losses are proportionately larger for institutions with higher Tobin's Q ratios. This implies that operational loss events produce a stronger market value impact for institutions with stronger growth prospects.

A similar analysis of de Fontnouvelle focuses mainly on the normalized cumulative abnormal return. He shows that there is strong and robust evidence that the market does fall more than one-to-one for internal fraud announcements (especially for firms with strong shareholder rights) while externally-caused losses have no reputational impact. Another important conclusion is that the market reaction to operational losses is immediate and significant, even when the loss amount is small relative to firm size. Thus, the market does consider operational losses to be capital events, through reputational effects.

The approach we follow is similar to de Fontnouvelle and Cummins. Besides, we model stock returns with standard Brownian motion and GARCH model.

The paper has the following structure. Section 2 is devoted to the methodology overview (model description). The event study application is performed in Section 3. Section 4 concerns value at risk and the determination of the economic capital and section 5 concludes with comments and further research projects.

2. MODEL DESCRIPTION

In this section, we describe the "technical blocks" that compose our model. In particular, we present the main characteristics of operational risk and the cumulative abnormal return estimation using different theoretical models.

2.1 AN OVERVIEW OF OPERATIONAL RISK

With the regulatory spotlight on Operational Risk management, there has been ever increasing attention devoted to the quantification of Operational Risk.
The Operational Risk potential devastating power has been shown by many large operational losses; some of the best known Operational Risk incidents are the $9 billion loss of Banco National due to credit fraud in 1995, the $2.6 billion loss of Sumimoto Corporation due to unauthorized trading activity in 1996, the $1.7 billion loss and subsequent bankruptcy of Orange County due to unauthorized trading activity in 1998, the $1.3 billion trading loss causing the collapse of Barings Bank in 1995, the $0.75 billion loss of Allied Irish Bank in 2002, the loss of $2 million of Prudential Insurance of America in 2002.
The Basel Committee on Banking Supervision has added a new minimum capital charge for operational risk as part of the Basel II Capital Accord, scheduled to be implemented in 2006–2007 (Basel Committee, 2001). Besides, in order to develop a better risk management, the Committee has published guiding principles for the management of operational risk (Basel Committee, 2001, 2003a). The major rating firms have published reports discussing operational risk management and analyzing the implications of operational risk for the assignment of financial ratings (e.g., Moody's Investors Service, 2003; Fitch Ratings, 2004).

The new regulatory framework in banking sector (Basel II) and the project of the new solvency regime in insurance sector (Solvency II) recognizes the importance of Operational Risk by requiring its explicit treatment with the determination of a specific capital requirement.

There is no generally accepted definition of Operational Risk in the financial community. In this paper we refer to the definition proposed by the Basel Committee on Banking Supervision in 2001: "*the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events*". This definition has been adopted for the insurance sector until now.

In this categorization Operational Risk includes the following event types: business disruption and system failures; clients, products and business practice; damage to physical assets; employment practice and workplace safety; execution delivery and process; external fraud; internal fraud.

In a previous paper (Angela et al., 2007), we developed a comprehensive model to quantify the capital charge necessary to cover the Operational Risk in a financial institution.
The input data derive from OpData, an operational losses database supplied by OpVantage, a division of Fitch Risk Management.
The data are collected from public sources and in the database only losses, whose amounts exceed a truncation threshold of $ 1 million, are registered during the period 1972-2006.

In the OpData, operational losses are categorized according to the Basel Committee's event type's classification:

1) Business Disruption and System Failures;
2) Clients, Products and Business Practice;
3) Damage to Physical Assets;
4) Employment Practice and Workplace safety;
5) Execution Delivery and Process Management;
6) External Fraud;
7) Internal Fraud.

For each loss the following information is available:
- classification by event type;
- firm name;
- loss event description;
- loss amount in local currency;
- loss amount in dollars;
- loss amount in current value dollars (based on CPI);
- loss data;
- country;
- total assets of the firm.

2.2 THE CUMULATIVE ABNORMAL RETURN

The theoretical models we used for simulating return time series are the following:

I. Single index model (market model);

We assume that for each event $i = 1, \dots, n$ (where n is the total number of events) at time t, the *log-returns* $r_{i,t}$ are given by the relation

$$r_{i,t} = \alpha_i + \beta_i \cdot r_{M,t} + \varepsilon_{i,t}$$

where α_i and β_i are constant, $r_{M,t}$ is *log-return* of the Market index and the random variable $\varepsilon_{i,t}$ is the disturbance factor.

II. Geometric Brownian motion model;

This model assumes the well known hypothesis that stock prices A_t follow the stochastic process:

$$dA = \mu \cdot A \cdot dt + \sigma \cdot A \cdot dW$$

where μ and σ are constant and W_t is a Wiener process. We then perform Monte Carlo simulations by discretizing the process dA.

III. GARCH(1,1) model;

In this model, *log-returns* satisfy the following equations:

$$\begin{aligned} r_{i,t+1} &= \mu_i + \eta_{i,t+1} \\ h_{i,t+1} &= \omega_i + \beta_i \cdot h_{i,t} + \alpha_i \cdot \eta^2_{i,t} \\ \Im_P\left(\eta_{i,t+1} \mid I_t\right) &= N\left(0, h_{i,t}\right) \end{aligned}$$

where μ_i, $\omega_i > 0$, $\beta_i > 0$ and $\alpha_i > 0$ are constant; $\Im_P\left(\cdot \mid I_t\right)$ denotes the objective probability law conditional on the information set I_t and finally, $N(\cdot,\cdot)$ represents the normal distribution.

For each event, models' parameters are estimated by considering 250 trading days periods which terminate 20 days before the event announcement (in such a way that the "estimation window" does not overlap with the "event window").

In order to estimate abnormal returns, we need two time series of stock return data for each event. The first one for the estimation period (as we said above); the second one is the event window where the abnormal returns are calculated. The event window E will start 20 days before the event and terminate 25 days after the event (the event is denoted by *day zero*). With this convention, we can denote $\mathrm{E} = (-20; 25)$.

We denote for each event i ($i = 1, \ldots, n$) the theoretical stock returns as $\hat{r}_{i,t}$ and the empirical stock returns as $r_{i,t}$. The abnormal return *AR* for each event i in the event window $\left(-w_1; w_2\right) \subseteq \mathrm{E}$ is defined as the difference between empirical and theoretical returns:

$$AR_{i,t} = r_{i,t} - \hat{r}_{i,t} \qquad \forall t \in \left(-w_1; w_2\right)$$

Abnormal returns are generally computed for event windows surrounding the event day. In order to allow for the possibility of information leakage before the loss events, the event window starts *20* trading days prior to each event. Furthermore, in order to allow the market to fully react after an event, the event window ends *40* trading days after the event. We can also tabulate *AR* results for windows of various lengths that are subsets of the original window.

We assume then that the conditional abnormal returns are independent and identically distributed. Under these hypotheses, we can aggregate the abnormal returns across events within any given time period. The average abnormal return across all events (at day t) in the chosen event period is computed as:

$$\overline{AR}_t = \frac{1}{n} \cdot \sum_{i=1}^{n} AR_{i,t}$$

We compute then the cumulative abnormal return (*CAR*) for event i in the event window $(-w_1; w_2)$ as:

$$CAR_i = \sum_{t=-w_1}^{w_2} AR_{i,t}$$

The mean cumulative abnormal returns (mean *CAR*) in the event window $(-w_1; w_2)$, also called cumulative average abnormal returns across the n events is defined as the mean of *CAR*s for each event:

$$\overline{CAR} = \frac{1}{n} \cdot \sum_{i=1}^{n} CAR_i = \frac{1}{n} \cdot \sum_{i=1}^{n} \sum_{t=-w_1}^{w_2} AR_{i,t}$$

Using de Fontnouvelle approach, we define the normalized *CAR* as follows.
We can view the *CAR* (for event i) as the function:

$$CAR_i(x) = \sum_{t=-w_1}^{x} AR_t \qquad \forall x \in (-w_1; w_2)$$

Let us denote λ_i the loss occurred for event i and Θ_i the total asset of the financial institution which suffered the loss. The abnormal loss can be defined as

$$AL(x) = \Theta_i \cdot e^{CAR(x)} - \Theta_i = \Theta_i \cdot \left(e^{CAR(x)} - 1\right) \qquad \forall x \in (-w_1; w_2)$$

If $AL(x) = 0$, no abnormal loss occurred in the event window taken into consideration; if $AL(x) < -\lambda_i$ the abnormal loss (absolute value) is greater than the announced loss. The normalized abnormal loss is then given by

$$NAL(x) = \frac{AL(x)}{\lambda_i} = \frac{\Theta_i \cdot \left(e^{CAR(x)} - 1\right)}{\lambda_i} = \frac{e^{CAR(x)} - 1}{\lambda_i / \Theta_i}$$

We deduce that if $NAL(x) = -1$, the abnormal loss is equal to the announced loss while if $NAL(x) < -1$ the abnormal loss is greater than the announced loss. According to de Fontnouvelle, a reputational effect occurs whenever $NAL(x) < -1$.

<u>*Remark*</u>.

$$\frac{\Theta_i \cdot \left(e^{CAR(x)} - 1\right)}{\lambda_i} = \frac{e^{CAR(x)} - 1}{\lambda_i / \Theta_i} \simeq \frac{CAR(x)}{\lambda_i / \Theta_i} = NCAR(x)$$

where *NCAR* is the normalized *CAR*.

3. A MODEL APPLICATION

The data analyzed in our paper come from the OpVar operational loss database distributed by OpVantage, a division of Fitch Risk Management. The database consists of publicly reported operational loss events worldwide from 1978 through 2006 covering a number of industries, including banking and insurance. The bank and insurance losses are categorized according to the Basel Committee's definition of operational risk event types (see at this purpose the previous paragraph), and the bank losses are further categorized according to the Committee's business lines hierarchy. The database also provides a complete description on the events and event dates (presented as "settlement date").

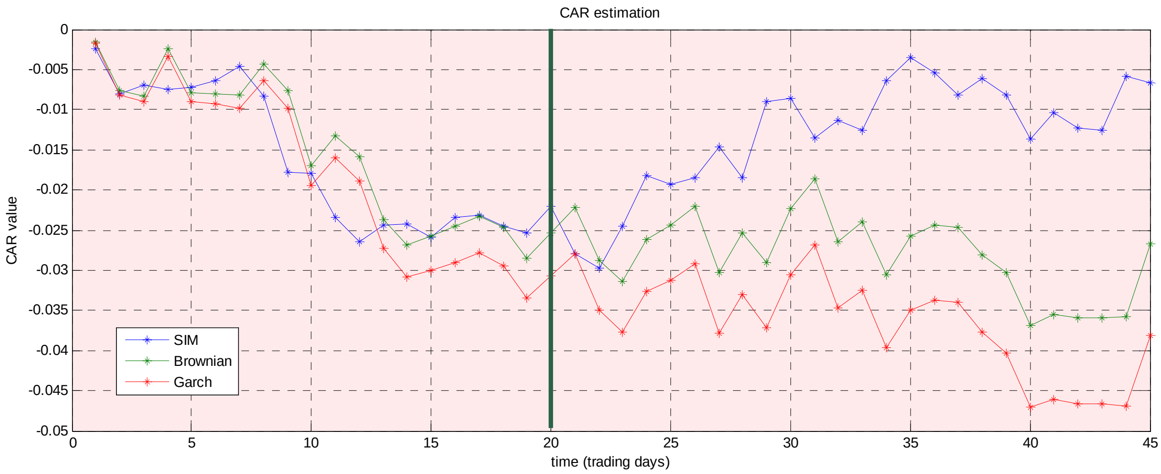
The OpVar database reports all publicly announced losses that exceed a threshold of $1 million (truncation data is a very common problem for operational risk databases). However, in order to estimate the market value impact of "high" losses, we take into consideration in our study losses which exceed at least $20 million.

Besides, we focused our analysis on financial institutions.

We have taken into consideration internal frauds, which are more likely to produce reputational effects (see de Fontnouvelle et al.; Cummins et al.). Indeed, we assume that relatively large losses are more likely to affect stock prices due to their size (and also from an accounting perspective). Moreover, high frequency, low severity losses should be anticipated events already incorporated in a firm's expense budget and therefore embedded in current stock prices.

We have excluded from our study financial institutions which were not publicly traded at the event window and we also excluded financial institutions which presented multiple events in the event window (clustering of events in the same window event can produce a biased estimation of the parameters needed for the theoretical model). Furthermore, we have eliminated from the sample the event or event date which could not be verified.

We present in the following graph the CAR estimation for the event window $(-20;+25)$ for the three theoretical models. The announcement date corresponds to $t = 20$.



We observe that after a sharp negative impact which starts before the announcement of the event, a gradual recovery of the initial value occurs. The negative impact which occurs some days before the announcement is interpreted as information leakage before the event. The numerical values in the event window $(-20;t)$ are reported in the following table.

t	*SIM*	*GBM*	*Garch*
-18	-0.80%	-0.77%	-0.82%
-16	-0.75%	-0.25%	-0.34%
-14	-0.64%	-0.80%	-0.92%
-12	-0.83%	-0.43%	-0.64%
-10	-1.79%	-1.69%	-1.95%
-8	-2.65%	-1.58%	-1.89%
-6	-2.42%	-2.69%	-3.08%
-4	-2.34%	-2.46%	-2.91%
-2	-2.46%	-2.47%	-2.94%
0	-2.20%	-2.53%	-3.07%
2	-2.97%	-2.88%	-3.50%
4	-1.82%	-2.62%	-3.27%
6	-1.85%	-2.20%	-2.92%
8	-1.84%	-2.54%	-3.31%
10	-0.86%	-2.23%	-3.06%
12	-1.13%	-2.65%	-3.48%
14	-0.64%	-3.06%	-3.96%
16	-0.54%	-2.44%	-3.38%
18	-0.62%	-2.81%	-3.77%
20	-1.37%	-3.69%	-4.71%
22	-1.23%	-3.59%	-4.66%
24	-0.58%	-3.58%	-4.69%

Table 1. CAR values

4. VALUE AT RISK AND THE ECONOMIC CAPITAL

We remind that the most efficient methods of hedging against financial risks are to allocate an appropriate *economic capital* in order to face losses due to some specified risk category. This capital can be defined as the maximal possible loss incurred within a specified confidence level over a specified holding period (time horizon). From a statistical point of view, this capital also called Value at Risk (VaR) is just the quantile of the loss distribution at the specified confidence level. In other words, VaR at a confidence level α must satisfy the relation:

$$P\left(\text{Loss} > \text{VaR}\right) = 1 - \alpha$$

The new regulatory framework in banking sector (Basel II) and the project of the new solvency regime in insurance sector (Solvency II) require explicitly the determination of a specific capital requirement in order to hedge market, credit and operational risk (based on value at risk estimation). In this section, we attempt to define *reputational* VaR in a similar way.

The Reputational VaR will be estimated in a “small” event window (about one month, i.e. about 20 days of open market) surrounding the reputational event. Indeed, reputational events have a sharp negative impact (see Cruz, 2002) and after a while a progressive recovery occurs (the kind of recovery depends strongly on the specific financial institution). For these reasons, the reputational VaR is estimated in a short time horizon where the negative reputational impact is observable. Finally, the “capital at risk” can be considered as the shareholders’ value.

In order to estimate the reputational VaR, we set up a frequency/severity approach to model the “reputational losses” (a similar approach has been adopted to model operational losses, see Angela et al., 2007). We assume, for simplicity, that reputational effects are exclusively caused by internal losses events. The frequency is then represented by the frequency of internal events. In a previous paper (Angela et al., 2007) we showed that the annual frequency (for the whole database) of the event type “internal frauds” is well fitted by a Poisson distribution with parameter $\lambda = 18.97$. We must then rescale event frequency at firm level.

Finally, the severity is given by the CAR (whenever negative). In the previous section, we presented CAR’s mean estimation for several events windows (for the set of events which constitutes our sample). In order to allow more variability, we estimate through best fitting techniques the optimal continuous distribution which represents CAR values (for a given window event). For example, when considering the event window $(-14;+6)$ where the reputational effect is more evident, the CAR values’ distribution is well fitted by a logistic distribution with parameters $\alpha = -0.0113$ and $\beta = 0.02227$. We considered here the CAR estimated with the market model. The reputational losses distribution is then given by the convolution between frequency and severity distributions. We set up at this purpose a Monte Carlo simulation with the following steps:

- extract a random number of events from the frequency distribution (take into consideration the event window length);
- for each event extract a random loss from the severity distribution;
- calculate the total loss as the sum of losses for each event obtained in the previous step;
- repeat the previous three steps N times in order to obtain a simulated vector Λ of losses;

- determine the statistics of Λ. In particular, the reputational VaR is given by the quantile of Λ at the given confidence level.

Numerical results.
The CAR statistics in the event window $(-14;+6)$ are reported in the following table:

mean	-0.0113
std. dev.	0.0404
skewness	-0.5451
kurtosis	3.1552

Table 2. CAR distribution

The numerical simulation performed through a Monte Carlo method with 10,000 replications gives the following results:

mean	-0.002
std. dev.	0.0026
skewness	-0.1250
kurtosis	3.3698
VaR 95%	-0.0057
VaR 99%	-0.0077
VaR 99.9%	-0.0108

Table 3. Simulated reputational losses

We deduce for example that the reputational VaR at a 99.9% confidence level is 1.08% of the shareholders' value (for a monthly event window). The economic capital needed to face reputational effects increases with the required confidence level.

5. CONCLUSIONS

Our paper analyzes operational loss impact due to internal frauds on stock returns for financial institutions in the period 2000–2006 using the OpVar database. We conduct an event study analysis of the market value impact of these operational loss events on bank and insurance stocks through the evaluation of the cumulative abnormal return in a window event surrounding the event date.

This study focuses on operational loss events where the reported loss amount is at least $20 million. The event study is based on a subset of these events affecting firms that were publicly traded at the time of the event for which we could verify the event date and we also excluded the presence of multiple events in the event window.

We observe an evident reputational effect due to internal fraud events. The reputational effect is revealed through a sharp negative impact on the CAR values. This negative impact progressively weakens after sometime. We finally estimate the reputational VaR at a given confidence level for a monthly event window which represent the economic capital necessary to hedge negative reputational effects.

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