2010

What Financial Risk Managers Can Learn from Six Sigma Quality Programs

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ABSTRACT

As the financial crisis of 2008 has revealed, there are some flaws in the models used by financial firms to assess risk. Credit, volatility, and liquidity risk were all inadequately modeled by supposedly sophisticated financial institutions employing dozens of financial engineers with advanced degrees. It is now clear that some of the underlying assumptions of the statistical models utilized were seriously flawed, and interactive and systemic effects were improperly modeled. Correcting these modeling flaws is one approach to preventing a reoccurrence. However, another approach is suggested by Six Sigma quality programs used in manufacturing and service industries. Some basic tenets of the Six Sigma programs are directly applicable to improving risk management in financial firms and in portfolio design. These include the features of *over-engineering, robust design*, and *reliability engineering*

Keywords: risk management, VaR, Black Swan event, Six Sigma, portfolio design

INTRODUCTION

In March of 2008 Bear Stearns was acquired by JP Morgan Chase after becoming insolvent. Bear Stearns had been considered one the best Wall Street firms in managing risk. Within a few months Lehmann Brothers had gone bankrupt, Merrill Lynch had been acquired by Bank of America, Wachovia merged with Wells Fargo, and Washington Mutual with JP Morgan Chase. American International Group (AIG) was bailed out by the federal government and many hedge funds have failed. What had caused so many prominent financial institutions to succumb in such a short time? The common explanation is sub-prime mortgages defaulting, but the real problem is much more fundamental—a failure of risk management.

The no down-payment, no income verification mortgages issued by many reputable financial institutions may have started the problems, but they would not have spread worldwide without the explosive advance in securitization of these assets (Collateralized Debt Obligations or CDO's) by financial firms and the high credit ratings assigned to them by the rating agencies Standard & Poor's and Moody's. The problems would probably not have grown to be a global financial crisis if so many other financial institutions had not purchased these risky assets including many banks in Europe and hedge funds around the world. Once the dominos began falling, liquidity dried up, and equity markets plummeted. The outcome became a financial crisis leading to a global recession which still continues.

How could these sophisticated financial institutions have been so wrong in their assessment of credit and market risk? After all, many had invested millions of dollars in risk modeling and believed that they had a good handle on risk management. With increasing power of computer hardware and software, firms were able to build complicated models using advanced statistical techniques and Monte Carlo simulations. To develop these models they hired dozens of mathematicians, statisticians, physicists, and computer scientists, and a new profession was created—the financial engineer. Very few top executives responsible for risk management likely understood these models, but they confidently used them to take ever-riskier positions to increase profitability, often driven by competitive pressures. Short-term oriented compensation schemes fostered excess risk-taking in many of these financial firms. Few believed that there were any flaws in the model.

Clearly there were some critical elements in the risk models that caused them to fail when they were most needed. In the next section we will examine some of the deficiencies of these models. In subsequent sections Six Sigma quality programs will be explained and it will be shown how the process and methods of Six Sigma can be applied to financial instrument and portfolio design. The case will be made for robust portfolio design and reliability engineering used as the way to achieve robustness. The last section draws some conclusions.

FLAWS IN RISK MODELING

The most commonly used model to measure risk is the VaR or Value-at-Risk. It is based on the Gaussian or normal probability distribution widely used for many applications in business, science, education and other fields. By specifying an acceptable confidence level for unlikely occurrences (such as a 20% chance of a fall in the price of a stock), risk managers could feel comfortable that these rare events had such a low probability they could be neglected. A three sigma confidence level indicates a 0.3 percent chance (3 in 1000) of the event occurring. The probabilities were based on historic price and volatility data for various types of assets. This stochastic approach to risk management seemed safe and reasonable *as long as the underlying assumptions of the statistical model are valid.* However, as recent events have dramatically illustrated some of the underlying assumptions are clearly not valid.

The most serious flaw in the VaR models is the assumption that the underlying distribution is Gaussian when in fact it is often Cauchian. The Cauchy curve is leptokurtic, meaning it has much more area in the tails (i.e. a fat-tailed distribution) than the normal distribution. There is much evidence that many asset prices follow a distributive pattern that is closer to a Cauchy than a Gaussian distribution [10], [5], [8]. This means that rare events such as a sharp fall in a market occur much more frequently than a normal distribution would predict. With the Gaussian model an event like the September 29, 2008, drop in the DJIA of 777 points or 7% had a probability of *1 in a billion*, a probability so small that it can be neglected and is essentially unpredictable with conventional forecasting models [16]. These *Black Swan* events happen much more often than any Gaussian model can predict. Taleb [14] defines a Black Swan event as one that is rare, has an extreme impact, and is retrospectively (though not prospectively) predictable. The 2008 crash can be seen as a Black Swan event that the models did not predict, even with a low probability (which would make it a *Grey Swan* event). Since a Black Swan event cannot be predicted, what can a risk modeler do? Suggestions will be offered below on how to mitigate the consequences of such events.

SIX SIGMA QUALITY PROGRAMS

Beginning in the 1980's at Motorola Corporation, Six Sigma quality programs have slowly spread through American manufacturing and recently have been applied in service businesses like banking, hospitals, and even government. The basic idea behind Six Sigma is to reduce variability in processes to improve quality and increase efficiency. The name Six Sigma refers to six standard deviations from the mean. This signifies a level of quality equal to three defects per billion opportunities based on the normal distribution. To many observers this seems like an unnecessarily high level of quality that is not only unattainable but too expensive. However, when one considers several characteristics of products and processes as well as how Six Sigma programs are carried out, these objections are not valid. The cost criticism can be rejected based on the experience of companies like GE that have found that the savings from reduction in defects (i.e. scrap, rework, warranties, etc) and improved process efficiency far outweigh the costs of implementing the program [4].

For a product with multiple parts, the reliability of the product is a multiplicative function of the reliability of its component parts. For example, in a product with a thousand parts, each one having a reliability of six sigma, the overall reliability of the product is about three sigma (3 defects per thousand). Many products have more than one thousand parts—a car has about 2000-3000 parts and a jetliner 200,000-300,000 parts and components. Therefore, designing in very high levels of individual component performance is essential to reliability of the finished product. This suggests one fundamental aspect of Six Sigma that has direct applicability to financial modeling—what we might call *over-engineering.*

Rather than assume that we are correctly modeling the underlying distribution with the Gaussian, Six Sigma builds in a margin or error for fat tails. Although Six Sigma statistical processes are also based on the normal distribution, the high levels of sigma applied provide a much greater safety margin than the normal three sigma assumption of VaR. Mean shifts, another weakness of financial models, is allowed for explicitly in Six Sigma by targeting a high level of standard deviations. Even if the mean does shift, as it is assumed likely to do, in Six Sigma the confidence level is still very high. This again illustrates the concept of over-engineering the process to account for rare but expected or unexpected occurrences.

A further weakness of traditional financial models is the interactive effects between financial instruments and markets. Six Sigma quality programs face a similar problem in complex processes with many interacting variables. An example is a metal plating process where temperature, humidity, fluidity, and other factors all affect process results. Six Sigma has developed ways to analyze these interactive effects and determine the best combination of variables to maximize process efficiency.

Another element of Six Sigma that has applicability to financial risk modeling is *reliability engineering.* This concept is used in product design where failure of one component can lead to failure of others and even complete product failure. Especially when components operate in series it is essential to build in high levels of reliability and use redundant systems as backup. An example is an auxiliary power or hydraulic system on a airplane that kicks in if the main system fails. Design of financial products can also take account of the interactive effects of the instruments and markets and attempt to build in reliability. It would involve extensive stress testing and simulation of performance under a variety of conditions. This concept will be considered in the next section along with other suggestions and a process for applying Six Sigma to the design of financial products.

Applying a Six Sigma Approach to Risk Management

Six Sigma quality programs emphasize a *process* approach to improving system reliability and performance. A process approach stresses the sequencing and interactive effects in a system rather than compartmentalizing the steps and activities. As was discussed above, the failure of risk managers to account for systemic risks in investment portfolios contributed to the financial crisis. The most widely used framework is the *DMAIC* process developed at General Electric which includes the following steps: Define Measure, Analyze, Improve, and Control (DMAIC). This same approach is applicable to portfolio design for financial instruments and risk management systems for these portfolios. In this section we will discuss how the DMAIC process can be used by financial firms to better design investment products and control for risk.

The first stage in applying the DMAIC process to portfolio design is to *Define* the types of financial products to be considered in terms of the desired return to risk profile, the types of instruments that can be considered, and the investment horizon. These of course should be determined by top management of the firm, not by the quant's developing the products. Without these parameters clearly defined, financial engineers will not have clear guidance in terms of the products they should develop. As the recent financial crisis illustrates, this failure to have clear goals and constraints led to some products being offered that were not well thought out and introduced a high level of unexpected and undesired risk.

The second step in the DMAIC process is to *Measure*. In a manufacturing process this would normally involve collecting statistical data and finding process capabilities. The analogue in financial product design would be to perform statistical tests and simulations using historical data to determine the density distributions of the instruments. The goal of these tests would be to ascertain how the instruments perform independently and together in a portfolio. More advanced measurements would attempt to find the systemic effects on the portfolio of liquidity and credit crises. This was a deficiency in the design of many of the financial products that imploded in 2007 and 2008 such as CDO's. A *process capability study* determines the distribution of results of a machine or process in terms of a density function (usually the normal distribution) to see if it can meet design specifications. For a financial instrument this would involve finding the distribution of returns over a period.

The third stage of the DMAIC process is to *Analyze*. For financial products this could involve the technique called *Design of Experiments (DOE)*. This method has been used in manufacturing for many years to determine interactive effects in processes. As noted above, interactive effects between financial instruments such as varying and asymmetric correlations were poorly understood and modeled. DOE provides a tool to analyze these kinds of influences on an investment portfolio. For financial instruments this could be done by simulation methods. For example, various asset categories could be combined in a systematic way in hypothetical portfolios to see how they perform under differing market scenarios. These interactive effects are a key element in another portion of analysis of portfolios called *stress testing*. The systemic effects of disappearing market liquidity and rapidly changing credit-worthiness on portfolios were poorly modeled in the recent crisis. Stress testing using DOE and simulations can provide valuable insight into how investment portfolios will respond under different economic and market scenarios.

To *Improve* is the next step in designing financial products by the DMAIC process. Here a couple of techniques from the Six Sigma tool box can be useful. The first of these is *reliability engineering.* Reliability engineering involves designing products to be *robust* under difficult operating conditions. This is accomplished through several techniques including *standardization* and *redundant systems* as well as the previously discussed DOE. Standardization tends to make physical products more robust because of fewer number of parts reducing complexity and interactive effects and the streamlining of assembly and testing improving quality and reliability. Applied to financial products the analogue would be to use established financial instruments that have a track record of performance under different market conditions rather than new and customized instruments.

Redundancy is an essential element in complex products to assure reliability. This can take the form of parallel systems that backup the primary system in case of failure. In the case of financial products this could be achieved by the use of financial hedges that will offset any opposite movement in the underlying instrument. The concept of *portfolio insurance* is relevant here. There are various ways to achieve this in an investment portfolio by taking offsetting long and short positions and the use of options. A common hedge is to take out-the-money puts to hedge against a large market drop. For hedging against counterpart risk, Credit Default Swaps (CDF) can be used. CDF's contributed to the recent financial crisis because of the huge volume outstanding and their lack of transparency. They were undoubtedly being used as a speculative instrument rather than a hedge by many of the participants, but can be an effective hedge against credit risk if used properly.

The last stage of the DMAIC process is to *Control.* Although risk management issues should be considered throughout all five steps in the process, they are the main focus of the last stage for financial products. The most important part of the control process is assigning clear-cut responsibility for this activity. It should be at a high enough level in the firm to have real control which was a problem with some of the financial firms most impacted by the recent crisis where control responsibility was diffuse and ineffective. Control also involves frequent reporting of essential information and separation of the trading, sales, and reporting roles. Compensation systems should not encourage excessive risk taking.

The overall process for designing and controlling financial products following the DMAIC model will allow for a more systematic and thorough process that has the potential to prevent some of the problems which surfaced in the recent financial crisis. The ad hoc and diffuse nature of risk management in many financial firms was revealed during this crisis, and a more integrated and rational process is clearly called for. In the next section we will discuss the case for robust portfolio design.

The Case for Robust Portfolio Design

The financial crisis that began in 2007 affected many financial firms in commercial and investment banking, hedge funds, private equity funds, and insurance companies. But one major category of financial institution escaped the havoc. These are the derivatives exchanges throughout the world. Not one derivates exchange experienced distress in the crisis [15]. The reason for this is that derivative exchanges apply, and have applied for years, over-margining of positions. The margins that counterparties must maintain with the exchange are very conservative. The primary approach to establishing margin requirements at most derivative exchanges is the SPAN (Standard Portfolio Analysis of Risk) developed by the Chicago Mercantile Exchange (CME) in 1988. SPAN calculates the potential worst-case asset loss based on several price and volatility scenarios to set the margin. This conservative approach worked well with the chaos in the global asset and credit markets in the face of a sudden increase in volatility and correlation breakdowns. It is a financial equivalent of over-engineering.

In contrast Basel-II did not provide the necessary protection to banks that it was designed for. Basel-II was based on a belief that banks had sophisticated risk modeling and could establish the levels of capital needed to assure solvency. However, these risk models were mainly VaR types of models and proved clearly inadequate to the task. Varma [15] calls Basel-II a "sophisticated but fragile" system in contrast to the derivatives exchanges risk management approach which is "crude but robust". The need for a conservative approach and a margin of safety is revealed here. As was mentioned previously, asymmetrical and non-normal distributions cannot be modeled adequately using VaR techniques. Attempts have been made to improve upon VaR which have some potential. Goh, et al [7] recently developed PVaR for Partitioned Value-at-Risk. Their method divides the asset return distribution into positive (gains) and negative (losses) half-spaces. This generates better risk-return tradeoffs for portfolio optimization than the Markowitz model and is useable when asset return distributions are skewed or abnormal.

In the next section we will discuss some new approached to stress testing and reliability engineering methods that can contribute to robust portfolio design.

Reliability Engineering for Robust Financial Products

The obvious failure of risk management models based on VaR has triggered a search for new approaches that improve upon VaR or replace it. Several methods that adjust VaR for asymmetries and non-normality were discussed in the previous section. Increasingly there is interest in *Expected Shortfall (ES)* models that focus on the area in the tails of the distribution rather than the cutoff at 95% or 99% confidence levels as VaR does. The ES models are specifically designed to measure the potential for large losses and the amount of capital required to be prepared. ES allows losses to be calculated in the tail of a fat-tailed distribution whereas VaR does not. This can be accomplished by using a power law as described in Varma [15].

Pang's [12] approach models the stock or option prices as a simple, deterministic non-linear transformation of a log-normal hidden process. He does not assume stationarity nor normality and thus his approach can deal with asymmetric and leptokurtic distributions. His model is able to explain some anomalies in financial markets such as negative volatility skewing and realized volatility being lower than implied volatility. This has application for options pricing and determining hedge ratios as well as giving indications of rich-cheap stocks or options.

Diversification across asset categories and countries can provide some degree of risk mitigation in a portfolio, but this can break down as markets become more correlated in times of market stress. Building portfolios to maximize returns and minimize volatility using historical data and sophisticated models is essential in portfolio design. But to be truly robust, the portfolio must be over-engineered. This can be accomplished through several hedging methods that provide *portfolio insurance.*

There are several persuasive reasons to insure an investment portfolio against large and unexpected losses. The most obvious is the revealed weaknesses of VaR models to protect against large losses. The flaws in the VaR models were discussed above and include non-normal distributions with fat-tails and skewness and non-stationarity. This leads to poor performance of these models, particularly in the short-run [2]. It has proven extremely difficult to "time the market" and foresee changes in direction. Estrada [3] found that if an investor had been able to avoid the 10 worst days on the NYSE from 1900 to 2006, they would have had a portfolio 206% more valuable than a passive investor in the Dow Jones Industrial Average (DJIA). Conversely, an investor who missed the 10 best days during this same period would have a portfolio 65% less valuable than a passive investor. Predicting these market booms and busts is practically impossible, and the investor is much better off to insure the portfolio against extreme events.

Portfolio insurance methods include the use of offsetting long and short positions for price and market risk. These positions can be costly in terms of return that is sacrificed to reduce risk. Another hedging method is to use options. Far out-of-the-money options can be used to insure against extreme price moves at a modest cost of the premium which is low for such options. To reduce the premium cost further one can write an offsetting option but, of course, must assume some risk to do so. Simulations [6] find that out-of-the-money put options reduce ES and coincident extreme losses.

To insure against counterparty risk one instrument that can be used is the Credit Default Swap (CDS). For a series of premium payments counterparty risk can be transferred to someone else. This of course assumes that the CDS counterparty does not themselves default which has turned out to be a problem in the recent credit crisis. Other methods of portfolio insurance will probably be developed in reaction to recent events allowing for further refinement of reliability engineering for investment portfolios.

CONCLUSIONS

Fractal models can mimic what happens in market crises [11]. They are able to represent graphically "wild randomness" after the fact but are not useful for prediction [2]. By definition *Black Swan* events are unpredictable and thus cannot be mathematically modeled [14]. Since these events can have devastating effects on an investment portfolio, how can an investor or a firm prepare for them? There is no way to completely prepare for an unpredictable event but one can certainly mitigate its effects. In an investment portfolio this can be accomplished through the Six Sigma methods outlined in this paper.

First, the Six Sigma process can be applied to the design of risk management systems. It provides a structured approach to collect data, analyze it, and develop financial products with an integrative plan-achieve-control structure as part of the process. Three key concepts of Six Sigma quality programs have direct applicability to design of investment portfolios. These are the principles of *over-engineering, robust design,* and *reliability engineering.* Over-engineering of a financial product involves combining different instruments that provide an optimal return-risk tradeoff that is immune to extreme tail events. If well done, the result is a robust design for the portfolio that will be able to respond in predictable ways to both expected and unexpected market shocks and survive Grey and Black Swan events. Reliability engineering provides an extra layer of protection using portfolio insurance methods to hedge for extreme events using options, Credit Default Swaps, and other instruments and requires stress testing and simulation to build in reliability and robustness.

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