Credit Risk Transfer, Credit Loss Models and Real Estate Valuations

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***Abstract*—Credit risk is a perennial topic in the estate evaluation area. This work is a complement for the existing three credit losses estimating models PD(probability of default), LGD(loss given default) and EAD(exposure at default) since these three models cannot provide the insights from a behavioral perspective. Compared to the three existing models, this research derives the credit loss part of the unpaid principal balance of the mortgage from the forecast of agent behaviors. In real estate finance, default and prepayment risks are the most commonly types of credit risk to be considered from the lender perspective. Default risk of the former usually comes from high debt-to-income ratio, high loan-to-value ratio and bad credit history. Prepayment risk is risk with the premature return of principal on a mortgage. Lenders would add prepayment penalty to the real estate price to take care of this risk. In the event of prepayment, the loan is shortened, and the lender fail to collect future interest. This project studies how to model real estate value losses from the advent of credit events like default and prepayment. The study models the probability, intensity and severity of the credit risk as well as size of the impact.**

***Index Terms*—Credit risk, default risk, Prepayment risk, debt-to-income ratio, loan-to-value ratio.**

I. Introduction

Mortgages valuation is always one of the most important parts in the economies. The mortgage valuation is one type of assessment that the mortgage lender used to confirm the property's value. The purpose of this study is to come up with some insights on the valuation of mortgages from a behavioral perspective. From the options pricing perspective, the study believes that one can default or prepay as their options before the mortgage matures. The study thinks that the LTV(loan-to-value) and DCR(debt coverage ratio) of the underlying properties are two important factors that drive the exercise of these options. Thus, this study presents a rigorous framework to forecast LTV as well as DCR on the economic and market information we know.

This study mainly discussed the credit loss on commercial real estate. Credit risk or counterparty risk refers to the uncertainty about whether a counterparty will honor a financial obligation. In real estate finance, default and prepayment risks are the most commonly types of credit risk to be considered from the lender perspective. Default risk is the inability of the debt issuer to pay the interest and principal on the obligation. Lenders usually require a higher interest rate for bearing default risks, usually regard as the default premium. In the event of default, lenders could loose from part of the interest payments up to the entire value of the real estate property. Default risk tend to increase when housing prices drop as home equity shrinks and people are more willing to hold cash and wait. Decreased housing prices are often associated with economic downturn and credit crunch, meaning that banks tighten their credit lending policy or make mortgages more expensive. Microeconomic reasons of default could vary between primary home residence and commercial/investment property. Default risk of the former usually comes from high debt-to-income ratio, high loan-to-value ratio and bad credit history. While the latter one defaults because of low debt coverage ratio, referring to the difficulty of collecting property rents or high vacancy rates [1]. Prepayment risk is risk with the premature return of principal on a mortgage. Lenders would add prepayment penalty to the real estate price to take care of this risk. In the event of prepayment, the loan is shortened, and the lender fail to collect future interest. Prepayments tend to happen when market interest rates fall, strong inflation and housing price keep rising. Richard and Roll (1989) models the speed of refinance as a function of effective interest rate (coupon rate/mortgage interest), seasonal impact and burnout factor (prepayment gets slower when more houses are refinanced) [2].

Usually the mainstream models to predict the credit loss are PD (probability of default), LGD (loss given default) and EAD (exposure at default). However, this study does not follow the approaches that mentioned above since they cannot provide the insights from a behavioral perspective. In this study, the credit loss is derived as part of the UPB (Unpaid principal balance) of the mortgage from the forecast of agent behaviors. The credit loss model would start with a “Top-down” approach where regional level property vacancy rate and rent growth are forecasted by national and regional economic indicators followed by prediction of property value for each individual loan and their LTV and DCR ratios. The losses of individual loans are determined by these ratios and portfolio level loss are weighted by housing market conditions at different economic regions. With data on macroeconomic indicators, housing markets and yield curves, as well as hypothetical loan amortization schedules, we would like to explore credit loss modeling and analyze different modeling techniques in recovering the true losses on real estate property value.

II. Literature Review

A. LTV (Loan-to-Value) and DCR (Debt Coverage Ratio)

LTV and DCR are two important ratios to measure the credit loss from default. The loan-to-value (LTV) ratio is an assessment of lending risk that financial institutions and other

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lenders examine before approving a mortgage. Typically, loan assessments with high LTV ratios are considered higher risk loans. Therefore, if the mortgage is approved, the loan has a higher interest rate [3]. DCR measures the ability of a people to use its rent income to repay all its debt obligations, including repayment of principal and interest on both short-term and long-term debt. A ratio of less than 1 is not optimal because it reflects the people's inability to service its current debt obligations with rent income alone.

B. Adjusted-Rate Mortgage (ARM) and Fixed-Rate Mortgage (FRM)

Adjustable-rate mortgage (ARM) and fixed-rate mortgage (FRM) are two general types of mortgage. Adjustable-rate mortgage (ARM)'s interest rate applied on the outstanding balance varies throughout the life of the loan. With an adjustable-rate mortgage, the initial interest rate is fixed for a period of time. After that, the interest rate resets periodically, at yearly or even monthly intervals. Fixed-rate mortgage has a fixed interest rate for the entire term of the loan. The mortgage carries a constant interest rate from beginning to end. Fixed-rate mortgages are popular products for consumers who want to know how much they'll pay every month. The consumers choose ARM and FRM based on their own situations. ARM is risker for a risk-averse household with a large mortgage, risky income, high default cost, or low moving probability. On the contrary, the household who faces mobility risk, with a smaller mortgage, risky income, low default cost, or high moving probability will choose ARM. Also, when servicing risks increase through higher loan-to-value ratios and debt servicing ratios, interbank interest rates are high, or current inflation is higher and mortgages originated at low rates, the ARM is risker than FRM. However, in an environment with uncertain inflation and mortgages originated at high rate the interest rate, the FRM is risker. Nevertheless, households achieve higher utility if they finance their real estate purchase using a fixed-rate mortgage (FRM) instead of an adjustable-rate mortgage(ARM) [4].

C. Previous Models of Estimating Credit Losses

The three mainstream models used today are PD, LGD and EAD. PD (probability of default) measures the likelihood of a default over a particular time. This structural model measures the variance between the asset of the company and liability values. When the company's value increases, its PD decreases. If the debt of company increases, its PD increases. Finally, if the company´s asset volatility increases, its PD increases [5]. The second model is LGD (loss given default). It calculates how much the bank losses if a borrower default on a loan. To estimate potential credit losses, the formula is usually applied: Potential Credit Loss = Probability of Default * Loss Given Default. Unlike the LGD, EAD (exposure at default) consider the total value that the bank is exposed to when loan default happens. EAD is always defined as EAD = bal0 + EAD factor * undrawn0. In this function, bal0 stands for the facility outstanding dollar amount at current time, undrawn0 means the facility undrawn dollar amount at current time [6]. EAD factor is the credit conversion factor. Although these three models are useful in forecasting the credit loss, they fail to consider the behavioral perspective. Therefore, this study provides a new view in forecasting the credit loss.

As for the model of mortgage default on real estate, the default decision depends not only on the extent to which a borrower has negative home equity, but also on the extent to which borrowers are constrained by low current resources. As for default rate of the ARM and FRM that the research studies, ARMs and FRMs have similar overall default rates and similar sensitivities to the level of house prices, but the other drivers of default are different. ARM defaults tend to occur when interest rates and inflation increase, driving up required payments on ARMs, while FRM defaults tend to occur when interest rates and inflation decrease [7]. For this reason, ARM default risk is highest for mortgages originated at low rates, while FRM default risk is highest for mortgages originated at high rate. Additionally, reference [7] shows the pattern of mortgage premia as interest rates varies. The model that they set implies that FRM premia tend to increase with the initial level of interest rates, because high initial interest rates increase the value of the borrower's options to refinance.

This dynamic model of households' mortgage decisions incorporating labor income, house price, inflation, and interest rate risk. Using a zero-profit condition for mortgage lenders, it solves for equilibrium mortgage rates given borrower characteristics and optimal decisions. The model quantifies the effects of adjustable versus fixed mortgage rates, loan-to-value ratios, and mortgage affordability measures on mortgage premia and default. Mortgage selection by heterogeneous borrowers helps explain the higher default rates on adjustable-rate mortgages during the recent U.S. housing downturn, and the variation in mortgage premia with the level of interest rates [8].

III. Sample and Methodology

A. Discussion of Data and Sample

The data in the following paragraphs are used to demonstrate the trend of DCR and LTV ratios under the next period as well as under which conditions people will default. At first the study introduced variables and define the time period of these variables. Additionally, my study elaborated reasons why the research chose these variables and how the study simulated these 4 variables with 120 time periods into the future. Finally, the study presented the sources of the data which are most from authoritative institutions and platforms.

B. Discussion and Explanation of Data Set

Based on the literature review, the LTV and DCR can help us realize the true losses on real estate property value. The LTV is calculated as $LTV = \text{unpaid loan amount} / \text{property value}$ and DCR is calculated as

$$DCR = (\text{rent} - \text{expense}) * (1 - \text{vacancy rate}) / \text{debt payments}$$

During the repayment period, if the LTV is higher than certain level or DCR is lower than certain level, it appears that people cannot repay this loan and this loan is default. In this way, the loss on real estate property value is the present value of the remain repayment of the loan. Thus, the study showed the credit risk by presenting the real estate value losses from the advent of credit events like default and prepayment.

C. Discussion of Sample

In order to calculate the LTV as well as the DCR, the study collected the data of

- rent growth
- vacancy rate
- GDP growth rate
- number of privately owned housing starts
- house price index growth
- 1-month interest rate
- 10-year interest rate
- CPI change rate
- Estate value growth rate

The Table I shows the statistical information of the data.

The study firstly applied the VAR regression model to get these four variables (vacancy rate, rent, rent housing starts for 5-units or more and capital) at the national level based on the historical data. The study selected the data of vacancy growth from the first quarter of 1956 to the second quarter of 2020 and the data of property value from first quarter of 1981 to the second quarter of 2020. Also, the time span of expense and rent growth were all from the third quarter of 2001 to the second quarter of 2020. All these variables are collected quarterly. Then the study worked on a small simulation first which is 1000* 120 quarters (30 years). In other word, this study used Monte Carlo Simulation to generate 1000 different paths of these 4 variables with 120 time period.

As for the source of the original data that used in the VAR regression model, the study referred the website https://fred.stlouisfed.org/. This website provided this study with the latest and detailed information.

TABLE I: THE STATISTICAL INFORMATION ABOUT DATA

	N	Min	Max	Average	Stdev	Median
rent growth	74	-0.15%	1.18%	0.63%	0.26%	0.65%
vacancy	74	5.70%	11.10%	8.70%	1.41%	9.15%
gdp growth	74	-9.62%	2.25%	0.83%	1.40%	1.04%
Privately Owned Housing Starts	74	72666.7	503000	290649	91747.3	308333
hpi growth	74	-3.15%	3.81%	0.79%	1.42%	1.01%
1-month	74	0.01%	5.11%	1.25%	1.46%	0.91%
10-year	74	0.69%	5.10%	3.14%	1.09%	2.92%
CPI change	74	-2.29%	1.54%	0.50%	0.56%	0.55%
the change of real estate at market value	74	-13.54%	9.62%	1.39%	3.49%	1.68%

D. Assumption of the Methodology

To get rent/expense from rent/expense growth, the study set the rent/expense ratio at 1 and used the forecasted rent/expense growth to calculate the actual rent and expense. As for the debt payments and unpaid loan amount in the function, the study assumed that there is 30 years fixed rate mortgage with a loan amount about 1 million and the note rate (APR) was 3.65%. After setting the fixed rate mortgage loan and its note rate, the study calculated the amortization schedule of this mortgage and provided debt payment every quarter and the left principal balance on the mortgage. At last, after completing above process and getting these data, the study got the LTV and DCR matrix.

E. Discussion of Methodology & Model

In this section, the study interpreted the data that it chose in the first part. Initially The research used the VAR regression model to forecast the vacancy rate, rent growth, rent housing starts for 5-units or more and the change of real estate at market value in the next period. Then, the research conducted the Monte Carlo Simulation to generate 1000 different paths of these 4 variables with 120 time periods. Finally, the study graphed the trend of LTV as well as DCR during the 120-time period and got the conclusion.

F. Discussion and Explanation of Methodology

The study constructed a quantitative mold to complete the research. This research mainly applied VAR regression model to get the result.

VAR regression model is a commonly used econometric model. VAR model uses all current variables in the model to regress several lagging variables of all variables. The VAR model is used to estimate the dynamic relationship of the joint endogenous variables without any prior constraints. The VAR model constructs the model by taking each endogenous variable in the system as a function of the lag values of all the endogenous variables in the system, thus extending the univariate autoregressive model to the "vector" autoregressive model composed of multivariate time series variables.

The VAR regression model allowed the study to generate and forecast the variables in the future. Under the help of VAR regression model, the study can apply Monte Carlo Simulation to generate 1000 different paths of these variables and calculated the LTV as well as DCR. At last, the study could get the present value of the loss.

IV. ANALYSIS AND FINDINGS

A. Evaluating the Vacancy Rate, Rent Growth Rate, Rent Housing Starts and Capital Growth Rate

As for the VAR regression model in this study, the research assumed

$$\mathrm{Yt} = \mathrm{C} + \mathrm{A1}(\mathrm{yt}-1) + \mathrm{A2}(\mathrm{yt}-2) + \ldots. + \mathrm{Ap}(\mathrm{yt}-\mathrm{p}) + \mathrm{et}$$

where: C is an $n \times 1$ constant vector and Ai is an $n \times n$ matrix. et is an n by 1 error vector. In this research, the lag is 1 and the exogenous variables are 1-month and 10-years treasury rates. And vacancy rent growth referred to the vacancy rate. POHS referred to rent housing starts for 5-units or more. GDP referred to GDP growth. HPI referred to house price index growth. Capital referred to the change of real estate at market value. Year referred to 10-year treasury rate. Month referred to 1-month treasury rate. Const referred to constant.

To forecast the vacancy rate, the function was:

$$\mathrm{vacancy} = \mathrm{vacancy.l1} + \mathrm{rent.l1} + \mathrm{gdp.l1} + \mathrm{pohs.l1} + \mathrm{const} + \mathrm{month} + \mathrm{year}$$

The Table II shows the result:

TABLE II: THE RESULT OF MODEL

	Estimate	Std. Error	*t* value	Pr(>|t|)
vacancy.l1	-0.028248	0.012468	-2.266	0.02656 *
rent.l1	0.708418	0.068132	10.398	7.7e-16 ***
hpi.l1	0.020894	0.011544	1.810	0.07459
const	0.004087	0.001347	3.034	0.00338 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.001253 on 70 degrees of freedom

Multiple R-Squared: 0.7734, Adjusted R-squared: 0.7636

F-statistic: 79.62 on 3 and 70 DF, p-value: < 2.2e-16

After using in sample prediction, the absolute percentage difference between the actual value and predicted value is -4.284143%. This difference is very small. The study could conclude that this predicting model was precise.

To forecast the rent growth, the function was:

$$rent = rent.l1 + vacancy.l1 + hpi.l1 + const + month + year$$

The Table III shows the result:

TABLE III: THE RESULT OF MODEL

	Estimate	Std. Error	*t* value	Pr(>|t|)
vacancy.l1	1.003e+00	4.394e-02	22.816	<2e-16 ***
rent.l1	2.938e-01	2.869e-01	1.024	0.309
gdp.l1	2.888e-02	6.436e-02	0.449	0.655
pohs.l1	-5.575e-09	8.234e-09	-0.677	0.501
const	-1.200e-03	5.353e-03	-0.224	0.823

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.003572 on 68 degrees of freedom

Multiple R-Squared: 0.9412, Adjusted R-squared: 0.93

F-statistic: 272.1 on 4 and 68 DF, p-value: < 2.2e-16.

However, in this case, although the p-value of gdp.l1 and pohs.l1 is relative higher, the absolute percentage difference between the actual value and predicted value is -0.1742808%, which means that the forecast vacancy rate is very similar to the actual vacancy rate. This model could predict the vacancy rate successfully.

To forecast the rent housing starts for 5-units or more, the function was:

$$Pohs = cpi.l1 + gdp.l1 + hpi.l1 + HS.l1 + const + month + year$$

The Table IV shows the result:

TABLE IV: THE RESULT OF MODEL

	Estimate	Std. Error	*t* value	Pr(>|t|)
cpi.l1	-7.976e+05	1.058e+06	-0.754	0.4536
gdp.l1	2.376e+06	9.008e+05	2.638	0.0104 *
hpi.l1	5.760e+05	4.683e+05	1.230	0.2230
HS.l1	7.694e-01	7.061e-02	10.896	<2e-16 ***
const	7.362e+04	3.041e+04	2.421	0.0182 *
month	4.453e+05	4.653e+05	0.957	0.3420
year	-1.129e+06	6.463e+05	-1.747	0.0853

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 39190 on 67 degrees of freedom

Multiple R-Squared: 0.8348, Adjusted R-squared: 0.82

F-statistic: 56.43 on 6 and 67 DF, p-value: < 2.2e-16

To estimate the change of real estate at market value, the function was;

$$capital = capital.l1 + rent.l1 + const + month + year$$

The Table V shows the result:

TABLE V: THE RESULT OF MODEL

	Estimate	Std. Error	t value	Pr(>|t|)
capital.l1	0.36242	0.11429	3.171	0. 0.00227 **
rent.l1	-1.51203	1.76701	-0.856	0.39512
const	0.02364	0.02123	1.113	0.26949
month	0.59021	0.42478	1.389	0.16917
year	-0.33402	0.51361	-0.650	0.51764

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0327 on 69 degrees of freedom

Multiple R-Squared: 0.1818, Adjusted R-squared: 0.1344

F-statistic: 3.833 on 4 and 69 DF, p-value: 0.007164

After getting these coefficients, the study could predict them in the future and did the Monte Carlo Simulation.

B. Evaluating the Credit Loss

After getting the significant data from above section, the study now can apply them into calculating the DCR as well as LTV in the next 120 periods. When DCR is lower than 1.20 or LTV is higher than 75%, the debtors is unable to repay the debt. Then the credit loss is the present value of the remain loan that has not repaid in time.

In this paper, the research used R-Studio to monitor the different paths of LTV and DCR in 120 periods and graph the trend of them. After that the study presented each credit loss from DCR and LTV.

C. The Credit Loss from DCR (Debt Coverage Ratio)

The study set a standard that the loan is default when its DCR is lower than 1.20. In this case, the debtor cannot perform their duty of repaying the loan. The study applied a graph to illustrate this situation. The Fig. 1 showed the trend of DCR. In this graph, the x-axis is the time assumed from 2000 to 2030. The y-axis is the DCR in 120 period.

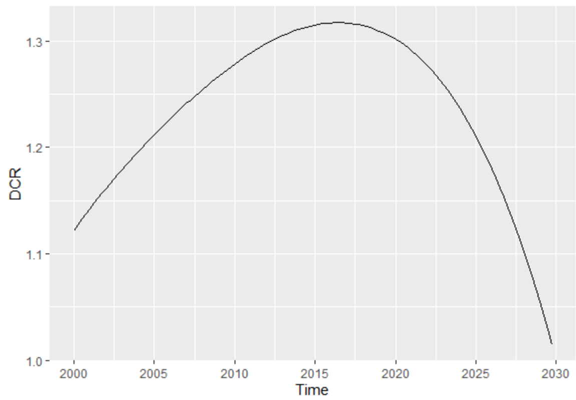

Fig. 1. The trend of DCR.

According to the graph, the study presented a result that the DCR firstly increases at a low rate as the rent income rises and then decreases also at low rate as the rent income declines. The overall graph is parabola. As for data collected from Monte Carol simulation, the study got a conclusion that from period 1 to period 18 and from period 103 to period 120, the loan is default. In other word, the debtor is inability to pay back loan in these two periods. Thus, the credit loss equal to the present value of the loan in these two periods. After calculation, the present value of the loan in default time is \$190409.51. As a result, in this case, the estimate credit loss of real estate is also \$190409.51.

D. The Credit Loss from LTV (Loan-to-Value Ratio)

The set a standard that the debtor cannot pay back the loan when the loan's LTV is higher than 75%. In other word, when borrowers request a loan for an amount that is at or near the 75%, lenders perceive that there is a greater chance of the loan going into default. This is because there is very little equity built up within the property. The Fig. 2 showed the change of LTV within 120 periods.

According to the graph, the overall trend of LTV is declining. However, from period 1 to period 60 to period 80, the graph becomes flat. This change mainly results from the largely decrease of the property value. The research also illustrated that the LTV is lower than 75% after period 7. Therefore, from period 1 to period 6, the loan is default. The borrower cannot pay back the loan during this period. After calculation, the present value of the loan in this period is $75551.05. In conclusion, the credit loss based on the LTV is $75551.05.

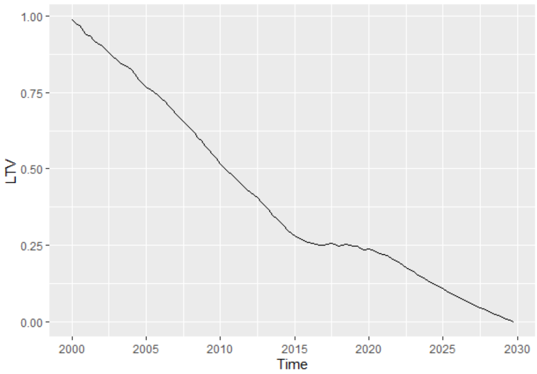

Fig. 2. The trend of LTV.

V. Conclusion

In general, the behavioral perspective including default and is always one of the most important factors in evaluating the credit loss. The default risk as well as prepayment risk are mentioned when we talked about the behavioral perspective. However, the prevail models such as EAD, PD, LGD ignore this aspect to evaluate the credit loss. Thus, the new model that this study applied provide a new view to evaluating the credit loss.

In this paper, the study proposes evaluation methods based on VAR regression model that can provide quantitative measures of model accuracy for credit loss models. This method forecasts the needed data and then the study uses this data to calculate the DCR and LTV. If the DCR or LTV is higher than a certain level, then the study determines that this loan defaults and the credit loss is the present value of the loan.

Several aspects of the study require additional research. For instance, the impact of policy interventions, such as Dodd-Frank Act, may change the credit loss. However, most of the future research in this area should consider more on behavioral perspective like default risk and prepayment risk.

Conflict of Interest

The author declares no conflict of interest.

Author Contributions

Lingxiao Dan conducted the research, collected the data, and analyzed the data. He wrote the whole paper.

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