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The impact of low interest rates on banks' non-performing loans

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Abstract

The paper examines the impact of a low interest rate environment on banks' credit risk measured by the non-performing loan (NPL)/total loans ratio. We analyse a unique sample of annual data on 823 banks from the Eurozone, Denmark, Japan, Sweden, and Switzerland for the 2011-2017 period, which also covers the period of zero and negative rates. We conclude that after 1 year of low interest rates, the NPL ratio increases. Our results are mostly consistent with the findings of previous research, and the majority of differences can be explained by the changes in the economic environment during the period with low interest rates.

AMS/JEL classification: C33, E43, G21

Keywords: banks, credit risk, low interest rates, non-performing loans

Introduction

In this paper, we contribute to the literature by analysing the impact of a low interest rate environment on banks' credit risk measured by the non-performing loan (NPL)/total loans ratio. After the 2007-2009 global financial crisis (GFC), central banks in several advanced economies decided to ease the macroeconomic environment by reducing interest rates towards the zero lower bound (ZLB). The motivations of the central banks differed, however. Some central banks, such as the European Central Bank, Sveriges Riksbank and Bank of Japan, cut rates to arrange further monetary easing to boost the economy and keep up with the inflation target (Demiralp et al., 2017; Hattori 2017). Other central banks, such as the Danmarks Nationalbank and the Swiss National Bank, employed the policy of negative interest rates mainly to prevent the excessive inflow of capital and thus prevent the overheating of the local economy (Bech & Malkhozov 2016).

This paper's objective is to model and analyse the potential impact of low interest rates on commercial banks and their credit risk management. Lowering overnight policy interest rates usually translates into bank-offered deposit rates following the same trend—cutting interest rates under the zero bound should theoretically yield the same policy targets as lowering interest rates in the range above zero. However, in the ZLB situation, banks might become reluctant to charge negative rates on deposits for some customers, such as retail clients. This can be naturally channelled into changes in risk structure, with banks preferring riskier loans to compensate for the change in costs (Bech & Malkhozov 2016).

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For the analysis, this paper uses a data set of Eurozone, Japanese, Swedish, Swiss and Danish commercial banks originating from the Orbis Bank database with observations for 823 different banks. The model controls for the effect of the negative interest rates, explains the bank-specific factors (for example, the size of the banks or the primary focus of business) and accounts for other macroeconomic variables in the examined countries. The specific objective of this paper is to test the following hypothesis: "A low-interest rate environment will influence the banks' NPL ratio after 1 year."

The remainder of the paper is structured as follows. Section 2 summarizes recent literature focusing on the effects of monetary policy on banks' profitability and the NPL ratio. Section 3 discusses the tools and methodology used for the analysis. Section 4 provides a description of the variables. In Section 6, we undertake empirical analysis, discuss key results and compare them with other researchers' findings. Section 7 summarizes the findings of this paper and makes final remarks.

1. Literature review

This paper analyses the changes in the credit risk management of banks after the GFC, including the ZLB period. This paper builds on the recent literature on the effects of the recent ZLB period on banks' profitability and credit risk management, which we divided into two groups. First, the effects of monetary policy and the ZLB on banks' profitability have been recently studied by Borio et al. (2017), Demiralp et al. (2017), Lucas et al. (2018), Claessens et al. (2018) or Bikker & Vervliet (2018).

Second, several studies have examined bank credit risk management and risk behaviour during the ZLB period. One of the first studies was developed by Ahmad & Ariff (2007), who analysed the determinants of credit risk proxied by the level of non-performing loans (NPLs) on cross-sectional data obtained from the Orbis Bank database. They examined the effects in developing and developed countries using a dataset of 23,000 observations over the 1996-2002 period. They found that the bank-related variables are potentially more useful for explaining risk in emerging countries than in developed countries. Chaibi and Ftiti (2015) examined the determinants of credit risk proxied by NPLs in Germany and France in the 2005–2011 period. Using the system GMM framework, they found that these variables are useful in explaining the NPL in the examined countries.

Ghosh (2015) focused on banking data in the US in the period from 1984 until 2013 and concluded that capitalization, liquidity risks, poor credit quality, greater cost inefficiency and banking industry size significantly increase NPLs. Furthermore, the author argued that state-level economic conditions should be taken into account when designing regulatory policies targeted at the quality of banks' asset portfolios.

Dimitrios et al. (2016) analysed the possible effects of various bank-related and macroeconomic variables, such as return on assets (ROA), loan to deposits ratio or inflation, tax level, and GDP. They considered the data of 138 Eurozone banks for the period between 1990 and 2015 and found the macroeconomic and bank-specific variables to be significant in explaining the dependent variable.

Radivojevic et al. (2017) performed a cross-country analysis over a sample of 25 emerging countries from the 2000–2011 period. They estimated both static (using a fixed effects estimator) and dynamic (using GMM methods) models to evaluate the determinants of the NPL ratio. Among other things, they found i) a significant link between the NPL ratio and GDP, ii) a negative effect of profitability variables, and iii) a dynamic persistence of the NPL.

This paper builds on the abovementioned recent literature on the effects of the ZLB on banks' profitability and credit risk management. Based on these papers, we formulated our hypothesis: a low-interest rate environment will influence banks' NPL ratio after 1 year.

2. Methodology

In this section, we discuss the basic methodological framework used in our paper. The system GMM is an estimation method developed by Arellano & Bond (1991) and is a standard methodology used for panel data. For instance, the GMM was applied in the abovementioned studies conducted by Borio et al. (2017) and Chaibi & Ftiti (2015). We use an implementation of system GMM that was developed in Roodman (2018). We estimate the models with a collapsed matrix of instruments, which reduces the number of instruments. The model can be formulated as the following regression model:

$$y_{i,t} = \alpha + x_{i,t}\beta + \mu_i + \nu_{i,t} \quad (1)$$

where $i = (1,...,N)$ are individual groups, $t = (1,...,T)$ represent the year, $y_{i,t}$ is the explained variable, $x_{i,t}$ is a matrix of regressors, μ_i is a group-specific constant term and $\nu_{i,t} \sim i.i.d.N(0, \sigma_\epsilon^2)$ is a variable capturing exogenous shocks to the model.

Depending on the circumstances, Equation 1 can be estimated with different approaches. For example, if $x_{i,t}$ contains only exogenous variables and μ_i represents constant terms, one can use a pooled ordinary least squares (OLS) regression. If μ_i is unobserved and correlated with $x_{i,t}$, then a fixed effects estimator can be employed. However, all time-invariant variables are eliminated with fixed effects. Alternatively, if μ_i is uncorrelated with $x_{i,t}$ and if we assume that these effects are similar to $v_{i,t}$ but invariant in time, a random effects approach can be used (Greene, 2003).

The advantage of these methods is the simplicity in their formulation and calculation. Nevertheless, the assumptions they require to produce unbiased and efficient estimators are often violated with financial data. Most importantly, these methods are static—they do not allow us to unbiasedly estimate a model of the following form:

$$y_{i,t} = \alpha + \varphi y_{i,t-1} + x_{i,t}\beta + \mu_i + \nu_{i,t} \quad (2)$$

Because it does not hold that μ_i is uncorrelated with the lagged $y_{i,t-1}$ term that is now endogenous to the model, the abovementioned methods are unusable for the estimation of Equation 2. These issues were addressed by Arellano & Bond's (1991) difference GMM estimator, which estimates the model using first differences with lags of the dependent variables used as instruments, which also allows some of the regressors in $x_{i,t}$ to be specified as endogenous.

Nevertheless, as Roodman (2009a) pointed out, the difference GMM method has a weakness if there are missing observations in the dataset because if a particular $y_{i,t}$ is missing from the sample, then we subsequently lose observations for $\Delta y_{i,t}$ and $\Delta y_{i,t+1}$.[3] Arellano & Bover (1995) and Blundell & Bond (1998) proposed another transformation of the data that instead of differencing the preceding observation uses the averages of all future observations (not requiring the dataset to be perfectly balanced and using all observations available); this estimator is known as system GMM. This estimator also has other convenient properties over difference GMM—with differencing, we might lose a portion of the information because some of our stock bank-specific variables can be almost invariant in time (Chaibi & Ftiti 2015); this would also cause problems with variables controlling for the bank heterogeneity.

3. Variable description

In this analysis, we use a panel data set from the Bank Focus database covering Denmark, the Eurozone, Japan, Sweden, and Switzerland. The database combines the content from Bureau van Dijk and Moody's Investor and Analytics data. Overall, it covers more than 40,000 institutions internationally.

[3] Where $\Delta yi,t = yi,t - yi,t{-}1$

The dataset on banks consists of annually collected data from banks' balance sheets and income statements from a total of 19 countries,[4] with the majority of large Eurozone banks included in the dataset. A total of 823 banks are included in the analysis (see Table A.1 in Appendix). These include banks categorized as bank holdings & holding companies, commercial banks, cooperative banks, real estate & mortgage banks, and savings banks. In our dataset, we selected only the banks that had available results in both 2011 and 2017 (the minimal and maximal years in the analysis, respectively) and that had a minimum of USD 1 million in assets in those years (to exclude micro banks from the analysis).

We selected variables based on studies on the impact of interest rates on banks´ profitability (Borio et al., 2017; Claessens et al., 2018, Hanzlík and Teplý, 2019) and on credit risk management (Chaibi and Ftiti 2015, Dimitrios et al., 2016; Radivojevic et al., 2017). Descriptions of bank-specific variables are provided in Table 1, bank-specific dummy variables by bank size in Table 2, country-specific variables in Table 3 and dummy variables indicating the ZLB in Table 4.

Table 1: List of Bank-Specific Variables

Variable	Description
NPL	The ratio of non-performing loans to total gross loans for assessing asset quality
log(Assets)	Natural logarithm of total banks' assets
EquityToAssets	Book equity to assets ratio for controlling for different levels of banks' leverage
LoansToDeposits	Customer loans to customer deposits ratio as a proxy for banks' risk preferences
ROAE	Return on average equity to control for the differences in banks' profitability
CostToIncome	A ratio of operating expenses to operating income as a proxy of banks' efficiency

Source: Authors

The dummy variables included in the empirical analysis are designed to capture the heterogeneity in the dataset. We distinguish between two categories of bank-specific dummy variables. First, we control for bank business models. The largest business model in the dataset is cooperative banks, accounting for 46.5%, followed by savings banks, with 25.8% of the total, and the third-largest category is commercial banks, covering 20.4% of the data. Second, we use variables for dummies to observe the effect of bank size (Table 2).

Table 2: Bank-Specific Dummy Variables by Bank Size

Variable	Description
HoldingBank	Equals 1 if the bank is classified in the Orbis Bank database as a *Bank holding & Holding company*.
CommercialBank	Equals 1 if the bank is classified in the Orbis Bank database as a *Commercial bank.*
CooperativeBank	Equals 1 if the bank is classified in the Orbis Bank database as a *Cooperative bank*.
MortgageBank	Equals 1 if the bank is classified in the Orbis Bank database as a *Real Estate & Mortgage bank*.
SavingsBank	Equals 1 if the bank is classified in the Orbis Bank database as a *Savings bank*.
SmallBank	Equals 1 if the bank assets in the financial year 2017 were less than USD 1 billion.

[4] All included countries listed alphabetically: Austria, Belgium, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia, Spain, Sweden, and Switzerland.

LargeBank	Equals 1 if the bank assets in the financial year 2017 were greater than USD 30 billion.

Notes: Authors

Table 3: Country-Specific Variables

Variable	Description
Unemployment	General unemployment rate for the country where the bank resides, in percent. Data from the International Financial Statistics, International Monetary Fund (IFS IMF).
GDPGrowth	Country-specific percentage change of the real gross domestic product, in percent. Data from the IFS IMF.
InterestRate3M	3-month short-term interbank rate. Data for Denmark, Japan, Sweden and Switzerland from the IFS IMF, data for the Eurozone from Eurostat.
Slope	Slope of the yield curve approximated by the difference between the yield of the 10-year government bond and 3-month interest interbank rate. Data for 10-year government bond for Denmark, Japan, Sweden, and Switzerland were obtained from the IFS IMF, data for the Eurozone were acquired from Eurostat.
InflationChange	Percentage change in consumer prices in the respective countries. Data from the IFS IMF.

Notes: Authors

In contrast with the periods considered in the previous studies covered in the literature review, the period we investigate, 2011-2017, is characterized by low interest rates, low inflation, a depressed slope of the yield curve—in some cases even negative—and a modest level of unemployment. To estimate the effect of the ZLB and test our hypothesis, we employ dummy variables indicating whether a given country attained zero lower bound in the given year or the previous period. We construct the dummy variables depicted in Table 4.

Table 4: Dummy Variables Indicating the ZLB

Variable	Description
MonIR.L0	Equals 1 if the country crossed the zero lower bound in the current period (period $t = 0$, time window 2011–2017)
MonIR.L1	First lag of the variable *MonIR.L0* (period $t = -1$, time window 2010–2016)
MonIR.L2	Second lag of the variable *MonIR.L0* (period $t = -2$, time window 2009–2015)
MonIR.L3	Third lag of the variable *MonIR.L0* (period $t = -3$, time window 2008–2014)

Notes: Authors

In Section 5, we refer to these variables with the notation *MonIR. Lλ*, where λ is the number of lags of a variable. For example, when $\lambda = 2$, the name of the variable would be *MonIR. L2*, and this would represent the second lag of the monetary interest rate dummy variable.

The dummy variables are constructed using the dataset obtained from central banks. However, for the purpose of the estimation, we use data grouped by year and averaged. We decided to work with yearly averages, as it is a common practice in financial accounting to average the terms that were a source of the year's ending balances. We also decided to suppress the effect of the one-year period in 2010 in Sweden, where the Swedish interest rate dropped below the zero lower bound after the GFC. We are mainly interested in the effects of a long-term negative interest rate environment.

4. Results and discussion

In this section, we present the results of the estimation and the main findings of the hypothesis testing, followed by a discussion of key outcomes and a comparison with other researchers' findings. The hypothesis states that a low-interest rate environment will influence banks' NPL ratio after 1 year.

Similar to Borio et al. (2017), we are interested in whether the monetary policy that might affect the strategy of banks can have an observable effect on the quality of the asset portfolio. Lopez et al. (2018) examined the determinants of banks' profitability and concluded that there might be observable changes in the interest income proportions, which is closely linked to the loan portfolio. Therefore, we might expect that when the market conditions change and consequently, the generation of the same level of profit as in the preceding years is more challenging, banks might tend to seek more risky positions in lending, and the credit risk measures might worsen.

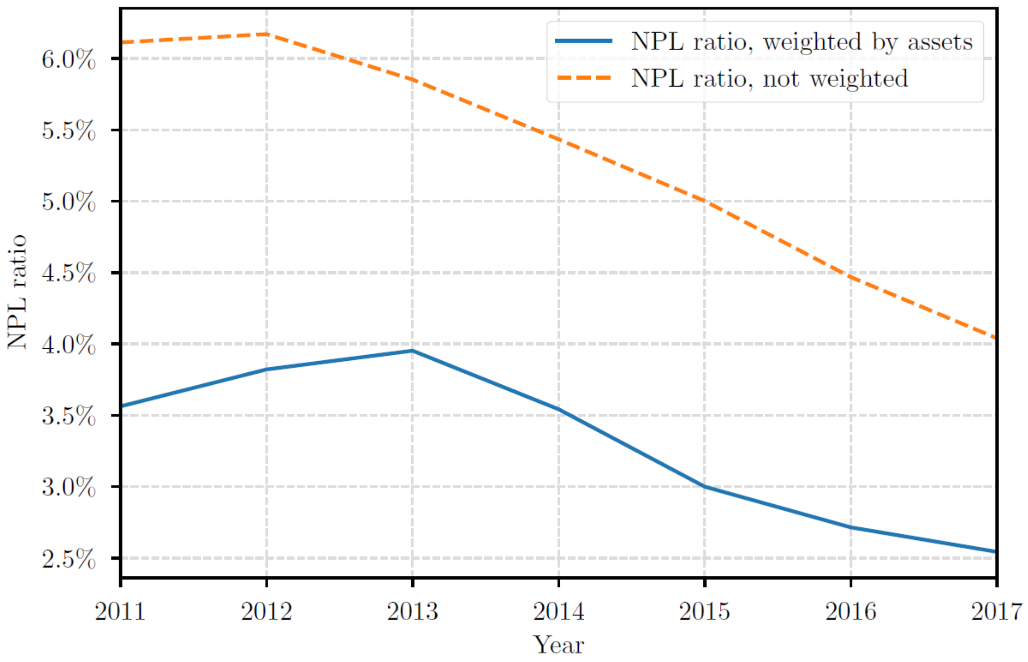
4.1 Descriptive analysis of non-performing loans

The majority of countries experienced a declining or stagnating level of NPLs after the GFC. Nevertheless, in our data set, we identified a few clear outliers, such as Cyprus, Greece, Italy and Portugal, where NPLs accumulated over time. These countries coincide with those most severely affected by the sovereign debt crisis after 2009 (Acharya et al, 2018; De Marco, 2019). Therefore, we further decided to exclude these countries from the analysis. [5]

Figure 1 shows NPLs at an aggregated level. We present two series: i) NPL weighted by assets, corresponding to the aggregated levels reported in regulatory reports, and ii) an unweighted mean of NPL, which is a more accurate visualization for our analysis because an unweighted NPL is estimated. The difference between these two—beyond the different level itself—shows that the smaller banks (represented by the unweighted NPL), on average, peaked one year sooner than the banks in the weighted sample (which more precisely illustrates the trend in the larger banks) and thus indicates the need to control for size and bank business model in the estimation. Table A.1 in the Appendix presents the final distribution of countries in the analysis.

[5] We estimated models including all countries. However, the Hansen J test of overidentifying restrictions p-value suggests that the instruments included in the model are not specified correctly.

Figure 1: Non-performing loans in 2011-2017 (average by year)



Source: Authors' computation, data from the Orbis Bank database.

4.2 Model estimation results

To test our hypothesis, we estimate the following model:

$NPL_{i,t} = \alpha + \varphi NPL_{i,t-1} + \theta MonIR.L\lambda_{i,t} + \rho_1 InterestRate3M_{i,t} + \rho_2 InterestRate3M_{i,t-1} + x_{i,t}\beta + \mu_i + \nu_{i,t}$
(3)

where $NPL_{i,t}$ is the explained variable, and on the right side, we include constant α, the first lag of NPL, $NPL_{i,t-1,}$ and $MonIR.\ L\lambda_{i,t}$ is a dummy variable indicating whether the given observation attained the zero lower bound in that period, lagged λ periods (where we estimate variants for λ = (0,1,2,3)). The variables $InterestRate3M_{i,t}$ and $InterestRate3M_{i,t-1}$ control for the effect of the interbank interest rate and its lag, $x_{i,t}$ is a matrix of other variables, ϕ, ϑ, ρ_1, ρ_2 and β are coefficients of variables and finally, μ_i is an error term of fixed components and $v_{i,t}$ error term of exogenous shocks.

The initial variable selection is based on the literature review. In our final presented model, we use variables that are believed to have an impact on the explained variable. The impacts of the variables included in the model are summarized in Table 5 for bank-specific parameters and in Table 6 for macroeconomic variables.

Table 5: Expected effect of the bank-specific and bank dummy variables explaining non-performing loans

Variable (sign)	Description
EquityToAssets (−)	Highly leveraged banks generally need a higher income to cover the cost of debt; thus, we expect the relationship to be negative. This variable is treated as endogenous.

LoansToDeposits (+)	We use this variable as a proxy for riskiness—the banks' willingness to lend (Dimitrios et al. 2016). We hypothesize that higher levels of the loans to deposits ratio will lead to higher levels of NPL; treated as endogenous.
log(Assets) (−)	We expect NPL to decrease with bank size because larger banks might be more efficient than smaller banks. This variable is treated as exogenous to the model.
CooperativeBank (−)	In the European context, cooperative banks can be considered to be a stable institution (Kuc and Teplý 2018); we expect this group to have lower NPL than other bank types.
MortgageBank (−) SmallBank (+)	A higher share of collateralized housing loans should also result in a lower level of NPL. We predict that the group of smaller banks will have more NPL than the base group because they cannot utilize the concept of economies of scale.

Source: Authors

Table 6: Expected effect of the macroeconomic variables explaining non-performing loans

Variable (sign)	Description
InterestRate3M (+/−)	The immediate effect of the interbank interest rate can be negative or positive.
Slope (+)	For the slope of the yield curve, we expect a positive relationship with the NPL. Greater differences between the long term and short-term yield might indicate a structural problem in the economy.
InflationChange (+/−)	Negative or positive impact — inflation either above or below the inflation target can be harmful to the economy. However, the effect of inflation on NPLs can be twofold: On the one hand, if inflation is high and real wages remain unchanged, the value of outstanding debt would decrease, and then, a negative effect can be expected; on the other hand, if wages do not keep pace with inflation, the effect can be positive.
GDPGrowth (−)	A negative effect on the NPL is expected — a declining economy might imply worsening asset quality in the economy. Including GDP in the model allows us to control for the economic cycle.
Unemployment (+)	Higher unemployment could theoretically transform into the deteriorating ability of customers to repay loans. It can have a direct effect on households, which will have a lower cash inflow and generally consume fewer products. Therefore, it would also affect firm because their income would be affected as well.
MonIR _Lλ (+)	We hypothesize the effect to be positive — in a low interest rate environment, banks might try to pursue riskier positions.

Source: Authors

The estimation of Equation 1 using the two-step system GMM results is shown in Table 7, while different columns display different lags of *MonIR.Lλ*. Table 8 presents the same estimated models with two-step system GMM results with errors robust to heteroskedasticity and autocorrelation. The estimated coefficients of the *EquityToAssets* and *LoansToDeposits* are aligned with our expectations. However, neither coefficient is significant in the robust form of estimation. We confirm that the group of cooperative banks, on average, has lower NPL. For the estimated model in the second column, this holds even in the robust specification. Similarly, the coefficient for real estate & mortgage banks is significant and of similar size, even though we cannot confirm this in the robust form. We also find that smaller banks have, on average, lower NPL, which is also captured with the continuous logarithm of banks' assets; however, this effect is only marginally significant for some models and only in non-robust estimates.

Table 7: Non-performing loans estimation results, two-step system GMM

	(1) NPL	(2) NPL	(3) NPL	(4) NPL
L.NPL	0.998***	0.988***	0.994***	0.994***
EquityToAssets	-0.0551	-0.125***	-0.0177	-0.0446
LoansToDeposits	0.0000353	0.0000431	0.0000425	0.0000368
CooperativeBank	-0.0977	-0.158**	-0.0370	-0.0872
MortgageBank	-0.195*	-0.411***	-0.139	-0.185*
SmallBank	0.171*	0.209*	0.136	0.148
log(Assets)	0.00451	-0.0338	0.0225	0.00393
InterestRate3M	-0.583**	-0.718**	-0.562	-0.654*
L.InterestRate3M	0.378**	0.575***	0.418*	0.405**
InflationChange	-0.107***	-0.118***	-0.116***	-0.111***
GDPGrowth	-0.279***	-0.301***	-0.286***	-0.274***
Slope	0.534***	0.718***	0.471***	0.498***
Unemployment	-0.0605***	-0.0894***	-0.0566***	-0.0537***
MonIR.L0	0.0342			
MonIR.L1		0.356***		
MonIR.L2			0.00558	
MonIR.L3				-0.0236
Constant	0.464	1.503*	-0.0464	0.431
Observations	4610	4610	4610	4610
Instruments	32	32	32	32
Number of groups	827	827	827	827
Observations per group	6	6	6	6
Wald statistic p-value	0.0000	0.0000	0.0000	0.0000
A-B AR(1) p-value	0.0049	0.0051	0.0050	0.0051
A-B AR(2) p-value	0.1864	0.1740	0.1988	0.1922
Hansen J p-value	0.0021	0.1073	0.0022	0.0029

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Authors

The immediate effect of the interbank interest rate is negative; the NPL increases when the interest rate decreases. This effect is, however, corrected with the first lag of the *InterestRate3M* variable, where after the next year, the effect has the opposite sign and a smaller size. Nevertheless, this effect is only significant in the non-robust version. We found a negative connection between NPL and inflation. Hence, it is likely that inflation, on average, might decrease the value of borrowed assets.

The coefficients for the GDP growth and the slope of the yield curve both appear to be significant—*GDPGrowth* has a negative effect as expected; thus, with the increase in the output of an economy, the level of NPL decreases, while *Slope* has a positive relationship with NPL. This outcome is in line with our expectations. Nevertheless, we discovered a negative relationship between unemployment and NPL. This is in contrast to our expectations, and the result is significant even in Table 8 displaying the results with robust statistics.

Table 8: NPL estimation results, two-step system GMM with robust errors

	(1) NPL	(2) NPL	(3) NPL	(4) NPL
L.NPL	0.998***	0.988***	0.994***	0.994***
EquityToAssets	-0.0551	-0.125	-0.0177	-0.0446
LoansToDeposits	0.0000353	0.0000431	0.0000425	0.0000368
CooperativeBank	-0.0977	-0.158	-0.0370	-0.0872
MortgageBank	-0.195	-0.411	-0.139	-0.185
SmallBank	0.171	0.209	0.136	0.148
log(Assets)	0.00451	-0.0338	0.0225	0.00393
InterestRate3M	-0.583	-0.718	-0.562	-0.654
L.InterestRate3M	0.378	0.575	0.418	0.405
InflationChange	-0.107**	-0.118***	-0.116***	-0.111***
GDPGrowth	-0.279***	-0.301***	-0.286***	-0.274***
Slope	0.534**	0.718***	0.471	0.498*
Unemployment	-0.0605*	-0.0894***	-0.0566*	-0.0537*
MonIR.L0	0.0342			
MonIR.L1		0.356**		
MonIR.L2			0.00558	
MonIR.L3				-0.0236
Constant	0.464	1.503	-0.0464	0.431
Observations	4610	4610	4610	4610
Obs. per group	6	6	6	6
Number of groups	827	827	827	827
Instruments	32	32	32	32
Wald statistic p-value	0.0000	0.0000	0.0000	0.0000
A-B AR(1) p-value	0.0055	0.0057	0.0061	0.0061
A-B AR(2) p-value	0.1869	0.1747	0.1995	0.1930
Hansen J p-value	0.0021	0.1073	0.0022	0.0029

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Authors

Finally, we found that only the model in the second column with the lag of the dummy variable controlling for the negative interest rate environment in both Tables 7 and 8 has a significant coefficient. Consequently, if for any lag, we can claim to have a significant effect, it would be the first lag signifying the one-year latency, provided the models are correctly specified.

The p-value for the Wald statistic for all models suggests that our overall results are significant. In our models, we have a total number of 827 instrumented by 31 variables. Thus, the effects of instrument proliferation should not cause complications.[6] The Arellano-Bond tests for autocorrelation indicate significance of the order one autocorrelation and nonsignificance of the order two. Therefore, we can argue that the specification of the models including the first lag of the dependent variable is not unsuitable.

However, only for the models in column (2), which estimate the possible effects *MonIR. L1,* we cannot reject the null hypothesis of the Hansen J test that the instruments are exogenous (on a 10% level). Moreover, even with the p-value of 0.136, we need to be cautious about interpreting the instruments as correctly specified because, as Roodman (2009b) notes, p-values of approximately 0.4 are generally agreed to be reliable. We also provide another test to determine whether our estimates are close to the true values. Roodman (2009a) argues that an estimate of the lagged dependent variable should lie between the estimate of the pooled OLS estimate (which suffers from upward bias) and the fixed effect estimate (which suffers from downward bias). Nevertheless, our results show that the value of the estimated parameter for the system GMM is likely to be higher than or equal to the value of the OLS estimate (see Table A.2 in Appendix for more details).

Finally, we try to assess the robustness of the model by estimating modified models that include the *MonIR. L1* variable; non-robust results can be found in Table 11. Most notably, the variation in column (2) significantly improves the p-value of the Hansen J statistic. Nevertheless, even two other variations confirm the stability of our results when the significance and direction of the estimated coefficients do not change. On the other hand, the estimated lagged coefficient of the NPL still shows high persistence because the estimated value is only marginally lower than 1.

The model in column (4) of Table 9 also shows an alternative, where we include all available dummy bank-related variables. The effect of *ln(Assets)* deteriorates; nonetheless, other bank types are not significant, and *ln(Assets)* most likely captures the size effect more effectively than the inclusion of dummy variables for small banks and large banks. Similar to other studies, we also estimate a model including the variable for return on average assets. Column (5) of Table 9 shows the results of this model. However, in our case, we find the coefficient to be only marginally significant, and it further shifts the Hansen J p-value to rejecting the hypothesis of exogeneity of instruments. Hence, we believe that the specification in Table 7 may be the superior choice for our dataset.

[6] To the best of our knowledge, there is, however, no clear rule on how to determine the optimal number of instruments, but generally, the problem arises when the number of instruments is close to the number of groups.

Table 9: NPL estimation, alternative models, two-step system GMM

	(1) NPL	(2) NPL	(3) NPL	(4) NPL	(5) NPL
L.NPL	0.943***	0.983***	0.954***	0.988***	0.892***
EquityToAssets	-0.105***	-0.175***	-0.220***	-0.177***	-0.123**
LoansToDeposits	0.0000311*	0.0000536**	0.0000311*	0.0000427*	0.0000836***
ROAE					-0.0102*
Constant	1.467*	2.872**	3.375***	2.658*	2.899***
HoldingBank				0.203	
CommercialBank				-0.141	
CooperativeBank	-0.200*	-0.279***		-0.373**	-0.168*
MortgageBank	-0.215***	-0.493***		-0.563***	-0.468***
SmallBank	0.129	0.157		0.212*	0.0854
LargeBank				-0.137	
log(Assets)	-0.0523	-0.0885*	-0.128***	-0.0720	-0.0985**
InterestRate3M	-0.323*			-0.759**	-0.0840*
L.InterestRate3M	0.253*			0.614***	0.104
InflationChange	-0.0769***	-0.127***	-0.0898***	-0.107***	-0.119***
GDPGrowth	-0.297***	-0.304***	-0.274***	-0.294***	-0.235***
Slope	0.498***	0.909***	0.755***	0.877***	0.911***
Unemployment		-0.0934***		-0.0793***	-0.0764***
MonIR.L1	0.267***	0.364***	0.355***	0.335***	0.160**
Observations	4610	4610	4610	4610	4610
Instruments	31	30	26	35	39
Number of groups	827	827	827	827	827
Obs. per group	6	6	6	6	6
Wald st. p-value	0.0000	0.0000	0.0000	0.0000	0.0000
A-B AR(1) p-value	0.0053	0.0054	0.0058	0.0054	0.0051
A-B AR(2) p-value	0.1859	0.1823	0.1823	0.1776	0.2034
Hansen J p-value	0.0100	0.5964	0.3725	0.1859	0.0532

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Authors

4.3 Summary of results

In the previous subsection, we show a significant relationship between the low interest environment delayed by one year, although weakened in terms of model specification. Table 10 compares our findings to those of other studies. The coefficients of the lagged variable on NPL are positive and in the range between 0 and 1. However, our estimations are above those of other authors; hence, our outcomes show higher persistence in the data.

The solvency ratio *EquityToAssets* in our estimations has a different sign than that of Radivojevic et al. (2017), examining emerging countries, and that of Ghosh (2015), focusing on a United States sample. Nevertheless, we agree with the results of Chaibi and Ftiti (2015) exploring French and German banks and with the results of Ahmad and Ariff (2007) for the bank sectors in Japan, Mexico, and Thailand.

Table 10: Comparison of estimated signs and significance levels for the coefficients of NIM determinants in previous studies

Variable	This thesis	Aligned	Against
L.NPL	+ [+]	+ Chaibi & Ftiti (2015) + Radivojevic *et al.* (2017) + Dimitrios *et al.* (2016) + Ghosh (2015)	/
EquityToAssets	− [0]	− Chaibi & Ftiti (2015) −/0 Ahmad & Ariff (2007)	+Radivojevic *et al.* (2017) + Ghosh (2015)
LoansToDeposits	+ [0]	+/0 Ahmad & Ariff (2007) **0** Dimitrios *et al.* (2016)	/
CooperativeBank	− [−]	/	/
MortgageBank	− [0]	/	/
InterestRate3M*	− [0]	**0** Ghosh (2015)	+ Chaibi & Ftiti (2015)
InflationChange	− [−]	−/0 Dimitrios *et al.* (2016)	+ Radivojevic + Chaibi & Ftiti (2015) + Ghosh (2015)
log(Assets)	**0** [0]	−/0 Ahmad & Ariff (2007) **0** Ghosh (2015)	+ Chaibi & Ftiti (2015)
GDPGrowth	− [−]	− Chaibi & Ftiti (2015) − Radivojevic *et al.* (2017) −/0 Dimitrios *et al.* (2016) − Ghosh (2015)	/
Unemployment	− [−]	/	+ Chaibi & Ftiti (2015) + Radivojevic *et al.* (2017) + Dimitrios *et al.* (2016) + Ghosh (2015)
MorIR.L1	+ [+]	/	/

Notes: +: significant positive relationship; −: significant negative relationship; **0**: nonsignificant result; **[ ]**: robust result; −/**0** or +/**0**: significant only in some specifications. If a cell is empty with "/", authors did not use this explanatory variable; * here we omit the lag of this variable because its effect is smaller.

Chaibi and Ftiti (2015) detected a significant positive relationship with the interest rate variable. They argue that an increase in the interest rate can transform into an increase in the debt burden and thus have a positive effect on NPL. However, their period of interest (2005–2011) was not affected by an ultra-low interest rate environment.

We also found an opposite effect of inflation than most authors did. Nevertheless, as we argued before, we can expect inflation to have an impact in both directions. All studies tend to agree that GDP growth has a negative effect on NPL. On the other hand, our estimates of unemployment are the exact opposite of what other authors estimated, and they are also not aligned with our expectations. This outcome might be related to the situation after the GFC—this estimate could be improved by future study when more data are available. Our analysis shows that exclusion of the *Unemployment* variable from the model does not affect the significance of the other coefficients.

To conclude, we do not reject our hypothesis because we discovered that after 1 year of low interest rates, the level of the NPL ratio increases. Additionally, we observed a (non-robust) self-correcting effect of the interbank interest rate, where in the current year, the effect is positive, and the effect of the previous year is negative and marginally smaller than the effect in the current year.

In our paper, we estimated a complex dynamic model with a relatively high number of variables. Therefore, we contributed to the research by analysing the bank heterogeneity controlling for banks' business models. We found that only a dummy variable for mortgage banks has a marginal effect, while we rejected the cooperative bank dummy variable as a determinant of the NPL ratio.

4.4 Further research opportunities

We see three further research opportunities. First, to improve the estimates, one could also try to include variables controlling for the policy regimes in different countries, as suggested by some authors. However, this is beyond the scope of this paper. Second, the results could also be improved when more data become available. Specifically, to study the low interest rate environment, it would be interesting to attempt to replicate the results after the interest rates increase. Finally, a longer analysed period and a higher number of banks might reveal interesting new findings.

5. Conclusion

This paper analyses the effects of the low interest rate environment on bank credit risk measured through the NPL ratio. Using the GMM, we examined a sample of 823 banks limited to the countries within the Eurozone, Denmark, Japan, Sweden, and Switzerland from 2011 until 2017. We found a significant one-year delayed effect on the NPL ratio of the variable controlling for the below-zero monetary interest rates, under which the NPL increases. Therefore, we did not reject our hypothesis. We also discovered a marginally significant self-correcting effect of the interbank 3-month interest rate. The NPL ratio changes in the same direction as the interbank interest rate in the current year, but the lag of this interbank interest rate with an effect of a lower size corrects the movement in the opposite direction.

We compared our results employing recent data to other studies that estimated the drivers of NPL, including Chaibi and Ftiti (2015), Dimitrios et al. (2016) and Radivojevic et al. (2017). Within this comparison, we found our results to be mostly consistent with those of previous research, and the majority of the differences can be explained by the changes in the economic environment during the ZLB period.

To conclude, our contribution to the literature is twofold. First, we used a large data set covering the 2011-2017 period. As a result, we were able in the case of the NPL ratio to confirm the significance of some determinants of credit risk previously found to be significant (though the previous authors focused on earlier periods and different geographical scopes). On the other hand, we identified some determinants as nonsignificant or having an opposite impact. These outcomes can be the subject of further research. Second, using a system GMM, we were able to observe the effects of bank heterogeneity, where we controlled for different bank business models and found a significant impact of the heterogeneity (in non-robust specifications). We found a significant effect of the category of mortgage banks on the NPL ratio.

Therefore, we believe that the outcomes of this work can be useful for consideration of the potential impacts of monetary policies. Commercial bankers can also benefit from this study in terms of understanding the relations between credit risk measures, such as the NPL, and bank-specific and macroeconomic variables. Finally, this paper can serve as a support for future academic research.

6. Literature

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7. Appendix

Table A.1: Number of banks by country and their non-performing loans in 2015 (in %)

	Number	of total	Mean	Median
Austria	23	2.8%	7.10	5.41
Belgium	10	1.2%	3.82	2.65
Switzerland	14	1.7%	1.89	0.69
Germany	141	17.1%	2.54	2.12
Denmark	31	3.8%	13.82	10.89
Estonia	2	0.2%	1.27	1.27
Spain	10	1.2%	8.10	8.63
Finland	4	0.5%	1.33	1.25
France	51	6.2%	3.92	3.16
Ireland	5	0.6%	15.20	14.17
Japan	473	57.5%	5.05	4.46
Latvia	3	0.4%	8.85	8.48
Luxemburg	11	1.3%	2.10	1.17
Latvia	1	0.1%	14.43	14.43
Malta	2	0.2%	4.94	4.94
Netherlands	17	2.1%	7.33	3.23
Sweden	13	1.6%	0.20	0.12
Slovenia	6	0.7%	17.43	17.09

Slovakia	6	0.7%	7.16	5.86
All	**823**	**100.0%**	**5.00**	**3.57**

Table A.2: NPL estimation results, comparison of fixed effects, pooled OLS and system GMM

	(1) Fixed effects	(2) Pooled OLS	(3) two step system GMM
L.NPL	0.502***	0.902***	0.988***
	(38.19)	(169.10)	(16.19)
Observations	4610	4610	4610
Wald statistic			19744.0
F statistic	319.3	1960.7	

Note: Output of other explanatory variables is omitted. The same estimation specification as for the model in the second column of Table 9 is used

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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