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DATE: May 14, 2021

SUBJECT: Predicting Individuals' Financial Resilience in the Philippines

Executive Summary

The Philippines registered one of the highest economic growth rates in the world in the pre-COVID-19 era. However, deeply entrenched inequality persists, and it is a puzzle for policymakers who want to make growth more inclusive for all Filipinos. With the COVID-19 pandemic likely to deepen these inequalities, it is crucial to determine the most important factors that build financial resilience and the characteristics of the financially vulnerable.

Using 2017 Philippine survey data from the World Bank Global Financial Inclusion (Findex) Database, logistic LASSO regression and decision tree models were generated to predict and produce inferences on the most important predictors of financial resilience.
25 predictive features were chosen based on the components of the Multidimensional Financial Resilience Framework from a similar financial vulnerability study in 2019.

Accuracy scores for all models were all in the 60-65% range, even for the benchmark random forest model. This highlights the need for more granular survey data, as several factors remain unmeasured by the current dataset. Despite the models' low predictive performance, inferences were consistent across the models. Income level and saving behavior consistently emerged as the most important predictors. In this regard, policymakers could consider interventions such as the enhancement of micro-credit initiatives, broadening of financial safety nets, expansion of social protection measures such as agricultural insurance and healthcare coverage, and added focus on saving behavior in financial literacy programs.

Background

Posting an average economic growth of 6.4% from 2010 to 2019, the Philippines has benefited from one of the fastest economic growth rates in the world. However, deeply entrenched inequality persists as a conundrum to policymakers who seek to make growth more inclusive for all Filipinos (Oxford Business Group, 2020). The COVID-19 pandemic has battered the country, which now faces its worst economic contraction in more than 70 years (Venzon, 2021). The pandemic is also likely to wield a larger impact on vulnerable households and further deepen inequalities, as pandemics have historically done (Jurzyk, et al., 2020).

A World Bank (2020) survey on the impact of COVID-19 found that 40% of households experienced income losses, especially non-farm entrepreneurs. The study further notes that "the poor and vulnerable, many of whom work in the informal sector, are especially likely to experience significant welfare losses, given their limited capacity to manage risks" (World Bank, 2020, p. 44). Households have employed various coping strategies to survive the pandemic, such as borrowing from informal lenders and loan sharks and "[attempting] to sell assets, [but finding it] difficult to find buyers" (Economic Policy Research Institute, 2020, p. 20).

To increase financial safety nets for the vulnerable sector, the Philippine government has implemented various interventions such as agricultural insurance subsidies (World Bank, 2020); Credit Surety Fund for micro, small, and medium enterprises (Bangko Sentral ng Pilipinas, 2018); Emergency Cash Transfer (ECT) for targeted financial assistance to the poorest households (World Bank, 2020); and an enabling regulatory environment for digital and mobile payments (Hannig & Jansen, 2010). Nonetheless, there have been recommendations to "assess [the] targeting of social protection programs" (Economic Policy Research Institute, 2020, p. 24) given the disparities observed between the recipients of financial assistance from different government units.

As an emerging economy, the Philippine government must contend with limited capacity and resources. Policies should be crafted to provide the greatest assistance to those in greatest need. Empowering the vulnerable to achieve financial resilience is key to lifting them out of poverty and helping them stay out of it. If we can determine the most important environmental factors that build financial resilience and the characteristics of the financially vulnerable, then we can come up with better targeted interventions to curb the financial insecurity experienced by a significant proportion of the people and help them achieve upward economic mobility.

A statistical learning model that could accurately predict and produce inferences on the most important predictors of financial resilience would contribute to more impactful policymaking. Some attendant questions that we could ask are: What role does financial access play in financial empowerment? To what extent do financial technologies empower citizens against financial shocks? Is there a gender divide in financial capability? What is the link between income level and financial resilience?

Data

A survey conducted in Australia assigned individuals financial vulnerability scores based on the multidimensional financial resilience framework. This identifies economic resources, financial resources, financial knowledge and behavior, and social capital as key components of financial resilience (Salignac, Marjolin, Reeve, & Muir, 2019). They also measured respondents' demographic variables such as educational attainment, home ownership, employment status, income level, gender, and age (Salignac, Marjolin, Reeve, & Muir, 2019).

While a dataset of a breadth similar to the Australia survey would be ideal in answering the research question, granular financial inclusion data in the Philippines remains limited. Nonetheless, the publicly available Global Financial Inclusion (Global Findex) Database could provide individual-level information on access, use, and perception of financial services and technologies that may be useful in assessing the determinants of financial resilience (Demirgüç-Kunt, et al., 2018).

The Global Findex comprises of "nationally representative surveys of adults aged 15 and above" (Demirgüç-Kunt, et al., 2018). In the Philippines, data collection took place through computer-assisted personal interviews of 1,000 respondents conducted from July to August 2017 (Demirgüç-Kunt, et al., 2018). Variables include demographic information, ownership of financial products, use of financial products, financial access, and reasons for lack of access. The survey also gathered data on financial resilience, which it frames as the ability of the respondent to gather emergency funds within the next month amounting to 5% of the Philippine Gross National Income (GNI) per capita. Estimates place this at "4 weeks of pay for an average worker in the Philippines" (Kempis & Morduch, 2020).

Using the Global Findex dataset to examine the determinants of financial resilience has immediately perceptible limitations in terms of the timeliness of data collection and the narrow proxy measure for financial resilience. Moreover, model accuracy may be hampered by the lack of relevant demographic variables such as geographic location and occupation, as well as the presence of only one numeric variable in the dataset (i.e., age).

There may also be concerns of measurement errors due to self-reporting. Especially since face-to-face interviews were conducted, it is possible for respondents to misunderstand, incorrectly recall, or withhold information that they deem shameful (for instance, their ability to satisfy the condition for financial resilience). Nonetheless, the conduct of the interviews in the respondents' native languages such as Filipino or Cebuano might have curbed misunderstanding and response bias.

Data Preprocessing

In selecting predictive attributes for the model, the primary consideration was to capture characteristics that may conceivably possess links to an individual's financial resilience. Table 1 shows the list of variables chosen for this purpose, which is patterned after the Australia study's framework for the key components of financial resilience (Salignac, Marjolin, Reeve, & Muir, 2019). Most are binary variables, except for: (1) age, which is numeric/ratio; (2) education level, which is ordinal; and (3) income quintile, which is ordinal.

Table 1: Predictive Attributes Selected for the Model

Economic Resources (5)	**Financial Resources** (5)	**Financial Knowledge and Behavior** (10)	**Social Capital** (1)	**Demographic Variables** (4)
• Income Quintile[1] • 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*[2]	• Borrowed from Family/Friends*	• Age • Sex • Education Level[3] • Part of Workforce

** denotes behavior in the past 12 months.*
[1] *Income Quintile* classifies respondents into the poorest up to the richest 20% of households.
[2] *Online Transaction* is a feature generated by merging responses to the use of the Internet in making bill payments or online purchases.
[3] *Education level* classifies respondents into "Primary or lower", "Secondary", and "Tertiary or more". However, it is uncertain whether academic completion is required to be considered under "Secondary" or "Tertiary or more".

To eliminate missing data, observations were dropped where respondents refused or did not know the answer to any of the selected attributes. This trims the dataset from 1,000 to 977 data points with 25 predictors and 1 target variable. Both education level and income quintile are ordinal attributes in the source dataset, but the former was converted to binary variables while the latter was converted to integers because of its equally spaced intervals.

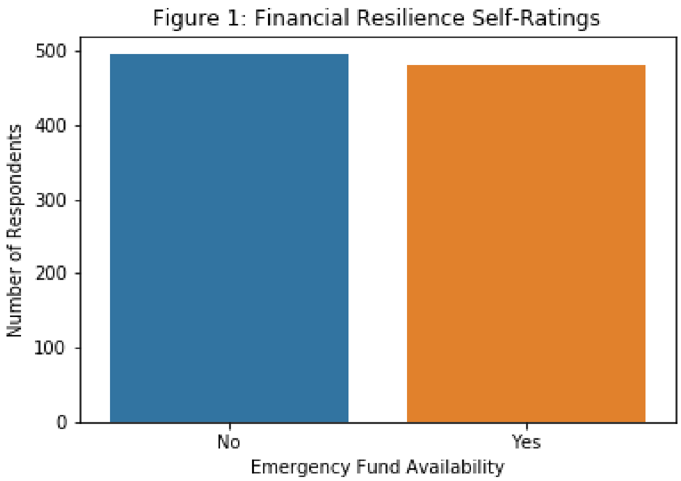
Data Characterization

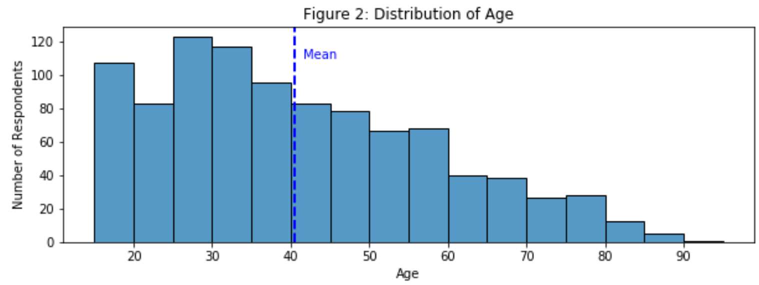
Descriptive statistics in Table 2 show reasonable values for both age and income quintiles. For age, the standard deviation of 17.5 suggests that the data is reasonably spread out and that the majority of respondents are of working age (i.e., aged 23 to 58). The comparably lower median of 37 (against the mean of 40.5) suggests that older respondents are possible outliers who are pulling the mean upwards. However, I decided not to drop these observations as they may provide useful information on one's financial resilience as one ages. Finally, results on the income quintile suggests a uniform distribution, which means that our sample is representative across socioeconomic classes.

Table 2: Descriptive Statistics for Numeric Variables

Variable	**Minimum**	**Mean**	**Std Deviation**	**Median**	**Maximum**
Age	15	40.6	17.5	37	95
Income Quintile	1	3.1	1.4	3	5

Figure 1 shows that we are dealing with a balanced target variable. Since the outcomes occur equally frequently, the model should be able to learn substantially about each class to make an adequate prediction. Nonetheless, possible rare cases may be gleaned from Figure 2, which shows that age possesses a right-skewed distribution. This is expected given the Philippines' median age of 24 (O'Neill, 2021). To maintain interpretability, age will be kept as is. However, should model performance be compromised, variable transformation may be undertaken as in Figure 3, which shows that logged age more closely resembles a normal distribution. This may be supplemented by undersampling on the left tail and oversampling on the center as well as the right tail.





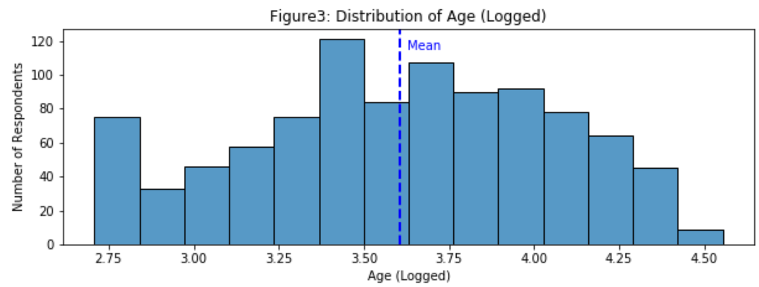
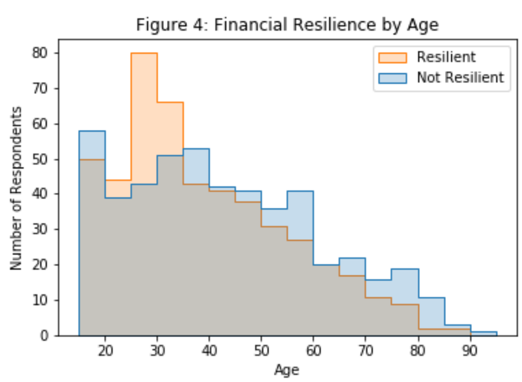
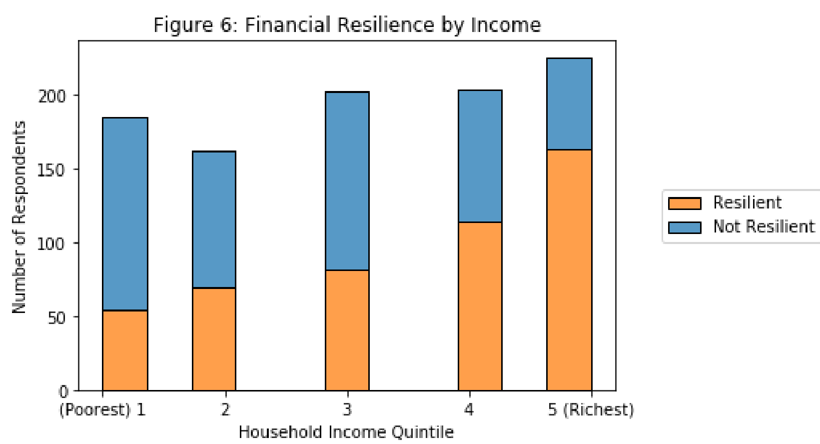


Figure 4 shows that financial resilience is roughly equally distributed across age, except for respondents aged 20 to 40, which are predominantly resilient. Figure 5 expands on this by investigating the interaction between workforce participation and age in determining resilience. A significantly higher percentage of individuals not in the workforce reported less resilience, except for those in their late 20s to early 30s, who were significantly more financially resilient than their counterparts – possibly because their exclusion from the labor force is by choice[1].



[1] The labor force comprises both the employed and the unemployed job-seekers. It excludes unpaid workers, family workers, and students. (Source: World Bank via https://data.worldbank.org/indicator/SL.TLF.TOTL.IN)

Confirming earlier results, Figure 6 shows that we have a balanced dataset in terms of income quintile. As expected, richer households tend to report higher financial resilience, although the proportion of non-financially resilient among the highest socioeconomic class is a surprising result (at 30%).



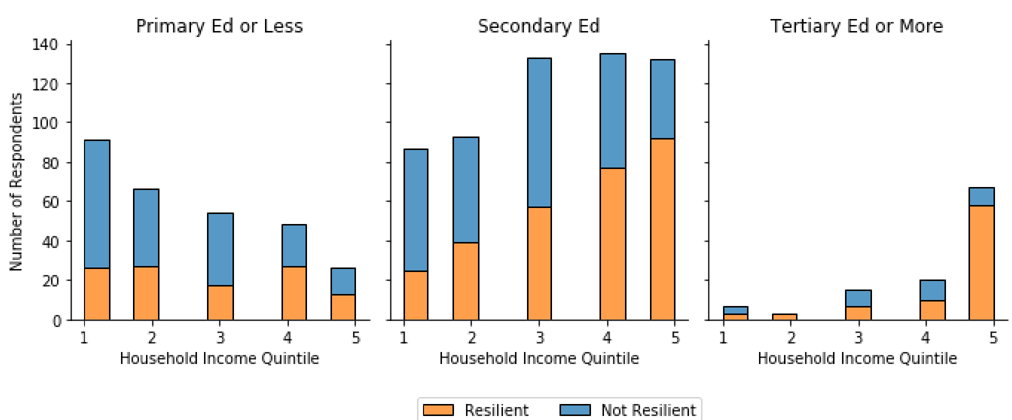
As shown in Table 3, the majority of respondents were classified as recipients of secondary education, although it is unclear whether the Findex survey requires degree completion for a respondent to be considered as secondary- or tertiary-educated. At 11.5% frequency, tertiary-educated respondents are rarer cases. Depending on the homogeneity of this sub-population, oversampling may be considered to provide the model more training data.

Table 3: Frequency Tabulation for Education Level

Education Level	Frequency	Relative Frequency (%)	Cumulative Frequency	Cumulative Relative Frequency (%)
Primary or less	285	29.2	285	29.2
Secondary	580	59.4	865	88.5
Tertiary or more	112	11.5	977	100.0

Examining the interaction between education and income level, it may be seen in Figure 7 that the educated tend to be more financially resilient. However, they also tend to belong to the higher socioeconomic classes. It would be interesting to determine which predictor turns out to have stronger links to financial resilience.

Figure 7: Financial Resilience by Income Quintile and Education

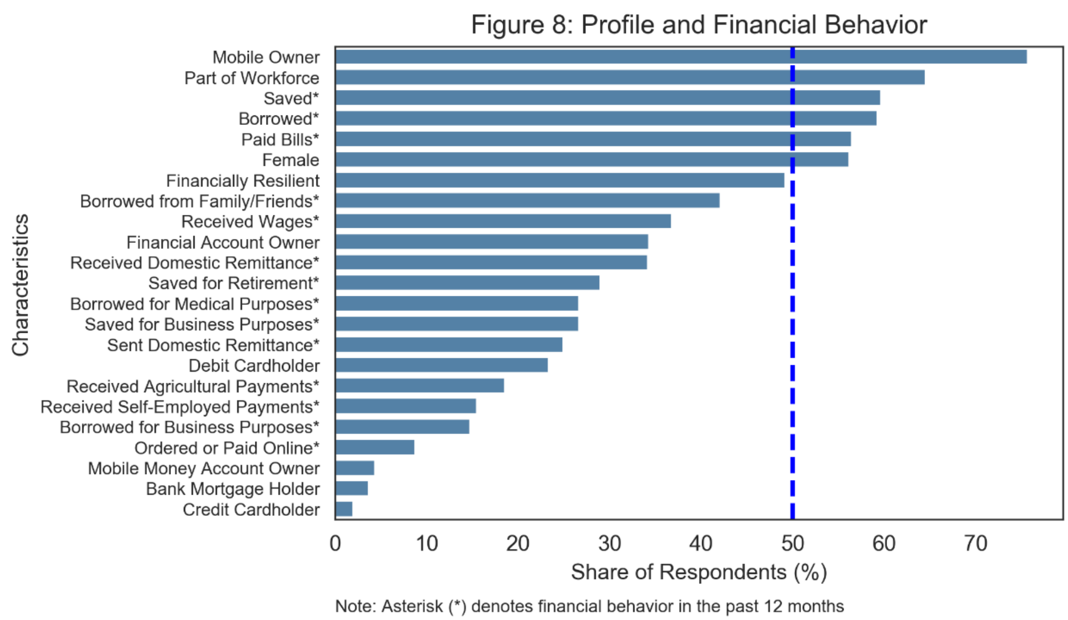


Gender gaps have been widely noted in much of financial inclusion literature (e.g., Sahay & Cihak, 2018). Table 4 shows a similar gap, although the result is less pronounced compared to other country-level studies that have used the Global Findex (Hussain, et al., 2019).

Table 4: Financial Resilience by Sex

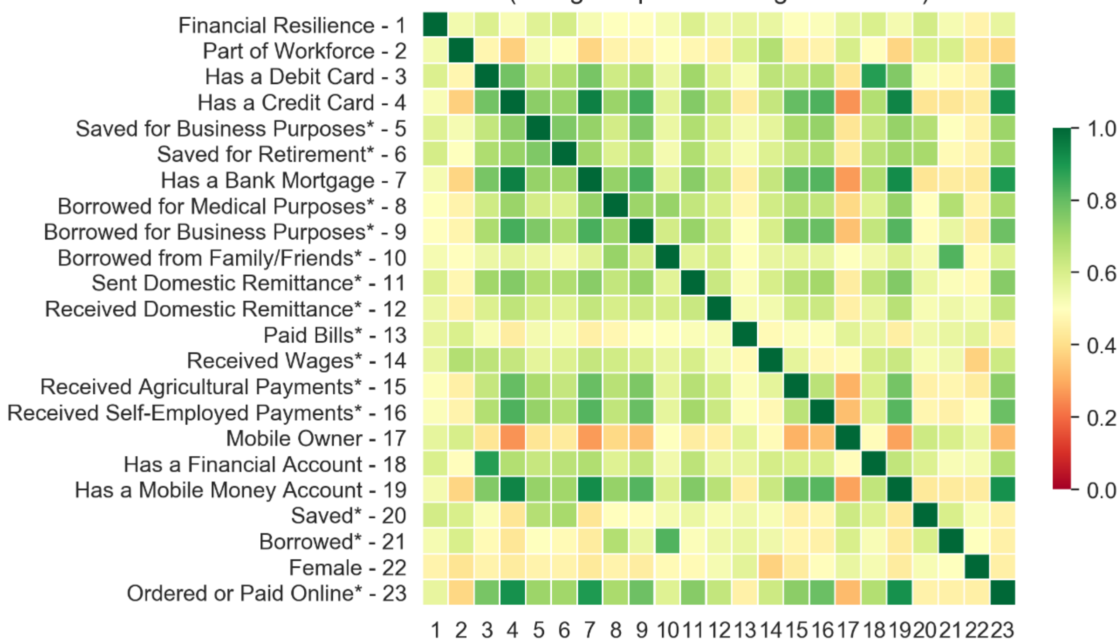
Sex	Not Financially Resilient	Financially Resilient	Total	Financial Resilience (%)
Female	297	252	549	45.9
Male	199	229	428	53.5

Figure 8 shows a graphical summary of the frequency tabulations generated by the binary variables selected for the model. That a majority of indicators fall below 50% highlights the long journey that remains towards financial development. This also indicates other possible rare cases that may crop up, as less than 10% of respondents responded positively to the bottom 4 indicators, i.e.: conduct of online transactions, and ownership of mobile money account, credit card, or bank mortgage.



The predominantly binary nature of our variables makes correlation (and the related Variance Inflation Factor) inappropriate for checking possible multicollinearity across our variables. The Simple Matching Coefficient (SMC) would be a more suitable measure as we are interested in both positive (1-1) and null (0-0) matches of our respondents' demographic and financial characteristics. Figure 9 uses SMC to assess similarity among binary attributes, including our outcome variable. Financial resilience does not appear to be strongly connected to any specific attribute. Moreover, large SMCs (of at least 0.9) were found for combinations of the bottom 4 indicators identified in Figure 8, suggesting that respondents belonging to this case are few but homogenous.

Figure 9: Similarity between Binary Variables
(Using Simple Matching Coefficient)



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

Methodology

Based on our research question, our model choice should be equipped to handle classification problems and provide meaningful inferences on the predictive power of the various attributes. On the other hand, data characterization indicates that (1) overfitting should be sufficiently addressed given the presence of 25 predictors based on domain knowledge; (2) our model should be robust to outliers, considering our rare binary cases and older respondents; and (3) our model should be able to handle redundant/irrelevant and interacting variables, the former of which is possible given the various related financial indicators included in our parameters and the latter, evident from the various visualizations provided in the earlier section. Thus, the models that appear most suited for our research objective are the Logistic LASSO Regression and the Decision Tree.

Logistic LASSO Regression

The logistic regression belongs to a set of parametric techniques that is touted as the 'workhorse of social science' (Brodnax, 2021). Their wide use as the base for statistical analysis may be attributed to their interpretability and portability from theoretical to empirical. Logistic regression predicts the probability that a particular entity belongs to a specific class. It does so by generating maximum likelihood estimates based on the combination of characteristics that led to previous occurrences of the outcome. In other words, it determines likely predictors of known outcomes and assesses new data against this model to predict which outcome is most likely given a specific set of values for the predictors.

Logistic regression has also been used in similar studies analyzing financial inclusion. One such study uses Findex Data collected from selected Southeast Asian countries in 2014 to study the determinants of financial inclusion, defined as access to a financial account (Tjahjadi & Ajani, 2018). The research used individual characteristics and factors related to borrowing to predict the level of inclusiveness across different income levels and countries.

In our case, logistic regression is well-suited because it deals well with irrelevant, redundant, and interacting variables – all concerns raised in earlier sections. However, the technique tends to be sensitive to outliers, so issues may arise with the robustness of the results amidst the presence of rare cases in the age variable as well as some financial indicators.

Since it seeks the combination of predictors that will best fit existing data, logistic regression models tend to overfit as the parameters increase. To aid in model generation, LASSO can be used as a shrinkage method to zero out irrelevant coefficient estimates. Through LASSO, we will be able to narrow down which predictors of financial resilience are most important. However, before performing LASSO, we must first standardize our features to eliminate issues with scaling that may cause larger-ranged variables such as age to dominate the regression model.

Decision Tree

Decision tree is a non-parametric technique that splits known cases into groups as homogenous as possible, and then classifies new data based on rules generated from these splits. It is widely used for its straightforward interpretability and accessibility to the non-technical audience. Decision tree is likewise robust to irrelevant variables and outliers, which will come in handy given our relatively large number of parameters and the rare cases that we noted during data characterization.

Decision tree has likewise been used to determine key factors in financial inclusion. Aiming to segment Indian survey respondents into the financially excluded and included, Tiwari, et al. (2019) generated classes based on a composite measure of financial inclusion (composed of bank account ownership, access to loan requirements, insurance coverage, and access to digital banking). They then generated a decision tree that classified individuals as included or excluded based on demographic, social, and economic variables.

Like logistic regression, decision tree may be prone to overfitting as the number of parameters increases. Too many variables may cause the decision tree to accidentally overstate the importance of irrelevant variables. Nonetheless, this should not preclude us from using the algorithm. Various methods would address possible model overfitting, such as hyper-parameter tuning to limit tree size or pruning to penalize larger trees.

Findings

To begin my analysis, I computed for the baseline financial resilience rate (49.2%). This means that if we were to tag all observations as financially resilient, we will obtain an accuracy of 49.2%. Likewise, if all respondents would be tagged financially vulnerable, our accuracy will stand at 50.8% (i.e., 100% less the financial resilience rate).

For my model building, I ran different decision tree and logistic regression models based on selected hyper-parameters. The values chosen for the hyper-parameters were based on a comparison of the train and test means generated by the validation curve. To maximize accuracy and minimize overfitting, test means were maximized while maintaining a tolerable difference between the training and test mean scores. The chosen models were then ran against the same set of training and test data, split at 30% to allow the models to train on a substantial training set (683 observations) while keeping a sizeable test set (294 observations).

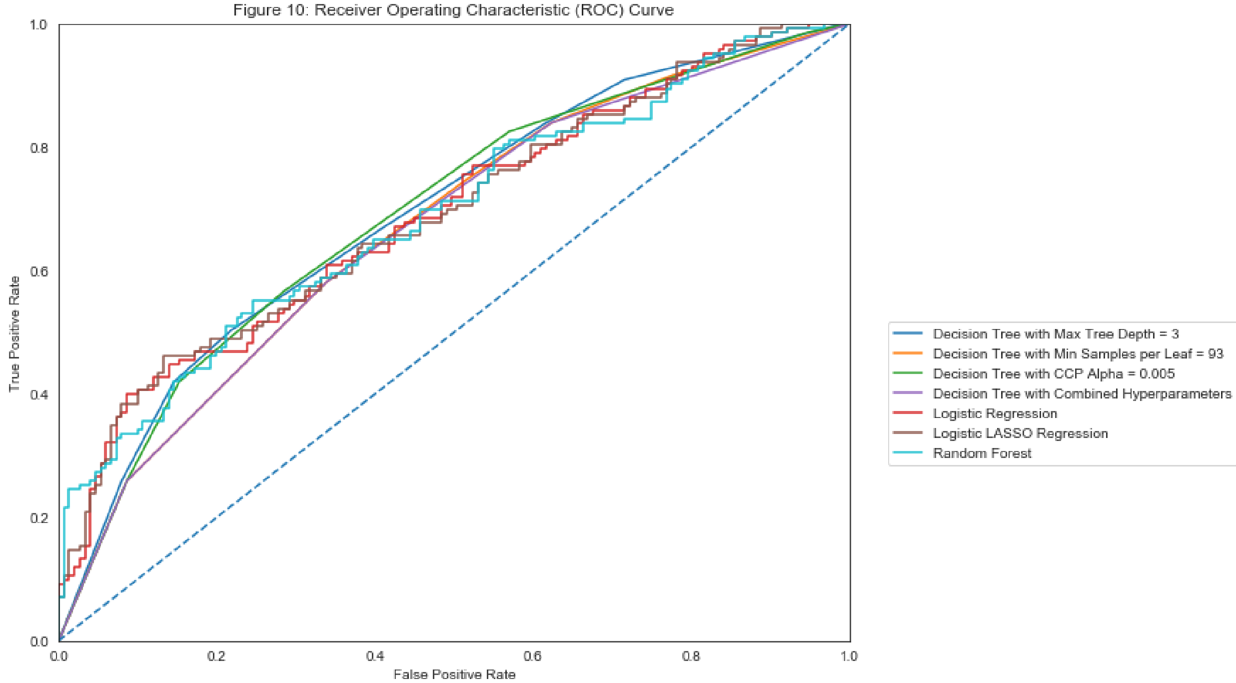
Table 4 compares the accuracy scores of the different models on the test data. The accuracy scores hovered in the 62-64% range. Considering that both the decision tree and logistic regression may sacrifice accuracy for interpretability, I added a benchmark to determine whether higher predictive accuracy could be achieved. Random Forest (with a maximum tree depth of 3 and 1,000 estimators) emerged with the best predictive score from the cross-validation of a pool of models including Naïve Bayes, Linear Discriminant Analysis, K-Nearest Neighbors, Neural Networks, Random Forest, and Support Vector Machines. However, applying Random Forest to the training and test data still resulted in a test accuracy score below 65%.

Table 4: Accuracy Scores across the Different Models

Classifiers	**Hyper-parameter**	**Accuracy Score (in %)**
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

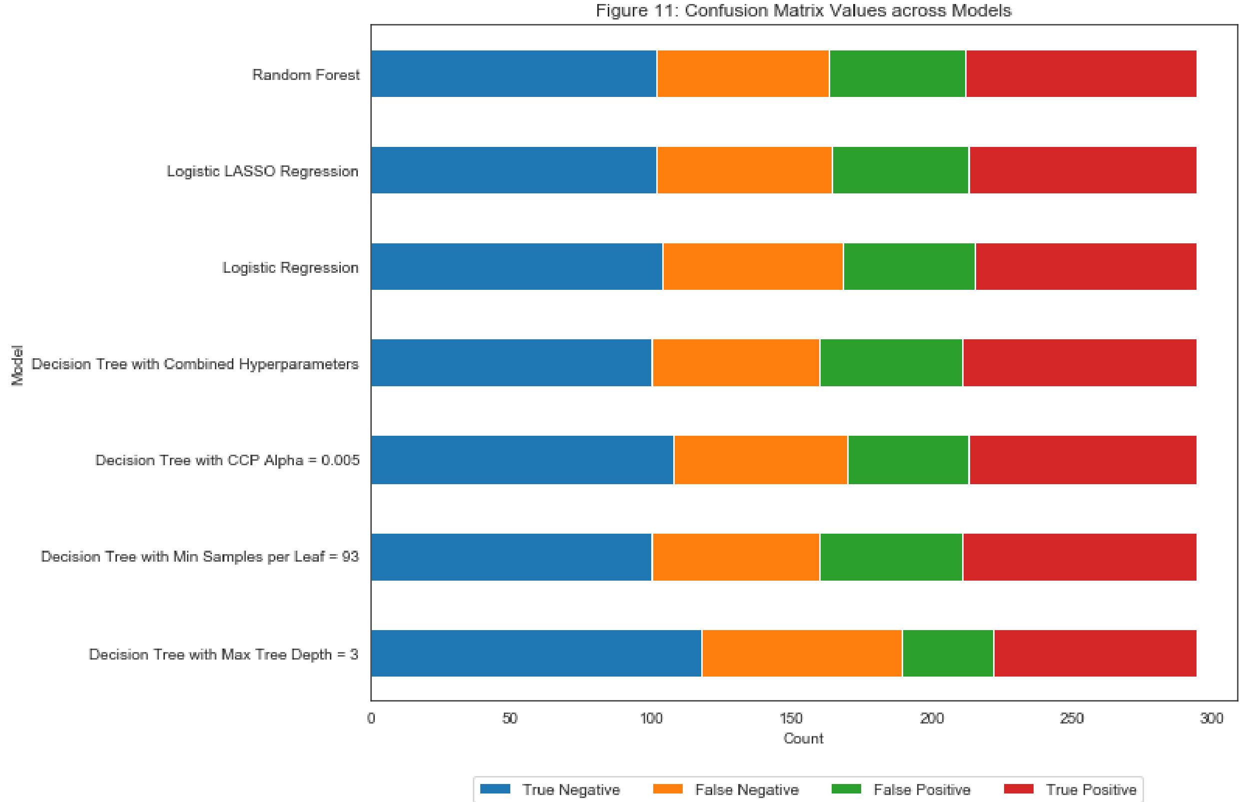
The Receive Operating Characteristic (ROC) curve in Figure 10 shows a graphical comparison of the different models' predictive performances. All models follow roughly the same path – all better than 50% chance but far from the ideal where the curve hugs the top left corner of the axis (signifying the ability to achieve high true positive rates while keeping false positive rates low). Nonetheless, logistic regression models tend to produce better results at lower and higher false positive rates while decision trees tend to perform better towards the middle.

Figure 10: Receiver Operating Characteristic (ROC) Curve



While accuracy is important to distinguish the financially resilient from the financially vulnerable (which would thereby facilitate the proper targeting of interventions), it is more important to dissect the components of these accuracy measures and assess the nature of the models' misclassifications. Figure 11 compares values taken from the models' confusion matrices. We can see that the Decision Tree with a Maximum Tree Depth of 3 yields the highest number of true negatives and fewest false positives (where "positive" means financially resilient and "negative" means otherwise). This model would be the most suitable out of the current suite of models if we would like to cover as many of the financially vulnerable as possible. However, the high number of false negatives would mean that interventions would also be received by a sizeable number of individuals who are already financially resilient.

Figure 11: Confusion Matrix Values across Models



Inference

The logistic regression and logistic LASSO regression shared 5 of the top 6 variables in terms of magnitude of coefficients. Figure 12 highlights these key features in yellow, i.e.: online transactions, sending of remittances, borrowing for business, saving for retirement, and gender. On the other hand, variables in gray were identified as part of the top 6 features in only one of the models. One would notice that income quintile was the most significant in the logistic LASSO but ranked lower in the logistic regression.

Figure 12: Logistic Regression and Logistic LASSO Regression Coefficients

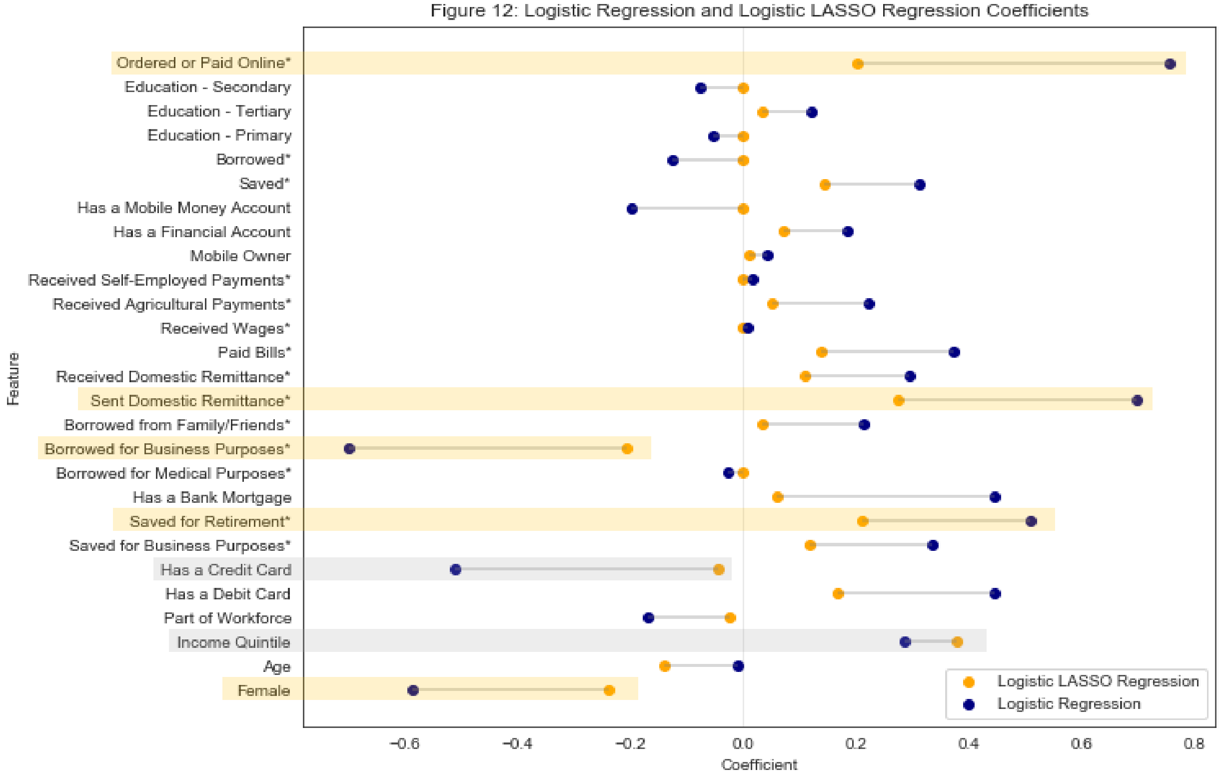
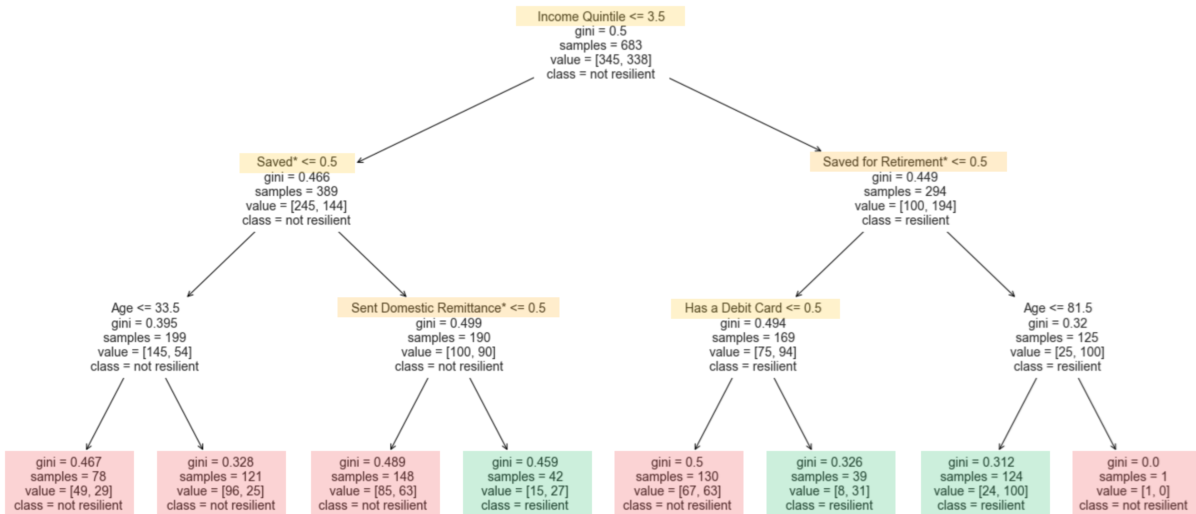


Figure 13 shows the decision tree with the highest accuracy and highest true negatives. Like logistic LASSO regression, income quintile emerged as the most important, followed by savings – whether for retirement for the richer respondents or just being able to save for those in the lower income classes. Sending domestic remittances were also identified as more indicative of resilience for lower-income respondents, while owning a debit card was identified positively with financial resilience for higher-income respondents. Nonetheless, it must be noted that the Gini scores remain high across all nodes. Respondents must be segregated further to better identify who are the financially resilient and who are not.

Figure 13: Decision Tree (Max Depth = 3)



In terms of feature importance for the decision tree and random forest models as gleaned from Figure 14, the results are similar with the Decision Tree chosen for Figure 13 (which is tagged “Decision Tree 1” in Figure 14). The top predictors are income quintile and both forms of saving behavior (i.e., saving per se and saving for retirement).

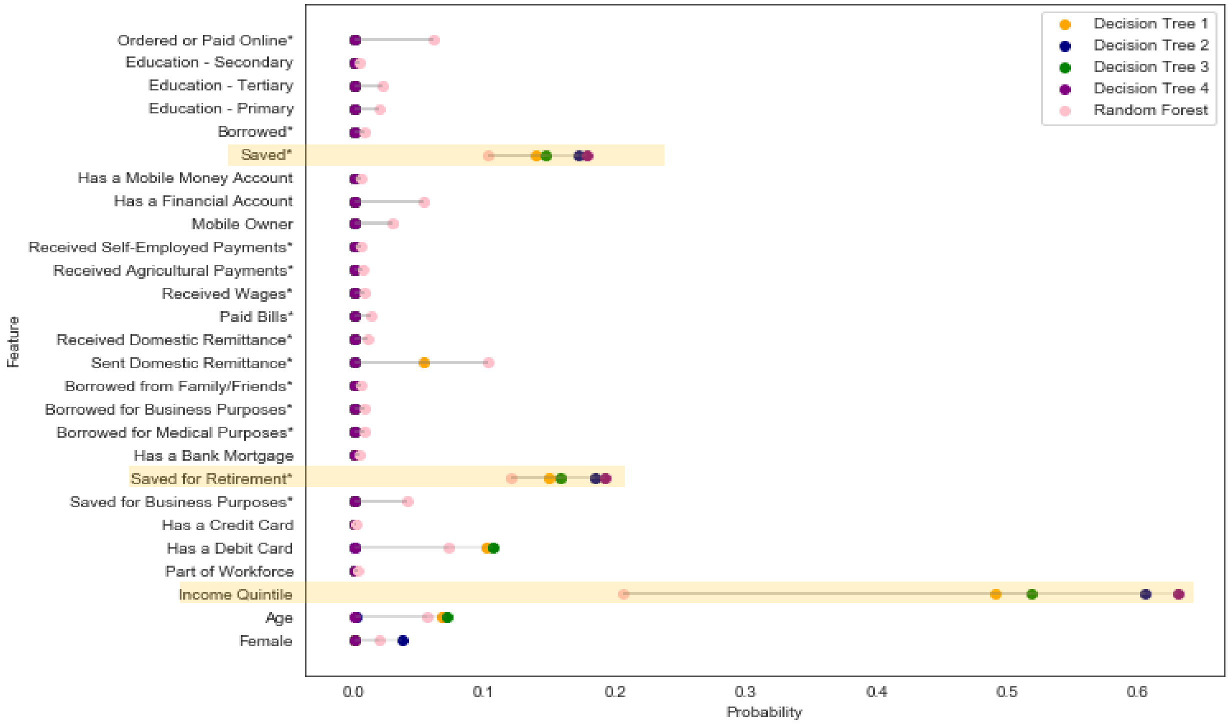


Figure 14: Feature Importance across Decision Tree and Random Forest Models

Conclusion

The consistent below-70% accuracy of the various models highlights the need for more granular survey data, as several factors remain unmeasured by the current dataset. The demographic information and financial access indicators captured by the Findex database are not enough to know who the financially vulnerable are. Financial resilience may be more accurately predicted through the introduction of additional demographic variables relating to home ownership, employment status, and industry as well as information across the different dimensions of financial resilience in the spirit of the Australia study (Salignac, Marjolin, Reeve, & Muir, 2019).

Nonetheless, despite the relatively low accuracy of the models, it may still be worthwhile to consider the salient inferences derived from the models. For instance, income level consistently ranked as the most important feature in the models. In this regard, policymakers could craft programs targeted towards improving employment and compensation especially for those in the lower socioeconomic classes.

The Philippine government currently implements a conditional cash transfer (CCT) program which benefits around 20% of the population (World Bank, 2017). However, the decision tree's choice to split after the 3rd income quintile may indicate that it is not just the poorest of the poor who face increased financial vulnerability. A broadening of financial safety nets may be considered so that social protection can extend to households with income levels in the bottom 60% of the population. Moreover, enhancing micro-credit opportunities may help the entrepreneurial poor tap into additional funding sources that would allow them to earn income and become self-sufficient.

Saving behavior was likewise identified as a key predictor in most of the models, although it was an interesting result that the decision tree identified different forms of savings as important for the different socioeconomic classes. For those with lower income levels, the act of saving, in whatever form or for whatever purpose, mattered. However, for those with higher income levels, saving for one's retirement mattered.

The importance of having the ability to save for poorer households illustrates the need to protect them against shocks such as disasters or medical emergencies. For instance, the government may consider setting up agricultural insurance programs for lower-income farmers whose earnings may be sensitive to weather-related disruptions. Healthcare coverage may also be reassessed to determine the extent of out-of-pocket payment required from poorer beneficiaries.

On the other hand, for those with higher income levels, saving for the future may matter more than saving for other purposes (e.g., saving for business or for a major purchase). Since even those with higher incomes can become financially vulnerable, these results may imply the need to instill the value of financial discipline, which may begin with financial literacy classes in primary education. Financial literacy programs can also delve more into the importance of setting aside savings for the future.

Nonetheless, it must be noted that these insights come with an important caveat – that the validity of the findings may be limited by the low accuracy coupled with other considerations on the dataset such as (1) the narrow proxy measure for financial resilience used in the Findex survey; (2) timeliness of the survey results, given that it was conducted in 2017; and (3) possible measurement errors because the survey hinges on self-reporting by the respondents.

Future considerations for study may cover the improvement of the current models' predictive accuracy. Misclassified instances may be investigated to check if there are specific population segments that were not properly represented. Oversampling could be done on rare cases. Variable transformations may also be considered, such as converting education to a numeric variable, binning on age, or creating composite financial access indicators.

Implementation Appendix

Since the Findex Dataset comprised mostly of binary variables, preparing the dataset for model building required little reshaping and pre-processing. The extent to which these steps were done was discussed in the *Data Preprocessing* section. While this exercise did not require significant data wrangling by virtue of the abundance of binary variables, these binary variables also led to the most interesting aspect of technical implementation in the study – the Simple Matching Coefficient (SMC) heatmap.

While I initially attempted to plot the usual correlation heatmap, I realized that the predominantly binary nature of the variables renders correlation inappropriate. The SMC would be a more suitable measure as we are interested in both positive (1-1) and null (0-0) matches of our respondents' demographic and financial characteristics. To generate the SMC matrix, I created a function which returns a data frame of SMCs based on columns in an input data frame. The resulting SMC matrix can readily be plotted into a heatmap.

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