

Commercial real estate loans in Europe: does loan-to-value at origination predict default risk?

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AGENDA

- ❑ **Why CRE matters for financial stability and objectives of the study**
- ❑ **Key features of CRE lending**
- ❑ **Loan-to-value at origination and default risk**
 - Empirical evidence
 - Econometric framework
- ❑ **Conclusions and future research**

Relevance of CRE markets for financial stability

- ❑ **Commercial real estate (CRE) markets** are a key source of financial stability risk, as real estate booms and busts have often played a central role in systemic financial crises.
- ❑ Weakness in CRE markets can amplify banking vulnerabilities, making the **monitoring of CRE lending essential for macroprudential authorities**.
- ❑ **Loan-to-value at origination (LTV-O) is a key macroprudential indicator**: high LTV loans may increase both bank losses and borrower default risk, particularly when borrowers become financially constrained or fall into negative equity ("underwater").
- ❑ While LTV-O is a well-established predictor of default risk in residential real estate (RRE) markets, empirical evidence for the CRE market remains limited (e.g., Mokas & Nijsskens (2019) and Jiménez & Saurina (2003). Few works with application of Anacredit data for CRE (Ryan et al., 2022 and Horan et al., 2022).

Research Questions and Main Findings

- 1) How do CRE lending and portfolio characteristics differ across euro area countries?
- 2) Is LTV-O a reliable predictor of default probability after controlling for borrower and loan characteristics?

Main evidence

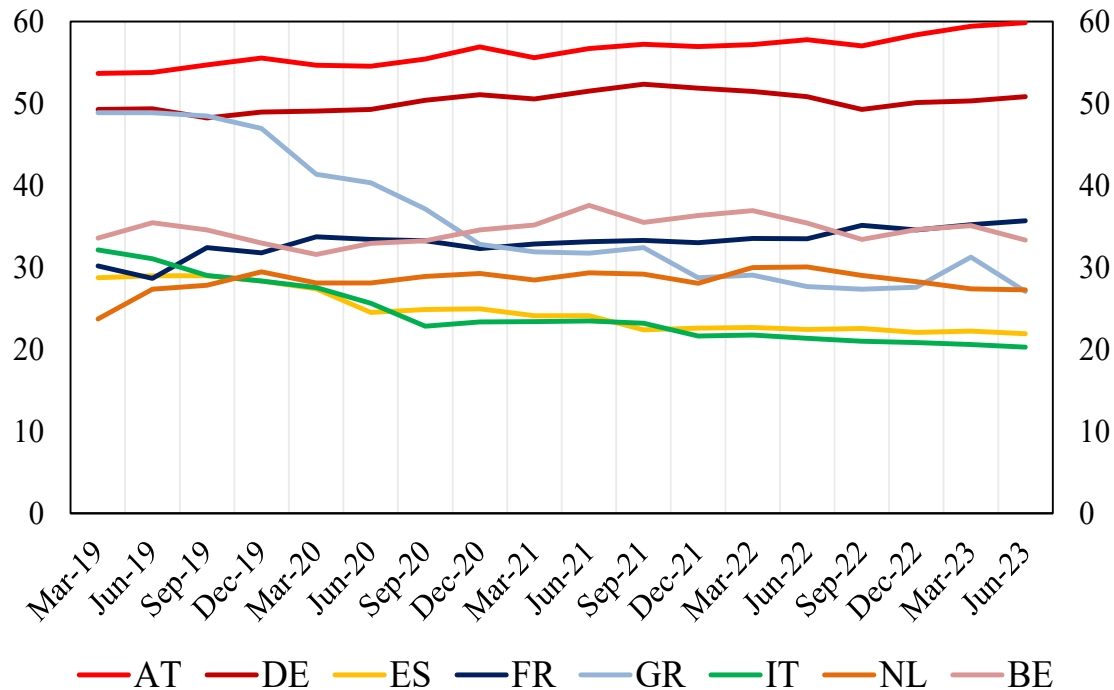
- ❑ The **share and the composition of bank CRE loans varies significantly across countries**
- ❑ The **NPL ratio for CRE loans is generally higher than those of other loans to NFCs**
- ❑ The **regression analysis shows a positive and statistically significant relationship between LTV-O and default probability in Italy and Spain**, after controlling for loan and borrower characteristics. By contrast, no significant relationship is found for Germany and France.

What are CRE loans?

- ❑ **CRE loans are defined according to the ESRB framework:** *loans granted to legal entities either collateralized by CRE property (i.e. any income-producing RE property, either existing or under development, including rental housing; or RE used by the owners of the property for conducting their business, and includes social housing) or whose purpose is acquiring a real estate property.*
- ❑ **The analysis relies on AnaCredit,** a granular and harmonised euro-area credit register with detailed information for the computation of LTV ratios and cross-country comparison.
- ❑ The descriptive analysis covers eight euro-area countries over the period 2019-2023. The regression analysis focuses on Italy, France, Germany and Spain and on loans originated since September 2018, covering around 80% of total CRE exposures.
- ❑ Cross-country differences reflect both reporting practices and characteristics of national CRE markets. To ensure comparability, the analysis relies on a set of assumptions designed to aimed at maximising cross-country harmonisation. **Some findings may be sensitive to methodological choices, including the definition of CRE exposures and LTV ratios.**

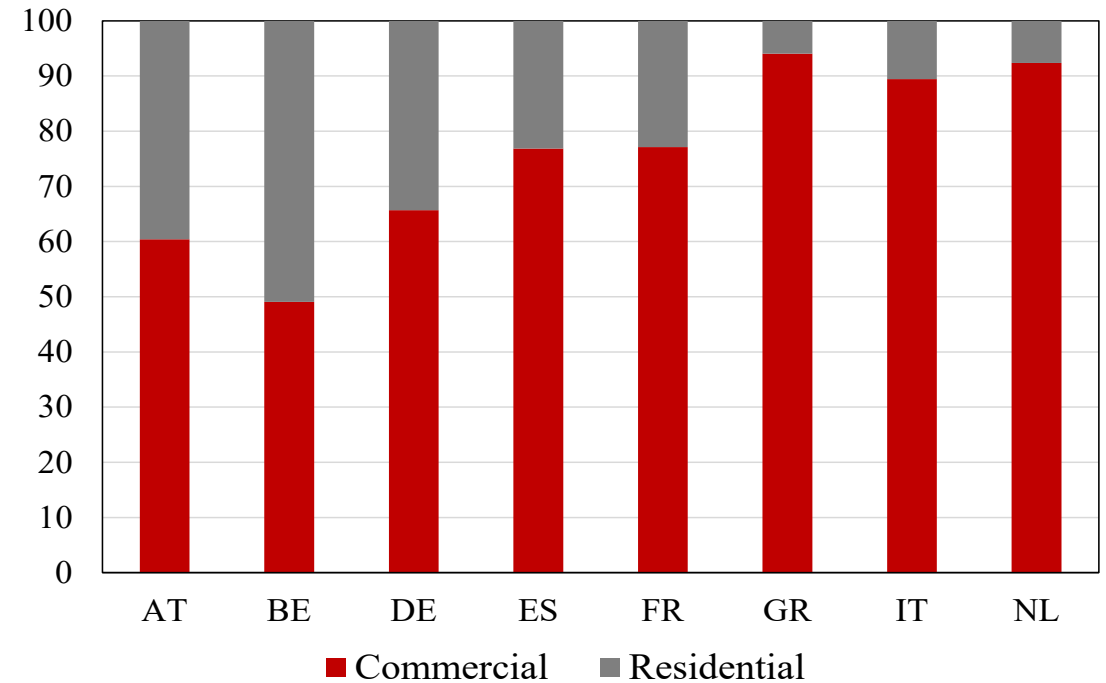
CRE exposure and portfolio composition differ significantly across countries

Share of CRE loans over total loans to NFCs



Source: AnaCredit, quarterly data. Data include securitizations.

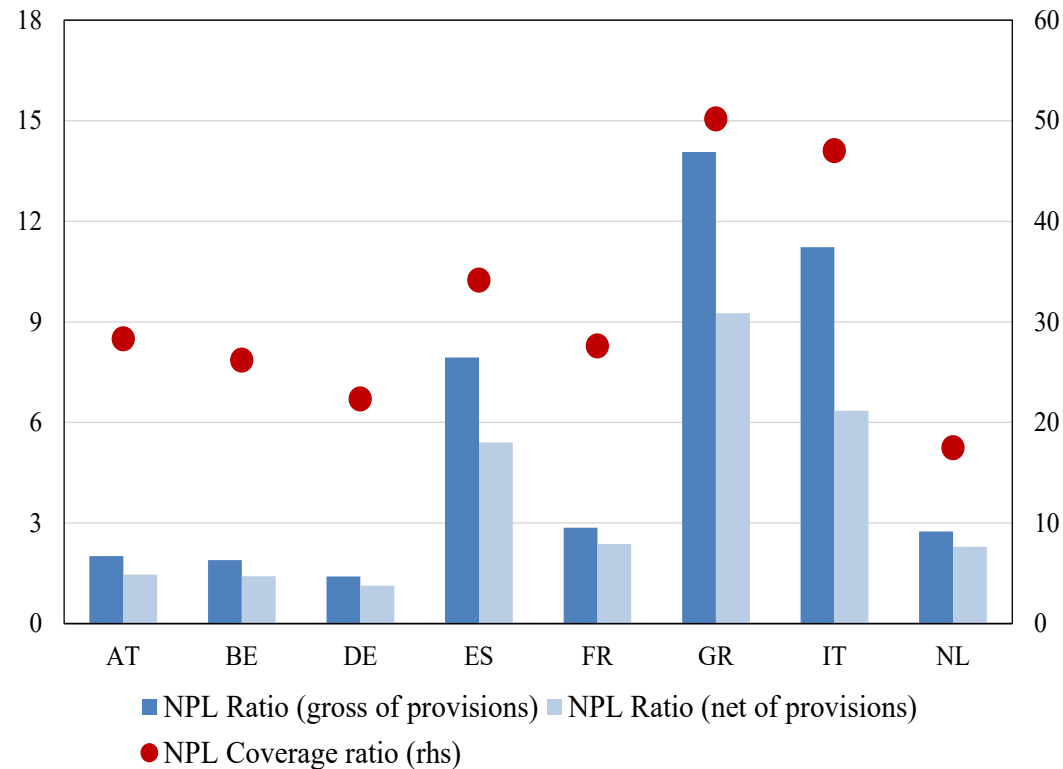
Composition of CRE loans by type of collateral



Source: AnaCredit, June 2023.

Credit quality of CRE loans is worse than for other NFC loans

NPL and coverage ratios

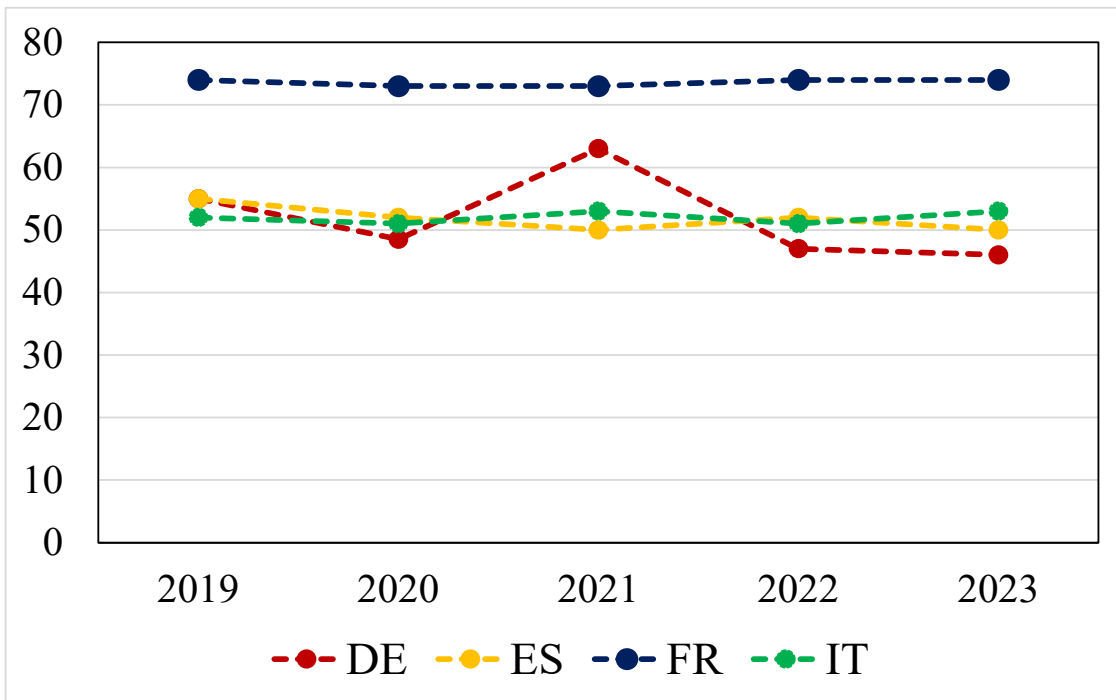


Source: AnaCredit, June 2023

- ❑ Credit quality is highly heterogeneous across countries: in June 2023 Italy (11.2%) and Greece (14.1%) recorded the highest gross CRE NPL ratios.
- ❑ Despite relatively high NPLs, Italy shows improving asset quality, with the NPL ratio declining from 16% in early 2022 and supported by a high coverage ratio (47%).

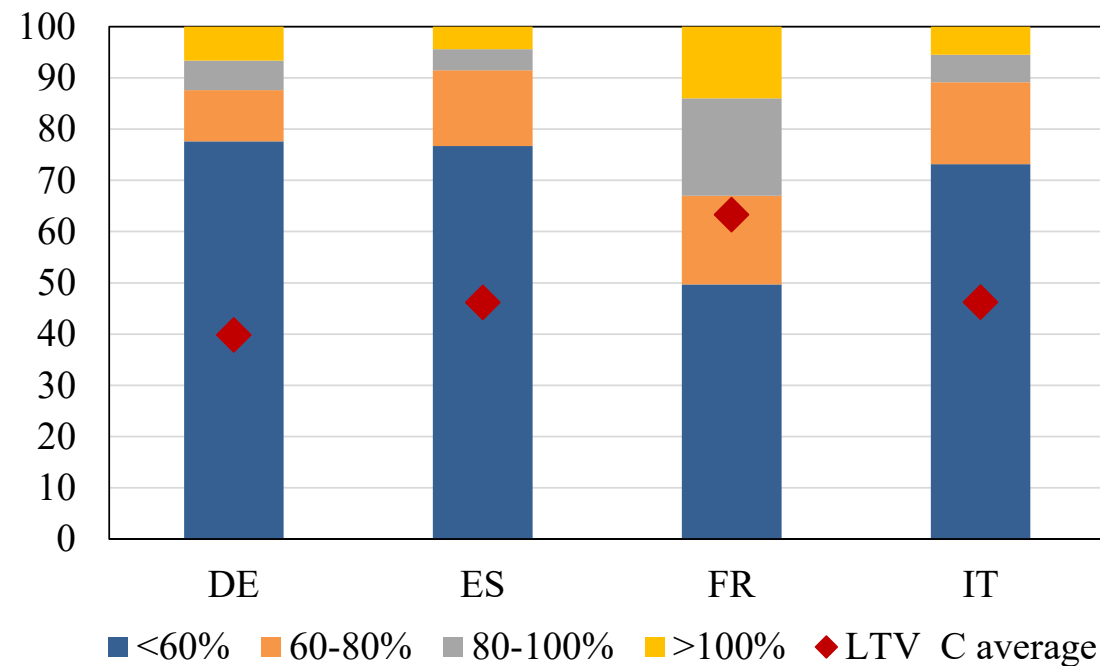
Cross-Country Evidence on LTV at Origination and Current LTV

Evolution of LTV at origination



Source: AnaCredit. Note: LTV is defined as the ratio of the gross amount of the loan to the value of the collateral. For LTV-O average value over the year for 2019-2022, over the first two quarters for 2023.

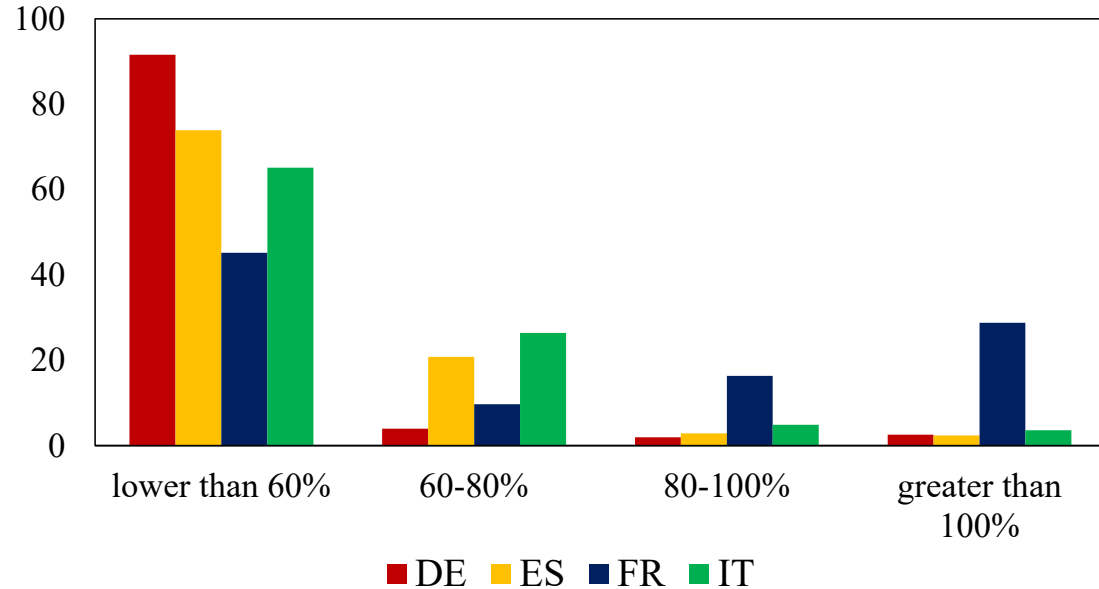
Distribution of current LTV



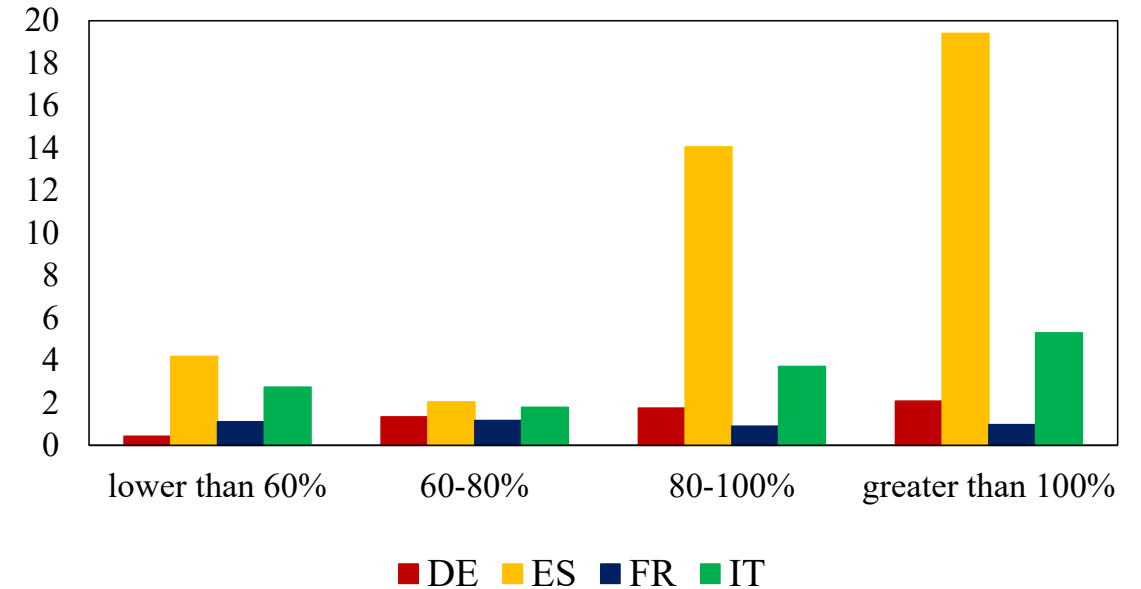
Source: AnaCredit, June 2023.

High LTV-O is associated with higher NPL ratios in Italy and Spain

CRE loans over LTV classes



NPL loans over LTV classes



Source: AnaCredit, June 2023.

Source: AnaCredit, June 2023.

- In Italy and Spain, NPL ratios increase markedly for loans with LTV-O above 80%. Germany and France show a flatter pattern, indicating a weaker link between LTV-O and default risk.

Regression analysis: Do LTV-Os predict default?

❑ Loan-level multivariate regression of default risk on LTV-O.

- ❑ Sample: collateralized CRE loans originated since September 2018 and observed up to June 2023.
- ❑ Focus on France, Germany, Italy and Spain, representing about 80% of CRE exposures in AnaCredit.
- ❑ We estimate the probability (P) that loan i granted by bank k to firm j is in the status of NPL (NPL_{ijk}) at the reference date t (June 2023) by using the following logit specification:

$$P(NPL_{ijk} = 1 | X^1, X^2, \theta^k) = f(X_{ijk0}^1, X_{j0}^2, \theta^k) = p$$
$$\log\left(\frac{p}{1-p}\right) = \alpha + \beta_1 * X_{ijk0}^1 + \beta_2 * X_{j0}^2 + \gamma\theta^k + \varepsilon_{ijk} \quad (1)$$

X^1 are loan characteristics at the time the loan was granted ($t=0$), including LTV-O, interest rate type, year of issuance, the purpose of loan, loan type and size; X^2 are firm characteristics, such as total bank debt (as a proxy of level of indebtedness and firm size), the borrower's PD and the activity sector; θ^k is the bank category (significant and less significant) and ε_{ijk} is the error term.

Regression analysis: main results

- ❑ **High LTV-O is a significant predictor of default risk in Italy and Spain**, even after controlling for borrower, loan and bank characteristics. The effect is economically meaningful: in Italy, loans with LTV-O above 80% show a 130–180 bps higher probability of deterioration (baseline default 3%); in Spain, the effect ranges from 170 to 360 bps (baseline default rate 4.8 per cent).
- ❑ **No significant relationship is found in Germany and France**, suggesting cross-country heterogeneity in the LTV-O–default nexus.
- ❑ **Loan vintage matters**: older loans exhibit a higher probability of default across all countries.
- ❑ **Borrower ex-ante risk is highly predictive**: loans granted to firms with higher ex-ante PDs are significantly more likely to become non-performing (e.g. +290 bps in Italy for $PD > 5\%$).
- ❑ **Firm indebtedness increases default risk, while larger loans tend to be associated with lower risk**, possibly reflecting larger borrowers and stricter lending standards.

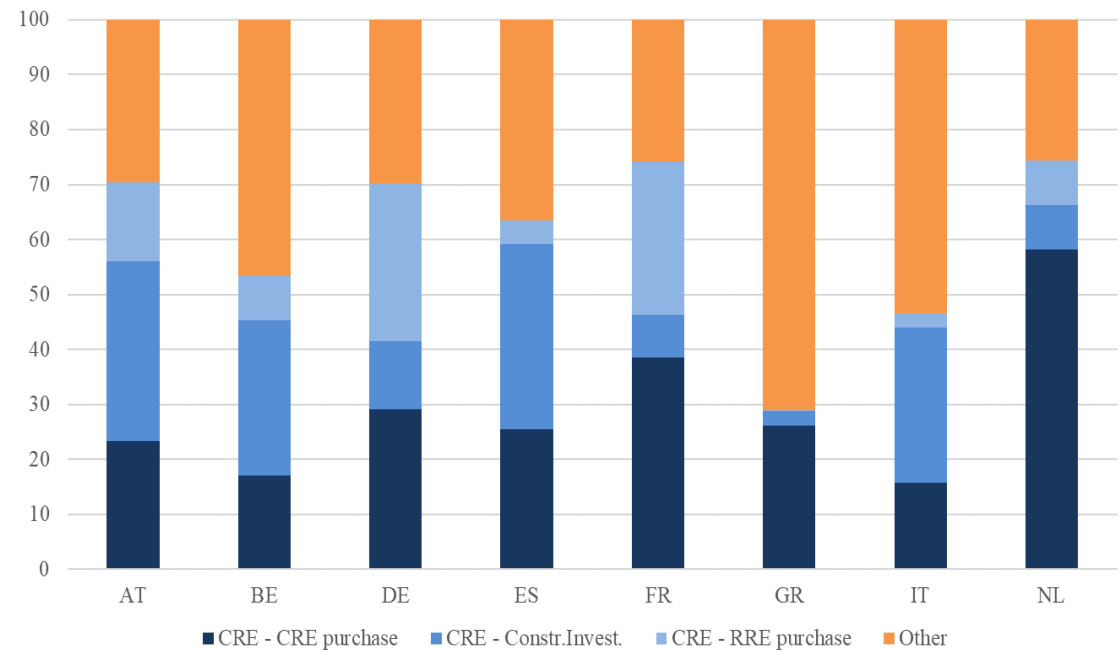
Conclusions and future research

- ❑ **CRE lending is highly heterogeneous across euro-area countries**, both in terms of loan characteristics, collateral structure and credit quality.
- ❑ **LTV at origination is a significant predictor of default risk in Italy and Spain**, but not in Germany and France, highlighting the importance of country-specific lending practices.
- ❑ Caveats:
 - Results are sensitive to the definition of CRE loans and LTV measures adopted (e.g. protection value vs allocated protection value).
 - The evidence is based on a relatively short AnaCredit time series and a limited set of countries, suggesting caution in generalizing the results.
- ❑ Ongoing research: Extending the analysis of CRE loans in Italy by incorporating firm-level characteristics and exploring the use of machine learning techniques for default prediction

Thank you for the attention

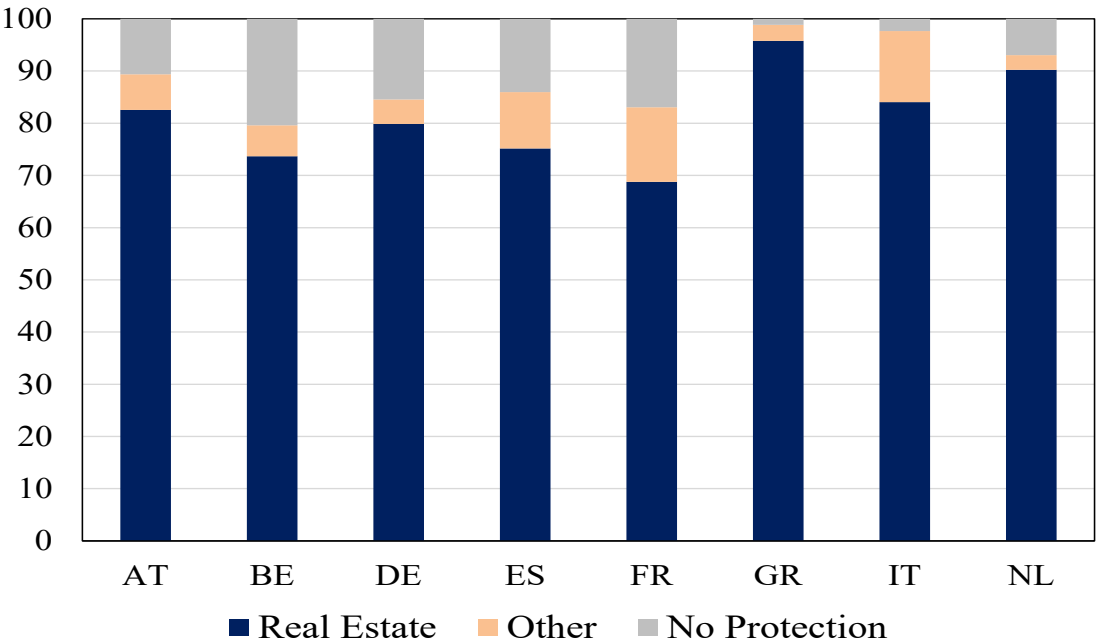
Annex 1: Characteristics of CRE loans – purpose and type of collateral

By purpose



Source: AnaCredit, June 2023

Type of collateral



Source: AnaCredit, June 2023.

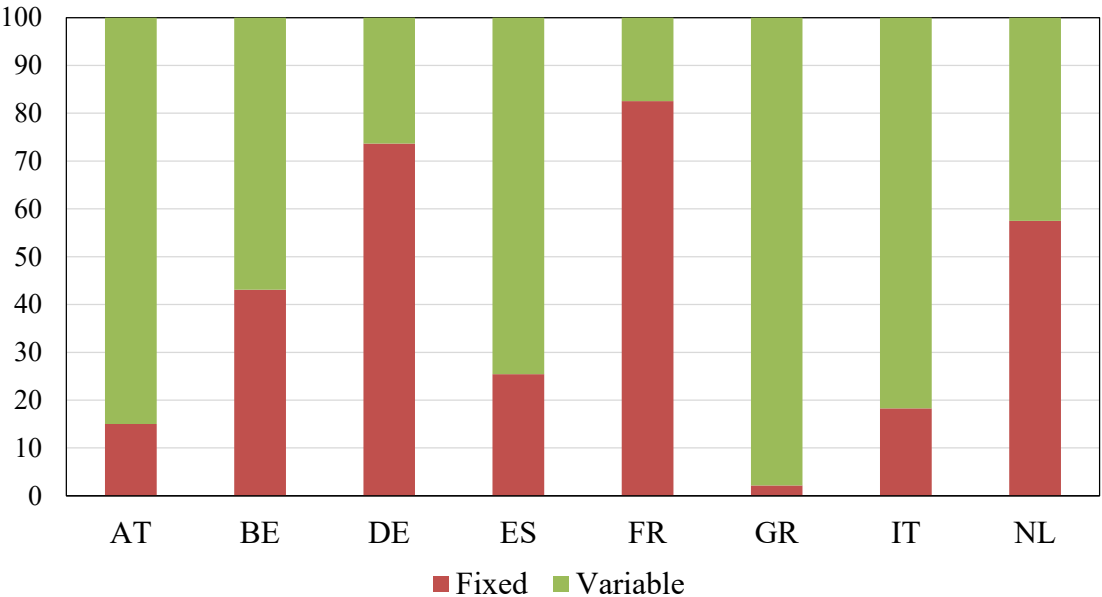
Annex 1: Characteristics of CRE loans – type of instruments

	Germany		Spain		France		Italy	
	ONA	share	ONA	share	ONA	share	ONA	share
Deposits	-	-	-	-	-	-	-	-
Finance Leases	0.6	0.1%	3.5	3.3%	20	5.6%	12	8.9%
Credit Lines (no revolving)	391	67.6%	19.5	18.1%	92.5	25.7%	0.5	0.3%
Other Loans	157	27.1%	81	74.4%	240	66.5%	118.5	86.6%
Residual: Overdrafts + Credit Card + Trade Receiv. + Revolving Credit	30	5.1%	4.5	4.1%	8	2.3%	5.5	4%
<i>Total</i>	578	100%	108	100%	361	100%	137	100%

Source: AnaCredit, June 2023; € billion and per cent

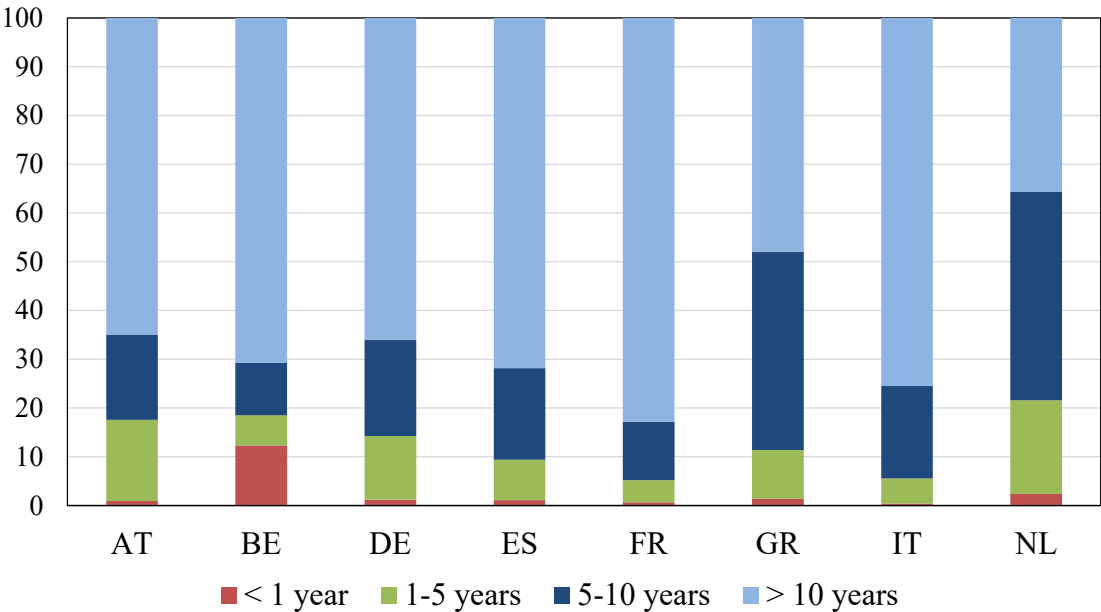
Annex 1: Characteristics of CRE loans – interest type and maturity

Interest type



Source: AnaCredit, June 2023

Maturity at origination



Source: AnaCredit, June 2023.

Annex 2: Loan-to-value definition

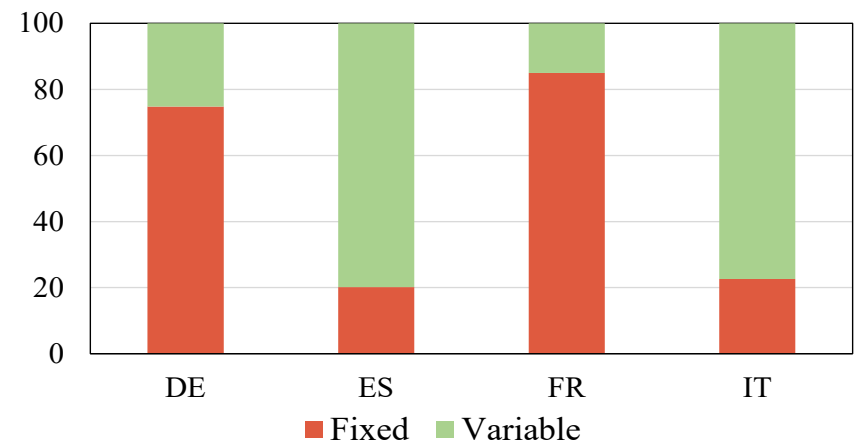
- ❑ There are different ways to calculate LTV from AnaCredit:
 - **Loan-by-loan ratio of outstanding nominal amount (ONA) over protection allocated value (PAV)**, that is the maximum amount of the protection that can be considered as credit protection by the bank for the instrument in the case of default;
 - **Loan-by-loan ratio between ONA and protection value (PV);**
 - **By property, assigning the proportion of amount according to the ONA** of each instrument linked to a specific real estate protection pledged as collateral and then using PV at the denominator.
- ❑ **The choice between PV or PAV for the calculation of LTV is controversial.** From Supervisory reviews LTVs in terms of PVs may appear closer to values reported in bank reports than LTVs based on PAVs for different reasons.
- ❑ Overall, PAVs have a prudential perspective and can give an indication of possible loss coverage in the case of default, on the other hand PVs seems more objective and useful in the case of cross bank/cross country comparison.
- ❑ For Italy, the three approaches lead to very consistent results

Annex 3: What are the characteristics of loans with high LTVs?

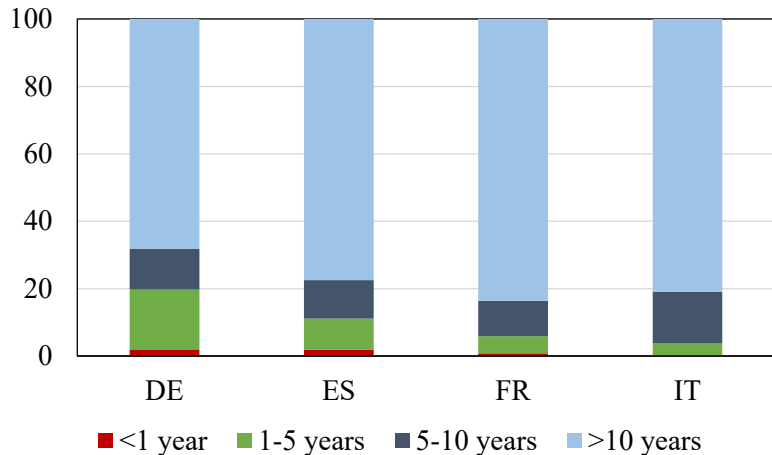
- ❑ We analyze the characteristics of loans with a high LTV-O **to better understand their overall riskiness**. We focus on attributes that could amplify or mitigate vulnerabilities for banks, also in term of potential losses, **including the type of interest rate, maturity at origination, loan size, and additional guarantees**.
- ❑ High **LTV-O loans are generally riskier in Italy**, all else being equal. These loans typically feature variable rates, long maturities, and large sizes.
- ❑ **However, a significant portion of these high LTV loans in Italy - over 65 per cent - has additional protections**, such as financial, personal, or state guarantees (including those introduced during the pandemic). In Spain, the situation is similar but the proportion of loans with additional protections is lower.
- ❑ **In Germany, the primary concern is the large size of these loans**. In all the cases the vast majority of loans have maturity at origination greater than 10 years.

Annex 3: Characteristics of loans with high LTV-O

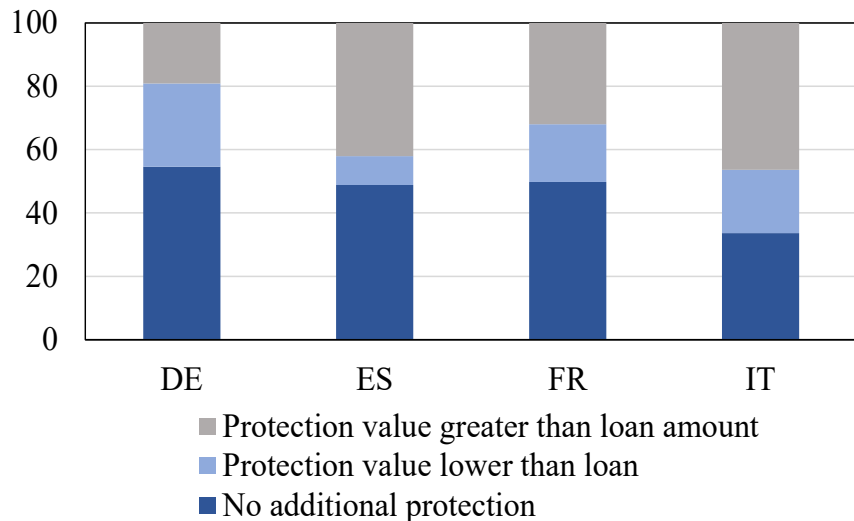
a) Interest rate type



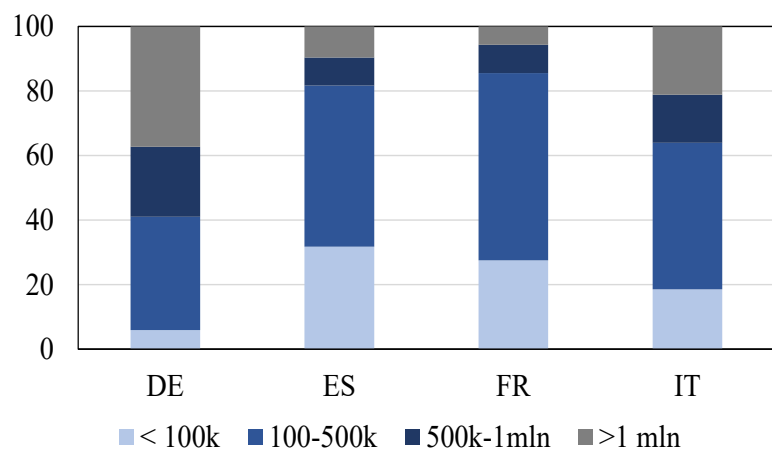
b) Maturity at origination



c) Additional guarantee



d) Amount



Annex 4: Regression variables

Variables	Description
Dependent variable	
<i>NPL dummy</i>	Equals one if loan status is not performing and zero otherwise
Independent variables	
Loan characteristics	
<i>LTV_O_class_1: <60</i>	Equals one if LTV-O is lower than 60 per cent and zero otherwise
<i>LTV_O_class_2: 60_80</i>	Equals one if LTV-O falls between 60 and 80 per cent and zero otherwise
<i>LTV_O_class_3: 80_100</i>	Equals one if LTV-O falls between 80 and 100 per cent and zero otherwise
<i>LTV_O_class_4: >100</i>	Equals one if LTV-O is larger than 100 per cent and zero otherwise
<i>type_intrate_variable_MIR</i>	Equals one if a variable interest rate (or an interest rate with a fixation period shorter than 1 year) applies to the loan and zero otherwise (MIR definition)
<i>constr_investment</i>	Equals one if the loan purpose is 'construction investment' and zero otherwise
<i>log(loan orig)</i>	Logarithm of loan outstanding nominal amount at origination
<i>Loan type</i>	Set of dummy variables controlling for loan type (according to AnaCredit classification); there are three 3 loan types: <i>Credit Lines no revolving, Finance Leases, Other Loans</i>
<i>Loan age</i>	Set of dummy variables controlling for the time of loan origination; there are 5 categories: <i><6 months, between 6 months and 1 year, between 1 year and 2 years, between 2 and 3 years, more than 3 year.</i>
Firm characteristics	
<i>pd_class_1: <0.5</i>	Equals one if the debtor's probability of default at loan origination is lower than half per cent and zero otherwise
<i>pd_class_2: 0.5-2</i>	Equals one if the debtor's probability of default at loan origination falls between half and two per cent and zero otherwise
<i>pd_class_3: 2-5</i>	Equals one if the debtor's probability of default at loan origination falls between two and five per cent and zero otherwise
<i>pd_class_4: >5</i>	Equals one if the debtor's probability of default at loan origination is larger than five per cent and zero otherwise
<i>pd_class - missing</i>	Equals one if no information on the debtor's probability of default is available and zero otherwise
<i>log(total debt)</i>	Logarithm of overall firm's debt to the banking system at loan origination
<i>Firm's economic activity</i>	Set of dummy variables controlling for the firm's industry (NACE); there are 5 categories (<i>Manufacturing, Construction, Real estate services, Other services, Others</i>)
Other variables	
<i>SSM significance</i>	Dummy variable controlling for the credit institution significance; 1 for <i>Significant (SI)</i> , 0 for <i>Less Significant (LSI)</i>

Annex 4: Marginal effects

	Italy	Germany	Spain	France
Dependent variable				
NPL status				
Loan Characteristics				
<i>LTV_O_class_1: <60</i>	baseline	baseline	baseline	baseline
<i>LTV_O_class_2: 60_80</i>	not significant	not significant	not significant	not significant
<i>LTV_O_class_3: 80_100</i>	0.013	not significant	0.017	not significant
<i>LTV_O_class_4: >100</i>	0.018	not significant	0.036	not significant
<i>type_intrate_variable_MIR</i>	not significant	0.012	0.021	0.001
<i>constr_investment</i>	0.004	not significant	-0.027	not significant
<i>log(loan orig)</i>	-0.14	not significant	-0.10	-0.17
<i>loan type: credit line non rev.</i>	baseline	baseline	baseline	baseline
<i>loan type: leases</i>	not significant	0.004	not significant	not significant
<i>loan type: other loans</i>	not significant	not significant	0.022	0.004
<i>loan age: <6mths</i>	baseline	baseline	baseline	baseline
<i>loan age: 6mths_1yr</i>	0.014	0.009	0.026	0.011
<i>loan age: 1-2yrs</i>	0.026	0.017	0.018	0.018
<i>loan age: 2-3yrs</i>	0.032	0.021	0.030	0.023
<i>loan age: >3yrs</i>	0.042	0.024	0.034	0.026
Firm Characteristics				
<i>pd_class_1: <0.5</i>	baseline	baseline	baseline	baseline
<i>pd_class_2: 0.5-2</i>	0.012	not significant	not significant	not significant
<i>pd_class_3: 2-5</i>	0.018	0.011	not significant	0.007
<i>pd_class_4: >5</i>	0.029	0.020	0.037	0.012
<i>pd_class - missing</i>	0.019	0.009	0.006	0.008
<i>log(total debt)</i>	0.002	not significant	0.002	0.001
<i>economic activity: manif</i>	baseline	baseline	baseline	baseline
<i>economic activity: costr</i>	not significant	-0.011	-0.023	-0.003
<i>economic activity: RE services</i>	not significant	-0.015	-0.031	-0.013
<i>economic activity: other services</i>	not significant	-0.006	-0.017	not significant
<i>economic activity: other</i>	-0.013	-0.008	-0.027	-0.005
Other variables				
<i>SSM significance: LSI</i>	not significant	0.01	-0.02	not significant