Forecasting the Net Interest Margin and Loan Loss Provision Ratio of Banks in Various Economic Scenarios: Evidence from Poland

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The aim of stress-testing is to test the resilience of the banking sector to negative developments on the financial markets and in the real economy. One of the key issues in stress-testing is the translation of various scenarios into bank-level risk parameters and the determination of their impact on banks’ profitability or loss-bearing capacity. This paper has two objectives. The first is to identify key macroeconomic determinants of the loan loss provision ratio and net interest margin. The second is to show how satellite models can be applied in stress-testing exercises to determine the impact of macroeconomic outcomes on banks. We contribute to the empirical literature by defining macroeconomic determinants for credit risk on the basis of three different credit portfolios (consumer, mortgage, and corporate) for banks operating in Poland. Our estimation results suggest that economic growth, the labour market, and market interest rates have a significant influence on the net interest margin and loan loss provision ratio.

Keywords: net interest margin, loan loss provision ratio, stress-testing, financial stability, panel estimation
JEL Codes: E51, G21, C33

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1. Introduction

Banks serve an important role in both the financial system, and the economy. The global financial crisis (GFC) vividly demonstrated the importance of having

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1 Some of the concepts in this paper were presented at the IMF-Bank of Russia Seminars: Recent Developments in Macroprudential Stress Testing, 4–5 September 2018 in Moscow. I would like to thank all the participants for their useful comments and suggestions. The views expressed are my own and should not be attributed to the National Bank of Poland. All errors are my sole responsibility.
sound banks capable of withstanding unexpected and extreme shocks. Indeed, only banks that are resilient to adverse economic shocks, and are able to generate sufficient income in times of distress, can act as sound and efficient financial intermediaries throughout the economic cycle. This is a prerequisite for ensuring a smooth flow of credit to the real economy in periods of economic instability as well (Kok et al., 2017).

With the aim of ensuring a financial system that functions well and supports economic growth, macro stress tests are often used for forward-looking evaluation in a forward-looking manner of the resilience of the banking sector to adverse macroeconomic and financial developments (Dees et al., 2017). Put simply, the key tasks in financial stress testing include (Henry and Kok, 2013): (i) developing a severe but plausible economic scenario, (ii) translating the macroeconomic scenario into microeconomic consequences for financial institutions’ balance sheets, (iii) assessing the behaviour of financial institutions under stress, (iv) deciding on financial infrastructure resilience criteria, and (v) communicating the results. In this paper we direct our attention to the second pillar of the stress testing process, considering the design of the macrofinancial linkage models (‘satellite models’) that are used to translate a macroeconomic scenario into risk parameters at the bank level and to determine the impact of this scenario on banks’ profitability or loss-bearing capacity (see Ong, 2014).

Macroeconomic slowdowns can affect banking system stability through several channels. In general, lower economic growth reduces the ability of households and corporates to repay their loans, leading to deterioration in the quality of banks’ loan portfolios. This means lower profitability due to increased provisions for impaired loans, and can lead to a decrease in banks’ capital adequacy ratios. On the other hand, economic conditions may also influence banks’ margins: for instance, a decrease in economic activity can lead to lower demand for credit and other financial services, which in turn reduces potential gains for banks. Therefore, once a set of scenarios has been produced within a consistent macroeconomic framework, the next step is to determine the impact of the various outputs on the balance sheets and income statements of financial institutions.

Macroeconomic models typically do not include financial variables crucial to the assessment of banks’ condition, such as credit risk or interest margins. Stress-testing exercises therefore use so-called ‘satellite models’ that translate macroeconomic outcomes into figures on balance sheets. Ideally, these models should be estimated exclusively on data from crisis periods to ensure that they capture correlations that materialise under conditions of stress. However, there is often insufficient data coverage to permit a focus on crisis periods alone. The other drawback of this approach is that the regulatory environment changes over time, shaping banks’ reactions to developments in economic conditions. As a result, satellite models are usually estimated on a full sample from mostly
non-crisis periods, producing two projections: baseline and adverse. Model projections are subject to judgement-based adjustment to account for regulatory and market changes in lending standards.2

Our goal is to shed light on the relationship between key components of bank profitability (net interest margin (NIM)), a key risk element (loan loss provision, (LLP) ratio), and macroeconomic factors. With the help of satellite models, we focus on the impact of various macroeconomic scenarios on banks’ risk-performance ratios. With this in mind, we set two objectives. First, we aim to examine in more depth the relationship between selected elements of profit and loss accounts and macrofinancial variables. Second, we attempt to develop benchmark models that can be used to project the LLP ratio and NIM into the future, taking as input the macroeconomic projections resulting from a specific scenario. To the best of our knowledge, we are the first researchers to define the macroeconomic determinants for credit risk on the basis of three different credit portfolios (consumer, mortgage, and corporate) for banks operating in Poland.

The rest of the paper is structured as follows. In Section 2 we review the literature concerning the determinants of LLP and NIM. In Section 3 we briefly describe how macrofinancial scenarios were developed. In Section 4 we discuss our empirical strategy and data. In Section 5 we present the results from our two satellite models, and in the last section we conclude.

2. Literature review

The empirical literature on the factors influencing credit risk and its interrelationship with macroeconomic conditions is grounded in theoretical models of the business cycle, which give an explicit role to financial intermediation (Nkusu, 2011). Financial accelerator theory, as discussed in Bernanke and Gertler (1989), Bernanke et al. (1999), and Kiyotaki and Moore (1997), is very much in the spirit of these models, and has become the most influential theoretical framework for modelling macrofinancial linkages.

Various studies have been carried out on the effects of the business cycle on the aggregate default rate of corporates and households. On the micro level, a comprehensive survey of the literature concerning cyclical effects on the major credit risk parameters (probability of default (PD), loss given default (LGD), exposure at default (EAD)) is provided by Allen et al. (2004). All three credit risk parameters are found to be highly exposed to cyclical effects, implying a considerable impact on portfolio credit risk and capital requirements.

2 Just as all models do, stress tests rely on historical data to estimate empirical relationships among data series. Given typical econometric techniques, these models reflect average past relationships between variables, rather than the variables’ interactions under stress. This renders the substantial role of judgement in the exercise acceptable, even desirable.
The empirical literature identifies broad groups of macroeconomic drivers for non-performing loans (NPLs): benign economic conditions, as captured by real GDP or other indicators such as industrial production, construction, or rising commodity or food prices, depending on the specificities of each country, mean that borrowers can service their loans; the number of NPLs therefore decreases (Ghosh, 2016; Beck et al., 2015).

Numerous panel data studies explain NPLs in a cross-country context (Nkusu, 2011; Klein, 2013; Castro, 2013; Beck et al., 2015), while other studies focus on a single country’s financial sector (De Bock and Demyanets, 2012; Louzis et al., 2012; Ghosh, 2016). Castro (2013) finds that the macroeconomic environment significantly affects banks’ credit risk, a phenomenon which was particularly in evidence during the recent financial crisis, and documents the significant impact of GDP growth, share price indices, the unemployment rate, interest rates, credit growth, and the real exchange rate dynamics.

Empirical literature on the determinants of NIM is based on the dealership model developed by Ho and Saunders (1981). In this model, a bank is a risk-averse financial intermediary between borrowers and lenders. It charges a fee for providing liquidity services, i.e. for immediately accepting deposits and granting loans. Whenever the volume of loans does not match the volume of deposits, the bank resorts to the short-term money market to cover the gap. In so doing, the bank becomes more vulnerable to refinancing or reinvestment risk. This risk is covered by the imposition of a fee, which increases with interest rate volatility. Additional explanatory factors underpinning interest spreads are the average transaction size, the bank’s degree of risk aversion, and the degree of competition in the reference market (Bologna, 2018).

Angbazo (1997), and Maudos and de Guevara (2004) do away with some of the simplifying assumptions and extend the model by incorporating credit risk and interest rate risk. They show that banks with more risky loans and higher interest-rate risk exposure select loan and deposit rates to achieve higher NIM. Empirical research stemming from these contributions has focused on the use of additional control variables. Most studies use proxies for credit risk (Maudos and de Guevara, 2004), interest rate risk (Entrop et al., 2015; Hawtrey and Liang, 2008; Maudos and de Guevara, 2004), and operating costs (Liebeg and Schwaiger, 2006; Entrop et al., 2015) as the key explanatory variables underpinning NIM; market structure and institutional factors are also controlled for in much of the available research.

Finally, macroeconomic factors too influence the NIM since changes in the economic conditions affect the banking system as a whole at a given point in time. In most empirical studies, GDP growth is used as a control variable and is assumed to have a positive correlation with NIM (Horvath, 2009; Gunter et al., 2013). Many papers take into account market interest rates of different maturities and/or their respective standard deviation to consider the development of both the short
and the long end of the yield curve. Only a few papers include such additional macroeconomic variables as inflation (Horvath, 2009; Entrop et al., 2015) and market interest rate spreads (Rumler and Waschiczek, 2016).

3. Adverse scenario development and simulation

The starting point for the stress-testing framework is the process of designing an appropriate macrofinancial scenario. It generally consists of two steps. The first step concerns the main systemic risks identified as pertinent at a given juncture. These risks will need to be mapped to scenario building blocks that correspond to the general storyline that the stress-tester is aiming to capture. As for the second step, once the scenario building blocks have been defined and expressed as exogenous shocks to specific variables representing the relevant risk factors, the impact of these shocks on the wider macroeconomic and financial environment must be quantified using relevant modelling techniques (Henry and Kok, 2013).

According to the Basel Committee on Banking Supervision (2017), scenario design is a critical aspect of supervisory stress tests. Hence, considerable attention is paid to the scenarios and their severity when authorities publish their stress-testing results. Nearly all countries use macroeconomic forecasting models to generate paths for key macroeconomic variables. While some jurisdictions use the same model that is used by central banks for monetary policy projections, others appear to rely on smaller, simpler macroeconomic models.

At the ECB, systemic risks are identified on the basis of regular financial stability monitoring exercises, which apply a wide range of systemic risk indicators and early warning models for this purpose. On the basis of this list of key risks, the ECB carries out a systemic risk assessment to gauge the impact of these risks materialising on the resilience of the financial system and its ability to support the real economy. Once systemic risks have been mapped onto exogenous shocks, various shock simulation tools are employed to determine the relevant shock sizes and profiles. In the next step, the macrofinancial scenario is generated by relevant macroeconomic models, using the calibrated shocks as inputs. The output of these models is a projected path for a broad range of country-specific macrofinancial variables (Henry and Kok, 2013).

In Poland, the National Central Bank of Poland (NBP) uses the structural macroeconometric model NECMOD in order to produce a coherent scenario, employing a broad selection of macrofinancial variables (Budnik et al., 2009). The projected financial position of the banking sector is examined on the basis of two scenarios which span a three-year horizon: a reference scenario and a shock scenario. The central path of the NBP’s macroeconomic projection is taken from its Inflation Report (Narodowy Bank Polski, 2015a), prepared with the assumption of constant interest rates, which serves as the reference scenario. The adverse scenario is designed on the basis of the main systemic risks to the banking sector identified as pertinent at a specific juncture. This set of risks is mapped onto exogenous shocks
(see Narodowy Bank Polski, 2015). The calibrated shock profiles serve as the input to dynamic macroeconometric models used to project macroeconomic and financial variables, which constitute the output for the scenario (see Figure 1) (Borsuk and Krzesicki, 2019).

**Figure 1.** Stressed GDP and CPI compared to fan charts

![Graph showing stressed GDP and CPI compared to fan charts](source: Narodowy Bank Polski (2015))

Historically, the main factor affecting the profitability of Polish banks was the number of write-offs for bad loans and net interest income. In this paper, we present econometric models that quantify the influence of the macroeconomic variables generated for the baseline and adverse scenarios on credit risk costs (proxied with LLP) and NIM. This is achieved by applying a satellite model which relates balance sheet and profit and loss (P&L) account items, on the one hand, with macroeconomic variables, on the other.

### 4. Empirical strategy

#### 4.1. Data

Our empirical analysis is based on quarterly data reported by all the commercial banks operating on the market from 1997 to 2015, covering approximately 85%
of the banking sector in Poland. We do not include cooperative banks, which account for about 10% of the total assets of the banking sector. However, two association-leading banks are included in the sample due to their systemic importance for the more than 500 stand-alone cooperative banks operating in Poland. Data coverage is therefore broad enough to represent a meaningful mass of banks, while keeping the number of participants involved at a feasible level.

To account for mergers and acquisitions, we carefully go through all M&As and ensure that only the merged entity or the acquiring bank remains in the sample after a takeover. For example, if bank A was acquired by bank B, we sum up the historical data for these banks and leave only active bank B in the sample. In addition, we exclude from our calculations banks for which insufficient observations are available, i.e. banks that do not have data for at least eight quarters, or have an insignificant share of a given portfolio. Finally, before running the regressions, all data are winsorised at the 1st and 99th percentiles to reduce the effect of outliers.

In credit models, accumulated credit risk losses are represented by the stock of LLPs, which reduce the balance sheet value of impaired loans. There are several reasons for the choice of this variable, which is normalised between banks by dividing it up between portfolios containing different types of loans (Głogowski, 2008): (i) the definition of a non-performing loan changed several times during the sample period, (ii) data on non-performing loans has been available only since mid-2003, (iii) the format of supervisory data does not allow the flow of impaired loans to be broken down by type of borrower, type of loan, or loan currency before 2008, and (iv) data on the PDs and LGDs of banks’ portfolios are not available, so a representative sample cannot be formed. In order to perform stress-testing exercises, LLPs (a balance sheet item) must be converted into impairment losses (an income statement item). Due to the high correlation between these, impairment flows can be estimated on the basis of changes in LLPs after adjusting for the effect of portfolio sales and other write-offs.³

For NIM, we model annualised net interest income as a percentage of average levels of assets. However, we make some small corrections to the nominator, deducting interest earnings from debt securities and adding loan commissions. The rationale for this adjustment is that interest on bonds is in most cases fixed until the bond expires, while loan commissions are sensitive to market conditions and economic developments (in other words, they largely depend on credit growth).

Many bank risk studies highlight the strong negative relationship between economic cycle and bank risk exposure. As economic conditions for businesses worsen during recessions, the riskiness of intermediation tends to increase. Thus, macroeconomic conditions can be a trigger for systemic changes that are of great

³ This adjustment can be made by adding the average difference between those two items from the last eight quarters.
significance for credit risk. On the other hand, NIM exhibits persistence over time and tends to react very slowly to any change in economic conditions. In comparison to LLP ratio, NIM shows less variability during the period analysed (Figure 2). The downward trend is mainly associated with interest rate cuts, which were historically very high in Poland. The relationship with other macroeconomic variables is not so obvious or straightforward, which means that the process of model specification is not an easy task.

Figure 2. Development of NIM, LLP, and economic cycles in Poland, %

Credit risk is inherent in lending – the traditional activity of banks – and creates the most significant risk exposure for all the banks in our sample. Polish banks’ balance sheets largely consist of loans and receivables (68%). Of these loans and receivables, the mortgage loan portfolio is the biggest, representing 33% of all loans. Other relevant lending portfolios include corporate and consumer loans (30 and 13% respectively). As credit risk is the most significant type of risk exposure for Polish banks, factors driving losses in credit portfolios merit a great deal of attention.

Net interest income represents a substantial part (65%) of the operating income of all banks in the sample, as most of the Polish commercial banks maintain a traditional business model, with a large share of loans and deposits in relation to total assets. For this reason, the importance of NIM as a measure of the profitability of financial intermediation cannot be neglected.

Given the above, we base the model selection process on expert judgement and a statistical procedure (see Section 4.2 below). We consider economic growth and the condition of the labour market and financial markets as the main determinants of NIM and LLP. The final selection results are summarised in Tables 1 and 2. Along with the variables specified in the tables, we also test many other explanatory
variables that, according to the literature, could have a significant impact on NIM (e.g. interest rate volatility, or the shape of the yield curve) and LLP (e.g. house prices, or CDS spreads). In fact, we consider more than 30 explanatory variables for use in the models. Preference is given to variables for which forecasts can be obtained from the macro model (NECMOD).

Table 1. Credit risk models – explanatory variables

| Variable                  | Abbreviation | Sign | Description                                                                 | Unit           |
|---------------------------|--------------|------|------------------------------------------------------------------------------|----------------|
| CHF exchange rate         | CHF          | +    | Influences instalment of mortgages denominated in CHF                        | Level (PLN)    |
| GDP                       | GDP          | -    | Proxy for economic activity                                                 | Change (YoY, %) |
| Interest rate             | WIBOR        | +    | Most loans in Poland are floating-rate loans, so this affects the size of instalments | Level (%)     |
| Employment                | EMP          | -    | Proxy for unemployment and company condition                                | Change (YoY, %) |
| Real wage fund            | WAGE         | -    | Determines disposable income and so loan repayment capacity                  | Change (YoY, %) |

Note: this table presents the macroeconomic variables (with notation and description) that influence the LLP ratio of Polish banks; YoY – year-over-year. Sign denotes a theoretically expected sign.

Table 2. NIM model – explanatory variables

| Variable                  | Abbreviation | Sign | Description                                                                 | Unit           |
|---------------------------|--------------|------|------------------------------------------------------------------------------|----------------|
| GDP                       | GDP          | +    | Increased economic activity leads to higher demand for credit, allowing banks to use higher margins | Change (YoY, %) |
| Short term interest rate | WIBOR        | +    | Banks tend to charge higher commissions and margins in times of tightening monetary policy | Level (%)     |
| Credit losses             | PROV_RATIO   | -    | No interest is paid on non-performing loans                                 | Level (%)     |

Note: this table presents the macroeconomic variables (with notation and description) that influence NIM of Polish banks; YoY – year-over-year. Sign denotes a theoretically expected sign.

4.2. Methodology

The effect of realisation of adverse macroeconomic scenarios on credit risk cost projection and NIM projection is captured using econometric panel models. These models combine data from individual banks’ regulatory reports with macroeconomic indicators. It is assumed that all banks are influenced by changes in their economic environment in the same way. Credit losses are modelled separately in three portfolios: consumer, corporate, and mortgage. Due to the lack of data on individual borrowers, it is assumed that these portfolios are homogeneous.

To account for banks’ individual characteristics in terms of their credit loss and NIM-generating process, we decided to use a fixed effects panel model. The standard version of the fixed effects model takes the following form (Diggle et al., 2002):
where: $y_{it}$ – dependent variable, $\alpha_i$ – individual effects, $x_{it}$ – explanatory variables, $\beta$ – parameters, common for all banks, $\varepsilon_{it}$ – error term. In this model we assume that the reaction to changes in economic environment ($\beta$) is the same for each individual bank. This obvious shortfall of the particular model is caused by the lack of data to estimate individual banks elasticities to the external changes in economic environment.

Both credit losses and NIM do not tend to change rapidly over time, because credit conditions and loan quality are the result of past decisions to grant a loan. The quality of a credit portfolio largely depends on the credit policy from the moment the credit is granted. The NIM of a portfolio is influenced by the conditions of a contract which is already signed. To capture the high persistency of both credit losses and macroeconomic processes, lagged variables are used:

$$y_{it} = \gamma y_{i,t-1} + x_{it}^{T} \beta + (\alpha_i + \varepsilon_{it}).$$  

(2)

The use of a dynamic model creates a problem concerning the correlation between lagged dependent variables and individual effects. It is proven that the inclusion of a lagged dependent variable in a panel framework can yield biased and inconsistent estimates due to the correlation between the lagged dependent variables and the error terms (Nickell, 1981 and Kiviet, 1995). However, this problem can be avoided by use of the estimation techniques proposed by Blundell and Bond (1998), based on the System Generalised Method of Moments (S-GMM) method. The approach combines the original equation in levels and an equation in differences:

$$y_{it} = \gamma y_{i,t-1} + x_{it}^{T} \beta + (\alpha_i + \varepsilon_{it}),$$  

(3)

$$y_{it} - y_{i,t-1} = (\gamma y_{i,t-1} - \gamma y_{i,t-2}) + (x_{it}^{T} - x_{i,t-1}^{T}) \beta + (\varepsilon_{it} - \varepsilon_{i,t-1}).$$  

(4)

To conclude, as our baseline estimator, we use the S-GMM technique for the dynamic panel data models to estimate cross-bank regressions. As GMM becomes inconsistent as the number of instruments becomes too large, we restrict the maximum lag to four periods.\(^4\) In comparison with the conventional static

\(^4\) GMM performs best with large cross-section dimension $N$ and relatively small time dimension $T$, so $N$ in most cases should be greater than $T$. An important issue with GMM is the problem of 'too many instruments', since the number of instruments should be less than the number of the cross-sections, as was highlighted by Roodman (2009).
panel data regression model, the S-GMM technique seems more efficient and consistent in estimating the coefficients, and also controls for the potential issues of heterogeneity, autocorrelation, and endogeneity. Finally, we perform several post-estimation validation tests, including the Hansen test, which verify the overall strength of the instruments. The estimated models are also checked for autocorrelation using the AB test (see Arellano and Bond, 1991).

Several unit root tests applied in the time-series literature have been extended to panel data. The issues involved in combining the individual unit root tests applied on each series when the panel data are both heterogeneous and non-stationary are tackled by Im et al. (2003), Maddala and Wu (1999), and Choi (2001). We follow the augmented Dickey-Fuller (ADF) test, which takes potential serial correlation in the error term into account; this is achieved by introducing lagged terms of the dependent variable. The Fisher-ADF panel unit root test indicates that most of the variables employed in the regressions are stationary even at the 1% significance level (Table 3).

| Variable          | Level  | Variable | Level          |
|-------------------|--------|----------|----------------|
| Cons_loans_cover  | 138.8342 (0.00) | WAGE      | 3591.7113 (0.00) |
| Corp_loans_cover  | 128.0587 (0.07) | WIBOR     | 390.9048 (0.00)  |
| Hous_loans_cover  | 73.0196 (0.44)  | EMP       | 350.5661 (0.01)  |
| NIM               | 143.9432 (0.44) | CHF       | 4.1855 (0.50)    |
| GDP               | 1093.0429 (0.00) | PROV_RATIO | 4.1572 (0.00)    |

Note: $p$-values for the Fisher-ADF panel unit root test are computed using the asymptotic chi-squared distribution, and are given in brackets.

Model selection is based on the statistical significance of the explanatory variables, the consistency of the signs with economic theory, in- and out-of-sample forecasting error, the determination coefficient, and the shock sensitivity of the model. It is essential for the credit loss or NIM model to have the correctly specified sign, so that hypothetical worsening of economic conditions leads to an increase in credit losses and dwindling NIM. Moreover, the stress-testing model is properly estimated if it can reproduce real credit losses in real-life macroeconomic

Contradicting the single time-series spurious regression literature, Baltagi (2008) indicates that the panel data spurious regression estimates give a consistent estimate of the true value of the parameter as both $N$ and $T$ tend to infinity. This is because the panel estimator averages across individuals and the information in the independent cross-section data in the panel gives a stronger overall signal than in the case of pure time series. As our sample (both $N$ and $T$) is large we have decided not to transform the data into differences in order not to lose the long-term relationship between our interest variables. What’s more, one of the problems with unit root tests is that they often give mixed results, something we have also experienced using alternative methods of testing.
conditions. To account for this, the following in- and out-of-sample forecasting errors were calculated (Wooldridge, 2010):

- **MAE (ABSOLUTE)** – mean average absolute error
- **MAPE** – mean average percentage error
- **MAPE ASSETS** – MAPE weighted by each bank’s assets
- **RMSE** – root mean squared error

All those errors are calculated in-sample and, more importantly, out-of-sample, with a three-year testing horizon. Asset-weighted errors are included so that the models better reflect the general condition of the banking sector instead of concentrating on smaller banks’ behaviour. Another reason for this is that smaller banks tend to shape their credit portfolio in accordance with reasons that may not be correlated with economic conditions, but rather with internal corporate capital flows or regional events. In the case of small banks, it should be noted that a relatively limited number of events (such as defaults) that can happen at random may result in bigger portfolio changes. In Figure 3 it can be seen that models produce quite reasonable out-of-sample forecasts for periods affected by the GFC and European debt crisis (2008–2011).

**Figure 3.** Out-of-sample forecasts for LLP ratio and NIM over the period of the GFC, %

![Graph showing out-of-sample forecasts for LLP ratio and NIM over the period of the GFC.](source: author’s calculations)
5. Results

The estimated coefficients for macroeconomic variables in credit risk equations have the expected signs and are statistically significant (Table 4). The lagged LLP ratio is significant in each estimated model, which indicates the high persistency of credit losses over time. Looking at the macroeconomic variables, it can be seen that consumer credit losses diminish with GDP growth and wage fund growth, while interest rate growth has the opposite effect. All economic variables are lagged for two periods. Corporate losses are also strongly adversely correlated with GDP growth. The other significant factor is employment, which can be treated as a proxy for the financial condition of firms. House loans depend on GDP and the CHF exchange rate. This is a result of the significant loans portfolios of FX houses, which are denominated mostly in CHF.

Table 4. Estimation results

|                      | Cons_loans_ratio | Corp_loans_ratio | Hous_loans_ratio | NIM        |
|----------------------|------------------|------------------|------------------|------------|
| Cons_loans_cover (-1)| 0.9619***        |                  |                  |            |
|                      | (0.01)           |                  |                  |            |
| Corp_loans_cover (-1)|                  | 0.9532***        |                  |            |
|                      |                  | (0.01)           |                  |            |
| Hous_loans_cover (-1)|                  |                  | 0.8441***        |            |
|                      |                  |                  | (0.00)           |            |
| NIM(-1)              |                  |                  |                  | 0.9206***  |
|                      |                  |                  |                  | (0.00)     |
| GDP(-2)              | -0.1284***       | -0.662***        | -0.0084***       | 0.0092**   |
|                      | (0.04)           | (0.015)          | (0.00)           | (0.00)     |
| WAGE(-2)             | -0.0268***       |                  |                  |            |
|                      | (0.00)           |                  |                  |            |
| WIBOR(-2)            | 0.0354***        |                  |                  | 0.0098***  |
|                      | (0.00)           |                  |                  | (0.00)     |
| EMP(-2)              |                  | -0.0343***       |                  |            |
|                      |                  | (0.01)           |                  |            |
| CHF (-2)             |                  |                  | 0.0015***        |            |
|                      |                  |                  | (0.00)           |            |
| PROV_RATIO(-1)       |                  |                  |                  | -0.0063**  |
|                      |                  |                  |                  | (0.003)    |
| Observations         | 2294             | 2869             | 1177             | 2191       |
| Number of banks      | 44               | 52               | 30               | 43         |
| Hansen test          | 0.616            | 0.619            | 0.961            | 0.585      |
| AR(2)                | 0.561            | 0.279            | 0.714            | 0.826      |

Note: standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Parameter estimates for other insignificant explanatory variables are not reported in the table. All models also underwent a series of statistical tests (AR(2) Arellano-Bond test (1991) and Hansen J test) for the GMM approach. The test results indicate the validity of the instruments used, as the over-identifying restrictions are fulfilled, and further show the absence of second-order autocorrelation in the residuals when using this estimator. Source: author’s calculations

In the NIM equation, short-term interest rates are found to be positively associated with banks’ NIMs. This result is also found in other studies (e.g. English et al., 2012; Claessens et al., 2018; Altavilla et al., 2017). The short-term interest rate result reflects the fact that bank deposit rates are typically
lower and stickier than market rates (since banks provide transaction services). In particular, banks often fund a portion of their interest-earning assets with non-interest-bearing liabilities, which primarily correspond to demand and transaction deposits. Therefore, a shift of the yield curve primarily affects the income side. NIM are also found to be positively associated with economic growth. Indeed, improving macroeconomic conditions should lead to an increase in credit demand and consequently in supply, and thus to an expansion of banks’ interest-earning opportunities. Conversely, low asset quality tends to compress NIMs. Interest rate volatility and the shape of the yield curve, two common drivers of NIM often mentioned in other studies, were economically and statistically insignificant and are excluded from the estimation process (as are the rest of the insignificant variables).

Figure 4. Forecasts for LLP ratio and NIM – base and adverse scenarios

Finally, a baseline and an adverse economic scenario for a three-year horizon between end-2015 and end-2018, prepared for stress-testing purposes, were plugged into the models to determine how the models projected banks’ behaviour under conditions of stress. The results are presented in Figure 4. It seems that the adverse scenario affects consumer and corporate loan losses much more than house loan losses and NIM. This result is consistent with
economic intuition. Households will first default on consumer loans, and only then will decide to default on their mortgage. It may also be true that clients who were given a mortgage are in a better financial state than other clients. Corporates are very vulnerable to economic conditions, especially if investment loans are considered. NIM exhibits persistence over time and tends to react very slowly to any change in economic conditions.

6. Conclusions

The use of macro stress tests to assess bank solvency has developed rapidly over the past few years. One of the key steps in the stress-testing framework is translating the scenarios into variables affecting the valuation of bank balance sheet components and banks’ capacity for loss absorption.

In this paper, we investigate the determinants of NIM and LLP ratio in the Polish banking sector. We assess the extent to which macroeconomic variables influence NIM and LLP. Furthermore, we show how satellite models can be employed to quantify the influence of the macroeconomic variables generated for the baseline and adverse scenarios on credit risk costs and NIM. This is achieved by applying a satellite model which relates balance sheet and profit and loss account items with macroeconomic variables. The results of our estimations suggest that economic growth, the labour market, and market interest rates have a significant influence on the NIM and LLP ratio.

The principal rationale for including only macrofinancial variables and not considering bank-specific variables is to be able to stress these parameters in the adverse scenario. Although adding some of the traditional risk-performance indicators (e.g. C/I, CAR, Size, or ROE) would possibly improve historical model fit, we would not be able to simultaneously establish a reliable forecast for these variables given our scenario. The only exception is credit losses, which are included in the NIM equation, but these are a direct result of the credit risk models.

Although the models presented in this paper perform relatively well in the out-of-the-sample forecast exercise, further analytical work is required, mainly as regards capturing non-linear effects and the interactions between risks.

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