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Martin Hodula, Milan Szabo, Lukáš Pfeifer, and Martin Melecký *

Abstract

This paper studies the effects of regulatory recommendations concerning maximum (i) loan-to-value (LTV), (ii) debt-to-income (DTI) and (iii) debt service-to-income ratios (DSTI) on new loans secured by residential property. It uses loan-level regulatory survey data on about 82,000 newly granted residential mortgage loans in the Czech Republic from 2016 to 2019 to estimate the average effects of the Czech National Bank's regulatory recommendations and their heterogeneous effects depending on borrower, loan, bank and regional characteristics. The studied response variables include the mortgage loan size and lending rate and the value of the property with which loans are secured. The machine learning method of causal forests is employed to estimate the effects of interest and to identify any heterogeneity and its likely drivers. We highlight two important facts: (i) value-based (LTV) and income-based (DTI and DSTI) limits have different impacts on the mortgage market and (ii) borrower, loan, bank and regional characteristics play an important role in the transmission of the recommended limits.

Abstrakt

Tento článek se zabývá vlivem regulatorních doporučení ohledně maximálního (i) poměru výše úvěru k hodnotě zajištění (LTV), (ii) poměru výše dluhu k příjmům (DTI) a (iii) poměru dluhové služby k příjmům (DSTI) u nových úvěrů zajištěných rezidenční nemovitostí. Využívá data na úrovni jednotlivých úvěrů z regulatorních šetření o zhruba 82 000 nově poskytnutých hypotečních úvěrech na rezidenční nemovitosti v České republice od roku 2016 do roku 2019. Odhaduje průměrné efekty regulatorních doporučení České národní banky a jejich heterogenní dopady v závislosti na charakteristikách věřitele, úvěru, banky a regionu. Zkoumané vysvětlované proměnné zahrnují výši a úrokovou sazbu hypotečního úvěru a hodnotu nemovitosti, jíž je úvěr zajištěn. K odhadu vlivu úroku a k identifikaci případné heterogenity a jejích pravděpodobných příčin je využito strojové učení, konkrétně metoda tzv. kauzálních lesů. Zdůrazňujeme dvě důležité skutečnosti: (i) limity založené na hodnotě nemovitosti (LTV) a na příjmech (DTI a DSTI) mají na hypoteční trh odlišné dopady a (ii) významnou roli při transmisi doporučených limitů hrají charakteristiky věřitele, úvěru, banky a regionu.

JEL Codes: E44, G21, G28, G51, R31.

Keywords: Borrower-based measures, causal forests, Czech Republic, macroprudential recommendations, residential mortgage loans.

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1. Introduction

Many countries have experienced the situation in which rapid growth of housing loans and house prices reinforce each other, leading to a build-up of systemic risk. Rising leverage of households has historically been followed by busts in mortgage loan markets and increases in unemployment (Mian et al., 2017). Policymakers have proposed and implemented various macroprudential policies to weaken the feedback loop between credit and house prices and to reduce the vulnerability of bank mortgage loan portfolios (Cerutti et al., 2017a). In this regard, borrower-based measures have been particularly favoured, having been adopted by more than 60 countries since 1990 (Alam et al., 2019). Nevertheless, the degree to which borrower-based measures are effective in cooling and de-risking the mortgage loan market remains an open question, a question which is also scrutinized politically, because such measures could disadvantage some segments of the population in financing their housing more than others and thus promote inequality in access to housing finance.

Using supervisory survey data on all newly granted residential mortgage loans in the Czech Republic, this paper examines the effects of three non-binding borrower-based measures (recommendations) on mortgage lending. Combining loan-level data with borrower and bank-level information and data on regional property prices, unemployment and GDP, the paper estimates the effects of adjusted limits for the loan-to-value (LTV), debt-to-income (DTI) and debt service-to-income (DSTI) ratios. The borrower-based measures were recommended by the Czech National Bank (CNB), the micro and macroprudential supervisor for the Czech financial system. The Czech experience is interesting because of the non-binding nature of the borrower-based measures, the combination of value-based and income-based measures and the combination of both hard and soft limits. While the hard limit cannot be breached, banks are allowed to extend mortgages above the soft limit for a small proportion of their portfolios. To our knowledge, our paper is the first to provide evidence on the effects of central bank recommendations (not regulations) on mortgage lending markets.

The CNB started to apply an LTV cap at the beginning of the expansionary phase of the financial cycle in mid-2015. It gradually lowered this cap and subsequently introduced income-based DTI and DSTI limits in 2018. Banks responded by reducing their LTI, DTI and DSTI ratios to the recommended limits (CNB, 2020). In the paper, we search for channels through which the ratios were reduced and assess the impact of the recommendations on bank interest rate policy. The observed decline in the LTV, DTI and DSTI ratios on new mortgages after the introduction of the recommendations could have been spurred, on the one hand, by a reduction in the size of new mortgages, associated with the purchase of cheaper property or the securing of additional financing from other sources. On the other hand, the LTV ratio may have decreased because of an increase in the denominator, i.e. collateral value. This could have happened either through the collateralization of additional property or by banks valuing collateralized property less conservatively. Similarly, it was unclear how banks would respond to the recommendations in terms of the interest rates charged on new mortgage contracts. Bank interest rates could have either declined due to a general decrease in mortgage vulnerability or increased as a result of active management of soft-limit loans.

Our estimates suggest that, after the LTV lending limits were recommended, the mortgage loan size decreased slightly on average relative to the control group with similar borrower, bank and regional characteristics. At the same time, the required collateral value increased. The DTI and DSTI limits subsequently introduced to further cool the mortgage market were more effective. The income-based limits helped reduce the average loan size much more than the LTV limits alone and encouraged repricing to higher lending rates as banks aligned their pricing policies with the regulatory perception of riskiness. Moreover, the income-based limits reduced the possibility of using higher collateral valuation to increase the loan size.

The estimated average effects, however, are surrounded by significant heterogeneity driven by certain borrower, loan, bank and regional characteristics. Specifically, the average positive effect of the LTV recommendation on collateral value varied systematically with the market share of the lending bank, the value of loan repayments and the growth of regional property prices. Banks with the largest market shares granted loans based on much higher collateral value compared with other banks. Loans with higher repayments also carried systemically higher collateral value. And, loans in regions with higher property price growth showed a greater increase in collateral value than loans from other regions.

The decrease in loan size, which was initially modest after the LTV recommendation took effect and then marked after the additional DTI and DSTI recommendations were introduced, varied with loan maturity – longer maturity loans showed a greater drop in loan size. The loan size reduction also differed with the borrower's age, being largest for borrowers between the ages of 25 and 35. It further varied with the borrower's income and the loan repayment size – high-income and high-repayment borrowers reduced their contracted loan size relative to similar borrowers in the control group. Finally, the estimated change in loan size differed with regional per capita GDP and the unemployment rate – borrowers located in regions with higher GDP per capita and lower unemployment rates reduced the contracted loan size more.

We contribute to the literature on borrower-based measures aimed at limiting household over-indebtedness by (i) analysing the effects of the recommended LTV limits first separately and then jointly with the recommended DTI and DSTI limits, and (ii) highlighting that borrower, loan, bank and regional characteristics play an important role in the transmission of the recommended limits. A few other papers analysing LTV/LTI limits find results broadly consistent with ours. For example, Acharya et al. (2020) show that loan-to-income and loan-to-value limits in Ireland have led to reallocation of housing loans from low-income to high-income borrowers and from urban to rural counties. Araujo et al. (2020) show that following the imposition of LTV limits, Brazilian borrowers increased their down payments and began to purchase more affordable houses. Cesnak et al. (2021) show that LTV limits in Slovakia mainly affected younger borrowers up to the age of 35. In the literature, our paper is probably closest to that of Grodecka (2020).

Using a real business cycle model calibrated on Swedish data, Grodecka (2020) highlights that the effectiveness of LTV as a measure to limit excessive risks related to the property market has to be reassessed and is probably lower than previously shown. We offer complementary evidence on the LTV measure in the country context of the Czech Republic, whose mortgage market is more in line with the prevailing EU models than Sweden's.[1] Our findings may therefore be more transferable to other EU countries. Moreover, we examine the transmission channels through which borrower-based limits (LTV, DTI and DSTI) impact the market, and our results thus offer a more detailed insight into the possible interactions between the limits and their macro-prudential effectiveness in de-risking mortgage loan markets.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature. Section 3 describes the Czech mortgage loan market in relation to those of major euro area and OECD countries as well as the regulatory recommendations, their aim and the sequence in which

[1] The Swedish mortgage market is rather specific and characterized by longer maturity and multi-generation loan contracts.

they were introduced. Section 4 describes the data and estimation methodology. Section 5 discusses the estimation results for both the average and heterogeneous effects, including their estimated drivers. Section 6 performs robustness checks. Section 7 concludes.

2. Literature Review

The growing number of macroprudential interventions in housing loan markets have created a variety of policy shocks whose effects demand exploration (Cerutti et al., 2017b). The ability to use loan-level data is particularly important for such explorations. Currently, most papers in the relevant literature use cross-country data (see, for example, Claessens et al., 2013; Cerutti et al., 2017b; Akinci and Olmstead-Rumsey, 2018) and employ dummy-coded indices to capture the occurrence of a macroprudential policy action.[2] Country-level data complicate the identification of a regulatory shock and make it impossible to analyse the channels of transmission. Using country- or bank-level data is useful to the extent that it allows one to explore the macroeconomic implications of introducing macroprudential measures (Fidrmuc and Lind, 2020). Similarly, relying on dummy-coded indices to capture macroprudential policy actions allows the cross-country context to be exploited, but falls short on capturing the intensity of the policy action. For example, a 5 percentage point increase in the LTV limit is effectively treated at par with a 10 percentage point increase. Therefore, dummy-coding of policy actions does not allow for an estimation of the quantitative effects of policies, which is generally a key issue for policymakers (Alam et al., 2019).

The current EU practice distinguishes two categories of borrower-related risks: (i) those associated with collateral value, i.e. property prices, and (ii) those connected with consumers' income and debt servicing capacity (ESRB, 2018). Prudential policy tools, which target borrower-related risks directly, restrict the volume of credit extended to borrowers with risky characteristics. They include loan-to-value (LTV), debt-to-income (DTI) and debt service-to-income (DSTI) caps. LTV caps can primarily limit loss given default (LGD), while DTI and DSTI caps can primarily reduce the probability of default (PD). Both types of measures can also lower the exposure to default, because they can also limit the amount that a person can borrow in relation to, for example, her accumulated savings or expected income.

During economic booms, house prices tend to be overvalued and households are known to project (irrationally expect) house prices to rise continuously (Piazzesi and Schneider, 2009; Favara and Song, 2014; Engsted and Pedersen, 2015; Granziera and Kozicki, 2015). This risky situation is generally associated with growing demand for property and fuelled by an easing of credit standards, which can reinforce the feedback loop between house prices and housing loans (Iacoviello and Neri, 2010; Favara and Imbs, 2015; Jordà et al., 2015; Justiniano et al., 2019). Such a market situation can be risky for the stability of the banking sector, because mortgage lending rates and capital buffers do not reflect the risks of collateral overvaluation and a possible decline in borrowers' income when the bubble bursts. If such risks are identified by the macroprudential policy authority, one primary tool for mitigating them is a stricter LTV limit. The LTV limit is set to reflect the downside risk stemming from the volatility of property prices. With the LTV limit tightened, the expected coverage rate of outstanding loan principal by the sale of collateral in the event of default increases. As a result, when purchasing property, borrowers cannot enter into loan commitments that significantly exceed the collateral value and, even in bad times, the reduced property value will serve as sufficient collateral. The LTV limit therefore aims to reduce lenders' losses in the event of default and a simultaneous fall in property prices and is the most commonly used macroprudential tool targeted at risk exposures to

[2] Araujo et al. (2020) provide a meta-analytical summary of this strand of literature.

property prices in current international practice (Cerutti et al., 2017b; Alam et al., 2019), including at the EU level.

The empirical literature generally confirms that following the introduction or tightening of LTV limits, the size of loans extended decreases. Many papers rely on dummy indices to capture the occurrence of LTV-style regulation (Jácome and Mitra, 2015; Fendoğlu, 2017; Akinci and Olmstead-Rumsey, 2018). Some authors use a narrative identification strategy to capture the intensity of LTV changes (Richter et al., 2019; Alam et al., 2019). Some papers (closer to ours) employ micro-level data, which allows one to disentangle the transmission channels through which the market copes with new regulations (Armstrong et al., 2019; Araujo et al., 2020; Acharya et al., 2020).

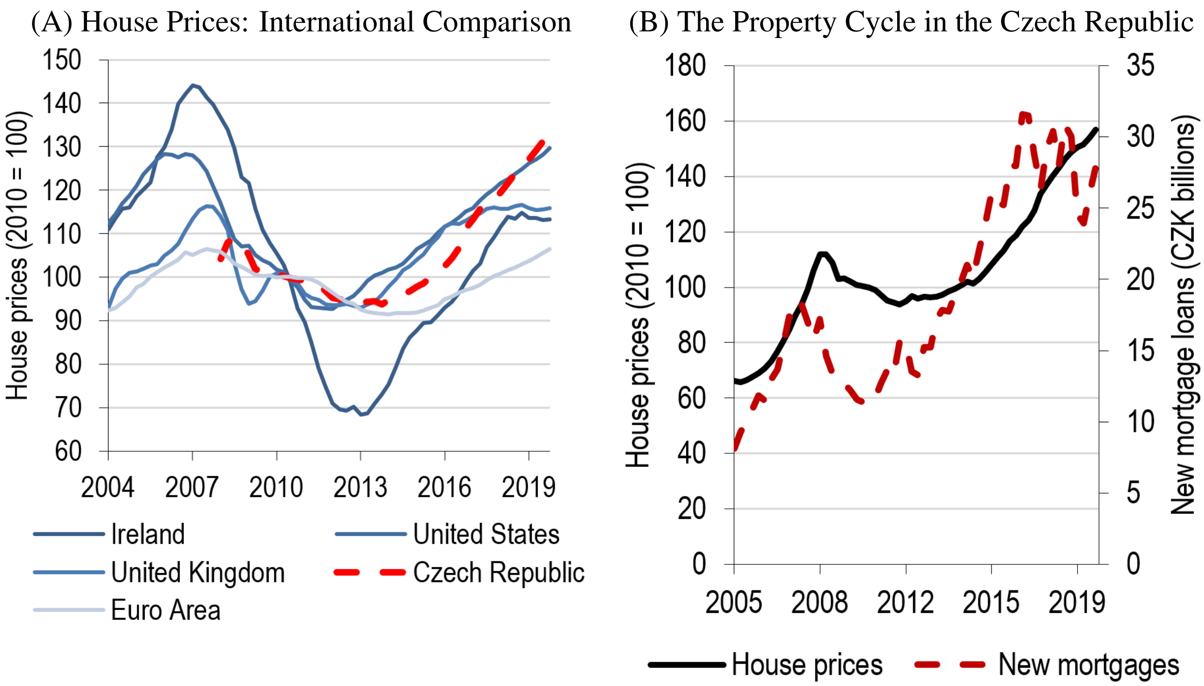
Even with property prices around their equilibrium level or with properly calibrated LTV limits, a risk to financial stability can arise if households accumulate excessive debt relative to their expected debt servicing capacity. This increases the probability of default, especially during periods of economic stress. Losses or declines in borrower income, or increases in (adjustable) lending rates, can trigger such risk. The DTI ratio serves as an indicator of a borrower's ability to repay her debt, for example, how many (net) annual incomes it will take to settle her total debt (all her debt to formal financial institutions). The DSTI ratio serves as an indicator of a borrower's ability to service her loan obligations out of her net income – after deducting common expenses, how much is left from the borrower's income to cover the service payments (interest and principal) on her loan(s). Income limits are targeted at reducing the probability of default during an economic downturn (ESRB, 2018). These limits can also be used to enhance the effectiveness of LTV limits in de-risking the mortgage loan market, because lenders will be restricted to loans that do not exceed the caps on all borrower-based measures for all contracted and contemplated loans simultaneously. In addition, income limits are binding even for the provision of unsecured loans, which borrowers may tap to relax their binding constraints if only LTV limits are in place.

On a large sample of banks in ten Asian economies, Morgan et al. (2015) find that economies with LTV polices have expanded residential mortgage loans by 6.7% per year, while non-LTV economies have expanded them by 14.6%, suggesting that LTV policies have been effective. Claessens et al. (2013) and Cerutti et al. (2017a) suggest that the effect of LTV limits differs from the effect of DSTI limits because lower DSTI limits can moderate the growth of credit, while no such evidence is found for LTV limits. Using dummy variables to mark the imposition of LTV limits on a large international sample, Kuttner and Shim (2016) show that lowering the LTV limit is less effective than introducing a DSTI limit in reducing credit growth. Félix et al. (2021) use credit registry data and the difference-in-differences method to estimate the effects of LTV policy on households. They highlight an improvement in the risk profile of households following the introduction of LTV limits. Such limits reduced household leverage, as constrained households took out smaller loans and reduced their loan-to-income ratios. They also find that the policy affected the housing choices of households, because constrained households bought cheaper houses.

3. The Czech Residential Mortgage Market and Regulatory Measures

The Czech property market had been growing rapidly in the run-up to the Global Financial Crisis (GFC), similar to the property markets of other OECD countries. From the international perspective, the post-crisis boom was more pronounced in the Czech Republic than in the euro area, the United Kingdom, Ireland and the United States (Figure 1). However, the Czech market did not experience any major bust. From 2008 to 2010, GDP growth remained positive at an average of 0.2% per annum and the unemployment rate increased only marginally – from 4.5% in 2008 to 7.2% in 2010. Likewise, property prices did not decline dramatically (Figure 1). As a result, the banking sector did not experience any major increases in non-performing mortgage loans or funding dry-ups. This allowed mortgage lending to grow and property prices to bounce back soon after the GFC and to grow rapidly between 2015 and 2017 on the back of a concurrent easing of monetary policy rates. The CNB assesses the risks associated with exposures secured by residential property by evaluating the degree of overvaluation of house prices, the easiness of credit standards and the evolution of new loans – overvalued prices and easy credit standards are indicators of the riskiness of new loans and, together with the volume of new loans, they indicate the total size of the risks associated with the provision of new loans (Hejlová et al., 2021).

Figure 1: The Property Cycle and House Prices



Note: The left-hand figure shows real house prices (2010 = 100) obtained from the OECD database, as expressed by the ratio of nominal prices to the consumer expenditure deflator in each country, both seasonally adjusted.
Source: Czech Statistical Office, Czech National Bank and OECD

Observing this development, the Czech National Bank – the national financial market regulator and macroprudential authority – decided to act to manage the possible systemic risks. It announced its intention to introduce borrower-based measures in the Czech residential property market and then implemented them soon after on 16 June 2015 by issuing a Recommendation on the Management of Risks Associated with the Provision of Retail Loans Secured by Residential Property (henceforth the Recommendation). The Recommendation follows the guidance of the European Systemic Risk Board (ESRB),[3] the recommendations of other international authorities, and EU legislation.[4] It pursues one intermediate objective of macroprudential policy, namely to prevent excessive growth of mortgage lending and household over-indebtedness. The Recommendation

[3] ESRB Recommendation on Intermediate Objectives and Instruments of Macroprudential Policy (ESRB/2013/1).
[4] Financial Stability Board (2012): FSB Principles for Sound Residential Mortgage Underwriting Practices; European Banking Authority (2013): Opinion of the European Banking Authority on Good Practices for Responsible Mortgage Lending; Directive 2014/17/EU on Credit Agreements for Consumers Relating to

defines correct procedures and standards for the provision of loans secured by residential property, enhancing existing bank internal risk management systems and encouraging a prudent approach to providing loans secured by residential property.[5] The main objective of the Recommendation is therefore to increase the resilience of the mortgage portfolio to potential adverse developments.

The measures were aimed at enhancing the resilience of lenders and borrowers and at limiting the negative feedback loop between credit and house price dynamics. Originally, the Recommendation contained, among other things, LTV caps, which were set to become effective in June 2015. Since then, the CNB has tightened and expanded the Recommendation twice (Table 1). In the latest version relevant for the period under review, the Recommendation (effective from October 2018) stated that providers should ensure that the LTV ratio of no retail loan secured by residential property exceeds 90%. It also recommended that providers should ensure that new retail loans secured by residential property with an LTV of 80–90% did not exceed 15% of the total amount of retail loans secured by residential property provided in the current quarter. The Recommendation also set an upper DTI limit of 9 (with an optional 5% of new loans to bear a higher DTI) and an upper DSTI limit of 45% (with an optional 5% of new loans to bear a higher DSTI). The CNB's Recommendation was then gradually relaxed (the LTV ratio) or abolished (the DTI and DSTI ratios) in April and June 2020 in the expectation that banks would be sufficiently prudent in setting lending standards during the uncertainty associated with the coronavirus pandemic.

The CNB deals with any shortcomings in adherence to the recommended limits by regulated entities by imposing remedial measures and, where necessary, an additional capital requirement (Pillar 2) for an inadequate approach to risk management. On 1 August 2021, an amendment of the Act on the Czech National Bank, promulgated under number 219/2021, entered into force. It enables the Czech National Bank to set upper limits on one to three borrower-based indicators as a binding measure, as opposed to the non-binding nature of the recommendations analysed in this paper.[6] Since 2021, the Recommendation has contained certain conditions related to the provision of mortgage loans which are not regulated by the Act on the Czech National Bank and specified by the Provision of a General Nature. These include a maximum maturity of 30 years, acceptable methods of principal repayment, and conditions for increasing the principal of an existing mortgage loan.

Table 1: Borrower-Based Measures Applying to New Mortgage Loans from 2015 to 2018

Announced	Effective (A)	Hard caps (B)	Soft limits
16 June 2015	16 June 2015	LTV 100%	10% (LTV 90–100%)
14 June 2016	1 October 2016	LTV 95%	10% (LTV 85–95%)
14 June 2016	1 April 2017	LTV 90%	15% (LTV 80–90%)
12 June 2018	1 October 2018	LTV 90% DTI 9; DSTI 45%	5% (debt limits) 15% (LTV 80–90%)

Source: Czech National Bank

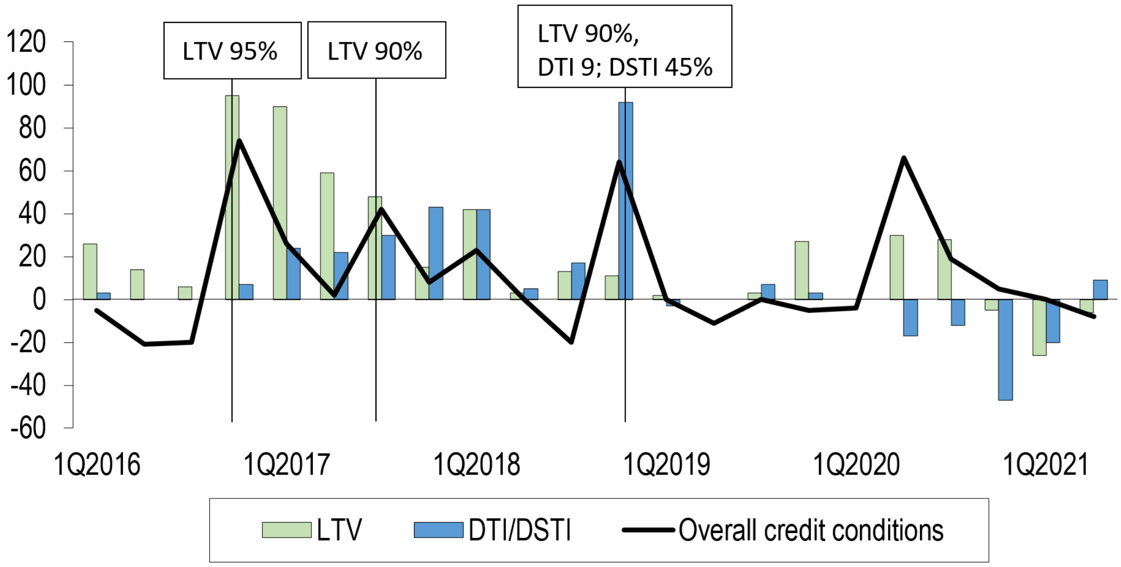
Residential Immovable Property and Amending Directives 2008/48/EC and 2013/36/EU and Regulation (EU) No 1093/2010.

[5] Details on the Recommendation can be found on the CNB website: https://www.cnb.cz/en/financial-stability/macroprudential-policy/recommendation-limits-applicable-to-mortgage-loans/

[6] Provision of a General Nature on Setting Upper Limits on Credit Ratios According to the Act on the Czech National Bank (since 2021), setting specific upper limits on the LTV, DSTI and DTI credit ratios.

Reportedly, the Recommendation significantly affected credit standards in the Czech banking sector (Figure 2). Based on information obtained from the bank lending surveys[7] conducted by the CNB on a quarterly basis, the 2016 tightening – involving a reduction in the share of new loans with LTV ratios exceeding 80% – was viewed by commercial bank officials as the most significant one.

Figure 2: Change in the Overall Credit Conditions as Reported by Banks' Officials



Note: The net percentage is calculated as the difference between the market share of banks reporting a tightening of credit standards/conditions, or an increase in demand for loans, and the market share of respondents reporting an easing of credit standards/conditions, or a decline in demand for loans, for a given question.
Source: Czech National Bank, Bank Lending Survey (Question 10)

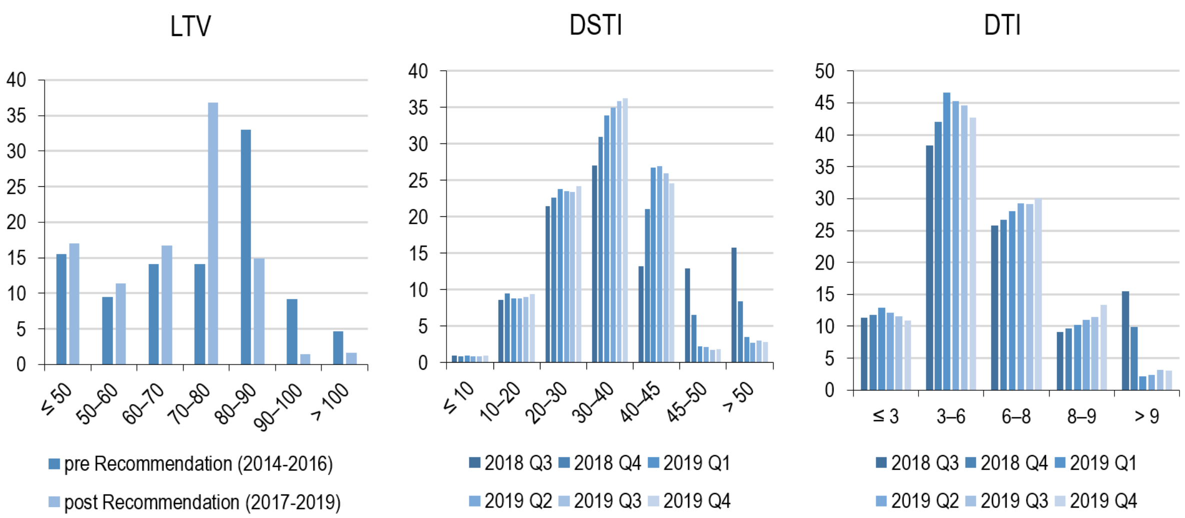
Following the introduction and subsequent tightening of the recommended LTV limits, the share of loans with LTVs above 80% fell significantly (Figure 3). Albeit with a delay, the banks affected by the Recommendation were broadly compliant with the LTV limits by the end of 2017. Loans with LTVs of 80–90% accounted for 15% and 12% of new lending in 2017 Q3 and Q4 respectively on average across banks, in compliance with the maximum recommended ratio of 15% at the individual bank portfolio level (the soft limit).

However, the CNB survey (CNB, 2020) revealed that almost 16.5% of loans had an LTV ratio exactly equal to the 80% limit and 5.3% of loans had an LTV ratio exactly equal to the individual 90% limit in 2019. The results of the CNB survey may thus indicate partial "optimization" of collateral value. Lenders may have an incentive to reduce the LTV level by optimistically assessing the value of property (especially unbuilt new property) to get just below the individual or portfolio limit. Another escape route from the LTV limits may have been concurrent provision of unsecured (consumer) loans to partially finance property purchases (extended several months before, or simultaneously with, the approval of the mortgage loan).[8]

[7] Bank lending surveys are a standard tool allowing central banks and other users to obtain valuable information about both the credit supply side (credit standards and terms and conditions for approving loans as stipulated by banks) and the credit demand side (demand for loans among households and corporations as perceived by banks) above and beyond regular reporting data.
[8] However, combining secured and unsecured loans could be in breach not only of the CNB Recommendation, but also of the Consumer Credit Act if it were to cause a loan applicant to become over-indebted.

The effectiveness of LTV limits can be enhanced by the simultaneous introduction of income limits (DTI and DSTI), which can reduce the scope for evading the LTV limits, particularly in relation to concurrent provision of unsecured (consumer) loans. Therefore, we consider not only the impact of LTV limits on the amount of the mortgage loan, its collateral and the mortgage lending rate, but also the reinforcing effect of income limits on these variables. Such combination of limits can be effective because lenders are likely first to restrict loans which breach multiple limits simultaneously.

Figure 3: Recommended Limits: Fulfilment and Loan Distribution



Note: Share of loans in volume provided in %. Volume provided means the reference volume in the Recommendation applicable at the time.
Source: Czech National Bank

The introduction of DTI and DSTI limits led to a further significant tightening of credit standards, as evidenced by bank lending surveys (Figure 2). At the same time, the DTI and DSTI values fell for newly issued mortgage loans (Figure 3). The decline in credit risk indicators (LTV, DTI and DSTI) led to the targeted reduction in the vulnerability of bank mortgage loan portfolios. The belt-and-braces approach through recommended LTV limits combined with income-based DTI and DSTI limits thus appears to be more effective.

4. Data and Methodology

Section 4.1 describes our data treatment, section 4.2 sets out our identification strategy and section 4.3 presents the method we employ in our analyses.

4.1 Data

The Czech National Bank regularly assesses compliance with its recommendations by mortgage lenders. Since the second half of 2015, the CNB has been conducting semi-annual surveys of mortgage lenders to monitor compliance. The survey contains anonymous individual data on all newly provided retail loans secured by residential property. We use information on individual mortgage loans granted during the 2016–2019 period. The data were collected in seven rounds of surveys. We use these surveys as the main data source and match the loan-level data with other datasets: regional unemployment rates and regional GDP per capita obtained from the Czech Statistical Office, as well as regional transaction prices of flats constructed by Deloitte.

The survey contains loan information and borrower characteristics (Table A1). The borrower characteristics are aggregated values if the mortgage loan is granted to multiple applicants. For example, net income is aggregated as the total net income declared by all borrowers in the mortgage loan contract. The only exception is reported age, which is available for the main borrower only.

We check the data for possible errors in reports and exclude such data entries. These include, for instance, mortgages with a borrower age of less than 18 or more than 70 years, a loan maturity of less than 5 years or more than 40 years, an interest rate fixation period of more than 20 years and a number of loan applicants of more than 4. Furthermore, we winsorize extreme values for the loan amount and collateral value and borrower-based measures such as LTV identified with the 1st and 99th percentiles. We had to drop loans with incomplete information, primarily mortgages without a reported postcode. Unfortunately, this is usually caused by banks' reporting limitations, and a few banks were completely dropped from the study due to missing postcodes. Postcodes are used to match loans to regions. Finally, we discard banks with insufficient representation in each group (less than 350 loans). In total, we work with 81,844 reported mortgage loans (with 58% loss of observations due to missing information and data cleaning).

The loan characteristics were expanded to include variables related to the regulatory recommendations. Because the portfolio limits are set with respect to the volume granted by the bank in a given quarter, we calculated the distance to the bank's recommended portfolio LTV limit (the "soft limit" in Table 1) based on the date on which each mortgage was granted and the days until the end of each quarter. Lastly, reported mortgage loans are linked to the bank's market share, and the average mortgage interest rate of a given bank in a given month (by interest rate fixation length buckets) is used to calculate the distance to the average interest rate.

In Table A2, we show how borrower and mortgage characteristics differ across three "richest" and "poorest" regions according to their level of GDP per capita. Across the distribution of regions, borrowers located in "rich" housing markets borrow more, have higher LTI and LSTI but lower LTV, and purchase more expensive properties compared with borrowers located in "poor" housing markets. Not surprisingly, the "rich" regions have significantly higher house prices, which echoes the observed higher average loan size. Borrowers in "richer" regions are generally more indebted (about 30% more), which should mechanistically translate to higher observed DTI and DSTI indicators.

4.2 Identification Strategy

Figure 2 showed that banks had relatively loose credit standards prior to the tightening of the recommended LTV limits in 2016, although a regulatory hard LTV cap on individual loans of 100% was already in place. Figure 3 illustrates that the LTV, DTI and DSTI distributions of new mortgage loans changed after the LTV and DTI-DSTI recommendations were introduced. This context and the findings about the intermediate outcomes guide our identification strategy.

We assume that the sequential changes in the loan distribution can be causally attributed to the introduction of recommended limits in essentially two main rounds of regulatory tightening (first an LTV tightening and then the introduction of DTI and DSTI limits). In the quasi-natural experiment that we evaluate, we assign loans to three groups: a control group and two treatment groups.

The control group consists of mortgages granted between 1 January 2016 and 14 June 2016.[9] The control group captures mortgages issued under the first Recommendation, which set a hard LTV cap of 100% but was not viewed by banks as binding.

The two treatment groups (waves) comprise mortgages issued after the hard LTV cap of 90% was recommended (first wave) and those granted after the recommended DTI and DSTI limits were introduced (second wave). The first treatment group captures mortgages granted after 1 June 2017, i.e. when the recommended 90% limit on the LTV ratio became effective (Table 1). The second treatment group consists of mortgages issued under the ensuing DTI and DSTI recommendation (Table 1), with the recommended LTV limit remaining in place and unchanged. Table 2 shows the dates used to assign loans and Figure A1 offers a visualization of the control and treatment periods side-by-side, depicting the average LTV of the mortgage loans granted by our sample banks and its dynamics. Using the machine learning algorithm of causal forests (Athey and Imbens, 2016), we estimate the causal effect of the recommendations (LTV and DTI-DSTI) on the mortgage loan market by comparing the differences between the control and treatment groups in each wave of recommendations while allowing the treatments' effects to vary across subgroups based on borrower, loan, bank and regional characteristics (conditional variables). We attribute the changes obtained from this setup to the tightening of the value-based (LTV) and income-based (DTI-DSTI) limits.

Table 2: Control and Treatment Period

	Treatment			**Control**		
	minDate	maxDate	N	minDate	maxDate	N
LTV	1/6/2017	31/12/2017	37,019	1/1/2016	14/6/2016	28,104
LTV-DTI-DSTI	1/10/2018	14/6/2019	16,721	1/1/2016	14/6/2016	28,104

Note: minDate/maxDate denotes the minimum/maximum date of when the mortgage was granted to be included in the control or treatment group. N denotes the number of mortgages.

Addressing endogenous selection out of treatment. In our evaluation, we need to ensure that the estimated differences relative to the control group are due to the treatment and not to structural changes in the economy or the changing composition of lenders or borrowers. This is addressed primarily through the choice of comparison group and by controlling for observable borrower, lender, bank and economic characteristics. We deal with borrower selection in two ways. Our more direct method accounts for changes in the borrower population by controlling for a number of key observable variables, such as age, income and debt. In addition, our estimation method shuts down the effects of entry and exit (at least based on observables), as it is based on loan-by-loan matching. That is, for each mortgage loan originated before, during, or after the treatment period, we find a matching mortgage loan based on the monitored characteristics. The advantage of the causal forest is that it forces the control sample to mirror changes in our observables in the treatment samples.

Dealing with non-random treatment sample choice. The quasi-experimental design of our analysis could be a complication. In particular, the set of mortgage loans in our sample is apparently non-random because we can only observe issued loans that already satisfy certain

[9] We prefer mortgages reported for the first half of 2016 without those for the second half of 2015 because the former presumably have better data quality, as they were reported in the second round of the survey. The cutoff date of 14 June is chosen to account for the frontloading that probably happened after the announcement of the intended Recommendation and before its actual date of effect.

conditions. Since we cast our statistical net on the entire portfolio of mortgages, we also need to deal with the fact that some borrowers were more sensitive to economic shocks during the period studied, and this could have induced changes in their mortgage loan or borrowing choice unrelated to the treatment. We address this mortgage loan selection concern via a set of robustness checks. First, we separate the effect of the treatment across constrained and unconstrained loan groups (based on their LTV score). This approach resembles the structure of standard difference-in-differences analysis. Despite the fact that we do not observe the same mortgage loans before and after treatment, we assume that those which were above the LTV limit threshold in the control period would be more treated than those below the threshold in that period. We further remove trend-induced changes to our observables by controlling for changes in the average values of our main variable of interest for which we evaluate treatment effects.

4.3 Estimation Methodology

In the potential outcome framework described in Rubin (2005), each unit (in our case, a newly granted loan) has two potential outcomes based on binary treatment. Let $Y_i(W_i = 1)$ be the outcome if the unit was treated (denoted by $W_i = 1$), i.e. the loan was granted under either one or all of the recommendations introduced and the loan thus belongs to the treatment group in our setting. Then $Y_i(W_i = 0)$ is the outcome if the unit was not treated. The causal (treatment) effect of a recommendation on the i-th loan could be estimated as the simple difference between the potential outcomes. However, we cannot observe both the factual and the counterfactual at the same time. The goal of causal inference is to solve the missing data problem (also known as the "fundamental problem of causal inference") and, under some assumptions,[10] to estimate the causal effects.

Starting with a simple linear regression, the average treatment effect can be estimated under the assumptions as a coefficient of a dummy variable that encodes treatment status (β_1 in eq. 1).

$$Y_i = \alpha + \beta_1 W_i + \beta_2 X_i + ... + e_i \tag{1}$$

Here we are particularly interested in the conditional average treatment effect (CATE) – conditional on covariates x – defined as:

$$\tau(x) = E[Y_i(W_i = 1 - Y_i(W_i = 0)|X_i = x] \tag{2}$$

Exploring possible treatment heterogeneity with CATEs can provide valuable information about how to improve the targeting of recommendations and what mechanisms/conditionalities drive the results. Understanding how different subgroups respond can help improve the design of borrower-based measures and boost their effectiveness. Continuing with the exposition of the linear regression, the usual way is to introduce the interaction of a chosen covariate (also called a moderator) and the treatment dummy variable.

$$Y_i = \alpha + \beta_1 W_i + \beta_2 X_1 + \beta_3 W_i X_i + ... + e_i \tag{3}$$

Another approach to estimating CATEs is to use machine learning algorithms. Machine learning methods are an attractive option that minimizes the need for parametric assumptions. Specifically, we employ an extension of the regression tree and the random forest algorithms proposed by

[10] As we work with observation data, we have to make several important assumptions: common support (Rosenbaum and Rubin, 1983), the stable unit treatment value assumption (Cox, 1992) and unconfoundedness of the treatment assignment W_i with the potential conditional response: $W_i \perp (Y_i(1), Y_i(0)|X_i)$ (Rosenbaum and Rubin, 1983).

(Wager and Athey, 2018) to search for treatment heterogeneity over high-dimensional functions of covariates rather than a small number of subgroups (typically confined to the interaction terms in linear models). The causal forest is a flexible, non-parametric estimator that calculates observational, conditional average treatment effects for an entire sample and allows for many possible nonlinear interactions between covariates (and the treatment). Yet the logic and assumptions stay very similar to those for estimating the linear regression. The causal forest can be viewed as a more flexible nonlinear approach that inherently allows for rich interactions between the treatment status and any covariate. That flexibility is the main motivation for employing this method in preference to linear interaction models.

The goal of a standard regression tree algorithm is to predict the outcome variable by producing binary splits of the data that partition the covariate space into mutually exclusive leaves. By minimizing the mean squared error (MSE), the algorithm determines the variable on which to split and the split points – see Bishop (2006) for the formal explanation. The predicted outcome for a unit with a covariate vector in the assigned leaf is the average outcome for the observations in the same leaf. Because the predictions of individual trees are usually noisy, the ensemble method of random forests emerges from averaging over many regression trees using bootstrapped samples without replacement. This ensemble method reduces the variance of the estimates – see the pioneering paper by Breiman (2001). Athey and Imbens (2016) introduce causal trees that modify the standard regression tree algorithms. Even though the causal tree shares the same binary tree structure, unlike the standard regression tree algorithms, causal trees cannot minimize the standard MSE due to the unknown true treatment effects.[11] Therefore, causal trees minimize the expected MSE of the predicted treatment effects, which is equivalent to maximizing the variance of the predicted treatment effects across leaves minus a penalty for within-leaf variance.[12] The predicted treatment effects for units with covariates in the leaf are obtained by the difference in means between the treated units and the control units within the leaf outcomes. Wager and Athey (2018) show how causal trees can be aggregated into causal forests by averaging over many causal trees using bootstrapping and counteracting over-fitting.

We explore the treatment effects for the three main variables of interest. Because LTV is the ratio of the loan amount to the price of the financed housing property, we estimate the treatment effect on these two variables. The relative size of the estimated effects helps us explore the channels through which the market coped with the recommendation(s). For instance, a client breaching the recommended LTV limit may decrease her LTV score by reducing the loan size and purchasing a cheaper property or by securing additional financing from other sources. Furthermore, the LTV ratio can be lowered by increasing the value of the collateral backing the mortgage loan. This can be done either by the client pledging an additional property or by the bank valuing the property less conservatively. We estimate and compare the impact of tightened value-based (LTV) limits and the subsequent introduction of income-based (DTI and DSTI) limits. In addition, we assess the impact of the recommendation(s) on bank loan pricing, as measured by the distance of the individual mortgage rate to the average mortgage rate in the market (the mortgage rate gap).

We implement the causal forest algorithm using honest[13] generalized random forests (Tibshirani et al., 2020). We estimate first $e(x) = E[W_i|X_i = x]$ and second $\mu(x) = E[Y_i|X_i = x]$ with random

[11] Alternatively, standard regression trees can be employed to estimate the treatment effects of transformed outcomes by inverse propensity scores weighting. Athey and Imbens (2016) show that causal trees give better results in simulations.

[12] See Athey and Imbens (2016) for the formal derivation.

[13] A tree is honest if, for each training sample i, it only uses the response Y_i to estimate the within-leaf treatment effect or to decide where to place the split, but not both.

forests, where Y_i denotes the dependent variable of unit i. Finally, we estimate $\tau(x)$ over the neighbourhood $N(x)$ obtained from the split structures:

$$\hat{\tau}(x) = \frac{\sum_{\{i:X_i \in N(x)\}} \{Y_i - \hat{\mu}(X_i)\}\{W_i - \hat{e}(X_i)\}}{\sum_{\{i:X_i \in N(x)\}} \{W_i - \hat{e}(X_i)\}} \tag{4}$$

The causal forest algorithm has several hyperparameters: the minimum node size for the individual causal trees, the number of variables tried for each split, the size of the bootstrapped samples for each tree and the regularization parameter. The hyperparameters are tuned by cross-validation. Motivated by Basu et al. (2018), the procedure starts by training a pilot causal forest on all covariates in the specification (Table A4). The final forest is then trained on important covariates that attain above-median variable importance. The variable importance measure is a depth-weighted average of the number of splits on the variable of interest. Additionally, we enable for clustering of errors at the bank level.

We report the CATEs and the average treatment effects (ATEs – the unconditional expected values of the CATEs).[14] Finally, we perform a simple test for the presence of heterogenous treatment effects. We divide the CATE estimates into two groups (above and below the median CATE) and test if the ATEs of these two groups differ from each other using t-tests for various characteristics to uncover the most important characteristic behind the heterogeneous treatment effects.

5. Estimation Results

Borrower-based measures are becoming a standard policy tool for addressing imbalances in the residential mortgage loan market. Beyond average effects, policymakers, lenders and the public at large are keen to better understand the heterogeneity in the responses of market participants to the introduction of borrower-based limits. This section discusses our estimates of the average and heterogeneous effects of borrower-based limits on mortgage lending secured by residential property in the Czech Republic.

We focus on two periods during which the CNB tightened or introduced new borrower-based lending limits – our treatment variables. The response variables of interest are the mortgage loan size, the value of the pledged residential property and the mortgage loan rate (its deviation from the average market rate). The estimated treatment effects on these response variables help us understand how effective the regulatory recommendations were in rebalancing the mortgage loan market and reducing the build-up of systemic risk. We estimate the effects of the two waves of regulatory recommendations on the response variables at the average (the average treatment effect) and also study the variations around this average effect (through heterogeneous treatment effects) conditional on various borrower, bank, loan and regional characteristics.

5.1 The Effects on Loan Size and Pledged Property Value

Table 3 reports the estimated average treatment effects (ATEs) and the statistics for the presence of heterogeneous treatment effects (HTEs). The estimates show that following the introduction of recommended LTV limits, the average loan size dropped by approximately CZK 19,000, while collateral value increased by about CZK 220,000. The former magnitude appears economically less significant given the average pre-treatment loan size of CZK 1,650,000, suggesting a reduction

[14] Specifically, the ATEs are obtained by plugging the causal forest predictions into a doubly robust average treatment effect estimator explained in Chernozhukov et al. (2018).

of 1.2%. The latter magnitude is economically significant given that the average pre-treatment collateral value was CZK 2,590,000, translating into about a 8.5% increase. The ATEs of the recommended limits on DTI and DSTI (in addition to the LTV cap) vary. The ATE on the loan size is almost eighteen times greater than in the case of the LTV limit, reducing the average loan size by an additional CZK 340,000 (or 20.6%). The ATE on collateral, interestingly, is statistically insignificant, partly because the estimated ATE is more than five times smaller in magnitude.[15]

Table 3: Average and Heterogeneous Treatment Effects on Loan Size and the Value of Pledged Property

	LTV	**LTV-DTI-DSTI**
A) Size of mortgage loan		
Average Treatment Effect (ATE)	**-18,973**	**-342,290**
	(-33,104; -4,841)	(-378,988; -305,593)
Heterogeneous Treatment Effect (HTE)	7,278	**364,051**
	(-17,162; 31,718)	(295,636; 432,466)
No. of observations	65,123	44,825
B) Value of pledged property		
Average Treatment Effect (ATE)	**223,331**	43,024
	(127,309; 319,353)	(-881; 86,930)
Heterogeneous Treatment Effect (HTE)	**214,721**	**161,291**
	(63,781; 365,660)	(33,541; 289,041)
No. of observations	65,123	44,825

Note: The table shows the estimated average treatment effect (ATE) in the national currency (CZK). The heterogeneous treatment effect is a t-test of the differences between the ATEs for the groups above and below the median of the estimated treatments. The results in Panel A show the estimated ATE on the size of a mortgage loan and the results in Panel B show the estimated ATE on the value of pledged property. The columns show two model specifications. In the LTV column, the ATE of tightening the LTV limits is estimated. In the LTV-DTI-DSTI column, the ATE of introducing the DTI and DSTI limits on top of the existing LTV limit is estimated. Standard errors are clustered at the bank level. 95% confidence interval in parentheses. Significant estimates are highlighted in bold.

The combination of a negative ATE of LTV limits on loan size and a positive ATE of the same on collateral value may raise questions about the effectiveness of LTV limits for curbing risks in mortgage lending. Our results suggest that although the LTV limits lowered demand for, and the granting of, larger loans, their de-risking effect may have been partially offset by borrowers pledging properties of a higher value and/or by pledging additional property. While the LTV limits may have encouraged borrowers to put more equity/savings against their mortgage loans, borrowers may have also used various strategies to increase the value of the collateral accepted by banks. And banks may have actively collaborated on those strategies. By contrast, the introduction of additional

[15] The documented insignificant effect of income-based limits on collateral value serves as one check against a possible bias due to the insufficiently addressed dynamics of continuously rising house prices during the period under investigation. One might argue that the positive treatment effect on collateral value identified after the LTV limits were tightened could have been somewhat inflated by the rising property prices, despite the fact that we control for apartment prices across different regions. However, the fact that we identify no effect of the Recommendation on collateral value after the introduction of the recommended DTI and DSTI limits suggests that the result is not driven primarily by rising house prices and, as such, is informative about the likely effect of the Recommendation.

income-based limits (DSTI and DTI) may have corrected the incentives through a "belt-and-braces" approach that left little room for arbitrage by either borrowers or banks. The income-based limits helped significantly lower the average loan size while keeping the average value of pledged property rather unchanged and in check. Therefore, the combination of income-based and LTV limits appears to have been much more effective in de-risking the residential mortgage loan market in the Czech Republic compared with LTV limits alone.[16]

To further examine the significant heterogeneous treatment effects for both the recommended LTV limits and the package of recommended LTV, DTI and DSTI limits, we run additional tests. Specifically, Tables 4 and 5 report ATEs conditional on selected factors, including borrower, loan, bank and regional characteristics, for both the LTV and the income-based recommendations. The tables then formally test the difference in the average ATEs between the 30% of mortgages with the highest and the 30% of mortgages with the lowest value of a given characteristic. If the t-test of the difference for a given factor is significant, we interpret this as empirical evidence that this factor is a significant driver of the heterogeneity for a given treatment. A visual presentation of the ATEs conditional on statistically significant covariates is available in Appendix C.

Heterogeneous treatment effects on mortgage loan size. We estimate significant heterogeneous treatment effects stemming from the varying maturity of new mortgage loans. The DTI and DSTI recommendation states that the average maturity of new mortgage loans should not exceed 30 years. As banks increased their compliance with this recommendation, the loan size of the 30% of mortgage loans with longest maturity declined significantly more than the loan size of the 30% of mortgages with the shortest maturity. Interestingly, we document this heterogeneity only for the recommendations on the income-based limits. This would suggest that following the introduction of the recommended DSTI limit, longer loan maturity was used to spread instalments over a longer period to effectively lower the debt service. However, this was only possible for mortgages with a maturity of up to 30 years, after which it was necessary to reduce the amount of the mortgage loan granted. In other words, the DSTI limit together with the loan maturity limit very effectively reduces the risk associated with excessive debt service. This is because without a loan maturity limit in place, borrowers can comply with DSTI limits by requesting longer and longer maturities and lowering their monthly repayment.

We estimate a larger treatment effect on the mortgage loan size for the 30% of mortgage loans with the youngest main borrower compared with the 30% of loans with the oldest borrower, particularly after the recommendations on income-based limits were introduced. Judging from the average treatment effects for individual age groups, the loan size reduction is greatest for mortgage loans with borrowers between the ages of 25 and 35. This unintended heterogeneous treatment effect was recently addressed by an amendment of the CNB law that went into force on 1 August 2021. The amendment states that more lenient conditions will be offered to mortgage loan applicants under the age of 36 years. Based on our analysis, the amendment and its upper limit of 36 years are well justified as a targeted intervention to correct the unintended consequences of uniformly applied prudential measures for de-risking mortgage loan markets. The documented larger treatment effect on younger borrowers is tightly linked to the former finding of a larger treatment effect for loans with longer maturity. Typically, younger borrowers choose longer maturities, which, from a prudential point of view, can be justified by their longer economic activity. So, anything that restricts loan amounts for long maturity loans will mechanistically have more of an effect on younger borrowers.

[16] See also Grodecka (2020) for similar evidence in a different country context.

Further, the income-based recommendation lowered the loan size for borrowers with the highest income and borrowers with the highest loan repayments. This finding suggests that, before the income-based recommendations were introduced, high-income borrowers were much more leveraged in terms of their income than lower-income borrowers, who often could not obtain a mortgage loan.

Heterogeneous effects by income level work along the spatial dimension. We find that the loan size of borrowers located in regions with higher GDP per capita and lower unemployment rates was reduced more as a result of the recommended limits. Specifically, we find that, after the recommendations were introduced, the mortgage loan size of the 30% of loans with borrowers from regions with the highest GDP per capita (or the lowest unemployment rates) was reduced more than the loan size of the 30% of new loans with borrowers from regions with the lowest GDP per capita. This heterogeneous treatment effect thus improves equity in access to mortgages across regions with different levels of prosperity. Intuitively, "richer" regions experienced greater growth in property prices before the recommendation, fuelled in part by larger mortgages, with resident borrowers more likely to take out mortgage loans of a size that made them breach the yet-to-be introduced (recommended) limits.

Surprisingly, we find no statistically significant differences in the treatment effects on loan size between regular mortgage loans for financing the purchase of property for primary residence and mortgage loans for financing the purchase of rental property. This finding may be surprising, because the recommended LTV limits were much stricter for mortgage loans financing rental property. The hard LTV limit on mortgage loans financing rental property was set at 60%, while the hard LTV limit for residential mortgages was set at 90%. One explanation could be lacking loan contracts identified as mortgage loans financing rental property in the first place – only about 1% of all the observations in our sample involved such contracts. This suggests a substantial weakness in the approach to identifying buy-to-let mortgage loans when this mortgage loan type is more penalized.[17] The weak identification mechanism creates room for clients to avoid declaring the true purpose of property financed by mortgage loans.

[17] Buy-to-let mortgage loans are retail loans secured by residential property financing the purchase of residential property. The expected income from renting such property is included in the estimated net income of the borrower.

Table 4: Borrower, Loan, Bank and Regional Characteristics as Potential Heterogeneity in the ATE on the Mortgage Volume

	LTV			**LTV-DTI-DSTI**		
Variable	Low	High	Difference	Low	High	Difference
book_value	-13,041	-13,174	-133 (-23,881; 23,614)	-231,444	-230,114	1,324 (-78,025; 80,684)
net_income	-6,585	-25,014	-18,429 (-41,571; 4,714)	-162,654	-317,083	**-154,434** **(-238,478; -70,377)**
applicants_no	-13,520	-13,219	301 (-24,664; 25,265)	-224,417	-237,646	-15,362 (-93,705; 67,247)
debt	-9,523	-16,793	-7,270 (-36,371; 21,831)	-260,831	-215,486	38,201 (-39,245; 129,934)
dependents	-17,365	-8,893	8,472 (-23,756; 40,701)	-235,138	-235,493	-7,278 (-82,196; 81,486)
age	-15,000	-6,166	8,834 (-14,162; 31,830)	-258,773	-166,630	**93,357** **(2,131; 182,155)**
loan_repay	-7,331	-26,579	-19,248 (-44,728; 6,232)	-110,637	-440,176	**-324,835** **(-417,830; -241,247)**
regul_distance	-8,045	-16,985	-8,940 (-45,006; 27,126)	-255,315	-229,070	22,925 (-30,813; 83,303)
days_till_qend	-20,021	-14,443	5,578 (-16,946; 28,102)	-251,085	-223,944	28,684 (-51,049; 105,332)
net_income_norm	-3,559	-24,782	-21,222 (-48,934; 6,489)	-178,639	-314,818	**-134,086** **(-215,084; -57,273)**
maturity	-4,039	-23,317	-19,277 (-44,360; 5,805)	-134,063	-330,340	**-191,618** **(-268,168; -124,384)**
fixation	-9,407	-25,429	-16,021 (-52,965; 20,922)	-244,918	-211,277	28,282 (-33,231; 100,512)
market_share	-751	-42,089	-41,338 (-113,836; 31,160)	-217,677	-243,979	-26,778 (-145,510; 92,906)
house_prices	-5,901	-9,245	-3,344 (-26,552; 19,863)	-200,400	-167,946	30,921 (-47,304; 112,210)
gdp_pc	-11,537	-41,613	-30,076 (-62,176; 2,024)	-163,274	-385,065	**-215,289** **(-292,285; -151,297)**
unmpl	-49,708	-9,571	40,137 (-963; 81,237)	-574,701	-147,656	**410,539** **(332,306; 521,784)**

Note: The table shows the estimated average treatment effect (ATE) in the national currency (CZK) on the size of a mortgage loan for the 30% of loans with the lowest (Low) and the highest (High) value of a given characteristic (first column). Column 2 (LTV) shows the ATE of tightening the LTV limit. Column 3 (LTV-DTI-DSTI) shows the ATE of introducing the DTI and DSTI limits on top of the existing LTV limit. Standard errors are clustered at the bank level. 95% confidence interval in parentheses. Significant estimates at the 5% level are highlighted in bold.

Heterogeneous treatment effects on the value of pledged property. Table 5 tests for borrower, loan, bank and regional characteristics that could drive the heterogeneity in the treatment effects on collateral value – the value of pledged property – for both sets of recommendations. The data identifies that the heterogeneous treatment effect of the LTV recommendation on collateral value could have been driven primarily by three significant factors: regional property prices, the market share of the lender and the size of the loan repayment.

Specifically, we find that the 30% of loans from banks with the largest market share were issued with a significantly higher collateral value than the 30% of loans from banks with the lowest market share. This could imply that greater market power enables banks to focus on the higher end of the market with highly valued property, such as in and around major cities. Further, the 30% of loans from regions with the lowest property prices saw a greater increase in collateral value as a result of the LTV recommendations than the 30% of loans from regions with the highest property prices. This finding could reflect increased property price convergence as a result of the recommended LTV limits. In addition, we find that collateral value increased significantly more after the recommended LTV limits were introduced for the 30% of loans with the highest loan repayments than for the 30% of loans with the lowest loan repayments. This result may reflect either lending into a booming property market, with borrowers and banks riding the wave, or increased efforts by banks to assign a high value to pledged property at the higher end of the market (characterized by the highest loan repayments) because the customized nature of such homes implies high price dispersion and greater pricing discretion for appraisers.

Income-based recommendations (DTI, DSTI) were then introduced, also with heterogeneous treatment effects but with distinct drivers of heterogeneity. We find that, as a result of the recommended DTI and DSTI limits, collateral value decreased more for loans with longer maturity. Specifically, the 30% of loans with the shortest maturity (roughly below 10 years) experienced a positive treatment effect (an increase in collateral value), whereas the 30% of loans with the longest maturity (roughly above 30 years) experienced a significantly negative treatment effect and a decrease in collateral value. This finding can be explained through the workings of the DSTI limit. For borrowers with loans of shorter maturity, the DSTI limit was not as effective, because they could afford to buy property at a higher price, as loan maturities lower than 10 years also identify wealthier clients. While clients for which the DSTI limit was binding had the option to extend the maturity, the Recommendation also set the maximum loan maturity at 30 years. The 30-year limit may have been too short for some clients to meet the DSTI limit in a property market with rising prices and they may therefore have had to purchase (and pledge) a cheaper property.

Table 5: Borrower, Loan, Bank and Regional Characteristics as Potential Heterogeneity in the ATE on the Value of Pledged Collateral

	LTV			LTV-DTI-DSTI		
Variable	Low	High	Difference	Low	High	Difference
book_value	131,028	171,014	39,986 (-91,008; 170,981)	206,329	232,065	25,736 (-197,868; 249,339)
net_income	100,497	185,473	84,976 (-148,621; 318,573)	220,595	199,845	-20,750 (-282,628; 241,128)
applicants_no	113,808	240,400	126,592 (-26,535; 279,718)	211,344	253,693	42,349 (-205,395; 290,093)
debt	165,482	236,661	71,179 (-259,465; 401,823)	172,508	481,893	309,385 (-89,779; 708,550)
dependents	165,220	201,516	36,296 (-134,048; 206,640)	238,233	250,806	12,573 (-273,273; 298,419)
age	213,193	179,874	-33,319 (-186,400; 119,762)	212,140	299,471	87,331 (-186,604; 361,266)
loan_repay	52,884	325,102	**272,219** **(98,922; 445,515)**	86,404	420,668	**334,264** **(80,578; 587,949)**
regul_distance	172,243	130,073	-42,170 (-375,793; 291,454)	296,554	268,457	-28,097 (-419,792; 363,598)
days_till_qend	132,355	220,074	87,719 (-75,808; 251,247)	171,186	309,763	138,577 (-105,459; 382,612)
net_income_norm	199,264	155,031	-44,232 (-258,482; 170,017)	256,820	204,880	-51,940 (-355,781; 251,900)
maturity	141,770	201,928	60,158 (-110,617; 230,932)	274,019	138,879	**-135,140** **(-3,251; -267,029)**
fixation	164,903	187,184	22,281 (-113,820; 158,383)	142,980	260,217	117,237 (-233,375; 467,849)
market_share	109,040	182,536	**73,497** **(1,407; 145,587)**	181,480	77,343	-104,137 (-586,379; 378,105)
house_prices	256,255	171,224	**-85,031** **(-168,730;-666)**	527,009	81,020	**-445,989** **(-706,791; -185,187)**
gdp_pc	221,877	124,847	-97,031 (-460,696; 266,635)	254,238	325,350	71,112 (-302,382; 444,606)
unmpl	142,583	187,487	44,903 (-305,389; 395,195)	428,073	215,578	-212,495 (-590,014; 165,025)

Note: The table shows the estimated average treatment effect (ATE) in the national currency (CZK) on the value of pledged property for the 30% of loans with the lowest (Low) and highest (High) value of a given characteristic (first column). Column 2 (LTV) shows the ATE of tightening the LTV limit. Column 3 (LTV-DTI-DSTI) shows the ATE of introducing the DTI and DSTI limits on top of the existing LTV limit. Standard errors are clustered at the bank level. 95% confidence interval in parentheses. Significant estimates at the 5% level are highlighted in bold.

5.2 The Treatment Effects on Mortgage Loan Rates

So far, we have examined how banks adjust their lending approach in response to recommended borrower-based limits in terms of the treatment effects on loan size and collateral value. Next, we focus on the impact of the recommendations on bank pricing of mortgage loans – the lending interest rate. The recommendations may have reduced the credit risk of all borrowers that stayed in the market, with all banks thus reducing their lending rates on average. Or, the pool of eligible borrowers may have shrunk because riskier borrowers were pushed out of the market and banks were forced to compete for the remaining borrowers, including by lowering the price of loans. However, in the Czech context, lending rates increased due to the recommendations. The existence of a soft limit under which banks have the option of providing a certain proportion of total loans with higher prudential ratios in the current quarter (15% in the case of LTV and 5% in the case of income-based limits) is an interesting feature worth accounting for. Banks can manage this soft limit through risk-sensitive pricing by assigning a risk premium to riskier mortgage loans within the bounds of this soft limit. To partially control for this rolling market premium, we construct our mortgage loan rate measure as the difference between the actual interest rate agreed in the mortgage contract and the average market mortgage rate at a given time and for a given maturity basket. By doing so, we also aim to filter out other market-wide effects, such as changes in the monetary policy rate, the yield curve and systemic credit risk.

We start by estimating the average treatment effect. A positive treatment effect would imply that the distance to the average rate increased relative to its value before the recommendations took effect. Table 6 reports the estimated ATEs and the tests of the HTEs. On average, we identify a positive treatment effect, suggesting a general increase in mortgage rates following the introduction of the recommendations. This suggests that banks have always fully exploited the soft limit options with higher risk pricing (15% of contracted loans within a given quarter in the case of LTV and 5% in the case of income-based limits) and increased risk premiums on mortgage loans with high prudential ratios.

Table 6: Average and Heterogeneous Treatment Effects on the Distance to the Average Loan Rate

	LTV	**LTV-DTI-DSTI**
Average Treatment Effect (ATE)	**0.179** (0.067; 0.291)	**0.339** (0.220; 0.458)
Heterogeneous Treatment Effect (HTE)	-0.046 (-0.264, 0.172)	0.119 (-0.065, 0.303)
No. of observations	65,123	44,825

Note: The table shows the estimated average treatment effect (ATE) on the distance to the average loan rate. The heterogeneous treatment effect is a t-test of the differences between the ATEs for the groups above and below the median of the estimated treatments. Column 2 (LTV) shows the ATE of tightening the LTV limit. Column 3 (LTV-DTI-DSTI) shows the ATE of introducing the DTI and DSTI limits on top of the existing LTV limit. Standard errors are clustered at the bank level. 95% confidence interval in parentheses. Significant estimates are highlighted in bold.

Specifically, Table 6 shows that, after the recommended LTV limits were introduced, the distance to the average mortgage rate increased by about 0.18 percentage points (p.p.). We estimate a larger positive treatment effect for the recommended DTI and DSTI limits of 0.34 p.p. This can be explained by their greater binding nature relative to the LTV limits and by the more constrained opportunity to use soft limit options (only 5% of loans breaching the prudential ratios). The HTE values are not statistically significant, implying that the treatment effect on the distance to the average rate is rather homogeneous across new loans with different borrower, loan, lender and regional characteristics.

6. Robustness Checks

In causal forest estimation, the constrained and unconstrained separation is set implicitly. To make an explicit distinction between more and less constrained borrowers, we separate the effect of the treatment across constrained and unconstrained loan groups in both the control and the treatment periods. Due to the existence of both hard and soft LTV limits, we can observe constrained and unconstrained loan groups in the control and the treatment periods. We assess whether a loan was more likely to be treated (constrained) by the recommendations based on its LTV ratio. Constrained loans, which form the treatment group, are classified as loans with LTV ratios equal to or higher than 80%. Unconstrained loans, which form the control group, have LTVs below the 80% threshold.[18]

Table 7 provides average values for some key covariates used in our analysis across the treatment and control groups for constrained and unconstrained loans. After the first treatment (by LTV), the loan amount increased by 22.8% in the unconstrained group but by only 8.5% in the constrained group. After the second treatment (by LTV-DTI-DSTI), we observe 38.7% higher loan size growth in the unconstrained group and 14.6% lower loan size growth in the constrained group. This is accompanied by growth in collateral value, which differs between the two groups (33.7% unconstrained versus 24.4% constrained). These summary statistics suggest that, consistent with the regulatory objective, the introduction of borrower-based limits led to lower growth in the size of mortgage loans for the group of constrained (targeted) clients. Collateral value responded unexpectedly after the LTV limit was tightened for the constrained loan group and may need to be studied further in future research. After the income-based recommendations (DTI and DSTI limits) were introduced, we observe a similar response in collateral value across the unconstrained and constrained loan groups.

After the LTV limit was tightened, the average LTV fell from 90% to 84% in the constrained client group and rose from 52% to 64% in the unconstrained client group. This is reflected in a significantly larger increase in the down payment variable for the constrained group (72.5% vs. 7.6%). In line with the regulatory objective of reducing the risk in bank mortgage loan portfolios, the riskiness of constrained clients declined – their PDs decreased by 0.5 p.p. on average, while the PDs of unconstrained clients dropped by only 0.2 p.p on average. However, the constrained loan group experienced a 0.07 p.p. increase in the interest rate gap measure, because the LTVs of these loans were above the regulatory threshold. In the LTV-DTI-DSTI model, the differences in the responses of these variables (PDs and interest rates) between the two groups were even more pronounced. The down payment increased by 91.8% (vs. 20.9% for the unconstrained group), PD decreased by 0.36 p.p. (vs. 0.08 p.p.) and the interest rate gap increased by 0.2 p.p. (vs. 0.1 p.p.). Furthermore, the income-based limits led to a decrease in the indebtedness of clients – the debt of constrained clients decreased by 14.6%, while that of unconstrained clients increased by 19.0%.

[18] We cannot split the sample of mortgages according to their DTI and DSTI values. During the first rounds of data collection which form our control period, DSTI was not included among the set of mandatory indicators to be reported by banks and, as such, is not available to us and cannot be manually calculated and added.

Table 7: Summary Statistics for Constrained and Unconstrained Borrowers

Variable	Control period		Treatment period	
	Unconstrained	Constrained	Unconstrained	Constrained
		LTV		
Size of mortgage loan	1,414,671	1,932,577	1,736,561	2,096,625
Collateral value	2,877,291.07	2,241,432	3,398,898	2,672,469
Number of loan applicants	1.50	1.47	1.52	1.49
Distance to average rate	-0.07	-0.08	0.01	0.08
PD (72% market share)*	0.91	1.53	0.89	1.03
Net income	481,233	466,652	530,501	532,198
Mortgage maturity	21.08	26.38	22.93	27.11
Down payment	1,393,611	236,081	1,500,054	407,242
Repayment amount	7,091.87	7,940	8,092	8,606
Debt	611,501	587,423	660,746	611,813
LTV	0.52	0.90	0.56	0.84
LTI	3.30	4.52	3.66	4.33
LSTI	0.19	0.22	0.20	0.21
		LTV-DTI-DSTI		
Size of mortgage loan	1,414,671	1,932,577	1,961,565	2,215,110
Collateral value	2,877,291	2,241,432	3,847,072	2,789,138
Number of loan applicants	1.50	1.47	1.52	1.52
Distance to average rate	-0.07	-0.08	0.10	0.21
PD (72% market share)*	0.91	1.53	0.83	1.17
Net income	481,233	466,652	573,676	560,619
Mortgage maturity	21.08	26.38	24.62	27.64
Down payment	1,393,611	236,081	1,685,194	452,751
Repayment amount	7,092	7,940	9,202	9,652
Debt	611,501	587,426	727,599	501,886
LTV	0.52	0.90	0.56	0.83
LTI	3.30	4.52	3.82	4.31
LSTI	0.19	0.22	0.21	0.22

Source: Czech National Bank

Table 8 shows the estimated ATEs for the two groups of clients. We generally observed a strong and statistically significant treatment effect for constrained clients, as expected. After the LTV limits were tightened, collateral value increased by a significant CZK 280,000 for constrained clients. By contrast, no such effect occurred for unconstrained clients. Further, collateral value did not change significantly after the income-based limits were introduced, and the ATEs for constrained clients are insignificant.

We also observe that the tightening of LTV limits increased mortgage interest rates only for the constrained group of borrowers. Specifically, the ATE of 0.2 suggests that following the tightening of the LTV limits, the distance to the average mortgage rate increased by about 0.2 p.p. After the introduction of the DTI and DSTI limits, we observe a positive treatment e affect for both groups but find a statistically larger effect for constrained borrowers. These estimates are quantitatively similar to our baseline estimates and show that banks were much stricter in their pricing of loans that breached the soft limit, which had to bear an additional credit risk premium.

Table 8: Average Treatment Effects for Constrained and Unconstrained Borrowers

	Constrained	Unconstrained
A) LTV		
ATE for size of mortgage loan	-13,442	-7,979
	(-39,271; 12,388)	(-19,737; 3,779)
ATE for value of pledged property	**281,641**	-27,213
	(189,568; 373,713)	(-154,299; 99,872)
ATE for distance to average rate	**0.196**	0.109
	(0.083; 0.309)	(-0.043; 0.261)
No. of observations	23,874	41,249
of which treatment group	11,167	25,852
B) LTV-DTI-DSTI		
ATE for size of mortgage loan	**-231,118**	**-259,694**
	(-301,238; -160,999)	(-292,058; -227,329)
ATE for value of pledged property	-54,786	**283,526**
	(-148,466; 38,893)	(115,780; 451,273)
ATE for distance to average rate	**0.360**	**0.281**
	(0.230; 0.490)	(0.117; 0.445)
No. of observations	17,076	27,749
of which treatment group	8,842	13,641

Note: 95% confidence interval in parentheses. Significant estimates are highlighted in bold.

As an additional robustness check, we specify the two variables of interest – the mortgage loan size and the value of pledged collateral – in differences from their average values. By doing so, we aim to address potential concerns related to time-specific endogeneity driving our estimates. By specifying the variables as gaps, the estimated treatment effect reveals whether the mortgage loan size or the collateral value responded differently from the average market portfolio. The estimates are reported in Table D1 in the Appendix. The estimated ATEs are both quantitatively and qualitatively similar to the baseline estimates presented in Table 3.

7. Conclusions

This paper examined the effect of recommended LTV, DTI and DSTI limits on the size of newly granted residential mortgage loans, the value of the property pledged to secure them and the associated mortgage loan rate – more specifically its deviation from the average mortgage market rate in the Czech Republic. Using the causal forest estimation methodology, we focused on identifying the average treatment effects and tested for the existence of possible heterogeneous treatment effects on the population of all new residential mortgage loans.

We estimated that the recommended LTV limits reduced the average loan size and increased the interest rate on newly granted loans after their introduction. However, they also increased the value of the property pledged to secure the loans – presumably because borrowers and banks tried to arbitrage away a part of this new binding constraint. However, the positive effect on collateral value was very heterogeneous. The main heterogeneity factors include the lending bank's market share, the growth of regional property prices and the value of loan repayments. Banks with the largest market share granted loans based on much higher collateral value compared with other banks – perhaps because their greater market power enabled them either to skim the higher end of the market, or to carry out over-inflated appraisals of the pledged property more easily in high value markets with high price dispersion. Future research could investigate the two hypotheses rigorously. In addition, loans from regions with initially lower property prices exhibited significantly higher growth in collateral value, because property prices probably converged towards regions with initially higher property values.

Because the mortgage loan market was not de-risked as much as the regulator had expected after the recommended LTV limits were introduced, additional borrower income-based limits (DTI and DSTI) were recommended. The additional DTI and DSTI limits provided banks and borrowers with tighter "belt-and-braces" incentives that were harder to evade. We estimated that the additional DTI and DSTI limits – together with the earlier recommended LTV limits – reduced the average mortgage loan size significantly and much more effectively than the LTV limits alone – about twenty times more. Interestingly, their effect on loan size was not accompanied by any significant average increase in the value of pledged property. Also, the mortgage rate increased substantially more than after the recommended LTV limits were introduced (0.34 p.p. versus 0.18 p.p. after LTV), as banks may have further aligned their risk pricing with the recommendations of the regulator (the CNB). Importantly, the average effects of the total LTV-DTI-DSTI package of recommendations on loan size involved significant heterogeneity, but its effect on mortgage loan rates was quite homogeneous.

For the loan size effect, the first heterogeneous factor is new loan maturity. Specifically, after the DTI-DSTI recommendation was introduced, longer loan maturity was used to spread instalments over a longer period to effectively reduce the debt service. However, this was only possible for mortgages with shorter maturity; applicants for longer maturity loans – particularly around the 30-year threshold – had to reduce their mortgage loan size. This conclusion suggests that a cap on DSTI, together with a limit on loan maturity, very effectively reduces the risk associated with excessive debt service. Mortgage loans with longer maturities are granted to a greater extent to younger clients. Therefore, the second heterogeneous factor is the borrower's age. The loan size reduction effect appears to be largest for borrowers between the ages of 25 and 35.[19] The third and fourth factors are geo-spatial: regional per capita GDP and the unemployment rate. Specifically, borrowers located in regions with higher GDP per capita and lower unemployment rates reduced their loan size more as a result of the recommended limits. These heterogeneous treatment effects therefore improved equity in access to mortgage loans across regions with different levels of prosperity.

Although the LTV-DTI-DSTI package had no significant average effect on collateral value, some significant (heterogeneous) effects were observed depending on loan maturity. Collateral value decreased more for loans with longer maturity. On the one hand, borrowers with loans of shorter maturity did not find the new limit to be binding and could still afford to buy a more expensive property by extending the loan maturity. On the other hand, borrowers at the other end of the spectrum, facing the 30-year maturity limit set out in the recommendation, may have been forced to opt for a cheaper property.

[19] This unintended consequence of the recommendation is addressed by a legal amendment effective from 1 August 2021 providing for advantageous treatment of borrowers under the age of 36.

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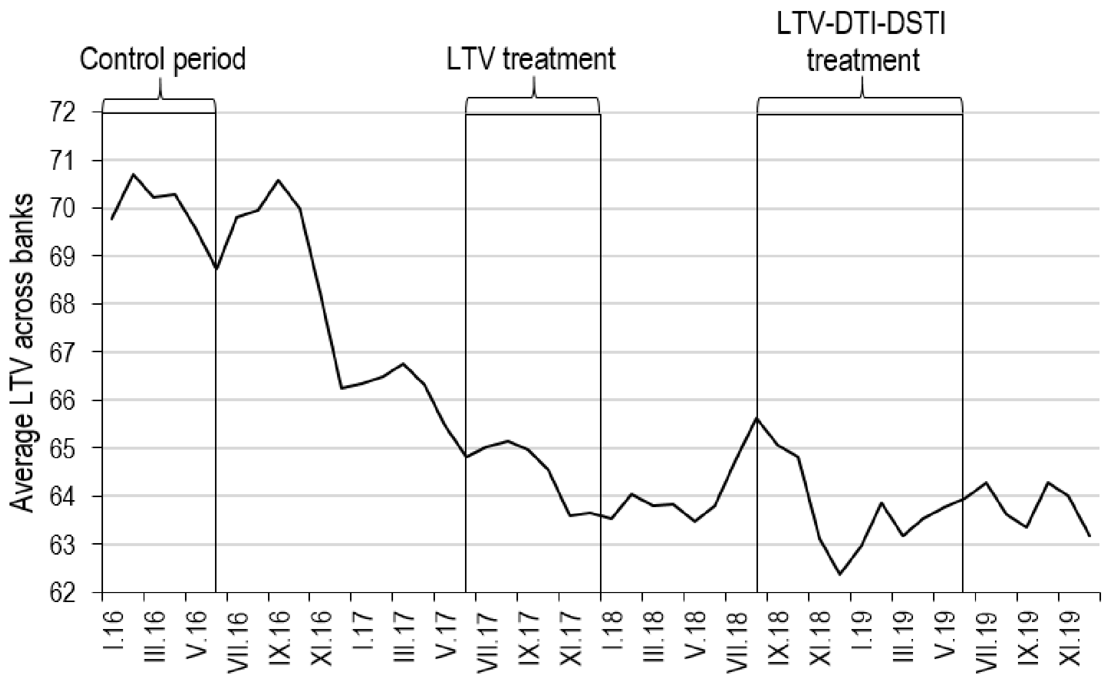
Appendix A: Sample Details

Figure A1: Time Assignment of Control, LTV Treatment and LTV-DTI-DSTI Treatment Periods



Source: Czech National Bank

Table A1: Descriptive Statistics

Mnemonics	Description	Unit	q10	Mean	Median	q90
age	Applicant age	Years	31	36.99	36	52
applicants_no	Number of loan applicants	Units	1	1.5	1	2
book_value	Net book value of existing loans secured by same property	CZK	0	82,704	0	481,374
collateral_value	Pledged property value which enters LTV denominator	CZK	1,700,000	3,057,036	2,700,000	6,700,000
days_till_qend	Number of days until end of quarter in which loan was granted	Units	27	47.45	47	86
debt	Total value of debt as at date of loan	CZK	0	635,031	101,009	2,900,000
dependents	Number of dependents declared by borrower(s)	Units	0	1.16	1	3
distance_avg_rate	Calculated as difference between interest rate on mortgage and average interest rate	Units	-0.21	0.02	-0.06	0.76
fixation	Length of fixation	Months	59	70.13	59	120
gdp_pc	GDP per capita in region of origin of mortgage	CZK	386,789	471,868	418,354	997,560
house_prices	q-on-q growth of house prices in region of origin of mortgage	Units	0.01	0.04	0.03	0.12
interest_rate	Mortgage interest rate	%	1.89	2.25	2.09	3.09
intermediation	1 if loan was not mediated and 0 otherwise	-	-	-	-	-
loan_amount	Loan amount which enters LTV numerator	CZK	950,000	1,815,070	1,500,000	4,157,700
loan_category	1 for mortgage loans and 0 for building savings loans (bridging)	-	-	-	-	-
loan_repay	Loan repayment	CZK	4,598	8,201	6,976	18,001.07
loan_type	1 for refinancing loans and 0 for new loans	-	-	-	-	-
lsti	Ratio of instalment to net income	Units	0.13	0.21	0.2	0.39
lti	Ratio of loan amount to net income	Units	2.16	3.88	3.52	8.05
ltv	Ratio of loan amount to collateral amount	Units	0.51	0.66	0.71	0.9
market_share	Market share of bank in mortgage market	Units	0.06	0.18	0.21	0.32
maturity	Loan maturity	Years	20	24.2	27	32
net_income	Net annual income of loan applicant	CZK	321,600	519,675	443,682	1,103,689
regul_distance	"Distance" of bank from lending limit as implied by LTV/DSTI at date of loan	Units	0.03	0.06	0.07	0.14
rental	1 if loan is identified for rental and 0 otherwise	-	-	-	-	-
unmpl	Rate of unemployment in region of origin of mortgage	%	2.1	3.06	3.1	5.1

Source: Czech National Bank

Table A2: Summary Statistics Across Regions

	June 2017 – December 2017			**October 2018 – June 2019**		
	Average total	"Rich"	"Poor"	Average total	"Rich"	"Poor"
GDP per capita	465,725	600,638	346,347	470,321	633,614	361,763
Unemployment rate	3.27	2.35	3.53	3.25	1.71	2.73
House prices	0.04	0.03	0.06	0.04	0.02	0.03
Size of mortgage loan	1,760,446	2,219,211	1,539,471	1,790,207	2,408,798	1,676,381
Collateral value	2,925,162	3,876,869	2,538,353	2,955,679	4,362,257	2,768,451
Number of loan applicants	1.50	1.47	1.47	1.50	1.48	1.47
Distance to average rate	-0.01	-0.01	0.08	0.00	0.12	0.21
Probability of default (client)	1.06	0.82	0.91	1.04	0.81	0.92
Net income	531,013	578,302	510,349	570,264	623,611.97	537,990
Mortgage maturity	23.88	24.57	23.74	24.20	25.52	24.77
Down payment	1,040,867	1,474,982	879,145	1,054,119	1,728,121.30	951,775
Repayment amount	7,914	9,791	7,081	8,163	11,119	8,010
Debt	696,280	805,196	622,127	674,743	738,199	610,154
LTV	0.66	0.63	0.67	0.67	0.61	0.67
LTI	3.86	4.31	3.38	3.89	4.31	3.44
LSTI	0.20	0.22	0.18	0.21	0.24	0.19

Note: "Rich" and "Poor" regions are defined and calculated as the average of the three regions with the highest/lowest GDP per capita.
Source: Czech National Bank

Table A3: Number of Loans per LTV Bucket

LTV bucket	LTV model	LTV-DTI-DSTI model
0–60	22,100	15,238
60–70	9,013	6,382
70–80	10,136	6,129
80–90	19,500	13,276
90–100	2,257	1,887
over 100	2,097	1,893

Source: Czech National Bank

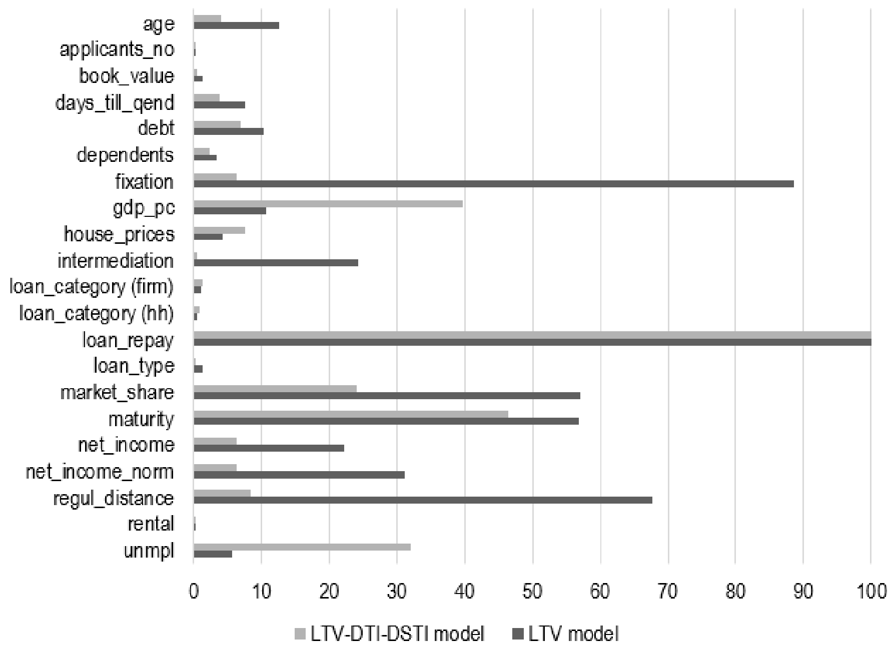
Table A4: Covariates Considered in Each Model for Splitting

Specification	Mortgage	Client	Bank	Region
Loan Volume and Collateral	applicants_no; book_value; days_till_qend; fixation; intermediation; loan_category (firm); loan_category (hh); loan_repay; loan_type; maturity; rental	age, debt; dependents; net_income	market_share; regul_distance	gdp_pc; house_prices; unmpl
Distance to Average Rate	applicants_no; book_value; days_till_qend; collateral_value; fixation; intermediation; loan_amount; loan_category (firm); loan_category (hh); loan_repay; loan_type; maturity; rental	age, debt; dependents; net_income	market_share; regul_distance	gdp_pc; house_prices; unmpl

Appendix B: Variable Importance

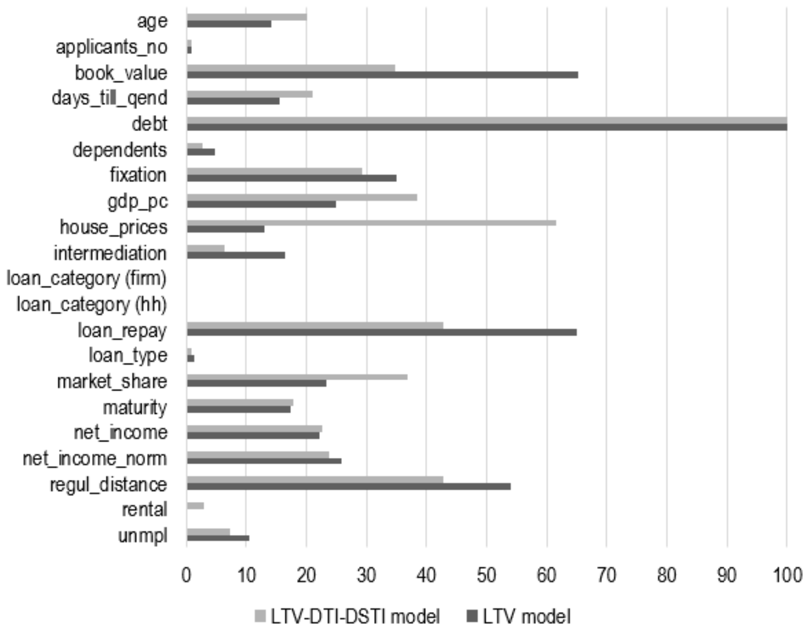
The variable importance measure is a depth-weighted average of the number of splits on the variable of interest. Figures B1, B2 and B3 give the covariate names and values for the variable importance measure, with larger values indicating greater importance. The importances are scaled such that the most important variable has variable importance equal to 100. In the case of the loan amount, the results indicate that the trees split most often on loan-related characteristics (e.g. loan repayment and maturity), but also on bank characteristics (e.g. bank market share and distance to regulation) in the case of the LTV model and regional characteristics in the case of the DTI-DSTI model. In the case of the value of pledged collateral, the total debt of the loan applicant is the most important model variable, followed by loan and bank characteristics. For the model tracking the treatment effect of the borrower-based limits on the distance to the average rate, bank market share and regulatory distance are among the most important variables, together with several loan characteristics (e.g. fixation length and loan volume).

Figure B1: Variable Importance: Loan Volume



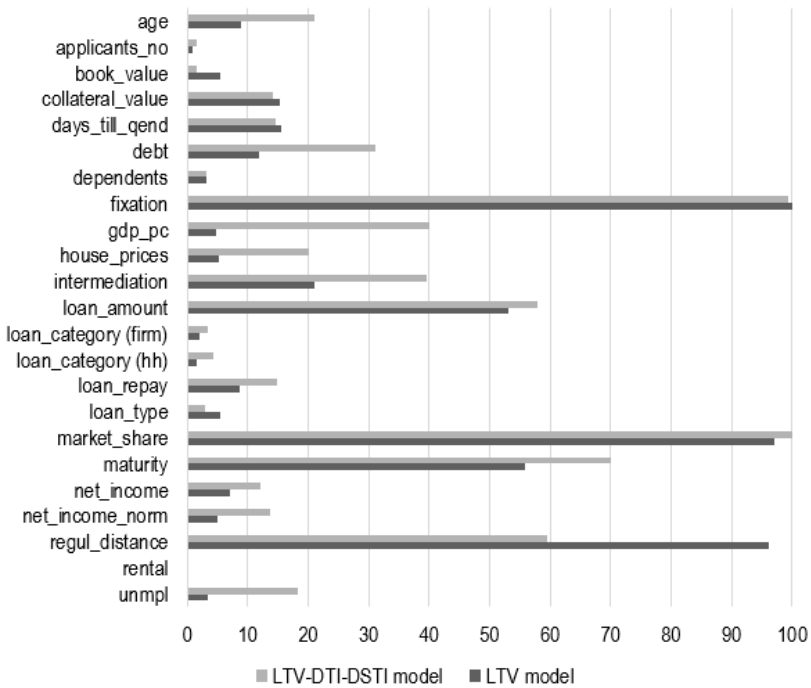
Source: Czech National Bank

Figure B2: Variable Importance: Value of Pledged Collateral



Source: Czech National Bank

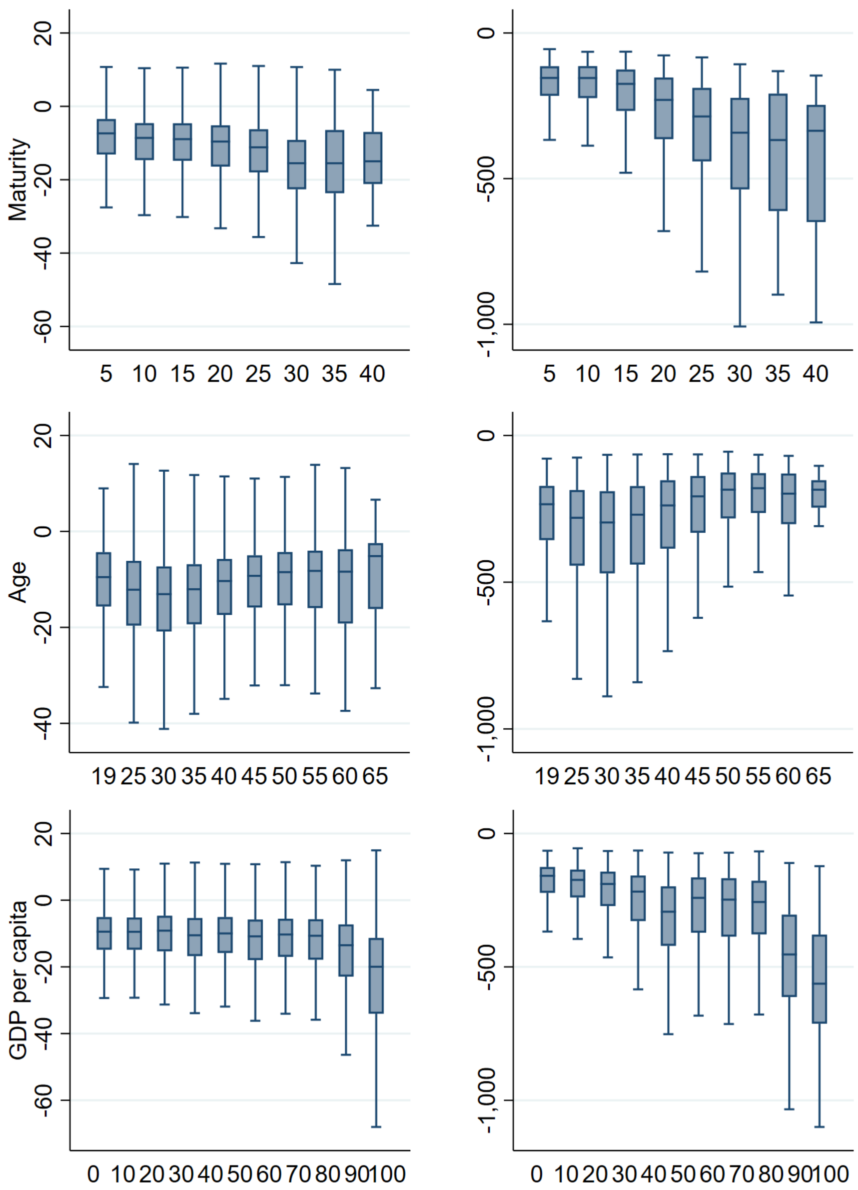
Figure B3: Variable Importance: Distance to Average Rate



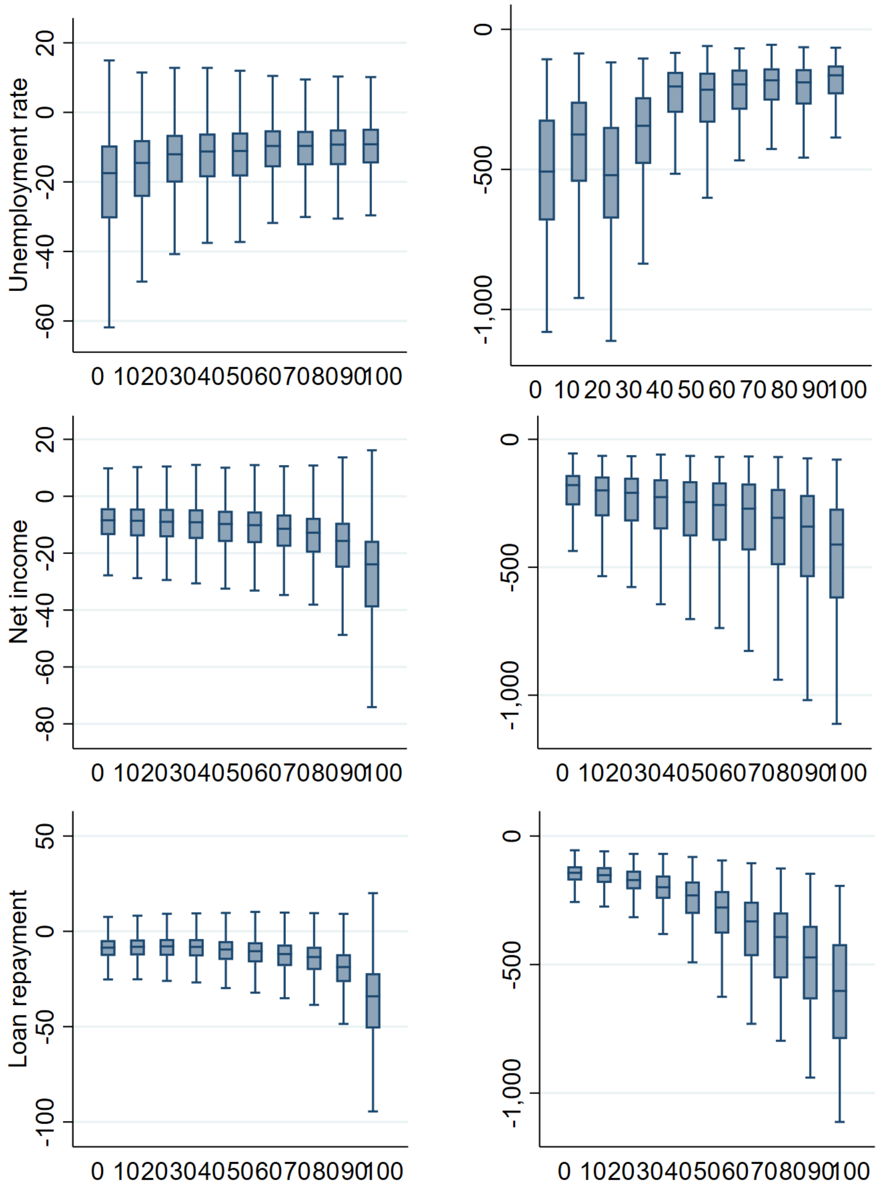
Source: Czech National Bank

Appendix C: Candle Graphs

Figure C1: ATEs on the Loan Volume Conditional on Significant Covariates As Implied by the T-Test

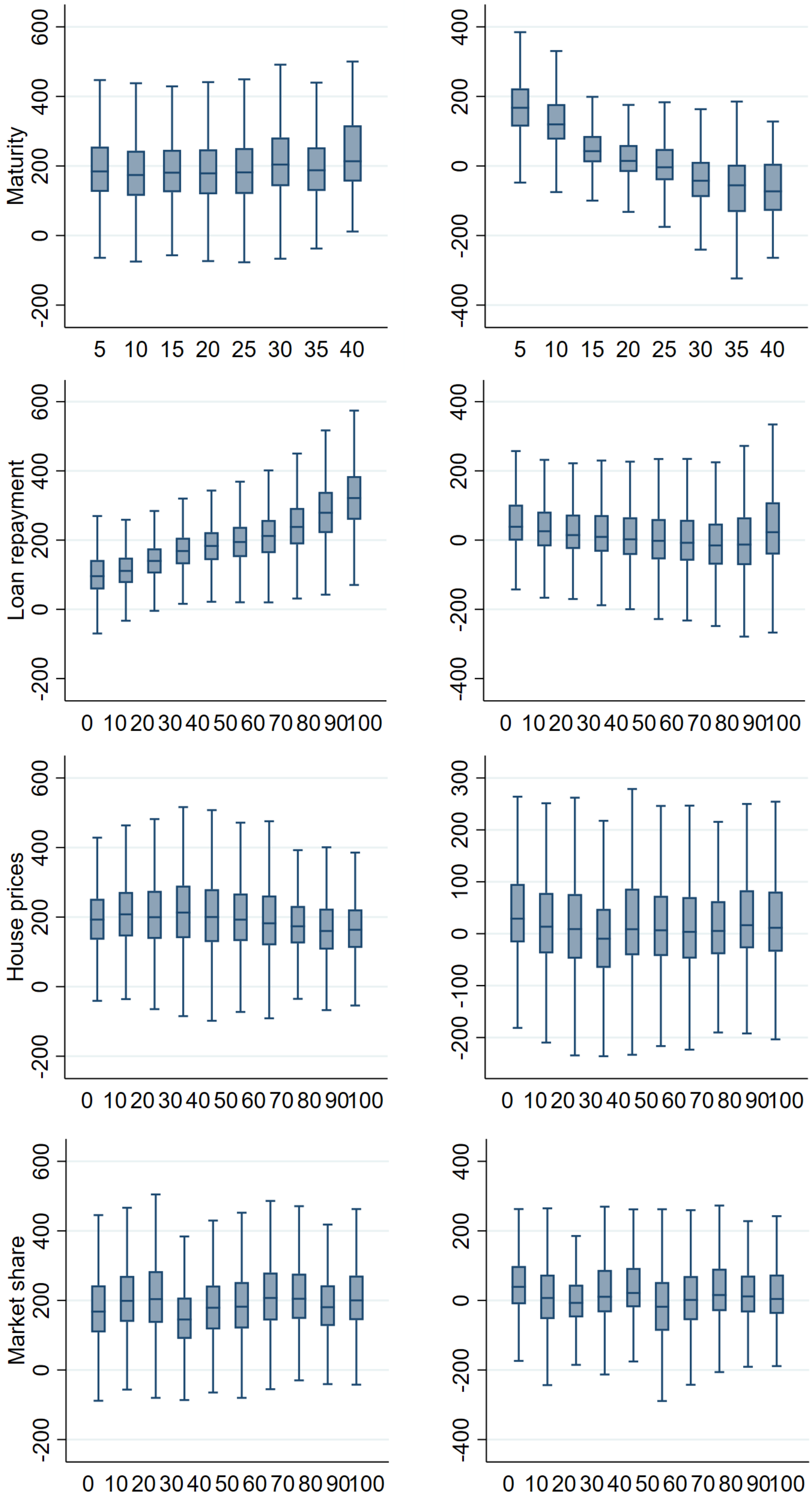


(graph continues on next page)



Note: The x-axis for loan maturity and age is in years, while for the rest of the covariates it depicts the quantiles of the distribution into which the mortgage loans were split equally. The y-axis depicts the average treatment effect in CZK thousands.

Figure C2: ATEs on the Value of Pledged Collateral Conditional on Significant Covariates As Implied by the T-Test



Note: The x-axis for loan maturity is in years, while for the rest of the covariates it depicts the quantiles of the distribution into which the mortgage loans were split equally. The y-axis depicts the average treatment effect in CZK thousands.

Appendix D: Additional Estimates

Table D1: Average Treatment Effect on the Distance to the Average Mortgage Loan Size and the Average Value of Pledged Collateral

	LTV	LTV-DTI-DSTI
A) Distance to average mortgage loan size		
Average Treatment Effect (ATE)	**-84,220**	**-326,697**
	(-108,224; -60,219)	(-361,485; -291,910)
No. of observations	65,123	44,825
B) Distance to average value of pledged property		
Average Treatment Effect (ATE)	**172,484**	131,653
	(63,210; 281,759)	(-15,274; 278,580)
No. of observations	65,123	44,825

Note: 95% confidence interval in parentheses. Significant estimates are highlighted in bold.

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