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Predictive Modeling of Default Scenarios in the CMBS Market: A Macroeconomic Approach

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Abstract: This study analyzes potential default risks in Mortgage-Backed Securities (MBS) using time series data from 2010 to 2023. Employing Vector Autoregression (VAR) models to forecast economic indicators and calculate DTI and LTV ratios, which are crucial for predicting defaults in the MBS market. Our analysis, based on two economic models, examines the influence of macroeconomic factors and credit default risks on residential and commercial properties, such as Fixed-Rate and Adjustable-Rate Mortgages. The findings suggest that despite the significant impact of the pandemic, the likelihood of default in the American MBS market over the next 15 years remains relatively low. The study emphasizes the significance of comprehending the relationship between macroeconomic conditions and MBS default risks, providing a comprehensive methodology for future research.

Keywords: mortgage-backed securities, default risks, time-series model, Vector Autoregression (VAR) model

1. Introduction

The investment environment for Mortgage-Backed Securities (MBS) is significantly influenced by macroeconomic factors and the inherent risk of credit defaults. Policymakers and investors must understand these risks, as MBS defaults can have a significant impact on financial markets and potentially threaten global financial stability [1]. There is an increasing use of big data and statistical methods [2], this report addresses the need for sophisticated analysis by introducing an innovative approach to time-series analysis. Employing Vector Autoregression (VAR) models, our study aims to forecast economic conditions and evaluate credit default risks in the MBS sector, specifically distinguishing between commercial and residential properties and further delving into Fixed-Rate Mortgages (FRM) and Adjustable-Rate Mortgages (ARM) within residential property MBS. Our goal is to provide insights into predicting MBS default risk and to establish a replicable research framework for similar future analyses. This approach generates valuable forecasts of potential defaults, it also sheds light on the economic factors that drive these risks. It is important to note, however, that this method has certain limitations.

The initial approach adopts a top-down methodology and constructs a Vector Autoregressive (VAR) model based on macroeconomic variables to understand how macroeconomic factors interact and influence the MBS market [3]. This model aims to forecast critical factors such as loan amounts and the future value of properties. However, after a comprehensive evaluation of the data's characteristics, the VAR(5) model, which can capture the data dynamics, was chosen over the

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VARMA (1,1) model due to its better performance in producing more minor errors when back-tested against actual data. See Appendix 1 for model performance metrics of the two models.

The report sections explore two distinct scenarios: the Stable-State Economic Model (SSEM) and the Pandemic-Influenced Economic Model (PIEM). Subsequently, the predicted values for debt payments, rental income, loan amounts, and property values were utilized to determine two evaluation metrics: the Debt-to-Income Ratio (DTI) and the Loan-to-Value Ratio (LTV). By analyzing forecasted DTI and LTV ratios, this study aims to predict possible MBS market defaults. It is assumed that a DTI above 1.2 reflects an excessive debt burden where debt payments exceed a significant portion of the borrower's income, thus increasing the risk of default. An LTV greater than 0.8 suggests that the borrowed amount is a significant part of the property's market value, which reduces the borrower's equity. If the property values decrease, it could result in the borrower's negative assets, which increases the risk of default.

The data for this study spans from 2010 to 2023, sourced primarily from the Federal Reserve Economic Data (FRED) and adjusted to a quarterly frequency to align with the periodic reporting of economic indicators. Our time series models integrate a wide array of data, including Real GDP, Disposable Personal Income, Unemployment Rate, Consumer Price Index, and loan and property values across commercial and residential sectors. Collectively, these variables provide a holistic view of the economy, touching on aggregate performance, personal income levels, housing market trends, and inflation.

2. Preliminary Notes

2.1. Sourced Data Description and Processing

All the data used in this report is sourced from the Federal Reserve Economic Data (FRED). We have selected the nationwide statistics-based data from 2010 and 2023 to capture relatively complete historical business cycle data for the prediction [4]. The data are transformed quarterly to ensure they have the same biases as many economic indicators, such as GDP, are reported quarterly.The following table shows the macroeconomic indicators used in constructing the model. Refer to Appendix 2 for the original data linked to model construction.

Table 1. Description of Parameters in the Model

Category	Indicators	Description
Macroeconomic	Real_GDP Growth Rate (%)	Real Gross Domestic Product
	Unemployment Rate	Change to quarterly
	Consumer Price Index	Index 2015=100
	Disposable Personal Income	Percent Change from Preceding Period, Quarterly, Seasonally Adjusted Annual Rate
Real Estate Market	Residential Real Estate Loans	One-to-Four-Family Residential Mortgages Millions of Dollars
	Commercial Real Estate Loans	Trillions of Dollars, Seasonally Adjusted
	Residential Property Price Index	"S&P/Case-Shiller U.S. National Home Price Index. Index Jan 2000=100, Seasonally Adjusted
	Commercial Property Values	Commercial Real Estate Price Index, Trillions
	Interest Rate	30-year Fixed Rate Mortgage in the US

2.2. Overview of the two Scanrios's VAR models

Our methodology utilizes two Vector Autoregression (VAR) models, each tailored to a specific timeframe to assess MBS default risk. Model 1 (2010-2023) leverages an extensive dataset to capture the market's nuanced response to a tumultuous economic decade, including the pandemic's profound impact. Model 2 (2010-2020), delineating a pre-pandemic landscape, provides a comparative baseline of market trends in a less volatile economic climate. The VAR model is a foundational tool in our analysis, providing a structured approach to understanding the dynamic interrelationships among multiple time series data relevant to the MBS market. The mathematical representation of our VAR model can be formulated as follows:

$$Y_t = C + \phi_1 \times Y_{t-1} + \Phi_2 \quad \times Y_{t-2} + \ldots + \Phi_p \quad \times Y_{t-p} + \varepsilon_t \tag{1}$$

Here, $Y_t$represents the vector of observed time series at time t, which includes the key economic indicators. The VAR model integrates these series, denoted from $Y_{1(t)}$ to $Y_{n(t)}$, into a comprehensive system. Each lagged term$\phi_i Y_{t-1}$represents the impact of past values of the economic indicators on their current values, allowing the model to incorporate historical data into predicting future states.

c is a vector of constants or intercepts, p is the lag period, set to be 5 in this model.

ϕ_1, ...$\phi_p$are the matrices of coefficients capturing the influence of p-lagged observations.

Y_{t-1} is the 9-dimension vector of observations at time t-1

$\varepsilon_t$is the vector of error terms at time t, assumed to follow a multivariate normal distribution with mean zero

The first step is to do the data cleaning, which includes identifying and removing outliers using Z-scores and testing data stationarity with the Augmented Dickey–Fuller test. For non-stationary data, the differencing method is applied once to trade off between stationarity and loss of information. Next, the VAR(5) model is used, choosing a lag period of 5 to optimize the Akaike Information Criterion (AIC) value and the Durbin-Watson statistic to reduce residual correlation. In the forecasting phase, they predicted data for the next 15 years, covering four quarters per year, and reversed the differencing for non-stationary variables to return to the original data scale.

Multi-faceted adjustments are applied to refine the forecast values. Forecasts were first aligned with the historical mean, ensuring they stayed within three standard deviations to maintain realism. For columns expected to be exclusively positive, like loan amount and property values, any negative forecasts were substituted with the historical mean, upholding data integrity. Additionally, adjustments were made based on historical volatility, keeping forecasted values within three standard deviations of this measure.

2.3. Analytical approach of LTV and DTI

In real estate investment, the Loan-to-Value (LTV) ratio and the Debt-to-Income (DTI) ratio are fundamental indicators for evaluating the financial health and default risk of investment properties. Based on the forecast property values and loans generated from the previous 2 scenario models, we use further assumptions to calculate the residential and commercial properties LTV and DTI.

The LTV ratio is a critical measure that compares the amount of a loan to the value of the property [5]. It is calculated as

$$Loan - To - Value(LTV) = \frac{loan\ amount}{Property\ value} \tag{2}$$

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For calculating the LTV of commercial properties, MBS models provide directly usable data because both the loan amount and property values are in dollars.

Regarding residential LTVs, values are calculated based on a 15-year projection of the S&P/Case-Shiller U.S. National Home Price Index generated from the models. The valuation is standardized to the 2000 housing dollar value, a baseline (equated to 100).

The debt-to-income (DTI) ratio is a critical measure of default risk and indicates the ratio of debt payments to rental income on a property [6]. It is essential to maintain a low DTI ratio to ensure financial stability. It can be calculated as

$$Debt - To - Income(DTI) \ = \frac{debt\ payment}{Rental\ Income} \tag{3}$$

$$(Monthly)\ Debt\ Payment \ = \ Principle \ \times \frac{r(1+r)^n}{(1+r)^n - 1} \tag{4}$$

$$Principle \ = \ Property\ value \ \times \ (1 - \ down\ payment\ ratio) \tag{5}$$

$$(Monthly)\ Rental\ income \ = factor_i \ \times \ property\ value \tag{6}$$

The $factor_i$ is the percentage of monthly rental income derived from property values.

$$factor_{residential} \ = \ 2.5\%$$

$$factor_{commercial} \ = \ 7.5\%$$

The assumed down payment ratio for commercial and residential properties in the United States is 20%, based on reports from USbank [7]. The loan tenure is set at 30 years, and this assumption is also utilized within this report. To calculate the monthly rental income of residential properties, we use the 2% rule for investment properties and assume a 2.5% monthly rental income based on the property value [8]. We categorize residential properties into fixed rates and ensure consistent time frames. For commercial properties, the capitalization rate set by FeldmanEquities ranges from 3% to 20%. In this model [9], we assume 7.5% to calculate the DTI.

3. Main Results

3.1. VAR Models Forecast Outcomes

The forecast results from the Pandemic-Influenced Economic Model (PIEM 2010-2023) reveal that accounting for pandemic factors in the forecast, the aforementioned parameters indicate a consistent trend during the pandemic years. Compared to historical data, the forecasted data exhibit a wider range of fluctuations. The Stable-State Economic Model (SSEM 2010-2020) predicts a significant decrease in the upper limit of future data compared to the 2023 model, excluding pandemic factors. Nevertheless, significant fluctuations in future data are still observable. Please refer to Appendix 3&4 for detailed visual representations of the outcomes of the two models.

3.2. Default Risk Analysis Based on LTV and DTI

In assessing the default risk of MBS, we set LTV > 1.2 or DTI > 0.8 to indicate a high probability of default. Figure 1 outlines the default probabilities based on these criteria. Refer to Appendix 8 for the exact default probability number

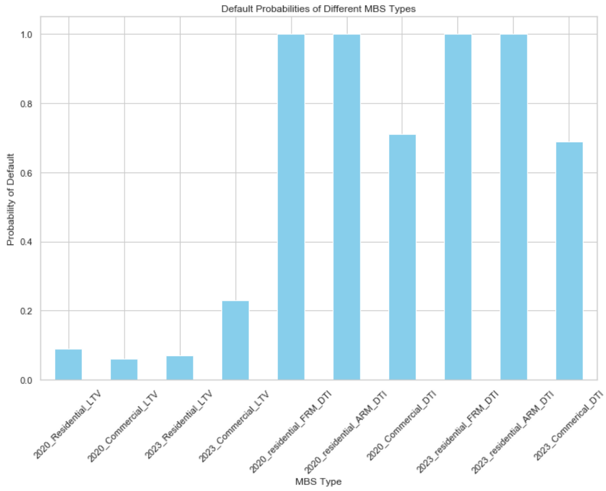

Figure 1: Overview of the default probability

Analysis reveals that the 2020 and 2023 models predict extremely high default probabilities for the DTI metric, especially for residential DTI at 100% and commercial DTI at around 70%. However, the LTV metric shows a relatively lower default probability, with residential LTV and commercial LTV under 10%, yet commercial LTV rising to 23% in the 2023 model. This indicates a higher risk of default for residential loans, suggesting substantial mortgage repayment pressures for homeowners. In contrast, the risk for commercial loans is slightly lower, though the economic uncertainties during the pandemic period add to future unpredictability.

The stark contrast between DTI and LTV indicators is attributable to their different reflections on financial health. The high default probability indicated by DTI might be due to forecasted rental income being insufficient to cover debt obligations, increasing the risk of default. Conversely, the LTV ratio implies higher property value than the loan amount, decreasing the likelihood of default. Combining the effect of the two indicators, the overall default probability remains relatively low in the next 15 years.

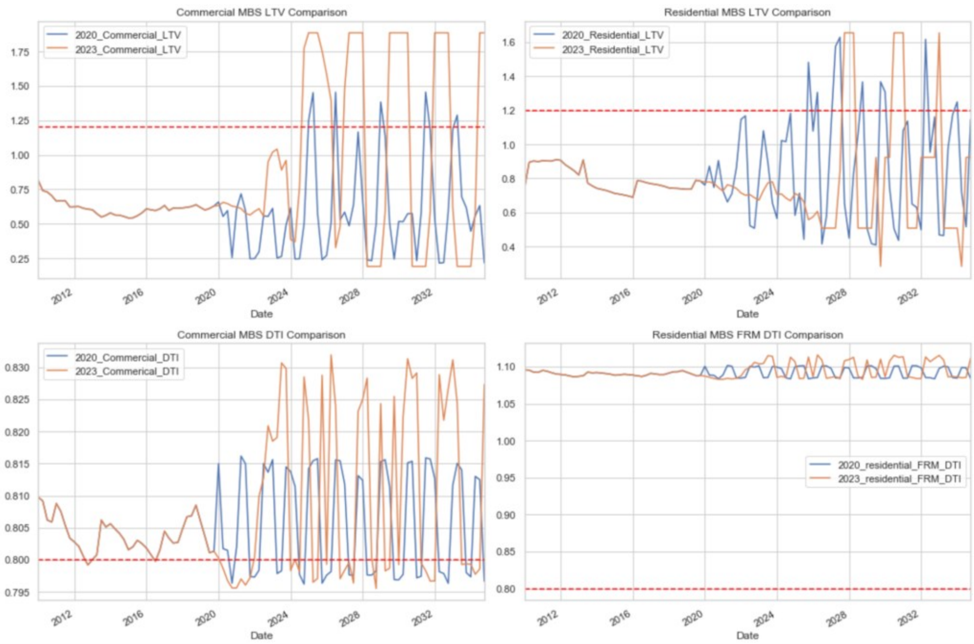

Figure 2: Detailed default probability comparison

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Distinct trends in Loan-to-Value (LTV) and Debt-to-Income (DTI) ratios emerge for commercial and residential sectors across models in the Mortgage-Backed Securities (MBS) market analysis. The 2023 model for commercial MBS frequently exceeds the LTV default threshold (LTV = 1.2) and increases default risks compared to the 2020 model. Conversely, residential MBS maintain lower LTVs in both models, typically remaining below the default threshold, indicating reduced default risks.

For debt-to-income (DTI) comparisons, commercial mortgage-backed securities (MBS) in both models often surpass the default threshold (DTI = 0.8), indicating substantial future risks in the retail real estate market. These comparative insights illuminate diverse risk profiles in the MBS market, underscoring the disparities between commercial and residential MBS concerning prospective defaults.

Refer to Appendix 5 for an analysis of the trends in Debt-to-Income (DTI) for both Fixed-Rate Mortgages (FRM) and Adjustable-Rate Mortgages (ARM) in the 2020 and 2023 models. The DTI patterns are remarkably alike in both models, surpassing the default threshold consistently (illustrated by a solid red line at DTI = 0.8).

The DTI values for Fixed-Rate Mortgages (FRMs) fluctuate between 1.08 and 1.12. Both models exhibit parallel fluctuation patterns, although the 2023 model indicates slightly higher DTI values for FRMs, particularly towards the latter part of the time series. This increase could be attributed to recent economic shifts or an increased anticipation of future market risks. Nevertheless, the heightened market volatility incorporated into the 2023 model does not significantly alter the default risk appraisal for residential MBS, indicating a stable risk profile over time.

4. Conclusion

This study embarked on a comprehensive exploration of default risks within Mortgage-Backed Securities (MBS), primarily focusing on commercial and residential properties. Utilizing time-series data from 2010 to 2023, we constructed VAR models to predict critical economic indicators. These forecasts were instrumental in calculating pivotal metrics - the Debt-to-Income Ratio (DTI) and the Loan-to-Value ratio (LTV) - essential for assessing potential defaults in the MBS market. Our analysis highlighted notable differences in default risks as revealed by LTV and DTI metrics. The residential MBS displayed a higher default risk, underscoring substantial mortgage repayment pressures. In contrast, commercial loans exhibited a relatively lower risk. The divergence between DTI and LTV indicators reflects their respective measures of repayment capacity and asset value. By integrating all indicators, the overall probability of default for MBS in the United States is controllable and can be effectively managed within acceptable risk parameters.

The Pandemic-Influenced Economic Model (PIEM) unveiled significant market volatility, posing new challenges for financial market regulation. Regulatory bodies are urged to adopt flexible policies during economic crises, adjusting capital requirements and lending standards dynamically. Market intervention measures, such as liquidity support, are also recommended.Investors should adapt their strategies in response to market volatility. This includes enhancing asset diversification, improving risk management practices, and being more responsive to market dynamics. The findings from our study can guide policy adjustments, particularly in risk management and market regulation, to mitigate potential impacts on the financial market.

Many constraints and limitations are still encountered. Firstly, the source data used are complex, with intricate correlations among variables. While these correlations were considered in the calculations, future research might benefit from a more refined dataset that better aligns with the specific nuances of the topic.Additionally, the data sources must be improved to capture the full complexity of the global mortgage-backed securities (MBS) market. This gap suggests the potential for more comprehensive data acquisition in future studies. The chosen VAR model, while helpful, may not be the most suitable for the research question at hand. Further investigation into alternative models could enhance the research's accuracy. In the data-cleaning phase, outliers were removed based on their Z-score about the mean. However, this approach is more appropriate for rate-based data than absolute values. Future studies should distinguish between these data types and apply tailored cleaning strategies.Stationarity testing also presented challenges. Some data remained non-stationary even after one differencing iteration, indicating a need for a more thorough treatment of such data. Furthermore, the Durbin-Watson Statistics could have been better, suggesting that correlation within the data requires more nuanced handling. Moreover, The forecasted data could have been more optimal, leading to the introduction of various post-processing methods. This outcome prompts a reevaluation of the forecasting process. Additionally, the study found that rental income, factored as a percentage of property value, varies across different locations. This variability should be accounted for in future analyses.

Lastly, the report recommends that researchers explore new models and analytical tools, such as machine learning and artificial intelligence technologies. These innovative approaches could significantly improve the accuracy and depth of predictions, offering valuable insights for future studies in the MBS market domain.

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Appendices

Appendix 1: Model performance metrics

Metric	VARMA(1,1)	VAR(5)
Log Likelihood	-221.037	11285.119
AIC	874.073	-555.839
BIC	1269.060	-538.536
HQIC	1022.038	-549.539

Appendix 2: Comprehensive interpretation of macro indicators

1. Real GDP ($ billion) Sources: https://fred.stlouisfed.org/series/GDPC1
2. All-Transactions House Price Index:https://fred.stlouisfed.org/series/USSTHPI
3. Unemployment Rate:https://fred.stlouisfed.org/series/UNRATE

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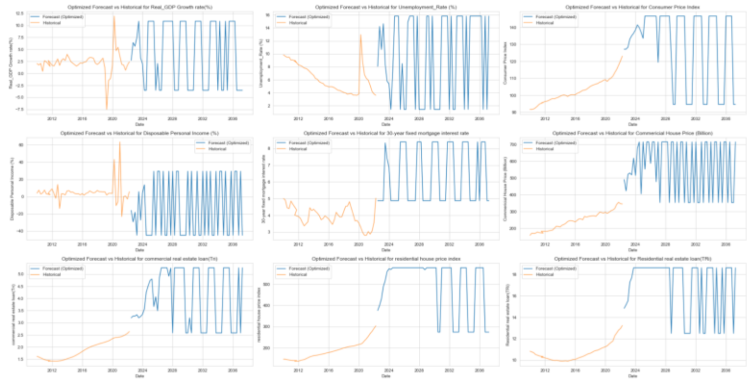
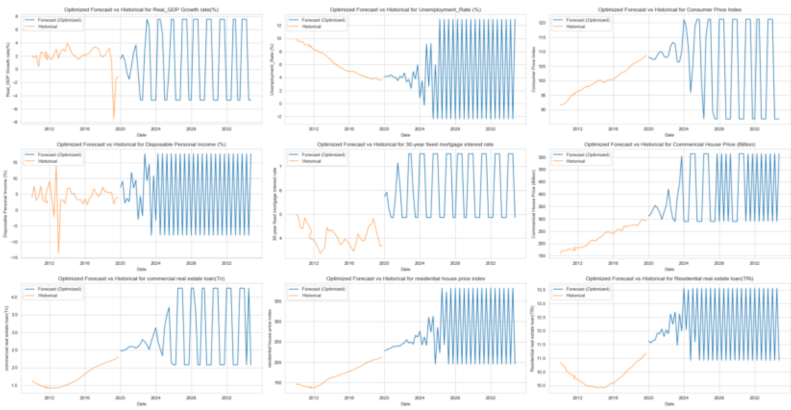
4. Consumer Price Index:https://fred.stlouisfed.org/series/CPALTT01USQ661S
5. Disposable Personal Income (%):https://fred.stlouisfed.org/series/A067RP1Q027SBEA
6. Residential real estate loan Sources:https://fred.stlouisfed.org/series/RHEACBM027SBOG
7. Residential Property Price Index Sources:https://fred.stlouisfed.org/series/CSUSHPISA
8. Commercial real estate loan: https://fred.stlouisfed.org/series/CREACBW027SBOG
9. Commercial Property Values: https://fred.stlouisfed.org/series/BOGZ1FL075035503Q
10. 30-year Fixed Rate Mortgage: https://fred.stlouisfed.org/series/MORTGAGE30US

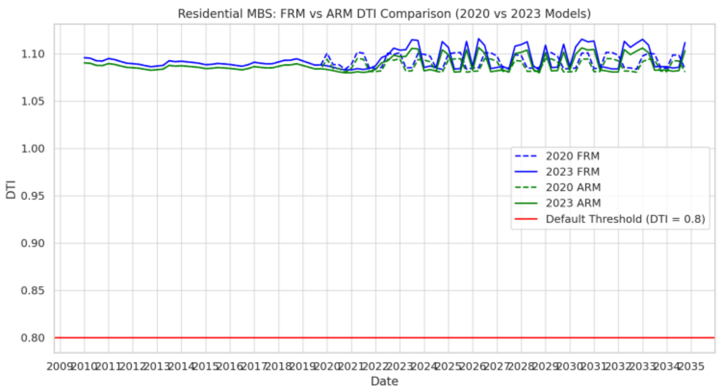
Appendix 3: The forecast outcomes of the Pandemic-Influenced Economic Model



Appendix 4: The forecast outcomes of the Stable-State Economic Model Model



Appendix 5: Residential MBS FRM and ARM detail



Appendix 6: **Durbin Waston statistics for the "*PIEM 2010-2023" model***

Economic Indicator	**DW**	**Economic Indicator**	**DW**
Real GDP Growth rate (%)	1.8475	Residential house price index	1.7677
Unemployment Rate (%)	1.6066	Commercial real estate loan	1.4839
Consumer Price Index	1.9255	Commercial House Price	1.5573
Disposable Personal Income	1.7107	30-year fixd interest rate	1.2749
Residential real estate loan	1.2822		

Appendix 7: Durbin Waston statistics for the "SSEM 2010-2020" model

Economic Indicator	**DW**	**Economic Indicator**	**DW**
Real GDP Growth rate (%)	1.5370	Residential house price index	0.6328
Unemployment Rate (%)	1.1458	Commercial real estate loan	1.9608
Consumer Price Index	1.5595	Commercial House Price	2.1979
Disposable Personal Income	1.9359	30-year fixd interest rate	2.1166
Residential real estate loan	1.0087		

Appendix 8 Probability of Default for different types of MBS

MBS Type	**Probability**	**MBS Type**	**Probability**
2020_Residential_LTV	0.09	2020_residential_ARM_DTI	1.00
2020_Commercial_LTV	0.06	2020_Commercial_DTI	0.71
2023_Residential_LTV	0.07	2023_residential_FRM_DTI	1.00
2023_Commercial_LTV	0.23	2023_residential_ARM_DTI	1.00
2020_residential_FRM_DTI	1.00	2023_Commerical_DTI	0.69