home loans

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Executive Summary

Overview	RiskyLending Pty Ltd specialises in brokering home loans and has a commission-based relationship with ConnBank. For the past three years, they've received a 4% commission on the value of each loan that remains stable, without clawback, for the first 12 months, but recently, Connbank has decided to reduce commission rates to 2.5% and increase the clawback period to 18 months		
Profitability	**Factors Impacting Profitability** Influence of age, income, and occupation demographics as well as interest rates on loan sizes and ultimately, profitability.	**Profitability Before Change** Prior to change in clawback period and commission rate there was stable profitability at **$103m**, influenced by key factors.	**Profitability After Change** Change in clawback period and commission rate caused reduction in profitability by **42%.**
Business Model Viability	**Types of Macroeconomic Factors** The impact of fluctuations in cash rate, inflation rates, unemployment and housing approvals on the size and amount of loans	**Macroeconomic Impact on Profits** Macroeconomic factors find a negative loan demand growth rate as well as a negative clawback growth rate	**Mitigation of Effects** Analyse the issue, assess market and customer impact, implement mitigation plans, and establish a continuous monitoring and feedback loop.
Future Road Map	**Short-Term Strategies** Variable to Fixed Rate Adjust term of loans	**Long-Term Strategy** NFT-based Mortgages	**Short-Term Strategies** Offer Debt Consolidation Internal Refinancing

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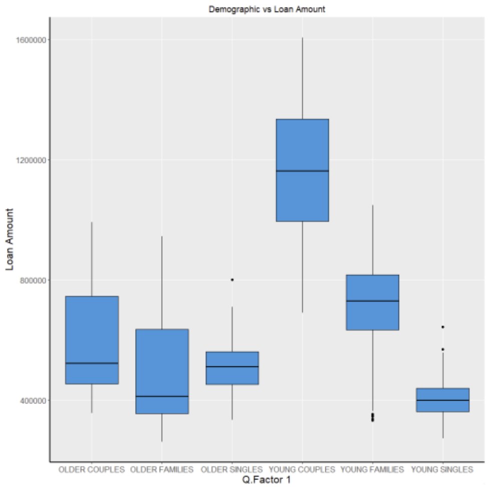
Exploratory Data Analysis: Factors Impacting Profitability

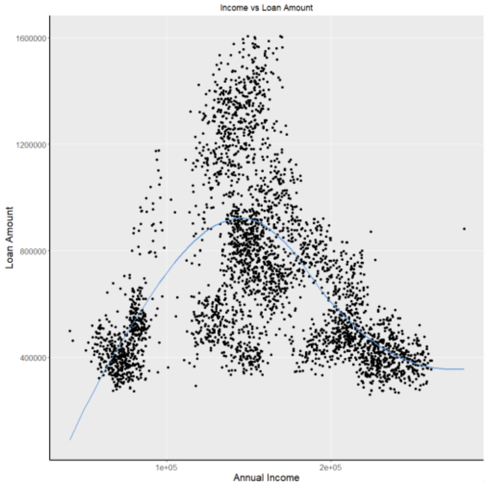
Age Demographic

- Young couples are observed to take out the largest loans
- While targeting young couples may offer immediate gains, a sole focus on this group could expose RiskyLending to risks, particularly in the face of uncertain macroeconomic conditions.



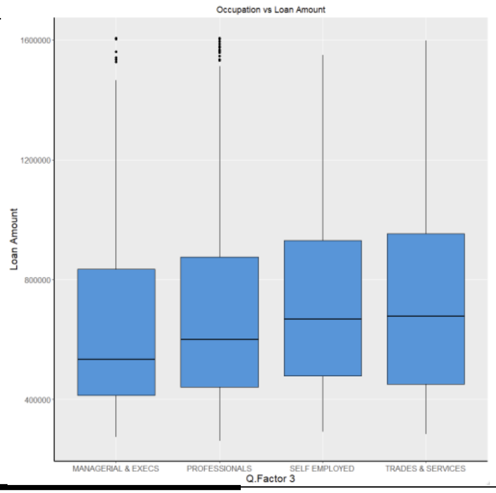
Income

- The graph reveals a non-linear, parabolic relationship between annual income and loan amount
- Presents an opportunity for RiskyLending to focus on middle to high-income earners for larger loans
- There is a need to investigate why higher income earners are taking out smaller loans



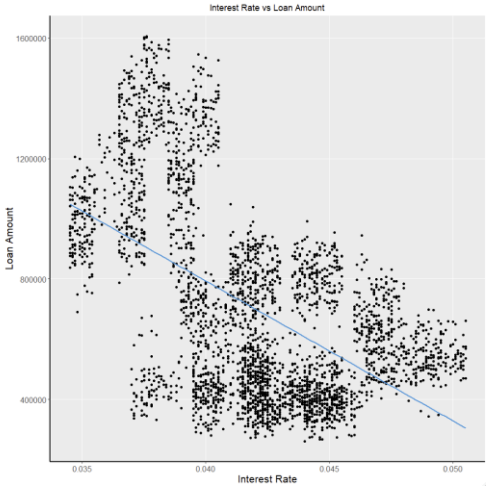
Occupation

- Loan amounts across various job types show general uniformity, but professionals stand out with high outliers
- Opportunity to capitalise on this trend by developing specialised loan products or promotional campaigns tailored to attract professionals.



Interest Rate

- The moderate negative correlation between interest rates and loan amounts suggests that higher rates are likely to discourage potential borrowers from taking out larger loans.
- A need for RiskyLending to consider diversifying its loan product offerings to maintain or grow its commission revenue.



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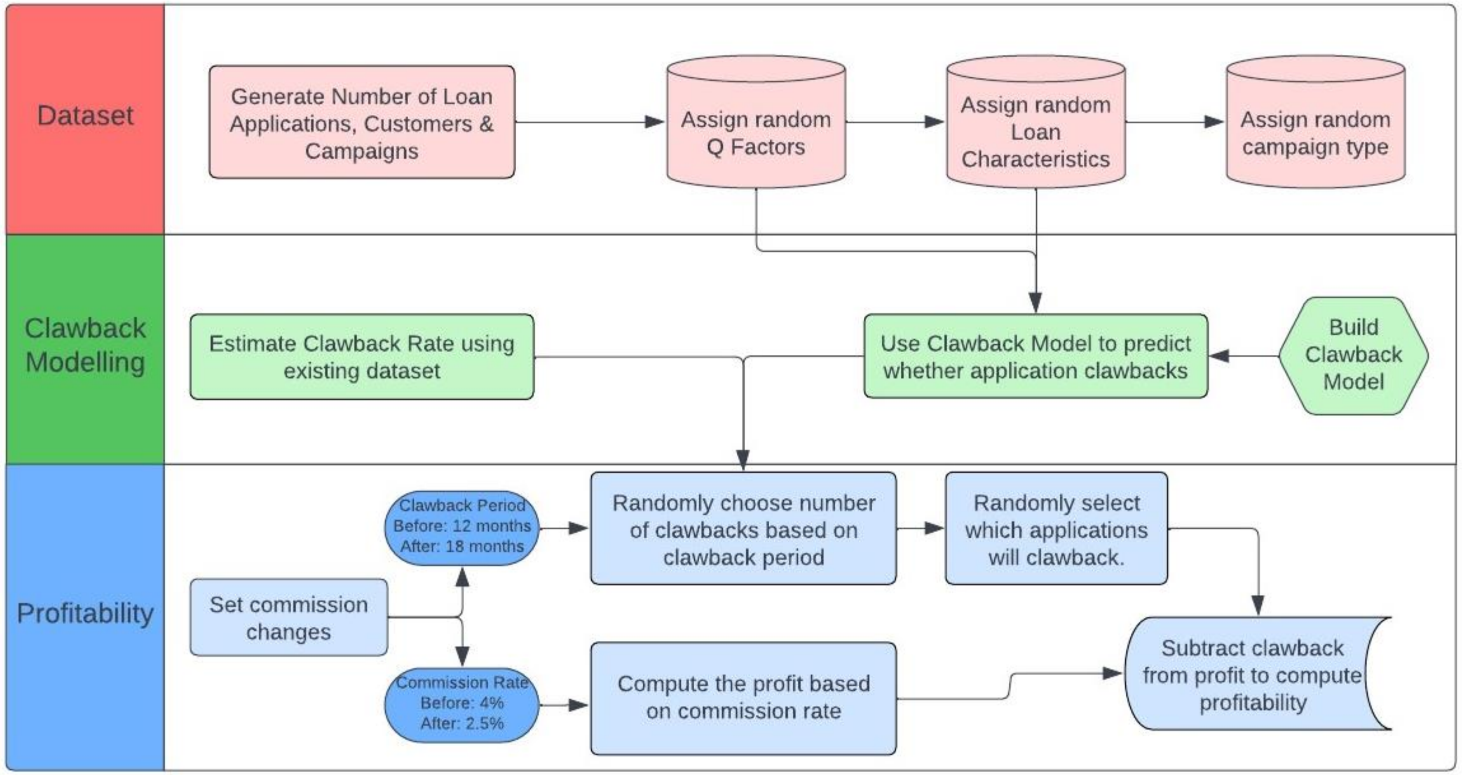
Modelling Profitability: Simulation Methodology and Assumptions

Simulation Methodology



Simulation Assumptions

1. **Demand for loans remains constant**
2. **Number of campaigns is constant**
3. **Constant home values and property market remains stable**
4. **Deposit rate is between 10-30%**
5. **Poisson Process to simulate clawback**
6. **No time value of money**

Modelling Profitability: Machine Learning Models to predict Clawback

$$\underbrace{\text{Close Reason}}_{\text{Dependent Variable}} = \underbrace{\text{Q Factor 1 + Q Factor 2 + Q Factor 3 + Loan Amount + Home Value + Annual Income + Interest Rate + Term}}_{\text{Independent Variables}}$$

Multinominal Logistic Regression

Model Accuracy

Classification Accuracy	72.97%
Default Classification Rate	93.50%
Refinance Classification Rate	73.71%
None Classification Rate	52.88%

Model Characteristics & Key Findings

1. **Statistical Method:** Fits data using a logistic function to predict and understand variables with multiple categories.
2. **Coefficients**: Coefficients are easy to interpret impact on clawback. Almost all variables are statistically significant.
3. **Poor Model**: Yields a low classification accuracy and low 'None' classification rate when performed against a sample test data.

Random Forest Decision Tree

Model Accuracy

Classification Accuracy	96.12%
Default Classification Rate	~100%
Refinance Classification Rate	~100%
None Classification Rate	88.38%

Model Characteristics & Key Findings

1. **Decision-based Tree:** Creates a flowchart which sorts data into categories based on criteria derived from independent variables
2. **Machine Learning Algorithm**: Uses a random forest ML algorithm that improves robustness of predictive model.
3. **Excellent Model**: Yields a high classification accuracy when performed against a sample test data.

Monte Carlo Simulations: Profitability Before Commission Changes

Current Profitability

- The current profitability of RiskLending's business model yields **$80.201 million**

Commission Conditions

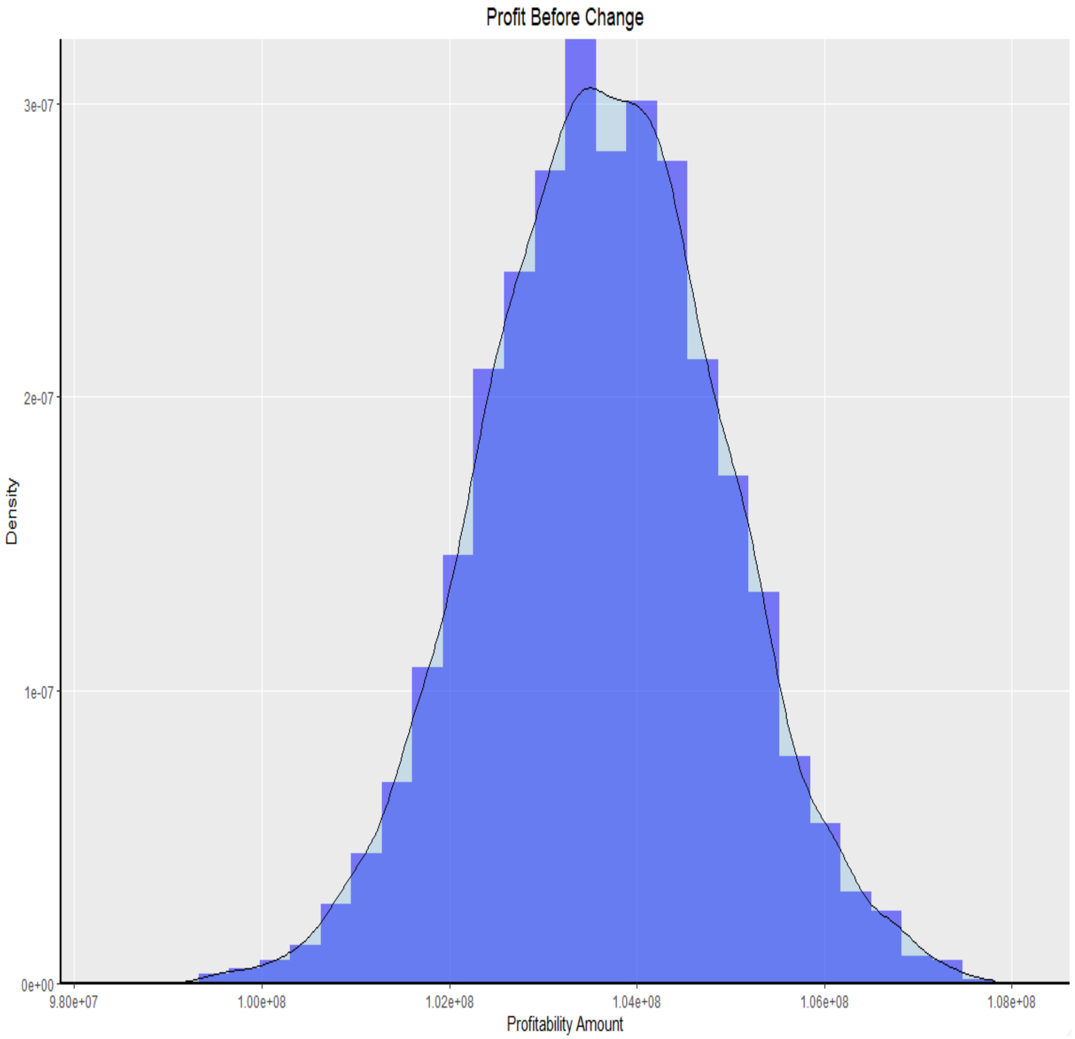
- **Commission Rate**: 4%
- **Clawback Period**: 12 months

Profitability Before Change

- The graph depicts results from a Monte Carlo Simulation using 5,000 simulations, modeling the profitability of RiskyLending before changes in clawback period and commission rates.
- The higher simulated profit compared to its current profitability is due to configuring the independent variables to be uniformly random as part of the Monte Carlo Simulations
- The very low standard deviation suggests that there is a low risk profile in RiskyLending's loan portfolio

Summary Statistics

Mean	$103.64m
Standard Deviation	$1.28m
Minimum	$98.37m
Maximum	$107.83m
Skewness	-0.0251
Kurtosis	3.0273



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Monte Carlo Simulations: Profitability After Commission Changes

Profitability After Change

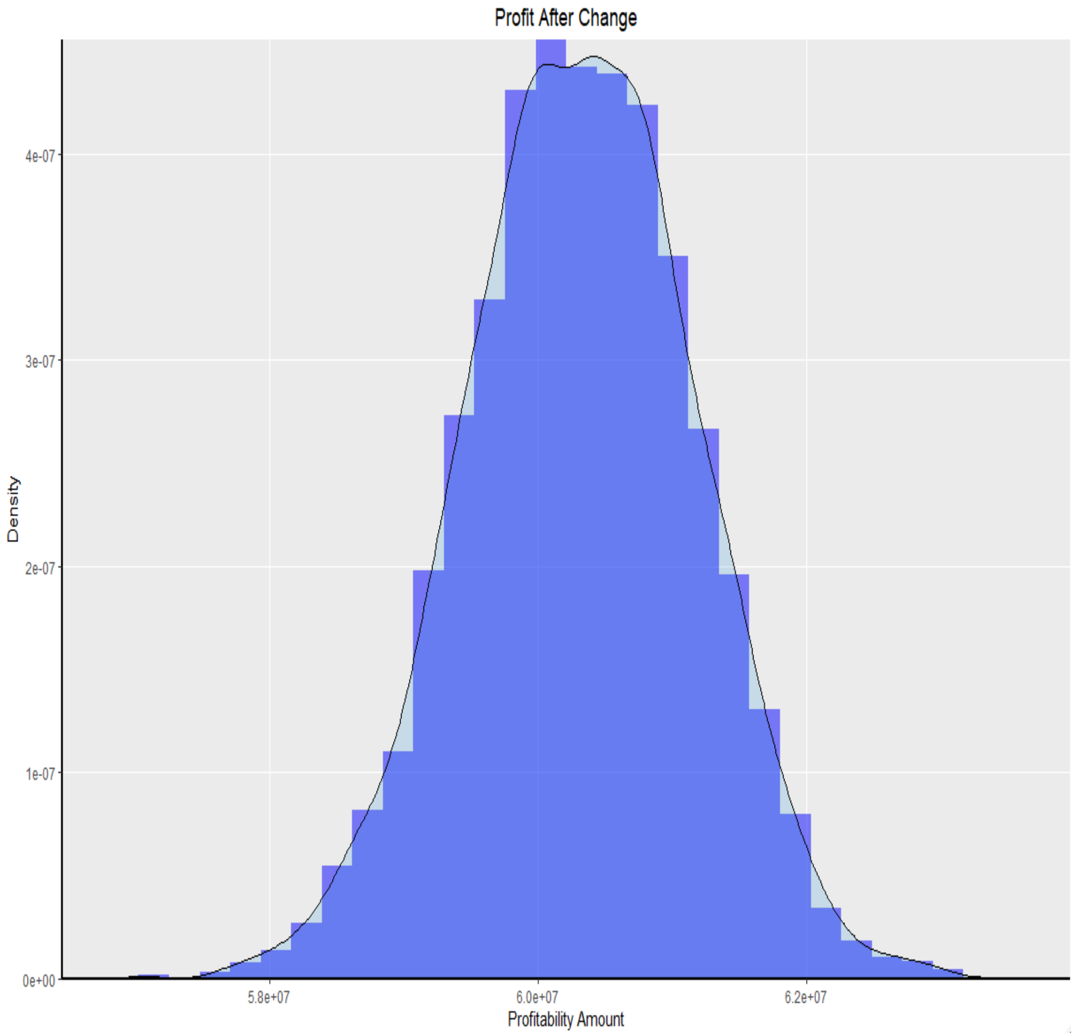
- The graph displays results from a Monte Carlo Simulation using 5,000 simulations, representing RiskyLending's profitability after the changes in clawback and commission rates.
- The average is around $60 million which is a considerable 42% decrease when commission conditions changed
- The lower commission rate caused overall profits from loan applications to decrease systematically
- The longer clawback period resulted in more customers refinacing or defaulting on their loans
- The negative skewness implies there is a small skewness to the left, meaning there is a higher chance of lower profits.

Commission Conditions

- **Commission Rate**: 2.5%
- **Clawback Period**: 18 months

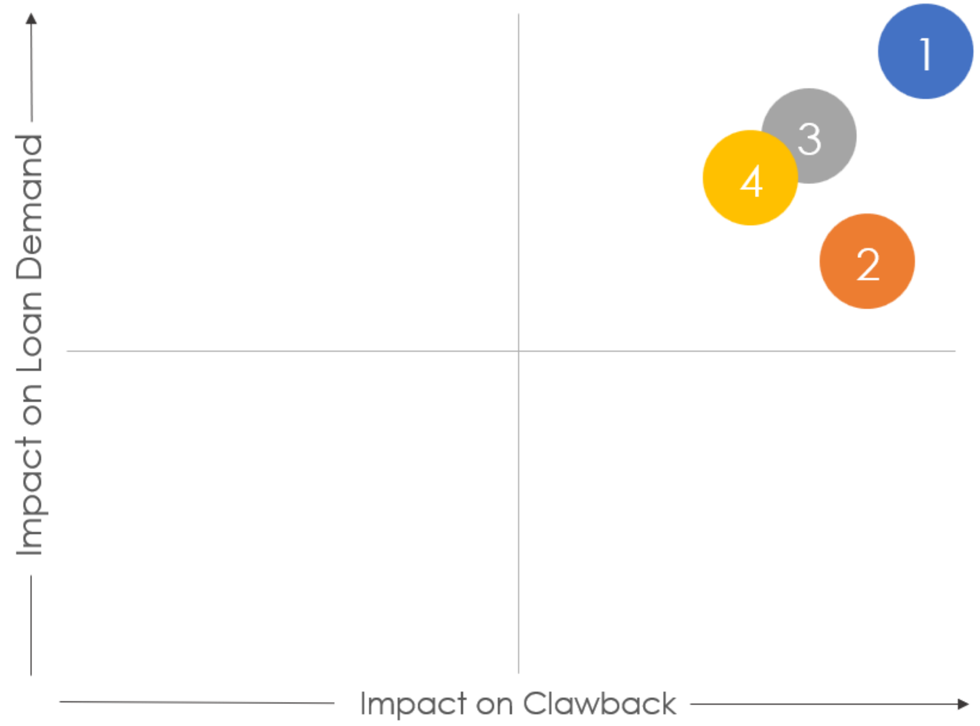
Summary Statistics

Mean	$60.32m
Standard Deviation	$0.848m
Minimum	$56.96m
Maximum	$63.56m
Skewness	-0.0465
Kurtosis	3.094



Risk Assessment: Macroeconomic Influences on Loan Portfolio

RISK HEAT MAP



1	Cash Rate	• Fluctuations in the cash rate affect borrower defaults and repayments, influencing clawback rates • Cash rate changes influence the broader housing market, affecting the demand for loans
2	Inflation	• In an inflationary environment, the cost of living rises, affecting borrowers' ability to repay loans • Moderate inflation could increase the value of real assets like property, potentially driving higher demand for home loans
3	Unemployment	• Rising unemployment rates could lead to an increase in loan defaults or early repayments and may reduce the pool of eligible borrowers • A surge in unemployment could also affect consumer confidence, discouraging new loans
4	Housing Approvals	• More housing approvals signals a growing property market which increases consumer and investor confidence and the willingness to take out larger loans.

Linear Regression Models on Demand for Loans & Clawback Rate

$$\underbrace{\text{Loan Commitments or Refinance}}_{\text{Dependent Variable}} = \underbrace{\text{Cash Rate + Inflation Rate + Unemployment Rate + Housing Approval Rate}}_{\text{Independent Variables}}$$

Demand for Loans - Loan Commitments

Accuracy & Characteristics of Model

Mean Squared Error	2.66%
Multiple R-Squared	0.3953
Adjusted R-Squared	0.3555

Clawback Rate – Refinanced Loans

Accuracy & Characteristics of Model

Mean Squared Error	2.93%
Multiple R-Squared	0.6411
Adjusted R-Squared	0.6334

Model Characteristics & Key Findings

1. **Loan Commitments:** We use the macroeconomic number of **loan commitments** as an indicator for the demand for loans.
2. **Refinanced Loans:** We use the macroeconomic number of **refinanced loans** as an indicator for the clawback rate.
3. **Accurate Model**: Yields a low regression error with a high R-squared value when performed against a sample test data.

Estimated Macroeconomic Values, 2025 (from Factset)

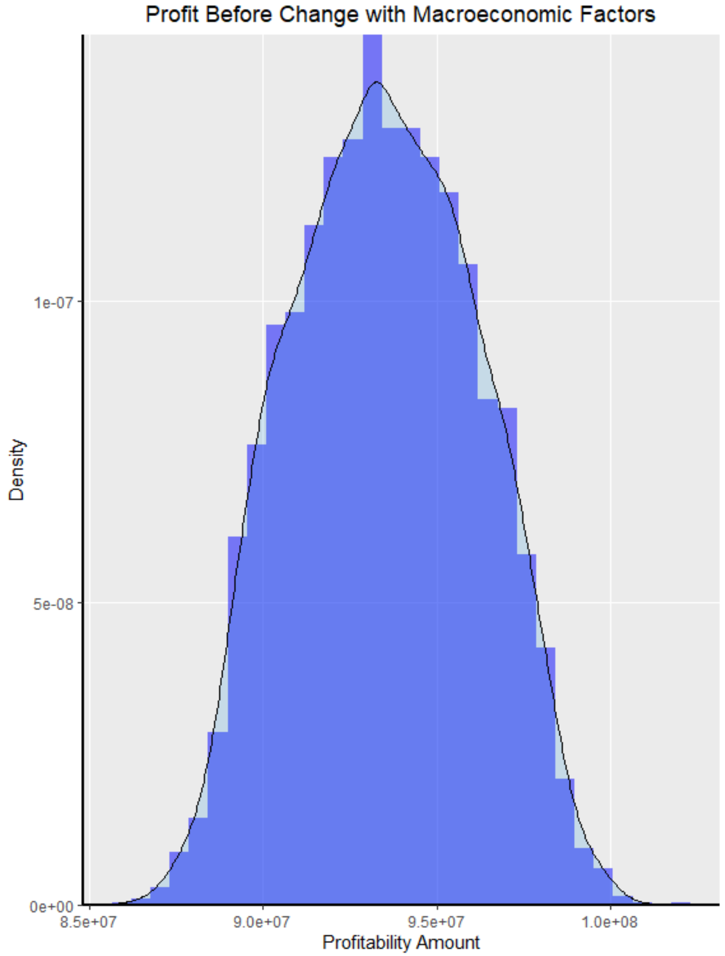
Cash Rate	3.6%
Inflation Rate	3%
Unemployment Rate	4.7%
Housing Approvals	7%

Forecasted Growth Rates Loan Indicators

Loan Demand Growth Rate	-17.6%
Clawback Growth Rate	-4.79%

Monte Carlo Simulations: Macroeconomic Effects on Profitability

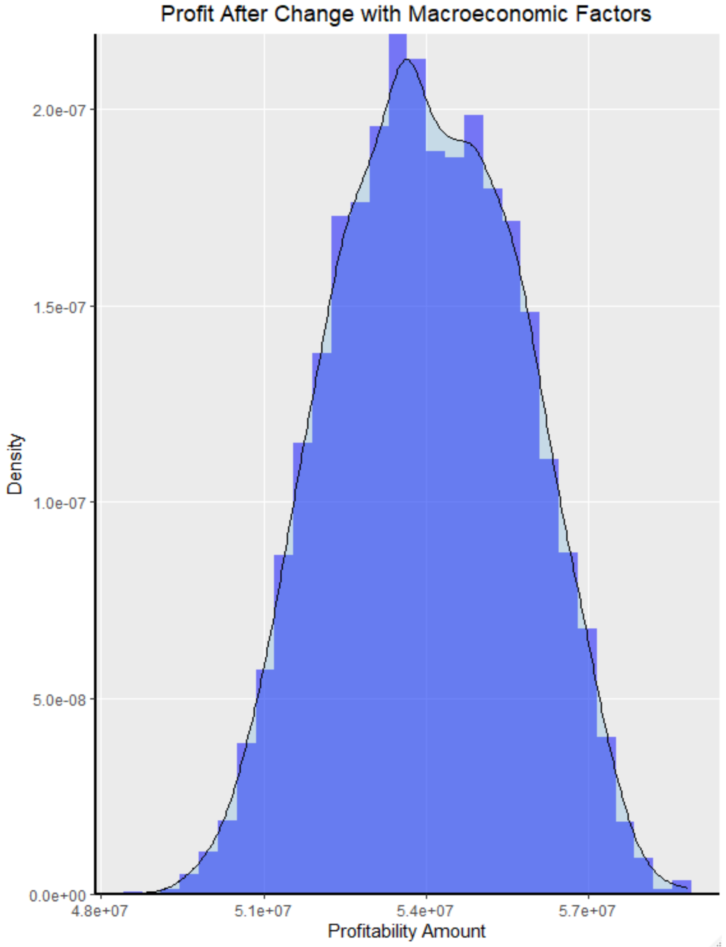
Before Commission Changes



Summary Statistics

Mean	$93.50 m
Standard Deviation	$2.61m
Minimum	$85.84 m
Maximum	$101.9 m
Skewness	-0.0763
Kurtosis	2.333

After Commission Changes



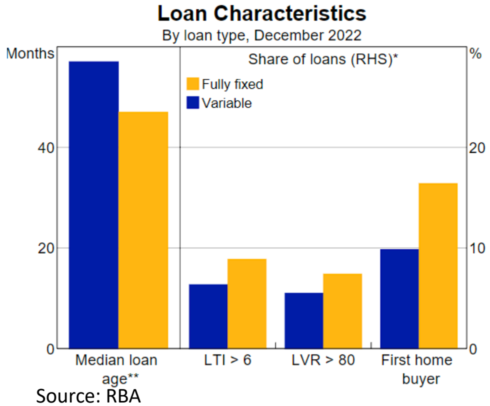
Summary Statistics

Mean	$54.01 m
Standard Deviation	$1.70m
Minimum	$48.69 m
Maximum	$58.82 m
Skewness	-0.1098
Kurtosis	2.411

Short-term strategies

Change from Variable Rate to Fixed Rate Loans

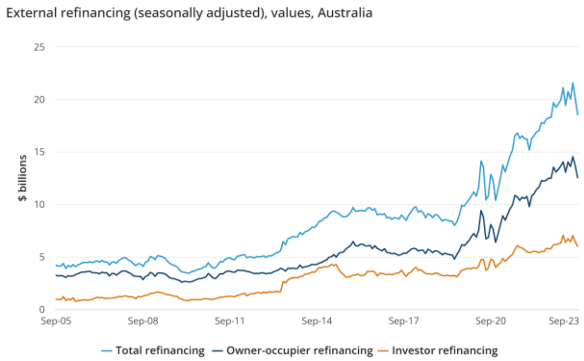
- Provide borrowers with more stability and predictability in their repayments
- Reduce likelihood of refinance or default
- Reduce the frequency of clawbacks, thereby stabilising commission revenue



Source: RBA

Adjusting the Term of the Loan

- Tailor loans to individual customer needs, potentially reducing the risk of default
- Improved customer retention can enhance RiskyLending's profitability by reducing administrative costs associated with loan replacements



Source: RBA

Offer Debt Consolidation

- Debt consolidation options can attract borrowers looking to streamline high-interest debts into a single, more manageable payment.
- Reduce the likelihood of borrowers refinancing their loans, as they can manage other debts via their existing mortgage.
- Improve customer loyalty and reduce the incidence of clawbacks, benefiting its bottom line.

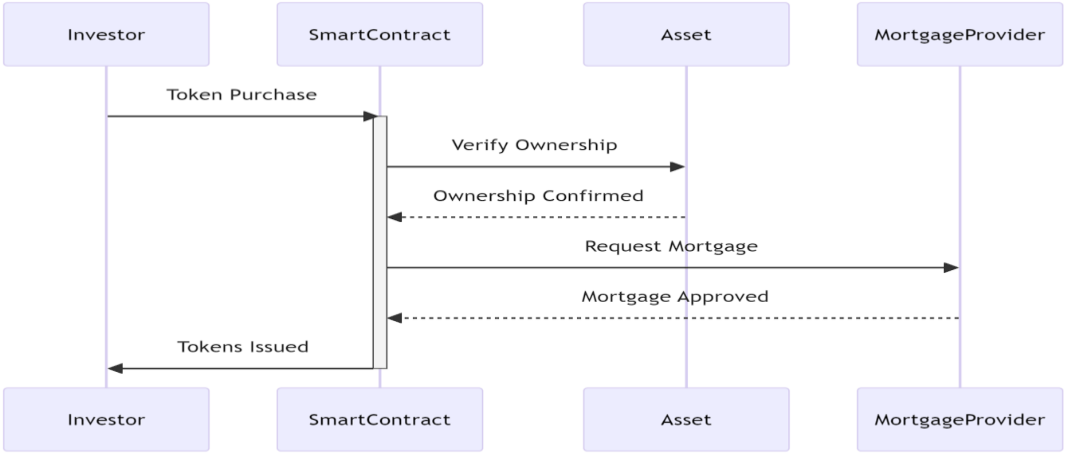
Allow Internal Refinancing for Cash-Out

- Can address specific financial needs for homeowners, such as home improvement or debt payment.
- Assist retain existing customers who might otherwise look to refinance externally.
- Retaining more customers in this manner can reduce administrative costs and improve the company's profitability.

NFT-based Mortgages

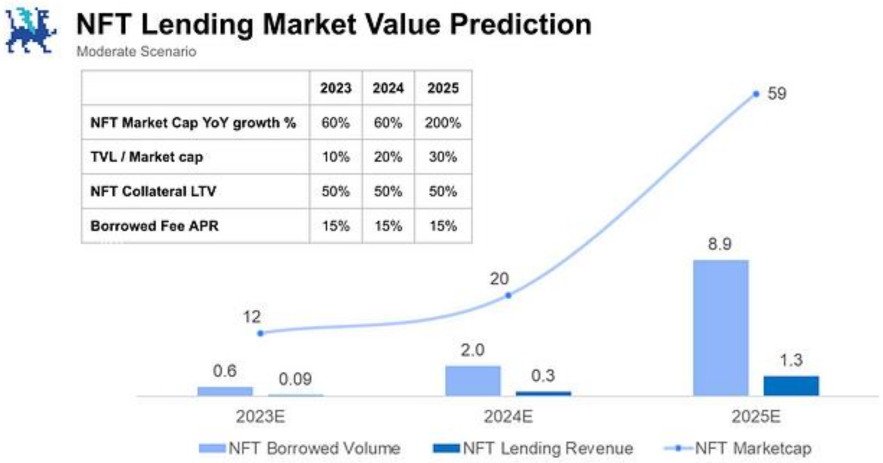
A Brief on Tokenisation – Streamlining and Global Market Access

- NFTs used to represent individual mortgage contracts tokenized on a blockchain
- Lenders can use NFTs to store mortgage metadata such as:
  - Who owns the mortgaged property until debt is paid
  - Borrower data
  - Mortgage’s history of transactions
- NFTs are globally accessible
  - Allow expansion of target market by promoting investments from foreign investors



Transparency, Market Differentiation and Risk Mitigation

- The blockchain technology underlying NFTs offer greater transparency and security in mortgage transactions
- Allows more customised loan products, targeting specific customer needs and thereby increasing market share
- Allow for more flexible risk management strategies, like easily selling off portions of a loan to diversify risk
  - Provides resilience to economic downturns or changes in interest rates



	2023	2024	2025
NFT Market Cap YoY growth %	60%	60%	200%
TVL / Market cap	10%	20%	30%
NFT Collateral LTV	50%	50%	50%
Borrowed Fee APR	15%	15%	15%

Source: IOSG Ventures

Appendix

Main Deck

Appendix

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Appendix 1: Multinominal Logistic Regression Model

```
Call:
vglm(formula = `Close Reason` ~ `Q  Factor 1` + `Q Factor 2` +
    `Q Factor 3` + `Loan Amount` + `Home Value` + `Annual Income` +
    `Interest Rate (p.a.)` + `Term (months)`, family = multinomial,
    data = data_balance[train.set.1, ])

Coefficients:
                               Estimate Std. Error z value Pr(>|z|)
(Intercept):1                 7.947e+01  5.799e+00  13.705  < 2e-16 ***
(Intercept):2                -3.648e+01  3.155e+00 -11.562  < 2e-16 ***
`Q  Factor 1`OLDER FAMILIES:1  4.125e+00  4.486e-01   9.196  < 2e-16 ***
`Q  Factor 1`OLDER FAMILIES:2 -2.405e+00  2.243e-01 -10.721  < 2e-16 ***
`Q  Factor 1`OLDER SINGLES:1   3.049e-01  7.236e-01   0.421 0.673457
`Q  Factor 1`OLDER SINGLES:2  -4.869e+00  4.278e-01 -11.381  < 2e-16 ***
`Q  Factor 1`YOUNG COUPLES:1  -7.643e+00  7.702e-01  -9.924  < 2e-16 ***
`Q  Factor 1`YOUNG COUPLES:2   4.895e+00  4.328e-01  11.311  < 2e-16 ***
`Q  Factor 1`YOUNG FAMILIES:1 -5.886e+00  4.178e-01 -14.091  < 2e-16 ***
`Q  Factor 1`YOUNG FAMILIES:2  1.836e+00  2.232e-01   8.225  < 2e-16 ***
`Q  Factor 1`YOUNG SINGLES:1  -7.922e+00  4.637e-01 -17.083  < 2e-16 ***
`Q  Factor 1`YOUNG SINGLES:2  -6.072e-01  3.398e-01  -1.787 0.073932 .
`Q Factor 2`MAINSTREAM:1      -9.223e-01  2.741e-01  -3.365 0.000765 ***
`Q Factor 2`MAINSTREAM:2       1.530e+00  1.677e-01   9.119  < 2e-16 ***
`Q Factor 2`PRIME:1           -7.424e-01  4.952e-01  -1.499 0.133816
`Q Factor 2`PRIME:2            3.692e+00  3.039e-01  12.149  < 2e-16 ***
`Q Factor 3`PROFESSIONALS:1    2.465e-01  1.763e-01   1.398 0.162243
`Q Factor 3`PROFESSIONALS:2    4.872e-01  8.408e-02   5.794 6.86e-09 ***
`Q Factor 3`SELF EMPLOYED:1    1.060e+00  2.253e-01   4.707 2.51e-06 ***
`Q Factor 3`SELF EMPLOYED:2    1.413e-01  1.312e-01   1.077 0.281644
`Q Factor 3`TRADES & SERVICES:1 4.214e-01  2.168e-01   1.943 0.051958 .
`Q Factor 3`TRADES & SERVICES:2 8.873e-01  1.166e-01   7.606 2.82e-14 ***
`Loan Amount`:1                3.432e-05  1.161e-06  29.568  < 2e-16 ***
`Loan Amount`:2                5.525e-06  5.840e-07   9.460  < 2e-16 ***
`Home Value`:1                -2.622e-05  9.030e-07 -29.033  < 2e-16 ***
`Home Value`:2                -4.956e-06  4.731e-07 -10.475  < 2e-16 ***
`Annual Income`:1             -8.264e-05  3.643e-06 -22.680  < 2e-16 ***
`Annual Income`:2             -2.012e-06  2.438e-06  -0.825 0.409259
`Interest Rate (p.a.)`:1      -1.418e+03  1.288e+02 -11.009  < 2e-16 ***
`Interest Rate (p.a.)`:2       8.547e+02  7.077e+01  12.077  < 2e-16 ***
`Term (months)`:1             -1.960e-01  1.066e-02 -18.382  < 2e-16 ***
`Term (months)`:2             -7.722e-03  4.278e-03  -1.805 0.071061 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Names of linear predictors: log(mu[,1]/mu[,3]), log(mu[,2]/mu[,3])

Residual deviance: 7518.31 on 12950 degrees of freedom

Log-likelihood: -3759.155 on 12950 degrees of freedom

Number of Fisher scoring iterations: 7

Warning: Hauck-Donner effect detected in the following estimate(s):
'`Home Value`:1', '`Interest Rate (p.a.)`:1', '`Interest Rate (p.a.)`:2'
```

Table 1. Multinominal Logistic Regression Model Output

Logistic Equation Models

Equation 1: Default vs Refinance

$$\log\left(\frac{Pr(Y = \text{Default})}{Pr(Y = \text{Refinance})}\right) = \ldots$$

Equation 2: None vs Refinance

$$\log\left(\frac{Pr(Y = \text{None})}{Pr(Y = \text{Refinance})}\right) = \ldots$$

Model Accuracy

75%:25% data split

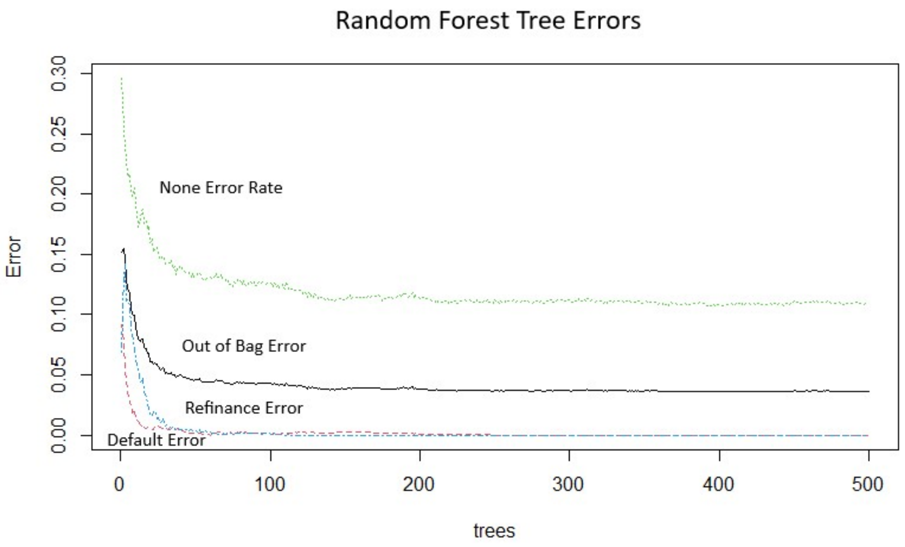
Training Data

Accuracy	72.38%
Default True Positive Rate	94.03%
Refinance True Negative Rate	72.33%
None True Positive Rate	50.35%

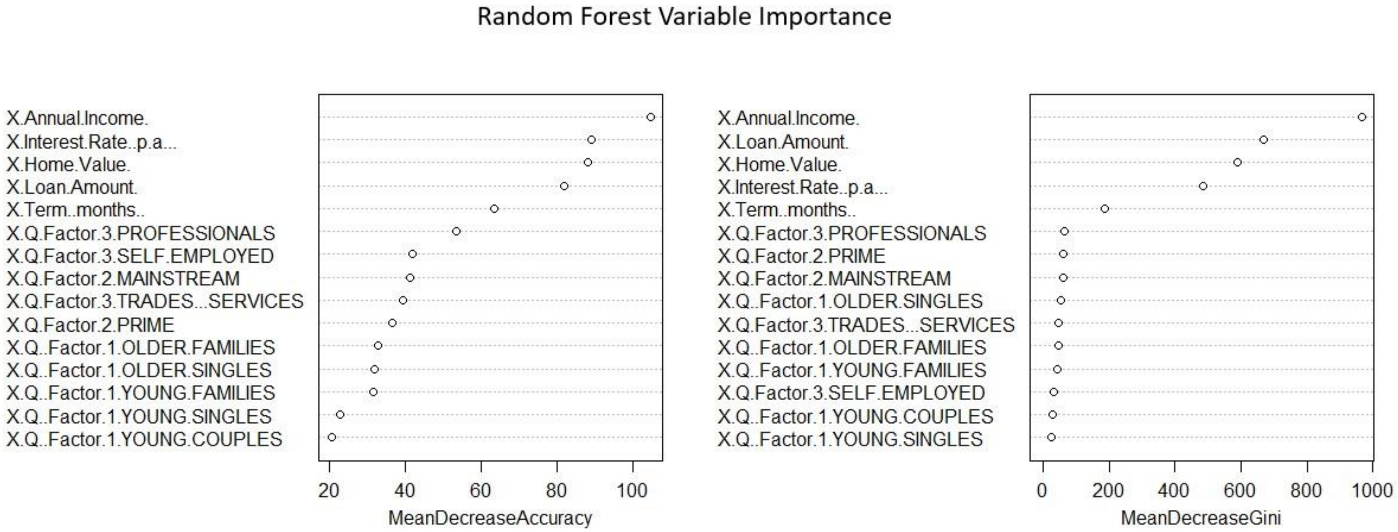
Test Data

Accuracy	72.97%
Default True Positive Rate	93.50%
Refinance True Negative Rate	73.71%
None True Positive Rate	52.88%

Appendix 1: Multinominal Logistic Regression Model



Graph 1. Random Forest Tree Errors



Graph 2. Random Forest Variable Importance

Model Accuracy
75%:25% data split

Training Data

Accuracy	98.38%
Default True Positive Rate	100%
Refinance True Negative Rate	100%
None True Positive Rate	95.14%

Test Data

Accuracy	96.12%
Default True Positive Rate	100%
Refinance True Negative Rate	100%
None True Positive Rate	88.38%

Appendix 3: Linear Regression Macroeconomic Models

```
Call:
lm(formula = Total.Loans ~ Cash.Rate + Inflation + Unemployment +
    Housing.Approvals, data = macro_loan_data[train.set.3, ])

Residuals:
     Min        1Q    Median        3Q       Max
-15353678  -4068388    -44911   3850552  16242266

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       71807513    5025815  14.288  < 2e-16 ***
Cash.Rate         -1640835     250969  -6.538 5.90e-10 ***
Inflation           779726     462131   1.687   0.0932 .
Unemployment      -4513230     765104  -5.899 1.71e-08 ***
Housing.Approvals   283537     110815   2.559   0.0113 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6492000 on 185 degrees of freedom
Multiple R-squared:  0.3593,    Adjusted R-squared:  0.3455
F-statistic: 25.94 on 4 and 185 DF,  p-value: < 2.2e-16
```

Loan Commitments Model Accuracy
75%:25% data split

Training Mean Squared Error	2.45%
Test Mean Squared Error	2.66%

ANOVA Table

```
Analysis of Variance Table

Response: Total.Loans
                   Df     Sum Sq    Mean Sq F value    Pr(>F)
Cash.Rate           1 7.8399e+14 7.8399e+14 18.6004 2.619e-05 ***
Inflation           1 1.9010e+15 1.9010e+15 45.1021 2.230e-10 ***
Unemployment        1 1.4128e+15 1.4128e+15 33.5197 2.974e-08 ***
Housing.Approvals   1 2.7594e+14 2.7594e+14  6.5467   0.01131 *
Residuals         185 7.7976e+15 4.2149e+13
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Call:
lm(formula = Refinancing ~ Cash.Rate + Inflation + Unemployment +
    Housing.Approvals, data = macro_loan_data[train.set.3, ])

Residuals:
    Min       1Q   Median       3Q      Max
-6786617 -1436413  -184557  1532101  7583239

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       23283116    1943926  11.977  < 2e-16 ***
Cash.Rate         -1081034      97072 -11.136  < 2e-16 ***
Inflation          1535837     178747   8.592 3.50e-15 ***
Unemployment      -1713145     295933  -5.789 2.98e-08 ***
Housing.Approvals   102186      42862   2.384   0.0181 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2511000 on 185 degrees of freedom
Multiple R-squared:  0.6411,    Adjusted R-squared:  0.6334
F-statistic: 82.62 on 4 and 185 DF,  p-value: < 2.2e-16
```

Refinanced Loans Model Accuracy
75%:25% data split

Training Mean Squared Error	4.09%
Test Mean Squared Error	2.93%

ANOVA Table

```
Analysis of Variance Table

Response: Refinancing
                   Df     Sum Sq    Mean Sq  F value    Pr(>F)
Cash.Rate           1 2.9009e+14 2.9009e+14  46.0035 1.542e-10 ***
Inflation           1 1.5540e+15 1.5540e+15 246.4474 < 2.2e-16 ***
Unemployment        1 2.0397e+14 2.0397e+14  32.3474 4.961e-08 ***
Housing.Approvals   1 3.5840e+13 3.5840e+13   5.6838   0.01813 *
Residuals         185 1.1666e+15 6.3057e+12
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table 3A. Linear Regression Loan Commitments Model Output
Table 3B. Linear Regression Refinanced Loans Model Output

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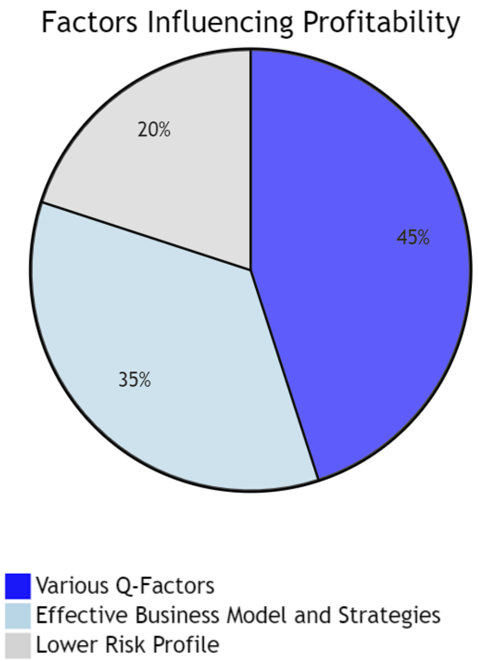
Appendix 4: Factors influencing Profitability and Mitigating changes in profitability

Factors Influencing current Profitability

1. **Effective Business Model & Strategies**:
   35% - This suggests that RiskyLending's business model and strategies were effective in generating stable profits.

2. **Accounting for Various Q-factors**:
   45% - The various Q-factors likely account for market conditions, customer demographics, and interest rate variations, among other factors.

3. **Lower Risk Profile**:
   20% - The shape of the distribution indicates that extreme profitability outcomes were less likely, pointing to a lower risk profile for the company.



Ways to mitigate change in profitability

1. Analyse Profit Decline: Understand the extent of the decline in profitability.

2. Assess Impact on Market & Customer: Evaluate how market conditions and customer behaviours are affecting profitability.

3. Develop Mitigation Plans: Create strategies to counter the negative impacts identified.

4. Implement Strategies: Put the mitigation plans into action.

5. Monitor & Evaluate: Track the effectiveness of the implemented strategies.

6. Feedback Loop: Use the evaluation results for continuous improvement.