Predicting Individuals' Financial Resilience in the Philippines

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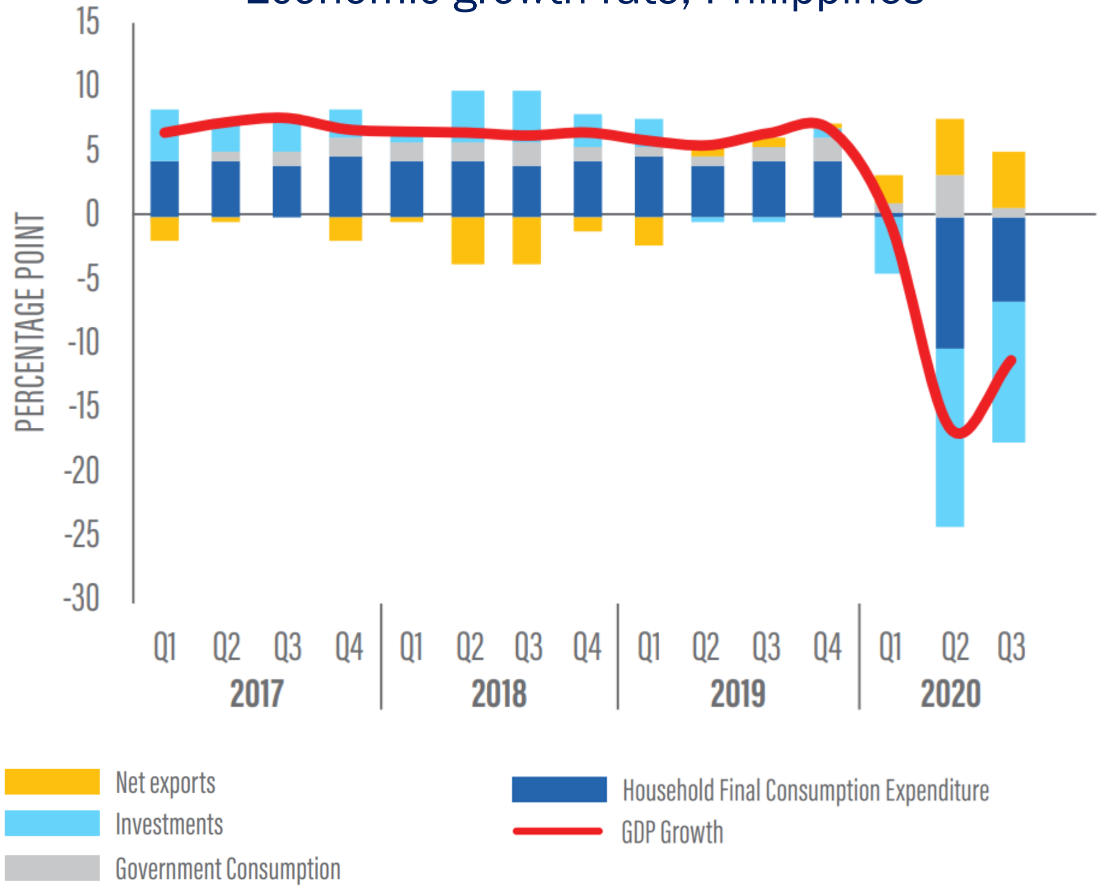
PPOL565 PROJECT PRESENTATION

4 MAY 2021

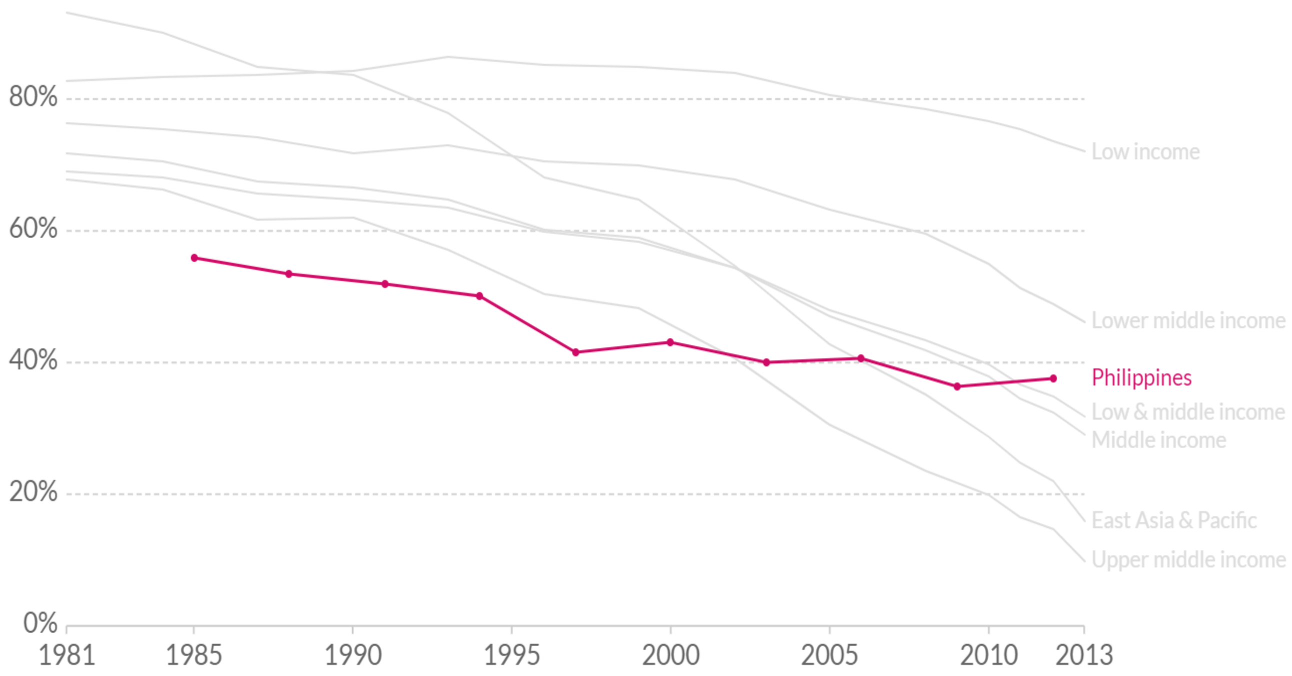
Context

The policy conundrum of inequitable growth

Economic growth rate, Philippines



Share of population living with less than 3.10 int'l $ per day



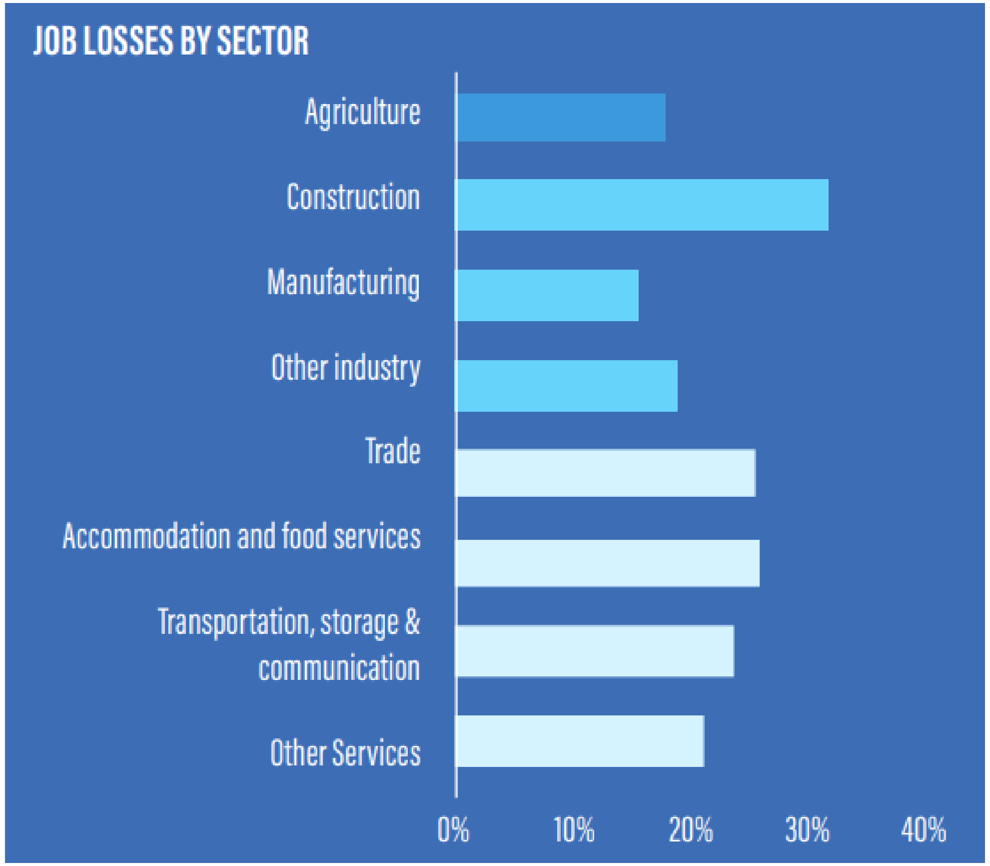
Source: World Bank Philippines Economic Update (December 2020 Edition)

Source: Our World in Data

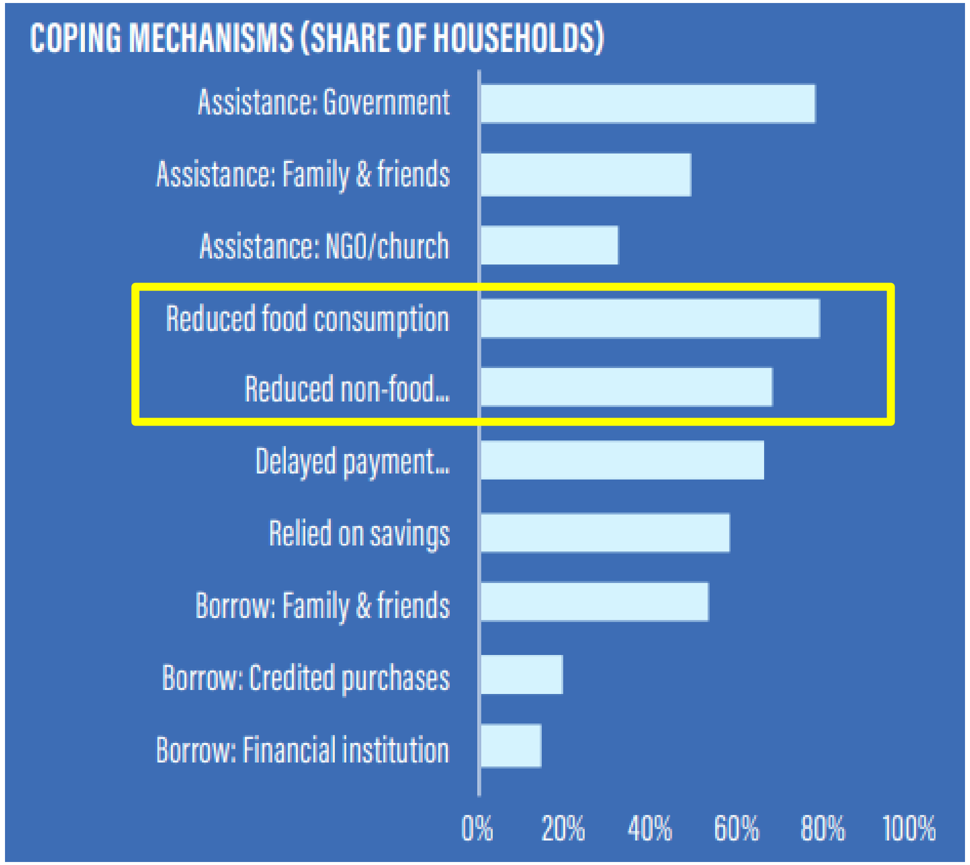
Context

The COVID-19 pandemic will further deepen inequalities

Across-the-board job disruptions…



…forced households to reduce consumption



Source: World Bank Survey (August 2020)

Research Question

What determines financial resilience?

Data

SOURCE: Global Financial Inclusion (Global Findex) Database

- 1,000 respondents in the Philippines (977 valid)
- Personal interviews from July to August 2017

TARGET: Financial Resilience

- Ability to gather emergency funds within the next month amounting to 5% of the Philippine Gross National Income (GNI) per capita
- Around 4 weeks of pay for an average worker in the Philippines

Data

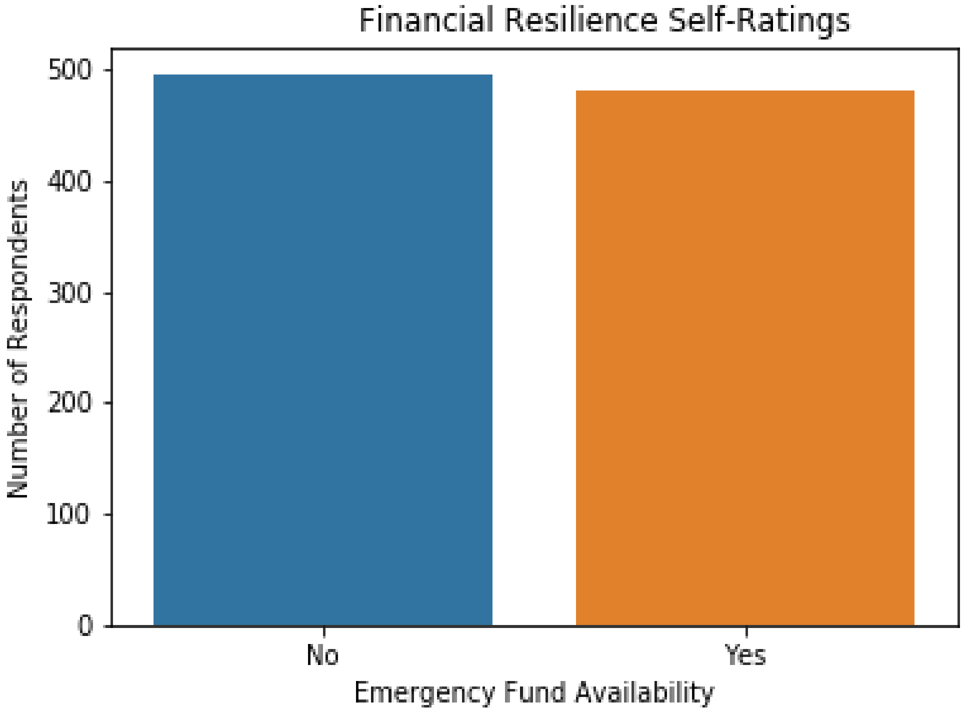
FEATURES: **Based on the Multidimensional Financial Resilience Framework** (Salignac, et al., 2019)

Economic Resources (5)	Financial Resources (5)	**Financial Knowledge and Behavior** (10)	Social Capital (1)	Demographic Variables (4)
• Income Quintile • Received Wages* • Received Agricultural Payments* • Received Self-Employed Payments* • Mobile Phone Owner	• Financial Account Owner • Debit Cardholder • Credit Cardholder • Mobile Money Account Owner • Bank Mortgage Holder	• Saved* • Saved for Business Purposes* • Saved for Retirement* • Borrowed* • Borrowed for Medical Purposes* • Borrowed for Business Purposes* • Sent Domestic Remittance* • Received Domestic Remittance* • Paid Bills* • Online Transaction*	• Borrowed from Family/Friends*	• Age • Sex • Education Level • Part of Workforce

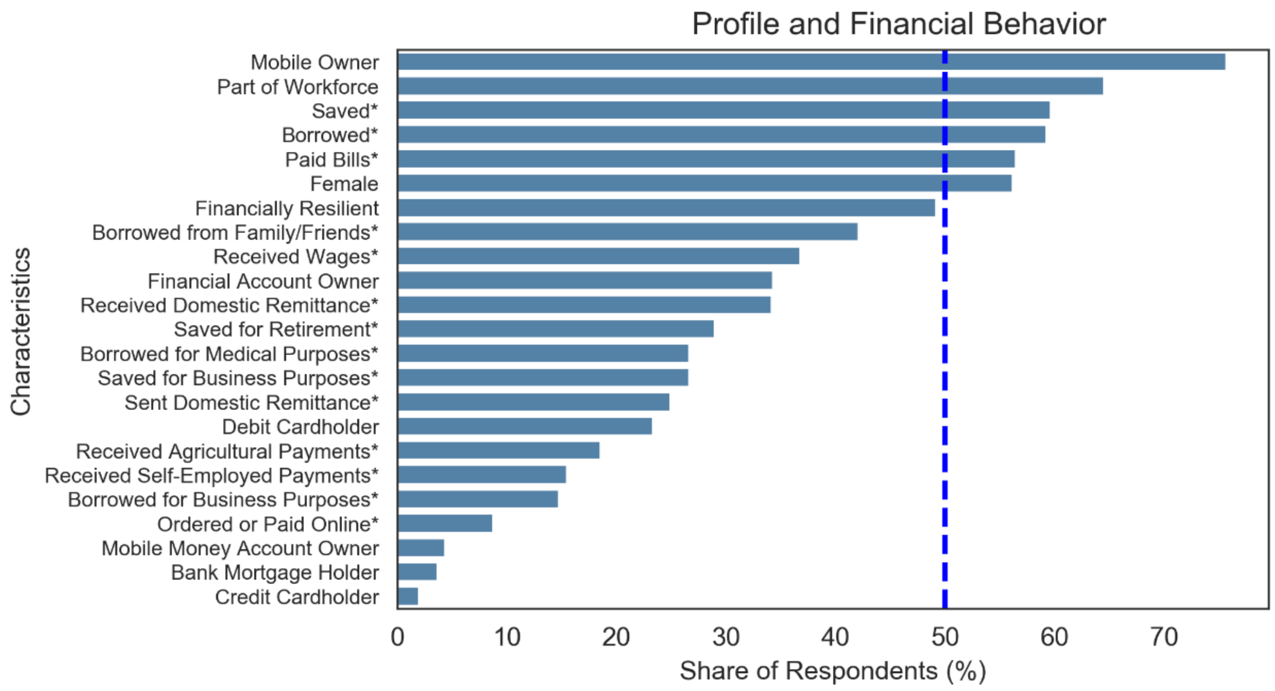
** denotes behavior in the past 12 months*

Modeling Considerations

Balanced outcome



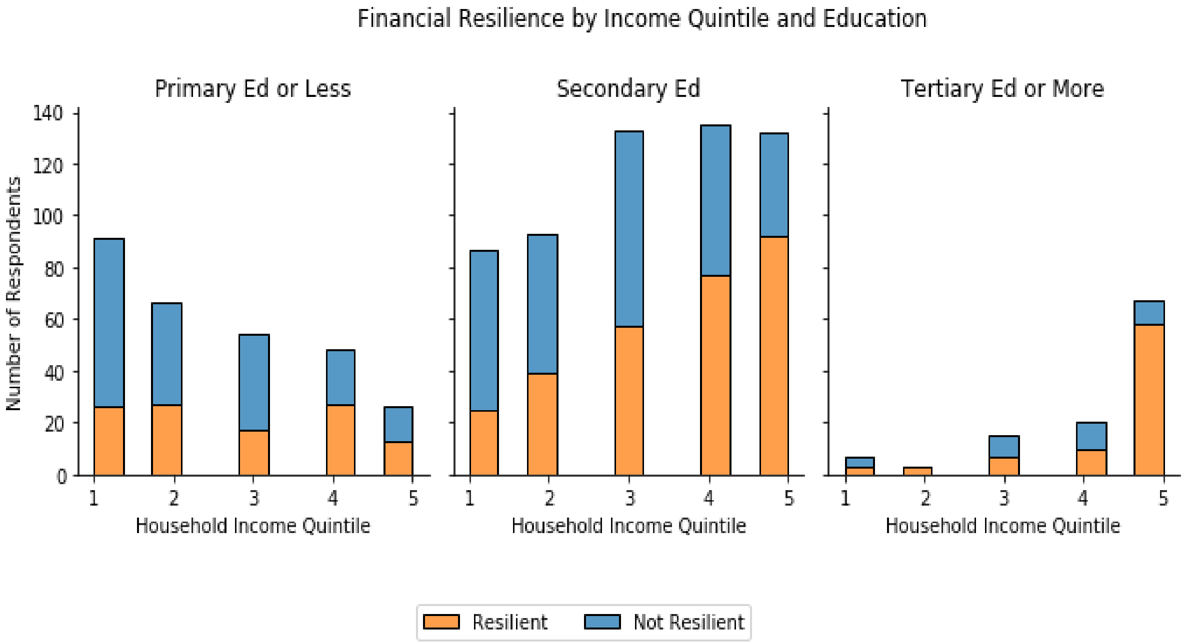
Rare cases & redundant variables

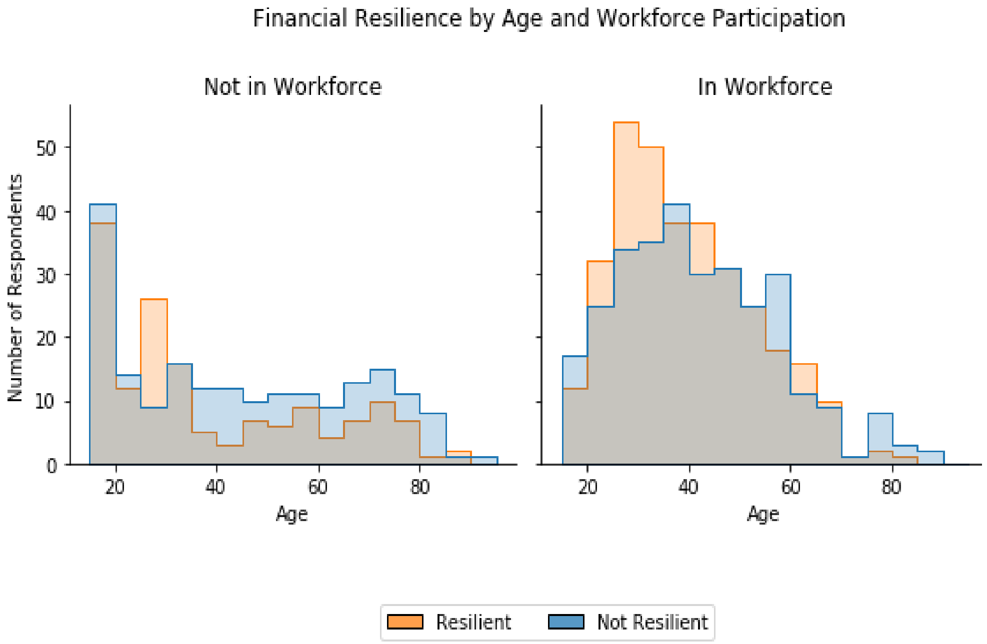


Note: Asterisk (*) denotes financial behavior in the past 12 months

Modeling Considerations

Rare cases & interacting variables





Modeling Techniques

PARAMETRIC: **Logistic LASSO Regression**

NON-PARAMETRIC: **Decision Tree (with Pruning)**

RATIONALE:

- Derive meaningful inferences
- Address possible overfitting from 25 predictors
- Robust to outliers (rare binary cases and older respondents)
- Handling of redundant/irrelevant and interacting variables

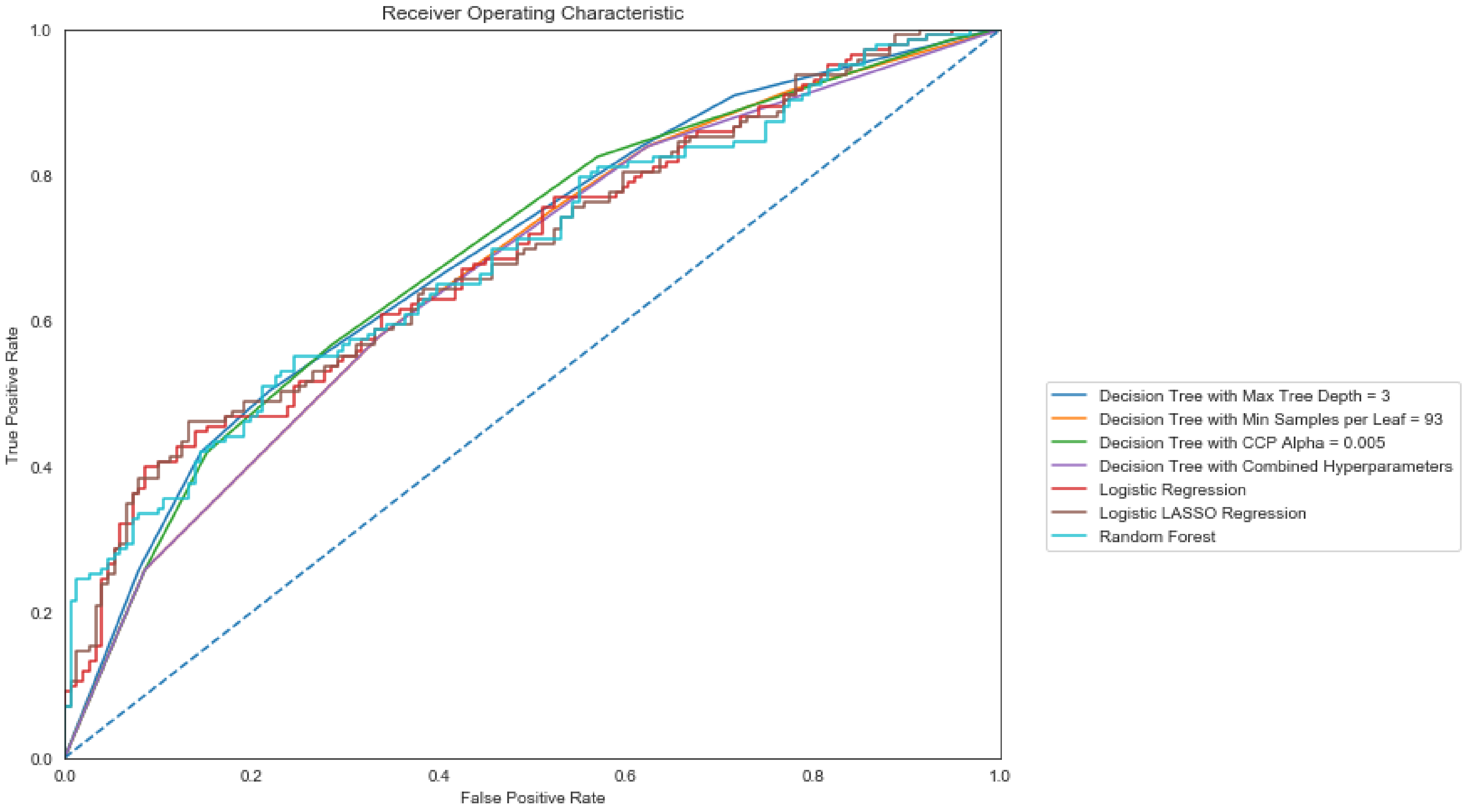
Prediction Performance

ACCURACY SCORES

Classifier	Hyper-parameter	Accuracy Score
Decision Tree	Maximum Tree Depth = 3	64.6%
	Minimum Samples per Leaf = 93	62.2%
	Cost Complexity Pruning Alpha = 0.005	64.3%
	Combination of 3 previous values	62.2%
Logistic Regression	*none*	62.2%
	LASSO (L1 penalty) with C = 0.2	62.2%
Random Forest	Maximum Tree Depth = 3 Estimators = 1,000	62.6%

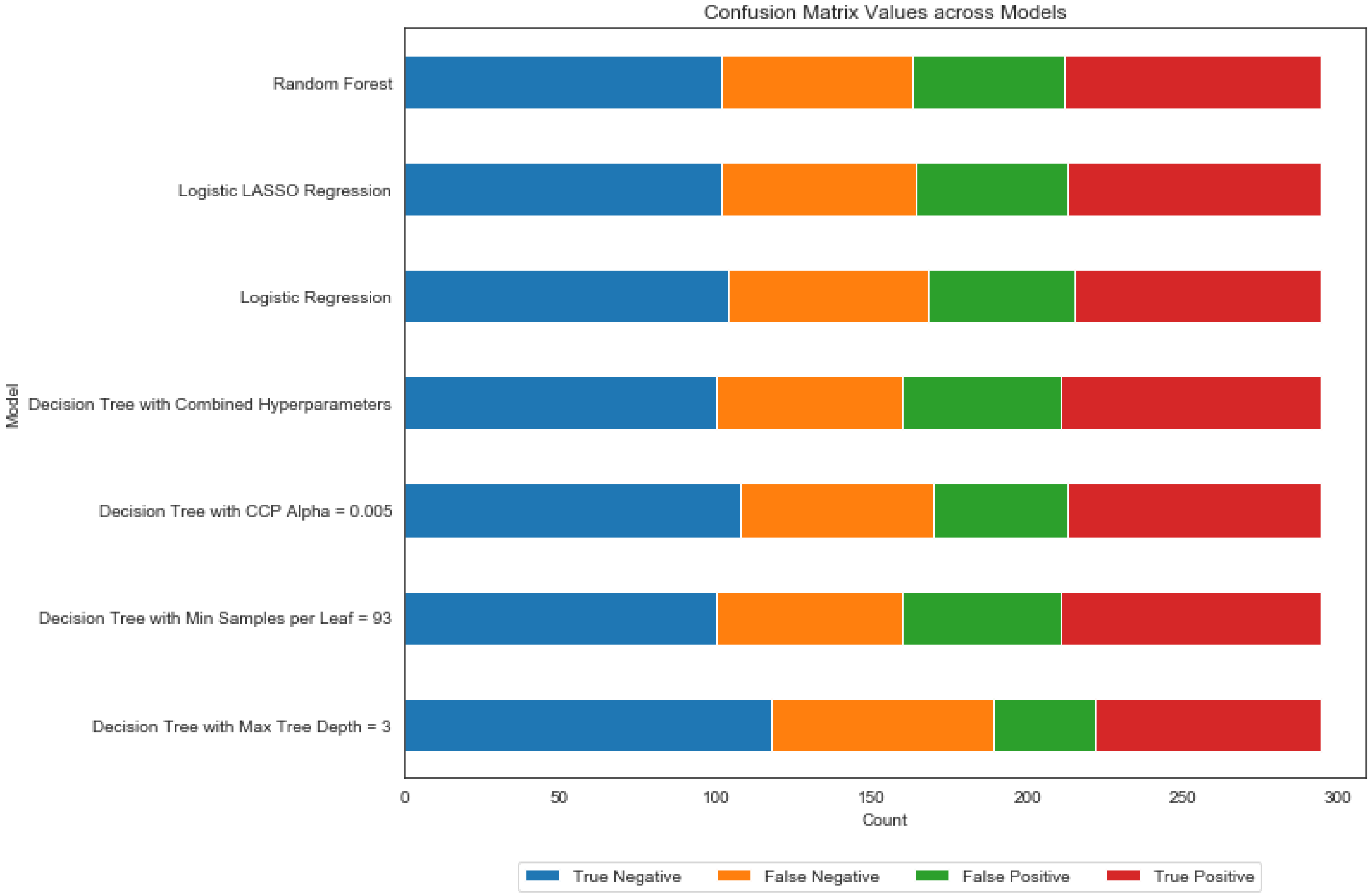
Prediction Performance

ROC CURVE



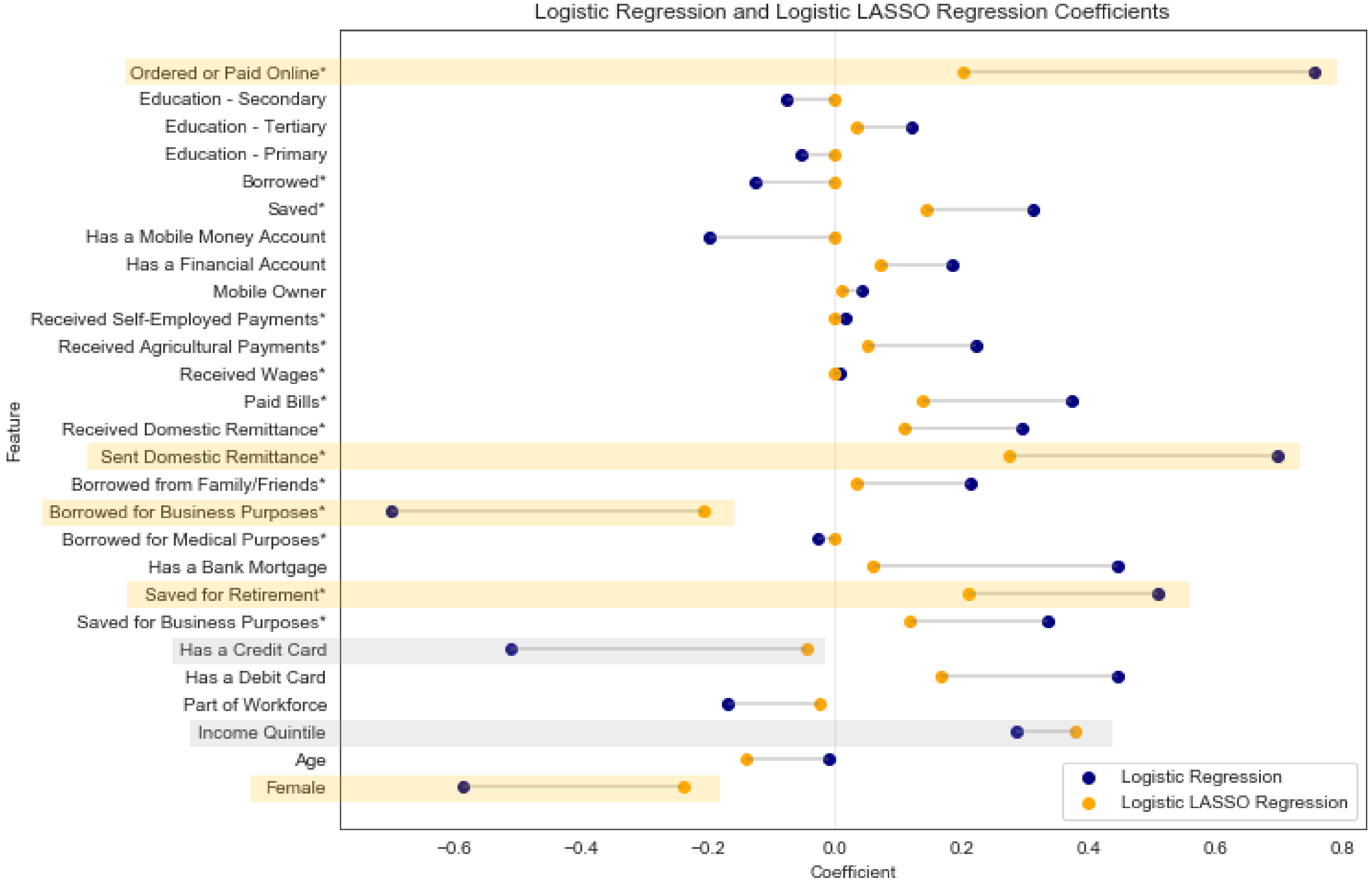
Prediction Performance

CONFUSION MATRIX



Inference

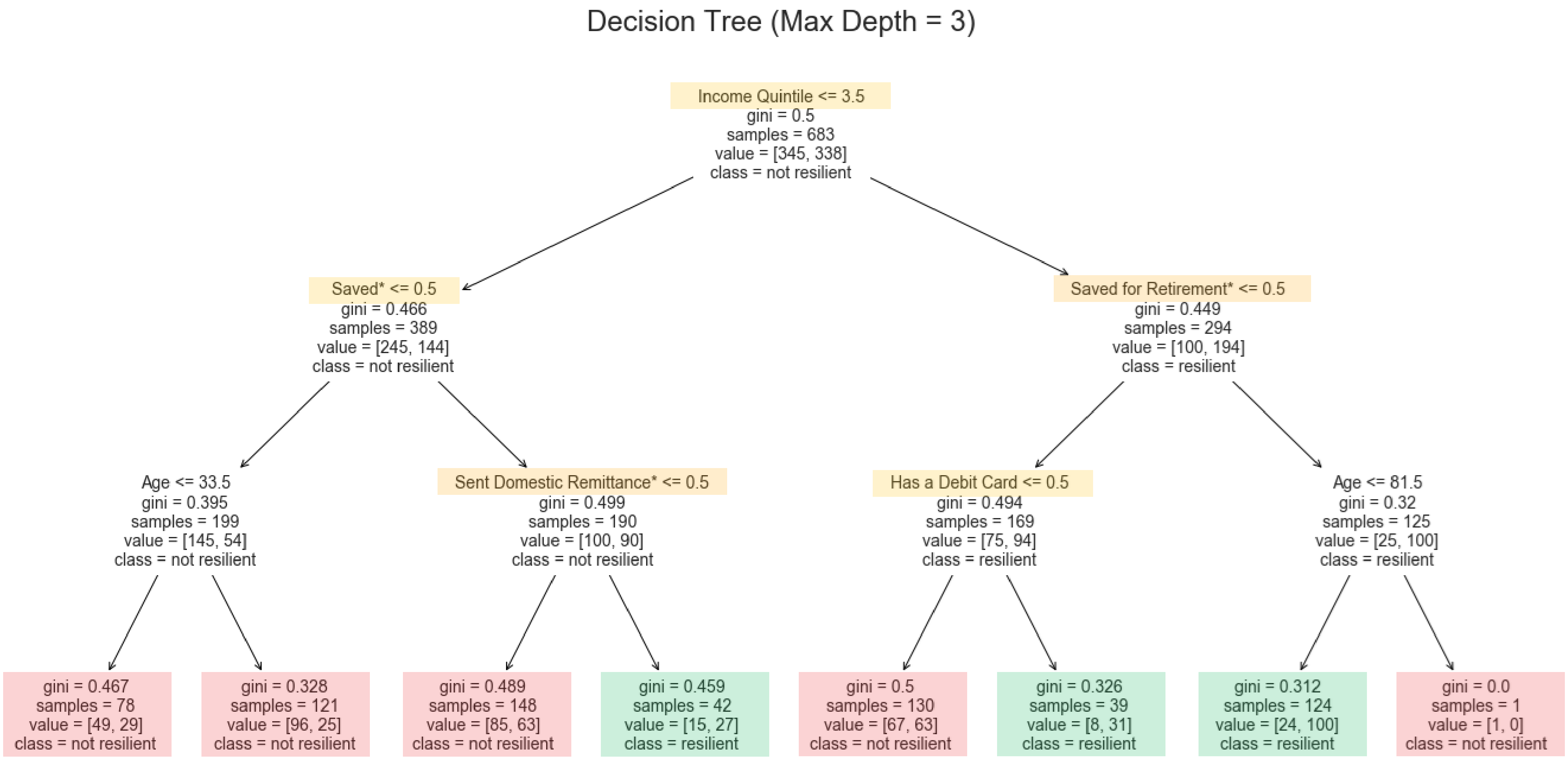
LOGISTIC REGRESSION



*Highlighted 6 largest coefficients (in absolute terms)

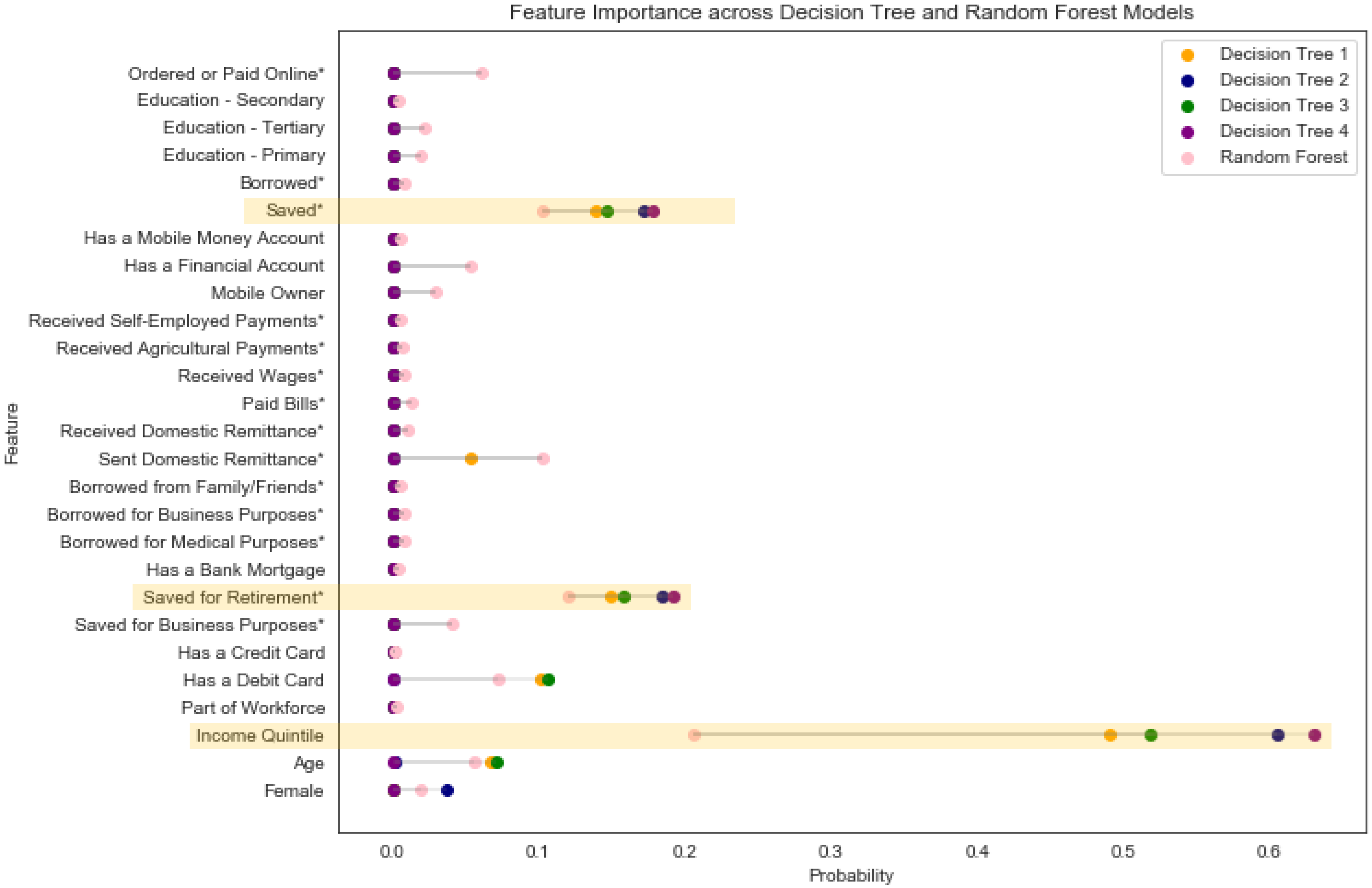
Inference

DECISION TREE



Inference

DECISION TREE & RANDOM FOREST



Conclusion

POLICY IMPLICATIONS

- Need for more granular data
- Most significant predictors
  - Income - Microcredit; Financial safety nets
  - Savings - Financial literacy programs

LIMITATIONS

- Narrow proxy measure for financial resilience
- Timeliness
- Possible measurement errors

MODEL IMPROVEMENTS

- Investigate misclassified instances
- Oversampling on rare cases
- Variable transformation (e.g., education, age, composite financial access indicators)

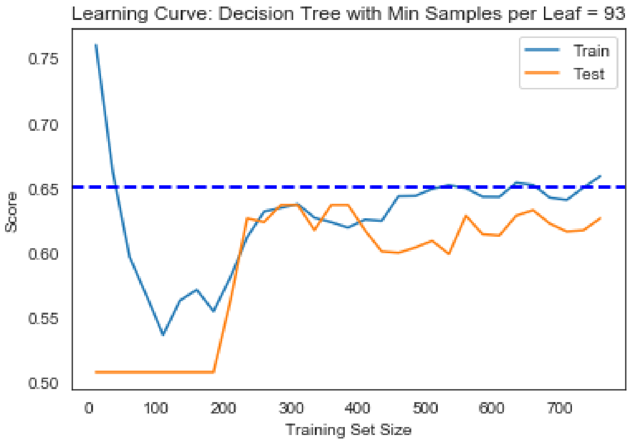
Thank you for your time!

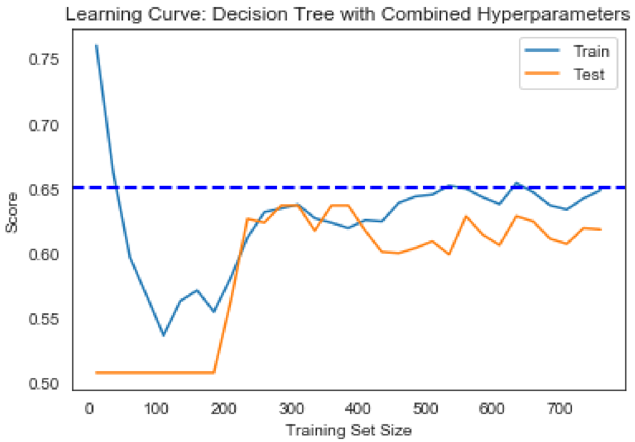
PREDICTING INDIVIDUALS' FINANCIAL RESILIENCE IN THE PHILIPPINES

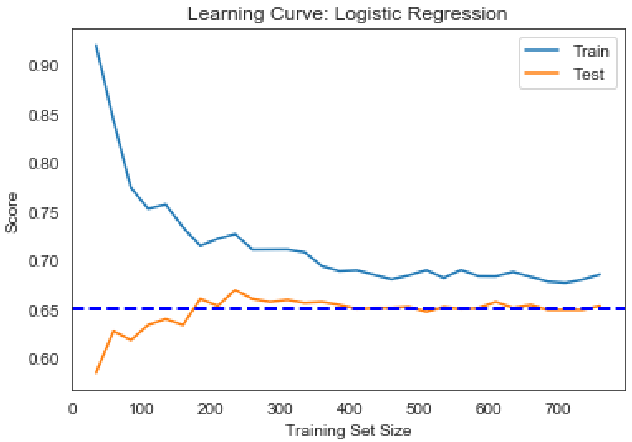
PPOL565 PROJECT PRESENTATION

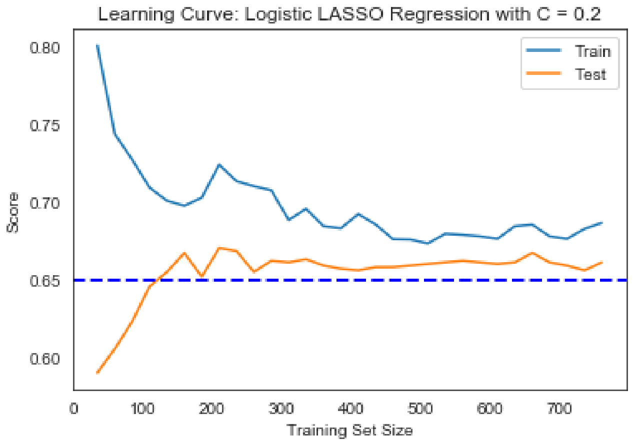
Appendix: Prediction Performance

LEARNING CURVE









Appendix: Regression Coefficients

LOGISTIC REGRESSION