

A Practical Example of the Nonperforming Loans Projection Approach to Stress Testing

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Using a case study approach, this chapter illustrates the process of developing a balance sheet stress testing model for a relatively large banking sector of regional importance. The chapter first discusses the importance of ensuring consistent data for stress testing and of choosing the appropriate econometric setup. Given the unique characteristics of the data set—short time period, large number of banks—the model applies the System Generalized Method of Moments estimator that also deals with so-called dynamic panel bias. The setup consists of credit risk models for projecting the impact of macroeconomic shocks on the delinquency ratios of loans to seven main economic sectors, as well as a satellite model for credit growth to determine the absolute increase in nonperforming loans (NPLs). On the basis of projections for additionally required provisions, preprovision net income and change in risk-weighted assets (RWA), the expected change in capital adequacy ratios is then calculated. The stress test results for the country at hand illustrate that severe shocks in the stress scenarios cause a considerable increase in NPL ratios, whereas the average capitalization ratio does not fall by much. This discrepancy is attributable to banks' high preprovision net income absorbing the cost of additional loan losses and the relative inelasticity of RWA under the Basel I framework applied in this country.

METHOD SUMMARY

Overview	The model estimates the nonperforming loan (NPL) ratio under stress as a function of macroeconomic and financial variables in a panel data setting and determines the change in regulatory capital given assumptions about credit growth, NPL transition, preprovision net income, and dividend payout.
Application	The method is appropriate in situations where information on loan portfolios and macroeconomic data is reliable and available at quarterly frequency.
Nature of approach	Balance sheet-based.
Data requirements	<ul style="list-style-type: none"> • Accounting information on capital, loans and risk-weighted assets (RWA). • Supervisory data on classified loans and provisions. • Macroeconomic data.
Strengths	The model is based on financial statements and accounting rules. It explicitly takes into account banks' profits as first line of defense.
Weaknesses	<ul style="list-style-type: none"> • Assumptions are required on the amounts of transitioning NPLs and corresponding loan loss provisions from one category to another. Estimates of expected credit growth are essential for determining the changes in NPLs and RWA. • Primarily intended for banking systems operating under the Basel I framework.
Tool	Standard econometrics package.

This chapter describes the features of a stress testing model that was developed for a small open economy with a relatively large banking sector. As most banks in the sector follow a traditional intermediation model focused on lending and bank

regulation as governed by the Basel I Accord, a balance sheet approach to stress testing was deemed appropriate. The approach presented in this chapter is relatively straightforward compared with modeling techniques used to assess more

sophisticated and complex banking systems, particularly those using the internal ratings–based (IRB) approach of Basel II (e.g., Schmieder, Puh, and Hasan, 2011). The stress testing framework presented here comprises two main elements: (1) an econometric model that statistically relates past-due loans to macroeconomic variables; and (2) a template to predict nonperforming loans (NPLs), provisioning, and capital adequacy ratios (CARs). Specifically, the stress testing module consists of the following:

- A set of dynamic panel data models estimated to ascertain the relationship between an indicator of loan quality for the main economic sectors of the economy and selected macroeconomic and financial variables. The results of these models are combined with projections of those variables found to affect credit quality to project the path of NPLs for each of the loan categories under a baseline and two stress scenarios.
- A template specifically designed to aggregate the impact of the postshock increase in NPLs from the sectoral models and calculate the amount of additionally required provisioning, which, combined with projections of other income items and some auxiliary calculations, yields the predicted change in banks' CARs.

The purpose of this study is to describe both the options in designing a credit risk model and the reasons for the methodology eventually chosen. Given that commonly agreed best practices in stress testing are just now emerging (see Basel Committee on Banking Supervision [BCBS], 2009) from among the numerous existing empirical approaches (see Sorge, 2004), the stress tester faces a set of choices when building a credit risk model. These choices concern, inter alia, the econo-

metric setup of the credit risk model, the definition of the dependent variable, methods for projecting explanatory and other noncredit risk variables, and ways to convert a stress-induced increase in loan delinquencies into impaired capital positions. To this end, the chapter discusses the pros and cons of the panel estimation approaches commonly used in stress testing and also gives reasons for the method chosen for the country case at hand.

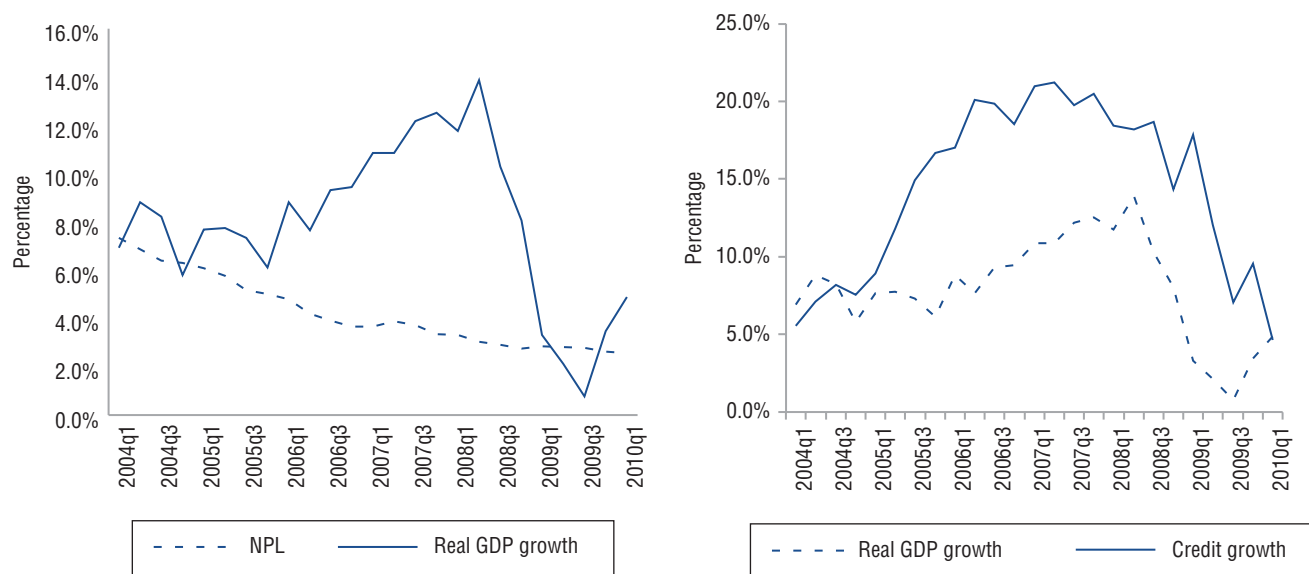
The chapter is structured as follows. Section 1 describes the structure and quality of the data supplied. Section 2 discusses the characteristics of the credit risk model and set of variables and why this particular approach was chosen among several alternatives. Section 3 describes the selection of stress test scenarios and the method for projecting NPLs. Section 4 shows how projected loan losses affect bank capital and presents the stress test results. Section 5 concludes the chapter.

1. BACKGROUND

A. Recent macroeconomic and financial developments

The country for which the stress testing model was developed can be characterized as a small open economy with a relatively sizable banking sector. The openness of the economy makes the banking system susceptible to external shocks, which were accounted for in the selection of explanatory variables for the credit risk model. The outward orientation also coincides with a significant presence of foreign-owned banks.

Bank credit evolved broadly in line with economic developments, but NPLs remained fairly stable (Figure 30.1). Credit growth was rapid during the expansionary phase pre-



Source: National Statistical Office.

Figure 30.1 Evolution of GDP Growth, Credit Growth, and the Overall Nonperforming Loan (NPL) Ratio

ceding the global financial crisis—even exceeding the buoyant GDP growth—but then slowed down considerably as banks became more cautious amid the volatile international trade and financial environment. Banks also restricted their lending in anticipation of softening demand for housing and lower tourism receipts. However, these expectations largely did not materialize during the downturn as ongoing projects in commercial real estate and infrastructure helped sustain economic growth. The seeming stability of NPLs was, however, partly attributable to write-offs during the downturn. Overall, NPLs—defined as the sum of substandard, doubtful, and loss loans—steadfastly declined by 5 percentage points between 2004 and 2010 despite volatile economic and credit growth.

The soft landing of the economy and tight supervision of banks during the downturn helped preserve financial stability. Banks remained adequately capitalized and highly liquid throughout, which was also the result of the strict regulatory regime mandating exposure limits, timely recognition of loan losses, and ample liquidity buffers. The application of the Basel I framework meant that most loans carried a 100 percent risk weight.

B. Stress testing data

Although overall credit developments were consistent with the general soundness of the financial system, the data supplied by the supervisory authority showed that the composition and riskiness of loan portfolios differed widely at the level of individual banks. This was to be expected for a regional financial center hosting investment banks, corporate banks, and consumer credit institutions. The variation in loan quality within and certainly across banks provided a basis for estimating a credit risk model in a panel setting.

For any credit risk model, high-quality data are an essential precondition. Considerable time and effort were necessary in ensuring that the data inputs for the stress testing system were sufficiently complete and consistent. This process encompassed checking the data series submitted by the authorities for consistency as well as for missing or illogical values. Presumed inconsistencies or inaccuracies prompted a resubmission of data until the data set as a whole was deemed sufficiently accurate and reliable for estimation purposes.

Series of key macroeconomic and financial data were available at the quarterly frequency. Macroeconomic data are published by the national statistical office with a lag of one quarter, while bank-specific data become available with about a one-month lag. Data for some aggregated sectors of the economy were available but were somewhat lacking in granularity. Although the time series were rather short, the available period covered important macro events, including the credit boom preceding the global financial crisis and the crisis period itself.

Data on banks' credit portfolios were obtained from the supervisory authority. The official database contains information on bank loans extended to the main economic sectors.

The supervisory authority also collects data at the debtor level, but these are not exploited and thus not readily available for analytical purposes. Consistent information on bank balance sheets and income statements was available for 41 banks from 2003:Q1 to 2010:Q2. Loans at the individual banks' level were aggregated and classified into seven sectoral categories on the basis of similarity of characteristics and their contributions to GDP, namely, the primary sector, manufacturing, construction, commerce, services, as well as mortgage and consumer loans.

Notwithstanding the wide scope of available data, doubts about data integrity initially remained. For most of the banks, the data were continuous and consistent throughout the sample period. Some data gaps were found for the smaller banks, which were subsequently dropped from the sample in order not to skew the regression outcome. The sample period was also restricted by the availability of consistent data, as there had been a structural change in data reporting in 2002. In the sample, inconsistencies were identified and purged before conducting the estimations. Still, these inconsistencies were transmitted to the supervisory authority to help identify the sources of data issues so that appropriate remedial action could be taken to improve data quality.¹

2. ECONOMETRIC CREDIT RISK MODEL

Most credit risk models in stress testing involve econometric estimations of the determinants of loan impairment. Although empirical approaches clearly differ in their econometric designs (see Foglia, 2009), all of them seek to establish a robust long-term relationship between certain measures of loan delinquency and the underlying macroeconomic and financial drivers of loan quality. Available specification options include (1) the use of panel data comprising individual banks or aggregated data for the entire system; (2) various definitions of the dependent variable denoting loan impairment and estimation with ordinary least squares (OLS) or bank-specific fixed effects; and (3) setups with or without dynamic elements, including instrument variable and co-integration techniques.

In the country case at hand, a dynamic panel data model was deemed appropriate. This type of model accounts for inertia in the dependent variable by including its lagged value among the explanatory variables. The particular setup chosen—the Generalized Method of Moments (GMM)—also deals appropriately with the bias arising from including this lagged variable as well as the possible endogeneity of explanatory variables (see Section 2.B). Given that the dependent variable displayed a unit root, a co-integration approach also was considered but ultimately discarded because some of the explanatory variables turned out to be integrated at different orders.

¹ A long series of consecutive zeros in the data, although seemingly implausible, was not considered an inconsistency per se.

A. Dependent variable

The stress tester typically faces the choice of the most appropriate measure of loan quality. Many models use either the absolute amount of NPLs as the dependent variable or the NPL ratio relating impaired loans to total loans. The projection of this variable itself can be considered an intermediate indicator in the stress testing exercise, and in some cases, stress testers deduct the increment in NPLs—somewhat erroneously—directly from banks' capital position. An alternative measure of loan impairment is either the stock of loan loss provisions or the provisioning flows, perhaps set in relation to total loans. This measure has the clear advantage of not having to translate the projected increase in NPLs into additional provisioning. In practice, however, provisioning is not driven fully by credit risk because banks resort to over- (or under-) provisioning to smooth income, and therefore the variable typically reacts less to changes in the explanatory variables, rendering the statistical relationship less robust (as in this case). Other models use as dependent variable Moody's KMV expected default frequency (EDF), such as Åsberg and Shahnazarian (2008); or other measures denoting the probability of default (PD), as discussed in Moretti, Stolz, and Swinburne (2008); or even loan transition rates (Bank of Japan, 2007).

This study used as dependent variable the share of past-due loans in total loans, including special mention loans. This measure of loan quality produced a better fit than provisioning measures, and estimates of PDs were not available. The ratio of past-due loans to total loans was preferred over the absolute amount because it is a widely applied indicator of loan quality (including by the supervisory authority in this case). Also, the ratio did not systematically trend up compared with the absolute amount of NPLs by virtue of the underlying positive loan growth. However, use of the NPL ratio then required the projection of credit growth in order to obtain a projection of the ratio's denominator (see Section 4.B).

A wide definition was chosen for the measure of delinquent loans. It included not only the usual definition of NPLs that ranged from substandard (Category 3) to loss loans (Category 5) but also the special mention loans in Category 2. This inclusion made sense because such loans also require provisioning, and, although the corresponding rate was low at 2 percent, the large volume of loans in this category still required a significant amount of provisions. It also had a better econometric fit as the migration from Category 1 to 2 was more pronounced than in the lower categories. As we will show, the projected increase in NPLs that the credit risk model produced needed to be distributed across the nonnormal loan categories, and including special mention loans in NPLs avoided an underestimation of additional provisions that would have invariably arisen if these loans had been omitted.

This NPL variable was augmented by an estimate of loan write-offs. This estimate accounts for the significant increase in write-offs during the global financial crisis amounting to approximately 0.5 percent of total loans during 2008:Q4–

2009:Q4. This add-on was deemed necessary to correct for the benign effect that write-offs had on the NPL ratio. Some banks actually experienced falling NPL ratios during the crisis on account of higher-than-usual write-offs. However, as data on loan write-offs had not been collected by the supervisory authority, the write-offs needed to be proxied by taking the observed negative change in the category of irrecoverable (defaulted) loans from one quarter to the next.² Although admittedly an imperfect proxy,³ it helped to account for abnormally large drops in defaulted loans that likely represented write-offs. Considering that a certain amount of write-offs is normal in good times, only the difference between this proxied amount and the average quarterly average write-off (between 2003:Q1 and 2008:Q3) was added back onto NPLs.⁴

In addition, the NPL variable underwent a standard logistic transformation. Given that the dependent variable was bounded between zero and one by construction, the logit-transformed value was used to create an unrestricted variable in the regression and thus avoided nonnormality of the error term. It also accounted for nonlinearities in the sense that larger shocks to the explanatory variables may have caused a large, nonlinear response in the transformed dependent variable. Specifically, the NPL ratio was transformed as follows:

$$\text{logit NPL} = \ln \left(\frac{\text{NPL}}{1 - \text{NPL}} \right).$$

The estimated logit NPL ratios were later appropriately retransformed to the normal measure.

B. Independent variables

Given the country's high degree of openness, a wide range of explanatory variables potentially affecting loan quality were considered. It was imperative that the economic meaning of the macroeconomic factors used be clear, with no counterintuitive relationship to the dependent variable. In view of this, the set of domestic macro variables considered initially included real GDP growth, changes in the indices of sectoral activity, and changes in employment, as well as—at the bank level—interest rates charged on loans to a particular sector and profitability measures. External variables included GDP growth of the main trade partners, exports of goods to these markets (and, separately, their prices), prices of principal commodity imports such as oil and cement, exchange rates, and the London interbank offered rate as a principal international interest rate. These variables were deemed to affect NPLs by improv-

² To account only for significant amounts, only differences were taken that were greater than 10 percent of loans in that category.

³ It could well be that part of that difference is owed to upward loan reclassifications rather than write-offs. In the absence of information on the migration of loans, one has to make the assumption that the bulk of loans disappearing from that category indeed represented write-offs.

⁴ To avoid jumps in the NPL ratio after the crisis period (i.e., in 2010:Q1), the additional write-offs were maintained in the subsequent NPLs for the first half of 2010.

ing or worsening the capacity of borrowers to service their debt with banks. As a secondary effect, swings in activity also affected credit growth and therefore the NPL ratio via the changes in the denominator.

Consequently, the specification of any of the sectoral credit risk models can be represented in the following form:

$$\ln\left(\frac{NPL_{i,t}}{1-NPL_{i,t}}\right) = \mu + \alpha \ln\left(\frac{NPL_{i,t-1}}{1-NPL_{i,t-1}}\right) + \sum_{j=1}^n \beta X_{j,t} + \varepsilon_{i,t},$$

where in addition to the logit-transformed NPL for bank i in period t , $X_{j,t}$ represents the j th explanatory variable selected for a given specification, μ is a constant, and $\varepsilon_{i,t}$ is the idiosyncratic disturbance term assumed to be independent across banks and serially uncorrelated (after the inclusion of the lagged dependent variable).

C. Estimation procedure

To account for the different business focus of banks, we specified a set of sectoral panel data models. The use of dedicated sectoral models has the advantage of first identifying the industry-specific drivers of credit risk and then weighing these exposures according to their shares in the loan portfolio of each bank. This proper identification of credit risk exposures was difficult with an economy-wide model that basically assumed that banks were equally exposed to the macro factors in that model.

The seven sectoral panel models used quarterly data for the sectoral exposures of between 31 and 41 banks⁵ during 2003:Q1–2010:Q2. As several banks entered the system toward the end of the sample period, the panel was unbalanced, but the incomplete time series, even if rather short, nonetheless may have provided valuable information and could be accommodated by the estimation procedure. In the case of bank mergers and acquisitions, the data of the acquired banks were added to the acquiring bank, which in individual cases led to jumps in the total loans of the merged bank but not necessarily in the NPL ratio.

Given the relatively short time dimension of the panel, a lagged dependent variable in a conventional estimation setup causes so-called dynamic panel bias (Nickell, 1981). Regular OLS estimation, with or without fixed effects, produces biased coefficient estimates for short time series (of only 30 periods in this case). This distortion is caused by the correlation of the lagged observations with the unobserved fixed effect when nonmodeled shocks lead to a bias in the fixed effects. Under a simple OLS estimation, the coefficient would be biased upward, because individual negative shocks that are not modeled enter the error term and skewed both the error and the dependent variable downward. Removing the fixed effects by applying the within-group estimator that regresses deviations from the respective means would not eliminate this

bias but rather would lead to an underestimation of the coefficient of the lagged dependent variable. These models, though clearly not correct, are instructive nonetheless as they establish a ceiling and a floor for the estimated coefficient.⁶

Appropriately specified dynamic panel models thus were applied to remove dynamic panel bias. Both the Difference GMM and the System GMM approach were considered (see Holtz-Eakin, Newey, and Rosen, 1988; Arellano and Bond, 1991; Arellano and Bover, 1995). These setups use past observations uncorrelated to the fixed effects as instruments in order to arrive at plausible and unbiased coefficient estimates for the lagged dependent and independent variables. Essentially, Difference GMM uses past levels as proxies for current differences, whereas System GMM uses past differences as instruments for current levels, adding a transformed equation to the original one and so allowing for the inclusion of time-invariant regressors that would disappear in Difference GMM.⁷ Although potentially the superior estimator, System GMM assumes that changes in any instrument are uncorrelated with the fixed effects and that the errors are not serially correlated. It also poses the potential problem that the instrument count doubles (as two instruments per observation are used), which in short samples tends to cause the Sargan test⁸ for the validity of instruments to break down. Mindful of these caveats, when applied to the different panels of sectoral NPLs, System GMM produced coefficient estimates for lagged NPLs that were generally within the aforementioned credible range, whereas this was not the case in any panel regression under Difference GMM.

For each panel, a System GMM specification was chosen, while considering optimal lags. For one thing, unit root tests determined the optimal number of lags as instruments to remove autocorrelation in the NPL series,⁹ thereby limiting the instrument count.¹⁰ For another, using lags of the covariates

⁶ See Roodman (2009).

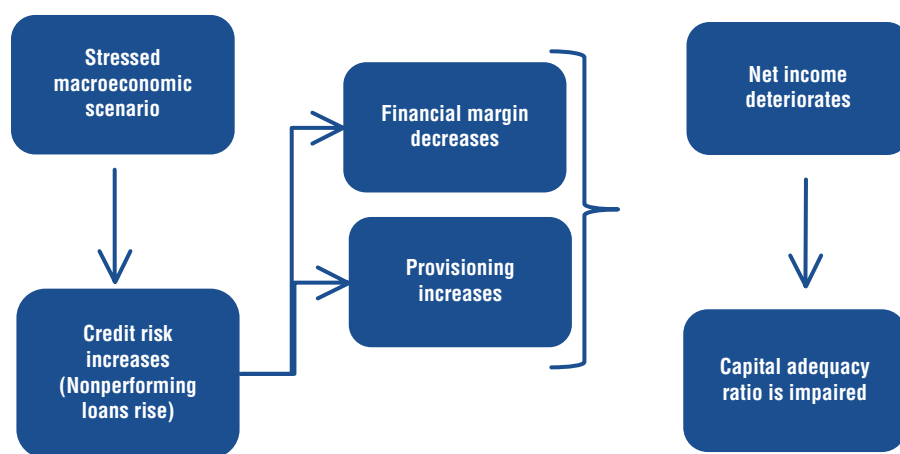
⁷ Difference GMM may perform poorly if the dependent variable is close to a random walk, because past levels provide little insight into future changes and thus become weak instruments. In this case, System GMM may be superior as it utilizes both difference and level information (see Roodman, 2009).

⁸ See Sargan (1958).

⁹ Here, the criterion was that the lag length chosen would remove autocorrelation for 80, in some cases 90, percent of banks. In the event, the lag length ranged from one in most panels to four in the mortgage panel.

¹⁰ As a general rule, the number of instruments should not exceed the number of units included in the sample if the GMM is to be applied appropriately to a panel and sensible statistics are to be obtained from the Sargan test for overidentifying restrictions. It was borderline for this panel of banks as the instrument count (for four of the seven panels using one or two lags of the lagged NPL variable between 54 and 81 instruments) slightly exceeded the number of banks in the sample (between 30 and 38 in these panels) such that validity could still be assumed. However, even in these cases, and certainly in the panel using the maximum number of 177 instruments, the Sargan test tended to produce implausibly high values—near one—so that the validity of the instruments could not be proved beyond doubt. By contrast, the Arellano-Bond AR(2) test did not find any evidence of second-order correlation in the differences of the idiosyncratic error term (which would indicate first-order serial correlation in the levels).

⁵ Offshore banks were omitted as they are prohibited from dealing with residents and have no formal relationship with the onshore banking sector.



Source: Authors.

Figure 30.2 Transmission Channel from Macroeconomic Shocks to Capital Adequacy Ratio

generally produced more significant estimates than the contemporaneous observations, which was plausible as it took time for deteriorating economic conditions to affect debtors' repayment capacity and subsequently for loans to be classified as delinquent. Clearly, the explanatory variables differed in how a shock affected loan quality, and therefore each commanded a unique lag.

For illustrative purposes, the Appendix shows the estimation results, which suggest that a decline in economic activity had the most significant impact on loan impairment:

- In five out of seven sectoral panels, a decline in real GDP growth—lagged by one period for personal loans and three periods for corporate loans—turned out to be highly significant.¹¹
- Loans to the commerce sector reacted to the economic growth of the main trading partner more than to domestic growth.
- For the loans to the primary sector, changes in the lagged activity indicator for the agricultural sector (being the largest primary sector) gave a better link to loan impairment than overall GDP growth.
- In five of the seven panels, a supplementary variable other than economic growth depicting idiosyncratic risk germane to the sector was found to have explanatory power. Specifically, in three models (mortgage loans, services, and the primary sector), the interest rate on loans to that sector charged by each bank—the only fairly robust firm-level variable—was significant at the 5 and 10 percent levels.

- Furthermore, the percentage change in exports to the main trading partner was found to be a good predictor for delinquencies in loans to the commerce sector.
- NPLs in consumer loans responded additionally to swings in the growth rate of employment.¹²

3. STRESS TEST DESIGN

This section summarizes the design of the credit risk stress test based on scenario analysis. First, it describes the transmission of shocks emanating from a deterioration in macroeconomic variables to key banking variables (i.e., NPLs, loan loss provisions, capital ratio). It then presents the rationale for different stress test scenarios, providing a brief explanation of the underlying assumptions. Finally, it explains the method used to deal with prediction bias in order to seamlessly project the resulting expected NPL ratios of each bank.

A. Transmission of shocks

The assumed economic shock increases NPLs and ultimately affects banks' CARs through increased provisioning and lower net operating margins. As shown in Figure 30.2, these two adverse effects reduce bank profits or even cause losses and consequently affect the CAR, other things being equal. In building the stress testing module, various worksheets in Excel were created to flesh out these relationships between NPLs and key explanatory variables.

¹¹ The quarterly rate of growth of the seasonally adjusted GDP series (using the Census X12 method in EViews with default settings) was used rather than the year-on-year growth rate, because it produced a better fit econometrically.

¹² Quarterly employment growth was taken as a proxy for changes in the unemployment rate, which is collected once a year but not quarterly as the panel estimation calls for.

B. Macroeconomic scenarios

In the stress testing literature, the use of extreme but plausible scenarios for the drivers of credit risk is advocated. As pointed out in BCBS (2009, p. 2), “a stress test is commonly described as the evaluation of the financial position of a bank under a severe but plausible scenario to assist in decision making within the bank.” In that sense, the selection of an appropriately grave yet realistic scenario is central to the validity of stress testing. Indeed, during the global financial crisis, most credit risk models failed to forecast the severe stress experienced by many banking systems, precisely because the assumptions about macroeconomic developments turned out to be much too benign (Alfaro and Drehmann, 2009). It obviously is difficult to gauge *ex ante* whether a certain scenario meets the “extreme but plausible” criterion, but it would be fair to say that many such stress test scenarios had not appropriately considered tail risks or hard-to-model feedback effects from a banking sector under stress onto the economy and back (see Jones, Hilbers, and Slack, 2004).

Against this background, our simulations considered three macroeconomic scenarios of varying severity: (1) a baseline scenario reflecting the expected path of macroeconomic and financial variables, mostly based on IMF projections and some additional expert judgment; (2) a scenario of severe stress depicting the most extreme historical changes observed in each of the explanatory variables; and (3) a moderate stress scenario incorporating variations centered between the baseline and the severe scenarios.

The baseline scenario used the IMF forecast for the key macroeconomic variables at the time. Assumptions about exports to the main trading partner and interest rates reflected also the (pessimistic) expert judgment of the supervisory authority. By contrast, the most extreme historical variations for each of the variables were used for the severe stress scenario. Under this scenario, the worst deterioration in both macroeconomic and financial variables during the sample period was taken (quarterly data between 2003:Q1 and 2010:Q2; for local GDP growth starting in 1996:Q1), which corresponded to the 97th percentile or about two standard deviations. Finally, the moderate stress scenario considered the midpoint in projected variations between the baseline and the severe stress scenarios.

The flexibility of the stress testing module meant that the preceding choice of scenarios did not preclude other, more extreme, scenarios. In principle, simulated scenarios not based on historical values easily could be applied by adjusting the corresponding template.

C. Projecting nonperforming loans

Using the results of the econometric estimations, the increase in the wide definition of NPLs (including special mention loans) for each bank and economic sector under the three

scenarios was projected. The methodology was divided into three steps, as follows:

$$\begin{aligned} \text{Observed Data: } & NPL_{t-30}, NPL_{t-29}, \dots, NPL_t \\ \text{Projected Data: } & NPL_{t+1}, NPL_{t+2}, \dots, NPL_{t+6} \\ \text{Projection Method: } & NPL_t = \alpha + \beta_1 NPL_{t-1} + \beta_2 X_t + \beta_3 X_t + \varepsilon_t \\ & NPL_{t+1} = \alpha + \beta_1 NPL_t + \beta_2 X_{t+1} + \beta_3 X_{t+1} + \varepsilon_{t+1} \\ & \dots \\ & NPL_{t+6} = \alpha + \beta_1 NPL_{t+5} + \beta_2 X_{t+6} + \beta_3 X_{t+6} \\ & \quad + \varepsilon_{t+6}, \end{aligned}$$

where NPL is the ratio of NPLs to total loans (wide definition), α is the constant term, β is a vector of estimated parameters, and X represents a vector of explanatory variables depicting macroeconomic and financial conditions. The predicted NPL ratios were determined as follows:

- First, the value for NPL_t (given X_t , which in some cases meant using the lagged values) and NPL_{t+1} (given projected X_{t+1}) was calculated using the econometric model.
- Next, the difference between these two predicted values was determined.
- Finally, the estimated difference was added to the observed NPL_t to obtain the projected NPL_{t+1} .

This recursive methodology was employed to minimize the deviation of the predicted values of NPL ratios in 2010:Q3 from the observed values one quarter earlier. This approach represents a practical way to deal with out-of-sample prediction error that stems from unexplained deviations of the observed current NPL ratio from the one that the model would project based on the historical patterns. Put differently, idiosyncratic shocks that are not modeled cause the model to over- or underestimate the NPL ratios, which in some cases can lead to a large difference between the two numbers. The method described is able to remove a large part of this prediction error, although abnormally high NPL ratios are projected to return to its longer-term levels over time in an error-correction fashion.

4. STRESS TEST OUTCOME

A. Projected nonperforming loans and loan loss provisions

As could be expected from the differing degree of severity of the assumed shocks, the increase in the projected NPL ratio under severe stress six quarters out is a multiple of the change in the baseline scenario (Table 30.1). Across credit types, the NPL ratios rise was found to be strongest in loans to the commercial sector (not reported).

Obtaining the projected increase in loan loss provisions required an out-of-sample forecast of the provisions-to-total-loans ratio that predicted both variables separately. Credit growth was estimated using satellite models that computed the comovement of GDP growth with credit growth for each bank in the sample. Specifically, linear univariate models

TABLE 30.1

Projected NPL Ratios (in percent)							
Scenario	Jun 2010	Sep 2010	Dec 2010	Mar 2011	Jun 2011	Sep 2011	Dec 2011
Baseline	5.4	5.3	5.5	5.6	5.6	5.8	6.0
Moderate	5.4	5.4	5.6	5.8	6.0	6.4	7.0
Severe	5.4	5.4	5.8	6.1	6.5	7.2	8.3

Source: Authors.

TABLE 30.2

Projected Provisions-to-Total-Loans Ratios (in percent)							
Type	Jun 2010	Sep 2010	Dec 2010	Mar 2011	Jun 2011	Sep 2011	Dec 2011
Baseline	0.9	0.9	0.9	1.0	1.1	1.2	1.3
Moderate	0.9	0.9	1.0	1.1	1.2	1.3	1.6
Severe	0.9	0.9	1.0	1.2	1.3	1.6	1.9

Source: Authors.

regressing past changes in total loans of each bank on GDP growth were estimated in order to calculate this variation. For banks whose total loans turned out not to be robustly related to GDP, the average historical change in total loans during the sample period was taken. In addition, the effective provisioning rates (as defined by total loan loss provisions divided by total loans) for each bank and risk category were used to forecast the increase in the provisioning flow under each of the scenarios.¹³ In order to project the share of impaired loans in each of the loan classification categories, similar satellite models were estimated.¹⁴

The difference in both the projected provisioning ratios between the severe stress scenario and baseline scenario was less pronounced than for the projected NPL ratio (Table 30.2). Also, the change in the ratio during the projection period was smaller because delinquent loans in the less affected categories (special mention to doubtful) did not require full provisioning.

B. Projected capital adequacy ratios

The final step of the stress test exercise consisted of forecasting banks' CARs by determining separately the projected capital and risk-weighted assets (RWA). RWA were calculated in line with the country's bank regulation that was based on the Ba-

sel I Accord. Therefore, each type of loan (i.e., commercial loans and consumer loans) was weighted 100 percent except mortgage loans, which carried a risk weight of 50 percent.

Thus, the RWA were calculated as follows:

$$RWA_t = RWA_{t-1} + \Delta Non_{mort,debt_t} + 50\% * \Delta Mort_{Debt_t}.$$

That is, the RWA of the current period equaled the RWA of the previous period plus the entire change in the volume of nonmortgage loans and 50 percent of the change in mortgage loans. For the CAR, the following formula was used:

$$CAR_{t+1} = (Capital_t + After-Tax Profits_{t+1} * Profit Retention Rate) / RWA_{t+1},$$

where

$$After-Tax Profits_{t+1} = Net Revenue_t - \Delta Provisioning_{t+1} - \Delta Interest Income_{t+1},$$

where

$$\Delta Interest Income_{t+1} = Implicit Interest Rate * \Delta(\Sigma Substandard, Doubtful, Loss Loans).$$

As can be seen from these formulas, the capital ratio was calculated by dividing the forecast capital by the projected amount of risk-weighted assets. The projection of capital itself was calculated by adding to current capital the projected increase in retained earnings, that is, the share of expected after-tax profits that was not distributed to shareholders. In turn, to estimate after-tax profits in $t+1$, the following components were added up:

- the observed net revenue in the previous period;
- the projected stress-induced increase in provisioning; and
- the projected decline in interest income calculated using implicit interest rates and the increase in loans that did not generate earnings. This variation in impaired loans was calculated using the share of loans in each loan category and the estimate of credit growth, as explained.

¹³ The effective provisioning rates rather than the statutory ones were taken because loans in the system were amply collateralized (total guarantees accounted for about 60 percent of loans on average), and even when applying a haircut to the value of the collateral, which would be prudent in a stress scenario, its remaining value would still be large enough to require provisioning well below that using statutory rates.

¹⁴ For three categories of impaired loans (special mention, doubtful, loss) fixed-effects panel data models with GDP growth as explanatory variable were estimated. The separate models project the share of normal, special mention, doubtful, and loss loans in total projected credit. The remaining fifth loan category, substandard loans, is then backed out as the difference between 100 percent and the share of the four other loan categories.

TABLE 30.3

Projected Capital Adequacy Ratios (in percent)							
Scenario	Jun 2010	Sep 2010	Dec 2010	Mar 2011	Jun 2011	Sep 2011	Dec 2011
Baseline	16.3	16.1	15.9	15.7	15.4	15.2	14.9
Moderate	16.3	16.1	15.9	15.7	15.4	15.1	14.8
Severe	16.3	16.1	15.9	15.7	15.4	15.1	14.7

Source: Authors.

Assuming that some banks remain profitable even under stress, the increased provisioning costs should be channeled through the income statement instead of deducting it directly from capital. Bank profits act as a first line of defense in cushioning the cost push associated with rising loan losses. Indeed, as Čihák (2007) observes, banks normally are profitable—many even under stress—and therefore it is necessary to account for such profits that will need to be exhausted before the regulatory capital is reduced.

The stress test results show that the considerable increase in NPLs under stress and provisions affects capital positions to a lesser degree. Under the baseline scenario, the CAR decreases from 16.3 to 14.9 percent (Table 30.3). This decline in the CAR is explained by (1) an increase in RWA as a result of solid credit growth (under the assumption that bank owners do not inject capital to keep it constant); (2) a decline in revenues (due to a predicted reduction in the net operating margin of institutions); and (3) a conservative profit retention rate of only 25 percent based on historical evidence and judgment by the supervisory authority. Compared with the baseline scenario, the system's CAR declines by only another 0.2 percentage points under severe stress.

There are two principal reasons for this muted response in the CARs. Banks generally remained profitable even under stress, which cushioned the provisioning shock, and RWA grew less strongly owing to slower credit growth in the stress scenarios.¹⁵ This lack of any significant impact on the CAR is not uncommon in stress testing credit risk under the Basel I Accord, as the risk weights of loans stay constant under stress and move only with projected credit growth; under Basel II, they increase and sometimes dramatically so.

5. CONCLUSION

This chapter presented key elements of a credit risk model comprising individual sectoral panel data models and the steps needed to translate the projected increase in past-due loans into a change in the CAR. Given the numerous choices available in designing the credit risk model and the needs of the particular supervisory authority, this study put forward the reasons for applying each of the key features of the model chosen. In doing so, emphasis was placed on explaining the operational details

of the stress testing module, namely, the procedures for projecting loan delinquencies, provisioning, and credit growth.

Our model applied the “NPL projection approach” whereby banks' NPL ratios as a measure of loan impairment were regressed on a set of explanatory macroeconomic and financial variables in dynamic panel models. To account for the different business models of the large number of banks in the sample, seven sectoral credit risk models were estimated. On the basis of three scenarios spanning expected to extreme-but-plausible developments, the NPLs and additional loan loss provisions first were projected using the models and then channeled through banks' projected income statements to obtain the stress-induced variation in the CARs.

The stress test outcome highlighted an important finding that is particularly relevant for banking systems under the Basel I Accord. The projected drop in the CAR under stress was much less pronounced than the stronger increase in NPLs would suggest. Indeed, the considerable deterioration in loan quality caused by the assumed macroeconomic shocks was not sufficient to severely affect banks' capital positions because of the beneficial effect of strong bank profits as the primary shock absorber and the slower growth of RWA under stress, allowing the denominator of the CAR to rise less than in normal times.

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¹⁵ To run more meaningful economic stress tests under Basel I (or the standardized approach of Basel II), Schmieder, Puhr, and Hasan (2011) propose calculating “quasi-IRB risk weighted assets” based on implied credit risk parameters (PDs and loss given default, or credit losses).

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Appendix

System GMM Estimation: Impact of Macroeconomic Variables on Loan Impairment

Appendix table

Variable	Construction	Commerce	Manufacturing	Primary Sector	Services	Mortgage	Consumer
NPL ratio (–1)	0.726 (12.95)***	0.795 (14.03)***	0.605 (8.72)***	0.782 (11.93)***	0.428 (7.82)***	0.628 (6.39)***	0.764 (9.16)***
Real GDP growth (–1) or (–3)		–0.031 (–2.69)***	–0.046 (–2.03)**		–0.072 (–2.30)**	–0.083 (–2.02)**	–0.021 (–3.43)***
Real GDP growth trading partner (–5)	–0.072 (–2.06)**						
Growth of exports to trading partner (–2)		–0.006 (–2.82)***					
Employment growth (current period)							–0.036 (–3.24)***
Change in activity index/ agriculture (–4)				–0.022 (–1.97)**			
Lending rate sector (–1) or (–3)				0.048 (1.67)*	0.037 (2.07)***	0.115 (1.75)*	
Constant	–0.957 (–4.00)***	–0.525 (–2.86)***	–1.641 (–6.34)***	–1.145 (–2.95)***	–2.744 (–7.83)***	–1.898 (–3.23)***	–0.753 (–2.33)**
Observations	677	769	762	589	712	601	921
Number of banks	36	38	38	33	36	30	41
Instruments	99	81	177	54	56	56	111
Lags dependent variable	3	2	4	1	1	1	1
Lags independent variable	1	1	1	1	1	1	2
Arellano-Bond (1)	0.00	0.00	0.00	0.00	0.00	0.02	0.00
Arellano-Bond (2)	0.14	0.94	0.23	0.22	0.18	0.54	0.78
Sargan Test	1.00	1.00	1.00	0.98	0.98	0.99	1.00

Source: Authors.

Note: GMM = Generalized Method of Moments; NPL = nonperforming loan.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

