Stress Testing the Enterprise Sector's Bank Debt: A Micro Approach*

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This paper describes Norges Bank's micro stress-testing framework for assessing the Norwegian banking sector's losses on loans to the nonfinancial enterprise sector. Using projected macro variables and a stock-flow approach, annual financial statements of every firm in Norway are projected five years ahead. The loan loss potential is then assessed using a credit-scoring model. We present a backtest of projections, taking the history of macro variables as given. Our results are fairly good using a relatively simple setup, and we conclude that stock-flow projections of financial statements can be useful for stress testing banks' loan portfolios.

JEL Codes: G21, G32, G33, M49.

1. Introduction

The credit quality of banks' loans to the enterprise sector is of great importance when measuring banks' credit risk. During the Norwegian banking crisis of 1988–93, a large part of banks' losses were on loans to the enterprise sector. Even today we expect that an economic downturn will lead to larger losses on loans to the enterprise sector than on loans to the household sector.

Norges Bank's SEBRA database contains annual financial statements for every limited liability company in Norway. The financial

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statements provide valuable information about the risk characteristics of individual firms. Even in favorable macroeconomic periods, there will be some firms in a vulnerable financial situation. Financial statements for such firms provide useful information about the banking sector's loss potential on loans to the enterprise sector.

Norges Bank uses several models in its stress testing of financial stability; see Andersen et al. (2008). Our paper deals with Norges Bank's micro approach for stress testing the banking sector's losses on loans to the nonfinancial enterprise sector.[1] This approach consists of four steps:

(i) Norges Bank's macroeconomic models are used to predict the development of key macro variables in a given stress scenario. The stress scenario will normally cover a period of five years. The macroeconomic models used in connection with stress testing are described in Andersen et al. (2008). The macro variables we use in our micro approach are GDP growth, the borrowing rate for the nonfinancial enterprise sector, the growth in households' employment income, the inflation rate, the real exchange rate, and the growth in house prices.

(ii) Annual financial statements for every firm are projected, primarily based on empirical models which depend on the aforementioned macro variables. Based on the projected financial statements, Norges Bank's SEBRA model is used to predict a yearly probability of default (PD) for each firm.

(iii) The expected potential loss on the banking sector's loans to the enterprise sector is calculated by multiplying each firm's bank debt by its PD and summing over all firms. This expected potential loss is transformed to an estimated loss for the banking sector. This transformation involves the use of an empirical model for loss given default (LGD).

(iv) The final step is the measurement of the impact of the estimated loan loss on the banking sector. The impact will depend on the banking sector's initial capital adequacy and its lending growth, profit before loan losses, and dividend payouts in the

[1] Norges Bank has also modeled the banking sector's stock of nonperforming and doubtful loans to the enterprise sector by a macro approach; see Berge and Boye (2007).

stress years. Projections of these quantities are carried out in a separate bank model; see Andersen et al. (2008).

Feedback effects to the macroeconomic models from the loan losses projected in step (iii) are not considered, which constitutes a clear limitation to the setup. In particular, we would expect that the magnitude of loan losses typically prevailing in a stress scenario would limit the availability of credit to both households and firms. A weakening in credit conditions may in turn affect GDP growth and further depress the financial strength of the enterprise sector. In this paper we do not take this issue further. Our focus is on steps (ii) and (iii). We analyze how to best translate the output from the macroeconomic models into projections of financial items that are used by the SEBRA model in its predictions of PDs. To project financial items, we utilize the stock-flow structure of financial statements and a set of simple assumptions for liquidity management and dividend policy. The accuracy of the projections is evaluated through backtesting of the predicted PD for the enterprise sector. We do this by taking the historical development of the macro variables in step (i) as given and projecting the financial statements five years ahead, using financial information only from the initial year together with the macro variables.

Our approach gives ample opportunities for tailoring a specific stress scenario. Each independent financial item represents a handle we might pull to create a tailored stress scenario. For example, to measure the impact of a wage shock, we can sharply increase payroll expenses. In such a scenario, labor-intensive enterprises will be hit the hardest. In other scenarios the shock may come through a sharp increase in interest expenses or through write-downs of fixed assets and investments, and so forth.

The paper proceeds as follows. Section 2 describes the SEBRA model and the associated database, which is the basis for our stress testing of the banking sector's losses on loans to the enterprise sector. In section 3 we describe how the (debt-weighted) PD for the enterprise sector and a measure of LGD are calculated. Section 4 gives an overall description of how financial statements are projected at the firm level and presents the empirical models and auxiliary assumptions used in the projections. The results of the backtests are reported in section 5. Section 6 presents an empirical model for LGD and shows an application of our stress-testing framework using scenarios from Norges Bank's Financial Stability Report 1/08. Section 7 concludes.

2. The SEBRA Model and the Associated Database

An important part of Norges Bank's stress-testing framework for banks' losses on loans to the enterprise sector is a bankruptcy prediction model, called the SEBRA model. The associated database contains annual financial statements for every limited liability company in Norway in the period 1989–2006.[2] Some additional information, such as industry code, year of formation, and location, is also stored in the database. In the SEBRA model we utilize data from the firms' unconsolidated financial statements.[3] We receive financial statements for most firms about nine months after the end of the financial year. For each financial year, the database contains about thirty items from the profit-and-loss account and about fifty items from the balance sheet of each firm. The financial statements provide information about the total bank debt of each firm. We do not have information about which bank(s) the firm has borrowed from.[4]

The SEBRA model predicts bankruptcy probabilities as logistic functions of variables that are based on key financial items from the financial statement. The model belongs to the class of "generalized additive models" (GAMs).[5] All variables in the SEBRA model utilize data from the same financial year. Thus, based on the financial statement of a firm for one year, we are able to predict the bankruptcy probability for the next year. Two versions of the SEBRA model have been developed: a basic version and an extended version. These versions are described in Bernhardsen and Larsen (2007),

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[2]The database also contains annual financial statements for a smaller set of firms back to 1981.

[3]We also have access to consolidated financial statements for a limited number of firms for the period 1992–2006, but we do not use this information.

[4]Kredittilsynet (The Financial Supervisory Authority of Norway), which also uses the SEBRA model, does have access to such information. Kredittilsynet regularly uses the SEBRA model in its on-site inspections of banks.

[5]The general functional expression for the SEBRA model is given in appendix 1.

while an earlier version of the model is described in Eklund, Larsen, and Bernhardsen (2001).

The last versions of the SEBRA model have been estimated on financial statements from the period 1990–2002 and bankruptcies in the period 1991–2005.[6] The three core variables in the basic version of the SEBRA model are as follows:[7]

$$\mathrm{x}_1 = \frac{\text{Earnings Before Depreciation and Amortization (EBDA)}}{\text{Total Debt}} \tag{1}$$

$$\mathrm{x}_2 = \frac{\text{Book Value of Equity}}{\text{Book Value of Total Assets}} \tag{2}$$

$$\mathrm{x}_3 = \frac{\text{Cash and Deposits} - \text{Short-Term Debt}}{\text{Operating Revenue}} \tag{3}$$

The numerator in x_1 is an estimate of cash earnings after taxes. Since x_1 measures cash earnings as a share of total debt, this variable is a measure of the debt-servicing capacity of the firm. The inverse of x_1 shows how many years it will take to repay the debt given the current year's cash earnings. x_2 is the equity ratio, which is a measure of financial strength. The variable x_3 is a measure of liquidity. In addition to the three core variables, there are two sets of indicator variables in the basic version of the SEBRA model. The first set measures whether or not the book value of equity is less than paid-in equity, i.e., whether the firm has an accumulated net loss. The second set measures the age of the firm. This set consists of a dummy variable for each age in the interval from one year to eight years. The inclusion of age dummies means that the model can be interpreted within the class of hazard-rate models.

The basic version of the SEBRA model was developed with stress testing in mind. An important criterion in the development process was that the model should depend on few variables, but include the most critical ones. Bernhardsen and Larsen (2007) document that the deterioration of predictive power compared with the extended

[6] The reason for the different time periods is that the estimation is based on the event bankruptcy, which occurs with a time lag compared with the release of the last financial statement.

[7] The balance-sheet items included in equations (1)–(3) are measured at year end.

version of the SEBRA model is relatively small. Another consideration when developing the basic version of the SEBRA model was that it should be possible to make good projections of the explanatory variables included in the model.

By using the misclassification approach to binary dependent models outlined in Hausman, Abrevaya, and Scott-Morton (1998), we take the observed event of bankruptcy as a noisy proxy for the unobserved event of default.[8] Under the assumption that the conditional probability of bankruptcy given default does not depend on the explanatory variables, the basic version of the SEBRA model is able to predict PDs.[9] The advantage of predicting PDs instead of bankruptcy probabilities is that it makes our stress-testing framework more compatible with the Basel II framework, where PD and LGD are central credit-risk parameters.

3. PD for the Enterprise Sector and Implied LGD

This section describes how we aggregate *probability of defaults* (PDs) for individual firms to arrive at the (debt-weighted) PD for the enterprise sector. This PD is used to calculate an implied measure of *loss given default* (LGD).

We denote the probability of default for firm i in year t by $\mathrm{PD}_{i,t}$. Moreover, let $\mathrm{D}_{i,t-1}$ denote the bank debt of firm i at the end of year $t-1$, i.e., at the start of year t. The *expected potential loss* (EPL) for the banking sector regarding this firm in year t is then given by

$$\mathrm{EPL}_{i,t} = \mathrm{PD}_{i,t} \cdot \mathrm{D}_{i,t-1}. \tag{4}$$

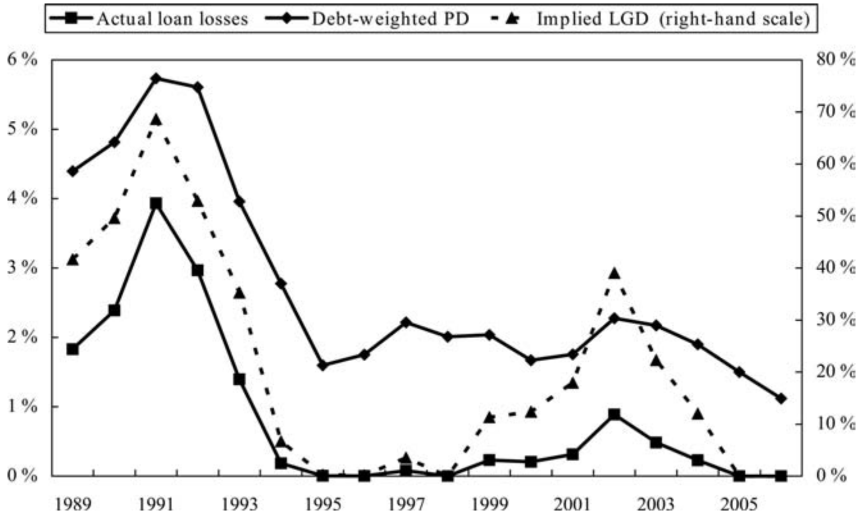
By aggregating over all firms, we obtain the expected potential loss for the banking sector in year t. This aggregate, denoted EPL_t, can be interpreted as an estimate of the total loss for the banking sector before realization of collateral. By dividing EPL_t by the aggregate bank debt, we find the (debt-weighted) PD for the enterprise sector in year t:

$$\mathrm{PD}_t = \frac{\mathrm{EPL}_t}{\mathrm{D}_{t-1}}. \tag{5}$$

[8] Each bank has information about defaults among its customers. Norges Bank does not have access to such information.

[9] For details, see appendix 2.

Figure 1. Implied LGD for Banks' Loans to the Enterprise Sector in the Period 1989–2006



3.1 Calculation of Implied LGD

Normally, the banking sector's actual loan losses (ALL)—i.e., the losses after realization of collateral—will be lower than EPL. Based on the historical series of ALL and our prediction of EPL based on historical data, we get an implied estimate of LGD in year t:

$$\mathrm{LGD}_t = \frac{\mathrm{ALL}_t}{\mathrm{EPL}_t}. \tag{6}$$

LGD varies strongly over time and its peaks are associated with economic downturns. This is due to the impairment of the value of collateral in downturns. Figure 1 illustrates the implied LGD for the period 1989–2006 calculated as the actual loan losses as a percentage of total loans divided by the predicted (debt-weighted) PD.[10]

The main objective with stress testing is to predict the banking sector's future loan losses in various scenarios. By using predicted financial items as input to the SEBRA model, we obtain annual estimates of EPL for future years. We then need a model for LGD

[10]To avoid negative values for the implied LGD, we have set $\mathrm{ALL}_t = 0$ in years with net reversals of earlier loan losses, i.e., in years when $\mathrm{ALL}_t < 0$.

to convert these EPLs to annual estimates of the loan losses. We have modeled the implied LGD, i.e., the dotted line in figure 1. The empirical model is presented in section 6.

4. Projections of Financial Statements

The starting point for our stress testing of banks' losses on loans to the enterprise sector is the development of macro variables in a given stress scenario. This information must be translated to the micro level, which in our case means the financial statement of each firm. We use aggregate growth rates from empirical models to project the main items in the financial statement of every firm. In addition, we use simple "rule-of-thumb" assumptions regarding the liquidity management and dividend policy of each firm.

A financial statement consists of a profit-and-loss account (table 1) and a balance sheet (table 2). There are some differences between projections of items in the profit-and-loss account (flow variables) and projections of items in the balance sheet (stock variables). Most of our projections are of flow variables, but we also project important stock variables like debt and paid-in equity. The development of some stock variables, like total assets and cash & deposits, is partly determined by the projected flow variables.

The distribution of net profit between dividend payment and retained earnings affects both cash & deposits and the equity ratio. We assume that firms follow a pecking-order rule regarding the distribution of net profit. The starting point of the rule is the projected cash earnings of the firm. We assume that this is the amount that is available for strengthening the stock of cash & deposits and for payment of dividends. This means that negative cash earnings automatically reduce the stock of cash & deposits. On the other hand, higher operating revenue will normally necessitate a higher stock of cash & deposits and other current assets. For firms with positive cash earnings, we assume that cash & deposits are targeted to grow by the same rate as operating revenue. If the cash earnings are not sufficient to cover this increase, we assume that cash & deposits only grow by the available amount. If there is still something left of the cash earnings after the allocation to cash & deposits, and the equity ratio is above 10 percent, we assume that 35 percent of the remaining cash earnings are paid as dividends. This is a rough estimate

Table 1. Main Items in the Profit-and-Loss Account

Profit-and-Loss Account	
Operating Revenue	(E)
– Cost of Goods Sold	(E)
– Payroll Expenses	(E)
– Depreciation	(H)
– Write-Downs	(E)
– Other Operating Expenses	(H)
= Operating Profit	
+ Interest Income	(H)
– Interest Expenses	(E)
+ Net Other Financial Items*	(H)
= Profit Before Taxes	
– Income Tax	(H)
= Net Profit	
– Dividend	(H)
= The Year's Retained Earnings	

* = Includes write-downs on investments.
(E) = Projected based on empirical model.
(H) = Projected based on heuristic.

based on results of a study we have conducted of dividend payments in Norwegian firms in the period 1989–2005.[11]

The equity ratio is influenced by the current year's retained earnings and debt growth. Write-downs have a pronounced impact on net profit, and thereby on retained earnings. Write-downs for

[11]The study shows that the dividend level in the enterprise sector varies largely during the period. One reason is frequently changing tax regimes for dividends. Over the period 1992–2005, about 40 percent of firms with a positive net profit paid dividends. Among these firms, about 70 percent of their net profit was paid out as dividend. If the total dividend is divided among all firms with a positive net profit, this gives a payout ratio of about 28 percent. Our assumption is related to "the remaining cash earnings," which is a somewhat different measure than net profit.

Table 2. Main Items in the Balance Sheet

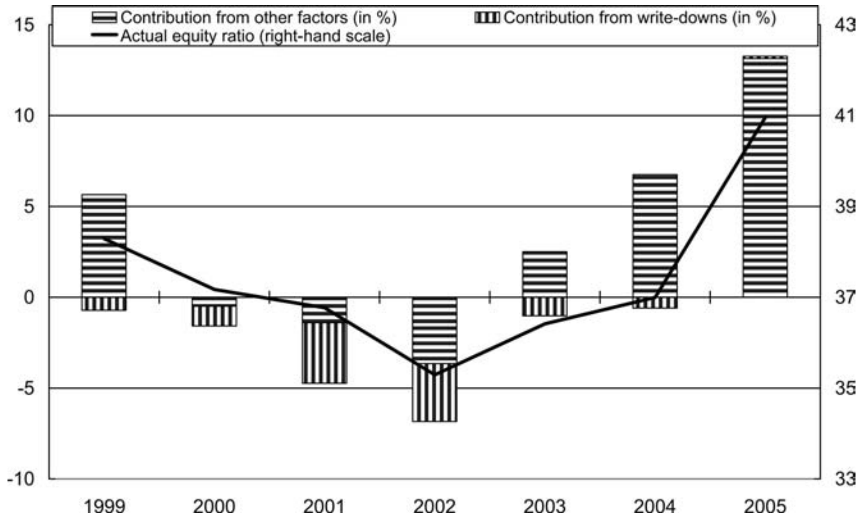
Balance Sheet	
Assets	
Long-Term Assets	
Intangible Assets	
Fixed Assets	
Long-Term Investments	
+ Current Assets	
Cash & Deposits	(H)
Other Current Assets	
= Total Assets	
Equity and Liabilities	
Equity	
Paid-In Equity	(H)
Retained Earnings	(H)
+ Debt	(E)
Long-Term Debt	
Short-Term Debt	
= Sum Equity and Liabilities	

(E) = Projected based on empirical model.
(H) = Projected based on heuristic.

impairment are often associated with economic downturns. The normal cycle is a low level of write-downs in economic upturns, and increasing write-downs as the economy moves deeper into a downturn. Figure 2 shows the relative effects of write-downs and other factors, like net profit (before write-downs) and debt growth, on the equity ratio in the mild economic downturn in Norway in 2001–03. Our decomposition shows that about two-thirds of the decrease in the equity ratio in 2000 and 2001, and about half the decrease in 2002, can be attributed to write-downs. It is therefore important to project write-downs in order to get good projections of the equity ratio of each firm.

To sum up our procedure for projecting financial statements, first the flow variables needed to calculate next year's cash earnings

Figure 2. Effect of Write-Downs on the Equity Ratio



are projected. Then a heuristic assumption for the firm's use of cash earnings to strengthen liquidity holdings and pay dividends is applied. Next, the remaining flow variables are projected to calculate retained earnings. By adding the estimate for injections of paid-in equity, the total equity is determined. Finally, the stock variable debt is projected, thereby determining total assets. We then have the means for calculating the variables used in the SEBRA model. The procedure is repeated up to five years ahead. Subsection 4.1 describes in more detail how each financial item is projected.

4.1 Projections of Financial Items

We expect close relationships between the macro variables at hand and many of the financial items we want to project, at least at the aggregate level. Payroll expenses are expected to be closely related to households' employment income. Interest expenses should be closely related to credit growth and to changes in interest rates, and so forth. Such presumptions give a good starting point for finding useful forecasting models.

Because our panel database is not complete, level information on aggregated financial items is not entirely consistent over time. Also, since our goal is to project financial items for a stationary population of firms, we do not want to capture effects from entries and exits of firms. We therefore choose to construct series of growth rates for aggregated financial items, including only firms that are represented in the data in any two consecutive years.[12] The estimation sample consists of yearly series covering the period 1985–2006. In our development of forecasting models, we choose to fit autoregressive distributed lag models (ADLs) in the constructed growth rates. By this formulation we may force long-run restrictions on growth rates but still remain open for flexibility in the short run. For example, we would like projected revenue to grow in line with GDP over time. We generally find that the growth rates align relatively rapidly, so predictions are not drastically different from that of a static model in growth rates. However, since the fit of the ADLs are generally better than with a static model, and since we appreciate the separation between long-run interpretations and short-term flexibility, we decide to go with the ADLs.[13] The resulting empirical models are presented in table 3. Variable names in lowercase letters and italics denote growth rates measured in percent, and Δ denotes the absolute change from the previous year. The dependent variables (DEP) are operating revenue (REV), payroll expenses (PAY), total debt (DEBT), interest expenses (IEX), and costs of goods sold (CGS). Explanatory variables include (real) GDP, the consumer price index (CPI), the real export weighted exchange rate (RX), household's employment income (INC), and the average borrowing rate for the enterprise sector (BOR). All financial items are measured in nominal terms.

Operating revenue is found to depend positively on both nominal GDP and the real exchange rate, the latter representing the competitive power of the export sector.[14] In steady state, i.e., when $\Delta rev = \Delta gdp = \Delta \mathrm{RX} = 0$, the model gives that the growth rate of operating revenue will be exactly 5 percent when nominal GDP

[12]The constructed series will then imitate growth rates from a stationary population even though the sample composition changes over time.

[13]Another alternative would be to calculate synthetic levels of the financial items using the constructed growth rates and then fit an error-correction model in the levels. We left this alternative unexplored.

[14]A higher value of the real exchange rate variable represents a real depreciation, thus the positive sign.

Table 3. Regression Results

	dep_{t-1}	Δgdp_t	gdp_{t-1}	Δcpi_t	cpi_{t-1}	ΔRX	Δinc_t	inc_{t-1}	BOR_{t-1}	bor_t	$debt_t$	Δrev_t	constant
Δrev_t	−0.79	2.06	1.64	2.06	1.64	0.62							−4.25
	(−4.02)	(5.71)	(4.56)	(*)	(*)	(2.82)							(−2.45)
Δpay_t	−0.85						1.45	1.65				0.38	−3.57
	(−4.35)						(4.1)	(6.82)				(3.22)	(−1.61)
$\Delta debt_t$	−0.84	2.11	1.60	2.49	3.10				−0.73				0
	(−4.56)	(2.21)	(3.06)	(1.97)	(4.60)				(−2.57)				(***)
iex_t										1	1		
										(**)	(**)		
Δcgs_t												1	
												(**)	

(*) Coefficient restriction $gdp = cpi$ imposed.
(**) Definition relation (not rejected).
(***) Constant = 0 imposed (not rejected).

growth is 5 percent, which is in line with commonly applied figures for the sum of long-term GDP and inflation.

Payroll expenses are found to depend on households' employment income and operating revenue. In steady state, i.e., when $\Delta pay = \Delta inc = \Delta rev = 0$, estimated coefficients give that the growth rate of payroll expenses will be 4.5 percent, which is somewhat low but still fairly reasonable.

Total debt is found to depend on GDP, CPI, and the borrowing rate for the enterprise sector. In steady state, i.e., when $\Delta debt = \Delta gdp = \Delta cpi = 0$, debt can grow in line with nominal GDP at 5 percent only if the borrowing rate is set to 10.3 percent. This is about 3 percentage points above what we initially expected, and may be due to the unusually high interest rates in the first part of the sample or to the fact that debt growth was somewhat higher than GDP growth over the sample period. However, our assessment was that the potential misalignment of growth rates was not of such magnitude that we needed to impose restrictions on coefficients in the estimation.

For interest expenses, which for each firm may be approximated by multiplying the average borrowing rate over the financial year by the firm's average interest-bearing debt, simply setting $iex = bor + debt$ did fit nearly as well as any empirical model we estimated. On similar grounds, we ended up setting the growth rate of costs of goods sold equal to growth in operating revenue. Figures 6–9 in appendix 3 show actual and fitted growth rates for operating revenue, payroll expenses, debt, and interest expenses during the sample period, and the projected paths in the baseline scenario and stress scenario from Norges Bank's Financial Stability Report 1/08.

We also need empirical models for write-downs of assets. We find that write-downs at the aggregate level are best modeled as a percentage of aggregate book value of assets, instead of as growth rates. Since there are great differences in the magnitude of write-downs on different types of assets, we found it necessary to model fixed assets, long-term investments, and short-term investments differently. The financial reporting of write-downs became more detailed in 1999, so we only have the period 1999–2006 available for estimation. This gives us an absolute minimum degrees of freedom, and we therefore turned to the method of static regressions with some a priori determined coefficient restrictions applied. Write-downs on

Table 4. Regression Results for Write-Downs

Models for Write-Downs	*eqi*	*cpp*	constant	$\sqrt{MSE}$
Fixed Assets	−0.016	−0.04	1.27	0.14
	(−7.43)	(−4.19)	(*)	
Long-Term Investments	−0.04	−0.04	2.6	0.95
	(−2.78)	(−1.26)	(*)	
Short-Term Investments	−0.13		−0.54	1.02
	(−10.2)		(*)	

(*) Constrained.

all three categories of assets were modeled as a function of the growth in a broad equity index (EQI) and the growth in commercial property prices (CPP). The coefficients were constrained such that the aggregate write-downs equaled their averages over the period 2004–06[15] when the growth rates for EQI and CPP were set to their long-run averages of 5 percent. The resulting regression results are shown in table 4.

In order to project write-downs, we need projections of both equity prices and commercial property prices. We have elected to project commercial property prices by assuming that they will grow in line with the predicted house prices. To obtain a forecast of the growth rate of the broad equity index, we use a simple dividend-discounting model; see appendix 4. Figure 10 in appendix 3 shows actual and fitted write-down percentages for long-term investments.

The other financial items to be projected are depreciation, paid-in equity, interest income, other operating costs, and income tax. Below we explain our assumptions regarding these items. Based on the historical ratios for the period 1989–2005, we project yearly depreciation as 8.5 percent of the stock of tangible fixed assets at year end. We find that changes in paid-in equity are difficult to model. We have therefore set the annual growth rate of paid-in equity to 9 percent, which is equal to the median for the period 2000–04. Interest income is shifted with the changes in the enterprise

[15] We view this period as the most normal subperiod in the estimation sample 1999–2006. For short-term investments we consider valuation adjustments which can be either positive or negative.

sector's borrowing rate, which seems conceptually fine but unfortunately does not fit too well with data. Other operating costs vary little from year to year, so we elected to let this item grow with the consumer price index. In order to construct the liquidity variable that enters the SEBRA model, we have to project short-term debt specifically. Similarly, to calculate our measure of (debt-weighted) PD for the enterprise sector, we need projections of the bank debt in each firm. We have elected to apply the growth rate of total debt to all types of debt. Finally, income taxes are calculated as the projected profit before taxes, multiplied by the income tax rate of 28 percent.

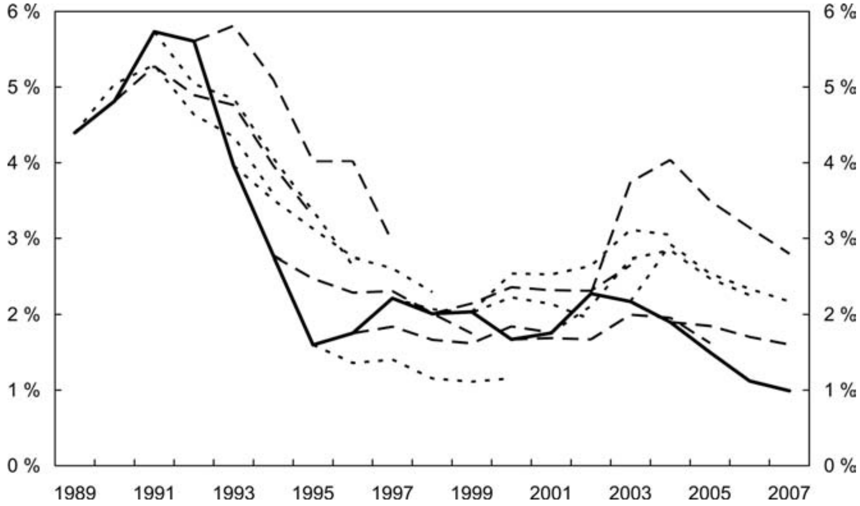
5. Results of Backtests

To evaluate the fit of our projections of (debt-weighted) PDs for the enterprise sector, we carry out backtests. Financial statements for each year from 1988 to 2003 serve as the starting points for the backtests. The projections in each backtest cover a five-year period; e.g., if we start from the observed financial statement of 1991, the backtest covers the projections of financial statements for the period 1992–96 and the predictions of PDs for the period 1993–97.[16] Since our task is not to evaluate the uncertainty in forecasting core macroeconomic variables, but rather to evaluate if a portfolio of financial statements can be projected conditional on the macro variables, we use the actual development of the macro variables in the backtest period. The actual values of the macro variables for the first year of the backtesting period are used to make forecasts of the growth rates of financial items that year, using the empirical models and heuristics presented in section 4. This forecasting process is repeated for each year in the backtesting period.

The backtest period includes two economic downturns: the banking-crisis years 1988–93 and the mild downturn in 2001–03. We have elected not to use financial statements from the period 1982–87, due to incompleteness of the SEBRA database before 1988. This means that we are only partly able to backtest the period prior to

[16] Keep in mind that the predicted PD for year t is based on the financial statements for year $t - 1$.

Figure 3. Backtests of Projected PDs for the Enterprise Sector



the banking-crisis years, when risk built up. Some of the empirical models and heuristics, like the models for write-downs and the heuristic for the growth of paid-in equity, are based on the period 1999–2005. The backtests that do not cover this period are therefore partly out of sample. The results of the backtests are presented in figure 3. The solid line shows PDs for the enterprise sector based on the actual financial statements. The dotted and dashed lines show projections of PDs from the different starting points.

With the exception of the projected paths starting in 1992 and 2002, both the direction and the development over time of the projected paths seem satisfactory for stress-testing purposes. All paths starting in the early banking-crisis years seem to drag the PDs down in a reasonable manner, while paths starting in the late 1990s seem to pull the PDs moderately upward and down again as the economy recovers. The two projected paths that do not fare that well—i.e., the paths starting in 1992 and 2002—are both related to a weak initial year and a temporary fall in operating revenue in the enterprise sector.

The fit of the projected paths is somewhat poorer than what we would expect from an empirical model estimated on the historical series of PDs. However, such a comparison is not completely fair since we have not designed our stress-testing framework to fit this measure specifically. It is important to bear in mind the simplicity of our setup. The fit can probably be improved markedly if the setup is modified in light of the experiences from the backtests. As long as one sticks to theoretically sound modifications of the setup, it should be possible to make improvements without significantly increasing the risk of overfitting.

6. Application of the Stress-Testing Framework

In order to apply our framework to assess banks' loan losses, we need to project the measure of LGD defined in section 3. We have modeled LGD as a function of GDP growth and the change in the real growth rate of commercial property prices. The rationale is that GDP growth says something about the general economic condition, while commercial property usually is the most important collateral for banks' loans to firms. Changes in the growth rate of commercial property prices may therefore capture surprises to the value of banks' collateral. The estimated model is

$$\begin{aligned}\Delta \mathrm{LGD}_t = \underset{(4.98)}{28} - \underset{(2.05)}{0.43} \cdot \Delta cpp_t + 0.31 \cdot \mathrm{Dummy}_{1991} \\ - \underset{(4.97)}{0.62} \cdot \left[\mathrm{LGD}_{t-1} + \underset{(2.08)}{9.88} \cdot gdp_{t-1} \right], \qquad (7)\end{aligned}$$

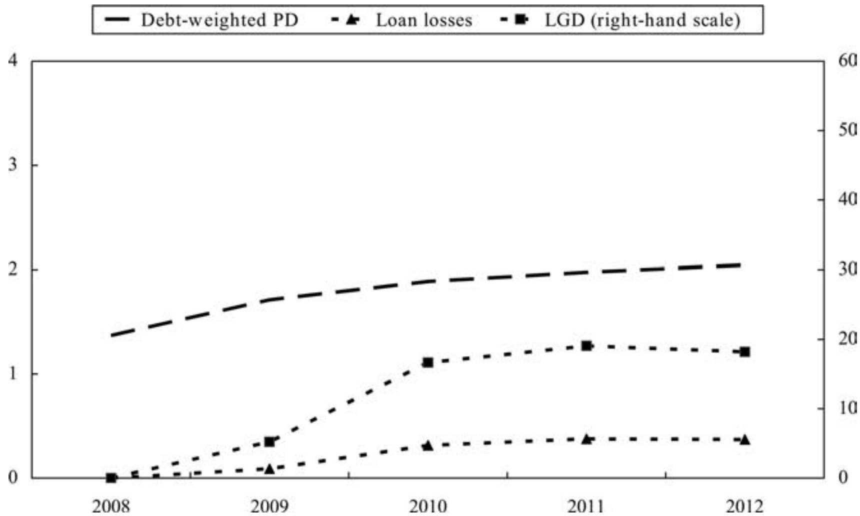
where *gdp* denotes the growth rate of the real gross domestic product in mainland Norway and *cpp* denotes the real growth rate of commercial property prices. We use a dummy for the year 1991, which was the peak of the banking crisis in Norway. In the long run, commercial property prices grow at a steady rate, so LGD only depends on *gdp*. Assuming a GDP growth of 2.5 percent gives a long-run LGD at 20.5 percent, which seems plausible.

We have applied the micro stress-testing framework to forecast banks' loan losses for the period 2008–12. We take the baseline scenario and stress scenario outlined in Norges Bank's Financial Stability Report 1/08 as the basis for projections. In the stress scenario, a weakening of households' confidence in their own financial situation and in the general outlook for the Norwegian economy lead

Table 5. Forecasted Paths for Macro Variables in Two Scenarios

	Real GDP		Wage Income		Real FX Rate		Borrowing Rate		Property Prices	
Year	**Baseline**	**Stress**	**Baseline**	**Stress**	**Baseline**	**Stress**	**Baseline**	**Stress**	**Baseline**	**Stress**
2007	5.99	5.99	10.10	10.10	92.98	92.98	6.44	6.44	11.34	11.34
2008	3.54	2.59	8.21	8.00	89.30	85.79	7.07	8.02	−0.53	−9.19
2009	2.02	−1.49	5.50	3.33	90.39	81.43	6.66	9.38	5.18	−19.75
2010	2.35	−0.22	5.16	3.52	91.61	83.58	6.21	8.49	4.82	−8.87
2011	2.65	3.58	4.87	6.16	92.03	89.83	6.28	6.64	4.80	13.09

Figure 4. Projection of Loan Losses in the Baseline Scenario (in percent)

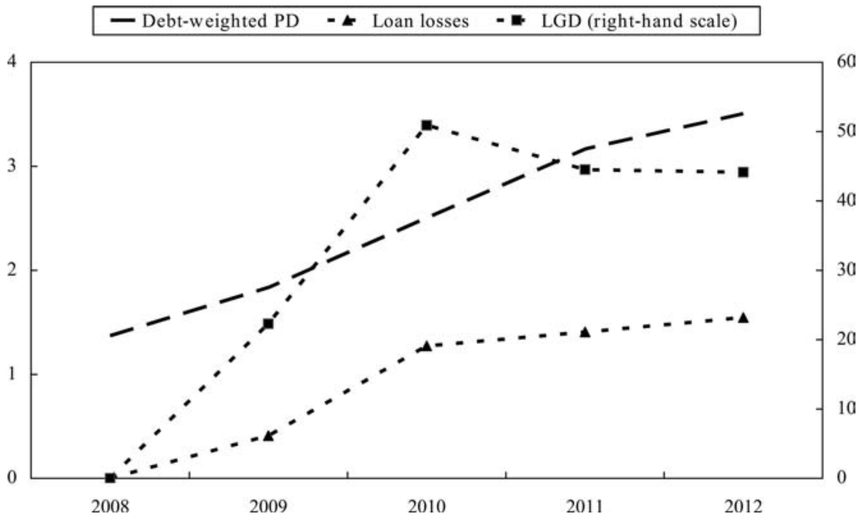


to a sharp fall in house prices. At the same time, interest rates are increased substantially in response to prospects for higher inflation. In table 5 the baseline and stress scenarios are outlined in terms of the macro variables we employ, while figures 6–10 in appendix 3 show the corresponding projections for firms' operating revenues, payroll expenses, debt growth, interest expenses, and write-downs of long-term investments.

In the baseline scenario, PD normalizes somewhat from a historically low level; see figure 4. LGD increases from its level of zero in 2008 and converges to the estimated long-run average of 20 percent. The combined effect is that the projected loan losses increase only slightly, to approach levels close to the average losses over the last two decades.

In the stress scenario (figure 5), both PD and LGD increase sharply, and by 2012 the projected loan losses exceed the level experienced in 2002 by almost 70 percent. However, loan losses are still well below the level experienced at the peak of the Norwegian banking crisis in 1991. This holds even if we replace our projected value of LGD with the implied LGD derived for the banking-crisis period.

Figure 5. Projection of Loan Losses in the Stress Scenario (in percent)



7. Concluding Remarks

In this paper we presented Norges Bank's micro stress-testing framework for assessing banks' losses on loans to the enterprise sector. We presented empirical models and heuristics for projecting financial statements at the micro level. We find that average growth rates for financial items like operating revenue, various operating expenses, and debt are well forecasted conditional on macroeconomic variables, even on a five-year horizon. Back tests of (debt-weighted) PDs for the enterprise sector indicate that our framework performs reasonably well. Our conclusion is that stock-flow projections of financial statements can be a powerful tool for stress-test analyses. The approach has several advantages that make it a useful supplement to empirical models fitted directly to historical series of loan losses or default rates. First, series of historical loan losses typically have little variation except from crisis periods, which often are distant in time. Thus, the problem of overfitting can be severe, and stress testing will always involve large comparative shifts in models fitted mostly to small data variations. Stock-flow projections of financial statements are more structural in nature and may relieve us from some of these obstacles. Moreover, our approach puts emphasis on the initial financial situation of each firm rather than on initial losses or average default rates. Default rates can change rapidly, particularly in a situation where many firms are close to defaulting and the macroeconomic condition starts to worsen. Our approach lets the initial situation in the enterprise sector be of great significance for the outcome of the stress tests. The approach is also applicable for stress testing individual banks' loan portfolios, and can easily be broken down to the industry level. The approach seems particularly useful for smaller banks with little or incomplete data on their historical losses.

There are several possibilities for improvement that could be investigated. First, the macroeconomic models, the bank model, and our model for the enterprise sector should be integrated in order to assess feedback effects. Norges Bank's macroeconomic model for stress testing does in fact include credit as a driving factor of GDP growth. Hence, if the effect of loan losses on bank lending can be reliably assessed in Norges Bank's bank model, it may be possible to iterate feedback effects using the micro and macro models interchangeably. In such an integrated exercise, we would probably see a deeper impact on GDP, higher loan losses, increasing risk premiums on loans, and lower credit growth in stress scenarios.

Appendix 1. Functional Expression for the SEBRA Model

Let p(B) denote the bankruptcy probability. The general functional expression for the SEBRA model is

$$\begin{aligned} \mathrm{p(B)} &= \mathrm{F}[\alpha + \beta_1 \cdot \mathrm{T}_1(\mathrm{x}_1) + \beta_2 \cdot \mathrm{T}_2(\mathrm{x}_2) + \cdots + \beta_n \cdot \mathrm{T}_n(\mathrm{x}_n)] \\ &= \frac{1}{1 + \exp(-[\alpha + \beta_1 \cdot \mathrm{T}_1(\mathrm{x}_1) + \beta_2 \cdot \mathrm{T}_2(\mathrm{x}_2) + \cdots + \beta_n \cdot \mathrm{T}_n(\mathrm{x}_n)])} \end{aligned} \tag{8}$$

where

$$\mathrm{T}_j(\mathrm{x}_j) = \frac{1}{1 + \exp\left(-\left[\frac{\mathrm{x}_j - m_j}{s_j}\right]\right)}. \tag{9}$$

$\mathrm{T}_j(\mathrm{x}_j)$ is a cumulative logistic function, and the parameters m_j and s_j are estimated for each variable x_j using (9).

The SEBRA model has flexible compensation rates. How much the variable x_j has to increase when the variable x_k decreases for the bankruptcy probability to remain constant will therefore depend on both x_j and x_k. This is not true for the standard logit model.

Appendix 2. Use of the Misclassification Approach to Predict PDs

Even though we only have data for bankruptcies, the misclassification approach makes it possible, given certain assumptions, to transform bankruptcy probabilities to probabilities of default (PDs). Our method for predicting PDs may be described as a combination of two parts: generalization of the logit model for bankruptcies and a linear scaling of probabilities.

Let X denote the vector of variables in the basic version of the SEBRA model, and β a vector of coefficients associated with these variables. Assume that the true model relates to the probability of default and that bankruptcy occurs with a fixed probability given default. Then the probability of default can be expressed as

$$\mathrm{PD} = \mathrm{F}(\beta \cdot \mathrm{X}), \tag{10}$$

where $\mathrm{F}(\cdot)$ is the cumulative logistic density function.

Let B, D, and $\mathrm{D^C}$ denote the events of bankruptcy, default, and nondefault, respectively. Moreover, let $\mathrm{p}(\cdot)$ denote an arbitrary probability. Then the bankruptcy probability can be written as

$$\mathrm{p(B) = p(B\,|\,D) \cdot PD + p(B\,|\,D^C) \cdot p(D^C)}. \tag{11}$$

By definition, $\mathrm{p(D^C)} = 1 - \mathrm{PD}$. By utilizing this relationship and (10), the bankruptcy probability can be written as

$$\mathrm{p(B)} = r + (1 - q - r) \cdot \mathrm{F}(\beta \cdot \mathrm{X}), \tag{12}$$

where

$$r = \mathrm{p(B\,|\,D^C)} \text{ and } q = 1 - \mathrm{p(B\,|\,D)}. \tag{13}$$

r and q are misclassification probabilities. r is the probability of registering bankruptcy when there has not been a default, while q is the probability of not registering bankruptcy when there has been a default. Since it seems unlikely that an enterprise that has not defaulted should be registered as bankrupt, one would expect very few misclassifications of the first type; i.e., one would expect r to be zero. Historically, only a portion of the defaults eventually leads to bankruptcy. One would therefore expect $q \in \langle 0, 1 \rangle$.

The model in (12), with r and $(1-q-r)$ taken as constants, gives a generalization of our original logit model for bankruptcy probabilities. Let us now estimate the following model for bankruptcy probabilities, where $\hat{g}$, $\hat{h}$, and $\hat{\beta}$ are estimated simultaneously by the method of maximum likelihood:

$$\hat{\mathrm{p}}(\mathrm{B}) = \hat{g} + \hat{h} \cdot \mathrm{F}(\hat{\beta} \cdot \mathrm{X}). \tag{14}$$

Then $\hat{g}$ can be interpreted as an estimate for r and $(1 - \hat{g} - \hat{h})$ as an estimate for q. If the estimation results in $\hat{g} = 0$ and $\hat{h} = 1$, this indicates that there are no misclassifications. The estimated equation based on data from the SEBRA database for the period 1990–96 is

$$\hat{\mathrm{p}}(\mathrm{B}) = \underset{(-0.21)}{0.00} + \underset{(-17.10)}{0.49} \cdot \mathrm{F}(\hat{\beta} \cdot \mathrm{X}). \tag{15}$$

The t-values in (15) mean that the hypothesis $\hat{g} = 0$ is not rejected, while the hypothesis $\hat{h} = 1$ is rejected. The rejection of $\hat{g} > 0$ backs up the hypothesis that there is a zero probability of registering bankruptcy in the case that there has not been a default. The rejection of $\hat{h} = 1$ rejects the original logit specification. Thus, we have rejected the logit model in favor of the misclassification model. We interpret the scaled individual bankruptcy probability $\mathrm{F}(\hat{\beta} \cdot \mathrm{X}) = \frac{\hat{\mathrm{p}}(\mathrm{B}) - \hat{g}}{\hat{h}}$ as an estimate of the probability of default. However, this interpretation requires that the true model relates to the probability of default and that bankruptcy occurs conditional on default. This assumption, which seems reasonable, cannot be truly validated. Moreover, it is required that the misclassification probabilities r and q can be estimated as constants, which is only true if they are independent of X. If one suspects that this latter requirement does not hold, one could turn to the semiparametric approach suggested in Lewbel (2000). For a further description of the misclassification approach regarding binary choice models, see Hausman, Abrevaya, and Scott-Morton (1998).

Appendix 3. Figures of Fit of Empirical Models

Figure 6. Actual and Fitted Growth Rates for Operating Revenue (in percent)

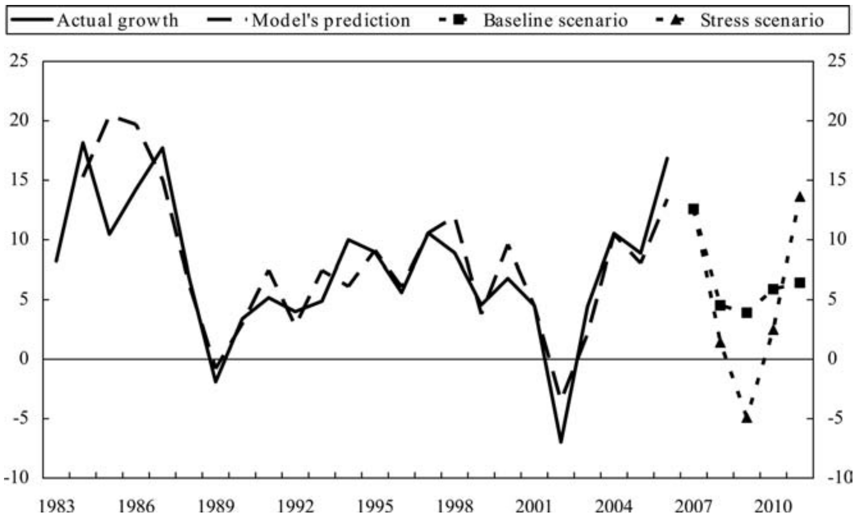


Figure 7. Actual and Fitted Growth Rates for Payroll Expenses (in percent)

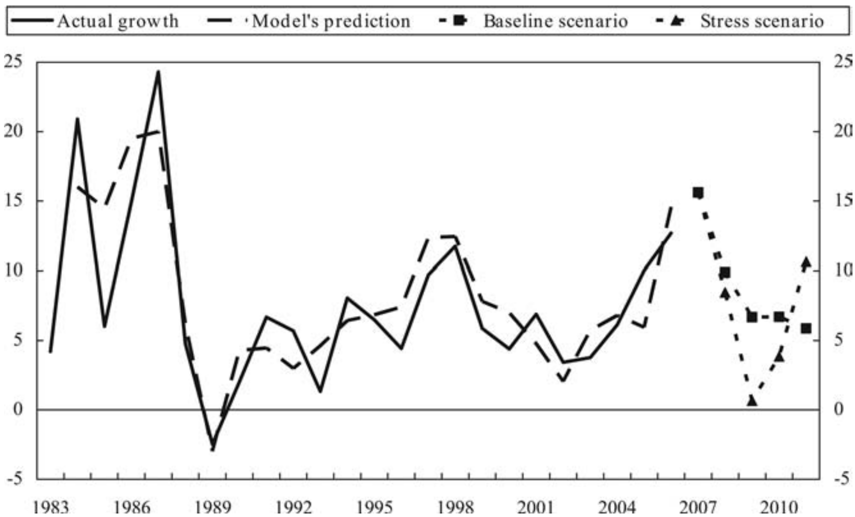


Figure 8. Actual and Fitted Growth Rates for Debt (in percent)

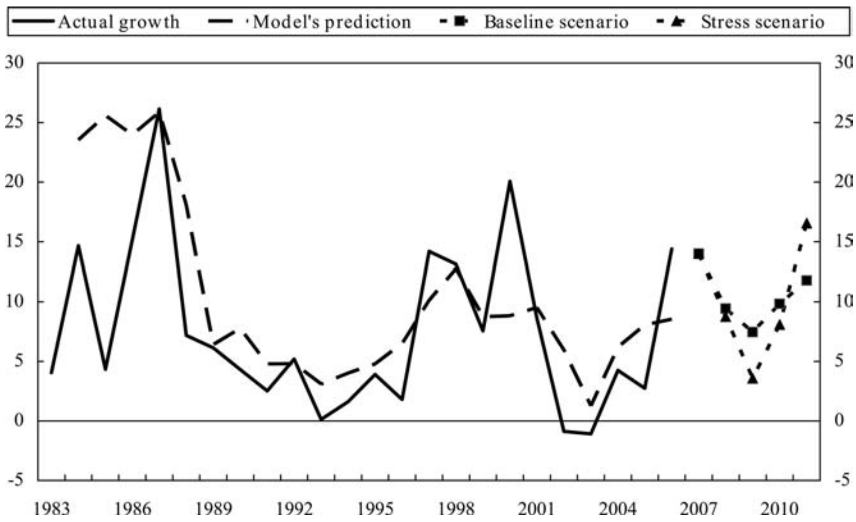


Figure 9. Actual and Fitted Growth Rates for Interest Expenses (in percent)

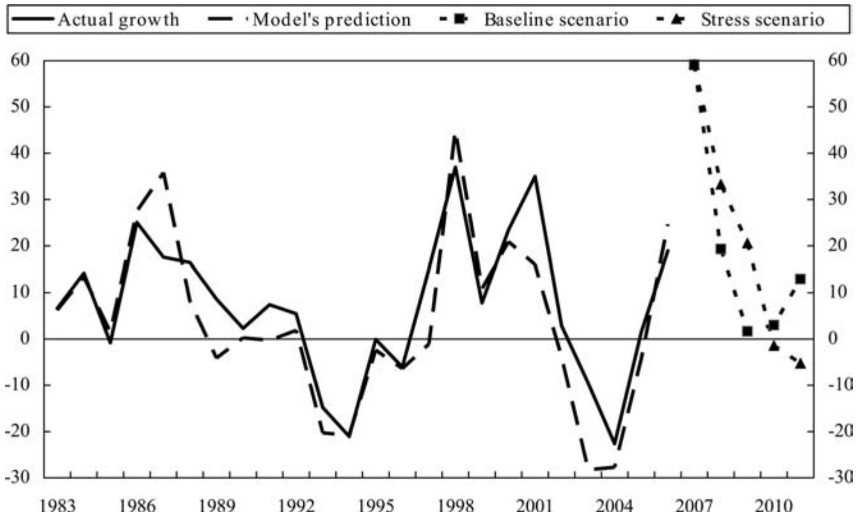
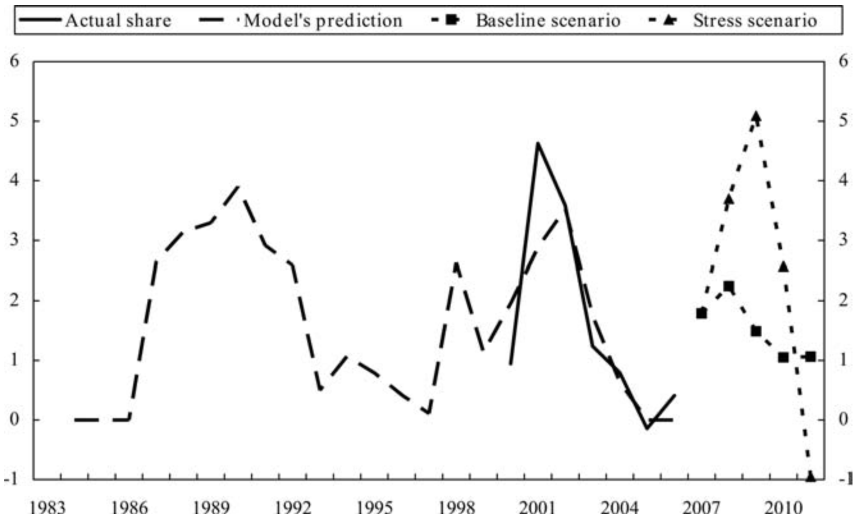


Figure 10. Actual and Fitted Write-Down Percentages for Long-Term Investments



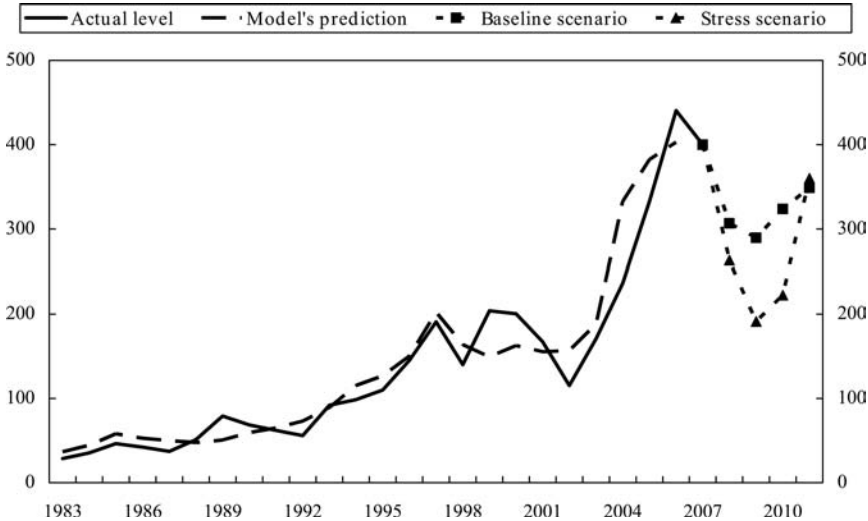
Appendix 4. Use of a GDP Discounting Model to Project Equity Prices

We assume that the yearly dividend payment from the equity market constitutes a constant share λ of GDP. Moreover, we assume that each period, investors forecast GDP to grow by a constant yearly rate g, which they update by placing a weight of 0.2 on the current year's GDP growth and a weight of 0.8 on the long-term average of 5 percent (nominal). Furthermore, they calculate the discounting rate i the same way, using the weight 0.2 for the current year's borrowing rate for the enterprise sector and the weight 0.8 for the borrowing rate's long-term average of 6.5 percent (nominal). Given assumptions which ensure that the infinite geometric series of discounted dividend payments converges, the formula for the level of the equity index (EQI) at the end of year t can be written as

$$\mathrm{EQI}_t = \lambda \cdot \mathrm{NGDP}_t \cdot \frac{1 + i_t}{i_t - g_t}, \tag{16}$$

where NGDP is nominal GDP. We use the parameter λ to link the right-hand side of (16) to the current level of the equity index, i.e., to the level at the start of the projections. Given equation (16), shifts

Figure 11. Actual and Fitted Levels for the Equity Market



in NGDP and i will shift the level of the equity market. Figure 11 shows actual and fitted levels of the equity index.

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