

Systemic Risk Monitor: A Model for Systemic Risk Analysis and Stress Testing of Banking Systems

In 2002 the Oesterreichische Nationalbank (OeNB) launched in parallel several projects to develop modern tools for systemic financial stability analysis, off-site banking supervision and supervisory data analysis. In these projects the OeNB's expertise in financial analysis and research was combined with expertise from the Austrian Financial Market Authority (FMA) and from academia. Systemic Risk Monitor (SRM) is part of this effort. SRM is a model to analyze banking supervision data and data from the Major Loans Register collected at the OeNB in an integrated quantitative risk management framework to assess systemic risk in the Austrian banking system at a quarterly frequency. SRM is also used to perform regular stress testing exercises. This paper gives an overview of the general ideas used by SRM and shows some of its applications to a recent Austrian dataset.

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1 Introduction

The primary mandate of central banks is to achieve and maintain price stability. Safeguarding and maintaining financial stability has always been regarded as a necessary prerequisite for this task. Institutionally, this combination of tasks was until very recently achieved by putting the central bank in charge of the oversight of individual financial institutions. Following the lead of the U.K., many countries, including Austria, have transferred responsibility for the oversight of individual financial institutions to newly established financial supervisory authorities, while the central banks kept the mandate to safeguard and maintain systemic financial stability. These institutional developments have forced central banks to arrive at answers to the new question what it means to maintain systemic financial stability without having ultimate responsibility for the oversight of individual financial institutions.

In 2002 the Oesterreichische Nationalbank (OeNB) launched in parallel several projects that aim to develop modern tools for systemic financial stability analysis and off-site banking supervision. In these projects the OeNB's expertise in financial

analysis and research was combined with expertise from the University of Vienna, the University of Applied Sciences Vorarlberg, the Vienna University of Technology and the Austrian Financial Market Authority (FMA; see OeNB and FMA, 2005).

Systemic Risk Monitor (SRM) is part of this effort. SRM is a model to analyze banking supervision data and data from the Major Loans Register collected at the OeNB in an integrated quantitative risk management framework. The purpose of SRM is to assess systemic risk in the Austrian banking system at a quarterly frequency. SRM is also used to perform regular stress testing exercises.

1.1 An overview of the model

The basic idea of the SRM model is to combine standard techniques from modern quantitative market and credit risk management with a network model of the banking system. In contrast to standard risk management models, SRM makes the step from the individual institution perspective to the system level. This step is the major challenge to be met by any systemic risk model. Only at the system level the two major reasons for simultaneous problems become

visible: correlated exposures and financial interlinkages. The risk of simultaneous difficulties of institutions and the financial losses incurred in such events is the key focus of systemic financial stability analysis.

The model intentionally does not rely on a sophisticated theory of economic behavior. The consequences from a given liability and asset structure being exposed to realistic shock scenarios are uncovered in terms of problems of institutions. The model is designed to exploit existing data sources. Although these sources are not ideal, our approach shows that with the available data we can start to consider financial stability at the system level and provide quantitative judgements of systemic financial stability and systemic risk.

1.2 Related research

SRM can draw on a rich modern literature dealing with risk management and risk monitoring problems for banks or insurance companies (see McNeil et al., 2005, for an overview). The change of perspective from the individual institution level to the system level is the main methodological innovation of SRM. It is this system perspective, where SRM had to explore new territory. SRM mainly builds on research by Elsinger et al. (2006b) and Boss (2002). This paper gives an overview of the general ideas used by SRM and shows some of its applications to a recent Austrian dataset. Readers interested in technical details are referred to the model documentation, which can be received from the authors upon request (see Boss et al., 2006).

2 The SRM Model

The basic structure of the SRM model can be best described at an intuitive

level by a simple picture showing the individual model components as well as their interrelation. Chart 1 displays the modular construction of SRM.

As a starting point it is perhaps best to begin with the middle layer of Chart 1, showing three boxes: *Market risk losses*, *Noninterbank credit risk losses* and *Interbank network model*.

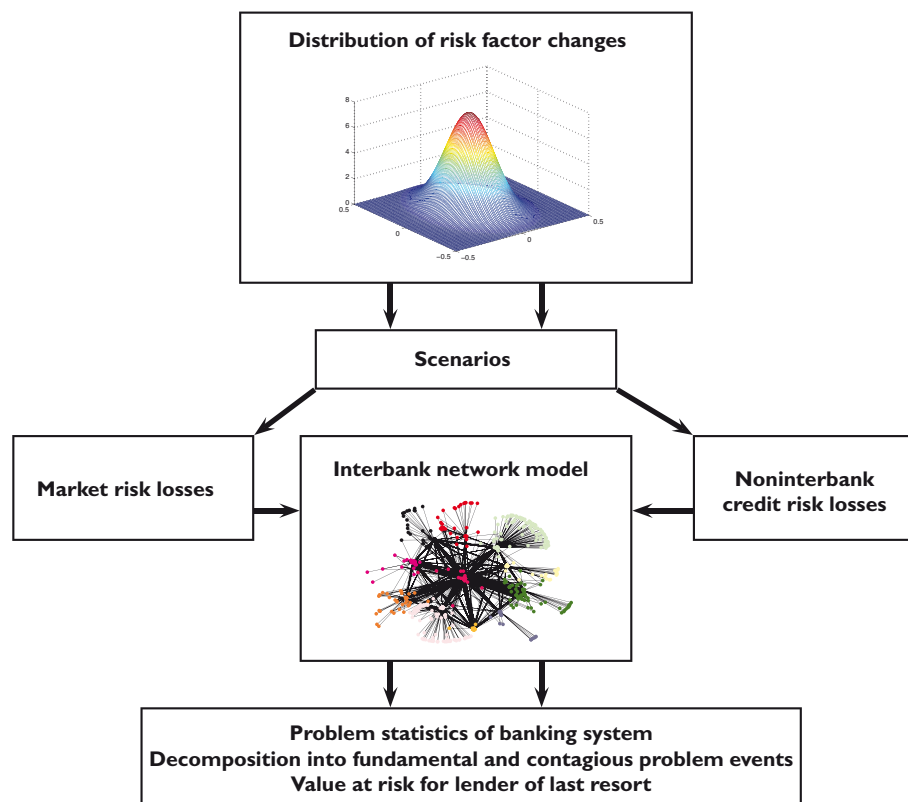
SRM describes the Austrian banking system at the end of each quarter as a system of portfolios. Each portfolio in the system belongs to one bank and typically consists of collections of securities such as stocks and bonds across domestic and foreign markets (the *Market risk losses* box), a collection of corporate loans and loans to households (the *Noninterbank credit risk losses* box) as well as interbank positions (the *Interbank network model* box).

The value of each portfolio is observed from the data at the end of each quarter. The future portfolio values one quarter later (approximately 60 trading days) are random variables. Thus the difference between the portfolio values at the observation date and the portfolio values a quarter from the observation date, i.e. the gains and losses in the banking system, is subject to uncertainty. It is the distribution of these gains and losses we are interested in.

We adopt the usual risk management practice of thinking of future portfolio values as a function of time as well as of risk factors. Risk factors are market prices that determine portfolio values, such as stock market indices, interest rates and foreign exchange rates, as well as macroeconomic variables that have an impact on the quality of loan portfolios. To analyze the distribution of portfolio gains and losses in the banking system, we have to specify the distribu-

Chart 1

Basic Structure of SRM¹



¹ Chart 1 shows the basic structure of the SRM model. Banks' noninterbank portfolios are exposed to shocks from a risk factor change distribution of market and credit risk factors. The value of interbank positions is determined endogenously by the network model and a clearing mechanism that makes all financial claims consistent *ex post* after shocks have been realized. The clearing of the interbank market determines the solvency of other banks and defines endogenous probabilities of problem events as well as the respective recovery rates. The output consists of statistics on problem events, a decomposition into fundamental and contagious problem events and an estimate of the amounts of liquidity a lender of last resort has to stand ready to inject into the system.

tion of *risk factor changes*. All individual modeling steps as well as the practical challenges that arise in SRM have to do with the details of how we describe the functional relation between risk factor changes and portfolio losses.

The top box of Chart 1 symbolizes a multivariate risk factor change distribution. In SRM such a distribution is estimated every quarter based on past observations of market price changes and changes of macroeconomic variables that have an impact on problem event probabilities.

The modeling strategy treats the marginal risk factor distributions and

the dependency structure separately. While marginal distributions are chosen according to statistical tests that select for each risk factor a model which gives the best out-of-sample density forecast of changes in each risk factor over a three-month horizon, dependency is modeled by fitting a grouped t-copula to the data. Together, the marginal distributions and the copula characterize the multivariate risk factor change distribution.

For the simulation of scenarios, vectors of risk factor changes are drawn at random from this distribution. Each drawing of risk factor changes from the multivariate distri-

bution characterizes a scenario, symbolized by the box *Scenarios*. Scenarios are then translated into profits and losses at the system level in two steps. In a first step each scenario is analyzed with respect to its impact on the value of market and noninterbank credit positions.

In a second step, these positions are combined with the network model. The network model basically checks whether given the gains and losses from the portfolio positions and given the capital of the banks, they are able to fulfill the financial obligations resulting from their interbank relations. Thus the network model combines all financial positions and bank capital in an overall system of bank net values. The network model does this by applying a clearing procedure that provides the final system of bank net values for each scenario. Simulating many scenarios, we get a distribution of problem events and gains and losses that allows us to make probability assignments for problem events over a three-month horizon.

The market risk losses and the losses from noninterbank credit risk are generated by two submodels that translate scenarios of risk factor changes into the respective scenario losses: a market and a credit risk model.

For marketable securities the situation is fairly simple. Supervisory data allow us a fairly coarse reconstruction of positions of securities at market values that are held on the bank balance sheet. The picture is coarse because individual stocks are lumped into Austrian and foreign, and interest rate- and currency-sensitive instruments are mapped into broad maturity and currency buckets. Consider, for instance, a simple stock

portfolio consisting of Austrian and foreign stocks. Risk factor changes are then the logarithmic changes in the Austrian and a foreign stock price index. To calculate gains or losses from the stock portfolios, we can use a linearized approximation of the loss function. This amounts to simply multiplying the position values with the risk factor changes to get the portfolio gains and losses. For interest rate- and currency-sensitive positions, we can equally arrive at gains and losses by using linearized losses and the relevant risk factor changes, which are changes in different exchange rates or interest rate changes for different maturities and different currencies.

For loans to nonbanks the situation is more complicated because the dependence between loan losses and risk factors is more indirect. We do not have a simple analogue to market returns. Defaults of loans in certain industry sectors – the units into which we break down loans in SRM – depend mainly on risk factors describing the aggregate state of the economy. Due to the discrete nature of the default events (either an obligor defaults or not), linearized losses are of little importance for the analysis of credit risk. Therefore SRM uses a credit risk model to calculate losses from loan portfolios. Our credit risk model is based on Credit Risk+ (see Credit Suisse, 1997) and has been adapted to explicitly take into account the dependency of default rates on the state of the macroeconomy. The basic idea is that the default probability of a loan in a particular industry sector, for instance construction, depends on a set of macroeconomic variables according to a function the parameters of which are statistically estimated from historical data. Given a realiza-

tion of macroeconomic variables and the implied probability of default for different industry sectors, loan defaults are assumed to be conditionally independent. Under this assumption a loan loss distribution can be derived for each bank for each value of macroeconomic risk factor changes. Loan losses are then calculated by independent draws from these loan loss distributions.

From this discussion we see a fundamental modeling choice taken in SRM: Following the literature on risk management of individual institutions, the analysis is undertaken for a given set of portfolios observed at the observation time. The value of the portfolio is assumed to be completely determined by the risk factors and no behavioral considerations are taken into account. The longer the time horizon under consideration, the more problematic is such an assumption. In particular, in our framework, where we aim at an integrated analysis of portfolio positions which can be easily changed with other positions that are much more difficult to change, even at a 60-trading day horizon, this assumption is debatable for some of the portfolio positions. We ask the following question: given the portfolio positions we observe today in the system and given the future realizations of risk factors, how would these changes influence portfolio values *ceteris paribus*? This allows a statement about the risk inherent in the current banking system.

2.1 Using SRM for Financial Stability Analysis

We use four main risk concepts to look at the simulation output:

1) analysis of fundamental and contagious problem events;

- 2) analysis of probability distribution of problem events according to rating classes;
- 3) analysis of aggregate loss distributions;
- 4) quantification of resources that might have to be mobilized by a lender of last resort.

Since the risk of bank problems is a major concern for a central bank, we put a particular focus on probabilities of problem events. The network model allows us to distinguish problem events that result directly from changes in risk factors from events that result indirectly from contagion through interbank relations. We call problem events fundamental if they result directly from risk factor movements and we call them contagious if they are a consequence of interbank relations. Apart from analyzing the number of fundamental and contagious problem events, we look at the probability distribution of problem events according to the OeNB's rating classes. We look at the aggregate loss distribution both for all risk categories taken together and for certain subcomponents such as market risk, credit risk and contagion risk. Finally we make an attempt to quantify the resources a lender of last resort might have to mobilize to prevent problems in the banking system.

2.2 Using SRM for Stress Testing

One advantage of a quantitative model is that it allows the consideration of hypothetical situations. In the context of systemic risk assessment, one kind of thought experiment is of particular importance. Usually it is of interest to know how the risk measures for the banking system will behave when there are extreme risk factor changes. Such thought experiments are known as stress tests. Sys-

temic risk monitor provides a coherent framework to consistently conduct such stress testing exercises.

In a stress test, one or more risk factors of interest are constrained to take extreme values, like a certain drop in GDP or a hike in interest rates. Since we have a complete model of the multivariate risk factor distribution we can then perform a model simulation under the constraint that certain risk factors are at their stressed values. The risk measures of the model can then be studied relative to the baseline simulation based on the unconditional risk factor change distribution calibrated to historical data. The main advantage of this approach is its consistency with the dependency structure of the risk factors and therefore its consistency with the quantitative framework. Such an approach is advocated by Elsinger, Lehar and Summer (2006a) or by Bonti, Kalkbrenner, Lotz and Stahl (2005).

3 Data

The main sources of data used by SRM are bank balance sheet and supervisory data from the monthly reports to the OeNB (known by their German acronym MAUS) and the OeNB's Major Loans Register (Großkreditevidenz, GKE). In addition we use default frequency data in certain industry groups from the Austrian business information provider and debt collector Kreditschutzverband (KSV), financial market price data from Bloomberg and Datastream and macroeconomic time series from the OeNB, the OECD and the IMF International Financial Statistics.

Banks in Austria file monthly reports on their business activities to the central bank. In addition to balance sheet data, the so-called MAUS reports contain a fairly exten-

sive assortment of other data that are required for supervisory purposes. They include figures on capital adequacy, interest rate sensitivity of loans and deposits with respect to various maturity buckets and currencies, and foreign exchange exposures with respect to different currencies.

To estimate shocks on bank capital stemming from market risk, we include positions in foreign currency, equity, and interest rate-sensitive instruments from MAUS. For each bank, we collect foreign exchange exposures in USD, JPY, GBP and CHF only, as no bank in our sample reports had open positions of more than 1% of total assets in any other currency at the observation date. We collect exposures to foreign and domestic stocks, which are equal to the market value of the net position held in these categories. For the exposure to interest rate risk, we use the interest rate risk statistics, which provide exposures of all interest-sensitive on- and off balance sheet assets and liabilities with respect to 13 maturity buckets for EUR, USD, JPY, GBP and CHF as well as a residual representing all other currencies. On the basis of this information we calculate the net positions in the available currencies – neglecting the residual – with respect to four different maturity buckets: up to 6 months, 6 months to 3 years, 3 to 7 years, more than 7 years. For the valuation of net positions in these maturity buckets, we use the 3-month, 1-year, 5-year and 10-year interest rates in the respective currencies.

To analyze credit risk we use, in addition to the data provided by MAUS, the Major Loans Register, which provides us with detailed information on banks' loan portfolios to nonbanks. This database contains

all loans exceeding a volume of EUR 350,000 on an obligor-by-obligor basis.

We assign the domestic loans to nonbanks to 13 industry sectors (basic industries, production, energy, construction, trading, tourism, transport, financial services, public services, other services, health, households, and a residual sector) based on the NACE classification of the debtors. Furthermore we add regional sectors (Western Europe, Central and Eastern Europe, North America, Latin America and the Caribbean, Middle East, Asia and Far East, Pacific, Africa, and a residual sector) for both foreign banks and nonbanks, which leaves us with a total of 18 non-domestic sectors. Since only loans above a threshold volume are reported to the GKE we assign domestic loans below this threshold to the domestic residual sector. This is done on the basis of a report that is part of MAUS and provides the number of loans to domestic nonbanks with respect to different volume buckets. No comparable statistics are available for nondomestic loans. However, one can assume that the largest part of cross-border lending exceeds the threshold of EUR 350,000 and hence we do not lose much information on smaller cross-border exposures.

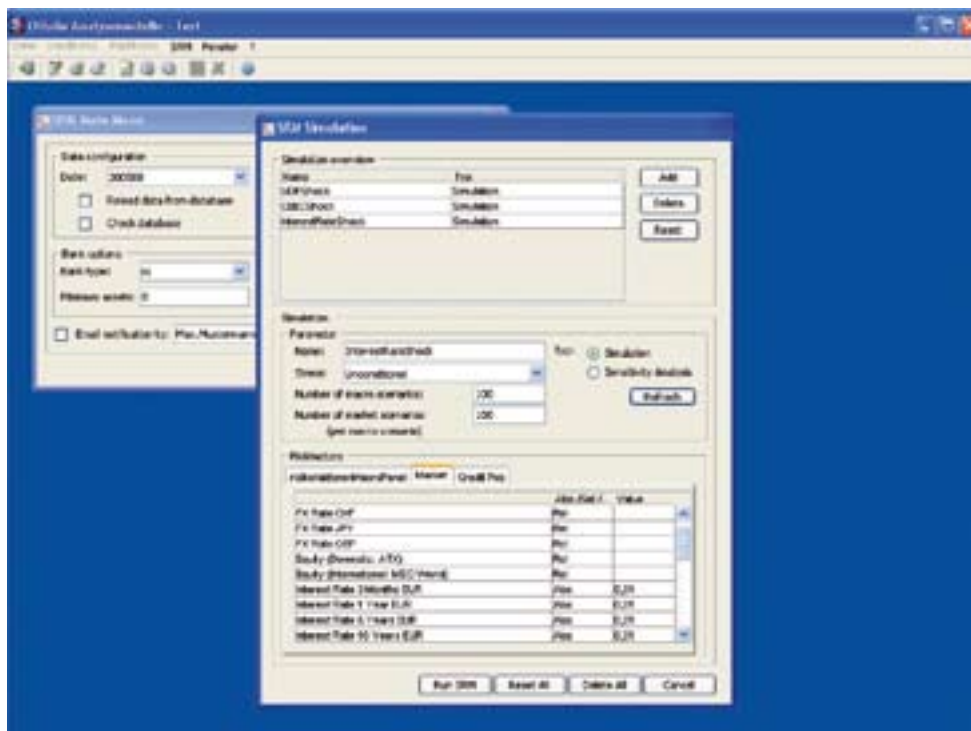
The riskiness of an individual loan to domestic customers is assumed to be characterized by two components: the rating which is assigned by the bank to the respective customer and the default frequency of the industry sector the customer belongs to. The bank's rating is reported to the GKE and is mapped at the OeNB onto a master scale, which allows assigning a probability of default to each loan. The default frequency data are from the Austrian business information

provider and debt collector Kredit-schutzverband (KSV). The KSV database provides us with time series of insolvencies and the total number of firms in most NACE branches at a quarterly frequency starting in 1969. This allows us to calculate a time series of historically observed default frequencies for our 13 industry sectors by dividing the number of insolvencies by the number of total firms for each industry sector and quarter. The time series of default frequencies is explained by macroeconomic risk factor changes, for which we use an econometric model. This estimated equation enables us to translate macroeconomic risk factor changes into probabilities of default for each industry branch. These default probabilities serve as input to the credit risk model. To construct insolvency statistics for the private and the residual sectors, where no reliable information on the number of insolvencies and sample sizes is available, we take averages from the data that are available. Default probabilities for the nondomestic sectors are calculated as averages of the default probabilities according to the ratings that are assigned by all banks to all customers within a given foreign sector.

4 Applications

The OeNB uses the SRM model mainly for two applications: systemic risk assessment and stress testing. Systemic risk assessment involves a simulation at the end of each quarter as soon as all new data are available. The output of this simulation is a risk report with a detailed account of our four risk measures. In the stress tests one or more risk factors of interest are deliberately set to an extreme value and the simulation is performed conditional on the assumption that

Screenshot of the SRM Interface



Source: OeNB.

these risk factors are at their hypothetical extreme realizations. The output of this simulation can then be compared with the baseline simulation.

To make SRM operational, it is implemented such that it can be accessed via an interface called from the analyst's desk. The interface is a Java client application which gives users the possibility to run certain pre-defined simulations (including a variety of regular stress tests) as well as to parameterize individual simulations. The level of parameterization covers the point in time for which the simulation is run, data included in the model, various alternative model components as well as their parameters. Additionally, stress tests can be defined for market and credit risk factors. The parameters chosen are

stored at database level and written to configuration files, which are read by the application at runtime. The models themselves are implemented in Matlab script language, version 14.3, a programming language for technical computing, which provides object-oriented means to include various model components and store complex data sets. Although SRM functionality can be accessed through Matlab's standard user interface, in its end-user implementation the source code of SRM is compiled as C Code and called via the SRM interface. In either case output is written to Microsoft Excel files for further analysis, which are sent as an e-mail attachment to the analyst's desk by SRM after a simulation request has been finished. A screenshot of the interface is shown in Chart 2.

4.1 Regular Supervisory Data Analysis and Stress Tests

Systemic Risk Monitor will be used to perform regular analyses of supervisory data with respect to systemic risk problems. It will also be used as a stress testing tool. We will now illustrate output generated by SRM by looking at some examples based on a recent simulation for the last quarter of 2005. We present our results always for a regular simulation of the current economic situation together with two stress tests: Stress test number one simulates an unexpected drop in GDP. Stress test number two assumes a parallel upward shift in the euro yield curve.

4.2 Fundamental and Contagious Problem Events

The network model generates a multivariate distribution of bank's problem events across scenarios. We interpret the relative frequency of problem events as a probability.

Our method allows a decomposition of problem events into events resulting directly from shocks to the risk factors and those that are conse-

quences of a domino effect. Bank problems may be driven by losses from market and credit risks (fundamental problem events). Bank problems may, however, also be initiated by contagion: as a consequence of other bank problems in the system (contagious problem events).

We can quantify these different cases and are able to give a decomposition into fundamental and contagious problem events. Table 1 summarizes the according probabilities both in the current situation as well as under both stress scenarios. These probabilities are grouped by the number of fundamental problem events. The column "fundamental" shows the percentage of scenarios where we encounter such events. The number of scenarios where in addition contagion occurs is reported in the "contagious" column.

Table 1 shows that in the base case simulation of the current situation we have no scenario with more than 5 fundamental problem events. None of the scenarios including up to 5 fundamental problem events shows contagion. This result is consistent with

Table 1

Probabilities of Fundamental and Contagious Problem Events ¹						
%	Current situation		GDP stress		Interest rate stress	
	Fundamental	Contagious	Fundamental	Contagious	Fundamental	Contagious
0	74.49	0.00	68.53	0.00	60.27	0.00
1 to 5	25.51	0.00	31.27	0.00	39.73	0.00
6 to 10	0.00	0.00	0.13	0.00	0.00	0.00
11 to 20	0.00	0.00	0.05	0.00	0.00	0.00
21 to 50	0.00	0.00	0.02	0.02	0.00	0.00
More than 51	0.00	0.00	0.00	0.00	0.00	0.00
Total	100.00	0.00	100.00	0.02	100.00	0.00

Source: OeNB.

¹ A fundamental problem event is due to the losses arising from exposures to market risk and nonbank credit risk, while a contagion is triggered by problems of another bank that cannot fulfill its promises in the interbank market. The probability of occurrence of fundamental problem events alone and concurrently with contagious problem events is observed. The time horizon is one quarter. The column Current situation shows the result for a simulation without stress. The Column GDP stress shows the case of a stress test with an unexpected drop in GDP. The column Interest rate stress shows the stress test with a parallel upward shift in the euro yield curve. Data are from December 2005.

the findings in Elsinger, Lehar and Summer (2006a), who show that contagion is a rare event given a risk factor change distribution calibrated to historical data. In situations of stress, the picture changes: When we have a drop in GDP, up to 50 fundamental problem events can occur, and there can also be some contagion once we have 21 to 50 fundamental problem events. The stress test for an interest rate hike looks less spectacular. The simulations show no contagion effects but the number of scenarios where at least one and up to at most five problem events are expected to occur increases. The analyst using SRM has the opportunity to look deeper into the microstructure of these results and find out details about the institutions that are most severely hit under the stress scenario.

4.3 Probability Distribution of Problem Events According to the OeNB Master Scale

To get a more precise idea about the distribution of risk within the banking system, we map the probabilities of problem events into the OeNB master scale. This distribution of ratings, which is implied by our simulation, is shown in table 2.

Table 2 shows that in the base case simulation, about 95% of banks are

expected to be in a triple or double A rating at the end of the first quarter of 2006. Under the assumptions of our two stress scenarios, the number of top-rated institutions decreases slightly. The biggest increase under stress can be observed in the lower rating classes.

4.4 Aggregate Loss Distributions

Turning from problem events to the distribution of losses over the next quarter, we can draw pictures of the losses due to credit risk, market risk and contagion risk as well as due to the combination of all of these risks. Contrary to familiar pictures from the practice of risk management, these distributions are derived from an integrated analysis of all portfolio positions and their change in value due to the entire distribution of risk factor changes. Thus rather than analyzing credit and market risk in isolation, these graphs give us the results of an integrated analysis.

Chart 3 shows four loss distributions. From the figures we can see – as in standard quantitative risk management – whether or not the system has enough capital to absorb extreme losses. Therefore loss distribution figures give a first overview of the shock absorption capacity of the system.

Table 2

Probability Distribution of Problem Events According to the OeNB Master Scale¹

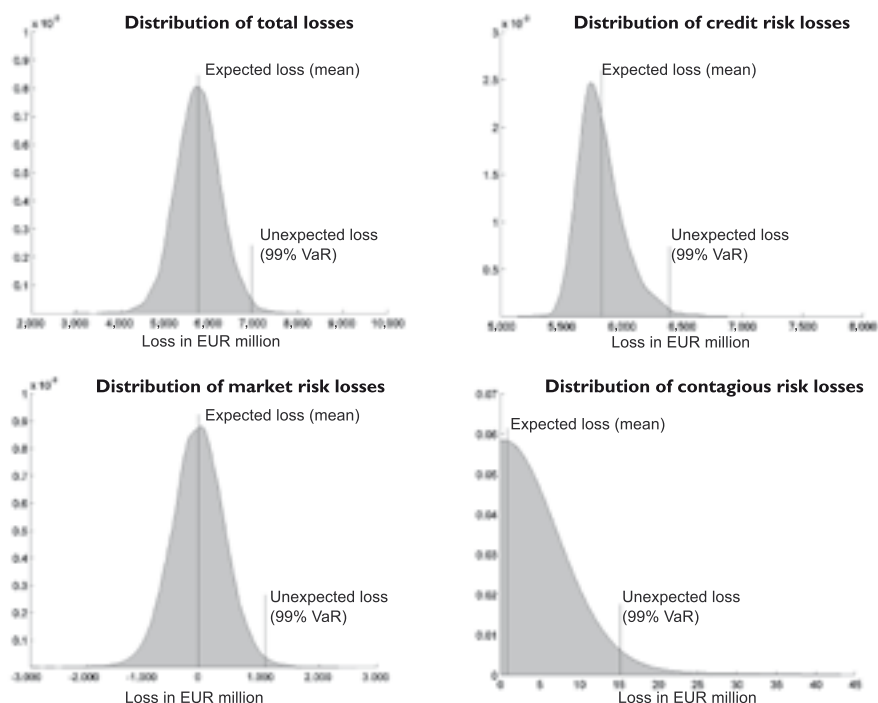
OeNB Master Scale	Current situation			GDP stress		Interest rate stress	
	S&P	abs.	rel.	abs.	rel.	abs.	rel.
1 to 2	AAA to AA	800	94.67%	779	92.19%	791	93.61%
3 to 4	A to BBB	23	2.73%	35	4.14%	22	2.61%
5 to 7	BB to CCC	22	5.22%	31	7.46%	31	6.05%

Source: OeNB.

¹ Share of banks in OeNB rating classes. Data are from December 2005.

Chart 3

Loss Distributions: Total, Market, Credit and Contagion Risk¹



Source: OeNB.

¹ Densities of loss distribution for the entire banking system. The densities are shown for the entire portfolio and separately for market and credit risk as well as for the losses due to contagion. Data are from December 2005.

4.5 Changes in System-Wide VaR under Stress

We analyze the distribution of losses relative to regulatory capital, that is, we look at the distribution of losses as a percentage of regulatory capital and determine certain quantiles of this distribution. In our case we analyze the mean and the 99% quantile (or the 99% value at risk). We look at these measures for the different sub-categories, total losses, market losses, credit losses and contagion losses. The results for the base case as well as for the stress scenarios are reported in table 3.

Table 3 shows that the Austrian banking system is very well capitalized. Even under the stress scenarios capital is sufficient to absorb potential losses that result from risk factor movements.

4.6 Value at Risk for the Lender of Last Resort

A relevant aspect of our model for the regulator is that it can be used to estimate the cost of crisis intervention. We estimate the funds that would have to be available to avoid contagion or even fundamental problem events for different confidence levels. A lender of last resort's cost of preventing problems in the banking system is calculated as the amount required to prevent problem events. A lender of last resort's cost of preventing contagion is calculated as the amount required to prevent all but fundamental problem events. Hence, interbank liabilities are not fully insured but just sufficiently to prevent contagion.

Since problem events occur rarely in the base scenario the amounts that must be available to prevent these

Table 3

Mean and 99% Quantile of Loss Distribution Relative to Regulatory Capital ¹								
%	Total ²		Market		Credit ²		Contagion	
	Mean	99%	Mean	99%	Mean	99%	Mean	99%
Rel. VaR								
Current situation	1.56	4.04	-0.18	2.11	1.74	2.82	0.00	0.03
GDP stress	1.68	7.42	-0.15	5.68	1.82	2.99	0.01	0.05
Interest rate stress	3.87	6.23	2.11	4.34	1.75	2.87	0.01	0.04

Source: OeNB.

¹ Mean and 99% quantile of the distribution of losses relative to regulatory capital for total losses, losses from market risk, losses from credit risk and losses from contagion risk. This relative VaR is shown for the baseline simulation, for the case of a GDP stress test and for the case of the euro yield curve stress test. Data are from December 2005.

² In order to reflect the risk-bearing capacity with respect to different risk categories, the volume of specific and general provisions for credit risk losses as of end-2005 was subtracted from the mean and the 99% quantile of the distribution of credit losses and total losses, respectively, before the respective numbers were divided by regulatory capital.

Table 4

Costs of Avoiding Problem Events ¹						
Quantiles	Current situation		GDP stress		Interest rate stress	
	95%	99%	95%	99%	95%	99%
Resources	29.16	31.58	29.16	44.71	1.24	21.4

Source: OeNB.

¹ In the first bottom row we give estimates for the 95% and 99% percentiles of the avoidance cost distribution across scenarios. Amounts are in EUR million. Data are from December 2005.

events are low. The analysis shows that for the quarter ending in December 2005 a lender of last resort can expect that even if crisis scenarios simulated by the model do actually occur, the amounts to be mobilized for crisis intervention will be small.

5 Conclusions

Systemic Risk Monitor implements a new framework for banking system risk assessment. The innovation is that SRM analyzes risk at the level of the entire banking system rather than at the level of an individual institution.

Conceptually, it is possible to take this perspective by carrying out a systematic analysis of the impact of a set of market and macroeconomic risk factors on banks in combination with a network model of mutual credit relations.

Whereas the modelling of noninterbank market and credit losses is rooted in standard quantitative risk management techniques, the combination with an interbank network model to arrive at total gains and losses in the banking system in SRM is new. Both the generalizations of standard individual risk management techniques and the simultaneous consideration of portfolio values across the system for given risk factor changes as well as the resolution of bilateral claims via a network clearing model focus on the main issues for an institution in charge of monitoring systemic financial stability: the probability of joint problems of institutions and their financial consequences. The system perspective uncovers exposures to aggregate risk that remain invisible for banking supervision that relies on the assess-

ment of single institutions only. We distinguish problems caused directly by a macroeconomic shock from those triggered by problems of other banks in the interbank market.

We hope that SRM will prove useful as a tool of macro-prudential risk analysis and that the framework will be of interest to other institutions with a mandate to safeguard and maintain systemic financial stability.

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