Stress Testing Macro Economic Scenarios

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Outline

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Deterministic and Stochastic Scenarios

- *Deterministic scenario:*
  A state s of the world at the time horizon,
  as far it is of relevance to the portfolio value.
  "Certainly the state of the world will be s."
  The value of every risk factor is specified.
- *Stochastic scenario:*
  a set S of states
  "The world be in some state in the set S."
  No further probability information given.

Generalised and Partial Scenarios

A probability distribution s
over the states of the world at the time horizon,
usually not the predicted or true distribution.

- “GDP will grow by 2.5%, all other variables are distributed conditionally on this."
- “Interest rates will be up by 75 bp, all other variables distributed uniformly."

Traditional Stress Tests

What is it?

Current state of the market: s_{CM}
Hence, current portfolio value: $P(s_{CM})$.

Performing stress tests:

1. Select scenarios $s_{\text{stress1}}, s_{\text{stress2}}, \ldots$ (according to some criterion)
2. Calculate portfolio values $P(s_{\text{stress1}}), P(s_{\text{stress2}}), \ldots$
3. Compare these values with $P(s_{CM})$.

Stress test = scenario analysis

Traditional Stress Tests

How to select scenarios

How to select scenarios

- Standard scenarios
- Historical scenarios
- Subjective worst case scenarios

Dangers of Traditional Stress Tests

An Example

For a sample portfolio of equities:
Stress tests with standard and historical scenarios may nourish a false illusion of safety

Scenario	Relative Loss	Plausibility
Worst DPG	- 11%	once in 10 yrs.
Black Friday	- 4%	once in 19 yrs.
Worst Case	-18%	once in 8 yrs.

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Dangers of Traditional Stress Tests

- A stress scenario for one portfolio might be a lucky strike for another portfolio
- Stress tests with standard and historical scenarios may nourish a false illusion of safety
- Subjective worst case scenarios are often too implausible to trigger management action

Dangers of Traditional Stress Tests

But:

Stress Tests can be the basis of informed risk decisions ...

- ... if the scenarios are plausible
- ... if we are confident that there are no scenarios which are worse and more plausible

Maximum Loss

AD: The scenarios with prob density above a certain level.
“Scenarios above a certain minimal relevance threshold”
(For normal or t-dist AD is an ellipsoid.)

$$\mathrm{MaxLoss}_{AD}(P) := \max_{s \in AD} (P(s_{CM}) - P(s))$$

“Above the plausibility threshold nothing worse than MaxLoss can happen.”

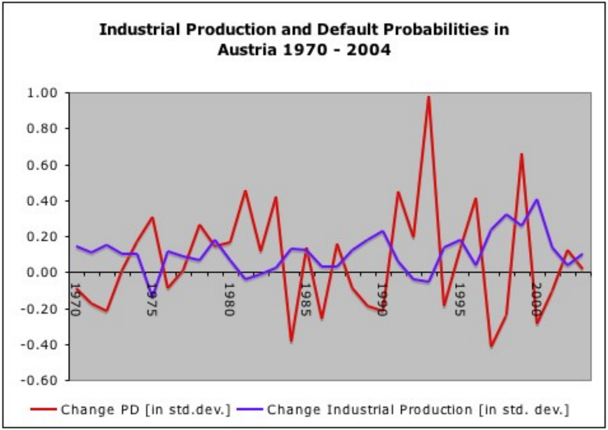
Outline

Macroeconomics matters for credit risk

Many ingredients of credit risk models depend on the macroeconomic situation

- default rates and other rating transition probabilities
- recovery rates
- exposure at default
  (depends often on interest rates, which are partially macro)

Macroecomics and Credit Risk



Macroeconomic Risk Factors in Credit Risk Models

The task

Include macroeconomic variables in credit risk models

- dependence of PDs (and transition probabilities) on macroeconomic variables
- dependence of exposure at default and collaterals on interest rates, equity indices etc, which are partially macro

Example 1: Credit Portfolio View (Wilson/McKinsey, Nickell et al.)

$$P_{j,t} = \frac{1}{1 + \exp(-Y_{j,t})}$$

$$Y_{j,t} = \beta_{j,0} + \beta_{j,1} X_{j,1,t} + \beta_{j,2} X_{j,2,t} + \ldots + \beta_{j,m} X_{j,m,t} + \nu_{j,t}$$

$P_{j,t}$: cond. PD for obligor in country/industry j
$Y_{j,t}$: macroeconomic index for country/region j
β_j: coefficient vector to be estimated from default data in country/region j
$X_{j,t}$: vector of macro variables for country/region j
evolution modelled by an autoregressive model
$\nu_{j,t}$: error term

Example 2: Structural default models with macroeconomic variables (Pesaran, Schuermann)

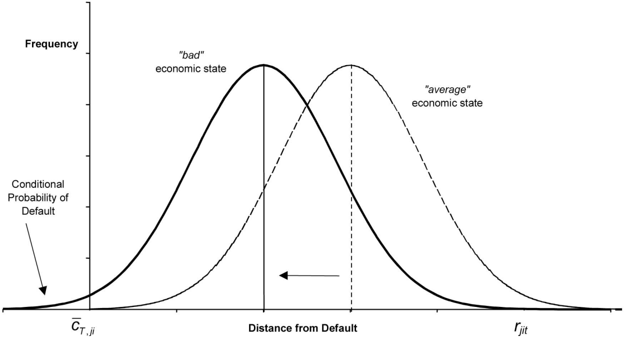
- structural model: firm (equity) value below threshold triggers default
- model firm (equity) value as

$$r_{ij,t} = \mu_{ijt} + \xi_{ij,t}$$

μ_{ijt}: forecastable conditional mean,
depending on macro variables, firm specific 'alphas',
regional fixed and time trend effects, global exogeneous variables

$\xi_{ij,t}$: error distribution, involving firm shocks,
macro shocks, exogeneous shocks

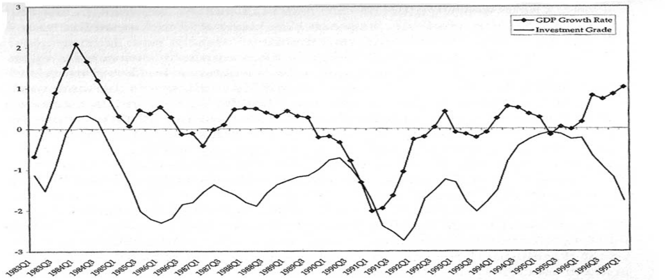
Example 2: Distance from default conditional on macro variables (Pesaran, Schuermann)



Distance from default conditional on state of the economy

Source: Pesaran and Schuermann 2003

Example 3: Rating Transition Matrices Depending on Macro Variables



GDP Growth Rate vs. Upgrade/Downgrade Ratio
Source: D. Duffie, K. J. Singleton, Credit Risk, Princeton (2003), p.89

Rating transition matrices are not constant.
They vary with the marcoeconomic cycle.

Example 3: Rating Transition Matrices Depending on Macro Variables

- Transition matrix generated by intensity matrix $\Pi(t,s) = \exp(\Lambda(s-t))$.
- Kavvathas 2001: Intensity Matrix $\Lambda_{ij}(t) = \exp\left(\eta_{ij} + \gamma'_{ij} X(t)\right)$.
- Lando 1998: Assume stochastic generator matrix Λ, which can be diaganolised: $\Lambda(t) = B\mu(t)B^{-1}$ and for eigenvalues of Λ: $\mu_j(t) = \gamma_{j0} + \gamma_{j1} \cdot X_t$ (affine dependence on a macroeconomic state process X_t.)

Warning: These double-stochastic models assume conditional independence of defaults given macroeconomic state. This is probably violated empirically (Das, Duffie, Kapadia, Saita 2005).

Example 4: Dependence of interest rates on other macro variables

Challenge:
Interest rates depend on markets and on central bank decisions taking into account the macroeconomic situation

- Quick and dirty: Take (some) interest rates as macro variables
- Nelson-Siegel yield factors dependent on macro variables (Diebold etc.)
- Include macro-variables in no-arbitrage term structure models (Rudebusch, Piazzesi, etc.)

Outline

Modelling Macroeconomic Data

A brief introduction to the basics options for macroeconomic models in a credit risk framework

Modern econometric modelling of the macroeconomy follows three different broad approaches:

- Large scale simultaneous equation models.
- Dynamic stochastic general equilibrium models.
- Various forms of vector autoregressive models.

Modelling Macroeconomic Data

Large scale simultaneous equation models

- These models go back to the 1950s. Usually developed and used by national research institutes and central banks.
- Basic building blocks: Equilibrium conditions, expectations equations and dynamic adjustment equations.
- Disadvantage for use in credit risk modelling: Very large and complex, difficult to correct for misspecifiaction and difficult to estimate.
- Viewed with scepticism by modern macroeconometrics.

Modelling Macroeconomic Data

Dynamic stochastic general equilibrium models

- Based on stylized intertemporal competitive general equilibrium models. All macroeconomic relations derived from intertemporal optimizing behavior under technological and financial constraints as well as economic equilibrium conditions.
- Strongly based on modern macroeconomic theory.Today mainly used by central banks.
- Disadvantage for use in credit risk modelling: Very complex and relies on many strong assumptions about individual behavior, rationality and the working of market mechanisms. Using the models with data requires usually many approximations.

Modelling Macroeconomic Data

Vector Autoregression (VAR)

- Focus is on a small set of core macroeconomic variables with a particular emphasis on statistical fit. Extensively used in macroeconomic forecasting.
- Cointegration allows for long-term relations between macro-variables (e.g. PPP)
- Particularly suited for use in credit risk modelling because ideally constructed for studying the response of core variables to shocks. Easy to implement.
- Disadvantage: Stress testing requires the connection of data to economic stories and economic theory. This connection can be achieved with VARs only by adding more structure and thus greater model complexity.
- A particularly useful example of this approach is the Global VAR model by Pesaran et. al.

Outline

The Task

Wanted:

- Scenarios from the multivariate distribution function of credit, market, and macro risk factor changes
- at a common time horizonof 3m to 1 yr
  given daily data of market variables and quarterly data of macro variables

Two Approaches

- Approach 1:
  Estimate joint distribution and draw scenarios from estimated distribution
- Approach 2:
  Non-parametric methods to determine scenarios directly from historical data
  “Historical Simulation”

Approach 1

Three steps:

1. Determine the marginal distribution of each risk factor at the common time horizon
2. Determine the dependence structure of risk factors by estimating the copula function
3. Calculate joint distribution from marginals and copula using Sklar's theorem

Estimating the Marginals

Five decisions

- Presence of autocorrelations?
- Do errors have constant volatility?
- Which distribution of error terms? (Normal, Student, or EVT, ...)
- Optimal Length of time window for parameter estimation?
- How to estimate distribution of market variables at long time horizon?

Estimating the Copula

1. transform univariate time series to uniform
   with inverse distribution function estimated for marginals
2. Choose a parametric family of copulas
   e.g. Gauss, t-, grouped t-, etc.
   Against Gaussian: Zero tail dependence not plausible in crashes, if prices of several securities tend to drop sharply.
3. Choose member of family
   by estimating parameters from multivariate data (with uniform marginals)

Approach 2

- Non-parametric methods to determine scenarios directly from historical data
  "Historical Simulation with time series of different frequencies"
- No other alternative to get scenarios from joint distributioin if some risk factors have continuous distribution and others discrete distribution

Outline

Evaluate Partial Scenarios

Start from:

- Portfolio model: determines portfolio value in function of risk factor values
- Joint distribution of risk factors
- Partial scenario: fixes the value of some but not all risk factors

Task: Evaluate portfolio behaviour in scenario

Approach 1

Extend partial scenario to full scenario

- fill in values of risk factors not specified by partial scenario: Expectation Value conditional on values of specified risk factor values

Result: unambiguous profit/loss number
Disadvantage: Disregard remaining risk of non-specified risk factors

Approach 2

Analyse distribution conditional on specified risk factor values

1. full joint distribution and specified risk factor values determine conditional risk factor distribution
2. approximate conditional profit-loss distribution by Monte Carlo draws from conditional risk factor distribution and portfolio evaluation
3. characterise conditional profit-loss distribution by expectation value, expected shortfall, VaR etc.

Illustrate Approach 2

Scenario	Δ GDP	Δ IR	Exp. P/L	Exp. Shortfall
Current Situation	$\pm 0\%$	± 0	+2%	3.5 bn
GDP stress	-5%	- -	-6.1%	6.2 bn
GDP/IR stress	-5%	-150 bp	-2%	6.8 bn

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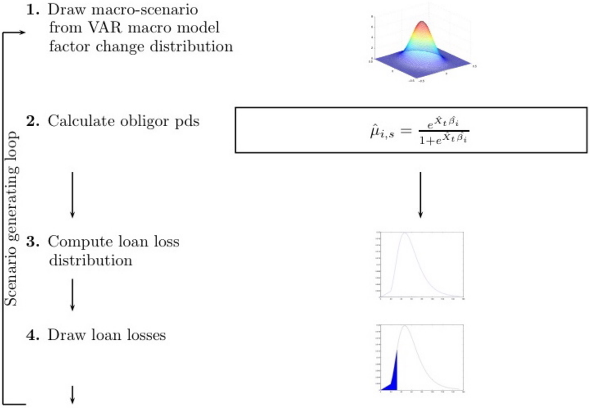
OeNB Systemic Risk Monitor

Macro Stress testing at the Austrian Central Bank

- Systemic Risk Monitor (SRM) is a software developed by the Austrian Central Bank (OeNB) for systemic financial stability analysis and stress testing of banking systems.
- One of the core modules in SRM is a credit risk model where obligor pds depend explicitly on macro variables.
- While SRM focuses at a banking system rather than an individual bank the general approach might be interesting for individual banks working on macro stress testing.

OeNB Systemic Risk Monitor

The credit risk module



OeNB Systemic Risk Monitor

Our experience in practice

- Explaining probabilities of default by macro variables alone gives a poor fit.
- Macroeconomic variables have to be supplemented by individual firm variables.
- The simulation is computationally intensive.

OeNB Systemic Risk Monitor

A typical stress test

- The general principle of the stress tests is based on conditional credit portfolio loss distributions.
- Two stress tests are considered: GDP drop by and a parallel shift in the yield curve.
- We compare the distribution of losses relative to regulatory capital under normal conditions and under stress.

OeNB Systemic Risk Monitor

Output of the stress test

Scenario	Δ GDP	Δ IR	Credit Risk Mean	Credit Risk 99%
Current situation	±0	±0	1.74	2.82
GDP stress	-2%	–	1.82	2.99
Interest rate stress	–	+120 bp	1.75	2.87

And here are the main points again ...

Stress Testing ...

- ... measures risk coherently (whatever your scenarios are)
- ... can be the basis of informed risk decisions if one is sure there are no worse scenarios above a plausibility level
- ... should be done systematically by identifying worst case scenarios

And here are the main points again ...

Credit Risk and Macro Variables

PDs, exposure at default, and collateral values depend on the state of the economy.

Risk management has to take this into account:
Credit risk models have to encompass macroeconomic variables

And here are the main points again ...

To perform macro stress tests ...

- ... determine macro scenarios
- ... draw values of other risk factors from joint distribution
- ... analyse the resulting conditional P/L distribution