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Does the financial market compensate investors for operational Losses?

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ABSTRACT

It is well known that several industries, like the hotel industry, are subject to low frequency high impact events resulting from their operations. However, there is a dearth of academic research in this area. In this paper we propose an innovative methodology to study the problem using a combination of Asset Pricing Models and an original database. We find that asset prices compensate investors not only for market and credit risk, but also for operational risk.

1. Introduction

The impact of operational risk on firm performance is an important topic that has received little attention in the literature. Operational risk is the loss resulting from inadequate or failed internal processes, people and systems or external events [22]. External shocks, such as hurricanes, terrorist attacks, the Zika epidemic or the COVID-19 impact consumer travel decisions and reshape their travel preferences. At the same time, the hotel industry is increasingly vulnerable to internal risks such as food security and cybersecurity [17]. This lack of scholarly attention is most likely due to the absence of reliable data.

Although operational risk management is one of the biggest challenges for the hotel industry, researchers have not been able to develop instruments to assess their impact on business performance. In this study, we will use an innovative methodology introduced by Mithra, S., Karathanasopoulos, A., Sermpinis, G. and Dunis, C. [20] to calculate operational risk measures for listed companies. Operational risk is defined as the risk arising from operational activities in conducting business. In that respect, it could affect such different areas like I.T. failure (physical or software), damage to physical assets (natural disasters or imprudence), administrative errors, fraud and other operational activities. As a consequence, operational risk affects several aspects of business.

In this article, we want to test if there is a risk premium associated with extreme events affecting a business's operations. We will use three measures related to operational risk such as operational Value at Risk (VaR), number of operational extreme events and the average size of those extreme operational losses (also known as expected shortfall, ES). The framework proposed in this article to infer whether there is a risk premium associated with those extreme events follows the Arbitrage Pricing Model's (APM) [23] basic insights. According to this theory, any required return can be thought of as having two components: a risk-free rate, and a set of risk premiums. The first component is compensation required for the expected loss of purchasing power, which is demanded even for a riskless asset. The second component is extra compensation for unexpected events (possible losses and profit), which depends on the asset considered, say, expected returns should include rewards for accepting risk.

To the best of our knowledge, there is no single study that has analyzed the effects of operational risk on the performance of stock returns, and even less research on operational extreme events. In this paper we will try to shed some light on this conundrum. The main difference between measures based on standard deviation and downside deviation is that downside risk uses an exogenous reference rate instead of the mean return [19], while it is well known that most investors do not assign the same importance to earning than losses. Therefore, our objective in this paper is to evaluate whether investors are compensated for facing operational risk (mainly, operational extreme events). This will be done by testing the efficacy of different configurations of the APM including those with operational risk factors to evaluate the required returns by investors using data from the hotel industry.

The rest of the paper is organized as follows. The next section presents the basic features of the model. Section 3 then develops our modelization for operational risk. We obtain operational risk as the residual risk that remains once market and credit risks are removed. Section 4 introduces the empirical analysis while Section 5 analyzes the main results. The last section contains the concluding remarks.

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2. Risk premium

The APM provides an approximate relation for asset returns with an unknown number of unidentified factors. We take the perspective of a US-based, internationally diversified investor [3]. Thus the risk-free rate should compensate this investor for the dollar's expected loss of purchasing power, and the risk premium should compensate the investor for bearing different risks (market risk, credit risk, operational risk, etc.). Our empirical model may be seen as an extension of the APM model extensively analyzed in the literature (see [14] for a recent summary). We focus on the class of linear asset pricing models [13,21] in which the equilibrium expected stock return can be written as:

$$RR_i - r_F = a_0 + \sum_{j=1}^{K} b_{ij} F_j + e_i \tag{1}$$

where RR_i is the uncertain return for company i, r_F is the risk free rate, a_0 represents a performance measure, meaning the return generated by company i independently of the level of risk it faces (this is expected to be 0 on average), F_j are risk factors with j = 1, …, K, and b_{ij} represents the sensitivity of asset (company) i to factor j and e_i the error terms.

In this paper, we will investigate the following question: *Do stock returns compensate investors for market, credit and operational risk?* We will analyze different models suggested by the literature and derived from the Capital Asset Pricing Model (CAPM) and APM. In particular, our models will consider eight possible factors:

- Market risk (F_1): This factor is the Beta calculated as in the CAPM or the sensitivity to the Equity Risk Premium. The first implication of the theoretical model is that the price of systematic risk is positive ($b_{i1} > 0$).
- Size (F_2): to evaluate the size effect as in Fama and French [12]. Several authors [2,5] argue that the discount due to the size effect appears to price several factors that have not been accounted for ($b_{i2} < 0$).
- Leverage (F_3): measured here by the importance of debt (D), will denote the importance of leverage and credit risk. Consequently, if a highly leveraged firm faces a higher risk of failure, then expected returns should compensate for this risk ($b_{i3} > 0$).
- Value (F_4): to measure the value effect [4]. Value stocks are expected to pay higher returns than Growth stocks. We will use the price-to-sales ratio (P/S) to measure this effect ($b_{i4} < 0$).
- Volatility (F_5): will evaluate the volatility effect (suggested by [1]). The volatility effect is expected to be positive in theory, since riskier investments are expected to produce higher returns, but many researchers and practitioners found that assets with higher idiosyncratic volatility provide lower return (the volatility puzzle). Then, we do not have a clear expected sign for this parameter ($b_{i5} \gtreqless 0$).

And we will introduce three additional factors to evaluate the effects of operational extreme losses on firm performance.

- VaR (F_6): is the operational value at risk or the maximum losses for a 95% level of confidence.
- ES (F_7): Expected shortfall or the average extreme operational losses. Meaning, the average losses higher than the VaR at the 95% confidence level.
- Number of operational extreme events (extreme losses) (F_8): the number of losses higher than the VaR at the 95% confidence level.

3. Operational risk factors

We obtained Operational Risk Factors as in [20]. Meaning, we operate in three steps. The point of departure is the assumption that total risk for company i, $RR_i(TT)$ is composed of market risk $R_i(M)$, credit risk R_i(C) and operational risk R_i(OP), or

$$RR_i(TT) = R_i(M) + R_i(C) + R_i(OP)$$

Consequently, we obtain operational risk as the residual risk that remains once market and credit risks are stripped out [18]. Then, the first step is to calculate credit risk. We used the idea that shareholders' equity behaves as a call option and consequently we can use the Black & Scholes formula [6] to calculate the credit risk for a given asset. As explained in Hull et al. [16], expected return resulting from credit risk $\omega_i(t)$ can be obtained by maximizing:

$$\omega_i(t) = r_f(t) - \left(\frac{\ln[N(d_2) + \left(\frac{N(-d_1)}{L}\right)]}{(T-t)} \right) \tag{2}$$

With

$$d_1 = \frac{-lnL}{\sigma_A\sqrt{(T-t)}} + 0.5\sigma_A\sqrt{(T-t)},$$

$$d_2 = d_1 - \sigma_A\sqrt{(T-t)},$$

$$L = \frac{D(t)e^{-r(T-t)}}{A(t)} = \frac{D^*(t)}{A(t)},$$

where T is the maturity of debt, σ_A is the volatility of assets for company i, A(t) is the total value of assets for company i at t, D(t) is the total value of debt for company i at t and N(.) is the cumulative distribution function for the Normal distribution. The estimation of $\omega_i(t)$ requires the estimation of L, which requires D(t), which is calculated using financial statements that are available for all publicly listed companies. We will also need to estimate the values for A(t) and σ_A using Merton's credit risk model:

$$\mathrm{E}(t)\sigma_E = N(d_1)A(t)\sigma_A,$$

$$\mathrm{E}(t) = A(t)N(d_1) - D^*(t)N(d_2), \tag{3}$$

where E(t) is the market value of equity for company i and σ_E is the stock price volatility. Then, we calculated operational risk ($\mu_i(t)$) as the residual risk or the difference between market risk (calculated as in the CAPM or $\beta_i\left[r_M(t) - r_f(t)\right]$, where r_M is the return from a market index and r_f is the risk free rate) and credit risk ($\omega_i(t)$ in Eq. (2)).

Once we isolate the operational risk for each hotel, we proceed to calculate the different extreme risk measures. Where the Value at Risk (VaR) is measured as the five percentile of the distribution of operational losses. Meaning the value of losses that will never be attained with 95% confidence. Then we calculate the Expected Shortfall (ES) or the average value of those extreme losses that will only occur on 5% of the observations. Finally, we calculate the number of losses (or number of months, since we are using monthly data) that those losses exceed the VaR value.

4. Empirical analysis

To run the estimations, we have collected monthly data for publicly traded companies (i.e. share price, market capitalization, debt, return-on-equity and equity) in the hotel industry from DATASTREAM. We used five years of observations for the period January 2014 to December 2018. This time span allows us to use recent information for companies from two developed regions

(USA and Europe) and a developing one (India). This information was supplemented by balance sheet data, which is publicly available for traded companies. We have computed the average value for those five years using annual data for assets, debt and P/Sales. Then, we applied the same methodology to get the annual average market risk premium using monthly data.

For the construction of the operational risk database, we also used monthly data for the three month Euribor as the risk free rate and the Euronext 100 as the market index for Europe; T-bill and the Standard & Poor's 500 index as the risk free rate and market index (respectively) for the USA and the SBIN and Nifty 51 for the risk free rate and market index for India. Only traded companies from the USA and Europe were included in the sample since the companies from those regions are recognized for having the lowest level of operational risk in the industry (and the highest standards). India was included as a representative of developing regions but only for those companies traded on the Bombay stock exchange. India is one of the only stock markets in the developing world where several companies from the hotel industry are traded. All companies that went bankrupt, were privatized or went public during the period of analysis were eliminated from the sample to focus only on operational risk and not on failures or resurrections. As a result, we have 47 companies with 59 values to create a panel with 2773 observations.

To construct the operational database we proceed in three steps. First, we applied the CAPM methodology to obtain market risk premium measured as $\beta_i \left[r_M(t) - r_f(t)\right]$. Second, we separated market risk from idiosyncratic risk (operational and credit risk). We applied the methodology described in Eqs. (2) to (3) as in [15] using Matlab to obtain credit risk. Finally, we calculated operational risk ($\mu_i(t)$) as the residual risk or the difference between market risk ($\beta_i \left[r_M(t) - r_f(t)\right]$) and credit risk ($\omega_i(t)$ in Eq. (2)).

Then, we proceeded to calculate the three operational extreme measures using the historical simulation approach. Value at Risk (VAR95) is defined as a threshold value such that the probability of extreme losses due to operational misbehavior exceeds this value in only 5% of the cases. Or, with a level of confidence equal to 95%, the VAR95 gives us the maximum operational losses that we will expect to suffer during the period. The second extreme factor that we estimated using this methodology was the Expected Shortfall (or ES95). The ES95 gives us more information about the expected value of those extreme losses, i.e. the expected losses that are greater than the VAR. Consequently, the ES95 gives us an idea of the expected losses on the tail of the distribution. The last extreme factor we use is the number of extreme losses, meaning the number of observations that exceed the VAR95. Meaning, ES95 gives us information about the size of the extreme losses while the number of those operational extreme events, give us information about their frequency.

Summarizing our methodology, first we used the time series for each company to construct the operational risk database and to calculate their different individual operational extreme risk factors (VAR95, ES95 and ELO or number of extreme operational losses). Then we implemented a cross-sectional analysis (based on Eq. (1)) to identify the risk premium associated with each risk factor. Our Beta factor (F_1) is calculated in the same way as CAPM, which was introduced previously to calculate market risk when developing the operational risk database and consequently estimated using time series data. Factors 2, 3 and 4 are calculated as the average of the five years under analysis. We also use the volatility of equity for the whole period of analysis, as an additional risk factor, because researchers have recently shown that it is an important explanatory variable for returns in cross section analyses. In Table 1 we present the definition of variables while Table 2 presents the summary statistics.

Table 1
Definition of variables.

Variables	Definition
$ER_i = RR_i - r_F$	Average excess return per hotel group.
Beta	Beta per hotel obtained from the CAPM.
Debt	Average total liabilities per hotel group.
Assets	Average total assets per hotel group.
Sales	Average P/sales ratio per hotel.
VOLeq	Volatility of equity per hotel group using the five years of monthly data.
DUMeur	European hotel group = 1.
DUMind	Indian hotel group = 1.
ELO	Number of total extreme operational losses.
VAR95	Operational value at risk with a 95% confidence level.
ES95	Average extreme operational losses higher than the VAR95.

Table 2
Summary statistics of the sample (n = 47).

	Mean	Median	Maximum	Minimum
$RR_i - r_F$	9.06%	7.69%	58.74%	−32.81%
Debt[a]	2'775'933	117'916	18'227'029	610
Assets[a]	3'762'352	239'655	28'189'591	1'175
P/Sales	2.425	2.04	9.51	0.06
VOLeq	11.17%	10.15%	3.69%	1.85%
ELO	2.936	2	13	0
VAR95	−14.91%	−13.9%	0	−41.46%
ES95	−19.69%	−17.72%	−2.75%	−46.7%

[a]In thousands (USD).

5. Results

To analyze the effectiveness of the APM in our sample, we focus on the implications of leverage for the risk factors that have attracted substantial attention in the empirical literature on the cross-section of stock returns: we use the Beta that was calculated in the same way CAPM was calculated, we have also introduced the price-to-sales ratio (similar to [4]) as an indicator of value stocks or the value effect. We also measured size (measured by total assets) and stock volatility as an alternative measurement for Beta for market risk (see [11] and [10]). We then extend the model to consider measures of operational extreme events. The idea is to test an APM that takes into account not only market risk and leverage but also operational risk (as derived in the theoretical part).

We have reported eight different configurations to estimate the APM model (Table 3), all of them significant using the F criteria. The most important observation is that the accuracy of the models, measured by the adjusted R^2, increase when we include the operational risk variables for all the different configurations and those variables are always significant. Additionally, this importance is not affected by regional factors (regional dummy variables are not significant).

Model 5 looks very appealing in terms of the goodness of fit but it does not pass the test of multicollinearity that exists between ES95 and VAR95. This was as expected since for the normal distribution, ES95 is a multiple of the VAR95 and although we use the historical simulation approach, our tests show that the residuals are approximately normally distributed and consequently, the results from the normal approach should be close to those of the historical simulation approach.

We have therefore focused our attention on model 7. Even though its adjusted R^2 is not very high (0.368), it is the highest of our sample once homoscedasticity and multicollinearity have been considered and is in line with previous research [7–9]. Under such a configuration, all the variables are significant at a 95% confidence level, except VAR95 that is significant at

Table 3
Empirical results for the Asset Pricing Model Revisited (APMR).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
a_0	0.094*** (0.022)	0.046 (0.034)	−0.027 (0.050)	−0.180* (0.090)	−0.252*** (0.074)	0.016 (0.052)	−0.184*** (0.066)	−0.105** (0.050)
Beta	−0.073** (0.029)	−0.085*** (0.029)		−0.016 (0.029)			0.000** (0.000)	
Debt		0.000 (0.000)		0.000*** (0.000)	0.000** (0.000)		0.000** (0.000)	
Assets		0.000 (0.000)		0.000** (0.000)	0.000** (0.000)		−0.184*** (0.066)	
Sales		0.019* (0.010)		0.028*** (0.009)	0.030*** (0.009)			
VOLeq			1.052** (0.403)	1.345** (0.602)	1.432** (0.558)	2.103*** (0.611)	1.990*** (0.603)	2.530*** (0.555)
ELO				−0.046*** (0.013)	−0.052*** (0.012)		−0.047*** (0.012)	−0.030*** (0.009)
VAR95				−3.573*** (1.066)	−3.945*** (1.026)		−1.278* (0.695)	
ES95				1.540** (0.681)	1.581** (0.670)	0.817** (0.368)		
DUMEur				−0.074 (0.059)				
DUMind				−0.036 (0.041)				
Adj. R^2	0.105	0.175	0.113	0.494	0.502	0.184	0.368	0.290

*Significant at 90%-level.
**Significant at 95%-level.
***Significant at 99%-level.

a 90% level. We present the p–p plot and the scatterplot (Appendix) showing the absence of homoscedasticity. We have also analyzed multicollinearity checking the VIF values and they are less than 10, as expected. Additionally, following [24], the odds ratio is overwhelmingly in favor of model 7 with respect to models 3 (1.772X10^-8) and 8 (3.822X10^-5) for the period of analysis.

We observe that the sign of the parameters is also as expected. VOLeq has a positive sign as suggested by the theory, showing that there is no volatility puzzle in our sample. The coefficient of this variable is high, positive and significant explaining that an important part of the return continues to be attributed to market risk (as predicted by the CAPM). For Debt and Assets, although both variables are significant, their impact will be small on performance for the period under analysis given the fact that the estimated parameters are very low.

Finally, the two new measures we used to capture operational extreme events are also significant. Note that we are using negative values for extreme losses, i.e. a negative coefficient for VAR95 means that increasing the value at risk for operational losses will also increase the required returns by investors in the hotel industry. This result has very important implications. There are previous studies that have analyzed value at risk for market risk but none of them analyzed how value at risk of operational losses affect expected returns. Note that the size of this parameter is also high reflecting the impact of this term on the expected return of investors. We should not forget to mention the effect of the frequency of those extreme losses. The number of losses is a positive value but has a negative coefficient. This looks counterintuitive, since it implies that the higher the frequency of extreme operational events (those in the negative tail of the distribution), the lower the expected return by investors. However, it might also mean that if the frequency of those events increases (ceteris paribus), then the effect of each extreme event will be less important and then the expected return should decrease (see Table 3).

6. Concluding remarks

Our results show that the cross section of stock returns can be explained by market risk (volatility of equity), credit risk (debt and total assets), and operational risk factors (value at risk and total number of operational extreme losses). Although all of them are significant, only volatility of equity and value at risk affect positively required returns by investors, while the number of extreme losses have a negative impact. As those events become more frequent, we believe agents are less affected by behavioral biases like fear of extreme losses and consequently require less compensation for that risk.

The results of this paper are extremely important because they show that investors care not only about market and credit risk, as shown by the previous literature, but also about operational risk. More precisely, operational extreme events that are rare but immensely harmful also affect investors. Then, any effort to build a database using public data will be extremely useful for them. That is an important reason to continue working on developing operational risk databases for different industries. A future research agenda should include not only an extension to other sectors of the economy but also additional methods with which the data can be analyzed.

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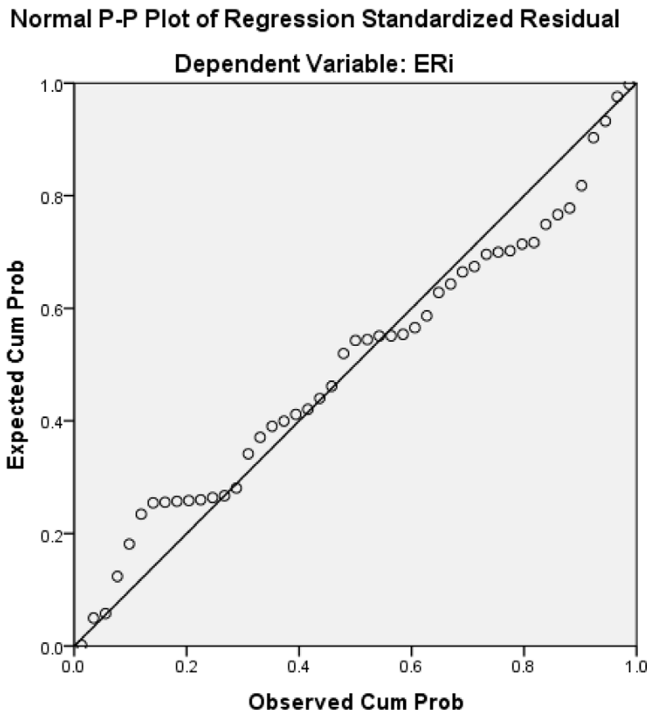
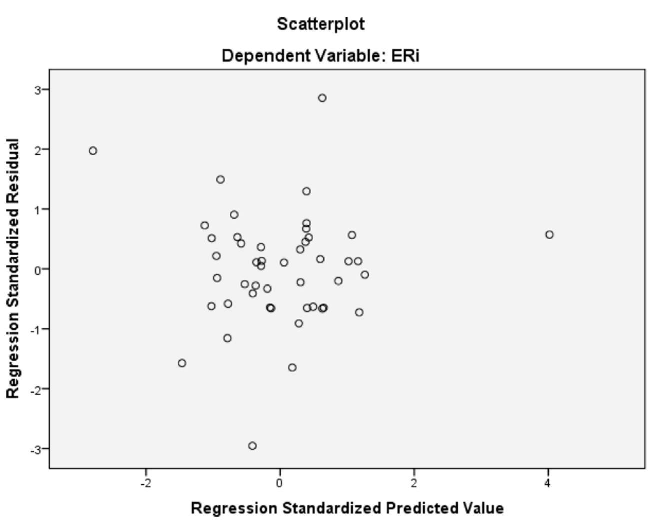
Appendix





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