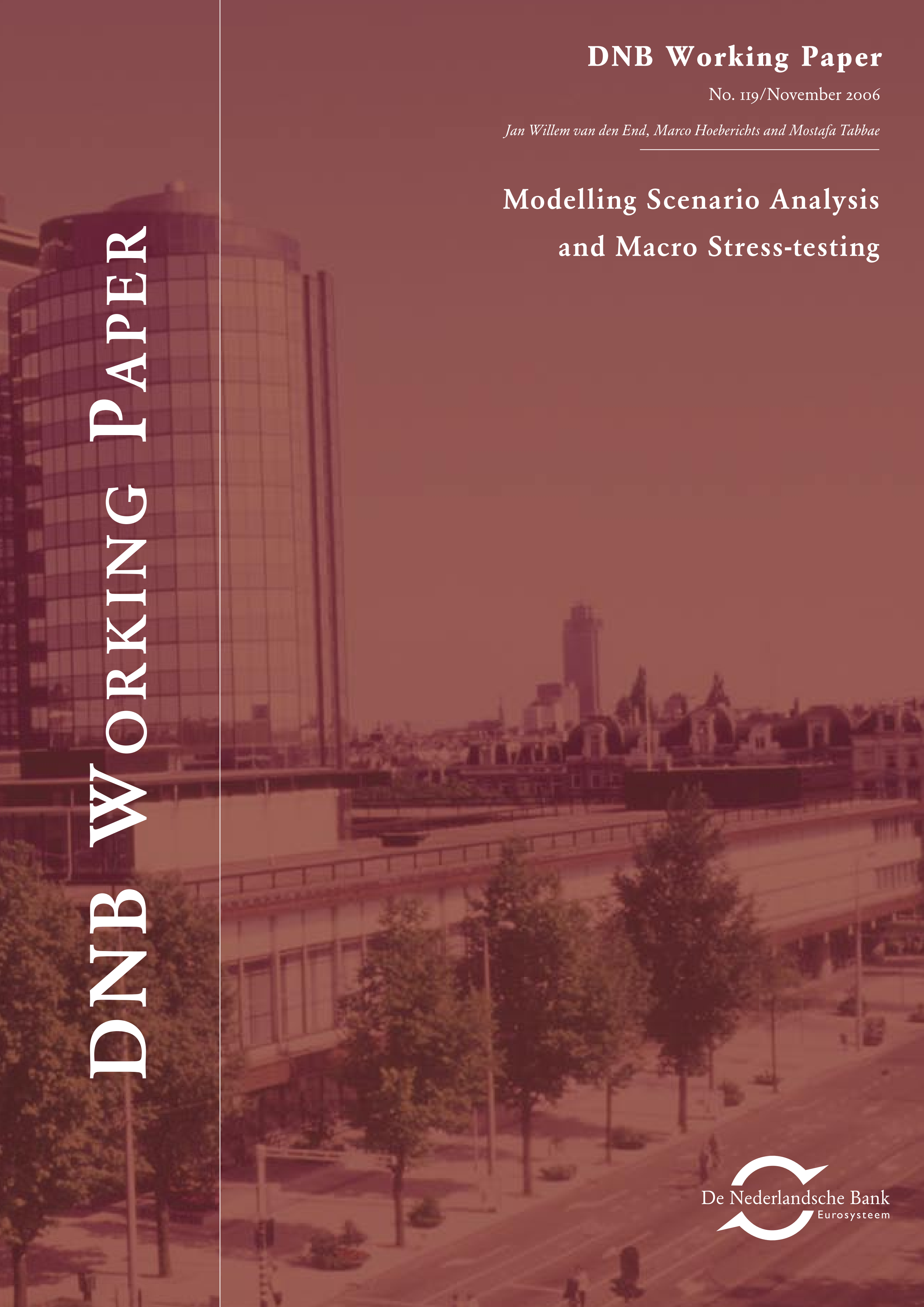

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Modelling Scenario Analysis and Macro Stress-testing

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Eurosysteem

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Jan Willem van den End, Marco Hoeberichts and Mostafa Tabbae*

* Views expressed are those of the individual authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Modelling scenario analysis and macro stress-testing

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Abstract

Macro stress-testing has become an important tool to assess financial stability. This paper describes a tool kit for scenario analysis and macro stress-testing. It is based on a model which maps multivariate scenarios to banks' credit and interest rate risks by deterministic and stochastic simulations. Our approach is an extension of existing macro stress-testing models as it distinguishes between probability of default on the one hand and loss given default on the other and allows for separate models for domestic and foreign portfolios. Another contribution of the paper is that the stochastic simulations generate loss distributions which provide insight in the extreme losses and allow for changing correlations between risk factors in stress situations. The methodology is applied to the Dutch banking sector.

Key words: banking, financial stability, stress-tests, credit risk, interest rate risk

JEL Codes: C33, E44, G21

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Introduction

Most central banks and some supervisors are publishing financial stability reports as part of their duties regarding safeguarding the stability of the financial system. Scenario analysis and stress-testing are core instruments in most monitoring frameworks for financial stability. DNB presents scenarios in its bi-annual publication 'Overview of Financial Stability in the Netherlands' (OFS). The pivotal role played by scenarios distinguishes the OFS from most other Financial Stability Reports, which are mostly descriptive in nature. In the Risk Outlook of the FSA, some alternative scenarios are used to assess the likely impact on the financial sector, but these are only qualitative scenarios (FSA, 2006). The use of scenarios is intended to raise the awareness of market participants to downside risks and encourage them to be more forward looking in their risk management. It therefore makes the assessment of financial stability forward looking.

This paper describes the current state of techniques that are used by DNB for scenario analysis and stress-testing. Section 1 presents a general framework for stress-testing and explains DNB's approach of modelling macro scenarios. Section 2 deals with methods that could be used to map these macro scenarios to the portfolios of banks. Section 3 and 4 explain the models of DNB for stress-testing of credit risk and interest rate risk. With these models, the first round effects of stress scenarios can be simulated. In section 5 this is done with a deterministic and a stochastic model. Section 6 concludes and points to areas of possible further research.

1 Scenarios

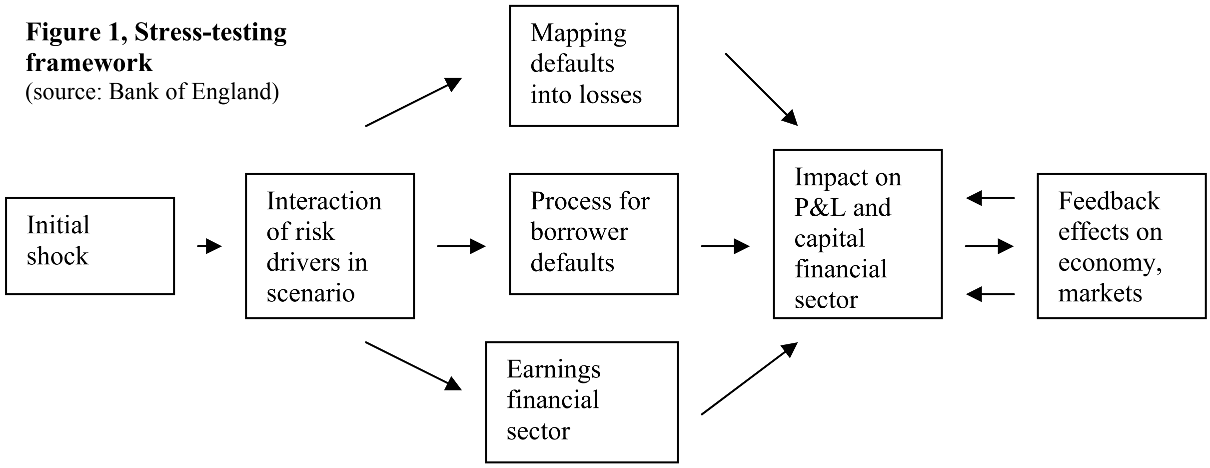
Figure 1 presents a stylised framework for macro stress-testing. The process begins with the selection of extreme but plausible shocks. These can be univariate shocks in single risk factors such as an isolated decline of equity prices. Univariate shocks can be combined into multivariate scenarios, in which various (macro) risk factors change. For instance, in one of the scenarios that we use, a depreciation of the dollar exchange rate is combined with a falling GDP and rising interest rates. Multivariate scenarios are more realistic than univariate shocks (also called sensitivity tests), since in stress situations risk factors usually interact. Scenarios can be developed through a number of methods (Hoggarth et al, 2005). First, they can be designed with a macroeconomic model, which generates projections of macro variables, sometimes as deviations from a base line scenario. These scenarios can be based on historic events (e.g. the 1998 emerging market crisis) or on hypothetical assumptions. Secondly, scenarios can be developed by a probabilistic method, in which shocks are based on stochastic simulations of macro variables (Drehmann, 2005). The tail outcomes of such simulations present extreme scenarios. As an alternative, a scenario could be based on the tail outcomes of distributions of financial sector losses. In this so-called 'reverse engineered' approach, the change in the (macro) risk factors that corresponds to these losses determine the scenario. A third approach - used to stress-test credit portfolios of banks - is based on transition matrices of credit ratings. Herein, adverse scenarios are presented by transition matrices that are due in a recession (Peura and Jokivuolle, 2003). Lastly, scenarios can be defined as the second round effects in the banking sector emanating from contagious defaults of banks (Elsinger et al, 2004).

In this paper we follow the first approach and design multi-year scenarios with a macroeconomic model. First, a base scenario for the Dutch economy is projected which is based on DNB's macro model MORKMON (Van Els, 2005). This model is also used for the projections of economic growth and inflation over a horizon of one to three years. For the financial stability assessment, next to the base scenario some alternative, hypothetical scenarios are developed with the NIGEM model.[1] MORKMON and NIGEM are large-scale structural econometric models. These models have their shortcomings for stress-testing since overshooting and spill-over effects of financial prices, that are typical for stress situations, should be added by assumption because they are not part of the model itself. Besides, the estimated parameters may not be stable in stress situations. VAR models are more flexible but do not provide for an economic foundation structure of a stress scenario, like structural macro models do. Analysing the economic reasoning behind scenarios is an important element in using hypothetical scenarios for financial stability policy. Structural macro models help to achieve this and contribute to the consistency of the generated paths of macro variables. Hypothetical scenarios might seem less plausible than historic scenarios, but they can be forward looking and sufficiently flexible to formulate events that could significantly affect the financial sector.

The alternative scenarios are specified by assuming a set of initial shocks. These shocks are used as exogenous input in NIGEM. The interactions between the initial shocks and the other macro economic variables over the scenario horizon follow from the model. Monetary policy rates are assumed to remain constant in this analysis, so monetary rules like the Taylor rule are excluded. The type and size of the shocks are based on extreme percentiles of time series and fundamental imbalances, e.g. the overvaluation of house prices or exchange rates. These 'realisations' are the starting point for the construction of the hypothetical scenarios which are further based on an economic assessment (expert opinion) of how risk factors could evolve in the future. Besides, the specification of the scenarios depends on their potential impact on the Dutch financial sector. This is done by tailoring the scenarios to the main risk exposures of the financial institutions, on both sides of the balance sheet. The Dutch financial sector is much exposed to movements of international risk factors, owing to their large cross-border exposures. The main risk exposures of the Dutch banks - which are the subject in this paper - are related to (international) interest rate and credit risk. Hence, these factors feature prominently in our scenario analysis.

[1] World model of the National Institute of Economic and Social Research (http://www.niesr.ac.uk).

Figure 1, Stress-testing framework
(source: Bank of England)



DNB’s analysis of financial stability in the OFS is centred around a base and alternative hypothetical scenarios. In several recent issues of the OFS (see for example DNB, 2005) two alternative scenarios, the Malaise scenario and the Global correction scenario, have been formulated (see Annex 1). These scenarios were centred around two diverging trends of interest rates. The most important financial stability risk in the Malaise scenario concerns the implications of falling interest rates and a flattening yield curve for financial institutions. In the Global correction scenario, both credit and market risks are adversely affected by increasing interest rates. By presenting these two scenarios, the OFS tries to encourage market participants to take into account both directions of possible interest rate shocks in their risk management.

2 Approaches for stress-testing

The mapping of a macro scenario to the portfolios of the financial sector is the third step in the stress-testing framework (the boxes in the middle of Figure 1). For this, most central banks follow a top-down approach, i.e. use inhouse models. Most models are specified for estimating credit risk of banks. Such models relate the position of borrowers to macro variables (‘Process for borrower defaults’ in Figure 1) and relate borrowers’ defaults to losses of the financial sector (‘Impact on P&L and capital’ in Figure 1). This last step could also be performed directly (see arrow in Figure 1 pointing from ‘Interaction of risk drives’ to ‘Mapping defaults into losses’), without explicitly estimating the process for borrower defaults. By this, the first round effects of shocks on the financial sector are estimated. Modelling second round effects (i.e. feedback effects on the economy and the financial markets, see the far right panel in Figure 1) is more complex and remains an issue that is yet in its early stage of development. This paper follows the mainstream literature and focuses on first round effects only.

Sorge and Virolainen (2006) distinguish several types of stress-testing models. In the ‘piecewise approach’, a direct relationship between macro economic variables (such as economic growth, interest rates and unemployment) and several financial soundness indicators is estimated using so called balance sheet models. The estimated coefficients of these models can subsequently be used to simulate the impact of adverse macro scenarios on the financial system. Balance sheet models can either be structural models or reduced-form (estimated by time series or panel data techniques). The latter embed the reduced-form equations into structural macroeconometric models, like the model of Norges Bank that has included financial stability variables (e.g. debt service ratios) in a macroeconometric model (Bardsen et al, 2006). The other strand of models is the 'integrated approach', in which multiple risk factors (credit, market risk etc.) are combined to estimate a probability distribution of aggregate losses that could arise in a stress scenario. Several studies have modelled default probabilities as non-linear functions of macro variables (following Wilson, 1997), or have incorporated them into a value-at-risk measure (Sorge and Virolainen, 2006).

Another way to map the macro scenarios to the portfolios of the financial sector is the bottom-up approach. This is usually followed by the IMF in Financial Sector Assessment Programs. In the bottom-up approach, the central bank or supervisor co-ordinates the macro stress-tests by designing the scenarios that the institutions subsequently run with their internal models. The results are then aggregated by the co-ordinator to the level of the financial system, usually by a weighted sum of the individual outcomes without taking into account any interdependencies between institutions. This approach allows for fitting the macro stress-tests to the risk profiles and risk management of the institutions. Another advantage is that the involvement of the institutions contributes to their risk awareness. Disadvantages are that bottom-up stress-testing is quite laborious and has limited flexibility (because of the lengthy process of instructing the institutions and collecting the outcomes) and that the comparability of the outcomes is not self-evident. Several central banks regularly organise bottom-up stress-tests (e.g. Bank of Finland, Bank of Ireland, Banco d'Espana). DNB uses a combination of bottom-up and top-down methods to perform macro stress-tests. Both are found to complement each other and provide for a cross check. This paper is confined to the top-down approach of DNB.

3 Credit risk

For stress-testing the credit risk of the banking sector, we have developed reduced-form balance sheet models. This stress-testing method is intuitive and straightforward to implement. The models are mainly developed to quantitatively underpin the scenario analysis, by quantifying the first round effects of shocks. They do not necessarily provide a good fit of the complexities of second round effects related to the interlinkages and feedback effects within the financial sector and with the economy. These could be addressed by linking the results of the balance sheet models to other models, like the macromodel MORKMON (which is not worked out in this paper). This follows the Bank of England which uses a suite of models to capture systemic risks in stead of a single model (Large, 2005).

3.1 Model

In modelling credit risk, we use two basic equations. In equation 1, the relationship between borrower defaults and some key macro variables is estimated (process for borrower defaults). In equation 2, the default rate together with some macro variables are used to explain loan loss provisions (LLP) and map defaults into losses. This procedure is given by the following equations:

$$\lambda(Defaultrate)_t = \alpha + \beta_1\, GDP_t + \beta_2\,(RL_t - RS_t) + \upsilon_t \tag{1}$$

$$\lambda\left(\frac{LLP}{CRED}\right)_{i,t} = \textit{fixed effects}_i + \beta_1\; GDP_t + \beta_2\, RL_t + \beta_3\; \lambda(Defaultrate)_t + \eta_t \tag{2}$$

$Defaultrate_t$ is the number of defaults relative to the population of firms. GDP_t stands for real GDP growth, RL_t for the long-term interest rate, RS_t for the short-term interest rate and RL_t - RS_t for the term spread. $(LLP/CRED)_{i,t}$ is the ratio between LLP and loans outstanding of bank i. The regressors have been chosen out of various macro variables because their parameter estimates provide for a good fit and have the expected sign, see section 3.3 (we have also estimated the equations including real effective exchange rate, unemployment, house prices, stock prices and oil prices). By using different constant terms in equation 2 (*fixed effects*$_i$)[2], the structural differences in the level of provisions for each bank is taken into account. This is done to include bank specific characteristics, which in other studies are included through bank specific control variables (e.g. in Bikker and Hu, 2002). While the inclusion of such micro data provides insight into the underlying bank fundamentals, for our purpose of linking bank's balance sheets to macroeconomic scenarios we can restrict the model to the limited number of key variables that drive macro scenarios. The parameters represent the marginal effects (assumed to be uniform across banks) of macro variables on loan loss provisions, allowing for bank-specific intercepts. In the equations, non-linear functions of $Defaultrate_t$ and $(LLP/CRED)_{i,t}$ – the logit – are used to extend the domain of the dependent variable to negative values and to take into account the possible non-linear relationships between the macro variables and LLP. Non-linearities are likely in stress situations as shocks could lead to extreme outcomes in credit losses (credit risk is inherently not normally distributed). Several other studies on stress-testing models take non-linearities into account by a logit transformed provision ratio (Lehmann and Manz (2006) and Bundesbank (2006)); others include squares and cubes of macro variables (Drehmann et al, 2005). The logit is defined as:

$$\lambda(X)_t = \ln\left(\frac{X_t}{1 - X_t}\right) \tag{3}$$

[2] We have tried random effects estimation as well. This gives a near-singular matrix as a result of too little cross-section observations in the foreign loans model. For domestic and total loans, estimation with random effects gives parameter estimates very similar to those obtained with fixed effects.

where X_t is $Defaultrate_t$ in equation 1 and $(LLP/CRED)_{i,t}$ in equation 2. By our two basic equations the Loss Given Default (LGD) can be derived implicitly, by using the identity:

$$EL\ (Expected\ Loss) = PD\ (Probability\ of\ Default) * LGD * EAD\ (Exposure\ at\ Default) \quad (4)$$

In terms of our model equations, EL/EAD is approximated by ($(LLP/CRED)_{i,t}$ and PD by $Defaultrate_t$. In most macro stress-testing models, LGD is assumed to remain constant. By estimating equation 1 and 2 and then including $(\overline{LLP/CRED})$ and $(\overline{Defaultrate})$ in identity 4, LGD can be estimated implicitly. This allows for determining the impact of stress scenarios on LGD, next to the impact on Defaults ($Defaultrate_t$) and losses ($(LLP/CRED)_{i,t}$). While both $Defaultrate_t$ and $(LLP/CRED)_{i,t}$ are regressed on the same macro variables, the impact of the macro variables on default risk is isolated from their impact on losses. The implicit method is different from (and less efficient than) modelling LGD separately as is done by, for instance, Coleman et al (2005) who explain the LGD out of the loan-to-value ratio and the age of the loan. Their method requires detailed information on the level of individual loans, which for instance could be taken from credit registers. Such data are not available for the Netherlands. Several studies show quite different outcomes of LGDs in downturns, dependent on the underlying portfolio and the region (Frye, 2000, Altman et al, 2004, Trück et al, 2005). In pillar 1 of the Basel 2 framework, banks are required to use an LGD parameter that reflects economic downturn conditions were necessary to capture the relevant risks (Basel Committee on Banking Supervision, 2005). By deriving LGD implicitly from developments in macro variables our approach draws a parallel with this requirement.

Besides LGD, we also take into account the typical risk factors that drive the credit risk of different banks portfolios. This is done by specifying different model versions for $(LLP/CRED)_{i,t}$ and $Defaultrate_t$ for the domestic and foreign loan books, next to the total loan book, as in equations 5-7.[3]

$$\lambda\left(\frac{LLP\_dom}{CRED\_dom}\right)_{i,t} = fixed\ effects_i + \beta_1\ GDP\_NL_t + \beta_2 RL\_NL_t + \beta_3\ \lambda(Defaulrate\_NL)_t + \eta_t \quad (5)$$

$$\lambda\left(\frac{LLP\_for}{CRED\_for}\right)_{i,t} = fixed\ effects_i + \beta_1\ GDP\_EU_t + \beta_2 RL\_NL_t + \beta_3\ \lambda(Defaulrate\_world)_t + \eta_t \quad (6)$$

$$\lambda\left(\frac{LLP\_total}{CRED\_total}\right)_{i,t} = fixed\ effects_i + \beta_1\ GDP\_EU_t + \beta_2 RL\_NL_t + \beta_3\ \lambda(Defaulrate\_world)_t + \eta_t \quad (7)$$

Defaultrate_NL and *Defaultrate_world* are the failure rate of domestic businesses, resp. the default rate on global corporate bonds. As in equation 1, they are explained by GDP_t and RL_t - RS_t, which in case

[3] The model estimations for LLP on foreign loans are based on data of the three banks that have foreign exposures outstanding.

of *Defaultrate_NL* are the growth rate of domestic GDP, resp. Dutch interest rates and in case of *Defaultrate_world* the growth rate of US GDP, resp. US interest rates. *LLP_dom (LLP_for)* and *CRED_dom (CRED_for)* stand for LLP, resp. loans outstanding in the domestic (foreign) portfolios and *LLP_total* and *CRED_total* for LLP, resp. loans outstanding in the consolidated portfolio of the banks. The domestic loan book of the Dutch banks is dominated by retail (mostly mortgage) loans, while the foreign and the consolidated portfolios are dominated by wholesale exposures. To fit these different risk profiles of the portfolios, the credit quality of domestic loans is explained by domestic risk factors (*GDP_NL* and *Defaultrate_NL* in equation 5) and the credit quality of the foreign and consolidated loan portfolios by global risk factors (*GDP_EU* and *Defaultrate_world* in equation 6). With respect to the consolidated loan portfolio of the banks, equation 7 includes credit risks from foreign branches or subsidiaries abroad. By this group-wide approach, cross-border risks are taken into account to some extent.

3.2 Data

The modelling of the credit risk of Dutch banks is restricted by the availability of data. As is suggested by Jones et al (2004), we use LLP as a reference value for credit quality (LLP being the additive provisions), since sufficiently long series of non-performing loans (NPL) are not available. A disadvantage of using LLP is that it is an accounting concept, which does not necessarily reflect default risk when it is incurred. Another data limitation is that no sectoral break-down of credit portfolios of Dutch banks is available, for instance of retail vs. wholesale loans. To allow for the different risk profiles of portfolios, we apply the available break-down in domestic, foreign and total loans. *Defaultrate_NL* and *Defaultrate_world* are determined by bankruptcies in the domestic corporate sector over the number of registered Dutch companies,, and worldwide defaults on corporate bonds over the number of bonds outstanding worldwide, respectively. *RL* is the ten years government bond yield, whereas *RS* is the three months risk free rate. Source of the bank specific data (LLP, CRED and the macroeconomic variables) is DNB. Sources for *Defaultrate_NL* and *Defaultrate_world* are Statistics Netherlands, and Standard&Poors, respectively.

The credit risk models were estimated with annual data, covering the 1990-2004 period (longer time series are not available). This limited number of observations could reduce the robustness of the model estimations. Quarterly data are only available from 1998 onward. By using annual data more business cycles are included. The number of observations is increased by including cross-sectional data in the estimations of equations 5-7. We used a panel data set of the largest five banks in the Netherlands, which represent approximately 85% of the banking sector's total assets.

3.3 Estimation results

Tables 1 and 2 in Annex 2 show the estimation results of equations 1, with *Defaultrate_NL* and *Defaultrate_world* as dependent variables. The parameter estimates of *GDP* and *RL - RS* are both significant with the expected (negative) sign. A decreasing term spread either means that short term rates increase, e.g. through tightening monetary and financial conditions, or that long term rates decrease, which may reflect a subdued outlook for inflation and the business cycle. Both could raise credit risk. Besides, the yield curve is an indicator for the business cycle. A flattening curve might point to decelerating economic growth, which again could raise credit risk.

Tables 3-5 in Annex 2 show the results of the panel regressions of equations 5-7. Herein, *Default rate* has been included as an explanatory variable. The estimation results show that it contributes significantly to explaining $(LLP/CRED)_{i,t}$, both in the case of domestic, foreign and consolidated exposures. The other parameter estimates, for *GDP* and one year lagged *RL*, also have the expected (negative, resp. positive) sign and are significant most of the times. In all three equations, interest rates are leading on $(LLP/CRED)_{i,t}$, as could be expected since interest rates usually lead the business cycle and hence credit quality. The different size of the fixed effects suggests that the Dutch banks have a different sensitivity to macroeconomic developments, owing to their typical risk profiles.

4 Interest rate risk

4.1 Model

Macro stress-testing models are usually confined to credit risk (ECB, 2006). However, interest rate risk is another important source of banks' profitability and capital base and hence their stability. Changes in interest rates affect earnings by changing net interest income and other interest sensitive income and expenses (earnings perspective). Changes in interest rates also affect the underlying value of the bank's assets, liabilities and off-balance sheet instruments because the present value of future cash flows change when interest rates change (economic-value perspective). Since the economic-value perspective takes into account the potential impact of interest rate changes on the present value of all future cash flows, this would be the preferred measure for interest rate risk (Basel Committee on Banking Supervision, 2004). However, most banking assets (i.e. loans) are held to maturity by which the economic-value perspective is less relevant in practise. Besides, there are data limitations involved in modelling the value effect of interest rate risk as long time series of banks' balance sheets at economic value are not available (only since 2005 banks have to report (parts of) their balance sheets at fair value, according to the International Financial Reporting Standards, IFRS).

For macro stress-testing only a few central banks have modelled interest rate risk, as part of modelling the banking sector's profitability. The Bank of England explains interest income out of GDP growth, in a reduced form fashion (Bunn et al, 2005). A new model developed at the Bank of England also takes into account the interest rate effects on the economic value of a bank (Drehmann et al, 2006). Banque de France specified a reduced form equation for the interest income based on a panel dataset of French banks (De Bandt and Oung, 2004). The yield spread, its volatility, lending growth and the cost of risk are used as explanatory variables. We specified a similar model for the growth rate of the net interest income of Dutch banks in equation (8),

$$\Delta Ln(NetInterestIncome_{i,t}) = fixed\ effects + \beta_1 GDP_t + \beta_2 GDP_{t-1} + \beta_3\ GDP_{t-2} + \beta_4\ RL_{t-1} + \beta_5\ RS_t + \mu_t \qquad (8)$$

in which the growth rate of net interest income is explained by the growth rate of real GDP (including two lags), the lag of the long-term interest rate and the current short-term rate in the euro area. The lags have been chosen so as to yield the best fit. When *GDP* increases, we expect $NetInterestIncome_{i,t}$ to increase through an expanding supply of loans (volume effect). *RS* is representative for the banks' cost of funding, which on average is attracted at short terms. Hence, a rise of *RS* lowers a bank's interest rate margin and reduces $NetInterestIncome_{i,t}$. *RL* is representative for the banks' lending rate, since on average banks loans are issued on longer terms (80% of the loans of Dutch banks has a maturity of five years or more). Hence, an increase of RL_t increases $NetInterestIncome_{i,t}$. The lag of *RL* is used rather than the current rate because the change of the market interest rate will not immediately affect the interest rate that banks receive on their outstanding loans. The parameters of *RS* and *RL* capture the price-effect on net interest income. Including the term spread of interest rates rather than *RS* and *RL* separately would seem intuitively more logical, but this is tantamount to applying a restriction on the parameters of *RS* and *RL*. Testing this restriction reveals that it does not hold.

4.2 Data and estimation results

The interest rate risk model was estimated with annual data, covering the 1994-2005 period (more historic data are not available), including cross-sectional data for $NetInterestIncome_{i,t}$ (based on the same set of banks as in the credit risk model). Estimation results are summarized in Table 6. We find significant parameter estimates with the expected signs for all parameters, except for one-year lagged GDP. The combined effect of GDP_t, GDP_{t-1} and GDP_{t-2} is larger than the effect of RL_t and RS_t, which implies that the volume effect is more important than the price effect. The adjusted R-squared of the interest rate model is lower than those of the credit risk models, which could be expected since the explanatory power of models with variables in terms of changes (as in the interest rate model) is usually lower than of models with variables in terms of levels (or ratios as in the credit risk models).

5 Simulation of scenario effects

After having designed the scenarios and specified the stress-testing models, both can be linked by simulating the impact on financial sector exposures. First, we conduct deterministic scenario analysis, by using the average macro variables as projected by NiGEM as input in the stress-testing model. This assumes no uncertainty about the forecasted macroeconomic variables. The advantage of this approach is that the results are easy to understand and provide insight in the quantitative links between macro variables and financial soundness indicators. However, the deterministic analyses only generates one future path of outcomes without allowing for uncertainty in the projections. However, uncertainty is inherent to hypothetical scenarios, even more if they have a multi-year horizon. We therefore perform stochastic scenario analysis as well, to generate probability distributions of the impact on the financial sector. This yields a more complete description of the scenario outcomes, attaching a likelihood to it, next to the impact which results from the deterministic scenarios. The tails of the distributions also provide insight in the extreme losses which is relevant from a financial stability perspective. The deterministic and the stochastic scenario analyses have been based on the Malaise scenario and the Global correction scenario from DNB's recent OFS (see Annex 1). In the output, we are able to distinguish the impact on domestic exposures, from the impact on foreign exposures, based on the different model versions for both.

5.1 Deterministic scenarios

In the deterministic scenarios for credit risk, the deviation of the macro variables from the base line (following from the MORKMON and NiGEM model simulations) are input in equations 1-2 and 8. By this, the impact on credit risk (Default rate, LGD and LLP) and interest income can be projected over the one to three years horizons. These are point estimations since they result from using the path of macro variables as projected by the NiGEM model as input in the stress-testing model.

Figures 2a-f show the projected log-transformations of changes in *Default rate*, *LGD* and *LLP/CRED*, of which the three year results are cumulative effects. The figures clearly show that the Global correction scenario has the largest impact on credit risk, raising *LLP/CRED* on average by 65 to 92%. In this scenario, both the rise in interest rates and the decline of GDP adversely affect credit risk, whereas in the Malaise scenario the decline of interest rates compensates for the subdued business cycle effect. The impact over time of the Global correction scenario illustrates the benefit of a multi-year horizon. The impact on foreign exposures is more frontloaded than on domestic exposures, which are substantially affected only after three years. A likely reason for this is that movements of international risk factors take time to affect the domestic economy and hence the credit quality of domestic loans. The wholesale exposures, that dominate the foreign loans, are more directly affected by international risk factors. The average total loss in the Global correction scenario in the three years period is EUR 2.2 billion, which equals around ¼ of one years' profits and 2.5% of total own funds of the Dutch banking sector (2005 data[4]). The total capital ratio of the banking sector declines from 11.5 to 11.2% ceterus paribus. This relatively low impact is partly related to the low base levels of PDs and LLPs in 2004. As could be expected, the Malaise scenario has most adverse consequences for the domestic loan book, which is more dependent on developments in the euro area than the consolidated book, which is internationally diversified.

Figure 2a Global correction & domestic credit portfolio
percentage change, deviations from base scenario

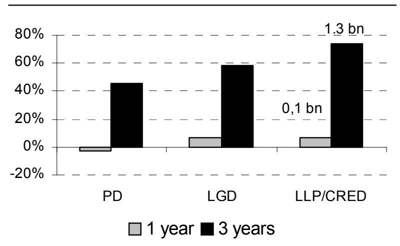


Figure 2b Global correction & foreign credit portfolio
percentage change, deviations from base scenario

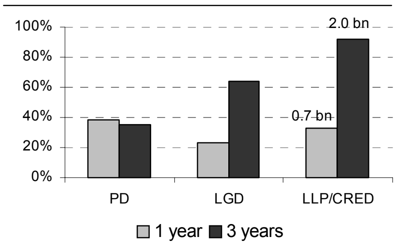


Figure 2c Global correction & total credit portfolio
percentage change, deviations from base scenario

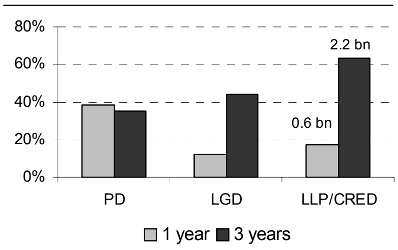


Figure 2d Malaise & domestic credit portfolio
percentage change, deviations from base scenario

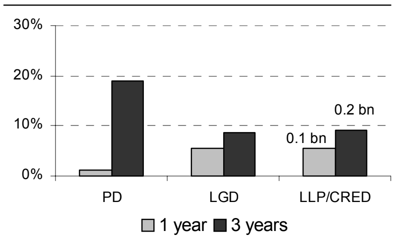


Figure 2e Malaise & foreign credit portfolio
percentage change, deviations from base scenario

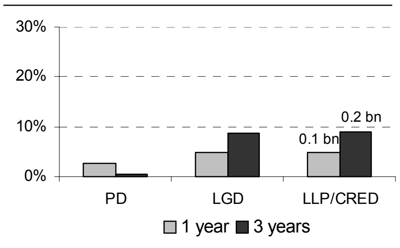
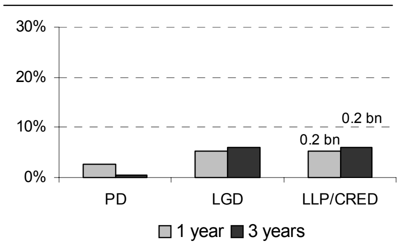


Figure 2f Malaise & total credit portfolio
percentage change, deviations from base scenario



Figures 2g-h show the simulated effects on interest income. The Global correction scenario appears to have a more negative impact on interest income than the Malaise scenario, although in the former the (relatively sharp) decline of GDP is accompanied by a widening term spread of interest rates. In the Malaise scenario, both the change of interest rates (through a tightening term spread) and GDP have an adverse impact on interest income. Even so, the Global correction scenario has the most negative impact due to the dominating influence of the volume effect over the price effect.

Figure 2g, European malaise & interest income
EUR bn, deviations from base scenario

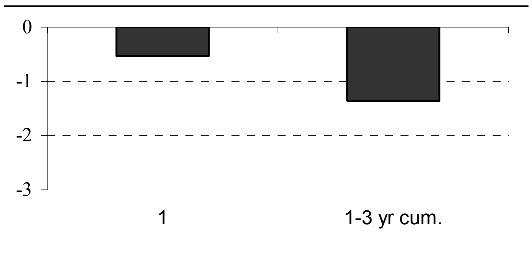
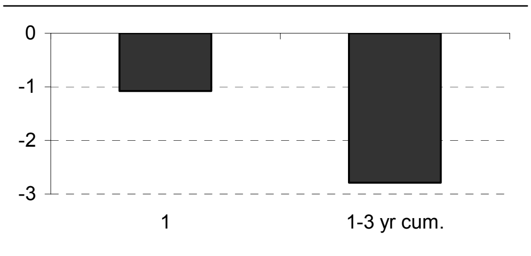


Figure 2h, Global correction & interest income
EUR bn, deviations from base scenario



4 The sum of the separate outcomes for losses on domestic and foreign loans is not equal to the outcome for the total loan book since by estimating two equations a larger part of the variance is explained. Besides, the log transformation does not allow for a simple summation of the model outcomes.

5.2 *Stochastic simulation of credit risk in base scenario*

The stochastic scenario analysis is based on Sorge and Virolainen (2006), who simulate default rates over time by generating macroeconomic shocks to the system. The model for credit risk that governs the joint evolution of *Default rate*, *LLP/CRED* and the associated macroeconomic shocks is given by equations 1 and 2 and a set of univariate autoregressive equations of order 2 (AR(2)), to estimate the macroeconomic variables:

$$x_t = k_0 + k_1\, x_{t-1} + k_2\, x_{t-2} + \varepsilon_t \qquad (9)$$

where $k_{0..n}$ are the regression coefficients to be estimated for the macroeconomic factors (x_t) used in equations 1 and 2. Equation 9 is estimated with GDP growth rates and interest rate levels which are non-stationary according to unit roots tests. As an alternative, we also tried a multivariate specification by modelling the macroeconomic factors (x_t) as a Vector Autoregression (VAR) model. The VAR (2) model takes into account the correlations between the macro variables.

$$X_t = K_0 + K_1\, X_{t-1} + K_2\, X_{t-2} + \varepsilon_t \qquad (10)$$

where X_t is a vector of macroeconomic variables, $K_{0..n}$ is a vector of coefficients to be estimated and ε_t is a vector of innovations.

The system of equations 1,2 and 9 (or 10) is completed by a vector of innovations, E, and a variance-covariance matrix of errors, $\sum$:

$$E = \begin{pmatrix} \upsilon \\ \eta \\ \varepsilon \end{pmatrix} \sim N(0,\Sigma) \quad , \quad \Sigma = \begin{bmatrix} \sum_{\upsilon} & \sum_{\upsilon,\eta} & \sum_{\upsilon,\varepsilon} \\ \sum_{\eta,\upsilon} & \sum_{\eta} & \sum_{\eta,\varepsilon} \\ \sum_{\varepsilon,\upsilon} & \sum_{\varepsilon,\eta} & \sum_{\varepsilon} \end{bmatrix}$$

With this system of equations the future paths of the macroeconomic variables, *Default rate* and *LLP/CRED* can be simulated with a Monte Carlo method. The simulations are carried out by taking random draws of variables $Z_{t+s} \sim N(0,1)$. These are transformed into correlated innovations in the macroeconomic factors, *Default rate* and *LLP/CRED* by $E_{t+s} = A'\, Z_{t+s}$, where A' results from the Cholesky decomposition[5] $\sum = AA'$. The simulated error terms and the initial values of the macroeconomic variables are then used to derive the corresponding values of the macroeconomic variables (x_{t+s}), $Defaultrate_{t+s}$ and $(LLP/CRED)_{t+s}$ by using equations 1,2 and 9 (or 10). With these outcomes and the information on outstanding exposures of the banking sector, distributions of credit losses can be determined. Figures 3a-b show the probability distributions of losses over a one and a

[5] The results are not dependent on the order of the error terms in matrix $\sum$ since the simulated innovations are applied to the corresponding equations 1,2 and 9 (or 10).

three years horizon (the horizons have no material influence since all the simulations are based on a normal distribution). These results are conditional on the bank exposures in the most recent available year of the data series (2004) and present a stochastic base scenario for the next years. The stochastic base scenario differs from the deterministic base scenario as projected with the macroeconomic models since it takes into account the uncertainty around the average future paths of macro variables. Like a typical distribution of credit risk, the simulated distributions of losses are skewed to the right, due to the correlation structure of the innovations.[6] It is striking that the loss distributions for domestic exposures are more skewed than the distribution for total exposures. This can be explained by the volatility of domestic GDP, which is larger than the volatility of euro area GDP (GDP is the most important driver in the model).

Figures 3a-b show that the outcomes of the simulations based on the AR-model (9) and the VAR-model (10) are almost similar. This indicates that the specification of the model which generates the macro factors has no material influence, from which we may conclude that the statistical objections (such as the non-stationarity of the data) are neither materially important. The robustness of the model has also been explicitly tested for alternative specifications of the variance-covariance matrix of errors $\sum$.[7] This is done by applying impulse responses of one standard deviation to the error terms of the macro economic factors (ε) and to the covariance between these error terms in $\sum$. Figures 3c-d show that the system of equations is fairly robust to different specifications of $\sum$; the probability distribution of losses on total loans is barely affected. The impulse responses have a larger impact on domestic loan losses (the average expected loss changes by around 6%) which is most pronounced for extreme losses (the 1% tail outcome changes by nearly 20%). We also checked for the sensitivity of the outcomes for a different starting year from which the scenario estimations proceed. To this end, the system of equations was re-estimated for total and domestic loans with a cut-off date of the data series at 2001, which we assumed to be the new starting year of the simulations. The resulting probability distributions of losses were subsequently applied to the exposures outstanding at end-2001. Figures 3e-f indicate that the shape of the loss distributions does not change much if another starting year is used, which again illustrates that the model is fairly robust.

[6] All elements in the variance-covariance matrix of errors $\sum$ are positive, except for the correlation between the error terms of the interest rate and GDP (however, the parameter estimates for interest rate and GDP have an opposite sign in equation 2 (positive resp. negative), by which the effect of the negative correlation between the error terms has the same direction on *LLP/CRED*).

[7] Implicitely, $\sum$ also changes due to the specification in an AR, respectively VAR mode.

Figure 3a Base scenario, domestic portfolio
Probability distribution of credit losses

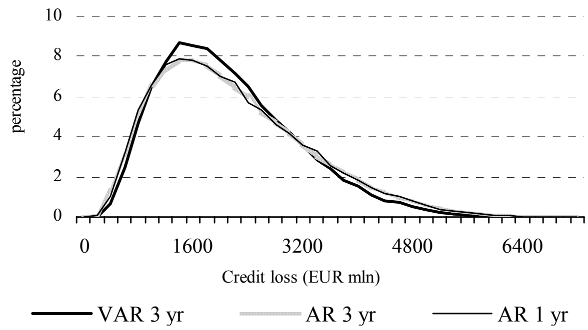


Figure 3b Base scenario, total portfolio
Probability distribution of credit losses

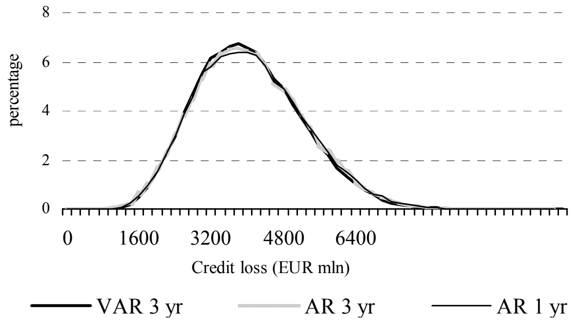


Figure 3c Robustness check (base sc., domestic port.)
Probability distribution of credit losses, horizon 3 yrs (cum.), VAR

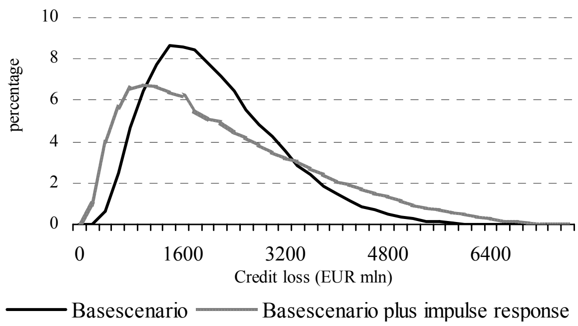


Figure 3d Robustness check (base sc., total port.)
Probability distribution of credit losses, horizon 3 yrs (cum.), VAR

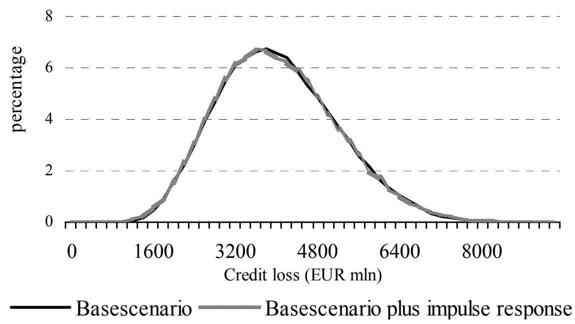


Figure 3e Different starting yr (base sc, domestic port.)
Probability distribution of credit losses, horizon 3 yrs (cum.), VAR

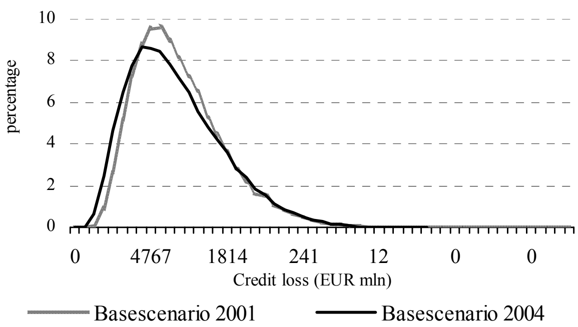
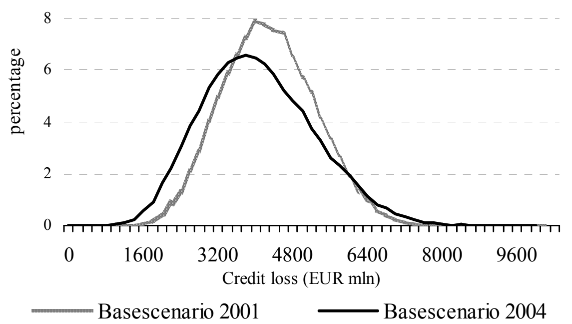


Figure 3f Different starting yr (base sc, total port.)
Probability distribution of credit losses, horizon 3 yrs (cum.), VAR



Since *LLP/CRED* and *Default rate* are separately modelled, the probability distribution of LGD is also dependent on the simulated macroeconomic variables (implicitly via identity 4). This comes close to the 'integrated approach' for macro stress-testing, in which all parameters are functions of a vector *X* of macroeconomic variables, which evolve over time following an autoregressive stochastic process, and can be summarised into a value-at-risk measure (Sorge and Virolainen, 2006):

$$VaR_t(\tilde{y}_{t+1} / \tilde{x}_{t+1 \geq} \bar{x}) = f\{ E_t(x_t); PD_t(x_t); LGD_t(x_t); \Sigma_t(x_t) \} \tag{11}$$

where $\tilde{y}_{t+1} / \tilde{x}_{t+1 \geq} \bar{x}$ represents the uncertain future realisation of the aggregate credit loss ($\tilde{y}_{t+1}$) for the financial system in the event of a simulated macroeconomic stress scenario (i.e. conditional on a tail realisation of $\tilde{x}_{t+1 \geq} \bar{x}$). The difference with a 'fully integrated approach' is that the effect on market prices is not taken into account since our model is a default mode (with losses stemming from counterparty defaults) and not a mark-to-market framework (with changes in portfolio values associated with changes in credit quality), such as for example the model of Drehmann (2005).

5.3 Stochastic simulation of credit risk in stress scenarios

To simulate the hypothetical stress scenarios, the future values of the macroeconomic factors as projected by the NiGEM model are included to re-estimate the VAR model (10). The resulting new error terms (ε_t) change the corresponding elements in the variance-covariance matrix $\sum$. Next, Monte Carlo simulations are carried out by taking random draws of $Z_{t+s} \sim N(0, \sigma_{stress} / \sigma_{base})$[8] for the innovations in the macro variables used in the VAR model (10) , and $Z_{t+s} \sim N(0,1)$ for the innovations used in equations 1 and 2 in the model. Loss distributions for the assumed stress scenario can then be determined with the simulated paths for macroeconomic variables (x_{t+s}), $Defaultrate_{t+s}$ and $(LLP/CRED)_{t+s}$, as in the base scenario. To simulate the Malaise and Global correction scenarios, the VAR model (10) is re-estimated, including equations for *GDP* (the explanatory variable in equations 1 and 2), *RL* (explanatory variable in equation 2) and *RL-RS* (explanatory variable in equation 1). This approach differs from Sorge and Virolainen (2006), who only simulate single-factor shocks in GDP and the interest rate. We apply multi-factor simulations by taking into account simultaneous changes in the macro economic variables and their interactions, as happen in the macro scenarios. The interactions are taken into account in the variance-covariance matrix $\sum$, including the change in the correlations which result from re-estimating the VAR for the macroeconomic factors. This is an important advantage of our approach since in stress situations the historical correlations between risk factors can change.[9]

The stochastic simulations have been applied to the domestic, foreign and total portfolios of the banks, by using equations 5-7 in the simulations. As in the deterministic scenarios, the impact of the Global correction is larger than the Malaise scenario (Figures 4a-f). In the latter, the probability distribution of credit losses is close to the base scenario, since the decline of interest rates compensates for the subdued business cycle effect. Over the three years horizon in the Global correction scenario, the average credit loss on the total, resp. the foreign and domestic loan portfolio of the Dutch banks increases by EUR 1.9 bn, resp. 0.5 and 0.7 bn compared to the base scenario.[10] This is less than

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8 σ_{stress} results from the error terms of the re-estimated VAR model (10) and σ_{base} from the error terms of the original VAR . By the ratio $\sigma_{stress} / \sigma_{base}$, the innovations in the stressed macro factor are normalised by the respective standard deviation of the error terms in the base scenario.

9 Maximum stress could be simulated by assuming full correlation between the macro variables (i.e. interest rate and GDP growth). However, the model does not allow for a high (absolute) covariance that would be imposed in the variance-covariance matrix, since then it is no longer positive definite which in turn precluded a Cholesky decomposition. The maximum absolute covariance that could be imposed equalises to a correlation coefficient of 0.77. Simulations that we have conducted with imposed (limited) higher covariances between interest rate and GDP growth indicate that a higher covariance does not lead to significant higher outcomes for loan loss provisions.

10 The sensitivity of the outcomes to different specifications of the variance-covariance matrix $\sum$ is limited; including impulse responses of one standard deviation to the error terms of the macro economic factors (ε) and

indicated by the deterministic scenarios, but note that the outcomes of the deterministic and stochastic simulations are not fully comparable since they are based on different model structures (in the stochastic scenarios the macroeconomic variables are estimated by VAR models). The benefit of stochastic simulations is that they provide insight in the possible extreme outcomes in the right tail of the probability distributions. Compared to the base line, in the Global correction scenario the tail outcomes are much larger since the probability distribution is flatter.[11] This is most pronounced for the foreign portfolios where the loss amount at the 99th percentile more than doubles from around EUR 0.8 bn in the base scenario to around EUR 1.8 bn in the stress scenario (3 years horizon, Figure 4b). This compares with an increase of extreme losses in the total loan portfolio from around EUR 7.1 bn in the base scenario to around EUR 9.5 bn in the stress scenario (99th percentile, 3 years horizon, Figure 4c). The relatively strong flattening of the distribution of foreign loans losses indicates the sensitivity of this portfolio to shocks in international risk factors, in particular of *Defaultrate_world*, for which the coefficient in equation 6 (explaining *LLP_for*) is much larger than in equation 7 (explaining *LLP_total*). Besides, the covariance between GDP and the interest rate which results after Cholesky decomposition is larger in case the system of equations is estimated with *LLP_for* than with *LLP_total*. The stronger interaction between the macro variables leads to more widely dispersed simulation outcomes.

Figure 4a Global correction & domestic portfolio
Probability distribution of credit losses, horizon 3 yrs (cum.)

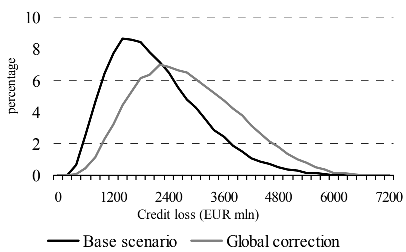


Figure 4b Global correction & foreign portfolio
Probability distribution of credit losses, horizon 3 yrs (cum.)

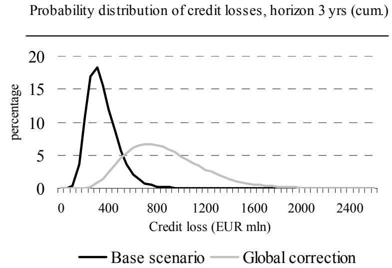


Figure 4c Global correction & total portfolio
Probability distribution of credit losses, horizon 3 yrs (cum.)

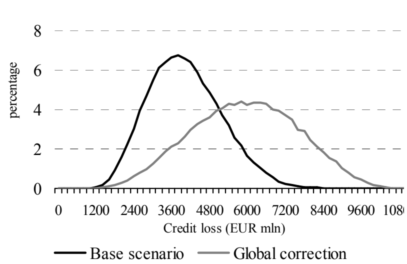


Figure 4d Malaise & domestic portfolio
Probability distribution of credit losses, horizon 3 yrs (cum.)

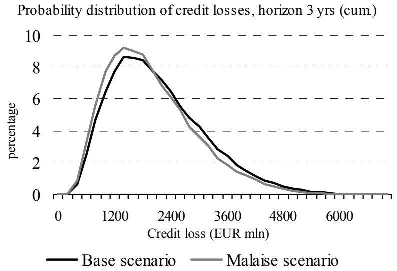


Figure 4e Malaise & foreign portfolio
Probability distribution of credit losses, horizon 3 yrs (cum.)

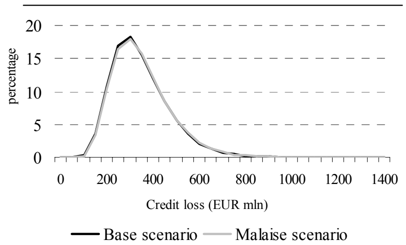
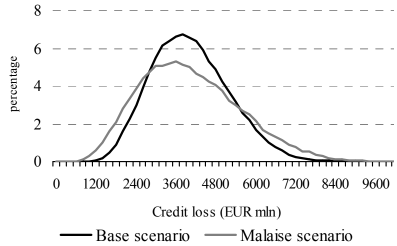


Figure 4f Malaise & total portfolio
Probability distribution of credit losses, horizon 3 yrs (cu



5.4 Stochastic simulation of interest rate risk in stress scenarios

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to the covariance between these error terms in ∑ changes the estimated average losses by less than 1% and the one percent extreme loss by less than 5%.

[11] The kurtosis of the probability distribution for the base scenario is -1.00 and for the global correction scenario -1.52 (3 years horizon).

Stochastic simulations can also be applied to net interest rate income, by using equations 8, the VAR model (10) and a vector of innovations E, with $E = \begin{pmatrix} \mu \\ \varepsilon \end{pmatrix} \sim N(0,\Sigma)$, in the same way as we used the system of equations 1,2 and 10 and vector E for credit risk. For this, the simulated error terms in E and the initial values of the macroeconomic variables are used to derive the corresponding values of the macroeconomic variables (x_{t+s}) and net interest income ($NetInterestIncome_{t+s}$). With these outcomes and the total net interest income of the banking sector, distributions of the change in net interest income can be determined. Next, distributions can be determined for the assumed stress scenarios. Like in the stochastic simulations for credit risk, the future paths of the macroeconomic variables in the Malaise and Global correction scenarios (projected by the NiGEM model) are included to re-estimate the Vector Autoregression model 10, following the multi-factor approach. The stochastic simulations have been applied to the net interest income of the banks.

Figures 5a-b show the probability distributions of the *change* of net interest income over a three-years horizon for each scenario. In the stress scenarios, the distributions shift to the left which means that the banks' income growth turns out lower than in the base scenario. On average and compared to the base scenario, the growth of net interest income is EUR 1.5 bn lower in the Malaise scenario and EUR 0.9 bn lower in the Correction scenario, which is significant from an economic perspective.[12] Note that in the deterministic approach the adverse effect of the Global correction scenario is larger than the Malaise scenario, which again illustrates that the stochastic and deterministic simulations my lead to different outcomes. It is worth mentioning that the distribution of credit risk (e.g. for the base scenario of domestic loan losses in Figures 4a) is flatter than the distribution of interest income (kurtosis -0.94 for LLP/CRED versus -0.48 for interest income, three years base scenario). From this it follows that the extreme outcomes of changes in interest income in the stress scenarios are closer to the tail outcomes of the base scenario than in the case of credit risk (interest income changes at the 1% percentile (left tail) of the interest income distribution are just EUR 10 to 30 mln worse than the outcomes at the 1% percentile in the base scenario). The relatively fat tailed distributions of credit risk correspond to the nature of credit risk, which is usually driven by a limited number of large defaults.

[12] The outcomes of the simulations based on the AR-model (9) and the VAR-model (10) are of comparable magnitude (average loss of EUR 0.8 (AR) vs 1.5 bn (VAR) in the Malaise scenario and EUR 1.2 (AR) vs. 0.8 bn (VAR) in the Correction scenario, while the 1% tail losses per scenario are almost similar in both specifications). This underlines the robustness of the model for different specifications, including for changes in the variance-covariance matrix of errors ∑, which is influenced by the specifications in an AR vs. VAR mode.

Figure 5a Global correction & interest income
Probability distribution of change of net interest income, horizon 3 years (cum)

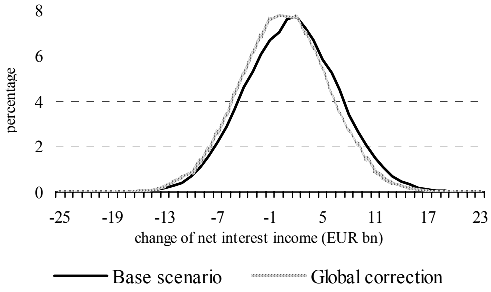
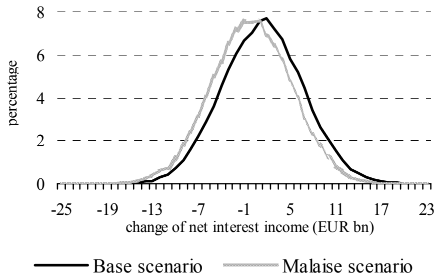


Figure 5b Malaise & interest income
Probability distribution of change of net interest income, horizon 3 years (cum)



6 Conclusion

Scenario analysis is an important tool for assessing the possible impact of low-probability events and extreme shocks. Macro models help to structure the scenario analyses. To map macro scenarios to the portfolios of the banking sector, we developed macro stress-testing models, which quantify the first round effects of credit and interest rate risk. The contributions of our approach are the inclusion of loss given default, next to probability of default (PD) and expected loss (by LLP), and the separate modelling of credit risk in domestic and foreign portfolios. Hereby, cross-border risks are taken into account to some extent, which is usually a missing dimension in macro stress-testing models. Another important contribution of this paper is the multi-factor approach in applying deterministic and stochastic simulations of the macro scenarios. This approach takes into account simultaneous changes in the macro economic variables and their interactions. Moreover, the stochastic simulations allow for the changing correlations between risk factors which is typical for stress situations. To some extent this gives in to the objection that stress-testing models are based on statistical relationships that are assumed to remain constant, which might not be the case in stress. By including credit risk and interest rate risk, the main sources of risk for the banking sector are modelled. Compared to the base line, the worst scenario for credit risk results in an average loss on the total loan portfolio of Dutch banks of around EUR 2 bn and for interest income of nearly EUR 3 bn, which represents just around 5% of banks' own funds in total.

Applying macro stress-testing to liquidity risk seems an interesting area for further work. Due to financial innovations, credit and market risks are increasingly correlated, which has made banks more dependent on market liquidity. Modelling liquidity risk might contribute to quantifying the interlinkages within the financial system, which is a main challenge for the further development of macro stress-testing models. Another challenge is the modelling of second round effects. Most stress-testing models, like our approach, are confined to estimating first round effects of shocks. Estimating second round effects would require more complex models than the reduced form equations that are standard practice in macro stress-testing, since to analyse feedback effects, the interlinkages between the economy and the financial sector should be modelled. This is an important area for further research.

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Annex 1, Scenarios OFS
(source: DNB, 'Overview of Financial Stability in the Netherlands', December 2005)

Base scenario

The base scenario is based on the MORKMON estimates from the DNB Quarterly Bulletin of June 2005. In conformity with the expectations of most market participants (see Box 2), this foresees continuing high oil prices, a gradual increase in international bond yields and a steady depreciation of the US dollar. As a result, growth in the euro area will lag behind this year, but the economic recovery in the Netherlands will gather momentum and become more broadly-based. Global balance of payment imbalances will be reduced in a gradual and orderly manner.

Malaise scenario

This scenario centres on the loss of consumer and producer confidence in the euro area, either due to continuing high unemployment or the stagnation of European integration. Weak producer confidence and the high oil prices depress the propensity to investment, while the low consumer confidence and high unemployment produce a negative consumption shock and stagnation of house prices. The slump in demand causes intra-European trade to stagnate, pushing the Netherlands into recession. In this scenario European long-term interest rates fall sharply, by 150 basis points over three years, leading to a substantial flattening of the yield curve. This trend is reinforced by hedging behaviour of institutional investors. In the case of rising inflation, due to knock-on effects of the high oil price, interest rates would fall less sharply. The most important financial stability risk in the 'Malaise scenario' concerns the implications of falling interest rates and a flattening yield curve for financial institutions, notably life insurance companies and pension funds (see later in this OFS).

Global correction scenario

This scenario revolves around a correction of the Global balance of payments imbalances by a series of sharp shocks. Loss of confidence among investors and/or abrupt adjustments in the reserve management of Asian central banks put capital flows to the US under pressure, triggering a sharp adjustment of the US dollar and US interest rates. The assumption is that the trade-weighted dollar depreciates in the first quarter of this scenario by 40%[2] with US capital market rates rising in three years by 250 basis points, sparking a sharp steepening of the yield curve. This has negative repercussions for the US asset markets such as the stock market and the housing market. Though the Global imbalances are considerably reduced (the US current account deficit drops almost 3.5% of GDP within three years), this scenario contains various financial stability risks. Owing to the traditional correlation between US and European long-term interest rates, it is assumed that the European bond yields also increase and that the European yield curve steepens, so that corrections also occur in the European stock markets and housing markets. The Dutch economy would be hard hit by negative wealth effects and exports would decline. In this scenario the sharp rise in risk-free interest rates brings the search for yield to an abrupt halt, causing a worldwide repricing of risk premiums. This process could possibly be reinforced by the role played by hedge funds in less liquid market segments. A shift will occur towards liquid and less risky instruments (money market paper, deposits etc.). In other words the scenario assumes a flight to liquidity so that bonds are sold and interest rates rise. But it is also conceivable that a 'global correction' triggers a flight to quality whereby investors flee to seemingly safe (e.g. European) government bonds. In that case a rise of European bond yields is less likely.

Annex 2, Estimation results

Table 1

Dependent Variable: Defaultrate_NL
Method: Least Squares
Sample(adjusted): 1990 2004
Included observations: 15 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.467771	0.075671	-59.04210	0.0000
GDP_NL(-1)	-0.099056	0.020716	-4.781655	0.0006
GDP_NL (-2)	-0.061563	0.026878	-2.290489	0.0427
RL_NL – RS_NL	-0.040272	0.022301	-1.805842	0.0984

R-squared	0.884164	Mean dependent var	-4.951403
Adjusted R-squared	0.852572	S.D. dependent var	0.224713
S.E. of regression	0.086282	Akaike info criterion	-1.839220
Sum squared resid	0.081890	Schwarz criterion	-1.650407
Log likelihood	17.79415	F-statistic	27.98726
Durbin-Watson stat	1.166764	Prob(F-statistic)	0.000019

Table 2

Dependent Variable: Defaultrate_World
Method: Least Squares
Sample(adjusted): 1990 2004
Included observations: 15 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.167943	0.340573	-9.301796	0.0000
GDP_US	-0.274346	0.106450	-2.577229	0.0242
RL_US – RS_US (-1)	-0.264742	0.114209	-2.318043	0.0389

R-squared	0.581765	Mean dependent var	-4.331406
Adjusted R-squared	0.512059	S.D. dependent var	0.772027
S.E. of regression	0.539283	Akaike info criterion	1.779703
Sum squared resid	3.489909	Schwarz criterion	1.921313
Log likelihood	-10.34777	F-statistic	8.345985
Durbin-Watson stat	1.018424	Prob(F-statistic)	0.005352

Table 3

Dependent Variable: LLP_dom
Method: GLS (Cross Section Weights)
Date: 10/11/06 Time: 13:31
Sample: 1990 2004
Included observations: 15
Number of cross-sections used: 5
Total panel (unbalanced) observations: 70
One-step weighting matrix
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RL_NL (-1)	0.161596	0.024048	6.719703	0.0000
GDP_NL	-0.058435	0.031959	-1.828432	0.0723
Defaultrate_NL	1.024793	0.237794	4.309586	0.0001
Fixed Effects				
_B1--C	-1.984858			
_B2--C	-1.665652			
_B3--C	-2.105242			
_B4--C	-2.002257			
_B5--C	-2.921763			

Weighted Statistics			
R-squared	0.974651	Mean dependent var	-7.373950
Adjusted R-squared	0.971789	S.D. dependent var	2.846001
S.E. of regression	0.478015	Sum squared resid	14.16688
Log likelihood	-36.59645	F-statistic	340.5557
Durbin-Watson stat	1.723957	Prob(F-statistic)	0.000000

Unweighted Statistics			
R-squared	0.585081	Mean dependent var	-6.314645
Adjusted R-squared	0.538236	S.D. dependent var	0.716942
S.E. of regression	0.487185	Sum squared resid	14.71566
Durbin-Watson stat	1.216367		

Table 4

Dependent Variable: LLP_for
Method: GLS (Cross Section Weights)
Date: 10/11/06 Time: 13:30
Sample: 1990 2004
Included observations: 15
Number of cross-sections used: 3
Total panel (balanced) observations: 45
One-step weighting matrix
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RL_NL(-1)	0.212122	0.035307	6.007975	0.0000
GDP_EU	-0.034776	0.029689	-1.171330	0.2488
GDP_EU (-1)	-0.128909	0.037544	-3.433563	0.0015
Defaultrate_World	0.417467	0.076761	5.438511	0.0000
Fixed Effects				
_B1--C	-4.430738			
_B2--C	-4.335226			
_B3--C	-4.537242			

Weighted Statistics			
R-squared	0.915117	Mean dependent var	-5.520565
Adjusted R-squared	0.901715	S.D. dependent var	1.054518
S.E. of regression	0.330597	Sum squared resid	4.153184
Log likelihood	-8.714074	F-statistic	68.27926
Durbin-Watson stat	1.366650	Prob(F-statistic)	0.000000

Unweighted Statistics			
R-squared	0.529370	Mean dependent var	-5.262504
Adjusted R-squared	0.455060	S.D. dependent var	0.451088
S.E. of regression	0.332993	Sum squared resid	4.213617
Durbin-Watson stat	1.311052		

Table 5

Dependent Variable: LLP_total
Method: GLS (Cross Section Weights)
Date: 10/11/06 Time: 13:26
Sample: 1990 2004
Included observations: 15
Number of cross-sections used: 5
Total panel (unbalanced) observations: 70
One-step weighting matrix
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RL_NL (-1)	0.143650	0.014111	10.18035	0.0000

GDP_EU	-0.080854	0.011284	-7.165255	0.0000
GDP_EU (-1)	-0.089214	0.013623	-6.548577	0.0000
Defaultrate_World	0.169996	0.029523	5.758118	0.0000
Fixed Effects				
_B1--C	-5.381231			
_B2--C	-5.266910			
_B3--C	-5.809869			
_B4--C	-6.017495			
_B5--C	-6.964475			

Weighted Statistics			
R-squared	0.994418	Mean dependent var	-9.024547
Adjusted R-squared	0.993686	S.D. dependent var	4.610516
S.E. of regression	0.366350	Sum squared resid	8.186951
Log likelihood	-3.240300	F-statistic	1358.423
Durbin-Watson stat	1.459658	Prob(F-statistic)	0.000000

Unweighted Statistics			
R-squared	0.724672	Mean dependent var	-6.017800
Adjusted R-squared	0.688563	S.D. dependent var	0.732702
S.E. of regression	0.408895	Sum squared resid	10.19892
Durbin-Watson stat	1.055330		

Table 6

Dependent Variable: RBG?
Method: GLS (Cross Section Weights)
Date: 10/16/06 Time: 10:41
Sample: 1994 2005
Included observations: 12
Number of cross-sections used: 5
Total panel (unbalanced) observations: 59
One-step weighting matrix
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RL_NL(-1)	0.014011	0.005966	2.348383	0.0229
RK_NL	-0.026748	0.007030	-3.805114	0.0004
GDP_NL	0.018078	0.005520	3.274929	0.0019
GDP_NL(-1)	-0.013547	0.005975	-2.267337	0.0278
GDP_NL(-2)	0.029524	0.004669	6.323905	0.0000
Fixed Effects				
_B1--C	0.001766			
_B2--C	0.047973			
_B3--C	0.010840			
_B4--C	0.061644			
_B5--C	0.022466			

Weighted Statistics			
R-squared	0.368281	Mean dependent var	0.120418
Adjusted R-squared	0.252251	S.D. dependent var	0.108861
S.E. of regression	0.094135	Sum squared resid	0.434205
Log likelihood	75.20348	F-statistic	3.174014
Durbin-Watson stat	2.154730	Prob(F-statistic)	0.004263

Unweighted Statistics			
R-squared	0.262849	Mean dependent var	0.095616
Adjusted R-squared	0.127454	S.D. dependent var	0.107315
S.E. of regression	0.100243	Sum squared resid	0.492388
Durbin-Watson stat	2.542727		

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