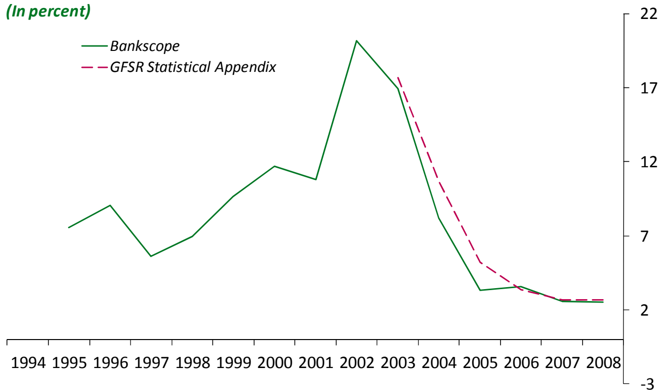
Annex 1.6. Analyzing Nonperforming Loans in Central and Eastern Europe Based on Historical Experience in Emerging Markets[1]

This annex explains the data sources and the technical details of the estimations presented in Box 1.2.

Data

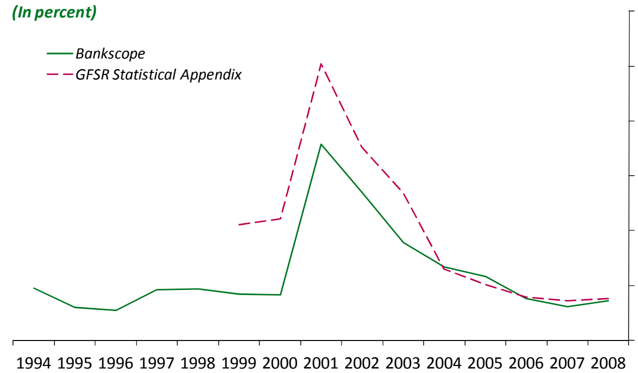
The reason for undertaking a "what if" exercise, rather than estimating coefficients directly for Central and Eastern Europe (CEE), is that Bankscope data on asset quality is sporadic for CEE countries. This is partly because western parent banks report cross-country consolidated statements, and partly because the series are short. For the countries in the estimation sample, however, Bankscope has relatively good coverage and the series are long enough to capture the dynamics of complete credit cycles (Figures 1.45 and 1.46 show examples).

Figure 1.45. Argentina: Nonperforming Loans as a Share of Total Loans
(In percent)



Sources: Bankscope; national authorities; and IMF staff estimates.

Figure 1.46. Turkey: Nonperforming Loans as a Share of Total Loans
(In percent)



Sources: Bankscope; national authorities; and IMF staff estimates.

Bank-level data is used to calculate NPL ratios, complemented with official aggregate data for Colombia, the Philippines, and the Dominican Republic. To capture the "true" NPL ratio for each bank, the Bankscope balance sheet category "Total problem loans" is used, as it includes both nonperforming and restructured loans, and then divided by total customer loans. The NPL ratios are aggregated up for each country and checked against the GFSR statistical appendix, as well as for the market share captured by the available data. Care has been taken to exclude series, or end-observations, with definitional changes in the estimation sample, so as to avoid structural breaks in the data. Exchange rates are expressed in local currency per US dollar or euro. Data on real GDP growth and exchange rates are taken from the *WEO* database.

Modeling and Estimation

The asymmetry in the data around spikes in the NPL ratio, with high persistence in the aftermath of a crisis, leads us to two estimate two different model specifications; one using the percent change in NPL ratios, and one using the percentage-point level of NPL ratios. Panel unit root tests do not indicate that the NPL ratios in the sample are nonstationary, but modeling the NPL ratio in percent changes rather than levels increases comparability and scalability of the

[1] This annex was prepared by Kristian Hartelius.

model predictions, as NPL definitions and levels vary across countries. Furthermore, analysts often consider loan loss provisions on a bank's income statement when moving from asset quality to implications for capitalization, which would be a function of the change in NPLs on the balance sheet. However, a model in changes tends to exaggerate the persistency of shocks when the data is asymmetrical as in the sample, whereas a model using the level of NPL ratios handles the asymmetry better. Both model specifications contain real GDP growth and exchange rate movements expressed in percent changes.

The models are fixed effects Vector Auto Regressions with one lag.[2] The data in the estimation sample is stationary, and the impulse response functions of the two models are shown in figures 1.47 and 1.48, for Cholesky identified shocks. They indicate sound long-term properties, have the expected signs (the figures show responses to positive shocks), and are statistically significant. A negative shock to real GDP growth leads to an increase in the NPL ratio, as does an exchange rate depreciation shock.[3] Notably, even the model using NPL ratios in levels (model 2) indicate that GDP and exchange rate shocks have effects on the NPL ratio that linger for more than 4 years.

The models produce sensible long-term forecasts for the countries in the estimation sample (not shown). Idiosyncratic factors in certain countries may have led the exchange rate to trend up or down, or may have caused persistent declines or increases in the NPL ratio, over the sample period. Such idiosyncrasies are handled relatively well by country-specific fixed effects when producing out-of-sample forecasts for the countries in the sample. However, for the purpose of applying the models to the CEE region, the models are re-fitted on de-meaned changes in the exchange rate and NPL ratio, so that the estimated fixed effects produce mean reversion to zero in these variables. The estimated impulse responses to shocks remain unchanged in the re-fitted models, whereas the long-term dynamics are steered towards a neutral steady state.

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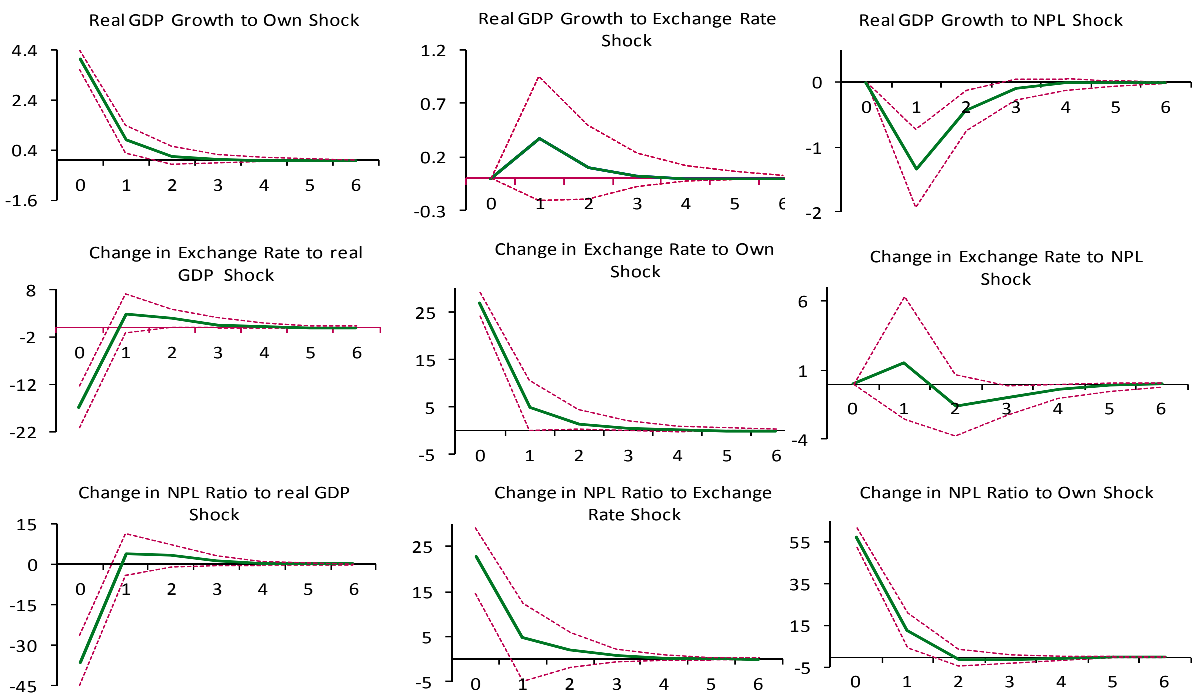
[2] The code used to estimate the model and produce impulse response functions was written by Inessa Love at the World Bank.

[3] The exchange rate shock studied is orthogonal to the GDP shock.

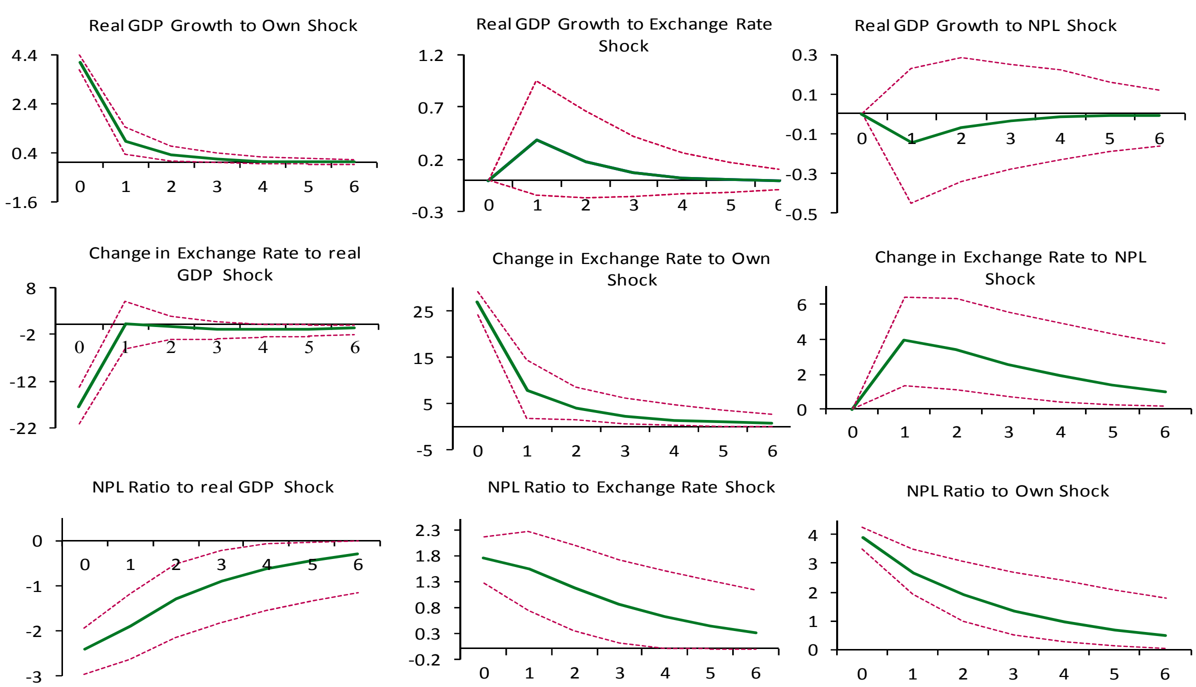
Figure 1.47. Impulse Response Functions - Model 1



Source: IMF staff estimates.

Note: Dashed red lines represent 90 percent confidence bands. One standard deviation Cholesky orthogonal shocks.

Figure 1.48. Impulse Response Functions - Model 2



Source: IMF staff estimates.

Note: Dashed red lines represent 90 percent confidence bands. One standard deviation Cholesky orthogonal shocks.

Simulations

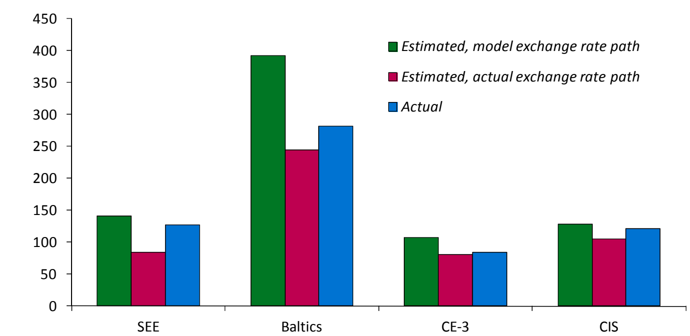
The simulations can be thought of as answering the following question: "What should we expect for NPLs in the CEE region, if bank asset quality and exchange rates respond to GDP shocks as they have typically responded in emerging markets previously, given initial conditions in CEE and the size of GDP shocks that have hit the region?" They are done for both models by applying the estimated coefficients to data for European countries, simulating the models from 2008 and onward.

When applying the models to countries in the CEE region, the cross-country average fixed effects in the sample are used. A real GDP shock in period *t* is translated into the models by dividing the difference between the WEO data (or forecast) for period *t* and the model prediction for the same period by the standard deviation of GDP shocks in the estimation sample (which is 4 percent). The simulations are based on consecutive shocks, where the dynamic model predictions are updated in each period based on shocks in the previous period.

The simple average of the two model forecasts in each time period is used for final projection purposes. In addition to complementing each other as described above, the two models are biased in opposite directions when forecasting NPL ratios for countries with very high or very low levels of NPLs, meaning averaging across them produces more reliable forecasts.

When controlling for actual exchange rate developments, the model simulations fit the Baltic and the CE-3 data better, but under-predict NPL formation in south eastern Europe and the CIS (Figure 1.49).[4]

Figure 1.49: Change in Nonperforming Loan Ratio During 2009
(In percent)



Source: IMF staff estimates.
Note: CE-3 = Czech Republic, Hungary, and Poland; CIS = Russia and Ukraine; SEE = Bulgaria, Croatia, and Romania.

[4] The simulations are conditioned on actual exchange rates and WEO exchange rate forecasts as a series of consecutive shocks to the model exchange rate, orthogonal to the GDP shocks in the baseline simulations.