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Macroeconomic determinants of Polish banks' loan losses – results of a panel data study

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Abstract

The paper investigates the links between business cycle variables and loan losses of Polish commercial banks. A panel approach was chosen in order to make maximum use of available supervisory data, and to capture the impact of bank profile on loan losses. Loan losses are proxied by the flow of loan loss provisions.

We find a significant influence of real GDP growth, changes in real interest rate, and labour market variables such as changes in unemployment rate. Due to the high share of FX loans to households, the influence of exchange rate is also examined, but the results are inconclusive. The differences in loan losses between banks can be attributed to differences in business profile, described by classification of banks into “strategic groups”, as well as the structure of loan portfolio.

The paper concludes with an example of a stress testing exercise conducted using scenarios generated through the National Bank of Poland’s macroeconomic model.

JEL Classification: G21

Keywords: credit risk, banks, Poland, panel data, stress tests

Introduction

Credit risk – understood as default risk in the loan[1] portfolio – is the most important type of risk undertaken by the Polish banking sector. The claims on nonfinancial customers (corporations and households, excluding the general government sector), which are the main source of credit risk, account for over 45% of banking sector assets. Banks' credit risk is of interest to the central bank, since high credit losses, diminishing the banks' capital resources, can disturb the functioning of the financial sector. This in turn would have an adverse influence on the standing of households and corporations. Recent economic literature underscores the importance of the link between the business cycle and banks' loan losses. This link is particularly important for financial stability analysis. The aim of this paper is to investigate the link between macroeconomic trends in the Polish economy and the banks' loan losses. We also take into account bank-specific characteristics which can lead to differences in loan losses between individual banks.

The paper consists of 5 sections. The first one presents a short review of the relevant literature. Next, we discuss the variables used in the model. The third section contains the empirical results. The fourth part presents the results of a stress-testing exercise. The final section concludes and indicated the avenues for further research.

1 Corporate bond holdings play a very marginal role in the balance sheets of Polish banks, due to the small scale of this market.

1

Literature review

Two main strands of work on empirical modelling of loan losses can be distinguished in the literature. The first strand consists of models aiming to describe the probability distribution of losses that a bank can incur on a given portfolio of credit exposures. The CreditMetrics, CreditRisk+, KMV and CreditPortfolioView models are classical examples of this approach (see e.g. Crouhy et al. [15], Wilson [44], CSFP [38]). These models in general aim to describe the unconditional (with respect to economic conditions) probability distribution of loan losses. Consequently, most of them (apart from CreditPortfolioView, and, to some extent, KMV) do not directly describe the link between the business cycle and the level of loan losses (in other words, they do not provide point forecasts). The natural application of this class of models is the calculation of credit risk VaR, making them an useful tool for risk management and capital allocation.

The second strand of work consists of models striving to provide a functional relationship between measures of credit risk (banks' loan losses, probabilities of default) and macroeconomic conditions as well as other factors (such as banks' actions, described by their individual characteristics). The ability to provide point forecasts on the basis of macroeconomic scenarios makes these models[2] interesting for supervisors and central banks as tools for macro stress tests.[3] An equally important use of these models is the identification of macroeconomic factors influencing loan losses. This in turn offers guidance for financial stability monitoring.

The model presented in this paper belongs to the second strand. The aim is to identify a set of macro and microeconomic variables which explain the evolution of loan losses in the Polish banking system, for the purpose of forecasts and stress tests. The models belonging to this strand of research can be divided into several groups:

- Models using individual bank data (microeconomic) and macroeconomic data to model loan losses or the percentage of classified/nonperforming loans at individual bank level (e.g. Gizycki [22], Quagliariello [39]).
- Models explaining loan losses or the percentage of classified/nonperforming loans using aggregate data for the banking sector in one (e.g. Whitley, Windram and Cox [42], Hoggarth, Logan and Zicchino [27]) or several countries (e.g. Bikker and Hu [10], Pesola [35] and [36]).
- Models explaining the bankruptcy probability of corporations (on the level of individual firms or industry averages). Together with data on the exposure of the banking sector towards the investigated corporations or industries and data on collateral prices (approximated e.g. by real estate price indices) these models can be used to explain and forecast loan losses (see Bernhardsen [8], Andreeva [4], Sorge and Virolainen [40], Boss [12]).

A review of the results obtained in these papers enables us to identify a set of variables which can approximate the economic processes responsible for the evolution of loan losses and loan quality.

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2 The Merton model – forming the backbone of the KMV model – can also be used to forecast probabilities of default (in terms of averages for sectors of the economy or individual debtors). When combined with a model linking share prices with macroeconomic factors, it can also be used to conduct stress tests. For an example of this approach developed at the Bank of England see Drehmann [17].

3 Macro stress tests can be defined as a quantitative assessment of the resilience of the financial system to large negative disturbances (low-probability, high-impact events). Such analyses, started by the IMF as part of the Financial System Assessment Program are an increasingly popular tool for financial stability analysis.

1

1.1 Research using individual bank data

One of the earlier papers investigating the factors shaping loan quality was produced by Clair [14]. Using data for Texas banks, he points to a link between "excessive" loan growth (in relation to the phase of the business cycle) and loan quality. Fast loan growth reduces loan quality and the effect is most pronounced for banks with low capital adequacy ratios.

Pain [34] investigated the factors influencing charges to loan loss provisions (LLP)[4] at major UK banks between 1978 and 2000, distinguishing between commercial and mortgage banks. For commercial banks, the most important factors were: UK and world GDP growth (negative), the level of real interest rates and average loan growth rate for the whole banking sector. As far as bank-level variables were concerned, loan portfolio concentration (measured by the Herfindahl-Hirschmann index, calculated using industry shares – positive influence), share of loans extended to the commercial real estate sector (positive influence – interpreted as a high-risk sector) and the cost to income ratio (small positive influence) were found to be significant. For mortgage banks, the significant macroeconomic factors were: UK GDP growth and real interest rates (deflated using real estate prices). Bank-level factors in this model were: cost to income ratio, net interest margin (positive influence – an increase in NIM was interpreted as a sign of banks expanding their business towards more risky customers) and the share of mortgage-secured loans in the portfolio.

Quagliariello [39] developed static and dynamic panel models explaining the flow of new LLP and new nonperforming loans (both expressed as percentage of loan portfolio) at Italian banks between 1985 and 2002. In his model, the increase in NPL is described by GDP growth (negative), the level of long-term interest rates (positive), the spread between deposit and lending rates (average for the banking sector, positive influence), loan growth at bank level (negative influence with a one year lag, interpreted as loan growth being a sign of good business conditions)[5] and cost to income ratio (negative influence). The flow of new LLP is explained by GDP growth, long term interest rates, stock market index (proxy for business cycle and possibly the value of corporations' asset which could serve as collateral), spread between deposit and lending rates, flow of new NPL and bank profitability measured by ROA.

Jimenez and Saurina [28] use a panel model to describe the share of NPL in Spanish banks' loan portfolios between 1984 and 2002. As in other research, they find a negative influence of lagged GDP growth and a positive influence of real interest rates. Loan portfolio concentration, measured by HHI (higher concentration increases the share of NPL) and the share of secured loans are also found to have a significant influence. The authors pay particular attention to the influence of loan growth on NPL. In their model, an increase in loan growth rate worsens loan quality with a four-year lag. They also find that higher loan growth at bank level (as compared to average for the sector) is an additional factor influencing loan quality. Since the dependent variable exhibits significant "memory", which is natural for balance-sheet ratios, the model has an autoregressive component and is estimated using the Arellano-Bond approach.

Kearns [30], building on the model of Bikker and Metzemakers [11], presents a panel model describing the flow and the stock of LLP as percentage of loans for 14 Irish banks between 1982 and 2003. In his model, GDP growth, unemployment rate, loan growth, share of loans in assets and the share of income before tax and LLP in net income from banking activity are significant risk drivers. The last variable is interpreted as an indicator of income smoothing behaviour of banks. The existence of this phenomenon had been

[4] In this paper, the term "loan loss provisions" refers also to "impairment charges" under IFRS, as well as accounting categories named otherwise in some jurisdictions (e.g. "specific provisions", "write-downs") which perform the same function – recognizing the decrease in balance sheet value of a loan in the event of default or decrease in creditworthiness of the borrower. For the sake of clarity, the term "loan loss provisions", abbreviated as "LLP", is used throughout the paper.

[5] This can also be a statistical effect, increasing the denominator of the dependent variable.

previously suggested by Fudenberg and Tirole [19], while Kanagaretnam, Lobo and Mathieu [29] found this effect for US banks.

Apart from the variables considered by Kearns, Bikker i Metzemakers [11] investigated also the influence of banks' capital resources (the share of capital in balance sheet total). In their model, estimated on bank-level data from 29 OECD countries they find a negative influence of this variable. They explain this by the existence of regulations allowing some of the provisions to be included in capital for regulatory purposes and the consequent ability of banks to boost their capital adequacy ratios through higher LLP charges.

Berger and DeYoung [7] consider the possible links between banks' loan quality, their cost efficiency and capital resources. They propose four hypotheses:

- "bad luck" – a deterioration of loan quality is the cause of lower cost efficiency. According to this hypothesis, a deterioration in loan quality due to an exogenous shock (for example a bankruptcy of an important borrower) increases the bank's expenses on collection, workout arrangements etc., which leads to lower cost efficiency.
- "bad management" – low cost efficiency causes a deterioration of loan quality. Here, inadequate management skills are reflected in weak cost control. This lack of skills is also visible in low quality of credit risk management, leading to lower loan quality.
- "moral hazard" – low capital adequacy causes a deterioration in loan quality. Low capital adequacy, signifying higher probability of bank's bankruptcy or supervisory action, induces the management to "gamble for resurrection", taking on more risk to boost returns and their position. This leads to lower loan quality.
- "skimping" – high cost efficiency causes a deterioration in loan quality. If high cost efficiency is caused by a reduction of resources allocated to risk management, then this policy would lead to worse loan quality.

Berger and DeYoung use Granger causality tests to verify these hypotheses using panel data for US banks between 1985-1994. They find some evidence of "moral hazard' for weakly capitalised banks, but do not find compelling evidence that would allow them to choose between one of the hypotheses linking cost efficiency and loan quality. Williams [43] does a similar investigation for savings banks from Denmark, France, Germany, Italy, Spain and the UK between 1990 and 1998. His results suggest that "bad management" is the most likely phenomenon in Europe.

Gizycki [22] presents a model explaining the share of classified loans in Australian banks' assets between 1990 and 1999. Apart from variables used in other work described above (GDP growth, loan growth, real interest rates, an autoregressive component), the author finds a statistically significant influence of lagged share of interest payments in the income of households and corporations on loan quality. The model also includes the influence of real estate boom on loan quality (by including a commercial real estate price index – a fall in real estate prices lowers loan quality 3 quarters ahead) and the share of construction in GDP (a higher share causes lower loan quality 1 year ahead).

Gerlach, Peng and Shu [21] investigate the factors shaping the share of NPL in the portfolios of retail Hong Kong banks between 1994 and 2002. Their results are similar to most other research – they find significant influence of contemporaneous GDP growth, nominal interest rates, inflation and changes in real estate prices. The authors find that real estate prices have a smaller influence on loan quality of banks with high share of real estate loans in their portfolio. They conclude that real estate prices could be interpreted as a business cycle indicator, which would produce the observed effect under the assumption that real estate loan quality is less sensitive to business cycle than other loans.

1.2 Research on aggregate data

Delgado and Saurina [16] build a simple ECM model explaining the share of classified loans in Spanish commercial and savings banks' portfolio between 1981 and 2001. In their model GDP growth and the level of interest rates are significant both in the long-run and the short-run equation. They do not find a significant influence of the debt burden of corporations and households or loan growth.

Whitley, Windram and Cox [42] develop ECM models describing loan quality of mortgage loans and credit card loans for UK banks between 1985 and 2002. In contrast to the findings of Delgado and Saurina, they find that interest burden of households has a strong influence on loan quality. A similar finding with regard to corporate loan quality and corporate bankruptcy rates is found by Hoggarth, Logan and Zicchino [27].

The issue of loan quality has also been investigated using VAR models. Gambera [20] builds a set of simple VAR models explaining loan quality of the banks in the Federal Reserve seventh district, broken down by bank size and type of loan. Loan quality in these models is explained by borrower incomes, business cycle indicators, unemployment rates and the number of initiated bankruptcy proceedings. Babouček and Jančar [5] include loan quality in a simple macroeconomic VAR model for the Czech economy, dealing with the interactions between the exchange rate, foreign trade flows, money supply, lending, unemployment rate, inflation and short-term interest rates. In their model, a deterioration in loan quality contributes to a decrease in unemployment and an increase in inflationary pressure. The authors explain this by interpreting a decrease in loan quality as a symptom of a looser credit policy of banks.

A VAR model was also used to explain the quality of foreign exchange loans in the Polish banking sector (see Głogowski and Żochowski [24]), broken down into loans to corporations and households. The model for corporate loan quality includes the nominal zloty/euro exchange rate, export growth and GDP growth. The model for the household sector includes a yearly change of the unemployment rate in place of export growth. Both models indicate that a slowdown in economic growth and a depreciation of the local currency negatively influence FX loan quality.

Some papers used data on banking sectors of several countries to describe the link between macroeconomic conditions and loan quality or loan losses. Pesola [35] uses data for Scandinavian countries including the 1990s banking crisis to build a model explaining the level of loan losses. The author attributes the high level of loan losses to the combination of negative and unexpected changes in GDP growth and real interest rates coupled with high indebtedness. This mechanism is incorporated in the model through "surprise" variables, calculated as the product of the difference between expected and realised GDP growth (or interest rates) and the ratio of loans to GDP. The results confirm the role of macroeconomic "surprises" in the evolution of loan losses. The results are confirmed by a later paper (Pesola [36]) which also includes data for several Western European countries.

1.3 Models of bankruptcy probability

The third group of papers investigates the factors shaping loan losses through models of default (or bankruptcy) probability. These models can deliver a forecast of loan losses based on the data on banks' exposures towards the relevant classes of borrowers, as well as assumptions regarding LGD.[6] An example of this is the paper by Sorge and Virolainen [40]. The authors build PD models for six sectors of the Finnish economy. They find a significant influence of GDP growth, sector-level leverage and interest rates. These models are then used to simulate probability distributions of loan losses on a representative loan portfolio, under the assumption of explanatory variables following an AR process (similar to the CreditPortfolioView model). Boss [12] adopts a similar approach.

[6] Usually, this amounts to assuming a fixed value for LGD, estimated on the basis of supervisory data, analyses of balance sheets of companies in bankruptcy, or other sources. Sorge and Virolainen assume LGD of 50%.

The sensitivity of probabilities of default to macroeconomic factors can also be investigated using borrower-level data. Research for Poland (Głogowski [23]) based on the data on banks' large exposures pointed to a statistically significant influence of GDP growth, industry-level profitability and liquidity, as well as real interest rates on the one-year probability of a borrower's transition to the lowest quality category (according to supervisory loan classification scheme).

1.4 Conclusions from the review

The variables used in the research reviewed above pertain to several areas which are crucial for the modelling of loan losses:

Income of borrowers. These variables approximate the changes in free cash flows that borrowers can use to service their debt. This category includes GDP growth (or related measures such as output gap), unemployment rate, wages, measures of corporate profitability and liquidity.

Debt service costs. These costs are usually approximated by changes in nominal or real interest rates.

Debt burden. These variables approximate the vulnerability of borrowers to changes in income and debt service costs – they approximate the "income buffer" of borrowers. The most commonly used measures include: the ratio of interest payments to corporate or household income, leverage, or the ratio of loans to sales income, disposable household income or GDP. The ratio of debt service costs to borrower income is widely used by banks in the process of assessing the riskiness of potential borrowers. However, the use of similar measures calculated using aggregate data, where the data on income include all agents (not just borrowers) can result in misleading conclusions in the case of countries where the proportion of population using banking services is expanding rapidly (as is the case in Poland). In such a situation growing aggregate debt burden, resulting from an increase in the number of borrowers, does not have to lead to an increase in credit risk (understood as the ratio of expected losses to the value of loans).

Bank actions. Loan growth, interpreted as a proxy for the restrictiveness of banks' lending policy[7] is one of the most prevalent indicators of bank behaviour. Its usefulness can be limited in countries where the share of population using banking services increases rapidly, for reasons similar to the case of debt burden indicators. "Income smoothing" and "moral hazard" behaviour has also been suggested in the literature. The existence of the first phenomenon can be investigated by using past profitability as an explanatory variable (a positive influence on loan losses would support the existence of "income smoothing"). The probability of "moral hazard" behaviour should increase with decreasing capital adequacy. Some authors investigate the influence of bank portfolio diversification (described by concentration measures) on loan losses. Despite statistically significant influence of these variables found in some papers, it seems more likely that portfolio diversification should influence primarily the variability of loan losses over time and not their average level. Finally, bank efficiency (e.g. cost efficiency), as long as it is a reasonable approximation of management quality, can also explain loan losses.

Collateral. Changes in the value of security and the share of secured loans influence loan losses through their impact on LGD. Real estate prices are the most common proxy for collateral value.

[7] Keeton [31] considers the link between banks' lending policy and loan losses from a theoretical perspective. Fast loan growth can also be caused by increase in loan demand, sparked by borrowers' optimistic expectations regarding their future incomes. Tsomocos [41] considers this phenomenon in a general equilibrium framework. He concludes that in such a situation borrowers may accept higher probability of defaulting, even if default bears a utility cost. Such behaviour of borrowers increases the amount of defaulted loans.

2

Data

2

The models presented in this paper were estimated using quarterly financial reports of commercial banks based in Poland. These obligatory reports are sent to the National Bank of Poland for supervisory purposes. The data covers the years 1997-2006.

2.1 Dependent variable

The first choice that needed to be made concerned the dependent variable, representing banks' loan losses. The papers reviewed above used several approaches (share of nonperforming loans, flow of LLP etc.). Looking at bank balance sheets, the accumulated credit risk losses are represented by the stock of loan loss provisions, which reduce the balance sheet value of impaired loans. An approximation of credit risk losses incurred by a bank in a given period is the net flow of loan loss provisions (charges to provisions minus release of provisions). This variable (normalised between banks by dividing it by the value of loans to the nonfinancial sector), denoted *N_LLP_f_ln_nf* was chosen as the dependent variable. This choice was motivated by several causes:

Until the adoption of IFRS in 2005, all banks in Poland had to follow loan regulatory loan classification rules. The regulations established 5 loan quality categories (regular, special mention, substandard, doubtful, loss), as well as the criteria for classifying loans into each category and the required minimum coverage of loans in each category by LLP. The definition of adversely classified loans changed several times during the sample period – the regulations were changed in 2004 (the minimum arrears period was raised from 30 to 90 days and collateral was recognised for classification purposes) and 2005 when IFRS were adopted (gradually) by some banks (see [3], [1] and [2]). The changes in classification rules brought about large changes in the share of adversely classified loans in banks' portfolios (in the most extreme cases of some small banks this ratio dropped from 50% to almost zero). The changes in regulations influenced also the flows of LLP, but the changes were much less extreme.

Data on nonperforming (not equivalent to adversely classified, due to some features of the loan classification scheme) loans are available only since mid-2003.

Some tax and accounting regulations in Poland discouraged the banks (until 2004) from moving old, fully provisioned NPLs off the balance sheet (see NBP [32]), resulting in their accumulation in the balance sheet. Consequently, the share of non-performing and/or adversely classified loans in a bank's portfolio reflects to some extent its accumulated loan loss history and not just the current performance of the loan portfolio. Apart from possible problems with estimation (nonstationarity), it is difficult to interpret the results from the point of view of financial stability.

This model forms a part of a wider research project aiming to develop tools for forecasting and stress testing the main items of the balance sheet and profit and loss account of the banking sector. This made it natural to choose a dependent variable which is directly linked to the P&L account.

It is reasonable to expect that flows of LLPs will differ between the types of loans. The optimal set of explanatory variables can also be different for each type of loans. The format of supervisory data does not allow, however, to split the flows of LLP by type of borrower, type of loan, or loan currency. Such breakdown is available for data on the level of LLP. The use of these time series also poses some difficulties, as the level of LLP is influenced by the sales of NPLs and moving NPLs off the balance sheet. These transactions started to take place in the Polish banking sector only in 2004, after legal uncertainties were clarified. The use of quarterly differences in the level of LLP would consequently require significant data cleaning and thus it was decided to focus on the total (at bank level) flows of LLPs. The definition of the dependent variable places no restrictions on the range of values it may take[8] and consequently no transformations of the dependent variable were applied.[9]

2.2. Explanatory variables

The candidate explanatory variables which were considered for use in the model are presented below.

Borrower income. The basic variable from this area was real GDP growth. Apart from this aggregate measure, other considered variables included the financial standing of corporations (described by pre-tax profitability and liquidity ratios) and labour market conditions. The labour market trends were described by a yearly change (to bypass seasonal effects) in unemployment rate calculated on the basis of the Labour Force Survey (*D4_unempl*). The change of the unemployment rate should have better explanatory power than the level of the unemployment rate, since it is reasonable to expect that an increase in the unemployment rate would be correlated with the number of borrowers who became unemployed during that period. Apart from the changes in the unemployment rate, quarterly changes in the number or persons employed in the economy (seasonally adjusted) was used as an alternative[10] (*D1_n_empl_ds*). To account for possible inter-bank differences in the sensitivity to labour market developments, in some specifications these variables were weighted by the share of loans to households at each bank. Weighted variables were denoted as *D4_unempl_wgt* and *D1_n_empl_ds_wgt*. It has to be mentioned that labour market variables can also approximate the financial standing of companies, which influences their decisions on the optimal level of employment.

Debt service costs. These costs were approximated by several measures. Two types of interest rates were used. The first one was calculated as the average weighted real lending rate for each bank (*b_ir_r_wgt* – average lending rate for loans to households and corporations, weighted for each bank by the shares of these groups of customers in the loan portfolio). Since bank-level interest rates are not available for all banks, the weighted interest rate was calculated on the basis of average lending rates published by the NBP. Real interest rate for corporate loans was calculated as the interest rate on 1-year zloty loans deflated using PPI. Real interest rate for household loans was calculated as the interest rate on consumer loans (cash loans until 2002), deflated using CPI. The choice was motivated by the need to minimise the structural break due to the change in interest rates reporting scheme in 2002. An alternative measure of interest rates was the 3-month interbank rate (WIBOR) deflated by CPI. The changes of this interest rate can be a good approximation of changes in lending rates as long as risk premia on loans are stable. This assumption is not true for the whole sample – margins on loans stabilized only around 2001. An advantage of this measure is the ease of use in forecasts and stress tests, as it does not require forecasting margins which can be problematic.

A significant proportion of loans extended by Polish banks is nominated in foreign currencies. Some of these loans were taken out by households without matching FX income. Consequently, changes in the exchange rate can influence the cost of loan repayment and the burden it places on household incomes. A depreciation of the zloty can thus increase loan losses of banks which have a large proportion of FX loans in their portfolios. On the other hand, during the investigated period the quality of FX loans was better than that of zloty loans, which suggests that the influence of exchange rate changes could have been minor.

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8 The net flow of LLP can be negative if the release of LLP is larger than the charges to LLP in a given quarter. In theory, it can also take on values greater than 1 if a bank is forced to create high provisions for a loan extended in the quarter in question.

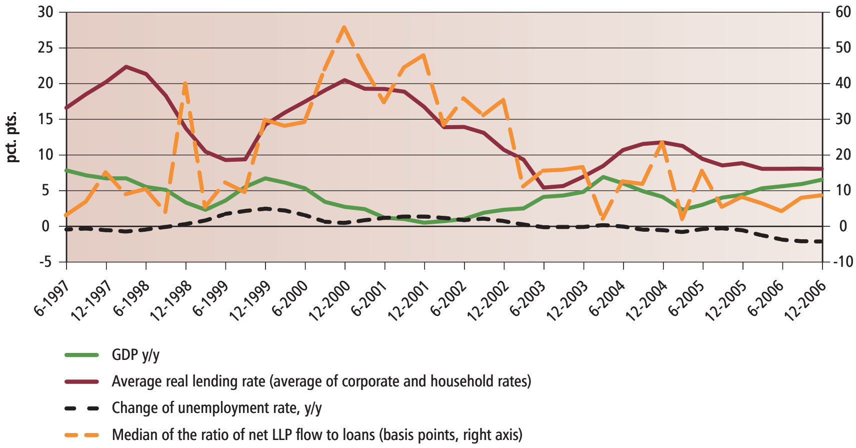
9 A logit transformation is commonly applied when the share of NPL (by definition taking on values between 0 and 1) is used as the dependent variable.

10 Seasonal adjustment was performed by regressing the variable on quarterly dummies.

Moreover, recently extended mortgage loans form a large part of FX loans. Research for these loans in some countries suggests a link between the probability of default and the "age" of mortgage loans. The maximum probability of default seems to occur about 5 to 8 years after the extension of the loan (e.g for Switzerland Burkhardt and De Giorgi [13] find the maximum at about 6 years). Since the majority of FX mortgage loans in Poland have been extended after 2003, most of these loans is still in the period of relatively low PD. For this reason the link between exchange rate changes and LLP may prove to be weak or statistically insignificant. To test this link, we used yearly changes of nominal EUR/PLN exchange rate.[11] Changes in the nominal exchange rate should be the best approximation of changes in actual debt service costs for a borrower with no FX income. Effective interest rates (nominal and real – PPI and CPI deflated) were used as alternatives. The influence of foreign interest rates (average of 3-month interbank rates for US dollar, Swiss franc and euro (DEM until 1998)) was also investigated.

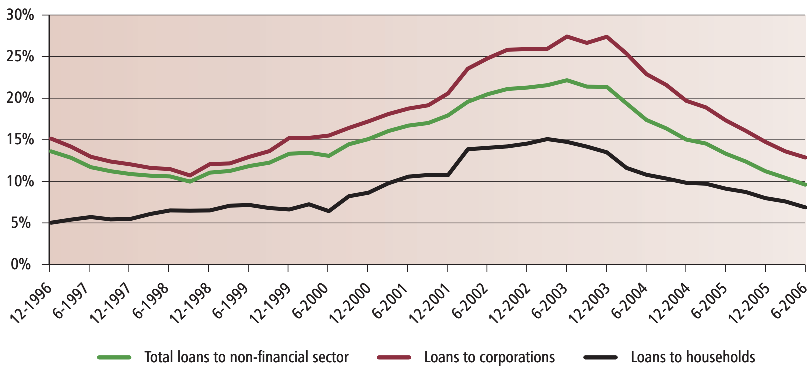
Chart 1 presents the evolution of main macroeconomic variables and loan losses. A slowdown in economic growth and an increase in unemployment rate precede an increase in loan losses. The level of real interest rates changes approximately in line with loan losses (especially after 2000).

Chart 1
Evolution of loan losses and main macroeconomic indicators



Note: Real lending rate calculated as average of lending rates on household and corporate loans.
Source: Author's calculations based on data of National Bank of Poland and Central Statistical Office.

Chart 2
Share of adversely classified loans in banks' portfolios



Source: Author's calculations based on data of National Bank of Poland and Central Statistical Office.

[11] DEM/PLN rate was used before 1999.

Borrower debt burden. The measures of debt burden have been calculated separately for corporations and households. For the corporate sector, debt burden was calculated as the ratio of corporate loans to quarterly sales of corporations (*kred_cor_przychody*). The debt burden of households was defined as the ratio of household loans to quarterly total wages[12] (*kred_gd_place*).

Bank actions. The investigation in this area started from bank-level credit growth (*b_ln_nf_gr_qq*) and deviation from sector median (calculated for each period). Changes in loan growth rate can be interpreted, to some extent as changes in a bank's lending policy. Bank's capital resources, measured by the deviation of the capital adequacy ratio from sector median[13] (*dm_car*), were included to account for the possibility of "moral hazard" behaviour. As an alternative measure, two dummy variables taking on the value of 1 if the capital adequacy ratio was below 10% or 9% (*low_car10* and *low_car9*) were used. However, the changes in the definition of the capital adequacy ratio make it difficult to interpret these variables. Banks' efficiency was measured by the cost to income ratio[14] which is a common simple measure of cost efficiency.[15] Polish tax and loan classification regulations do not lend themselves easily to "income smoothing", mainly because of quite prescriptive loan classification regulations. To account for the possibility of this phenomenon, past profitability measured by ROA and ROE was also tested as an explanatory variable. If "income smoothing" behaviour exists, then these variables should have a positive influence on LLP.

Bank profile. The magnitude of credit risk differs between types of loans and classes of borrowers (differences in loan portfolio quality illustrate this – see Chart 2). A bank's loan losses can be influenced by the composition of its loan portfolio. This was taken into account in two ways. First, the classification of banks by so-called "strategic groups" in the sense of Porter [37] was used (the methodology is described in Hałaj and Żochowski [25] and [26]). Strategic groups are defined as groups of companies taking similar decisions in key areas of their business. In the case of banks these decisions are reflected in the composition of assets and liabilities. In the mentioned paper, the authors identify (through cluster analysis) 5 groups of banks in the Polish banking system: retail, corporate, universal, regional (apex banks for the cooperative banking sector) and specialised (car finance and mortgage) banks. Membership in groups is described by dummy variables *group1 – group5* (1 – retail, 2 – corporate, 3 – regional, 4 – specialised, 5 – universal). Strategic groups theory suggests that companies belonging to different groups exhibit different profitability. In this paper, it was investigated whether the differences in business profile described by the classification into strategic groups influence the level of loan losses and the sensitivity of loan losses to macroeconomic factors. Apart from the strategic groups classification, the share of loans to households in loans to non-financial sector (*b_hh_ln_share*) was used as a supplementary measure of business profile.

Collateral. Information on types of assets accepted as collateral is limited and so the only variable considered was the share of real estate loans in loans to households (*b_hous_ln_share*). A high share of these loans can lower loan losses for several reasons. First, they are mostly mortgage-secured, which lowers LGD.[16] Second, in many countries, real estate loans exhibit the lowest default rates of all loan categories, as

[12] Total wages were calculated as the product of the number of employed outside the agricultural sector and the average gross wage.

[13] The use of deviation from median was motivated by the fact that during the sample period the regulations defining the capital adequacy ratio changed twice, bringing about abrupt changes in the value of the capital adequacy ratio at all banks.

[14] General expense plus depreciation and amortization charges divided by the sum of net interest income and net non-interest income.

[15] More sophisticated measures, for example based on input-output analysis, give a more comprehensive view of a bank's efficiency, accounting for more aspects of management than just cost control. A thorough investigation of the link between bank efficiency and loan losses is beyond the scope of this paper and consequently the simpler C/I measure was used.

[16] Polish tenant protection laws can however limit the effectiveness of mortgage as collateral. See NBP [32].

the default penalty for owner-occupier borrowers is high. The short average "age" of mortgages may overstate the influence of this category of loans (relative to a long-run average impact, which may be possible to estimate after an economic slowdown). The lack of long enough and representative enough time series of real estate prices made it impossible to use such data.

Finally, dummy variables were used to gauge the impact of the changes in loan classification (*dummy_reg04* – value of 1 for all quarters of 2004) and the introduction of IFRS (*dummy_ifrs* – value of 1 for all quarters of 2005).

3

Estimation results

3.1 Estimation sample selection

The dataset consisted of 2661 observations on 108 commercial banks which existed in Poland between December 1996 and September 2006. To ensure that the results are not skewed by outliers, the following restrictions were jointly applied:

- only functioning banks were taken into account (banks in bankruptcy or liquidation were excluded),
- in order to limit the role of newly created or heavily restructured banks (where financial indicators are usually distorted by low base effects) as well as banks in weak financial condition (whose actions, often influenced by restructuring programmes, can be unrepresentative) only observations where the capital adequacy ratio was between 4% and the 95-th percentile of the distribution (about 80%) were used,
- observations with the values of the dependent variable outside the range between 5th and 95th percentile were discarded,
- similar restrictions as for the dependent variable were placed on the explanatory variables describing individual bank characteristics, with the exception of dummies and variables whose definitions put a limit on their values.

The descriptive statistics of variables considered during the estimation are presented in table 1. The robustness of estimates was tested by re-estimating the models using an extended sample (limiting the dependent variable to the range between 1st and 99th percentile). In this case, its range of values is much larger than in the baseline case (the maximum increases from 1.8% to 6.3% and the minimum falls to -0.72% from -0.53%). The results obtained using the extended sample are very similar to the ones obtained on the baseline sample, which are presented below, both with regard to statistical significance of coefficients and the scale and direction of influence of explanatory variables.

3.2. Estimation results

As a general rule, all explanatory variables were lagged at least one quarter. The first reason for this choice is the accounting treatment of loan losses: there is a gap between the moment when the financial condition of the borrower deteriorates, resulting in a non-payment of a loan and the moment when the loan is classified as impaired and a loan loss provision is created. Through most of the sample this gap was set to 30 days by prudential regulations (90 days from 2004). Banks using IFRS (since 2005) are to some extent free to choose the arrears "threshold", but it can be expected that their choice would be similar to Basel 2 regulations (where arrears of 90 days are one of the triggers of default). The use of lagged explanatory variables also alleviates any potential endogeneity problems.

The choice of optimal set of macroeconomic explanatory variables was further complicated by the fact that some of them are strongly correlated and autocorrelated, which can lead to approximate collinearity, compromising the quality of estimates. When choosing explanatory variables, preference was given to variables whose forecasts can be obtained from existing models (such as the NBP's macroeconometric model ECMOD [18]), to make it easier to use the obtained model as a "satellite" in forecasts and stress tests. The analysis of correlation between potential explanatory variables resulted in the following conclusions:

- profitability and liquidity indicators for the corporate sector were dropped as they are highly correlated (with absolute values of correlation coefficients between 0.6 and 0.8) with changes in the unemployment rate,
- debt burden indicators are highly correlated (about 0.5) with GDP growth and changes in the unemployment rate and consequently their use may be problematic,
- the correlation between foreign interest rates and WIBOR is above 0.8, what discourages the use of foreign interest rates,
- year-on-year GDP growth rates exhibit high autocorrelation at lags of up to 3 quarters (between 0.3 and 0.8), suggesting the use of lags separated by at least 4 quarters,
- year-on-year changes of the unemployment rate also exhibit autocorrelation (between 0.3 and 0.9) at lags of up to 4-5 quarters, suggesting the use of at most one lag of this variable.

Table 1
Descriptive statistics of explanatory variables – under restrictions on dependent variable and capital adequacy

Variable	Definition	No. obs.	Average	Std. dev.	Min	Max	Unit
N_LLP_fl_ln_nf	Flow of LLP as % of loans	2048	0.293276	0.442677	-0.53966	1.884023	pct. pts.
b_hh_ln_share	Share of household loans	2048	0.408441	0.301504	0	0.994116	
b_hous_ln_share	Share of housing loans	2048	0.060758	0.142733	0	0.94631	
b_ln_fx_share	Share of FX loans	2048	0.21883	0.242817	0	0.99876	
cost_income	C/I ratio	2036	0.732602	0.416525	-0.49239	7.241677	pct. pts.
dm_c_i	C/I ratio – deviation from sector median	2036	0.037556	0.41413	-1.11179	6.469577	pct. pts.
roa_pretax	ROA before tax	2048	0.372545	1.755007	-70.4304	5.608135	pct. pts.
roe_pretax	ROE before tax	2048	0.042841	0.077909	-0.8227	1.263608	pct. pts.
b_ln_nf_gr_qq	Loan growth q/q	2048	9.816275	54.13443	-76.5942	2161.119	pct. pts.
dm_ln_nf_gr_qq_all	Loan growth q/q – deviation from sector median	2048	5.770894	53.92336	-75.5538	2153.809	pct. pts.
group1	Dummy – retail banks	2048	0.112305	0.315818	0	1	
group2	Dummy – corporate banks	2048	0.152344	0.359442	0	1	
group3	Dummy – regional banks	2048	0.100586	0.300853	0	1	
group4	Dummy – specialised banks	2048	0.131348	0.337863	0	1	
group5	Dummy – universal banks	2048	0.445801	0.497175	0	1	
Car	Capital adequacy ratio	2048	18.8021	12.01681	4.039954	80.29581	pct. pts.
dm_car	CAR – deviation from sector median	2048	18.65529	12.01439	3.891135	80.13627	pct. pts.
low_car_10	Dummy for CAR < 10%	2048	0.13916	0.346198	0	1	
low_car_9	Dummy for CAR < 9%	2048	0.084473	0.278163	0	1	
Gdp	Real GDP growth y/y	2048	4.0697	2.003263	0.4	7.7	
liq_1	Cash liquidity ratio – corporate sector aggregate	2048	20.75439	5.589661	15.5	32.6	pct. pts.
liq_2	Quick liquidity ratio – corporate sector aggregate	2048	84.28242	7.888181	72.9	100.3	pct. pts.
corp_profit	Pre-tax profitability – corporate sector aggregate	2048	2.756446	1.953172	-1.31112	6.923178	pct. pts.
kred_gd_place	Loans to households as % of aggregate wages	2048	167.3579	51.90144	105.1807	294.6061	pct. pts.
kred_cor_przychody	Corporate loans as % of corporate sales	2048	45.23782	7.216761	29.61964	56.29083	pct. pts.
rwib3m.	WIBOR3M rate, CPI-deflated	2048	6.337331	2.552212	1.566018	10.73239	pct. pts.
eur_sr_waz	EUR/PLN exchange rate, quarterly average, weighted by share of FX loans	2048	4.031044	0.290613	3.4883	4.7763	

Table 1 (cont'd)

Variable	Definition	No. obs.	Average	Std. dev.	Min	Max	Unit
eur_qoq	EUR/PLN exchange rate, quarterly change	2048	0.360212	3.934779	-7.6314	9.89287	pct. pts.
Neer	Nominal effective exchange rate	2048	46.41587	2.957677	40	52.3	
usdlib3m	LIBOR USD 3M	2048	4.165934	1.917412	1.11	6.81125	pct. pts.
chflib3m	LIBOR CHF 3M	2048	1.479686	0.973755	0.16	3.52	pct. pts.
fibor3m	FIBOR 3M (DEM – EUR)	2048	3.191805	0.831783	1.958	4.996	pct. pts.
d4_unempl	Unemployment rate y/y change	1849	0.679665	2.041497	-4	4.7	pct. pts.
d4_unempl_wgt	Unemployment rate y/y change, weighted by share of household loans	1849	0.278086	1.075525	-3.92735	4.584946	
d1_n_empl_ds	Employment in the corporate sector, q/q change	2048	0.054071	65.47638	-142.689	141.3111	thous.
d1_n_empl_ds_wgt	Employment in the corporate sector, q/q change, weighted by share of household loans	2048	0.236162	9.865503	-133.158	112.4676	thous.
b_ir_r_wgt	Bank-specific estimated interest rate, CPI-deflated	2048	13.36631	5.647137	-1.329	22.26241	pct. pts.

Source: Author's calculations based on NBP and CSO data.

The starting point was a fixed effects model.[17] This model was used to test the statistical significance of explanatory variables. The lag distribution for explanatory variables was chosen through an elimination of lags with statistically insignificant coefficients, starting from 8 lags.[18] The existence of autocorrelation in residuals was also investigated. The Bhargava DW test (see Bhargava et al. [9]) indicated the presence of autocorrelation[19] and the models were estimated taking this into account.[20] Apart from fixed effects, random effects specification was also investigated, especially when dummy variables indicating membership in strategic groups (which change mostly over the cross-section dimension and little over the time dimension) were present in the specification. The Hausman test was used to choose between fixed and random effects specification. The details of the estimated models are presented in the tables 2, 3, and 4. The following variables were used in the final specifications:

- *gdp* – year-on-year GDP growth,
- *real_wib3m* – three-month WIBOR interbank rate, CPI-deflated,
- *D4_unempl* – year-on-year change of the unemployment rate,
- *d1_n_empl_ds* – de-seasoned quarterly change in the number of persons employed in the economy,
- *dm_car* – capital adequacy ratio – deviation from sector median,
- *b_hous_ln_share* – bank-level share of housing loans in loans to households,
- *b_hh_ln_share* – bank-level share of loans to households in loans to the non-financial sector,
- *dm_ln_nf_gr_qq_all* – bank-level loan growth, deviation from sector mean,
- dummy variables for classification into strategic groups. Interactions of group classification and macroeconomic variables were used to investigate possible differences in sensitivity to macroeconomic factors. Interaction variables were denoted by prefixes *g1* through *g5*,

[17] A fixed effects specification does not require the assumption of no correlation between explanatory variables and individual effects. Since explanatory variables include bank-specific characteristics, such correlation cannot be excluded a priori.

[18] All models were estimated with Stata 9.0SE, using procedures xtreg and xtregar.

[19] Baltagi-Wu LBI statistics (see Baltagi et al.[6]) are also reported.

[20] A dynamic model using the Arellano-Bond approach was also investigated, but preliminary results were unstable and sensitive to the choice of instrumental variables.

3

- quarterly dummies used to account for seasonality (denoted *q1*, *q2*, *q3*}),
- dummies for regulatory changes.

The estimated coefficients for macroeconomic variables have the expected signs: an increase in real interest rates, and increase in unemployment rate, a fall in employment and a slowdown in GDP growth increase the loan losses of banks. Changes in the exchange rate, however, do not influence loan losses. This result is upheld even when the change in exchange rate is weighted with bank-level share of FX loans in portfolio.

Debt burden variables are not found to have significant influence. The joint effects of interest rate changes and debt burden were also not significant. An alternative solution would be to use debt burden variables calculated on the basis of CSO consumer finance surveys (see NBP [33], pp. 22-26 and Zajączkowski and Żochowski [45]). However, the accuracy and representativeness of these data are far from perfect.[21]

Table 2

Estimation results: changes in employment as explanatory variable, fixed effects model with AR(1) disturbance

Variable	Coefficient	Std. Err.
L2.dm_ln_nf_gr_qq_all	0.003728***	0.001241
L4.dm_ln_nf_gr_qq_all	0.003170***	0.001162
L4D.rwib3m	0.027472***	0.010386
L.b_hh_ln_share	0.663455***	0.161117
L.b_hous_ln_share	-1.011840***	0.25851
L2.d1_n_empl_ds	-0.001163***	0.000182
L3.d1_n_empl_ds	-0.000611***	0.000178
L4.d1_n_empl_ds	-0.000626***	0.000167
L2.dm_car	-0.003004	0.001862
group4	-0.183825**	0.083234
Dummy_reg04	-0.071999*	0.04059
Dummy_ifrs	-0.025748	0.042529
q1	-0.149346***	0.025131
q2	-0.069741**	0.027973
q3	-0.112924***	0.02651
Intercept	0.265803***	0.053581
N	1436	
Hausman χ^2 (14)	39.11	p-value: 0.0004
Bhargava et al. Durbin-Watson	1.5981178	
Baltagi-Wu LBI	1.8668553	
Error term autoregression coefficient ρAR	0.27180124	

Significance levels: * – 10%, ** – 5%, *** – 1%.
L is the lag operator (LS.variable(t)=variable(t-S)), D is the difference operator (D.variable(t)=variable(t)-variable(t-1)).
Reported Hausman test statistics refer to the choice between random and fixed effects models.
Source: Author's calculations.

In the area of measures of bank business profile, the structure of bank lending portfolio has the most pronounced effect. Somewhat surprisingly, a higher share of loans to households in portfolio increases loan losses. Research for banking systems in developed countries often shows than lending to households is in general less risky than lending to corporations. This can be explained by a higher share of housing loans in loans to households in those countries.[22] This is corroborated by the negative influence of the share

[21] Due to a relatively small percentage of households which have taken out bank loans in the whole population (surveys estimated this percentage at around 10% in 2004) and the fact that CSO surveys base their sample size on the whole population of households, the conclusions for the population of borrowers may be inaccurate due to small sample problems. Furthermore, consumer finance surveys suffer from selection bias as it is common for higher income households to refuse to participate.
[22] The share of housing loans in loans to households in Euro area countries amounted to 69% in 2005, while the same figure for Poland stood at 37%.

of housing loans on loan losses. The classification of banks into strategic groups has only minor effects – loan losses are on average lower at specialised banks, while universal banks have a higher than average sensitivity to unemployment changes and corporate banks have a higher sensitivity to GDP growth.

Table 3
Estimation results: GDP growth and change in unemployment rate as explanatory variables, random effects model with AR(1) disturbance

Variable	Coefficient	Std. Err.
L2.dm_ln_nf_gr_qq_all	0.002606**	0.001134
L4.dm_ln_nf_gr_qq_all	0.003230***	0.001065
LD.rwib3m	0.018020*	0.010705
L2D.rwib3m	0.029160***	0.011243
L4D.rwib3m	0.021258**	0.009851
L.b_hh_ln_share	0.509281***	0.071499
L.b_hous_ln_share	-0.506402***	0.129059
L.pkb	-0.018327**	0.00741
L5.pkb	-0.010357	0.006306
L.d4_unempl	0.026301***	0.007528
L2.dm_car	-0.005588***	0.001372
group4	-0.134560**	0.05484
Dummy_reg04	-0.031021	0.042976
Dummy_ifrs	-0.111963***	0.043102
q1	-0.172162***	0.025651
q2	-0.108377***	0.027344
q3	-0.122931***	0.026871
Intercept	3.334669***	0.980104
N	1522	
Hausman χ^2 (17)	4.06	p-value: 0.9994
Bhargava et al. Durbin-Watson	1.5925142	
Baltagi-Wu LBI	1.8618574	
Error term autoregression coefficient ρAR	0.28290327	

Significance levels: * – 10%, ** – 5%, *** – 1%.
L is the lag operator (LS.variable(t)=variable(t-S)), D is the difference operator (D.variable(t)=variable(t)-variable(t-1)).
Reported Hausman test statistics refer to the choice between random and fixed effects models.
Source: Author's calculations.

Banks with low capital resources experience higher loan losses. However, the influence of capital adequacy is significant only at a short lag. This result does not seem to support the moral hazard hypothesis, as any changes to lending policy due to a "gamble for resurrection" approach would affect loan losses after a longer period (since the time needed for extension of loans under looser policy at a scale significant for the whole portfolio and the time needed for them to "go bad" seems much longer than 6 months).

Table 4
Estimation results : GDP growth and change in unemployment rate as explanatory variables, group-specific sensitivity, random effects model with AR(1) disturbance

Variable	Coefficient	Std. Err.
L2.dm_ln_nf_gr_qq_all	0.002644**	0.001132
L4.dm_ln_nf_gr_qq_all	0.003373***	0.001066
LD.rwib3m	0.018231*	0.010704
L2D.rwib3m	0.029884***	0.011232
L4D.rwib3m	0.019767**	0.009851
L.b_hh_ln_share	0.490450***	0.074849
L.b_hous_ln_share	-0.511053***	0.127353
L.pkb	-0.018053**	0.007402
L5.pkb	-0.010345	0.006295
L5.g2_pkb	-0.000819*	0.000432
L.d4_unempl	0.012205	0.009239
L.g5_d4_unempl	0.030948**	0.012137
L2.dm_car	-0.005508***	0.001364
group4	-0.136769**	0.054344
Dummy_reg04	-0.028494	0.042917
Dummy_ifrs	-0.109788**	0.043074
q1	-0.172338***	0.025608
q2	-0.109822***	0.027306
q3	-0.121996***	0.026836
Intercept	3.325580***	0.977649
N	1522	
Hausman χ^2 (19)	5.27	p-value: 0.9992
Bhargava et al. Durbin-Watson	1.5910264	
Baltagi-Wu LBI	1.8584192	
Error term autoregression coefficient ρAR	0.28297537	

Significance levels: * – 10%, ** – 5%, *** – 1%.
L is the lag operator (LS.variable(t)=variable(t-S)), D is the difference operator (D.variable(t)=variable(t)-variable(t-1)). Reported Hausman test statistics refer to the choice between random and fixed effects models.
Source: Author's calculations.

The effects of regulatory changes in 2004 and 2005 are uncertain, as the significance of dummy variables varies between specifications.

3

4

A stress testing exercise

This section provides an example of a macro stress test exercise conducted using the credit risk model developed above. The exercise was based on balance sheet data of commercial banks as of end of March 2007.

4.1 Stress scenario construction

The choice of stress scenarios is one of many areas where financial stability analysis is much more art than science. In principle, several approaches may be considered.[23] The first question that needs to be answered concerns the use of macroeconomic models (regardless of whether they are estimated or calibrated). While their use should support the internal consistency of the scenario, concerns arise over their ability to accurately reflect the behaviour of the economy in response to "tail events". An alternative approach is to use the behaviour of the economy during a past crisis period as a stress scenario. While this approach by definition uses an internally consistent response of the economy to a "tail event", the causes of past crisis events may be very different to present financial stability risks.

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Table 5
Definitions of stress scenarios

Scenario definition	Transmission channels – macro model	Transmission channels – credit risk model
Oil prices double permanently	• lower foreign growth → lower foreign demand • positive inflation impulse causing monetary policy reaction → higher real interest rates → lower economic growth, higher unemployment	• increasing losses: higher real interest rates, lower economic growth, higher unemployment • decreasing losses: none
30% depreciation of domestic currency for 8 quarters	• positive inflation impulse causing monetary policy reaction → higher real interest rates • higher foreign demand through higher export competitiveness → higher economic growth, lower unemployment, increase in inflationary pressure → further increase in real interest rates	• increasing losses: higher real interest rates • decreasing losses: higher economic growth, lower unemployment
Decrease in domestic demand through shock to consumer wealth	• lower private consumption through wealth effect → lower economic growth, higher unemployment, decrease in inflationary pressure → monetary policy reaction → slightly lower real interest rates	• increasing losses: lower economic growth, higher unemployment • decreasing losses: slightly lower real interest rates

Note: the words "lower" "higher" are used to signify comparisons with the baseline scenario.
Source: Author's compilation.

If a macroeconomic model is used, the second crucial question is the choice of the source of shocks that hit the economy in a crisis scenario. One solution is to choose them "ad-hoc" i.e. through expert assessment. This type of choice is easier to communicate in terms of an economic "story" behind the scenario, but it may be hard to assess the probability of its occurrence. Another solution is to choose a scenario with a pre-specified probability of occurrence. This can be done by using distributions of residuals from macroeconomic models and/or fancharts as a starting point. The economic logic behind these scenarios may be however much harder to communicate.

23 The brief discussion here is limited to the case when the model used for evaluating credit risk (or other types of risk) delivers point forecasts.

In the exercise presented in this paper the choice was made to investigate stress scenarios based on three ad-hoc shocks, whose impact on the economy would be assessed through the NBP's macroeconomic model of the Polish economy ECMOD (see Fic et al. [18]). This was done to facilitate the communication of results. The stress scenarios are summarised in Table 5. The simulations were run assuming a monetary policy reaction according to a Taylor rule minimising the deviations of inflation from target and GDP from potential. This type of monetary policy function captures the essential features of monetary policy, but does not constitute a prediction of how monetary policy would react in a crisis. The time horizon of simulations was 3 years which is the same as for official NBP inflation projections. While this type of time horizon makes macro feedback effects a potential worry, no attempt has so far been made to include them in the models used.

4.2 Stress test results

The impact of stress scenarios on the banking sector is summarised in Table 6. The results confirm that the profitability and capitalisation of the Polish banking sector are sufficient to absorb an increase in loan losses caused by adverse macroeconomic scenarios. The oil price increase scenario has the highest impact on loan losses. It also highlights that policymakers might have to face a significant dilemma when reacting to supply-side shocks to the economy.

The stress test results, while informative, are nevertheless subject to significant model risks. The largest source of model risk is probably the housing loans portfolio which has been expanding very rapidly since 2004 and consequently its reaction to macroeconomic shocks has not yet been observed. Another source of uncertainty lies in the apparent lack of reaction of loan losses to exchange rate changes. Given that FX loans account for 27% of all loans to the non-financial sector and 45% of loans to households[24] (the vast majority of which have no hedge) this risk is potentially significant. These risks need to be monitored and stress tested using other approaches (for an example, see Zajączkowski and Żochowski [45]).

Table 6
Results of stress scenarios

	Average yearly LLP flow as % of capital	Average % of 2006 profit before LLP needed to cover LLP
Baseline	4.8%	24.9%
Oil shock	7.5%	38.6%
FX shock	5.4%	28.1%
Domestic demand shock	6.8%	35.4%

Source: Author's compilation.

[24] As of end of March 2007.

5

Conclusions

This paper identified several macroeconomic factors that influence loan losses of Polish banks. The results are generally comparable with results obtained for other countries. In contrast to some other countries, debt burden measures are not found to influence loan losses. The structure of the loan portfolio is identified as an important factor determining differences in loan losses between banks.

There are several caveats attached to the results. The sample contains only one full business cycle which is generally considered to be a minimum for such research. The Polish banking sector underwent rapid development during that period – many types of lending products (mortgage loans, credit cards) which were of little importance in 1997 now have a large influence on the performance of banks. The rapid growth of mortgage lending, coupled with rising property prices in 2005-2006 is a significant source of uncertainty both with regard to the ability of the model to produce accurate forecasts and future financial stability.

Future development of the model could aim at identifying ways to include meaningful measures of debt burden and of risks related to exchange rate movements, as well as developing a dynamic specification of the model.

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