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Introduction
by Rajna Gibson

In November 2001, the Swiss National Science Foundation launched a National Centre of Competence in Research (NCCR) in the area of finance, more specifically financial valuation and risk management. The centre, named Finrisk, engages in academic research, doctoral education and knowledge transfer centred around the themes of value creation (both real and financial) and on the management of the risks inherent to value creation.¹

Finrisk has a strong commitment to transfer its know-how to the financial services industry and to work in close collaboration with practitioners who are actively engaged in risk management. This book, “Risk and Risky Management”, is written mainly by Finrisk professors to answer fundamental questions about risk management. It is intended to serve as a reference to practitioners who have to deal with complex problems raised by the multi-dimensional nature and the rapid pace of innovation characterizing risk management decisions. Risk management offers the challenge of integrating people, information systems, business processes, incentives and capital allocation in a dynamic environment.

The book is structured into three main parts. Part I, titled “Corporate Risk Management”, starts by describing why firms should invest scarce resources in risk management and why their risk management policies should be clearly articulated. Threats to efficient firm-wide risk management, such as perverse incentives, informational asymmetries and poor accounting policies, are discussed in some detail. Part II, titled “Quantitative Risk Management”, starts by asking what is a proper risk measure and then follows with a description of the current state of the art in the quantitative management of major financial risks such as market and credit risks and their dependencies. The limitations of quantitative risk management techniques are acknowledged by an examination of a new source of risk called “model risk”. Next, new ideas from behavioural and evolutionary finance are introduced as a fruitful avenue for future risk management of pension fund assets. Part III, titled “Regulation and Macroeconomics”, is devoted to the analysis of the recent Basel II Capital Accords and its effects on the banking sector. The book concludes by emphasizing the need for risk management at the macroeconomic level, in particular to prevent systemic crises in global financial markets.

In a recent book titled “The New Financial Order: Risk in the 21st Century”, Robert Shiller highlights the importance of risk management for social welfare. His vision extends risk management to a number of previously neglected yet economically significant risks, by introducing products such as livelihood insurance or inequality insurance. The author states: “Ultimately, the New Financial order is about applying risk management technology to the major problems of our lives”. While less futuristic and less ambitious, the goal of “Risk and Risky Management” is also aimed at harnessing the benefits of risk management for financial institutions.

I would like to thank the academic members of Finrisk as well as the practitioners who have contributed to “Risk and Risky Management”. My special gratitude goes to Paola Varini who was the initiator and manager of this project. Let us hope that “Risk and Risky Management” will represent a first step towards an ongoing dialogue between Finrisk and practitioners about the value-added as well as the limitations of risk management.

¹ For more details about Finrisk, see page 72.

Unterschrift R. Gibson
Risk Management in Commercial Banks
Michel Habib, Swiss Banking Institute, University of Zurich

Why manage risk in commercial banks?
Why manage risk in commercial banks? The question is perhaps not as naïve as it sounds. The fact is that commercial banks need not be risky, for they can confine themselves to holding liquid, risk-free assets such as short-term government bonds. Such "narrow banks" would not be entirely devoid of risk, as they could still be victims of fraud for example, but the very simple nature of their assets would make it relatively easy for them to guard against such occurrences. Certainly, there would be little need for extensive risk management, and for the pervasive apparatus of regulation that characterizes the commercial banking industry.

The answer, of course, is to be found in the worn-out but nonetheless valid formula "no risk, no reward." A number of profitable, but risky investment opportunities are likely to present themselves. The purpose of risk management in banks is to provide an opportunity for banks to exploit such projects, yet preserve the safety of the deposits the banks have been entrusted with. This last requirement is likely to be paramount, especially for those depositors whose very limited wealth renders them unable to bear much if any risk.

How to manage risk in commercial banks?
Risk in commercial banks has been managed in three main ways.

The first way in which risk has been managed is through equity. By acting as a "cushion" or "shock absorber" that absorbs the shocks on the asset side of the balance sheet, equity—in so far as it retains some positive value—serves to maintain the value of depositors’ claims even as the risk inherent to the investment projects into which depositors’ funds have been invested may result in a sizeable decline in the value of such investments.

The second way in which risk has been managed is through diversification. The lack of perfect correlation amongst investment projects makes it possible for a bank to decrease the risk of its portfolio of assets by investing in a large number of investment projects. The bank thereby decreases the probability that its depositors’ claims will be impaired.

Diversification has its limits, however, if only because there are investment projects, the proper appraisal and monitoring of which may be beyond the necessarily limited skills of a given bank. The bank may then be well advised to forego such projects despite the diversification benefits they may bring the bank.

The third way in which risk has been managed is through the nature of the claims held by banks. It should come as no surprise that bank assets consist primarily of loans rather than equity stakes, even in those jurisdictions where there are no restrictions on banks’ holdings of such stakes. The value of a loan made to a project, although not immune to the changing fortunes of the project, is very much less affected by these fortunes than is an equity stake in the project. This makes loans less risky than equity stakes and, all else equal, more appropriate a vehicle for bank investment in risky projects.

The preceding three ways of managing risk are related, for equity is used to bear that risk which remains after all opportunities to reduce it through diversification and the judicious choice of claims have been exhausted.

All three ways of managing risk have been in use for many years. Recent years have seen the introduction of a number of new ways of managing risk. These allow a bank to decrease the risk it bears, in turn decreasing the bank’s need for equity. Conversely, these new ways of managing risk allow a bank to increase the risk it bears. A bank may wish to increase the risk it bears if the compensation it receives for taking on risk is greater than the compensation it has to pay shareholders for providing the additional equity made necessary by the increase in risk.

In order to discuss these new ways of managing risk and their possible value to banks, it is useful to distinguish amongst three types of risk, and three requirements that risk imposes. The three types of risk are the well-known market risk, credit risk and operational risk. The three requirements that risk imposes are the requirements to appraise, bear and control risk.

To illustrate the three types of risk, consider how they affect the prototypical asset of a bank, a loan. A rise in interest rates will decrease the market value of a fixed-rate loan, for the bank’s funds are tied in an asset now paying less than the opportunity cost of capital. This is an example of market risk. Should the rise in rates lead to a worsening of economic conditions that adversely affects a borrower’s cash flows, the borrower may have difficulty servicing and may even default on the loan. This is an instance of credit risk. Finally, a loan officer may be bribed into making questionable loans to a borrower, or the bank may see a decline in its loan book that reflects a loss of market share to more efficient competitors. These are two examples of operational risk.

Recent years have seen a profusion of counter-parties willing to take on, at a price, many of the risks faced by commercial banks, thereby offering these institutions the opportunity to decrease the equity they require. Other counter-parties have asked banks to take on, at a price, some of the risks faced by these parties. The challenge for banks is to identify those transfers of risk that are value-creating. In so doing, the three requirements to appraise, bear and control risk may prove to be helpful.

Consider market risk. Few if any parties can claim to control that risk, and the ability to appraise it—or inability thereof—is probably the same across parties. So these two considerations are unlikely to play much of a role in determining whether a bank should retain market risk or cede it to a counter-party, such as financial markets for example. Turning to the ability to bear risk in general, and market risk in particular, it should be clear that financial markets have a much greater ability to bear risk than even the largest, best capitalized commercial bank. A large enough negative shock to assets may jeopardize the viability of the bank by wiping out its equity, but it is difficult to imagine circumstances under which the same would apply to financial markets, whose combined values are in the trillions of CHF. This observation may explain the popularity of such financial instruments as interest rates and currency derivatives, which essentially transfer interest rate and currency risks onto financial markets.

Now turn to credit risk. The same reasoning as for market risk suggests that financial markets are a more appropriate bearer of credit risk than are commercial
banks. Note, however, that the requirements to appraise and control risk are here of primary importance. This is because not all borrowers are creditworthy, not all creditworthy borrowers are of equal creditworthiness, and even loans made to creditworthy borrowers may yield little or no return to lenders if improperly structured and monitored. Such structuring and monitoring—such appraisals and control—is probably best done by banks, which are in repeated and close contacts with their borrowers.

The requirement that risk be borne suggests that credit risk should be allocated to financial markets. The requirements that risk be appraised and controlled suggest that the same risk should be allocated to banks. An arrangement that serves to separate risk bearing from risk appraisal and control, thereby making possible the allocation of the former function to financial markets and the latter two functions to banks, should therefore be very successful. Securitization is an attempt at such an arrangement. It leaves loan origination (risk appraisals) to banks, sells the loans piecemeal in financial markets (risk bearing) and retains the originating banks to service the loans (risk control).

Not surprisingly, securitization has proven to be a great success. This success has, however, been limited to loans that are relatively easy to appraise and control, such as credit card and automobile receivables. In contrast, the securitization of commercial and industrial loans has met with little success. To a certain extent, the failure of securitization in the case of commercial and industrial loans can be explained as follows. The desire to avoid credit losses provides a bank with the incentive to do its utmost in structuring and monitoring a loan. There is therefore the fear—at least on the part of some investors—that a bank freed from credit risk by securitization will fail to perform the desired levels of structuring and monitoring. Should the bank be in a position to reassure investors on these matters, such fears should subside and need not impede securitization. This appears to be relatively easy to do for credit card and automobile receivables. In contrast, perhaps given their opaque nature, it appears to be more difficult to do for commercial and industrial loans. Even in such cases, the bank can commit to performing the proper structuring and monitoring, by maintaining a junior tranche in the securities that have been issued. This is because such a tranche makes the bank the primary beneficiary to the proper structuring and monitoring of the loans.

However, such a solution may be considered to defeat the purpose of securitization, for it requires the originating bank to retain much of the credit risk securitization is purposely intended to transfer to investors. This may be evidenced by the name commonly given to the junior tranche, specifically “toxic waste”.

Much of what we have said about credit risk applies to operational risk. In this case too, the requirement that risk be borne suggests that operational risk be allocated to financial markets, and the requirements that it be controlled and appraised suggests that it remains with the bank. How, then, do we explain the stress put on insurance in dealing with operational risk? Perhaps one possible explanation is this. Our understanding of operational risk is still quite limited. An institution to which was delegated the responsibility for dealing with the operational risk of many commercial banks would likely acquire know-how on how to appraise and control such risk faster than would each bank on its own. The institution would then make such know-how available to all banks. An insurer providing operational risk cover may be viewed as exactly one such institution. The requirement that insurance be provided, which distinguishes an insurer from a risk consultant, may be viewed as a device through which the institution bonds the quality of the know-how it provides.

A very brief discussion of other financial institutions

We now briefly turn our attention to other financial institutions. Much of what we have argued above should apply to other financial institutions such as investment banks, finance houses, and insurance companies. Of course, the exact nature of the liabilities of these institutions clearly impacts the nature of their assets, and the manner in which these institutions manage risk. Consider for example non-life insurance companies. The longer-lived nature of their liabilities—as compared to those of commercial banks—suggests that non-life insurance companies can diversify across time as well as across investment projects in their choice of assets. This makes it possible for non-life insurance companies to hold riskier assets than do commercial banks. Indeed, it is generally the case that loans made by non-life insurance companies have longer maturity and lower seniority than do those made by commercial banks.

Conclusion

This brief note has attempted to present a rigorous framework for thinking about risk management in commercial banks and other financial institutions. It has nonetheless left a number of questions unanswereds. Foremost amongst these is how to extend securitization beyond credit card and automobile receivables to a wide range of assets, in order to combine the risk bearing abilities of financial markets with the risk appraisal and control abilities of financial institutions. Success in doing so should make possible a marked decline in financial institutions’ exposure to risk, and constitutes an important research topic.

What should a Company’s Risk Policy be?

Giovanni Barone Adesi, University of Southern Switzerland, Lugano

A company risk policy must determine which risks the company is willing to take and in so doing it must pay attention to industry practices. A company must present to investors and company officers any departure in its risk policy from industry standards. This clear definition of corporate risk policy offers the necessary guidance to the people who have to implement it.

The strategic importance of risk management for corporate survival implies that a company’s board of directors must approve its risk policy. To minimize operational risk, risk managers should report directly to the board. And to allow for timely corrective action, they should also communicate regularly with senior management. An efficient management information system is therefore a necessary part of implementing corporate risk policy.

There is always some risk in the pursuit of profit, and risk policy aims to control the likelihood of the firm incurring large losses. Exactly how large “acceptable” losses can be depends on the economic capital of the firm and its appetite for risk. In valuing these elements, companies need to consider the greater difficulty of
operating after they have incurred large losses – and with them, perhaps, loss of rating and reputation – in a market that is likely to be more turbulent than usual.

Violations of these principles have led to high-profile corporate mishaps: underestimating the capital or liquidity necessary to survive in markets under strain, failing to define corporate objectives or to quantify acceptable risk, and failing to separate executive and risk management functions are mistakes that have precipitated large losses and, on occasion, corporate demise.

Consider a few examples. Long-Term Capital Management, perhaps the best known case, underestimated the capital necessary to survive markets under strain. Drexel and Enron died of ill repute. In the early nineties, Banc One got into trouble for keeping investors in the dark about its efforts to hedge the market risk of its own stock. More recently, American Barrick sacked the officer responsible for its hedging program, which, as gold prices rose, suddenly lost its shine. Metalgesellschaft failed to quantify its risk exposures and their related hedges. Barings and Sumitomo failed to separate executive authority from risk control, and took hefty losses.

Firms that want to prevent such calamities need to define risk policies and practice them carefully. To identify new risks before they produce irreparable losses, firms must pay attention, day-in day-out, to the conditions in which they operate. And they would do well to remember the old caveat: the most dangerous risk is always the one just neglected.

A classic example of the problems addressed by principal-agent theory is the fall of Barings, the British bank that went bankrupt in February 1995 when its internal monitoring and incentive structure induced an employee to run up losses that were larger than the bank’s entire capital. One of the three divisions of Barings, Barings Securities, was a major figure in Asian financial markets. It was active on all major stock exchanges. One of its activities was arbitrage between the Nikkei 225 futures traded on the Singapore Monetary Exchange and the Osaka Stock Exchange. Although these activities were essentially risk-free, because of the small price differentials of the contracts, they involved very large sums of money. Since 1993 in Barings Futures Singapore, a young trader named Nick Leeson had been running the division where most of these arbitrage operations took place. Leeson’s division appeared to be highly profitable, so he got large bonus payments – in 1993, more than five times his base salary of around $300,000. In late 1994 Leeson began speculating with unhedged futures positions on the Nikkei. This, of course, involved much higher financial leverage and risk than in Barings’ usual operations. After adverse market movements in January 1995, Leeson speculated on even larger scale, until total losses exceeded one billion US dollars. On February 23, 1995, Leeson fled Singapore. Three days later, Barings went under.

The Barings case has several noteworthy features. First, top management seems to have been honest and well intentioned. Top manager, Peter Baring, a widely respected member of the founding family, controlled the bank through a charitable trust. Second, Leeson operated with very few controls from inside Barings; in his division, the back office and front office operations were not separated. The execution and the accounting of his transactions were not handled by separate entities, as is usual in the business. And third, Leeson’s pay was strongly linked to short-term performance. In fact, Leeson’s bonus evaluation for 1994 was scheduled for February 24, a day after Leeson fled and only some weeks after he had taken his wildest gambles.

The Barings case extreme. It involved massive management failure. If top managers did not act fraudulently (which has not been proved), they showed a degree of ignorance that can only be explained by incompetence and blind fixation on ill-understood accounting profits. Yet, the fraudulent activity in the Singapore office was not an “accident”, as most commentators saw it at the time. It was the predictable consequence of the design of Barings incentives.

At the heart of the problem is a key insight from principal-agent theory: monetary incentives and monitoring can be complements or substitutes, i.e., the strategic interaction of these two management tools can vary widely across contexts. Monetary incentives

Risk Management and Risk Creation: The Role of Incentives
Ernst-Ludwig von Thadden, University of Lausanne

Corporate risk management is usually concerned with understanding and controlling events that hit a firm from outside. Typical examples are product market risk, counter-party risk, currency risk, and risk from forecasting errors. Good financial economists describe these types of risk using the mathematical concept of a “random variable.” They devise hedging strategies to minimize the impact of these random events on the firm’s balance sheet. Such hedging strategies are an important part of risk management.

But there is also another type of risk: self-made risk. In practice, self-made is just as important as the other risks. Self-made risk includes threats to the firm from uncontrolled activities inside the firm (even when nothing in the firm’s environment changes unexpectedly). These threats can be significant. Table 1 lists the five biggest corporate bankruptcies in the US between January 2001 and June 2002.

Table 1: The Biggest Corporate Bankruptcies in the US, 2001/2002

<table>
<thead>
<tr>
<th>Company</th>
<th>Market Value: 1/99</th>
<th>Market Value: 7/02</th>
</tr>
</thead>
<tbody>
<tr>
<td>WorldCom</td>
<td>230.7</td>
<td>103.9</td>
</tr>
<tr>
<td>Enron</td>
<td>82.2</td>
<td>63.4</td>
</tr>
<tr>
<td>Global Crossing</td>
<td>34.7</td>
<td>25.5</td>
</tr>
<tr>
<td>Adelphia</td>
<td>26.3</td>
<td>24.4</td>
</tr>
<tr>
<td>Kmart</td>
<td>42.2</td>
<td>17.0</td>
</tr>
</tbody>
</table>

**Note:** All values in Billion. Source: BankruptcyData.com

Leeson’s bankruptcy of Kmart, was not the direct result of fraud. In the four other bankruptcies, and in many more, the firm was not hit by an unfortunate extraneous event; it operated in a way that benefited individuals excessively and made massive losses unavoidable.

The field of economics that studies self-made risks and conflicts is principal-agent theory. At its center are problems of asymmetric information and incentives. Among the central insights of principal-agent theory are (1) ill-designed incentives can create enormous risks, but (2) designing optimal incentive contracts is generally a complex problem. Despite its complexity, principal-agent theory makes a number of fairly robust predictions about the design of monetary incentives, monitoring, and risk taking. These go back to the Nobel Prize winning work of Mirrless, Holmström, and others in the 1970s, and can be illustrated in many practical examples.

A classic example of the problems addressed by principal-agent theory is the fall of Barings, the British bank that went bankrupt in February 1995 when its internal monitoring and incentive structure induced an employee to run up losses that were larger than the bank’s entire capital. One of the three divisions of Barings, Barings Securities, was a major figure in Asian financial markets. It was active on all major stock exchanges. One of its activities was arbitrage between the Nikkei 225 futures traded on the Singapore Monetary Exchange and the Osaka Stock Exchange. Although these activities were essentially risk-free, because of the small price differentials of the contracts, they involved very large sums of money. Since 1993 in Barings Futures Singapore, a young trader named Nick Leeson had been running the division where most of these arbitrage operations took place. Leeson’s division appeared to be highly profitable, so he got large bonus payments – in 1993, more than five times his base salary of around $300,000. In late 1994 Leeson began speculating with unhedged futures positions on the Nikkei. This, of course, involved much higher financial leverage and risk than in Barings’ usual operations. After adverse market movements in January 1995, Leeson speculated on an even larger scale, until total losses exceeded one billion US dollars. On February 23, 1995, Leeson fled Singapore. Three days later, Barings went under.

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typically motivate employees to work harder. They may put in longer working hours, try harder, think of new business ideas or put them in place, or make similar, greater efforts. If effort is the main problem, i.e., if the employee has few alternatives but to increase her efforts to earn more money, then monetary incentives can take the place of monitoring. In such case, the employer does not have to control the employee tightly if he wants her performance to improve; the monetary incentives motivate her to act in the employer’s interest. However, if the employee has other ways to boost her performance, unmonitored monetary incentives can be dangerous. The most important, most dangerous alternative to making more effort is taking more risk. If the employee can improve her observed performance by taking higher risks instead of working harder, then the company needs to monitor her more closely to ensure that her improved performance results, not from taking more risk, but from actually working harder. In this case, monetary incentives and monitoring are complements: increasing one means increasing the other. Otherwise, the organization creates risk.

What is the main insight here? Corporate risk is, to some extent, endogenous (i.e., caused by factors inside the system). The degree of endogeneity of this risk depends on the nature of the business. Financial institutions are special. In many industries, employees have limited scope for taking risk. For example, in most firms, using financial instruments to hedge currency risk in export markets is fairly standard, and top management can usually define its scope sufficiently well. In the financial industry, however, business transactions often involve, by their very nature, complex risks and design choices. These choices are not easy to define across the board and they therefore leave wide berth for individual discretion. Providing high-powered monetary incentives without a thorough understanding of these individual decision possibilities and without efficient monitoring mechanisms for individual activities can create risk and pervert the original risk-sharing function of financial instruments.

We can easily take our argument up one rung in the corporate hierarchy. Since monitoring is naturally more difficult at the level of top management than inside the firm, monetary incentives are an even more powerful tool higher up. But given the ambiguous relationship between monetary incentives and monitoring, this tool also carries more risk. In an environment in which top management is sufficiently well controlled, these risks can be perfectly tolerable, even desirable. In the US (the only country where such data is systematically available), the higher the sensitivity of CEO compensation to stock price volatility, the riskier are the firm’s policy choices, as measured, for example, by the size of R&D-investment, the sectoral concentration of the firm’s activity, and the level of leverage. The stronger the monetary incentives of the firm’s executives, the higher the risks they take.

To what extent is such risk-taking optimal? It is usually difficult to assess. In some cases, the question is answered clearly. In the bankrupt firms at the beginning of our discussion, top managers deliberately defrauded investors. This fraud took many forms. The most blatant was direct transfers to executives. According to estimates, between 1999 and 2001, Enron’s top executives pocketed more than $1.2 billion, mostly bonuses and option profits. And because of the very dynamic and uncertain environment in which these firms were operating, an important reason for their bankruptcies has been excessive risk-taking. With inadequate management control, excessive risk-taking is a perfect way for unscrupulous executives to enrich themselves. These excesses are not “accidents”—they are the logical response to ill-designed incentives.

This is exactly what seems to have happened in the wave of bankruptcies in the last two years, a phenomenon that Johnson, Ryan, and Tian (2003) document. The authors examine the relation between executive compensation and corporate fraud in a large sample of US firms between 1992 and 2001. They find that executives at “fraud firms” had significantly larger equity-based compensation and greater financial incentives to commit fraud than did executives at firms without such compensation features. Executives at fraud firms also earned significantly more total compensation by exercising larger fractions of their vested options than the control executives during the fraud years. Further, operating and stock performance measures suggest that executives who commit corporate fraud attempt to offset declines in performance that would otherwise occur. Hence, executives’ financial incentives play a decisive role in the performance of their firms, sometimes with devastating consequences for shareholders.

Shareholders who want to control the risk of their holdings must attend to the design of executive compensation and to the structure of management control. Part of the risk from holding equity can be diversified away through advanced risk management techniques, but part of this risk can and must be controlled directly by properly understanding and channeling management’s incentives for risk-taking. Similarly, management must understand the incentives for employees to take risks. Strong monetary incentives are only productive if they go hand-in-hand with good monitoring, in particular in areas that are complex and give rise to discretion in individual decision-making. Next to carefully designing monetary incentives, among a firm’s most effective risk management strategies are separating complementary activities [such as back-office and front-office operations], encouraging insiders to blow the whistle, and ensuring internal transparency.

Monitoring the Risks of Stock-Based Compensation Schemes

Heinz Zimmermann, University of Basel

In recent years, the impact of incentive contracts on management performance, shareholder value, and risk taking has become increasingly important and controversial. According to a survey published in the Financial Times (FT) Deutschland on July 31, 2002, by Ein Cheng, top executives and directors of the 25 biggest US firms that collapsed in 2001/2002 amassed $3.3 billion in salary and share sales in the three years their companies went bust. With managers earning excessive compensation in years when their firms perform poorly, with firms using inappropriate or dubious measures to assess how well their managers are performing, and with the widely-publicized misbehavior of managers, shareholders have begun to question the returns they can expect from firms that have aggressive performance-based compensation plans.

1 I would like to thank Paolo Varani for very helpful comments.
Stock Compensation Plans

A typical compensation package for top managers has three elements: (1) a flat salary, (2) a cash bonus based on accounting numbers (Return on Assets (ROA), Return on Equity (ROE) or growth figures, and (3) an option plan that gives the holder the right to buy a set number of company shares. In a recent compensation survey by Watson Wyatt (available from Watson Wyatt's website) of over 13,500 executives at more than 1,700 companies, the average CEO gets a salary of $US 490,000 and a bonus of $US 427,000, from which $US 844,000 is paid out in cash. These same CEOs get some $US 3 million (market value) in stock options. (All figures are 2002 averages).

What's the chief argument to support these arrangements? If managers' future wealth is tied to the overall performance of the company, the thinking goes, their interests are aligned with the shareholders' interests. This minimizes conflicts of interest and agency costs. But if we look at this argument from an economic perspective, it is more dubious.

A Theoretical Framework: The Principal-Agent Model

A useful theoretical framework for analyzing the problems in these compensation schemes is the principal-agent model, developed by Holmström (1979) and others2. It highlights the basic trade-offs between risk, observability, and incentives. The principal-agent model shows that there is an optimal contract between principals (shareholders) and risk-average agents (managers). In this optimal contract, compensation is based on stock-price related measures, not because the principal profits from high stock prices, but because these measures reveal valuable, broadly based information about the manager's actions3. Additional performance measures (accounting data) are best used to the extent that stock prices are not regarded as a sufficient statistic for the desired managers' actions, provided the production function that links the actions to firm value is known.

The Case of Stock Options

Unfortunately, the basic principal-agent model does not tell us much about how to implement and structure compensation schemes. As shown by Murphy (1999), since the early 1990s, "stock options have replaced base salaries as the single largest component of compensation in all sectors except utilities". Why is this? One main reason is that stock options offer a wide range of contract designs, including exercise price, time to maturity, and adjustment of terms. Further, shareholders rarely understood the costs of stock options. Traditional accounting practices never disclosed their market value. And sometimes, firms didn't even compute the market value. The true costs to shareholders may be substantially higher than the benefits for the managers. Outside investors are generally free to trade, hedge or sell (short) options. For executives, this is impossible. So they put a higher risk premium in the pricing of their options, which implies a lower value compared to outside investors.

Adverse Risk Incentives

There are severe incentive problems with options. The value of an option increases with the risk of the underlying stock, and managers' actions can affect that risk. In contrast, the value of stocks decreases, which implies a severe conflict of interest. Shareholders must, therefore, strictly control the risk of the managers' business strategy.

This kind of adverse risk incentive is not limited to options; it is inherent in all participation schedules that are asymmetrically exposed to risk. In the asset management industry, this has long been clear: asset managers are rewarded with a performance fee if the returns on their portfolios exceed the benchmark, but they suffer no consequences if they underperform. As Grinblatt and Titman showed already in 1987, this participation schedule amounts to a "free" option. The incentive for excessive risk-taking is obvious, particularly if the option is "out-of-the-money", i.e., if the portfolio manager starts under-performing. Despite the adverse incentives of these compensation structures, in the 1990s they became fairly standard in the asset management and fund industry, particularly the hedge fund business. There is an additional point to consider, however. If the benchmark (i.e., the exercise price of the option) is itself random, there is an incentive to lower the correlation between the business (or portfolio) and the benchmark. In this case, the performance fee exhibits the structure of an option to exchange one asset for another. An agent's incentive to deviate from the benchmark is, obviously, a substantial risk for the principal and must be supervised under any circumstances.

Evidence

Mutual funds offer an excellent database for studying incentive fees, because we can separate funds that have incentive fees from those that don't. Blake, Elton and Gruber (2003) report a "tendency of funds with incentive fees to attract superior managers and/or to obtain more effort from managers in place". While Blake, Elton and Gruber find that incentive fees have only a moderate impact on average returns, they find that incentive fees have a substantial impact on risk taking. There is little consensus whether this conclusion also applies to corporate managers. Murphy (1999) concludes that "there remains little direct evidence, however, on the returns a company can expect from introducing aggressive performance-based compensation plans". Frey and Osterloh (2002) even recognize a substantial danger in these plans in that they crowd out the work motivation of employees and managers that is an indispensable resource in large, complex organizations.

<table>
<thead>
<tr>
<th>Revenues</th>
<th>Bonus</th>
<th>in %</th>
<th>Total Cash Compensation</th>
<th>Stock Options Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>100m to 500m</td>
<td>380.5</td>
<td>244.9</td>
<td>58%</td>
<td>566.10</td>
</tr>
<tr>
<td>more than 100m</td>
<td>722.7</td>
<td>685.5</td>
<td>91%</td>
<td>1'356.60</td>
</tr>
<tr>
<td>Sector</td>
<td>Banking and finance</td>
<td>454.3</td>
<td>372.9</td>
<td>67%</td>
</tr>
<tr>
<td>Insurance</td>
<td>653.4</td>
<td>790.0</td>
<td>88%</td>
<td>1'283.50</td>
</tr>
<tr>
<td>Retail/Wholesale Trade</td>
<td>606.3</td>
<td>444.7</td>
<td>72%</td>
<td>983.70</td>
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<tr>
<td>Services</td>
<td>438.7</td>
<td>322.6</td>
<td>63%</td>
<td>684.60</td>
</tr>
<tr>
<td>All</td>
<td>490.0</td>
<td>427.4</td>
<td>66%</td>
<td>843.80</td>
</tr>
<tr>
<td>Position</td>
<td>CEO/President</td>
<td>291.1</td>
<td>166.3</td>
<td>56%</td>
</tr>
<tr>
<td>COO</td>
<td>327.2</td>
<td>271.1</td>
<td>60%</td>
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<tr>
<td>CFO</td>
<td>234.9</td>
<td>133.0</td>
<td>48%</td>
<td>354.40</td>
</tr>
</tbody>
</table>


2 For details, see the contribution of Thadden on page 10.
3 A potential problem of the Holmström model is to apply the "hidden action"/"hidden information" paradigm to a setting where the real difficulty is in "value actions".
Creating Knowledge

A second-grader does this when she amasses knowledge of the multiplication tables (example: $2 \times 2 = 4$). But what our second grader cannot do is tell us how much $1259 \times 200$ equals. Since she has never memorized $1259 \times 200$, she cannot tell you the result, because that is not in her times table. Correctly multiplying $1259 \times 200$ needs an analytical and cognitive ability that our second grader will only get to at Ackoff’s next level, understanding.

Understanding involves interpolation. It is, in Ackoff’s thinking, cognitive and analytical. It is a process by which people can create new knowledge out of old knowledge. So, the difference between understanding and knowledge is the difference between learning and memorizing.

Wisdom, the “highest” level, calls upon all the previous levels of consciousness, and brings to bear special human characteristics like moral and ethical codes. ... to Ackoff, achieving wisdom isn’t easy, because people first have to move through the four previous stages successively.

This is all fine and good if you are interested in the theory of knowledge, but what does Ackoff’s hierarchy have to do with banking? The recent past has shown how disastrous the absence of wisdom can be to institutions. More specifically, sophisticated science-based risk management instruments cannot substitute for or even approximate good judgment, moral and ethics.

The Importance of Data

Data may be the lowest level of content in the human mind, but it is, nonetheless, the key to Ackoff’s hierarchy. Why? Because the absence of data means lack of information and the impossibility of acquiring knowledge. Without data we cannot learn. In making decisions, data is the bank’s true treasure. Often, there is a mismatch between the quality of data and its importance to the bank. Such a mismatch always shows that, in its risk policy, the bank is not treating data issues with enough care.

Consider a standard market-risk report on a typical executive’s desk. To generate this report, market financial models are calibrated on market data. Risk controllers then apply their knowledge to the information as follows: If the Value-at-Risk (VaR) is largely below the limits, “market risk is far away from the executive risk acceptance set”. This is like the elementary school girl telling you that $2 \times 2 = 4$. No further information is needed. On the contrary, if VaR becomes larger than the risk limit, a comment that “market risk exceeds the risk acceptance level” will not be satisfactory. To obtain further information, more and finer data are needed. If they do not exist, a data based analysis of the causes is impossible. In such a case, risk controllers have to base their analysis solely on their wisdom. In other words, their qualifications, experience, rhetoric, persuasiveness and honesty of intentions go into their final statement about the causes. For the executive, however, such evaluations...
are hard to value. Should he believe the explanations? Or should he ask questions to validate the truthfulness of the information? Clearly, the lack of data leads to uncertainty about causes which, in turn, causes the executive’s risk exposure to exceed his risk tolerance. The lesson: executives should ask their management what kind of data are collected so that the quality of risk reporting information does not decrease when markets are strained.

Customer Advice: How many experts?

From a customer or investor view, Ackoff’s five levels define whether a profitable, long-term relationship with the financial institution results. For financial institutions, it is becoming more and more difficult for a single employee to meet the clients’ expectations by engendering all five levels. The increasing complexity of products and services is one reason that, today, comprehensive advice must come from a variety of experts. For institutions, comprehensive one-stop consulting would be more profitable and less risky, since each transmission of information is a source of risk. The frequency and severity of these risks varies for the different levels: data, information, and knowledge can be transferred to a new advisor rather easily. These categories can be codified or articulated and de-codified unambiguously. Understanding, however, is much harder to articulate and to de-codify. Wisdom, typically, cannot be transferred to another person.

It follows then that a large part of what defines a successful client-advisor relationship is inseparably linked to some specific employees. Therefore, knowledge should, at least in theory, not be split among different persons. In terms of Ackoff’s first four levels, experts in banking, quantitative finance, financial analysis, tax law, and economics would be desirable.

Is this realistic? The “Multidisciplinary Natural Sciences” program at the Federal Institute of Technology (ETH) in Zurich proves that such an ambitious task is doable in the natural sciences. In the first two years of study, the few students in this program get a multidisciplinary education in different fields, such as physics, mathematics, chemistry, biology. “Multidisciplinary” here means that, in each subject, the students must master the same content as students who are majoring in the subject. In contrast, economics has no multidisciplinary program. Universities tend to specialize their curricula; other programs, such as the MBA, are too superficial. As the ETH experience shows, multidisciplinary students are highly valued in academia and industry. Perhaps executives should suggest to universities that they offer multidisciplinary studies in economics, too.

Noise and Information

So far, we have not considered noise. Noise is sometimes contrasted with information. Basically, noise is what makes our observations imperfect: noise keeps us from knowing the expected return on a stock or a portfolio. Noise keeps us from knowing inflation and interest rates. And it keeps us from knowing whether or not a merger will pay. Essentially, noise is an arbitrary element in our expectations. This arbitrariness may reflect uncertainty or our lack of rationality.

The Importance of Noise for Bank’s profitability

In banking, it may seem that noise is more bad than good. But the opposite is true. Noise makes financial markets liquid but also imperfect. Consider purely rational investors. By the very definition of rationality, investors possess well-diversified portfolios. But if that were true, there would be almost no trading. Why?

Because, since investors are rational, errors in the valuation of future expected returns are not possible. In a market of rational investors, who only trade on information, trading would be much less frequent than we observe every day. Suppose, however, that noise-traders also define the market, and that they trade on noise as if it were information. These traders have different beliefs than the information-traders about future returns. They will trade even if, from an informed trader’s point of view, they’d be better off not trading. So, trading is going on because some investors are exploiting the beliefs of others. In this sense, noise traders provide the markets with liquidity. Since each trade means a risk-free profit for a bank, it is in the bank’s self-interest that there be enough noise in the market. A trading desk can basically take a zero risk exposure in its own books and just earn its profit from trading flows.

A goal for institutions is, therefore, to attract both informed traders and noise traders. To achieve this goal, institutions could think about creating noise. But creating noise implies delivering a good that the institution itself believes is no good. And obviously, this is not in the interest of the clients and investors. Banks are responsible for generating information in all good conscience. Clients and investors base their beliefs on this information. Whether they can do it rationally or not need not bother the institution. Events in the recent past have highlighted the heavy reputation damage and ensuing legal action an institution can face if it intentionally generates noise.

Figure 1: Noise or information?
The Limitations of Discounted Cash Flow
The DCF method is not without its disadvantages. These stem from its flexibility and versatility. In many cases, the only discipline imposed on the person estimating the cash flows is self-discipline, especially when estimating cash flows in the distant future. Given the difficulty of forecasting far into the future, some constant rate of growth in cash flows must be assumed beyond some future year. In general, valuations are extremely sensitive to this growth rate, which by necessity is assumed to go on forever. The choice of the growth rate can therefore be made to serve one or another party’s agenda. This naturally dents the credibility of DCF valuations.

While there are ways to guard against such manipulation, the structure of DCF valuation is such that even a party with no special agenda may be led astray. This is because DCF does not directly confront the person who performs the valuation with the requirement of stating his assumptions explicitly and ensuring that they are mutually consistent. For example, in the valuation of the Internet bank Egg prior to its initial public offering (IPO), a number of analysts appear to have severely underestimated the investment required to finance Egg’s predicted growth. The need to increase the invested capital in line with growth should have been reflected in low or even negative net cash flows in the years of high growth, but in a number of reports it was not. Clearly, an analyst aware of the requirements for internal consistency can reflect these requirements in his DCF valuation, but DCF is not structured to confront the analyst directly with them.

Accounting-Based Valuation Models
Accounting numbers have an important role even in DCF. They serve as the basis for computing tax. They often serve as a starting point for computing net cash flow. Nonetheless, they play no role as such in DCF valuation. This, in itself, need not be a limitation of DCF, for it is cash flows rather than earnings that make possible the compensation of investors for providing capital, through dividends and capital gains. The attractiveness of earnings, and of accounting-based valuation methods, resides in the internally consistent rules the accounting profession has developed for estimating these earnings, and the assets that generate them. This is true even in an age that has seen Enron and other examples of accounting manipulation.

The Residual Income Model
The Residual Income Model (RIM) is an accounting-based valuation model that, as it names implies, revolves around what is called residual income. Residual income is that part of income that is over and above the income the firm must earn in order to compensate its equity-holders for providing it with equity capital. (Readers familiar with the concepts of Economic Value Added (EVA©) and Economic Profit will recognize the similarities with residual income.) The income the firm must earn in order to compensate its equity-holders is often referred to as “normal profit”, and residual income – the income in excess of normal profit – is referred to as “supernormal profit”.

Managing Noise Risk
For unintentional noise, it is the knowledge and understanding capacities of the employees that minimize noise risk. Managing noise risk is a question of skills. Odd is the use of different and sometimes incompatible methodologies to generate information and the large numbers of units engaged in this business. How do executives make sure that only consistent and high quality information generates the key rates and figures presented to them?

How can executives exclude intentional noise risk? The most efficient way is to select senior board members who act with Ackoff’s “wisdom”. Only then will they themselves not produce noise, or allow their employees to produce noise. Some institutions enforce a written codex to implement wisdom. But wisdom cannot be codified.

From Cash Flows to Accounting Numbers in Valuation
Daniel Baur, Michel Habib, and Rudolf Volkart, Swiss Banking Institute, University of Zurich

Finance academics and finance practitioners have contrasted the use of cash flows with that of accounting numbers for valuation and appraisal. They have generally privileged cash flows for valuation, and have used accounting numbers mainly for reporting and controlling. Recently, however, academics and practitioners alike have reassessed the role of cash flow in valuation. They have recognized that the Residual Income Model (RIM), an accounting-based valuation technique, offers many advantages.

Cash is King: The Discounted Cash Flow Model
Cash flow has been the basic building block of the Discounted Cash Flow (DCF) model used for valuation. As many readers are no doubt aware, the DCF method consists in discounting the cash flows a given asset is expected to generate to obtain an estimate of its value.

The DCF method is extremely flexible and versatile. It finds applications in a wide variety of contexts, for a large number of purposes, such as the financial analysis of real investments (capital budgeting), the valuation and value management of individual business areas (business line valuation), the valuation of firms, notably for M&A transactions and initial public offerings (firm valuation), and the valuation of financial securities (security analysis). The flexibility and versatility of DCF is evidenced by the wealth of acronyms for DCF-based valuation and appraisal methods: PV (Present Value), NPV (Net Present Value), IRR (Internal Rate of Return), DDM (Dividend Discount Model), CFROI (Cash Flow Return on Investment), and so on. The most famous is no doubt the NPV.

Unintentional generation of noise is also a risk management topic that matters to executives. But what is “unintentional” generation of noise? Since any information about future events generated in banking ultimately depends on subjective valuations and beliefs of employees, there is always the chance that what the employees think to be a piece of information is, in fact, contaminated by noise or is even pure noise. Consider the daily closing prices of Credit Suisse Group shares from October 2001 to October 2002 (refer to Figure 1). Plotted against these prices are the 120 price expectations of analysts in several banks. All expectations are above the price path. Do we consider this “noise” or “information” for investors?
Second, the RIM makes explicit the trade-off between paying dividends and retaining earnings to finance growth. Thus, had some of the analysts valuing Egg used the RIM rather than DCF, they would have been less likely to fail to account for the cost of financing growth.

Third, the RIM recognises that even a firm that is now earning supernormal profits is unlikely to do so forever. As noted above, competition should eventually reduce margins to the point where only normal profits are earned. This is why there are no terms for the years and beyond. The value of $T$ – the length of the CAP – is therefore of central importance to the RIM.

There are other advantages to the RIM. The accounting forecasts necessary for the RIM are generally more easily available than the cash flow forecasts necessary for DCF. Indeed, there appears to be no cash flow equivalent to the detailed accounting forecasts provided by firms such as I/B/E/S.

Research currently taking place at the Swiss Banking Institute of the University of Zurich compares the explanatory power of the DCF and the RIM model for the share prices of the firms in the Swiss Market Index. Preliminary results suggest that, in line with our discussion, the RIM dominates. (Earlier work that compares EVA© to DCF likewise reports that EVA© dominates. See Volkart (1998).)

With RIM, we can compute the value of the equity of a given firm (see text box above).

The Residual Income Model, as an accounting-based valuation model, is naturally subject to the same limitations as are generally attributed to accounting numbers. RIM fails to account fully for intangible assets and may be distorted by the common divergence between accounting depreciation and economic depreciation that is attributable to inflation or technological obsolescence. In the absence of these accounting-based limitations, DCF and RIM would result in identical valuations, if both made the same assumptions about future cash flows and earnings. In a way, this is not surprising, for earnings eventually become cash flows, whether dividends or realized capital gains.

Advantages of the Residual Income Model
We can attribute the advantages of the RIM over the DCF model to the fact that the two models are not equally effective at inducing the person performing the valuation to make the "right" assumptions about future cash flows and earnings. This is true despite the limitations imparted to the RIM by the nature of accounting numbers. There are three main reasons that the RIM is more effective than the DCF.

First, the RIM requires the person performing the valuation to be clear about whether he expects the firm to earn supernormal profits and, if so, to ask what puts the firm in a position to earn such profits. Firms in a competitive industry generally cannot expect to earn supernormal profits, since competition should drive a firm’s margins down to where they just cover the firm’s costs, including its cost of equity.
II. Quantitative Risk Management
Risk Measures or Measures that Describe Risk?
Freddy Delbaen, Department of Mathematics, ETH Zurich

The definition of risk is extremely complicated if not impossible. When dealing with situations involving risk, human beings act in many, sometimes contradictory ways. Modern economics has tried to find a theory for such behaviour, but when testing these theories, researchers found out that we do not always behave according to these basic rules. It is not surprising that a theory that tries to describe risk or tries to measure risk is the subject of criticism. When we presented our approach, we were told that we cannot represent the risk by just one number. Unfortunately we need such a theory as we have to make decisions that deal with the availability of money under uncertainty. In such a case we have to give a yes-no answer, meaning a one-bit representation that uses a lot less information than a number. The applications of risk measurement go from classical lotteries to the regulation of financial business by the national or international authorities. In this little note we will try to give a small overview on how we see the problem.

Perhaps the easiest example lies in the analysis of a trivial lottery. Let us say that we are proposed a deal that consists of winning 50 with probability 1/2 or winning 150 with probability 1/2. The average is 100. But probably very few people are willing to pay 100 for this game. It would result in a future wealth of -50 or +50, each with probability 1/2. The game looks neutral or fair but most people would prefer to have 0 for sure than having +50 or -50 with probability one-half. This attitude is called risk averseness. We deliberately forgot to give monetary units, since we realise that the answer could depend on the fact whether the units were Rappen, CHF, KiloCHF or MegaCHF. But for the applications we have in mind, we cannot make distinctions between this – difficult to explain – influence of psychology. So we will suppose that we are risk averse. As a result we will not be willing to pay the average value for this lottery. We probably will be willing to enter the game for less than 100, where the exact quantity we would be willing to pay could be related to the amount of risk-averseness.

Let us say we are willing to pay 90. Although easy and simple, this example reflects already the basics of modern finance. The price we are willing to pay is not the average value! Usually translated by: “we want to be compensated for the risk we are taking” or “if there is no risk premium, we cannot enter the deal”. There are at least two viewpoints that both merit to be mentioned. The first viewpoint is that when calculating prices, we change the probabilities. In our example this would mean that the probabilities we were using were not 0.5–0.5 but rather 0.4–0.6. By following this viewpoint prices become averages and this has the important consequence that prices are linear, meaning that the price of the sum of two positions is the sum of the prices. In modern terminology, we replaced the original measure by a so-called risk neutral measure. This practice of changing the measure to cope with risk averseness is not new. In life insurance, the mortality table used for pensions and for pure death risk are not the same. Also the age used to calculate the life insurance premium is not the age of the person but is lower or higher depending on whether a pension or a capital has to be insured. The second viewpoint is that prices are calculated by a different procedure not leading to a linear price mechanism. The former viewpoint is applicable to a very efficient market, where transaction costs are negligible and where products can be bought and sold without restrictions (“going short is allowed”). The latter viewpoint is applicable to more general situations and allows for a more detailed modelling of the diversification effect. By not assuming that prices are linear we can say that the price of the sum of two positions is greater than the sum of the prices since by buying two positions we might benefit from diversification or might benefit from the fact that we eliminate risk completely. This is for instance the case in a large company or bank where one unit takes a position in a foreign currency and another unit takes an opposite position, sometimes without knowing from each other that such positions exist.

In this example we supposed that the probability measure was known. This is in many cases a very optimistic assumption. In economics, where we talk of future outcomes for a financial deal or when we talk of the probability that the market will move in one or other direction, the word probability is not used in a physical sense. In is not the result of a statistical estimation based on many observations of experiments all done in more or less the same circumstances. The probability measure is rather the outcome of a personal analysis of the real world and is therefore rather subjective. This explains (but it is by far not the only explanation) that somebody wants to buy a stock and others would rather prefer to sell it. When we deal with large sums, risk averseness may disappear. This is for instance the case when we buy car insurance or life insurance. We are willing to pay a premium much higher than the average claim we will cause. Maybe that we attribute a higher probability to the event of causing an accident or maybe we are afraid of the consequences or maybe we just buy insurance because the law says we have to.

But how did we define risk in this example? We will not give a definition but rather use the word in a non-mathematical sense. When referring to measures of risk or risk-measures we do not claim that we have a precise mathematical definition of the concept “risk”. It might therefore be better to speak of measures that describe risk, or measures that allow us to give the manager or decision-maker a “quantitative” tool to compare – or better help to compare – different alternatives. We know that the theory has shortcomings but we also realise that if we want quantitative tools, we better use a theory instead of unfounded number juggling. To be useful, such a theory should be free of contradictions and it should reflect the basic thinking on risk taking. Therefore we want to be very precise on the definitions of the measures of risk and allow ourselves to remain silent when it comes to the definition of risk itself. The former we consider as a mathematical object, to be defined in a precise way, the latter we consider as a concept from real life subject to different interpretations and strongly dependent on the mood of the persons.

One of the first applications of measures of risk – although not called that way – was probably the calculation of premiums in insurance. Long before the theory was invented, insurers knew that the premium for an insurance had to be higher than the average pay-out. The reasoning is simple: we know that if a large group is insured, the final realisation of the claims will result in a sum that is not equal to the expected value but will be around this value, sometimes bigger, sometimes smaller. If only the mean value were used, the company would lose each time the deviation was positive. Nowadays we know, thanks to probability theory, that such a situation will eventually lead to

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1 For an example, see the contribution of Hens, page 46.

2 That the premium is higher than the average and not lower is not in contradiction with the example where we adviced a number before the average. It is simply the fact that the income is taken with a positive sign and the pay-out is taken with a negative sign.
bankruptcy, no matter how high the starting capital was. The first idea is then to use the deviation from the mean or average value to measure the risk taken and to calculate the loading or extra part of the premium. This suggests that we could use the standard deviation as a good measure. In modern finance this idea was used by Markowitz in his portfolio theory and it was also at the basis of the Capital Asset Pricing Model (CAPM). However the standard deviation has a big disadvantage. It treats the negative and the positive deviations from the mean in the same way. In our lottery example this means that the “50” was given the same influence as the “150”. Markowitz already realised this and in the footnotes of his book, he said that other measures can be used, e.g. the semi-variance. The CAPM itself can be obtained without referring to the standard deviation and it follows already from simple arbitrage arguments or even better it already follows from what is usually called the “law of one price”, an extremely weak form of consistency between market prices. In insurance the use of the standard deviation is doubtful when we have to deal with probability distributions with fat tails. In such cases the standard deviation might not even exist. This is the case for reinsurance problems. The distributions used there, usually have fat tails and reflect the overshoot over a high level. These so-called extreme value distributions are the topic of recent scientific research and their use in insurance and finance is well accepted. It is clear that we need more sophisticated tools than just standard deviation.

Another example that got a lot of attention and became important was the value at risk or VaR. Given the probability distribution of the future wealth of a financial institution, the value at risk at the level α, is the quantity that is defined in such a way that in less than α% of the cases the wealth will drop below this level. In practice the time horizon used is the ten day period and the level is quite low, typically 0.5%, 1% or 5%. When this risk measure is used, we will accept positions as safe when in say, less than 1% of the cases, we get into trouble. In earlier days this definition as a quantile was not used, it was rather replaced by a multiple of the standard deviation. The author remembers a discussion where the subject was whether the multiple would have to be 3 or 5. This practice of course not very intelligent. It uses the fact that the quantile is defined through the standard deviation and the mean, a fact that is only valid for a small class of probability distributions and is not satisfied by the extreme value distributions already mentioned. Also the positions built by the traders can have strange form*. The standard deviation technique works quite well for the normal distribution but it does not for others. Here the word “normal distribution” is misleading. It suggest that the other distributions are abnormal and that in normal situations we indeed get the normal distribution. This remark is not only meant as a joke, some people even believe it. It would be better to adapt the French terminology and speak of “Gaussian distributions”, the big advantage being that it suggests that it is a technical term.

The value at risk, even when seen as a quantile, has some dangers. When used we will accept positions that with high probability are good and that with a very small probability lead to bankruptcy. For the stockholder of a company this seems good, since in any case he/she is not liable for the amount of the bankruptcy. The situation changes if viewed from the side of the regulator, who is supposed to protect “Society”. From his/her viewpoint the amount of the bankruptcy might be more important than just the fact that there is a bankruptcy.

Inside a financial institution, the use of value at risk is even more problematic. When applied to individual business units, it could lead to a position that is good in 99% of the cases but in one percent of the cases leaves the company with a big loss, a loss that has then to be covered by the gains of the other business units. The use of value at risk seems to lead to more risk-taking, it favours “free riders” and so called “doublet strategies”, where in 99% of the cases the trader gets a gain (and consequently a bonus) and in one percent the trader makes a tremendous loss, and gets fired or is really severe, causes the company to file for bankruptcy. It favours the practice “take the money and run”.

We proposed a more structural approach to risk measures and we started from a set of basic properties a risk measure would need to satisfy. These properties were discussed with practitioners and were tested against their opinion on how to deal with risky situations. The interested reader can look up our papers on risk measures* to get an idea and to see a discussion of the different properties we set forward. Since then, the theory has evolved a lot and we are presently working on a dynamic version of this theory. It is impossible to even summarize the main points in this theory. So let us make just a couple of remarks. The risk measures are defined on the set of random variables so that it is possible to use correlation models when dealing with different positions. This reflects the fact that the acceptance of a new deal, say a new insurance contract or a new kind of option, is dependent on the other elements in the portfolio. The risk measures we propose are coherent, meaning that diversification has a positive impact. A diversified portfolio needs less economic capital than a non-diversified portfolio. (In a credit portfolio the use of value at risk on the individual loan level would rather give the opposite, as was illustrated by Albanese). Since we know that in practice and especially in economics the exact distribution of the future outcomes is difficult to get, we propose the use of different probability measures. This allows for stress testing to be built in.

The fact that diversification is rewarded and not punished also allows to treat the capital allocation problem in a consistent way. The capital allocation problem is the following. Once the economic capital for the firm is calculated, how can you allocate this capital to the different business units? This is not an investment problem. Phrased in another way, we could say that each business unit requires its own economic capital but that because they are in a bigger entity, they could benefit from the diversification effect. The problem is how? Such problems are important since more and more, business units are evaluated on their returns. But return on what? The use of coherent risk measures allows to define the risk adjusted capital for each business unit in a coherent way, meaning that the outcome is fair in a game theoretic sense.

It is difficult to predict whether the coherent risk measures will eventually replace the use of VaR. We already observed that they are used more and more.

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3 There is a mathematical theorem that says that any distribution can be arbitrarily approximated by a position in one stock and the options written on it.

4 See Artzner-Delbaen-Eber-Heath “Thinking Coherently” in Risk Magazine November 1997 or the Pisa lecture notes of the author, see http://www.math.ethz.ch/~delbaen.
How Reliable are the Company’s Forward-Looking Instruments?
Oliver Scaillet, HEC Geneva and FAME

Recent years have seen advances in financial engineering, financial innovation and deregulation. The activities of large, internationally active financial institutions have grown more complex. With this complexity have come innovations in the ways these institutions measure and monitor their exposure to risk. If only because efficient risk management bolsters long-run performance, financial institutions can no longer forego risk monitoring. Managing financial risk management means predicting the future. But such prediction raises questions: Can we simply use the best market guess, namely forward exchange rates, to predict future spot exchange rates? If not, how can we produce better forecasts, and evaluate their reliability? Should stress-testing procedures be supplemented? What form should they take? What follows are some guidelines on these issues and a discussion of the design of a financial prediction system that works for managing risk. Although the challenge of predicting foreign exchange will be our main illustration, our points are valid for other sources of financial risks as well.

The Forward Rate Anomaly
Ask an economist to forecast exchange rates, and he will think first of the unbiased forward rate hypothesis. No wonder in a world without arbitrage, the twin assumptions of risk neutrality and rational expectations imply that the forward exchange rate should be an unbiased predictor of realized future spot exchange rates. This no-bias property follows from the so-called uncovered interest rate parity, which implies that the expected return on a forward contract is nil. Basically, it says that, on average, an investor who borrows in a country with a low interest rate, then converts the funds to the currency of a country with a high interest rate and finally lends in that high-rate country won’t earn a profit or suffer a loss.

Unfortunately, empirical support for the unbiased hypothesis is weak. Estimated coefficients have the opposite sign from the one the theory predicts. In reality, forward exchange rates tend to over-estimate changes in spot exchange rates. This regularity is called the forward rate puzzle. Peso-problems are often cited for the failure of the unbiased forward rate hypothesis. Peso-problems arise when, at the time of decision, investors rationally expect the occurrence of a future event that never happens.

Preprocessing
Before you feed data into a forecasting model, you need to collect, inspect, clean and select it. Since bad input will impair even the best predictor, data quality and preparation are vital. Preparation usually involves some visual inspection to find outliers (sparse extreme observations), missing values, trends, seasonalities, or any so-called nonstationarities (explosive and irregular behavior).

Design
There are two broad kinds of forecasting methods: parametric and nonparametric. Parametric methods rely on a parametric specification of the forecasting formula. Their parameter values need to be estimated. This specification can be linear or nonlinear. The most well known linear example is the standard linear regression, whose estimation is performed via ordinary least squares. Nonparametric methods do not require any particular parametric assumption but usually require some smoothness properties of the forecasting formula. These nonparametric techniques include standard nonparametric statistical techniques such as local linear smoothers, nearest neighbor methods, and techniques borrowed from the engineering literature and based on particular learning mechanisms such as neural networks and genetic algorithms.

Evaluation
Proper evaluation is, of course, critical in developing a prediction system. First, it has to measure exactly the desired effect (prediction accuracy). Variability of prediction errors should be assessed. Second, proper evaluation has to balance overfitting and robustness. For this purpose, Occam’s razor, known among model builders as the parsimony principle – among models that perform equally well, prefer the simplest one – is useful for picking prediction models. More formal statistical tests based on goodness-of-fit, in-sample and out-sample performance may also be extremely helpful. The evaluation should lead, if necessary through a feedback step, to a revision of the financial prediction system.

Stress Testing
Thus far, our interest has been future levels of spot exchange rates. We assumed that prediction is based on adequate financial engineering. The activities of large, internationally active financial institutions have grown more complex. With this complexity have come innovations in the ways these institutions measure and monitor their exposure to risk. If only because efficient risk management bolsters long-run performance, financial institutions can no longer forego risk monitoring. Managing financial risk management means predicting the future. But such prediction raises questions: Can we simply use the best market guess, namely forward exchange rates, to predict future spot exchange rates? If not, how can we produce better forecasts, and evaluate their reliability? Should stress-testing procedures be supplemented? What form should they take? What follows are some guidelines on these issues and a discussion of the design of a financial prediction system that works for managing risk. Although the challenge of predicting foreign exchange will be our main illustration, our points are valid for other sources of financial risks as well.

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When we determine levels of risk capital, we should address, first and foremost, the disturbances that occasionally stress institutional solvency—the negative tail of the profit and loss distribution that is so central to modern risk management. Fitting stress scenarios into formal risk modeling is cardinal. Experts have adopted the generic term “stress-testing” to describe the techniques the finance industry uses to gauge their vulnerability to exceptional, but nonetheless plausible events. Consolidated stress-testing in firms was introduced in response to the amendment to the Basel Capital Accord in 1996, which made approval of the “models approach” to a firm market-risk capital requirement, conditional on the presence of a firm-wide stress-testing program.

The most popular of these techniques involves determining the impact on the value of a portfolio, at a firm or business unit level, of a move in a particular market risk factor (a simple sensitivity test) or a simultaneous move in a number of risk factors. This move reflects an event that the firm’s manager believes may occur in the foreseeable future (scenario analysis). The scenarios are created either by drawing on a significant past market event (historical scenarios) or by thinking through the consequences of a plausible market event that has not yet happened (hypothetical scenarios). Here, due consideration must go to sharp variations that have occurred in a mere matter of days: Enron default, ABB fall, Alsthom and Worldcom crashes, to name a few. Some firms use other techniques to capture their exposure to extreme market events: a maximum loss approach (in which risk managers estimate the combination of market moves that would be most damaging to a portfolio) and extreme value theory (the statistical theory concerned with the behavior of the “tails” of a distribution of market returns).

The Use of Stress-Testing

Most of the time, stress tests supplement Value-at-Risk (VaR). VaR is thought to be a critical tool for tracking the riskiness of a firm portfolio day-to-day, and for assessing the risk-adjusted performance of individual business units. However, VaR has been of limited use in measuring firms’ exposures to extreme market events. This is because, by definition, such events occur too rarely to be captured by empirically driven standard statistical models. Furthermore, when price movements themselves are large, observed correlation patterns between various financial prices and joint evolution of risks tend to change. Stress tests offer a way to measure and monitor the portfolio consequences of extreme price movements of this type.

Limitations of Stress-Testing

A stress test estimates the exposure to a specific event, but not the probability that the event may occur. As noted, stress tests enable managers to track a firm’s exposure to price changes during plausible events, without obliging them to develop a formal statistical model for such events. In the specification of a stress test, the risk manager has to make numerous decisions based on judgment and experience. For their stress tests, most banks pick a small number of ad hoc scenarios. So there is no guarantee that the risk manager will choose the “right” scenarios, or interpret and communicate the results effectively. In particular, misinterpretation can induce a disclosure risk by putting a trading desk or the whole bank at a disadvantage when it needs to roll its positions over or modify them. Stress tests also impose a high computational cost, particularly in collecting the data from diverse business units and from revaluing complex option-based positions. A further limitation is that most firms model market risk separately from credit risk. They do not integrate market and credit risks in a systematic way in their stress tests. Further, some forms of risk that are understood to be important, such as liquidity and operational risk, are difficult to quantify precisely, and are often assumed to be negligible, an expedient but dubious simplification. Not surprisingly, stress testing has yet to take hold formally or consistently across the financial community.

Towards Better Risk Management

The results of stress tests may get into managers’ hands, but they are rarely part of formal risk modeling. From this process decisions emerge on matters like the limits on proprietary position-taking, capital charges on traders and trading units, and the appropriateness of the risk-manager modeling assumptions. Because of their intuitive appeal, stress tests are perceived as a good way to get risk managers, senior managers and business unit heads to talk about the risks they are taking and how they monitor and manage them. This perception is valid, and it explains why stress tests are so important for managing risk. Nevertheless we would like to emphasize that stress tests are only part of the process through which financial firms set their quantitative and qualitative risk-management policies. By better integrating all the parts of a risk management system, with a carefully designed prediction system at the center, senior managers and business-unit heads should be able to figure out more efficiently whether or not the firm’s risk exposure is within its appetite.

Assessing and Managing Model Risk

Rajna Gibson, Swiss Banking Institute, University of Zurich

Any financial model, by definition, is simplified. It imperfectly represents the economic world in which agents make investment, trading or financing decisions under uncertainty. Financial and technological innovation has enabled banks, securities houses and regulators to rely on more complex risk management models. These models allow them to price, trade and manage single and aggregate positions that are subject to multiple risk factors. Nowadays, at least in theory, we can explain and quantify the effects of market, credit, liquidity and operational risks on the value of a financial institution’s trading portfolio, on the outcome of a dynamic hedging strategy, and on the allocation of a firm’s economic capital. Yet, traders, risk managers, shareholders and academics easily forget the basic assumptions, the theoretical limitations and the imperfections that limit the validity of their models.

A large number of highly reputable banks and financial institutions have suffered extensive losses that stemmed from over-confidence in faulty models. In the 1970s, for instance, Merrill Lynch lost $US 70 million in its stripping of US government bonds into interest-only and principal-only securities. Instead of using an annuity yield curve to price the interest-only securities and a zero coupon yield curve to price the principal-only securities, Merrill Lynch based its pricing on a single 30-year par yield. This caused large pricing errors that the market immediately arbitrated after
issue. In 1997, the Bank of Tokyo-Mitsubishi had to write off $US 83 million on its US interest rate swaptions book because it had used an inappropriate pricing model: the bank was calibrating a simple Black-Derman-Toy model with at-the-money swaptions, which caused in-pricing errors for out-of-the-money and Bermuda swaptions.

A Definition of Model Risk

Broadly speaking, model risk results when a financial institution uses an inappropriate theoretical model or uses an appropriate model in an inadequate framework or for the wrong purpose. In their 1999 article, Gibson, Lhabitant, Pistré and Talay describe the three main origins of model risk. First, model risk can arise from incorrect modeling. It includes errors in model identification, as well as specification and estimation errors. Suppose we’re interested in hedging a US dollar denominated interest-rate derivatives book. To hedge this book, should we rely on an arbitrage or an equilibrium asset-pricing model? Let’s assume that the trader chooses to rely on an arbitrage-free continuous-time term structure model. First, he has to specify the number of factors that drive the term structure’s random evolution. Then he has to define their joint stochastic process. And finally, he has to estimate the parameters for using the model. Estimation errors are only a nested subset of the more broadly defined modeling errors that can harm any given model’s hedging or pricing performance.

Second, model risk can arise from market imperfections. These include transaction costs, short selling restrictions or tax considerations that, on the one hand, limit our ability to trade or hedge continuously, but on the other hand also limit the effectiveness and the gains associated with a specific strategy. For instance, the simulated results from a Black and Scholes delta-hedging strategy will certainly deviate from the actual outcome if the model is applied to hedge long-term illiquid index options or to hedge small-cap written options.

Finally, model risk may also arise when a model is specified correctly but used improperly. A good example would be if we use the Black and Scholes model to price and hedge bond-written options, and we thus ignore that the price dynamics of the underlying asset – the risk-free bond – violate the log normality assumption. Similarly, not having reliable, clean data can also be a source of model risk. With credit risk and operational risk management models, this problem is acute. This third source of model risk can also find its origin in inappropriate incentive mechanisms established in a given firm (or provided by a country’s legislation). Compensation policies should be structured to deter traders and portfolio managers from choosing models that artificially boost the firm’s short-term profitability and risk exposure.

Intentional Versus Unintentional Model Risk

The Metallgesellschaft case is an example of the difficulty of assessing the proper origin of model risk. Can we say with confidence that the losses Metallgesellschaft incurred on its hedging strategy resulted from the company unintentionally using too simple a one-to-one (oil forward versus oil futures) hedging model? Or should we attribute the losses to the conscious choice of a one-factor oil contingent claims model for speculating on the evolution of the oil basin? Clearly, there is an ethical dimension to model risk. In order to avoid “intentional model risk,” firms must enforce proper risk management and incentive-compatible remuneration policies.

The Consequences of Model Risk

The consequences of model risk for the health and reputation of firms in the financial services industry are easy to grasp. Model risk generally translates into financial losses and damaged reputations. Even bankruptcies. Widespread reliance on financial models in risk management and regulation standards (at least for the large financial institutions) can also destabilize the entire financial system. In a recent study, Basak and Shapiro [2001] show that if all the financial institutions in an economy rely on the VaR criterion to manage market risks, they can exacerbate stock market volatility during market downturns. So, it comes as no surprise that regulators and central banks concerned with the (potential) externalities of these risks on the stability of the financial system welcome both the definition of reliable financial models and their proper application in managing the exposures of global market players to market, credit and liquidity risks.

Related to the nature of model risk is the issue of whether and to what extent it is a diversifiable source of risk in the economy. If model risk cannot be fully diversified, agents in the market should price this residual risk exposure. When there is a systemic model-driven failure in the financial markets, an important consideration for the financial services industry is to determine who should bear the cost–the clients, the shareholders, the bondholders or the government.

Since the study of financial decision-making under uncertainty is not a pure science, model risk is here to stay. Any rational or behavioral financial model depends on simplifying assumptions to describe how agents make decisions in the real world. This is particularly important for quantitative risk management models whose “precise output figures” are often taken at face value without considering the fragility and the limitations of the assumptions on which they rest.

Model Risk Management:

Recommendations and Conclusions

Since model risk is unavoidable, financial institutions should assess and manage it properly. Here are some simple guidelines:

- Financial institutions should rely on independent model vetting. The role of vetting is to control the soundness of the model and of its applications.
- Financial institutions should always assess the quality and consistency of their databases before using them to implement a new model.
- Model risk management presupposes that an integrated risk management culture in the financial institution exists. Indeed, the partial or improper modeling of risk factors dependencies is an important source of model risk.
- The vetting of models should take into account changing market environments. The risk factors’ dynamics may change over time because of changing political, economic or cultural trends. Financial products can also change because of financial innovation, legal considerations, and changes in the demand for them. Financial institutions should always factor these considerations into their decisions to use a given model for pricing and hedging.
- Financial institutions should adopt incentive-compatible remuneration policies that prevent employees from opportunistically managing model risk and thereby exposing the firm to excessive short-term risk.
- Financial institutions should regularly educate their staff since financial engineering and risk management techniques are subject to rapid modeling and technological changes.

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1. See the contribution of von Thadden, page 10.

2. See the contribution of von Hens, page 46.
Aside from following these recommendations, financial institutions should never view model risk management as a tool for finding “the perfect model.” They should see it as a process that helps them to be aware of and to control the potential losses they may incur from using its imperfect models. Thinking of model risk management more pragmatically, consider the analogy between model applications and medical consumption practices. A sound financial model should come with a list of its model risk counter-indications, just as a prescription drug comes with a list of its potential side effects. Firms should develop an internal monitoring process to gather, analyze, store and disclose information about the origins and the potential consequences of model risk on their profitability.

The late Fisher Black once said, “I sometimes wonder why people still use the Black and Scholes formula since it is based on such unrealistically simple assumptions.” Perhaps, the answer can be found in his 1986 Presidential Address at the American Finance Association. “In the end, a theory is accepted not because it is confirmed by conventional empirical tests, but because researchers persuade one another that the theory is correct and relevant.” Let us hope that by developing our awareness of model risk and by adopting techniques to mitigate model risk, we can replace complacency with a healthy skepticism about our imperfect risk management models.

The increase is achieved by augmenting the multiplier accordingly, depending on the number of violations during the backtesting period.

VaR Prediction Procedures

How can we develop accurate statistical VaR prediction procedures to measure the historical risk of a trading portfolio? ... structure for the volatility of returns. It is well known that volatility is highly time varying and partly predictable. This time-varying structure is even more relevant for estimating the two-week horizon VaR of financial instruments that are particularly sensitive to volatility. We also need to avoid making overly simple assumptions about the conditional distribution of returns, i.e., the distribution of return shocks conditional on the estimated volatility. A reasonable, simple approach that avoids overly strong assumptions about the stochastic structure of conditional returns is resampling past filtered returns to compute out-of-sample confidence intervals and VaRs (both based on the estimated volatility process and the simulated filtered returns). In the literature, this approach is known as “historical simulation.” It yields the estimated statistical VaR that prevails under the historical market conditions of a sample of current and past market data information (about five years’ worth). When we apply historical simulation or related techniques to estimate VaR, we need to correctly estimate the predictable structure of volatility. To this end we apply cross-validation techniques or robust estimation procedures.

Stress Testing and Related Methodologies

Pure statistical VaR is only a partial measure of the risk of a portfolio. It depends on the specific volatility structure and returns-distribution in the data sample used to compute the VaR predictions. It also assumes that the quality of the data on the returns of the portfolio is satisfactory. In reality, estimated volatility structures vary with time, and typically, we need to update the estimated volatility process regularly, whenever we have new data. This is easy if the structural part of volatility changes relatively smoothly over time. However, with unanticipated events, like a crisis in equity or emerging markets, or a change in monetary policy, the volatility dynamics and the returns distribution change rapidly. And, if the VaR model does not include the possibility of such structural breaks, these changes are hardly forecastable. Structural breaks in volatility that can be mapped to some past historical patterns of volatility could be incorporated in ... data do not sufficiently reflect. A cautionary, realistic risk measurement procedure takes such aspects into account.

One option is to extend a purely statistical VaR measure by using some stress testing scenarios for which we can estimate or simulate VaR. Stress scenarios should consider both market direction

Market Risk: A Primer

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Market risk results from adverse price movements or volatility in the assets of a firm’s portfolio. It comes from exposure to market variables like interest rates, exchange rates, equities, and commodities. To determine the capital charge needed to cover these risks, the Basel Committee on Banking Supervision, among others, has adopted or at least recommends using Value at Risk (VaR). VaR is the potential loss associated with a price movement of a given probability over a specified time. Under the Basel Committee’s Internal Models Approach, every day, financial institutions must report their VaR at the 99% confidence level for one day and over two-weeks (ten trading days). The capital charge for market risk on any given day equals the larger of two numbers – either the previous day’s two-week VaR, or the average of the two-week VaR from the last 60 trading days – multiplied by a fixed number pegged on a scale from three to four. This number is termed the multiplicator and, as regulators argue, accounts for the possibility of model risk.

To control the way financial institutions report their true VaR, the Basel Committee recommends so-called “backtesting.” If an institution correctly reports its daily VaR, the actual daily losses exceed the reported VaR only 1% of the time. Trading days on which the actual loss exceeds the reported VaR is considered an exception. Every quarter, regulators look at the number of VaR exceptions for a financial institution over the last twelve months. If the number is “high,” they can increase the capital market charges over the next quarter.

VaR is the potential loss associated with a price movement of a given probability over a specified time.

3 For differences between Information, Knowledge and Understanding see Vanini, page 16.

4 Several univariate or multivariate models of the GARCH family can be used for this purpose.

5 For model risk, see the contribution of Gibson, page 33.
scenarios and/or market volatility scenarios. Take note, however, that the Board of Directors must approve the definition of stress scenarios and the method for determining their probabilities. In some cases they can be suggested by some observed past stress events and stress dynamics, which are insufficiently represented in the data used to estimate the statistical VaR. In other cases, they can be suggested by stress events that, under current market conditions, seem likely enough. Stress scenarios should span at least an approximate minimal set of mutually-exclusive, conditional stress-market conditions. To avoid unrealistically conservative risk-measurement policies, the firm should calibrate them to fit a moderate set of mutually-exclusive stress conditions.

Backtesting and Model Testing
Backtesting monitors the quality of a VaR prediction model when new market data become available. In a reliable VaR measurement model, VaR exceptions should not significantly exceed the expected average number of violations. The Basel Committee’s Internal Models Approach recommends heavy sanctions for insufficient backtesting performance. So, one necessary condition of a useful VaR model is sufficient backtesting performance. Several statistical tests are useful here: tests of the correct number of VaR exceptions, or tests of the correct autocorrelation structure in the VaR exceptions. All backtesting exceptions should undergo detailed analysis to establish their cause. Only in some well-justified cases should this analysis lead to changes in the VaR prediction model. More importantly, backtesting can help analyze the quality of a VaR prediction model more generally, not only the number of violations. Indeed, any VaR prediction model will estimate the underlying true VaR. Nevertheless, such estimates are subject to possible distortions and/or efficiency losses under different hypotheses on the returns-generating process. Therefore, backtesting can help quantify the efficiency and robustness of any VaR prediction procedure. This then satisfies the necessary requirement of a correct mean number of VaR exceptions. The time variability of VaR figures estimated by competing VaR prediction models under different returns distributions can give us some hints. To this end, bootstrapping real data or Monte Carlo simulations can be useful. But remember, we should prefer statistical VaR prediction models that imply more stable VaR profiles over time and across several realistic return dynamics. Indeed, they should leave some more room for risk management procedures where adapting outstanding risk exposures according to some VaR limit can occur more smoothly and, thus, more feasibly.

Recommendations and Conclusion
Models for estimating or predicting historical VaR should include a time varying structure for volatility. They should not assume too simple a structure for the conditional distribution of returns. Historical simulation can easily meet these two basic requirements. Nevertheless, if you want to correctly estimate the predictable structure of volatility, avoid overfitting.

You can extend pure statistical VaR measures by using stress-testing scenarios and techniques. These will allow you to use conditional stress events that your data does not amply represent to measure pure statistical VaR. Stress scenarios should consider both market direction scenarios and market volatility scenarios. And they should be calibrated to fit a moderate set of mutually exclusive stress conditions.

In terms of the observed number of VaR exceptions over the relevant backtesting periods, a useful VaR model must have adequate backtesting performance. You should also apply backtesting to quantify the efficiency and the robustness of a prospective VaR prediction model.

What are the Major Risks from Financial Instruments?
The Case of Credit Risk
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Forms of Credit Risks
Default risk is the risk that an obligor or counter party fails to meet its contractual obligations. For a financial institution the most important default risks are credit risks, the risks that an obligor of a bond or a loan will not make full payment on interest and principal. But there are also many cases when counterparty risk from other contracts (notably OTC derivatives) becomes significant.

The credit risk of a single obligor essentially has two components: the timing risk, which concerns the time of default (and also if a default will happen at all), and the magnitude risk, which concerns the size of the loss suffered when the obligor defaults.

While an occasional default of an individual obligor is an unfortunate but natural part of banking (although it can have a significant impact on profits), many joint defaults of several obligors can threaten the very existence of a financial institution. Thus, unless the default concerns a very large single exposure, the real risk to a financial institution lies in portfolio credit risk, the risk of many obligors defaulting in a short time.

Default risk is not a static quantity; it changes over time. The fluctuations give rise to credit-driven market risk for assets whose market price is materially affected by default risk. We should not view market risk as an additional risk of traded assets with default risk, but rather as an early-warning signal for changes in the underlying default risk. Such traded assets that carry market risk include defaultable bonds, loans (if traded), positions in credit derivatives (in particular credit default swaps), credit-linked notes, and investments in tranches of collateralized debt obligations.

Models and Measurement
There are many theoretical approaches for modeling and measuring credit risks. The choice of model is largely dictated by the availability of data and the particular risks involved in the problem at hand. All models have their strengths and weaknesses, and they...
sometimes rely on strong assumptions. So, risk-managers should know the weaknesses of their models and check that the results are plausible.¹

For single-name default risk modeling, the most fundamental approach is a statistical estimation of the obligor’s probability of default (PD). Probability of default is based on a set of fundamental accounting ratios and other quantifiable characteristics of the obligor. Typical models of this type are credit scoring models, Logit and Probit-regression models, and models based upon techniques from survival analysis. A common application of these models is as an internal rating model. Generally, both the accuracy and timeliness of the inputs and the quality of the dataset being used to estimate the model influence the model’s performance decisively. Statistical models are also the most common method for estimating the recovery rates of obligors.

Related to the statistical models are default risk models that are based on ratings by external rating agencies such as Moody’s KMV, Standard and Poor’s or Fitch. Again we ... concentrate on the US-market, these models are less popular among European banks than among North-American banks.

If equity price data for the obligor is available, the firm’s value approach (pioneered by Black and Scholes (1973) and Merton (1974)) tries to use this equity price data combined with the obligor’s balance sheet to infer default probabilities. The first advantage of this approach over the purely statistical models is that equity prices react much more accurately and quickly to news about the firm than accounting figures do. The second advantage is that the model explicitly recognizes the volatility of the firm’s business activities. Nevertheless, their empirical performance has been mixed. The best known commercial implementation is the model developed by KMV (now Moody’s KMV), which combines the firm’s value approach with an extensive historical database to overcome some of the difficulties of the pure Black and Scholes model.

Finally, in the best of all situations there is even price data on defaultable bonds issued by the obligor, or on credit default swaps (CDS) written on the obligor. In this case, default risk is directly priced, and the PD can be implied from these prices. Usually, these implied probabilities carry significant risk premia and liquidity premia, so directly comparing historical probabilities is impossible.

Despite the large number of models, the methodology for single-name default-risk analysis and estimation is comparatively well understood. Even if the errors at an individual level may be rather large, there is hope that these errors are unsystematic and will therefore not affect the overall risk assessment of a loan book too much. For portfolio default risk, on the other hand, there is a much larger degree of uncertainty. The risk manager has much freedom in choosing many of the models’ parameters; often, there is simply too little data to clearly estimate them. For example, by changing the correlation parameters, almost every portfolio default risk model can be tweaked from perfectly independent defaults to perfectly dependent defaults. The risk manager can do this while keeping the individual default probabilities unchanged. Consider, for example, a portfolio of 10,000 obligors with 1% individual default probability. In the case of perfect independence, the number of defaults is very close to 100, but if all defaults were perfectly dependent, we would observe 0 defaults with 99% probability and 10,000 defaults with 1% probability.

The most common portfolio credit risk models for assessing enterprise-wide credit risk are Credit Metrics (RiskMetrics Group) and CreditRisk+ (CSFB) and the refinements of these models that have appeared recently. While these models are linked to a fixed time-horizon, the class of copula-based portfolio credit risk models explicitly models timing risk. “Copula” is the technical term for a distribution function of a vector of random variables on [0,1] which has uniform marginal distributions. Basing a model on a copula allows the risk manager to introduce timing risk and to model the dependence between the times of defaults separately from the individual distributions of the default times. As such models are easily calibrated to market data, they are also used in the context of credit derivatives and other traded structures.

Case Study: The Mezzanine Tranche of a Collateralized Debt Obligation
A good example to illustrate the concepts involved in assessing the credit risk of a loan portfolio is a tranche of a collateralized debt obligation (CDO). This example is simplified; real-world CDOs are more complex than the one presented here, and so are the models used to price and risk-manage them. Consider a CDO written on a reference portfolio (RP) that consists of a large number (1,000) of homogeneous obligors, all with a common default probability of p=3% and a common average recovery rate of R=40%. We normalize the individual exposure size to 1 and assume zero interest rates.

The tranche under consideration is a mezzanine tranche from KL=4% of the reference portfolio to KU=11% of the reference portfolio. The final payoff of this tranche at the time horizon is:

\[ K_U - L, \text{ if the final cumulative loss } L \text{ of the RP is less than } K_L, \text{ i.e. if } L < K_L, \]
\[ K_U - L, \text{ if the loss } L \text{ is between } K_L \text{ and } K_U, \text{ i.e. if } K_L < L < K_U, \]
\[ 0, \text{ if the loss } L \text{ is larger than the upper boundary of the tranche, i.e. } L > K_U. \]

Essentially, the investor in the tranche bears all losses between 4% and 11% of the reference portfolio. (Of course, an adequate coupon payment compensates him for this risk.) Our investor should be particularly interested in three numbers:

- The probability of survival \( p^* = P[L < K_L] \) or (one minus) the probability of the tranche being hit;
- The probability of wipeout \( p^{**} = P[L > K_U] \); and
- The expected loss of the tranche \( E = E[(L-K_U)1_{(L > K_U)}] \); here expressed as percentage of the tranche’s notional amount.

It should be noted that, because of the significant wipeout-risk, the payoff structure is significantly different from the payoff structure of a defaultable bond. Thus, even though such tranches are rated by rating agencies, these ratings cannot have the same meaning as they would have for defaultable bonds.

These three key parameters only depend on the distribution of the losses L at the time horizon, which we are going to model using the Vasicek (1987) model. The Vasicek model can be viewed as a limiting case of the Credit Metrics model for large portfolios of homogeneous obligors, all of which have the same default probability, recovery rate, and bivariate asset correlation coefficient. In this model the distribution of \( L \) is:

\[ F(x; \mu, \rho, R) = P[L \leq x] = \Phi \left( \frac{\Phi^{-1}(x/(1-R)) - \Phi^{-1}(\mu)}{\sqrt{1-\rho}} \right) - \Phi^{-1}(\mu) \]

¹ For model risk, see contribution of Gibson, page 33.
Here $\Phi$ denotes the cumulative normal distribution function, $p\Phi$ is the individual default probability of the obligors in the portfolio, $R$ is the average recovery rate, and $\rho = p\Phi$ is the asset correlation coefficient. (Note that the asset correlation is not equal to the correlation coefficient of the default indicator functions between two obligors, it is just a parameter in the distribution.)

The case $\rho = 1$ corresponds to the limiting case of perfect dependence between all obligors, and $\rho = 0$ to the limiting case of perfect independence.

Table 1 below shows the values of the three key numbers of the tranche under certain stress scenarios for individual default probability $p$, recovery rate $R$ and asset correlation $\rho$. The input parameters $p$ (the credit quality of the portfolio) and $R$ (the average recovery rate) have a significant influence on the risk in the expected directions. The second panel showing the influence of the asset correlation $\rho$ is particularly interesting: In the benchmark case of independent defaults (asset correlation $\rho = 0$), the mezzanine tranche is almost risk-free because almost surely a proportion of $p$ of the portfolio’s obligors defaults, and this scenario does not hit the mezzanine tranche. As we increase $\rho$, we increase the deviations from this case by adding probability mass to the good scenarios (fewer than $p$ defaults) and probability mass to the bad scenarios (more than $p$ defaults). As argued before, the limiting case as $\rho = 1$ would be $0$ defaults with $f_\rho = 97\%$ probability and total default with $p = 3\%$ probability. Thus, in the limit both hitting-probability and wipeout-probability will take the value $3\%$. But for lower values of $\rho$ these risks are actually larger, as can be seen in the case of the hitting probability which takes a local maximum for $\rho = 40\%$ and decreases again for $\rho = 60\%$.

These are the risks within the model, but equally important are the risks that were not captured in the model, for example, Recovery correlation risk. There is empirical evidence that recovery rates are systematically lower when default rates are high, which adds to the losses precisely when they are already high. Second, it can be shown that the risk of the transaction increases when the portfolio becomes more heterogeneous, even if the average default probability in the portfolio remains constant. The intuitive reason is that all “bad” obligors that are added are more likely to hit the (equity and) mezzanine tranche, while all “good” obligors mainly benefit the senior tranche.

Finally, there is model risk in the way the dependency is modeled. The Vasicek model uses a Gaussian dependency structure, but a very much different loss distribution can be reached using a different dependency structure, even with the same individual default probability and even with the same joint default probability for any pairs of two obligors.

Table 1

<table>
<thead>
<tr>
<th>Individual Default Probability</th>
<th>0.0%</th>
<th>1.0%</th>
<th>2.0%</th>
<th>3.0%</th>
<th>4.0%</th>
<th>5.0%</th>
<th>6.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hitting Probability (at 4%)</td>
<td>0.00%</td>
<td>1.39%</td>
<td>5.59%</td>
<td>11.44%</td>
<td>18.08%</td>
<td>24.96%</td>
<td>31.76%</td>
</tr>
<tr>
<td>Wipeout Probability (at 11%)</td>
<td>0.00%</td>
<td>0.27%</td>
<td>0.62%</td>
<td>1.25%</td>
<td>2.12%</td>
<td>3.54%</td>
<td>5.38%</td>
</tr>
<tr>
<td>Expected Loss</td>
<td>0.00%</td>
<td>0.31%</td>
<td>1.31%</td>
<td>3.70%</td>
<td>6.07%</td>
<td>10.07%</td>
<td>13.85%</td>
</tr>
<tr>
<td>Asset Correlation</td>
<td>0.0%</td>
<td>10%</td>
<td>20%</td>
<td>30%</td>
<td>40%</td>
<td>60%</td>
<td>100%</td>
</tr>
<tr>
<td>Hitting Probability (at 4%)</td>
<td>0.0%</td>
<td>7.43%</td>
<td>11.44%</td>
<td>12.70%</td>
<td>12.83%</td>
<td>11.44%</td>
<td>3%</td>
</tr>
<tr>
<td>Wipeout Probability (at 11%)</td>
<td>0.06%</td>
<td>0.82%</td>
<td>1.99%</td>
<td>3.09%</td>
<td>4.54%</td>
<td>3%</td>
<td></td>
</tr>
<tr>
<td>Expected Loss</td>
<td>0.0%</td>
<td>1.44%</td>
<td>3.78%</td>
<td>5.45%</td>
<td>6.41%</td>
<td>7.16%</td>
<td>3%</td>
</tr>
<tr>
<td>Recovery Rate</td>
<td>70%</td>
<td>60%</td>
<td>50%</td>
<td>40%</td>
<td>30%</td>
<td>20%</td>
<td>10%</td>
</tr>
<tr>
<td>Hitting Probability (at 4%)</td>
<td>2.36%</td>
<td>5.02%</td>
<td>8.14%</td>
<td>11.44%</td>
<td>14.77%</td>
<td>17.99%</td>
<td>21.10%</td>
</tr>
<tr>
<td>Wipeout Probability (at 11%)</td>
<td>0.13%</td>
<td>0.39%</td>
<td>0.62%</td>
<td>1.42%</td>
<td>2.16%</td>
<td>3.02%</td>
<td>3.98%</td>
</tr>
<tr>
<td>Expected Loss</td>
<td>0.47%</td>
<td>1.25%</td>
<td>2.39%</td>
<td>3.70%</td>
<td>5.30%</td>
<td>7.06%</td>
<td>8.83%</td>
</tr>
</tbody>
</table>

Key risk figures for the CDO example for different parameter values. Unless otherwise stated, the fixed parameters are: Individual default probability $p = 3\%$, recovery rate $R = 40\%$, and asset correlation $\rho = 20\%$. Nevertheless, even an imperfect model will give important indications on the overall level of risk in the portfolio.

Recommendations

The main tasks of a credit risk manager follow the classical three steps: identification, measurement and management.

First, it is vital not to miss any credit exposures. Managing single-name exposure concentrations is relatively straightforward (e.g., on the market for credit derivatives). They can become a danger to the institution only if the risk manager fails to identify and/or manage them. Although theoretically obvious, collecting and aggregating credit exposures across an entire institution is, in practice, quite challenging. Next is credit risk modeling, where there are two risks the credit manager needs to be aware of. First, frequently there are significant problems in data collection and data quality for the models’ inputs. These range from noise and gaps in historical datasets to the often-arbitrary translation of non-standard exposures into loan-equivalents. Second, significant model risk remains. None of the current credit risk models completely covers all risks, even of such a standard problem as a loan portfolio. The risk manager must therefore know the strengths and weaknesses of his models. Nevertheless, even an imperfect model will give important indications on the overall level of risk in the portfolio. And it will identify risk concentrations that the risk manager might otherwise have overlooked.

The final step is actually managing the credit risk. There are the classical instruments for managing the origination process by setting limits. Calculating these limits, risk contributions and capital charges is one of the main challenges in managing risk internally. Externally, modern credit derivatives allow the bank to transfer the risk of a loan portfolio fully or partially to investors outside the institution. Using these processes will more ultimately move the bank away from being an investor in the obligor’s business, towards serving as an intermediary and loan supervisor for the final investors in securitized loan portfolios.

2 See the contribution of Gibson, page 33.
Managing Dependent Risks
Alessandro Juri and Sandro Merino, UBS Zurich

What is dependence?
There are words or concepts that we often use in our everyday life which we believe to be familiar with. Their meaning and interpretation appears to be very clear and at first sight we assume that no confusion could ever arise from their use. Yet, when dealing with these concepts in a specific (scientific) context they need to be defined with greater precision and higher abstraction in order to avoid ambiguities and naive statements arising from a superficial use.

“Dependence” is an interesting instance of this kind; particularly in the context of finance where the ever-increasing complexity of products that are exposed to a variety of “dependent” risks requires a clarification of that concept. Consulting a dictionary, we find, among other ones, the following definition of dependence: “The state of being determined, influenced, or controlled by something else.”

However, if the degree of dependence and its impact is to be quantified, then the natural language becomes the mathematical one. It may be surprising to non-specialists that the mathematical definition of (in-)dependence is a relatively new concept and was only consolidated around 1930, where two events are said to be independent if the probability of their joint occurrence equals the product of the single event probabilities. An often-encountered idiosyncrasy of mathematics is that a rich concept is defined indirectly through its negation. In fact, in probability theory dependent random variables are simply defined as random variables that are not independent, i.e. dependence is the negation of independence. This definition appears to be impractical to deal with however it is a consequence of the subtle and very rich nature of the concept of dependence as was observed by Kalmogorov himself:

“Thus one comes to perceive, in the concept of independence, at least the first germ of the true nature of problems in probability theory”.

In particular, we see that defining dependence as the negation of independence, implies that the equality characterizing independence i.e. that the probability of two independent events equals the product of the single event probabilities) no longer holds. Thus, relaxing the “usual” independence assumptions typical of many stochastic models and which are often due to convenience rather than to the nature of the phenomenon being investigated, yields much less tractable models. The latter, have nevertheless to be considered in any situation where the effect of dependent risks cannot be neglected. It is therefore not surprising that only recently, i.e. in the last ten years, the mathematical literature on the risk management of dependent risks showed some significant developments.

The main message sent by this recent research is the following: it is (intuitively) clear that the probabilistic mechanism, i.e. the dependence structure governing the interactions between random variables is completely described by their joint distribution, i.e. by specifying the probability of all combined events. However, in most applied situations we are far from knowing the probabilities of all combined events and only the marginal behaviors, i.e. the distributions of the single variables, are known.1 To tackle the problem of describing the probabilities of all combined events, a flexible and powerful approach consists in first determining the marginal distributions and then trying to determine the (unknown) joint distribution by means of copulae and/or stochastic orders. The former are often called dependence structures and can be viewed as “marginal free” versions of joint distribution functions fully capturing the dependence properties of the several random variables. Furthermore, stochastic orders are useful tools for comparing different dependence structures thus allowing to describe the impact of modelling dependence effects with different copulae allowing to measure the risk due to a dependence structure (copula).

Why model dependent risks?
The reasons behind the study and modelling of dependencies in finance and insurance are of different type. One motivation is that widely used scalar dependence measures, such as linear correlation, generally do not provide a satisfactory description of the underlying dependence structure. In fact, these dependence measures only capture particular aspects and not the entire dependence structure. Examples conflicting with common sense intuition can easily be constructed highlighting the limitations of such simplistic dependence measures. This is e.g. the case for linear correlation outside the Gaussian world – often navigated by finance. For the same reasons variance or Value-at-Risk have severe limitations when measuring portfolio risk since extreme events are not appropriately taken into account.

A second motivation is given by situations where no model incorporating dependencies is available or whenever a superficial treatment of dependence may lead to a dramatic underestimation of risk. Taking care of dependences becomes therefore important in order to extend standard models towards a more realistic description. The area of credit risk is a source of many model problems with a real world background. For example when pricing credit derivatives such as collateralized loan obligations (CDOs) or credit default swap baskets (CDS baskets), the question of the dependence between the several random variables describing the different counterparties in the portfolio plays a crucial role since the credit risk latent in the portfolio is strongly affected by different dependence assumptions.2 For instance, one of the most popular models for a loan book, relies on the analysis of the dependence structure governing the default times of an homogeneous portfolio of firms. However, in most applied situations we are far from knowing the probabilities of all combined events and only the marginal behaviors, i.e. the distributions of the single variables, are known.1 To tackle the problem of describing the probabilities of all combined events, a flexible and powerful approach consists in first determining the marginal distributions and then trying to determine the (unknown) joint distribution by means of copulae and/or stochastic orders. The former are often called dependence structures and can be viewed as “marginal free” versions of joint distribution functions fully capturing the dependence properties of the several random variables. Furthermore, stochastic orders are useful tools for comparing different dependence structures thus allowing to describe the impact of modelling dependence effects with different copulae allowing to measure the risk due to a dependence structure (copula).

1 For implications of missing knowledge see Vanini, page 16.
2 For credit risk, see Schönbucher, page 39.
random variables, allow to better face the problem of the lack of data which is typical for extreme events.

A final reason is of more intrinsic type. To compare risks with respect to criteria like risk aversion or some other kind of preference, one is compelled to analyze and order dependence structures. For example, the concept of “risk diversification”, possibly one of the most ambiguous terms used in the financial community, implicitly relies on the comparison of dependence structures. In fact, risk diversification requires a prior understanding of the dependence of the different risks involved since only then it becomes possible to choose an optimal (so called diversifying) exposure to the different sources of risk.

Modelling dependent risks:
Opportunities and limitations
Stochastic models for dependent risks usually extend existing models allowing for more accuracy and flexibility. Thus, they constitute a significant improvement towards a more efficient and realistic risk management. The fact that a model incorporates directly a dependence structure (copula), provides a transparent description of the relationships between its constituent objects (random variables) avoiding therefore fallacies arising from a naive use of simple numerical dependence quantities such as linear correlation. Furthermore, such models initiate a change in the way both academics and practitioners think about dependent risks, thus triggering a creative educational process.

The reverse side of the medal is that it is usually difficult to choose the appropriate dependence structure (copula) for the problem at hand. Often, the only possibility is to start with some guess such as a parametric family of copulæ and then try to fit the parameters. Moreover, finding data justifying that guess empirically is not always easy so that the models obtained often suffer a certain degree of arbitrariness. Some remedy is provided by models for conditional joint extremes where limiting results shed some light on the underlying dependence structure.

Finally, one should not forget that even the most sophisticated model is based on some hypothesis representing the “rules of the game”. Thus, it is not to expect or pretend that every possible scenario or situation can be modelled mathematically. There may be some types of risk, such as for instance operational risk, that are manageable by means of stochastic models only in a limited way.

Behavioral and Evolutionary Finance
New Ideas for Managing the Assets of Pension Funds
Thorsten Hens, Institute for Empirical Research in Economics, University of Zurich

It is well documented that the average performance of pension funds falls behind the average performance of a market portfolio. Traditional finance blames the regulation of pension funds for this short-fall. Behavioral and evolutionary finance suggest new ideas for managing the assets of pension funds that may help avoid the short-fall. In contrast to traditional finance, this new paradigm of finance is not based on the hypothesis of complete rationality, but rather on the psychology of the investors.

The Issue: Short-Fall of Pension Funds Returns Behind the Market Portfolio

Pension funds are quite reliable in their predictions of the amount of money they can levy from their working members and also about the amounts they need to pay to their retired members. Indeed, the demographics of society dictate the gap between the two. Governments have a vital interest in well-functioning pension funds that increase the wealth of their members without taking too much risk. This is why, for example, pension funds are regulated not to take too big stakes in any one company, one asset class, or one country. At the same time, pension funds are required to generate a minimum rate of return. As the current debate in Switzerland shows, in a falling stock market, these two requirements seem compatible only when regulation lowers the required minimum rate of return from the previous 4% to now 3.25% and soon 2%. Also, as it is well documented (see for example the book by Davis and Steil (2001)), that the annual returns pension funds generate fall considerably short of the returns of the corresponding market index.

<table>
<thead>
<tr>
<th>Short Fall Behind Market Returns (Annual for Period 1980-1995)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canada</td>
</tr>
<tr>
<td>Germany</td>
</tr>
<tr>
<td>Japan</td>
</tr>
<tr>
<td>Netherlands</td>
</tr>
<tr>
<td>Sweden</td>
</tr>
<tr>
<td>UK</td>
</tr>
<tr>
<td>US</td>
</tr>
</tbody>
</table>


What is the reason for this short-fall? Is decreasing the required minimum return really all we can do about it?

Traditional Finance:
Short-Fall Due To Regulations
According to the view in traditional finance, stated most boldly in Fama’s (1970) efficient market hypothesis, the reason for the short-fall of pension funds must be (excessive) regulation. The efficient market hypothesis claims that, at any time, market prices fully reflect all available information. So, if the market is efficient, even with the cleverest strategy, it is impossible to beat the market. But if, because of regulation, you are blocked from buying the market portfolio, you must fall short of market performance. The “proof” of the market efficiency hypothesis rests on the anticipation principle and is thus ultimately linked to the rationality of the investors. If, at any time, prices fully reflect all information, then, from one point to the next, prices have to change randomly. Any non-random change would already have been anticipated. In a market with unpredictable returns, the best you can do is stay idle and follow the passive strategy – buy a broad index. Any active strategy will eventually fall short of the market since it will only incur unnecessary trading costs that decrease the returns of the portfolio.

Behavioral Finance: Market Anomalies and Their Psychological Explanations
Recent econometric analyses of market returns, for example the excellent book by Lo and MacKinley (1999); A Non-Random Walk Down Wall Street; have undermined the efficient market hypothesis. Stock market prices show excess volatility, short-term momentum and long-term reversal. And indeed, we can explain these stock market anomalies using typical
“behavioral traps” in which almost everybody falls when they select random processes. If you’re unsure about the truth of this claim, consider the following example from Kahneman and Tversky (1979).

**Example**
A fund manager is known to beat the market in 2 out of 3 years. Which of the following track records most likely represents his performance?

(a) BLBBB  (b) LBLBBB  (c) LBBBBB?

Here B means “Beat the market” and L “Lose to the market.”

The typical answer in this example is that track record (b) is most likely the true track record. However, track record (b) is identical to track record (a) and the condition that, initially, the fund manager has lost to the market. This initial condition is, however, not certain; it occurs only with probability 1/3. Hence track record (a) is more likely than track record (b). Yet, assuming that even in a small sample, the proportion of the statistical law, which in this case is 2 out of 3, has to be reflected, most people chose (b) because in (b) the proportion of L and B resembles most closely 2/3. Kahneman and Tversky (1979) call this misjudgment the “representativeness bias”.

To link the representativeness bias to short term momentum and long-term reversal, imagine that a stock, or the market as whole, has recently produced a nice sequence of good (bad) returns. Even after a short time, investors prone to the representativeness bias tend to infer that the statistical law governing the returns of the stock has fundamentally changed to the positive (negative) and, hence, stock prices will spur upwards (downwards). Supposing the statistical law, however, did not change. Eventually, more evidence would be available, and stock prices would revert back.

**Momentum and reversal due to the representativeness bias is just one example of market anomalies that may have psychological explanations. Other examples include (see Shefrin (2000) or Montier (2002)):

- Short-term momentum of stock prices after positive earnings surprises, which can be explained by the inability of investors to correctly update a prior on the arrival of new information.
- Increasing volatility of asset returns when prices fall, which can be explained by “get eventis”, i.e., the tendency of investors to take excessive risks after incurring losses.
- Co-movements of assets with the market in which they are listed, rather than with their identical twins in other markets (e.g., Shell Transport and Trading and Royal Dutch Shell) which can be explained by “mental accounting”, i.e., the tendency to structure portfolios into too narrow asset classes.
- The puzzle that closed end funds are priced far from their net asset values, which can be explained by the preferrence investors have for the delivery of regular payments rather than having to “ding into capital”, i.e., to realize capital gains.
- Excessive trading volume in stock markets, which can be explained by “overconfidence”, i.e., the effect that almost 75% of the traders think they are more clever investors than the average trader.

Evolutionary Finance: Survival of the Fittest at Wall Street

As we argued above, the market is not as efficient as traditional finance believes. Hence, it is possible to outperform the market if you know market anomalies and their explanations well. DeBondt and Thaler (1985), for example, pointed out a rather simple way of exploiting the representativeness bias. A portfolio of “Past Time Losers” outperforms a portfolio of “Past-time Winners” and, therefore, over a horizon of 3 to 5 years, the simple “contrarian strategy” of buying past-time losers outperforms the market.

DeBondt and Thaler’s contrarian strategy is an early example of a strategy of a behavioral hedge fund. Nowadays, very sophisticated behavioral strategies that try to exploit market anomalies have emerged. Fuller&Thaler Asset Management, for example, is known to have successfully exploited short-term momentum after earnings surprises. We can also find behavioral hedge funds in Switzerland. The Swiss company AlphaSwiss, for example, takes positions with respect to momentum and reversal on 1500 US-stocks, taking into account the liquidity of the markets. Investing in individual hedge funds is, of course, very risky, and a careful selection of fund managers is necessary. The ongoing innovation process has now reached a state where we can also invest in the performance of any hedge fund strategy.

Evolutionary finance provides a systematic analysis of active asset market strategies, for example, those performed by behavioral hedge funds trying to outperform the market. This most recent field of finance is based on biological models reminiscent of Charles Darwin’s ideas. Evolutionary finance sees the stock market as a market selection mechanism in which some active strategies gain capital at the expense of other active strategies. This theory takes the ongoing process of innovations into account. This process leads to unforeseen and rapid changes of the pool of existing strategies and also generates ever-new market anomalies. Based on some new mathematics, the theory of random dynamical systems, in subproject 3 of NCCR-Finrisk, we develop evolutionary finance models that may ultimately help pension funds not fall short of the market.

[Graph: Value Added Monthly Index]
III. Regulation and Macroeconomics
The Basel II Proposal: A Critical Assessment

Supervisors and bankers generally agree on the objectives of the new proposal: they are meant “to strengthen financial stability”. From a macroeconomic view, “financial stability” means the absence of strains that curtail the intermediation function of the financial system. From this view, financial stability can be consistent with failures of individual financial institutions, so long as it does not impair the financial system’s basic functions. In principle, a competitive financial system should eventually eliminate weak financial institutions, without impairing the whole system.

Beyond this general agreement on “financial stability”, some aspects of Basel II are controversial among bankers, regulators, and academics. Among the six most important criticisms are (1) the proposed internal rating-based credit risk approaches have a pro-cyclical effect and thereby weaken financial stability. The Basel II risk models consider a bank’s external environment as independent of the actions of the bank itself. This can lead to a destabilizing outcome of the sum of individually “prudent” risk management measures. (2) The proposal is overly complex and creates an excessive administrative burden for banks and supervisors. It puts small- and medium-sized banks at a competitive disadvantage and reduces the accountability of supervisors for their judgments of bank risk. (3) The operational risk charge is fundamentally flawed and could even distract from good risk management. (4) Lending to small- and medium-sized enterprises will suffer disproportionately. (5) Internal ratings provide opportunities to “game the rules.” (6) The proposal does not go far enough to enhance the role of market discipline.

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The Individual Bank: Decision Rules

The proposed Accord is not a minor refinement of the existing regulatory regime; it is a wholesale reform of bank regulation. It not only influences the system as a whole, it impinges on every bank in many ways, and necessitates that they thoroughly assess every possible alternative.

To smooth this assessment process for single banks, consider the risk situations a bank faces. For all types of risk (credit, market, operational, liquidity, reputational, strategic), it is important to distinguish among:

- Customary risks: Day to day changes or “volatility” of market prices, quality of trade execution, ultimate credit quality, variations in deposits, etc.
- Cyclical risks: These risks emerge as a result of the underlying business cycle of the bank’s business. “Trends” in the economy of a country, credit deterioration, interest rate sensitivity to inflation, etc.
- Event risks: Out-of-the-ordinary risks, headline risks. “Discontinuities” such as a market crash, political unrest, earthquake, terror attack.

Under the influence of academic research, regulators have focused their interest, to a large extent, on the first risk dimension, which can be described as “volatility.” Such risk measures are short-term: the recent past and the immediate future. Existing techniques pay insufficient attention to the change of risk through the cycle and to event risk. The second and third dimensions are more difficult to understand and to model, yet both categories tend to be more important for the survival of an individual financial institution.

1 For market risk, see the contribution to Leippold and Trojani, page 36.
What criteria should the board and management of a bank use to select among alternative reactions to Basel II? Possible criteria are:

- Comply with the minimal legal requirements;
- Comply with the expectations of the regulator (regulators intend to reward more sophisticated approaches);
- Pursue the bank’s own interest, which is to maximize the shareholder value and to secure the survival over the business cycle;
- Minimize capital;
- Optimize the risk-/return-profile of the bank;
- Comply with the expectations of other stakeholders (customers, employees; bondholders, counterparties).

I recommend that the banks strive for criteria 1, 3, 5, and 6, in this order of priority. Pleasing the regulator does not seem to be a useful strategy, and minimizing capital cannot be a solid foundation. The history of domestic credit losses in Switzerland in the early 1990s does not support the assumption that more advanced risk management methods are better than simpler ones. The most sophisticated international institutions incurred the largest credit losses; the locally active Raiffeisen banks incurred the smallest ones. Minimizing capital by meeting only the minimal capital requirements was never a suitable option for Swiss banks. Even in the worst periods of the last decade, the banking system exceeded the legal capital requirement by over 20% (although the big banks exceeded the legal requirement by only 6%). At the end of 2002, the excess was over 50%, for some banking groups even over 100%.

Choices for the Individual Bank
The first choice the individual bank has to make is selecting the regulatory approach for credit risk. In view of the criteria mentioned earlier, the actual approach a bank chooses seems relatively unimportant. Even if a bank can comply with the requirements of an advanced approach, it is not obvious that the bank should decide on this approach as the regulatory standard. Relevant is only the absolute overall level of capital, not the computation and the allocation to different risk categories. The standardized approach exposes a bank less to the volatility of regulatory equity requirements than the more advanced methods.

The second choice refers to how individual banks treat operational risk. The ongoing modifications to the proposal (even the definition of operational risk has changed since the first draft) do not recommend aggressively implementing advanced regulatory methods of measuring operational risk. For individual banks, it is much more important to focus on managing operational risk than on measuring it. The “Sound Practices for the Management and Supervision of Operational Risk” that were recently published by the Basel Committee are a solid starting point for such a strategy. After all, capital is certainly not a substitute for managing operational risk well.

The third question refers to business strategy and regulatory arbitrage. Should banks adjust their strategies? Should they arbitrage the new Accord? Banks should strictly apply risk and cost adjusted pricing. The basis should not be regulation, but rather the banks’ own risk assessments. If regulatory capital requirements are too low (for example, for politically motivated lending to the middle class) or too high, the bank should not apply the regulatory standard for pricing. Avoiding regulatory arbitrage is one of the main goals of the new Accord. But banks are unlikely to achieve this. More detailed rules do not prevent arbitrage; they just make arbitrage more sophisticated and more expensive.

The fourth choice refers to questions of market discipline and transparency. Market discipline cannot merely complement regulation; to a certain degree, it may even substitute it. The informed and professional opinion of the market may act as a counterbalance to a purely formula-based judgment and the assessment of the supervisors. It may, therefore, be a good policy for banks to adhere to high disclosure and reporting standards for risk and risk management and to carefully observe market signals, such as bond spreads and ratings. The final choice a bank has to make is elaborated in principle 1 of Pillar 2 of Basel II. “Banks should have a process for assessing their overall capital adequacy in relation to their risk profile and a strategy for maintaining their capital level.” This principle relates to credit risk, market risk, interest rate risk in the banking book, operational risk, liquidity risk, reputational risk, and strategic risk. Ultimately it is the board of directors who shoulder responsibility for managing every bank, and this means: defining the right level of capital.

A Regulatory Perspective on Basel II
Paul Philipp Flockermann, EBK, Berne

New international standards
Comprehensive globalisation of financial markets, the huge increase in derivatives trading and the process of concentration in the banking sector as a result of takeovers and mergers make stability in the internationalsystem more important than ever. Banks can only be financially stable if the banking regulatory system is based on international standards. That is why international harmonisation of regulations is increasingly necessary.

In its thorough overhaul of the 1988 Capital Accord (Basel I), the Basel Committee on Banking Supervision (“Basel Committee”) has been concerned first and foremost to lay down new minimum regulatory standards for major international banks. In relation to credit exposures, current capital adequacy regulations are clearly not risk-sensitive enough. Even for loans, risk-weight allocation under Basel I is far too imprecise, and the risks associated with modern financial instruments are scarcely reflected in the regulatory framework. The same is true for credit risk mitigation effects based on the holding of securities or credit derivatives. Under Basel I-style regimes, allowing for portfolio effects is scarcely conceivable.

With a view to enhancing the risk sensitivity of capital adequacy requirements under the regulation, the Basel Committee is seeking, in the transition to Basel II1, to adapt the regulatory framework to the realities of modern credit risk management. It has been guided in this process by the methods developed by major international banks. The downside is that regulating capital adequacy will become very much more complex and expensive.

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1 The Third Consultative Paper is available online at www.bis.org.
Modern credit risk management

The crucial importance of good credit risk management was dramatically demonstrated in Switzerland when a swingeing CHF 42 billion was lost in value adjustments, provisions and domestic loan write-offs between 1991 and 1996. Swiss banks undertook a thorough rethink of their credit risk management and are now already employing methods that will form part of Basel II. For example, the major banks in particular are using stochastic modelling to analyse credit portfolio exposures. Each bank tries to ensure that overall interest earnings on its credit portfolio will exceed the sum of refinancing costs, operating costs and losses. In a situation of widely fluctuating losses, this is not always achievable. Each bank assesses anticipated rates of loss on its credit portfolio over a time horizon of its own choosing. In order to cushion the impact if actual loss rates fail to match projections, the banks keep a proportion of their capital resources as a buffer. Tying up capital in this way incurs an opportunity cost. By using stochastic models, a bank can work out how much economic risk capital it is “sensible” to allocate to the credit portfolio. Part of this calculation involves weighing the cost of limiting insolvency risk against the earnings expectations of the bank’s shareholders.

Banks’ internal credit-rating systems are another aspect of modern risk management with which Basel II is particularly concerned. Not only do these systems provide the basis for probability-of-default estimates for use in stochastic risk modelling, they also offer the possibility of controlling and compensating for credit risks. In its lending business, a bank can use the rating as a yardstick when deciding whether or not to grant a loan. If it does decide to lend, the rating can help to determine whether it will require securities, purchase hedging instruments or grant an uncollateralised loan. The bank will then take various factors into account in determining the rate of interest on the loan: namely refinancing, administrative, risk and capital retention costs.

The Basel II rules certainly do not require that all banks use stochastic risk modelling or that all borrowers should be subject to credit rating. They offer every bank a choice of procedures for calculating capital adequacy requirements in accordance with the regulations. Standardised approaches can be applied by any bank without difficulty. Major international banks, however, should already have modern risk management systems in place. Modern methods of risk management and analysis should thus already play a part in determining their capital adequacy requirements. It is envisaged by the Swiss Federal Banking Commission (EBK) that only major banks will use internal ratings-based (IRB) and advanced measurement (AM) approaches, and these are the only approaches which require substantial outlay. Apart from the fact that Basel II is about more than capital adequacy, it is therefore misleading to equate it with IRB and AM approaches.

Regulators, banks and markets

Until now, banking regulation has mainly consisted of defining minimum capital adequacy requirements. The Basel II regulatory framework is new in that it formally and explicitly covers three aspects: the so-called “three pillars”. Each of these areas of regulation should be seen as a safety net for a stable banking system.

In laying down minimum capital requirements – the first pillar of Basel II – the regulator’s aim is to impose what he sees as a “healthy” relationship between risks and capital resources as a buffer in the event of losses. Given the range of modern financial instruments currently in use, achieving this aim is not easy. In pursuing it, the complexities of IRB and AM approaches and of the Asset Securitisation Framework are probably a necessary evil.

Retaining the level of capital resources required under Pillar One without a sound system of risk management is pointless. Under Pillar Two, which is concerned with supervisory systems, banks have a duty of sound risk management. This entails, inter alia, developing internal methods of evaluating the relationship between capital resources and risks incurred. Banks that use IRB approaches are required to apply economic risk capital models and stress tests for assessing their capital buffer with regard to credit risk. For other banks, very much simpler approaches are envisaged. In no case, however, will a bank be absolved of the responsibility to increase its capital base, if internal assessment indicates that it should rise above the level required by the regulator.

The purpose of the disclosure requirements – which constitute Pillar Three – is to enable the market to check whether banks have the level of capital cover that it would expect. If a bank’s capital resources are deemed by the market to be inadequate, market forces will compel it either to reduce its exposure or to increase its cover.

The complexity of Pillar One has been a target of much public criticism but there are several reasons why a strong first pillar is a good idea, notably the fact that banks are driven primarily by the interests of their management and shareholders. In particular, the goal of achieving high return on equity is at odds with maintenance of a substantial capital safety buffer. When banks find themselves in difficulty they measure the damage in terms of negative impact on their management and shareholders. Regulators, on the other hand, also have to consider potential negative impact on the economy, the bank’s creditors and the taxpayer. From a regulatory perspective, the damage caused when a bank runs into difficulty can be much more severe.

Regulatory capital adequacy requirements

There is no doubt that credit risks are the predominant type of risk for universal banks, and this is reflected in capital adequacy requirements. In the year 2002, for example, in the Swiss banking system, the level of capital cover for credit risks was 30 times greater than that for market risks. Under Basel II there will be a new capital requirement on operational risk of around 12% on average. This paper will therefore focus solely on the standardised approach and the two types of IRB approaches for credit risks.

In the standardised approach, ratings by external agencies such as Moody’s, Standard & Poor’s or Fitch may be used to determine capital adequacy requirements. As only a small number of banks are rated by such agencies, there will be little change in this respect. It is true that risk-weighting under the standardised approach represents a change from Basel I, but in terms of methodology the procedure scarcely differs from the current regime, and it thus has a very low level of risk sensitivity. Nonetheless, for most banks – excepting at least those which play a key role in the system – the standardised approach is appropriate.

The Basel Committee’s aim in introducing the IRB approaches is to achieve a risk-sensitive system of capital cover involving the use of modern risk management methods. Banks’ internal rating systems thus play a significant part in IRB approaches. In order to ensure, however, that in any bank the same credit
portfolio will be covered by virtually the same minimum level of capital resources, Pillar One tightly regulates the internal methods used with this type of approach. The range of requirements placed on internal rating systems is such that even banks whose systems already enable forecasting may have to make changes. Moreover, the regulations require the calculation of regulatory capital adequacy requirements on the basis of a given internal stochastic credit risk model. This regulatory corset is a feature of Pillar One and is designed not just to promote a level playing field: standardising the rules under which capital adequacy requirements are determined allows the Basel Committee to impose its notion of a “reasonable” relationship between capital resources and risk by means of regulation.

Admittedly not all the IRB-approach requirements are straightforward. For example, rating systems have to be applied to virtually all categories of borrower. In the case of sovereign and bank borrowers, lack of data makes it virtually impossible to confirm estimated probabilities of default (PD) and, in particular, losses given default (LGD). The existence of a national supervisory body, however, should mean that practical solutions can be found in every case.

Because the use of IRB approaches clearly enhances the risk-sensitivity of capital adequacy requirements, these may be higher or lower than what they would be under a standardised approach. On an average risk profile, however, application of IRB approaches leads to reduced capital adequacy requirements. This tendency is justified, because we can assume that the use of an IRB approach will imply, or indeed be predicated on, a highly developed system of risk management.4

The supervisory provisions under Basel II’s second pillar require banks to put in place a sound system of risk management appropriate to their size. However, there is also provision for the regulator to increase capital adequacy requirements. The very proximity of IRB and standardised approach clearly creates a danger that banks with a low level of capital cover may be tempted to boost their returns by granting high-interest, poor-quality loans while using the standardised approach to credit risk (i.e. engaging in what is termed “moral hazard behaviour”). Due to lack of risk sensitivity, such a bank would not be required under Pillar One to ensure an adequate level of capital cover, but if a regulator recognises that a bank using the standardised approach has a highly exposed credit portfolio, it is empowered under Pillar Two to insist on a reduction in the level of exposure or an increase in capital cover. Banks with highly rated creditors, on the other hand, are not entitled to any easing of capital adequacy requirements.

In Switzerland, where 11% of GDP is generated by banks and the total assets of all the banks are five times greater than GDP, protecting the banking system is exceptionally important. Indeed, the EKB is to make it mandatory for all banks to maintain a capital buffer at least 20% greater than that required under Pillar One. Because the two major banks play such a key role in the system, the EKB will fix a similarly ample buffer requirement for them, to be determined separately. The EKB’s aim here is to counter any erosion of the Swiss banks’ generally good capital cover levels.

The Basel Committee takes seriously the criticism that approaches to credit risk under Basel II will have a cyclical effect. The use of a flatter risk-weight curve5 for the small-business portfolio under the IRB approach may make it easier for this category of borrowers to obtain credit. In Switzerland, however, the cyclical impact of Basel II approaches will also be cushioned for a quite different reason. Swiss banks have a comfortable level of capital cover. In 2002, assets eligible for inclusion as capital resources stood at 159% of the required capital cover level. In fact, in the case of 63% of all banks, the coverage was more than double that required. A credit shortage is thus unlikely.

Transparency
Of the three security nets that constitute Basel II’s three pillars, there is no doubt that minimum capital requirements are the most important from the regulator’s point of view, to be encouraged. In the case of major international banks, the costs incurred in developing rating systems for use in IRB approaches are, for the most part, necessary investments in improved risk management.

Costs
There are substantial costs associated with the development of rating systems. Nonetheless, it is quite clear that, as a component of credit risk management, they make good sense and, from the regulator’s point of view, are to be encouraged. In the case of major international banks, the costs incurred in developing rating systems for use in IRB approaches are, for the most part, necessary investments in improved risk management. For a bank that does most of its business at regional level, however, the cost of applying an IRB approach is unjustifiably high. The EKB therefore anticipates that, at least in Switzerland, use of IRB approaches will be confined to a small number of banks.

The Basel Committee’s aim in introducing the IRB approaches is to achieve a risk-sensitive system of capital cover involving the use of modern risk management methods.

A step in the right direction
Essentially, Basel II is a step in the right direction. Highly complex regulation is a necessary evil if the regulator wishes to enforce minimum standards of capital cover in relation to risks. Although standards for quantifying operational risk are still at the development stage, pressure under the AM approach to compile loss data for this category of risk is to be welcomed. Pillars Two and Three are not entirely new: elements of them are already to be found in some national regimes and in regulatory practice.
Systemic Risk
Hans Genberg, Graduate Institute of International Studies, Geneva

Shortly after Russia defaulted on its debt on August 17, 1998, bank lending to emerging markets in Asia and Latin America all but stopped. It did not seem to matter whether the economies in question were healthy or not; all suffered sharp reductions in capital inflows. In fact, it appeared as if the crisis in Russia had spread like a contagious disease to other parts of the world.

On September 23, 1998 it was announced that a consortium of large financial institutions had rescued Long-Term Capital Management from liquidation. The Federal Reserve Bank of New York had orchestrated the rescue, and the NY Fed’s Chairman, Alan Greenspan, justified this intervention on the grounds that a failure to intervene could lead to severe disruptions in financial market activity in the US.

These two examples illustrate what economists refer to as the risk of a systemic crisis: namely that the entire financial system in a country or region is threatened by an event in another country, by the failure of one institution, or by a disturbance that is common to several countries or regions.

While there is no single clear-cut formal definition of what constitutes a systemic crisis and its associated notion of systemic risk, experts usually consider the following to be indicative (Kaufman, 2000):

- A high correlation and clustering of bank failures in a country, a number of countries, or globally (a systemic banking crisis);
- A clustering of exchange rate depreciations in a number of countries (a systemic currency crisis);
- Simultaneous declines in the prices of a large number of securities in one or more markets in a country or across countries (a systemic financial crisis).

How do we explain the emergence of systemic crises?

One source of systemic risk is an event in a single institution that propagates to many other institutions in the same country, or in many countries. The most straightforward transmission happens when the affected institution has direct business dealings with several others, and is unable to honor its financial commitments. The other institutions are adversely affected, and they, in turn, may “transmit” the problem further into the financial system. Whether the transmission of the initial disturbance causes a fully-fledged systemic crisis depends in part on the size of the shock and in part on whether the other institutions in the system are, or are at least perceived to be, healthy.

It should be obvious that the size of the initial shock is important, and we will not discuss it further here. However, the importance of the perceptions of the financial health of infected institutions does deserve further analysis. Suppose Bank A suffers a negative shock that prevents it from honoring certain commitments to Bank B. If Bank B is financially weak, the transmission of the shock may be sufficient to render it insolvent as well, and a domino effect may lead to problems in the entire financial sector. Here we have an example of one event in one institution in a fragile financial sector bringing down the entire sector.

If the initial shock had occurred in Bank B rather than in Bank A, the end result would have been the same – because of the underlying weakness of the whole sector.

Suppose now that Bank B is financially strong enough to weather the disruption caused by Bank A’s failure. Two outcomes are possible. The good outcome: the public has confidence in the health of Bank B, and the systemic crisis does not occur. The less desirable outcome: under the suspicion that Bank B is also financially fragile, the public may cause a “run” on that bank as well, which might cause it to fail. Recall that a run on a bank occurs when clients scurry to withdraw their deposits. If the bank cannot immediately liquidate a corresponding amount of its assets, it may not be able to honor all requested withdrawals and may have to close. A single solvent bank would probably be able to borrow in the interbank market to deal with such a situation, but if the withdrawals affect a large part of the banking system, this solution would not be available. There, the Central Bank, as a lender of last resort, would have to intervene. In the second case from our example above, the “less desirable outcome”, Bank A’s failure leads to Bank B’s demise, even though it was, objectively speaking, solvent. So why did it occur? Asymmetry of information is an inherent feature of a financial system; depositors have only imperfect information about the quality of the assets of the bank, and will therefore necessarily act on only partial knowledge about its financial strength. So-called demonstration effects may then come into play, whereby banking clients take their decisions (to withdraw deposits, for example) not on objective criteria but according to what other clients are doing or because they perceive a weakness in some other financial institution.

We can distinguish between different types of systemic risk according to the nature of the initial disturbance and the transmission mechanism. One case occurs when a common shock shakes the entire system. Another happens when an event that originates in a single institution spreads to the rest of the system through direct financial linkages. And a third arises when other institutions are affected purely by demonstration effects. Clearly, what measures a government should put in place to deal with systemic risk will depend on which of these three sources are most important. Before taking up this issue, let us look at a concrete example where all three sources of systemic risk are likely to have played an important role.

The 1997/1998 Crisis in South-East Asia

In July 1997 the Thai Bhat came under attack in the foreign exchange markets. Despite the Bank of Thailand's intervention, the currency rapidly lost some 40% of its pre-crisis value. Shortly thereafter, other currencies in the region depreciated by similarly large, or larger, amounts, and stock markets experienced substantial losses. An event that started in the foreign exchange market in one country rapidly spread to other countries and other markets, a clear-cut example of systemic crisis.

All three sources of systemic crises mentioned above were present in the South-East Asia episode. The initial disturbance was the attack on the currency. This had the effect of a common shock that rapidly affected a large portion of the financial system in Thailand as a result of the mismatch in currency denomination of assets and liabilities. Financial institutions in Thailand had borrowed abroad in US dollars and lent locally in Bhat. The currency depreciation increased the value of liabilities, but left the value of the assets unchanged. Some domestic lending was denominated in US dollars as well, which shifted the mismatch to the domestic debtors who then had debt-service payments in dollars but income in the local currency. This gave rise to a large amount of non-performing loans, and ultimately to difficulties for the financial institutions.
The problems in the Thai foreign exchange market spread to other markets and other countries. Facing balance sheet problems, local banks and financial institutions tried to liquidate assets. This led to sharp falls in share prices and real estate prices. Foreign creditors with exposures in Thailand attempted to cut back on investments in emerging markets in general to meet capital adequacy rules or simply to meet internal prudential norms. Hence, many countries, some of them on other continents, came under the influence of the disturbance in Thailand’s foreign exchange market. These effects are examples of transmission of the initial shock through direct financial linkages.

As noted, other countries in the region rapidly faced similar problems, which caused depreciation of currencies and stock markets to fall. Were these the result of direct transmission of the initial disturbance, or the consequence of demonstration effects? And in the latter case, were the affected countries attacked because of objectively fragile economic situations, or because of herding by international investors? Research on these issues has not reached firm conclusions, but many economists would argue that all elements were present in making the Thai crisis a South-East Asia crisis and, indeed, a crisis in the entire international financial system.

Who should manage systemic risk? How?
Managing systemic risk, which is, by its very nature, a systemic problem, must be done at the system level. This implies that individual financial institutions cannot, and will not do it. Of course, individual institutions must be aware of the possibility of systemic events occurring. And they must position themselves not to be fatally wounded by them. But as a group, they cannot insure against them. Of course, if systemic crises are defined as events where correlations between asset returns are high, the benefits from diversification will be correspondingly diminished.

If systemic risk has to be managed at the system level, it becomes an issue of public policy, either nationally in the case of national systemic crises or internationally in the case of international crises. On the national level, the central bank is normally expected to act as a lender of last resort to prevent a localized event from spreading to the whole financial system. On the international level, there is no corresponding institution other than the International Monetary Fund. On occasion, the Bank for International Settlements may be thought of as filling a similar function. Whenever public institutions intervene to rescue financial institutions (or countries), there is the risk that they create a moral hazard problem whereby the institutions subject to potential rescue are induced to take on too much risk. A large literature shows how important this effect really is, especially in the context of IMF rescue packages.

Finally, institutional arrangements are particularly important in limiting or dealing with systemic crises. A good example is the active debate on how best to deal with default on sovereign debt issues — whether it should be through some form of international bankruptcy court, or through collective action clauses in bond contracts.

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Systemic Risk (Genberg)

Biographical Notes
Biographical Notes

**Giovanni Barone-Adesi** is Professor of finance theory and dean of economics at USI in Lugano, Switzerland. After graduating from the University of Chicago, he has taught at the University of Alberta, University of Texas and the University of Pennsylvania. His main research interests are derivative securities and risk management. He is the author of several models for valuing and hedging securities. Especially well-known are his contributions to the pricing of American commodity options and risk management. He is advisor to several organizations.

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On October 1, 1995, **Freddy Delbaen** was appointed full Professor at the Chair of Financial Mathematics at ETH Zurich. He directs many projects in this field. Born on November 21, 1946 in Duffel, Antwerp, Belgium, Freddy Delbaen studied mathematics at the Free University of Brussels (VUB) and graduated from there in 1971. The subject of his Ph.D. dissertation was mathematical economics. Freddy Delbaen has published many papers in journals dealing with pure and applied mathematics, as well as insurance and financial mathematics. He is a member of several editorial boards of journals, such as Insurance Mathematics and Economics, Finance and Stochastics, etc. He is co-editor of Mathematical Finance.

**Paul Philipp Flockermann** has been member of the Risk Management Group of the Swiss Federal Banking Commission (EBK) since 2002. Born 1970 in Bonn, Germany, he studied physics at the ETH Zürich and graduated from there in 1994. He was awarded the Dr. sc. math. from the ETH in 2002 for a dissertation in the field of dynamical systems under the supervision of Professor Oscar E. Lanford III.

After having finished his studies in Economic Science at the University of Zurich **Hans Geiger** continued with a doctoral study which he finished in 1969 with a doctoral thesis on the economic use of computers. A research project for Credit Suisse Zurich in 1970 was the beginning of a partnership which lasted until 1996. Within this time Hans Geiger was head of accounting, international credit business and chief information officer. For ten years he was a member of the executive board of Credit Suisse in areas such as foreign exchange, precious metal, bank relations and also the logistic management. In 1997 Hans Geiger was promoted as Ordinarius at the University of Zurich and is now teaching as Professor for the Swiss Banking Institute. In the same year he became chairman of the board of directors of Telekurs Holding until 2000. Professor Geiger has published articles on a wide variety of subjects (see: www.isb.unizh.ch). He is vice-chairman of the board of directors of Bank Vontobel. His main areas of research and teaching are payment systems/clearing/settlement, credit business, operational risk management. He is a member of the European Shadow Financial Regulatory Committee and of SUERF (Société Universitaire Européenne de Recherches Financières), as well as member of the board of trustees of the Swiss Banking School. In 2002 he became a member of the governmental commission on integrated financial supervision in Switzerland (Kommission Zimmerli).

**Hans Genberg** is Professor of international economics at the Graduate Institute of International Studies in Geneva. A Swedish national, Hans. Genberg pursued university studies in the United States obtaining a BA degree in Mathematics from Macalester College and MA and Ph.D. degrees in Economics from the University of Chicago. Hans Genberg has been a visiting Professor at the Graduate School of Business of the University of Chicago and the Ecole des HEC of the University of Lausanne. He has also held visiting appointments at the International Monetary Fund and the World Bank. He is currently member of the Executive Board and the Scientific Board of the international center FAME in Geneva. Hans Genberg’s teaching and research deals primarily with international finance, monetary economics and macroeconomics.

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Markus Leippold is assistant Professor of finance at the Swiss Banking Institute of the University of Zurich. Prior to moving back to academia he was working for Sungard, Trading and Risk Systems, and the Zurich Cantonal Bank. His main research interests are term structure modelling, asset pricing, and risk management. He obtained his PhD in financial economics from the University of St.Gallen, Switzerland, and has published in several journals such as Journal of Financial and Quantitative Analysis, Journal of Economic Dynamics and Control, and European Finance Review.

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Olivier Scaillet, Belgian, is Professor of probability and statistics at HEC Genève and FAME. He holds both a master and Ph.D. from University Paris IX Dauphine in applied mathematics. Professor Scaillet’s research expertise is in the area of derivatives pricing, econometric theory and econometrics applied to finance and insurance. He has published several papers in leading journals in econometrics and finance, and co-authored a book on financial econometrics. He has been one of the winners of the bi-annual award for the best paper published in the Journal of Empirical Finance on the topic of quantitative risk management. He is also a long term advisor for the research teams of BNP Paribas located in Paris and London.

Philipp J. Schönbucher is assistant Professor for Quantitative Risk Management at the Department of Mathematics of ETH Zurich. He holds degrees in mathematics (Oxford) and economics (Bonn) and a Ph.D. in economics (Bonn). His publications include papers on credit risk modelling, credit derivatives pricing, stochastic volatility modelling, option pricing in illiquid markets, real options and term structure models. His main area of research is credit risk modelling and credit derivatives pricing in which he has been active since 1996. Furthermore, he is author of a book on “Credit Derivatives Pricing Models” (Wiley 2003).

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Fabio Trojani is assistant Professor of statistics and quantitative methods for finance at the Università della Svizzera Italiana (USI) in Lugano, Switzerland. He graduated in 1991 at the University of Zurich in Economics (main subject: econometrics) where he obtained in 1997 a Ph.D. in Econometrics and Finance. Fabio Trojani’s teaching at USI covers topics such as statistics, financial econometrics, portfolio theory and quantitative methods for finance. He is also a visiting Professor at the Cass Business School (former City University Business School) in London and at the Università dell’Insubria sede di Varese, Italy, where he teaches undergraduate and Ph. D. courses in stochastic processes for finance. Fabio Trojani’s recent research in econometrics focuses on small sample inference and on statistical procedures that are robust to model misspecification. These issues are crucial for many financial applications where either a model misspecification cannot be excluded or a moderate set of data is available. Examples of such applications are robust estimation of interest rate and stochastic volatility models or the development of a robust risk management based on robust VaR estimation procedures. Finally, research in theoretical finance deals with robust asset pricing, assets and liabilities management, and the equilibrium implications of VaR regulation.

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NCCR Finrisk
The Swiss Research Network in Finance

In November 2001 the Swiss National Science Foundation (SNSF) launched the National Centre of Competence in Research “Financial Valuation and Risk Management” (NCCR Finrisk). Directed by Prof. Rajna Gibson from the University of Zurich, the NCCR Finrisk constitutes a Swiss Research Network in Finance integrating over 30 Professors from the Universities of Basle, Geneva, Lausanne, Lugano, Neuchâtel, St. Gallen, Zurich and ETH Zurich.

The main goal of NCCR Finrisk is to promote competitive research focusing on the dynamics of real and financial wealth creation and redistribution. In this respect, the NCCR Finrisk research program places strong emphasis on the analysis and management of the financial and non-financial risk factors that affect the wealth creation and redistribution processes. In parallel, NCCR Finrisk promotes knowledge transfer activities in order to disseminate its research to the private and public sectors. It also aims at stimulating interactions between academics and practitioners. Finally, NCCR Finrisk intends to improve the quality of higher-level education in Switzerland. Therefore, it supports efforts to build an internationally recognized Swiss Doctoral Program in Finance.

Research
The NCCR Finrisk research program on Financial Valuation and Risk Management is divided into 10 individual research projects:

Project 1: Mathematical Methods in Financial Risk Management
- Head: Freddy Delbaen (ETH Zurich)
- delbaen@math.ethz.ch

Project 2: Conceptual Issues in Financial Risk Management
- Head: Rajna Gibson (University of Zurich)
- rgbisson@bs.unil.ch

Project 3: Evolution and Foundations of Financial Markets
- Head: Thorsten Herz (University of Zurich)
- thansa@unil.ch

Project 4: Corporate Finance
- Head: Michel Habib (University of Zurich)
- habib@bs.unil.ch

Project 5: Credit Risk
- Head: Ennio Micheli (University of Lausanne)
- mmicheli@unige.ch

Project 6: Interest Rate and Volatility Risk
- Head: Giovanni Barone-Adesi (University of Lugano)
- giovanni.barone@unil.ch

Project 7: Law and Finance
- Head: E. L. van Thadden (University of Lausanne)
- elvethadden@hac.unil.ch

Project 8: Asset Pricing and Portfolio Management
- Head: Heinz Zimmermann (University of Basel)
- heinz.zimmermann@unibas.ch

Project 9: Macro Risks, Systemic Risks and International Finance
- Head: Hans Reissberg (HEC Geneva)
- reissberg@hec.unige.ch

Project 10: Financial Econometrics for Risk Management
- Head: Olivier Scaillet (University of Geneva)
- olivier.scaillet@hec.unige.ch

Knowledge Transfer
NCCR Finrisk offers a dialogue platform between researchers and practitioners interested by the applications of modern finance. A key feature of the NCCR Finrisk program is its focus on disseminating applications of its research results. Knowledge transfer activities include:

- The development and implementation of applied research projects in Finance in collaboration with the financial services industry,
- The joint realization of conferences, seminars, round-table events with partners from the financial services industry,
- The organization of high-level courses in Finance for academics and practitioners,
- The coaching of industry-led applied research projects.

Education
The NCCR Finrisk promotes advanced education in Finance within Switzerland – most notably at the doctoral level. Our goal is to establish a first-class Swiss doctoral program in Finance, which unifies and extends the existing structures already in place. To this end, an intensive cooperation between the Universities of Basle, Geneva, Lausanne, Lugano and Zurich has now been established and has led to the creation of the Swiss Doctoral Network in Finance, including over 100 doctoral students in Finance. Educational activities include:

- The organization of high-level courses in Finance offered to all doctoral students from the network universities,
- The organization of the annual Swiss Doctoral Workshop in Finance with the collaboration of internationally renowned Professors from abroad,
- The funding for several doctoral grants.