MN5608 - Risk Management

Group A Essay

Anastasia Akchurina, Ivan J Ben, William Culliton, Mungo Somerville

University of St Andrews

2024

Securitization and the 2007-08 Financial Crisis

Introduction

The financial crisis of the 2007-2008 period remains one of the worst seen cases of financial tragedy in modern economic history the ramifications of which reshaped the global financial landscape, especially on the front of regulatory scrutiny/framework, market dynamics, risk profiling and toxic leveraging. No financial crisis in history, has led to the same level of policy reform and government intervention that the 2007-2008 crisis has lend itself to. The aftermath of the crisis saw sweeping reforms, most notably the Dodd-Frank Wall Street Reform and the Consumer Protection Act of 2010, in the pursuit of rectifying the systemic weakness exposed by the crisis. It still stands as a reminder of the complexities inherent in the financial markets and the mismanagement of which could lead to catastrophic and devastating consequences.

To understand the failure of the markets, we need to first understand the process of securitization, which in its simplest form is pooling of various types of financial assets and investment vehicles and 'repackaging' them into marketable securities. Why is securitization done? The primary purpose of securitization is the dilution of risk. When investment vehicles (mortgages, car loans, credit card debts) are pooled together, the credit risk associated with these are spread out making them attractive to a broader range of investors which would then transfer the credit risk from the original lenders to the broader market. This practice of securitization (specifically of credit-based entities) grew exponentially and gained momentum in the years leading up to the 2007-2008 crisis, particularly in the context of the US housing market. It involved complex financial instruments, namely Mortgage-Backed Securities (MBS) and Collateralized Debt Obligations (CDOs), which were designed to distribute risk more effectively but resulted in creating inter-dependencies and exposures that were poorly understood and inadequately managed. Most conventional studies, focus on the events leading up to the crisis and very few reports focus on the complexities of the instruments held. Till date, there tends to be limited resources in understanding complex structured products (such as MBS and CDO's). This report would focus on an in-depth analysis of the instruments whilst studying the shortcomings that lead to the 2007-2008 crisis. This is done by detecting the mechanisms of securitization, evaluating the incentives it created for market participants and finally, analysing the impacts of this on the financial system.

Build-up to the Crisis

As mentioned above, securitization, initially a tool for financial diversification and risk management had evolved significantly in the years leading up to the crisis. Since the 1970's and 1980's, banks had frequently employed the use of MBS and CDO's as a method to free up capital by selling their mortgage loans to government-sponsored entities such as Fannie Mae and Freddie Mac. As with most financial instruments, over time the practice expanded with private financial institutions adopting similar techniques for various types of credits (including but not exhaustive to car loans, student loans, credit card loans, small business loans etc.).

The late 1990's and early 2000's saw advancement of technology and by extension financial engineering which helped further fine tune and streamline the securitization practices. Financial institutions began to bundle or pool a diverse range of assets to create what is now known as Collateralized Debt Obligations (CDOs). CDO's are complex financial instruments that facilitated of repackaging of lower-grade debt (inc. toxic debt) into securities that had the appearance of secure but were highly risky. This period saw the emergence of Synthetic CDOs, which were based on Credit Default Swaps (CDS) which further complicates the risk assessment.

Housing Market Boom

Concurrent with the evolution of securitization was the unprecedented growth of the US Housing Market. At the time, banks were offering low-interest rates and easy credit conditions (minimal to very flexible KYC, Due diligence and risk profiling). Procurement of housing loans by banks had become easy which led to a surge in home buying and refinancing activities. Lenders, incentivized by the lucrative prospect of selling off their loans through securitization, loosened their lending standards making it the easiest period in modern banking to procure credit. Subprime mortgages (loans offered to borrowers with poor credit history and high risk of default) saw a substantial increase.

Proliferation of Mortgage-Backed Securities (MBS) and Collateralized Debt Obligations (CDOs)

The Housing Market Boom, combined with the surge in securitization of debt lead to investors ranging from large institutional players to smaller entities drawing to these securities primarily due to their higher yield and perceived safety, backed by credit ratings that did not accurately reflect the underlying risk. This booming securitization market, fueled by a constant supply of mortgages, created a self-reinforcing cycle, further inflating the housing bubble.

The Mechanics of Securitization

Securitization typically consists of pooling of financial assets and are then sold to a Special Purpose Vehicle (SPVs) which financed the purchase by issuing securities. These securities, backed by the cash flows from underlying assets are then sold to investors. This process diversified risk by converting illiquid assets to liquid securities hence spreading the credit risk to a wider pool of investors. Post-pooling of the assets, the issuer would then create multiple classes of securities- *tranches.* Tranches, essentially prioritized claims against the collateral pool and some investors held more senior claims than others. This meant that in the event of possible default, the losses are absorbed by the lowest priority class of investors before the higher priority investors would be affected. The pooling of the assets and tranches meant that some securities would be highly risky whilst some would be relatively safer. The structured finance market is a 'rated' market'. This meant that they were under the oversight of credit rating agencies and had to be given a rating. Owing to the complexity of the investment vehicles and underlying collateral, this caused an information asymmetry between lenders and investors which meant credit rating served as a focal point for the quality of security. (See: Benmelech, E. et al (2010)).

Credit Rating agencies are financial service firms that issue credit ratings, which are opinions on the creditworthiness of the issuer or security. (See; FCA, *Credit Rating Agencies,* 2019). Credit Rating agencies were elemental in the securitization process, providing ratings that are foundational in understanding and determining the risk and value of said securities. Unfortunately, credit rating agencies assigned overly optimistic ratings to complex securitization products. As noted in the study by Benmelech, E. et al (2010), the deterioration in creditworthiness of structured products began in 2007. The '*downgrading'* of a financial security is the reduction in its credit rating assigned by a ratings agency. As evident from the graph (*Number of Downgrades vs Upgrades of Structural Finance Products*) almost 8,000 downgrades happened in 2007 which was almost a ten-fold increase in comparison to 2006. The situation worsened in 2008, with the first three quarters witnessing 36,880 downgrades. To put this into context, this was worse than the cumulative downgrading of security over a span of almost two decades (1990-2008).

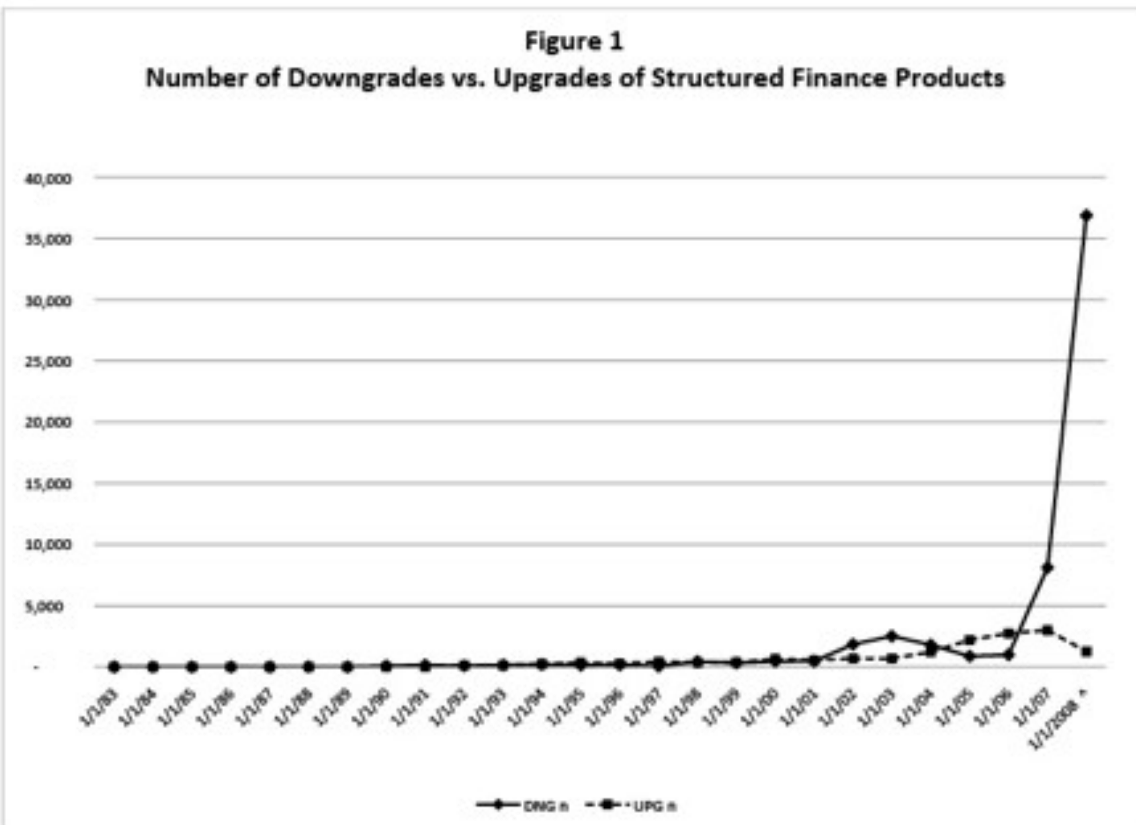


Figure 1 - Graph Source: (Benmelech, E. et al (2010)).

The process of securitization and the use of credit ratings led to another dilemma; it enabled investors to participate in asset classes from which they would have been otherwise prohibited. For example, an investor who is only able to invest in A grade security would be prohibited from holding B-rated corporate bonds. However, if said B-grade bonds were wrapped in a Collateralized Loan Obligation (CLO) and were AAA-rated could be investible. To further incentivize investors, the structured finance usually had higher interest rate than similarly rated corporate or sovereign bonds thus making it an attractive investment vehicle. Read: Benmelech, E. et al (2010)).

The increased demand for CDO's and MBS led to the 'Originate-to-Distribute' model. The presence of securitization allows banks to alter their lending process. So, where you would traditionally have a model that combines originating a loan and holding it till maturity, with the OTD model, banks originate mortgages and then sell them off to be a part of securitization. The issues from the OTD models are three folds:

1. Securitization can be used for regulatory arbitrage. For example, banks can reduce capital requirements by selling loans and in exchange purchasing MBS. This allows banks to circumvent capital requirements which were designed to ensure stability. By removing said loans from their balance sheets and replacing them with less risky MBS, banks appeared to be more financially secure than they were and obscuring the risk they were exposed to.
2. Loan sales can help banks by allowing them to earn revenue through the OTD model. Banks would originate loans and then sell them, profiting from origination fees (See Graph: *The Bank Business Model*) and servicing rights without bearing the long-term credit risk associated. This practice would further encourage the issuance of more loans, contributing to a surge in lending malpractices, particularly in the housing market as can be seen from the subprime mortgages.
3. Another potential agency problem more relevant for mortgage and debt lending was that lenders had less incentive to screen loans that they are planning to sell. There have been arguments that banks did less screening for subprime mortgages as they planned to sell. (e.g. Keys, et al. 2010). Lenders had considerably reduced incentives to rigorously screen loan applicants under the OTD model, especially for mortgages that were to be sold off. The lapse in due diligence contributed to the proliferation of highrisk loans, a significant factor in the housing bubble burst and the subsequent financial crisis.

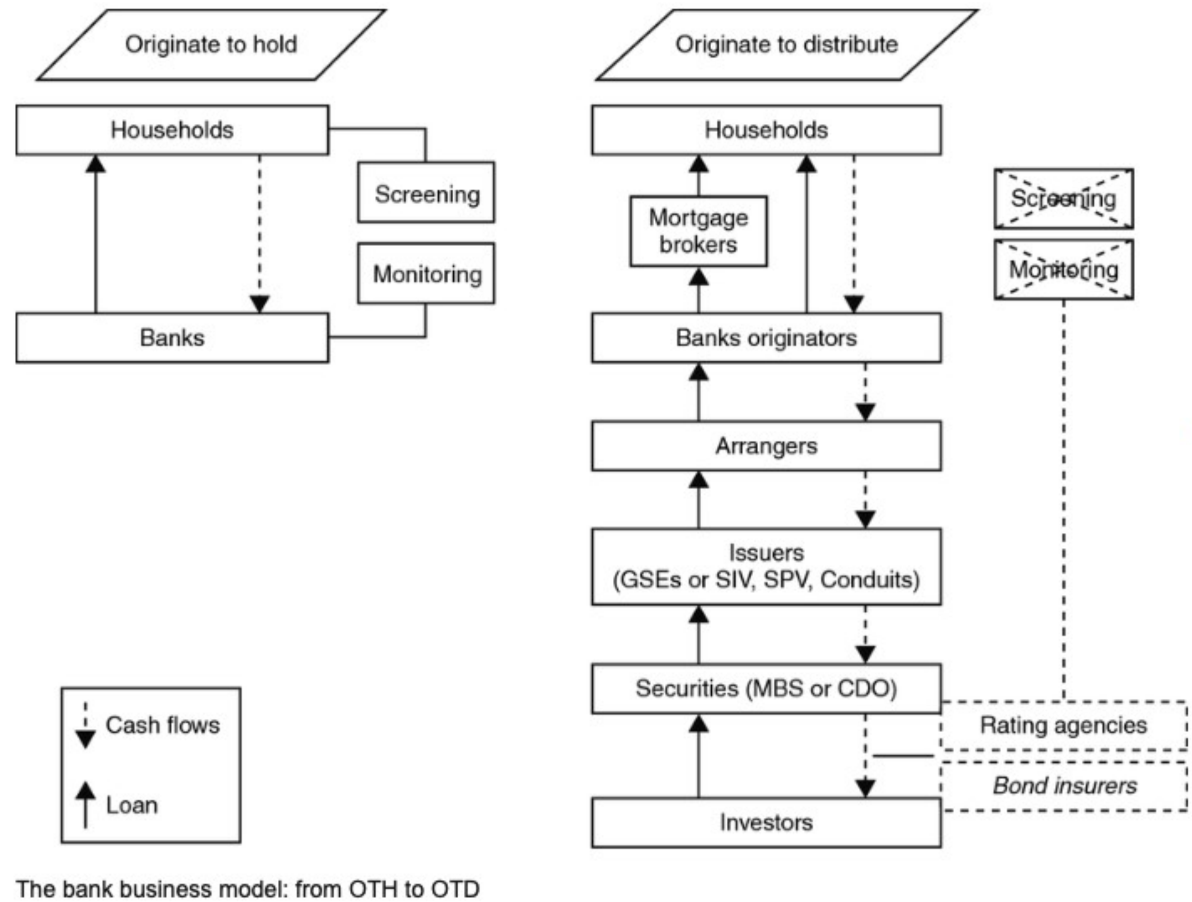


Figure 2 - Diagram Source: Giovanni Ferri; Research Gate

Investment Vehicles in Depth

Asset-Backed Securities (ABS)

An asset-backed security (ABS) can be defined as a security that is 'backed' by the cashflow of a range of different pooled receivables or loans. ABS' can be collateralised by any asset that has a cashflow, but usually business or consumer loans are used, such as student loans, automobile loans or receivables on a credit card. This differs from an MBS as they are strictly made up from mortgages. By using a cashflow from a financial asset as collateral on a loan, firms can diversify their sources of capital, borrow cheaper and reduce the size of their balance sheet (Agarwal et al, 2010).

Different ABS' can possess different structures, but Sabarwal (2006) establishes that they all must have three common features.

1. A lender who pools the loans together and transfers them to a special-purpose-entity (SPE).
2. The SPE issues several securities that are backed by the receivables on the loans.
3. The servicer collects the proceeds on the loans and allocate them to the investor.

How these features are implemented can vary significantly and can be determined by different cashflow patterns and different investor needs. This is shown in the usage of master trusts for a credit card ABS and an issuance trust to reduce the time required to issue a security.

Since its establishment in the 1970s, the ABS market grew rapidly from an issuance of $10 billion a year in 1986 to just under $900 billion in 2006, in the US. However, when the credit crunch hit in 2007, the ABS market came to a massive halt. Although the crisis came originally from mortgage defaults, the uncertainty quickly spread to other consumer loan markets and restricted the purchasing of ABS. To help with liquidity problems in the market, the Fed launched the Asset Backed Securities Loan Facility (TALF) which effectively dropped the ABS spreads.

Mortgage-Backed Securities (MBS)

Mortgage-Backed Securities (MBS) emerged as pivotal instruments in financial markets, designed to pool mortgage loans and sell them as securities to investors. This innovative approach aimed to mitigate inherent loan risks by distributing them across a wide investor base, thereby enhancing liquidity in the housing market and allowing lenders to efficiently manage their balance sheets (Gorton, 2009). However, the proliferation and subsequent misuse of MBS contributed significantly to the financial crisis of 2007-08, revealing systemic vulnerabilities within global financial markets (Acharya et al., 2009).

❖ *The Appeal and Mechanism of MBS*

The underlying appeal of MBS to financial institutions was multifaceted. Primarily, these securities offered a mechanism for risk diversification and promised higher yields compared to other fixed-income securities, making them attractive to both institutional and retail investors. The process involves pooling diverse mortgage loans, including prime and subprime, and then issuing securities backed by these loans. Investors in MBS were thus exposed to the mortgage lending market indirectly, assuming the default risk in exchange for potential returns (Gorton & Metrick, 2012). As the housing market boomed, driven by low interest rates and lenient lending standards, the demand for MBS soared. This demand encouraged lenders to lower underwriting standards even further, leading to an increase in mortgage issuance, particularly subprime mortgages, which carried a higher risk of default (Mian & Sufi, 2009).

❖ *Catalyst for the 2007-08 Financial Crisis*

The expansion of MBS, especially those backed by risky subprime mortgages, played a critical role in precipitating the financial crisis. The "originate-to-distribute" model as mentioned earlier fundamentally altered lenders' incentives, encouraging the production of loans for securitization and sale rather than for investment. This shift led to a notable deterioration in lending standards, as financial institutions, driven by the fees associated with loan origination and securitisation, increasingly overlooked the creditworthiness of borrowers (Keys et al., 2010). This process was further exacerbated by the overly optimistic ratings assigned by credit rating agencies to these complex securities. The agencies failed to account for the systemic risk posed by the bundling of subprime loans, leading to a widespread underestimation of the real risk associated with MBS (Acharya et al., 2009).

- ***Aftermath and Regulatory Response***

The collapse of the housing bubble, precipitated by rising default rates among subprime borrowers, led to a sharp decline in the value of MBS. This decline had a cascading effect on the financial sector, leading to liquidity crises and the eventual collapse of major financial institutions worldwide. The crisis underscored the dangers of complex financial innovations when coupled with mismanagement and inadequate regulatory oversight. In response, significant regulatory reforms were introduced globally to improve the transparency of securitization practices and ensure more rigorous assessment of credit risk. These reforms aimed to prevent a recurrence of such a crisis by enhancing regulatory oversight and aligning the incentives of lenders with the long-term health of the financial system (Kroszner & Strahan, 2011).

The 2007-08 financial crisis illuminated the critical role MBS played in the global financial ecosystem, highlighting the need for robust regulatory frameworks to manage the risks associated with financial innovation. As financial markets continue to evolve, the lessons learned from the crisis remain pivotal in guiding future regulatory and industry practices to ensure financial stability and protect against systemic risk.

Subprime Mortgage Crisis

The roots of the housing bubble can be traced back to the proliferation of subprime lending. Subprime mortgages can be defined as loans that were given to borrowers with poor credit histories and higher default risks (relative to prime mortgages). This incentive of high returns owing to the higher interest rates associated with these mortgages due to their risky nature. This incentivized financial institutions to bundle risky loans into MBS and CDOs selling them and providing the perception of diversification and distributing whilst masking the underlying credit risk.

The issue began exposing itself as interest rates began to rise and economic conditions worsened which led to many defaults between subprime loans. As the subprime loans made a fairly large proportion of these assets, a sharp increase in foreclosures led to a correctionl with the prices of houses plummeting to an all time low and bursting the housing bubble. The decline in housing prices was reflective to MBS and CDOs by eroding their value as the assets backing these entities had quickly lost their value. The collapse of the housing market further triggered a domino effect with financial institutions globally. As banks and financial institutions at this point were heavily investing in MBS and CDOs or had offered Credit Default Swaps (CDS) on those securities, essentially insuring them against default, the erosion of securities value delivered substantial losses to them. The financial institutions in order to finance these entities had heavily borrowed money, essentially operating on high leverage.

Multiple Linear Regression Model for Mortgage Interest Rate

Multiple linear regression is a powerful statistical technique used to analyse the relationship between a dependent variable and multiple independent variables. In the context of mortgage interest rates, understanding the factors influencing these rates is crucial for various stakeholders in the housing market, including homebuyers, lenders, and policymakers. By fitting a multiple linear regression model, we can quantify the impact of various economic indicators on mortgage interest rates and make predictions based on historical data.

The analysis was conducted in Python and the following dataset was chosen – US Macro-Economic Factors data from 2002-2022. This dataset contains month-wise details about all the macro-economic factors of US over two decades from 05/2002 to 05/2022. The data was sourced and compiled from official websites of US government like FRED, CENSUS, OECD, Conference Board.

We start by data exploration which involves visualising the relationships between the dependent variable (mortgage interest rates) and independent variables (economic indicators). The average mortgage interest rate is plotted against the year, providing an initial glimpse into the trend over time (see Figure 3). This scatterplot allows us to observe any potential patterns between the variables.

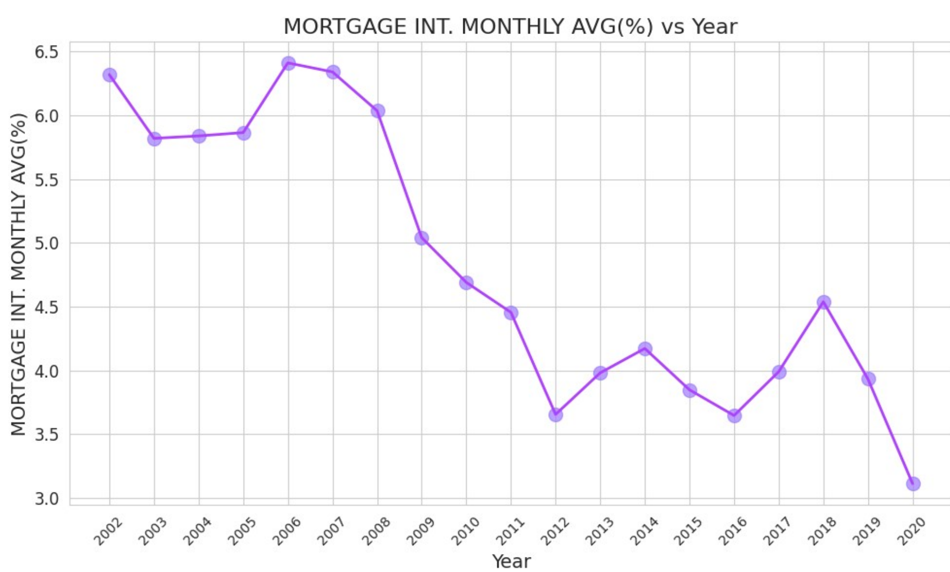


Figure 3 – Mortgage Interest Rate Plotted against Year variable

Once the exploratory analysis is complete, the next step taken is to fit multiple linear regression models to the data and choose the best model based on the AIC (Akaike Information Criterion) score – the lower the score, the better the model, however, AIC cannot be negative.
The output of the regression models provides valuable insights into the relationship between mortgage interest rates and the selected independent variables. The model with the lowest AIC score (7.814) turned out to be the one with Unemployment Rate, Consumer Confidence Index, Producers purchase index, Inflation Rate, Corporate Bond Yield and Monthly Home Supply predictor variables. The coefficients associated with each independent variable indicate the magnitude and direction of their impact on the dependent variable (mortgage interest rates)(see Figure 4).

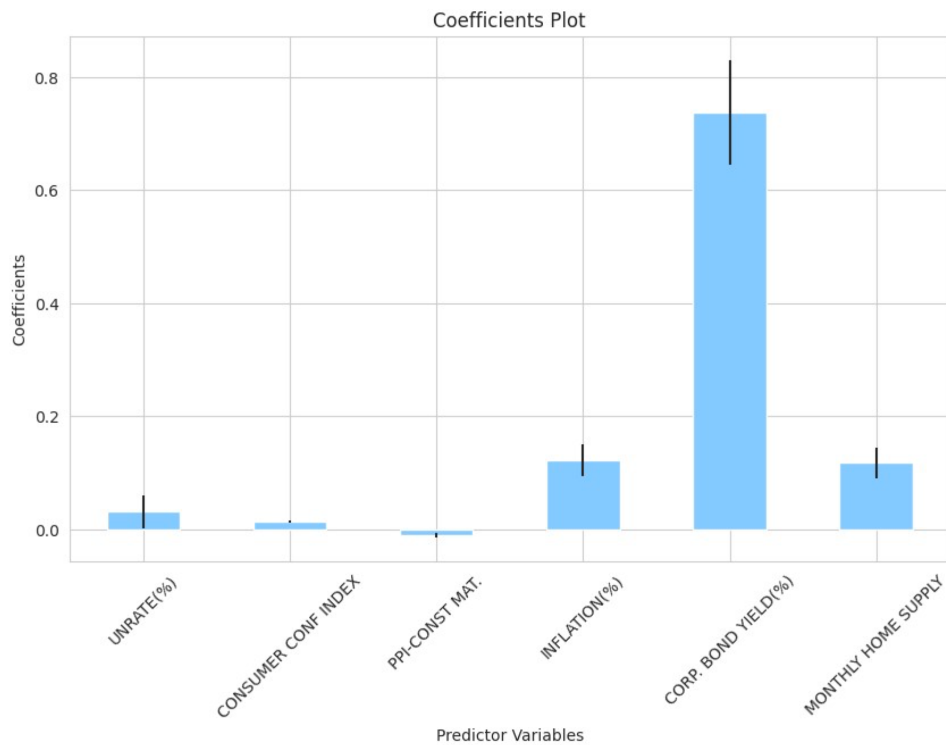


Figure 4 – Coefficients Plot for the model with the lowest AIC score

The coefficient of determination (R-squared) measures the proportion of variance in the dependent variable that is explained by the independent variables included in the model. In this case, the R-squared value of 0.951 indicates that approximately 95.1% of the variability in mortgage interest rates can be explained by the independent variables in the model.

Furthermore, the F-statistic and associated p-value assess the overall significance of the regression model. A low p-value (< 0.05) indicates that the regression model is statistically significant, suggesting that at least one independent variable has a non-zero effect on the dependent variable.

Furthermore, we create a scatterplot which compares the predicted mortgage interest rates generated by the best multiple linear regression model (**model1**) to the actual observed values (see Figure 5).

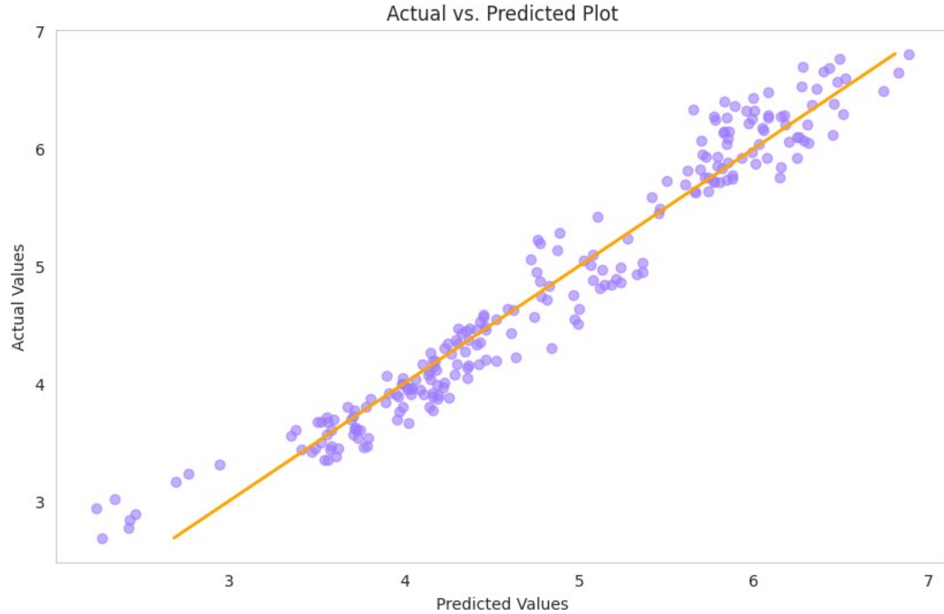


Figure 5 – Scatterplot – The actual observed values plotted against the predicted mortgage interest rates

In conclusion, fitting a multiple linear regression model to analyse mortgage interest rates allows us to identify significant economic indicators and their impact on interest rate fluctuations. By understanding these relationships, stakeholders can make informed decisions in the housing market, whether it's predicting future interest rates, assessing risk, or implementing policy measures.

References

Acharya, V., Philippon, T., Richardson, M., & Roubini, N. (2009). The Financial Crisis of 20072009: Causes and Remedies. *Financial Markets, Institutions & Instruments*, 18(2), 89–137.

Agarwal, S., Barrett, J., Cun, C. and De Nardi, M. (2010). The Asset-Backed Securities Markets, the Crisis, and TALF. *Economic Perspective*s, 34(4).

Benmelech, E. (2010). The Credit Rating Crisis. NBER. Available at: https://www.nber.org/reporter/2010number1/credit-rating-crisis (Accessed: 14 March 2024).

C. Spatt, *"Credit Ratings Shopping, Selection and the Equilibrium Structure of Ratings,"* Working Paper, November 2008

E. Damiano, H. Li, and W. Suen*, "Credible Ratings,"*Theoretical Economics*, 3 (September 2008), pp. 325-65. F. Sangiorgi, J. Sokobin,*

Financial Conduct Authority; (2019) *Credit Rating Agencies*. Available at URL (https://www.fca.org.uk/firms/credit-rating-agencies)

Giovanni Ferri, How regulation of finance got it wrong and how it still does, (2013) Research Gate. Available at URL (https://www.researchgate.net/figure/The-bank-business-model-from-OTH-to-OTD_fig2_256374608)

Gorman, L. (2018). *Evaluating the Role of Credit Ratings in the 2008 Crisis.* NBER. Available at: https://www.nber.org/digest/aug18/evaluating-role-credit-ratings-2008-crisis (Accessed: 14 March 2024).

Gorton, G. (2009). The Subprime Panic. *European Financial Management*, 15(1), 10-46.

Gorton, G., & Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial Economics*, 104: 425–451.

Keys, B. J., Mukherjee, T., Seru, A., & Vig, V. (2010). Did Securitization Lead to Lax Screening? Evidence from Subprime Loans. *The Quarterly Journal of Economics*, 125(1), 307362. Kroszner, R. S., & Strahan, P. E. (2011). Financial Regulatory Reform: Challenges Ahead. *American Economic

P. Bolton, X. Freixas, and J. Shapiro*, "The Credit Ratings Game,"* NBER Working Paper No. 14712, February 2009

Purananandam, A. *Originate-to-Distribute Model and the Subprime Mortgage Crisis.* (2010), SSRN. Available at URL (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1167786)

Rosen, R. *The Impact of the originate-to-distribute model on banks before and during the financial crisis.* 2010-2020. EconStor. Available at URL (https://www.econstor.eu/bitstream/10419/70587/1/641316275.pdf)
Sabarwal, T. (2006). 'Common Structures of Asset-Backed Securities and Their Risks', *Corporate Ownership and Control*, 2(4).

US Macro-Economic Factors data from 2002-2022 – dataset chosen for the analysis. Available on Kaggle at URL (https://www.kaggle.com/datasets/sagarvarandekar/macroeconomicfactors-affecting-us-housing-prices/data)

Appendix

Multiple Linear Regression Model for Mortgage Interest Rate

```
import pandas as pd import numpy as np
import statsmodels.api as sm import
matplotlib.pyplot as plt import seaborn as
sns

data = pd.read_csv('/content/DATA.csv') data
```

{"summary":"{\n \"name\": \"data\",\n \"rows\": 241,\n \"fields\": [\n {\n \"column\":
\"DATE\",\n \"properties\": {\n
\"dtype\": \"object\",\n \"num_unique_values\": 241,\n
\"samples\": [\n \"01-05-2020\",\n \"01-11-2021\",\n \"01-11-2003\"\n],\n
\"semantic_type\": \"\",\n
\"description\": \"\"\n }\n },\n {\n \"column\":
\"UNRATE(%)\",\n \"properties\": {\n \"dtype\":
\"number\",\n \"std\": 1.987057709340361,\n \"min\":
3.5,\n \"max\": 14.7,\n \"num_unique_values\": 64,\n \"samples\": [\n 9.1,\n
9.9,\n 3.6\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"CONSUMER CONF INDEX\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
25.871004365392068,\n \"min\": 25.0,\n \"max\": 138.4,\n

\"num_unique_values\": 209,\n \"samples\": [\n 125.1,\ n 104.7,\n 94.5\n],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n }\ n },\n {\n \"column\": \"PPI-CONST MAT.\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\": 40.479899748439,\n \"min\": 143.8,\n \"max\": 352.857,\n
\"num_unique_values\": 203,\n \"samples\": [\n 264.6,\ n 313.083,\n 193.9\n],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n }\
n },\n {\n \"column\": \"CPIALLITEMS\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\": 11.087024876727213,\n \"min\": 75.8595375,\n \"max\": 123.3227996,\n \"num_unique_values\": 236,\n
\"samples\": [\n 101.6167617,\n 85.43690959,\n 87.20302763\n],\n
\"semantic_type\": \"\",\n
\"description\": \"\"\n }\n },\n {\n \"column\": \"INFLATION(%)\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 1.6416445561075286,\n \"min\": 2.097161358,\n \"max\": 8.581511485,\n
\"num_unique_values\": 241,\n \"samples\": [\n 0.117926351,\n 6.809002873,\n 1.765030341\ n],\n
\"semantic_type\": \"\",\n
\"description\": \"\"\n }\n },\n {\n \"column\": \"MORTGAGE INT. MONTHLY AVG(%)\",\n \"properties\": {\n
\"dtype\": \"number\",\n \"std\": 1.119850144908779,\n
\"min\": 2.684,\n \"max\": 6.806,\n
\"num_unique_values\": 230,\n \"samples\": [\n 5.484,\
n 3.47,\n 2.868\n],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n }\ n },\n {\n \"column\": \"MED HOUSEHOLD INCOME\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\": 7475.321506329884,\n \"min\": 42409.0,\n \"max\": 68703.0,\n \"num_unique_values\": 19,\n \"samples\": [\n 67521.0,\n 56516.0,\n 49777.0\n],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\ n },\n {\n \"column\": \"CORP. BOND YIELD(%)\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\": 1.0790039285702282,\n \"min\": 2.14,\n \"max\": 6.75,\n \"num_unique_values\": 177,\n
\"samples\": [\n 2.35,\n 3.87,\n 5.44\n],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\n },\n {\n \"column\": \"MONTHLY HOME SUPPLY\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 1.895763366392405,\n \"min\": 3.3,\n \"max\": 12.2,\n \"num_unique_values\": 68,\n \"samples\": [\n 7.4,\n 3.4,\n 5.6\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n

}\n   },\n   {\n   \"column\": \"% SHARE OF WORKING POPULATION\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0.802917621647184,\n   \"min\":

64.92412865,\n \"max\": 67.29843266,\n
\"num_unique_values\": 20,\n \"samples\": [\n 64.92412865,\n
66.92166376,\n 67.26293826\ n],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\n },\n {\n \"column\": \"GDP
PER CAPITA\",\n \"properties\": {\n \"dtype\":
\"number\",\n \"std\": 8840,\n \"min\": 37860,\n
\"max\": 74737,\n \"num_unique_values\": 81,\n
\"samples\": [\n 55683,\n 74737,\n 58263\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"QUARTERLY REAL GDP\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
1708.435162072053,\n \"min\": 13477.356,\n \"max\": 19806.29,\n
\"num_unique_values\": 81,\n \"samples\": [\ n 17141.235,\n 19699.465,\n
17812.56\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"QUARTERLY GDP GROWTH RATE
(%)\",\n \"properties\": {\n \"dtype\": \"number\",\n
\"std\": 1.4539098656990375,\n \"min\": -8.937250501,\n
\"max\": 7.547534636,\n \"num_unique_values\": 81,\n
\"samples\": [\n 0.448993402,\n -0.14422708,\n 0.496888796\n],\n
\"semantic_type\": \"\",\n
\"description\": \"\"\n }\n },\n {\n \"column\":
\"CSUSHPISA\",\n \"properties\": {\n \"dtype\":
\"number\",\n \"std\": 36.780757753375376,\n \"min\": 120.724,\n \"max\": 304.831,\n
\"num_unique_values\":
241,\n \"samples\": [\n 148.185,\n 126.669,\n
232.673\n],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\n }\n]\ n}","type":"dataframe","variable_name":"data"}

Data Cleaning

```
# Checking for missing values missing_values
= data.isnull().sum()

# Printing the number of missing values for each
column print("Missing values per column:") print(missing_values)
```

```
Missing values per column:

DATE                         0
UNRATE(%)                    0 CONSUMER
CONF INDEX                   0 PPI-CONST MAT.
0 CPIALLITEMS                0
INFLATION(%)                 0 MORTGAGE
INT.   MONTHLY  AVG(%)       0   MED
HOUSEHOLD INCOME            17
```

```
CORP. BOND YIELD(%)              0 MONTHLY HOME SUPPLY              0 % SHARE OF
WORKING POPULATION     5 GDP PER CAPITA                 0
QUARTERLY REAL GDP                   0 QUARTERLY
GDP GROWTH RATE (%)              0 CSUSHPISA
0 dtype: int64
```

```
# Deleting rows with missing values
data = data.dropna()

# Checking for missing values missing_values
= data.isnull().sum()

# Printing the number of missing values for each
column print("Missing values per column:") print(missing_values)
```

```
Missing values per column:
DATE                          0
UNRATE(%)                   0 CONSUMER CONF INDEX
0 PPI-CONST MAT.                          0 CPIALLITEMS
0
INFLATION(%)                    0 MORTGAGE INT.
MONTHLY AVG(%)        0 MED HOUSEHOLD
INCOME           0
CORP. BOND YIELD(%)            0 MONTHLY
HOME SUPPLY                   0 % SHARE OF
WORKING POPULATION        0 GDP PER
CAPITA                  0
QUARTERLY REAL GDP                 0 QUARTERLY
GDP GROWTH RATE (%)           0 CSUSHPISA
0 dtype: int64
```

```
# Converting 'Date' column to datetime format
data['DATE'] = pd.to_datetime(data['DATE'])

# Extracting year from the 'Date' column data['Year']
= data['DATE'].dt.year
```

```
<ipython-input-6-e973746631fd>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html# returning-a-view-versus-a-copy
  data['DATE'] = pd.to_datetime(data['DATE'])
```

<ipython-input-6-e973746631fd>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html# returning-a-view-versus-a-copy data['Year'] = data['DATE'].dt.year data.head()

{"summary":"{\n \"name\": \"data\",\n \"rows\": 224,\n \"fields\": [\n {\n \"column\": \"DATE\",\n \"properties\": {\n \"dtype\": \"date\",\n \"min\": \"2002-01-05 00:00:00\",\n \"max\": \"2020-01-12 00:00:00\",\n \"num_unique_values\": 224,\n \"samples\": [\n \"2020-01-03 00:00:00\",\n \"2013-01-12 00:00:00\",\n \"2011-01-03 00:00:00\"\ n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"UNRATE(%)\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 2.013569786412521,\n \"min\": 3.5,\n \"max\": 14.7,\n \"num_unique_values\": 63,\n \"samples\": [\n 4.5,\n 10.0,\n 6.7\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"CONSUMER CONF INDEX\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 26.039731625310456,\n \"min\": 25.0,\n \"max\": 138.4,\n \"num_unique_values\": 194,\n \"samples\": [\n 75.0,\n 135.1,\n 105.4\n],\n \"semantic_type\": \"\",\ n \"description\": \"\"\n }\n },\n {\n \"column\": \"PPI-CONST MAT.\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 26.946407993415335,\n \"min\": 143.8,\n \"max\": 248.0,\n \"num_unique_values\": 186,\n \"samples\": [\n 187.1,\ n 160.1,\n 150.2\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\
n },\n {\n \"column\": \"CPIALLITEMS\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 9.794821637435845,\n \"min\": 75.8595375,\n \"max\": 109.8967585,\n \"num_unique_values\": 219,\n \"samples\": [\n 89.31553433,\n 98.20941114,\n 75.9861107\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"INFLATION(%)\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 1.256734011993761,\n \"min\": 2.097161358,\n \"max\": 5.600122908,\n \"num_unique_values\": 224,\n \"samples\": [\n 1.539326963,\n 1.501735618,\n 2.681603255\ n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\":

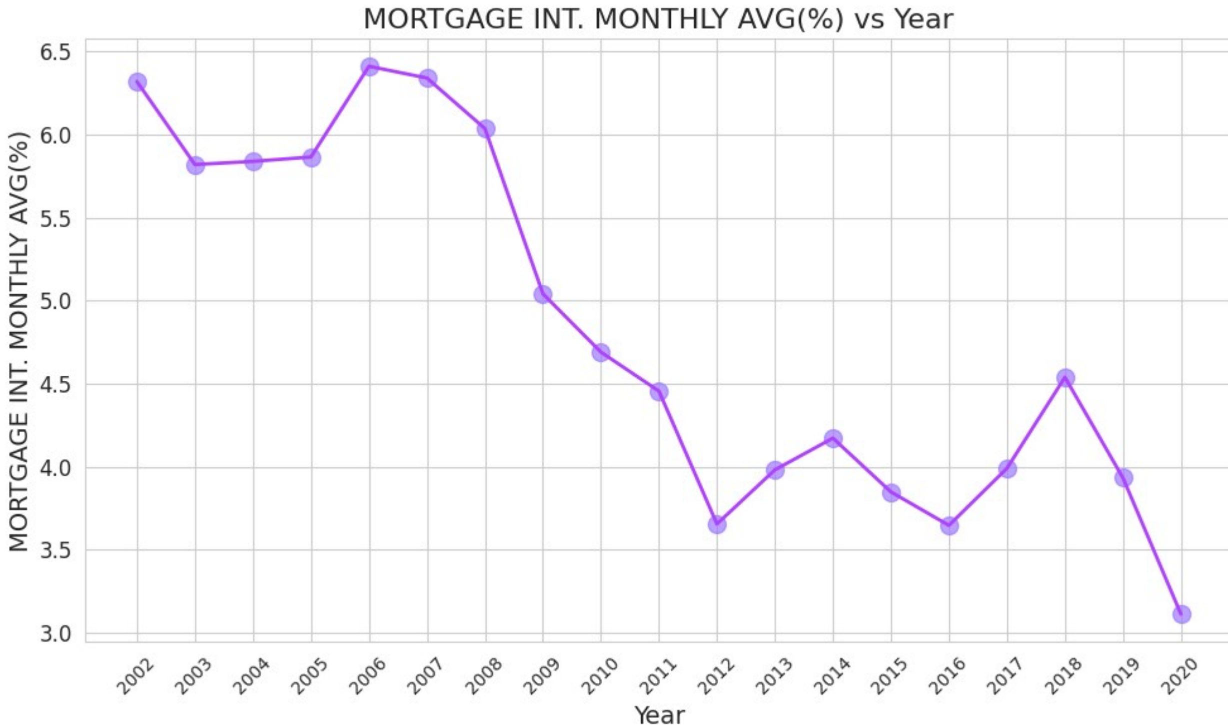
\"MORTGAGE INT. MONTHLY AVG(%)\",\n \"properties\": {\n
\"dtype\": \"number\",\n \"std\": 1.0776506719117496,\n
\"min\": 2.684,\n \"max\": 6.806,\n
\"num_unique_values\": 216,\n \"samples\": [\n
5.6325,\n 6.485,\n 6.0875\n],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\ n },\n {\n \"column\": \"MED HOUSEHOLD INCOME\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
7475.321506329884,\n \"min\": 42409.0,\n \"max\":
68703.0,\n \"num_unique_values\": 19,\n \"samples\": [\n
67521.0,\n 56516.0,\n 49777.0\n],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\ n },\n {\n \"column\": \"CORP. BOND YIELD(%)\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
1.0220425990296402,\n \"min\": 2.14,\n \"max\": 6.75,\n \"num_unique_values\": 160,\n
\"samples\": [\n 5.61,\n
5.5,\n 5.52\n],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\n },\n {\n \"column\":
\"MONTHLY HOME SUPPLY\",\n \"properties\": {\n \"dtype\":
\"number\",\n \"std\": 1.938394923611979,\n \"min\":
3.3,\n \"max\": 12.2,\n \"num_unique_values\": 67,\n \"samples\": [\n 7.3,\n
7.0,\n 3.9\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"% SHARE OF WORKING
POPULATION\",\n \"properties\": {\n \"dtype\":
\"number\",\n \"std\": 0.7444323666492891,\n \"min\":
65.08089532,\n \"max\": 67.29843266,\n
\"num_unique_values\": 19,\n \"samples\": [\n
65.08627785,\n 66.11387763,\n 67.1707618\ n],\n
\"semantic_type\": \"\",\n
\"description\": \"\"\n }\n },\n {\n \"column\": \"GDP
PER CAPITA\",\n \"properties\": {\n \"dtype\":
\"number\",\n \"std\": 7606,\n \"min\": 37860,\n
\"max\": 65501,\n \"num_unique_values\": 75,\n
\"samples\": [\n 65501,\n 43285,\n 62377\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"QUARTERLY REAL GDP\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
1552.2498327736198,\n \"min\": 13477.356,\n \"max\": 19202.31,\n
\"num_unique_values\": 75,\n \"samples\": [\ n 19202.31,\n 14767.846,\n
18590.004\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"QUARTERLY GDP GROWTH RATE
(%)\",\n \"properties\": {\n \"dtype\": \"number\",\n
\"std\": 1.486057114305515,\n \"min\": -8.937250501,\n
\"max\": 7.547534636,\n \"num_unique_values\": 75,\n

\"samples\": [\n 0.469097618,\n 1.110882508,\n 0.833910909\n],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\":

\"CSUSHPISA\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 35.68899907559635,\n \"min\": 136.529,\n \"max\": 304.831,\n \"num_unique_values\": 224,\n \"samples\": [\n 151.338,\n 142.525,\n 155.606\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"Year\",\n \"properties\": {\n \"dtype\": \"int32\",\n \"num_unique_values\": 19,\n \"samples\": [\n 2020,\n 2015,\n 2009\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n }\n]\ n}","type":"dataframe","variable_name":"data"}

Data Exploration

```
# Setting style sns.set_style("whitegrid")

# Grouping by year and calculating the average mortgage interest rate for each year
average_interest_by_year = data.groupby('Year')['MORTGAGE INT. MONTHLY AVG(%)'].mean().reset_index()

# Plotting scatterplot with customized aesthetics plt.figure(figsize=(10, 6))
plt.scatter(average_interest_by_year['Year'],
average_interest_by_year['MORTGAGE INT. MONTHLY AVG(%)'], marker='o', color='#9E7BFF', alpha=0.7, s=100) plt.plot(average_interest_by_year['Year'],
average_interest_by_year['MORTGAGE INT. MONTHLY AVG(%)'], color='#B041FF', linestyle='-', linewidth=2)
plt.title('MORTGAGE INT. MONTHLY AVG(%) vs Year', fontsize=16) plt.xlabel('Year', fontsize=14)
plt.ylabel('MORTGAGE INT. MONTHLY AVG(%)', fontsize=14)
plt.xticks(average_interest_by_year['Year'].astype(int), rotation=45) plt.yticks(fontsize=12)
plt.grid(True) plt.tight_layout() plt.show()
```



Fitting Multiple Linear Regression Model

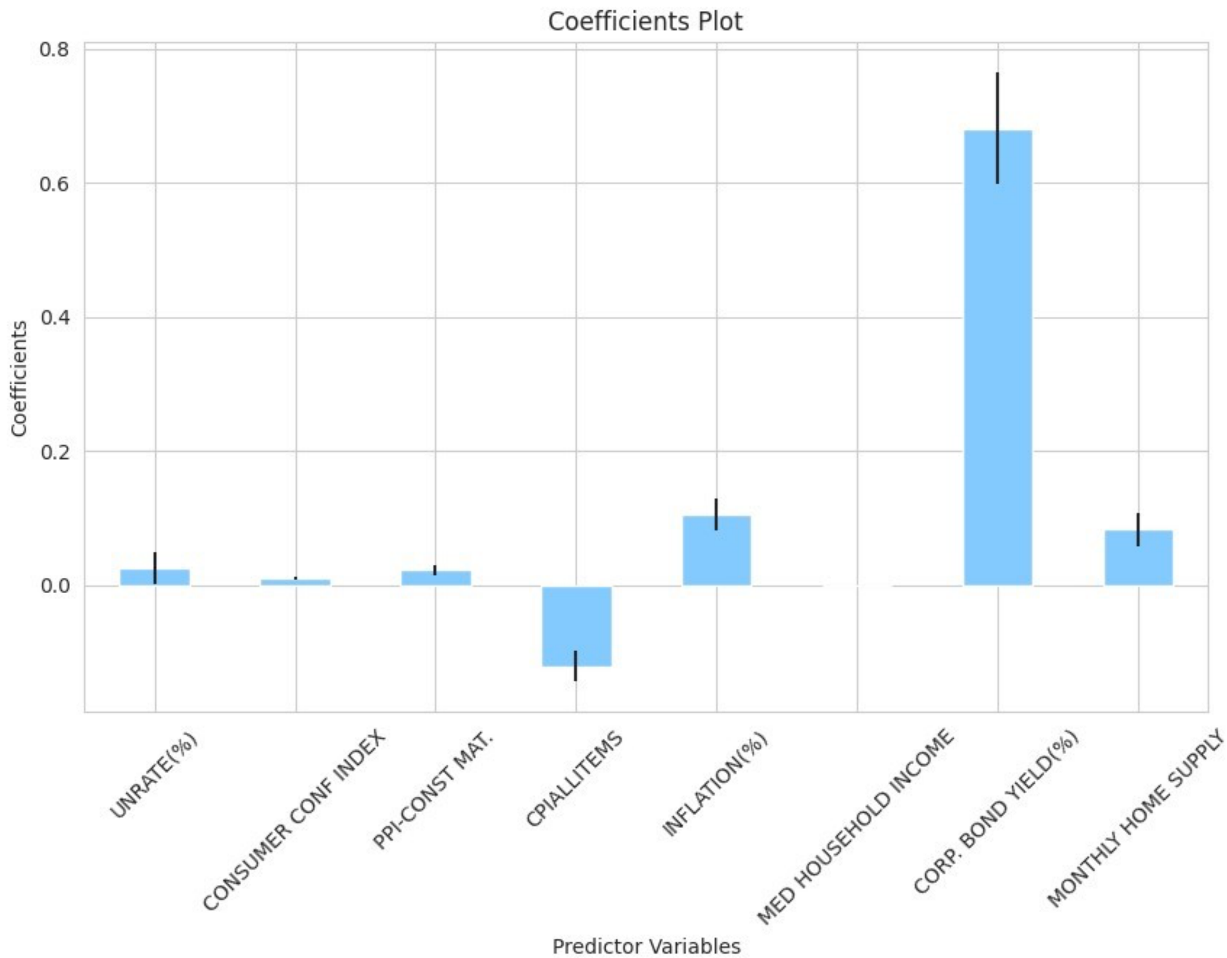
```
# Selecting predictor variables and response variable
X = data[['UNRATE(%)', 'CONSUMER CONF INDEX', 'PPI-CONST MAT.',
 'CPIALLITEMS', 'INFLATION(%)', 'MED HOUSEHOLD INCOME', 'CORP. BOND
 YIELD(%)', 'MONTHLY HOME SUPPLY']] y = data['MORTGAGE INT. MONTHLY
 AVG(%)']

# Adding a constant term to the predictor
variables X = sm.add_constant(X)

# Fitting Multiple Linear Regression
Model model = sm.OLS(y, X).fit()

print(model.summary())

OLS Regression Results
===============================================================================
==
==================
Dep. Variable:     MORTGAGE INT. MONTHLY AVG(%)   R-squared:         0.967
Model:                              OLS   Adj. R-squared:    0.966
Method:                   Least Squares   F-statistic:       797.3
Date:                  Thu, 04 Apr 2024   Prob (F-statistic):
3.04e-155
Time:                          06:15:30   Log-Likelihood:    49.298
```

```
No. Observations:                 224   AIC:
-80.60
Df Residuals:                     215   BIC:
-49.89
Df Model:                           8

Covariance Type:            nonrobust

==============================================================================
==
==================
                         coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
------------------
const                  4.8139      0.585      8.236      0.000
3.662       5.966
UNRATE(%)              0.0248      0.012      2.044      0.042
0.001       0.049
CONSUMER CONF INDEX      0.0098      0.001      7.616      0.000
0.007       0.012
PPI-CONST MAT.           0.0222      0.004      5.977      0.000
0.015       0.030
CPIALLITEMS            -0.1213      0.012    -10.407      0.000
-0.144      -0.098
INFLATION(%)             0.1046      0.012      8.483      0.000      0.080       0.129
MED HOUSEHOLD INCOME  3.978e-05   7.62e-06      5.221      0.000    2.48e-05    5.48e-05
CORP. BOND YIELD(%)      0.6811      0.042     16.152      0.000
0.598       0.764
MONTHLY HOME SUPPLY      0.0827      0.012      6.680      0.000
0.058       0.107
==============================================================================
== ========
Omnibus:                        6.255   Durbin-Watson:                 0.518
Prob(Omnibus):                  0.044   Jarque-Bera (JB):              6.355
Skew:                           0.411   Prob(JB):
0.0417
Kurtosis:                       2.936   Cond. No.                   2.38e+06
==============================================================================
== ========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

[2] The condition number is large, 2.38e+06. This might indicate that there are

strong multicollinearity or other numerical problems.

```
# Coefficients Plot plt.figure(figsize=(10, 6))
coefficients = model.params.drop('const')
coefficients.plot(kind='bar',
yerr=model.conf_int().diff(axis=1).iloc[:, 1]/2, color='#82CAFF') plt.title('Coefficients Plot') plt.xlabel('Predictor Variables') plt.ylabel('Coefficients') plt.xticks(rotation=45)
plt.show()
```




```
# Selecting predictor variables and response variable
X1 = data[['UNRATE(%)', 'CONSUMER CONF INDEX', 'PPI-CONST MAT.', 'INFLATION(%)', 'CORP. BOND YIELD(%)', 'MONTHLY HOME SUPPLY']] y1 = data['MORTGAGE INT. MONTHLY AVG(%)']
```

```
# Adding a constant term to the predictor variables X1 = sm.add_constant(X1)

# Fitting Multiple Regression Model without CPIALLITEMS and MED HOUSEHOLD INCOME variables model1 = sm.OLS(y1, X1).fit()
print(model1.summary())

                            OLS Regression Results
================================================================================
==
==================
Dep. Variable:     MORTGAGE INT. MONTHLY AVG(%)   R-squared:          0.951
Model:                                 OLS   Adj. R-squared:     0.949
Method:                      Least Squares   F-statistic:        698.0
Date:                     Thu, 04 Apr 2024   Prob (F-statistic):
7.53e-139
Time:                             06:15:30   Log-Likelihood:     3.0929
No. Observations:                      224   AIC:
7.814
Df Residuals:                          217   BIC:
31.70
Df Model:                                6

Covariance Type:                 nonrobust

================================================================================
==
==================
                     coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------
-----------------
const                1.1327      0.519      2.184      0.030
0.111       2.155
UNRATE(%)              0.0307      0.015      2.070      0.040
0.001       0.060
CONSUMER CONF INDEX     0.0137      0.001     10.763      0.000
0.011       0.016
PPI-CONST MAT.        -0.0104      0.002     -5.936      0.000      -
0.014      -0.007
INFLATION(%)           0.1224      0.014      8.486      0.000
0.094       0.151
CORP. BOND YIELD(%)     0.7370      0.047     15.607      0.000
0.644       0.830
MONTHLY HOME SUPPLY     0.1172      0.014      8.339      0.000
```

0.089 0.145
==
== ========
Omnibus: 6.653 Durbin-Watson: 0.441
Prob(Omnibus): 0.036 Jarque-Bera (JB): 6.785
Skew: 0.425 Prob(JB):
0.0336
Kurtosis: 2.937 Cond. No. 7.07e+03
==
== ========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.07e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
# Selecting predictor variables and response variable
X2 = data[['UNRATE(%)', 'CONSUMER CONF INDEX', 'PPI-CONST MAT.', 'CPIALLITEMS', 'INFLATION(%)', 'CORP. BOND YIELD(%)', 'MONTHLY HOME SUPPLY']]
y2 = data['MORTGAGE INT. MONTHLY AVG(%)']

# Adding a constant term to the predictor variables X2 = sm.add_constant(X2)

# Fitting Multiple Regression Model without CPIALLITEMS and MED HOUSEHOLD INCOME variables model2 = sm.OLS(y2, X2).fit()
print(model2.summary())
```

OLS Regression Results

==
==
===================
Dep. Variable: MORTGAGE INT. MONTHLY AVG(%) R-squared: 0.963
Model: OLS Adj. R-squared: 0.962
Method: Least Squares F-statistic: 808.9
Date: Thu, 04 Apr 2024 Prob (F-statistic):
3.80e-151
Time: 06:15:30 Log-Likelihood:
35.931
No. Observations: 224 AIC:
-55.86
Df Residuals: 216 BIC:
-28.57
Df Model: 7 Covariance Type: nonrobust

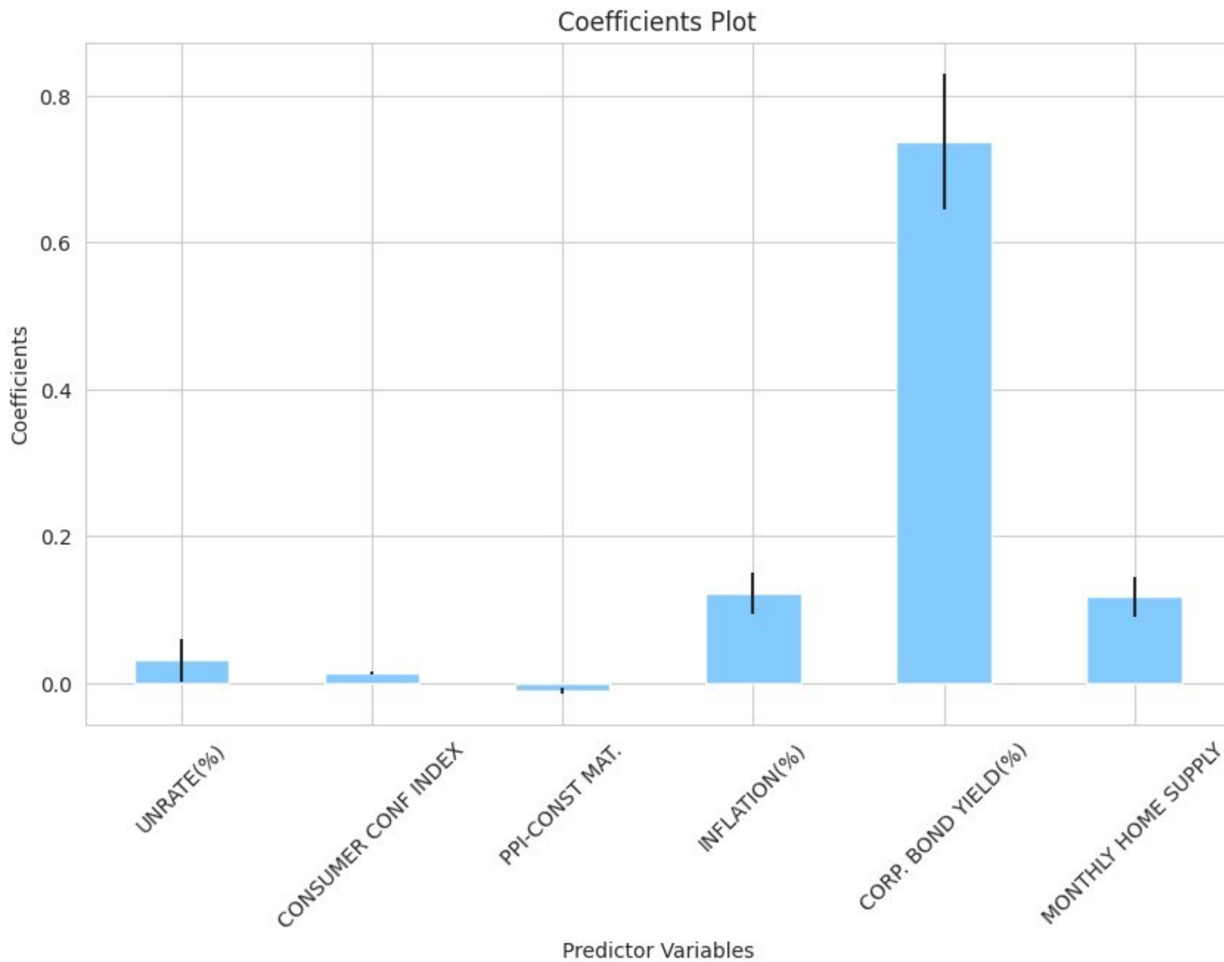
```
==============================================================================
==
==================
                         coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
------------------
const                  4.7895      0.619      7.737      0.000
3.569       6.010
UNRATE(%)              0.0288      0.013      2.244      0.026
0.004       0.054
CONSUMER CONF INDEX     0.0137      0.001     12.442      0.000
0.012       0.016
PPI-CONST MAT.         0.0205      0.004      5.238      0.000
0.013       0.028
CPIALLITEMS           -0.0973      0.011     -8.579      0.000      -
0.120      -0.075
INFLATION(%)           0.0946      0.013      7.333      0.000
0.069       0.120
CORP. BOND YIELD(%)     0.6220      0.043     14.460      0.000
0.537       0.707
MONTHLY HOME SUPPLY     0.1060      0.012      8.667      0.000
0.082       0.130
==============================================================================
== ========
Omnibus:                       15.630   Durbin-Watson:                   0.562
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               16.886
Skew:                           0.617   Prob(JB):
0.000215
Kurtosis:                       3.533   Cond. No.                     1.06e+04
==============================================================================
== ========

Notes:
[1]   Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2]   The condition number is large, 1.06e+04. This might indicate that there are strong
multicollinearity or other numerical problems.
```

Calculating AICs for model, model1 and model2 - choosing the best model based on the AICs' values. The lower AIC, the better the model. AIC cannot be negative. The best model is model1.

```
from statsmodels.tools.eval_measures import aic

#   Computing   AIC   for   model
nobs_model      =      len(model.model.endog)
df_model = len(model.params)
aic_model = aic(model.llf, nobs_model, df_model)

# Computing AIC for model1
nobs_model1    =    len(model1.model.endog)    df_model1    =
len(model1.params)
aic_model1 = aic(model1.llf, nobs_model1, df_model1)

# Computing AIC for model2
nobs_model2    =    len(model2.model.endog)    df_model2    =
len(model2.params)
aic_model2 = aic(model2.llf, nobs_model2, df_model2) aic_model
-80.59592345202714
aic_model1
7.814290304356632
aic_model2

-55.861806233654534
```

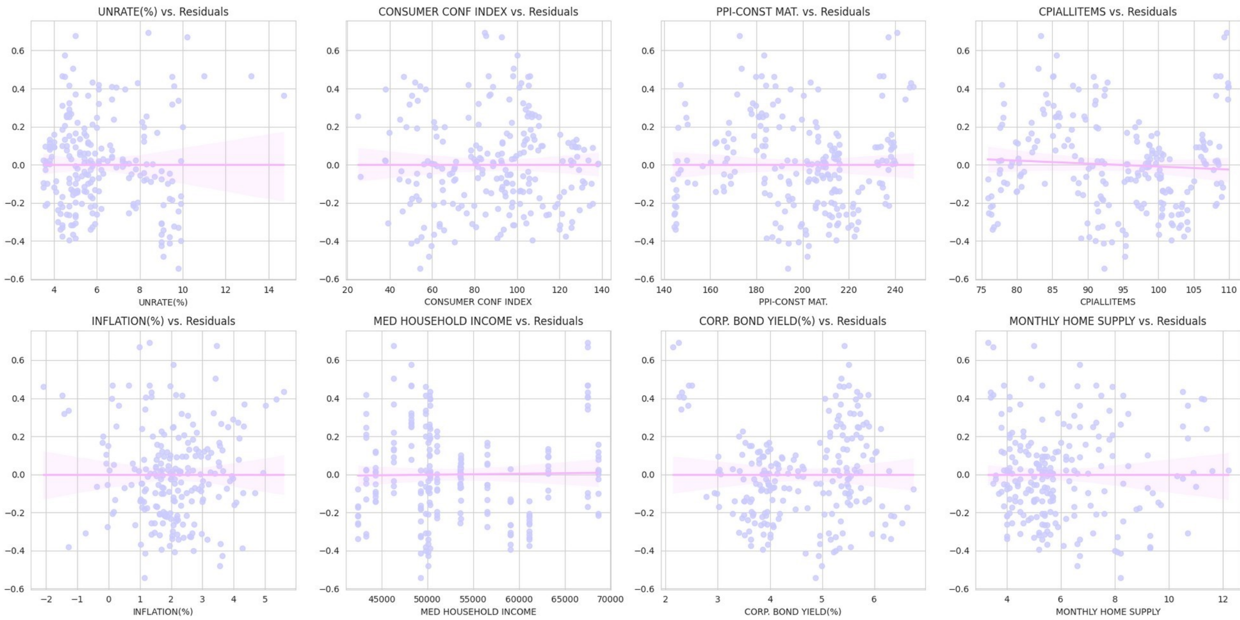
Coefficients Plot for the final model1

```
# Coefficients Plot for Final model1 plt.figure(figsize=(10, 6))
coefficients = model1.params.drop('const') coefficients.plot(kind='bar',
yerr=model1.conf_int().diff(axis=1).iloc[:,   1]/2,   color='#82CAFF')   plt.title('Coefficients
Plot')   plt.xlabel('Predictor   Variables')   plt.ylabel('Coefficients')   plt.xticks(rotation=45)
plt.show()
```



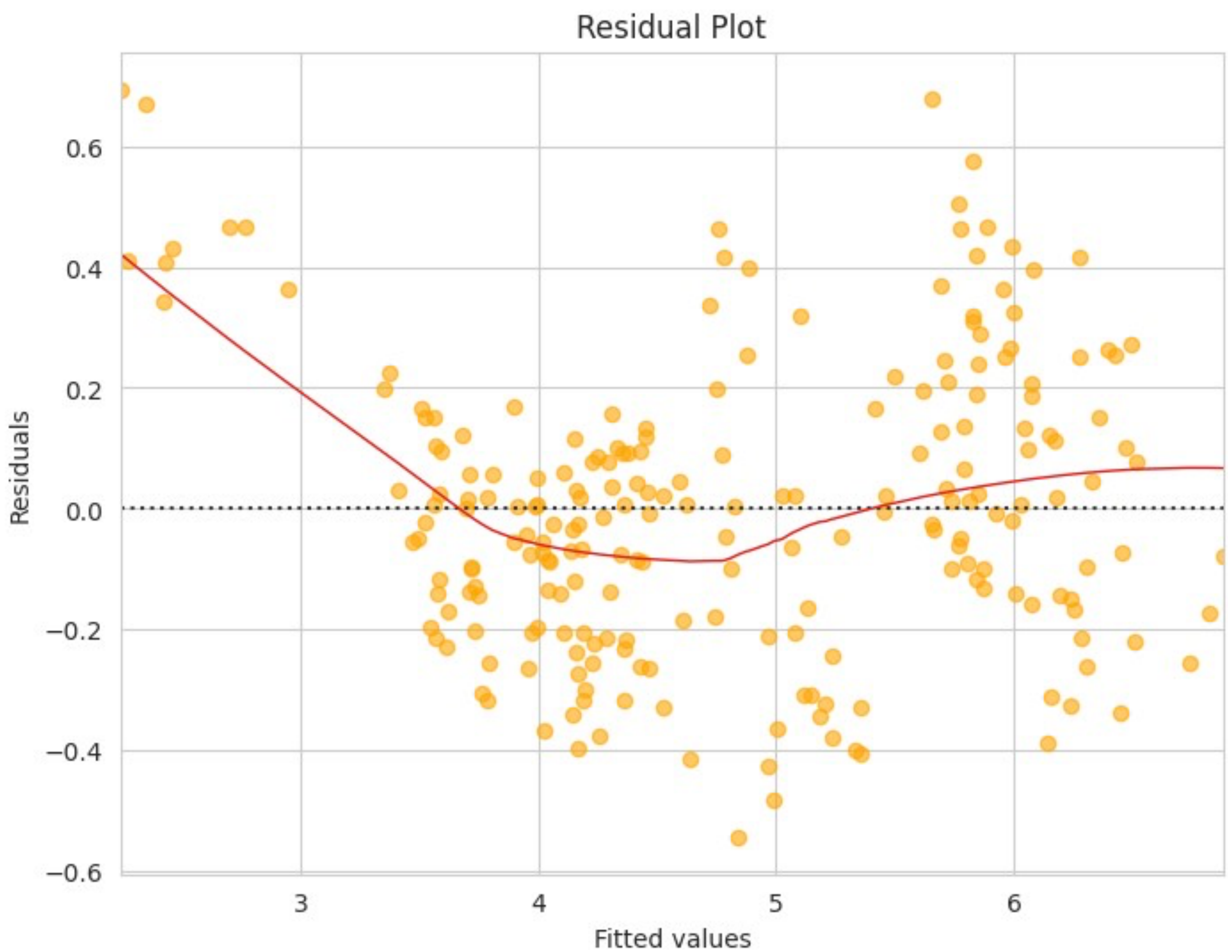
Partial Regression Plots

```
# Partial Regression Plots
fig, axs = plt.subplots(2, 4, figsize=(20, 10)) for i, col in enumerate(X.columns[1:]):
sns.regplot(x=X[col], y=model1.resid, ax=axs[i//4, i%4], line_kws={'color': '#F9B7FF'},
scatter_kws={'color': '#CCCCFF'})          axs[i//4, i%4].set_title(f'{col} vs. Residuals')
plt.tight_layout() plt.show()
```



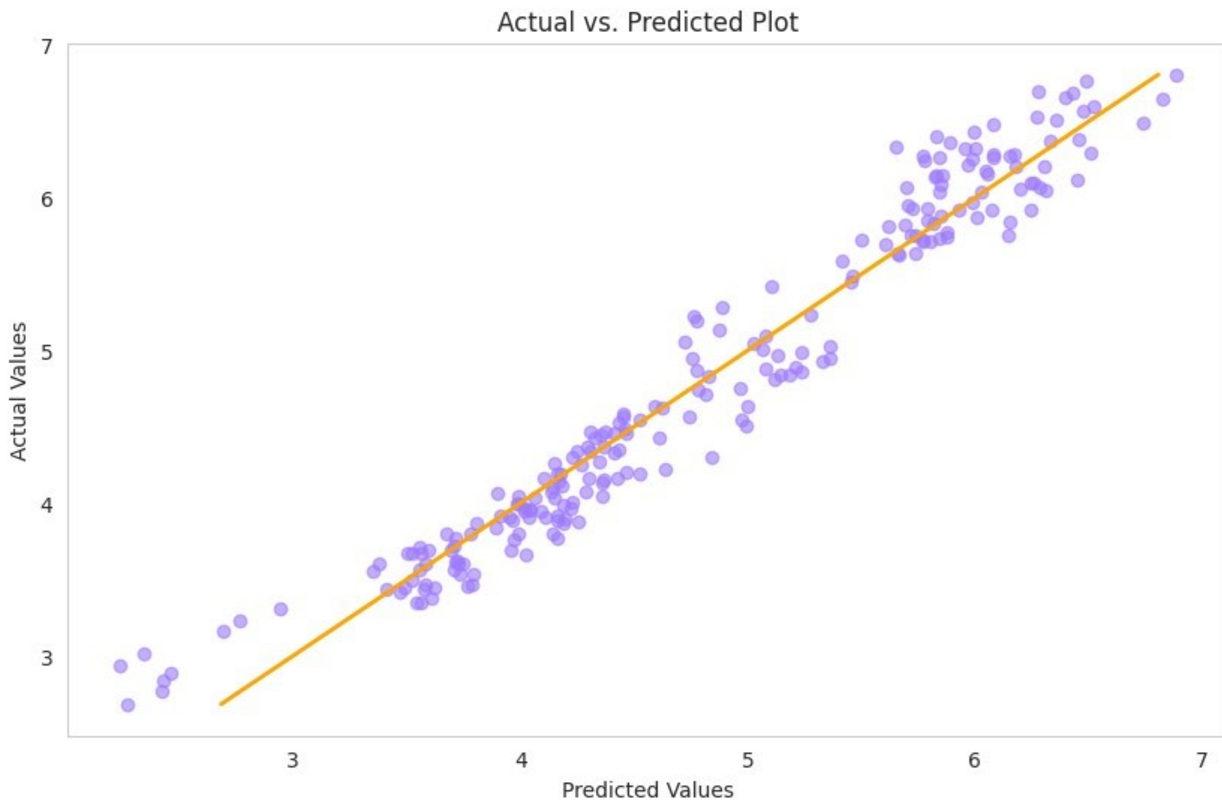
Residual Plot

```
# Residual Plot
plt.figure(figsize=(8, 6))
sns.residplot(x=model1.fittedvalues, y=model1.resid, lowess=True, scatter_kws={'color':
'#FFA500', 'alpha': 0.6}, line_kws={'color':
'#E41B17', 'lw': 1}) plt.title('Residual Plot')
plt.xlabel('Fitted values')
plt.ylabel('Residuals') plt.show()
```



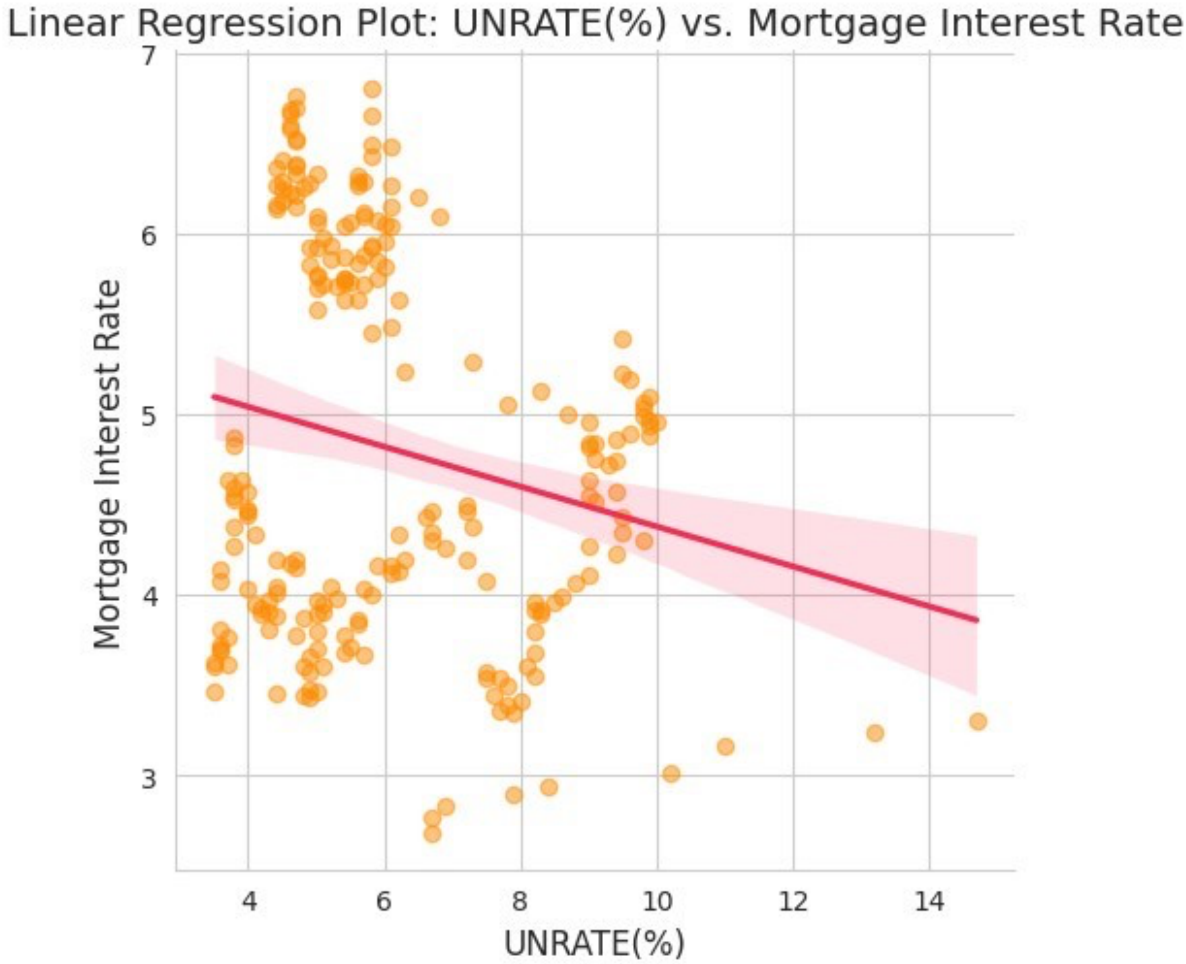
Actual vs Predicted Plot

```
# Actual vs. Predicted Plot plt.figure(figsize=(10, 6))
plt.scatter(model1.fittedvalues, y, color='#9E7BFF', alpha=0.6) plt.plot([y.min(), y.max()],
[y.min(), y.max()], color='#FFA500', lw=2)
plt.title('Actual vs. Predicted Plot')
plt.xlabel('Predicted Values') plt.ylabel('Actual
Values') plt.grid(False) plt.show()
```

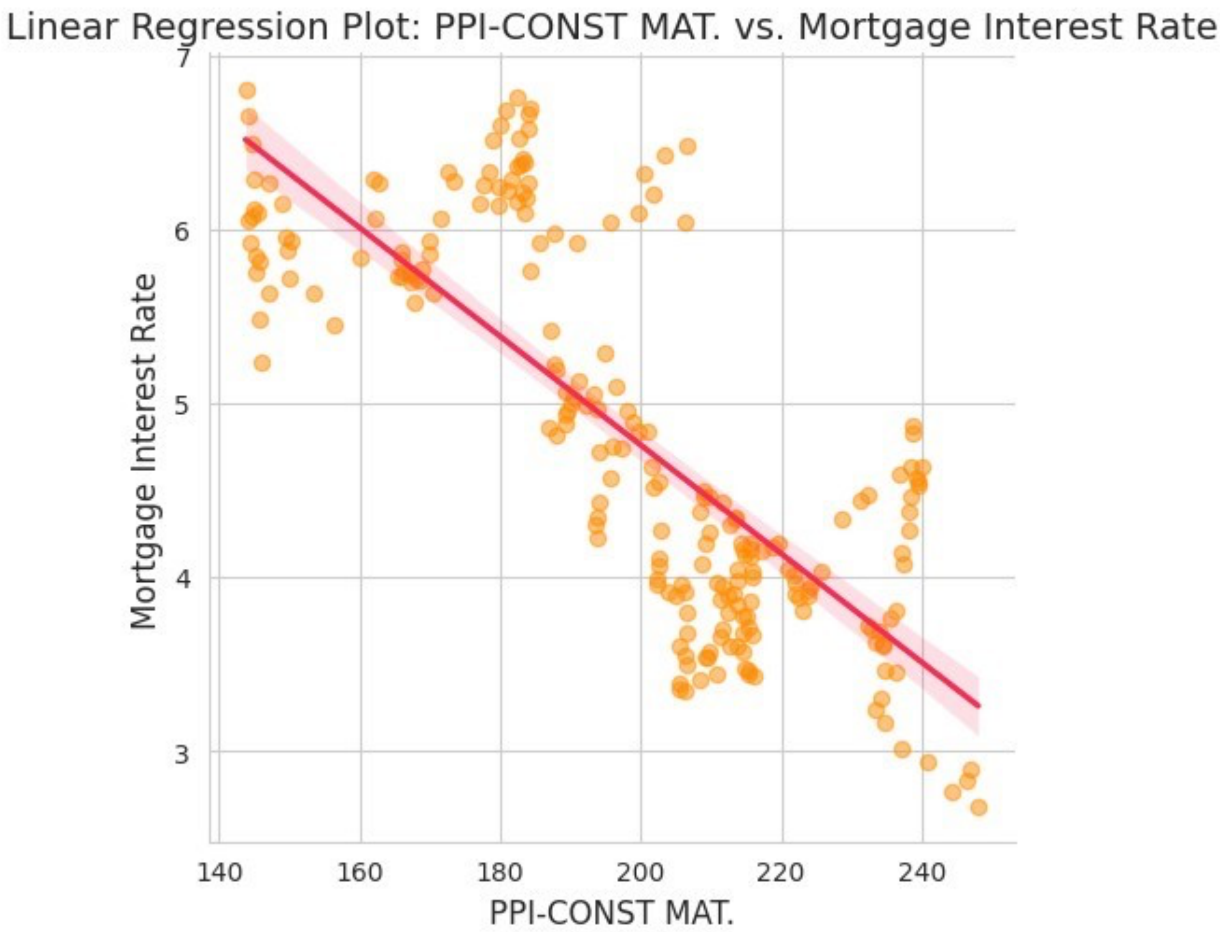


Linear Regression Plots for Each Predictor Variable

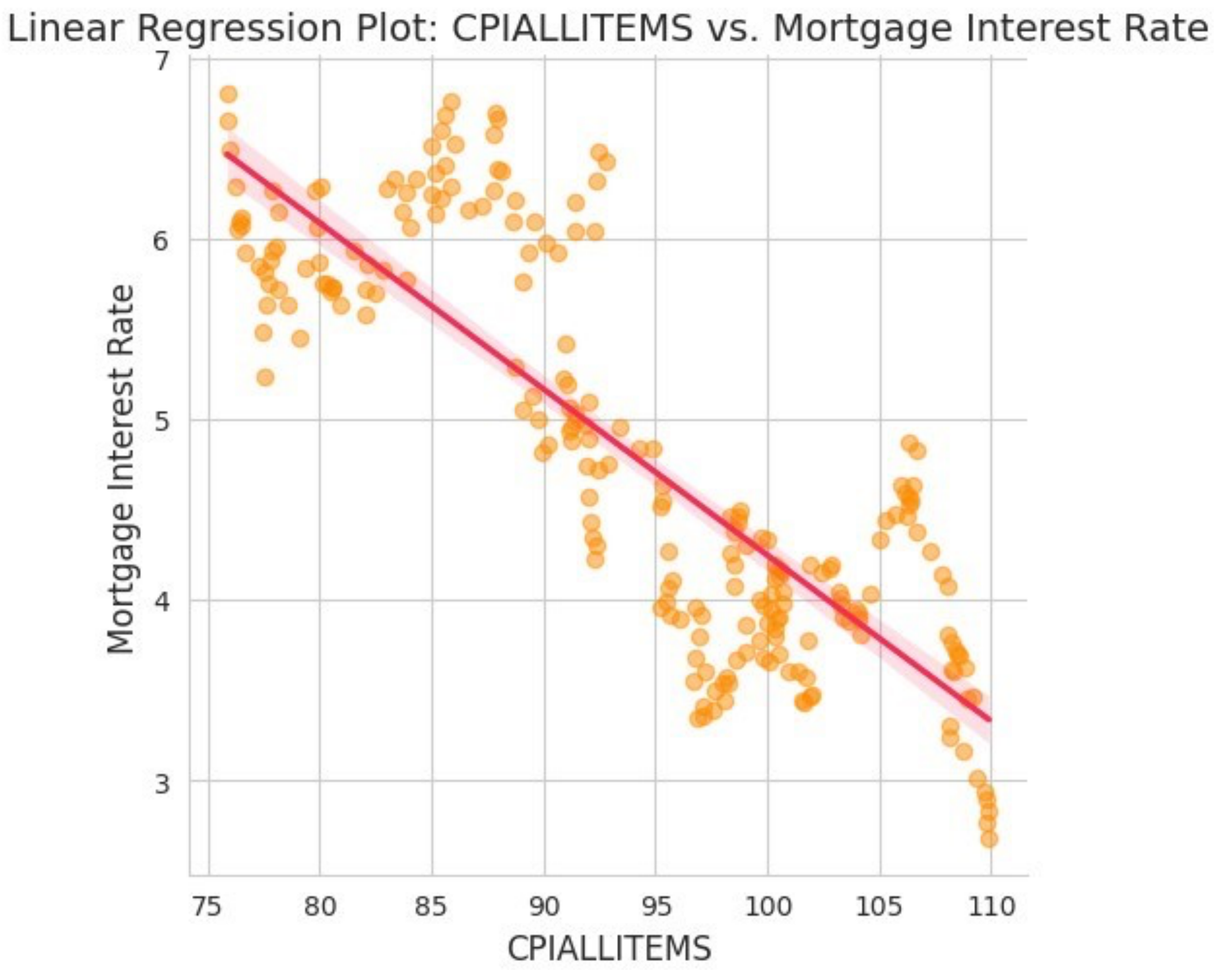
```
# Plotting linear regression plots for each predictor variable for predictor in X.columns[1:]:     sns.lmplot(x=predictor, y='MORTGAGE INT. MONTHLY AVG(%)', data=data, scatter_kws={'color': '#FF8C00', 'alpha': 0.5},
line_kws={'color': '#FA2A55'})
    plt.title(f'Linear Regression Plot: {predictor} vs. Mortgage Interest Rate', fontsize=14)
plt.xlabel(predictor, fontsize=12)
    plt.ylabel('Mortgage Interest Rate', fontsize=12)    plt.show()
```


Linear Regression Plot: UNRATE(%) vs. Mortgage Interest Rate
Mortgage Interest Rate
UNRATE(%)
7
6
5
4
3
4
6
8
10
12
14

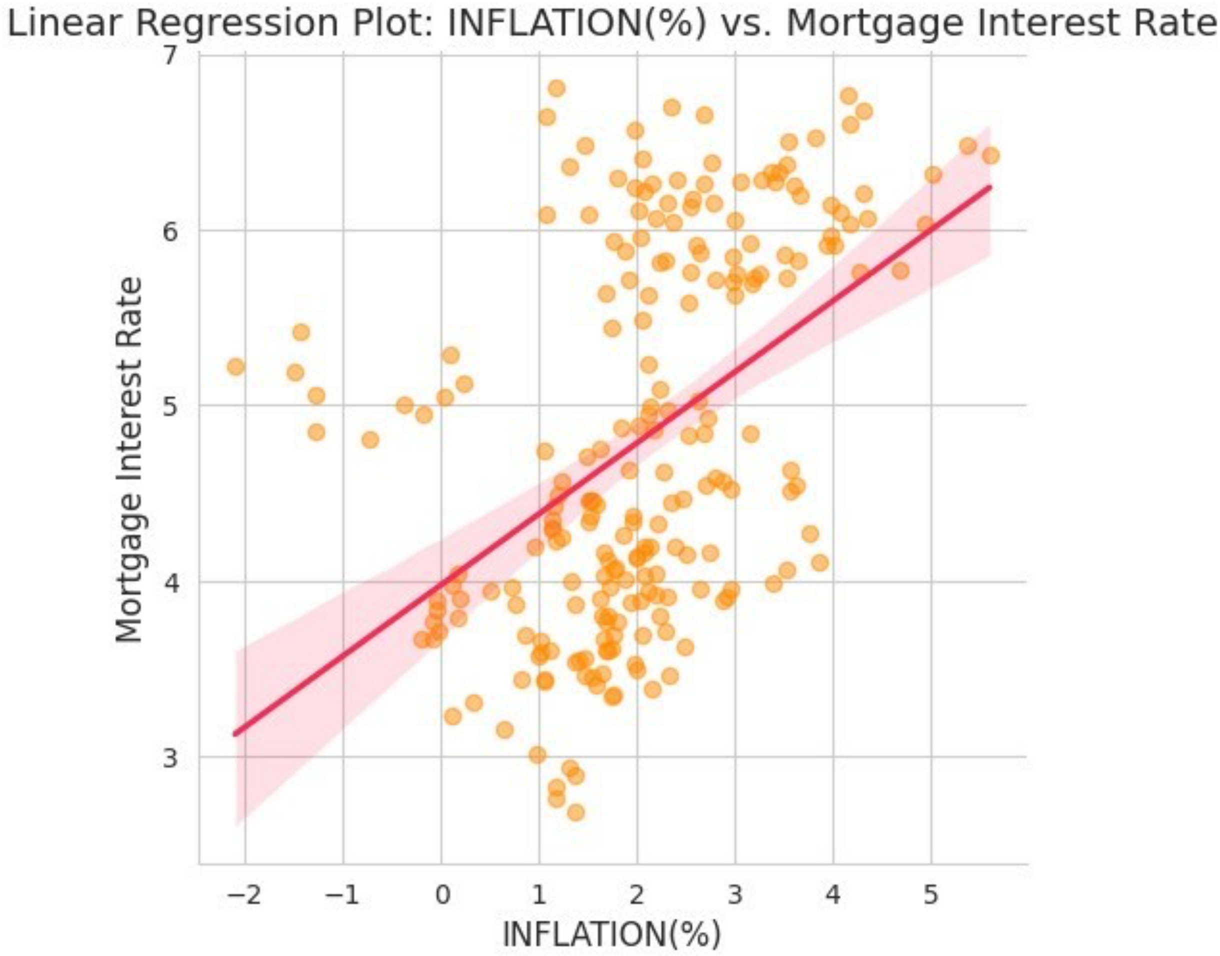

Linear Regression Plot: CONSUMER CONF INDEX vs. Mortgage Interest Rate
Mortgage Interest Rate
CONSUMER CONF INDEX
7
6
5
4
3
20
40
60
80
100
120
140



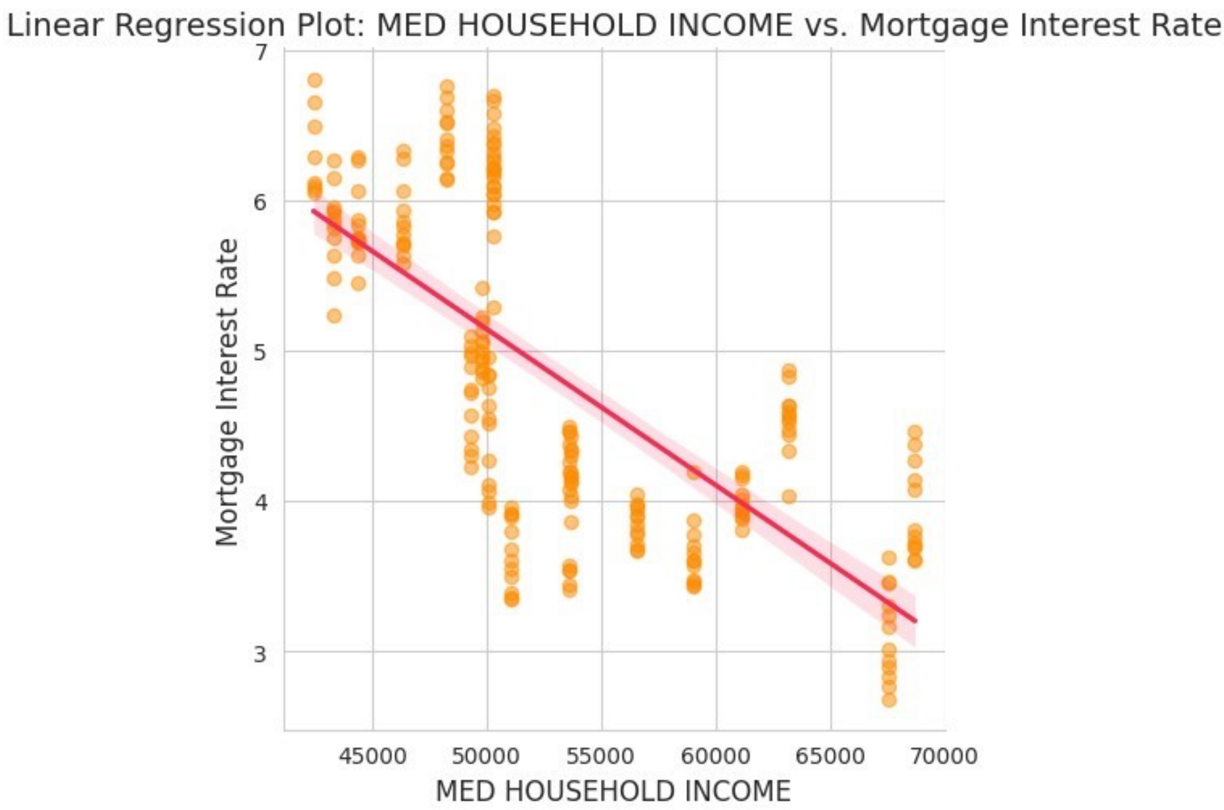
Linear Regression Plot: PPI-CONST MAT. vs. Mortgage Interest Rate
Mortgage Interest Rate
PPI-CONST MAT.
7
6
5
4
3
140
160
180
200
220
240



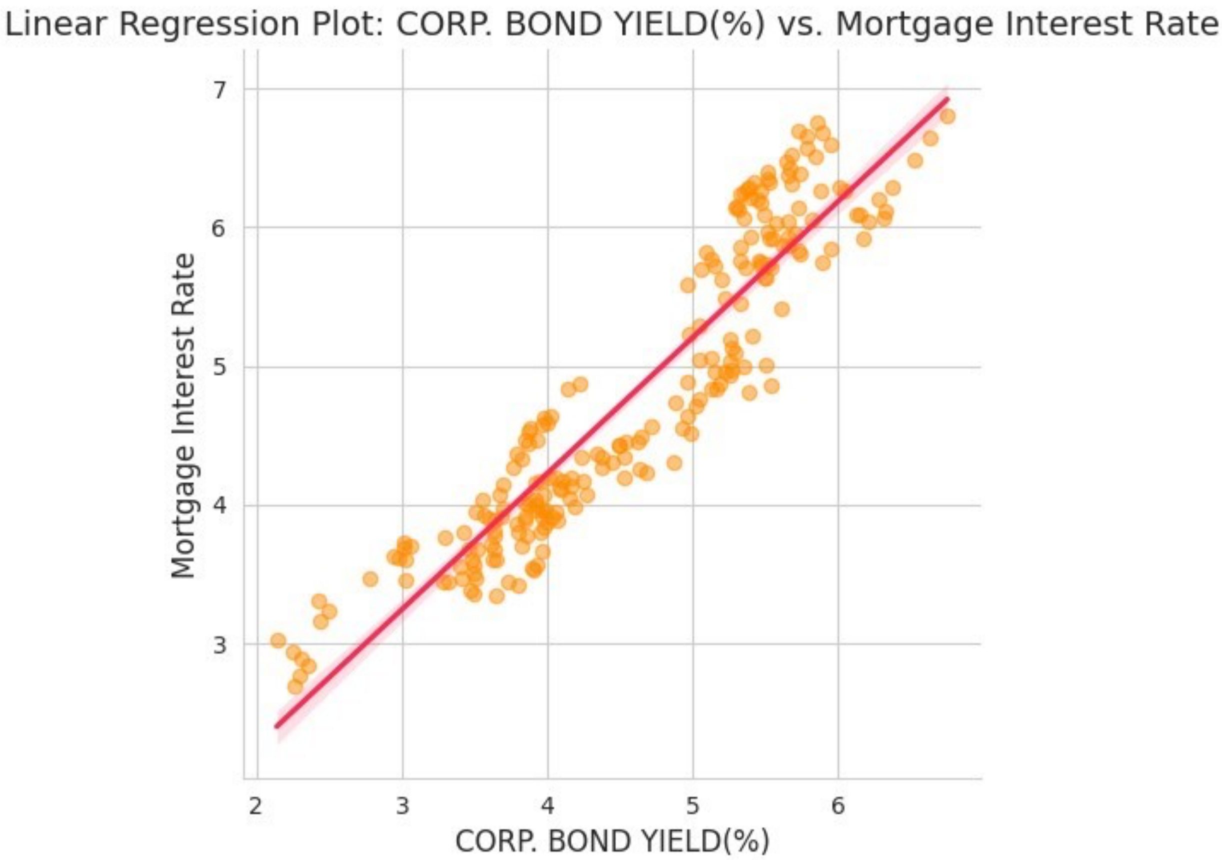
Linear Regression Plot: CPIALLITEMS vs. Mortgage Interest Rate
Mortgage Interest Rate
CPIALLITEMS
7
6
5
4
3
75
80
85
90
95
100
105
110

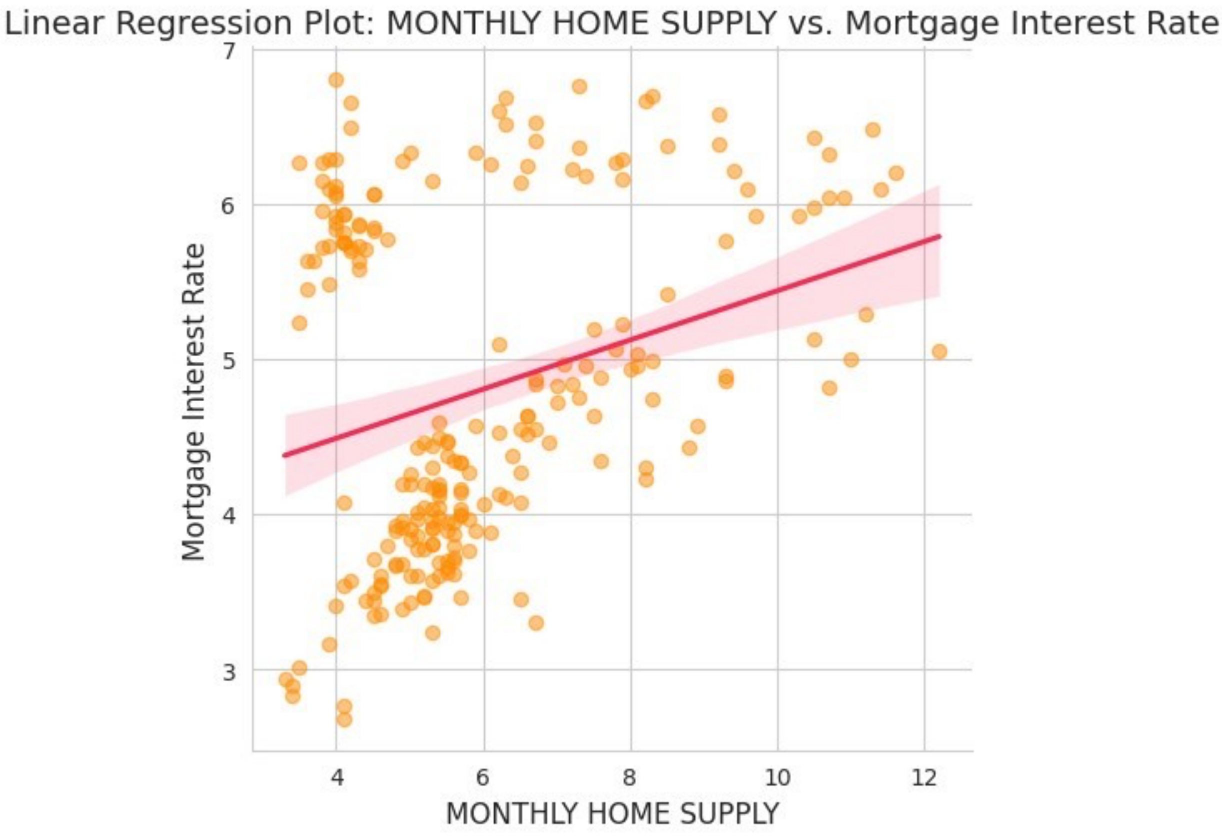


Linear Regression Plot: INFLATION(%) vs. Mortgage Interest Rate
Mortgage Interest Rate
INFLATION(%)
7
6
5
4
3
−2
−1
0
1
2
3
4
5



Linear Regression Plot: MED HOUSEHOLD INCOME vs. Mortgage Interest Rate
Mortgage Interest Rate
MED HOUSEHOLD INCOME
7
6
5
4
3
45000
50000
55000
60000
65000
70000


Linear Regression Plot: CORP. BOND YIELD(%) vs. Mortgage Interest Rate
Mortgage Interest Rate
7
6
5
4
3
2
3
4
5
6
CORP. BOND YIELD(%)


Linear Regression Plot: MONTHLY HOME SUPPLY vs. Mortgage Interest Rate
Mortgage Interest Rate
7
6
5
4
3
4
6
8
10
12
MONTHLY HOME SUPPLY