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The Risks of Financial Risk Management

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Preface

Around mid-2007 various high-profile and supposedly sophisticated financial institutions ran into trouble. Now, in the early spring of 2008, the situation is still developing and ultimate losses remain unknown. Currently, figures up to US$1000 billion get bandied about.[1] Public opinion has been quick to put the blame on financial institutions' allegedly poor risk management practices, or on fraudulent commission or bonus-driven practices. Since little of firms' proprietary risk management models has been made known, the quality of individual institutions' risk management is judged purely by results. And, as pithily expressed by March/Shapira some time ago, "Society values risk taking but not gambling, and what is meant by gambling is risk taking that turns out badly"[2].

However, the questions raised by recent events regarding the extent of risk management skills of financial institutions are undoubtedly as real as they are important. This paper, which includes a case study of the recent crisis, seeks to shed light on some aspects of these questions by providing an overview of the limitations and side effects of conventional current financial risk management.

On a more personal note, my interest in the topic was initially piqued upon reading Nassim Taleb's *Fooled by Randomness* and its examination of the challenge of distinguishing the relative roles of skill and luck in both financial markets and life.[3]

Finally, I wish to thank my two thesis supervisors Prof. Dr. Marcel Tyrell (European Business School; Oestrich-Winkel) and Prof. Dr. Alexander Eisenkopf (Zeppelin University; Friedrichshafen) for excellent assistance provided. My family's support during the writing process was similarly much appreciated.

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[1] Cf. Tett (2008); Dattels et al. (2008), pp. 10-11.

[2] March/Shapira (1987), p. 1413.

[3] Cf. Taleb (2007b).

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List of Abbreviations

ABS	Asset-Backed Securities
ABX	An Asset-Backed Securities Index
APT	Arbitrage Pricing Theory
BET	Binominal Expansion Technique
CAPM	Capital Asset Pricing Model
CDOs	Collateralized Debt Obligations
CDS	Credit Default Swap
CEO	Chief Executive Officer
Cf.	Compare
CFO	Chief Financial Officer
CRO	Chief Risk Officer
EDF	Expected Default Frequency
ERM	Enterprise Risk Management
ETL	Expected Tail Loss
EVT	Extreme Value Theory
FAS	Financial Accounting Standard
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
G-30	Group of Thirty
IAS	International Accounting Standard
i.i.d.	Independent and Identically Distributed
IMF	International Monetary Fund
LDC	Less Developed Country
LTCM	Long-Term Capital Management
MBS	Mortgage-Backed Securities
MPT	Modern Portfolio Theory
N/A	Non-Applicable
OECD	Organisation of Economic Co-operation and Development
OTC	Over-the-Counter
P&L	Profit and Loss
RAROC	Risk-Adjusted Return on Capital

SIV	Structured Investment Vehicle
s.l.	*Sine Loco* (Without Indicated Place of Publication)
T-Bill	Treasury Bill
USD	US Dollar
VaR	Value at Risk
VAR	Value at Risk

List of Symbols

A	Efficient Portfolios
AAA	Triple-A (Highest Quality Credit Rating)
α	Alpha
α	Power Law Exponent
B	Tangency Portfolio
β	Beta
N	Number of Instances
μ	Mean
$\bar{r}$	Expected Return
r_f	Risk-free Rate
rf	Risk-free Rate
$\overline{R}_M$	Expected Return on Market Portfolio
rm	Expected return on Market Mortfolio
σ	Standard Deviation
σ^2	Variance
$\sum$	Covariance Matrix

1. Introduction

Episodes of financial instability are a well-documented fact of economic history.[4] This, in combination with the numerous systemic and non-systemic banking crises internationally on record[5], suggests that financial institutions, and especially banks, operate in a high-risk environment. As may be expected, this situation has not escaped industry and regulatory body attention. Already early on, certain forms of regulation and of organizational techniques of prudence emerged.[6] Then, with the onset of the 1970s, conditions for the international financial services industry began to undergo increasingly rapid changes. Attendant to the end of the post-World War II "golden age of capitalism"[7], the determining economic arrangements of the period, such as most prominently the Bretton Woods system of pegged exchange rates, disintegrated. Key economic variables including economic growth rates (which tended to decrease markedly in the developed countries), exchange rates, inflation rates, and interest rates started to exhibit significantly higher volatility.[8] In short, (financial) markets were becoming increasingly complex, uncertain, and risky.[9] In response, new, derivative, financial instruments (futures, options, swaps, etc.) were introduced to better facilitate risk trading and management.[10] By now, derivatives market sizes are enormous[11] as is their role in both risk management and as a source of risk. In effect, both the broader institutional and economic changes and the financial industry's reaction to them greatly

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[4] For a historical overview of financial instability see Kindleberger/Aliber (2005); for an analysis of stock market instability see Sornette (2003).

[5] For an overview of a total of 163 systemic, borderline or non-systemic banking crises since the late 1970s see Caprio/Klingebiel (2002); see also section 2.1 for more details from this study.

[6] To give one example, the so-called "3-6-3 rule" in banking can be seen as a technique of prudence. Cf. Rebonato (2007), p. 118: "… the 3-6-3 rule: raise money at 3% (from the depositors), lend it at 6%, on the golf course by 3 P.M. … society was, in effect, buying via the 3-6-3 arrangement a form of insurance against the systemic risk associated with bank failures."

[7] Marglin (1991), p. 4.

[8] Cf. Marglin (1991); Crouhy et al. (2001), pp. 5-6.

[9] Cf. Kindleberger/Aliber (2005), p. 6: "… the conclusion is unmistakable that financial failure has been more extensive and pervasive in the last thirty years than in any previous period."

[10] Cf. Crouhy et al. (2001), pp. 5-9.

[11] The June 2007 total notional amount of outstanding OTC derivatives contracts was US$516 trillion with a corresponding gross (replacement) value of US$11 trillion; cf. Bank for International Settlements (2007), p. 3.

added complexity and opacity to the financial system. New derivative instruments with non-linear pay-off profiles created blow-up risks while complicating risk supervision by top management and regulatory authorities. A number of ensuing high-profile blow-ups in the 1990s brought the issue of financial risk management firmly to the forefront of both top management and regulatory body attention[12].

This paper looks at the new risk management practices that have evolved since and highlights how the practice of risk management itself creates new risks. These risks that arise through attempts to control the first-order risks that are the target of firms' financial risk management are referred to here as the "risks of financial risk management". Financial service providers' models of and processes for rendering identified risks manageable for the individual institution are referred to by the broad designation "financial risk management".

It is suggested that the risks of financial risk management take various shapes. First, and most straightforward, there is model risk; a term which refers to the fact that every model is only an (imperfect) abstraction from reality; in practice this can produce severe problems. Second, the application of identical risk management policies across financial firms, to address risk modelled as exogenous, can inadvertently boost endogenous risk and thereby create systemic risk and liquidity risk. A third risk is behavioural risk, stemming from the possibility that risk management function might encourage certain undesirable cognitive biases. Fourth is incentive risk, since risk management systems are not immune to gaming and may actually increase risk-taking incentives. Fifth is reputational risk.

The paper is structured as follows: Section 2 sets the scene and provides necessary background by giving examples of financial blow-ups and the risks they illustrate. Section 3 then delineates the concept of risk. Section 4 presents the rationale for risk management at the level of individual institutions. Section 5 outlines conventional current financial risk management models and processes. Building on this, Section 6 explores the risks that arise from these modes of risk

[12] A further factor were the possibilities offered by information technological progress; cf. Dowd (2002), p. 3.

management. Section 7 applies the previously developed framework in a case study of the 2007/2008 subprime mortgage crisis. Section 8 concludes.

2. Financial Blow-Ups

This section lists a number of salient financial blow-ups and assesses their broader significance in terms of risks illustrated.

2.1 Banking Crises

It can be argued that banking is a both riskier but also more profitable industry than is generally appreciated. This section points out the risks; the profitable upside is presented in section 2.3.1. In the period 1970-1999, Caprio/Klingebiel have found "… 113 systemic banking crises (defined as much or all of bank capital being exhausted) …"[13] affecting 93 countries and "… 50 borderline and smaller (non-systemic) banking crises in 44 countries …"[14]. Most affected in terms of absolute monetary costs most affected where Japan (1990s), China (1990s), and the United States (1984-1991), with total costs of US$960 billion[15], US$428 billion[16] and US$180 billion[17] respectively. In terms of the respective share of country GDP, Argentina and Indonesia were hit most severely with net losses amounting to 50% or more of (one-year) GDP[18]. While there seem to have been fewer crises in the developed countries, Japan incurred the biggest absolute costs in the 1990s, and other developed countries such as Finland, Sweden and Norway faced significant crises as well in the late 1980s and early 1990s.[19] Also, in the United States there was a dangerous combination of highly significant threats to the banking system in the early 1980s. At the end of 1982, shortly after the onset of the LDC debt crisis in August 1982, the eight largest, or money-centre banks, were at risk. Their average outstanding LDC loan

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13 Caprio/Klingebiel (2002), p. 31.

14 Ibid.

15 Cf. Jorion (2007), p. 35.

16 Cf. Caprio/Klingebiel (2002), p. 36.

17 Cf. ibid. p. 49; the figure is indicated to refer to clean-up of savings and loan associations.

18 Cf. Honohan/Klingebiel (2002), p. 25.

19 Cf. ibid.; Caprio/Klingebiel (2002).

exposure was 217% of capital and reserves, and they might have become insolvent without the benefit of regulatory forbearance.[20] Shortly thereafter, in the so-called savings and loan crisis of 1984-1991, over 1400 savings and loan associations and 1300 banks failed.[21] It can be generalized that banking crises often result from a combination of market risk (interest risk), credit risk (concentration risk), liquidity risk and systemic risk.

2.2 Salient Institutional Blow-Ups

The following sections look at salient blow-up of individual institutions in the fields of investment banking and hedge funds.

2.2.1 Investment Banks

This subsection comprises three parts that address blow-ups in connection with rogue trading, derivatives mis-selling and losses on credit derivatives.

2.2.1.1 Derivatives and Rogue Trading

Barings Bank, Daiwa Bank, Nomura Corp. (in 1995 or 1996) and Société Générale (in early 2008) stand for some of the biggest “rogue trading”-related losses in investment banking. All lost in excess of US$1 billion, with top-losses, at Société Générale, reaching in excess of US$7 billion.[22] In each case, unauthorized use of derivatives by individual “rogue” traders created the huge losses. As one result, these (mid-1990s) scandals contributed to creating an impression of derivatives being extremely risky. As such they were influential in furthering calls for tighter derivatives regulation and for more advanced risk management. However, it has been stressed, that all four cases resulted from unauthorized (“rogue”) trading rather than from poorly understood, overly complex derivatives trading per se.[23] In all four instances there appears to have

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[20] Cf. Federal Deposit Insurance Corporation (1997), p. 199; p. 207.

[21] Cf. Caprio/Klingebiel (2002), p. 49.

[22] For brief reconstructions of the Barings, Daiwa and Nomura blow-ups see Tschoegl (2005), pp. 723-729; the Société Générale incident is still too recent for a definite account but see, for instance, Arnold et al. (2008). The following discussion draws on these sources.

[23] Cf., for instance, Tschoegl (2005), p. 729: “In all three cases [i.e. Barings, Daiwa and Nomura, note of the author], derivatives were only the instruments that the traders used to implement

been insufficient separation between front office and middle/back office functions. In the first three cases there was insufficient synchronous separation, i.e. traders fulfilled both functions at the same time. At Société Générale the alleged "rogue" trader was promoted from a back/middle to a front office function. Therefore, rather than representing market risk (although this was a contributing factor), current risk management theory regards these (and similar) losses as primarily the outcome of operational risk[24] following from poor processes and management[25].

2.2.1.2 Derivatives Mis-Selling

Investment banks that sell derivatives are occasionally accused of selling clients unsuitable products. The clients usually claim to have not been properly advised of the risk profiles of products bought. The result can be highly significant reputational damage for the involved investment bank. Often there is the threat of litigation and in many cases a settlement is reached between the bank and its customer(s). Well-know examples from the 1990s include Bankers Trust's derivatives transactions with Procter & Gamble and Gibson Greetings as well as Merrill Lynch's association with the Orange County bankruptcy scandal.[26] While legal risk is technically part of operational risk, the in this case arguably even more significant reputational risk is not. The abovementioned cases demonstrate that financial institutions' risk management should not disregard possible impacts of (seemingly) extra-financial risks on the institution.

2.2.1.3 Credit Derivatives

Recently, a great number of banks in various countries have incurred substantial subprime mortgage related losses. A large part of the losses were

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rather simple bets. In each case, the essence of the problem was unauthorized trading that the culprit undertook to enhance his firms profitability and therefore his own career and pay."

[24] Cf., for instance, Power (2007), p. 108: "… it is more historically accurate to say that the history of Barings (and many other financial scandals in the mid-1990s, such as Daiwa) were retrospectively constructed and represented as 'operational risk' management failures."

[25] Cf. Tschoegl (2005), p. 734: "Risk management is a management problem. The debacles were not random events and they were not unfortunate draws from a known distribution of outcomes. They were the result of a failure of governance…"

[26] These and other contested transactions are recounted in a popular, insider-account style in Partnoy (1999).

incurred in connection with structured finance instruments such as mortgage-backed securities (MBS) or collateralized dept obligations (CDOs) that the banks warehoused, held directly or that were held off-balance sheet in bank-sponsored vehicles. This topic will be explored in more detail in the case study in section 7. It suffices to mention at this point that these losses stem from a variety of types of risk including model risk, credit risk, systemic risk, liquidity risk and behavioural risk.

2.2.2 Hedge Funds

In this section two of the most noteworthy hedge fund blow-ups and a highly significant episode of turbulence in the quantitative hedge fund space in August 2007 are presented.

2.2.2.1 LTCM

The best-known hedge fund crisis is the 1998 near-collapse of Long-Term Capital Management (LTCM), a seemingly sophisticated hedge fund that had been the largest in the industry before its difficulties.[27] Meaning to avert a potential systemic crisis, the Federal Reserve Bank of New York brokered a last-minute bailout by a consortium of leading banks.

LTCM was established in 1994 and included among its 15 partners eminent ex-Salomon Brothers bond arbitrage traders (most notably John Meriwether) as well as such distinguished financial economists as 1997 Nobel prize laureates Robert C. Merton and Myron Scholes.[28] LTCM's trading was centred on "convergence" or "relative value" strategies.[29] In its first three years (1994-1996) the hedge fund saw superior returns. When 1997 returns (17% after fees) proved comparatively disappointing, the partners forcibly returned capital to investors so as to regain performance by increasing leverage. This strategy ran

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[27] Lowenstein (2002) offers an interesting narrative description and analysis of the fund, its trades and near collapse; cf. MacKenzie (2005) for an account that emphasizes the sociological dimensions of real-world arbitrage. The following discussion draws on both sources.

[28] Cf. Douglas Breeden, quoted in Lowenstein (2002), p. 40: "They [Long-Term] are in effect the best finance faculty in the world."

[29] Cf. MacKenzie (2005), p. 66: "LTCM's basic strategy was 'convergence' and 'relative-value' arbitrage: the exploitation of price differences that either must be temporary or that have a high probability of being temporary."

afoul when Russia defaulted on its domestic currency government bonds on August 17, 1998. Russia's default precipitated a so-called "flight-to-quality" that quickly translated into a full-blown liquidity crisis. As described by MacKenzie:

> "As arbitrageurs began to incur losses, they almost all seem to have reacted by seeking to reduce their positions, and in so doing they intensified the price pressure that had caused them to make the reductions."[30]

LTCM now faced illiquid markets because its portfolio was both large relative to the market and because its previous success had attracted many imitators that now were in similar positions. Once the markets started to consider the possible collapse of LTCM, things turned from bad to worse. Margin calls triggered a positive, i.e., self-reinforcing, feedback loop that LTCM (and its imitators) could do little to stop. In the end, LTCM was bailed out shortly before it ran out of capital. By then, LTCM had lost a total of about US$ 4.5 billion since January 1,1998.[31] The LTCM case is highly illustrative of a number of risks. Market and credit risk evidently were factors. But arguably more significant were the endogenously created liquidity and systemic risks arising from the interactions of market participants. It is interesting to note that a number of recent subprime-related hedge fund losses may have followed a similar pattern.[32]

2.2.2.2 Amaranth Advisors

Representing the largest hedge fund failure to date, Amaranth Advisors in mid-September 2006 "…lost 65% of its $9.2 billion assets under management in little over a week"[33] on overly large natural gas (futures) spread trades.[34] The fund was subsequently suspended and liquidated. According to analysis by Chincarini, the fund might have taken on excessive amounts of liquidity risk (by holding exaggeratedly large positions relative to the market) but also, according to Chincarini's simulated value at risk (VaR) figures, considerable market risk.[35] In her analysis, Till infers that "9-standard-deviation event" may have taken

[30] MacKenzie (2005), p. 74.

[31] Cf. Lowenstein (2002), p. 234.

[32] Cf. Khandani/Lo (2007), p. 19.

[33] Till (2006), p. 2.

[34] Cf. Till (2006).

[35] Cf. Chincarini (2007)

place on September 15, 2006, one particularly bad day for the fund.[36] Amaranth's founder and CEO Maounis subsequently claimed that Amaranth's risk management was not to be faulted:

> "We viewed the probability of market movements such as those that took place in September as highly remote … we had assigned full-time, well-credentialed and experienced risk professionals to model and monitor our energy portfolio's risks."[37]

While individual analyses may differ as to exact probabilities, the blow-up of Amaranth was due to a combination of market and liquidity risk. It illustrates that liquidity risk is a potentially very serious risk and that active risk management does not necessarily provide the protection desired.

2.2.2.3 Quant Hedge Funds in August 2007[38]

In early August 2007, several supposedly marked-neutral quantitative long/short equity hedge funds (also know as "quants") sustained three days of very heavy losses (August 7-9) before making an incomplete recovery on day four (August 10). This came so unexpected that Goldman Sachs' CFO Viniar proclaimed: "We were seeing things that were 25-standard deviation moves, several days in a row…"[39]. Based on simulation results, Khandani/Lo put forward that the turbulence possibly originated from

> "… a rapid unwinding of one or more large long/short equity portfolios, most likely initially a quantitative equity market-neutral portfolio. This unwind created a cascade effect that ultimately spread more broadly to long/short equity portfolios"[40].

Khandani/Lo suggest a number of significances of this episode; three of them relevant for this paper. First, the episode arguably points out "… the need for measures of illiquidity risk, and that volatility is an inadequate measure of risk…"[41]. Second, one may entertain that "… quantitative models may have failed in August 2007 by not adequately capturing the endogeneity of their risk

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[36] Cf. Till (2006), p. 8.

[37] Maounis (2006), p. 5.

[38] The following paragraph is based on Khandani/Lo (2007).

[39] Viniar, quoted in Khandani/Lo (2007), p. 2.

[40] Ibid., p. 54.

[41] Ibid., p. 47.

exposures"[42]. Third, the episode is a first indicator of unforeseen channels of problem propagation across seemingly unrelated market segments.[43]

To recapitulate, the episode illustrates once more the (still) hard to predict quality of (endogenous) liquidity risk, alerts to the danger of excessive reliance on conventional risk models (and their standard deviations) and, finally, it indicates that new linkages between market segments in periods of crisis may create new and unprecedented sources of risk.

2.3 Blow-Ups in Context

Before progressing further, it is necessary to put the aforementioned blow-ups into context. While said blow-ups exemplify that things can go wrong, they clearly stand for the extreme cases. To gauge if the risks effectively taken on by financial actors can be justified on economic grounds, the incidence of blow-ups and losses has to be assessed in comparison with the complete relevant returns universe. For instance, if banks or hedge funds as a whole did on average lose their accumulated profits (if any) every few years, risk-taking would certainly appear highly imprudent. Making such an assessment is however complicated by the fact that it is unknown what time span's analysis would suffice for a robust result. For instance, if returns within a specific returns universe are drawn from an underlying left-skewed, leptokurtic distribution, short-term observations (that are likely to be interpreted as suggestive of a different underlying distribution) might result in an overestimation of profitability. It should be noted that in the case of the underlying distribution following a power-law (e.g., a stable Paretian), missing so-called "outliers" makes a decisive difference.[44] Keeping these caveats in mind, some highly suggestive statements (referring to specific sample periods) can be made about the attractiveness of banking and hedge fund returns.

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[42] Khandani/Lo (2007), p. 46; Cf. also, ibid: "… if a certain portfolio strategy is so popular that its liquidation can unilaterally affect the risks that it faces, then the standard tools of basic risk models such as Value-at-Risk and normal distributions no longer hold."

[43] Cf. ibid., p. 54.

[44] Cf., for instance, Mandelbrot/Taleb (2005).

2.3.1 Banking

According to a recent McKinsey study by Dietz et al., by the year 2006

> "…banking became the industry with the highest absolute level of profits… In fact, those of US banks alone - $328 billion in 2006 – were larger than the combined profits of the retailing, pharmaceutical, and automotive industries around the world. What's more, in that year the banking industry's profits per employee were estimated to be 26 times higher than the average of all other industries, and its $2.8 trillion in revenues equalled 6 percent of the global GDP." [45]

Dietz et al. also provide graphically represented estimates (for the years 1970-1999) and actual data (for the years 2000-2006) for the percentage share of global banking profits in total global corporate profits. They suggest that in the period 1970-1992 banking's share of profits stayed mostly in the range 5-6,5% with just one low at 4% in 1987. In the period 1993-2006, banking's share of total corporate profits picked up and (except for a slump in 2001) increased rather steadily to just below 10% in 2006.[46] For the purpose of this paper, three aspects are worth drawing attention to. First, banking as whole (at a global level) has been profitable in every single year at least since 1970, the first year estimates are provided for. Second, banking has been highly profitable which is indicated by the sizable share of global corporate profits maintained throughout. Third, leading up to 2006 banking profits and profit shares have reached historical highs so that most recently incurred lower profitability levels have to be seen against this background. In conclusion, the sample period 1970-2007 gives no indication that banking as a whole is unprofitable or that profit levels are unattractive. On a critical note, Dietz et al. do not fully explain how their results are derived. The 1970-2000 estimates, for instance, are referenced as "Estimated based on trends, predominantly using banking data in key global markets"[47]. As a result any existent methodological flaws remain unobservable.

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[45] Dietz et al. (2008), p. 3.

[46] Cf. ibid., p.4; Exhibit 2.

[47] Ibid.

2.3.2 Hedge Funds

Hedge funds are, for a variety of reasons, often accorded a special place when financial risks are discussed. First, there is the fact that hedge funds are largely unregulated in that they are able to freely choose financial strategies. Second, there is a general lack of transparency of the industry that does not go together well with the occasional, invariably well-publicized, spectacular blow-up. Third, there is the rapid growth of the industry[48] which is amplified in its significance by hedge funds' characteristically high leverage and very active trading.[49] It should also be mentioned that hedge funds are a category that is more easily defined negatively than positively.[50] Hence, as Crockett points out, "There are, in fact, no universally accepted criteria for characterizing a particular institution as a hedge fund"[51]. It is therefore not surprising that measuring "hedge fund profitability" is a non-trivial and as yet unresolved issue. Noyer explains:

> "A whole body of research has been devoted to look at hedge funds performance. The results are not all conclusive, in part due to data availability and reliability."[52]

Malkiel/Saha, in an examination of hedge fund risk and return, conclude:

> "Correcting for such biases [i.e. backfill of good results only and survival biases; note of the author], we found that that hedge funds have returns lower than commonly supposed. Moreover, although the funds tend to exhibit low correlations with general equity indices – and, therefore, are excellent diversifiers – hedge funds are extremely risky along another dimension: The cross-sectional variation and the range of individual hedge fund returns are far greater than they are for traditional asset classes."[53]

Table 1 suggests the extent that hedge fund performance has been over-estimated, and the relative performance of hedge funds returns in comparison with the S&P 500 and the U.S. T-Bill. Results for individual hedge fund style

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[48] Cf. Papademos (2007), p. 115: "By early 2007, several data providers indicated that, on the basis of joint internal and commercially distributed hedge fund data samples, the total capital under management by single-manager hedge funds globally was rapidly approaching the USD 1.5 trillion mark." This is significantly up from corresponding figures of "approximately $50 billion in 1990" and "approximately $1 trillion by the end of 2004" given in Malkiel/Saha (2005), p. 80.

[49] Cf., for instance, Ferguson/Laster (2007), p. 46.

[50] Cf. Bookstaber (2007a), p. 243-247. For instance, ibid., p. 244: "… there is no such thing as a hedge fund. It is not part of a homogeneous class that can be analyzed in a consistent way. … What we call alternative investments is really the wide world of investments minus that small slice known as traditional management."

[51] Crockett (2007), p. 20.

[52] Noyer (2007), p. 106.

[53] Malkiel/Saha (2005), p. 87.

categories[54], that often exhibit high kurtosis and negative skew, are not reported here for purposes of clarity.

Table 1: Hedge Fund Performance, 1995-2003

Investment Type	Annual		Sharpe Ratio	Skewness	Kurtosis
	Return	Standard Deviation			
Hedge fund universe	8,82%	9,21%	0,50	-0,25	2,51
CSFB hedge fund index	13,41	10,36	0,89	0,07	1,90
S&P 500	12,38	21,69	0,38	-0,64	0,28
U.S. T-Bill	4,2	1,78	0,00	-0,89	-0,80

Source: Adapted from Malkiel/Saha (2005), p. 81.

In the case of hedge funds it can thus not be unequivocally answered whether the risk taken can be justified. While hedge funds as a whole seem to underperform (at least some) broad market indices such as the S&P 500, their attraction depends on individual risk preferences as well as on the benefits they can add in terms of portfolio diversification.

3. The Concept of Risk

This section explores the concept of risk as it applies in the context of financial institutions. The word "concept" is chosen deliberately because risk is not a directly observable, objective fact of the natural world. Rather, the great challenge of risk management is precisely that the various relevant "risks" need to be construed by the concerned actors. This construction of risk is usually undertaken with the help of quantitative models and technologies of observation (to derive the probabilities of risk events) against the background of both (subjectively arrived at or otherwise given) preferences and prices (that are usually based on asset-pricing models).[55] Thus it is only through models and in the context of a particular set of preferences that risk can be identified, captured, quantified, and given a (monetary) value.

[54] Cf. Cornell (2003) for an overview of the risks associated with different hedge fund styles.

[55] Cf. Lo (1999), who refers to probabilities, preferences and prices as the "The Three P's of Total Risk Management" (this is the title of Lo's article).

The first part of this section introduces pertinent sociologist approaches to (financial) risk. In the second part, several conceptualizations of risk found in the financial economics literature are reviewed.

3.1 Economic Sociology

For a broad perspective on the concept of risk and its role for financial institutions it is helpful to look at how (economic) sociologists have approached the topic. In particular, this section refers to sociology to address, first, whether risk exists as a recoverable, objective aspect of an institution's environment and, second, the organizational role of risk management.

The social constructivist theory in sociology holds that perceptions and representations (of reality) are neither simple nor unmediated. Instead, it is argued that the specific (socially mediated) practices/modes of perception and representation themselves play a large role in "constructing" the objects of their attention.[56] This general idea has entered the field of economic sociology where it inspired, among other things, further development of and interest in the concept of "performativity".[57] Performativity here denotes the idea that models, methodologies, and theories affect both the actors' view of reality as well as, by the from this resulting actions, reality itself. The following quote by Kalthoff serves well to illustrate this meaning of the concept of performativity:

> "Die externe Welt der Märkte fließt in die kalkulativen Praktiken der Bankwirtschaft und Finanzmärkte ein, wird dort übersetzt und neu geordnet und wirkt als so rekonfigurierter Sacherhalt auf das ökonomische Geschehen, das es darstellt und kalkuliert zurück."[58]

Kalthoff goes on to quote Robert C. Merton with a statement that seems to similarly suggest such mutual influence of market realities and state-of-the-art financial economic theory:

> "… as real-world financial intermediation and markets become increasingly more efficient, the continuous-time model's predictions about actual financial prices,

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[56] Cf. Berger/Luckmann (1967).

[57] Cf., for instance, the collection of articles in MacKenzie et al. (eds.) (2007).

[58] Kalthoff (2007), p, 8.

> products and institutions will become increasingly more accurate. In short, that reality will eventually imitate theory."[59]

This strand of sociology as advanced by Kalthoff explicitly seeks to depart from the idea of mathematical realism and its assumptions that specific practices of calculation faithfully depict reality and do not themselves affect it.[60] Instead, Kalthoff's constitution-theoretical (german: "konstitutionstheoretische") reformulation of a sociology of calculation[61] takes performativity as its premise:

> "Ökonomisches Rechnen bringt nicht schon existierende Objekte in eine sichtbare Ordnung, sondern die Objekte werden erst durch die Verfahren der Kalkulation hervorgebracht. In diesem Sinne konstituiert die Berechnung ökonomische Objekte, indem sie sie fixiert."[62]

Such sentiments that economic objects such as risks, cannot be recovered from the environment by trivial counting and observation, echo in a sense Luhmann:

> "Die Außenwelt selbst kennt keine Risiken, denn sie kennt weder Unterscheidungen, noch Erwartungen, noch Einschätzungen, noch Wahrscheinlichkeiten – *es sei denn als Eigenleistung beobachtender Systeme in der Umwelt anderer Systeme*."[63]

Thus, making risk accessible for an actor (individual, institution, etc.) is more than a measurement problem.[64] It often has a direct effect on the actor and on the environment and can thereby create what is referred to as endogenous risk (see section 6.1.4.1.1). Yet, (as also shown below) measurement problems rightly figure prominently in the field of risk management.

Following a somewhat different research programme, Power draws attention to the organizational role played by the concept of risk. Although he agrees that the concept of risk remains "elusive" and "essentially contested"[65], Power emphasizes that:

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[59] Merton (1992), p. 470, quoted in Kalthoff (2007), p. 3.

[60] Cf. Kalthoff (2007), p. 3.

[61] Cf. ibid., pp.3-4.

[62] Ibid., p. 3.

[63] Luhmann (2003), pp. 14-15; emphasis original. PLEASE NOTE: In the remainder of this paper, "The Risks of Financial Risk Management", all emphases that originally exist in the texts quoted will be indicated in their relevant footnote by the remark "emphasis original".

[64] Cf. ibid., pp. 15-16.

[65] Power (2007), p. 3.

> "… it has become an empirical fact that the concept of risk in its raw form has acquired social, political and organizational significance as never before, and this needs explanation…"[66]

In other words, Power raises the question of why risk (management) has gained such prominence in a variety of organizational fields in recent years. Attempting a response, Power finds "… a new kind of organizing authority for the category of risk"[67] where risk management is the locus of "… a new reflexivity of organizations and organizing…"[68] and where "… risk and its management has become a lens through which a certain kind of rational organizational design can be envisioned"[69]. [70]

Power contends that risk management supplies an "… 'as if' logic or grammar of risk"[71] that allows to abstract from issues of essential (Knightian) uncertainty (see section 3.2.1) or unmanageable (Luhmannian) danger[72]:[73]

> "When objects of concern are described in terms of risk, they are placed in a web of expectations about management and actor responsibility. The apparent risk-based description of organizational life and personal life corresponds to widespread expectation that organizations must be seen to act *as if* the management of risk is possible."[74]

According to this argument, by constructing risks, risk management provides management both with a basis for reasoned decision-making at the same time that it creates a basis on which its responsibility can be asserted. Yet, if it is the organization that selects relevant risk objects and models to capture them, having to make such selections introduces factors that are prior or external to

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[66] Power (2007), p. 3.

[67] Ibid., p. 4.

[68] Ibid., p. 4.

[69] Ibid., p. vii.

[70] Cf. Power (2005).

[71] Ibid., p. 6.

[72] Cf. Luhmann (2003), p. 30-31: „Entweder wird der etwaige Schaden als Folge der Entscheidung gesehen, also auf die Entscheidung zugerechnet. Dann sprechen wir von Risiko, und zwar vom Risiko der Entscheidung. Oder der etwaige Schaden wird als extern veranlasst gesehen, also auf die Umwelt zugerechnet. Dann sprechen wir von Gefahr."

[73] Cf. Power (2007), pp. 5-6.

[74] Ibid., p. 6; emphasis original.

risk management. This argument does not imply that choices are made arbitrarily or that models are not tested for efficacy. Rather, it introduces the previously mentioned concept of performativity. Millo/MacKenzie put this well:

> "Naturally, any map, be it a geographical map or a risk map, is charted wile incorporating a particular perspective. That is, an actor's point of view is the initial coordination according to which risks are defined and risk assessments are made. Therefore, the way an organizational actor depicts its risks is contingent upon how that actor perceives itself, its goals and its relationships with other actors. Consequently, since risk management is not only a description of a given reality but includes a prediction and is operated upon as a blueprint for action, it includes a constitutive (or performative) element. The way organizations depict their risks has a significant effect on the way they will react to events and to other actors." [75]

This necessarily very brief review of selected economic sociologist approaches to risk management clearly identifies a possible source of risk in risk management. Even if one were to accept the need to reduce essential uncertainty to manageable risk for corporate governance purposes, making this "as if" assumption of general manageability is likely to create its own risks. This may be especially so if (possibly, over time) the "as if" claims are taken at face value. Then, on the one hand management mistakes, and on the other hand disappointed stakeholders suspecting fraudulent misrepresentation or incompetence, might ensue.

3.2 (Financial) Economics

This section gives a short historical overview of risk measurement frameworks developed within the field of (financial) economics and their underlying definitions of risk.[76] These definitions have formed the basis of risk management models and practices introduced in later sections. They are also the basis for the numerous, mostly ratio-based, risk-adjusted performance measures, such the Sharpe Ratio, Sortino Ratio, Treynor Ratio, or Jensen's alpha[77]; it is, however, beyond the scope of this paper to further explore these performance measures.

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[75] Cf. Millo/MacKenzie (2007), p. 5.

[76] Cf. Bernstein (1998) for a fascinating history of the concept of risk. This section draws in part on Bernstein's identification of salient turning points and figures in the history of risk (concepts).

[77] Cf. Culp/Mensink (2003), pp. 109-116, for risk-adjusted performance measures.

3.2.1 Knight's Distinction between Risk and Uncertainty

The Concise Oxford Dictionary defines risk as "a chance or possibility of danger, loss, injury, or other adverse consequences" or "a person or thing causing a risk or regarded in relation to risk"[78]. Such a definition of the term as referring to the eventuality ("chance") of something that is not desired ("adverse") taking place, specifies risk as a function of imperfect knowledge about future states of the world and of a given set of preferences. In short, only the combination of incomplete knowledge and the possible realization of a (subjectively) unwanted state of the world is referred to as a risk. If the unwanted occurrence were (assumed to be) certain it would no longer be (regarded as) a risk. Risk is thus ubiquitous under conditions of uncertainty involving possible adverse exposure.

In 1921, the economist Frank Knight departed from this everyday use by drawing a seminal distinction between "risk" and "uncertainty"; he proposed:

> "The practical difference between the two categories, risk and uncertainty, is that in the former the distribution of the outcome in a group of instances is known (either through calculation *a priori* or from statistics of past experience), while in the case of uncertainty this is not true, the reason being in general that it is impossible to form a group of instances, because the situation dealt with is in a high degree unique. The best example of uncertainty is in connection with the exercise of judgement or the formation of those opinions as to the future course of events, which opinions (and not scientific knowledge) actually guide most of our conduct."[79]

For Knight, risk is probabilistically knowable and therefore manageable while uncertainty is unknowable. It has been remarked that in Knight's distinction, "Risk relates to objective probabilities. Uncertainty relates to subjective probabilities"[80]. It is, however, beyond the scope of this paper to retrace the debate on whether objective probabilities exist. Suffice it to mention that proponents of a strictly subjective interpretation assert that all probability measures are but expressions of (mere) belief; this view's domain of the

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[78] Thompson (ed.) 1995), p. 1189.

[79] Knight (2006), p. 233.

[80] Holton (2004), p. 20.

unknowable therefore extends much further than Knight's.[81] At any rate, Knight introduced an important distinction that serves as a reminder of the limits of risk management. Risk management relies on knowledge/observations of past and present states of the world but must assume a view of the (probable) future. Thereby it inescapably gains exposure to Knightian uncertainty. One might argue that, provided risk management pays regard to this, Knightian uncertainty is a (partly) indirectly manageable "known unknown" but that it turns into a much more dangerous "unknown unknown" (see section 6.1.1.1) if disregarded.[82]

3.2.2 Modern Portfolio Theory

Below, the two main steps in the development of modern portfolio theory (MPT) are delineated.

3.2.2.1 Step One: Markowitz

A milestone for modern finance and its conceptualization of risk was Harry M. Markowitz's 1952 seminal paper "Portfolio Selection".[83] The paper considers how investors should form equity portfolios in the context of (partial) uncertainty.[84] Markowitz rejects that the investor should single-mindedly maximize expected returns but instead examines

> "… the rule that the investor does (or should) consider expected return a desirable thing *and* variance of return an undesirable thing."[85]

The groundbreaking contribution of Markowitz was to suggest that return variance can (often) stand in as a measure of (financial) risk.[86] On the basis of

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[81] Cf. Holton (2004), p. 19; cf, also de Finetti, quoted in ibid.: "Probability, too, if regarded as something endowed with some kind of objective existence, is no less a misleading misconception, an illusory attempt to exteriorize or materialize our true probabilistic beliefs."

[82] Cf. the general claim of Bernstein (1998), p. 197: "*The essence of risk management lies in maximizing the areas where we have some control over the outcome while minimizing the areas where we have absolutely no control over the outcome and the linkage between effect and cause is hidden from us..";* emphasis original.

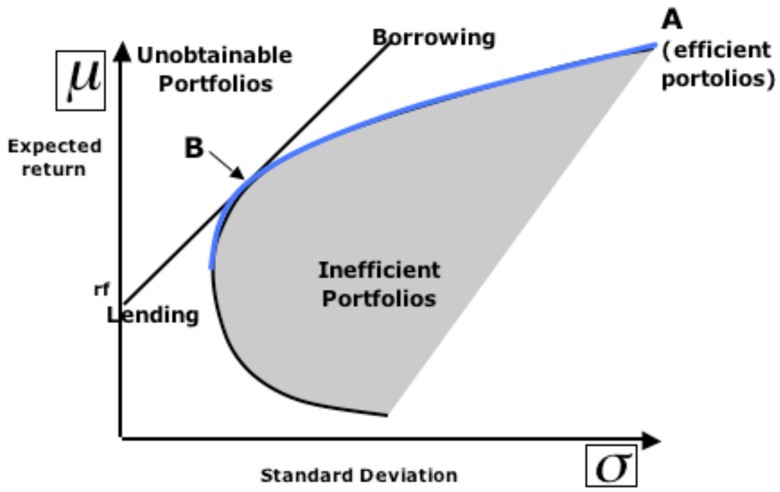
[83] Markowitz was awarded the1990 Nobel Prize in Economics for his theory of portfolio selection.

[84] Cf. Markowitz (1952).

[85] Ibid., p. 77; emphasis original.

this insight, it becomes possible to assign a numerical value to investment risk. Markowitz establishes that, if investors care both about return and variance (i.e., risk), superior results can be achieved through proper portfolio diversification. Markowitz suggests a portfolio investment decision rule based on expected return μ and variance of return σ^2: Investors should weigh individual equities in such a manner (by taking the covariances between individual stocks into account) that, for a given desired level of return, the portfolio variance is minimized. This is referred to as mean-variance optimization. All thus selected portfolios are regarded as efficient portfolios reflecting different risk appetites.[87]
In Figure 1, these efficient portfolios are represented by the thick blue line A; unobtainable and inefficient portfolios are also indicated and lie, respectively, to the left and right of this line. If borrowing and lending at a risk-free rate (i.e., the option of leverage) are introduced there is further room for improvement. Without leverage, only risk-return combinations in the shaded area in Figure 1 are obtainable. With leverage, the superior risk-return combinations represented by the straight line starting at r_f (representing the risk free interest/borrowing rate) and touching on the tangency portfolio B become obtainable.[88]

Figure 1: Markowitz's Mean-Variance Framework



Source: Adapted from Brealey et al. (2006), p. 187.

[86] Cf. Markowitz (1952), p. 89: “The concepts ‘yield’ and ‘risk’ appear frequently in financial writings. Usually if the term ‘yield’ were replaced by ‘expected yield’ or ‘expected return,’ and ‘risk’ by ‘variance of return,’ little change of apparent meaning would result.

[87] Cf. Markowitz (1952).

[88] The previous paragraph and Figure 1 draw on Brealey et al. (2006), pp. 186-188.

However, there are a number of well-known limitations to Markowitz's suggested operationalization of risk and his method of portfolio selection. First of all, as recognized by Markowitz himself, it "… starts with the relevant beliefs about the securities involved…"[89]; i.e. the required inputs (means, covariances) must be somehow (and reliably) obtained. This can create serious estimation problems and thereby creates an exposure to what is described in section 7.2.1 as model risk.[90] Secondly, mean-variance optimization focuses exclusively on the first two central moments of the returns distributions. Yet only normal distributions are fully described by the first two central moments. As stated by Koh et al.:

> "Mean-variance analysis is appropriate when returns are normally distributed or investors' preferences are quadratic. The reliability of mean-variance analysis therefore depends on the degree of nonnormality of the returns data and the nature of the (nonquadratic) utility function."[91]

In fact, Markowitz's 1952 paper itself does (briefly) acknowledge that some investors' utility might be a function of the first three central moments (i.e., mean, variance, skewness).[92] Shortly later, Tobin's liquidity preference theory[93] did however assume both normally distributed portfolio returns and quadratic utility functions.[94] By now, however, there is considerable evidence that prices and returns in various financial markets exhibit fat-tails (leptokurtosis) and are thus clearly inconsistent with normal or lognormal distributions.[95] It should be

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[89] Markowitz (1952), p. 91.

[90] Cf., for instance, Jobson/Korkie (1990), p. 544: "A major problem, which belies the implementation of this [i.e., Markowitz's; note of the author] normative theory of portfolio analysis, is the formation of rational expectation regarding the mean-return premium vector μ and the covariance matrix $\sum$ that is appropriate for the investors' holding period."

[91] Koh et al. (2005), p. 351; the quote is from a discussion of hedge fund performance measures.

[92] Cf. Markowitz (1952), pp. 90-91.

[93] Cf. Tobin (1958).

[94] Cf. Los (2003), p. 4; ibid. pp. 4-5: [Tobin's] "… liquidity preference theory, shows that any investment risk level (as defined by the second moment of asset returns) can be attained by a linear combination of the market portfolio and cash, combined with the ability to hold short (borrow) and to hold long (invest). The market portfolio contains all the non-diversifiable systematic risk, while the cash represents the "risk-free" asset, of which the return compensates for deprecation of value caused by inflation."

[95] See Mandelbrot (1963) for a pioneering paper.

obvious that relying on classical mean-variance optimization in non-normal environments can have adverse results. To give a specific example, research shows that returns of hedge funds and of individual hedge fund categories cannot be described by a normal distribution. Rather, they are characterised by negative skewness and high kurtosis (fat tails).[96] Brooks/Kat find:

> "Since they look only at the mean and the standard deviation, the Sharpe ratio and mean-variance analysis are not suitable for the evaluation of the performance of (portfolios containing) hedge funds."[97]

In a similar vein, Weisman warns that hedge funds may

> "… engage in essentially informationless strategies that can produce the appearance of return enhancement without necessarily providing any value to an investor."[98]

Clearly, this exemplifies an instance of model risk (see section 7.2.1); in this case the risk lies in choosing an inappropriate proxy for risk.

A third point to take note of is that variance is a symmetric risk measure. If investors are more concerned with downside (than with upside) risk, other, asymmetric, risk measures such as *lower partial moments* or *semivariance*[99] may be more appropriate.

3.2.2.2 Step Two: CAPM

The Capital Asset Pricing Model (CAPM) of Sharpe[100] and Lintner[101] is a direct extension of the approach of mean-variance optimization suggested by Markowitz. Although theoretically elegant, the data requirements of Markowitz's approach were impractical, especially for (large) portfolios. Therefore, the CAPM's simplification of risk, into diversifiable idiosyncratic firm-risk on the one hand and undiversifiable systemic market-risk measured solely by β on the

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[96] Cf. Malkiel/Saha (2005), p. 81; Brooks/Kat (2002).

[97] Brooks/Kat (2002), p. 43.

[98] Weisman (2003), pp. 262-263; Weisman mentions specifically how short-volatility, illiquid security, and St. Petersburg investment strategies can have this effect.

[99] Cf. Clarke (2003), pp. 54-55, for an exposition of lower partial moments and semivariance.

[100] Cf. Sharpe (1964).

[101] Cf. Lintner (1965).

other, greatly eased calculation and enabled real-time application.[102] Instead of (the) variance (of returns), CAPM uses β (beta) as its risk measure. The main difference between these two risk measures is that β is a measure of (a specified portfolio's or asset's) marginal (returns) variance:[103]

> "The major insight of the CAPM is that the variance of a stock by itself is *not* an important determinant of the stock's expected return. What is important is the market beta of the stock, which measures the covariance of the stock's return with the return on a market index, scaled by the variance of that index."[104]

In short, the CAPM suggest that assets' risk and return are fully characterized by their beta:

> "Under the assumptions of the CAPM, and if a risk-free asset exists, the market portfolio is the tangency portfolio and … the expected returns of financial assets are determined by
>
> $$\bar{r} - r_f = \beta(\bar{R}_M - r_f)$$
>
> where $\bar{R}_M$ is the mean return of the market portfolio, [and r_f is the risk-free rate; note of the author] and β is the beta computed against the return of the market."[105]

Figure 2 depicts the direct, proportional relationship between β and expected return postulated by the CAPM. The increasing returns of higher beta assets are understood as risk premiums. Per definition, the market portfolio has a β of 1. Finally, all investments in the CAPM model-world must plot on the so-called security market line.[106]

Clearly, the CAPM seems to suggest an easy way to measure risk. The problem is just that the theory does not fit empirically observable facts; i.e., the CAPM does not work in practice. As Fama/French review:

> "The attraction of CAPM is that it offers powerful and intuitively pleasing predictions about how to measure risk and the relation between expected return and risk. Unfortunately, the empirical record of the model is poor – *poor enough to invalidate the way it is used in applications*."[107]

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[102] Cf. Allen et al. (2004), pp. 1-2.

[103] Cf. Grinblatt/Titman (2002), p. 149.

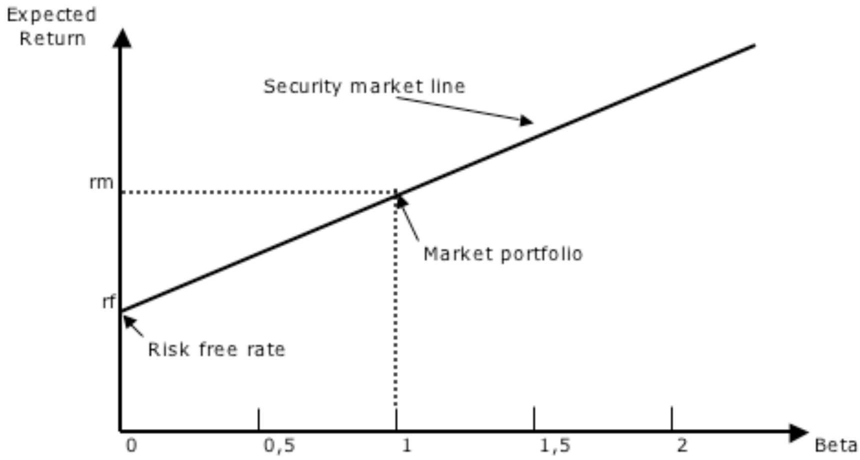
[104] Cf. Ibid., p. 151; emphasis original.

[105] Ibid., p. 153; the original number designation of the equation is omitted in the quote.

[106] Cf. Brealey et al. (2006), pp. 188-189.

[107] Fama/French (2004), p. 1; emphasis original. See the whole article for reasons of the failure.

Figure 2: The CAPM Framework



Source: Adapted from Brealey et al. (2006), p. 189.

This suggests that relying on the CAPM or β to manage or measure risks (or assess the alleged α [alpha] of investment strategies) may expose one to model risk and consequently not result in desired results.

3.2.3 Multi-Factor Models

This section outlines the Arbitrage Pricing Theory (APT) and the Fama-French Three-Factor-Model. The APT of Ross[108] linearly regresses returns against various macroeconomic factors that are each assigned a β-coefficient. APT assumes that the risk premiums of individual stocks represent exposure to macroeconomic factors only since idiosyncratic risk can be diversified away. One advantage of the multi-factor APT is that it does not rely on the being able to measure the market portfolio. On the other hand, the ATP suffers from the disadvantage that it does not specify what the individual factors represent.[109] It has also been argued that it will always be possible to precisely regress to unspecified factors in sample, but that this could lead to over-fitting.[110]

The Fama-French Three-Factor-Model[111] holds three specified factors responsible for stock returns: the market factor (market return minus risk free

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[108] Cf. Ross (1976).

[109] Cf. Brealey et al. (2006), pp. 199- 200.

[110] Cf. Connor/Korajczyk (1989), p. 387: "The APT can be subject to overfitting because the pervasive factors are identified from asset return data that also are used to test the model."

[111] Cf. Fama/French (1995).

rate), the size factor (small cap stock return minus large cap stock return), and the book-to-market factor (high minus low book-to-market ratio stock returns).[112] Although, the Fama-French model seems to be empirically more successful than the CAPM, it is still not settled why that is the case. Are the factor-betas risk-related, an artefact of data-mining or do they reflect cognitive biases?[113]

3.3 Section Summary

The discussion in this section has shown, that risk should not be interpreted as an objective, directly recoverable fact of the environment. Rather, risk only becomes accessible through models that focus on certain, prior, interpretations of risk. It was also suggested that the different models function imperfectly, and that, according to Knight, some phenomena are essentially uncertain and cannot be approached probabilistically.

4. The Rationale for Risk Management

In this section, the case for active risk management at the individual firm level is made from a number of perspectives, including that of shareholders, debt holders, customers, managers, and regulators. Overall, a strong case for risk management, resting on a number of market imperfections becomes apparent. This suggests why, even though in stylised, perfect markets risk management would be irrelevant, empiriclly, most financial institutions take risk management very seriously.[114]

4.1 Shareholder Perspective

Should financial institutions such as banks manage their risks? For investors, from a shareholder value perspective, the answer depends on whether active risk management facilitates shareholder value creation.[115] Yet, first of all,

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[112] Cf. Brealey et al. (2006), p. 203.

[113] Cf. Montier (2002), pp. 88-9.

[114] Cf, for instance, Deloitte & Touche (2007).

[115] Cf., for instance, Schröck/Steiner (2005), p. 54: "... the central role of risk in the banking business is merely a necessary condition for the management of risks. Only the fact that risk management can also create value makes it a sufficient condition, assuming that value maximization is the ultimate objective function in banks."

according to the Modigliani Miller Theorem, in perfect markets total firm value is independent of firm capital structure.[116] This is because, given the assumption of perfect, complete and frictionless markets, the individual shareholder is as well put as the firm to conduct any risk management and, in particular, chose a desired level of leverage.[117] Secondly, it should also be noted that the CAPM (see section 3.2.2.2) implies that well-diversified investors need only worry about systemic, i.e. market, risk but not about idiosyncratic firm risk. This follows from the principle that (if a risk-free asset exists) all investors hold the market portfolio (in varying proportions to their total investments and thus select their desired risk-return level).[118] Thus, at least from a shareholder perspective, neoclassical theory with its stylised frictionless markets simply leaves no room for financial institutions' risk management.[119]

In practice, however two points ought to be considered. First, the actual market portfolio is impossibly broad, and possible proxies are non-confirmable.[120] Hence, the typical investor certainly does not hold it. Second, actual markets exhibit a variety of imperfections and frictions such as taxes, bankruptcy costs, and asymmetric information. Smith/Stulz show that taxes, financial distress costs, and risk aversion of management all can lead value-maximizing firms to engage in hedging.[121] The same argument arguably applies to other risk management practices, such as diversification and insurance. In the case of taxes, tax codes involving differing marginal tax rates[122] or asymmetric treatment of profits and losses[123] provide a value-maximizing rationale for hedging. In the case of financial distress costs, credible commitment to hedging

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[116] Cf. Modigliani/Miller (1958).

[117] Cf., for instance, Grinblatt/Titman (2002), pp. 741-742; Mason (1995), p. 177.

[118] Cf. Mason (1995), p. 160: "Here [in the CAPM; note of the author] the individual decides not which risks to bear, but how much risk to bear (market risk, that is, since all nonmarket risk is assumed to be diversified away in the market portfolio). The result is that while different individuals may decide to bear different amounts of risk, all individuals bear the same type of risk. That is, all individuals hold risky assets in the same proportion."

[119] Cf. Mason (1995), p. 177.

[120] Cf. Roll (1977).

[121] Cf. Smith/Stulz (1985).

[122] Cf. ibid., pp. 392-394.

[123] Cf. Grinblatt/Titman (2002), p. 744.

(and other risk management practices) can help to assure bondholders "… that expected bankruptcy costs are not as high as the firm's investment policy would otherwise suggest"[124]. By reducing bankruptcy costs and inspiring greater stakeholder confidence, this might result in lower financing costs and the ability to take on more debt[125]; all of which might contribute to shareholder value.

There are also factors that apply specifically to financial institutions. Financial distress costs play a larger role for financial institutions than for other firms because financial institutions are often highly leveraged and need to have constant access to short term financing. Hence they face significant costs not only in the case of insolvency but also if liquidity dries up in circumstances of heightened uncertainty. Additionally, recent regulatory, risk-based capital requirements in which (proven) proprietary risk management can substitute for equity capital give an added incentive for risk management at the firm level (see section 5.3). Also, in the case of closely-held financial institutions (such as, for instance, many hedge funds), owner-managers, and investors that have invested a significant share of their net worth, have additional reasons to engage in risk management because they cannot optimally diversify their investments.[126]

Opacity is a further determining reason why shareholders might prefer financial firms to engage in risk management for them. Financial institutions, such as banks or even more so hedge funds, are opaque institutions with highly complex and dynamic investments that simply cannot be - and for competitive reasons do not want to be - closely observed by outsiders.[127] As Mason writes:

> "The combination of information sensitivity, operating fluidity, and instrument complexity makes the problem of monitoring financial firms' creditworthiness difficult, if not impossible, for most customers and regulators."[128]

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[124] Smith/Stulz (1985), p. 398.

[125] Cf.,for instance, Brealey et al. (2006), p. 723; Grinblatt/Titman (2002), p. 747.

[126] Cf. Smith/Stulz (1985), p. 403, for the incentives of closely-held firms to hedge.

[127] Cf. Mason (1995), p. 159: "…financial firms are relatively opaque. To preserve a competitive advantage, financial firms must carefully manage the amount and type of information that they share with other parties. But this works directly against keeping customers and regulators fully informed."

[128] Mason (1995), p. 183.

However, as pointed out by Rebonato, to be in the (neoclassical) position of being able to replicate firms' risk management, "… the external investors should know just as well as the inside managers what risk factors the firm … is exposed to"[129].[130] This will hardly ever be the case. What is more, if a firm's results are highly volatile, even estimating the underlying becomes problematic as Rebonato suggests:[131]

> "In short, if the true parameters that describe the behavior of a firm are not known exactly *a priori* (i.e., if we live on planet earth), reducing the volatility of a firm's returns by engaging in risk management can make investing in the firm much more easy to understand, and therefore more appealing to investors."[132]

Rebonato surmises also that "… the ability to spot with ease the good underlying trend may more than compensate for some loss in expected returns"[133]. To understand the quote's reference to a reduction in expected returns, two aspects of risk management need to be pointed out. First, to establish and operate a risk management function is usually associated with additional costs. Second, if equity is considered a call option and if risk management reduces the volatility of firm value, then risk management should tend to decrease the option value. From a pure option valuation perspective, investors should prefer volatility and therefore dislike risk management.[134] Which effect of risk management on shareholder value is dominant is likely to vary depending on specific institutional contexts.

4.2 Debt Holder Perspective

If the pay-off profile of stocks is akin to a call option, the pay-off profile of debt is akin to a written put (cf. Figure 3). This gives rise to an obvious conflict of interest between equity and debt holders. For instance, as shown in Figure 3,

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[129] Rebonato (2007), p. 110.

[130] Cf. ibid.

[131] Cf. ibid., p. 111.

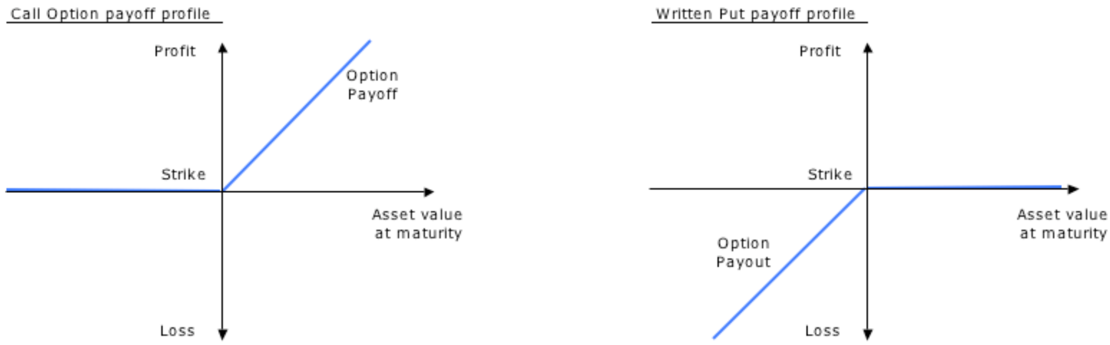
[132] Ibid., p. 114; emphasis original. Also, cf. Rebonato (2007), p. 115, for anecdotal evidence that high-volatility financial institutions, such as the investment bank Goldman Sachs, generally trade at lower earnings multiples than their competitors.

[133] Ibid., p. 112.

[134] Cf., for instance, Grinblatt/Titman (2002), p. 756.

while equity holders should prefer volatility of firm value since they profit on the upside, debt holders should not since they loose on the downside and have no upside. Thus, debt holders should be in favour of volatility decreasing firm risk management.

Figure 3: Comparison of Payoffs – Holding a Call vs. Writing a Put Option



Source: Adapted from Brealey et al. (2006), p. 545.

4.3 Customer Perspective[135]

Importantly, financial institutions also engage in risk management because it significantly affects their ability to attract customers. First of all, customers often engage the services of financial firms for the explicit purpose to shed, or otherwise manage, risks. Mason writes:

> “Financial firms play a central role in the *provision* of risk management services, among other financial services, to both individuals and firms. Financial firms facilitate the allocation of risk in a number of ways. … The essence of *creditworthiness* in the provision of all of these services gives risk management within financial firms a special significance.”[136]

Secondly, even if customers do not actively seek to reduce their risk exposure, they still often are averse to adding to it and having to consider and manage exposure to financial firm risk. Mason explains:

> “Customers of financial firms purchase services that perform important economic functions. … Such a customer strictly prefers a financial claim that will pay, with certainty, the specified amount of money on the specified date. Customers of financial firms are thus very concerned with creditworthiness.”[137]

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[135] This section draws on Mason (1995).

[136] Mason (1995), p. 181; emphasis original.

[137] Mason (1995), p. 182.

Therefore, in contrast to investors who actively take on firm risk, customers prefer to have no exposure to the risk of financial institutions. For the previously mentioned reasons of institutional opacity, the financial institution is in a better to position to engage in risk management than its individual customers.[138]

4.4 Management/Corporate Governance Perspective

Managers are in a principal-agent relationship with the residual claimants of the firm. They are (often) evaluated by shareholders according to perceived performance. In the absence of full information, random negative firm results can be mistaken as an indication of poor management skills. If firms immunize their exposure towards certain parameters of their environment through risk management, management can focus more decisively on the factors it is best-placed to control and shareholders can better monitor management efforts and skills. While this lowers agency costs, such simplified monitoring can also be in the interest of mangers themselves[139] allowing more effective signalling of skills.[140]

4.5 Regulator Perspective

Regulators have long been concerned with controlling the amounts of risk financial institutions, and in particular banks, can take on; only hedge funds represent at present a contested partial exception from regulatory oversight. In fact, "In virtually every country, banking is one of the most regulated of enterprises"[141]. In a sense, regulation is a particular form of risk-management-by-standard-setting that authorities impose on the industry. This section describes why regulators seek to constrain banks' risk-taking behaviour. According to standard economic theory, market regulation can only be justified

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[138] Cf. Mason (1995), p. 182: "… customers consider the bearing of financial firm risk extraneous to the central reason they contract with the financial firm. It is simply more efficient for the financial firm to address the issue of creditworthiness than for each individual customer to do so."

[139] The interests of managers in specific cases depend on the respective forms of the income and utility functions of managers in respect to firm results; cf. Smith/Stulz (1985), pp. 399-403.

[140] Cf. Mason (1995), p. 178; Rebonato (2007), p. 111; Grinblatt/Titman (2002), pp. 749-751; Brealey et al. (2006), p. 723.

[141] Fight (2004), p. 75.

in the presence of market failure; in the case of banking, suggested types of market failure are negative externalities, asymmetric information, and moral hazard.

Negative Externalities[142]

It is often remarked that banks are central to a well-functioning economy. And because of banks' centrality as intermediaries, their failures may result in substantial negative externalities to economies. These externalities are due to systemic risk: a term which refers to the danger that one initial bank failure may precipitate additional bank or non-bank failures somewhere else in the economic system. Because banks' assets are not as liquid as their liabilities, i.e., liquidity at any moment is just a fraction of liabilities, banks are vulnerable to bank runs, i.e. the concerted withdrawal of deposits by depositors. It has also been put forward that "Banks left to themselves will accept more risk than is optimal from a systemic point of view"[143] unless constrained by appropriate regulation.[144]

Asymmetric Information

As previously pointed out, financial institutions are opaque. Consequently, bank insiders have better information than outsiders. This informational asymmetry can be a contributing factor in the creation of contagion and systemic crisis:[145]

> "In the most extreme case of this information asymmetry, depositors cannot distinguish solvent from insolvent banks. As a result, news that one institution is failing can be interpreted as information that other institutions are in difficulty."[146]

To give a topical example, such a lack of transparency was influential in the drying up of the interbank market in the summer of 2007. Regardless of specific examples, informational asymmetries suggest a role for close banking supervision and regulation.

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[142] This paragraph draws on Biggar/Heimler (2005), pp. 6-8.

[143] Feldstein (1991), p. 15.

[144] Cf. ibid.

[145] Cf. Biggar/Heimler (2005), p. 8.

[146] Ibid.

Moral Hazard

Since informational asymmetries complicate monitoring by customers, and in order to lessen systemic risk, many countries have introduced explicit deposit insurance schemes.[147] The difficulty with deposit insurance is however that it gives rise to moral hazard:

> "… both banks and depositors can engage in imprudent banking practices, secure in the knowledge that if the high-risk loans do not pay off, deposit insurance protects their principal. This pattern is an example of moral hazard: those who insurance shelters from the negative consequences of risks have an incentive to take greater risks."[148]

Although administration of deposit insurance schemes can be official, private or joint in various countries[149], to limit the negative consequences of moral hazard, the schemes arguably need to be integrated into an appropriate regulatory (and broader institutional) environment.[150] This implies that containing moral hazard can be cited as a further argument for regulation.

4.6 Enterprise Risk Management

A further significant factor for mangers, and also from a general perspective that includes shareholders and regulators, is the ascendancy of enterprise risk management (ERM) in which the enterprise is considered as a portfolio of variously risky assets.[151] It is through ERM that "… risk and its management has become a lens through which a certain kind of rational organizational design can be envisioned"[152]. In financial institutions' ERM, financial risk management practices and models such as VaR contribute to a "*financialization of governance*"[153]:[154]

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[147] Cf. Demirgüc-Kunt/Kane (2002); also, ibid., p. 176: "Today, most OECD countries and an increasing number of developing countries feature some form of explicit depositor protection."

[148] Ibid. (2002), p. 176.

[149] Cf. ibid., p. 181.

[150] Cf. Demirgüc-Kunt/ Kane (2002).

[151] Cf. Power (2007), p. 70.

[152] Ibid., p. vii.

[153] Ibid., p. 75; emphasis original.

[154] Cf. Power (2007).

> "… VaR and RAROC are categories of practice which have made the relationship between shareholder value and risk management newly thinkable and actionable during the 1990s, providing a clear application of the logic and language or risk-return and a value or opportunity-based grammar for risk management in general."[155]

In the context of financial institutions, ERM's comprehensive and standardized firm-wide risk-management processes assist top-management, shareholders, and regulators in various ways. First, they keep top-management apprised of firm-level risk and of how (the risks of) individual parts of the organization add to whole firm (portfolio) risk through diversification or concentration effects.[156] Second, this knowledge allows management to fine-tune how much risk the whole firm is taking on and to price different risks efficiently.[157] Third, information gained through ERM processes may allow top-management to better control risk-taking in the individual parts of the firm. Fourth, accurate knowledge of risk taken on by specific sections or individuals allows for a far better performance appraisal and can help to prevent the gaming of (performance) bonus schemes by employees.[158] Fifth, as previously mentioned, risk management information helps outsiders to assess the performance of top-management and the firm itself. Sixth, risk management information compiled for ERM purposes may also allow regulators to better supervise financial institutions.

4.7 Section Summary

To summarize, risk management has the potential to improve organizational monitoring, control, and performance appraisal by top-management, shareholders, debt holders, regulators and other stakeholders. From a principal-agent theoretical perspective, the additional knowledge and transparency created at various levels by risk management helps ensure that agents act

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[155] Power (2007), p. 75.

[156] Cf., for instance, ibid., p. 70.

[157] Cf. Bessis (2002), p. x; also, ibid: "Banks who do not differentiate risks lend to borrowers rejected by banks who better screen and differentiate risks. By overpricing good risk, they discourage good borrowers. By underpricing risks to risky customers, they attract them."

[158] Cf. ibid.: "Comparing performances without risk adjustment is like comparing apples and oranges. The rationale of risk adjustment is in making comparable different performances attached to different risk levels, and in general making comparable the risk-return profiles of transactions and portfolios."

according to principals' interests. The additional transparency created by efficient risk management processes has the potential to lower overall monitoring costs, although this depends on the costs of the risk management processes themselves. Finally, appropriate regulations that prescribe risk management practices can help avoid or lessen the negative impact of market failure at the macroeconomic level.

5. Financial Risk Management

In order to manage its risks a financial institution first of all needs to know them. Acquiring the knowledge of risks involves assigning measurements on the basis of a chosen methodology to perceived, classified expressions of risks. That is to say, there are several steps involved in the process: 1) the division of "risks" into meaningful, observable classifications, 2) the choice of an appropriate model-based method to measure the risks belonging to the individual classifications, and, at last, 3) the use of the chosen method to generate measurements of the specific risks.[159] Then, having acquired (or construed; see section 3.1) this risk knowledge, the institution's management can begin to apply various policies to manage (limit, diversify away, increase, etc.) the identified risks. This section reviews, first, the commonly used classification of risks, second, the fundamental current risk management and measurement methods, and, third, how knowledge of risk is used to manage financial risk. In addition, the final part of the section gives an outline of the regulatory environment.

5.1 Classification of Risks

Figure 4 shows the great range of different activities modern banks are engaged in. Consequently, the categories of risks banks face and their relative importance respectively vary according to business lines.[160] Moreover, the types of risks faced by ostensibly very different financial institutions can resemble each other more than the risks faced by different business lines within the same institution. For this reason, it is meaningful to speak of financial risk

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[159] Cf., for instance, Jorion (2007), p. 497.

[160] Cf. Hull (2007), p. 372.

management in general rather than to constrain the discussion to banks exclusively.

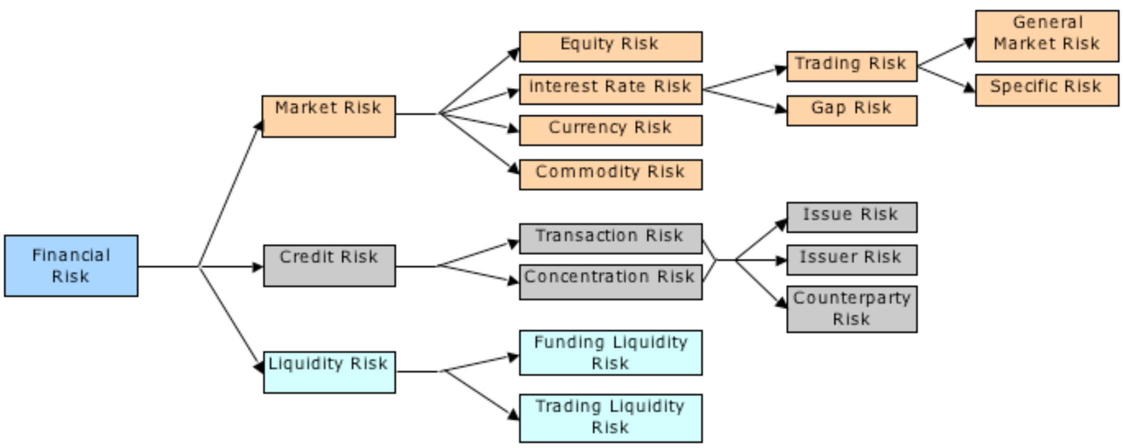
Figure 4: Banks' wide Range of Activities

Business Division	Business Line
Commercial Banking	Retail Financial Services Corporate-Middle Market Large Corporate
Investment Banking	Advisory Services Mergers & Acquisitions Leverages Buyouts Banks & Financial Firms Assets Financing Commodities Securitization
Trading	Derivatives Equity Fixed-Income
Private Banking	Assets Management
Others	Custody...

Source: Adapted from Bessis (2002), p. 4.

In the literature, the main (financial) risks financial institutions face are usually classified as market risk, credit risk, and operational risk. Oftentimes liquidity risk is also mentioned as a major separate risk category. It is obvious that there are other non-financial risks, such as strategic and business risk, that are important. The main categories of financial risk can be further sub-divided in more narrow sub-categories. In Figure 5 this is illustrated (in a non-exhaustive way) using market, credit and liquidity risk as examples. It should be mentioned that risk designations vary considerably in the literature.

Figure 5: Financial Risk and various Subcategories



Source: Adapted from: Crouhy et al. (2001), p. 38, p. 39.

5.1.1 Market Risk

A desire to gain better knowledge of market risk (in connection with derivative instruments) prompted the early advances in risk management in the 1990s. Market risk can be defined as

> "… the risk of loss (or gain) arising from unexpected changes in market prices (e.g., such as security prices) or market rates (e.g., such as interest or exchange rates)."[161]

As indicated in Figure 5, market risk can further be divided into equity risk, interest rate risk, currency risk and commodity risk. These subdivision can be further broken down and so on. Fundamentally, there are two basic ways to look at market risk: if one considers risk in currency terms, one is concerned with absolute market risk whereas, if one considers risk in terms of distance from a benchmark (as many investment funds do), one is concerned with relative market risk.[162] One should further note that the various types of market risk all occur in one of two shapes either as directional risk or as non-directional risk. Directional risk refers to linear exposures to changes of market prices or rates. Non-directional risk refers to non-linear exposures, exposures to volatility risk (i.e., unexpected changes in volatility) and exposures to basis risk (i.e. unexpected changes in the price relationship between a financial variable and its intended hedge[163]).[164] According to Jorion, "Market risk is controlled limits on notionals, exposures, VAR measures, and independent supervision by risk mangers"[165].

5.1.2 Credit Risk

Most generally, "*Credit risk* is the risk that a change in the credit quality of a counterparty will affect the value of a bank's [or other financial institution's; note of the author] position"[166]. For instance, if some counterparty defaults on its

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[161] Dowd (2002), p. 1.

[162] Cf. Jorion (2007), p. 22.

[163] Cf. Crouhy et al. (2001), p. 34.

[164] Cf. Jorion (2007), p. 22.

[165] Ibid., p. 23.

[166] Crouhy et al. (2001), p. 35; emphasis original.

obligations for whatever reason, the financial institution suffers losses to the amount of the replacement value of cash flows lost. This implies that there are only losses if the replacement value is positive. The loss itself is a function of the original exposure, i.e. cash flows at risk, on the one hand and the recovery rate, i.e. the proportion of value that can be recovered, on the other.[167]

It should be noted that actual defaults are not the only source of credit risk. Other sources of credit risk derive from perceived or actual changes in the credit quality of the counterparty short of actual default. For instance, credit rating downgrades agencies or a deteriorating market perception can lead to mark-to-market losses. To the extent that market perception is involved, credit and market risk overlap.[168]

There are a number of specific forms of credit risk. One subcategory includes sovereign, political and country risks. All three broadly refer to loss exposures in cross-border business connected to foreign government or foreign regulatory body policies and decisions (such as, in the extreme, default on sovereign debt or imposition of capital controls).[169] Another type of credit risk is settlement risk. Settlement risk designates the loss exposure if a two-way payment transaction (e.g., a foreign-exchange transaction) should fail to settle. This occurs if one party defaults after the other has already fulfilled its obligations. While pre-settlement exposure amounts just to the net value of obligations, settlement risk (for the first party to pay out) comprises the full amount of obligations.[170] Jorion states that:

> "Credit risk is controlled by credit limits on notionals, current and potential exposures, and increasingly, credit enhancement features such as requiring collateral or marking to market."[171]

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[167] Cf. Jorion (2007), p. 24; Crouhy et al. (2001), p. 35.

[168] Cf. Jorion (2007), pp. 24-25; Crouhy et al. (2001), p. 35.

[169] Cf. Fight (2004), pp. 145-161, for country, sovereign and political risk; cf. Jorion (2007), p. 25, for a very brief description of sovereign risk.

[170] Cf. Fight (2004), pp. 165-166; Jorion (2007), p. 25.

[171] Jorion (2007), p. 25.

5.1.3 Liquidity Risk[172]

Liquidity risk can be sub-divided into funding liquidity risk and asset liquidity risk.[173] Asset liquidity risk designates the exposure to loss consequent upon being unable to effect a transaction at current market prices due to either relative position size or a temporary drying up of markets. Having to sell in such circumstances can result in significant losses. Funding liquidity risk designates the exposure to loss if an institution is unable to meet its cash needs. This can create various problems, such as failure to meet margin calls or capital withdrawal requests, comply with collateral requirements or achieve roll over of debt. These problems may force an institution to liquidate assets; in such a case, asset liquidity and funding liquidity risks may combine if the institution is forced to sell illiquid assets at fire-sale prices. In such a situation, if portfolio leverage is high, the forced selling may create a positive feedback loop between falling prices (resulting in margin calls) and additional rounds of forced selling.[174] Liquidity risk is managed through controlling concentrations and relative market sizes of portfolios in the case of asset liquidity risk, and through diversification, securing credit lines or other back-up funding, and limiting cash-flow gaps in the case of funding liquidity risk.[175]

5.1.4 Operational Risk

The Basel II Framework, in § 644, offers the following concise definition of operational risk:

> "Operational risk is defined as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk."[176]

The category of operational risk is a more recent arrival on the stage of financial risk management than the previously detailed categories. It was only in the

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[172] This paragraph draws on Jorion (2007), p. 23; Crouhy et al. (2001), p. 36.

[173] Cf. ibid.: Other terms offered in the two aforementioned sources for asset liquidity risk are market/product liquidity risk (Jorion) or trading-related liquidity risk (Crouhy et al.). Funding liquidity risk is also referred to as cash-flow risk (Jorion).

[174] Cf. ibid.

[175] Cf. Jorion (2007), p. 23.

[176] Bank for International Settlements (2006), p. 144.

1990s that the term gained prominence and wide acceptance in financial risk management discourses.[177] The late arrival of operational risk might have been connected to the fact that it does not refer to an immediately obvious category.[178] Rather, and more so than the other risk categories, it is an evidently construed risk. It was introduced to enable the focusing of management attention on a broad set of diverse and thus before arguably somewhat unseen or neglected risks.[179] Power writes:

> "Operational risk was conceived as a composite term for a wide variety of organizational and behavioural risk issues which were traditionally excluded from formal definitions of market and credit risk. The explosion of operational risk discourse gave new structure and rationality to what had traditionally been regarded as a risk management residual and negatively described as non-financial risk."[180]

These risks include human error and fraud (failure of people), model risk, inadequate controls and systems (failure of internal processes) as well as business and system disruptions caused by external events; a selection of these risks is listed in Table 2. The last significant component of operational risk is legal risk. Legal risk covers potential damage resulting from litigation, from settling a case out of court, or from changes to specific laws.[181]

Table 2: Various Subcategories of Operational Risk

1. People risk:	Incompetency Fraud
2. Process risk:	
A. Model risk	Model/methodology error Mark-to-model error
B. Transaction risk	Execution error Product complexity Booking error Documentation/contract risk
C. Operational control risk	Exceeding limits Security risks Volume risk
3. Technology risk:	System failure Programming error Infromation risk Telecommunications failure

Source: Adapted from Crouhy et al. (2001), p. 487.

177 Cf. Power (2007), p. 103.

178 Cf. ibid, p. 125.

179 Cf. ibid., pp. 124-25.

180 Ibid., p. 103.

181 Cf. Jorion (2007), pp. 26-27, pp. 518-519; Crouhy et al. (2001), pp. 37-38, p. 487.

The inclusion in the operational risk category of model risk and exposure to losses due to inadequate controls and systems evinces that operational risk can be a result of imperfect or failed risk management. This was very likely an additional reason why it was conceptualized later than the other risk categories. The main ways to address operational risk involve adding resiliency to the institution through contingency planning, adding system redundancies, strict separation of different functional roles (such as front-office, middle-office, and back-office), and the setting up of effective control systems.[182]

5.1.5 Other Categories of Risk

Various other categories of risk can be enumerated, some of the most significant of which are reputational risk and strategic risk. Reputational risk refers to exposure to losses stemming from reputational impairment.[183] The reduced reputation may be due to perceived incompetence, negligence or misconduct of the institution. In section 2.2.1.2, for instance, Bankers Trust was mentioned to have incurred severe reputational damage after being accused mis-selling derivatives. Strategic risk refers to potential losses deriving from top-management's strategic choices.[184]

5.2 Risk Measurement Methodologies

Having defined the various risk categories (and their subdivisions), the next step is to choose an appropriate model-based method that will then be used, in the final step, to generate measurements of the specific risks. The chosen methods specify which risk factors and risk exposures need to be captured and quantified to serve as inputs for the final calculations. Table 3 illustrates the factors and exposures that need be captured if, for instance, various VaR methods for market, credit or operational risk or expected loss methods for credit and operational risk are chosen.

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[182] Cf.Jorion (2007), p. 27.

[183] Cf. ibid., p. 495.

[184] Cf. ibid., p. 517.

Table 3: Steps in Measuring Financial Risk

Steps	Market Risk	Credit Risk	Operational Risk
1. Define risk categories	Interest rate Equity Currency Commodity	Default Downgrade	Processes People Systems External events
2. Choose method	Market VaR	Credit VaR Expected loss	Operational VaR Expected loss
Measure risk factors	Volatility Correlations	Default and recovery distributions	Loss frequency
Measure exposure	Duration Delta Mapping	Current and potential exposure	Loss severity
3. Generate Measurements (by applying method)			

Source: Adapted from: Jorion (2007), p. 497.

In the remainder of section 5, the most important risk measurement methods and tools (except those already introduced in section 3.2) are described in historical order; see Table 4 for a timeline. The risk factors and risk exposures required by the methods are also referred to but are not a focal point.

Table 4: The Evolution in Risk Measurement

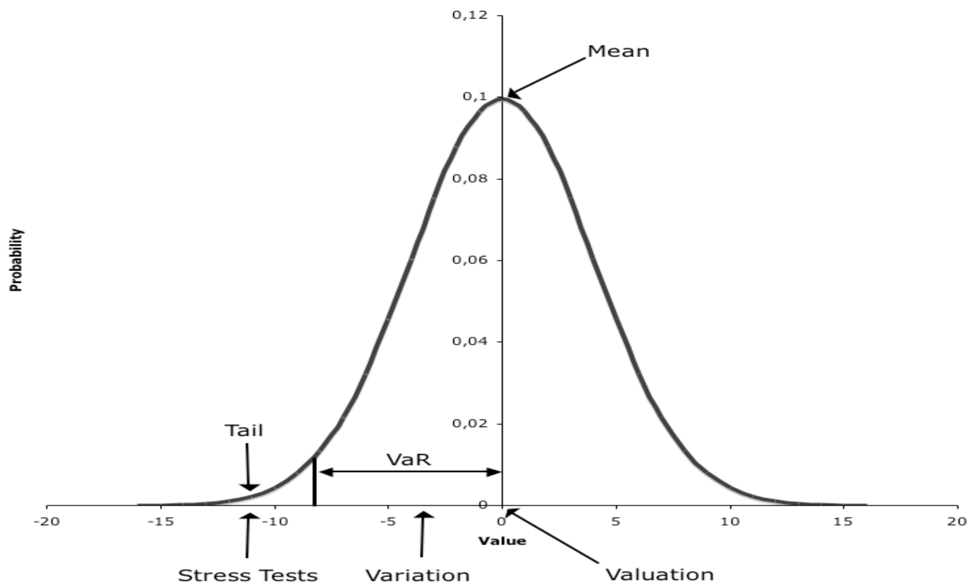
Year	Risk Measurement Methods and Tools
1938	Bond duration
1952	Markowitz mean-variance framework
1963	Sharpe's single-factor beta model
1966	Multi-factor models
1973	Black-Scholes option-pricing model, "Greeks"
1983	RAROC, risk-adjusted return
1986	Limits on exposure by duration bucket
1988	Limits on "Greeks"
1992	Stress testing
1993	Value-at-Risk (VaR)
1994	RiskMetrics
1997	CreditMetrics
1998-	Integration of credit and market risk
2000-	Enterprise risk management

Source: Adapted from: Jorion (2007), p. 16.

5.2.1 Measure What?

Choosing a risk measurement method presupposes entertaining some specific purpose and a notion of what to do with the results. In other words, a specific method is chosen because one desires to acquire knowledge about a certain aspect of reality and because there is some reasoned belief that the chosen method will produce this knowledge. Figure 6 illustrates the idea of how different interests in respect to an instrument's profit and loss distribution bring about the use of different models and methods. Classical (risk-neutral) valuation methods focus predominantly on the expected mean. An interest in ordinary payoff variations, i.e. high frequency, low impact risk, may lead to using a VaR method. An interest in extreme, worst-case payoff scenarios, i.e. low frequency, high impact risk, may prompt the conduct of stress tests. In short, the different methods shine their spotlight on different aspects of reality and no single method can deliver the full picture.[185]

Figure 6: Focusing on different Parts of the (Profit and Loss) Distribution



Source: Adapted from Jorion (2007), p. 21.

5.2.2 Notionals

Historically, financial institutions' (market) risk management efforts were initially focused on notional values. Figure 7 depicts the evolution of risk measures used. In the first step, measuring and limiting individual desk's/trader's notional amounts of exposure dominated risk management. With notionals in the spotlight, this approach disregards price correlations of positions, volatilities of prices, and whether positions are long or short. Summing long and short notional exposures or disregarding correlations may lead to significantly overstated portfolio risk. Also, for many derivatives the notional value is significantly different from their market value, i.e., replacement cost.[186]

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[185] Cf. Jorion (2007), pp. 20-21.

[186] Cf. Crouhy et al. (2001), pp. 179-182.

Figure 7: Increase of Sophistication in (Market) Risk Management

Source: Adapted from Crouhy et al. (2001), p. 180.

5.2.3 Factor Sensitivity Measures[187]

Later, risk management made increasing use of "factor sensitivity measures"[188] such as duration (bonds) or the "Greeks" (derivatives). Duration has long been used to measure the exposure of fixed-income instruments to interest rate risk. It gives approximate, first-order, exposures for parallel shifts of the yield curve; risks besides interest rate risks are disregarded.[189] In the derivatives markets, the so-called "Greeks" refer to the various factor sensitivities of derivative prices. For instance, delta measures the response (in the derivative's value) to a small change in the price of the underlying; gamma in turn measures the response of delta to a small change in price of the underlying; vega gives the effect of a small change in the price volatility of the underlying, and so on.[190] Unfortunately, since the individual Greeks cannot be summed and are not additive across different markets, the Greeks cannot provide the institution with a measure for its total (portfolio) risk. The same reasoning suggests a limited effectiveness of position limits based on the Greeks. Finally, the Greeks apply to small changes in the various risk factors only and relying on them presupposes that dynamic hedging is possible; i.e., the risks of drastic market moves and liquidity holes must in that case be disregarded.[191]

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[187] This paragraph draws on Crouhy et al. (2001), pp. 182-187.

[188] Ibid., p. 182.

[189] Cf. Dowd (2002), p. 4.

[190] For a fuller impression of risk and derivatives see Hull (2005), for a comprehensive and academic treatment, or Taleb (1997a), for a practitioner perspective.

[191] Cf. Dowd (2002), p. 7.

5.2.4 Value at Risk

Below VaR is presented in considerable detail, reflecting the central position of the methodology in current financial risk management.

5.2.4.1 The Rise of VaR

The next, highly significant, step for modern financial risk management was taken when J. P. Morgan announced its newly-developed VaR methodology in 1993, and then in 1994 made RiskMetrics™, a stripped-down version of it, freely available to the public.[192] The ensuing developments in risk management can be referred to as "a revolution"[193] that "… is totally changing the way institutions approach their financial risk"[194]. While VaR was originally developed for the measurement of market risk, the methodology has proved its wider versatility. Its range has expanded greatly to now cover other categories of risk from credit risk over operational risk to liquidity risk, and, maybe most importantly, total firm risk.[195]

There are a number of reasons for the rapid rise of VaR in financial risk management. They centre on the fact that VaR methodologies deliver "… a single, summary, statistical measure of possible portfolio losses"[196] in "normal" market environments.[197] In other words, VaR methodologies promise to facilitate the comprehensive aggregation of risks across instruments, markets and risk factors that eluded the previous notional or factor sensitivity-based methodologies. VaR allows institutions to aggregate risks at the desired level because "… it provides a *common* consistent measure of risk across different positions and risk factors"[198] and because "… it takes account of the

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[192] Cf. Dowd (2002), pp. 8-9.; also, Allen et al. (2004), p. 2: "Part of the reason leading to the widespread adoption of VaR was the decision of JP Morgan to create a transparent VaR measurement model, called RiskMetrics™"

[193] Jorion (2007), p. vii.

[194] Ibid.s

[195] Cf., for instance, ibid., pp. 27-28.

[196] Linsmeier/Pearson (1996), p. 3, (quoted in Dowd (2002), p. 10).

[197] Cf. Ibid.

[198] Dowd (2002), p. 10; emphasis original.

correlations between different risk factors”[199]. According to Dowd, VaR can be put to many uses, including (1) the setting of (overall firm as well as lower-level) risk targets by top-management, (2) the determination of capital allocation and capital requirements at the various levels, (3) the official disclosure of firm risks, (4) the comparison of portfolio risk implications of potential investments, (5) the implementation of “portfolio-wide hedging strategies”[200], and (6) the assessment and remuneration of employees on a risk-adjusted basis.[201] Dowd summarizes:

> “In short, VaR can help provide for a more consistent and integrated approach to the management of different risks, leading also to greater risk transparency and disclosure, and better strategic management.”[202]

5.2.4.2 Definition

“Value at risk (VAR) is a statistical measure of downside risk based on current positions”[203] and, for a given position, can be defined as “… *the worst loss over a target horizon such that there is a low, prespecified probability that the actual loss will be larger*”[204]. In a different wording, “… VaR is the distance of the first [or otherwise specified; note of the author] percentile from the mean of the [forward; note of the author] distribution”[205]. This definition includes two parameters that need to be chosen based on specific circumstances (e.g., regulatory requirements[206]), a holding period or target horizon, and a prespecified probability or confidence level.

In the below example[207], depicted by Figure 8, the target horizon is set (in step three) at ten (trading) days, and the relevant confidence level is set (in step four) at 99% which for normal distributions translates into a multiplicative factor of 2.33. Besides these two parameters, the current position needs to be marked

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[199] Dowd (2002), p. 10..

[200] Ibid., p.11.

[201] Cf. ibid., pp. 10-11.

[202] Ibid., p. 11.

[203] Jorion (2007), p. 105.

[204] Ibd., p. 106; emphasis original.

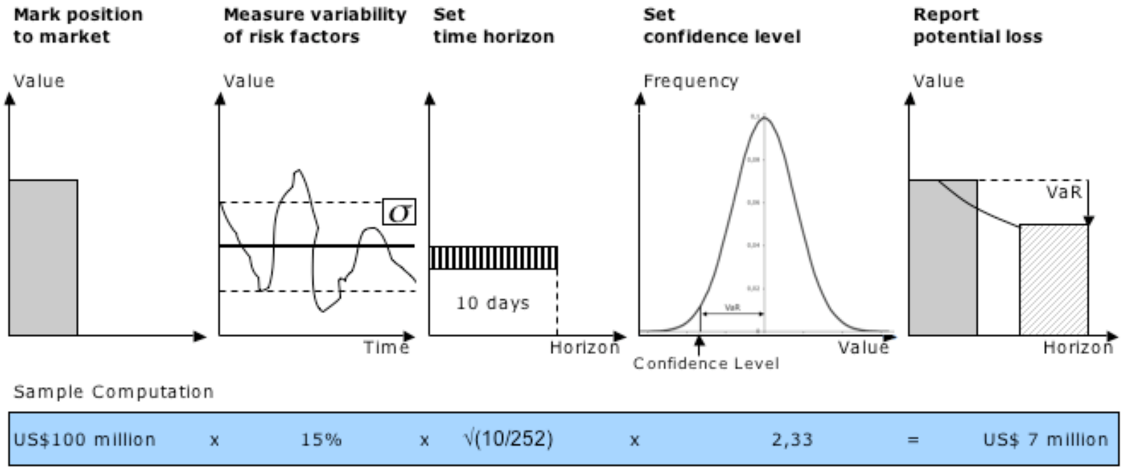
[205] Crouhy et al. (2001), p. 189.

[206] Cf.ibid., p. 187.

[207] Both the example and Figure 8 are based on Jorion (2007), p. 107.

to market (i.e., step one: here US$100 million). Also, the risk factor's (in this case annualized) standard deviation needs to be determined (i.e., step two: here assumed to be 15%). In step five, the VaR can be computed.

Figure 8: How to compute VaR



Source: Adapted from Jorion (2007), p. 107.

As is suggested by the above example, VaR increases with the target horizon. Also, VaR figure tends to increase with the specified confidence level because a point farther out in the left tail of the distribution is specified.[208] It should further be noted that, unless the true underlying (forward) distribution is positively known, VaR is to be considered as "… an *estimator*, or function of the observed data"[209]. For this reason, VaR numbers' precision should not be overstated.[210] Finally, VaR does, expressly, neither indicate the worst loss possible[211] nor inform about "… the extent of average losses that exceed VAR"[212]. The problematic aspects of the use of VaR for risk management purposes are developed below in section 6.1.2.3. For now, it suffices to repeat, that VaR promises a simple, easy-to-derive statistical measure that, for the first time, allows aggregation of risks at the level of the whole firm.[213]

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[208] Cf. Dowd (2002), p. 23.

[209] Jorion (2007), p. 106; emphasis original.

[210] Cf. ibid., p. 106, p. 123.

[211] Cf., for instance, Crouhy et al. (2001), p. 187.

[212] Jorion (2007), p. 135.

[213] At this point, it should also be briefly mentioned that there exist a number of VaR tools, including component, incremental, and marginal VaR, that can help to actively manage portfolio risk; cf. Jorion (2007), pp. 166-175.

5.2.4.3 Deriving VaR

Since VaR refers to a (forward distribution) quantile, determining that distribution (and its parameters) is a crucial issue. Depending on the methodological decision made at this point, one speaks of either nonparametric, parametric or Monte Carlo VaR.

5.2.4.3.1 Nonparametric VaR

In the nonparametric approach to VaR, no parameters of the forward distribution are estimated or assumed from theoretical reasoning. Instead, the distribution is simulated from (recent) empirical returns data. Historical simulation is the main example of a nonparametric VaR method. [214] In historical simulation, first a sample period is selected in which each (daily, monthly, etc.) change in the values of risk factors is treated as one observation. Second, the actual to-be-simulated current portfolio is then revalued using the historical changes in the risk factors gathered in step one. Third, the resulting portfolio values are grouped in a histogram, the desired quantile of the distribution (thereby) determined, and the VaR read off.[215] In this basic historical simulation, each past observation has equal weight. However, good arguments can be made for more advanced approaches that assign different weights based, for instance, on the age of the observation or the volatility at the particular time the observation was made.[216]

While nonparametric approaches help one avoid having to presume a certain type of analytic (forward) distribution, the downside is that results are completely dependent on the sample period used. Fundamentally, nonparametric approaches rely on sufficient similarity of the future with the past.[217] Nonparametric approaches also make inefficient use of the historical

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[214] Cf. Dowd (2002), p. 57; Dowd, ibid., points out that "… we can also carry out non-parametric estimation using bootstrap methods, non-parametric density estimation methods (e.g., kernels), and principal components and factor analysis methods."

[215] Cf. Crouhy et al. (2001), pp. 206-211.

[216] Cf. Dowd (2002), pp. 65-71.

[217] Cf. ibid., pp. 72-73, p. 57.

data.[218] However, if sample periods are too long, they may contain data that has become irrelevant (as underlying conditions have changed).[219]

5.2.4.3.2 Parametric VaR

Parametric VaR approaches seek to estimate the parameters of the underlying distribution by fitting a distribution to the observed data.[220] Two of the main parametric approaches are based on the normal and the Student-t distributions respectively.[221] A theoretical argument based on the central limit theorem sometimes leads to the assumption of the normal distribution for portfolios. The central limit theorem is taken to imply that, even if their individual risk factors should exhibit leptokurtic distributions, well-diversified portfolios with independent risk factor returns are normally distributed.[222] Similarly, on the level of individual positions, the assumption of a multivariate normal distribution of returns is often made.[223] Once a (multivariate) normal distribution can be assumed, and its mean and variance have been derived, it becomes very easy to calculate the VaR at any desired confidence level.[224] There is, however, a general danger that this ease of derivation might prompt the adoption of the normal distribution where it is unwarranted. If normality is rejected, a Student-t distribution can be used to better accommodate leptokurtosis.[225] Besides by mean and variance, Student-t distributions are characterized by a "degrees of freedom"-parameter that determines tail-fatness.[226] Because of the fatter tails,

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[218] Cf. Allen et al. (2004), pp. 49-51; ibid, p. 50: "Nonparametric methods' precision hinges on large samples, and falls apart in small samples."

[219] Cf. Dowd (2002), p. 73; Allen et al. (2004), pp. 50-51.

[220] Cf. Allen et al. (2004), p. 48: "With parametric models we use all available data, weighted one way or another, in order to estimate parameters of a given distribution."

[221] Cf. Dowd (2002), pp. 77-104, for a fuller discussion of the various parametric approaches.

[222] Cf. Crouhy et al. (2001), p. 193; Dowd (2002), p. 82. The central limit theorem states, according to Crouhy et al. (2001), p. 193, "… that the independent random variables of well-behaved distribution will possess a mean that converges, in large samples, to a normal distribution." However, Dowd (2002), p. 82, notes that "… the central limit theorem applies only to the central mass of the density function, and not to its extremes."

[223] Cf. Dowd (2002), p. 96.

[224] Cf. Dowd (2002), pp. 78-82

[225] Cf. ibid., p. 82-84.

[226] Cf. Crouhy et al. (2001), pp. 193-194.

using Student-t distributions should result in higher VAR figures than using the normal distribution.[227]

The main advantage of parametric approaches is their efficient use of data and the great amount of information they can provide; the downside is that this information can be seriously wrong if based on mistaken parametric assumptions.[228]

5.2.4.3.3 Monte Carlo VaR

The so-called Monte Carlo method is a hybrid between analytic and simulation approaches, and, according to Jorion, "… by far the most *powerful method* to compute VAR"[229]. Jorion argues, for instance, that of the VaR approaches only the Monte Carlo method is able to cope with credit risk.[230] Instead of taking historical returns data (i.e., just one single, specific sample path[231]) as a starting point (as in historical simulation), Monte Carlo starts by estimating parametric distributions for the individual risk factors pertinent to the simulation. Next, (with the help of some random-number generator[232]) Monte Carlo generates simulated price paths for them. The resulting scenarios are used to fully valuate the to-be-simulated portfolio and to generate a returns distribution. From this distribution VaR can be derived at the desired confidence level.[233]

The main advantages of Monte Carlo are, first, that risk factors may have any (including fat-tailed or skewed) distribution and, second, that it is able to assess complex portfolios (e.g., portfolios including instruments, such as straddles[234], with nonlinear exposures to the risk factors).[235] The main disadvantages are, first, the method's implementation is costly with regard to time, computational requirements, and human capital, and, second, model risk is introduced by the

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[227] Cf. Crouhy et al. (2001), p. 194.

[228] Cf. Dowd (2002), p. 102.

[229] Jorion (2007), p. 266; emphasis original.

[230] Cf. ibid., pp. 267-268.

[231] Cf. ibid., p. 264.

[232] Cf. ibid., pp. 312-313.

[233] Cf., for instance, ibd., pp. 265-266.

[234] Cf. Allen et al. (2004), pp. 97-98.

[235] Cf. Jorion (2007), p. 266; Crouhy et al. (2001), p. 218.

need to estimate the distributions of risk factors that serve as inputs to the simulation.[236]

5.2.4.4 Applying VaR to Different Risk Categories

As previously mentioned, VaR systems are currently used to measure and manage not only market but also credit, operational, liquidity and enterprise risk. Below, particular applications to market and credit risk are outlined. It is, however, beyond this paper's scope to introduce individual liquidity or operational risk-related VaR systems.

5.2.4.4.1 VaR and Market Risk: RiskMetrics™

To detail one specific example of a market risk VaR system, elements of the original RiskMetrics™ methodology are described. The RiskMetrics™ methodology assumes "… that returns are distributed according to the conditional normal distribution"[237]. To facilitate calculation, RiskMetrics™ maps positions to selected representative instruments such as various fixed income buckets, equity indexes, and commodity volatility series. Volatilities and correlations are then expressed and estimated respectively with reference to "…exponentially weighted daily historical observations…"[238] adopting a decay factor of 0.94 in the case of trading and 0.97 in the case of investing.[239]

5.2.4.4.2 VaR and Credit Risk

This subsection reviews three different credit VaR systems: CreditMetrics™, the "contingent claim approach" of Moody's KMV, and CreditRisk+.[240] While

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[236] Cf. Jorion (2007), p. 267. Also, cf. Allen et al. (2004), p. 101: "… generating scenarios in simulation and claiming that their distribution is relevant going forward is as problematic as estimating past volatility and using it as a forecast for future volatility. Generating a larger number of simulations cannot remedy the problem."

[237] Cf. J.P. Morgan/Reuters (1996), p. 64.

[238] Ibid., p. 39.

[239] Cf. ibid.

[240] There are a number of other approaches, including the CreditPortfolio View and the Reduced-Form Approach. For these models see Crouhy et al. (2001), pp. 344-347 and pp. 411-421 respectively.

necessarily brief, the review should allow for some general impression of the systems' main characteristics; the systems are compared in Table 5.

Table 5: Characteristics of three Credit Risk Systems

	Credit Migration Approach	Contingent Claim Approach	Actuarial Approach
Software/System	CreditMetrics	Moody's KMV	CreditRisk+
Definition of risk	Δ Market value	Default losses	Default losses
Credit events	Downgrade/default	Continuous default probabilities	Default
Risk drivers	Asset values	Asset values	Expected default rates
Transition probabilities	Constant	Driven by: - Individual term structure of EDF - Asset value process	N/A
Correlation of credit events	Standard multivariate normal distribution (equity factor model)	Standard multivariate normal asset returns (asset factor model)	Conditional default probabilites function of common risk factors
Recovery rates	Random (beta distribution)	Random (beta distribution)	Loss given default deterministic
Numerical approach	Simulation/analytic	Analytic/simulation	Analytic

Source: Adapted from Crouhy et al. (2001), p. 426.

CreditMetrics™

Published by J. P. Morgan in 1997, CreditMetrics™ is a so-called credit migration approach to portfolio credit risk modelling; it "… models the full forward distribution of the values of any bond or loan portfolio, say one year forward, where the changes in values are related to credit mitigation only…"[241]. That is, all changes in credit value (resulting from defaults and ratings up or downgrades) are considered. It is a VaR system since the volatility of credit values, the VaR, is derived rather than just one expected loss figure.[242]

To compute diversification benefits and concentration risks at the portfolio level, CreditMetrics™ models the correlations in obligors' credit quality migrations "… on the joint probability of equity returns"[243].[244]

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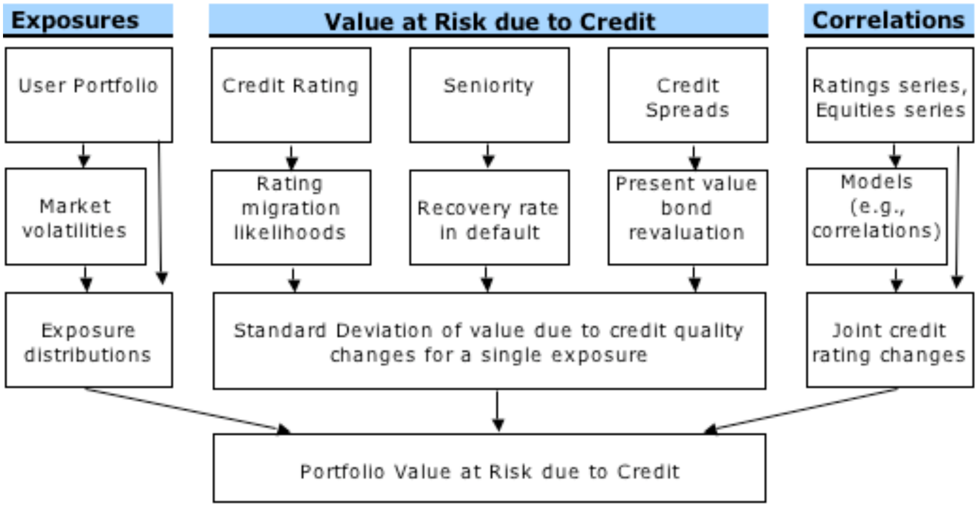
[241] Crouhy et al. (2001), p. 317.

[242] Cf. J. P. Morgan (1997), p. 5.; also, cf. Crouhy et al. (2001), pp. 315-355.

[243] Crouhy et al. (2001), p. 321.

[244] Cf. Crouhy et al. (2001), pp. 320-321.

Figure 9: The Components of CreditMetrics™



Source: Adapted from J. P. Morgan/Reuters (1997), p. 41.

Figure 9 displays the component parts of CreditMetrics™. To the left, the column beneath "Exposures" represents the individual steps of forward pricing the various credit ratings.[245] To the right, the column beneath "Correlations" represents the individual steps of deriving credit migration correlations; since these are unobservable, correlations of equity returns are used as a proxy.[246] The three columns beneath the heading "Value at Risk due to Credit" refer to the specification of a transition matrix, the specification of a horizon for credit (which is, usually, one year), the specification of model for forward pricing, and, finally, the derivation of the (one-year) VaR relating to single exposures.[247] At last, by integrating the inputs from the three sections, the "Portfolio Value at Risk due to Credit" can be derived as is graphically indicated in Figure 9.

Contingent Claim Approach of Moody's KMV

CreditMetrics™' weak point, according to Crouhy et al., is its "… reliance on ratings transition probabilities that are based on average historical frequencies of defaults and credit migration"[248]. Consequently, CreditMetrics™ does not

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[245] Cf. Crouhy et al. (2001), p. 343

[246] Cf. ibid. p. 342.

[247] Cf. ibid., pp. 321-330.

[248] Ibid., p. 357.

further differentiate credit quality within individual rating categories and assumes that the average of the past is a reliable guide to the future.[249]

Avoiding these weaknesses, structural models such as the contingent claim approach of Moody's KMV allow analyzing each credit on the merits of its specific features.[250] Based on Merton's option pricing approach to corporate debt[251], firm debts can be considered contingent claims backed by firm assets. If, at the maturity of debt, the value of firm assets is less than that of debt, the firm defaults. The contingent claim approach uses this framework to estimate the probability that a given obligor will default.[252] As Crouhy et al. describe the approach: "The probability of default is thus a function of the firm's capital structure, the volatility of the asset returns, and the current asset value."[253] Three steps are involved in determining default probabilities: First, volatility and market value of firm assets are estimated. Second, the so-called "distance to default" is computed. Third, "distance to default" is scaled (with reference to a default database) to the actual default probability.[254]

<u>CreditRisk+</u>

The last credit VaR methodology to be - very briefly - introduced is the actuarial CreditRisk+ model originally developed by Credit Suisse Financial Products. CreditRisk+ concerns itself exclusively with defaults. It is an actuarial model because it derives its default probabilities from "… historical statistical data of default experience by credit class"[255].[256]

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[249] Cf. Crouhy et al. (2001), p. 357; also, ibid.: "Indeed, these assumptions cannot be true since we know that default rates evolve continuously, while ratings are adjusted in a discrete fashion."

[250] Cf. ibid., p. 359.

[251] Cf. Merton (1974).

[252] Cf. Crouhy et al. (2001), p. 359.

[253] Ibid., p. 368.

[254] Cf. ibid., p. 369.

[255] Ibid., p. 403.

[256] Cf. ibid., pp. 403-404. For a little more detail, cf.ibid., p. 403: "Credit Risk+ assumes that the probability distribution for the number of defaults over any period of time follows a Poisson distribution. Under this assumption, CreditRisk+ produces the loss distribution of a bond or loan portfolio based on the individual default characteristics of each security and their pair-wise default correlations."

5.2.4.4.3 Operational Risk and VaR

As a prefatory remark it should be stated that "… operational risk management is still in its infancy"[257] and therefore very much in an ongoing process of development. One specific approach to operational VaR, the actuarial "loss-distribution approach", derives an (operational) loss distribution from observing loss frequency as well as loss severity distributions of risk events.[258] The main problem that arises here is with data collection.[259] As Jorion points out:

> "In practice, the database of operational losses must be built from both *internal data*, specific to the institution, and *external data*, from the experience of other firms."[260]

On the one hand, low impact/high frequency risk events should be amply represented in internal data. On the other hand, given that high impact/low frequency operational risk events often result in the demise of affected institutions, such events will usually not be represented at all in the data collected within the firm. Data on high impact/low frequency events needs to be taken from outside the firm, e.g. from industry data[261]. The most obvious difficulties that arise are that (1) not all significant operational losses may be reported due to reputational considerations of affected institutions, and (2) the losses reported in industry databases might reflect distinctly different firm environments and thus be inapplicable.[262]

5.2.5 Stress Testing and Scenario Analysis[263]

The role of stress testing is to provide information about an institution's exposure to the extraordinary (i.e., tail losses at higher confidence levels than those pre-specified by the VaR systems) or the unprecedented. To be more specific, stress testing can help to assess vulnerabilities to correlation

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[257] Jorion (2007), p. 491.

[258] Cf. ibid., pp. 498-501.

[259] Cf. ibid., p. 501.

[260] Ibid.,; emphasis original.

[261] Examples of operational loss databases are *SAS OpRisk* or *Fitch Risk/OpVantage*; cf. ibid., p. 502.

[262] Cf. ibid., pp. 501-502.

[263] This whole paragraph draws on Dowd (2002), pp. 201-216.

breakdown, liquidity holes, concentration risk, and macroeconomic risk. Stress testing can be divided into two broad forms: (1) Mechanical stressing of the various variables included in an institution's risk management methodologies to diagnose potential (mathematical) danger, and (2) scenario analysis where particular (historical or hypothetical), potentially harmful scenarios are specified and assessed in their impact. The main disadvantage of stress tests is that they, in contrast to VaR systems, do not assign probabilities to individual outcomes, which leaves it to the discretion of management to judge the significance of individual values or scenarios. Nevertheless, stress testing can be regarded as "a natural complement" [264] to VaR systems and it is, in fact, "… required by the Basel Committee as one of seven conditions to be satisfied to use internal models"[265]. Although stress testing must remain somewhat arbitrary, its contribution is to help risk management become aware of weak points in existing probability-based analysis.

5.2.6 The Rise of ERM and the CRO

In this final part of section 5, the progression of financial risk management towards enterprise risk management (ERM)[266] is delineated. As previously mentioned, VaR's province has been successively extended to cover additional categories of risk. As for ERM, Jorion puts forward that it represents "…an extension of the VAR approach, whose essence is centralization, to firmwide risks"[267]:

> "Like VAR, ERM considers aggregate risks, including market risk, credit risk, operational risk, and business risk. This integrated view brings powerful economies of scale. … Considerable cost savings can be achieved by hedging only *net* risks."[268]

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[264] Dowd (2002), p. 215.

[265] Jorion (2007), p. 357

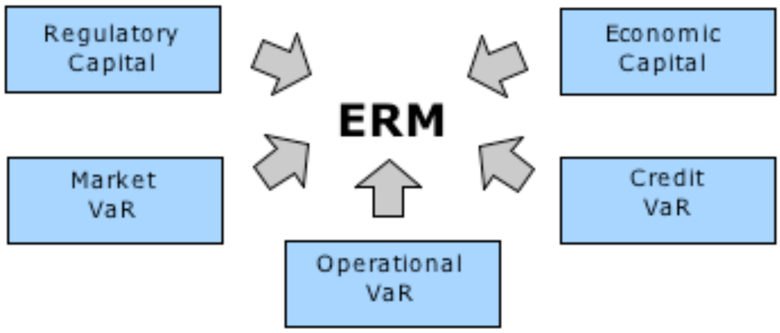
[266] Alternatively also referred to under the designations enterprisewide risk management, integrated risk management or firmwide risk management; cf. ibd:, p. 520.

[267] Ibid., p. 515.

[268] Ibid.; emphasis original.

ERM attempts to integrate the various individual risks, determine the necessary economic capital to support total firm risk and minimize (if this is a factor) the regulatory capital that needs to be held (see Figure 10). As also shown by Figure 10, the various VaR systems contribute directly to ERM. The purpose of ERM is to use knowledge acquired about all the risks faced by the institution to then improve the risk-return profile of the firm by selecting appropriate processes, strategies and positions (see Figure 11).

Figure 10: Elements ERM seeks to coordinate



Source: Adapted from Crouhy et al. (2001), p. 72.

Economic capital is the equity or risk capital the financial institution needs to set aside for unexpected losses.[269] At the firm level, these unexpected losses can be determined by integrating the various VaR measures into a total (firm) VaR figure. Due to diversification effects across the various risks[270], total VaR should be less than the sum of the various VaRs.[271] The remaining element in Figure 10 is regulatory capital. While a financial institution should want to hold enough economic capital to be able to withstand unexpected losses, it will however increase its profitability by minimizing regulatory capital it is required to hold (up to the point that regulatory capital is equal to, or less than, the figure for economic capital derived by the firm itself). If both internal risk assessment and regulatory practices were fully efficient, desired and prescribed levels of

[269] Cf. Jorion (2007), p. 404: "VAR can be viewed as a measure of *risk capital*, or economic capital required to support a financial activity."; emphasis original.

[270] Cf. ibid., p. 522: "Market risk has high volatility, zero skewness, and low excess kurtosis. This means that the distribution is broadly symmetric and does not have fat tails. Credit risk has negative skewness, reflecting losses from defaults, and higher kurtosis. Operational risk, in contrast, has low volatility but very high kurtosis, reflecting a very long left tail."

[271] Cf. ibid., pp. 523-524; and, ibid., p. 523: "A powerful implication of integrated risk management is that various types of financial risks diversify each other, which saves on economic capital. … This explains much of the consolidation we observe nowadays …".

economic/regulatory capital would coincide. Simplistic regulations or, possibly, the regulator's additional concern with (externalized) systemic risks and a possibly pre-emptive reaction to regulatory arbitrage or model failure may effect regulatory requirements at higher levels than those preferred by the firm. This in turn gives financial institutions the incentive to evade these requirements by what is referred to as regulatory arbitrage (see section 5.3). Under Basel II, regulators accept, subject to satisfactory back-testing and other conditions, proprietary internal risk models instead of the standardized general models for determining regulatory capital.[272] This is intended to make regulatory capital requirements more sensitive to the economic capital measures derived by the firms themselves. It is also both meant to take away some of the incentives for regulatory arbitrage and to encourage firms to establish powerful risk management functions (see section 5.3).

While, recently, the risk management function has been given a much more influential role, the financial industry is still in the process of transitioning to ERM. An international survey of 130 financial institutions representing assets of nearly US$21 trillion, conducted by Deloitte, found that:

> "Despite the high priority accorded risk management, however, most institutions do not yet effectively manage the full range of risks, and have not yet created an ERM program to achieve a comprehensive approach to risk management."[273]

Table 6 shows a few of the survey's results: For instance, in 2006, at 70% of institutions, risk management oversight responsibility was at the highest level (i.e., the board of directors); 84% of institutions had a CRO (usually reporting directly to the CEO or to the board); 35% of institutions had an ERM system in place while at 32% one was being established.

Table 6: Survey Data on ERM and on the CRO Position

Year	Risk management responsibility with board of directors	CRO function exists	CRO reports to CEO	CEO reports to board	ERM (existing)	ERM (being established)
2006	70%	84%	42%	37%	35%	32%
2004	59%	81%				
2002	57%	65%				

Source of Data: Deloitte & Touche (2007), pp. 3-4.

[272] Cf. Jorion (2007), pp. 61-64, pp.148-151.

[273] Deloitte & Touche (2007), p. 6.

While there is thus still a lot of room for further development of institutional risk management, the increasing importance of "risk" in corporate governance[274] is, arguably, already well reflected in the results.

Figure 11 displays some of the successive elements that are combined in ERM systems. The least sophisticated, basic element involves monitoring, and identifying and avoiding (pre-specified) risks through "limit management". The next element is "risk analysis" which includes both the previously introduced VaR systems and stress testing. The next element, "RAROC" (Risk-adjusted Return on Capital), enables the derivation and allocation of required economic capital, the measurement of risk-adjusted performance and the appropriate pricing of risks.[275] Drawing on, and communicating, these basal elements, the CRO and other senior risk managers are ideally implicated in strategy setting at the top-management level. It should be noted in this context that: "The senior risk people spend most of their time in descriptivist, mapping and communication mode: Agents of governance cannot be embroiled in risk analytics"[276].

Figure 11: The Building Blocks of ERM

Source: Adapted from Crouhy et al. (2001), p. 98.

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[274] Cf., as well, Power (2007), pp. 84-85, where it is suggested that "CROs may in due course challenge the professional pre-eminence of the CFO with a risk-based concept of the organization…".

[275] Cf. Crouhy et al. (2001), pp. 98-99.

[276] Power (2007), p. 84.

5.3 Regulatory Framework

This section outlines the main developments in the regulatory environment of financial institutions. A concise overview is provided in Table 7.

Table 7: Important Steps in the Development of the Regulatory Framework

Date	Designation	Characteristics and Aim	Shortcomings
Before 1988		Varying minimum capital ratios and standards	Arbitrary; internationally unequal
1988 (implemented 1992)	The 1988 BIS Accord ("Basel I")	Introduction of credit risk capital charge. Capital adequacy requirements: 1) Asset–capital multiple must be < 20 2) Cooke Ratio (introduced risk-weighing of assets)	Not differentiated enough; gave rise to regulatory arbitrage; neglect of market risk, operational risk and liquidity risk
1993	G-30 Report "Derivatives: Practices and Principles"	24 policy recommendations on how to (risk) manage derivatives (and market risk in general)	Just a recommendation not a regulatory document
1996	1996 Amendment ("BIS 1998")	Introduction of risk-based capital charge for market risks	Did not integrate different categories of risk
1998	FAS 133	Requires fair value accounting of derivatives on balance sheet	
1998	IAS 39	Requires marking-to-market of financial assets and liabilities	
2004 (implemented in EU with start of 2007 and 2008 respectively)	Basel II	Three pillars approach; Introduces capital charge for operational risk; Allows various approaches to measure risk categories	1) No diversification across risk categories assumed 2) No internal modelling of credit risk diversification allowed 3) Existence of "unrated" credit risk bucket

Source: This table draws on Hull (2007), pp. 165-194; Crouhy et al. (2001), pp. 45-96; Jorion (2007), pp. 42-65; Allen et al. (2004), p. 219.

Before the BIS Accord of 1988 ("Basel I"), regulatory bodies in different countries stipulated varying, but risk-insensitive, minimum capital ratios for banks.[277] Basel I represented a first effort at harmonizing international minimum capital standards and concerned itself mainly with credit risk. It followed a two-pronged approach: (1) It prescribed that banks' asset/capital multiple must not exceed 20. (2) It introduced the Cooke ratio (a measure based on risk-weighing assets on and off the balance sheet) for total institutional credit exposure.[278] The assigning of risk weights to credits, albeit imprecise and general, made the regulation more sensitive to the risks of individual firms. Nevertheless, the approach was overly simplistic, and risk categories other than credit risk (such as market risk, operational risk, liquidity risk, etc.) were entirely neglected in

[277] Cf. Hull (2007), p. 168; Crouhy et al. (2001), p. 46.

[278] Cf., for instance, Hull (2007), pp. 169-172; The minimum capital stipulated by Basel I was 8% of risk-weighted assets, cf. for instance, Jorion (2007), p. 55.

setting the Basel I standards.[279] According to Jorion, "This has led to *regulatory arbitrage*, which generally can be defined as a transaction that exploits inconsistencies in regulatory requirements"[280].

The 1993 Group of Thirty (G-30) report "Derivatives: Practices and Principles", with its 24 recommendations, summarized the then experience of the financial industry with managing (derivatives) market risk. It recommended marking positions to market and the use of VaR methods to measure financial risks.[281]

The 1996 Amendment of Basel I ("BIS 1998") introduced a capital charge for market risk (for all trading book assets).[282] Thus, capital to be held was further sensitised to actual risk.

Introduced in 1998, the accounting standards FAS 133 and IAS 39 were intended to create more transparency by forcing financial institutions to report their derivatives (FAS 133) or, more broadly, financial assets/liabilities (IAS 39) at fair (i.e., market) value.[283]

Basel II, published in 2004 and currently internationally in various stages of implementation, adopts a "three pillars" approach as can be seen in Figure 12. The first pillar, "minimum capital requirements", now includes capital charges for credit risk, market risk and operational risk.[284] For each risk category, different approaches, including internal ones, are allowed to determine risk charges.[285] Thus, financial institutions are given an incentive to develop sophisticated

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[279] Cf., for instance, Jorion (2007), p. 53, p. 56.

[280] Cf, for instance, ibid., p. 56; emphasis original.

[281] Cf. Crouhy et al. (2001), pp. 48-51; Jorion (2007), pp. 42-43.

[282] Cf. for instance, Hull (2007), p. 176-168.

[283] Cf. Jorion (2007), pp. 44-45.

[284] Cf., for instance, ibid., p. 58. The total risk charge is simply the sum of the credit, market, and operational risk charges, cf. ibid.

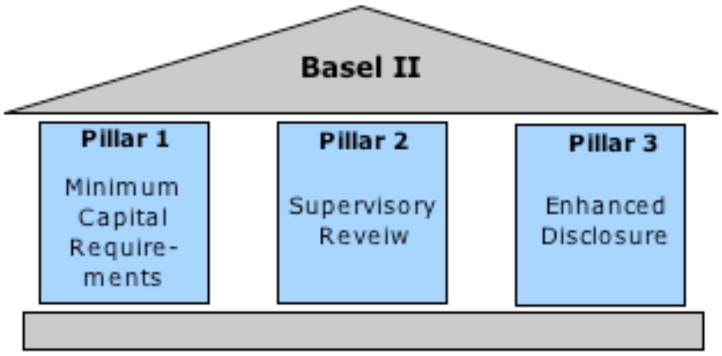
[285] To give some impression of Basel II, two short examples relating to market and credit risk stipulations follow:

(a) If the Internal-Models Approach is used, the market risk charge is determined in two steps: 1) The 10-trading day 99th percentile VaR is computed from a minimum of one year of data, 2) The market risk charge is whichever is higher – either the VaR of step one or the moving 60-trading day VaR average multiplied by a specified multiplicative factor (which, although dependent on circumstances, is at least 3). (Cf. Jorion (2007), pp. 61-63.)

(b) When it comes to the credit risk charge, banks are required "… to hold sufficient tier 1 and tier 2 capital to cover unexpected losses over a 1-year horizon at the 99.9 percent confidence level"." (Jorion (2007), p. 475.).

internal risk measurement and management capabilities.[286] The second pillar, "supervisory review", assigns regulators increased responsibilities. They are to safeguard that institutions observe minimum capital ratios, possess adequate risk management systems, and that any problems are quickly rectified.[287] The third pillar, "enhanced disclosure", is intended to give financial institutions incentives to manage risks prudently by encouraging disclosure of risk exposures and risk management systems and policies.[288]

Figure 12: The Basel II Framework



Source: Adapted from Bundesbank (2007).

6. The Risks of Financial Risk Management

Previous sections have described the risks which risk management is intended to address and the methods employed. This section advances one further step and explores the very risks that are created by (the models, processes and actions of) financial risk management. These risks refer to all the possibilities where risk management can fail. If the institution is relying on its risk management to function properly, these instances constitute new risks. Most broadly these risks can be designated as model risks; i.e., they arise not from the underlying phenomena themselves but from institutional model-based perceptions of and reactions to such phenomena. Generally speaking, model risk is a subtype of operational risk (see section 5.1.4).

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286 Cf., for instance, Jorion (2007), p. 62; in particular, ibid: "In fact, the market-risk charge generated by the internal VAR-based models approach is routinely much lower than the standardized risk charge."

287 Cf. ibid., p. 58.

288 Cf. ibid.; Hull (2007), pp. 190-191.

6.1 Model Risk

Model risk refers to risk that arises from the use of specific models. Models abstract from (an imperfectly known or even essentially unknowable) reality by isolating assumed key variables and then imputing cause and effect relationships between them. Therefore, any model is but the attempted reconstruction of reality from a specific vantage point. Occasionally, however, the successful track record of a model might tempt one to disregard that:

> "… even the finest model is only a model of the phenomena, not the real thing. A model is just a toy, though occasionally a very good one, in which case people call it a theory. A good scientific toy can't do everything and shouldn't even try to be totally realistic."[289]

Excessive reliance onto models will then translate into striking statements that, for instance, may speak of the firm's hedge funds being exposed to "… 25-standard deviation moves, several days in a row …"[290] (Goldman's CFO David Viniar in 2007). In fact, many statements could be cited that lament some financial institution's victimization by some unimaginable freak event or "perfect storm". Unless one were prepared to entertain that improbable events worthy of multiple (billion) lifetimes of the universe have in fact occurred within the last century, these kind of statements betray that the models of financial institutions (and financial theory) are at least occasionally unreliable.[291] In particular, they seem to grossly underestimate the probability of "extraordinary" events.[292]

Model unreliability might be due to two main factors. First, many models might just not be very good, for instance, due to technological and methodological imperfections. Second, risk management itself has been suggested to change (market) reality in a way that makes extreme events more likely by changing

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289 Derman (2003), p. 133.

290 Viniar, quoted in Khandani/Lo (2007), p. 2.

291 A more cynical approach would be to dismiss such statements as feebly concocted excuses that invariably follow large losses but bear no relation to the actual models and risk assessments used. This is not suggested here as a general approach.

292 Cf., for incstance, Jackwerth/Rubinstein (1996), pp. 1611-1612: "Take for example the stock market crash of October 1987. Following the standard paradigm, assume that stock market returns are lognormally distributed with an annualized volatility of 20% (near its historical realization). On October 19, 1987, the two month S&P 500 futures price fell 29 percent. Under the lognormal hypothesis, this is a -27 standard deviation event with probability 10^{-160}, which is virtually impossible."

exogenous risk into endogenous risk. Daníelsson, for instance, asserts, “Risk is not the separate exogenous stochastic variable assumed by most risk models; risk modelling affects the distribution of risk”[293]. This would be a more fundamental flaw than just simple model imperfection, since risk management would prepare one for exogenous risk while thereby creating vulnerability to far more serious endogenous risks. There have also been charges that risk management is less than fully scientific.[294] In fact, argues Danielsson, “To have numbers seems to be more important than whether the numbers are reliable”[295].

In the following, drawing directly on the typology and some of the arguments suggested by Derman, the different types of model risk are examined.[296] Section 6.1.1 introduces the limits of modelling from an epistemological perspective. Section 6.1.2 details some respects in which individual, previously presented risk (measurement) models, from mean-variance optimization over VaR to stress testing, may be deemed incorrect. Section 6.1.3 briefly refers to the danger of making mistakes while using a correct model. Finally, in 6.1.4 the risk of mis-applying models is explored in some detail. This overview of model risks suggests that model risk is a serious issue for financial risk management and that no undue reliance should be put on the results of any single risk model.

6.1.1 Inapplicability of Modelling

The most elementary type of model risk is to apply models where there is no meaningful way to do this. Some things simply cannot be known. Essential (Knightian) uncertainty cannot be reduced to quantifiable and thus tractable risk. A model might however make Knightian uncertainty appear as if it was quantifiable risk. In such instances having any model at all and relying on it

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[293] Danielsson (2001), p. 5.

[294] Cf. Taleb (1997b); Danielsson (2008).

[295] Danielsson (2008), p. 1.

[296] Derman (2003), pp. 134-136, divides model risk into: 1) Inapplicability of Modeling, 2) Incorrect Model, 3) Correct Model, Incorrect Solution, and 4) Correct Model, Inappropriate Use. These designations are borrowed in the following from Derman and adopted as section headings.

becomes a risk. In Derman's words: "In terms of risk control, you're worse off thinking you have a model and relying on it than simply realizing there isn't one"[297].

6.1.1.1 Epistemological Issues

Epistemology is the theory of knowledge. It deals with the issues involved in knowledge acquisition and validation. Taleb[298] and Taleb/Pilpel[299] put forward that, in risk management, a greater focus ought to be put on basic epistemological problems lest dubious knowledge claims be accepted.
A grounding in epistemology ideally sensitises to the important distinctions between what has been termed knowns, known unknowns, and unknown unknowns. These were memorably referred to by then US Secretary of Defense Rumsfeld:

> "… there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns -- the ones we don't know we don't know."[300]

The discussion of the "two epistemological problems"[301] relating to (1) knowledge concerning small probabilities and (2) self-reference that are outlined in Taleb/Pilpel[302] intends to draw out some of the known unknowns that risk management has to deal with. In particular, it becomes evident that: "In risk management terms, the bigger the event the less we have a clue"[303].

Small Probabilities

The first problem, concerning the estimation of small probabilities, brings up "…the classical problem of induction: making bold claims about the unknown

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[297] Derman (2003), p. 134.

[298] Cf. Taleb (2007a).

[299] Cf. Taleb/Pilpel (2007).

[300] Rumsfeld (2002).

[301] Taleb/Pilpel (2007), p. 6.

[302] Cf. ibid.

[303] Ibid., p. 7.

based on assumed properties of the known"[304]. In risk management, rare catastrophic, or, more technically, low probability/high impact events are those of the most potential significance. As Taleb/Pilpel write, "What matters in life is the equation *probability x consequence*"[305]. In other words, if their consequences may be extreme or possibly unbounded, risk management cannot afford to dismiss or disregard low probability events. This rather obvious conclusion is where the problem begins. Taleb explains:

> "… (1) the smaller the probability, the larger we need the sample size to be in order to make inferences, and the smaller the probability, the higher the relative error in estimating this probability. (2) Yet in these domains, *the smaller the probability, the more consequential* the impact of the absolute probability error on the moments of the distribution."[306]

In other words, knowledge decreases with the severity and thus potential importance of an event. The only way to attempt to get around this problem is "… by assuming a priori a certain class of distributions"[307]. Making such a distributional assumption is what leads to self-reference, the second problem.

Self-Reference

The problem with assuming some specific distribution is that probability distributions cannot be directly observed. To "know" how much, or if, data is sufficient, a distribution needs to be assumed - for the same data from which one is supposed to know the type of distribution:[308]

> "If (1) one needs data to obtain a probability distribution to gauge knowledge about the future behavior of the distribution from its past results, and if, at the same time, (2) one needs a probability distribution to gauge data sufficiency and whether or not it is predictive outside its sample, then we are facing a severe regress loop. We do not know what weight to put on additional data."[309]

Los, in a similar vein, states that

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[304] Taleb (2007a), p. 198.

[305] Taleb/Pilpel (2007), p. 6, emphasis original.

[306] Taleb (2007a), p. 198; emphasis original.

[307] Ibid.

[308] Cf. ibid., p. 199.

[309] Ibid., p. 199.

> "… the very fact that we cannot completely know the extent of the universe from which the event is drawn precludes the use of probability measures in most of real life. Probability only plays a role in games that have completely predefined rules. Most real life situations are not like well-defined games. … It is pseudoscience to presume and predefine such probability distributions before the finite empirical data sets have been analysed."[310]

The result is that the "true" probability distribution of most financial time series must remain a known unknown. Ayache sums up the possible, and dispiriting, implications of such a recourse on epistemology for risk management:

> "…the general quantitative trend has been … to pursue the dream of the ultimate stochastic process and the ultimate management of risk. Taleb's *essential uncertainty* (or central problem of risk management) marks the end of that road. … His essential uncertainty acts as a roadblock against any knowledge claim we may make *about* the probability distribution. No past data can help us infer the parameters of the random generator. We may not even be in a position to assume that the random generator is of a certain general type. For all we know, the random generator my itself be randomly changing, etc., etc."[311]

Taleb, true to his argument, forcefully rejects current risk management models as being only good in sample (i.e., the known) but failing out of sample (i.e., the unknown). He advocates, the use of Mandelbrotian scale-free distributions to assess the vulnerability to unknown out-of-sample events:[312]

> "There is a logical asymmetry: a true fat-tailed distribution can camouflage as thin-tailed in small samples; the opposite is not true. … we use power laws as risk-management tools; they allow us to quantify sensitivity to left- and right-tail measurement errors and rank situations based on the full effect of the unseen. We can effectively get information about our vulnerability to the tails by varying the power-law exponent α and looking at the effect on the moments or the shortfall …"[313]

6.1.2 Incorrect Model

Although "… all models are ultimately incorrect"[314] and while some "… models that are theoretically flawed or inappropriate can sometimes produce very good

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[310] Los (2003), p. 12.

[311] Ayache (2004), p. 29; emphasis original. It should be noted that Ayache, in the quoted article, proposes a somewhat different approach and interpretation than does Taleb; cf. Ayache (2004).

[312] Cf. Taleb (2007a), pp. 198-199.

[313] Ibid., p. 199.

[314] Derman (2003), p. 134.

results …"[315], one part of model risk stems specifically from making incorrect methodological decisions in model building.

In section 6.1.2.1 a small sample of methodological issues and possible missteps is offered. The issue of having to model risk factors according to some probability distribution (which cannot be positively known, cf. section 6.1.1.1) can often lead to an incorrectly specified model. The following sections demonstrate in what respect various popular models can be regarded as incorrect. Section 6.1.2.2 treats mean-variance optimization. Section 6.1.2.3 looks at VaR. Section 6.1.2.4 is focused on EVT.

6.1.2.1 General Methodological Issues

Models can fail for many reasons. As Derman enumerates, one might (a) chose a one-factor model where a multi-factor model would be more appropriate, (b) confuse stochastic with deterministic variables, (c) pick an unsuitable distribution, (d) overlook correlations between certain factors, (e) use outdated or otherwise currently invalid assumptions, (f) use a theoretical model that assumes frictionless markets in actual markets, (g) use a correct model that relies on mistaken data estimates, and (h) continue using a previously correct model after the market context has changed.[316] Further problems may arise with complex models due to overfitting or overparameterization, which can lead to failure when market conditions experience some (slight) changes and also generally hinders understanding as to the proper range of application of a model.[317] The following paragraph expands exemplarily on one of the above methodological issues – the problem of picking a suitable distribution.

[315] Dowd (2002), p. 218. Dowd continues to mention "simple options pricing models" as an example; ibid.

[316] Cf. Derman (2003), pp. 134-135.

[317] Cf. Hull (2007), pp. 352-353.

Table 8: Distributions and Models

Distribution types		
Unconditional (time independent)	Infinite variance:	symmetric stable Paretian asymmetric stable Paretian
	Finite variance:	Normal Student-t Mixed diffusion jump Compound normal
Conditional (time dependent)	GARCH:	Normal Student-t
	Stochastic volatility	Normal Student-t Generalized error distribution

Source: Adapted from J.P.Morgan/Reuters (1996), p. 66.

Table 8 lists a number of distributions, grouped according to their characteristics. First, distributions are grouped according to whether they are to be used in models where volatility is assumed to be conditional/time dependent such as in the various GARCH or other stochastic volatility models, or in models where volatility is treated as unconditional/time independent and where variance is either assumed to be infinite or finite. Table 8 indicates that normal and Student-t distributions can be applied in a large variety of contexts. The largest conceptual departure is the category of infinite variance stable Paretian distributions. As Table 8 indicates, stable Paretian distributions[318] do not assume a convergent, finite second moment. This is an interesting property from an empirical perspective, given that:

> "Some empirical financial distributions, such as the rates of return of the S&P500 Index exhibit such non-existent, i.e., non-convergent volatilities. Their variances are not only nonstationary, they are essentially unpredictable!"[319]

Considering the ubiquitous role of volatility, starting with Markowitz, in risk measurement and management models, the factual non-existence of a finite second moment out of sample may be a potential source of model risk.[320] At

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[318] I.e., the truly fat-tailed distributions Taleb was quoted recommending for risk management purposes in section 6.1.1.1.

[319] Los (2003), p. 72.

[320] Cf. ibid., p. 72 and p. 85; also, ibid, p. 441: "There is no stochasticity involved in indefiniteness! Probability cannot be substituted for ignorance … In such a case it may not be prudent to base a risk measure, such as VaR on the computed standard deviation, since that standard deviations remains undefined over time."

any rate, the wide variety of distributions and models is itself indicative of the fact that picking a suitable distribution is not a trivial task.[321]

6.1.2.2 Problems with Mean-Variance Optimization

As previously mentioned, mean-variance optimization presupposes the normal distribution. Moreover, it also depends on the means and variances being computationally available and remaining stable over the considered (holding) period. It was just mentioned in the last paragraph that there might be an issue with variance at least for a number of time series. Additionally, also previously mentioned, investors' (portfolio) returns might not be normally distributed after all. In which case, higher moments such as skewness or kurtosis need to be factored in. There are a number of further issues. One issue is that "… mean-variance optimization is highly prone to error maximization because such procedures tend to overuse statistically estimated information and thereby magnify the impact of estimation errors"[322].

A different, fundamental, issue is however whether Markowitz-type mean-variance optimization will result in optimal results in the long run value of a leveraged portfolio. As can be seen from Figure 13, Markowitz's model of arithmetic mean-variance optimization does not point out an optimal level of leverage since the arithmetic mean increases proportionally when risk (variance) is added. Conversely, it has been argued that Henry A. Latané's portfolio strategy of geometric mean maximization points out "… an optimal level of leverage to maximize the growth rate of the investor's total portfolio"[323]; this level is the geometric mean maximizing level.[324] Also, a geometric mean maximizing strategy "… will never lead to acceptance of investment programs with a nonzero probability of total loss …"[325].[326]

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[321] Cf. Los (2003), p. 71: "The scientific debate – about what kind of distributions best represent financial time series – is not yet settled, and maybe never will."

[322] Weisman (2003), p. 263, (Footnote 1).

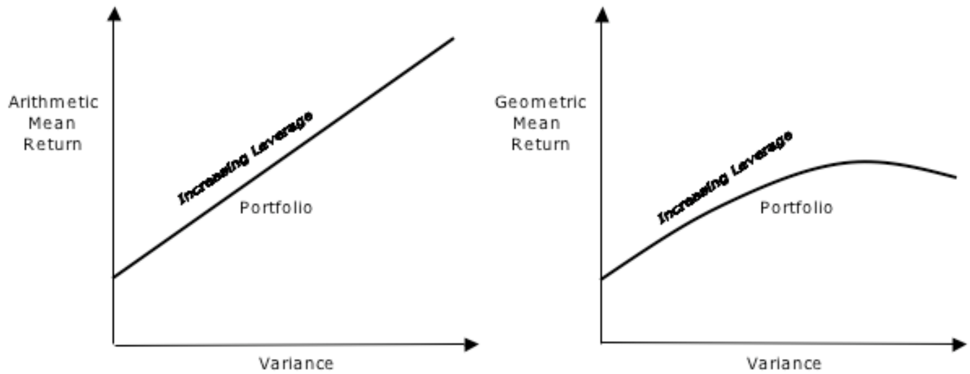
[323] McEnally (1998), p. 157.

[324] Cf. ibid; in particular, ibid., p. 157.

[325] Ibid., p. 158; the cause is that having to multiply by zero (after total loss) yields a geometric mean of zero, cf. ibid: 153: "… the product is always zero if one value in the series is zero."

[326] Cf. Ibid.

Figure 13: Arithmetic Mean vs. Geometric Mean Maximization



Source: Adapted from McEnally (1998), p. 157.

Nevertheless, it needs to be mentioned that various economists disparage geometric mean maximization.[327] In 1979, Paul Samuelson in fact expressed his annoyance by publishing an article "Why We Should Not Make Mean Log of Wealth Big Though Years to Act Are Long" in the *Journal of Banking and Finance* that contained, bar the final word, monosyllabic words only. His argument centred on the fact that superior performance is not guaranteed in every single case and that the approach might not necessarily be utility maximizing.[328]

6.1.2.3 Problems with VaR

There are a number of well-known problems with VaR systems. Dowd, for instance, reports "There is compelling evidence that model risk is a major problem for VaR models"[329]. Part of the model risk is due to some arguable "incorrectness" of the models, and part of the model risk is due to implementation issues and to what use VaR systems are put. In this section the emphasis is mainly on the former part; the latter part is discussed in later sections.

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[327] Cf., for instance, Samuelson (1971); Merton/Samuelson (1974).

[328] Cf. Samuelson (1979). His main points against geometric mean maximization in the paper are expressed as follows, on pp. 305-306: "When you lose – an you *sure can* lose – with *N* large, you can lose real big. … For *N* as large as one likes, your growth rate can well (and at times must) turn out to be less than mine – and turn out so much less that my tastes for risk will force me to shun your mode of play. To make *N* large will *not* (say it again, *not*) make me change my mind so as to tempt me to your mode of play."; emphasis original.

[329] Dowd (2006), p. 185.

The literature frequently refers to three seminal studies to show that different VaR models (or even different implementations of similar VaR models) may produce inconsistent results.[330] In the earliest of these studies, Beder applied eight common (either historical simulation or Monte Carlo-based) VaR methodologies to three hypothetical portfolios.[331] She found that

> "… the magnitude of the discrepancy among these methods is shocking, with VAR results varying by more than 14 times for the same portfolio. These results illustrate the VAR's extreme dependence on parameters, data, assumptions, and methodology."[332]

The second study, by Marshall/Siegel, showed that even within a single VaR model, implementation differences create significant variance in VaR results. In the study, vendors of RiskMetrics™-based VaR systems were supplied with identical test portfolios and datasets and asked to compute a number of specified VaR estimates. The resulting VaR estimates exhibited considerable variance that increased with asset class complexity. The most variance of VaR estimates resulted for "Interest Rate Options" with a standard deviation of 28%.[333]

In the third study, Berkowitz/O'Brian assess the accuracy of six U.S. commercial banks' VaR models.[334] They summarize: "Our findings indicate that banks' 99th percentile VaR forecasts tend to be conservative, and, for some banks, are highly inaccurate."[335].

Studies like the ones just mentioned suggest that considerable model risk is produced by a very high sensitivity of VaR results to VaR methodologies' specification or implementation details. To illustrate just how grave those risks can turn out, the near-collapse of LTCM in 1998 (see also section 2.2.2.1) may

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[330] Cf., for instance, Dowd (2006), pp. 185-186.

[331] Cf. Beder (1995).

[332] Ibid., p. 12.

[333] Cf. Marshall/Siegel (1996). It should be noted that Marshall/Siegel see themselves documenting "systems risk" rather than model risk in their paper. In the context of the present paper, the Marshall/Siegel paper is included at this point of the discussion to underline the sensitivity of VaR results. Also, irregardless what brings out different results in individual cases, the fact that VaR systems react so sensitively is an indication of a weakness in the model.

[334] Cf. Berkowitz/O'Brian (2002).

[335] Ibid., p. 1108.

serve as an object lesson. As can be gathered from Jorion[336], LTCM appears to have used a recent history-based VaR methodology; it is also suggested that LTCM aimed for a daily volatility of US$45 million in the late spring of 1998. Jorion calculates that assuming a daily standard deviation of US$45 million (which translates into a monthly standard deviation of US$206 million), LTCM's US$1,710 million losses in August 1998 constitute

> "… a 8.3 standard deviation event. Assuming a normal distribution, such an event would occur once every 800 trillion years, or 40.000 times the age of the universe."[337]

According to Jorion's estimates, the true daily volatility at the time might have been around US$100 million, in which case the August loss represented "… a 3.7 standard deviation event"[338]. Jorion continues, "Assuming now a distribution with fatter tails, such as the Student t(4), such an event should occur once every 8 years"[339]. Though brief and thus necessarily incomplete, this description - with the striking difference between either once every 8 years or once every 800 trillion years - is nevertheless suggestive of how sensitive VaR methodologies can be to estimation/calibration errors (daily volatility) and misspecification (probability distribution).

In fact, this evident potential to mislead the recipient of VaR reports has attracted sporadic instances of fierce criticism. In one of the early attacks on VaR, Taleb likened VaR to "charlatanism"[340] and argued that using (inherently unreliable) VaR models might be counterproductive in terms of risk reduction:[341]

> "You're worse off relying on misleading information than on not having any information at all. If you give a pilot an altimeter that is sometimes defective he will crash the plane. Give him nothing and he will look out the window."[342]

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[336] Cf. Jorion (2000), pp. 287-289; the following description relating to LTCM draws on this source.

[337] Ibid., p. 289.

[338] Ibid.

[339] Ibid.

[340] Taleb (1997b), no pagination.

[341] Cf. ibid.

[342] Ibid., no pagination.

The remainder of this section on model risk and VaR methods enumerates an assortment of relevant, but more technical, issues with VaR, and then mentions further types of risk connected with the use of VaR (which are more fully explored in later sections).

(1) Artzner et al. show that VaR is not an ideal risk measure. Specifically, they suggest two "… basic reasons to reject the value at risk measure of risks …"[343]:

> "(a) value at risk does not behave nicely with respect to the addition of risk, even independent ones, thereby creating severe aggregation problems.
> (b) the use of value at risk does not encourage and, indeed, sometimes prohibits diversification because value at risk does not take into account the economic consequences of the events, the probabilities of which it controls."[344]

The point referred to by (a) is that VaR does not have the property of subadditivity; this makes it an incoherent risk measure. Examples can be construed where combining two (option) positions into a portfolio results in a higher aggregated portfolio VaR than the sum of the separate VaRs of the positions.[345] The point referred to by (b) is that "Value at risk measurement also *fails* to recognize *concentration* of risks"[346]. For instance, if there are 100 different instruments (all paying out 4 percent per year) that all default with 2 percent probability and the 95th percentile VaR measure is calculated, a non-diversified one-instrument portfolio will show a smaller VaR than a fully diversified one.[347] The reasons for these shortcomings are that VaR ignores the losses in the tails beyond the predefined VaR percentile. However, a measure such as expected tail loss (ETL), which refers to the expected loss if (the) VaR (percentile) is exceeded, is coherent and thus a theoretically more desirable risk measure.[348] Since risk management arguably cannot ignore tail events (see

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[343] Artzner et al. (1999), p. 218

[344] Ibid.

[345] Cf. ibid., pp. 216-217.

[346] Ibid., p. 217; emphasis original.

[347] Cf. ibid., pp. 217-218, from where the example is adapted from.

[348] Cf. Jorion (2007); p. 114; Dowd (2002), pp. 31-35, which lists five reasons why ETL is superior to VaR as a risk measure.

section 6.1.1.1), considering ETL can help to give a fuller impression of the actual risks.[349]

(2) As pointed out, for instance, by Christoffersen et al., the scaling of 1-day (short term) risk measures to a longer horizon by multiplying by the square root of time is inappropriate if returns are non-i.i.d., i.e., in the context of heteroskedasticity.[350] This is a source of model risk since,

> "Operationally, risk is often assessed at a short horizon, such as 1 day, and then converted to other horizons, such as 10 or 30 days, by scaling by the square root of horizon…"[351]

(3) Christoffersen et al. also draw attention to another consequence – namely, a potentially poor tail fit - of using standard parametric methods to fit distributions to data:

> "Traditional parametric methods implicitly strive to produce a good fit in the regions where most of the data fall, potentially at the expense of good fit in the tails, where, by definition, few observations fall."[352]

(4), (5) and (6) The last three sources of model risk arising in the context of using VaR are more fully described in separate sections. Issue (4) is that a similar use of VaR across institutions might create feedback effects that lead to a breakdown of correlations and are a source of systemic risk.[353] Closely related, issue (5) is that general VaR models do not explicitly consider liquidity risks.[354] A number of approaches to include liquidity effects (or liquidity at risk)

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[349] Cf. Dowd (2002), p. 32: "The VaR tells us the most we can expect to lose if a bad (i.e., tail) event does *not* occur, and the ETL tells us what we can expect to lose if a tail event *does* occur."; emphasis original.

[350] Cf. Christoffersen et al. (2003), pp. 156-161; see also Daníelsson (2001), pp. 11-12, for a critique of using the square-root-of-time rule, especially, p. 12: "In fact, one can make a plausible case for the *square-root-of-time* rule to be twice as high, or alternatively half the magnitude of the real scaling factor."; emphasis original.

[351] Christoffersen et al. (2003), p. 156.

[352] Ibid., p. 166.

[353] Cf. Taleb (1997a), p. 449: "The essence of the VAR concept is correlation and diversification. The widespread use of these techniques leads to the simultaneous breakdown of both at times of excessive stress in the markets."

[354] Cf. ibid., p. 449: "The VAR method makes no allowance for the fact that liquidity could represent the largest risks in some markets. … Those not interested in the liquidation value of their portfolio need not be concerned about its market price risk."

have by now been put forward[355]; nevertheless liquidity remains a significant source of model risk. Issue (6) are the, possibly perverse, incentive effects created when VaR risk management methodologies are linked to performance evaluation.[356]

6.1.2.4 Problems with Stress Testing and Scenario Analysis

The main challenge of stress testing and scenario analysis is to identify the most relevant tests and scenarios. Otherwise there is a danger that they do not lead to an increased capability to act. Das, for instance, remarks:

> "Stress testing and EVT [extreme value theory; note of the author] generally show that you will own the world or be bankrupt depending on which way round you are. Nobody takes it seriously, they all think that it won't happen to them."[357]

Berkowitz thus recommends "… unification of stress-testing with the standard risk models …"[358] so "… that the scenarios that make up stress-testing be assigned probabilities"[359]. While such an approach might increase actionability, it seems clear that risk managers cannot be expected to (successfully) identify unknown unknowns and then attach probabilities to them.[360] It has also been suggested, that risk managers themselves are as unlikely to be unbiased as other kinds of experts when it comes to forecasting.[361]

6.1.2.5 Problems with Extreme Value Theory (EVT)

One consequence of the realisation that extreme events might be more frequent than expected and in addition (some argue) possibly drawn from a

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355 Cf. Dowd (2002), pp. 165-177.

356 Cf. Ju/Pearson (1998).

357 Das (2006), p. 166; it should be noted that this quote is from a non-academic text which is clearly reflected in the tone adopted here by Das.

358 Berkowitz (1999), p.12.

359 Ibid.

360 Cf. Das (2006), p. 166, for the continuation of the above quote: "In the end, risk management can only deal with the known unknowns. Unfortunately, it's the unknown unknowns that really matter."

361 Cf. Rebonato (2007), pp. 244-245. For a comprehensive study demonstrating that expert (political) judgment is, in general, unlikely to be more accurate than that of non-experts see Tetlock (2005).

different distribution (this is one criticism of VaR models[362]), was to analyse extreme and normal events separately. EVT is an effort to do this. In the definition of Daníelsson, “EVT is the theory of the behavior of extreme outcomes of statistical processes”[363]. Accordingly, EVT only concerns itself with the tails of distributions. It considers that there are three types of tails: those with finite endpoints (Weibull type), exponential (i.e., normal) ones (Gumbel type), and fat tails defined by power laws (Fréchet type).[364] The strong point of EVT is that one “… can discard all observations that are not in the tails, and ignore without prejudice the underlying distribution of data”[365]. The weak points are that, first, only the underlying distribution of data tells which part (i.e. percentiles) of the distribution ought to be regarded as the tail, and, second, there are difficulties with identifying the tail types (and respective tail indexes).[366]

6.1.3 Correct Model, Incorrect Solution

The third main type of model risk identified by Derman is using a correct model but nevertheless arriving at an incorrect solution:

> “You can make a technical mistake in finding the analytic solution to a model. This can happen through subtlety or carelessness. … It takes careful testing to ensure that an analytic solution behaves consistently for all reasonable market parameters.”[367]

The concept behind and possible ramifications of this model risk category are easily understood and so there is no need here for an expansive discussion.

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[362] Cf., for instance, Los (2003), p. 438: “… in times of distress, portfolio diversification tends to be defeated by increased positive inter-correlations between the extreme rates of return of the various portfolio investments. This severely diminishes the value of the VaR approach to financial risk management, since it appears that portfolios behave very differently in times of distress compared with in times of normality. In other words, portfolio variances and covariances are time-varying and they are varying in such a way that they defeat conventional risk diversification rules.”

[363] Daníelsson (2006), p. 511.

[364] Cf. ibid.

[365] Ibid., p. 513.

[366] Cf. ibid., pp. 513-514; also, Christoffersen et al. (2003), p. 167: “If tail estimation via EVT offers opportunities, it is also fraught with pitfalls, as is any attempt to estimate low-frequency features of data from short historical samples. … our data samples are terribly small relative to the demands placed on them by EVT.”

[367] Derman (2003), p. 135.

6.1.4 Correct Model, Inappropriate Use

The fourth category of model risk identified by Derman is using an essentially good model outside its intended purview of application:

> "There are always implicit assumptions behind a model and its solution method. But human beings have limited foresight and a great imagination, so that, inevitably, a model will be used in ways its creator never intended."[368]

Similar to the case of using a correct model to arrive at an incorrect solution, this category is essentially an example of implementation risk. It is, however, beyond the scope of this paper to detail the full multitude of possible implementation issues. Instead, in this subsection, one significant aspect, the connection of this model risk category with systemic risk and liquidity risk is looked at more closely. In fact, using present risk management models to prepare oneself against extraordinary (risk) events is arguably such an example of inappropriate use. The models might function well in normal times (where risk is exogenous) but actually make things worse (when there are problems) by escalating endogenous risk. This interpretation also offers a (partial) explanation why extreme events often seem to be drawn from a different distribution than normal events.

6.1.4.1 Systemic Risk and Liquidity Risk

The issues of systemic risk and liquidity risk are closely related and therefore discussed here in conjunction. An argument can be made that, collectively, risk management increases systemic risk, i.e., the volatility of the market value of the whole economy. Systemic risk is increased, according to the argument, because the aggregation of individual institutions' individually rational risk management decisions increases volatility both on the upside and on the downside of market movements.[369] In this case, risk management would aggravate (or possibly help to create in the first instance) both asset bubbles

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[368] Derman (2003), p. 135.

[369] Cf., for instance, Adrian/Shin (2008b).

and market slumps.[370] While on the upswing of the market financial institutions are likely to benefit from increased liquidity, on the downswing there is a danger of liquidity drying up. This danger of liquidity drying up, in some circumstances referred to as a "liquidity hole", represents liquidity risk. In the following, several mechanisms that create endogenous risk, such as feedback loops produced by pro-cyclical leverage, homogeneity of risk management systems, and so-called tight coupling, are described.

6.1.4.1.1 Endogenous Risk

Some critics of current risk management methods have argued that events at market extremes seem to be drawn from a different distribution than normal market events. Moreover, this difference is suggested to be, at least in part, the result of risk management.[371] See, for instance, the following quote:

> "The basic statistical properties of market data are not the same in crisis as they are during stable periods; therefore, most risk models provide very little guidance during crisis periods. … risk properties of market data change with observation."[372]

Admittedly, not all methodologies are the same in this respect. As previously mentioned, EVT, for instance, explicitly takes the possibility of differing tail-behaviour as its starting point.[373] Granted that there are some more differentiated approaches, the unequal behaviour in crisis nevertheless points to fundamental flaw in most risk management models: an inability to recognize and address endogenous risk. The flaw is fundamental because, in financial markets, endogenous risk is arguably more important than exogenous risk.[374] Additionally, risk management's neglect of endogenous risk has been

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[370] It seems reasonable to assume that this results in real efficiency and welfare costs to the general economy on both sides of the market cycle, although exploring this issue is beyond the scope of this paper.

[371] Cf., for instance, Daníelsson (2001); Daníelsson/Shin (2002); Daníelsson/Zigrand (2001); Morris/Shin (1999); Montier (2007).

[372] Daníelsson (2001), pp. 2-3.

[373] Yet other approaches, such as the Mandelbrotian fractal markets hypothesis, might put forward that behaviour at all percentiles/frequencies is in fact self-similar and scalable, cf. Mandelbrot (1997), especially, pp. 1-78.

[374] Cf. Daníelsson/Shin (2002), p. 1.

suggested to be itself an important contributing factor in the creation of endogenous risk.[375]

In simple terms, endogenous risks are those that arise from within a system and exogenous risks are those affecting the system from the outside. Danielsson/ Shin explain how the concept of endogenous risk is relevant in the context of financial markets:

> "Financial markets are the supreme example of an environment where individuals react to what's happening around them, but where individuals' actions drive the realized outcomes themselves. The feedback loop of actions to outcomes back to actions has a fertile environment in which to develop. Endogenous risk appears whenever there is the conjunction of (i) individuals reacting to their environment and (ii) where the individual actions affect their environment."[376]

This relevancy is, however, not reflected in risk management practices as Morris/Shin expound:

> "Conventional risk-management techniques rest on the assumption that risk management is a single-person decision problem – in the jargon, a 'game against nature'. That is, uncertainty governing price movements is assumed to be exogenous, and assumed not to depend on the actions of other decision-makers."[377]

According to a number of scholars and practitioners, assuming exogeneity of risk and neglecting its endogenous dimensions has serious consequences. In fact, it leads to a flawed approach to risk modelling that undermines the potential for effective risk management. Ignoring the effects of industry-wide risk management efforts is a huge risk management "blindspot"[378].[379] The significance of this blind spot is that, ultimately, to cite Danielsson again, "… most statistical risk modelling is based on a fundamental misunderstanding of the properties of risk"[380]. The same criticism of neglecting the issue of endogenous risk applies to the regulatory framework, which also mostly

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[375] Cf. Daníelsson (2001); Daníelsson/Shin (2002).

[376] Daníelsson/ Shin (2002), p. 5.

[377] Morris/Shin (1999), p. 53

[378] Morris/Shin (1999), p. 53; Danielsson/Shin (2002), p. 7.

[379] Cf. Morris/Shin (1999), p. 53; Danielsson/Shin (2002), p. 3-8.

[380] Daníelsson (2001), p. 4.

attempts to contain financial risks at the level of the individual institution.[381] Finally, there is an implication, drawn out by Daníelsson, that even if financial risk management did take second-round or endogenous effects into account, it would still be unable to develop any model that was able to capture the true state of the market:

> "Financial modeling changes the statistical laws governing the financial system in real-time ... The modelers are always playing catch-up with each other. This becomes especially pronounced as the financial system gets into a crisis."[382]

While some shortcomings of models may be forgivable, in this case there are important adverse real consequences. Daníelsson writes:

> "… risk modelling is not only ineffective in lowering systemic risk, but may exasperate the crisis, by leading to large price swings and lack of liquidity."[383]

From a practitioner perspective, Taleb emphasizes:

> "VAR players are all dynamic hedgers and need to revise their portfolios at different levels. As such they can make very uncorrelated markets become very correlated. Those who refuse to learn from the portfolio insurance debacle do not belong in risk management."[384]

Montier strikes a similar tone:

> "In an already fragile market environment glued together by overconfidence and myopia and momentum trading, the last thing that is needed is yet another source of positive feedback trading. Yet, many risk management tools are effectively just that. They may go by exotic names such as dynamic hedging or VaR, but the reality is that such strategies simply exacerbate market trends."[385]

Harper et al. make an explicit link to the role of regulatory minimum capital rules in contributing to systemic risk.

> "Value-at-risk calculations are based on historical market volatility. A rise in historical market volatility leads to an increase in the required value of regulatory capital. If market participants simultaneously sell down assets so as to decrease risk exposure and satisfy regulatory requirements, market volatility may be amplified. Risk management by individual firms may therefore increase market

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381 Cf., for instance, Daníelsson/Shin (2002), pp. 6-7.

382 Danielsson (2008), pp. 2-3.

383 Danielsson (2001), p. 5.

384 Taleb (1997b), no pagination.

385 Montier (2007), p. 444.

> volatility in the economy as a whole, undermining the intent of capital regulations."[386]

In fact, Danielsson/Zigrand underline that if all financial institutions, including hedge funds, were regulated and had to satisfy some minimum regulatory capital ratios, consequences could be dire:

> "If the economy is hit by a liquidity induced financial shock, regulated financial institutions are required to get rid of more risky assets. If all market actors are regulated, then there is no counterparty at any price and the financial crisis episode is likely to become much deeper than than [sic!] it otherwise would become."[387]

Positive Feedback Loops

The problem referred to in the last paragraph's quotations is that risk management models or regulatory requirements, while intended to reduce risk, can effectively create positive feedback loops that exaggerate both bubbles and slumps. Montier claims that, "One of the strongest implications of positive feedback systems is that a *moderate* move is exceptionally unlikely. Asset prices either don't move or they move very sharply"[388]. One particular mechanism, termed by Montier as "the vicious VaR circle"[389], is depicted in Figure 14. The figure suggests how a VaR (or other risk management method)-induced selling of assets can affect volatilities and correlations (i.e., inputs of risk management models) to such an extent that the VaR (or other) model prescribes further selling and so on. As Montier writes, "… the key determinants of how likely a vicious VaR circle is to occur are obviously leverage and the commonality of position""[390]. If positions are heterogeneous, selling of individual institutions will not affect volatility/correlation much and no feedback loop is created.[391] The exception here is an individual institution holding a position of sufficient size to move the market against itself; if forced to sell by regulatory

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[386] Harper et al. (2005), p. 766.

[387] Danielsson/Zigrand (2007), p. 33.

[388] Montier (2007), p. 441; emphasis original.

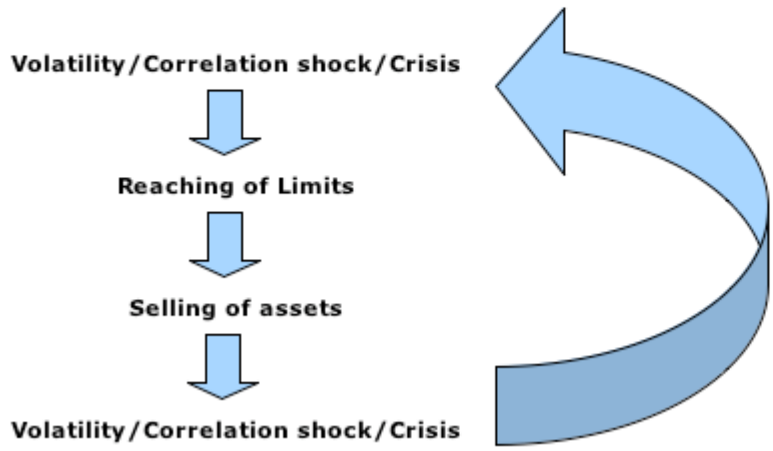
[389] Ibid. p. 440.

[390] Ibid.

[391] Cf. ibid., pp. 440-441.

requirement or internal risk management processes, such a firm can create its own vicious circle or liquidity hole. This example shows how systemic risk and liquidity risk are connected: When market actors are required to sell similar assets (and in the extreme case even sell the whole market) such co-ordinated selling results in moving the market against themselves and others holding similar positions, and potentially creates liquidity holes.

Figure 14: The Positive Feedback VaR/Risk Management Cycle



Source: Adapted from Montier (2007), p. 440.

<u>Tight Coupling</u>

The above example demonstrates that risk management can make markets more vulnerable to excessive volatility and drying up of liquidity. The responsible mechanism put forward was the positive feedback stemming from the common use of VaR across institutions. This paragraph describes in a little more detail in what ways risk management increases the chance of positive feedback loops. Specifically, the argument can be made that risk management advances "tight coupling" and thus reduces the resiliency of financial markets. The critical role of "tight coupling" is put forward in the following quote from Bookstaber:

> "The complexity at the heart of many recent market failures might have been surmountable if it were not combined with another characteristic that we have built into markets, one that is described by the engineering term *tight coupling*. Tight coupling means that components of a process are critically interdependent; they are linked with little room for error or time for recalibration or adjustment."[392]

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[392] Bookstaber (2007a), p. 144; emphasis original.

There are several aspects of current risk management that, in combination, have increased critical interdependence in markets. First, risk management homogenizes or synchronizes the preferences of various types of actors in financial markets. The result of this is amplified volatility. Compare the following quote by Danielsson/Zigrand:

> "… during crisis, VaR constraints change the risk appetite of financial institutions, effectively harmonizing their preferences. It is this effect which is most damaging, since during crisis it leads to higher volatility, larger drops in prices, and lower liquidity than would be realized in the absence of risk regulations."[393]

Second, risk management mechanisms and regulations, in particular the increasing use of mark-to-market accounting[394], not only harmonize "preferences" but, in fact, often leave financial institutions little choice in their course of actions. See, for instance, the following argument by Adrian/Shin:

> "For financial intermediaries, their models of risk and economic capital dictate active management of their overall value at risk (VaR) through adjustments of their balance sheets."[395]

As Adrian/Shin document, the result of combining marking-to-market of balance sheets and (VaR) risk management is pro-cyclical leverage of financial institutions.[396] Risk management and balance sheet-driven pro-cyclicyal leverage is thus identified as a shock-amplifying mechanism:

> "… pro-cyclical behavior is likely to exacerbate financial market fluctuations as institutions overturn the normal supply and demand responses by buying asset when the price rises and selling them when the price falls."[397]

Third, it should be noted, that the ensuing effects are system-wide and can create unexpected "tight coupling" between previously (seemingly) unconnected market segments as Bookstaber explains in the following quote:

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[393] Danielsson/Zigrand (2001), p. 23.

[394] Cf. Adrian/Shin (2007), p. 2: "In a financial system where balance sheets are continuously marked to market, changes in asset prices show up immediately on the balance sheet, and so have an immediate impact on the net worth of all constituents of the financial system."

[395] Adrian/Shin (2008b), p. 3.

[396] Cf. Adrian/Shin (2007); also, Adrian/Shin (2008a), p. 1: "… we find that institutions increase their leverage during booms and reduce it during downturns."; additionally, Adrian/Shin (2008a), p. 3: "… for a given amount of equity, a lower value at risk allows banks to expand their balance sheets … the banks' efforts to control risk will lead to pro-cyclical leverage."

[397] Adrian/Shin (2008a), p. 7.

> “Just like complexity, the tight coupling born of leverage can lead to surprising linkages between markets. High leverage in one market can end up devastating another, unrelated, perfectly healthy market. … If you can’t sell what you want to sell, you sell what you can.””[398]

Such linkages add to the complexity of the market by increasing the number of possible interdependencies. This enables contagion effects. At this point there is a danger that the contagion-based disturbance in a fundamentally unconnected market might result in further knock-on effects.

Rajan makes a similar point with respect to the consequences, in terms of systemic risk, of financial innovation in general:

> “While the system now exploits the risk bearing capacity of the economy better by allocating risks more widely, it also takes on more risks than before. Moreover, the linkages between markets, and between markets and institutions, are now more pronounced. While this helps the system diversify across small shocks, it also exposes the system to large systemic shocks – large shifts in asset prices or changes in aggregate liquidity.”[399]

At the close of this discussion of systemic and liquidity risk, it can be concluded that current risk management models, such as VaR, essentially conceptualize risk as being exogenous. By neglecting endogenous risk, they prescribe individually rational reductions of exposures (or, during a boom, increases) that create an increase in liquidity risk and systemic risk at the aggregate level.[400]

6.2 Behavioural Risk

In this, slightly more speculative, section, the question is examined whether the current approaches to risk management increase behavioural risk. For this purpose, a number of well-known behavioural biases and heuristics that distort human risk assessment are cited.[401] Ideally, risk management should act as a countermeasure to these human biases. It has, however, been argued by some

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[398] Bookstaber (2007b), p. 83.

[399] Rajan (2005), p. 27.

[400] Cf., for instance, Adrian/Shin (2008a), pp. 3-4.

[401] Cf. Shefrin (2006), p. 655: “The psychological aspects of risk assessment are known as *heuristics and biases*. Heuristics are rules of thumb. Biases are predispositions toward systematic errors. When it comes to assessing risks, humans are imperfect processors of information.”; emphasis original.

scholars and practitioners that risk management might, at least in part, amplify biases.[402] Below, some of the most relevant biases are described.

6.2.1 Overoptimism/Overconfidence/Illusion of Control

First, it has been documented that overoptimism is a common bias.[403] Second, as Shefrin writes: "One of the most robust findings by psychologists is that people are overconfident about difficult tasks"[404]. Moreover, overconfidence seems also to increase with expertise. Tetlock, for instance, researched the predictive accuracy of (political) experts versus non-experts, and their confidence levels relative to predictive accuracy.[405] He states: "Beyond a stark minimum, subject matter expertise in world politics translates less into forecasting accuracy than it does into overconfidence…""[406]. Apparently, as Warwick puts it: "Overconfidence is at its greatest in our own area of expertise – just when it can do the most damage"[407]. Third, factors such as familiarity (i.e., expertise) or involvement (i.e., commitment) seem to enhance optimism and contribute to some "illusion of control".[408] Heaton, in seeking to apply these kind of findings to managers, reviews:

> "First, people are more optimistic about outcomes that they believe they can control … survey evidence indicates that managers underplay inherent uncertainty, believing that they have large amounts of control over the firm's performance … Second, people are more optimistic about outcomes to which they are highly committed … mangers generally appear committed…"[409]

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[402] Cf, for instance, Rebonato (2007), p. 28: "… it would be helpful to structure our risk-management practices in ways that tend to minimize, not amplify, our cognitive limitations. … Unfortunately, current quantitative management of financial risk appears not just to disregard this rule, it actually often seems to work against the grain and to act as a 'cognitive bias amplifier.'"

[403] Cf., for instance, Weinstein (1980).

[404] Cf. Shefrin (2006), p. 658.

[405] Cf. Tetlock (2005).

[406] Tetlock (2005), p. 161.

[407] Warwick (2003), p. 145.

[408] Cf. Langer (1975). Note that "The Illusion of Control" is the title of Langer's article.

[409] Heaton (2005), p. 667. For a brief overview of optimism and control illusion biases in the case of managers see, also, Kahneman/Lovallo (1993), pp. 27-29.

Applied to financial risk management, there is thus a danger that it leads to an exaggerated belief, among top management, of being able to predict and control. One reason is that, as previously mentioned, significant organizational resources are invested into risk management, including in an increasing number of cases the creation of the prominent CRO role. This might be generally conducive to the development of overoptimism, overconfidence and control illusion biases. Bookstaber, for instance, suggests: "Layer one safety system on top of another and you will finally doze off into a world of unjustified complacency"[410]. Even more radical is the critique of Taleb, who suggests that risk management may actually be primarily about perception management:

> "From the standpoint of an institution, the existence of a risk manager has less to do with actual risk reduction than it has to do with the *impression* of risk reduction. … By 'watching' your risks, are you effectively reducing them or are you giving yourself the feeling that you are doing your duty?"[411]

6.2.2 Anchoring

Another cognitive bias that may affect the efficiency of risk management is anchoring. Anchoring refers to the empirical fact "… that when people are asked to form a quantitative assessment their views can be influenced by suggestions"[412]. Worryingly, people seem to (unconsciously) fix on any available (quantitative) clue when having to form an opinion under uncertainty. This was demonstrated by a Tversky/Kahneman study in which subjects' estimates where significantly influenced by the arbitrary clue provided by "… spinning a wheel of fortune in the subjects' presence"[413].

Anchoring effects can be argued to be a considerable problem for risk management. For instance, the VaR amounts are reported (to top management) at, in effect, arbitrarily set percentiles that contain only limited

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[410] Bookstaber (2007a), p. 161.

[411] Taleb (2007b), p. 41, emphasis original; also, cf. Taleb (1997b).

[412] Montier (2002), p. 5.

[413] Tversky/Kahneman (1982), p. 14; subjects' estimates varied considerably, depending on the result of the spin of the wheel of fortune, cf. ibid: "For example, the median estimates of the percentage of African countries in the United Nations were 25 and 45 for groups that received 10 and 65, respectively, as starting points. Payoffs for accuracy did not reduce the anchoring effect."

information about total risk faced.[414] Moreover, they are most often reported at exaggerated precision, i.e., without indicating the uncertainty in the VaR estimate itself.[415] At this point it should be noted, that, as Ross emphasises:

> "At the top of the organization, be it the regulatory commission or the firm, the executives and upper management have neither the time nor the inclination nor, perhaps, the training, to master the details of the risk and pricing models that are being used."[416]

In result, without being thoroughly familiar with all the quantitative aspects of arriving, for instance, at VaR figures, top management (and other decision makers) are likely to anchor on the in a sense arbitrarily arrived at output produced by risk management.

6.2.3 Framing

The previously mentioned more or less arbitrary setting of a VaR cut-off percentile also constitutes a framing issue. As Rebonato points out "… any change in percentile level can alter the ranking of investment returns, both between funded and unfunded ones and among funded ones"[417]. In other words, risk perception is clearly influenced by how the risk is represented in the course of conducting financial risk management.

6.3 Incentive Risk & Regulatory Arbitrage

A further issue is that risk managements methodologies, such as VaR, can be gamed. In effect, perverse incentives may flow from the introduction of risk management methodologies or regulations. Taleb brings forward:

> "…traders will find the smallest crack in the VAR models and try to find a way to take the largest position they can while showing the smallest amount of risk. Traders have incentives to go for the maximum bang because of the free option they're granted."[418]

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[414] Cf. Rebonato (2007), p. 131.

[415] Cf. Rebonato (2007), p. 57; also, ibid: "… *by neglecting the uncertainty in our statistical estimates we can reach completely, not marginally, different conclusions*."; emphasis original.

[416] Ross (2001), p. 10.

[417] Rebonato (2007), p. 215.

[418] Taleb (1997b), no pagination.

Ju/Pearson also point to the incentive effects of risk-based or risk-adjusted compensation and performance evaluation:

> "If the risk adjustment is done using value-at-risk, then traders will have clear incentives to enter into portfolios in which the estimated value-at-risk is low."[419]

They find that if "…systematic exploitation of the estimation errors…"[420] in models (by individuals constrained by risk limits or subject to risk-based evaluation) should occur, large biases in VaR measures can result.[421]
Moreover, as seen in section 6.1.2.3, VaR methods can, in principle, allow the concealment of concentration and tail risks. This, arguably, combines in the case of many financial institutions with "… intra-organisational incentives that actively reward decision makers for underestimating risks associated with low-probability events"[422].[423] Taleb/Martin criticize:

> "The manager thus has the incentive to pursue incremental returns with low frequency losses. … The fact that we have annual (or even quarterly) windows of evaluation of executives for strategies that blow up every one or two decades is a severe aberration of the system."[424]

In a similar argument, Koenig refers to "Darley's Law" to bring out that performance measurement systems, almost invariably, have negative side effects; Darley's Law itself is:

> "The more any quantitative performance measure is used to determine a group or an individual's rewards and punishments, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the action patterns and thoughts of the group or individual it is intended to monitor."[425]

Furthermore, these same considerations apply to financial institutions in their relationship with regulatory authorities. The gaming of regulatory requirements is called regulatory arbitrage. Danielsson, for instance, points out: "The reliance

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[419] Ju/Pearson (1998), p. 15.

[420] Ibid., p. 14.

[421] Cf. Ju/Pearson (1998).

[422] Taleb/Martin (2007), p. 188.

[423] Cf. Taleb/Martin (2007).

[424] Ibid., p. 189.

[425] Darley, quoted in Koenig (2006), p. 704; the source of the quote is not specified by Koenig.

on a single quantile of the P&L distribution by VaR is conducive to the manipulation of reported risk"[426]. Danielsson then underlines that due to such manipulation, albeit legitimate from a legal perspective, "… regulatory focus on a simple measure like VaR may thus perversely increase risk and lower profit, while the intention is probably the opposite"[427].[428] In fact, a substantial share of financial innovation in the recent past has arguably been driven by the intention of regulatory arbitrage. Compare, for instance, the following quote (see also the case study in section 7):

> "It is also no longer a secret that the anomalies in the Capital Accord [Basel I, note of the author] have been universally exploited by big banking institutions through clever innovations in the capital markets with the use of such vehicles as asset securitisation programmes, credit derivatives and other recent technological and financial innovations. In effect, banks have been able to lower their risk-based capital requirements significantly without actually reducing the material credit risk embedded in their banking portfolios."[429]

In conclusion, it depends on specific circumstances and incentive structures whether risk management and regulatory efforts succeed in risk control or whether actors find new, uncontrolled ways to take the risks they find (subjectively) appropriate, or that they are pressured to take by systemic forces.

6.4 Reputational Risk

The last risk of risk management to be briefly referred to is reputational risk (briefly mentioned before in section 5.1.5). If firms advertise their supposedly advanced risk management capabilities, and when then there is some risk event, reputational damage is likely to ensue. The reason is not only that risk management will be perceived to have failed; rather there may be an impression of previous misrepresentation, negligence or possibly even fraud. As March/Shapira observe: "Society values risk taking but not gambling, and what is meant by gambling is risk taking that turns out badly"[430]. In other words, since the general public can (basically) only observe the realized outcomes but

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[426] Danielsson (2001), p. 16.

[427] Ibid.

[428] Cf. ibid.

[429] Ong (1999), p. xvii

[430] March/Shapira (1987), p. 1413.

neither the underlying probability distributions nor the precise models and processes on which firms' risk management and strategies are based, the assessment of firms' risk management abilities will likely be highly sensitive to observed performance. This could make a single, but salient, risk event highly damaging (beyond the immediate financial loss) to a financial institution.

7. Case Study: The 2007/2008 Subprime Mortgage Crisis

This case study of the 2007/2008 subprime mortgage crisis[431] serves to illustrate some of the previous findings regarding the risks of financial risk management. Most notably, the crisis exposed issues concerning essential uncertainty, model risk and endogenous risk, but also concerning behavioural and incentive risk.

7.1 The Subprime Mortgage Crisis

After initial price declines for subprime-related securities in June and July 2007[432], the 2007/8 subprime mortgage crisis broke out with full force in early August 2007[433]. In the following months many financial intermediaries were negatively affected. In response, financial institutions have tried to reduce leverage with the result that credit markets have become much tighter and liquidity in many markets much reduced. Greenlaw et al. offer a baseline estimate of "… just under a $2 trillion contraction in intermediary balance sheets …"[434]. At the time of writing banks have already written down around US$180 billion.[435] Estimates of remaining future write-downs (plus other indirect effects) are, obviously, highly uncertain.[436] However, at least George Magnus, senior

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[431] At the time of writing, in March and early April 2008, developments are still unfolding.

[432] Cf. for instance, Adrian/Shin (2008b), p. 6: "The beginnings of the credit problems of 2007 were first manifested by falling prices of securities that are associated with the subprime sector. For instance, the ABX indices started to fall in June of 2007. The ABX indices track the credit default swaps (CDS) associated with various rated tranches of collateralized debt obligations (CDOs) written on subprime mortgages, and are compiled by the London firm Markit."

[433] Cf. for instance, Greenlaw et al. (2008), pp. 3-12.

[434] Ibid., p. 2.

[435] Cf. Bayer (2008).

[436] Cf. Greenlaw et al. (2008), pp. 12-25, for a comparison and evaluation of various loss estimates as well as a separate assessment of likely losses and their incidence by the authors.

economic advisor at UBS, believes that, taking all possible ramifications into account, total crisis-related losses could add up to US$ 1 trillion.[437] And, most recently, the IMF *Global Financial Stability Report* estimates "… aggregate potential writedowns and losses to be approximately $945 billion as of March 2008…"[438].

In the next two paragraphs, the origins of the crisis are briefly explained while keeping the discussion non-technical. In the years 2001-2006, there was tremendous growth in the US subprime mortgage market. Generally speaking, subprime mortgages are those with a comparatively higher risk of default.[439] This growth was facilitated by new forms of securitization that enabled banks and mortgage companies to adopt so-called "originate and distribute" strategies.[440] With these strategies, the loan originator (or often another financial institution, such as an investment bank, to which the loans have been sold on by the originator) securitizes the loans of some mortgage portfolio, oftentimes adds enhancement features, and then sells (most of) the securities on to investors. For instance, mortgage providers securitized mortgage pools as mortgage-backed securities (MBS). Such securities are then either sold directly to end investors, to structured investment vehicles (SIVs), or to the managers of special purpose vehicles/entities providing structured finance products such as collateralized debt obligations (CDOs).[441] It was argued - as the subprime crisis showed somewhat short-sightedly - that securitization raised market efficiency and reduces liquidity risk.[442]

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[437] Cf. Tett (2008), no pagination; Magnus in a *Financial Times* interview conducted by Gillian Tett: "If you want to take a sort of a round number, something close to $1,000 billion at the end of the day is not an impossible number."

[438] Dattels et al. (2008), pp. 10-11.

[439] Cf. Demyanyk/Van Hemert (2008), p. 6: "There is no consensus on the exact definition of a subprime mortgage loan. … The common element across definitions of a subprime loan is a high default risk."

[440] Cf. Fabozzi/Kothari (2007) for a discussion of the principles behind and the impact of securitization.

[441] Cf. Rosen (2007) for a concise explanation of mortgage securitization and the terms MBS, CDO, SIV. See Das (2005) for a comprehensive overview of credit derivatives.

[442] Cf. Fabozzi/Kothari (2007), p. 13: "… securitization reduces agency costs thereby making financial markets more efficient and improves liquidity for the underlying financial claims thereby reducing liquidity risk in the financial system."

It were the above-described types of securitization and structured finance products that created both investor demand for mortgage-backed securities and a corresponding willingness of financial institutions to supply the necessary mortgages. Thus, in order to increase origination, mortgages were successively extended to increasingly risky segments of the market that had previously been excluded.[443] As a result, the subprime segment began to take up an increasingly large share of the mortgage market.[444] There is also some evidence that the increase in mortgage supply contributed to the US housing appreciation through 2005.[445] It has been suggested, (see the following quote by Demyanyk/Van Hemert) that the true extent of the increases in risk implied by the expansion of the subprime segment was missed, although signs existed, as long as house prices kept appreciating:

> "Using the data available only at the end of 2005, we show that the monotonic degradation of the subprime market was already apparent. Loan quality had been worsening for five consecutive years at that point. Rapid appreciation in housing prices masked the deterioration in the subprime mortgage market and thus the true riskiness of subprime mortgage loans. When housing prices stopped climbing, the risk in the market became apparent."[446]

Not only was the risk missed, but, on the contrary, "… there was a deterioration of lending standards and a decrease in the subprime-prime mortgage spread during the 2001-2006 period"[447].

7.2 Risks of Risk Management

The subprime crisis affords a good example for the purposes of illustrating various risks of financial risk management.

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[443] Cf. Mian/Sufi (2008), p. 31.

[444] Cf. Demyanyk/Van Hemert (2008), p. 28: "Investors in search of higher yields kept increasing their demand for private-label mortgage-backed securities, which also led to sharp increases in subprime share of the mortgage market (from around 8 percent in 2001 to 20 percent in 2006) and in the securitized share of the subprime mortgage market (from 54 percent to 75 percent in 2006)."

[445] Cf. Mian/Sufi (2008), pp. 1-2: "Our central finding is that a rapid expansion in the *supply* of credit to zip codes with high latent demand for mortgages is a main cause of both house price appreciation from 2001 to 2005 and the subsequent sharp increase in defaults form 2005 to 2007."; emphasis original.

[446] Demyanyk/Van Hemert (2008), p. 29.

[447] Ibid., p. 5.

7.2.1 Model Risk

Model risk (see section 6.1) materialized in various forms during the subprime mortgage crisis. With Daníelsson, one can thus sum up the situation: "… the current crisis took everybody by surprise in spite of all the sophisticated models, all the stress testing, and all the numbers"[448]. Hard-hit investment bank Merrill Lynch, for example, writes in its annual report for the year 2007:

> "As a result of the unprecedented credit market environment during 2007, in particular the extreme dislocation that affected U.S. sub-prime residential mortgage-related and ABS CDO positions, VaR, stress testing and other risk measures significantly underestimated the magnitude of actual loss. Historically, these AAA rated ABS CDO securities had not experienced a significant loss of value."[449]

So, clearly, the models, and risk management in general, did not perform as expected. In fact, there are several aspects in which the models contributed to the severity of the crisis. The above Merrill Lynch quote mentions two of them – the reliance on ratings/rating agencies and the role of historical simulation in assessing the risks of new products.

<u>Rating Agencies</u>

The rating agencies provided ultimately unreliable ratings. While it can be discussed why the rating agencies arrived at these ratings (see sections 7.2.4 and 7.2.5, and below in this section), the investors, who used ratings as inputs in their investment decisions, certainly built their models on misleading inputs. There are several factors that may be responsible for unreliable ratings.

First, the major rating agencies use different proprietary models to rate asset-backed structured securities. However, Bluhm et al. point out one weakness of commonly used models. Moody's, for example, uses a method referred to as binominal expansion technique (BET) to rate CDOs.[450] Bluhm et al. demonstrate

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[448] Daníelsson (2008), p. 4.

[449] Merrill Lynch (2008), pp. 62-63.

[450] Cf. Bluhm et al. (2003), p. 271.

theoretically, in an example, that using BET "… significantly underestimates the *tail probabilities* of the original loss distribution"[451].[452] They continue to comment:

> "This does not come much as a surprise, because due to the *central limit theorem* binominal distributions tend to be approximately normal for a large number of bonds, whereas typical credit portfolio loss distributions are skewed with fat tails. Moreover, it is generally true that moment matching procedures do not automatically also fit the tails of the considered distributions in an accurate manner."[453]

Practically, this means that "… models ignoring fat tails, like the BET or other rating agency approaches, tend to underestimate the risk potential of senior notes"[454]. Such an underestimation seems to have occurred in the current crisis. Second, Daníelsson points out a problematic issue that can also contribute to an underestimation of tail risks. He argues that rating agencies

> "… underestimated the default correlation in mortgages, assuming that mortgage defaults are fairly independent events. Of course, at the height of the business cycle that my be rue, but even a cursory glance of history reveals that mortgage defaults become highly correlated in downturns. Unfortunately, the data samples used to rate SIVs often were not long enough to include a recession."[455]

Third, in a magazine article, Rosner further severely criticises what he regards as a fundamental fault with the current rating system:

> "The problem was that the ratings agencies faced a huge conflict of interest. Not only were they vouching for the securities' credit soundness, they were being paid large fees by the issuers of the securities to do so. … the more deals they could justify rating highly, the better their earnings – and the less incentive they had to rate conservatively."[456]

Forth, Taleb/Martin point out that "…ratings agencies tend to chase changes in risk, altering ratings after events evidencing increases or decreases in risk have occurred"[457].

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[451] Bluhm et al. (2003), p. 277; emphasis original.

[452] Cf. ibid., pp. 274-277.

[453] Ibid., p. 277; emphasis original.

[454] Ibid., p. 279.

[455] Danielsson (2008), p. 2.

[456] Rosner (2007), p. 15.

[457] Taleb/Martin (2007), p. 188.

Consequences of Model Failure

Relying on unreliable ratings in one's risk assessment can have dire consequences. For an example, compare the following quote by Crockett:

> "Asset-backed commercial paper was regarded as among the most liquid of instruments. So liquid, in fact, that the issuing banks charged very little for the liquidity enhancement features they offered, and did not regard the contingent liability they faced as requiring much, if any set-aside capital. The liquidity originated in the fact that the borrowing entities were highly creditworthy, and the valuation of the underlying collateral was regarded as well-founded (using ratings provided by rating agencies)."[458]

Finally, as Taleb/Martin affirm more broadly: "The recent subprime mortgage debacle illustrates the risks faced by low-probability, high-impact events."[459] Such events are almost impossible to predict by modelling because uncertainty, complexity, and tight coupling, are in most cases involved in their creation.

7.2.2 Uncertainty, Complexity, and Tight Coupling

Important in the development of the crisis and the incidence of losses were the factors uncertainty, complexity, or tight coupling. With the unfolding of the subprime crisis, unexpected linkages between seemingly disparate markets and actors emerged. The quantitative hedge fund turbulences in August 2007, detailed in section 2.2.2.3, are one instance where this became evident. Khandani/Lo thus state:

> "… August 2007 may be far more significant because it provides the first piece of evidence that problems in one corner of the financial system … can spill over so directly to a completely unrelated corner …"[460]

Such occurrences demonstrated the limits of prediction and modelling. Moreover, it had not been appreciated before, that subprime losses could trigger a much wider credit and liquidity crisis.[461] Uncertainty and a growing

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[458] Crockett (2008), p. 15.

[459] Taleb/Martin (2007), p. 188.

[460] Khandani/Lo (2007), p. 54.

[461] Cf. Caballero/Krishnamurthy (2008), p. 10: "As late as May of 2007, it would have been hard to predict that losses on subprime mortgage investments could have precipitated a crisis of the magnitude we are witnessing. For one, the subprime losses were relatively small: even worst-case estimates put these losses at USD 250 billion, which is a drop in the bucket relative to the trillion of dollars of financial instruments traded in the world's marketplaces."

recognition of the weaknesses of previously adopted models were then further instrumental in deepening the crisis. Caballero/Krishnamurthy argue:

> "The heart of the recent crisis is a rise in uncertainty – that is, a rise in unknown and immeasurable risk rather than the measurable risk that the financial sector specializes in managing. The financial instruments and derivative structures underpinning the recent growth in credit markets are complex."[462]

In other words, one could say that the crisis proved Knightian uncertainty (see section 3.2.1) to be an important factor in modern financial markets. Firstly, because Knightian uncertainty has arguably become more damaging due to increases in complexity and interconnectedness, and, secondly, because the new derivative instruments have made modelling significantly more difficult. In the current crisis this uncertainty was further compounded by a "… pervasive lack of information about the underlying economic condition of potential counterparties"[463]. This informational opacity is a direct consequence of, first, the way assets had been securitized, packaged and distributed, and, second, the relative newness of the instruments and the corresponding lack of a historical track record.[464] Caballero/Krishnamurthy thus assert: "These two factors, complexity and lack of history, are the preconditions for rampant uncertainty."[465] If previously "certain" actors in the financial markets begin to recognize, or perceive, Knightian uncertainty, the effects can be significant and produce endogenous risk.[466] This is examined in the next subsection.

7.2.3 Endogenous Risk

The subprime mortgage crisis is an object lesson for the importance of endogenous risk, and for how endogenous risk makes risk management models unreliable (see section 6.1.4.1.1). As Daníelsson fittingly remarks:

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[462] Caballero/Krishnamurthy (2008), p. 10.

[463] Eichengreen (2008), p. 23.

[464] Cf. Caballero/Krishnamurthy (2008), p. 10.

[465] Ibid.

[466] Cf. Ibid.,: "When many players disengage due to uncertainty, the effective supply of liquidity in the financial system contracts."

> "Day-to-day, when everything is calm, we can ignore endogenous risk. In crisis we cannot. And that is when the models fail."[467]

One major reason why models fail in such circumstances is that efforts to reduce exposure can create a viscous cycle that makes things worse and increases systemic risk (cf. section 6.1.4.1.1). In fact, risk management can increase liquidity risk in markets and trigger a liquidity crisis (cf. section 6.1.4.1.1).

Systemic and Liquidity Risk

As Tobias Adrian and Hyun Song Shin explore in their recent work, a lot of thinking about risk has traditionally adopted a misleading, static view of financial institutions that, by neglecting endogenous risk, implies a "domino model of financial contagion"[468] in which defaults are (mainly) responsible for financial contagion.[469] The wide-reaching effects of the initial subprime losses are, once more, compelling evidence that:

> "… the domino model is flawed. For a start, the domino model paints a picture of passive financial institutions who stand by and do nothing as the sequence of defaults unfold. … Second, the domino model does not take sufficient account of how prices and measured risks change. … the impact of price changes on balance sheets is likely to be much more potent in generating distress than outright defaults."[470]

Adrian/Shin examine how mark-to-market accounting and risk management systems combine to create balance sheet-driven pro-cyclical leverage of financial institutions (see section 6.1.4.1.1).[471] Leverage is thus a further important element that affects how institutions react in a (real or perceived) crisis such as the current subprime mortgage crisis. Adrian/Shin suggest the observer therefore to focus on the endogenous reactions to unfolding events:

> "The key to understanding the events of 2007 is to follow the reactions of the financial institutions themselves to price changes, and to shifts in the measured risk. … The key players are the financial intermediaries – the broker dealers and

[467] Daníelsson (2008), p. 3.

[468] Adrian/Shin (2008b), p. 2.

[469] Cf., for instance, ibid.

[470] Ibid., p. 3.

[471] Cf., for instance, ibid.

> commercial banks – whose balance sheets are highly leveraged and hence whose net worth is most sensitive to price changes and shifts in measured risk."[472]

In section 6.1.4.1.1, it was suggested how liquidity is endogenously affected. In the current crisis it became particular noticeable that:

> "Liquidity in markets and for individual intermediaries is much more interdependent than often realized. Markets are dependent on back-up liquidity lines from financial institutions, and institutions are dependent on continuous market liquidity to execute their risk management strategies.[473]"

Adrian/Shin argue that the credit lines extended by financial institutions to vehicles invested in MBS and CDOs made it difficult to contract balance sheets and caused banks to reduce their engagements in unrelated segments where this was possible:[474] This is another way in which unexpected linkages between market segments can be created during a crisis.

7.2.4 Behavioural Risk

There are some aspects of the subprime mortgage crisis that suggest that risk management and rating agency models may have amplified cognitive biases. For instance, it can be argued that anchoring (see section 6.2.2) on certain outputs of risk management and rating agency models may have been a factor. Moreover, the investment of substantial resources into the conduct of risk management, and the output generated by models (although in many cases likely based on historical simulation using date from a period of low volatility) presumably generated what can be described as overconfidence and an illusion of control (see section 6.2.1). Finally, the concentration on ratings, on exogenous risk, and on necessarily at least somewhat arbitrary VaR percentiles and stress tests could be seen as an instance of misleading framing (see section 6.2.3). Partnoy criticises, for example, that the way in which ratings are reported provides opportunities for manipulation:[475]

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[472] Adrian/Shin (2008b), p. 3.

[473] Crockett (2008), p. 14.

[474] Cf. Adrian/Shin (2008b), pp. 6-7; especially, p. 6: "… as credit lines got tapped, the balance sheet constraint at the banks began to bind even harder, making them even more reluctant to lend. … Their response was to cut off lending that was discretionary."[474]

[475] Cf. Partnoy (2006).

> "Put another way, credit ratings agencies are providing the markets with an opportunity to arbitrage the credit rating agencies' mistakes (or, more generously, the fact that rating categories cover a broad range of default probabilities, rather than a point estimate)."[476]

7.2.5 Incentive Risk: Gaming

Closely related to some of the concerns addressed in the last subsection under behavioural risk, an argument can be made that the subprime mortgage crisis provides evidence that various actors have attempted to game the risk management models, and especially the role played in them by the ratings assigned by rating agencies. Partnoy, for instance, suggested already in 2006 that one possible view of the motivation behind creating and selling CDOs was:

> "… because the methodologies used for rating CDOs are complex, arbitrary, and opaque, they create opportunities for parties to create a ratings 'arbitrage' opportunity without adding any actual value." [477]

Partnoy also considers that,

> "The process of rating CDOs becomes a mathematical game that smart bankers know they can win. A person who understands the details of the model can tweak the inputs, assumptions, and underlying assets to produce a CDO that appears to add value, though in reality it does not."[478]

As for the rating agencies themselves, Partnoy critizises sharply:

> "Thus, with respect to structured finance, credit rating agencies have been functioning more like 'gate openers' rather than gatekeepers. … No other gatekeeper has created a dysfunctional multi-trillion dollar market, built on its own errors and limitations."[479]

Additionally, one could also speculate that (actors at) financial institutions have purposefully neglected the (fat) tails of profit and loss distributions. This could also be interpreted as a form of gaming since, as mentioned in section 6.3, some current risk management models and regulations allow to hide or underestimate tail risk. Taleb/Martin, at least, put forward:

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[476] Partnoy (2006), p.78.

[477] Ibid., p. 75.

[478] Ibid., p. 79.

[479] Ibid., p. 80.

> "People seem to pay rating agencies for psychological comfort, or, more deceptively, to justify a certain class of risk taking – apparently not for any true empirical understanding of the risks involved."[480]

Also, it seems rather evident that regulatory arbitrage was implicated in the rapid growth of certain types of securitization. Eichengreen writes:

> "The growth of structured investment vehicles (SIVs) and conduits was not exactly a coincidence … By design, the creation of these off-balance sheet entities allowed banks to reduce the capital associated with a given risk profile."[481]

7.2.6 Reputational Risk

The potential for reputational damage (see section 6.4) when things go wrong has also been amply demonstrated by the current crisis as can be gathered by cursory newspaper reading. Because financial institutions are opaque, it is difficult for outsiders to accurately assess the activities of individual institutions. Thus, an impression of widespread bonus-driven gambling, incompetence or even fraud can be easily generalized to an institution that reports adverse results even when such surmises are not warranted.

8. Conclusion

This paper has provided an overview of (1) the conceptualization of financial risk, (2) the management of financial risk by financial institutions through current risk management models, and, centrally, (3) the very risks that are created or aggravated by the methods adopted to manage financial risk. Additionally, in section 7, these risks were illustrated with reference to the 2007/8 subprime mortgage crisis. On this basis, it can be concluded that there are, indeed, significant risks that are introduced into financial markets by the risk management efforts of financial institutions.

These negative side effects of risk management should not be neglected by financial institutions in their conduct of risk management. Similarly, regulators should take the potential negative side effects of prescribing certain modes of risk management (minimum capital ratios, etc.) into account. It is beyond the scope of this paper to offer concrete measures allowing to sidestep the

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[480] Taleb/Martin (2007), p. 188.

[481] Eichengreen (2008), p. 21.

described risks of risk management in their entirety. However, it is suggested that awareness at the institutional level of the limits of risk management can make a positive difference in that amplification of cognitive biases such as anchoring, overconfidence, overoptimism, or illusion of control may be avoided. Moreover, as Taleb/Pilpel suggest in the following quote, it may be expedient to distinguish more clearly between knowns and unknowns:

> "The solution is to take the *risks you know better* more aggressively than others; to use scepticism to rank knowledge about risks. Epistemology can easily allow us to rank situations based on their robustness to consequential estimation error."[482]

One may also suspect that adding further regulation in the quest of taming financial market risk will not produce entirely satisfactory results. Bookstaber, for instance, writes:

> "Normal accidents are borne of complexity, so adding safety checks to try to overcome these accidents can be counterproductive, because they add to this complexity."[483]

It would certainly also be of interest to quantify the relative significance of the individual risks of risk management. It should by now, however, be clear that this cannot be done with any degree of precision. The case study of the subprime crisis in section 7, and the examples offered in section 2, may lead one to conclude that endogenously generated (systemic and liquidity) risks through positive feedback effects are the most serious danger when there is a broader crisis. In normal environments, straightforward model risk deriving from the theoretical limitations of existing risk management and measurement models, and the incentive risk deriving from risk-adjusted performance assessments, can be expected to be of the most significance. Finally, it ought to be recognized that historical simulations based on "normal" market environments will be of limited predictive power when it comes to behaviour during crisis. At last, it should also be stated, that risk management definitely has a useful role to play in aiding financial institutions avoid accidental blow-ups during normal market times when risk is exogenous. However, care needs to be

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[482] Taleb/Pilpel (2007), p. 7; emphasis original.

[483] Bookstaber (2007a), p. 154.

taken that this added security during normal times does not come at the cost of increased insecurity once a crisis, and endogenous risk, materializes. This paper has pointed out a number of areas where exercising such care would constitute good risk management.

Bibliography

Adrian, T.; Shin, H. S. (2007), *Liquidity and Leverage*, Working Paper, September 2007, available at: http://www.princeton.edu/~hsshin/www/LiquidityLeverage.pdf (last retrieved: April 4, 2008).

Adrian, T.; Shin, H.S. (2008a), Liquidity, Monetary Policy, and Financial Cycles, in: *Current Issues in Economics and Finance*, Vol. 14, No. 1, January/February 2008 , pp. 1-7. - Available at: http://www.newyorkfed.org/research/current_issues/ci14-1.pdf (last retrieved: April 4, 2008).

Adrian, T.; Shin, H. S. (2008b), Liquidity and financial contagion, in: Banque de France, *Financial Stability Review: Special Issue on Liquidity*, No. 11, February 2008, pp. 1-7. – Available at: http://www.banque-france.fr/gb/publications/rsf/rsf_022008.htm (last retrieved: April 3, 2008).

Allen, L.; Boudoukh, J.; Saunders, A. (2004), *Understanding Market, Credit, and Operational Risk: The Value at Risk Approach*, Oxford et al. 2004.

Arnold, M.; Hollinger, P.; Milne, R.; O'Doherty, J.; Larsen, P. T. (2008), Der Händler, der die Bank in die Krise stürzte, in: *Financial Times Deutschland*, February 11, 2008, available at: http://www.ftd.de/koepfe/:Der%20H%E4ndler%20Bank%20Krise/315286.html (last retrieved: March 24, 2008).

Artzner, P.; Delbaen, F.; Eber, J.-M.; Heath, D. (1999), Coherent Measures Of Risk, in: *Mathematical Finance*, Vol. 9, No. 3, July 1999, pp. 203-228.

Ayache, E. (2004), The Back of Beyond, in: *Wilmott Magazine*, November/December 2004, pp. 26-31. – Available at: http://www.fooledbyrandomness.com/ayache4.pdf (last retrieved: March 31. 2008).

Bank for International Settlements (2007), *Triennial and semiannual survey on positions in global over-the-counter (OTC) derivatives markets at end-June 2007*, Basle November 2007. – Available at: http://www.bis.org/publ/otc_hy0711.pdf (last retrieved: March 23, 2008)

Bank for International Settlements [Basel Committee on Banking Supervision] (2006), *International Convergence of Capital Measurement and Capital Standards: A Revised Framework – Comprehensive Version*, Basle June 2006. – Available at: http://www.bis.org/publ/bcbs128.pdf (last retrieved: March 28, 2008).

Bayer, T. (2008), Vergangenheit holt die Banken ein, in: *Financial Times Deutschland*, March 14, 2008, available at: http://www.ftd.de/unternehmen/finanzdienstleister/:Vergangenheit%20Banken/330840.html (last retrieved: April 9, 2008).

Beder, T. S. (1995), VAR: Seductive but Dangerous, in: *Financial Analysts Journal*, Vol. 51, No. 2, September/October 1995, pp. 12-24.

Berger, P. L.; Luckmann, T. (1967), *The Social Construction of Reality: A Treatise in the Sociology of Knowledge*, New York, Toronto 1967.

Berkowitz, J. (1999), *A Coherent Framework for Stress-Testing*, FEDS Working Paper No. 99-29, June 22, 1999, available at: http://ssrn.com/abstract=181931 (last retrieved: April 1, 2008).

Berkowitz, J.; O'Brian, J. (2002), How Accurate Are Value-at-Risk Models at Commercial Banks?, in: *Journal of Finance*, Vol. 57, No. 3, June 2002, pp. 1093-1111.

Bernstein, P. L. (1998), *Against the Gods: The Remarkable Story of Risk*, New York et al. 1998.

Bessis, J. (2002), *Risk Management in Banking*, 2nd ed., Chichester (West Sussex) et al. 2002.

Biggar, D.; Heimler, A. [International Competition Network - Antitrust Enforcement in Regulated Sectors - Subgroup 1] (2005), *An Increasing Role for Competition in the Regulation of Banks*, Bonn June 2005, available at: http://www.internationalcompetitionnetwork.org/media/library/conference_4th_bonn_2005/Banking-AnIncreasingRoleForCompetition.pdf (last retrieved: March 27, 2008).

Bluhm, C.; Overbeck, L.; Wagner, C. (2003) *An Introduction to Credit Risk Modeling*, Boca Raton (Florida) 2003.

Bookstaber, R. (2007a), *A Demon of our own Design: Markets, Hedge Funds, and the Perils of Financial Innovation*, Hoboken (New Jersey) 2007.

Bookstaber, R. (2007b), The Myth of Non Correlation, in: *Institutional Investor*, Vol. 41, No. 9, September 2007, pp. 80-83. - Available at: http://bookstaber.com/rick/RickBookstaber_TheMythOfNonCorrelation.pdf (last retrieved: April 5, 2008).

Brealey, R. A.; Myers, S. C.; Allen, F. (2006), *Corporate Finance*, 8th ed., New York et al. 2006.

Brooks, C.; Kat, H. M. (2002), The Statistical Properties of Hedge Fund Index Returns and Their Implications for Investors, in: *Journal of Alternative Investments*, Vol. 5, No. 2, Fall 2002, pp. 26-44.

Bundesbank (2007), *Basel II – the new Capital Accord*, 2007, available at: http://www.bundesbank.de/bankenaufsicht/bankenaufsicht_basel.en.php (last retrieved: March 30, 2008).

Caballero, R. J.; Krishnamurthy, A. (2008), Musical chairs: a comment on the credit crisis, in: Banque de France, *Financial Stability Review: Special Issue on Liquidity*, No. 11, February 2008, pp. 9-11. – Available at: http://www.banque-france.fr/gb/publications/rsf/rsf_022008.htm (last retrieved: April 3, 2008).

Caprio, G.; Klingebiel, D. (2002), Episodes of Systemic and Borderline Banking Crises, in: Klingebiel, D.; Laeven, L. (eds.), *Managing the Real and Fiscal Effects of Banking Crises*, World Bank Discussion Paper No. 428, Washington (D.C.) 2002, pp. 31-49. – Available at: http://info.worldbank.org/etools/docs/library/83851/WBDP428.pdf (last retrieved: March 23, 2008).

Chincarini, L. B. (2007), The Amaranth Debacle: A Failure of Risk Measures or a failure of Risk Management?, April 5, 2007, available at: http://ssrn.com/abstract=952607 (last retrieved: March 24, 2008).

Christoffersen, P. F.; Diebold, F. X.; Schuermann, T. (2003), Horizon Problems and Extreme Events in Financial Risk Management, in: Warwick, B. (ed.), *The Handbook of Risk*, Hoboken (New Jersey) 2003, pp. 155-170.

Clarke, R. G. (2003), Measuring and Managing Investment Risk, in: Warwick, B. (ed.), *The Handbook of Risk*, Hoboken (New Jersey) 2003, pp. 45-56.

Connor, G.; Korajczyk, R. A. (1989), An Intertemporal Equilibrium Beta Pricing Model, in: *Review of Financial Studies*, Vol. 2, No. 3. 1989, pp. 373-392.

Cornell, B. (2003), Hedge Fund Risk, in: Warwick, B. (ed.), *The Handbook of Risk*, Hoboken (New Jersey) 2003, pp. 219-245.

Crockett, A. (2007), The evolution and regulation of hedge funds, in: Banque de France, *Financial Stability Review: Special Issue Hedge Funds*, April 2007, pp. 19-28. – Available at: http://www.banque-france.fr/gb/publications/rsf/rsf_042007.htm (last retrieved: March 25, 2008).

Crockett, A. (2008), Market liquidity and financial stability, in: Banque de France, *Financial Stability Review: Special Issue on Liquidity*, No. 11, February 2008, pp. 13-17. – Available at: http://www.banque-france.fr/gb/publications/rsf/rsf_022008.htm (last retrieved: April 3, 2008).

Crouhy, M.; Galai, D.; Mark, R. (2001), *Risk Management*, New York et al. 2001.

Culp, C. L.; Mensink, R. (2003), Measuring Risk for Asset Allocation, Performance Evaluation, and Risk Control: Different Problems, Same Solution, in: Warwick, B. (ed.), *The Handbook of Risk*, Hoboken (New Jersey) 2003, pp. 97-128.

Daníelsson, J. (2001), *The Emperor has no Clothes: Limits to Risk Modelling*, Working Paper, September 2001, available at: http://www.gloriamundi.org/ShowTracking.asp?ResourceID=453055781 (last retrieved: April 1, 2008).

Daníelsson, J. (2006), Forecasting Extreme Financial Risk, in: Ong, M. K. (ed.), *Risk Management: A Modern Perspective*, Amsterdam et al. 2006, pp. 509-536.

Daníelsson, J. (2008), The Paradox of Models, [Prepared for the LSE and Deutsche Bank conference on: The structure of regulation: lessons from the crisis of 2007], March 3, 2008, available at:

http://fmg.lse.ac.uk/upload_file/1027_J_Danielsson.pdf (last retrieved: April 1, 2008).

Daníelsson, J.; Shin, H. S. (2002), *Endogenous Risk*, Working Paper, September 21, 2002, available at: http://hyunsongshin.org/www/risk1.pdf (last retrieved: April 1, 2008).

Daníelsson, J.; Zigrand, J.-P. (2001), *What Happens When You Regulate Risk? Evidence from a Simple Equilibrium Model*, Working Paper, August 2001, available at: http://ssrn.com/abstract=289542 (last retrieved: April 1, 2008).

Daníelsson, J.; Zigrand, J.-P. (2007), Regulating hedge funds, in: : Banque de France, *Financial Stability Review: Special Issue Hedge Funds*, April 2007, pp. 29-36. – Available at: http://www.banque-france.fr/gb/publications/rsf/rsf_042007.htm (last retrieved: March 25, 2008).

Das, S. (2005), *Credit Derivatives: CDOs & Structured Credit Products*, 3rd ed., Singapore et al. 2005.

Das, S. (2006), *Traders, Guns & Money: Knowns and unknowns in the dazzling world of derivatives*, Harlow (England) 2006.

Dattels, P., Antoshin, S.; Craig, S.; Edmonds, M.; Hartelius, K.; de Imus, P.; McCaughrin, R.; Miyajima, K.; Moore, M.; Morris, C.; Saiyid, M.; Tower, I., Walker, C. (2008), Assessing Risks to Global Financial Stabilility, [chap. 1], in: International Monetary Fund, *Global Financial Stability Report: Containing Systemic Risks and Restoring Financial Soundness*, Washington (D.C.) April 2008, pp. 1-53, available at: http://www.imf.org/external/pubs/ft/gfsr/2008/01/pdf/chap1.pdf (last retrieved: April 9, 2008).

Deloitte & Touche (2007), *Global Risk Management Survey: Fifth Edition – Accelerating Risk Management Practices*, 2007, available at: http://www.deloitte.com.sg/dtt/cda/doc/content/me_fsi_global_risk_mgmt_survey2007.pdf (last retrieved: March 30, 2008).

Demirgüç-Kunt, A.; Kane, E. J. (2002), Deposit Insurance Around the Globe: Where Does It Work?, in: *Journal of Economic Perspectives*, Vol. 15, No. 2, Spring 2002, pp. 175-195.

Demyanyk, Y.; Van Hemert, O. (2008), *Understanding the Subprime Mortgage Crisis*, Working Paper, February 29, 2008, available at: http://ssrn.com/abstract=1020396 (last retrieved: April 7, 2008).

Derman, E. (2003), Model Risk, in: Warwick, B. (ed.), *The Handbook of Risk*, Hoboken (New Jersey) 2003, pp. 129-142.

Dietz, M.; Reibestein, R.; Walter, C. (2008), What's in store for global banking, in: *The McKinsey Quarterly*, January 2008, pp. 1-9, available at: http://www.mckinseyquarterly.com/PDFDownload.aspx?L2=10&L3=51&ar=2095 (last retrieved: March 25, 2008).

Dowd, K. (2002), *Measuring Market Risk*, Chichester (West Sussex) et al. 2002.

Dowd, K. (2006), Retrospective Assessment of Value at Risk, in: Ong, M. K. (ed.), *Risk Management: A Modern Perspective*, Amsterdam et al. 2006, pp. 183-203.

Eichengreen, B. (2008), Ten questions about the subprime crisis, in: Banque de France, *Financial Stability Review: Special Issue on Liquidity*, No. 11, February 2008, pp. 19-28. – Available at: http://www.banque-france.fr/gb/publications/rsf/rsf_022008.htm (last retrieved: April 3, 2008).

Fabozzi, F. J.; Kothari, V. (2007), *Securitization: The Tool of Financial Transformation*, Yale ICF Working Paper No. 07-07, 2007, available at: http://ssrn.com/abstract=997079 (last retrieved: April 8, 2008).

Fama, E. F.; French, K. R. (2004), *The Capital Asset Pricing Model: Theory and Evidence*, CRSP Working Paper No. 550; Tuck Business School Working Paper No. 03-26, January 2004, available at: http://ssrn.com/abstract=440920 (last retrieved: March 26, 2008).

Fama, E. F.; French, K. R. (1995), Size and Book-to-Market Factors in Earnings and Returns, in: *Journal of Finance*, Vol. 50, No. 1, March 1995.

Federal Deposit Insurance Corporation (1997), *History of the Eighties – Lessons for the future, Volume I: An Examination of the Banking Crises of the 1980s and Early 1990s*, s.l. 1997. – Available at: http://www.fdic.gov/bank/historical/history/vol1.html (last retrieved: March 24, 2008).

Feldstein, M. (1991), The Risk of Financial Crisis: Introduction, in: Feldstein, M. (ed.), *The Risk of Economic Crisis*, London 1991, pp. 1-18.

Ferguson, R.; Laster, D. (2007), Hedge funds and systemic risk, in: Banque de France, *Financial Stability Review: Special Issue Hedge Funds*, April 2007, pp. 45-54. – Available at: http://www.banque-france.fr/gb/publications/rsf/rsf_042007.htm (last retrieved: March 25, 2008).

Fight, A. (2004), *Understanding International Bank Risk*, Chichester (West Sussex) et al. 2004.

Greenlaw, D.; Hatzius, J.; Kashyap, A. K.; Shin, H. S. (2008), *Leveraged Losses: Lessons from the Mortgage Market Meltdown*, US Monetary Policy Forum Conference Draft, February 29, 2008, available at: http://www.brandeis.edu/global/rosenberg_institute/usmpf_2008.pdf (last retrieved: April 8, 2008).

Grinblatt, M.; Titman, S. (2002), *Financial Markets and Corporate Strategy*, 2nd ed., New York et al. 2002.

Harper, I. R.; Keller, J. G.; Pfeil, C. M. (2005), Does Risk Management Make Financial Markets Riskier?, in: Frenkel, M.; Hommel, U.; Rudolf, M. (eds.), *Risk Management: Challenge and Opportunity*, 2nd ed., Berlin et al. 2005, pp. 765-783.

Heaton, J. B. (2005), Managerial Optimism and Corporate Finance, in: *Advances in Behavioral Finance: Volume II*, Thaler, R. H. (ed.), New York et al. 2005, pp. 667-684.

Holton, G. A. (2004), Defining Risk, in: *Financial Analysts Journal*, Vol. 60, No. 6, November/December 2004, pp. 19-25.

Honohan, P.; Klingebiel, D. (2002), Controlling the Fiscal Costs of Banking Crisis, in: Klingebiel, D.; Laeven, L. (eds.), *Managing the Real and Fiscal Effects of Banking Crises*, World Bank Discussion Paper No. 428, Washington (D.C.) 2002, pp. 15-29. – Available at: http://info.worldbank.org/etools/docs/library/83851/WBDP428.pdf (last retrieved: March 23, 2008).

Hull, J. C. (2005), *Options, Futures, And Other Derivatives*, 6th ed., Upper Saddle River (New Jersey) 2005.

Hull, J. C. (2007), *Risk Management and Financial Institutions*, Upper Saddle River (New Jersey) 2007.

Jackwerth, J. C.; Rubinstein, M. (1996), Recovering Probability Distributions from Option Prices, in: *Journal of Finance*, Vol. 51, No. 5, December 1996, pp. 1611-1631.

Jobson, J. D.; Korkie, B. (1980), Estimation for Markowitz Efficient Portfolios, in: *Journal of the American Statistical Association*, Vol. 75, No. 371, September 1980, pp. 544-554.

Jorion, P. (2000), Risk management lessons from Long-Term Capital Management, in: *European Financial Management*, Vol. 6, No. 3, September 2000, pp. 277-300.

Jorion, P. (2007), *Value at Risk: The New Benchmark for Managing Financial Risk*, 3rd ed., New York et al. 2007.

J. P. Morgan/Reuters (1996), *RiskMetrics™ - Technical Document*, 4th ed., New York December 17, 1996. – Available at: http://www.rpi.edu/~guptaa/MGMT4370.08/Data/RiskMetrics1996.pdf (last retrieved: March 28, 2008).

J. P. Morgan (1997), *CreditMetrics™ - Technical Document*, New York April 2, 1997. – Available at: http://www.ma.hw.ac.uk/~mcneil/F79CR/CMTD1.pdf (last retrieved: March 29, 2008).

Ju, X.; Pearson, N. D. (1998), *Using Value-at-Risk to Control Risk Taking: How Wrong Can You Be?*, OFOR Paper Number 98-08, October 1998, available at: http://www.ace.uiuc.edu/OFOR/ofor9808.pdf (last retrieved: April 1, 2008).

Kahneman, D.; Lovallo, D. (1993), Timid Choices and Bold Forecasts: A Cognitive Perspective on Risk Taking, in: *Management Science*, Vol. 39, No. 1, January 1993, pp. 17-31.

Kalthoff, H. (2007), *Rechnende Organisation: zur Anthropologie des Risikomanagements*, 2007, available at: www.mpifg.de/maerkte-0702/papers/Kalthoff_Maerkte2007.pdf (last retrieved: March 26, 2008).

Khandani, A. E.; Lo, A. W. (2007), *What Happened to the Quants in August 2007?*, November 4, 2007, available at: http://ssrn.com/abstract=1015987 (last retrieved: March 24, 2008).

Kindleberger, C. P.; Aliber, R. Z. (2005), *Manias, Panics, and Crashes: A History of Financial Crisis*, 5th ed., Hoboken (New Jersey) 2005.

Knight, F. H. (2006), *Risk, Uncertainty and Profit*, Mineola (New York) 2006.

Koenig, D. R. (2006), Aligning Compensation Systems with Risk Management Objectives, in: Ong, M. K. (ed.), *Risk Management: A Modern Perspective*, Amsterdam et al. 2006, pp. 703-722.

Koh, F. C. C.; Koh, W. T. H.; Lee, D. K. C.; Phoon, K. F. (2005), Investing in Hedge Funds: Risks, Returns, and Performance Measurement, in: Gregoriou, G. N,; Hübner, G.; Papageorgiou, N.; Rouah, F. (eds.), *Hedge Funds: Insights in Performance Measurement, Risk Analysis, and Portfolio Allocation*, Hoboken (New Jersey) 2005, pp. 341-364.

Langer, E. J. (1975), The Illusion of Control, in: *Journal of Personality & Social Psychology*, Vol. 32, No. 2, August 1975, pp. 311-328.

Linsmeier, T. J.; Pearson, N. D. (1996), *Risk Measurement: An Introduction to Value at Risk*, July 1996, available at: http://www.exinfm.com/training/pdfiles/valueatrisk.pdf (last retrieved: April 11, 2008).

Lintner, J. (1965), The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, in: *Review of Economics and Statistics*, Vol. 47, No. 1, February 1965, pp. 13-37.

Lo, A. W. (1999), The Three P's of Total Risk Management, in: *Financial Analysts Journal*, Vol. 55, January/February 1999, pp. 13-26.

Los, C. A. (2003), *Financial Market Risk: Measurement and Analysis*, London, New York 2003,

Lowenstein, R. (2002), *When Genius Failed: The Rise and Fall of Long-Term Capital Management*, London 2002.

Luhmann, N. (2003), *Soziologie des Risikos*, Berlin, New York 2003.

MacKenzie, D. (2005), How a Superportfolio Emerges: Long-Term Capital Management and the Sociology of Arbitrage, in: Knorr Cetina, K.;

Preda, A. (eds.), *The Sociology of Financial Markets*, Oxford et al. 2005, pp. 62-83.

MacKenzie, D.; Muniese, F.; Siu, L. (eds.) (2007), *Do Economists Make Markets? On the Performativity of Economics*, Princeton (New Jersey), Woodstock (Oxfordshire) 2007.

Malkiel, B. G.; Saha, A. (2005), Hedge Funds: Risk and Return, in: *Financial Analysts Journal*, Vol. 61, No. 6., 2005, pp. 80-88.

Mandelbrot, B. (1963), The Variation of Certain Speculative Prices, in: *The Journal of Business*, Vol. 36., No. 4, October 1963, pp. 394-419.

Mandelbrot, B. B. (1997), *Fractals and Scaling in Finance: Discontinuity, Concentration, Risk*, [Selecta Volume E], New York et al. 1997.

Mandelbrot, B.; Taleb, N. N. (2005), How the Finance Gurus Get Risk All Wrong, in: *Fortune*, July 11, 2005, pp. 99-100. – Available at: www.fooledbyrandomness.com/fortune.pdf (last retrieved: March 25, 2008).

Maounis, N. (2006), *Remarks by Nick Maounis: President, Chief Executive Officer and Chief Investment Officer Amaranth Group Inc.*, [Transcript of Investor Conference Call], September 22, 2006, available at: http://online.wsj.com/documents/Maounis.pdf (last retrieved: March 24, 2008).

March, J. G.; Shapira, Z. (1987), Managerial Perspectives on Risk and Risk Taking, in: *Management Science*, Vol. 33, No. 11, November 1987, pp. 1404-1418.

Marglin, S. A. (1991), Lessons of the Golden Age: An Overview, in: Marglin, S. A.; Schor, J. B. (eds.), *The Golden Age of Capitalism: Reinterpreting the Postwar Experience*, Oxford et al. 1991, pp. 1-38.

Markowitz, H. M. (1952), Portfolio Selection, in: *Journal of Finance*, Vol. 7, No. 1, March 1952, pp. 77-91.

Marshall, C.; Siegel, M. (1996), *Value at Risk: Implementing a Risk Measurement Standard*, Working Paper 96-47, Wharton - Financial Institutions Center, June 1996, available at: http://ssrn.com/abstract=1212 (last retrieved: April 1, 2008).

Mason, S. P. (1995), The Allocation of Risk, in: Crane, D. B.; Merton, M. C.; Froot, K. A.; Bodie, Z.; Mason, S. C.; Sirri, E. R.; Perold, A. F.; Turfano, P., *The Global Financial System: A Functional Perspective*, Cambridge (Massachusetts) 1995, pp. 153-195.

McEnally, R. W. (1998), Latané's bequest: The best of portfolio strategies, in: Bernstein, P. L.; Fabozzi, F. J. (eds.), *Streetwise: The Best of the Journal of Portfolio Management*, Princeton (New Jersey), Chichester (West Sussex) 1998, pp. 151-160.

Merrill Lynch (2008), *Form 10-K (Annual Report)*, New York February 25, 2008, available at: http://ir.ml.com/downloads.cfm (last retrieved: April 9, 2008).

Merton, R. C. (1974), On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, in: *Journal of Finance*, Vol. 29, No. 2, May 1974, pp. 449-470.

Merton, R. C.; Samuelson, P. A. (1974), Fallacy of the lognormal approximation to optimal portfolio decision-making over many periods, in: *Journal of Financial Economics*, Vol. 1, No. 1, May 1974, pp. 67-94.

Merton, R. C. (1992), *Continuous-Time Finance*, Oxford et al. 1992.

Mian, A.; Sufi, A. (2008), *The Consequences of Mortgage Credit Expansion: Evidence from the 2007 Mortgage Default Crisis*, Working Paper, January 2008, available at: http://ssrn.com/abstract=1072304 (last retrieved: April 7, 2008).

Millo, Y.; MacKenzie, D. (2007), *Building a Boundary Object: The Evolution of Financial Risk Management*, Working Paper, November 2007, available at: http://ssrn.com/abstract=1031745 (last retrieved: March 26, 2008).

Modigliani, F.; Miller, M. H. (1958), The Cost of Capital, Corporation Finance, and the Theory of Investment, in: *American Economic Review*, Vol. 48, No. 3, June 1958, pp. 261-297.

Montier, J. (2002), *Behavioural Finance: Insights into Irrational Minds and Markets*, Chichester (West Sussex) et al. 2002.

Montier, J. (2007), *Behavioural Investing: A practitioner's guide to applying behavioural finance*, Chichester (West Sussex) et al. 2007.

Morris, S.; Shin, H. S. (1999), Risk Management with Interdependent Choice, in: *Oxford Review of Economic Policy*, Vol. 15, No. 3, Autumn 1999, pp. 52-62.

Noyer, C. (2007), Hedge funds: what are the main issues?, in: Banque de France, *Financial Stability Review: Special Issue Hedge Funds*, April 2007, pp. 105-111. – Available at: http://www.banque-france.fr/gb/publications/rsf/rsf_042007.htm (last retrieved: March 25, 2008).

Ong, M. K. (1999), *Internal Credit Risk Models: Capital Allocation and Performance Measurement*, London 1999.

Papademos, L. D. (2007), Monitoring hedge funds: a financial stability perspective, in: Banque de France, *Financial Stability Review: Special Issue Hedge Funds*, April 2007, pp. 113-123. – Available at: http://www.banque-france.fr/gb/publications/rsf/rsf_042007.htm (last retrieved: March 25, 2008).

Partnoy, F. (1999), *F.I.A.S.C.O.: The Inside Story of a Wall Street Trader*, New York et al. 1999.

Partnoy, F. (2006), How and Why Rating Agencies Are Not Like Other Gatekeepers, [San Diego Legal Studies Paper No. 07-46], in: Fuchita, Y.; Litan, R. E. (eds.), *Financial Gatekeepers: Can They Protect Investors?*, Baltimore (Maryland) 2006, pp. 59-99, available at: http://ssrn.com/abstract=900257 (last retrieved: April 9, 2008).

Power, M. (2007), *Organized Uncertainty: Designing a World of Risk Management*, Oxford et al. 2007.

Rajan, R. G. (2005), *Has Financial Development Made the World Riskier?*, Working Paper, September 2005, available at: http://www.kc.frb.org/PUBLICAT/SYMPOS/2005/PDF/Rajan.paper.0907.pdf (last retrieved: April 5, 2008).

Rebonato, R. (2007), *Plight of the Fortune Tellers: Why We Need to Manage Financial Risk Differently*, Princeton (New Jersey), Woodstock (Oxfordshire) 2007.

Roll, R. (1977), A Critique of the Asset Pricing Theory's Tests Part I: On Past and Potential Testability of the Theory, in: *Journal of Financial Economics*, Vol. 4, No. 2, March 1977, pp. 129-176.

Rosen, R. J. (2007), The role of securitization in mortgage lending, in: *Chicago Fed Letter*, No. 244, November 2007, no pagination, available at: http://www.chicagofed.org/publications/fedletter/cflnovember2007_244.pdf (last retrieved: April 8. 2008).

Rosner, J. (2007), Subprime Offender: The real villains of the mortgage crisis, in: *The New Republic*, September 10, 2007, pp. 14-15.

Ross, S. A. (1976), The Arbitrage Theory of Capital Asset Pricing, in: *Journal of Economic Theory*, Vol. 13, No. 3, December 1976, pp. 341-360.

Ross, S. A. (2001), Financial Regulation in the New Millennium, in: *Geneva Papers on Risk and Insurance*, Vol. 26, No. 1, January 2001, pp. 8-16.

Rumsfeld, D. H. (2002), *News Transcript: DoD News Briefing*, [Presenter: Secretary of Defense D. H. Rumsfeld], February 12, 2002, available at: http://www.defenselink.mil/transcripts/transcript.aspx?transcriptid=2636 (last retrieved: March 31, 2008).

Samuelson, P. A. (1971), The "Fallacy" of Maximizing the Geometric Mean in Long Sequences of Investing or Gambling, in: *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 68, No. 10, October 1971, pp. 2493-2496..

Samuelson, P. A. (1979), Why We Should Not Make Mean Log Of Wealth Big Though Years To Act Are Long, in: *Journal of Banking and Finance*, Vol. 3, No. 2/3/4, 1979, pp. 305-307. – Available at: http://www-stat.wharton.upenn.edu/~steele/Courses/434F2005/Context/Kelly%20Resources/Samuelson1979.pdf (last retrieved: March 31, 2008).

Schröck, G.; Steiner, M. (2005), Risk Management and Value Creation in Banks, in: Frenkel, M.; Hommel, U.; Rudolf, M. (eds.), *Risk Management: Challenge and Opportunity*, 2nd ed., Berlin et al. 2005, pp. 52-78.

Sharpe, W. F. (1964), Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, in: *Journal of Finance*, Vol. 19, No. 3, September 1964, pp. 425-442.

Shefrin, H. (2006), The Role of Behavioral Finance in Risk Management, in: Ong, M. K. (ed.), *Risk Management: A Modern Perspective*, Amsterdam et al. 2006, pp. 653-676.

Smith, C. W.; Stulz, R. M. (1985), The Determinants of Firms' Hedging Policies, in: *Journal of Financial and Quantitative Analysis*, Vol. 20, No. 4, December 1985, pp. 391-405.

Sornette, D. (2003), *Why Stock Markets Crash: Critical Events in Complex Financial Systems*, Princeton (New Jersey), Woodstock (Oxfordshire) 2003.

Taleb, N. (1997a), *Dynamic Hedging: Managing Vanilla and Exotic Options*, New York 1997.

Taleb, N. (1997b), The World According to Nassim Taleb, [Interview Transcript], in: *Derivatives Strategy*, December/January 1997, available at: http://www.derivativesstrategy.com/magazine/archive/1997/1296qaf753.asp?print (last retrieved: April 1, 2008).

Taleb, N. N. (2007a), Black Swans and the Domains of Statistics, in: *American Statistician*, Vol. 61, No. 3, August 2007, pp. 198-200.

Taleb, N. N. (2007b), *Fooled by Randomness: The Hidden Role of Chance in Life and in the Markets*, 2nd ed., London et al. 2007.

Taleb, N. N.; Martin, G. A. (2007), The Risks of Severe, Infrequent Events, in: *Banker*, Vol. 157, No. 979, September 2007, pp. 188-189. – Available at: http://www.fooledbyrandomness.com/thebanker.pdf (last retrieved: April 5, 2008).

Taleb, N.; Pilpel, A. (2007), Epistemology and risk management, in: *Risk&Regulation*, No. 13, Summer 2007, pp. 6-7. – Available at: http://www.lse.ac.uk/resources/riskAndRegulationMagazine/magazine/summer2007/pdf/RiskRegulation13Summer2007.pdf (last retrieved: March 31, 2008).

Tetlock, P. E. (2005), *Expert Political Judgment: How Good Is It? How Can We Know?*, Princeton (New Jersey), Woodstock (Oxfordshire) 2005.

Tett, G. (2008), Transcript: George Magnus of UBS, [Interview Transcript] in: *FT.com*, February 25, 2008, available at:

http://www.ft.com/cms/s/0/cf507b7e-e16c-11dc-a302-0000779fd2ac.html (last retrieved: March 23, 2008).

Thompson, D. (ed.) (1995), *The Concise Oxford Dictionary of Current English*, 9th ed., Oxford et al. 1995.

Till, H. (2006), *EDHEC Comments on the Amaranth Case: Early Lessons from the Debacle*, 2006, available at: http://www.edhec-risk.com/features/RISKArticle.2006-10-02.0711/attachments/EDHEC%20Comments%20on%20Amaranth%20Case.pdf (last retrieved: March 24, 2008).

Tobin, J. (1958), Liquidity Preference as Behavior Towards Risk, in: *The Review of Economic Studies*, Vol. 25, No. 2, February 1958, pp. 65-86. – Available at: http://cowles.econ.yale.edu/P/cp/p01a/p0118.pdf (last retrieved: March 26, 2008).

Tschoegl, A. E. (2005), The Key to Risk Management: Management, in: Frenkel, M.; Hommel, U.; Rudolf, M. (eds.), *Risk Management: Challenge and Opportunity*, 2nd ed., Berlin et al. 2005, pp. 721-739.

Tversky, A.; Kahneman, D. (1982), Judgement under uncertainty: Heuristics and biases, in: Kahneman, D.; Slovic, P.; Tversky, A. (eds.), *Judgement under Uncertainty: Heuristics and Biases*, Cambridge et al. 1982, pp. 3-20.

Warwick, B. (2003), Technology and the Capital Markets, in: Warwick, B. (ed.), *The Handbook of Risk*, Hoboken (New Jersey) 2003, pp.143-154.

Weinstein, N. D. (1980), Unrealistic Optimism about Future Life Events, in: *Journal of Personality and Social Psychology*, Vol. 39, No. 5, November 1980, pp. 806-820.

Weisman, A. B. (2003), The Risk of Informationless Investing: Hedge Fund Performance Measurement Bias, in: Warwick, B. (ed.), *The Handbook of Risk*, Hoboken (New Jersey) 2003, pp. 247-264.

Ehrenwörtliche Erklärung

Ich erkläre hiermit ehrenwörtlich, dass ich die vorliegende Master-Thesis mit dem Thema:

“**The Risks of Financial Risk Management”**

selbstständig und ohne fremde Hilfe angefertigt habe.

Die Übernahme wörtlicher Zitate sowie die Verwendung der Gedanken anderer Autoren habe ich an den entsprechenden Stellen der Arbeit kenntlich gemacht.

Ich bin mir bewusst, dass eine falsche Erklärung rechtliche Folgen haben wird.

Weingarten, den 12. April 2008

(Johannes Gaus)