

Risk Management Lessons from the Credit Crisis

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Abstract

Risk management, even if flawlessly executed, does not guarantee that big losses will not occur. Big losses can occur because of business decisions and bad luck. Even so, the events of 2007 and 2008 have highlighted serious deficiencies in risk models. For some firms, risk models failed because of known unknowns. These include model risk, liquidity risk, and counterparty risk. In 2008, risk models largely failed due to unknown unknowns, which include regulatory and structural changes in capital markets. Risk management systems need to be improved and place a greater emphasis on stress tests and scenario analysis. In practice, this can only be based on position-based risk measures that are the basis for modern risk measurement architecture. Overall, this crisis has reinforced the importance of risk management.

Keywords: *risk management, financial crisis, risk models, stress test*

JEL classifications: *D81 (decision-making under risk), G11 (investment decisions), G16 (government policy and regulation), G21 (banks), G32 (financial policy)*

“The best Wall Street minds and their best risk-management tools failed to see the crash coming,” New York Times, January 2, 2009

Many financial institutions that experienced large losses over the past few months apparently employed sophisticated risk management systems. That losses occurred does not necessarily imply that there were failures in risk management, however. As Stulz (2008) put it, “A large loss is not evidence of a risk management failure because a large loss can happen even if risk management is flawless.”

The scale of losses in the credit crisis that started in 2007 has been unprecedented. The International Monetary Fund (IMF) has estimated that total losses on US assets now exceed \$4,000 billion. The root causes of this crisis are many. Taylor (2008) argues that government actions and interventions “caused, prolonged, and worsened the financial crisis.” In addition, however, there were several layers of failures in the private sector. This goal of this presentation is narrowly focused on the role of risk management in this credit crisis.

This presentation is structured as follows. The first Section reviews and describes the structure of modern risk measurement systems. The key feature is that it relies on position-level information, unlike the traditional returns-based risk measures. The second Section then discusses the various types of risks that an institution is exposed to. A useful classification is into known knowns, known unknowns, and unknown unknowns. As Donald Rumsfeld put it, it is the risks in “the latter category that tend to be the difficult ones.” Nevertheless, risk managers have several tools at their disposal to manage risks better. The third Section draws risk management lessons from the credit crisis. The last Section concludes.

1. Risk Measurement Systems

To start with, let us describe the main components of modern risk measurement systems, which are described in Figure 1:

- From market data, construct the distribution of *risk factors* (e.g., normal, empirical, or other).
- Collect the portfolio *positions* and map them onto the risk factors.
- Use the *risk engine* to construct the distribution of portfolio profit and losses over the selected period. This can be summarized by a Value-at-Risk (VAR) number, which represents the worst loss that will not be exceeded at the pre-specified confidence level.

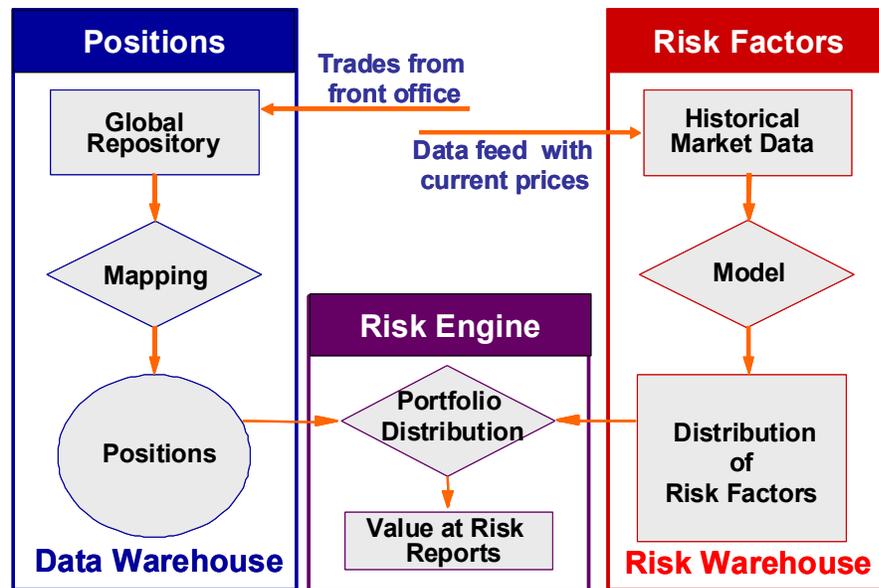


Fig. 1. Components of a risk measurement system

The key feature of this system is that it is *position-based*. Traditionally, risk measures have been built from *returns-based information*. The latter is easy and cheap to implement. It also accounts for dynamic trading of the portfolio. On the other hand,

returns-based risk measures suffer from severe drawbacks. They offer no data for new instruments, markets, and managers. They do not capture—or rather, are very slow at identifying—style drift. They may not reveal hidden risks. Lo (2001) gives the example of a hypothetical fund, called Capital Decimation Partners, which seems to perform very well, with a high Sharpe ratio. In this case, the fund holds a leveraged short position in an equity index option. As long as the option is not exercised, the portfolio generates a positive and steady return. The returns-based VAR is totally misleading. More generally, returns-based risk measures give no insight into the risk drivers of the portfolio.

Most of these drawbacks are addressed by position-based risk measures. They can be applied to new instruments, markets, and managers. These use the most current position information, which should reveal style drift or hidden risks. For example, Jorion (2007) shows that the risk of Capital Decimation Partners can be captured and controlled effectively by position-based risk systems. In addition, position-based systems can be used for forward-looking stress tests.

Position-based risk systems, on the other hand, have drawbacks. First, they require more resources and are expensive to implement. A large bank could have several million positions, in which case aggregation at the top level is a major technology challenge. Second, position-based risk measures assume that the portfolio is frozen over the horizon and ignores dynamic trading. To some extent, this problem can be mitigated by more frequent risk measurement. Finally, position-based systems are susceptible to errors in data and models. They require modeling all positions from the ground up, repricing instruments as a function of movements in the risk factors. In some cases,

standard approaches based on a fixed historical window are inappropriate.¹ In others, the modeling of instruments is quite complex, leading to model risk.

Even so, position-based risk measures are vastly more informative than returns-based risk measures. This explains why all modern risk management architectures rely on position-level information.

This does not mean that returns-based information is useless, however. In some cases, it can be combined with position-based information for more realistic risk measures. Also, risk managers need to backtest their risk systems. This involves systematic comparisons of the actual returns with the risk forecasts. With a well-calibrated system, the number of cases of losses worse than VAR, also called exceptions, should correspond to the confidence level. For example, backtests of a 1-day VAR at the 99 percent level of confidence over a period of one year should yield, on average, 2 to 3 exceptions per year (actually, 1% times 252, or about 2.5). Too many exceptions should lead the risk manager to re-examine the models.

In spite of all this apparatus, a number of banks suffered major losses during the credit crisis. In 2007 alone, for example, UBS suffered losses of \$19 billion from positions in mortgage-backed securities alone. Can we conclude from this information that its risk management system was flawed?

¹ Jorion (2008) analyzes the conventional application of VAR measures to Mergers and Acquisition (M&A) arbitrage portfolios. Such trading strategies involve payoffs that have discontinuous: either the acquisition goes through or not. This leads to skewed distributions that cannot be measured well with conventional risk methods using moving windows based on recent historical data. On the other hand, knowledge of the positions can be used to develop more realistic, forward-looking model of portfolio risk.

2. Classification of Risks

To analyze this point, risks can be classified into three categories: “known knowns,” “known unknowns,” and “unknown unknowns,” corresponding to different levels of uncertainty.

2.1 Known Knowns

Let us start with a flawless risk measurement system, where all the risks are perfectly measured. This implies that the risk manager correctly identifies all the risk factors and properly measures their distribution as well as the exposures of the current portfolio, leading to an appropriate description of the distribution of total profits and losses. Top management then decides on a particular risk-return profile for the business.

In this case, losses can still occur due to a combination of bad luck and the fact that management accepted too much exposure. As an example, take a long/short equity portfolio with an equity beta of 0.5. Figure 2 describes the distribution of annual return on U.S. equities since 1871. This information can be used to build a distribution of returns for the portfolio in question.

The S&P index lost 38% in 2008. As a result, this portfolio should have lost 0.5 times 38%, or around 19%. This loss is a combination of bad luck (i.e., a very large fall in the S&P index, but not unprecedented as U.S. stocks lost 43% in 1931) and exposure (i.e., having a high beta). If the distribution was properly measured, the outcome matched the risk forecast. In this case, the risk measurement system was flawless.

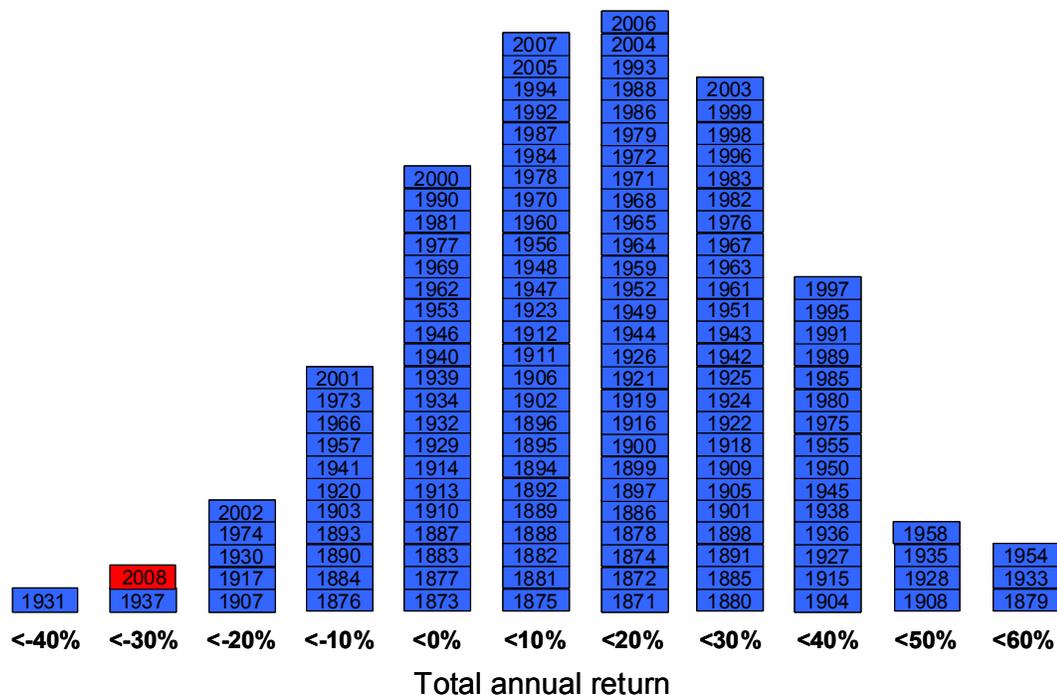


Fig. 2. Distribution of annual returns on S&P index

In some cases, the loss can exceed the VAR forecast. Indeed, it should. It is a misconception to interpret VAR as a worst-ever loss measure. Instead, VAR should be viewed as a measure of dispersion that should be exceeded with some regularity, e.g., in one percent of the cases with the usual 99 percent confidence level.

In addition, VAR does not describe the extent of losses in the left tail. Instruments such as short position in options could generate infrequent but extreme losses when they occur. To detect such vulnerabilities, the distribution of losses beyond VAR should be examined as well. This can be done, for example, with conditional VAR, which is the average of losses in the tail.

2.2 Known Unknowns

Even so, management systems do have numerous known blind spots. First, the risk manager could have ignored important known risk factors. Second, the distribution

of risk factors, including volatilities and correlations, could be measured inaccurately.

Third, the mapping process, which consists of replacing positions with exposures on the risk factors, could be incorrect. These fall in the broad category of *model risk*.

As an example of the first problem, many portfolios unexpectedly lost money on basis trades during 2008. These involve hedged positions. For instance, a trader could buy a corporate bond and at the same time purchase a credit default swap (CDS) that provides protection in case of default of the same name. Normally, if the position can be held to maturity with no extraneous risks, this should be an arbitrage trade. Since Long-Term Capital Management, we know that arbitrage trades are subject to mark-to-market risk. In practice, however, most risk management systems map both the bond and CDS to the same risk factor, which ignores the basis risk. During 2008, this basis widened sharply, leading to large mark-to-market losses on such positions that were not captured by most risk models.

As an example of the second problem of incorrect distributions, assume that the risk manager had estimated the volatility of the S&P index using a fixed 2-year period, 2005 to 2006. Because this period was unusually quiet, this would have understated the risk during the following two years. Figure 3 plots the daily volatility forecast for the S&P stock index using an Exponentially Weighed Moving Average (EWMA) with decay of 0.94. This model shows that during 2004 to 2006, volatility was very low, averaging 0.7% daily. As a result, many financial institutions entered 2007 with high levels of leverage. When volatility started to spike during 2007, risk models experienced many exceptions. The graph also shows a volatility forecast derived from the usual moving average (MA) model with a window of one year, which is typical of most VAR models based on historical simulation. The figure shows that the MA model systematically

underestimated the EWMA volatility starting in mid-2007, which is when banks' risk models started to slip.

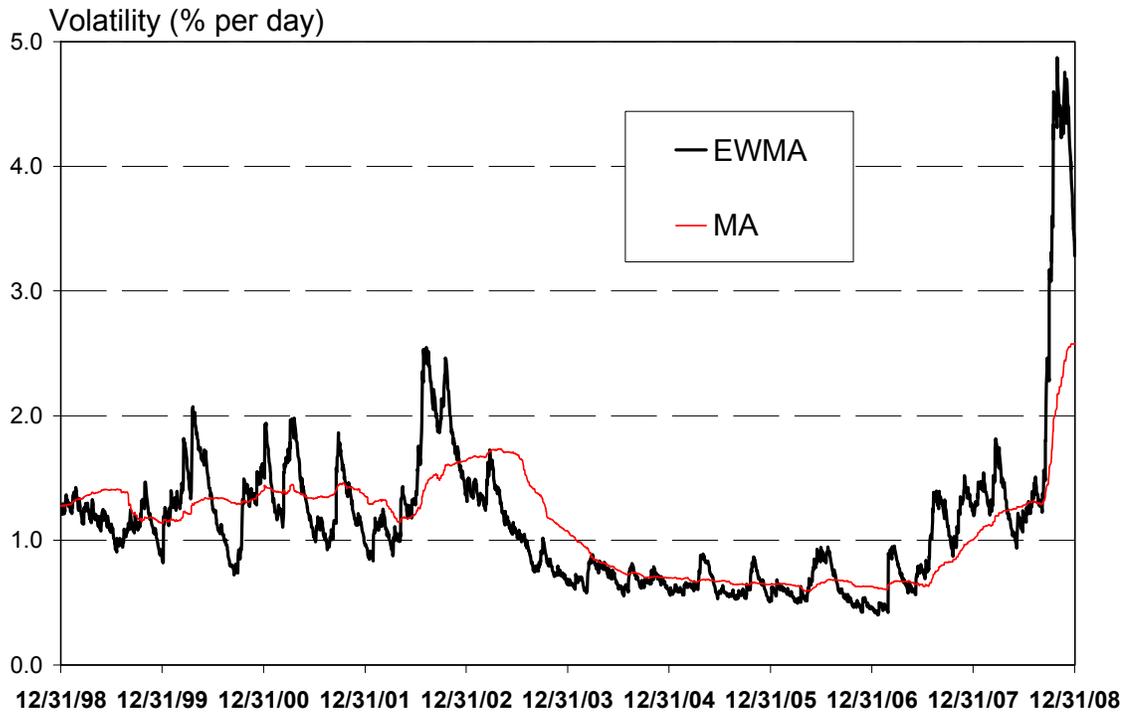


Fig. 3. Daily volatility forecast for the S&P index

This illustrates a known problem, which is that the parameters of the risk distributions can change over time. One solution is to adopt more responsive risk systems. Indeed, the Basel Committee now explicitly allows such systems.²

Another example of the second problem is the correlation structure used by credit rating agencies to rate different tranches of asset-backed pools. These tranches are rated using the standard industry technology of portfolio credit risk models. The first step consists of building a joint distribution of asset values for the underlying credits. Defaults occur when asset values fall below some cutoff point. The second step consists of building the distribution of total losses on the portfolio. In the third step, the width of

² See BCBS (2008).

the subordinated tranches is selected so as to achieve a target default probability, typically selected from a table of default rates from the history of various credit ratings.

The crucial assumption in this process is the asset or default correlation. A low correlation implies that the portfolio is unlikely to experience many simultaneous defaults, implying a tight loss distribution. As a result, the senior tranches should be safe even with thin layers of subordinated tranches. In practice, because the application of this structured product technology was calibrated to a period of rising home prices, correlations were understated, which led to an understatement of the risk of default for triple-A tranches.

As a result, many banks experienced large losses on super senior, AAA rated, tranches of securities backed by subprime mortgages. Investing in these tranches can be viewed as selling out-of-the-money put options, which involve nonlinear payoffs. As long as the real estate market continued to go up, the default rate on subprime debt was relatively low and the super senior debt was safe, experiencing no price volatility. As the real estate market corrected sharply, the put options moved in-the-money, which led to large losses on this super senior debt. Of course, none of these movements showed up in the historical data prior to 2007 because this period only reflected a sustained appreciation in the housing market but also because of the inherent nonlinearity in these securities.

In this case, the credit rating agencies offer a prime example of flawed risk management. This problem has been noted in the academic literature, however. It is well known that the output of portfolio credit risk models is very sensitive to the inputs.³ In

³ Grundke (2005), for example, shows that VAR measures are very sensitive to the assumption of asset correlation as well as the shape of the joint distribution function for asset values.

addition, standard models cannot seem to explain the observed patterns of default clustering, even prior to the credit crisis that started in 2007.⁴

As an example of the third problem, the mapping process itself can also be flawed. For example, UBS (2008) reports that it had mapped the AAA-rated tranches from structured credit to yield curves for regular AAA corporate bonds. This ignored the nonlinearities in the securities and was an act of blind faith in the credit rating. As explained previously, the process for building a triple-A tranche from a complex asset-backed securities pool is totally different from regular corporate credits. In this case, the mapping process was flawed and gave no warning sign of the impending risks. Even worse, because these investments were viewed as riskless but yielded substantially more than LIBOR, they infiltrated all units of the bank—and in large amounts.

More generally, the mapping process involves approximations and is often problematic for new products, which can be very dangerous given that new products are more profitable for a financial institution and hence more actively traded.

Finally, it is well known that risk management systems do not account for liquidity risk, which involves both *asset liquidity risk*, which is the price impact of large asset sales, as well as *funding liquidity risk*, which arises when the firm cannot meet cash flow or collateral needs. This is why the Basel Committee did not institute formal capital charges against liquidity risk. Yet, the BSCBS (2006) stated that “Liquidity is crucial to the ongoing viability of any banking organization. Banks' capital positions can have an effect on their ability to obtain liquidity, especially in a crisis.” Liquidity risk, however, is extremely complex and difficult to reduce to simple quantitative rules.

⁴ See for instance Das et al. (2008) for evidence of excess default correlation, and Jorion and Zhang (2009) for an analysis of contagion effects due to counterparty risk.

2.3 Unknown Unknowns

In the last category of risks are events totally outside the scope of most scenarios. This includes regulatory risks such as the sudden restrictions on short-sales, which played havoc with hedging strategies, or structural changes such as the conversion of investment banks to commercial banks, which accelerated the deleveraging of the industry. These risks affected the entire industry starting with the Lehman bankruptcy in September 2008.

Similarly, it is difficult to account fully for *counterparty risk*. It is not enough to know your counterparty; you need to know your counterparty's counterparties too. In other words, these are network externalities. Understanding the full consequences of Lehman's failure would have required information on the entire topology of the financial network. Such contagion effects transform traditional risks that can be measured into Knightian "uncertainty," a form of risk that is immeasurable.

Evaluating such risks will always be a challenge but their existence must be acknowledged. This can lead to higher capital cushions than otherwise. Management should also develop plans of actions when these risks start to develop.

In the end, however, financial institutions cannot possibly carry enough capital to withstand massive counterparty failures, or *systemic risk*. In such situations, the bank regulator becomes effectively the risk manager of last resort.

2.4 Implications for Economic Capital Analysis

The confluence of these known and unknown risk cast serious doubts on the recent practice of *economic capital analysis*. These are extensions of VAR methods to the total risk of the institution, including market, credit, and operational risk. Unlike the typical application of VAR to market risk, the horizon is long, typically one year and as a

result not many data points are available, especially to estimate quantiles at very high confidence levels, and when subject to economic cycles of 5-10 years.⁵

As an example, Deutsche Bank reported that its economic capital as of year-end 2007 was 13,611 million euros, using a 99.98% confidence level and annual horizon. In my view, it makes little sense to report five significant digits. This practice gives the erroneous impression of a very high degree of precision, which is not the case. In my opinion, this economic capital number is probably measured within a range of several billion euros, at best. The risk management industry has been guilty of misrepresentation of undue precision.

Likewise, the insurance giant AIG relied heavily on its “economic capital modeling initiative” to justify its foray into financial products. Up to 2007, it maintained that it had \$15 billion in excess of its required economic capital, out of a total of \$108 billion. The firm was massively short credit default options, however, and eventually required a \$170 billion bailout by the U.S. government because its failure would have endangered the stability of the financial system.

3. Risk Management Lessons

3.1 Lessons for Risk Managers

How can we deal with these problems? First, with experienced risk managers that should be aware of these issues. This is why risk management should be driven by people, not machines. Traditional risk measures are backward looking and assume that distributions are stable and relevant for the future. The risk managers, however, have at their disposal a powerful position-based risk management system, which allows the

⁵ See Rebonato (2007) for a lucid criticism of economic capital, which he calls “science fiction” numbers.

construction of forward-looking scenarios. Risk managers should also stress test their models, changing the assumptions for the distributions and parameters such as volatilities and correlations. Risk managers should also be prepared to react if they see developing signs of weaknesses in their models.

Let us go back to the experience of UBS in 2007. Normally, the bank should have experienced about 2 or 3 exceptions (i.e., 1 percent of 250 days). Instead, UBS suffered 29 exceptions during 2007. The difference is such that we can decisively conclude that the risk management system was flawed. To its credit, the bank performed a rigorous post-mortem analysis. In its annual report, UBS also explained that “as always, however, we learn from experience.... Consistent with our philosophy of continuous improvement, we are reviewing all aspects of market risk measures.”

This performance is compared to other banks in Table 1, which reports the number of exceptions for Goldman Sachs, Bear Stearns, JPM Chase, Credit Suisse, and UBS. Because the first two were investment banks, they report VAR at the 95% level of confidence. It is interesting to note that there is a fair amount of dispersion in the performance across banks. This should help dispel the notion that all risk management systems performed poorly during 2007. In addition, the banks that did worst in their category (Bear Stearns and UBS) suffered the most devastating losses.

Table 1
Number of Exceptions Reported in 2006 and 2007

This table describes the number of trading exceptions reported by selected investment and commercial banks. The confidence level is indicated between parentheses. “Expected” is the expected number of exceptions during a year at the selected confidence level. Actual numbers are reported for 2006, 2007 and each quarter of 2007.

Bank (confidence level)	Expected	2006	2007	Q1	Q2	Q3	Q4
<u>Investment banks</u>							
Goldman (95%)	13	3	10	0	1	5	4
Bear Stearns (95%)	13	0	27	1	0	10	17
<u>Commercial banks</u>							
JPM Chase (99%)	3	0	8	0	0	5	3
Credit Suisse (99%)	3	2	9	2	0	7	0
UBS (99%)	3	0	29	0	0	16	13

Nocera (2009) describes how the backtesting framework was used by Goldman Sachs. In December 2006, the bank noticed that losses on its mortgage desk had exceeded its VAR for several days in a row. After detailed analysis, the firm decided to “get closer to home,” i.e., to cut down its risk exposure. This explained why in the summer of 2007, Goldman Sachs avoided the pain suffered by Bear Stearns, Merrill Lynch, Lehman Brothers and the rest of Wall Street.

3.2 Lessons from Regulators

By now, a number of reports have been written on the risk management practices at major financial institutions, including the Senior Supervisor Group (2008). A striking observation is the range of quality of risk management practices. Some banks did well in 2007 while others suffered badly. The characteristics of winners and losers are compared in Table 2.

Table 2
Comparisons of Risk Management Practices

This table compares the risk management practices of banks viewed as winners and losers during the 2007 credit crisis, as reported by the Senior Supervisors Group (2008).

Practice	Winners	Losers
Organizational structure	-Cooperative	-Hierarchical
Business model	-Avoided CDOs, SIVs	-Exposed to CDOs, SIVs
Firm-wide risk analysis	-Shared information across firm	-No prompt discussion of risks across the firm
Valuations	-Developed in-house expertise	-Relied on credit ratings
Management of liquidity	-Charged business lines for liquidity risk	-Did not consider contingent exposures
Risk measurement	-Used both qualitative and quantitative analysis -Varied assumptions -Tested correlations	-Strict model application -Mapped to corporate AAA -No test of correlations

In general, institutions that lost the most had a hierarchical business structure where top management wanted to expand the structured credit business, which involved collateralized debt obligations (CDOs) and structured investment vehicles (SIVs), due to their perceived profitability. Top management in these firms did not encourage feedback and often did not pay attention to warning signals given by risk managers. Many of these institutions failed to develop their own valuations models for these complex structures and instead relied on credit ratings. In addition, they did not consider contingent exposures and did not charge business lines for potential claims on the bank's balance sheet, which encouraged expansion into structured credit. These institutions blindly applied models without consideration of their weaknesses and typically did not perform stress tests of correlations.

During 2007, for example, UBS ended up with losses of \$19 billion on super senior ABS tranches, which were found in the CDO warehousing book, in the trading

book, in the liquid Treasury book, and in a hedge fund subsidiary. As reported later by UBS (2008), there was no monitoring of net or gross concentrations of positions in this asset class at the firm-wide level.

A second influential report was issued by the Counterparty Risk Management Policy Group (CRMPG) in 2008. The report provides recommendations for improved corporate governance and enhancing oversight. It also discusses better risk monitoring, especially concentrations to asset classes on a net and gross basis. The report also advises conducting stress tests that focus on contagious situations.

Haldane (2009) argues that in effect, banks failed the stress test not because they do not have the tools to do so but instead because of misaligned incentives. Large banks did not perform meaningful stress tests because they knew that they were too big to fail and that regulators would step in. This is the argument advanced by Loffler (2008), who reports that standard time series models of US housing prices would have forecast a range of values that include actual changes.

This explains why regulators are now defining stress scenarios. In fact, the Federal Reserve Board is now requiring U.S. banks to evaluate whether they will have sufficient capital to withstand a stress scenario that reflects a severe downturn in the economy. The Basel Committee (2009) also advises the use of *reverse stress tests*: “Reverse stress tests start from a known stress test outcome (such as breaching regulatory capital ratios, illiquidity or insolvency) and then asking what events could lead to such an outcome for the bank.” Clearly, however, none of this analysis would be possible without position-based risk management systems.

4. Conclusions

Risk management, even if flawlessly executed, does not guarantee that big losses will not occur. Big losses can occur because of business decisions and bad luck. Even so, the events of 2007 and 2008 have highlighted serious deficiencies in risk models. For some firms, risk models failed because of known unknowns. These include model risk and liquidity risk. In 2008, risk models largely failed due to unknown unknowns, which include regulatory and structural changes in capital markets and contagion risks. Such risks, admittedly, are not amenable to formal measurement.

There are a variety of immediately implementable enhancements for risk management systems, however. This includes the overweighting of recent data in risk models, the use of stress tests and broader scenario analysis. All of these require position-based risk measures. In other words, this crisis has reinforced the importance of risk management. There is simply no alternative. Risk management will not go away as a core function of financial institutions

In the end, a risk management system simply cannot--and is not designed to--take the place of the judgment and business expertise of the users of the system. We will surely see substantial improvements in risk systems as a result of the credit crisis. As stated previously, “formal risk management models cannot substitute for judgment and experience.”

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