

EFFECTIVENESS OF A SOFT LTV LIMIT

Context: Introduction of the Soft LTV limit in Belgium

Soft Loan-To-Value (LTV) Limit

Loan-to-value: % of the property value that is covered by the mortgage loan

Soft: In contrary to a "hard" limit, a certain % of the bank loan portfolio is allowed to go over the limit

- tolerance margins that differ depend on the borrower type (see Table)
- Introduced by the National Bank of Belgium in January 2020 (announced in October 2019) following warnings from the ESRB

Limit	Loan Type	Threshold	Tolerance margins
LTV	Owner-Occupied	FTB	35% with LTV >90% 5% with LTV >100%
		Other OO	20% with LTV >90% 0% with LTV >100%
	BTL	80%	10% with LTV >80% 0% with LTV >90%
Pockets-of-risk	All loans	LTV < 90% & DSTI < 50%	5%
		LTV < 90% & DTI < 9%	

Ideal setup: Difference-in-Differences (DiD) regression

Comparing the constrained to the unconstrained borrowers

Constrained borrower: borrower who would have exceeded the LTV limit without the policy

Research Questions:

How have the constrained borrowers been impacted by the policy change?

- Did their average LTV effectively decrease?
- How did this impact other loan characteristics such as interest rates, maturity, loan amount, etc. ?
- How did the banks use their tolerance margins? Which types of borrowers got the exceptions?

Difference-In-Differences (DID)

DID treatment status: the constrained borrowers are the "Treated" in the DID model

$$LTV_i \text{ or } I[LTV > 90\%]_i \text{ or other Loan Characteristics} = \alpha_0 + \alpha_1 * Post_t + \alpha_2 * Treated_i + \alpha_3 * Post_t * Treated_i + \sum_{n=1}^N \beta_n * Borrower Controls_{n,i} + (\gamma * Post_t * FTB_i) + FE_{region/muni} + FE_{YearQuarter} + \epsilon_i$$

PROBLEM: treatment status in the post-policy period

In the **post-policy period**, we cannot disentangle the Treated (a.k.a. "constrained") borrowers from the Controls

- A borrower who would have chosen LTV>LIMIT might appear below the LIMIT
 - How do we identify those borrowers who are mixed with the controls in the post-policy period?

Solution: predicting the treatment status using pre-policy (2016-2018) data

Solution: Constructing the counterfactual through predictions

Purpose: Obtaining a treatment status to use in a DID regression

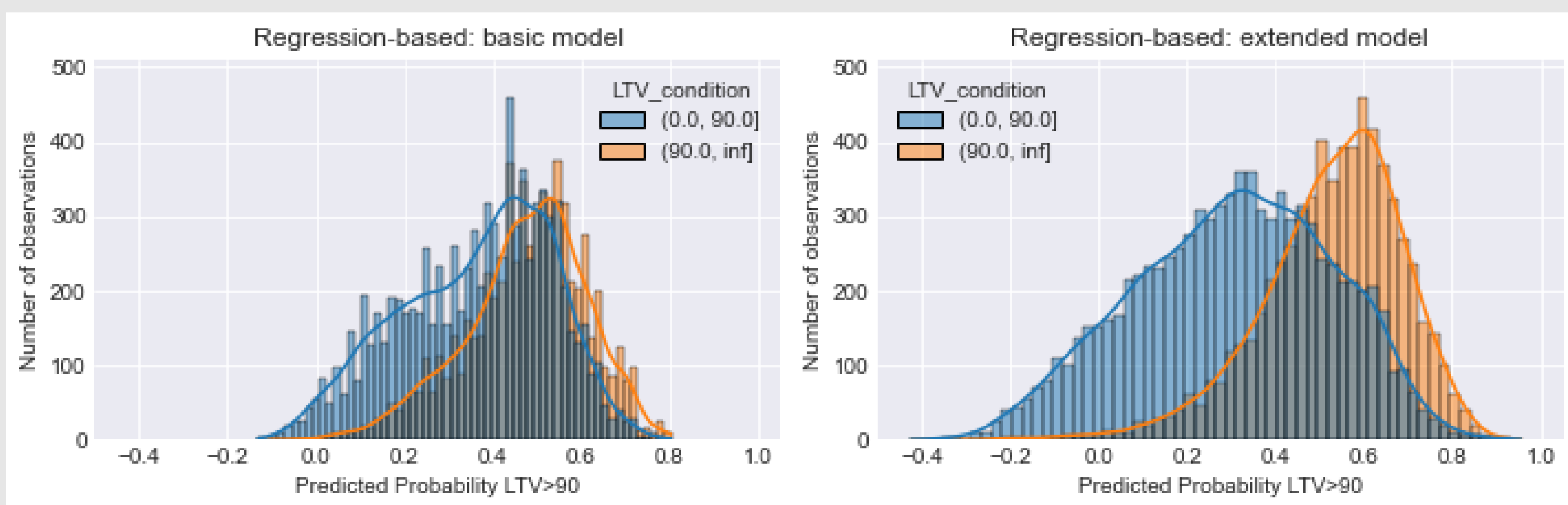
How? Predict counterfactual LTV, or probability of LTV>LIMIT, using pre-policy data (2016-2018)

- STEP 1: Use 2016-2018 data to estimate a model
- STEP 2: Generate predicted LTV/probabilities for the DID sample
 - 2019 (pre-policy period)
 - 2020-2021 (post-policy period)
- STEP 3: Treated vs. Control classification based on the predictions
 - Determining a threshold for the predicted probabilities

A) Regression-based predictions

Following previous literature (Abreu et al. (2024) and Tzur-Ilan(2023))

$$Pr[LTV > 90\%]_i = \alpha_0 + \sum_{n=1}^N \alpha_n * Borrower Controls_{n,i} + FE_{region} + FE_{province} + FE_{YearQuarter} + \epsilon_i$$



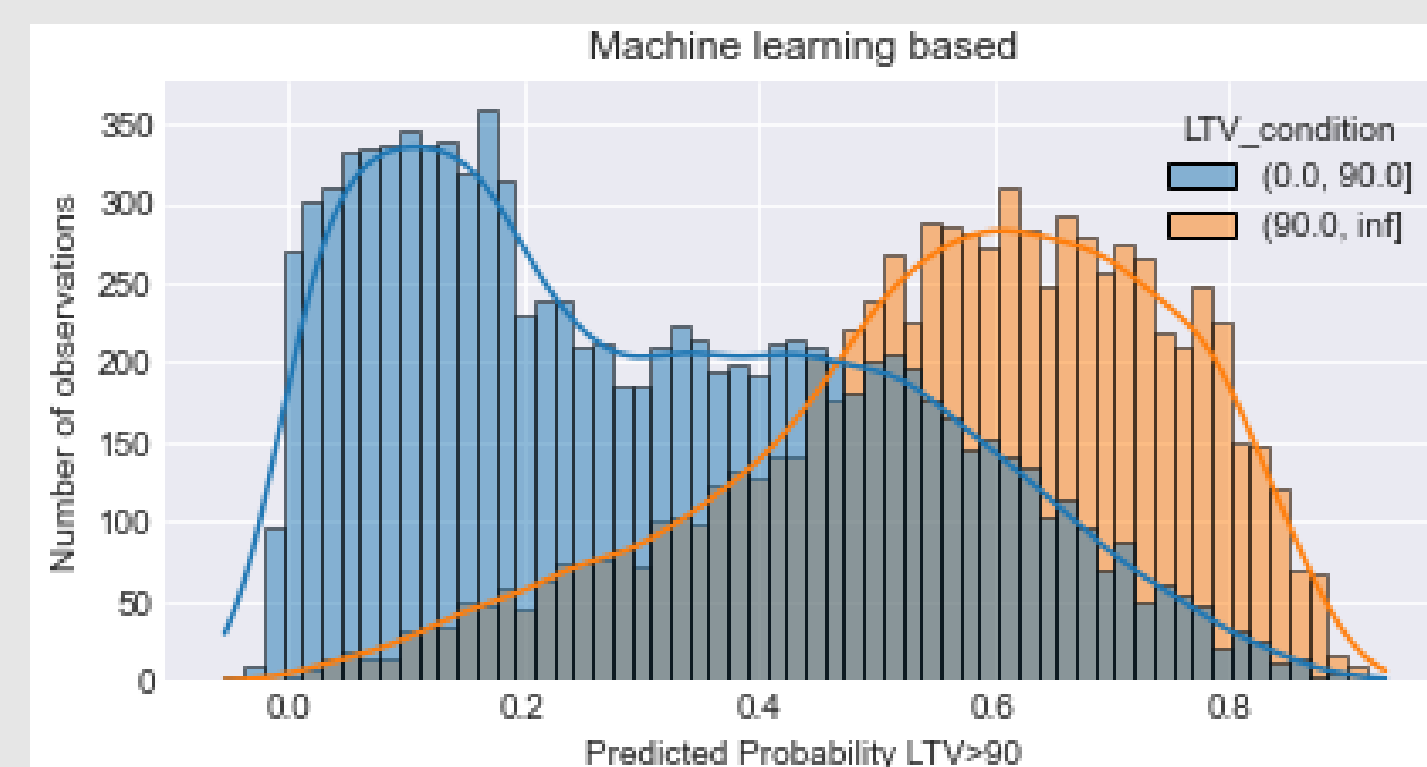
B) Machine Learning predictions

Purpose: improving classification accuracy

Several ML models have been tested: Random forest, XGBoost & LightGBM

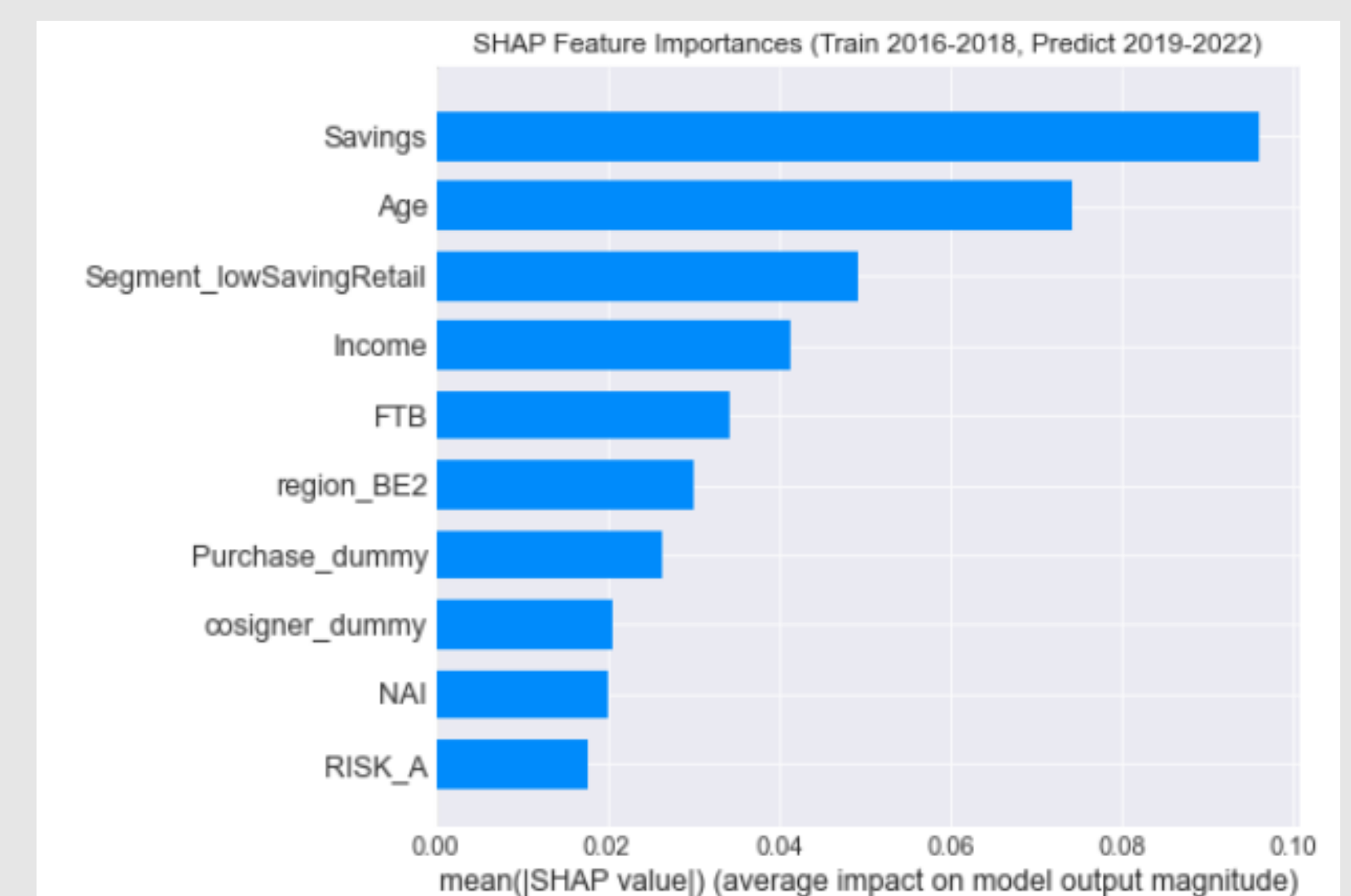
- Choice based on performance:** LightGBM predictions to make Treated vs Control classification
- Robustness checks:** using XGBoost predictions

	Predicting:Probability LTV>90							
	Model 0: OLS		Model 1: Random Forest		Model 2: XGBoost		Model 3: LightGBM	
	Training set	Test set	Training set	Test set	Training set	Test set	Training set	Test set
R ²	0.224	0.235	0.379	0.278	0.314	0.294	0.298	0.291
RMSE	0.431	0.433	0.386	0.422	0.407	0.417	0.412	0.418
MAE	0.383	0.387	0.333	0.377	0.345	0.359	0.351	0.361

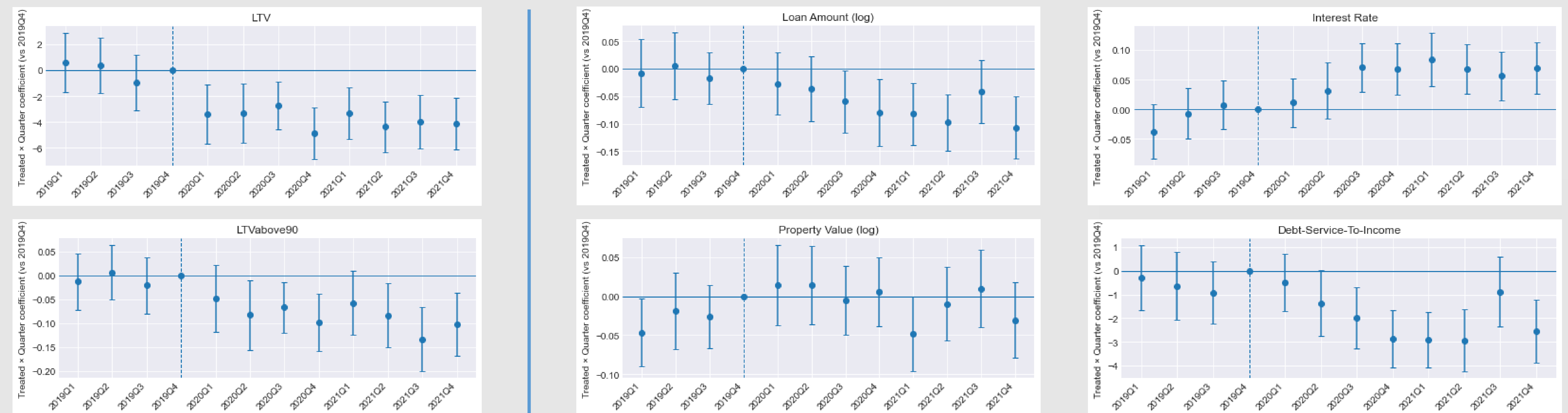


	# Observations	
	Actual LTV<90	Actual LTV>90
Predicted LTV<90	7578 (72.6% correct)	2859
Predicted LTV>90	1159	4355 (79.0% correct)

Note: Percentage corresponds to the proportion of correctly identified observations within the Treated group and within the Control group separately



Results: DID using the predicted treatment status



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