STAFF MEMO

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Lending growth, non-performing loans and loan losses

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At macro level, large loan losses for banks have often been preceded by periods of high lending growth. We analyse at bank level whether high loan growth also leads to more problem loans later on. The analysis is carried out on a panel of Norwegian banks covering the period 1996 – 2016. The applied methodology is similar to the one found in similar studies on Spanish banks as well as on banks in several OECD countries. We find a statistically significant positive relationship between past excessive loan growth at a bank and its amount of problem loans 2 – 3 years ahead. Unlike in the studies of other countries, the effect is not economically significant. Results do not indicate that excessive loan growth will never have any adverse effect at Norwegian banks, as our sample covers a relatively calm period in the Norwegian banking sector. Nevertheless, with a non-linear technique, we do find some indication that banks with much higher lending growth also experience proportionally much higher loan losses.

Key words: lending growth, loan losses, dynamic panel model, spline model.

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1. Introduction

Huge loan losses and banking crises have often occurred after a period of high aggregate growth in bank lending, such as in the banking crises of Norway and Sweden in the early 1990s.[2] Research papers from various countries, papers that will be discussed in more detail below, have examined whether individual banks that show particularly high generic growth in their lending also end up as the banks holding the largest share of problem loans or suffering the largest loan losses. By generic growth, we refer to growth in lending which is not due to mergers with or acquisitions of other banks. In general, these studies appear to indicate there is such a connection. The focus of the current paper will be banks operating in Norway between 1996 and 2016. As our discussion of previous literature makes clear, no empirical study has been done on Norwegian data of the relationship between individual banks' lending growth and subsequent loan losses.

Recent developments in segments of the Norwegian banking industry have, nevertheless, made such analyses more relevant. Over the past ten years, there has been strong growth in lending from a few new so-called consumer credit banks. These are banks that specialise in unsecured consumer loans, ie credit card debt and other unsecured loans to households. Since 2011, aggregate 12-month growth in gross lending from these banks has been above 40 percent. By comparison, aggregate 12-month growth in gross lending from other Norwegian banks has mostly been below 10 percent.[3]

In theories of asymmetric information in credit markets, it is commonly assumed that a bank has less information about the true probability of one of its borrowers defaulting than the borrower has. Such information gaps may be more or less closed when the bank-borrower relationship has lasted for some time, or if the bank has operated in the borrower's geographical or business area for some time. However, a bank that rapidly expands its lending will most likely attract new borrowers, perhaps in areas where the bank had previously not operated. Alternatively, a rapid expansion of lending may allow existing borrowers to increase their leverage. In the first alternative, the bank will be more vulnerable to asymmetric information problems and thus expect to suffer more loan losses. Similarly, a bank may record larger losses if it allows existing borrowers to become more highly leveraged.

But why would a rational profit/value-maximising bank pursue a business strategy that lowers the credit quality of its loan portfolio? As long as there

[2] See for instance Sandal (2004).
[3] See Chart 3.10 in Norges Bank's *Financial Stability Report* 2017.

are explicit or implicit guarantees of a bank's debt, it is optimal for a bank that maximises its shareholder value to take on more risk.[4] If new borrowers (or existing borrowers who assume more debt) are willing to pay a higher interest rate, the bank's shareholders will get the upside, while the potential downside is more or less covered by the guarantor(s). Then it will often be profitable for the bank to expand lending even if that increases expected loan losses, an expansion beyond what would be optimal without any guarantees.

Before presenting our empirical analysis, we will briefly discuss some previous studies on growth in bank lending and bank loan losses.

Salas and Saurina (2002) perform a panel study of Spanish banks for the years 1985 to 1997 and find evidence that high lending growth at Spanish savings banks, however not at commercial banks, results in higher problem loan ratios as long as three years afterward. Similarly, on a dataset covering Spanish banks between 1984 and 2002, Jiménez and Saurina (2006) find that above-average lending growth at individual banks results in higher non-performing loan ratios four years later. The effect is asymmetric, ie, only a positive difference in loan growth has any significant effect. Foos, Norden and Weber (2010) study a panel of more than 9,000 banks in 16 OECD countries (including Norway) between 1997 and 2007. They find that banks with loan growth in excess of the aggregate loan growth in their country recognise higher loan loss provisions relative to their outstanding loans two or three years after the excessive loan growth episode. Fahlenbrach, Prilmeier and Stulz (2016) study a panel of publicly listed US banks between 1974 and 2012. They find that the stocks of banks in the top quartile of three-year loan growth show significantly lower returns than the stocks of banks in the bottom quartile. In line with this result, they also find that banks in the fastest growing quartile after three years recognise significantly higher loan loss provisions than low-growth banks. A corollary of their findings is that investors in US bank stocks did not anticipate the relationship between high loan growth and subsequent high loan loss provisions.

Two Norwegian studies that developed early warning indicators apply logit models to estimate the probability that a bank experiences financial problems. The first one, Berg and Hexeberg (1994), uses data from the period 1988 to 1993, the time of the Norwegian banking crisis. The paper analyses the indicators that influence the probability that a bank would apply for external financial assistance during those years. Lending growth, however, turns out not to be a statistically significant explanatory variable.

[4] See e.g. Merton (1977), who shows that to a bank's owners the value of a flat-rate deposit guarantee can be modelled as a put option, the value of which increases with the risk of the bank's assets.

Similarly, Andersen (2008) applies a logit model on a dataset of Norwegian banks from the period 2000 to 2005. His aim is also to find bank-level variables that can predict the failure of a bank, where failure is defined as liquidation, acquisition by or merger with another bank, or its overall risk-weighted capital ratio falling below 8 percent. This study does not find evidence that a bank's loan growth has a significant impact on the probability of failure, either.

In this paper we pursue a research strategy that is different from the two previous Norwegian studies. We follow the same approach as the international studies mentioned above. Instead of positing the failure probability as the explained variable, we use three different measures of the relative size of a bank's problem loans as the left-hand-side variable. The measures are the loan loss ratio from the profit and loss statement, the loss provisions ratio and the ratio of defaulted loans, the latter two from the balance sheet. All of these ratios are measured relative to a bank's total loans. By using variables that are reported by all banks, rather than observations of a rare event like a bank failure, we expect to obtain more information from the data.

Our dataset covers the period between 1996 and 2016.

We estimate panel models that explain the three different measures of bank loan losses using loan growth with up to four-year lags as explanatory variables. By using lags of this length, we take account of the fact that defaulting borrowers rarely would default during the first year of a loan's term. Various control variables are also included.

Although some of the motivation for this paper is the recent appearance of high-loan-growth consumer lending banks, the length of the lags used in the models imply that very few observations of these banks are included in the dataset. Only two of these banks are included in our sample, with observation periods of four and six years.

The panel models we use are dynamic. Models are estimated with OLS, within estimation as well as two different GMM models to check our results' robustness to methodologies. We use annual data, as loan losses recorded in annual reports are usually more reliable than loan losses recorded in interim reports. For the loan loss ratio, our results indicate a positive statistically significant, but economically not significant effect of excessive loan growth (higher 12-month loan growth than the median bank) three years back in time when using all the three estimation methods. Looking at the ratio of defaulted loans, we also note a small positive and statistically significant effect from excessive loan growth with a two-year lag when using OLS and within estimations.[5] These models are linear, i.e., we assume the effect of loan growth on loan losses to be the same whether a bank posts growth of 1 percent or 50 percent. To check for the potential nonlinearity of this effect, we also estimate a simple spline model. Results indicate that for banks in the next-to-upper excessive growth quartile or quintile, there is a far stronger impact of loan growth on the loan loss ratio – but not on the two other problem loan indicators – than we find with the linear models.

Even if our results indicate that the effects of abnormal loan growth on loan losses may be rather small for a bank in Norway, one should be aware that similar studies on other OECD countries indicate far stronger effects from excessive loan growth. These differences may stem from the relative paucity of episodes of high loan losses among Norwegian banks in the period covered by our data. Furthermore, there are only three years of our sample where we observe an aggregate annual loan growth in the range of 15 to 20 %.

The paper is organised as follows: Data are described in Section 2, the dynamic panel data model is presented in Section 3, empirical results from this model follow in Section 4, Section 5 presents the spline model, and concluding remarks are given in Section 6.

2. Data

The data used in the analysis include annual financial reporting for all Norwegian banks, including their foreign branches, in the period 1995–2016. Data are obtained from Statistics Norway's banking statistics (ORBOF). Subsidiaries and branches of foreign banks are excluded. All banks that have merged during the period are treated as a single unit through the entire period, by aggregating figures for the relevant banks backwards. In this way, observations of loan growth solely due to mergers are excluded. Hence we focus on organic growth. We also exclude the first observation of any bank entering the estimation sample for the first time.

Variable selection and construction

The dependent variable measures the degree of problems in the bank's loan portfolio. We use three different alternatives for this measure:

[5] When we use quarterly data instead for the same model specification, we obtain similar results regarding our variables of interest for the loan loss and loan loss provision ratio. However, this robustness check is not reported.

1. Total loan losses in year t (from the profit and loss statement) measured as the percentage share of total loans at year-end, loan loss ratio (LL_{it}).
2. Loan loss provisions (from the balance sheet) measured as the percentage share of total loans at year-end, loan loss provision ratio (LLP_{it}).
3. The stock of defaulted loans[6] on the balance sheet measured as the percentage share of total loans at year-end, loan default ratio (DL_{it}).

The parameters of interest are the coefficients on abnormal 12-month loan growth (ALG_{it}), measured as the deviation from median growth during each year. We exclude residential mortgages from this measure. Owing to their nature, they contribute less to banks' loan losses than other loans. Furthermore, mortgage loans are secured loans with standard collateral, which implies that a bank that rapidly expands its mortgage portfolio is not subject to the same information vulnerabilities as a bank that rapidly expands its corporate or unsecured household loan portfolios.

New loans are assumed not to default immediately. Therefore, in our analysis, we include abnormal loan growth lagged two–four years back in time.[7] A positive coefficient for abnormal loan growth supports the hypothesis that high loan growth takes place at the expense of loan quality.

We control for each bank's solvency measured as the ratio of bank equity to total assets ($SOLR_{it}$), and size by including the bank's market share, measured as each bank's gross lending as a share of total lending($MSHARE_{it}$). Macroeconomic conditions affecting problem loans are implicitly controlled for by including a full set of time dummies in the regressions. Since we measure individual loan growth only as a deviation from sample annual median growth, aggregate loan growth will implicitly also be included in this dummy.

Table 1 summarises the main variables used in the analysis. Chart 1 shows the development in the median ratio of problem loans, according to our three measures, together with the median growth rate lagged three years.

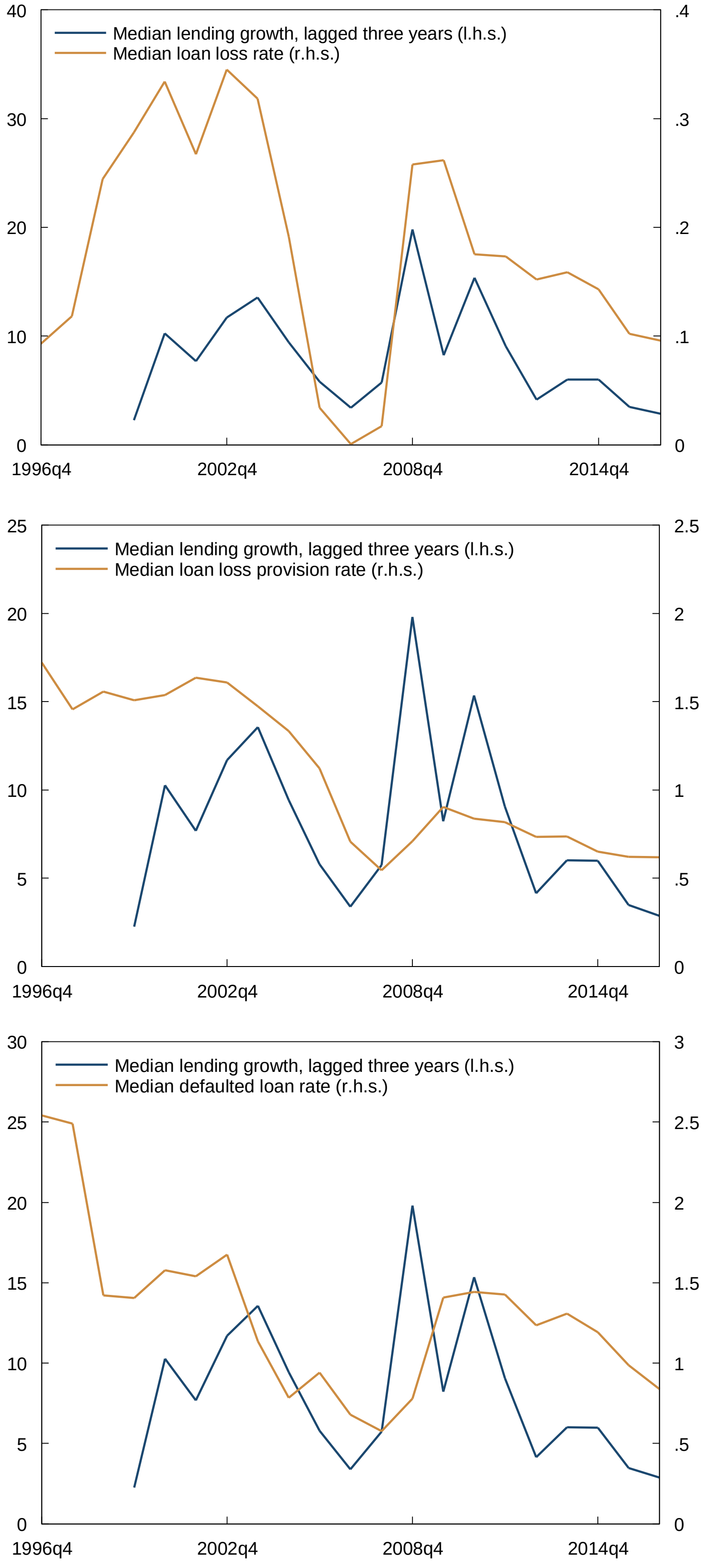
[6] In the Norwegian bank statistics prior to December 2009, loans were registered as in default when more than 90 days past due. In the period December 2009 – December 2017 the criterion was 30 days past due. As of January 2018 loans are again registered as in default when they are more than 90 days past due.
[7] Both the contemporaneous and previous year's loan growth rate are correlated with the dependent variable, the first -differenced problem loan ratios, through the denominator. This is an additional reason for lagging loan growth at least two years.

Table 1 Summary statistics

	Mean	Median	Std.err.	Min.	Max.
LL	0.252	0.169	0.417	-0.632	7.360
LLP	1.233	1.019	0.947	-0.00274	12.52
DL	1.711	1.220	1.874	0	25.49
LG	15.28	6.894	137.7	-95.85	4177.4
SOLR	10.91	11.05	27.04	-1289.7	26.41
MSHARE	0.897	0.108	4.066	0.000842	47.06
N	2338				

This table reports summary statistics of the variables included in the analysis. All variables are measured in percentage points. LL is the loan loss ratio, LLP the loan loss provision ratio and DL the defaulted loan ratio. LG refer to the 12-month change in gross lending, excluding mortgages. SOLR represents banks' solvency, the ratio of equity capital to total assets. MSHARE is the bank's market share.

Chart 1 Median lending growth and loan default ratios. Percent. 1996 – 2016



Source: Statistics Norway and Norges Bank

3. Dynamic econometric model

In this section, we present our model of banks' problem loans and motivate our choice of estimators. The dynamic panel data setting poses some challenges in estimating the model, which are discussed below. A more technical examination is included Annex A1, with reference to the presentations of the dynamic panel data model given in Bond (2002) and Roodman (2009).

The rate of problem loans y_{it} for bank i at time t is modeled as

$$\begin{aligned} y_{it} &= \boldsymbol{x}_{it}'\boldsymbol{\beta} + u_{it}, \qquad t = 1, 2, \ldots, T, \qquad i = 1,2, \ldots, n \\ u_{it} &= \eta_i + e_{it} \end{aligned} \tag{1}$$

where $\boldsymbol{x}_{it}$ is a vector of explanatory variables varying over time and potentially across banks, including previous loan growth, our variable of interest. The residual term u_{it} can be decomposed as a time invariant part η_i, which allows for unobserved differences between banks, and an idiosyncratic term e_{it}, varying across banks and time. We assume that both error components have zero mean and that they are uncorrelated,

$$E[\eta_i] = E[e_{it}] = E[e_{it}\eta_i] = 0$$

We restrict the idiosyncratic error to be independent across banks and serially uncorrelated.

If variables in $\boldsymbol{x}_{it}$ are correlated with the unobserved individual effects η_i, the OLS estimator of the parameters in (1) is inconsistent. A suited transformation of the model, most commonly the Within Groups or the first-difference transformation, eliminates this error component and thus avoids this source of inconsistency. However, in finite samples the consistency of the associated estimators relies on the assumption of no feedback effects from the dependent variable on future explanatory variables. In particular, this assumption rules out dependence of the left-hand-side variable on its own lags.

In evaluating the effect of excessive loan growth on future problem loans, this assumption may be troublesome. Defaulted loans and loan loss provisions, both being stock variables, are persistent in the sense that they may reflect the same problem loans over several periods. Therefore, when modelling these one should allow for dynamics by including lagged observations of the dependent variable in $\boldsymbol{x}_{it}$.

Loan losses, which are a flow variable, do not have this inherent dependency. If loan losses are high in one period, they need not be high in the next – when a loan or portion of it is lost, the loss will not be re-recognised in the bank's profit and loss statement. Of course, it may very well be that we observe high loan losses in several successive periods, for example, due to an adverse economic shock. In general, loan losses may reflect past losses through determinants of credit risk besides those captured in the right-hand side of the model in (1).

Thus, we include the lagged dependent variable in $\boldsymbol{x}_{it} = \left(y_{i,t-1}, \boldsymbol{w}_{it}\right)'$ and specify the dynamic panel data model

$$y_{it} = \alpha y_{i,t-1} + \boldsymbol{w}'_{it}\boldsymbol{\gamma} + \eta_i + e_{it}, \qquad t = 2..T, i = 1, 2..n \tag{2}$$

The regressor $y_{i,t-1}$ depends on both the individual effect η_i and the previous realisation of the residual, $e_{i,t-1}$. Hence, OLS, within and the first-difference estimator will produce biased estimates of the persistence coefficient α. This bias may also affect the estimates of $\boldsymbol{\gamma}$, if the variables in $\boldsymbol{w_{it}}$ are correlated with the lagged dependent variable.

Under the weaker assumption of predeterminedness of the right-hand-side variables, which allows these to be correlated with past, but not future, residuals, the difference GMM estimator derived by Arellano and Bond (1991) is a consistent estimator for the dynamic model. By first-differencing the model, the unobserved individual effects η_i are eliminated. Endogenous variables in the transformed model are then instrumented with their lagged levels. For highly persistent series, however, the first difference will be close to white noise and the lagged levels poor instruments. The latter is the case also if the variance of the individual error component is high relative to the variance of the idiosyncratic error. The difference GMM estimator may in such cases be subject to large finite sample bias (see Bond (2002)). Arellano and Bover (1994) and Blundell and Bond (1998) show that using the lagged first difference of the endogenous variables as instruments for the variables in levels improves the precision of the GMM estimator in such cases. This so-called system GMM estimator relies on the additional assumption that the covariance between the individual fixed effect η_i and the endogenous variable(s) is constant across time.

In an overidentified model, ie a model with more instruments than endogenous variables, the Hansen test can be used to assess the joint validity of the empirical moments associated with the instruments. A rejection of the null hypothesis of joint validity suggests that at least one instrument is correlated with the error term, thus not valid. Subsets of instruments may be tested applying a "difference-in-Hansen" test, comparing test statistics obtained with and without these instruments.

Both the difference and system GMM estimator are suitable for “small” T “large” n panels. Because the number of instruments tends to rapidly increase in T, the risk of overfitting to the endogenous variable might be high in longer panels. Also, the Hansen test for validity of the overidentifying restrictions is weakened when the instrument count is high (see Roodman (2009a, 2009b) for discussions of “the problem of too many instruments”). An effort to reduce the number of instruments may thus be necessary as T increases, either by restricting the number of lags used as instruments, and/or by collapsing the instrument matrix (see the more detailed presentation of these estimators in Annex A1). On the other hand, the greater T is, the lower the bias of the more straightforward within estimator is, which is consistent as $T \rightarrow \infty$.

There is no rule stating how many instruments are *too* many, but the following result can be utilised as a useful check of the GMM coefficients of a dynamic model: It can be shown that the OLS and within estimates of the coefficient α on the lagged dependent variable are biased in opposite directions, with the OLS estimator overestimating the persistence in y_{it} and the within estimator underestimating it. Any consistent estimate should thus be expected to lie between the OLS and within estimates, at least not significantly higher than the former or lower than the latter (Bond, 2002). Evaluating both OLS and within estimates in addition to those obtained with the GMM estimators might therefore help to detect potential problems of weak instruments or overfitting.

To sum up, we estimate the dynamic model in (2) with difference and system GMM, as well as with OLS and the within estimator. We chose to use only annual observations in our baseline regression, a “quite-small T, large n” sample suitable for the GMM estimators presented above. As a robustness check we estimate the model on quarterly observations. The sample length T is then a substantially higher number, which implies that the within estimator is less vulnerable to a violation of strict exogeneity. This check is not reported in the paper.

4. Results from a dynamic linear model

Results from the baseline specification are reported in Tables 2–4. For each of our three measures of problem loans, the model is estimated using both OLS and within regression, as well as the two-step difference and system GMM (i.e. the Arellano-Bond (1991) and Blundell-Bond (1998) estimator, respectively). The difference GMM estimates are obtained by instrumenting the differenced lagged dependent variable with the second to fourth lag of the dependent variable in levels. The remaining right-hand-side variables are treated as exogenous. For the system GMM estimator the second lagged difference is included as an additional instrument, instrumenting the lagged dependent variable in levels. In the absence of a golden rule specifying how many instruments are *too* many, we report results obtained both with and without restricting the number of instruments further by collapsing the instrument matrix. Robust standard errors clustered at bank level are reported for the OLS and within estimates. For the GMM coefficients Windmeijer's (2005) finite-sample corrected standard errors are computed. We include results from two misspecification tests for the GMM estimated models, the Arellano-Bond test for autocorrelation in the differenced error and Hansen's test for overidentification.[8] Note that the hypothesis of no first-order autocorrelation should be rejected, as the differenced error terms hold a first-order autocorrelation under the required assumption of no serial correlation in the errors in levels. A rejection of no higher-order correlation, however, would suggest that the lags of the endogenous variables are not valid instruments. Note also that the coefficients of interest, those associated with previous loan growth, are scaled with a factor of ten in all tables. Thus, these should be interpreted as the average percentage point change in the given measure of problem loan ratio from a 10 percentage point increase in past loan growth.

4.1. Effects on loan loss ratio

Table 2 presents results from estimating the effect of loan growth on future loan loss rates. Starting from the left, the first column presents coefficients estimated with OLS. The parameters of interest, the coefficients on the lagged values of absolute loan growth, are all non-negative. In particular, the coefficient on the third lag of abnormal loan growth $(L3.ALG)$ is positive and significant at the 5 percent level, but cannot be distinguished from zero at the third decimal place.

The coefficient on the lagged dependent variable is highly significant, which suggests that there is persistence in the loan loss ratio. Further, there is a significant negative coefficient on the contemporaneous solvency ratio, indicating that banks with higher solvency ratios on average have lower loan loss ratios. We find no effect from banks' market share on loan losses.

These OLS estimates are, however, not consistent if there are bank-fixed effects in the "true" model (i.e. $\eta_i \neq 0$ in equation (1)), due to the dependency between the lagged dependent variable and this error component.

[8] The GMM estimates and associated misspecification tests are obtained using the -xtabond2- package in Stata, as documented in Roodman (2009a).

Table 2 Regression results. Effect of loan growth on the loan loss ratio

	(1) OLS b/se	(2) within b/se	(3) diff1 b/se	(4) diff2 b/se	(5) syst1 b/se	(6) syst2 b/se
L.LL	0.457***	0.313***	0.344***	0.395***	0.355***	0.386***
	(0.065)	(0.069)	(0.090)	(0.066)	(0.078)	(0.062)
L2.ALG	0.003	0.004	-0.002	0.001	-0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
L3.ALG	0.000**	0.001***	0.001**	0.001*	0.000	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
L4.ALG	-0.000	-0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
SOLR	-0.008**	-0.016*	-0.079***	-0.068***	-0.072***	-0.069***
	(0.004)	(0.010)	(0.022)	(0.021)	(0.022)	(0.021)
MSHARE	-0.000	-0.014	-0.032	-0.033	-0.009	-0.035
	(0.001)	(0.011)	(0.027)	(0.034)	(0.014)	(0.042)
CONST	0.322***	0.327***			0.970***	0.955***
	(0.059)	(0.119)			(0.282)	(0.266)
Time ind.	Yes	Yes	Yes	Yes	Yes	Yes
Tot. obs.	1857	1857	1738	1738	1857	1857
N		119	117	117	119	119
Max. T		17	16	16	17	17
Ave. T		16	15	15	16	16
Min. T		1	0	0	1	1
No. inst			69	24	87	26
Overid, p			0.324	0.327	0.306	0.456
Overid,df			47	2	64	3
AR(1), p			0.007	0.003	0.006	0.003
AR(2), p			0.605	0.538	0.599	0.545
AR(3), p			0.214	0.248	0.219	0.242
AR(4), p			0.938	0.965	0.982	0.964

The dependent variable is the loan loss ratio (LL) in year t. Explanatory variables include the first lag of the dependent variable (L.LL), our measure of abnormal loan growth lagged two – four years (L2.ALG – L4.ALG), the solvency ratio (SOLR) and the market share (MSHARE) at time t. Coefficients on L2.ALG – L4.ALG are scaled in such a way that they represent the percentage point change in the left hand side variable from a 10 percentage point increase in abnormal loan growth. Time-fixed effects are controlled for by including a set of indicators for each year. Columns (1) – (2) report results from OLS and within regression, respectively. Columns (3) – (4) are obtained with difference GMM, where the lagged dependent variable is instrumented with up to three lags. The instruments used in computing the system GMM estimates in columns (5) – (6) include in addition the second lagged difference of the dependent variable. The instrument count is reported for the models estimated with GMM, as well as p-values and degrees of freedom from Hansen's test for over-identification and p-values from Arellano Bond's test for autocorrelation in the first differenced residuals. Robust standard errors are reported in parentheses. Significant coefficients indicated at *** p<0.001, ** p < 0.05, * p < 0.1.

The within estimates in column (2) are similar to the OLS results. The third lag of loan growth has a statistically significant, small, but positive coefficient. Again, the coefficient on the first lag of the dependent variable is positive and significant. The estimated persistence is smaller than in the OLS case, as expected from the bias in these coefficients. As discussed in Section 3, even though bank-fixed effects do not affect the within estimates, the within coefficients are biased in finite samples owing to feedback effects.

Instrumenting the lagged dependent variable, the GMM estimates reported in the remaining columns are not subject to this source of bias. Difference

GMM estimates are reported in columns (3) – (4). The misspecification tests do not reject validity of the instruments used in these specifications. Estimates in column (3), obtained without collapsing the instrument matrix, show similar results to those in previous columns; the coefficient on the lagged dependent variable is highly significant, the third lag of loan growth is significantly positive, now at the 5 percent level, and higher equity ratios is associated with lower loan loss ratios. Moreover, the persistence coefficient lies between the OLS and within estimate, as expected from a consistent estimator. The absolute value of the coefficient on $SOLR$, the equity ratio, does however increase quite substantially. These results hold as well when reducing the number of instruments as done in column (4), though the level of significance reduces to 10 percent for the coefficient on the third lag of abnormal loan growth.

Columns (5) – (6) report system GMM estimates. Again, none of the misspecification tests reject the validity of the instruments. We find no significant effect of loan growth on future loan losses from estimates obtained using the full set of instruments. Collapsing the instrument matrix, as done in column (6), the third lag is again significant at the 10 percent level.

Overall, our results indicate that the partial effect of a 10 percentage point increase in abnormal loan growth on the loan loss ratio three years ahead is about 0.001 percentage points. Though this result is statistically significant in most model specifications, it is not economic significant.

4.2. Effects on the loan loss provision ratio

Regression results using our second measure of problem loans as dependent variable, the loan loss provision ratio, are presented in Table 3. These results are consistent with what we find for the loan loss ratio. In particular, there is a statistically significant positive coefficient on the third lag of abnormal loan growth across all specifications.

As expected, the results suggest that this measure is more persistent, with the estimated coefficients on the lagged dependent variable about twice the size of those for the loan loss ratio.

Note that the overidentification test is rejected only at the 5.8 percent level in column (4). Since the Hansen's test for over-identification is weakened when the instrument count is high, one should not be too confident of a test barely significant at conventional levels, as in this specification. The significant results listed in column (4) are, however, not in conflict with those from the other columns.

Table 3 Regression results. Effect of loan growth on loan loss provision ratio

	(1) OLS b/se	(2) within b/se	(3) diff1 b/se	(4) diff2 b/se	(5) syst1 b/se	(6) syst2 b/se
L.LLP	0.832***	0.732***	0.819***	0.817***	0.801***	0.812***
	(0.018)	(0.027)	(0.034)	(0.051)	(0.039)	(0.053)
L2.ALG	0.005	0.007**	0.003	0.003	0.004	0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
L3.ALG	0.002***	0.002***	0.001***	0.002***	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
L4.ALG	-0.000	-0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
SOLR	0.002	0.006	-0.049*	-0.049*	-0.028	-0.048*
	(0.004)	(0.008)	(0.026)	(0.029)	(0.023)	(0.028)
MSHARE	-0.001	-0.024*	-0.059**	-0.063*	-0.010	-0.058
	(0.001)	(0.014)	(0.024)	(0.033)	(0.027)	(0.045)
CONST	0.281***	0.109			0.492*	0.743**
	(0.058)	(0.113)			(0.281)	(0.331)
Time ind.	Yes	Yes	Yes	Yes	Yes	Yes
Tot. obs.	1857	1857	1738	1738	1857	1857
N		119	117	117	119	119
Max. T		17	16	16	17	17
Ave. T		16	15	15	16	16
Min. T		1	0	0	1	1
No. inst			69	24	87	26
Overid, p			0.418	0.058	0.142	0.130
Overid,df			47	2	64	3
AR(1), p			0.000	0.000	0.000	0.000
AR(2), p			0.116	0.114	0.113	0.113
AR(3), p			0.633	0.673	0.695	0.676
AR(4), p			0.257	0.256	0.274	0.260

The dependent variable is the loan loss provisions ratio (LLP) in year t. Explanatory variables include the first lag of the dependent variable (L.LLP), our measure of abnormal loan growth lagged two – four years (L2.ALG – L4.ALG), the solvency ratio (SOLR) and the market share (MSHARE) at time t. Coefficients on L2.ALG – L4.ALG are scaled in such a way that they represent the percentage point change in the left hand side variable from a 10 percentage point increase in abnormal loan growth. Time-fixed effects are controlled for by including a set of indicators for each year. Columns (1) – (2) report results from OLS and within regression, respectively. Columns (3) – (4) are obtained with difference GMM, where the lagged dependent variable is instrumented with up to three lags. The instruments used in computing the system GMM estimates in columns (5) – (6) include in addition the second lagged difference of the dependent variable. The instrument count is reported for the models estimated with GMM, as well as p-values and degrees of freedom from Hansen's test for over-identification and p-values from Arellano Bond's test for autocorrelation in the first differenced residuals. Robust standard errors are reported in parentheses. Significant coefficients indicated at *** p<0.001, ** p < 0.05, * p < 0.1.

4.3. Effects on the defaulted loan ratio

Table 4 presents results for the third and last problem loan measure, the defaulted loan ratio. Here, the OLS estimates in the first column suggest a positive, significant effect on the second and third lag of abnormal loan growth. This holds also for the within estimates in the second column, but the coefficient on the fourth lag is significantly negative. Except from the results in column (5), the GMM results show a significant coefficient on the third lag. The magnitude of these coefficients is larger than what we found for the loan loss and loan loss provision ratio.

Even though the formal misspecification tests show no evidence of misspecifications in the difference GMM models, the estimated coefficients on the lagged dependent variable are below the within estimate, contrasting what is expected from a consistent, unbiased estimator. Unfortunately, exactly what this bias stems from is not obvious. It might be the case that the lagged levels of the dependent variable are weak instruments, in which case system GMM is the preferred estimator.[9]

In sum, our results suggest that an increase in the loan growth rate three years back in time, when seen in isolation, has a positive effect on all our three measures of problem loans. Owing to the persistence in these measures, the indirect effect through the lagged dependent variable also needs to be considered to evaluate the total effect from such an increase. Taking these dynamics into account, the effect from past loan growth tends to be more pronounced, at least on the loan loss provision and the defaulted loans rate. In the next subsection, we look at the effects of loan growth over longer periods, estimating a simpler model where the three lags of abnormal growth rates are replaced with a single variable for three-year abnormal growth.

[9] We have not tested whether these coefficients are significantly lower than the within coefficients. Estimating the variance of the two error components, we find that the individual error component is larger than the idiosyncratic component, suggesting that there might be a problem of finite sample bias due to weak instruments in the difference GMM coefficients.

Table 4 Regression results. Effect of loan growth on the defaulted loan ratio

	(1) OLS b/se	(2) within b/se	(3) diff1 b/se	(4) diff2 b/se	(5) syst1 b/se	(6) syst2 b/se
L.DL	0.769***	0.465***	0.417***	0.439***	0.672***	0.475***
	(0.036)	(0.038)	(0.052)	(0.070)	(0.055)	(0.058)
L2.ALG	0.028**	0.034***	0.016	0.015	0.009	0.016*
	(0.012)	(0.012)	(0.014)	(0.010)	(0.013)	(0.010)
L3.ALG	0.006***	0.004***	0.005***	0.004***	0.000	0.004***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.006)	(0.001)
L4.ALG	-0.002	-0.003***	-0.001	-0.001	-0.004	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.002)
SOLR	0.007	0.035**	-0.000	0.013	0.012	-0.003
	(0.008)	(0.017)	(0.036)	(0.044)	(0.046)	(0.040)
MSHARE	0.001	-0.027	-0.091	-0.095	-0.123	-0.093
	(0.001)	(0.025)	(0.077)	(0.068)	(0.089)	(0.067)
CONST	0.392***	0.181			0.278	0.796*
	(0.147)	(0.225)			(0.556)	(0.436)
Time ind.	Yes	Yes	Yes	Yes	Yes	Yes
Tot. obs.	1857	1857	1738	1738	1857	1857
N		119	117	117	119	119
Max. T		17	16	16	17	17
Ave. T		16	15	15	16	16
Min. T		1	0	0	1	1
No. inst			69	24	87	26
Overid, p			0.142	0.762	0.155	0.865
Overid,df			47	2	64	3
AR(1), p			0.000	0.000	0.000	0.000
AR(2), p			0.741	0.713	0.352	0.626
AR(3), p			0.305	0.270	0.234	0.245
AR(4), p			0.562	0.575	0.625	0.571

The dependent variable is the defaulted loan ratio (DL) in year t. Explanatory variables include the first lag of the dependent variable (L.DL), our measure of abnormal loan growth lagged two – four years (L2.ALG – L4.ALG), the solvency ratio (SOLR) and the market share (MSHARE) at time t. Coefficients on L2.ALG – L4.ALG are scaled in such a way that they represent the percentage point change in the left hand side variable from a 10 percentage point increase in abnormal loan growth. Time-fixed effects are controlled for by including a set of indicators for each year. Columns (1) – (2) report results from OLS and within regression, respectively. Columns (3) – (4) are obtained with difference GMM, where the lagged dependent variable is instrumented with up to three lags. The instruments used in computing the system GMM estimates in columns (5) – (6) include in addition the second lagged difference of the dependent variable. The instrument count is reported for the models estimated with GMM, as well as p-values and degrees of freedom from Hansen's test for over-identification and p-values from Arellano Bond's test for autocorrelation in the first differenced residuals. Robust standard errors are reported in parentheses. Significant coefficients indicated at *** p<0.001, ** p < 0.05, * p < 0.1.

4.4. Effects of loan growth over longer periods

In our baseline specification, we included three lags of abnormal loan growth. These variables may be highly correlated, as banks typically experience more than a single year of expansion. Thus, we test whether our results are sensitive to such correlation by constructing a single measure for abnormal loan growth over the past three years ($ALG3Y_{it}$), simply as the deviation from the median relative change in lending from year $t-3$ to year t. The estimation results are presented in Table 5. Note that, again, we do not include loan growth lagged less than two years, as the first lag of this measure is correlated with the (differenced) dependent variable through the denominator. The coefficient on abnormal three-year loan growth is scaled to represent the change in the left-hand-side variable from an average increase in the annual abnormal growth rate of 10 percentage points. In terms of three-year loan growth rates, this equals an increase in the deviation from the median bank of about 33 percentage points.

Results indicate that for the loan loss ratio there is a positive and statistically significant, but not economically significant, effect from high abnormal loan growth over three years. This is the case in five out of six model specifications. For loan loss provisions, this holds for all six model specifications. For the defaulted loan loss ratio, we find statistically significantly positive effects only in two model specifications, the OLS and within models. In all cases, the economic effects are small.

Estimates of the long run effects, the effect on each measure of problem loans from a permanent increase in loan growth, are computed using the coefficients in Table 5 and reported in Table 6. P-values indicate at which level of significance we would reject the null hypothesis that the long-run coefficients are equal to zero according to the Wald test.

For the loan loss ratio, as reported in Table 6 a), the long-run effect is about the same size as the short-run effect: small, yet significantly positive, except the coefficient obtained with the first system GMM estimates, which is not significant. For the loan loss provision ratio, the long run effect is between 0.006 and 0.007 percentage points according to the GMM estimates. Neither of the GMM estimates is statistically significant at conventional levels for the last problem loans measure, the defaulted loan ratio.

Even when the long-run effects are statistically significant, they are not economically significant. Evaluated at the sample mean (median), as reported in table 1, a 10 percentage point permanent increase in loan growth relative to the median is associated with a relative change of 0.39 percent (0.59 percent) in the long run loan loss ratio according to the GMM-estimates. For the loan loss provision ratio we find a relative change of 0.56 percent (0.68 percent), using the highest coefficient estimate of 0.007.

Table 5 Regression results. Effect of three years loan growth.

The dependent variable in table a)–c) is the loan loss ratio (LL) in year t, the loan loss provition ratio (LLP) and the defaulted loan ratio (DL), respectively. Explanatory variables include the first lag of the dependent variable, our measure of abnormal three year loan growth lagged two years (L2.ALG3Y), the solvency ratio (SOLR) and the market share (MSHARE) at time t. The coefficient on L2.ALG3Y is scaled in such a way that it represents the percentage point change in the left hand side variable from an increase in the average annual abnormal growth rate of 10 percentage points. Time-fixed effects are controlled for by including a set of indicators for each year. Columns (1) – (2) report results from OLS and within regression, respectively. Columns (3) – (4) are obtained with difference GMM, where the lagged dependent variable is instrumented with up to three lags. The instruments used in computing the system GMM estimates in columns (5) – (6) include in addition the second lagged difference of the dependent variable. The instrument count is reported for the models estimated with GMM, as well as p-values and degrees of freedom from Hansen's test for over-identification and p-values from Arellano Bond's test for autocorrelation in the first differenced residuals. Robust standard errors are reported in parentheses. Significant coefficients indicated at *** p<0.001, ** p < 0.05, * p < 0.1.

a) *Loan loss ratio*

	(1) OLS b/se	(2) within b/se	(3) diff1 b/se	(4) diff2 b/se	(5) syst1 b/se	(6) syst2 b/se
L.LL	0.457***	0.314***	0.344***	0.394***	0.355***	0.386***
	(0.065)	(0.068)	(0.090)	(0.066)	(0.078)	(0.062)
L2.ALG3Y	0.000*	0.000***	0.001***	0.001***	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
SOLR	-0.009**	-0.017*	-0.078***	-0.068***	-0.071***	-0.069***
	(0.004)	(0.010)	(0.022)	(0.021)	(0.023)	(0.021)
MSHARE	-0.000	-0.014	-0.033	-0.033	-0.010	-0.035
	(0.001)	(0.011)	(0.025)	(0.034)	(0.014)	(0.041)
CONST	0.324***	0.331***			0.944***	0.963***
	(0.059)	(0.119)			(0.268)	(0.255)
Time ind.	Yes	Yes	Yes	Yes	Yes	Yes
Tot. obs.	1857	1857	1738	1738	1857	1857
N		119	117	117	119	119
Max. T		17	16	16	17	17
Ave. T		16	15	15	16	16
Min. T		1	0	0	1	1
No. inst			67	22	85	24
Overid, p			0.362	0.325	0.355	0.453
Overid,df			47	2	64	3
AR(1), p			0.007	0.003	0.006	0.003
AR(2), p			0.605	0.538	0.600	0.545
AR(3), p			0.212	0.247	0.217	0.241
AR(4), p			0.954	0.967	0.985	0.967

b) Loan loss provision ratio

	(1) OLS b/se	(2) within b/se	(3) diff1 b/se	(4) diff2 b/se	(5) syst1 b/se	(6) syst2 b/se
L.LLP	0.830***	0.731***	0.820***	0.816***	0.798***	0.810***
	(0.018)	(0.027)	(0.035)	(0.051)	(0.038)	(0.053)
L2.ALG3Y	0.001***	0.001***	0.001***	0.001***	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
SOLR	0.002	0.005	-0.052*	-0.049*	-0.029	-0.047*
	(0.004)	(0.008)	(0.027)	(0.029)	(0.023)	(0.028)
MSHARE	-0.001	-0.023	-0.061***	-0.063*	-0.014	-0.057
	(0.001)	(0.014)	(0.023)	(0.033)	(0.024)	(0.046)
CONST	0.284***	0.115			0.471*	0.696**
	(0.058)	(0.113)			(0.286)	(0.331)
Time ind.	Yes	Yes	Yes	Yes	Yes	Yes
Tot. obs.	1857	1857	1738	1738	1857	1857
N		119	117	117	119	119
Max. T		17	16	16	17	17
Ave. T		16	15	15	16	16
Min. T		1	0	0	1	1
No. inst			67	22	85	24
Overid, p			0.315	0.058	0.183	0.128
Overid,df			47	2	64	3
AR(1), p			0.000	0.000	0.000	0.000
AR(2), p			0.118	0.114	0.113	0.113
AR(3), p			0.648	0.688	0.714	0.691
AR(4), p			0.251	0.249	0.263	0.254

c) Defaulted loan ratio

	(1) OLS b/se	(2) within b/se	(3) diff1 b/se	(4) diff2 b/se	(5) syst1 b/se	(6) syst2 b/se
L.DL	0.767***	0.464***	0.416***	0.438***	0.673***	0.474***
	(0.035)	(0.038)	(0.054)	(0.069)	(0.053)	(0.057)
L2.ALG3Y	0.004***	0.002**	0.003	0.002	-0.001	0.002
	(0.001)	(0.001)	(0.003)	(0.002)	(0.007)	(0.002)
SOLR	0.006	0.032*	0.001	0.014	0.013	-0.002
	(0.008)	(0.016)	(0.036)	(0.044)	(0.045)	(0.040)
MSHARE	0.001	-0.026	-0.088	-0.095	-0.114	-0.094
	(0.001)	(0.027)	(0.078)	(0.068)	(0.091)	(0.067)
CONST	0.416***	0.212			0.327	0.904**
	(0.145)	(0.223)			(0.525)	(0.415)
Time ind.	Yes	Yes	Yes	Yes	Yes	Yes
Tot. obs.	1857	1857	1738	1738	1857	1857
N		119	117	117	119	119
Max. T		17	16	16	17	17
Ave. T		16	15	15	16	16
Min. T		1	0	0	1	1
No. inst			67	22	85	24
Overid, p			0.136	0.748	0.154	0.858
Overid,df			47	2	64	3
AR(1), p			0.000	0.000	0.000	0.000
AR(2), p			0.735	0.705	0.340	0.616
AR(3), p			0.336	0.304	0.262	0.277
AR(4), p			0.554	0.570	0.626	0.568

Table 6 Long-run effects

The long-run coefficients are based on the coefficient estimates in Table 5, p-values from Wald-test reported below each coefficient.

a) Loan loss ratio

	(1) OLS	(2) within	(3) diff1	(4) diff2	(5) syst1	(6) syst2
Long-run coeff.	0.000	0.000	0.001	0.001	0.000	0.001
Long-run coeff., p	0.060	0.001	0.007	0.006	0.966	0.004

b) Loan loss provision ratio

	(1) OLS	(2) within	(3) diff1	(4) diff2	(5) syst1	(6) syst2
Long-run coeff.	0.007	0.004	0.006	0.007	0.007	0.006
Long-run coeff., p	0.000	0.000	0.007	0.004	0.026	0.006

c) Defaulted loans ratio

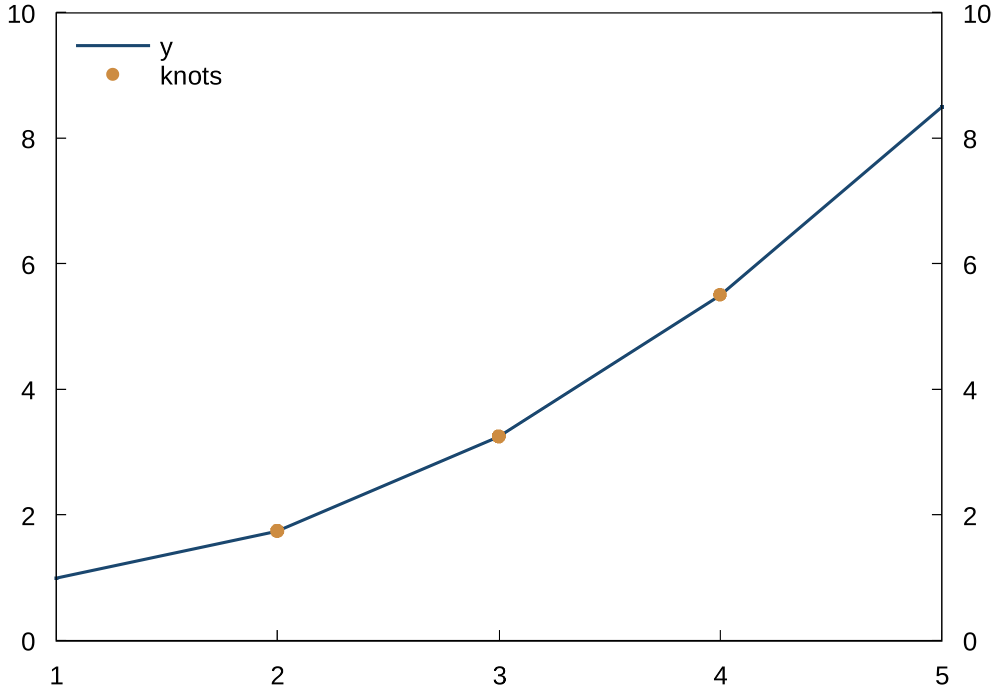
	(1) OLS	(2) within	(3) diff1	(4) diff2	(5) syst1	(6) syst2
Long-run coeff.	0.016	0.003	0.005	0.004	-0.004	0.004
Long-run coeff., p	0.000	0.012	0.268	0.298	0.871	0.285

5. Non-linear effects of loan growth

So far, we have assumed that the effect of high loan growth on future problem loans is linear, i.e. it has the same proportional effect whether the loan growth is 5 percent or 25 percent. Based on the theoretical explanations in Section 1 for why higher loan growth would lead to problem loans, this assumption of linearity may seem somewhat unrealistic. Instead, one might expect that banks with the highest loan growth would show a stronger effect from the loan growth on their relative amount of loan losses or problem loans.

In order to let the marginal effect of past loan growth on problem loan ratios differ across the distribution of abnormal loan growth, we construct linear *splines* with knots at different percentiles of the abnormal loan growth variable. Such splines allow us to estimate the relationship between the different problem loan ratios and past loan growth as piecewise linear functions. These functions are, however, restricted to be continuous, as illustrated in Chart 2. The slope of the regression function, the coefficients on past abnormal loan growth, might then differ between low-growth and high-growth banks.

Chart 2 Illustration of linear spline with three knots



In line with results from estimating the linear model in Section 4, we just use loan growth with a lag of three years in the simple spline model of this section. Use of several lags, all with splines, could result in "overfitting" the model.

The results from estimating the linear splines for each measure of problem loan ratios are reported in Table 7. In the upper panel, knots are constructed at every 25th percentile (quartile). In the lower panel, knots are placed at each 20th percentile (quintile). Note that we have not scaled the coefficients in these tables, as we did for the linear dynamic models in Section 4. That is, the coefficients represent the average change in the problem loans ratio associated with a 1 percentage point increase in past loan growth.

For the loan loss ratio, we find a significantly positive coefficient in the lowest and in the second-to-highest segment of the abnormal loan growth distribution in both panels. The coefficient of the latter is the higher one, as expected. In the upper panel the second-to-highest segment includes banks with growth rates of up to 6.8 percentage points above the median in a given year, in the lower panel between 2.2 and 8.9 percentage points above the median. For these banks, a one percentage point increase in loan growth is associated with a 0.012 percentage point increase in the loan loss rate three years ahead. For the average (median) bank in the 60th–80th percentile

Table 7 Regression results. Linear splines

Dependent variable indicated in column header. Model is estimated with OLS. Explanatory variable include abnormal loan growth lagged three years. L3.ALGk denotes the coefficient of segment k of the sample distribution of abnormal loan growth. Time-fixed effects are controlled for by including a set of indicators for each year. Robust standard errors clustered at the bank-level are reported in parentheses. Significant coefficients are indicated *** p<0.001, ** p < 0.05, * p < 0.1.

a) Knots at 25th, 50th and 75th percentile

	(1) LL b/se	(2) LLP b/se	(3) DL b/se
L3.ALG1	0.003***	0.007***	0.004
	(0.001)	(0.002)	(0.006)
L3.ALG2	-0.004	-0.001	0.018
	(0.004)	(0.008)	(0.016)
L3.ALG3	0.012**	-0.012	0.021
	(0.005)	(0.009)	(0.025)
L3.ALG4	0.000	0.000	0.001*
	(0.000)	(0.000)	(0.000)
CONST	0.321***	1.793***	1.746***
	(0.032)	(0.118)	(0.189)
Time ind.	Yes	Yes	Yes
Tot. obs.	1976	1976	1976

Knots at -6.426, 0 and 6.765.

b) Knots at 20th, 40th, 60th and 80th percentile

	(1) LL b/se	(2) LLP b/se	(3) DL b/se
L3.ALG1	0.003***	0.009***	0.004
	(0.001)	(0.002)	(0.007)
L3.ALG2	-0.002	-0.014	0.016
	(0.005)	(0.011)	(0.020)
L3.ALG3	0.001	0.019	0.011
	(0.006)	(0.015)	(0.030)
L3.ALG4	0.012*	-0.021*	0.023
	(0.006)	(0.011)	(0.027)
L3.ALG5	0.000	0.000	0.001*
	(0.000)	(0.000)	(0.000)
CONST	0.325***	1.847***	1.734***
	(0.036)	(0.128)	(0.197)
Time ind.	Yes	Yes	Yes
Tot. obs.	1976	1976	1976

Knots at -8.305, -2.301, 2.244 and 8.917.

of abnormal loan growth, with a loan loss rate of 0.214 (0.161) percentage points, this corresponds to a relative change of 5.61 percent (7.4 percent).

For banks in the top quantile, we do not find any significant effect on the loan loss ratio from loan growth. The upper quantile will, however, always include a number of banks showing extremely high recorded growth rate in lending, as these banks' lending outside the residential mortgage market was initially in insignificant amounts.[10]

Regarding the loan loss provision ratio, we find a significant positive coefficient only for the lowest growth rates in both specifications. When including knots at each quintile as in Table 7 b), the second-to-highest segment has in fact a negative coefficient, suggesting a negative relationship between higher growth rates and loan loss provision ratios for banks in this segment. The coefficient is, however, only significant at 10 percent.

For the last problem loan measure, the defaulted loans ratio, the only significantly coefficient is in the upper segment in both specifications. The coefficient is positive, but has no significant economic impact: With average (median) defaulted loan rates of 1.570 (0.937) points in the top quintile (>80th percentile) of abnormal loan growth, a 0.001 percentage point increase corresponds to a relative change of somewhat below (above) 0.1 percent.

The simple spline analysis in this section has indicated a possible convex relationship between abnormal loan growth and the future loan loss ratio of bank. However with regard to the other two problem loan measures applied in this paper, the spline analysis does not really lend support to such a relationship.

6. Concluding remarks

In this paper, we examine the relationship between excessive growth in lending and future problem loans. Huge loan losses and banking crises have often occurred after a period of high aggregate growth in bank lending, including the Norwegian banking crisis in the early 1990s. Theories of asymmetric information suggest that such a relationship may also exist at the individual bank level. Empirical studies of Spanish banks (Salas and Saurina, 2002, Jiménez and Saurina, 2006) as well as a large set of banks

[10] Note that residential mortgage loans are excluded from our growth in lending measure (cf Section 2).

in the OECD (Foos et al, 2006) support this theory: these papers find a positive relationship between individual banks' loan growth and future problem loans ratios. We use a similar identification strategy on Norwegian data from the period 1996–2016 and estimate a dynamic panel data model. Three measures of problem loans are included in the analysis: loan losses, loan loss provision ratio and defaulted loans, all measured relative to total lending. The results suggest a statistically significant, positive relationship between excessive growth in the past and all three measures of problem loans. That is, if a bank during a year has higher growth in lending than the median bank, the relative volume of its problem loans three years ahead will be higher. The economic effects are, however, not significant. We stress that these results should not be interpreted to mean that excessive loan growth never will have any adverse effect at Norwegian banks. Our sample covers a period absent major disruptions in the Norwegian banking sector and does not fully capture the consumer credit specialised banks, for which the highest growth rates have been observed over the last couple of years. A simple spline analysis suggests that the relationship between loan growth and loan losses might not be linear and that the effect of rapid expansions might have been substantial for banks in the next to upper intervals of excessive loan growth, if not for the average bank.

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A1. Annex

This section complements Section 3 and provides a more detailed presentation of the linear dynamic panel data model and the estimators according to Arellano and Bond (1991) and Blundell and Bond (1998) as presented in Bond (2002) and Roodman (2009a).

The linear panel data model is given as

$$y_{it} = \boldsymbol{x}'_{it}\boldsymbol{\beta} + u_{it}, \qquad t = 1, 2, \dots, T, \qquad i = 1,2, \dots, n \qquad (2)$$
$$u_{it} = \eta_i + e_{it}$$

where $\boldsymbol{x}_{it}$ is a vector of explanatory variables that vary over time and potentially across banks. The residual term u_{it} can be decomposed as a time invariant part η_i, which allow for unobserved differences between banks, and an idiosyncratic term e_{it} varying across banks and time. We assume that both error components have zero mean and that they are uncorrelated,

$$E[\eta_i] = E[e_{it}] = E[e_{it}\eta_i] = 0$$

and we restrict the idiosyncratic error to be independent both across time and between banks.

If regressors in $\boldsymbol{x}_{it}$ are correlated with the individual effects η_i, the OLS estimator of the parameters in (2) is inconsistent. A suited transformation of the model, most commonly the within groups or the first difference transformation, eliminates the time invariant error component and avoids this source of inconsistency. However, both these transformations might introduce new endogeneity problems as they rely on additional assumptions.

First, the within transformation eliminates η_i by expressing each observation as the deviation from its individual mean. The consistency of the associated within estimator relies on the demeaned regressors being uncorrelated with the demeaned error,

$$E\left[e_{it} - \frac{1}{T}\,(e_{i1} + \dots + e_{iT})\middle|\, \boldsymbol{x}_{it} - \frac{1}{T}\,(\boldsymbol{x}_{i1} + \dots + \boldsymbol{x}_{iT})\right] = 0.$$

Since the individual mean is a function of all T observations, this requires all explanatory variables in $\boldsymbol{x}_{it}$ to be *strictly exogenous.* That is, the regressors should be uncorrelated with both past, current and present errors.

Under the assumption of strict exogeneity, the first-difference estimator will as well yield consistent estimates, since it follows that $\Delta\boldsymbol{x}_{it} = \boldsymbol{x}_{it} - \boldsymbol{x}_{i,t-1}$ is independent of the differenced error.

The assumption of strict exogeneity rules might be strict. In particular it rules out dynamic, introduced for example when y_{it} depend on its own lags or other feedback effects from the dependent variable to (future) explanatory variables. The within estimator remain consistent as $T \rightarrow \infty$ even if strict exogenity does not hold, as the variables in levels become independent of their respective means (assuming the regressors are not contemporary correlated with the error term). Nevertheless, the bias might be large in finite samples, also when the number of individuals n is high.

The dynamic panel data estimator proposed by Arellano and Bond (1991) represent a possible solution when T is small and n is large. This estimator, the difference GMM estimator, as well as the system GMM estimator presented in Blundell and Bond (1998) relies on the weaker assumption of *sequential exogeneity*, or *predeterminedness*: regressors might be correlated with past and present, but not future errors. These estimators use the lagged levels of endogenous variables as instruments in the first differenced model.

For convenience, let $y_{i,t-1}$ be among the regressors in $\boldsymbol{x}_{it}$. The model in (2) is then the dynamic panel data model

$$\begin{aligned} y_{it} &= \alpha y_{i,t-1} + \boldsymbol{w}_{it}'\boldsymbol{\gamma} + u_{it}, \quad 0 < |\alpha| < 1 \\ u_{it} &= \eta_i + e_{it} \end{aligned} \tag{3}$$

where $\boldsymbol{\beta} = [\alpha, \boldsymbol{\gamma}\,]'$. The lagged dependent variable y_{it-1} is positively correlated with the error term u_{it} through its dependence on the individual effect η_i, implying that the OLS estimate of α holds a positive bias. That is, OLS overestimate the persistence in y. The feedback effects from the residuals at time $t-1$ to the time t regressor $y_{i,t-1}$violates the assumption of strict exogenity. Hence, the within transformed regressor $y_{it-1} - \frac{1}{T-1}(y_{i1} + \cdots + y_{it} + \cdots + y_{iT})$ and error $e_{it} - \frac{1}{T-1}\left(e_{i1} + \cdots + e_{i,t-1} + \cdots + e_{iT}\right)$ will be correlated in finite samples. This correlation can be shown to be negative, as the negative correlation between $y_{i,t-1}$ and $-\frac{1}{T-1}e_{i,t-1}$ and between e_{it} and $-\frac{1}{T-1}y_{i,t}$ dominates the positive correlation between the components $-\frac{1}{T-1}e_{is}$ and $-\frac{1}{T-1}y_{is}$, and induce a negative bias in the within estimate of α (Bond, 2002). Depending on the correlation between $y_{i,t-1}$

and the remaining regressors in $\boldsymbol{w}_{it}$, as well, estimates of the coefficients in $\boldsymbol{\gamma}$ may be biased.[11]

The difference GMM estimator is based on the first-differenced model,

$$\Delta y_{it} = \alpha \Delta y_{it-1} + \Delta \boldsymbol{w}_{it}\boldsymbol{\gamma} + \Delta e_{it}.$$

Due to its reliance on y_{it-1}, Δy_{it-1} cannot be independent from the differenced error $\Delta e_{it} = e_{it} - e_{it-1}$. However, if y_{it} is predetermined, the second lag of the dependent variable, y_{it-2}, is independent of Δe_{it} and can be used as instrument for Δy_{it-1}.

Conditional on $T > 3$, also deeper lags are valid as instruments, with associated moment conditions:

$$E\left[y_{i,t-s}\Delta e_{it}\right] = E\left[y_{i,t-s}(e_{it} - e_{i,t-1})\right] = 0, \qquad s = 2, ..(t-1), t \geq 3 \qquad (4)$$

To the extent that these deeper lags contain additional information, including them as additional instruments will increase the efficiency of the IV-estimator. With standard 2SLS, however, using deeper lags will decrease efficiency as this means to exclude the earliest observations for which deeper lags are not known. The Arellano-Bond estimator, which utilises the framework of Generalized Method of Moments (GMM) [12], lets the number of instruments vary with t – thus preserving the sample length. The GMM instrument matrix takes the form

$$\boldsymbol{Z_i} = \begin{bmatrix} y_{i1} & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & y_{i2} & y_{i1} & \cdots & 0 & \cdots & 0 \\ . & . & . & \cdots & . & \cdots & . \\ 0 & 0 & 0 & \cdots & y_{iT-2} & \cdots & y_{i1} \end{bmatrix} \qquad (5)$$

Each row in $\boldsymbol{Z_i}$ corresponds to the first-differenced equation at time $t = 3, 4 \ldots T$ and each column contains one of the instrument(s) used at time t. After differencing, no observations have to be kept out in order to serve as instruments. The associated moment conditions

$$E[\boldsymbol{Z_i}'\Delta \boldsymbol{e_i}] = 0, \quad i = 1, 2, \ldots, N \text{ with } \Delta \boldsymbol{e_i} = (\Delta e_{i3}, \Delta e_{i4}, \ldots, \Delta e_{iT})'$$

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[11] In our analysis, $\boldsymbol{w}_{it}$ includes lags of abnormal loan growth and $\boldsymbol{\gamma}$ is the parameter of interest. Under the null hypothesis, loan growth results in higher ratios of future problem loans, such that $\boldsymbol{w}_{it}$ and $y_{i,t-1}$ are indeed correlated.

[12] See e.g. Roodman (2009a) for a presentation of the GMM framework.

are equal to those listed in (4). The required predeterminedness of y_{it} holds if the error terms are serially uncorrelated and if the initial observation y_{i1} itself is predetermined,

$$E[y_{i1}e_{is}], \qquad s = 2, 3, \ldots, T,$$

since it follows that all y_{it} are uncorrelated with $e_{i,t+1}$ and all subsequent disturbances. Equivalently, that $y_{i,t-2}$ and deeper lags are independent of $(e_{it} - e_{i,t-1})$. Testing for autocorrelation in the errors is thus crucial for assessing instrument validity.[13]

Depending on how the additional regressors w_{jit} in $\boldsymbol{w}_{it}$ depend on the differenced error, more moment conditions are available. Any variable w_{jit} that is strictly exogenous, thus independent of Δe_{it}, is valid as an instrument in itself. In this case $(w_{ji3},\ w_{ji4}, .. w_{ji,T})'$ may be included as an additional column in the instrument matrix $\boldsymbol{Z_i}$. If w_{jit} is predetermined with respect to e_{it}, ie uncorrelated with e_{it} and subsequent errors, but correlated with $e_{i,t-1}$, it would need to be instrumented (due to the correlation between Δw_{ijt} and Δe_{it}). Since $w_{ji,t-1}$ and deeper lags in this case are valid instruments, $\left(y_{i,t-2}, \ldots, y_1\right)$ might be replaced with the vector $\left(y_{i,t-2}, \ldots, y_1, w_{ji,t-1}, \ldots, w_{ij1}\right)$ in the $(t-2)$th row of $\boldsymbol{Z}_i$. If w_{jit} is contemporarily correlated with the error term e_{it}, only $w_{ji,t-2}$ and deeper lags are valid instruments.

The empirical validity of subsets of instruments might be tested with a difference-in-Sargan or difference-in-Hansen test, depending on whether one-step or two-step GMM-estimators are used (see Roodman (2009a)).

The resulting IV-estimator, using all available instruments and preserving sample length, is efficient. Yet, there are two important caveats. The first relates to the instrument count, or the number of moment conditions. As the sample length T increases, the number of instruments increases rapidly, together with an increased risk of overfitting to the endogenous variables (the estimates will approach the biased first-difference estimates). Furthermore, the Hansen test for the validity of the overidentifying restrictions is weakened when the instrument count is high. Hence one should not be too confident in failing to reject the null at conventional levels when the instrument count is high (see Roodman 2009a, 2009b for discussions of “the problem of too many instruments”).

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[13] If the disturbances do hold some form of autocorrelation, deeper lags may still be valid instruments. For example, if the degree of serial-correlation in Δe_{it} is of order 2, then $y_{i,t-3}$ and deeper lags may still be used as instruments.

One strategy to reduce the number of instruments is not to use *every* available instrument for the endogenous/predetermined variables at time t, rather a subset of these instruments – eg up to the first 3 valid lags. Another, or additional, strategy is to "collapse" the instrument matrix,

$$\boldsymbol{Z}_{\boldsymbol{i}}^{coll} = \begin{bmatrix} y_{i1} & 0 & \cdots & 0 \\ y_{i2} & y_{i1} & \cdots & 0 \\ . & . & \cdots & . \\ y_{i,T-2} & y_{i,T-3} & \cdots & y_{i,T-1} \end{bmatrix}$$

which gives the following moment conditions:

$$E\left[\boldsymbol{Z}_i^{coll\,\prime}\,\Delta\boldsymbol{e}_{\boldsymbol{i}}\right] = \sum_{s=2}^{t} E[y_{i,t-s}\Delta e_{it}] = 0, \qquad t = 3, \dots, T$$

These moments are implied by (4), thus essentially the same. Nevertheless, in summing over the time-dimension, they convey less information than those associated with the uncollapsed matrix.

The second issue with the difference GMM estimator regards the strength of the instruments. If the instruments are weak, IV estimates might hold substantial finite sample biases. This issue arise when the instrumented variables are highly persistent. The first difference of a highly persistent variable will be close to white noise, for which its lagged levels are poor instruments. The same apply if the variance of the fixed effect is high relative to the variance of the idiosyncratic error term, that is when $Var(\eta_i)/Var(e_{it})$ is large. Arellano and Bover (1995) and Blundell and Bond (1998) show that for such variables, instrumenting levels with lagged differences, in addition to instrumenting differences with lagged levels, improves the precision of the GMM estimator. That is to include as additional instruments the lagged difference $\Delta\, x_{ji,t-1}$, as an instrument for the endogenous variable x_{jit} in the untransformed model in (equation (3)).[14] The additional moment conditions is given as

$$\mathrm{E}\left[\Delta x_{ji,t-1} u_{it}\right] = \mathrm{E}\left[\Delta x_{ji,t-1}(\eta_i + e_{it})\right] = 0, \qquad t = 3, \dots, T$$

and the resulting estimator is called the *system-GMM* estimator. Obviously, this estimator rely on the additional assumption that $\Delta\, x_{ji,t-1}$ is independent from the fixed effects,[15] equivalently that $E\left[x_{jit}\eta_i\right]$ is time-invariant, such that

[14] If x_{ijt} was instead predetermined, $\Delta\, x_{ijt}$ is uncorrelated with e_{it} and valid as an instrument.
[15] This additional assumption is not arbitrary. It can be re-expressed as a restriction on the initial conditions, which state that the first observations of the endogenous variables should not systematically deviate from their long-run

$$\mathrm{E}\left[\Delta x_{ji,t-1}\eta_i\right] = \mathrm{E}\left[(x_{ji,t-1} - x_{ji,t-2})\,\eta_i\right] = 0$$

To sum up, under the assumption of predeterminedness, the difference- and system-GMM estimators might provide consistent estimates for the dynamic panel data model in “small T, large n” samples. Nevertheless, one should be aware that new issues arise when applying these estimators. In particular, as the number of instruments rapidly increases in the length of the panel, there’s a risk of overfitting to the endogenous variables. Also weak instrument problems owing to persistent variables might lead to biases in finite samples. Comparing GMM estimates with more straightforward OLS and within estimates might be useful in detecting such problems.

mean. This is less likely to hold when the endogenous variables are indeed persistent, as discussed in Roodman (2009 b).