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Mortgage lending valuation bias under housing price changes and loan-to-value regulations

Endre J. Reite

NTNU Business School, Norwegian University of Science and Technology, Po. Box. 8900, NO-7491, Trondheim, Torgarden, Norway

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ABSTRACT

We examine valuation bias, regulatory loan-to-value limits, and real estate price fluctuations using unique data from two Norwegian banks. We investigate whether automated valuation methods significantly affect foreclosure discounts. Banks using multiple valuation methods tend to report loan-to-value bias by selecting the most optimistic value, underestimating and under-reporting risk in declining property markets. This risk increases near regulatory loan-to-value limits, and the findings are robust across homogenous and heterogeneous properties. We recommend reporting automated valuation estimates for all applicable properties and disclosing the percentage of valuations done with different methods to improve transparency and risk comparability between banks.

1. Introduction

According to Aikman et al. (2019), macroprudential regulations are crucial in mitigating future financial crises, with mortgage regulations serving as a fundamental component of these regulations. Implementing stricter loan-to-value (LTV) policies can significantly reduce household credit, house prices, and household consumption of durable goods (Mokas and Giuliodori, 2023). In the past twenty years, several countries have implemented rules about loan-to-value (LTV) ratios, which have been recognized as effective measures for curbing the expansion of mortgage debt (Morgan et al., 2019).

Norway introduced LTV regulations in 2010 by implementing amortization requirements on loans with LTV above 60 % and establishing an upper limit on LTV of 85 %. According to Gatt (2023), such regulations have been successful in several countries but require fine-tuning and increased knowledge. Böhnke et al. (2023) observed that over the last decades, Norway combines low country risk, a stable regulatory environment, high profitability, and high capital levels relative to the estimated risk in banks' portfolios, and Reite et al. (2022) reported that the real estate market had large differences in centrality and steadily rising housing prices and a housing market that recovered within a year of the 2008 financial crisis. Thus, Norwegian data provides insight into biases in the use of valuation methods without shocks to the real estate market or significant regulatory changes. Exploring an underlying willingness to employ biased (i.e., inflated) valuations in the face of mortgage regulatory limits on LTV may be relevant across countries and provide insight into a bias that must be considered when evaluating bank risk and regulating banks.

When facing stricter LTV regulations, we hypothesize that banks and their agents are incentivized to mitigate the effect of these regulations by choosing the highest valuation available when this valuation enables moving a mortgage from outside to within the regulatory limits. In this study, we employ micro-data from two Norwegian banks to explore whether such a bias exists and whether the valuation methods changes when market conditions change the difference between them.

E-mail address: endre.j.reite@ntnu.no.

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To expand the knowledge of incentives and valuation bias at the bank officer level (Agarwal and Ben-David, 2014), we explore a situation where government-mandated LTV policies are imposed. Systematic biases dependent on centrality and market conditions are essential because they can lead to material biases in portfolios, capital optimization, and reporting levels (Albertazzi et al., 2015; Ambrose et al., 2005). An improved understanding of valuation biases can increase transparency and contribute to understanding loss-given default in mortgage lending and potential biases arising when LTV regulations are tightened. Karamon and McManus (2022) show how employing automated valuations in mortgage lending can lower credit risk. We expand on this by exploring a bank's discretionary use of AVM, and real estate agent estimates when granting mortgages. An increased understanding of valuation and loss-given defaults can explain the differences in mortgage lending losses and one of the mechanisms behind the informational asymmetry between banks and investors. Such biases between banks and investors contribute to significant losses in securitized mortgage lending portfolios (Higgins et al., 2022).

Earlier studies have found appraisals to be upwardly biased (Calem et al., 2021) and that a need to refine costly unsecured debt (Reite et al., 2022), a steady increase in real estate prices (Galán and Lamas, 2023), and competition between banks (Conklin et al., 2020) can contribute to such bias. We hypothesize that government-mandated LTV policies may increase incentives to upwardly bias valuations by systematically choosing the less conservative valuations available. LTV regulations in Norway mandate amortization when loan-to-value exceeds 0.6. LTV, and LTV should not exceed 0.85 while allowing the bank limited room to deviate from these and other requirements such as liquidity and debt to income (flexibility quota).

At the portfolio level, appraisals exceed automated valuation model (AVM) valuations 60 % of the time and are 5 % higher than AVM valuations on average (Kruger and Maturana, 2021). Therefore, we explore why—and for which client—banks apply AVMs. We hypothesize that systematic bias in choosing valuation methods for different periods and clients can be linked to regulatory limits, fluctuations in real estate prices, and client- and collateral-specific criteria.

We shed light on this by exploring a unique inside data set with valuation methods for 12,005 randomly selected home mortgages from two banks between 2009 and 2018, along with the subsequent foreclosures or non-foreclosure sales of these properties in 2021.

Our approach and contribution to the research are threefold; we explore: (1) whether the choice of valuation method is significant in explaining variation in the foreclosure discount, (2) whether the bank has a significantly higher probability of employing the higher of two available valuations at or near regulatory limits on loan-to-value, and (3) how banks' choice of valuation methods (i.e., from real estate agents or AVM) changes with real estate prices. These contributions provide insight on how banks' valuation choices and flexibility in using valuation methods lead to bias in the risk of loss in the case of foreclosure.

2. Data and methodology

This study utilizes exclusive proprietary microdata obtained from two Norwegian banks. Using these data, we examine how banks operate automated valuation estimates or appraiser-made estimates based on the characteristics and centrality of loans.

To achieve this goal, we analyze a sample of data collected from 12,165 loans granted between 2009 and 2018, as presented in Table A1 in the Appendix. For this study, we exclude loans for purchases because the purchase price serves as the primary valuation applied by the bank, and the estimates provided by real estate agents and automated valuation models tend to converge at or near the purchase price during purchase transactions. Additionally, we link these data to 485 foreclosure cases with and without homeowner participation, incorporating information on valuation methods, clients, and loan characteristics at origination. Table A2 in the Appendix presents the loan application data for this subsample, and Table A3 variable definitions.

We first establish whether AVM use significantly impacts the observed foreclosure discount. By obtaining an AVM estimate for property ***I*** sold at time ***j*** without including information related to the sale of property ***i***, we estimate the market price based on location, size, type of property, and construction year. Using this estimate, we calculate the foreclosure discount, defined as:

$$Foreclosure\ discount\ =\ \frac{Price_{ij}\ -\ Estimate_{ij}}{Estimate_{ij}}, \tag{1}$$

and estimate what factors influence the foreclosure discount using the following:

$$Foreclosure\ discount\ =\ \beta_i X_i + \varepsilon_i. \tag{2}$$

The factors in vector X include homeowner participation in the foreclosure process, which can help reduce losses, along with credit risk, which lead to an increased risk of over-indebtedness (Melzer and Meltzer, 2017) or holdup issues (Agarwal et al., 2019). A low centrality of the foreclosed house relative to work or government institutions can plausibly influence the search process, thus reducing the probability of matching (Donner, 2020) and influencing the foreclosure discount. We also examine the valuation method effect by considering whether the bank employs an AVM estimate during loan granting.

$$X_i = \begin{bmatrix} Property\ charachteristics \\ No\ Participation \\ Credt\ risk \\ AVM \\ Liquidity \end{bmatrix} \tag{3}$$

The second part estimates factors influencing banks' probability of using AVM as a loan valuation method.

$$Probability\ of\ AVM = \beta_i X_i + \varepsilon_i \tag{4}$$

We employ credit risk and loan-to-value (LTV) to measure the client's perceived risk when the loan is granted. To measure if LTV limits influence the bias in the use of valuation methods, we construct two dummy variables; LTV AVM over and LTV REA 0.6 is "1" in cases where a switch from the AVM valuation to a real estate agent valuation results in the LTV switching from over to under the limit where amortization is required (0.6), and LTV AVM over and LTV REA under 0.85 are 1 when a switch from AVM valuation to real estate agent valuation leads to a loan moving from over to under the 0.85 LTV requirement. Both variables are "0" otherwise.

$$X_i = \begin{bmatrix} \text{LTV AVM over and LTV REA under.6} \\ LTV\ AVM\ over\ and\ LTV\ REA\ under.85 \\ Controls \end{bmatrix} \tag{5}$$

Despite the overall good performance of AVM (Kok et al., 2017; Kruger and Maturana, 2021). An alternative hypothesis is that the use of REA valuations may stem from these valuations' better ability to capture the actual value of certain types of houses such as non-homogenous houses with few comparable sales. We test this by subdividing our dataset into homogenous and new/heterogenous houses, based on the uncertainty level of the AVM estimate (i.e., to which extent there are recent comparable sales available to perform an estimate), leaving out houses with moderately uncertain estimates.

In our final specification, we replace these two dummy variables with two other dummy variables to capture changes in housing prices: increasing housing prices, which is "1" for period i, where season-adjusted housing prices have increased for more than three months, and "0" otherwise. Conversely, we introduce the dummy variable for decreasing housing prices, which is "1" for periods where housing prices have fallen by more than one-quarter. Fig. A1 illustrates the housing price fluctuations.

$$X_i = \begin{bmatrix} Increasing\ housing\ prices \\ Decreasing\ housing\ prices \\ Controls \end{bmatrix} \tag{6}$$

This analysis aimed to explore the systematic changes in the use of AVM as prices change. We further explore the difference between the AVM and valuation estimates of real estate agents in these periods.

3. Results and discussion

3.1. The choice of valuation methods and losses in a foreclosure

First, we explore whether our model explains the variation in the observed foreclosure discount in Model I, as shown in Table 1. Employing a standardized regression, we find that while no homeowner participation (*No Participation*) increases the foreclosure discount [0.794 (0.0820)], this factor is not readily predictable at origination. Credit risk also has a small but significant effect on the foreclosure discount [0.0878 (0.0384)]; notably, our hypothesis regarding the lower foreclosure discount when AVM is employed seems plausible in the initial regression with a larger and opposite effect than credit risk, with significance at the 1 % level [−0.419 (0.0753)]. The explanatory variables may depend on common exogenous factors. Models II–IV employ two-stage models with exogenous variables to explore whether each explanatory variable retains significance. In Model II, we use liquidity in the market and LTV as instruments of homeowner participation and find a significant effect of no homeowner participation on the foreclosure discount [2.79 (0.398)] and a significant proportion of the variation in the foreclosure discount explained (0.205). This finding is consistent

Table 1

Linear regression, and two-stage linear regression on the size of the foreclosure discount of houses in a bank portfolio (N-485).

	I	II	III	IV	V
Instrumented		No participation	Credit risk	AVM	No participation, Credit risk, AVM
Instruments		Liquidity, LTV	Time as a client, LTV	Liquidity, LTV	Liquidity, LTV, Time as a client
Constant	−0.0901	−1.12***	0.0472	0.844***	1.18**
	(0.0682)	(0.173)	(0.0563)	(0.131)	(0.527)
No Participation	0.794***	2.79***			−0.372
	(0.0820)	(0.398)			(0.718)
Credit risk	0.0878**		0.120**		−0.0748
	(0.0384)		(0.0573)		(0.118)
AVM	−0.419***			−1.72***	−2.12***
	(0.0753)			(0.221)	(0.517)
Control for property characteristics	✓	✓	✓	✓	✓
N	485	485	485	485	485
Adj. R^2	0.255	0.205	0.023	0.097	0.057

Notes:.
1 OLS and TSLS regression with dependent variable: Foreclosure discount.
2 Standard errors are in parentheses; * significant at the 10 percent level; ** significant at the 5 percent level;*** significant at the 1 percent level.
3 R^2 is McFadden's pseudo-R^2.

with earlier research on homeowners' incentives for high mortgage debt relative to property value (Ambrose et al., 2001; Foote et al., 2008) and liquidity effects (see also Donner, 2020; Forgey et al., 1996). Turning to Model III, we instrument credit risk with time as client and LTV. Interestingly, the proportion of foreclosure discounts explained by credit risk is small (0.023), while credit risk remains significant at the 5 % level [0.120 (0.0573)].

Liquidity and LTV are employed as instruments for AVM because the AVM estimate is more precise in more liquid markets and the bank may depend more on AVM as a rapid estimate when LTV and perceived risk is lower. Model IV in Table 1 shows that AVM was significant at the 1 % level in our two-stage model [−1.72 (0.0221)]. Model IV in Table 1 explains 9.7 % of the variation in the foreclosure discount. Turning to Model V in Table 1, we combine the instruments and explanatory variables and illustrate how AVM remains significant at the 1 % level in this model [−2.12 (0.517)]. The model explains 5.7 % of the total variation in the foreclosure discount. Therefore, the two-stage model supports our hypothesis that AVM use contributes to explaining the foreclosure discount and that the proportion of a portfolio where AVM I employed is a relevant measure when estimating the risk of future losses.

3.2. *The choice of valuation methods near regulatory limits on LTV*

Table 2 shows that we observe a significant reduction in the probability of employing AVM when the use of AVM leads to the loan exceeding an LTV of 0.85 [−0.742 (0.387)]. This indicates that the bank is more inclined to employ the higher valuation when this enables granting a loan without exceeding the government-mandated limit on LTV. In this manner, a bank can reduce the use of its flexibility quota, but also positively bias reported valuations at or near the regulatory limits. The relationship remains significant when controlling for loan characteristics and the client's credit risk and increases to the 5 % level when also controlling for the interaction between high LTV and high client risk in Model III [−0.810 (0.389)]. While the coefficient on loans with an AVM estimate over 0.60 and a REA estimate under 0.60 is also negative. This effect is not significant [−0.226 (0.273)] even at a 10 % level. When testing robustness by subdividing our data into homogenous (Model IV) and heterogenous/new (Model V), we find that AVM > 0.85 and REA < 0.85 retains significance at the 5 % level with similar coefficients across Models III, IV and V, while AVM > 0.6 and REA < 0.6 are significant at the 10 % level for homogenous houses in Model IV [−0.372 (0.204)].

3.3. *How do increasing and falling housing prices influence the choice of valuation method?*

Regarding our second analysis, we further explore when and why advisors in banks still employ valuation estimates other than AVM and whether this use fluctuates over time and with changing market conditions. Model I in Table 3 shows that banks' probability of employing AVM increases with increasing liquidity in the local real estate market [0.182 (0.049)]. We further find that the probability of a bank using an AVM estimate increases significantly when housing prices increase [0.501 (0.108)]. One plausible explanation is that AVM estimates are updated at the time of a loan, whereas real estate agent estimates, on average, are older. Thus, the AVM estimates are higher than the real estate agent estimates when housing prices grow. We further observe that when housing prices fall, the probability of employing AVM estimates decreases [−0.255 (0.119)]. This opposite effect was smaller yet significant at the 1 % level. These effects remained significant when various controls were introduced in Models II and III. This leads to an increase in the bias in valuation when real estate prices fall, as the bank prefers stale and more positively biased estimates over AVM.

4. Conclusion

The foreclosure discount relative to the estimated value of a property is lower for properties for which the bank employs an AVM. Therefore, the extent to which a bank uses AVM in valuation is of interest when estimating the loss-given default in a mortgage portfolio. Furthermore, banks introduce a valuation bias by switching between AVM and other valuation methods.

According to Kruger and Maturana's (2021) study, real estate agents tend to overestimate the value of properties. Our research

Table 2
The probability of a bank using AVM at or near government-mandated loan-to-value limits (N-12,165).

	I	II	III	IV	V
Const	−0.0754	−0.00455	−0.191	−0.219	−0.147
	(0.119)	(0.399)	(0.442)	(0.677)	(0.941)
AVM>0.85 and REA<0.85	−0.742*	−0.722*	−0.810**	−0.790**	−0.814**
	(0.387)	(0.388)	(0.389)	(0.343)	(0.411)
AVM>0.6 and REA<0.6	−0.226	−0.304	−0.384	−0.372*	−0.401
	(0.273)	(0.281)	(0.279)	(0.204)	(0.301)
Loan Characteristics	✓	✓	✓	✓	✓
Credit risk		✓	✓	✓	✓
Interaction HighLTV/Credit Risk			✓	✓	✓
N	12,165	12,023	12,023	9710	2011
Adj. R^2	0.183	0.188	0.193	0.199	0.189

Notes:.
1 Probit regression with dependent variable: The bank employs AVM in valuation.
2 Standard errors are in parentheses; * significant at the 10 percent level; ** significant at the 5 percent level;*** significant at the 1 percent level.
3 R^2 is McFadden's pseudo-R^2.

Table 3
The probability of employing an AVM estimate in valuation when housing prices fall or rise ($N = 12{,}165$).

	I	II	III
Constant	0.095***	0.093***	0.089***
	(0.021)	(0.023)	0.022
Price level	0.015	0.015	0.015
	0.043	0.043	0.043
Liquidity	0.182***	0.177***	0.163***
	0.049	0.061	0.068
Rising prices	0.501***	0.509***	0.510***
	0.108	0.106	0.107
Falling prices	−0.255***	−0.250***	−0.240***
	0.119	0.118	0.119
Loan Characteristics	✓	✓	✓
Credit risk		✓	✓
Interaction HighLTV/Credit Risk			✓
n	12,165	12,023	12,023
Adj. R^2	0.182	0.19	0.191

Notes:.
1 Probit regression with dependent variable: The bank employs AVM in valuation.
2 Standard errors are in parentheses; * significant at the 10 percent level; ** significant at the 5 percent level;*** significant at the 1 percent level.
3 R^2 is McFadden's pseudo-R^2.

builds on this finding by showing that this bias can lead to a lower price in the event of a foreclosure. Additionally, we discovered that banks are more likely to rely on real estate agent valuations to meet government-mandated loan-to-value (LTV) limits of 0.85, but we did not find a significant effect for the LTV limit of 0.60.

When housing prices increase, the use of AVM increases to rapidly incorporate price growth. Interestingly, we found the opposite effect when housing prices decreased. In these instances, banks then employ other valuation methods that do not reflect the decreasing prices to the same extent. Collectively, these findings indicate an upward bias in the valuation employed when housing prices decrease.

Our findings are limited to two banks in an economy where housing prices have grown with only minor readjustments. Expanding the study to use valuation methods in markets with more significant and lasting housing price decreases would increase the understanding of the bias in valuation methods in other market conditions.

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CRediT authorship contribution statement

Endre J. Reite: Conceptualization, Formal analysis, Methodology, Data curation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The author is affiliated with banks providing data for the research.

Data availability

The data that has been used is confidential.

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Appendix

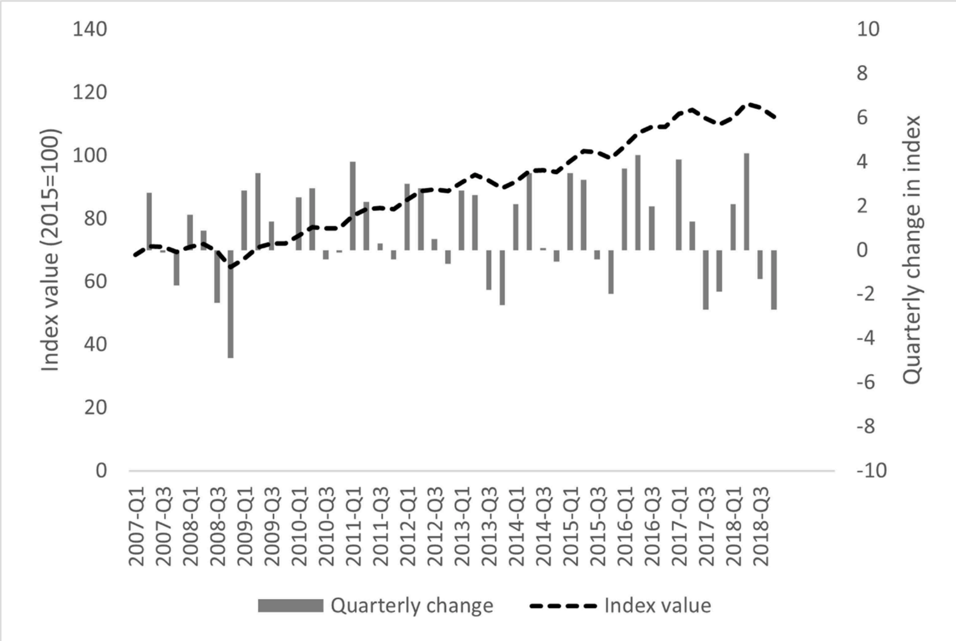

Fig. A1. Real Estate Housing Prices in Norway 2007–2019.

Table A1
Summary statistics – Foreclosed mortgages ($N = 485$).

	Mean	Median	SD	Min	Max
Panel a – the client					
Credit risk	4.441	4.000	2.951	-	9.000
Year client	6.266	5.000	5.787	-	25.000
Year last	3.177	2.000	4.075	-	21.000
Panel b – the collateral					
Liquidity	0.737	0.787	0.227	0.360	1.000
LTV	0.654	0.650	0.182	0.060	1.030
LTV_AVM	0.687	0.680	0.202	0.061	1.219
LTV_REA	0.629	0.626	0.180	0.060	0.990
Panel c – the choices/outcome					
AVM	0.472	0.000	0.500	0.000	1.000

Notes: SD, standard deviation; AVM, automated valuation method; LTV, loan-to-value; REA, Real estate-agent valuation.

Table A2
Summary statistics – All mortgages (N-12,165).

	Mean	Median	S.D.	Min	Max
Panel a – the client					
Credit risk	4.941	4.110	2.991	0.000	9.000
Year client	5.130	4.210	5.125	0.000	25.000
Year last	2.565	1.870	3.990	0.000	18.000
Panel b – the collateral					
Centrality	0.702	0.742	0.260	0.350	1.000
LTV	0.684	0.700	0.224	0.210	1.030
LTV_AVM	0.699	0.740	0.251	0.100	1.219
LTV_REA	0.648	0.681	0.212	0.110	0.990
Panel c – the choices/outcome					
AVM	0.410	0.000	0.512	0.000	1.000
No participation	0.433	0.000	0.496	0.000	1.000
Foreclosure discount	0.872	0.860	0.138	1.141	0.214

Notes: SD, standard deviation; AVM, automated valuation method; LTV, loan-to-value; REA, Real estate-agent valuation. Foreclosure discount defined as $\frac{Price_{ij} - Estimate_{ij}}{Estimate_{ij}}$,.

Table A3
Definition of variables.

Variable	Definition
Foreclosure discount	The difference between the estimate of housing value and the price, relative to the estimate of the house
Price	The realized price in the sale of a property
Estimate	The bank estimated the value of a property before a sale or default/foreclosure.
Property characteristics	The type of property (detached, semi-detached, or apartment), as well as the building year of the property, unit size, and presence of amenities.
No Participation	The property owner under foreclosure does not choose to participate in the selling process; they await a process by a court-appointed real estate agent and public foreclosure status.
Credit risk	The probability of a loan default based on the banks' credit risk model is separated into deciles.
AVM	Whether the automated valuation method (AVM) was employed in the valuation, the bank chose to base the loan upon
Liquidity	The average time on the market for houses in the county measured relative to the average time on the market.
LTV AVM over LTV REA under 60 %	The dummy variable is "1″ when the LTV from the AVM method is higher than 60 %, while the LTV measured by the real estate agent estimate is under 60 %, and "0″ otherwise.
LTV AVM over LTV REA under 85 %	The dummy variable is "1″ when the LTV from the AVM method is higher than 85 %, while the LTV measured by the real estate agent estimate is under 85 %, and "0″ otherwise.
Increasing housing prices	The dummy variable is "1″ when the two preceding quarters' housing price growth is positive and "0″ otherwise.
Decreasing housing prices	The dummy variable is "1″ when the two preceding quarters' housing price growth is negative and "0″ otherwise.
Heterogenous houses	Houses where the AVM model has a high level of uncertainty in the estimate due to lack of comparable sales with same size, building year and proximity to the estimated house.

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