Operational Risk and Emerging Markets

Abstract

Operational risk is currently gaining increasing importance in Finance. Presently, practically all literature has been devoted to operational risk measurement and qualitative management. However, little literature has been devoted to quantifying the impact of operational risk on share prices, yet share value tends to be a key incentive to managing risks. Furthermore the impact of operational risks (e.g. management, internal processes and controls) tends to be a significant barrier to investment in emerging markets.

In this paper, we quantify the impact on share prices from operational risk by applying the Single Index Model, which is one of the most recognised and popular models for share pricing in industry. Using monthly stock price data from major stock markets, we show that there exist variations in operational risk across different markets (developed versus emerging markets) as well as across different industry sectors.

Our results support the idea that analysing and managing operational risk improves investment performance. In particular, operational risk accounts for significant differences between emerging markets and developed markets in a way that is consistent with current literature on firm specific risk and management in emerging markets. This paper will therefore be of interest to industry, emerging market investors and analysis of operational risks.

Key words: Operational risk, emerging markets, sector, risk measurement, risk management, investment.

1 Introduction

Operational risk has increased over the years as markets and industries have become increasingly deregulated and more sophisticated. This has led to an increase in the quantity and reliance upon operational activities, leading to potentially higher losses from operational risks. For instance, most banks nowadays use advanced I.T. systems that operate on a global basis and employ sophisticated financial models. A simple operational risk such as data entry error may propagate throughout an entire system, affecting many investments.

Operational risk has been increasing in importance due to the recognition of large losses associated with it, there has been increasing regulatory emphasis on it (e.g. Basel Accord) and the need to understand it at it is currently a less well understood area compared to other risk factors e.g. credit risk. Furthermore, operational risk significantly affects all types of businesses, hence it is important to every industry sector.

The majority of operational risk research has been focussed on its measurement and management; there exists little research on its impact on share prices and the factors affecting operational risk from an investment perspective. This is even more surprising given that share price performance provides a key incentive for risk management and it is well known from a fundamentals analysis viewpoint that operational issues affect share performance. In fact, a major barrier to emerging market investment directly arises from the risk associated with operational issues.

In this paper, we investigate the impact of operational risk on share prices and the influence of markets and industry sectors upon them. We investigate the impact of the industry sector upon operational risk because it is well known that different sectors are exposed to different types of operational risks. For instance I.T. failures are more likely to impact the financial sector compared to the mining sector. We also investigate different markets (more specifically developed and emerging market) because it is well known that companies in emerging markets are typically less well run and regulated operationally than in developed markets, which can increase operational risks e.g. fraud.

This paper provides a number of contributions to the literature of operational risk. Firstly, we show that operational risk factors contribute to share price movements, rather than due to other risk factors such as market risk. Secondly, we show that operational risks and returns are dependent on the industry sector and the market (specifically emerging or developed). This is also consistent with expectations as we would expect factors such as market development (emerging versus developed) and industry sector (e.g. manufacturing versus retail) to fundamentally impact on operational risk.

Thirdly, we construct a tractable and viable method of measuring operational risk. Currently, many operational risk methods (for measurement or other uses) have significant data requirements and demanding implementation, which render them impractical for application, in particular this would be problematic for emerging markets where data is generally difficult to obtain. Furthermore, some of the more tractable operational risk measures can be fundamentally invalid or provide uninformative measures of operational risk (to be discussed further in section 2.2). We show that our method of measuring operational risk provides empirical results that are consistent with expectations e.g. higher operational risk in emerging markets.

Finally, our paper demonstrates the importance of accounting for operational risk factors in investment decisions. As operational risk varies between sectors and markets, some companies will be more exposed to operational risk compared to others which will impact share prices. In fact, our results are consistent with current practice of fundamental analysis of shares, where it is considered more important to assess operational issues in emerging markets than in developed markets.

The plan of this paper is as follows: in section 2 we introduce operational risk, defining it and providing a literature review of current research. In the next section we explain our method for measuring share price returns due to operational risk factors and measuring operational risk. In the next section we analyse our empirical results on operational risk from market data, which is taken over different markets and sectors. We finally end with a conclusion.

2 Introduction to Operational Risk

In this section we define and introduce operational risk and review current literature in the area.

2.1 Operational Risk Definition

Operational risk is a relatively new field of risk research, consequently there does not currently exist a consensus definition on it (Loader, 2002); in fact many companies have their own definitions of operational risk. There exist a range of generic definitions on operational risk, for instance Jarrow and Turnbull (Jarrow and Turnbull, 1996) emphasise the role of controls and procedures, the Basel Committee's definition includes the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events.

The essence of most operational risk definitions is that it is the risk arising from the operational activities in conducting business, rather than the business's 'financial' risk. Examples of operational risk therefore include (Chorafas, 2004): I.T. failure (physical or software), damage to physical assets (e.g. through natural disasters), administration errors (e.g. incorrect data entry), fraud and other operational activities. We should also note that all these risks affect all types of businesses and are not just restricted to the Finance sector, hence operational risk is an issue that is important to all business sectors.

A popular definition of operational risk assumes that total risk of company A , R(A), is given by

$$R(A) = R_M(A) + R_C(A) + R_{OR}(A), \tag{1}$$

where $R_M(A), R_C(A), R_{OR}(A)$ are the market, credit and operational risk, respectively, of company A. Therefore operational risk is defined as the residual risk remaining once market and credit risk are removed (Loader, 2002). This definition of operational risk emphasises the 'non-financial' aspect of risk that can affect a business. It also has the advantage of capturing all the wide spectrum of factors that can contribute to operational risk (e.g. from administrative errors to natural disasters) whilst still capturing the essence of operational risk. Additionally, such a definition (in contrast to other operational risk definitions) can be applied without bias to any particular sector, which is an important property for our paper.

In our paper we use the definition of operational risk as the residual risk once market and credit risk are removed. This is because, firstly, the purpose of our study is to investigate operational risk across different sectors and markets; we therefore require a definition that is not biased to any particular sector and is able to capture the wide range of factors that can contribute to operational risks. Secondly, this definition enables tractable modelling and measurement of operational risk and it significantly reduces data requirements. Such properties are highly valuable in operational risk compared to other areas of risk (to be discussed in more detail in sections 2.2 and 3). Moreover, reduced data requirements is a particularly important property in studying emerging markets, where obtaining any data can be difficult. Thirdly, this definition of operational risk leads to operational risk measurement that is not fundamentally or theoretically flawed unlike other operational risk measures e.g. the Basic Indicator Approach (to be discussed in sections 2.2 and 3).

2.2 Literature Review of Operational Risk

The literature in operational risk is relatively insignificant compared to other areas of risk research, however the literature is currently growing. A significant amount of operational risk literature has been dedicated to its measurement: the 3 main methods are the Basic Indicator Approach (BIA), the Standardised Approach (SA) and the Advanced Measurement Approach (AMA).

In BIA and SA the operational risk is measured by the amount of capital (also called capital charge) κ required to be held as a fund to cover potential operational risk losses. The BIA's capital κ_{BIA} is given by (Chorafas, 2004)

$$\kappa_{BIA} = \alpha E,$$

where α is a constant and E is the exposure indicator for an entire company. The SA measures operational risk by dividing a company into 8 business lines and the SA capital required κ_{SA} is derived by a similar approach to κ_{BIA}:

$$\kappa_{SA} = \sum_{i=1}^{8} \beta_i E_i,$$

where E_i is our exposure indicator for each business line i and β_i is a constant analogous to α but for each business line i. The terms E and E_i should represent a proxy for operational risk losses (or the operational risk losses in each business line for SA). This could be net profit (from each business line for SA) as net profit is approximately an indicator of the scale of business operations, which in turn should reflect the scale of operational risk exposure.

The AMA consists of 3 sub-groups: firstly, the Internal Measurement Approach which is an extension of SA whereby each business line is divided further into a set of operational risk factors. Secondly, the Loss Distribution approach which requires identifying every operational event, modelling each event's associated loss distribution and combining every event's distribution into one overall distribution to provide the operational risk (Shevchenko and Wuthrich, 2006). Thirdly, there are qualitative approaches, which include a variety of methods ranging from scenarios to scoreboards.

The motivations for the different measurement approaches relate to the fact that operational risk is notoriously difficult to model or measure and has demanding data requirements. Data relating to operational risk is typically unavailable to the public and may not exist, hence proxies are used to measure operational risk (such as net profit for the exposure indicator). Operational risk is also difficult to model due to the large and complex number of factors that can contribute to it, leading to modelling implementation and calibration problems.

The BIA and SA models are favoured for ease of implementation, do not require calibration and do not have demanding data requirements. However they have fundamental and empirical problems: if we choose the exposure indicator as net profit, then a company that is reducing its net profit each year is also improving its operational risk. This would be misleading as reducing operational risk should improve net profits. The AMA approaches may be theoretically more feasible but are generally intractable and have significant data requirements. For instance, in the Loss Distribution method we must calibrate the distribution of every operational event and combine them into 1 overall distribution, which is analytically and computationally non-trivial. The qualitative AMA methods are more tractable and have fewer data requirements but are significantly dependent on subjective opinion.

Another significant area of operational risk literature has been devoted to its risk management. The traditional method of managing operational risks has been to purchase insurance (e.g. insurance against natural disasters). In (Bazzarello et al., 2006) a method is proposed for managing operational risk through purchasing relevant insurance to hedge out operational risks; in (Peters et al., 2011) the cost of insuring against operational risk is investigated. Other literature focuses on managerial and governance issues to manage operational risk e.g. in (Benaroch et al., 2012) it is suggested that I.T. operational risk should be managed proactively and effectively.

The literature on operational risk in an investment context is limited, in particular with respect to share prices. One study by (Cummins et al., 2006) examines the impact of operational loss events upon share price movements, where the operational events are obtained from a proprietary operational risk database. There have been also other papers that examine particular aspects of operational risk upon stock prices e.g. (Palmrose et al., 2004) analyses the impact of earnings restatements upon stock prices (over a range of sectors). In (Bizjak and Coles, 1995) the impact on share prices on a range of firms from antitrust litigation is studied.

A major drawback of these studies is that they require a proprietary database of operational events, which can be difficult to obtain or non-existent in the case of emerging markets. Secondly, the database only consists of announced operational losses, consequently there is no analysis of unannounced operational losses on share prices. Moreover, operational loss databases tend to under represent low frequency but high severity risk events (Allen and Bali, 2007), yet these are typically the most useful or important operational risk events to examine. Such events are likely to be kept confidential (or unreported) (Allen and Bali, 2007), or may be misclassified as credit or market risk losses.

In (Allen and Bali, 2007) operational risk is examined without requiring a proprietary database; Allen and Bali estimate operational risk using share price and other market data that is more readily available and analyse empirical trends in operational risk. Although Allen and Bali analyse the impact of operational risk on share prices their study differs from ours in a number of aspects. Firstly, the method and data are limited to the US Banking and Insurance sector, hence they do not investigate a range of sectors and countries and the impact on operational risk (as in our study). Secondly, the model employed for operational risk measurement has significant data requirements, which would not be suitable for investigating emerging markets where data is not easily available (or does not exist).

The literature on the impact of emerging markets upon operational risk is practically non-existent. There has been much literature on individual aspects of operational risk (e.g. I.T. infrastructure, management etc.) and emerging markets, for instance in (Van Wyk et al., 2004), but these tend to be non-quantitative analyses (e.g. they discuss management initiatives). Moreover, no investigation is made upon the impact of the developed versus the emerging markets, or the impact of operational risk upon share price value. For instance in (Sun and Chang, 2011) there is quantitative operational risk analysis of banks in emerging markets but no comparison is made with developed markets (nor the impact on share value).

The lack of literature on operational risk and emerging markets is important to note given that it is well documented that emerging markets tend to suffer from a greater degree of operational risks e.g. fraud and ineffective operational procedures. Also it is well-known that operational risks are significant barriers to investment in emerging markets, hence an analysis of operational risk in such markets would be important. On the other hand, it is not highly surprising given that operational risk analysis can impose significant data requirements and it is well known that analysing emerging markets in genereal poses significant data issues.

3 Operational Risk Measurement Methodology

In this section, we explain our method for calculating the share returns due to operational risk factors, which in turn enables us to quantify the operational risk. We also show that our method is applicable across different markets and sectors.

3.1 Operational Risk Measurement by the Single Index Model

One of the purposes of our study is to measure the operational risk for different stocks. From standard risk measurement theory (Artzner et al., 1997), one can quantify risk by applying some statistical measure to a share return distribution, for instance quantiles (or Value at Risk) or standard deviation (Szegö, 2005). However, we are only interested in measuring operational risk rather than total risk, therefore we require a method of obtaining stock returns due to operational risk only.

In addition to measuring operational risk, we wish to investigate the variation in operational risk across different markets (including emerging markets), sectors and the impact on share price value. Consequently, this places constraints on the operational risk measures we can apply or formulate. Firstly, our operational risk measure must be flexible enough to be applicable across different sectors, hence cannot be designed for a particular sector (which some operational risk measures are aimed towards).

Secondly, the operational risk measure must also be applicable to emerging and developed markets, therefore it cannot have demanding data requirements that would exclude it from emerging market stocks. Therefore operational risk measures such as SA or the Loss Distribution approach would be unsuitable. Thirdly, we also want to relate the operational risk to share investment, hence abstract operational risk models (such as AMA) would not be able to achieve this. For instance, the Loss Distribution model directly models losses due operational events within the company but there is no method for relating these losses to share prices.

Using the Single Index Model (SIM) theory, modelling credit risk returns and our definition of operational risk, it is possible to quantify operational risk returns, measure operational risk and fulfil the operational risk measurement criteria previously discussed. Under SIM theory we model the return of asset i $r_i(t)$ by

$$\begin{aligned} r_i(t) &= \alpha_i + \beta_i[r_M(t) - r_f(t)] + r_f(t) + e_i(t), & (2) \\ \text{and } E[r_i(t) - r_f(t)] &= \alpha_i + \beta_i E[r_M(t) - r_f(t)], & (3) \end{aligned}$$

where:

- $r_M(t)$ denotes the return of the market or a stock market index;
- $r_f(t)$ denotes the riskless rate;
- α_i, β_i are the alpha and beta of asset i, respectively;
- $e_i(t)$ is the residual of asset i, with $E[e_i(t)] = 0$ and $var(e_i(t))$ can be non-zero (where var(.) denotes variance).

We note that $e_i(t)$ represents firm-specific risk returns and unanticipated returns in SIM theory, hence it is not purely a 'noise' term. Under SIM a stock's returns are due to market risk and non-market risk (also called firm specific risk). Furthermore, in SIM theory market risk returns are given by

$$\beta_i[r_M(t) - r_f(t)], \tag{4}$$

hence the total stock return with returns due to market risk removed is given by

$$r_i(t) - \beta_i[r_M(t) - r_f(t)]. \tag{5}$$

We also note in passing that this equation is also equal to

$$\alpha_i + r_f(t) + e_i(t), \tag{6}$$

by applying equation (2).

Using the definition of operational risk as the residual risk once credit and market risk are removed, we can therefore obtain stock returns due to operational risk if we can remove returns due to credit risk from equation (5). In other words, share returns due to operational risk factors for asset i $\varphi_i(t)$ is given by

$$\varphi_i(t) = r_i(t) - \beta_i[r_M(t) - r_f(t)] - y_i(t), \tag{7}$$

or alternatively,

$$\varphi_i(t) = \alpha_i + r_f(t) + e_i(t) - y_i(t), \tag{8}$$

where $y_i(t)$ is the returns from credit risk factors. Once we can calculate $\varphi_i(t)$ we can then obtain a distribution of operational risk returns of $\varphi_i(t)$ and therefore apply some risk measure to calculate the operational risk. In particular, in section 4 we applied Value at Risk at different quantiles and standard deviation.

To verify in terms of SIM theory the validity of $\varphi_i(t)$ representing share returns due to operational risk, we notice the expression for $\varphi_i(t)$ in equation (8) is a function of $\alpha_i, e_i(t)$ (with credit risk returns $y_i(t)$ removed). In SIM theory the terms $\alpha_i, e_i(t)$ give share returns due to firm specific risk; since operational risk is a firm specific risk therefore the returns from $\varphi_i(t)$ representing operational risk returns are consistent with SIM.

Our measurement of operational risk and operational risk returns has a number of advantages compared to alternative operational risk methods. Firstly, for an operational risk measure it does not have demanding data requirements, which is a significant advantage in operational risk measurement. The method requires easily available data such as stock prices and other market data (e.g. interest rates), which are readily available even in emerging markets. If one were to use operational loss databases then one could only study a limited number of markets and sectors, there would also exist validity issues for operational databases (as discussed previously).

Secondly, the model is tractable and does not have significant calibration or implementation problems, which is a significant advantage in operational risk measurement. The credit returns $y_i(t)$ implementation will be discussed in the next section; to implement SIM requires estimation of market risk returns r_M and β_i. The parsimony of estimation of SIM parameters is one of the model's advantages and many methods have been developed related to it (this will be discussed in more detail in section 4).

Thirdly, our method can be applied to a range of sectors without requiring modification. The SIM model (and calculation of $y_i(t)$) can be applied to any sector and does not require modelling businesses at the micro level, which would be theoretically challenging and cause significant calibration problems. Fourthly, the our operational risk measurement is consistent with theory; according to SIM theory (as explained previously) our operational risk returns measure returns due to operational risk factors. This is contrast to other operational risk measures such as the BIA and SA (as discussed previously).

Fifthly, the SIM is a well established asset pricing model of stocks; it and its variants (as well as the credit risk return model) are commonly used in industry. We can therefore directly see the impact on investment decisions and on share price performance. Other operational risk measures (e.g. AMA) are not directly related to investment models or share price performance.

Finally, we can measure operational risk returns (and therefore operational risk) over shorter time scales compared to current operational risk measures (as discussed in section 2.2). For instance, if one were to apply BIA or SA then time scales would be no shorter than the observation time scale of the exposure indicator data. If net profit were used, the shortest possible timescale for operational risk measurement would be 3 month periods. Such a timescale would not be particularly informative in understanding operational risk as we may not be able to capture all operational events and it would require many years of data to obtain a sufficient number of data points. This would limit the reliability of the operational risk anlysis, in addition to the theoretical and empirical issues relating to using BIA and SA.

3.2 Estimation of Credit Risk Factor Returns

We require a method of estimating $y_i(t)$ and the SIM theory provides no method on credit risk returns. Additionally, in the previous section we discussed a number of criteria that our operational risk measurement method should possess to enable measurement in a range of sectors and markets. An obvious measure of credit risk returns would be corporate bond yields for each stock, however such data is not always readily available and may not exist for many stocks, especially in emerging markets.

Other possible models to estimate credit risk returns include analytical models such as the Leland and Toft model (Leland and Toft, 1996) or Denzler et al. (Denzler et al., 2006), however these make unsuitable assumptions for our study (e.g. recovery rate in default is independent of the sector) and more stringent data requirements than using corporate bonds. Reduced form models (e.g. Jarrow-Turnbull model (Jarrow and Turnbull, 1995)) also have demanding data requirements but also are significantly dependent on model calibration for results.

An alternative method for calculating $y_i(t)$ is to apply Merton's structural model of default. This method has been applied in academic research and industry for a number of years, capable of producing realistic values. Also, the industry usage of Merton's model (along with SIM) means that we do not lose investment and share pricing insight, which is one of the purposes of the study. The principal idea behind Merton's model is that the credit risk event of default behaves like a European option. We assume that a company has an amount of debt due at a future time T and that the company defaults if the value of its assets is less than the required debt repayment at time T.

From financial theory we know that shareholders are residual claimers to the company in the event of default, therefore at time T the shareholders will own the amount leftover once the assets have paid off the debt. Now since the shareholder's share price can never be negative this implies the shareholder's value is given by

$$E(T) = [A(T) - D(T)]^+,$$

where

- T is the expiry date of the debt;
- E(T) is the market value of company's total equity at time T;
- A(T) is the total value of company assets at time T;
- D(T) is the total value of company debt at time T.

Therefore shareholder value behaves like a European call option.

As credit default behaves like a European call option it is possible to apply the Black-Scholes equation (Black and Scholes, 1973) and obtain the credit risk return associated with a stock. In (Hull et al., 2004) the credit risk return $y_i(t)$ is given by

$$y_i(t) = r_f(t) - \left(\frac{ln[N(d_2) + (N(-d_1)/L)]}{(T-t)} \right), \tag{9}$$

where

$$\begin{aligned} d_1 &= \frac{-lnL}{\sigma_A\sqrt{(T-t)}} + 0.5\sigma_A\sqrt{(T-t)}, && (10) \\ d_2 &= d_1 - \sigma_A\sqrt{(T-t)}, && (11) \\ L &= \frac{D(t)e^{-r(T-t)}}{A(t)} = \frac{D^*(t)}{A(t)}, && (12) \end{aligned}$$

and

- T is the credit risk return period for y_i at time t (and the expiry date of the debt);
- σ_A is the volatility of company i asset value;
- A(t) is the total value of company i assets at time t;
- D(t) is the total value of company i debt at time t;
- N(.) is the cumulative distribution function for the standard Normal distribution.

To estimate $y_i(t)$ requires estimation of L, which in turn requires D(t). The total liabilities for D(t) are obtained as they were in (Hull et al., 2004), using company financial statements and these are available for all publicly traded companies (including in emerging markets).

To determine $y_i(t)$ also requires calculating A(t) and σ_A, To estimate the variables A(t) and σ_A we use a set of equations from Merton's credit risk model:

$$\begin{aligned} E(t)\sigma_E &= N(d_1)A(t)\sigma_A, && (13) \\ \sigma_E &= \frac{\sigma_A N(d_1)}{N(d_1) - LN(d_2)}, && (14) \end{aligned}$$

where

- E(t) is the market value of the company's total equity at time t;
- σ_E is the stock price volatility.

The stock volatility σ_E can be estimated by standard methods and E(t) can be observed at time t as it is the stock price multiplied by the number of shares issued in the company. The typical method of determining the variables A(t) and σ_A is to solve the 2 equations by computational optimisation (see (Hull, 2000)). Equation (14) is difficult to computationally optimise, leading to sub-optimal results. Therefore to improve the accuracy of estimating A(t) and σ_A, we replaced optimising equation (14) with optimising the following equation (taken from Merton's model):

$$E(t) = A(t)N(d_1) - D^*(t)N(d_2). \tag{15}$$

This equation provides the required variables and leads to improved computational results.

From independent numerical experiments it was shown that equations (13) and (15) could not be optimised using basic computational solvers to provide sufficiently acceptable solutions (such as in Excel), in fact in many cases they cannot find any solution. The computational optimisation of equations (13) and (15) was therefore implemented in Matlab, using the fsolve function and option pricing functions in the Matlab financial toolbox.

In the Appendix under table 7 we give empirical results of using the Merton model to calculate the credit risk returns, using the same data used in the Experiment section (section 4). The mean risk free rates (Central Bank interest rates) are also given in the Appendix in table 8 for the same time period that the stock data is collected. One can therefore see from the Appendix that the mean credit risk spreads are therefore consistent with expectations; most of the stock companies in our data are high market capital companies with low financial risk, hence a low credit spread for such companies is expected.

4 Experiment

In this section we calculate the operational risk returns $\varphi_i(t)$ for 100 stocks, using data over 5 years, in 4 different industry sectors (utilities, basic materials (mining and raw materials), financial and the technology sector). The stocks were taken over 5 different markets: 3 emerging markets (China, India and South Korea) and 2 developed markets (USA and UK).

We calculate $\varphi_i(t)$ for each stock using the method discussed in section 3. We then calculate risk measures on the distributions obtained for $\varphi_i(t)$ to quantify the operational risk, specifically Value at Risk (VaR) and standard deviation. We also calculate other metrics of interest on the operational risk return distribution, such as skewness and kurtosis.

4.1 Data

All empirical market data (e.g. stock prices, interest data, financial statements) was taken from the past 5 years time sample 2007-12. A 5 year time period was chosen to provide sufficient data points to obtain a distribution on operational risk returns, which enabled operational risk measurement. A 5 year time period was also chosen to ensure operational risk returns were taken over an entire cycle of stock market returns, rather than during a boom or recession period only, which could bias operational risk returns. Furthermore, a 5 year time period enabled one to obtain all stock price data in emerging markets; longer time periods would not allow this.

The sectors were chosen to investigate the impact of different fundamental operational characteristics upon operational risks and share performance. The stocks were chosen to be representative of the desired industry sector but also on the basis of high market capital. This meant that the stocks were most likely to be actively traded, therefore prices would not be distorted by liquidity effects. Also, any new market or company information would be reflected into the stock prices within a short time period, which is important for operational risk measurement. Such properties are especially important in emerging markets where information is less easily disseminated and stock prices can be significantly affected by inactive trading compared to developed markets.

The stocks were taken over 5 different markets: 3 emerging markets (China, India and South Korea) and 2 developed markets (USA and UK). This was done to compare the operational risk performance of stocks in developed and emerging markets, in particular China was chosen due to its importance as an emerging market, India was also chosen as it has been cited in literature as having significant operational issues in business. South Korea was chosen as it is considered an emerging market but also is considered a market in an intermediate state between emerging and developed markets, hence it would provide an interesting market for operational risk analysis.

The stocks were taken from the following stock exchanges. Korea: Korea Stock Exchange, China: Shanghai Stock Exchange, India: National Stock Exchange of India, UK: London Stock Exchange, USA: New York Stock Exchange. These exchanges were chosen (rather than alternative exchanges) as they are the largest exchanges in their countries with the highest share trading volume, thereby reducing price distortions due to liquidity effects. For example, the National Stock Exchange of India and the Bombay

Stock Exchange are approximately the same size but the National Stock Exchange has a higher share trading volume. To obtain the stock market index returns r_M for each country, the indexes were chosen that were most representative of the exchange. The following stock indexes were used. Korea: KOSPI (Korea Composite Stock Price Index), China: SSE Composite Index, India: S&P CNX Nifty, UK: FTSE-100 Index, USA: NYSE US 100 Index.

It is worth noting that sector indices were not used in our experiments instead of stocks because sector indices are not technically traded, so there is technically no market capital associated with them and this is required for our credit risk return estimation. Additionally, some markets (particularly emerging markets) do not have suitable indices that enable equivalent comparisons over different countries e.g. a technology sector index may exist in 1 country but in another country only a internet sector index may exist. Furthermore, the weighting and selection criteria for each stock in an index varies with each index, thereby distorting the comparison of sector indices between countries.

4.2 Method

Our experiment involved calculating operational risk returns $\varphi_i(t)$ using equation (7) for 100 stocks. This was achieved using monthly stock price returns, monthly interest rate data for r_f and monthly market index returns for r_M. The monthly time period was chosen because an annual time frame would not necessarily capture the impact of operational events on stock prices. A weekly time frame was too short as weekly returns can be distorted by non-operational factors e.g. market sentiment.

The β_i was estimated by standard linear regression; we regress

$$Y = mX + C + \epsilon_i(t) \tag{16}$$

where

- Y=$r_i(t) - r_f(t)$;
- m=β_i;
- X=$r_M(t) - r_f(t)$;
- C is a constant;
- $\epsilon_i(t)$ is the error term.

Therefore β_i is estimated from the gradient of the regression equation. For equation (16), we used monthly stock returns, monthly market index returns and the monthly riskless rate over the time period 2007-12. There exist numerous built-in functions for standard linear regression for different packages; we used Matlab for our regression.

The market riskless interest rate data r_f is available from central bank websites for each country. As the riskless interest rate data can significantly differ between emerging and developed markets, the monthly operational risk returns were calculated with the riskless rate subtracted from them. This was to ensure that particular markets were not gaining high operational risk returns due to higher riskless rates in their respective country. Hence the results should give a fairer comparison of operational risk across different markets.

The credit risk return factors $y_i(t)$ were estimated using the method explained in section 3.2. The data on total liabilities and market capital are available from company annual reports (including for emerging markets), which are published publicly. To calculate σ_E associated with each monthly return we used daily stock price data and applied the method from (Buchbinder and Chistilin, 2007); this involved taking the standard deviation of daily stock returns during each month. The volatility can be scaled to any time scale using the square root of time rule (see (Hull, 2000) for more information).

4.3 Results

In this section we present our results; all figures are in terms of percentage stock returns and S.D. denotes standard deviation.

4.3.1 Operational Risk Returns by Market

Table 1: Operational Risk Returns by Market

Country	USA	UK	S.Korea	India	China
Mean	0.15	0.29	0.17	-0.51	0.29
S.D.	8.83	9.39	10.27	10.22	12.70
Kurtosis	6.70	6.54	7.87	3.72	3.33
Skewness	0.90	0.50	1.42	-0.13	0.36
Min.	-36.58	-47.00	-28.25	-62.56	-59.51
Max.	68.88	72.44	90.23	39.90	61.61
VaR 99%	-21.06	-24.00	-20.97	-23.74	-31.19
VaR 95%	-12.39	-13.74	-14.52	-15.08	-18.19
VaR 90%	-8.63	-9.76	-10.85	-11.52	-13.11

Figures 1-5: Graph of Operational Risk Returns by Market
(y-axis: frequency, x-axis: operational risk returns (%))

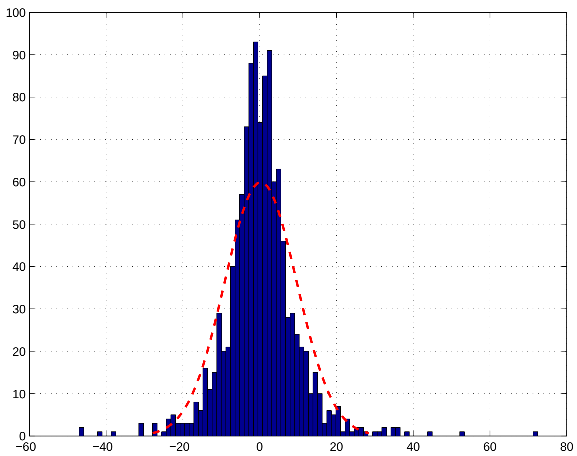

Figure 1: UK

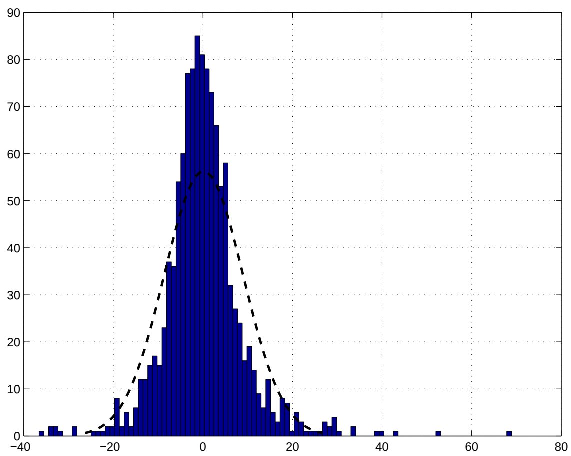

Figure 2: USA

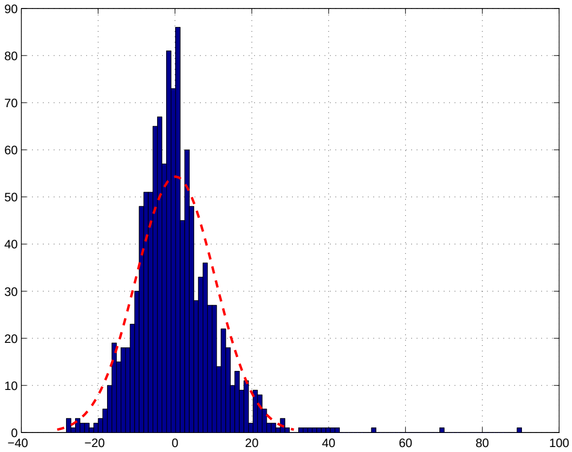

Figure 3: South Korea

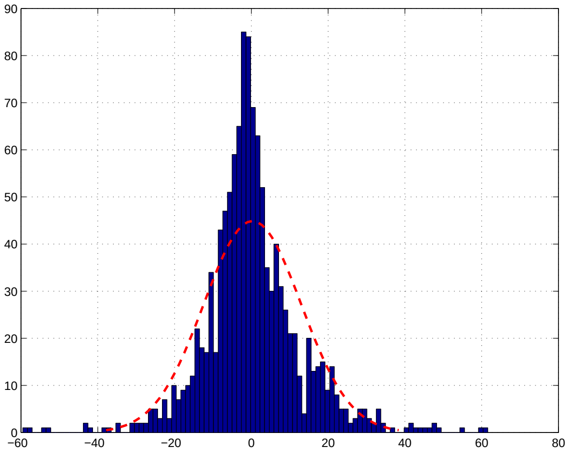

Figure 4: China

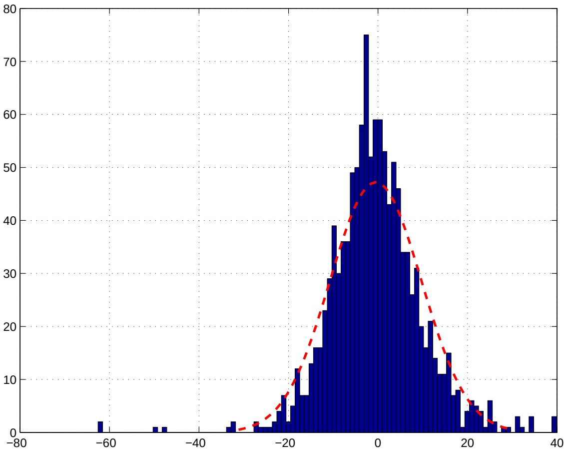

Figure 5: India

4.3.2 Operational Risk Returns by Sector

Table 2: Operational Risk Returns by Sector

Sector	Utilities	Technology	Basic Materials	Financial
Mean	-0.06	0.07	1.02	-0.71
S.D.	8.16	11.07	12.22	9.49
Kurtosis	3.18	4.41	4.83	6.47
Skewness	0.52	0.15	0.77	0.56
Min.	-35.18	-62.46	-59.51	-62.56
Max.	39.93	69.93	90.23	72.44
VaR 99%	-21.80	-25.94	-29.56	-23.67
VaR 95%	-13.26	-15.63	-16.14	-14.71
VaR 90%	-8.86	-11.93	-11.57	-10.28

Figures 6-9: Graph of Operational Risk Returns by Sector
(y-axis: frequency, x-axis: operational risk returns (%))

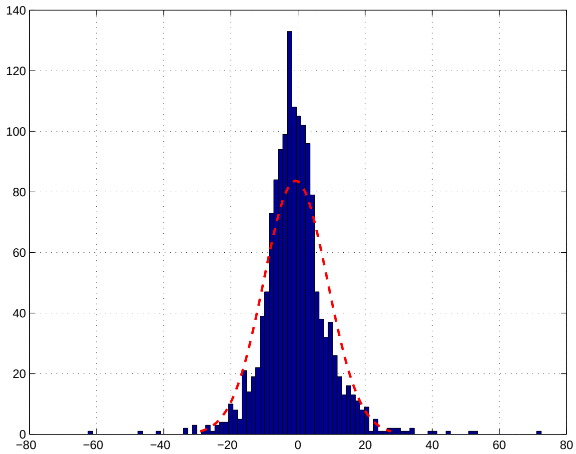

Figure 6: Financial Sector

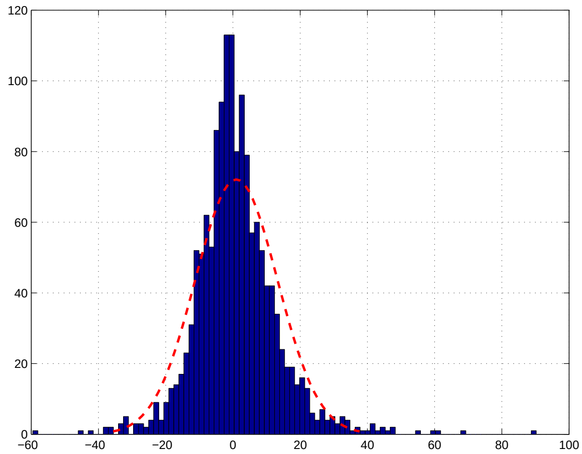

Figure 7: Basic Materials Sector

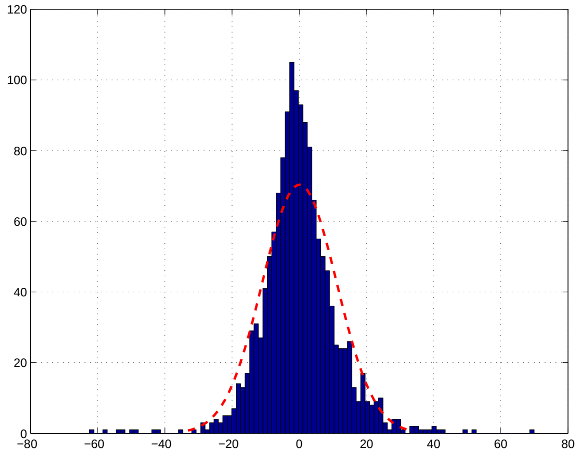

Figure 8: Technology Sector

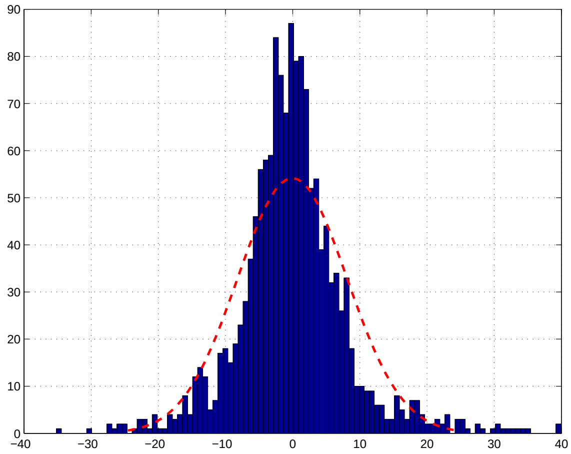

Figure 9: Utilities Sector

4.3.3 Operational Risk Returns by Market and Sector

Table 3: Technology Sector for each Market

Country	China	India	S.Korea	UK	USA
Mean	-0.17	-1.07	0.45	0.77	0.36
S.D.	15.07	11.10	12.25	8.50	6.30
Kurtosis	1.70	5.26	4.10	0.72	2.11
Skewness	-0.08	-0.62	1.21	-0.04	0.53
Min.	-57.58	-62.46	-28.25	-31.04	-20.09
Max.	49.50	39.59	69.93	24.92	25.76
VaR 99%	-43.27	-28.85	-23.85	-18.91	-13.83
VaR 95%	-22.10	-17.10	-15.65	-13.00	-7.94
VaR 90%	-16.15	-12.40	-12.90	-9.84	-6.01

Table 4: Financial Sector for each Market

Country	China	India	S.Korea	UK	USA
Mean	-0.98	0.05	-0.94	-0.99	-0.71
S.D.	7.72	9.36	8.74	10.99	10.31
Kurtosis	2.29	6.84	0.91	10.13	4.51
Skewness	0.02	-0.78	0.47	1.09	1.16
Min.	-30.28	-62.56	-27.52	-47.00	-33.64
Max.	26.37	33.89	33.07	72.44	52.29
VaR 99%	-23.96	-22.49	-18.81	-30.46	-21.08
VaR 95%	-13.17	-13.38	-15.37	-15.85	-13.59
VaR 90%	-8.54	-9.71	-10.15	-11.89	-10.44

Table 5: Basic Materials Sector for each Market

Country	China	India	S.Korea	UK	USA
Mean	1.78	-0.79	1.63	1.62	0.86
S.D.	15.51	10.49	11.25	10.97	12.10
Kurtosis	2.77	0.98	13.18	2.85	3.77
Skewness	0.61	0.18	2.04	0.23	0.61
Min.	-59.51	-33.81	-25.52	-45.85	-36.58
Max.	61.61	39.90	90.23	38.37	68.88
VaR 99%	-37.05	-26.72	-20.88	-24.47	-31.92
VaR 95%	-19.66	-16.39	-13.13	-14.04	-16.81
VaR 90%	-12.40	-12.53	-10.21	-9.73	-12.27

4.4 Discussion and Analysis

4.4.1 Market effect

The results are presented in the previous section and as can be seen from the graphs the operational risk returns are fluctuating over time, with positive and negative values. This is because operational events can improve or reduce gains for a company, for instance the installation of new and more efficient I.T. would improve operational gains. An analogy can be drawn with credit risk, where we have credit risk events (defaults) but the credit spreads themselves associated with companies are fluctuating over time.

As can be seen from table 1 the average returns from operational risk are approx-

Table 6: Utilities Sector for each Market

Country	China	India	S.Korea	UK	USA
Mean	0.54	-0.26	-0.51	-0.23	0.10
S.D.	10.74	9.85	8.10	5.98	4.35
Kurtosis	1.08	1.93	3.78	3.02	0.68
Skewness	0.26	0.82	0.81	-0.60	-0.34
Min.	-35.18	-24.78	-26.31	-27.35	-14.33
Max.	33.55	39.87	39.93	20.16	11.95
VaR 99%	-26.01	-20.88	-17.72	-17.99	-12.27
VaR 95%	-15.81	-14.33	-13.04	-9.39	-7.11
VaR 90%	-12.45	-10.75	-8.87	-6.50	-5.32

imately the same for all countries, with India with the lowest average. Consequently, the level of market development appears to have no impact on average stock returns. However, the developed markets tend to be achieving this average with a lower operational risk compared to emerging markets; at practically all VaR levels and standard deviation, emerging markets have higher losses than the developed markets. Also, the extreme losses are higher in emerging markets. Interestingly, South Korea, which is considered by some as an intermediate market between emerging and developed, also has risk levels between developed and emerging markets.

If we take the 'Sharpe ratio' (expected return to standard deviation ratio of operational risk returns adjusted for the riskless rate), we find that the developed markets tend to have a higher ratios. The Sharpe ratio is typically used to evaluate taking good risks or how well one is compensated for taking risks. In particular, South Korea and India have lower ratios than the UK and USA, China's ratio however is comparable to the developed markets. This suggest that the Chinese market, despite taking larger risks than other emerging markets, it is able to take 'better' risks than the other emerging markets.

We notice that there exists as significant difference in kurtosis between developed and emerging markets; there is effectively a doubling in value. The developed markets have therefore managed to shift their operational risk return distribution such that they are more frequently concentrated around small losses (and gains), whereas the emerging markets have not. Interestingly, South Korea, which can be argued is between emerging and developing, has a kurtosis comparable to the developed markets. We would expect these trends as developed markets would have greater regulation and management practises, which are typically implemented to remove high magnitude operational losses (this is supported by the differences in VaR in developed markets compared to emerging ones). For instance, utilities are more highly regulated in the developed markets compared to the emerging markets.

4.4.2 Sector effect

From table 2 we can see trends in operational risk and operational risk returns according to sectors. From table 2 we can see that there is no significant difference between sectors in terms of expected return from operational risk, although the financial sector has the lowest and the basic materials sector has the highest. However, in terms of risk the basic materials sector is generally the most riskiest in terms of VaR and standard deviation, with utilities the least riskiest. We would expect utilities to be operationally less risky as they are highly regulated (compared to other sectors) to prevent large scale operational risks, particularly those arising from health and safety issues. This is supported by utilities having the smallest minimum and maximum operational risk returns.

On the other hand we would expect the basic materials sector to encounter higher operational risk due to the nature of the business, involving operations that are intrinsically risky. If we take a 'Sharpe ratio' (or the expected return to standard deviation ratio adjusted for the riskless rate) we find the financial sectors are the lowest with the basic materials sector as the highest. This implies the financial sector takes bad operational risks in that the risks do not justify the expected returns, which would be consistent with the credit crunch events.

There are significant differences in kurtosis between sectors, in order of lowest to highest: utilities, technology, basic materials and financial. Consistent with the market results discussed earlier, a higher degree of regulation can reduce extreme losses, so that operational risk losses are more focussed around low magnitudes, hence we would expect the financial sector to have a higher kurtosis.

4.4.3 Sector and Market Effect

From tables 3-6 we examine each sector with respect to each Market. If we examine the expected returns for all sectors in tables 3-6, the returns do not significantly vary between emerging and developed markets. There are some minor trends (for example in table 4 only India has a positive expected return) but expected returns do not vary depending on sector or market. It is also interesting to note that the 'intermediate' market South Korea has an expected return in between the developed and emerging markets.

If we examine the risk levels for all sectors in tables 3-6, other than the financial sector, we notice that the emerging markets generally have higher VaR at all probability levels and standard deviation. Furthermore, South Korea the intermediate market also has operational risk levels in between emerging and developed markets. This suggests that market development impacts operational risk , returns and that developed markets are capable of achieving the same expected returns with lower risk (higher 'Sharpe ratio'). Interestingly, the financial sector is riskier in the developed markets compared to the emerging markets. This is a satisfactory result because it is consistent with literature suggesting that many financial services in developed markets lacked operational controls that caused losses (e.g. mis-selling financial products) but were not present in emerging market financial services.

In tables 3-6 there is no discernable trend in kurtosis, suggesting that kurtosis is a sector specific property rather than depending on the development of the market. Generally all sectors and in all markets have approximately the same magnitude of expected returns. However, on a VaR or standard deviation risk measure basis the sectors differ in terms of operational risk with the lowest risk sector being utilities and the highest risk sector being basic materials sector. As mentioned before, we would expect utilities to be operationally lower risk from a health and safety necessity but also operationally stable utilities are crucial to the functioning of basic services in any community. On the other hand, basic materials is an intrinsically more risky business in terms of operations, so we would expect higher operational risk levels.

5 Conclusion

In this paper we have quantified the impact of operational risk upon shares prices across a range of markets (including emerging markets) as well as across different industry sectors. Such a study is of particular value to investors in industry, where the impact of operational risks (e.g. management, internal processes and controls) can significantly influence investment in emerging markets. Additionally, we have provided a tractable method of measuring operational risk and its returns using empirically observable data; these provide a significant advantage in operational risk compared to current methods.

Our results provide useful conclusions about operational risk which would be of interest to industry and research. In particular, our paper shows that there exist significant differences between emerging markets and developed markets, which is consistent with management literature on operational risk. In other words, operational factors and regulation can affect returns between emerging and developed markets. Moreover, operational risks account for differences in stock returns between sectors, which would be expected due to the fundamentally different risks in operations in different sectors.

6 Appendix

Table 7: Credit Risk Returns by Market

Country	USA	UK	S.Korea	India	China
Return (%)	2.64	3.03	3.52	7.36	6.67

Table 8: Riskless Returns by Market

Country	USA	UK	S.Korea	India	China
Return (%)	1.55	2.30	3.33	6.73	6.18

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