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The Present and Future of Financial Risk Management

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ABSTRACT
Current research on financial risk management applications of econometrics centers on the accurate assessment of individual market and credit risks with relatively little theoretical or applied econometric research on other types of risk, aggregation risk, data incompleteness, and optimal risk control. We argue that consideration of the model risk arising from crude aggregation rules and inadequate data could lead to a new class of reduced-form Bayesian risk assessment models. Logically, these models should be set within a common factor framework that allows proper risk aggregation methods to be developed. We explain how such a framework could also provide the essential links between risk control, risk assessments, and the optimal allocation of resources.

KEYWORDS: economic capital, financial risk assessment, optimal allocation of resources, RAROC, risk control, regulatory capital

The role of risk management in financial firms has evolved far beyond the simple insurance of identified risks, to a discipline that centers on complex econometric and financial models of uncertainty. Financial risk management has been defined by the Basel Committee (2001) as a sequence of four processes: the *identification* of events into one or more broad categories of market, credit, operational, and "other" risks and into specific subcategories; the *assessment* of risks using data and a risk model; the *monitoring and reporting* of the risk assessments on a timely basis; and the *control* of these risks by senior management.

Of the trends in financial markets that have had a significant impact on risk management practices today, deregulation has been a main driving force. Since the 1970s the deregulation of capital flows has led to increased globalization (Sverrisson and Van Dijk, 2000); deregulation of industries has enabled the rapid expansion of new companies such as Enron (Bodily and Bruner, 2002;

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Bratton, 2003); and with the deregulation of financial operations new risks have been acquired—with some banks offering insurance products and insurance companies writing market and credit derivatives (Broome and Markham, 2000). Over-the-counter derivative markets rapidly overcame all others in notional size, but capitalization, on the global scale, decreased during this period, and by the early 1980s, some individual banks, if not national banking industries, had become highly vulnerable.

As a result, the supervision and regulation of banks and other financial firms has increased. In particular, capital adequacy requirements have been extended to cover more types of risks.[1] The first Basel Accord in 1988 covered only credit risks in the banking book; the Basel 1 Amendment in 1996 extended this to market risks in the trading book; and now the new Basel 2 Accord, which will be adopted by all G10—and many other—countries in 2007, refines credit risk assessments to become more risk sensitive and extends the calculation of risk capital to include operational risks. Also in Basel 2, minimum solvency ratios will now be applied to asset management and brokerage subsidiaries, as well as to traditional banking operations.

Some financial services have become concentrated into the hands of very few firms. Primarily this has been the result of deregulation leading to greater competition (Fraser and Zardkoohi, 1999; Stiroh and Strahan, 2003), but increased regulation of banking activities has also played a role. Under the new Basel Accord some services such as agency and custody will for the first time attract regulatory capital charges and consequently the best economic solution may be to outsource the service. On the other hand, all types of financial services—insurance, asset management and banking—are being merged into one large complex banking organization. This consolidation of services highlights the importance of a firmwide risk management function that is able to examine the total risks of the whole organization (Berger, Demsetz, and Strahan, 1999). Consequently, changes in regulatory supervision of banking activities include a move away from “product-based” capital requirements to “rules-based” capital requirements that may be uniformly applied across all subsidiaries in a large complex group so that risks and returns from all activities can be assessed on a comparable basis and properly aggregated.

Disintermediation in the traditional banking industry has played an important role in changing the structure of financial institutions. Rather than relying on a bank for bonds or loans, many large companies now favor the direct insurance of debt by issuing bonds and equity through the capital markets (Bhattacharya, Boot, and Thakor, 1998). As a result, banks are now relying more on flow business for their income, especially from fees and commissions on services in corporate finance. The decline of traditional banking has, however, been accompanied by a rise of other types of financial intermediaries, including pension and mutual funds and nonbank finance companies (Allen and Santomero, 1997). Instances of multilayered intermediation are now frequent and the structure of interlinkages

[1] As well as providing a margin for losses, the imposition of minimum solvency ratios might reduce the incentives to take risks; however, there is evidence that capital requirements are ineffective for the latter (Blum, 1999; Jones, 2000).

between different agents in the financial sector has become increasingly complex (Freedman, 2000). Thus new technological advances have facilitated the provision of financial services from new types of intermediaries, with Internet- and intranet-based technologies now providing improved communications, security, database, and order management.

Set against this background, this article envisions how financial econometric research might best lead the financial risk management industry in the future. Its outline is as follows: Section 1 examines how market, credit, operational, business, and systemic risks have been changing in response to the global trends in financial markets discussed above. Section 2 reviews the recent academic literature on risk assessment and highlights the most important sources of error in risk capital models. Section 3 takes a critical look at risk control, arguing that the current incentive system could fail to reduce market and credit risks and possibly increase systemic risk. Section 4 examines the major issues that are likely to be a focus for future research and outlines the framework for new elements of risk modeling. Section 5 concludes.

1 THE RISK MANAGEMENT IMPACT OF RECENT TRENDS IN FINANCIAL MARKETS

Increased capital flows, rapid dissemination of information, and faster transfers of funds have all served to increase market risks. For example, Figure 1 shows that the 5-year average volatility of the S&P 500 equity index is now more than 20%, an all-time high, and the index short-term volatility has been in excess of 15% for several years. Even more noticeable than index volatility is that individual stock volatility has increased dramatically during the past few years—particularly when measured at the intraday frequency. Figure 1 also shows that the 5-year average volatility of IBM stock has almost doubled since the beginning of 1990. The fact that stock index volatility has not increased apace is due to a decrease in correlation between returns to stocks within a domestic index. On the other hand, the correlation of stock returns within international industrial sectors has increased (Diermeier and Solnik, 2001).

Deregulation of capital flows in the worlds emerging economies has been the main catalyst for globalization in regions such as Eastern Europe and Asia, where the unchecked growth of capitalism, poor accounting standards, and inefficient financial intermediation precipitated some major credit crises during the 1980s (Bisignano, 1999). Figure 2 shows that Baa credit spreads in the United States recently rose again to the high levels of the early 1980s, precipitated first by the Russian debt crisis and then by the large number of company defaults in the U.S. communications sector. The increasing pace of technological advance was the catalyst behind the unprecedented price increases in technology stocks in the late 1990s. This enabled some communications companies to pay the ludicrous sums that governments demanded for their licenses by mounting huge debts on the promise of consumer demand, but this demand never materialized. With greater disintermediation of the debt than in

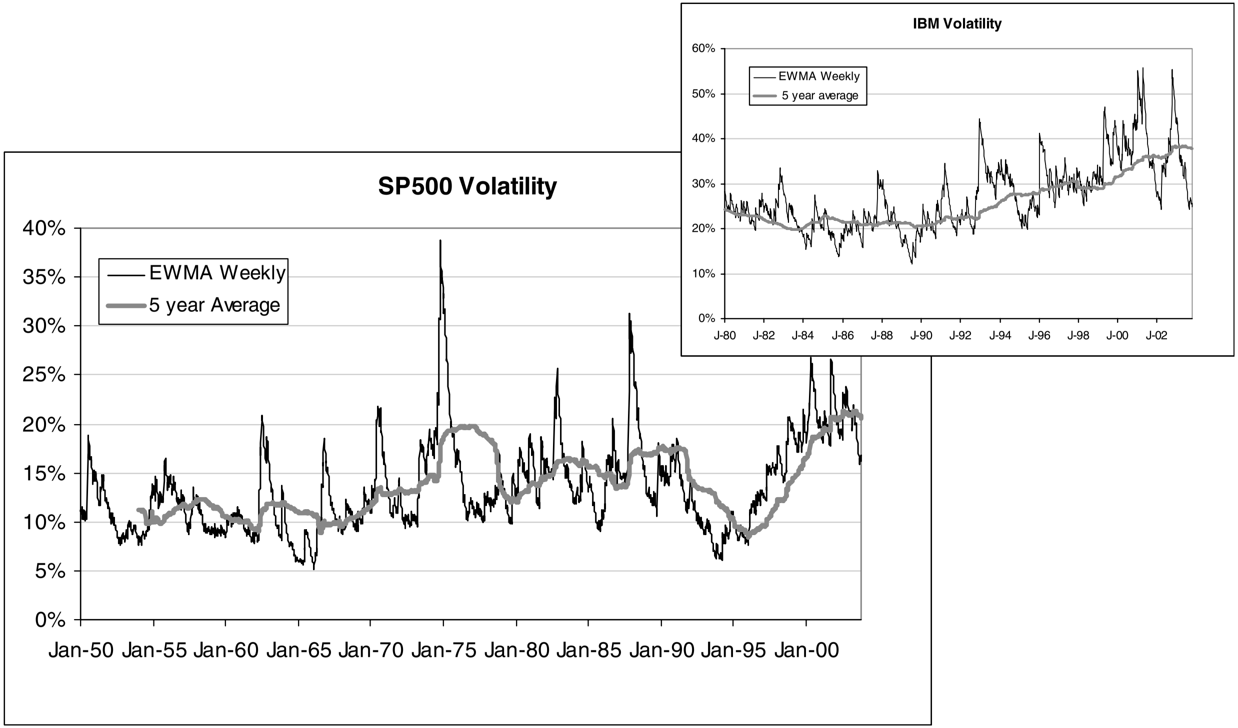

Figure 1 U.S. equity market statistical volatility. The main figure shows a 5-year equally weighted moving average statistical volatility of the S&P 500 index in dark grey bold, along with the more variable short-term exponentially weighted average (EWMA) estimate with the "RiskMetrics" smoothing constant 0.95. Inset is a graph showing similar volatility estimates for IBM stock over the same period. All data are weekly closing prices, adjusted for splits and dividends, from http://www.yahoo.com.

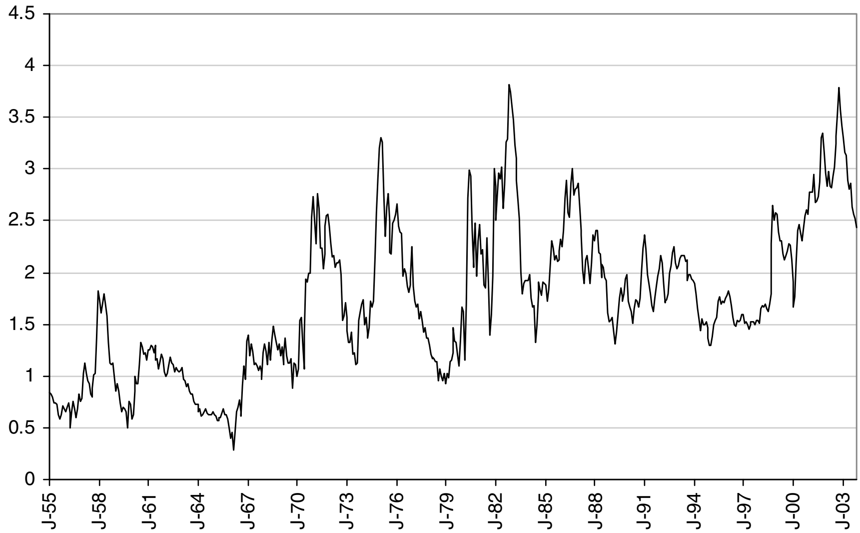

Figure 2 Baa credit spreads: 1955–2003.The graph shows a time series of monthly data on Baa credit spreads obtained by subtracting the 10-year U.S. Treasury yield from Moody's Baa bond index. Both series were downloaded from http://www.federalreserve.gov/releases/h15/data.htm.

the previous crises, banks suffered less, but economic growth in the United States and Europe has been depressed by the high default rates among technology companies such as WorldCom and Global Crossing.

Recent global trends in financial markets have increased many types of operational risks: the rapid growth of some new companies adopting dubious accountancy and management practices followed the deregulation of industries and subsequently there has been a marked increase in company fraud (e.g., Enron formed after deregulation of the U.S. energy market in the early 1990s); systems risks have risen with our increasing reliance on technology; the concentration of key financial services into a single geographical location increases operational risks arising from damage to physical assets. Financial institutions now offer highly structured products having access to a wide range of asset classes across the world and the complexity of these financial instruments highlights several types of operational risks: with less transparency in the trading and new and complex systems, systems risk have increased; products and business practice risks increase because of the danger of mispricing and misselling these products; and "human" risks in general increase because now only a few experienced people understand the systems and the products.

In preparation for the imposition of operational risk capital charges under the new Basel Accord, the risk management group of the Basel Committee prepared two quantitative impact studies (QIS) on operational risks in large banking conglomerates. QIS2, the first of these two studies (Basel Committee, 2002) examined operational losses from 30 large banks over the period 1998–2000. The results are reproduced in Table 1.[2] The highest-frequency risks were in retail banking services, particularly from such things as credit card fraud and check kiting, which fall into the external fraud category, and in execution, delivery, and process management in general. While total losses were also highest in these categories, these high-frequency, low-impact risks have a relatively small impact on the regulatory capital charge because their expected loss is normally covered by general provisions in the business. Loss severity per event was greatest for internal fraud in trading and sales, commercial banking and asset management, and for clients, products and business practice risks in corporate finance. The growth of complex structured products has clearly increased pricing model risk. Model risk is not a high-frequency, low-severity operational risk. It can impact the operational risk regulatory capital charge significantly and should therefore be a major focus for operational risk control.

Business risk, the risk of insolvency due to inappropriate management decisions, has grown as the structure of financial institutions continues to change. As the demand for banking loans declines but the need for corporate finance increases, this has the effect of reducing market and credit risk for banks, but they now face more business risks. A case in point is Abbey National, now the 6th largest British bank, but originally just a building society. Having obtained a license for retail banking, it rapidly expanded its services to treasury operations and corporate finance. This lasted only a few years, until large losses recently revealed how the management had overextended itself with these particular decisions. Business risk has also increased with the mergers and acquisitions that have accompanied consolidation of the financial industry (Cornette and Tehranian, 1992). Historically banking, insurance, and asset management have very different risk management cultures that can be difficult to merge. Irreconcilable differences can even arise between investment and commercial banking: for example, all the conglomerates formed after the "bang bang" in the United Kingdom in the 1980s, including BZW and CountyNatWest, have now failed. As a result, international accounting firms have developed new audit models to account for the growing importance of business risks when valuing the firm (Morgan and Stocken, 1998).

Systemic risk is the risk of a systemic event leading to mass insolvencies in the banking and other sectors. It arises from the "domino effect" emanating from a limited idiosyncratic shock when agents' behavior is homogeneous.[3] The similarity of risk management practices can increase systemic risk through increased "herding" behavior. For example, consider the traditional "portfolio insurance" strategies that are popular with pension funds (Rubinstein and Leland, 1981). If the price of some risky assets fall, the funds that have not performed well as a result must maintain their solvency ratio. They may be forced to sell risky assets

[2] The second study of operational losses, QIS3 (also available at www.bis.org), covered 90 banks over 1 year. Unfortunately that year was 2001, and so the results, while otherwise similar to those of QIS2, were dominated by a single event: the damage to physical assets in commercial banking operations located within the World Trade Center in Manhattan. Clearly, as remarked above, the concentration of key services into one location increases this type of operational risk.

[3] A systemic event arises when bad news within one firm, sector, or market contaminates other firms, sectors, or markets with adverse effects.

Table 1 Results from the Basel Committee Quantitative Impact Study 2.

	Internal Fraud	External Fraud	Employment Practices & Workplace Safety	Clients, Products & Business Practices	Damage to Physical Assets	Business Disruption & System Failures	Execution, Delivery & Process Management	**Total**
Corporate Finance	4	3	15	15	1	0.01	33	**71**
Trading & Sales	16	6	36	107	3	34	708	**910**
Retail Banking	419	3693	267	641	350	19	1758	**7147**
Commercial Banking	68	519	23	44	63	13	288	**1018**
Payment & Settlement	12	60	8	21	28	48	593	**770**
Agency & Custody	6	2	12	31	10	8	347	**416**
Asset Management	4	4	10	32	0.01	2	233	**285**
Retail Brokerage	4	2	11	94	9	187	420	**727**
Total	**533**	**4289**	**382**	**985**	**464**	**311**	**4380**	**11344**

continued

Table 1 *(Continued)* Results from the Basel Committee Quantitative Impact Study 2.

	Internal Fraud	External Fraud	Employment Practices & Workplace Safety	Clients, Products & Business Practices	Damage to Physical Assets	Business Disruption & System Failures	Execution, Delivery & Process Management	**Total**
Corporate Finance	3293	25231	6109	131012	16	0	28432	**194093**
Trading & Sales	68819	826	7837	89038	100	6221	325593	**498434**
Retail Banking	114937	198575	53836	385722	60174	1796	191617	**1006657**
Commercial Banking	78765	287275	3569	76159	13534	1359	135346	**596007**
Payment & Settlement	732	4767	718	1058	2045	2638	111993	**123951**
Agency & Custody	2265	267	374	7517	859	1707	43244	**56233**
Asset Management	8566	603	1037	8968	0	644	34302	**54120**
Retail Brokerage	426	596	1845	17387	561	5646	26029	**52490**
Total	**277803**	**518140**	**75325**	**716861**	**77289**	**20011**	**896556**	**2581985**

The QIS2 of the Basel Committee (2002) reported results on operational losses by operational risk type (i.e., by event category and business unit) from 30 large global banking institutions, each with tier 1 capital in excess of 3 billion euros, during the 3-year period 1998–2000. The upper table reports the total number of loss events in each risk type and the lower table reports the total losses in million euros, totaled over the 30 banks and over all 3 years.

and, assuming they sell the assets that are underperforming, the price of these will be depressed even further. But now the next level of funds, though not originally concerned by their solvency ratio, may be forced into selling assets. The vicious circle continues and a downward spiral in prices is instigated.

From this perspective, the trend toward increasing regulation of the financial industry could in fact be counterproductive because it imposes homogeneity on risk assessments and control (Kaufman, 1996). Increased integration of the financial industry has increased the contagion effect that is central to systemic risk (Rochet and Tirole, 1996). Systemic risk has also been enhanced by illiquidity spillover effects—where problems in one market induce firms to liquidate positions in other markets—and the concentration of key services in the hands of very few firms: in the event of a crisis, such as a terrorist attack or a major computer virus, an essential activity could be gravely affected with catastrophic consequences. There is a large academic literature on the development of theoretical models and on the mounting empirical evidence of systemic risks in the financial industry: a useful survey paper is given by DeBandt and Hartmann (2000).

Finally, the convergence of the industry toward large complex global organizations highlights the need for a firmwide risk management function that can take proper advantage of new diversification opportunities (Berger, Demsetz, and Strahan, 1999). Senior managers require consolidated risk reports that cover all activities and all risks in all locations. With the need to net many types of risks across the whole enterprise, a new type of risk model risk has emerged: "aggregation risk" may be defined as the model risk resulting from inappropriate assumptions about risk factor dependencies.

2 RISK ASSESSMENT

Firmwide risk assessments are linked via solvency ratios to capitalization. Thus banks have a definite interest in refining their minimum regulatory capital calculation methods, insofar as regulatory capital constraints could become biting. Also important for listed companies is the need to satisfy rating agencies that they hold sufficient capital to justify their credit rating. Equity analysts examine capitalization as a key element of firm value. But beyond regulations and ratings, accurate risk assessment and the corresponding linkage to capital is a tool for increasing shareholder value. It is the key input to management decisions on the global positioning of risks in an uncertain environment and consequently risk assessment underpins all aspects of effective risk control. Given the importance of accurate risk assessment of financial operations, it has been in the mainstream of academic research in finance for many years. Here we survey only some of the more recent papers.

2.1 Market Risk

The RiskMetrics product introduced by JPMorgan in the early 1990s set the standard for market risk assessment: a structural model of the profit and loss (P&L) distribution is obtained via mapping positions to risk factors and marking to market or model daily, and the risk metric of a lower percentile of the P&L distribution is termed the value-at-risk (VaR) (see http://www.riskmetrics.com). During the last decade there has been a vast amount of academic research on the use of VaR for market risk assessment. One strand develops superior risk metrics (following Artzner et al., 1999); another adapts standard VaR models for different portfolio effects such as liquidity, nonlinearity, and nonnormality (Bangia et al., 1999; Britten-Jones and Shaefer, 1999; Eberlien, Keller, and Prause, 2000; Glasserman, Heidelberger, and Shahabuddin, 2002); yet another applies risk factor dependency models based on copulas that are more appropriate for portfolio VaR than assuming simple linear correlations (Embrechts, McNeil, and Straumann, 1999; Embrechts, Höing, and Juri, 2003; Embrechts, Lindskog, and McNeil, 2003).

However, a recent strand of research has cast doubt on the efficiency of these structural VaR models for risk capital estimation. For instance, Berkowitz and O'Brien (2002) show that structural models are too conservative in their VaR estimates and have difficulty forecasting changes in P&L volatility. One reason is that many approximations are needed to overcome the theoretical and computational burden of aggregating the risks of thousands of individual positions. Another is that, being based on close of day values, they omit the intraday position changes that are implicit in daily P&L. Berkowitz and O'Brien demonstrate that reduced-form VaR forecasts based on the generalized autoregressive conditional heteroskedasticity (GARCH) models that were introduced by Engle (1982) and Bollerslev (1986) are better able to capture time-variability in P&L volatility, producing lower VaR estimates overall, but which nevertheless capture volatility clustering so that losses in excess of VaR are fewer and less excessive. Subsequently, Burns (2002) investigates the use of different GARCH models for reduced-form VaR forecasting, showing that more reactive GARCH models provide better forecasts than more persistent ones.

2.2 Credit Risk

There is no single "best practice" model for credit risk capital assessment, although the Basel 2 "Internal Rating Based" methodology provides a simple portfolio model (Gordy, 2003). Crouhy, Galai, and Mark (2000) survey the main approaches: the structural firm value models that are broadly based on the option theoretic approach of Merton (1974) and were popularized by the "CreditMetrics" methodology (see http://www.riskmetrics.com); the ratings-based models developed by the KMV corporation; the macroeconomic model of Wilson (1997); and the actuarial loss model of Credit Swisse First Boston (1997). While attempts have been made to recover a unified structure (Gordy, 2000; Hermann and Tasche, 2002), there are fundamental differences between them and no consensus on the best approach. In contrast to market risk, there has been little detailed analysis of the empirical merits of different models for credit risk capital assessment. Nickell, Perraudin, and Varotto (2001) suggest that both firm value and rating-based models substantially underestimate the risk of bond portfolios, but the marginal and joint distributions of important risk factors such as default and recovery rates are extremely difficult to model in the absence of reliable data. Consequently it is difficult to test these models (Jackson and Perraudin, 2000) and none has been sanctioned by banking regulators for the assessment of minimum regulatory capital. Academic research in this area has instead focused on the determinants of credit risk factors (Duffie and Singleton, 1997, 1999; Collin-Dufresne, Goldstein, and Martin, 2001), the dependency between risk factors (Hu and Perraudin, 2001), and the integration of credit risk to market VaR models (Duffie and Singleton, 2003).

2.3 Operational Risk

With institutions already mapping events to operational loss categories and building warehouses of operational risk data, the pivotal issue is increasingly the analytical methodologies, the so-called Advanced Measurement Approaches (AMAs). Even though the data collection is still at a relatively early stage, the AMA model design will influence the data collected, so users already need to know the modeling methodology, even if it is not fully implemented until a later stage.

At the time of writing the industry has (unofficially) agreed upon the actuarial loss model approach as "best practice" for operational risk assessment (Alexander, 2003; de Fontnouvelle, DeJesus-Rueff, and Rosengren, 2003; Embrechts, Furrer, and Kaufmann, 2003; Netter and Poulson, 2003). But many data reliability issues still need resolving. An internal loss experience for the important (low frequency, high severity) operational risk types is rare and any relevant data are likely to be in the form of risk self-assessments and/or external loss experiences. Also, for all risk types, the loss experience data require filtering because severity data are truncated and frequency data can be subject to significant reporting bias. Many variants of AMAs concern the design and validation of self-assessments, the scaling of external data, and the methods used to combine data from different sources.

2.4 Aggregation Risk

Currently each type of risk is assessed using a specific structural model and risk is assessed by a single metric, such as VaR, at a very early stage. A "bottom up" approach is standard where risks are assessed first at the instrument or event level by risk category (separately for credit, market, operational, and other risks), then individual assessments are progressively aggregated into portfolios of similar instruments or activities. These are aggregated over business units and, usually only at the very end, across major classes of risks, to obtain a global representation of firmwide risk. This process leaves no option but to apply very basic rules to aggregate risk capital first into broad categories, then across different business units, and finally over different categories of risk. Often individual risk estimates are simply added to obtain an approximate upper bound for capital—with aggregation based on an independence assumption being regarded as an approximate lower bound. However, neither of these bounds are necessarily correct, nor are they accurate.

To see this, Alexander and Pezier (2003) compare the aggregate risk capital assessment based on the assumption of independent risk factors with the upper bound assessment based on fully dependent risk factors. While the independency assumption gives an aggregate risk capital estimate that is a small fraction of the upper bound, it still does not provide a satisfactory lower bound when compared with real economic capital data from major banking conglomerates. They attribute this to many negative tail correlations between fixed income and equity risk factors.

2.5 Model Risk

All risk models have the same general structure. The model is based on assumptions about the behavior of the identified risk factors and some data are obtained on these risk factors. Given the model assumptions and the data, parameter forecasts are made to forecast the (profit and) loss distribution over the risk horizon of the model and the risk metric (usually a quantile or a standard deviation) is applied. Two types of model risk arise from (i) inappropriate assumptions and (ii) incomplete data. Both give rise to model risk because they generate uncertainty about parameter forecasts. Inappropriate assumptions include univariate and bivariate risk factor distributional assumptions (such as normality, constant volatility, and modeling dependencies with simple linear correlations). In the aggregation model, particularly crude assumptions are made about dependencies between broad categories of risk, as explained above.

Asset or risk factor marginal distributional assumptions are the main source of pricing model risk (Cairns, 2000; L'Habitant, 2000; Charemza, 2002; among others). However, little research is available on issues that specifically relate to model risk, with the exception of Derman (1997). What is clear is that in a firm-wide risk capital model, it is rather inane to focus on the model risk arising from marginal distributional assumptions when individual risk assessments are aggregated using only very basic dependency assumptions. For the purpose of economic capital allocation, and particularly for minimum regulatory capital calculations, it is the aggregation risk that really matters.

3 RISK CONTROL

Regulatory and technological changes have served to increase both the accuracy of risk assessments and the frequency with which risks are reported. But this trend toward more accurate "real-time" monitoring of risks is not necessarily a good thing. With real-time monitoring, traders are immediately aware of variations in VaR or whatever the risk metric used to set limits, and just knowing the risk in real-time *could* produce a panic reaction, even if there is no threat to the minimum solvency ratio. A limit could easily be breached intermittently in a particular activity, and when previously we wouldn't know it, now we do.

However, accurate real-time risk monitoring by itself does not increase systemic risk. It is only when many market participants react in the same way when they receive the same signals that the stability of the whole system can be threatened. Effective risk reduction depends primarily on the incentives given for risk control. But in the current system, junior managers are given "ownership" of risks; that is, at the same time as monitoring and reporting them, they also have the power to make decisions about the control of these risks. Moreover, these people are often rewarded on an individual basis—usually for reducing their "own" risks, regardless of the effect on other risks within the organization or other risks in the financial system—and common classical statistical objectives are applied to all, such as "minimize the variance of a hedged portfolio" or "maximize risk-adjusted return on capital."

There are good reasons why the current incentive system could fail to reduce market and credit risks and even increase systemic risk. First, when objectives are optimized regardless of the effect on other risks and returns in the organization, it is highly unlikely that global hedging will be efficient for the enterprise as a whole. The decisions made to control risk are best taken at the senior management level in the organization because senior managers could choose to increase some risks when this has global benefits to the organization. Second, the use of incentives based on classical statistical objectives tends to increase homogeneity in risk control. Many financial markets are dominated by the leading actions of a few large conglomerates, so when risk mangers in these organizations have incentives based on similar objectives, they have similar reactions to market events. Panic reactions could spread very quickly through the markets, leading to increased volatility and even mass insolvencies in the banking and other sectors.

Even though systemic risk is a primary concern for regulators, recent changes in regulations have served to increase homogeneity in the risk control process. By defining "sound" practices that increase the accuracy and frequency of risk reporting and prescribing internal models for regulatory capital that are also used for internal economic capital calculations, both signals and reactions to these signals are becoming more homogeneous. Many large banks have "real-time" VaR monitoring with frequent reporting to junior managers who are given incentives that are suboptimal from a firmwide perspective and are also based on statistical objectives that are fairly homogeneous across the banks that are operating that business activity. In portfolio management, the presence of different types of investors—arbitrageurs or hedgers, trend followers, or noise traders—has been shown to prevent the formation of asset price bubbles and crashes (DeLong et al., 1990; Shleifer and Vishny, 1997; Brunnermeier, 2001; Wurgler and Zhuravskaya, 2002). Similarly, senior management should aim to provide risk management incentives that induce heterogeneity in risk control.

4 FUTURE DIRECTIONS FOR RISK MODEL RESEARCH

We have seen that aggregation risk is an overwhelming source of risk capital model risk. Fine tuning of market and credit VaR estimates of individual instruments or small portfolios may impact the relative risk capital allocations within a particular activity, but since very crude aggregation rules have to be used, this has less impact on the risk capital at the level of the asset class or business unit. At the level of the firm, aggregation risk underpins the poor performance of structural risk capital models compared with the reduced-form alternative. We have also seen how another important model risk arises from incomplete data. This is significant in long-term market risks, in credit risk assessment where, for instance, multivariate default and recovery rate distributions for high credit ratings have virtually no historical basis, and it is naturally of great importance for operational risk assessment. Third, we have argued that effective risk reduction at the global level depends primarily on the incentives given for risk control. A quantitative model is required for risk control, a model that has an explicit link with the risk capital assessment model. Only in this way will the incentives given to individual managers induce truly efficient hedging of risks. In this section we examine how these three considerations could influence future research in risk management.

4.1 A Common Framework

Many large organizations are now changing their subsidiaries from independent legal entities to branches that fall under the jurisdiction of the regulator of the head office. As branches do not need to physically hold the necessary capital, new techniques for the proper aggregation of risks and new integrated risk systems will be on the agenda for future research.[4] The global positioning of risks is an immensely difficult task in the current environment. Financial risk management has focused on market and credit risks only, with some important, but less easily quantifiable risks being ignored. But we have seen that operational, business, and systemic risk are all likely to be perceived as being more important in the future. As new or previously less important risks take center stage and large complex banking groups are faced with the difficult tasks of aggregating risks from models that have completely different foundations and integrating systems that have completely different technologies and data warehouses, the need for a clear distinction between market, credit, operational, and other risks dissolves. In a perfect world, these traditional boundaries would be relaxed, as banks adopt a more "holistic approach" to risk management where all risks are assessed on similar principles and modeled within a single system. It is only within a unified framework such as this that we can develop proper methods for risk aggregation and thus aim for the efficient global positioning of risks.

The first step in this direction is to define a common risk assessment framework for all types of risk. However, very little academic research has focused on this area, with the exception of Alexander and Pezier (2003), who apply a reduced-form common risk factor model to investigate the effect of risk factor dependencies on market and credit risk aggregates. Using historical data on risk

[4] Risk aggregation should be distinguished from risk integration, despite the similarity of these terms to a mathematician. The implementation of an integrated risk management system that can monitor the net effect of many scenarios (such as a 1% rise in interest rates) is currently one of the great challenges facing risk managers of large conglomerates.

factors that are common to many business units and to different risk types, Alexander and Pezier compare the economic capital estimates obtained using the model with the actual economic capital data from several major banks. In the common factor model, the aggregation of risks is based on the historical distributions of risk factor and their correlations. Another advantage of modeling risks and returns in different business activities in the same framework is that it facilitates the constrained optimization of a risk-adjusted return performance objective and provides an explicit link between risk control and risk capital assessments.

No explicit link between risk control and risk assessment is necessary to comply with the 10 principles of risk management set out by the Basel Committee (2001) for the new accord. Nevertheless, such a link is essential for internal purposes. Business unit managers need to understand how risk controls affect their economic capital, and whether the benefits of reduced economic capital outweigh the costs of the controls. It is therefore unfortunate that recent legislation in the United States is likely to hinder the development of this link in the near future. Following the recent spate of large-scale company frauds, Enron being one particularly important example, the Sarbanes-Oxley Act of July 2002 has introduced new legislation for U.S. listed companies, holding chief executive officers (CEOs) and chief financial officers (CFOs) personally liable for the accuracy of their corporate disclosures. A reliable risk management process has become key to legal indemnity in the United States, yet many senior executives (or their legal representatives) seem satisfied with no more than a qualitative assessment of risk controls.

4.2 Bayesian VaR

With so much historical data available for assessing short-term market risks, some risk managers believe it is possible to assess long-term market risks with a reasonable degree of accuracy. This is unfortunate, even more so because this ethos has been carried into the development of risk-sensitive portfolio models of credit risk and to classical statistical models of operational risk based on historical loss experience data. But whatever the assumptions, all models are subjective and all data are incomplete. Even the decision to use “objective” historical market data is the result of a subjective choice. And since historical data on risk factor returns are not forward looking, they are incomplete. They contain no expectations of future returns. Different agents may justifiably have very different *prior* views about default rates, long-term volatilities, or any other important inputs.

Hence a key direction for future research in market and credit risk assessment is to incorporate prior beliefs about the future. Surprisingly, given the huge literature on Bayesian estimation, little research on this can be found in the risk management literature other than in Dowd (2000) and Siu, Tong, and Yang (2001). These papers apply Bayesian market VaR models to capture both a subjective view toward the financial markets and the information contained in historical data. Closed-form Bayesian VaR estimates obtained through conjugate prior assumptions contain classical VaR estimates as a special case corresponding to uniform priors. With risk managers now being required to provide subjective assessments of new types of risk (e.g., operational, business, and systemic risks) and forecasts of market credit risks over one year or more, more research on the use of Bayesian methods for forecasting all types of risk is needed.

Research into operational risk assessment is still at an early stage, yet the experience of handling such incomplete data has already been very instructive. The use of subjective data from expert opinions and/or "risk self-assessments" in addition to historical loss experiences is rapidly becoming standard practice in operational risk assessment. The industry already has much to learn from early research into Bayesian methods for operational risk assessment. Commercial AMA solutions, aiming to provide maximum flexibility in model design, offer many functional forms for frequency and severity distributions, but little guidance on how the type and source of data should influence their choice. The result can be a complex and expensive system that lacks transparency. Suppose a firm employs a negative binomial frequency distribution and a gamma severity distribution for internal loss experiences. Then how should the severity data be detruncated and combined with loss experience data from an external consortium, which may of course use a different truncation level? And if risk self-assessment data are used to provide subjective, but more forward-looking judgments on the loss model over the risk horizon, can psychologically meaningful questions be designed that are compatible with this choice of functional forms? If so, can the results be properly validated by risk assessments based on external data and how should they be updated using internal loss experiences? Further limitations are that (i) in order to deal with the diverse data types and sources that are characteristic of operational risks, these systems sometimes resort to ad hoc procedures; and (ii) they provide neither an assessment of dependencies between different types of operational risks, nor any link from risk control to risk capital assessment. In contrast, the Bayesian operational risk assessment methodologies advocated by Cruz (2002) and Alexander (2003), among others, are specifically designed to deal with multiple types of data.

4.3 Linking Risk Control with Risk Capital

We end this section by providing a brief outline of two new types of risk model. The first is a risk control model where subjective risk assessments in a Bayesian VaR model provide the link between risk control and risk capital. The second is a common factor risk assessment model that admits the proper aggregation of economic capital and, through the maximization of firmwide risk-adjusted return on capital (RAROC), can determine the optimal costs of capital that should be charged to each business unit in a risk management incentive scheme.

Figure 3 depicts a framework for an operational risk control process where the effect of risk control on operational risk capital can be assessed. The model is simplified so that only one key risk driver is associated with each risk indicator: product complexity affects the number of failed trades; systems quality (the age of the system, the staff expertise, and the systems resources) affects system downtime; and financial incentives (pay structure, bonus scheme, budgetary incentives, and so

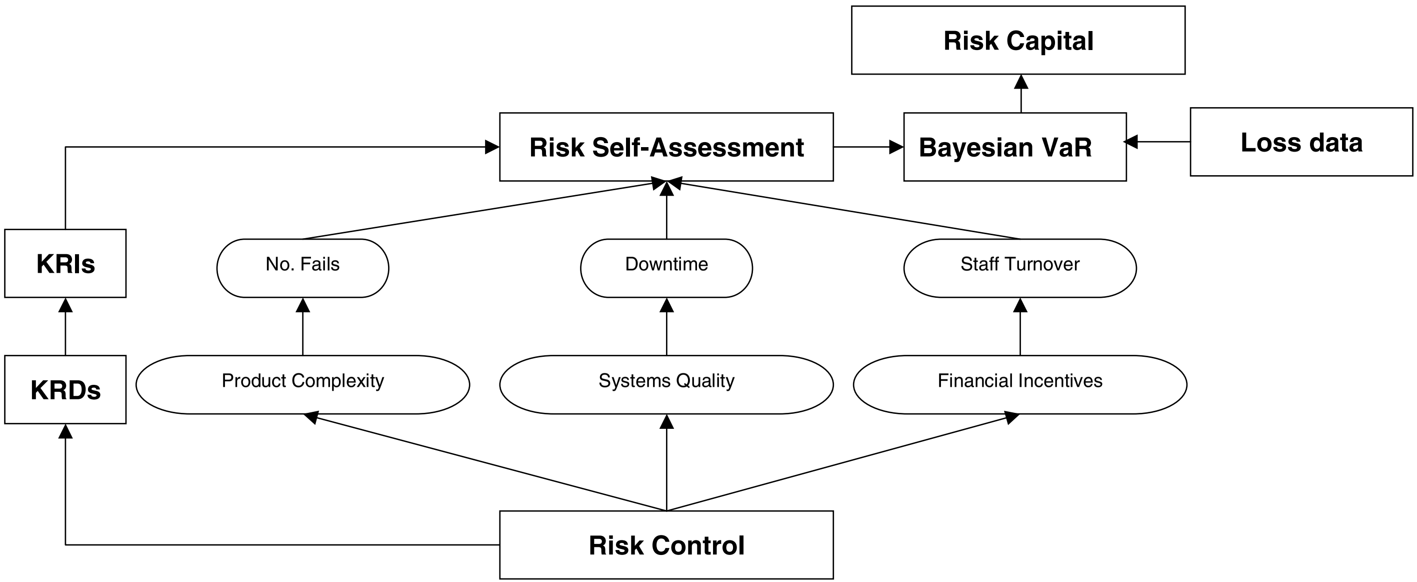

Figure 3 Linking operational risk control to risk capital.In operational risk a “key risk driver” (KRD) is a variable that can be directly affected by management actions. Examples of KRDs given here are product complexity, systems quality, and incentive schemes. One or more key risk drivers is linked to each “key risk indicator” (KRI)—although for simplicity only one KRD is depicted for each KRI here—and common KRDs can be used to identify dependencies between different types of operational risks. A KRI is a variable that is associated with the loss frequency and/or loss severity of an operational risk, such as the number of failed trades, systems downtime, and staff turnover. The object of this schematic is to show that when risk self-assessments are based on KRI values and when these risk self-assessments are used in conjunction with historical loss experience data to forecast the loss model, then the risk management process has an explicit link from risk control to risk capital.

forth) affects staff turnover.[5] The link from risk control to risk capital is provided when risk self-assessments are explicitly based on the values of key risk indicators. Then a Bayesian risk assessment model that combines two data sources—historical loss experiences and risk self-assessments—into a single loss distribution provides a risk capital estimate that is linked to the values of key risk drivers. This type of risk management model provides a framework for a scenario analysis that is capable of assessing the effect on capital limits as any risk driver is changed.

In our second example, Figure 4 depicts a common factor model that captures dependencies between broad risk categories across business units, and between business units across risk categories. This is the common factor model framework introduced by Alexander and Pezier (2003) for market and credit risk aggregation. Their results show that senior management could choose to increase economic capital in some of the more flexible lines of business because, when common risk factors are correlated, increasing the risks in some activities could have the effect of reducing the total economic capital for the firm. Figure 4 extends their framework to include the cost of capital charged to each business unit in the optimization objective function. Through the maximization of firmwide RAROC, the model can determine the optimal costs of capital that should be charged to each business unit in a risk management incentive scheme that will be optimal for the firm as a whole.

5 SUMMARY AND CONCLUSIONS

Up to now, financial econometric research has focused on the assessment of market and credit risk, with little work on other types of risk or on other risk management issues. But current trends in financial markets are changing our perception of the important risks. In particular, operational, business, and systemic risks are all becoming more important for the shareholders of the large banking conglomerates that exist today and for their firmwide risk management functions, whose primary aim is to allocate internal resources efficiently. Much of the literature concerns just one of the sources of model risk in risk capital models: the errors resulting from inappropriate risk factor distributional assumptions. While this is the main source of pricing model risk, there are other important sources of model risk in risk capital models and these should be examined in future research on risk assessment.

For the purpose of forecasting risk, all models are subjective and all data are incomplete. Even the use of a volatility forecast derived from a statistical model whose parameters are estimated using historical returns data is a subjective choice. And the data are incomplete because they contain no information on agents' beliefs about what will happen in the future. One of the lessons to learn from our early experiences with the assessment of operational risks is that subjective risk self-assessments and

[5] In the more general framework, several key risk drivers would be common to different key risk indicators and this framework could also be used to derive the dependencies between different types of operational risks that are needed for proper operational risk aggregation.

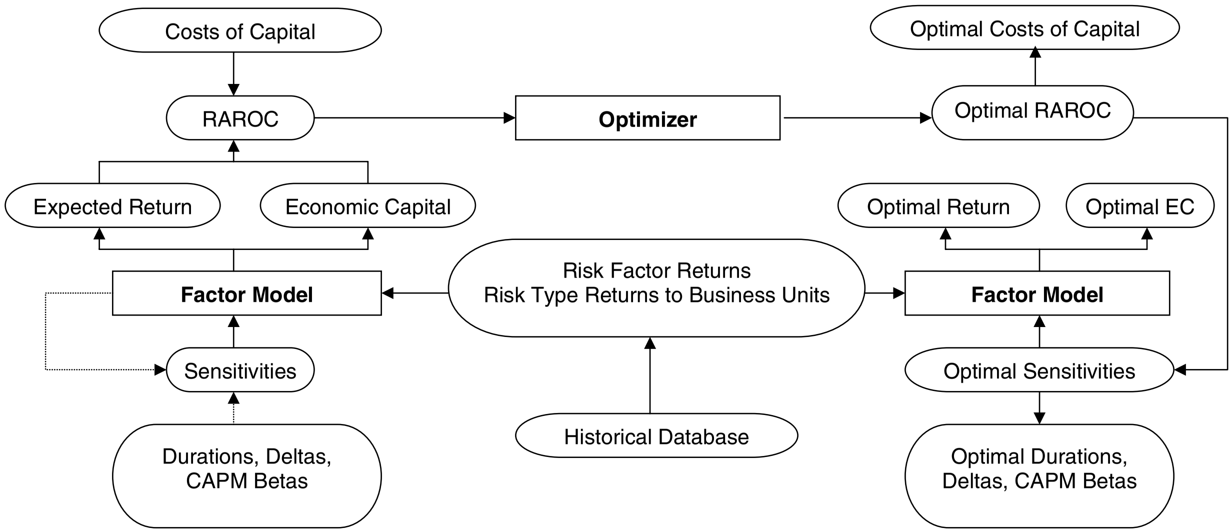

Figure 4 Application of common factor model to EC aggregation, risk control, and optimal incentive schemes.The linear factor model is $y = X\beta + \varepsilon$, where y is a vector of historical returns to each of the business units and each of the risk types, X is a matrix of common risk factor returns, β is a matrix of risk factor sensitivities (either given by price models or estimated by regression on the factor model, as indicated by the dotted lines), and ε denotes the residual returns. Expected returns are $E(y) = E(X)\beta + E(\varepsilon)$ and aggregate economic capital (EC) is determined from $V(y) = \beta' V\beta + V(\varepsilon)$. Total expected return (ER) is the sum of the components of E(y) and firmwide RAROC = $[ER - \alpha EC]/EC$, where the cost of capital α is fixed (e.g., to the risk-free interest rate). The optimizer maximizes RAROC by changing β subject to constraints on the feasible business activities and by changing the cost of capital charged to each business unit. Risk control then implements the optimal β and the optimal EC and costs of capital determine the incentive scheme.

expert opinions or data based on the experiences of other firms can improve upon assessments that are based solely on internal historical experiences. Thus it seems likely that a new strand of academic research will focus on proper Bayesian methods for assessing market, credit, and operational risks, combining data from multiple sources into one risk assessment for each risk class.

For a large banking conglomerate, the overwhelming source of risk capital model risk is that arising from the use of crude risk aggregation techniques. Senior managers may well ask what is the point in providing a relatively precise assessment of the market and credit risk for a portfolio when very crude aggregation rules are applied to aggregate risks into first business units and broad risk categories and then eventually for the whole firm? These crude rules are necessary because each broad type of risk is assessed via a structural model and there is little commonality between the models used for different types of risk. To derive proper methods for risk aggregation requires going back to the drawing board to redefine the framework of risk models. There is a clear need for further research into reduced-form VaR models based on common risk factors in which component risks can be aggregated using realistic assumptions about risk factor dependencies.

Financial econometric research could also broaden its scope to encompass some of the wider issues facing large conglomerates. Risk control is evolving toward the traditional management role, where optimal incentives are decided by senior management for the benefit of the entire firm, not an individual junior manager. This requires a business model for risk control, which not only accounts for costs but also includes *firmwide* benefits in the objective. We have argued that future research into risk capital assessment models should both quantify the effect of risk control on the risk assessment and derive optimal incentives for risk control. A framework for two risk models that incorporate these effects has been outlined.

In summary, we have argued that there is a clear need for further research into reduced-form VaR models that are set within a common framework, admit the proper aggregation of risk, are capable of incorporating prior beliefs about the future, and perhaps most importantly, provide an explicit link from risk control to the risk capital assessment and to the optimal allocation of resources. Although this agenda is very ambitious, with more resources available to academic research in financial risk management, much of this could be achieved during the next decade.

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