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How much do non-performing loans hinder loan growth in Europe?

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ABSTRACT

The severe recessions following the global financial crisis of 2007–2008 left numerous European banks with acutely distressed loan books. In the subsequent recovery, bank lending in Europe has fallen dramatically behind peer advanced economies. This paper focuses on how the post-crisis accumulation of non-performing loans (NPLs) has hindered bank lending in Europe. In assessing the effect of NPLs, we attempt to control for demand factors, simultaneity bias, and the alternative channels through which NPLs affect lending growth. Our primary data source, proprietary quarterly bank-level data from the European Banking Authority (EBA) for 2014–2019, provides detailed information on NPLs for around 200 banks in 30 countries in the European Economic Area. The weak lending growth during the observation period implicates a transmission channel in which NPLs decrease bank profits, increase bank funding costs, and erode bank capital. We find that the strength of the credit squeeze depends on the level of NPLs in the sample. After controlling for this, our estimate of the semi-elasticity of lending growth with respect to NPLs closely matches earlier studies. Given the vital role of bank lending in funding European investment, the possible depressing effect on economic growth from a large NPL burden represents an important policy consideration.

1. Introduction

There are multiple explanations for Europe's disappointingly weak growth in the 2010s. One cause commonly raised in public discussion is the poor state of the European banking sector, or more precisely, the large amounts of non-performing loans (NPLs) on European bank balance sheets.

The burden of NPLs remains a legacy of the economic hardship that followed the global financial crisis (see EBA 2019a and 2019b for details on the nature of the European NPL problem). At its worst, the stock of European NPLs reached €1 trillion. According to IMF Financial Soundness Indicators, the average share of NPLs in the EU during 2014–2018 was close to 10%, while the comparable number in other major advanced economies was 0.9%.[1] Among the many authorities

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[1] The 0.9 % cited here is the average for Australia, Canada, Japan, South Korea, and the United States. Behind the 10 % number for EU is widespread heterogeneity; the share of NPLs ranges from 0.9 % in Luxembourg and Estonia to 36–39 % in Cyprus and Greece. The average share of NPLs in the Commonwealth of the Independent States, the Middle East, and Africa, was also around 10 %, comparable to the EU NPL average. In Central and South America, as well as Developing Asia, the share of NPLs was below 5 % on average. Source: https://data.imf.org/.

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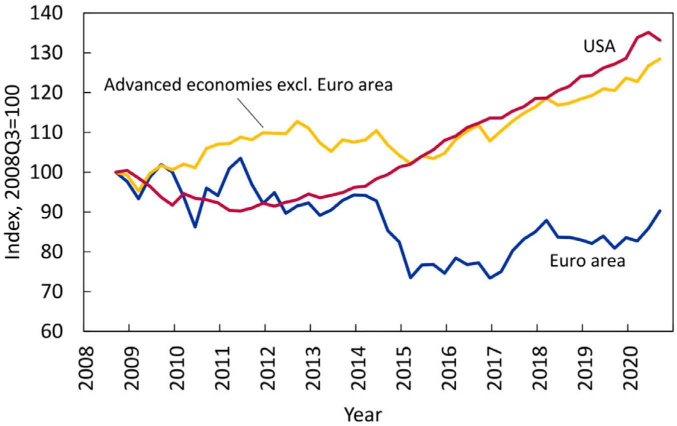

Fig. 1. Bank lending growth in euro area and other advanced economies. The graph shows US dollar-based index of aggregate bank lending stock to private non-financial sector. The series are normalized so that Index = 100 at the end of 2008Q3, which corresponds to the start of the global financial crisis. Source: BIS.

expressing concern, Mario Draghi, ECB president at the time, explicitly pointed out that there are still too many bad loans and structural weaknesses in the eurozone's banking system: "(t)hese [weaknesses] include inadequate internal governance structures in banks, ineffective and costly debt recovery procedures in some member states and misaligned incentives that prevent a quick resolution of NPLs" (Draghi, 2017).

Even if euro area recovery has slowly (and heterogeneously across member states) reduced the proportion of NPLs on bank balance sheets, the NPL problem persists (Enria, 2019).[2] The policy debate (see e.g. Nouy, 2017; Draghi, 2017; Constâncio, 2017; EU Commission, 2017; ESRB, 2017; ECB, 2019; and Enria, 2019) includes assertions that NPLs are behind the economic weakness in several European countries. Bad loans are not just blamed for the weak profitability of Europe's banking sector, but also for Europe's weak growth in bank lending and tepid recoveries in output and productivity. Bad loans may even have served as life-support for zombie firms (see e.g. Andrews and Petroulakis, 2017). Fig. 1 illustrates the drastically muted development of the bank lending in euro area as compared to other advanced economies. After the global financial crisis in 2008 and the euro area debt crisis in 2010–2014, the lending has fallen considerably behind the peer group of other advanced economies.

To shed light on the role of NPLs, we estimate the semi-elasticity of lending growth with respect to NPLs using a panel OLS regression with location-specific time fixed effects to control for loan demand arising from the bank's environment. This setup allows us to interpret the effect of NPLs as emanating from the bank (as opposed to outside demand). Carlson et al. (2013) show that location-specific fixed effects yield results comparable with a matching method in which the demand effects are controlled for by pairing banks that share some characteristics. In the estimation, we control for other potential factors affecting the lending growth such as the bank's profitability (measured by return on assets, ROA), capital adequacy (measured by Tier 1 ratio), and the coverage ratio of NPLs.[3] We use lagged regressors to cope with potential endogeneity of the explanatory variables (see further discussion in Section 2.3). To show that our results are robust against simultaneity bias, we carry out additional estimations using dynamic panel data estimators.

Our dataset is taken from the harmonized bank-level data on loans and NPLs for major institutional sectors maintained by the European Banking Authority (EBA).[4] The data are of high quality and employed routinely in European banking supervision activities and determination of central bank policy. They cover about 200 banks in 30 European countries for the period 2014Q3–2019Q1.[5] Most of the banks in the sample are large traditional banks that operate as bank holding companies, commercial banks, savings banks, or cooperative banks. On average, these banks have slightly more household loans than corporate loans (mortgages in Europe are typically carried in the bank balance sheets). In addition to this relatively fresh bank data, we use annual cross-country panel data covering 19 European countries for 1982–2017 and quarterly aggregate data for Finland for 1988Q1–2018Q1 as a robustness check.

Using the EBA data, our central estimate of the semi-elasticity of banks' quarterly lending growth to non-financial private sector (NFPS) with respect to NPLs is −0.08. The sectoral semi-elasticities for household and corporate loans are of similar magnitude. Even though we ignore the indirect effects, the depressing effect of NPLs on lending growth is quite significant. Using the full-sample, a one percentage point increase in the NPL ratio contributes to a 0.08 percent decrease in quarterly

[2] Although we have yet to see statistical evidence that the level of NPLs has reacted significantly to the Covid-19 pandemic, the latest available EBA data for 2020Q4 (EBA, 2020) show a rising volume of forborne loans that could foreshadow an increase in the level of NPLs due to the crisis. It remains to be seen how the phasing out of Covid-related measures (such as moratoria or public guarantees) will affect the level of NPLs.

[3] Unfortunately, the data do not include a bank-specific proxy for lending standards.

[4] We distinguish here between loans to firms, loans to households, and loans to the general government.

[5] Although the data only cover a relatively short period, we have almost 8,000 data points available in the three-sector panel.

lending growth to private non-financial sector – even as bank lending grew at an average quarterly rate of 0.3 percent during the sample period.

We find this semi-elasticity to be *inversely related* to the level of NPLs, and that this inverse relationship applies to both countries and sectors. In particular, semi-elasticity tends to be higher in absolute terms in low NPL countries and for household loans. Consistent with this, the additional Finnish dataset (with low NPL ratios) produces a higher semi-elasticity estimate than the EBA data. The effect could be caused by different structural features of the NPLs in low- and high-NPL samples or state-dependence in the transmission channel from NPLs to lending growth. Inspecting the level of NPLs in earlier studies, we find that the inverse relationship can explain some differences among the previous literature estimates. After adjusting for the level of NPLs, our estimates are in line with estimates based on advanced economy bank-level data reported by Carlson et al. (2013) and Cucinelli (2015).

To improve understanding on the channels through which NPLs affect lending growth, we estimate the effect of NPLs on bank profitability, capital adequacy, and funding costs. A one percentage point increase in NPLs decreases ROA by 0.04 percentage points and the Tier 1 ratio by 0.13 percentage points. The average cost of bond financing increases by four basis points and the average cost of deposit funding by roughly one percentage point. These findings support the notion of a transmission channel in which NPLs weaken the bank's profitability and balance sheet. As a consequence, the capital-constrained bank is forced to reduce its lending.

Turning to the earlier literature, NPLs are thought to affect bank lending through several channels. Berger and Udell (2004) find that banks tighten credit standards when credit quality is low. As an example of this tightening, (Jimenez et al., 2012), using panel data on Spanish corporate sector loan applications, show that banks are less likely to grant loans to businesses with poor track records in servicing debt.[6] Lown and Morgan (2006) find lending standards to be important driver of credit growth.

Aiyar et al. (2015b) conceptualize three interrelated channels through which NPLs hamper bank lending – *bank profitability, capital adequacy*, and *funding costs*. NPLs mechanically deteriorate a bank's profitability through increased loan loss provisions and lower interest income. Holding of non-performing assets ties up bank capital, which is simultaneously eroded by weak profitability. Moreover, the bank's deteriorated situation tends to raise its funding costs. Higher funding costs mean higher expenses, and hence lower profitability. Banks should expect to earn a positive net interest margin, so an increase in funding costs directly contributes to higher lending rates, and hence reduced lending. It is also well understood why profitability and capital adequacy matter for bank lending.[7]

There are many reasons why banks view new equity issuance as a relatively costly form of external finance (for a review, see e.g. Dagher et al., 2016). Hence, higher earnings and higher capital buffers help them avoid resorting to new external equity financing and keep their lending costs down. Like this article, the empirical challenge for the researcher is separating supply from demand when analyzing these effects. An overview of the empirics (and additional references) is provided in Carlson et al. (2013).

Estimates of the effect of capital adequacy on lending vary considerably. For example, Berrospide and Edge (2010) find only miniscule effects. Labonne and Lamé (2014) and Carlson et al. (2013) find a positive effect, but they note that the effect is nonlinear depending on the proximity of the capital constraint. Cucinelli (2015) obtains a negative effect, while Vinh (2018) find that both higher profitability and capital adequacy predict higher lending growth. (Jimenez et al., 2012) finds that weaker banks are less likely to grant loans, which links the three channels of Aiyar et al. (2015b) with the credit standard channel. Our results are consistent with the *bank profitability, capital adequacy*, and *funding costs* channels discussed above leading to reduction of credit supply through tightening of credit standards. While we observe that a bank's own financial constraints become tighter, part of the credit-curtailing could be related to the bank's idiosyncratic perception of its current customer base as particularly risky.

While numerous earlier studies report the effects of NPLs on lending growth, most of them deal with transition economies or developing economies (see e.g. Espinoza and Prasad, 2010; Klein, 2013; Nksu, 2011; Aiyar et al., 2015; Lu et al., 2005; Tomak, 2013; Vinh, 2018). Huljak et al. (2020), who consider twelve euro area countries using somewhat similar data to the current study, conclude that NPLs depress bank lending.[8] The studies by Carlson et al. (2013) with US panel data, and Cucinelli (2015) with Italian panel data, also find a negative loan growth effect from non-performing loans. Section 4 provides a more detailed overview of these studies together with a table of empirical estimates.

A separate group of studies considers the potential benefits of eliminating NPLs. Balgova et al. (2016), for example, analyzing the consequences of NPLs for a large set of countries, find they could achieve large gains by eliminating NPLs through active policy measures (up to two percentage points in terms of GDP growth). The magnitude of the NPL burden is also considered by Aiyar et al. (2015a,b), who provide a thorough review of the proposed measures to reduce Europe's NPL problem. Bergthaler et al. (2015) examine the NPL problem of small and medium-sized firms in Europe. Other contributions on the topic include Fell et al. (2016, 2017) and Grodzicki et al. (2015).

To summarize our contribution, nearly all previous studies have relied on data compiled prior to the global financial crisis. Many use data from a single country or country-level aggregate data. Here, we utilize a recent, but established, multi-

[6] Their data are exceptional in that it also includes information about loan applicants' prior ability to serve their debt service expenses. It turns out that a firm's poor performance in this respect clearly shows up negatively in acceptance in applications.

[7] Carlson et al. (2013) includes a useful footnote in this regard.

[8] Huljak et al. use a formidable ten-variable VAR workhorse. They distinguish between corporate and mortgage loans.

country bank-level supervisory dataset. Our setup helps distinguish the dampening effect of NPLs on lending growth as emanating from the constraint to bank balance sheets, instead of the macroeconomic environment. Further, the sectoral split of bank lending and NPL data allows us to eliminate possible aggregation bias and gives additional insight into sectoral dependencies. We confirm earlier findings that NPLs have a statistically significant dampening effect on bank lending growth, and show that the impact of NPLs on the credit supply results from the direct effect on capital and profitability. It is important to note that part of the effect could be attributed to a bank's idiosyncratic risk views which would be an interesting topic for future research.

The rest of the paper is structured as follows. Section 2 presents the data and the estimation approach. Section 3 reports the results. Section 4 discusses the magnitude of the NPL effect relative to earlier literature. Section 5 concludes.

2. Analysis

2.1. Data sources

2.1.1. Data used for main estimates

Our primary data source is the proprietary bank-level data from the European Banking Authority.[9] The data lie behind the EBA Risk Dashboard, which is only publicly available on a more aggregated level. This dataset comprises 225 major banks from 30 European countries (EU-27, Iceland, Norway, and the United Kingdom).[10] The data rely on implementing technical standards (ITS) on supervisory reporting introduced by the EBA, and provide a comprehensive set of harmonized data for European banks.

Comparability and reliability of the data are crucial issues when it comes to measures of asset quality. This is exemplified by the large publicity around the Asset Quality Reviews performed by the ECB. The data are organized into key risk indicators. The EBA obtains the underlying data from national supervisors, who collect the data as a part of their regular FINREP and COREP supervisory reporting. The sample of banks is reviewed annually by competent authorities and adjusted accordingly. The EBA data provides information about bank assets, asset quality, solvency, and profitability comparable across the countries included. This is particularly important given the issues that often arise when comparing non-performing exposures across countries. While these data have been used in analysis of non-performing exposures in EBA (2016) and EBA (2019a), we are unaware of any academic research articles that have made use of the data.[11]

Most of the 225 banks in our sample are traditional banks that operate as bank holding companies, commercial banks, savings banks, or cooperative banks. Additionally, about 5% of the banks are investment banks or related, and 16 banks are classified as specialized government credit institutions. The banks in this consolidated data are large; 95% of observations correspond to banks with balance sheets larger than €5 billion and 50% of observations involve bank balance sheets greater than €50 billion. This contrasts with studies that include many small banks. For example, Cucinelli (2015) studies 455 listed and unlisted Italian banks (possibly on an unconsolidated level), while our sample only includes 15 large Italian banks on a consolidated level.

Besides the sample, the main difference to previously used datasets is that we have separate loan and NPL data for each sector. The sectors encompass non-financial corporations, households, general government, credit institutions, and other financial corporations. In this article, we consider the three first sectors. Besides sectoral loans, we consider the loans to non-financial private sector, defined as the sum of non-financial corporate loans and household loans.

As discussed below in Section 2.3, we explain the bank-level lending growth, profitability, Tier 1 capital ratio, or funding costs using the NPL ratio (the percentage share of NPLs of gross loans; and for sectoral NPL ratio, the percentage share of NPLs of gross loans for the corresponding sector), return on assets (ROA), Tier 1 capital ratio, and the coverage ratio of NPLs.[12] A bank's funding costs are measured by average interest cost of its bond financing (of all such debt instruments issued) or average cost of deposit financing. While all these variables are available in the EBA data, not all variables are available for all banks. This reduces the number of banks available for estimation to between 153 and 191 depending on which variables and sectors are included. We also use macro series for inflation, output, and interest rates obtained from the IMF, Eurostat, and national central banks. The variables are summarized in Table 1(a).

While the data appears to be generally of high quality, we have detected some outliers in the loan series. These outliers seem to be related to corporate restructurings and we have removed them from the data.

2.1.2. Alternative data sources used for robustness checks

Because of the relatively short span and special nature of the sample period, we want to confirm our basic result using two alternative datasets that encompass a longer time-span. The first dataset is based on Finnish quarterly data on NPLs

[9] https://eba.europa.eu/risk-analysis-and-data/guides-on-data.

[10] The data are consolidated on two levels, leading to double-counting of some items. On one hand, we have the consolidated data of the ultimate parent that resides in some country. On the other, the subsidiaries are also consolidated at the subsidiary level as banks in their country of domicile. In the case of certain large international banks, loans in each sector are comprised of aggregated domestic and foreign loans, irrespective of the counterparty's country. European banks tend to have a strong home-bias, so this is likely a minor issue.

[11] EBA data differ from the data of the ECB's Individual Balance Sheet Item (IBSI), which is based on data reported for monetary policy purposes. While the IBSI data have been used in many academic studies, the EBA data are arguably better suited to analysis of non-performing exposures.

[12] For further data on the coverage ratio and its relationship to the NPL ratio, see EBA (2019).

Table 1
Definitions and descriptive statistics.

(a) Definitions and sources		
Variable	Definition	Source
Cost of bond financing	Percentage of average interest expense of debt securities issued (100 * FND 27). Formula: 100 * Interest expenses of debt securities issued at amortized cost / Debt securities issued at amortized cost.	EBA
Cost of deposit financing	Percentage of average interest expense of deposits (100 * FND 34). Formula: 100 * Interest expenses of deposits at amortized cost / Deposits at amortized cost	EBA
Coverage ratio	Percentage of coverage ratio of non-performing loans and advances – All sectors (100 * AQT 41.2). Formula: 100 * Accumulated impairment, accumulated negative changes in fair value due to credit risk for non-performing loans and advances / Total gross non-performing loans and advances.	EBA
Loans to non-financial private sector (NFPS)	Denominator of NPL (Total) – Total gross loans and advances – Non-financial corporations and households	EBA
Corporate loans	Denominator of NPL (F) – Total gross loans and advances – Non-financial corporations	EBA
Government loans	Denominator of NPL (GG) – Total gross loans and advances – General governments	EBA
Household loans	Denominator of NPL (HH) – Total gross loans and advances – Households	EBA
NPL (All)	Percentage share of non-performing loans and advances – All sectors (100 * AQT 3.2). Formula: 100 * Non-performing loans and advances / Total gross loans and advances.	EBA
NPL (NFPS)	Percentage share of non-performing loans and advances– Non-financial corporations and households. Formula: 100 * Non-performing loans and advances / Total gross loans and advances.	EBA
NPL (Firms)	Percentage share of non-performing loans and advances by counterparty sector – Non-financial corporations (100 * AQT 3.2.4)	EBA
NPL (Government)	Percentage share of non-performing loans and advances by counterparty sector – General government (100 * AQT 3.2.2)	EBA
NPL (Household)	Percentage share of non-performing loans and advances by counterparty sector – Households (100 * AQT 3.2.6)	EBA
ROA	Percentage return on assets (100 * PFT 24). Formula: Profit or loss for the year / Total assets	EBA
Tier 1 ratio	Percentage Tier 1 ratio (100 * SVC 1). Formula: Tier 1 capital / Total risk exposure amount	EBA
GDP	Gross domestic product volume index, yoy growth (percentage)	IMF
Inflation	Harmonized index of consumer prices, yoy growth (percentage)	Eurostat
Interest rate	Overnight currency-specific money market rate (percentage)	Central banks

Codes such as “FND 33″ in the variable definitions refer to variable identifiers in the EBA data.

and loan losses for the period 1988Q1–2018Q1. The data have been provided by the Bank of Finland and were collected by the Finnish Financial Supervisory Authority (FIN-FSA). In this data set, the NPLs are for all loans, while the loan losses are available separately for corporate loans and household loans.

The second dataset is an extensive annual cross-country dataset with loan losses (more precisely, loan losses divided by outstanding loans) that has been collected by the Bank of Finland from different central banks with several questionnaires over time (for details, see Jokivuolle et al., 2015). Because we do not have a sufficiently long cross-country series of NPLs, we use the loan loss rates as substitutes for NPLs. The cross-country dataset covers the period 1982–2017, but the sample period is shorter for some countries. This dataset does not provide disaggregation for various sectors.

Besides the above data on loan losses and NPLs, the robustness checks use macro series of the real GDP, real interest rate, house prices, stock prices, and, in the case of Finland, a Financial Stress Index and the government bond interest rate differential vis-à-vis Germany. The data are from the EU Commission’s AMECO data bank, Bloomberg, and the Bank of Finland. See Table 1(b) for details.

2.2. Descriptive statistics

Descriptive statistics of the EBA data are presented in Table 1(c). In contrast to some jurisdictions, European mortgages are predominantly carried on bank balance sheets. As a result, banks in our sample have more household loans than corporate loans. An average household loan portfolio is €52 billion vs. €44 billion average corporate loan portfolio. At €8 billion, the government loan portfolios are considerably smaller.

NPLs are most common for corporate loans with a mean NPL ratio at 12.9%, almost double the mean NPL ratio of household loans (7.3%). The corresponding number is 2% for the general government – in any case, the ratio is nonzero. The total share of NPLs shrank over the sample period from about 11% to around 5%. Banks that have high share of corporate NPLs often have high share of household NPLs as demonstrated by high correlation coefficient 0.80. Write-offs have been slow

Table 1b
Definitions and sources for Finnish quarterly and cross-country annual data.

Variable	Definition	Source
Alternative Finnish quarterly data		
Real loan growth	Growth rate of banks' real loans (percentage)	FIN-FSA
NPL	Ratio of non-performing loans to outstanding loans (percentage)	FIN-FSA
LL (Households)	100*LL/LV: Loan losses divided by outstanding loans (percentage)	FIN-FSA
LL (Firms)	100*LL/LV: Loan losses divided by outstanding loans (percentage)	FIN-FSA
GDP growth	Annual growth rate of real GDP (percentage)	Statistics Finland
Real interest rate	Real ex post interest rate from the three-month Euribor rate and the CPI growth rate (percentage)	Bank of Finland
Real house price growth	4-quarter growth rate of real house prices (percentage)	Statistics Finland
Real stock price growth	4-quarter real growth rate of stock prices (percentage)	Bloomberg
Interest rate differential	Interest differential vis-à-vis Germany for 10-year bond rates (percentage points)	Bloomberg
Stress index	Finnish Financial Stress Index calculated by the Bank of Finland	Bank of Finland
Alternative cross-country data		
Real loan growth	Growth rate of banks' real loans (percentage)	EU Commission
Loan losses	LL/LV: Loan losses divided by outstanding loans (percentage)	Bank of Finland
GDP growth	Annual growth rate of real GDP (percentage)	EU Commission
Real interest rate	Real ex post interest rate from the three-month Euribor rate and the CPI growth rate (percentage)	EU Commission
Real house price growth	4-quarter real growth rate of housing prices (percentage)	EU Commission
Real stock price growth	4-quarter real growth rate of stock prices (percentage)	EU Commission

Table 1c
Descriptive statistics.

Variable	**Mean**	**Std.**	**p10**	**p90**	**units**	**Obs.**	**Aggregation level**
Cost of bond financing	3.02	4.49	0.94	5.02	%	2730	Bank
Cost of deposit financing	0.78	0.75	0.12	1.63	%	3085	Bank
Coverage ratio							
...All loans	40.81	17.33	19.32	60.64	%	2996	Bank
...Firms	43.96	15.96	23.30	62.46	%	2973	Bank
...Government	−0.14	586.41	0.31	100.00	%	301	Bank
...Households	40.07	24.84	14.57	65.88	%	2898	Bank
Loans to non-financial private sector	95.28	158.40	4.01	328.40	EUR bn	2792	Bank
...growth	0.31	2.71	−2.62	3.08	%	2542	Bank
Firm loans	43.53	73.4	1.70	115.83	EUR bn	2804	Bank
...growth	0.10	3.61	−4.03	4.01	%	2538	Bank
Government loans	7.97	17.23	0.06	22.48	EUR bn	1908	Bank
...growth	−1.05	6.84	−9.36	7.44	%	1908	Bank
Household loans	51.94	91.76	1.50	170.31	EUR bn	2771	Bank
...growth	0.39	2.70	−2.20	3.05	%	2509	Bank
NPL (Total)	7.96	10.19	0.69	20.49	%	3032	Bank
NPL (NFPS)	9.98	11.76	1.36	24.31	%	2943	Bank
NPL (F)	12.85	14.51	1.33	33.23	%	3012	Bank
NPL (GG)	1.96	6.27	0.00	4.56	%	2521	Bank
NPL (HH)	7.30	9.99	0.82	15.04	%	2921	Bank
ROA	0.58	1.03	−0.10	1.54	%	3108	Bank
Tier 1 ratio	19.35	14.07	11.68	28.06	%	3628	Bank
GDP	2.71	2.47	0.95	4.76	%	3629	Country
Inflation	0.25	0.80	−0.58	1.02	%	3629	Country
Interest rate	−0.05	0.53	−0.36	0.46	%	3629	Country

Further descriptive graphics in the EBA Risk Dashboard available at: https://eba.europa.eu/risk-analysis-and-data/risk-dashboard.

and heterogeneous. According to Enria (2019), for those European banks with highest levels of NPLs, the majority of their NPLs are older than two years and more than a quarter are older than five years.

The coverage ratios for household loans and corporate loans are both a little over 40% on average. For government loans, the coverage ratios tend to be very low, and the data field is frequently empty. As discussed in Constâncio (2017), while about 60% of the distressed loans are in the non-financial corporate sector, a third are backed by commercial property. Many household loans are also collateralized. The collateral brings the total underlying coverage ratio considerably higher than the mean of 41% cited in Table 1(c).

To illustrate the relationship between loan growth and NPLs, we plot a scatter diagram with each bank's median NPL ratio on the horizontal axis and corresponding median loan growth on the vertical axis (see Fig. 2). We observe a clear adverse relationship for all sectors. The slopes of the corresponding bivariate regressions look plausible. Keeping in mind that the graphs only reflect the pairwise relationship, we must consider the estimates of Eq. (1) to see how the relationship works out when the control variables are present. Figs. 2a and 2b hint that the relationship between NPLs and lending growth may not be linear. As one might expect, an increase in the NPL ratio from 0% to 5% seems to have a larger impact

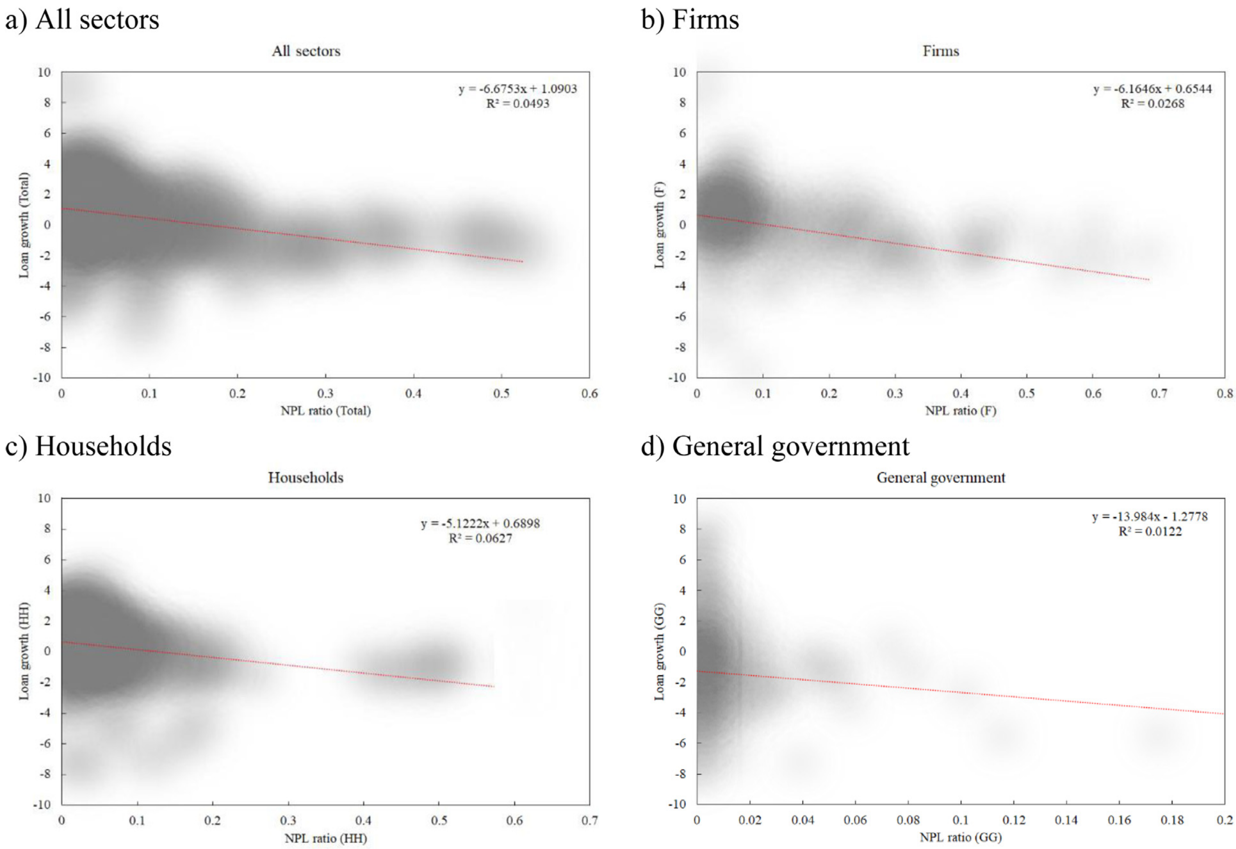

Fig. 2. Relationship between growth of NPLs and loans.
The vertical axis is median loan growth (%), while the horizontal axis denotes median NPL ratio (ratio between [0,1]). Hence, the semi-elasticity is the coefficient divided by 100.

on lending growth than an increase from 30% to 35%. Thus, the linear fit undershoots the observed lending growth at high NPL ratios.

As for the alternative datasets, the Finnish quarterly data for 1987–2018 and annual cross-country data for 19 European countries, the main difference vis-à-vis the EBA data is the length of the sample period. These datasets include two major periods of banking crisis: the early 1990s and the post-2008 period, and thus generate more differences across banks and over time. The corresponding descriptive statistics are collected in Table 1(d).

2.3. Estimation and hypotheses

We conduct our empirical analyses in a panel setup with a linear model, Eq. (1), presented below and estimated with OLS.

$$\Delta L_{b,s,t} = \beta_0 \Delta L_{b,s,t-1} + \beta_1 NPL_{b,s,t-1} + \tilde{\beta}' X_{b,s,t} + XFE_{b,s,t} + \varepsilon_{b,s,t}, \quad (1)$$

where the LHS variable is the quarterly loan growth in percentages $\Delta L_{b,s,t} = 100 \cdot (\log L_{b,s,t} - \log L_{b,s,t-1})$, ε is the error term, and $X_{b,s,t}$ and $\tilde{\beta}$ are a vector of control variables and the corresponding coefficients to be discussed in the next paragraph $X_{b,s,t} = [ROA_{b,t-1}, Tier1_{b,t-1}, COV_{b,t-1}, GDP_{c,t}, INF_{c,t}, INT_{c,t}]'$, and $XFE_{b,s,t}$ denotes one of the fixed effect specifications discussed below. The indices are *b = bank, c = country, s = sector, t=time*. Even if the coefficient estimates are OLS, we calculate the statistical significance using standard errors adjusted for clustering at the bank level. In the next few paragraphs, we discuss the control variables, the different fixed effect specifications, and how simultaneity is resolved in this setup.

Including the lagged loan growth on the RHS is consistent with most empirical specifications in the literature (see Carlson et al., 2013; Espinoza and Prasad, 2010; Keeton, 1999; and Vinh, 2018). The explanatory variable of primary interest is the lagged NPL, and our goal is to estimate the semi-elasticity β_1. We primarily express non-performing loans in percentage terms (100* non-performing loans / total loans). For some of the alternative datasets included in the robustness checks, we also consider "real value (euros) of NPLs" and "bank loan losses divided by total loans." The bank-level control variables are ROA, Tier 1 ratio (Tier1), and the coverage ratio of NPLs (COV), all expressed in percentage terms. Tier 1 ratio is typically included as a control in similar studies (see Carlson et al., 2013; Cucinelli, 2015; and Vinh, 2018). The motivation

Table 1d
Descriptive statistics for Finnish quarterly and cross-country annual data.

Variable	Mean	Std.	min	max	units	Obs.	Aggregation level
Finnish Q data							
Real loan growth	0.59	1.70	0.03	0.40	%	118	Country
NPL	2.25	2.94	0.27	13.28	%	118	Country
LL: Households	0.04	0.06	0.00	0.25	%	142	Country
LL: Firms	0.36	0.65	−0.05	2.71	%	142	Country
GDP growth	1.74	3.61	−9.86	6.95	%	142	Country
Real interest rate	2.04	3.67	−2.56	14.47	%	142	Country
Real house price growth	0.56	8.60	−22.0	24.0	%	142	Country
Real stock price growth	0.59	1.693	−3.47	4.24	%	142	Country
Interest rate difference	1.81	2.18	0.00	6.75	%	142	Country
Stress index	0.31	0.32	0.01	1.55	index	142	Country
Cross-country data							
Real loan growth	3.52	7.98	−21.13	43.42	%	361	Country
Loan losses	0.94	1.69	0.18	19.47	%	361	Country
GDP growth	1.86	3.17	−15,93	22.76	%	361	Country
Real interest rate	1.61	3.41	−13.21	17.25	%	361	Country
Real house price growth	1.12	7.76	−50.43	31.70	%	361	Country
Real stock price growth	3.76	22.91	−59.01	67.25	%	361	Country

is that a bank with an excessively low capital ratio may need to reduce lending to increase its capital adequacy due to bank capital requirements. Given that new bank equity issues are rare, the lending expansion of a bank that maintains a constant capital ratio should depend on bank profitability. Following Vinh (2018), we thus include ROA to more accurately capture the bank capital channel.

The rationale for the coverage ratio is that banks with larger provisions (measured by the coverage ratio) are in better shape and positioned to expand their lending more than banks with lower provision levels. Likely due to data availability issues, we have not seen the coverage ratio used in earlier studies. Note that as the control variables likely causally depend on NPLs, the total effect of NPLs on loan growth is greater than indicated by the coefficient of the NPL variable. As a simple alternative to the more elaborate fixed effect specifications discussed in next paragraph, we consider a set of country-specific macro variables the market interest rate (INT), inflation (INF), and the growth rate of GDP (GDP), as well as related combinations with time fixed effects or static country fixed effects.

Non-performing borrowers as an indication of general weakness in the economy has implications for credit demand. The reluctance of firms to invest may reduce lending growth. Banks may also find an increasing number of loan applicants too risky and refuse to lend (a supply effect). Alternatively, firms and households with inadequate income could be forced to take on debt to cover their expenses. Thus, the overall effect of the bank's lending environment is ambiguous. To capture these effects, the model includes country-specific time fixed effects (the baseline case), region-specific time fixed effects, bank-type*country*time fixed effects, or corresponding sectoral variants (country*sector*time FE, region*sector*time FE, country*bank_type*sector*time FE).[13]

Region-specific fixed effects (without the time dimension) have been used for similar purpose in Carlson et al. (2013). We identify the region within a country using the location of the bank's headquarters obtained from Orbis Bank Focus.

The most elaborate variant (bank-type*country*time fixed effects) captures the situation where banks with different business models face different loan demand. To this end, we use the specialization information from Orbis Bank Focus. Hence, we have, for example, different time fixed effects for German savings banks and German commercial banks. See Table S1 in the supplement for a summary of the bank specializations in our data. Controlling for the loan demand is crucial, since, from the policy point of view, it matters whether the standstill in bank lending has been caused by the bank or the customer.

To reduce potential simultaneity issues, we lag the bank-level variables by one period. A similar approach is often used in the earlier literature on this topic, and may rely on single-equation (Carlsson et al. 2013; and Cucinelli, 2015) or multiple-equation (Espinoza and Prasad, 2013; Keeton, 1999; Klein, 2013; and Vinh, 2018) reduced form relations.

Given that the causal link from lending to NPLs is well-established, it is worth elaborating why we believe this to be a minor concern for our estimation. First, on the level of the data, NPLs generally respond slowly to endogenous shocks as banks are expected to classify a loan as non-performing no sooner than one quarter after payment default. As noted in Section 2.1, a related characteristic of the European data is that most NPLs are several years old. This makes NPLs exogenous to concurrent lending behavior.[14] Even an immediate reverse causality could only affect the shortest maturity of NPLs. Second, we have strong reason to believe that the reverse causality is not immediate, but a slow process and so would not affect our estimates. Practically all analyses (e.g. Jokivuolle et al., 2015, and Ari et al., 2020) find that a key determinant of

[13] We typically include only one sector at a time in the estimation. Thus, the sectoral variants and index *s* are relevant only for the pooled specifications in Table 2c.

[14] The new ECB's database on NPLs (Ari et al., 2020) shows that the origins of NPLs are typically related to a crisis (banking or otherwise) that is fairly exogenous to the lending growth of banks.

NPLs and loan losses is excess indebtedness of firms and households. The increase in bank credit precedes the increase in NPLs by several years (cf. Ari et al., 2020, and Tölö et al., 2018).[15]

In the spirit of Gambacorta and Marquez-Ibanez (2011), we carry out additional robustness checks for simultaneity by instrumenting the potential endogenous variables using the system GMM estimator of Blundell and Bond (1998). The analysis is carried out in SubSection 3.1.1. We observe no signs of positive simultaneity bias in the NPL coefficient. The instrumented estimates are quite similar to the OLS estimates.

Our main hypothesis is that the coefficient of NPLs in Eq. (1) is negative, i.e.

Hypothesis 1. *A higher NPL ratio implies lower future credit growth for the bank.*

Given that the demand effects and any simultaneity are properly controlled, a coefficient found to be negative has an economic portent – the bank's poor financial state has caused the decline in lending growth. This is the classic *credit crunch effect* identified by Peek and Rosengren (1995).

A frequently overlooked topic is that many potential controls (e.g. bank profit and capital ratio) depend on NPLs. Fundamentally, NPLs affect lending growth through the three interrelated channels discussed in Aiyar et al. (2015b). When non-performing borrowers fail to service their debts, the bank's interest income decreases, eventually eroding bank capital. The bank may have to reduce lending to meet its capital requirements. This channel intimately links NPLs, bank profitability, bank capital, and lending growth. Additionally, depositors and investors may view a bank with high NPLs as risky. An increase in funding costs means deterioration in the bank's net interest margin. Thus, fewer loans are granted. To measure the total effect of NPLs on lending growth, we thus need to measure the impact of NPLs on the controls like ROA and Tier 1 ratio.[16]

In the light of the above discussion, we test three additional hypotheses on the effects of non-performing loans:

Hypothesis 2. *More NPLs imply lower bank profitability.*

Hypothesis 3. *More NPLs imply a lower capital ratio.*

Hypothesis 4. *More NPLs imply higher bank funding costs.*

Estimating these relationships proceeds as follows. For each of these equations, we use a broad set of control variables. For the sake of brevity, we do not consider the sectoral disaggregation of NPLs for Hypotheses 2, 3 and 4, relying only on the NPL ratio calculated for all loans. Our bank-level controls include ROA, Tier 1 ratio (Tier1), and coverage ratio (COV) as in Eq. (1).[17] We also include the macro variables GDP, inflation (INF), and interest rate (INT). To account for potential cross-country heterogeneity, we consider specifications with country fixed effects or country*time fixed effects.

For ROA and Tier 1 ratio, we lag the bank level explanatory variables by one period to be consistent with the approach in Eq. (1). The estimation equation for Hypotheses 2 and 3 take the form:

$$Tier1_{b,t} = \beta_0 NPL_{b,t-1} + \tilde{\beta} X_{b,t} + XFE_{c,t} + \varepsilon_{b,t}, \tag{2}$$

$$ROA_{b,t} = \beta_0 NPL_{b,t-1} + \tilde{\beta} X_{b,t} + XFE_{c,t} + \varepsilon_{b,t} \ . \tag{3}$$

where the control variable vector is $X_{b,t} = [ROA_{b,t-1}, COV_{b,t-1}, GDP_{c,t}, INF_{c,t}, INT_{c,t}]'$ and $XFE_{c,t}$ is either country FE or country*time FE.

We expect the funding costs to react quickly, so there we do not include a lag for the bank specific variables. The estimation equation for Hypothesis 4 takes the form:

$$Funding\ cost_{b,t} = \beta_0 NPL_{b,t} + \tilde{\beta} X_{b,t} + XFE_{c,t} + \varepsilon_{b,t}, \tag{4}$$

where the control variable vector is $X_{b,t} = [ROA_{b,t}, COV_{b,t}, GDP_{c,t}, INF_{c,t}, INT_{c,t}]'$ and $XFE_{c,t}$ is either country FE or country*time FE.

While Hypotheses 2–4 may seem trivially true, the magnitudes of the effects are of great interest. Models in Eqs. (2)–4 are estimated using OLS, but with standard errors adjusted for clustering at the bank level.

[15] When we compared the NPL ratio's sample average values over time with the average loan growth values, we found a clearly monotonic (negative) relationship between these variables. This suggests a relationship of permanent nature. In other words, banks with higher NPL ratios expand their loan stock at a slower rate than banks with fewer NPLs. Reverse causality does not explain such a permanent relationship. It is not plausible that banks that do not expand their lending will inevitably end up with high levels of bad loans.

[16] NPLs can also weaken the bank's reputation and lead to loss of new customers. This effect is difficult to isolate, however, without reliable reputation measures.

[17] We have verified that including additional controls such as asset encumbrance, share of non-interest income, share of liquid assets, logarithm of total assets of the bank, and the loans-to-deposits ratio, do not alter the results. The results are available upon request.

3. Results

3.1. Effect of NPLs on lending growth

This section tests Hypothesis 1, which posits that a higher NPL ratio leads to reduced lending growth, using Eq. (1) on our EBA bank data (2014Q3–2019Q1).

In Tables 2a–c, we report the effect of NPLs (and controls) on banks' lending growth to private non-financial sector and banks' sectoral lending growth. Overall, we find that the NPL coefficient is consistently negative across the different specifications, and that the size of the effect is significant. Table 2a columns (1–3) analyze the impact of NPLs among all loans to non-financial private sector. The semi-elasticity with respect to lending growth is about −0.1, meaning that a one percentage point increase in NPLs lowers the quarterly growth rate for loans by 0.1%. The coefficients change only a little when we move from country-specific time fixed effects to region-specific time fixed effects. Referring back to the discussion in Section 2.1, this is partly because banks in the EBA sample tend to be large and typically operate in a large geographical area, if not the whole country.[18] When we additionally include the bank-type dependence in the country-specifix time fixed effects, the magnitude of the effects drops somewhat indicating that there are bank-type dependent patterns in the relationship between NPLs and lending growth. Even so, the coefficients remain well within the ballpark of the baseline result.

Columns (4–6) in Table 2a explain a bank's total loan growth using sectoral NPL ratios. NPLs for corporate loans obtain on average semi-elasticity of −0.06 with high statistical significance, while the other sectors are not significant. This is understandable as the majority of Europe's non-performing loans are in the corporate sector. The magnitude of semi-elasticity is smaller because the sectoral NPL ratio is calculated relative to the sectoral loan book, not the entire loan book.

The last four columns (7–10) in Table 2a show the corresponding result when macro variables are used instead of location-specific fixed effects. Here, the magnitude of the semi-elasticities is somewhat smaller than in the fixed effect specifications, indicating that controlling for the bank's environment through location-specific fixed effects strengthens the result.

Table 2b columns (F.1–F.3), (G.1– G.3), and (H.1–H.3) show the effect of NPLs on loan growth in the respective sector for firms, general government, and households, respectively. The coefficients of NPL for firms and households loan growth both systematically show a statistically significant negative sign. For the general government loans, we find the correct sign, but the coefficient is not significant. The semi-elasticities of sectoral lending growth with respect to firm and household NPLs are approximately −0.08 and −0.10, respectively. It should be noted that the difference between the two semi-elasticities is not statistically significant at the 95% confidence level when we use robust clustered standard errors.

In Table 2c column (1–3), we pool the sectoral data into a single panel, which increases the number of observations and allows for the incorporation of sector-specific time-fixed effects. Here, the average semi-elasticity is −0.08. Column (4) in Table 2c shows the estimates when only sector fixed effects are present. As before, the magnitude of the estimate is smaller if we fail to control for the local demand.

We also find that the semi-elasticity of lending growth with respect to NPLs is quite sensitive to the level of NPLs. To show this, we split the sample into three subsamples by introducing two dummies D(5<NPL<10) and D(NPL>10) for the mid-NPL and high-NPL subsamples. To obtain the differential impact of the NPLs in the three subsamples, we interact the dummies with all the explanatory variables. As shown in Table 2d column (1), the semi-elasticity is −0.29 when we are restricted to the low-NPL subsample (NPL<5%). The semi-elasticity is −0.16 in the mid-NPL subsample, and −0.07 in the high-NPL subsample.[19]

Moreover, columns (2–4) in Table 2d show that when we estimate country-specific semi-elasticity for Germany, Spain, and Italy (the three countries with the largest numbers of observations in our sample), we observe the semi-elasticity to be highest in Germany, where the level of NPLs is lowest, and correspondingly lowest in Italy, where the level of NPLs is highest. This inverse relationship seems to hold across earlier literature estimates discussed in Section 4. The inverse relationship can be a result of several distinct effects. The low-NPL sample should include banks where the NPLs are relatively recent. The first time a bank encounters a bad loan problem, it may resort to credit-rationing for certain borrowers (see Jimenéz et al., 2013). As it may not immediately find less risky borrowers, the effect for the new NPLs is amplified. Additionally, we expect the effect of NPLs on bank funding costs to gradually saturate at higher levels of NPLs.[20]

We now turn to the control variables in Tables 2a–c. The coefficient of lagged loan growth tends to be positive and only occasionally statistically significant. The small value of this coefficient suggests that the bank specific loan growth adjusts relatively fast to changes in the control variables. The coefficient is negative for government loans. The outcome may reflect the seasonality and occurrence of some large short-term loans for this sector. We have verified that when this coefficient is not significant it makes little difference if we drop the lagged loan growth from the estimating Eq. (1). As an example,

[18] We also looked at the Eurostat database on regional development (REGIO). The REGIO database shows that the regional differences in cyclical developments (as opposed to levels of development) are, after all, rather small for most countries. In Germany, for example, the proportion of total variance explained by the first principal component of (54) regional unemployment rates is 0.98. With Italy, the corresponding number for 26 regions is 0.92.

[19] −0.16 is calculated as −0.294 + 0.134, and −0.07 is calculated as −0.294 + 0.224.

[20] More generally, the relationship between profits and NPLs should be non-linear. Moving from positive to negative loan growth rates also makes a difference. Detailed uncovering of this mechanism presents a tantalizing avenue for further research.

Table 2
Determinants of lending growth.

(a) Lending to non-financial private sector	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Loan growth$_{-1}$	0.072	0.08	0.079	0.045	0.082	0.093*	0.122**	0.049	0.137***	0.063	
	[1.56]	[1.14]	[1.88]	[0.87]	[0.96]	[2.00]	[3.14]	[1.33]	[3.35]	[1.59]	
NPL$_{-1}$ (NFPS)	**−0.098*** **	**−0.093*** **	**−0.080*** **				**−0.046*** **	**−0.097*** **	**−0.044*** **	**−0.091*** **	**−0.106*** **
	[5.34]	**[4.17]**	**[4.54]**				**[6.65]**	**[6.40]**	**[6.16]**	**[5.70]**	**[5.53]**
NPL$_{-1}$ (Firms)				**−0.069*** **	**−0.057** **	**−0.044** **					
				[5.77]	**[3.22]**	**[3.14]**					
NPL$_{-1}$ (Government)				**0.012**	**−0.001**	**0.01**					
				[1.51]	**[0.06]**	**[0.93]**					
NPL$_{-1}$ (Households)				**−0.007**	**−0.004**	**−0.001**					
				[0.28]	**[0.13]**	**[0.04]**					
ROA$_{-1}$	0.424***	0.554**	0.436**	0.399**	0.515*	0.520***	0.471***	0.417***	0.449***	0.390***	0.454***
	[3.83]	[2.88]	[3.27]	[3.19]	[2.34]	[3.36]	[4.30]	[3.72]	[4.16]	[3.56]	[3.92]
Tier 1 ratio$_{-1}$	−0.020	−0.045	0.003	0.011	−0.017	0.011	0.022	−0.019	0.023	−0.016	−0.023
	[0.86]	[0.84]	[0.12]	[0.48]	[0.60]	[0.41]	[1.75]	[0.78]	[1.78]	[0.64]	[0.90]
Coverage ratio$_{-1}$ (All)	−0.001	−0.003	0.001	0.004	0.004	0.006	0.011*	−0.006	0.011*	−0.006	−0.001
	[0.18]	[0.17]	[0.15]	[0.45]	[0.21]	[0.52]	[1.99]	[0.87]	[2.04]	[0.89]	[0.15]
GDP							−0.046	0.011	−0.041	0.016	
							[1.83]	[0.31]	[1.55]	[0.46]	
Interest rate$_{-1}$							−0.182	−0.119	−0.238*	−0.473	
							[1.68]	[0.36]	[2.10]	[1.34]	
Inflation rate$_{-1}$							−0.144*	−0.130*	0.022	0.027	
							[2.19]	[2.09]	[0.24]	[0.32]	
Country FE	No	No	No	No	No	No	No	Yes	No	Yes	No
Time FE	No	No	No	No	No	No	No	No	Yes	Yes	No
Country*time FE	Yes	No	No	Yes	No	No	No	No	No	No	Yes
Region*time FE	No	Yes	No	No	Yes	No	No	No	No	No	No
Country*type*time FE	No	No	Yes	No	No	Yes	No	No	No	No	No
R^2	0.490	0.710	0.703	0.530	0.758	0.728	0.138	0.194	0.176	0.230	0.487
N	2303	2303	2303	1956	1956	1956	2303	2303	2303	2303	2303
Banks	172	172	172	157	157	157	172	172	172	172	172

The dependent variable is quarterly lending growth in loans to non-financial private sector (NFPS) at the bank level. Figures within brackets are robust t-values, adjusted for clustering at the bank level. ***,**, and * indicate statistical significance at the 0.1, 0.01, and 0.05 percent levels, respectively.

Table 2b
Corporate, government, and household lending.

	(F.1)	(F.2)	(F.3)	(G.1)	(G.2)	(G.3)	(H.1)	(H.2)	(H.3)
Loan growth$_{-1}$	0.036	0.048	0.058	−0.104*	−0.078	−0.152*	0.261***	0.169*	0.194**
	[0.75]	[0.93]	[1.30]	[2.57]	[1.31]	[2.48]	[4.89]	[2.52]	[2.81]
NPL$_{-1}$ (Firms)	**−0.082*** **	**−0.084*** **	**−0.059** **						
	[5.56]	**[4.77]**	**[3.32]**						
NPL$_{-1}$ (Government)				**−0.046**	**0.013**	**−0.045**			
				[0.76]	**[0.08]**	**[0.58]**			
NPL$_{-1}$ (Households)							**−0.105*** **	**−0.110*** **	**−0.087* **
							[4.47]	**[3.42]**	**[2.60]**
ROA$_{-1}$	0.585***	0.736**	0.674***	0.567	0.438	0.660	0.402***	0.460*	0.476**
	[4.12]	[2.85]	[4.56]	[1.57]	[0.69]	[1.30]	[3.64]	[2.39]	[3.05]
Tier 1 ratio$_{-1}$	−0.082**	−0.082	−0.044	0.112*	0.191	0.143	−0.017	−0.013	0.005
	[3.22]	[1.69]	[1.23]	[2.07]	[1.40]	[1.64]	[0.94]	[0.31]	[0.25]
Coverage ratio$_{-1}$	−0.005	−0.009	−0.004						
(Firms)	[0.39]	[0.55]	[0.28]						
Coverage ratio$_{-1}$							0.005	0.000	0.007
(Households)							[0.77]	[0.01]	[0.75]
Country*time FE	Yes	No	No	Yes	No	No	Yes	No	No
Region*time FE	No	Yes	No	No	Yes	No	No	Yes	No
Country*type*time FE	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.398	0.658	0.620	0.334	0.595	0.569	0.521	0.756	0.702
N	2286	2286	2286	1562	1562	1562	2266	2266	2266
Banks	173	173	173	153	153	153	171	171	171

The dependent variable is quarterly lending growth in sectoral loans (*F*=firms, *G*=general government, *H*=households) at the bank level. Figures within brackets are robust t-values, adjusted for clustering at the bank level. ***,**, and * indicate statistical significance at the 0.1, 0.01, and 0.05 percent levels, respectively. For the government sector, we do not include the coverage ratio due to the low number of observations.

Table 2c
Pooled sectoral lending growth.

	(1)	(2)	(3)	(4)
Loan growth$_{-1}$	0.088*	0.071	0.077	0.098**
	[2.37]	[1.66]	[1.90]	[2.90]
NPL$_{-1}$ (sectoral)	**−0.086*** **	**−0.089*** **	**−0.064*** **	**−0.042*** **
	[6.38]	**[5.58]**	**[3.99]**	**[6.60]**
ROA$_{-1}$	0.516***	0.601**	0.602***	0.578***
	[4.80]	[3.21]	[4.40]	[5.89]
Tier 1 ratio$_{-1}$	−0.048*	−0.046	−0.015	−0.007
	[2.58]	[1.00]	[0.74]	[0.64]
Coverage ratio$_{-1}$	0.018	−0.461	0.472	0.031
(sectoral)	[1.18]	[0.68]	[0.68]	[1.58]
Sector FE	No	No	No	Yes
Country*sector*time FE	Yes	No	No	No
Region*sector*time FE	No	Yes	No	No
Country*sector*type*time FE	No	No	Yes	No
R^2	0.483	0.724	0.680	0.091
N	4761	4761	4761	4761
Banks	175	175	175	175

The dependent variable is quarterly lending growth in sectoral loans (firms, general government, or households) at the bank level. Figures within brackets are robust t-values adjusted for clustering at the bank level. ***,**, and * indicate statistical significance at the 0.1, 0.01, and 0.05 percent levels, respectively.

column (11) in Table 2a shows the baseline specification when we leave out the lagged dependent variable. We observe only a marginal increase in the NPL and ROA coefficients, so that the result is essentially unchanged. However, for example for household loans in Table 2b, the lagged dependent variable is significant and leaving it out significantly changes the estimate.[21]

We find ROA to be generally a highly significant driver of lending growth: the higher the return on assets (ROA), the higher the lending growth. Causality conceivably could run in the opposite direction, i.e. from lending growth to higher profits, but an unreported lead-lag analysis does not directly support this notion. Moreover, the ROA is affected by NPLs. A large amount of NPLs should be reflected in lower profits. Therefore, it is useful to re-estimate the basic estimating Eq. (1) without bank-specific controls. When doing so, we find that the role of NPLs clearly increases. This shows up in both coefficient estimates and their t-ratios (the results are available from the authors upon request). For this model specification,

[21] Since one does not know ex ante whether the dynamic specification is necessary, we recommend resorting to the dynamic specification when NPL elasticities can be estimated with different datasets.

Table 2d
Subsample specific semi-elasticity estimates.

	(1)	(2)	(3)	(4)
Loan growth$_{-1}$	0.127	−0.025	−0.184	0.116
	[1.71]	[0.34]	[1.31]	[1.04]
Loan growth$_{-1}$*D(5<NPL<10)	−0.182			
	[1.57]			
Loan growth$_{-1}$*D(NPL>10)	−0.059			
	[0.78]			
NPL$_{-1}$ (NFPS)	**−0.294****	**−0.195*****	**−0.101*****	**−0.129****
	[2.81]	**[10.67]**	**[6.08]**	**[3.15]**
NPL$_{-1}$ (NFPS)*D(5<NPL<10)	**0.134**			
	[1.06]			
NPL$_{-1}$ (NFPS)*D(NPL>10)	**0.224***			
	[2.11]			
ROA$_{-1}$	0.308	1.615**	0.412	0.215
	[1.81]	[3.36]	[1.71]	[0.68]
ROA$_{-1}$*D(5<NPL<10)	0.058			
	[0.17]			
ROA$_{-1}$*D(NPL>10)	0.175			
	[0.79]			
Tier 1 ratio$_{-1}$	−0.034	−0.040	0.105	−0.014
	[1.25]	[1.98]	[1.51]	[0.09]
Tier 1 ratio$_{-1}$*D(5<NPL<10)	0.002			
	[0.05]			
Tier 1 ratio$_{-1}$*D(NPL>10)	0.075			
	[1.95]			
Coverage ratio$_{-1}$	0.006	0.023	0.029	−0.047
	[0.80]	[0.82]	[1.02]	[1.53]
Coverage ratio$_{-1}$*D(5<NPL<10)	0.003			
	[0.27]			
Coverage ratio$_{-1}$*D(NPL>10)	−0.028			
	[1.78]			
D(5<NPL<10)	−0.887			
	[0.77]			
D(NPL>10)	−1.445			
	[1.44]			
Country	All	Germany	Italy	Spain
Mean NPL	23.1	5.0	19.7	9.2
Country*time FE	Yes	No	No	No
Time FE	No	Yes	Yes	Yes
R^2	0.502	0.367	0.288	0.275
Observations	2303	227	205	213
Banks	172	16	15	15

The dependent variable is quarterly lending growth in loans to non-financial private sector (NFPS) at the bank level. Figures within brackets are robust t-values, adjusted for clustering at the bank level. ***,**, and * indicate statistical significance at the 0.1, 0.01, and 0.05 percent levels, respectively.

we interpret the effect on lending growth of the NPLs as the sum of the direct effect and the indirect effect via the bank's profitability.

The Tier 1 capital ratio has some explanatory power, but the t-ratios mostly do not exceed the standard critical levels and the sign of the respective coefficients fluctuates. The Tier 1 ratio is significant only in three specifications: columns (F.1) and (G.1) in Table 2b and column (1) in Table 2c, and counter to expectations, the sign is sometimes negative. We can retrieve a positive statistically significant coefficient for the Tier 1 ratio if we leave out the other control variables and restrict the set to banks with Tier 1 ratios below 20% (results available upon request). This result is broadly consistent with the literature that reports large variation in the observed effect and weaker results or ambiguity in the presence of control variables.

The coverage ratio of NPLs is statistically significant in two specifications (columns 7 and 8 in Table 2a). In these cases, the sign of the coefficient is as anticipated; a higher coverage ratio implies higher future lending growth. Overall, the effect could partially be clouded by an opposite effect, whereby a higher coverage ratio means that, on average, a higher share of future NPLs or non-covered NPLs will be written down. Hence, a higher coverage ratio could indicate bank difficulties and reduced lending.

As for the macro variables, we find that they only have weak explanatory power. Interest rate and inflation obtain negative signs but are only occasionally and marginally statistically significant. The GDP coefficient is insignificant in all cases. This may be due to the relatively short sample period characterized by a steady growth of income and the low (almost constant) level of the interest rate.

Table 3
Dynamic panel data estimates of lending growth determinants.

	(1)	(2)	(3)	(4)
Loan growth$_{-1}$	−0.073***	−0.017	−0.016	−0.015
	[3.46]	[0.56]	[0.47]	[0.42]
NPL$_{-1}$ (NFPS)	**−0.114*** **	**−0.059*** **		
	[5.82]	**[7.35]**		
NPL (NFPS)			**−0.096***	**−0.080***
			[2.47]	**[2.18]**
ROA$_{-1}$	0.017	0.199		0.147
	[0.21]	[1.80]		[1.24]
Tier 1 ratio$_{-1}$	0.065*	0.038*		0.027
	[2.31]	[2.52]		[1.51]
Coverage ratio$_{-1}$	−0.018	0.015*		0.018*
	[1.86]	[2.57]		[2.23]
GDP$_{-1}$	−0.026	−0.050*	−0.028	−0.044*
	[0.84]	[2.18]	[1.21]	[2.02]
Interest rate$_{-1}$	0.100	−0.057	−0.031	−0.082
	[0.39]	[0.42]	[0.20]	[0.59]
Inflation$_{-1}$	−0.101	−0.110	−0.102	−0.087
	[1.62]	[1.87]	[1.32]	[1.18]
N	2313	2303	2313	2303
Banks	172	172	172	172
Instruments	–	9	12	15
Hansen J-test	–	0.291	0.071	0.041
Estimator	FE	SYS-GMM	SYS-GMM	SYS-GMM
Endogenous variables	–	Loan growth	Loan growth, NPL	Loan growth, NPL

The dependent variable in all equations is the growth rate of bank loans to non-financial private sector (NFPS) expressed in log differences. Numbers inside brackets are robust t-ratios. FE denotes the OLS fixed effect estimator. SYS-GMM denotes the Blundell and Bond (1998) System GMM estimator. Instruments for endogenous variables are collapsed and curtailed to the three first lags to reduce the number of instruments. The estimator uses forward orthogonal deviations to deal with gaps in the unbalanced panel. Hansen J-test denotes the respective marginal p-value.

Besides the controls shown in Table 2, we also consider the potential spillover effect of NPLs of other banks following the approach of Berrospide et al. (2016). The idea is that a contagion effect from NPLs of other banks at either the country or EU level could affect an individual bank's lending activity. Thus, we construct weighted aggregate NPL ratios (excluding the individual bank) and use the lagged values as additional regressors in our basic estimating Eq. (1). It turns out that these additional regressors have little, if any, explanatory power. They further suggest that the general level of NPLs in other banks is not of crucial importance in determining an individual bank's lending behavior. This, along with the stability of the coefficient estimates with respect to the various time fixed effect specifications, supports the notion that the above results capture a bank-specific loan supply effect.

3.1.1. Robustness check with alternative dynamic panel data estimators

The coefficient estimates in Tables 2a–d are OLS estimates (even though the standard errors are adjusted for clustering). Here, we also consider dynamic panel specifications. The reason is that in a fixed effect model the coefficient of the lagged endogenous variable can be subject to Nickell bias – a correlation between the regressor and the error term created by the demeaning process. This could potentially render all the estimated coefficients biased. We estimate the model using the FE and System GMM estimator. The SYS-GMM estimates give some idea of whether simultaneity issues matter in our sample. As discussed in Blundell and Bond (1998), the System GMM (SYS-GMM) estimator has significantly better finite sample properties in the case where the series are highly persistent.[22] As the number of time periods is 19, we use curtailing that includes only the first three lags and the collapsing method of Holtz et al. (1998) to reduce the number of instruments. To avoid loss of data from the data gaps that arise from removal of outliers, we also use Arellano and Bover (1995) forward orthogonal deviations. The results are presented in Table 3.

Column (1) in Table 3 reports the results for the fixed effect panel model. The NPL coefficient is close to those reported in Table 2a suggesting that our results are robust for unobserved bank-level heterogeneity. Among the control variables, the role of ROA is weakened compared to the earlier results, while the Tier 1 ratio obtains a positive sign and is statistically significant.

Columns (2) to (4) report SYS-GMM estimates. In column (2), the variables other than loan growth are treated as pre-determined. In this case, the NPL coefficient is about −0.06. Tier 1 ratio and coverage ratio obtain positive and significant

[22] When the Arellano and Bond (1991) estimator is applied to persistent data, the lagged levels of the series are only weak instruments for the first-differenced equations. Arellano and Bover (1995) and Blundell and Bond (1998) demonstrate that the System GMM approach, by allowing lagged first differences to be used as instruments in the level equations, corrects for the bias that would arise in a standard GMM estimator. In our sample, the first autocorrelation coefficient of the loan growth averages −0.04, while the first autocorrelation coefficient of the NPLs averages 0.86.

coefficients. If we make, the NPL coefficient endogenous and not predetermined as in column (3) and (4) the coefficient increases. When other bank level control variables are excluded the coefficient is about −0.10, and when other bank level control variable are included (as predetermined with lags), the NPL coefficient is −0.08. In the latter case, ROA and Tier 1 ratio obtain positive signs but are not statistically significant.

The coefficient estimates in columns (2–4) come quite close to those with OLS (i.e. Table 2a), suggesting that the possible simultaneity effects are small, and the choice of the estimator does not make a crucial difference in terms of the magnitude of the results.

We also refer to the qualitatively similar results of Huljak et al. (2020), who make use of a VAR model with a completely different identification strategy. Conventional time series tools like Granger causality tests provide additional information consistent with the overall estimation strategy.[23]

3.2. Effect of NPLs on profitability, capital adequacy, and funding costs

This section tests Hypotheses 2–4 regarding the three channels – funding costs, profitability, and capital adequacy – through which NPLs can affect lending growth using estimating Eqs. (2)–(4).

The results are reported in Table 4. In columns (1–2), we test the hypothesis on the effect of NPLs on bank profitability with time independent and time-dependent country fixed effects, respectively. In both cases, the result is the same: NPLs have higher explanatory power on bank profitability than any of the other explanatory variables and they are clearly a drag on bank profitability. A one percentage point increase in the NPL ratio reduces ROA by 0.04 percentage points. Among the other explanatory variables in columns (1–2), the coverage is marginally statistically (in)significant with a positive sign suggesting that higher coverage ratio indicates higher future profitability.

Columns (3–4) in Table 4 test the hypothesis on the effect of NPLs on capital adequacy. High NPLs are clearly associated with low capital adequacy. A one percentage point increase in NPL ratio decreases the Tier 1 ratio by 0.13 percentage points. The actual effect is larger than 0.13 as it comes through both NPLs and ROA (leaving out ROA will increase the magnitude of the coefficient). Hence, a bank burdened with NPLs is more vulnerable than other banks and faces difficulties maintaining its capital at sufficiently high levels to avoid breaching regulatory capital requirements. In columns (3–4), the coverage ratio is significant with negative sign, which indicates that the reverse effect mentioned before also plays role. Establishing a causal link could be difficult because coverage ratio and Tier 1 ratio are considerably more persistent variables than NPLs and lending growth.

We test the effect of NPLs on the cost of bond financing and deposit financing in columns (5–6) and (7–8) in Table 4, respectively. It is worth noting that the bank's funding mix on average leans heavily to deposits such that the deposits-to-assets ratio averages 60%. In contrast, debt securities only account for about 20% of funding. The NPL's coefficient is positive and mostly statistically significant. In the case of deposit funding, a one percentage point increase in the NPL ratio increases the cost of deposit funding by one or two basis points. This is marginal and possibly reflects the fact that deposits in European banks are largely covered by deposit insurance. The magnitude of the NPL's effect on the interest cost of bonds is somewhat larger. An increase in the NPL share of one percentage point increases the funding cost rate by about 4 basis points, which is fairly small from a historical perspective. It may reflect the fact that ECB monetary stimulus has driven down interest rate spreads in the euro area during the sample period. In any case, our result comes with a caveat that the average interest rate for issued securities does not distinguish security characteristics such as collateral. Nevertheless, in principle, the result suggests that NPLs become costly for bank funding such that deteriorating net interest margin eventually drives down lending growth. A similar result is obtained in Iaskarelis and Siklós (2019) using data from seven large European banks.

In columns (5–8) in Table 4, the control variables indicate that funding costs decrease with higher profitability although the effect is statistically significant only in column (5). Unremarkably, funding costs are also positively associated with the level of short-term market interest rate.

3.3. Robustness checks with alternative datasets

Here, we confirm the basic result that NPLs have a depressing result on lending growth using two other datasets that also have not been earlier used for this purpose in the literature, 1) the quarterly FIN-FSA data of NPLs and loan losses, and 2) the cross-country dataset of NPLs collected by researchers at the Bank of Finland (see Section 2.1). Recall that we can separate the loan losses for households and firms in the Finnish data, but in the cross-country data, the values are for the whole economy. For control variables, we use housing and stock prices, GDP growth rate, the real interest rate r (and for Finland, the Financial Stress Index, and the interest differential vis-à-vis Germany for 10-year bond rates).

The results in Table 5 follow the same lines as our previous results with the EBA bank-level data. Thus, an increase in the share of NPLs lowers the growth rate of bank lending with a (short-run) semi-elasticity of −0.4 (column 2 in Table 5),

[23] If one computes the Granger causality test statistic for the loan growth and NPL ratio variables, the hypothesis that NPLs do not cause loan growth can be rejected quite clearly (F = 10.56 (0.00)). In contrast, the opposite hypothesis cannot be rejected at conventional levels of statistical significance (F = 1.63 (0.20)).

Table 4
Effect of NPLs on other bank-specific variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROA	ROA	Tier 1	Tier 1	Cost of bond financing	Cost of bond financing	Cost of deposit financing	Cost of deposit financing
NPL (All)	**−0.037***** **[3.87]**	**−0.035**** **[2.92]**	**−0.131***** **[3.45]**	**−0.139**** **[3.10]**	**0.044*** **[2.21]**	**0.043** **[1.53]**	**0.022***** **[4.48]**	**0.010*** **[1.98]**
ROA			0.415 [1.78]	0.458 [1.65]	−0.164* [2.20]	−0.16 [1.44]	−0.015 [0.58]	−0.002 [0.05]
Tier 1 ratio	0.010 [1.84]	0.009 [1.62]			−0.015 [1.13]	−0.009 [0.60]	0.006 [0.84]	0.009 [1.03]
Coverage ratio	0.005 [1.96]	0.005 [1.93]	−0.076* [2.12]	−0.085* [2.19]	−0.001 [0.14]	0.002 [0.28]	−0.002 [0.77]	−0.001 [0.46]
GDP	−0.001 [0.07]		0.022 [0.48]		−0.017 [0.78]		−0.012 [1.55]	
Interest rate	−0.274* [2.07]		−1.491** [3.14]		0.858** [3.22]		0.615*** [4.98]	
Inflation rate	−0.012 [0.55]		0.049 [0.80]		−0.053 [1.42]		−0.051*** [4.28]	
Country FE	Yes	No	Yes	No	Yes	No	Yes	No
Country*time FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.361	0.513	0.397	0.460	0.272	0.424	0.344	0.444
Observations	2808	2808	2812	2812	2640	2640	2992	2992
Banks	185	185	186	186	170	170	191	191

The dependent variable is indicated in the second row of the table. Numbers within brackets are robust t-values, adjusted for clustering at the bank level. ***,**, and * indicate statistical significance at the 0.1, 0.01, and 0.05 percent levels, respectively. The lag structure of the explanatory variables is omitted for brevity; see estimation Eqs. (2)–(4) for details.

Table 5
Robustness checks with alternative datasets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Loan growth$_{-1}$	0.389***	0.305**	0.020	0.146	0.019	0.517***	0.406***
	[4.49]	[3.31]	[0.20]	[1.58]	[0.20]	[5.03]	[13.60]
NPL$_{-1}$	**−0.028****	**−0.373*****					
	[2.90]	**[3.88]**					
Loan losses$_{-1}$			**−0.033*****	**−0.132*****	**−0.027*****	**−0.009****	**−0.017****
			[4.20]	**[5.34]**	**[5.12]**	**[2.51]**	**[3.24]**
GDP	0.018	0.026	0.003	−0.029	0.253**	0.003	0.299**
	[0.35]	[0.53]	[0.70]	[0.58]	[2.61]	[0.01]	[3.47]
Interest rate	0.152*	0.210**	−0.126	−0.178**	−0.075	0.298***	0.578***
	[2.50]	[3.31]	[1.90]	[3.25]	[0.76]	[4.53]	[5.69]
House price	0.009	0.008	0.049	0.086***	0.037	0.206**	0.148***
	[0.37]	[0.33]	[1.50]	[4.19]	[0.87]	[3.29]	[5.14]
Stock price	−0.003	−0.002	−0.005	−0.004	−0.022*	0.031	0.015*
	[0.61]	[0.31]	[1.00]	[0.97]	[2.37]	[1.73]	[2.25]
Stress index	0.005	0.005	0.003	−0.009	0.007		
	[0.42]	[0.52]	[0.10]	[0.78]	[0.34]		
Rate differential	−0.152	−0.123	−0.126	−0.288*	0.435		
	[1.04]	[0.87]	[0.80]	[2.45]	[1.78]		
Constant	0.007**	0.008**	0.010***	0.012***	0.007	0.016**	
	[2.68]	[3.11]	[3.90]	[4.53]	[1.49]	[2.67]	
Elasticity	−1.162	−1.398	−0.691	−0.356	−0.841	−0.236	−0.446
SEE	0.0123	0.0120	0.0160	0.0122	0.0237	0.0780	0.0661
R^2	0.509	0.536	0.348	0.602	0.475	0.661	..
DW	2.16	2.11	1.85	1.78	1.97	2.12	..
NPL or LL	NPL/P	NPL/loans	LL/LV	HH LL/LV	F LL/LV	LL/LV	LL/LV
Data/Obs.	Q/116	Q/116	Q/142	Q/142	Q/142	Panel A/350	Panel A/331

The dependent variable is the growth rate of banks' real loans (quarterly rate with quarterly data and annual rate with annual data). NPL denotes either real non-performing loans (NPL/P) or their percentage ratio to (real) outstanding loans (NPL/LV). Loan losses denoted by LL are expressed as the percentage ratio between loan losses (LL) and loans (LV) either at the aggregate level, or separately for households (HH) and firms (F). Elasticity denotes elasticity with respect to NPLs or loan losses computed at sample mean values. The sample period for the Finnish quarterly data is 1988Q1–2018Q1 and for the 19-country cross-country panel data 1982–2017. GMM estimates (based on first differences) are reported in the 6th column. In that case, the J(19) statistic is 12.434 (with $P = 0.492$). Fixed cross-section effects are used with column (5). Robust t-ratios are inside parentheses. Abbreviation Q denotes quarterly and A annual data.

which is much higher than the number obtained from the EBA data. The result is consistent with the inverse relationship between the semi-elasticity and the level of NPLs, which is low in the Finnish data.

As for the impact of loan losses to banking lending, the coefficients are again of the correct sign suggesting that an increase in loan losses by one percentage point lowers the quarterly growth rate of loans by 3 percentage points (column 3 in Table 5). Note that loan losses are typically smaller than NPLs and affect the bank profitability and stock of loans more directly and thus the respective elasticities are different.

When we focus on firms and households separately, we find the coefficient quite different, reflecting very different levels of sectoral loan losses (columns 4–5 in Table 5), and the role of controls (particularly housing and stock prices) is more important. Again, we have to keep in mind that control variables such as housing and stock prices are potential determinants of NPLs, and absorb some of the total contributions of NPLs. Whether or not the control variables are introduced into the estimating specification, the coefficients of loan-loss variables still have the correct sign and can be estimated rather precisely. The final robustness check in columns (6–7) in Table 5 uses the annual cross-country panel data derived from both official sources and by requesting data from central banks and financial authorities. We use the same set of controls in the estimation here, except for the stress index and interest rate differentials. The equation is estimated both by OLS and by panel GMM to account for the nature of the dynamic specification and possible simultaneity between loan losses and loan growth.

The results again point in the same direction. Loan losses today reduce the growth rate of loans tomorrow. Here, the semi-elasticity is somewhat lower than with the Finnish quarterly data being about minus 0.01. However, the elasticity computed at the sample mean values comes quite close to the estimates with the Finnish quarterly data. Note that the loan loss rates with annual and quarterly data are of different magnitude. With annual cross-country data, loan growth is much more correlated than with quarterly cross-country data. Thus the lagged dependent variable is clearly significant in the estimating equation. If we drop this variable, the qualitative results do not change, but the coefficient values increase, i.e. the coefficient of lagged loan losses increases from 0.009 to 0.015, reflecting the long-run solution of the difference equation (6) in Table 5. In any case, no doubt remains as to the sizeable credit squeeze effect caused by loan losses as for NPLs.

Regarding control variables, both housing prices and stock prices behave as expected so that an increase in their prices tends to increase the demand for bank loans. A positive relationship is also obtained for the growth rate of bank loans and

Table 6
Survey of NPL elasticity estimates.

Study	Geography	Granularity	Type	N	Elasticity	Frequency	Mean NPL
This study, EBA data	EEA (30 countries)	bank	panel OLS	19 Q*181 B	−0.08[a]	Q	8.0
Cucinelli, 2015	Italy	bank	panel	7 Y*488 B	−0.22	A	8.2
Carlson et al., 2013	USA	bank	panel	51,622	−0.9	A	2.6
Espinoza and Prasad, 2010	GCC (5 countries)	country	panel VAR	426	−1.0	A	4.9
Keeton, 1999	USA	state	panel VAR	700	−0.03[b]	A	NA
Klein, 2013	CESEE (16 countries)	country	panel	224	−1.5[c]	A	8.3
Vinh, 2018	Vietnam	bank	one eq.	10 Y*34 B	−0.23	A	2.17

[a] Note the Q/Q frequency in contrast to other studies.[b] Keeton (1999) uses delinquency rates.[c] Klein (2013) uses elasticity w.r.t. the loans/GDP ratio.Values scaled from the original values. EEA = European Economic Area, GCC = Gulf Cooperative Council, CESEE = Central, Eastern, and South-Eastern Europe.

the growth rate of income or GDP growth. For the real interest rate variable, in almost all specifications, the sign is positive; that is hardly consistent with the respective demand curve. Of course, it makes more sense if we can assume that the supply factors dominate (i.e. a higher interest margin has a positive effect on the supply of bank loans).

These analyses show that the depressing effect of NPLs is qualitatively similar to the effect of realized loan losses in bank lending. Against this background, it would be useful to study the relationship between NPLs and loan losses (say, both the lead-lag relationship and the strength of the relationship). There is some casual evidence that NPLs of various sectors produce differing amounts of loan losses. It would be useful to investigate the actual size differences if, in fact, they exist. Finally, the length of time banks take to react to NPLs may be important. NPLs carried on the books for years are probably quite different from loans only been in default for, say, the past 90 days.

4. Comparison of semi-elasticity estimates to the literature

For policymakers, both the sign of the NPL effect *and its magnitude* are important. We try to open this issue by collecting some representative estimates to Table 6. As most studies are based on annual loan growth rates, it should be noted our estimate −0.08 can be multiplied by four to arrive at semi-elasticity for annual loan growth of about −0.24. The corresponding annual loan growth estimates for the two low-NPL subsamples (columns 1 in Table 2d) are about −1.2 and −0.6, respectively.

There are several caveats to the studies in Table 6. Some of these sources are not peer-reviewed, and the channel from NPLs to lending growth is often not their main focus. Moreover, the set of countries across studies looks quite different. The studies by Carlson et al. (2013) and Cucinelli (2015) use bank-level data in developed economies, and are thus somewhat more comparable to our study. Carlson et al. (2013), who study US banks, find the highest size of the effect −0.9. They obtain the same impact whether they use bank-characteristic and location based matching or simple location-specific fixed effects. The mean value of NPLs in their sample is low, which fits well the nonlinear pattern we observe in our datasets. Cucinelli (2015), in her study of Italian banks, reports semi-elasticity of −0.22, which is comparable to ours. The level of NPLs in her sample is also similar to ours. Hence, the suggested inverse relationship between semi-elasticity and the level of NPLs could bridge the gap between the estimates in Carlson et al. (2013) and Cuccinelli (2015).

Keeton (2002) uses aggregate data on US states and finds a small effect compared to rest of the literature, including our results. The studies for developing economies, Espinoza and Prasad (2010), Klein (2013), and Vinh (2018), find effects that are broadly in line with ours. They show a significant negative effect from NPLs to lending.

Overall, our results fit well with the literature. If we eliminate NPLs entirely (the sample average is now roughly 8%), we could increase the growth rate of bank loans by more than 0.6%, which is considerable compared with the sample average value 0.3%, which could make a significant difference to the overall economic situation in Europe. Bank lending affects investment and consumption and shows up in output growth. Several studies have tried to estimate the impact elasticity on output, and most of them come up with similar values. For example, the ECB cross-country study by Cappello et al. (2010) finds a short-run elasticity of about 0.1. An IMF study with data from developing countries by Garcia-Escribano and Han (2015) arrives at similar values. Combining these values with our estimated semi-elasticity of −0.3 suggests that the semi-elasticity of GDP with respect to NPLs is −0.03. That said, NPLs could affect output via other channels. Espinoza and Prasad (2010), Klein (2013), and Huljak et al. (2020) detect a considerably larger response when directly estimating the effect of NPLs on output.

Concluding remarks

Our results follow the same lines as most earlier studies, bolstering the view that non-performing loans (NPLs) are toxic for lending growth. We find that the effect is robust to demand effects related to different regions and bank types, suggesting that the observed effect is due to a reduction in the loan supply by the affected bank. The effect's size indicates that eliminating all NPLs from our sample of European banks would double the growth rate of bank loans.

As a new contribution, we find that a bank's overall lending growth is most sensitive to NPLs in its corporate loan portfolio, but that lending to households and government entities is also sensitive to NPLs in their respective portfolios. The finding that the effect of NPLs on lending growth is stronger at the lower level of NPLs should motivate banking supervisors and banks in following through on eradicating, or at least reducing, Europe's NPL problem.

It is worth noting that depressed lending effects originate not just from the direct losses associated with the NPLs, but the increased funding costs that make lending less profitable. Our estimates here are in line with Constâncio (2017) and others who highlight the NPL problem underlying the low aggregate profitability of European banks. Future work on estimating the effect of NPLs on funding costs would benefit from more granular data on funding instruments. We cannot say much at this point about other possible indirect channels such as reputation and loss of customers, but identification of the effects from these channels represents a stimulating challenge for future research.

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Supplementary materials

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