

The Complexities of Financial Risk Management and Systemic Risks*

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- *Risk-management systems in financial institutions have come under increasing scrutiny in light of the current financial crisis, resulting in calls for improvements to these systems and an increased role for regulators dealing with them.*
- *The basic theory and practice of modern risk management is complex. Given the serious failures manifest in the current crisis, some possible strategies that can improve the performance of risk management and regulatory practice should be considered.*
- *Prudential regulation should focus on failures within the financial firm and in the market interactions between firms.*
- *Market failures resulting from liquidity and systemic risks call for new techniques that will require the input and co-operation of financial institutions and regulators.*

The current international financial crisis has resulted in calls for improvements in risk-management systems in financial institutions (FIs), and an increased role for regulators dealing with these systems.¹ These recommendations make a distinction between macroprudential and microprudential regulation. Microprudential regulation deals with the detailed regulation of a bank, including its risks and capital adequacy. Macroprudential regulation focuses on system-wide risks, which result from risks that occur in the trading that takes place between banks and the rest of the financial system. This article will not deal with the various recommendations that have been made with regard to macroprudential regulation, but will focus instead on the important interface between microprudential and macroprudential regulation. This interface is critical in bank and FI risk management, as well as in attempts by microprudential regulatory systems to deal with the impact of systemic macroprudential effects on individual banks or FIs.

What is not widely appreciated are the complexities in managing risk-management systems. Designing and operating these systems is a difficult task, requiring a careful blend of modern finance and banking theory; quantitative methods; and judgment based on long experience in credit analysis, legal and accounting rules, and other key areas. Yet too often it is assumed that improvements can be made by better use of data, increased microprudential regulation, reducing perverse incentives, and so on. These are all worthy

* This article has drawn material from a longer and more technical working paper (Milne 2008b).

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1 There are several international reports. For example, see the de Larosière report (2009) to the European Central Bank. For the United Kingdom, see the *Turner Review* (Financial Services Authority 2009a) and the response of the Financial Services Authority (2009b). For the United States, see Acharya and Richardson (2009), which provides a detailed analysis of the crisis and of various regulatory failures and reforms.

objectives, but they miss the intricacy at the heart of the risk-management process. I will argue that the complex issues involved require careful analysis of the theory and application of modern risk-management systems, and, in particular, that the basic theories underpinning many asset-trading and risk-management systems in FIs have assumed away systemic effects. Thus, they mislead some FIs into taking on unmeasured systemic risks. Although experienced risk managers use the quantitative systems as a guide, they adapt decisions to take into account qualitative information and effects that are unmodelled, or were difficult to model, in the current systems. In spite of this complexity, however, and the serious failures manifest in the current crisis, there are ways to make the necessary changes. In this article, I propose to review some possible strategies that can improve the performance of risk management and microprudential regulatory practice.

Using this microanalysis, or “bottom-up” approach, permits light to be thrown on possible causes of systemic risks in the financial system. Links can also be drawn between the microprudential regulation of risk-management systems and the missing elements in these systems that imply systemic risks. To understand this argument, the basic FI risk-management problem needs to be explored, considering its strengths and weaknesses. FI risk-management systems should then be embedded in markets with interacting FIs, thus providing the links between FIs and financial markets. This latter technique is sometimes called a “network” approach,² but economists will recognize it as a general-equilibrium analysis for a competitive economy, or as a strategic approach in the industrial organization literature on oligopolies. An additional benefit of this type of analysis is that it provides a consistent framework for discussing both microprudential risk-management analysis and problems with systemic risk. The framework is not complete—there are serious gaps in our knowledge—but this can be a fruitful way of thinking about financial crises and prudential regulation.

Risk-Management Systems: The Issues

Risk-management systems have evolved over many decades. FIs that issue credit have long used credit-ranking systems to manage their credit books. As well, they use other methods to manage credit risk,

such as adjusting rates, collateral, and individual exposures, and procedures for workouts in default. Because much of the lending book was largely illiquid, banks had limited ability to hedge their risks. Over time, these systems have become increasingly mechanized through credit-scoring systems and other means. But big changes have occurred more recently when securitization allowed FIs increasingly to hedge and trade credit risks. This required different methods for pricing, hedging, and managing credit exposures that had to be integrated into more traditional systems. Fundamental problems occurred in that integration, problems that became obvious during the recent crisis.

The problems for private sector risk-management systems can be grouped in two broad categories: (i) the underlying theoretical formulation of risk-management systems, and (ii) statistical calibration. The existing models are a synthesis of traditional credit systems and the efficient-markets (Arrow-Debreu) model of trading, hedging, and pricing assets. This model, if taken seriously, implies that there is a dynamic factor structure that can be used to price assets. These factors (after diversification) can be traded in frictionless, competitive markets and used to price assets by arbitrage methods. In essence, the model is a general-equilibrium economy plus a dynamic linear system for hedging and pricing assets and their derivatives. Unfortunately, this model implies that the financial system and trading of financial derivatives do not add economic value; it is welfare irrelevant. Modern banking theory takes this theoretical deficiency seriously and introduces various frictions to make sense of banking, financial intermediation, and sophisticated financial systems. The internal credit and trading operations of FIs are not seen as substitutes for markets, but as complementary institutions, solving complicated agency and informational problems that the frictionless market cannot solve.³

Banking theory has made very limited inroads into the theory and practice of risk management, where modelling has been dominated by the frictionless, efficient-market model masquerading under the title of financial engineering. Literature on the latter topic has recently been attempting to cope with the theoretical complexities introduced by frictions (e.g., transactions costs and illiquidity) through reduced-form methods; however, the more general strategic problems of concern in the banking literature have been ignored. The theoretical risk-management

² For an early analysis of this problem, see Allen and Gale (2000). See also their survey of the more recent literature in Allen and Gale (2007, Chapter 10).

³ For an excellent, readable discussion of this point plus insightful comments relating to risk management and regulatory failures in the crisis, see Hellwig (2008).

literature and some approaches for introducing liquidity into the models are surveyed in this article. A further problem is that most banking-theory models are relatively simple and of low dimension. They are exploratory, examining logical possibilities that could be consistent with stylized facts, but are far from being operational in any risk-management system. This is one of the serious gaps in our knowledge.

Serious practitioners of risk management understand this complexity only too well and are aware of the dangers of fixations on spurious model and statistical precision.

The second deficiency in risk-management systems concerns calibration of the frictionless risk-management model. Calibration of risk-management models relies heavily on historical time-series and cross-section financial data, which exhibit well-known non-stationarities that are difficult to predict. Far from being a statistical analysis of a fixed mechanical system (the prototype for financial-engineering methods), sophisticated use of the models involves exploiting a degree of judgment to allow for non-quantitative observations, experience, financial market innovation, legal changes, and a myriad of other risks. Serious practitioners of risk management understand this complexity only too well and are aware of the dangers of fixations on spurious model and statistical precision (“polishing the hubcaps on a rustbucket”). Some progress is possible in this area, but the results may not be all that significant. Clearly, longer and more detailed data series will help, but the fundamental causes of the non-stationarity reduce the benefits of adding older data.

At the regulatory level, a further layer of complexity is added in dealing with systemic risks. Whereas the risk-management systems in FIs take the environment as given—assuming a partial, competitive, frictionless approach—systemic risks require a model of the financial system to track interactions between FIs and possible interactions with the real economy. An added requirement, if regulatory intervention is to be justified, is to explore plausible market failure(s).⁴

One such friction could be illiquid asset markets.⁵ There are prototype models that introduce various types of illiquidity into asset-portfolio models and arbitrage-pricing methods. In the following sections, some basic model approaches will be sketched, along with indications as to how they may be introduced into risk-management systems. Modelling illiquid markets can provide a consistent framework to explore a modified risk-management system for each FI and justify plausible regulatory intervention that is impossible in the frictionless model. In short, illiquid markets can yield a form of pecuniary externality where a trade in an asset by one FI can alter prices and spill over via price and/or wealth effects into other FIs.

Risk-Management Theory

The simplest model of a risk-management system is the conventional two-date portfolio model, where the FI has assets and liabilities today and the distribution of net returns can be estimated tomorrow.⁶ The objective of risk management is to obtain accurate estimates of the return distribution and, in particular, the tail loss (i.e., low-probability losses). This estimation problem is not straightforward.

The FI’s asset exposures are divided into various asset classes; e.g., stocks, mortgages and commercial loans, and derivatives products in the trading books. Each asset class has its own unique return characteristics and estimation problems. To begin, consider the basic portfolio model taught in every undergraduate or MBA investment course, which can be made more operational by assuming that asset returns can be explained by a linear function of some basic risks or “factors.” The easiest example of this type of argument is the so-called “market model,” in which stock returns are assumed to be a linear function of the short-term interest rate, the market return index, and a random-error term. Each random risk factor is multiplied by a “factor loading” that measures the relative importance of the risk factor in explaining the impact of that factor on the stock return being modelled. The model can be extended by adding other random factors; e.g., long-term bond yields. The assumption that returns are generated by random factors has a long history in applied finance and underlies all risk-management systems.

⁴ This approach has been stressed by Allen and Gale (2007). The argument has been taken up by Milne (2008a, 2008b) and Acharya et al. (2009).

⁵ I am not implying that this is the only type of externality possible. Counterparty risks would be another example.

⁶ Standard risk-management references discuss this type of model. See Crouhy, Galai, and Mark (2001) and Jorion (2007).

It became apparent in the 1970s that if an FI held a large, diversified equity portfolio—so that the portfolio-weighted random-error terms could be summed to approximately zero by the Law of Large Numbers—then the diversified portfolio return could be approximated by a linear combination of the factor returns. Furthermore, in diversified portfolios, the prices of the assets would be restricted by possible arbitrage trades. To illustrate, ignore the random errors (diversifiable terms) and assume that the number of factors is small—say, two. A current price for each factor can then be deduced using elementary linear algebra. Employing these factor prices, every current stock price can be written as a linear combination of the underlying factor prices employing the coefficients as weights. If this linear pricing rule was not true, then any investor could take a diversified portfolio of stocks and make unlimited profits. This factor-pricing theory has various names, depending on the application: the arbitrage-pricing theory; a 1-period version of financial derivative pricing; or the generalized Modigliani-Miller theorem (see Milne 2003, Chapters 4 and 7). Hedge funds use sophisticated variants of this basic methodology.

Financial economists observed that this 1-period method (or more sophisticated multi-period versions) for pricing assets was simple and relatively easy to implement with standard econometric techniques. But it had several limitations: The theory assumed a number of random factors, but did not explain how the factors were chosen, or whether the factors that were selected varied over time. In trying to identify the factors, regression or factor analysis (Principle Components) could be used to estimate the number and types of factors and the coefficients in the linear equation. The question was: Were these coefficients stable over time, or would they be conditional on observable market variables? These issues have never been fully resolved, although, after strenuous empirical testing, there are some candidates for common factors. (In standard investment MBA textbooks, the stock market index, the short interest rate, or industry factors derived from industry equity indexes are often quoted as candidates.)

A multi-period version of the model can be modified to allow for a multi-factor return structure, so that we can derive a conditional-factor structure for returns at each situation in the future. The factor structure of returns can therefore be reinterpreted as a conditional-factor model, where the coefficients should be interpreted as conditional, and the number of factors could (in principle) vary over time or events.

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This multi-period factor model (for a derivation, see Milne 2003, Chapters 8–10) can be used to price default-free bonds of different maturities. The trick is to observe that zero-coupon bond prices can be written as a factor-structure model (simple substitutions can be used to make the same argument for bond yields or forward rates). This implies that the common factors will affect bond prices, depending on the coefficients. Because bond prices converge to their face value at maturity, the coefficients cannot be stationary. Other restrictions rule out dynamic arbitrage strategies.

These factor models have a further use. They provide a building block for derivative pricing that approximates the celebrated continuous-time Black-Scholes-Merton option-pricing model (Black and Scholes 1973; Merton 1973). The idea is very simple: Assume that the stock price evolves according to a one-stochastic-factor model plus a constant. Assume that the random factor is a binomial random variable. Then, using the stock and the short-term government bond, a portfolio can be created to replicate any derivative on the stock, one period ahead. Thus, the option price must equal the price of the replicating portfolio (otherwise arbitrage profits exist). Using this argument iteratively over time—assuming that the volatility parameter on the random factor and the risk-free rate are constant over time—a dynamic portfolio strategy can be built to replicate any European option payoff on the stock at time of maturity. (The payoff to a European stock option is $\text{Max} \{S_T - X, 0\}$, where S_T is the stock price at a fixed exercise date T , and X is the fixed exercise price.) Given a dynamic portfolio strategy that replicates the option return at T , the initial value of the portfolio strategy and the initial option price must be equal to avoid an arbitrage opportunity.

This model is merely a simple prototype for more complex models that use more factors, or have more complex conditional-volatility structures. Assuming a factor structure for bond prices, it is an easy step to create a bond-option model where default-free bond prices follow a simple factor structure. By 1990, the several bond-option models then in existence were implemented in short order by major FIs on Wall Street.

The next step made the bold assumption that the same factor idea could be applied to corporate bonds that might default. An early model by Merton (1973) had demonstrated the basic idea. Using a comparison between a European stock option and a levered stock, he was able to price the levered stock with the Black-Scholes-Merton model. In turn, he was able, by assuming the Modigliani-Miller theorem, to deduce the value of the defaulting bond as a residual difference between the value of the firm and its equity value. This insight has spawned a whole battery of so-called “structural models” that extend this theory to price risky corporate debt. Various proprietary models have used structural models to price corporate debt.⁷

A second group of models—the “reduced-form” models (introduced by Jarrow and Turnbull 1995, and other theorists)—avoids describing the details of any firm’s financial structure but models default and recovery as other factors in the evolution of the bond price. This type of model permits the extension of the default-free theory to allow for default as an additional random factor. Although simple in outline, the model can be extended in several ways; e.g., by allowing for additional information in bond ratings to add realism to the bond-pricing model. Given this structure, it is easy to use the replicating-portfolio idea to create a perfect hedge for any credit derivative that can be dreamed up. Once the replicating portfolio is created, the price of the derivative must, by the familiar arbitrage-free argument, be the portfolio price. Other variations of these models have been developed recently to deal with complex derivatives on credit risks, and counterparty risks.⁸

Both types of models, and their generalized versions, have been used extensively in the credit industry to model, price, and hedge credit instruments. In turn, the models have been modified to analyze collateralized debt obligations, mortgage-backed securities, and many variations that had allowed previously illiquid loans to be securitized and sold as part of larger packages or tranches via conduits or special-purpose vehicles. The underlying factor models used in this theory assume particular probability distributions over factors that explain default risk. Having created risk factors, specified joint-probability distributions, and made assumptions on the covariances between defaults of individual loans, a theoretical portfolio of loans can be created that reduces risks

via standard diversification arguments. This loan portfolio can then be sliced into tranches with increasing degrees of default risk. The safest tranche is modelled to be almost risk free; the second tranche (or mezzanine) has higher risk; and so on. The tranches can then be sold in packages of risk that mimic corporate bonds with different default risks or credit ratings.

In addition to an FI’s trading, credit, and derivative risks, other risks can be incorporated into its risk-management system. In recent years, for example, there have been attempts to model operational risks. The idea is that some FI losses have been the result of errors in pricing, hedging, or processing information; employee fraud; computer system failures; acts of terrorism; and so forth. The evidence suggests that high-frequency small losses can be characterized with some degree of accuracy (e.g., small errors in entering data), but low-frequency, large losses (e.g., large-scale fraud or IT failure) are far harder to estimate; the FI must therefore rely on internal audits, backup systems, and other methods to reduce risks. The operational-risk models should be used with standard auditing and security practices to minimize the risks, given the costs of implementation. Other examples of risks that are hard to quantify are legal risks and reputational risks that can arise in trading complex securities.

Risk-Management Practice

Although the general theory outlined above appears straightforward, competent implementation requires judgment, experience, and knowledge of the pitfalls in using the models.⁹

To begin at the simplest level, consider the problem of the portfolio with equity one period ahead. Assuming a Gaussian or normal distribution factor model, the first step is to estimate the means and covariance matrix for the stocks. It is well known that the mean returns are measured with considerable error. The estimation of the covariance matrix will be sensitive to the choice of factors. Some methods use pre-specified variables; e.g., interest rates, industry returns, and stock indexes; others use principal-component analysis to derive implicit factors; and still others use copula methods.

A major drawback of these methods is that the estimation is based on time series and cross-sections

⁷ See Crouhy, Galai, and Mark (2001); and Caouette et al. (2008) for extensive discussions.

⁸ See Lando (2004) and Meissner (2005) for surveys of this literature.

⁹ See Crouhy, Galai, and Mark (2001) and Jorion (2007) for discussions. See also Hellwig (2008) and Milne (2008a, b) for more detailed critical observations on risk-management theory and practice in the context of the credit crisis.

of historical data. Furthermore, estimates of covariance matrices that measure the correlations between financial variables are not stable over time. Statistical techniques that accommodate non-stationarity in these estimates use time-series econometric methods. By using moving averages or ARCH-GARCH estimation techniques, it is possible to estimate parameters, but some practitioners find these techniques too noisy and not sufficiently forward looking. They prefer forward-looking implied volatilities and covariances derived from derivative-pricing models. Sophisticated FIs modify the parameters, particularly mean estimates, by incorporating analyst estimates based on careful examination of information published by corporations and the financial services industry.

We can show some basic examples of rapid changes in financial variables that defy simple time-series modelling from past observations. A quick perusal of U.S. corporate bond spreads (measuring default risk) over time, show low spreads until mid-2007, followed by a large spike over the duration of the financial crisis (Chart 1). Similarly, we can see the large spike from mid-2007 in the yield spreads for investment-grade financial issuers (Chart 2). Finally, observe measures of volatility in basic stock and option indexes (Chart 3) that defy simple times-series modelling without resorting to various “regime-switching” formulations. (It is not obvious that these techniques would have helped in July 2008.)

Derivatives based on stocks can be analyzed using variants of factor models where the net exposures will depend on the particular hedge and any residual risk. Because derivative models are approximations that

Chart 1: Yields on U.S. corporate bond spreads

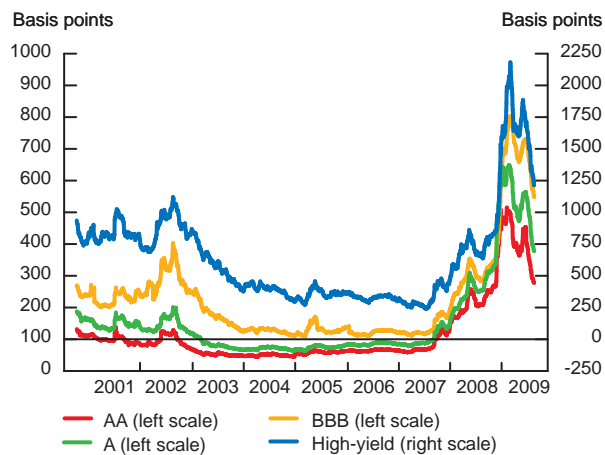


Chart 2: Yield spreads for investment-grade financial issues

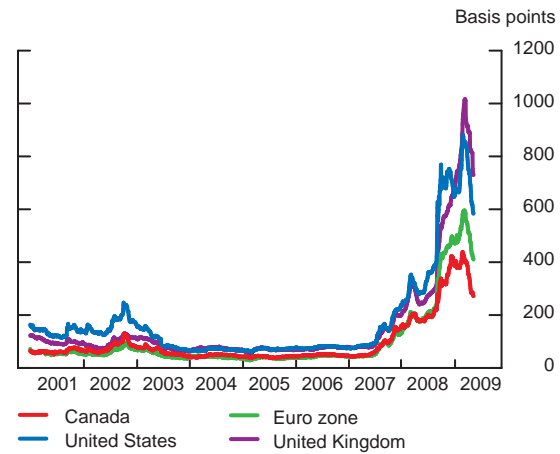
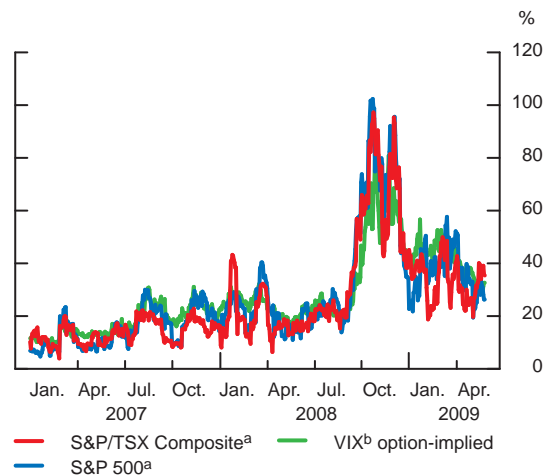


Chart 3: Volatility in global equity markets

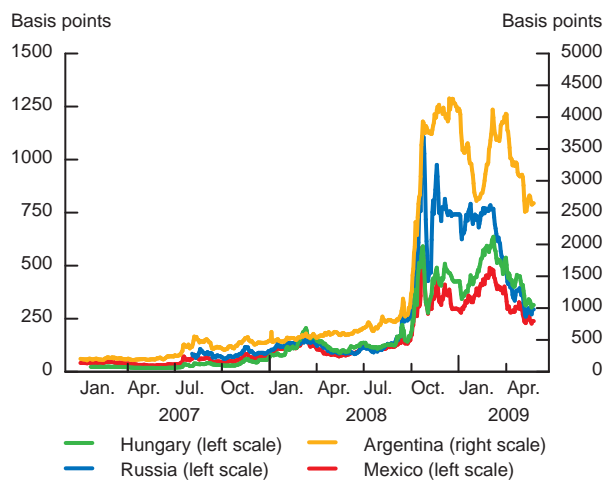


assume specific stochastic models for stock evolution, the approximate hedge will be sensitive to the number and type of stochastic factors (Brownian motion, jump process, variance gamma process, etc.) and the accuracy of the estimates of the distribution parameters. For exotic options (i.e., more complex functions of stock-pricing processes), the hedge can be very sensitive to the model assumptions and parameter estimates. Sensitivity analysis, which simulates such models using different stochastic processes, reveals that hedges can imply significant net exposures. Usually, competent risk management

limits such exposures, relying on imperfect correlations in the factors underlying each position to diversify the risks in the net exposure of the derivative portfolio. But in a situation of major market disruption, correlations can change rapidly, increasing in degree and destroying hedges, and can expose an FI to losses. In extreme cases, the losses can be very large, even forcing the FI into bankruptcy. For example, consider spreads on sovereign 5-year credit default swaps (Chart 4). Notice that until the crisis in 2007, the spreads are almost indistinguishable, but after the middle of 2007, and especially after mid-2008, the spreads jump and widen between countries, and become less correlated.

In exotic or complex derivative positions, lack of liquidity in the underlying securities can limit the effectiveness of hedge positions. If the underlying

Chart 4: Spreads on sovereign 5-year credit default swaps



Source: Markit

Last observation: 25 May 2009

security attracts significant transactions costs in trading, this complication should be incorporated into the hedging strategy to cover the costs of incomplete hedging. In many exotic derivatives markets, writers specialize and earn rents from their ability to hedge approximately. New entrants into these specialized areas should be wary that initial profits may disguise larger losses when prices move rapidly against them, or that sudden illiquidity in the underlying asset will make planned hedges very costly.

Similar problems confront traders in default-free bond markets. Models that use factors can be unstable over time. The estimation of parameters that corres-

pond to the term structure at any point in time can change in unpredictable ways, particularly in turbulent markets. For example, in 1998, Salomon Brothers (as related in Bookstaber 2007, Chapter 5) were using a model of the yield curve, the so-called two-plus model (two random factors plus a constant—with the constant signalling shifts in Federal Reserve policy). The model had worked well to produce a steady stream of arbitrage profits over several years. In 1998, these profits changed to a stream of losses as the fixed-income arbitrage group struggled with what seemed to be a change in the underlying model. It seemed that another random factor had appeared, leaving the group holding residual risks, which were causing large losses. The risk manager struggled to help the group, but in the end, it was shut down. The exit had to be disguised and undertaken over several weeks, since Salomon's large positions in the market were affecting bond liquidity and could entice arbitrageurs to exploit the company. The worst-case scenario would have occurred if Salomon's sales had driven down prices, leading other traders to dump bonds and driving prices even further down, thus exacerbating Salomon's losses. Bookstaber argues that this exit by Salomon's large bond-arbitrage group made the market less liquid and increased the difficulties faced by Long-Term Capital Management (LTCM) later in the year, when its bond-arbitrage position became untenable after the Russian bond default (another unmodelled risk).

Fixed-interest derivatives will clearly be affected by the underlying fragility of the bond/yield pricing model. If the model is misspecified, then hedging derivatives written on yields will imply residual risks. If the risks average out, then they can be contained. If they show persistent bias, then the model can lead to large losses unless swift risk-management action is taken to limit trades or change the model.

In all the above models, three major risks stem from model misspecification through either: (i) choosing the wrong number of random factors; (ii) inappropriate random factor distributions (e.g., normal, symmetric distributions rather than skewed distributions), and/or (iii) using poor parameter estimates for the coefficients or factor loadings on risky factors. These risks should be tested regularly by back-testing the models (looking for systematic deviations from the model using actual data), and checking the history of trades and the profit/loss outcomes on exposures. Because all models are merely approximations, losses and profits on exposures should be expected. In a well-specified and calibrated model, however, the history of profits and losses will expose biases. Any detected

biases should be examined, and appropriate action taken. Although this is easy to state as a general principle, in reality, the management and estimation of risks is far from perfect, especially in periods of high volatility, where correlations can change rapidly. New asset markets are particularly dangerous, in that they lack a long history of price data. A new financial instrument introduced in a bull market is especially risky, since statistical estimates may not include data from bear markets or volatile trading periods. This can lead to under-estimation of risks and to complacency in the risk-management system.

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Finally, we consider one of the most difficult markets to model effectively: the market for credit risks. We can model the short-term returns on risky bonds as a factor model. But, taking a longer-term view, bonds that have default risk can be modelled as a stochastic process where the bond prices depend on possible future default and the stochastic recovery rates. Because default can occur before the bond or loan expires, default becomes a strategic decision by the lender and the borrower. By using extra credit lines, a borrower can avert problems in paying the coupon or principal. Clearly, the astute lender will be aware of the borrower's net situation, collateral, other credit liabilities, etc. Furthermore, other lenders will be aware of any difficulties and will move to protect their loans. As is well known, borrowers with multiple creditors will initiate a strategic game where each player will act to protect their interests. Traditionally, banks, in lending to households or businesses, safeguard their interests by imposing collateral requirements and, in the case of large loans, through pre-emptive intervention and sophisticated workouts. Because default may be precipitated by bad luck or bad management, a single lender in a carefully managed workout can act to increase the value of its loan by taking actions within the confines of the bankruptcy code.

Credit derivative payoffs, hedging, and pricing will be sensitive to the specification of default and any strategic decisions by the defaulting firm or lenders. This effect has been observed recently in the United States, where strategic decisions on default and reinterpretations of the bankruptcy code are affecting the payoffs of credit derivatives.

With several lenders with different loan conditions, the workout is more complicated, since the interests of the lenders may diverge. For example, lenders with different seniority, collateral agreements, exposures through derivatives written on the borrower's debt, and so on can have very different responses to liquidation or other courses of action. A smoothly functioning workout requires legal and credit sophistication. The smaller the group involved, the easier it is, in general, to manage the workout. The more diverse and larger the group, the harder it will be to work together without generating mistrust and misunderstandings. Another factor is lenders who have been involved in previous workouts together. Lenders know that, in a recurring situation, taking a tough line in a current workout can rebound in retaliatory actions by other lenders in later workouts. The possibilities for gaming in repeated workouts, gaining reputations for toughness, etc. can lead to sophisticated play on the part of FIs. In turn, this can reduce the benefits to inexperienced lenders who are entrants in large loan markets.

Given these caveats concerning loan defaults, FIs run their loan books by using different models and procedures, depending on the type and scale of loan. Large loans are managed by using careful legal and credit analysis, with continual monitoring for signs of distress. Banks use in-house and proprietary models to analyze large loan or private bond exposures. These models may use detailed structural models as inputs to evaluate the firm's bond or, in the case of smaller loans, a reduced-form model may be used because it is not profitable to analyze the details of the firm. In reality, elements of both models are used, depending on the detail required. If the corporate bond is traded in a liquid market, the FI can use the market value to check its own valuation methods. But many corporate bond issues are illiquid, and constant marking-to-market is not an option, so that the FI must rely on its own valuations and outside credit-rating agencies.

Credit agencies specialize in evaluating corporate bonds and other credit instruments. Their evaluations use various models and data sources to give a bond a letter rating (AAA, AA, etc.) that reflects default risk and expected recovery rate. The agencies alter ratings infrequently, arguing that ratings should be "through the cycle." In other words, they do not use the most current data; the rating can lag until a major event triggers a changed rating. This lag has led to embarrassing situations in the past where large companies (e.g., Enron) have been in serious financial trouble and yet their bonds have been showing high

ratings. The current credit crisis has revived criticism of the accuracy, methods, and models of credit-rating agencies, and alleged perverse incentives in their rating of credit instruments.

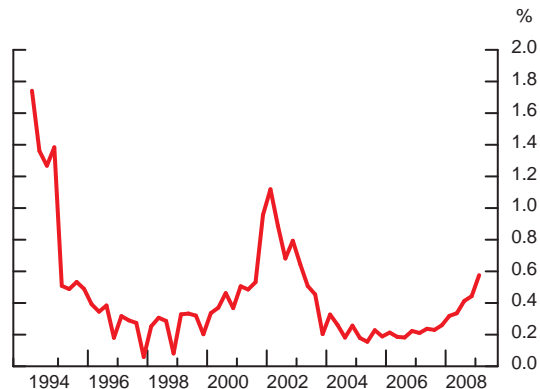
Small loans (e.g., home mortgages, car loans, credit card loans) require different methods for evaluation. Because these loans are generally for small amounts, FIs have developed inexpensive credit-scoring systems that allow rapid evaluation of credit risks. By bundling large numbers of these loans and tracking their performance, the lender can create a portfolio for which, in “normal times,” they can provide a reasonably accurate assessment of returns. To achieve an accurate valuation, there are several important caveats that must be taken into account.

First, the evaluation should draw a careful distinction between a healthy economy with low defaults for each risk class, and a recession, where default rates rise. In the latter case, default and recovery rates can alter rapidly, so that relatively safe loans can quickly become problematic loans. A loan book that looks healthy in normal times can become very risky in a recession. For example, observe the rapid changes in the level of provisions governing Canadian bank loans, which are required to deal with loan losses in previous and current recessions. These provisions vary over time, and in severity (Chart 5).

Loan books should be evaluated in normal times with normal time parameters and stress tested with recession-based parameters to check the exposures in a downturn. Unfortunately, evidence suggests that some FIs neglected to do this form of stress testing, either because they lacked sufficient time-series data, or they did not see the need to undertake such regular stress tests, because there was a perception in some quarters that monetary policy was making inflation-induced recessions a thing of the past.

Second, the FI should check the integrity of its lending and scoring systems. Because poorly designed incentive systems can lead to “loan-pushing” and collusion between loan officers and borrowers, the FI should be wary of adverse selection in its loan book. This process requires careful auditing and back-testing to check loan officer and credit histories. (This was a major failing in the originate-to-distribute model, where perverse incentives faced by mortgage originators increased default risks for the end lenders.) The FI should be wary that its highly rated loan portfolio may actually be of much lower quality, an occurrence that too often becomes apparent only in a general downturn.

Chart 5: Annualized specific provisions for Canadian bank loans



Source: Office of the Superintendent of Financial Institutions
Last observation: 2009Q1

Third, the loan book should recognize the interaction between interest rate changes and default risk. It is obvious that increases in interest rates can increase default rates and decrease recovery rates. Models of loan portfolios should include correlations between default risk, recovery rates, and interest rate risks. Whether these correlations are stable is another matter. The risk management should stress test the models to check the integrity of the system.

Fourth, given interest rate risk, loan portfolios will be open to prepayment risk where lower rates lead to prepayment of loans. If it is not modelled, prepayment will imply a fall in loan revenue when interest rates fall. Evidence from the 1980s and 1990s in the United States suggests that many consumers did not appear to take advantage of this prepayment option, but they have recently been much more aggressive in prepaying mortgages. Therefore, econometric models that rely on earlier data may be suspect.

Fifth, loan portfolios will face exposures on declines in asset prices. Falls in house prices, for example, will have a major impact on mortgage defaults when borrowers find their equity has vanished. This has been a very serious problem in the United States, given the extreme leverage on many mortgages (the so-called subprime problem). Similar risks occur in commercial real estate, where property valuations can decline rapidly in a downturn, exposing lenders to increasing default and recovery risks.

Sixth, other sources of borrower wealth and income can be impaired in a downturn, leading to difficulties in repaying loans. For example, rising unemployment in a region (the automobile industry is a good example) can lead to mortgage defaults. In addition, a regional

decline in an industry can have a negative impact on commercial loans so that commercial loan and mortgage defaults and recovery rates will be correlated.

Aggregation of Exposures

The FI can generate its consolidated return distribution by aggregating the loan, equity, trading, and derivative books, taking into account any correlations among the different books. In particular, model specification and parameter estimation are critical, but the model estimation should not be viewed in isolation from the rest of the risk-management system. This is especially true with credit risks, where default risk is sensitive to the incentives and actions of borrowers and other lenders.

The resulting estimated distribution of returns, especially the probability of losses of various degrees of severity, is examined, and the value at risk (VaR) calculated. Risk-management managers are well aware that the VaR measure is only as accurate as the estimated return distribution that has been generated. Furthermore, the VaR measure (which was originally motivated by assuming a normal distribution of returns on securities over a short horizon) can provide a biased measure of the risks faced by the FI if the distribution is not normal. Indeed, given the non-normal returns on defaulting bonds and widespread use of derivatives and other instruments, it should not be surprising that the loss tail of the aggregate distribution is not normal, but will be fat-tailed, or may even have large bumps owing to derivative exposures. In the case of banks and other regulated FIs, the reported distribution and VaR will be examined to see if they violate Basel II requirements (empirical rules of thumb as to the amount of capital that should be held by the FI to safeguard against default). Given the serious caveats discussed above concerning the generation of the return distribution, and the resulting VaR, we should be wary of the results and of any policy or regulatory actions based on the precision of such constructions.

Limitations in Banking and Risk-Management Theory and Practice

In the previous sections, the basic theory and practice of risk management were outlined, emphasizing hedging and the use of market valuations and derivatives. The theory that underlies these hedging and

pricing models assumes frictionless markets. Although risk-management practice tries to grapple with market liquidity in an ad hoc fashion, the basic risk-management theory is founded on symmetric information and competitive market models. This familiar efficient-markets model, if taken literally, implies that markets are complete and Pareto optimal and that any financial structure or derivative security can be priced by arbitrage-pricing rules. What is more, any financial structure has a zero net present value. In this model, if asset markets are complete, the allocations are efficient, leaving no role for government intervention to repair any market inefficiency. The model can be modified to be more realistic (i.e., so that asset markets are incomplete), but then the allocation is generally no longer efficient. Furthermore, it is well known that the introduction of new asset markets acts as a second-best modification that can have perverse welfare results.¹⁰

Traditional banking theory assumes, however, that financial markets, and the market for loans especially, are far from perfect. Loan markets (and markets with counterparty risks) are plagued by various degrees of asymmetric information and the possibility of strategic behaviour by lenders, borrowers, competing FIs, and regulators. The lender tries to sort borrowers according to risk and to avoid adverse selection in acquiring bad loans. Lenders try to avoid moral hazard, where borrowers will be tempted into taking riskier investments, paying higher dividends, and so on after the loan contract has been signed. Well-funded FIs can predate distressed competitors. Regulators and FIs are locked in a strategic game where their current actions, or perceived strategies, can have significant effects on the current or future behaviour of FIs and regulators.

Modern banking theory has tried to explain the structure and performance of banks by appealing to their historic role in collecting deposits and lending those funds to firms, households, and branches of government. Recall that demand deposits are callable

¹⁰ This result appears counterintuitive. One would expect that increasing the number and type of traded assets would improve welfare. In a partial-equilibrium analysis where all other asset prices are fixed, this might appear correct. But in a general-equilibrium analysis with incomplete asset markets with multiple periods and commodities, and multiple agents, where all the effects are traced through agent responses and market prices adjust, etc., there are examples where (i) all agents are better off; (ii) cases where some agents can be made worse off, some better off; and (iii) in some extreme cases, all agents can be made worse off. If an agent in the economy controlled the introduction of the new asset market, then they would choose to introduce the asset only if it benefited themselves, but not necessarily other agents—they would be a monopolist. (For early discussions of these second-best results, based on asset-exchange economies, see Hart 1976, and Milne and Shefrin 1986. For a textbook discussion, see Magill and Quinzii 1996.) At a practical level, there have been allegations in the United States that the introduction of certain derivative products by some FIs have had a deleterious impact on traders in related markets.

by the depositor. If the deposits are invested in liquid markets and the bank has sufficient equity to remain solvent, there is no problem with withdrawals on demand. But if the deposits are in higher-yielding and illiquid assets, then the bank must have sufficient lower-yielding liquid assets to satisfy withdrawals. In a classic paper, Diamond and Dybvig (1983) showed that it is possible to have a bank run where depositors panic trying to liquidate ahead of other depositors. In addition, they showed that a stylized model of government deposit insurance can eliminate the run equilibrium. This basic model has been extended in many directions to provide a rich set of theories exploring the sensitivity of the result to real shocks and other modifications.¹¹ Indeed, the role of deposits is not crucial, and they can be replaced by liquid short-term loans. This variation of the model is far more appropriate to investment banks and to non-bank asset-backed commercial paper conduits that do not issue deposits but finance illiquid long-term investments with short- and medium-term borrowing. These models provide a series of related frameworks to analyze the discussion in Bagehot (1873) and a subsequent large and informal literature discussing banking instability and regulation. This informal (and later, the formal) theory has been used to justify bank regulation, central bank intervention, and public deposit insurance schemes. But as Allen and Gale (2007) argue, regulations should be targeted to solve particular market failures: Unless particular failures can be identified, regulations and interventions aimed at vaguely specified “banking instability” may do more harm than good.¹²

A recent example of such an intervention has been the various support mechanisms to large U.S. banks introduced by the U.S. Treasury and Federal Reserve. These subsidies to FIs have been deemed necessary for the stability of the financial system, supporting FIs that are “too big, or too interconnected, to fail.” Some commentators argue that these FIs had a faulty business model that underestimated the risks inherent in credit markets. Because that business model failed, the FIs should have been forced to make an orderly exit from the market, and not had their businesses subsidized. The subsidies and precedents for future

subsidies will merely reinforce future moral hazard problems in regulating FIs.

Given the potential moral hazard inherent in insuring deposits (or other risky FI activities), government schemes require careful monitoring to contain the incentives of bank management to invest in risky loans that will increase default risk for depositors and, in turn, be passed on to the deposit insurance scheme. A private scheme would face the same problem. In principle, this is no different from the classic moral hazard problem facing bondholders or lenders in a levered firm. One reason given for having formal risk-management systems monitored by regulators in banks is to provide deposit insurance regulators with data to enforce capital requirements and to monitor and contain risks that would adversely affect their deposit insurance risks. These risks can be serious and amount to large sums: The Savings and Loans debacle in the United States is an historical example of the costs of loose regulation, perverse incentives for banks and regulators, and subsequent government bailouts.¹³

The Savings and Loans debacle in the United States is an historical example of the costs of loose regulation, perverse incentives for banks and regulators, and subsequent government bailouts.

Classical banking theory needs to be extended to deal with investment banking and other FI activity that does not rely on depositors. In this type of FI, the role of depositors is taken by short-term lenders operating through conduits and other structures. Although the model has some differences in detail, the basic story is very similar in that the FI is investing long and borrowing short. By creating off-balance-sheet entities, the FIs tried to reduce their exposures. But as recent events have demonstrated, the model failed spectacularly.

There is a fundamental problem with the theory of risk management. It is motivated by the efficient markets theory that is calibrated using sophisticated statistical methods. Alternatively, recent banking theory is motivated by small-dimension models (similar to the techniques used in modern industrial organization theory) where the complexity of the modern FI is

¹¹ See Freixas and Rochet (2008) and Allen and Gale (2007) for recent surveys.

¹² Allen and Gale observe that some liquidity crises can be misnamed. These liquidity “crises” may be optimal, depending on the source of the demand for liquidity and the structure of the financial market. If asset markets are competitive and complete, then liquidity demands by depositors can be efficiently accommodated by the private market and agents. But if asset markets are incomplete and/or uncompetitive and inefficient, then liquidity demands may imply inefficiency, and possible regulatory or central bank interventions may be justified. This is the ground for rationalizing liquidity intervention by central banks as a lender of last resort.

¹³ See Kane (1989); Stern and Feldman (2004); and Barth, Caprio, and Levine (2006).

characterized by a series of related, but not wholly consistent, models. Although this modern banking theory is highly instructive in exploring the subtleties of banking structures, it is not operational in the way that risk-management systems have been used by FIs. There is a clear gap between theory and practice in trying to have an operational theory that incorporates significant elements of the frictions we see in banking and other FIs and yet can be implemented using existing or obtainable data.

Risk-Management Systems: Problems in Modelling Liquidity and Other Systemic Risks

It has become apparent during the current crisis that financial risk-management systems have been inadequate in dealing with liquidity and other systemic risks.¹⁴ This is not just a matter of laxness on the part of banks or other FIs, but a serious deficiency in the basic theoretical models used in risk-management systems. Although there are attempts to add “liquidity” risks at the end of the risk-management analysis, these are an afterthought. Although we do have some simple theoretical models of asset markets, portfolio strategies, and asset pricing with various notions of illiquidity, these models would require much more work to integrate them into workable risk-management systems.

Illiquidity can be modelled in several ways. In the simplest formulation, it can be modelled by assuming a fixed bid-ask spread for the price of an asset. In other words, this approach assumes a more realistic situation, where traded assets have quoted (and different) bid and ask prices. This type of model introduces fundamental changes in asset-portfolio strategies where the bid-ask spread is modelled as part of the portfolio problem. Simple examples show that it will imply a more cautious use of illiquid assets and a greater holding of liquid assets in the face of more volatile liabilities. Other examples show that dynamic hedging of derivatives will imply approximate bands for derivative prices, rather than unique derivative prices obtained from conventional frictionless models. If bid-ask spreads can vary randomly and, in extreme cases, widen to such an extent that it is optimal not to trade in these situations, then ex ante optimal trading strategies will imply much more conservative behaviour.

¹⁴ This section draws on far more detailed and technical sections in Milne (2008b), which provides a bibliography of recent research in this area.

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A second notion of liquidity involves market depth, where the size of a trade can influence an asset price. Economists know that this phenomenon demonstrates market power on the part of the trader. Several recent papers have explored the consequences of market depth, theoretically and empirically. As a first step, consider a simple situation where an FI faces a liquid, riskless asset and an illiquid asset, where there is an underlying stochastic price process that will be affected by the FI's trades. Simple examples show that this problem is non-trivial to analyze, and can induce selling parcels of the asset over time, so as to avoid dumping the asset in a one-time fire sale. More complicated situations can be constructed when there are several illiquid assets, forcing the FI to choose which asset to liquidate, how much per period, and in which order. This problem involves a tricky analysis of dynamic portfolio rebalancing, owing to correlated risks and illiquidity.

A related but even more complex problem occurs when the FI is aware of other traders who can influence asset prices. To begin, consider two FIs that have simple portfolios of a riskless liquid asset and one risky illiquid asset. Assume that the risky asset has a residual demand coming from a large fringe of small traders. Economists recognize this model as a dynamic Cournot oligopoly model.¹⁵ Although the verbal description of the model seems simple enough, its analysis is far from straightforward. It is possible, for example, to construct situations where a distressed FI¹⁶ desiring to sell down the illiquid asset, will be front-run by their competitor (i.e. the competitor will sell the asset earlier than the distressed trader), thus driving down the price even further, before the competitor, exploiting the competitive fringe, buys back at a low fire-sale price. There are numerous variations on this story, some of which allow for strategic behaviour by an interventionist central bank. These strategic models are still in an elementary stage and require

¹⁵ The following discussion is a brief, informal exposition of the paper by Brunnermeier and Pedersen (2005). Recent research on strategic liquidity problems draws on the insights of this and more recent, related papers.

¹⁶ The distress can come from a variety of causes; e.g., mass withdrawals, major portfolio losses, binding VaR constraints, or margin calls that require portfolio rebalancing.

careful analysis to explore their many implications and deficiencies.

The oligopoly model of illiquidity can provide a convenient framework for exploring one source of systemic risk, where trades of one (or more) large FIs will affect asset prices and the wealth of other FIs. This pecuniary externality can affect a non-trading FI by reducing the value of its assets. If the asset price falls far enough, the non-trading FI may face VaR and/or margin constraints that will induce it to trade so as to rebalance its portfolio. As recent events have illustrated, if this phenomenon affects a number of FIs, it can induce a cascade of selling and further decreases in asset prices in a downward spiral.

Using this basic approach, it is not hard to see, in principle, how some types of systemic risks might be analyzed. The pecuniary externalities induced from trading in illiquid markets can spill over into the portfolio decisions of other FIs. Arguments that central bank intervention can be rationalized by attempts to reduce these price effects can be constructed.¹⁷ But such arguments should be explored carefully because FI behaviour will be influenced by potential regulatory intervention in illiquid markets, implying that FI strategies will economize on liquid balances, relying on expectations of substantial central bank intervention.

These are sketches of some simple ideas for modelling illiquid asset markets and the possibility of embedding them in a risk-management model. A bonus in this approach is that it will provide a framework for

analyzing possible market failures and, hopefully, allow the use of conventional microeconomic tools to analyze the effectiveness of appropriate policy instruments. For example, FIs will require knowledge of the aggregate behaviour of other FIs in the markets, if they are to model systemic risks in their risk-management systems. Regulators can play an important intermediary role in iterated stress-testing procedures to indicate possible feedbacks in asset prices from herd-like selling in certain asset markets. These types of regulatory intervention are at an early stage of development and require much more research and analysis.

Conclusion

In this article, I have outlined the complexity inherent in any modern risk-management system, which arises because there are shortcuts in the theoretical models. The professional risk manager must be aware of these simplifications and of the real dangers that flow from a mechanical application of the models. The problems are compounded by the difficulties in sensible calibration of model parameters. These are non-trivial problems that cannot be regulated away in any simple fashion. Furthermore, as has been indicated, systemic risks can be introduced by embedding the basic risk-management model of an FI within a market system or financial network. Far from being a novel problem, some (perhaps all) systemic-risk problems can be considered in the abstract as traditional market failures amenable to the tools of microeconomic analysis.

¹⁷ See Acharya, Gromb, and Yorulmazer (2008) for a recent example.

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