A Study to Diminish Housing Insecurity

Humana-Mays 2022 case competition

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1. Executive Summary

In the United States, about 3 million people spend the night without shelter every year, 1.3 million of whom are children. Americans have a 6.2% chance of experiencing homelessness in their lifetime. In a survey conducted by the US Census Bureau in 2020, nearly half of adult renters said that they were 'very likely' or 'likely' to be evicted from their homes in the next two months, which is equivalent to an estimated 3.7 million people reporting some form of housing insecurity[1].

Unsafe housing may have a negative impact on life and health. Homeless children are less likely to go to school or fall behind in their classes. They are more likely to suffer from hunger and poor physical and mental health, for example, they are four times more likely to suffer from respiratory infections than others[2]. Homeless people find it more difficult to obtain medical assistance. They face serious health threats, from cleaning and nursing wounds to lack of treatment for chronic diseases, and even lose their lives due to severe trauma.

The federal government provides housing assistance mainly through the Section 8 voucher program, which spends more than $19 billion annually to provide housing for more than 2 million people and families. In 2016, the U.S. The House of Representatives passed Bill 4888, which will allocate an additional 13.6 billion dollars to the Department of Housing and Urban Development in the next 10 years to eliminate homelessness nationwide[1]. The U.S. Department of Health and Human Services (HHS) has launched several in-home and community-based programs provided by Older Americans Act and Medicaid. These programs include Community Development Block Grant, HOME Investment Partnership Program and the Housing Trust Fund[3]. Centers for Medicare and Medicaid Services (CMS) has also offered non medical support through Special Supplemental Benefits for the Chronically Ill (SSBCI) [4].

Housing insecurity is caused by high housing cost relative to income, poor housing quality, unstable community or lack of sense of security caused by overcrowding. Therefore, we can improve this social problem mainly through ameliorating housing quality and security, improving community environment and providing financial assistance.

We have recommended the following solutions to this problem:

1) Humana can invest in structural home modifications of homes and work on sanitization for maintaining the quality and safety of houses.
2) We also observed a strike gap between Black homeownership rate and our recommendation is to revisit the policies of banking services. One of the recommendations would be to put a soft boundary over credit policies for first-time home buyers.
3) Variable down payment options based on salary slab would be beneficial for the home buyers and would inhibit them from spending 30% of their monthly salary.
4) In addition to Humana's current efforts we recommend constructing affordable, stable and cleaner neighborhoods. Our recommended pilot program will serve as a good starting point for several stakeholders who are working towards mitigating housing insecurity.

2. Case Context

2.1 Case Background

Humana, a leading health insurance company, is committed to helping individuals live their healthiest lives possible. They put their efforts into making their insurance products and business decisions that improves the health of their members and associates. The social determinants of health (SDOH) includes the conditions of people's living conditions that affect their health. The economic policies that affect an individual's health are included in structural determinants of health. The health related social needs (HRSNs) which is a term used by Center of Medicare and Medical Studies (CMS) in Accountable Health Communities (ACH) Model[3], are the urgent threats to health and are the results of structural and/ or social determinants of health. A wide range of social problems, including food insecurity, access to transit, loneliness, financial stress, and housing insecurity, are included in the health-related social needs. This analysis primarily addresses the issue of housing insecurity including lack of access to quality and safe houses, which causes health harming conditions to many individuals. It refers to a variety of issues, such as having problems making rent payments, living in close quarters or overcrowding, relocating frequently, or devoting a large portion of household income to housing. In America, 3.7 million people are reporting a form of housing insecurity and 7.7 million are behind on rent [4]. These situations could have a detrimental impact on physical and mental health of people and make it more difficult to afford medical care. So, in this analysis we are assisting Humana identify the Medicare members who are most likely suffering from housing insecurities and are proposing solutions that Humana can implement in order to reach their goal of improving community health through housing.

2.2 Problem Statement

The aim of this analysis is to focus on solving the business problem of identifying the Medicare members who are most likely to be struggling with housing insecurity issues by building a predictive model effectively and propose recommendations and solutions which can be extended to help individuals in overcoming their vulnerabilities and achieving their best health. Members that experience housing insecurity are probably not homogeneous and may experience their insecurities for a variety of reasons. As a result, there may be various solutions for various member segments. We identify different segments of population that are more vulnerable to this insecurity and propose solutions that are suitable for them. Our objective is to minimize any potential bias in the data so that our analysis and recommendations guarantee fairness and equity.

3. Data Preparation

3.1 Humana's Data Overview

On our initial exploration with the dataset, we identified there are 48,300 Humana MAPD members in which every member is associated with a binary flag to indicate housing insecurity condition. In these 48,300 members, we have around 2114 members who are identified with housing insecurity and these members constitute only 4.4% of the whole data.

Figure 1: Data distribution of Humana Data
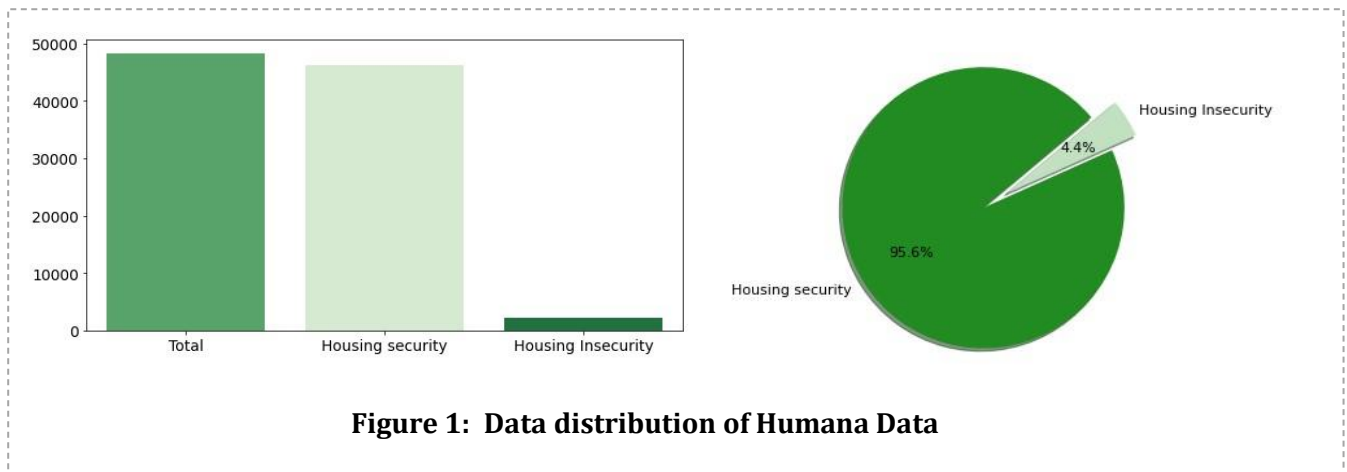
The dataset consists of 881 features that are recorded for every MAPD member. Our goal in this chapter will be to find patterns and flag the cases of members with Housing insecurity. We further focus on identifying important KPIs that need to be tracked for mitigating Housing Insecurity and possible recommendations that would benefit Humana.

To better understand data, we have categorized our features, based on the type of data sources. We have identified the following categories of features recorded for every Humana MAPD member (Figure 2)
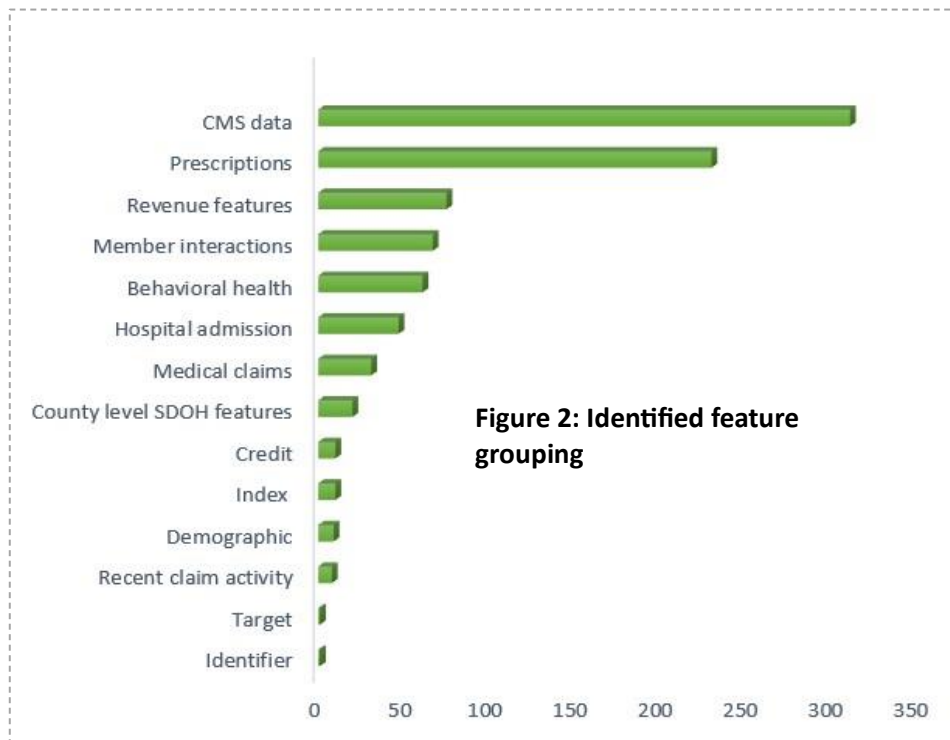
Figure 2: Identified feature grouping

Sample examples of the categories:

1. *CMS features:* Risk adjustment factor/amount and claims per month related injury/tumor etc.
2. *Prescriptions:* Count and cost per month related to prescriptions, Contraceptives in the last month etc.
3. *Revenue features:* Claims per month for a certain revenue code
4. *Member interactions:* count per month member interactions with email, live call etc.
5. *Behavioral health:* count of behavioral health claims related to autism. acute hospitalization etc.
6. *Hospital admission:* Admits per month for overall claims related to several diseases
7. *County level SDOH features*: Median house income, Primary care physician per 100K population, homicide rate etc.
8. *Credit:* Number of mortgages, % balance to high mortgage credit
9. *Index:* Student Index, RUCC category, Income index etc.

10. *Demographic:* Adult diabetes rate, international migration rate etc.
11. *Recent claim activity:* Days since last claim related to neoplasm, urgent care etc.
12. *Identifier*: Unique ID of Humana MAPD user
13. *Target:* Binary identifier to flag housing insecurity.

3.2 Data Cleaning and Imputation

The next step in the model development phase consists of extracting explanatory variables which are critical in distinguishing a Humana MAPD member with Housing insecurity.

We have used the following steps in our initial data cleaning.

- **Excluding Irrelevant features:**
  We have excluded 205 variables as they capture no information (all zeros) of MAPD members. This has significantly reduced the complexity of the model.

- **Filling null values:**
  - Most variables have nullable values, instead of excluded, we have opted in imputing those variables based on context. In the case of string datatype, we created a new category called "Unknown".
  - In the case of other numeric features, we have used KNN Imputer to fill in the missing values. In KNN algorithm, missing values are imputed using the mean value from three nearest neighbors found in the training set.

- **Assigning the correct variable type:**
  We also identified a few features tagged as objects instead of float data type. On exploring we found then having unexpected string variables like '*', We have excluded such rows from our analysis and converted these predictors to float.

3.3 Feature Engineering

- **Feature Encoding**
  We performed feature encoding where all categorical variables have been mapped to numeric values, in our case, we proceeded with one-Hot encoding and also dropped redundant dummy variable for every categorical feature.

- **Feature Engineering**
  We have observed several sparse features in the dataset which has only 1-2% of data. To increase the effect of such variables and reduce the complexity of the model we have engineered several of these weak predictors.

We have combined and segmented several claims per month with respect to behavioral, injury, infectious diseases, and respiratory diseases. By combining these features, we can achieve 10-15% of real data in a given column.

3.3 Feature Selection

Feature Selection is the fundamental step and identifying features that are relevant to a machine learning model is essential for model stability. In a gist, feature selection means that you select only those attributes that have a significant effect on the model's output. This reduces overfitting and improves the overall performance of the model.

3.3.1 ANOVA Test

The ANOVA test uses variance as its parameter to compare two or more independent groups. In our case, two-way ANOVA is applied as there are only two independent groups (Housing secured and Housing in-secured groups). F-Statistic can be calculated by

$$F = \frac{MST}{MSE}$$

$$MST = \frac{\sum_{i=1}^{k}(T_i^2/n_i) - G^2/n}{k-1}$$

$$MSE = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n_i}Y_{ij}^2 - \sum_{i=1}^{k}(T_i^2/n_i)}{n-k}$$

In this experiment, we used dependent variables (hi_flag) to characterize continuous features (independent variables). For instance, if the independent variable "rwjf_median_house_income" is chosen the hypothesis states.

Null Hypothesis: There is no significant difference between the mean Income among two groups of MAPD members.

Alternate Hypothesis: There is a significant difference between the mean Income among two groups of MAPD members.

Since value p is less than 0.5, we reject the null hypothesis. Therefore, we conclude that there is a significant difference in variance between the median house income of two groups of Housing insecurity.

3.3.2 Chi Square test:

Chi Square test is applied between two categorical variables from a population. It is used to determine whether there is a significant association or relationship between the two variables.

We used chi-square test for independence, to understand the association of our categorical variables. For instance for categorical features like RUCC category, CMS_Income_ind we performed Chi-Square test to understand the association between these features.

Here's the the hypothesis we have tested.

Null Hypothesis: There is no significant association between Gender and Loan Status features.

Alternate Hypothesis: There is a significant association between Gender and Loan Status features.

We investigated Chi-Square test on all categorical features and found all categorical variables in the data are statistically significant ($P < 0.05$)

3.3.3 Investigating multi-collinearity

Multicollinearity is the occurrence of high inter correlations among two or more independent variables in a multiple regression model. Multicollinearity can lead to skewed or misleading results, and it reduces the capability of a feature in predicting the dependent variable. We have used variance inflation factor (VIF) as a measure of the amount of multicollinearity. Using this method, we found 60 predictors which are having significant multicollinear issues.

3.3.4 Lasso for feature selection

Lasso regression has a very powerful built-in feature selection capability that can be used in several situations. It is a linear model that uses this cost function:

$$\frac{1}{2N_{training}} \sum_{i=1}^{N_{training}} \left(y_{real}^{(i)} - y_{pred}^{(i)}\right)^2 + \alpha \sum_{j=1}^{n} |a_j|$$

a_j is the coefficient of the jth feature. The final term is called *l1* (highlighted) penalty and α is a hyperparameter that tunes the intensity of this penalty term. The higher the coefficient of a feature, the higher the value of the cost function. While trying to minimize the cost function, Lasso regression will automatically select those features that are useful, discarding the useless or redundant features by making its coefficients equal to 0.

4. Modeling

4.1. Approach

After preprocessing the dataset, we decided to start modeling with Logistic Regression. We wanted to keep Logistic Regression as our benchmark model.

As our target variable is highly imbalanced with just 4.3% 1's and 95.6% 0's, our models were not able to identify the 1's. We decided to do an under sampling of 0's so that we can have 30% 1's and 70% 0's. We also tried other sampling techniques such as oversampling of 1's and SMOTE. We did not want to go with oversampling of 1's as that often leads to overfitting as we are taking the same records which are tagged 1, multiple times. SMOTE did not give us better results. So, we performed modeling after under sampling the data. We verified that our model is giving statistically consistent results by replicating the under sampling for multiple random seeds. To tackle the nonlinear high dimensional interactive relationship between the features, we decided to go with tree-based classification models as these supervised machine learning algorithms use a series of conditional statements to partition train data into subsets.

We started with a decision tree which is the simplest form of tree-based model. It makes decisions based on Entropy or Gini Index. Although decision trees are very simple to give insights based on decisions from the model, the disadvantage of decision trees is that they are non-robust and have less predictive accuracy. Due to small change in the data, the model can have high variance. So, we decided to handle this by bootstrapping and bagging through the famous algorithm Random Forest which is an ensemble of many decision trees. In this algorithm we build several decision trees on bootstrapped training samples and while building these trees, each time a split in a tree is considered a random subset of predictors is chosen. By this way, this algorithm de-correlates between the trees and reduces the variance of the

model. We then tried various gradient boosting frameworks such as LightGBM and XGBoost. We also tried a Neural network model but XGBoost with hyperparameter tuning gave the best results for us. By empirical experimentation we got the following results:

Models	AUC on Test
Random Forest	0.628
Neural Network	0.723
LightGBM	0.727
XGBoost	0.733

Due to superior predicting power and performance of XGBoost we decided to select it as our final model.

4.2 Final Model

XGBoost is an eXtreme Gradient Boosting algorithm. This algorithm has regularization implemented in it which helps reduce overfitting and has built in cross validation. It consists of several hyperparameters which can be tuned which gives us a better scope to explore the model.

The best set of hyperparameters were chosen by grid search and K fold cross validation and tuned accordingly. K fold cross validation helped us to ensure that the model is generalized well to data and prevent overfitting and underfitting. Grid search helped us to find the best hyperparameter combinations in an optimized way instead of changing the parameters one by one.

We further used the early stopping technique (we chose value of 10 for early stopping) with grid search which ensured that if there is no further improvement in model performance, the grid search will no longer choose that combination of hyperparameters. The hyperparameters that we used for our final model are:

- *Objective:* We chose binary:logistic. It defines the loss function which needs to be minimized.
- *Learning rate:* We chose it to be 0.1. It chooses the step size at each iteration while the model optimizes and prevents overfitting. It increases the robustness of the model by shrinking the weights on each step.
- *Colsample_bytree:* We chose it to be 0.5. This is the subsample of ratios of columns which is used when constructing each tree.

- *Gamma:* We chose it to be the default value of 0 as our grid search gave that result. It signifies the minimum loss reduction which is required to make a split.
- *Max_depth:* We chose it to be 3. This signifies the maximum depth of a tree.
- *Reg_lambda:* We chose it to be 0. This is the L2 regularization term on weights.
- *Scale_pos_weight:* We considered it sum(negative instances)/sum(positive instances). This helped in handling the imbalance classes.
- *Min_child_weight:* We chose it to be 4. It is the minimum sum of weights of all observations required in a child.
- *Subsample:* We chose it to be 0.5. This signifies the fraction of records that are randomly sampled for each tree.

We also used XGBoost for feature selection, the details are given below.

5. Modeling Analysis

5.1 Model Evaluation

As shown in the figure below, our best AUC score is 0.733 on test data which comes from XGBoost Classifier. We also examined other metrics for future evaluation.

Figure 3: AUC-ROC Curve on Test Data
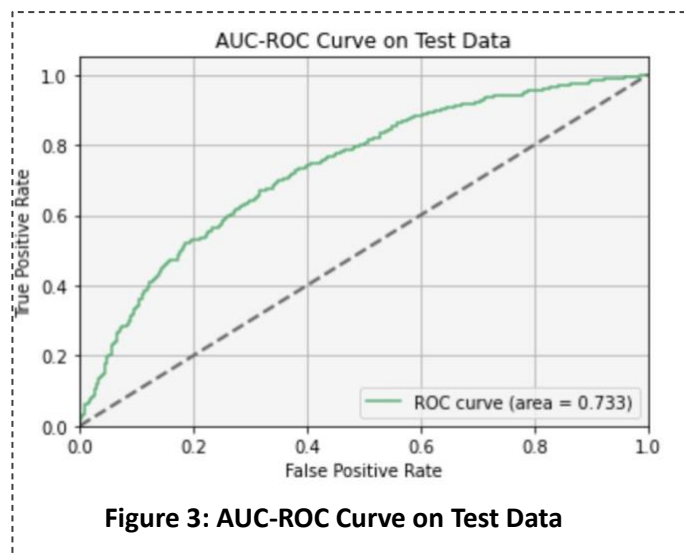
Through the classification report, we can observe that the recall rate of the housing insecurity group we care about has reached 0.82, which means that 82% of the human members with unsafe housing are identified by our model. However, the accuracy of our model is relatively less when separating the housing insecure group compared with the house security group since precision measures the proportion of real unsafe housing members among all members identified as unsafe housing by the model. The overall accuracy of precision and recall has reached 0.79 and 0.72 respectively, which we believe is a powerful model performance.

In the confusion matrix graph, in addition to accuracy, we also focus on False Negative Rate (FNR). In this project, this indicator means that the member is actually in a state of housing insecurity, while our model predicts that his living environment is secure. This is the worst case scenario, because based on the model we don't think we need to provide assistance to the member, but in fact the member really needs our help. Therefore, we chose the model with the lowest False Negative Rate.
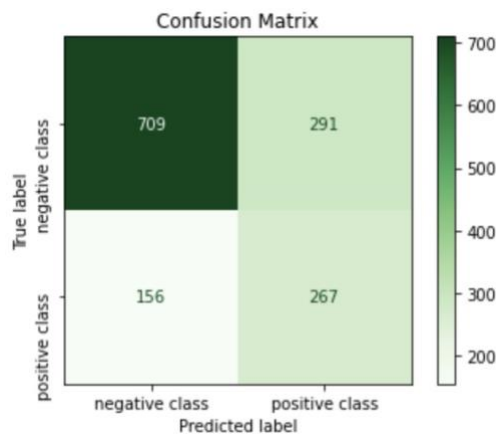

Figure 4: Confusion Matrix   **Figure 5: Classification Report**

In the figure below, we can observe the predicted probability distribution of different groups, where the red line indicates that the baseline is equal to 0.5. Consistent with the previous conclusion, our model accurately identified most house security members, but we also classified some house security members as house insecurity groups.

Figure 6: Predicted Probability Distribution
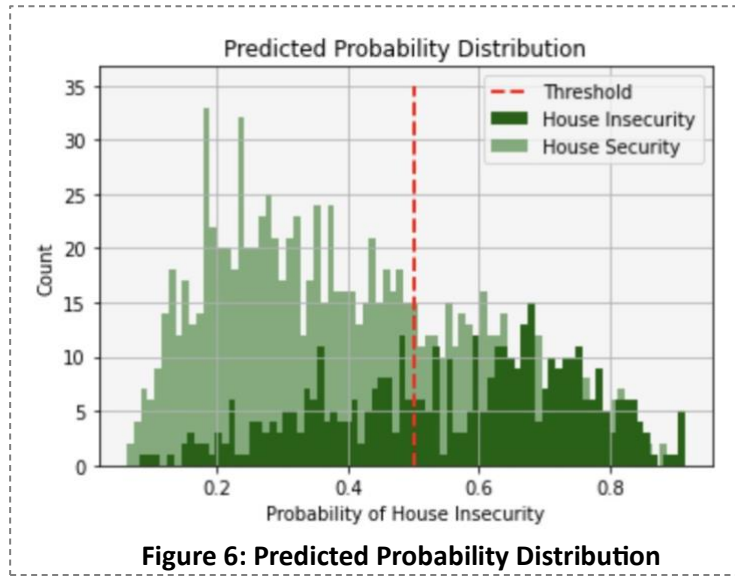
5.2 Fairness Diagnostic

Another reference indicator to measure the performance of the model is the bias of the model against sensitive variables. We have been pursuing that the model can ensure its algorithm fairness and unbiased operation in all classifications. Bias is often encoded in data in unexpected ways, and data science models tend to magnify this bias.

In this challenge, we introduced the Disparity Score to measure the fairness of the model. The disparity ratio is the ratio of the precision of each gender and race classification to the precision of the privileged group (White, Male). The maximum value of the disparity ratio is 1. On the basis of all the disparity ratios, the disparity score is the arithmetic mean of these ratios.

$$Disparity\ Score = \frac{\sum_{SV} \sum_{S} \min\left(\frac{S_n}{S_0}, 1\right)}{N}$$

The disparity score of our model is 97.65% which means that disparity related to gender and race do not appear to be a pervasive problem in our model.

5.3 Feature Importance/ Key Performance Indicator Analysis

To gain more insights, we want to know about the variables that make more contribution to the algorithm, so we looked at the top 30 variables in the XGBoost Classifier model and SHAP Value.
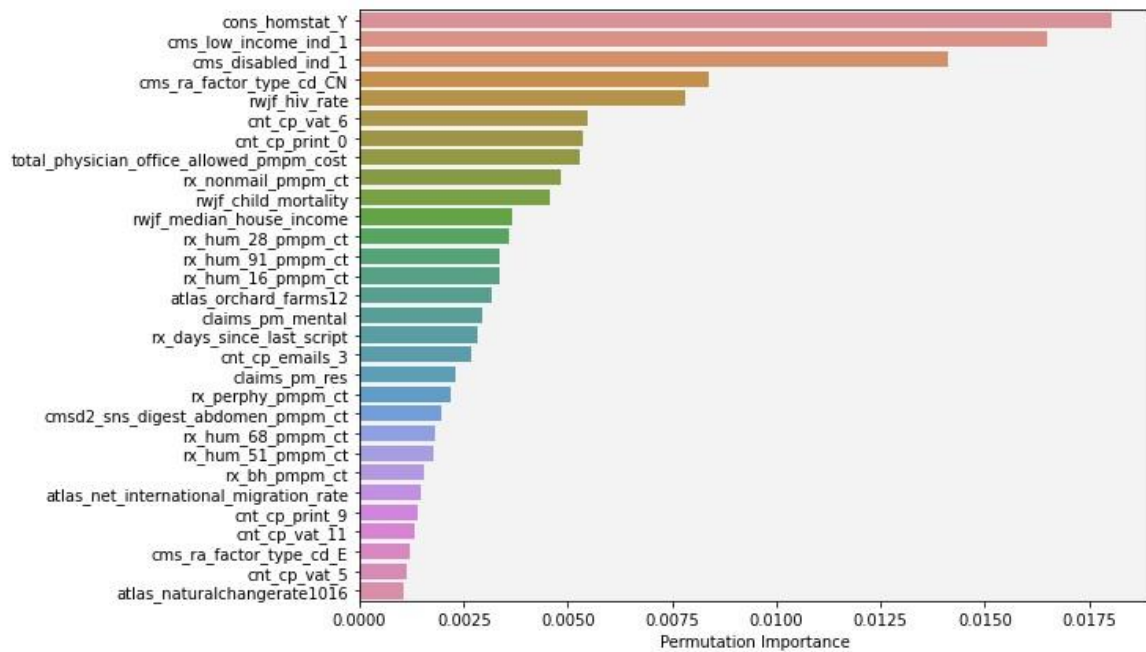

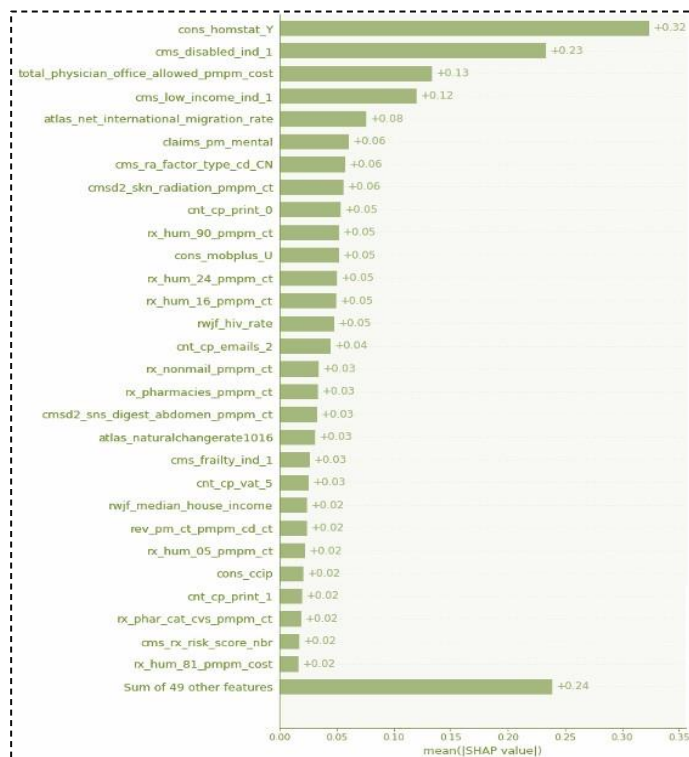**Figure 7: Top 30 Important Features from XGBoost**

**Figure 8: Top 30 Important features from SHAP values**

These variables can be summarized into four categories:

- **Demographic:**
  Mainly including homeowner status, population change, age, and scores or codes that can reflect the health status of members. (prefix are 'cons', 'cms' and 'atlas')

- **Pharmacy Claims Features:**
  Our data includes information about more than 90 diseases. Through the analysis of pharmacy claims, we found that HIV, respiratory diseases, psychiatric diseases, skin diseases and digestive diseases have significant differences when labeling different groups of members. (prefix is 'rx')

- **Finance:**
  Measure the financial status of members. The proportion of living insecurity among lowincome people is higher.

- **Interactive channels:** three channels are mainly involved in important indicators, namely VAT (IVR call), print (printed material) and email. (prefix is 'cnt_cp')

In addition, we learn the independent influences and interaction effects of important features by SHAP dependent plots.

The following figure shows the attributional relationship between risk scores and housing safety by using SHAP interaction values, which eliminates the influence of other feature interactions. As can be seen from the figure, the higher the health risk score, the greater the correlation with housing insecurity. When the health risk score is greater than 1, the risk of housing insecurity rises sharply.
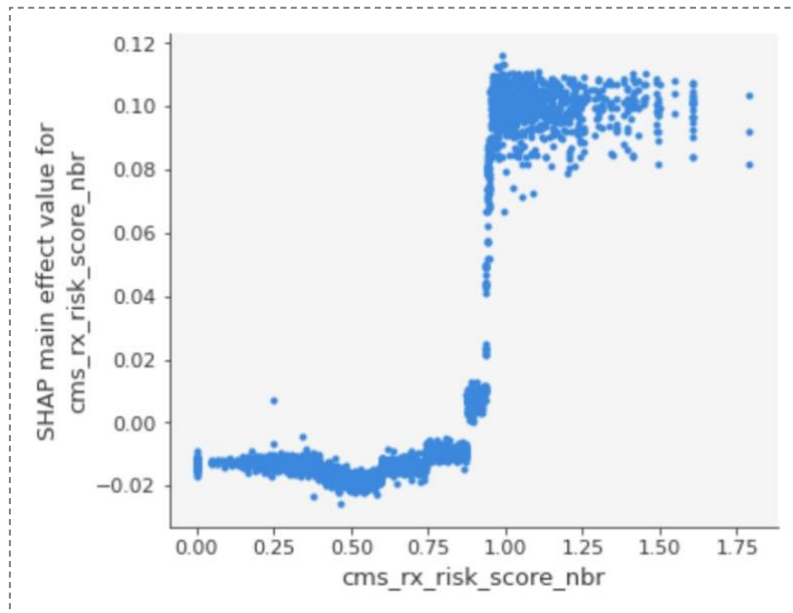
Figure 9: cms_rx_risk_score_nbr Dependency Plot

From the figure below, we can see that with the increase of the net migration rate, the housing security problem will worsen significantly, and more people are prone to housing insecurity. At the same time, the trend of net migration rate in this figure is interacted with other characteristics, among which the most important interaction variable is the count of prescriptions of a cancer-related inhibitor, which also indicates that with the increase of net migration rate, more demands are placed on medical resources.
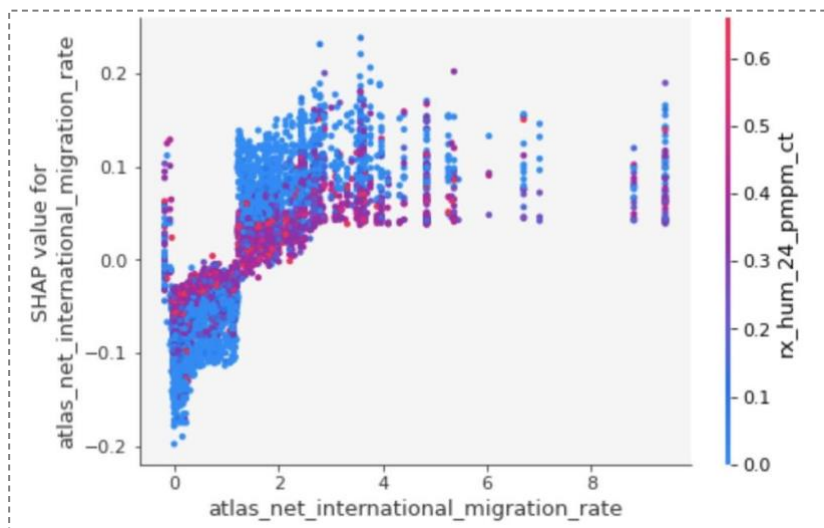

Figure 10: atlas_net_international_migration_rate Dependency Plot

6. Business Analysis and Recommendations

6.1 Potential pathways connecting Health and Housing

As access to stable and affordable houses helps boost mental and physical health and Humana decides to support individuals suffering from housing insecurities, we recommend some solutions that Humana can implement to alleviate housing insecurity among Medicare members. Four pathways have been identified in[8] to connect Housing and Health. We analyze these pathways individually to dig deep into the problems associated with housing and provide recommendations to mitigate them. Housing insecurity affects various population segments for a diverse range of reasons. So, we decided to segment the population and propose recommendations that are tailored to the specific segments.


Figure 11: Four pathways connecting health and housing
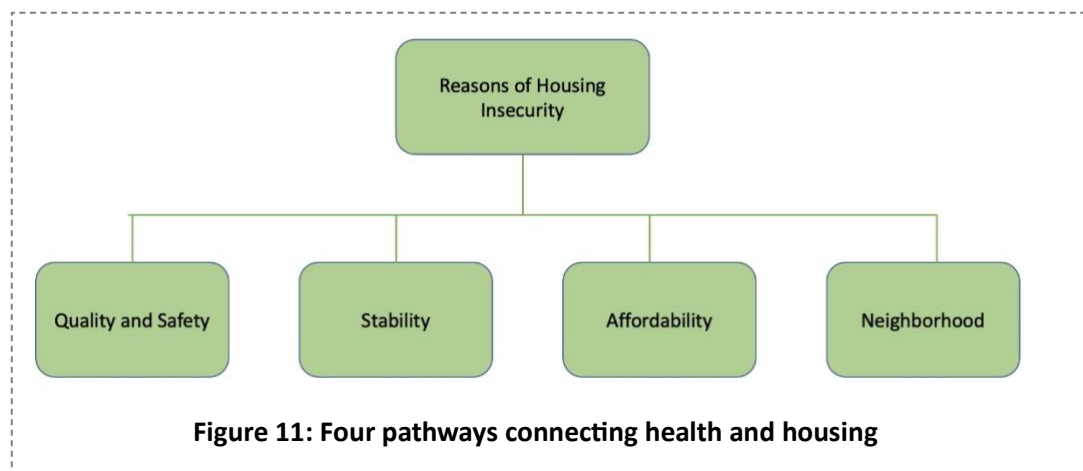
6.1.1 Quality and Safety

Housing insecurity and home quality go hand in hand. An individual may have health-harming problems as a result of a home's poor state. People of all ages can suffer from this but as we have Medicare data which typically provides coverage to those above 65 or with disabilities, we are focusing on that cohort.

For this section of people there could be fall hazards [8]. Three out of four adults of age 50 and older prefer to stay in their homes and communities as they age as per 2018 AARP Survey [12].

Also we know from "Universal Design" elements [13] that no-step entries, extra-wide hallways and doors to accommodate walkers and wheelchairs, and lever-style door and faucet handles facilitate elderly people, but only 57% of existing homes include more than one of these features. So, this could be an alarming situation for the elderly people where they can experience fall hazards and housing insecurity due to lack of quality housing. From the data we can see that Medicare Supplement members greater than age 65 are having most housing insecurity, as cms_disabled_ind =0 which represents member greater than 65 had more 1's of hi_flag shown in Figure 12
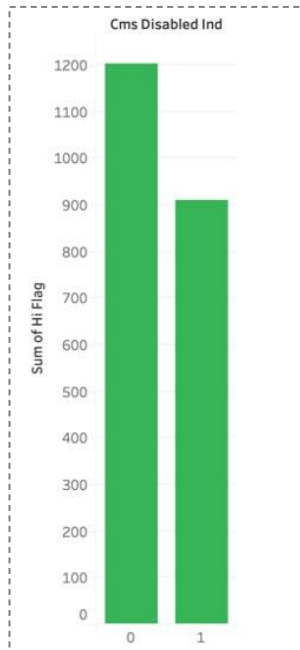
Figure 12: Barplot between cms_disabled_ind and hi_flag

If the house is having substandard living conditions such as pest infestation, mold, poor ventilation, and dirty carpets that can increase the chance of Asthma and other conditions [8]. Also people who cannot afford to pay all the utility bills, for them exposure to extreme hot and cold temperatures can be harmful and acts as an inception of various diseases.

A study in [10] has shown that over 3.7 million people are living in "doubled-up" households in 2019, which includes 2.2 million renters. People from south are in this situation as shown in Figure 13. Also, from Figure 14 we can see that the migration rate is also higher towards the south and west of the country. Due to shortage of space and economic hardship, overcrowded conditions arise and lead to housing instability.
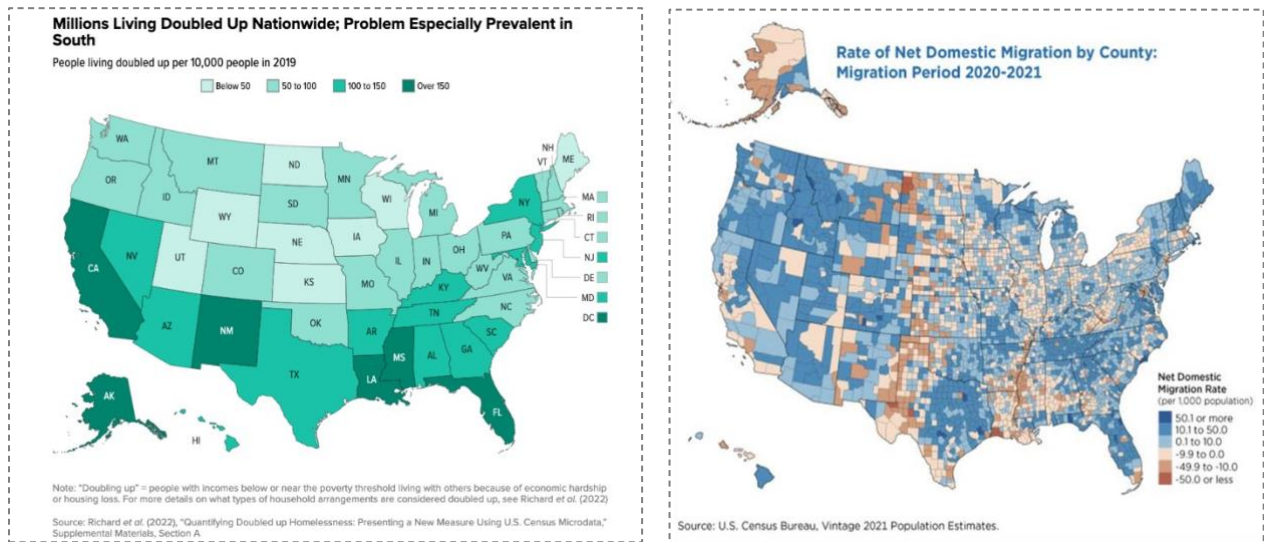
Figure 13: Map showing the distribution of "Doubled up" population Figure 14: Map showing the net Domestic Migration by County.

Assuming that the data is a statistically consistent representation of all Humana MAPD members, we have segmented the population to see who needs more care. We have selected some of the important features that were given by our best model and performed K-means clustering on them for the members who are having housing insecurity.

- *Group* **A**: In Figure 15, the red cluster represents population belonging to age 65 or older and lower median house income.
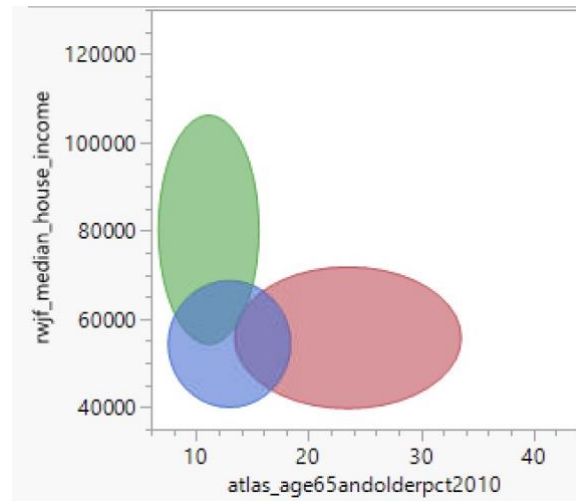
Figure 15: Clustering created with rwjf_median_house_income and atlas_age65andolderpct2019

- *Group B:* In Figure 16, the red cluster represents the population having higher cost of prescriptions related to Asthma drugs and lower median house income
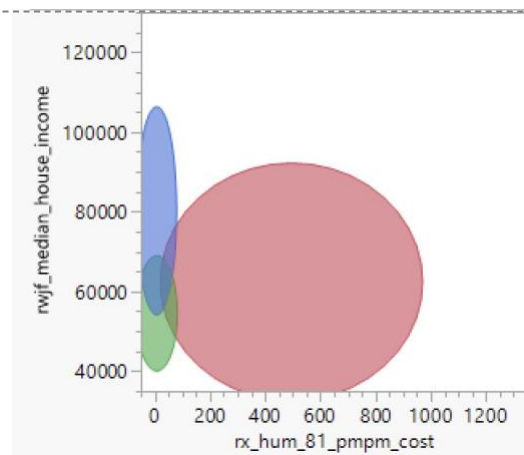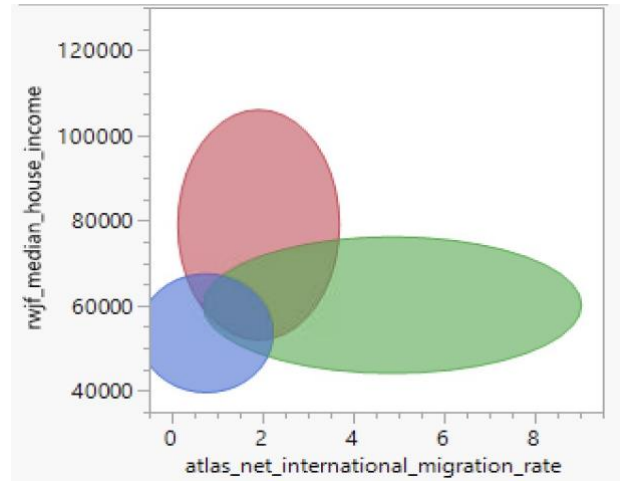

Figure 16: Clustering created with rx_hum_81_pmpm_cost and rwjf_median_house_income

- *Group C*: In Figure 17, the green cluster represents the population located in places with the highest international migration rate and lower median house income.
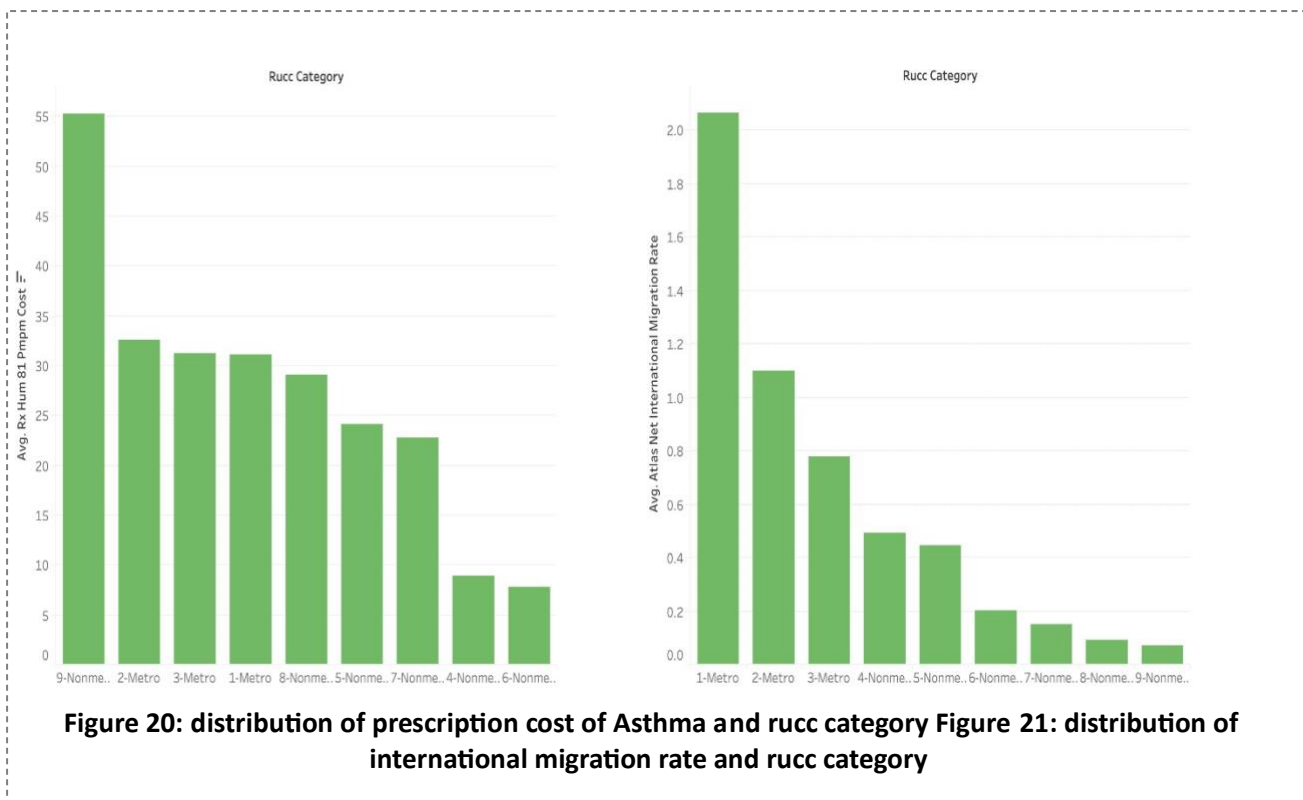
Figure 17: Clustering created with rwjf_median_house_income and atlas_net_international migration rate

From the data to see what segment of the population is having the most housing insecurity we filtered the data with hi_flag = 1 and created the following visualizations. In Figure xx we see that 4-Nonmetro is having the lowest median household income. We have binned the variable Atlas_Age65 and_olderpct2010 with bin size 5.99 and observe that in 4-Nonmetro area where percentage of population 65 or older is 17.97% and people are having the least median household income shown in Figure 18, they are having the most housing insecurity. So Group A people can be mostly identified here.
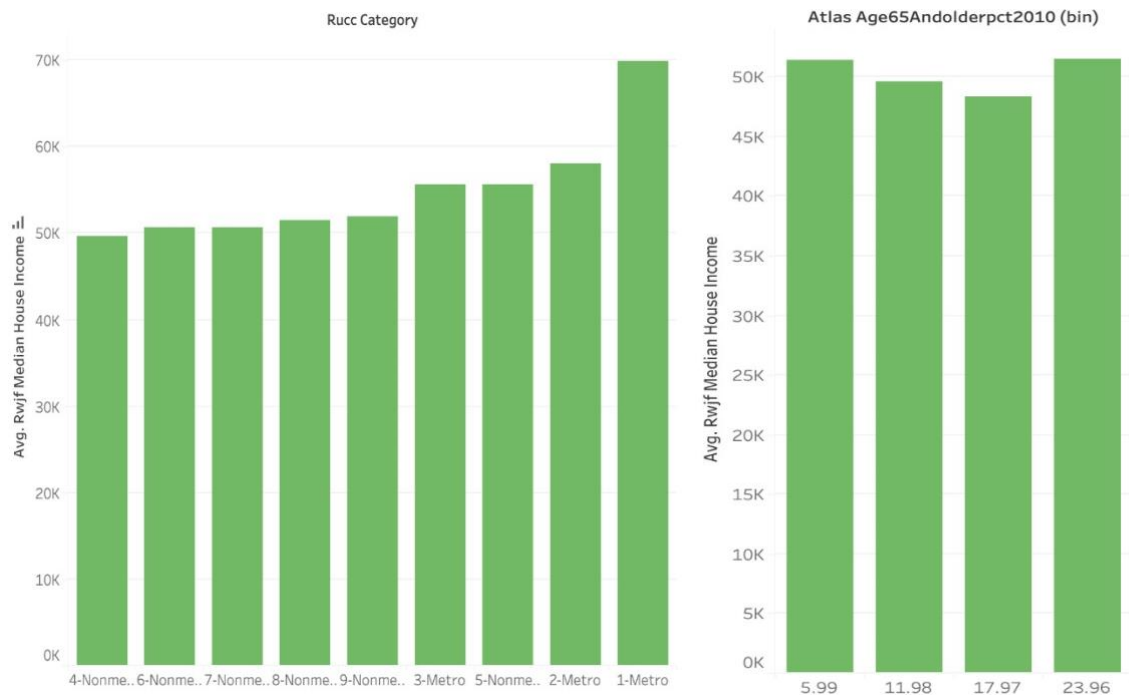
Figure 18: distribution of median house income and rucc category Figure 19: distribution of median house income with respect to binned percentage age65 and older in rucc cate gory 4 Nonmetro

In Figure 20 we can see that 9-Nonmetro area has the highest average cost per month of prescriptions related to asthma drugs. So group B people can be mostly identified here. People of group C can be mostly identified in the southern part of USA from Figure xx and Figure xx and in 1 - Metro area shown in Figure 21.

Figure 20: distribution of prescription cost of Asthma and rucc category Figure 21: distribution of international migration rate and rucc category

6.1.2 Stability and Affordability

Families in United States are paying too high a price to cover the cost of home. Rents and homeownership costs are skyrocketing while wages are not keeping pace. Today, nearly 17 million U.S households pay more than half of their income on a place to live. That means nearly 1 in 7 families are denied the stability that safe, decent, and affordable housing provides.

In 2020, 30% of all households had "unaffordable" rent or mortgage payments, defined as exceeding 30% of monthly household income. This is up 1.5 percentage points from 2019. More than 1 in 7 households paid over half of their income on housing. Cost burdens rose

most for those earning between US$30,000 and US$45,000, an increase of 4.2 percentage points, and for Black households, up 2.4 percentage points.

With home prices rising another 20.6% from March 2021 to March 2022 and rents jumping 12%, forthcoming data may show that unaffordability worsened even further in the past two years.

Racial disparities in housing today

Through our analysis of data, we found there is huge racial disparity among house insecurities among different racial populations. For instance, we are observing Hispanics (9%), Asians (7%) and Black (6%) are showing elevated proportions of housing disparity than whites.

Unfair homeownership as foremost cause of housing insecurity

Our study also showed strong correlation and alarming signs of racial discrimination and housing inequities with respect to house ownership rates between others race and whites. Through our analysis we found there is stark gap of 65 which is Black (15%) and white households (80%) in terms of homeownership rate.
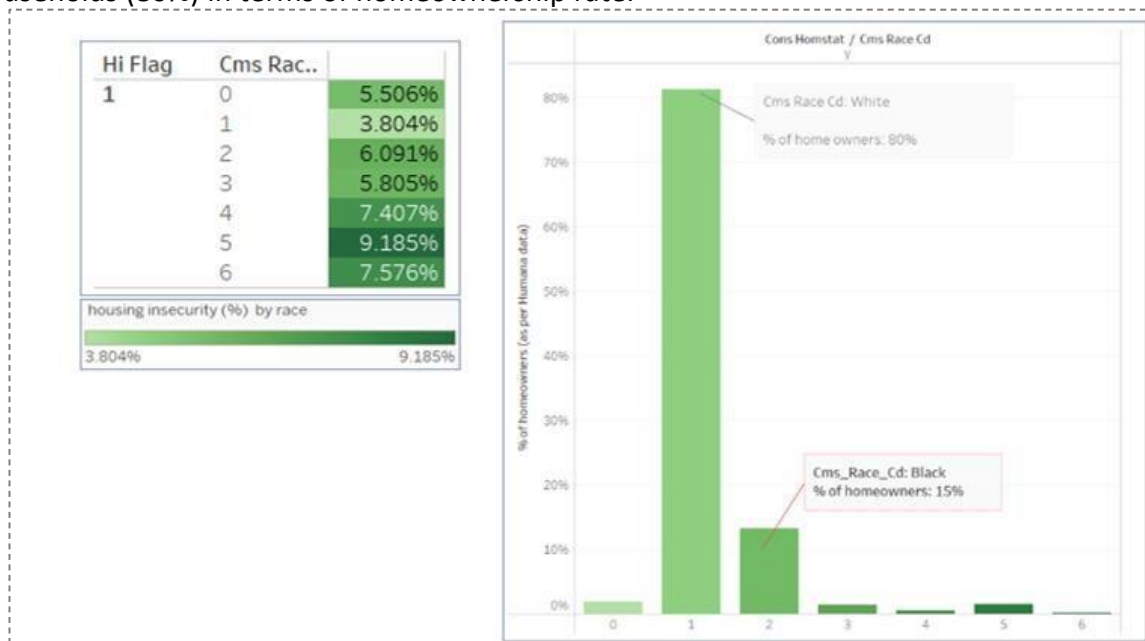

A significant racial gap in homeownership is a major reason for the tremendous wealth gap between blacks and white households and has resulted in significantly less housing stability, economic security, and wealth of black families. From (fig 1) we can see income gap among several race groups, in case of blacks, we are seeing majority of people's income are failing

short when compared to other races. This disparity in incomes would directly lead to less wealth, assets and would ultimately lead to housing insecurity.

<u>Possible Redlining limits the opportunities</u>
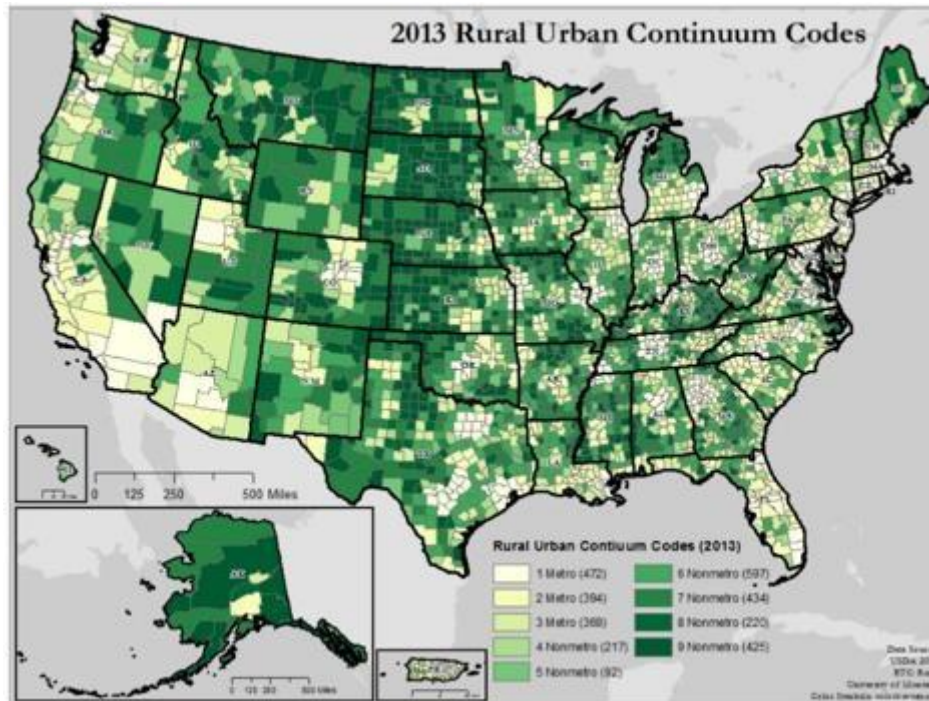
Redlining communities remain isolated and distressed and other races like blacks and Hispanics disproportionately live in these communities. As per recent statistics nearly half of all Black households live in segregated high poverty neighborhoods. As a result, generations of color are growing up in communities with vastly different resources and opportunities than other counterparts.
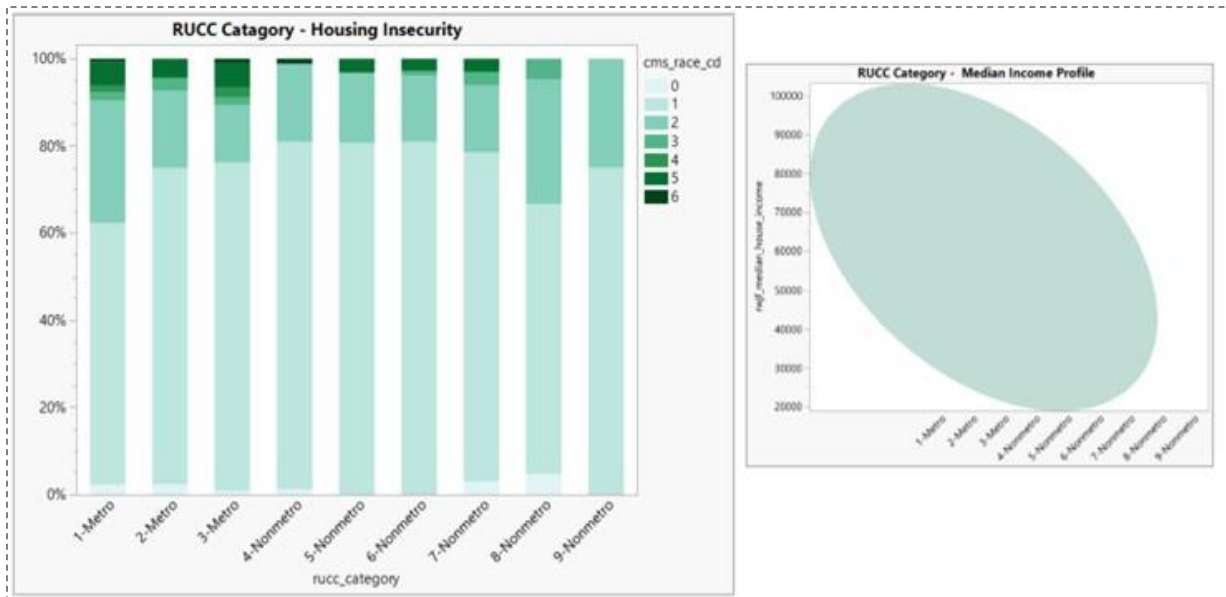
Figure 22: Race distribution by RUCC Category Figure 23: Income profile across RUCC Categories

Challenges:

Despite all these measures, there are few questions that remain.

1)   Are we attempting the right populations or neighborhoods?

2)   Are right members of population are getting benefitted?

From our analysis, we also found there are high income groups that are considered for lowincome subsidy from CMS. From (figure 24) we can observe for people who are receiving subsidy that mean income is about $60000 per annum which is above the national average. We also found low-income profiles, with less than $40000 per annum who are yet to receive subsidy.
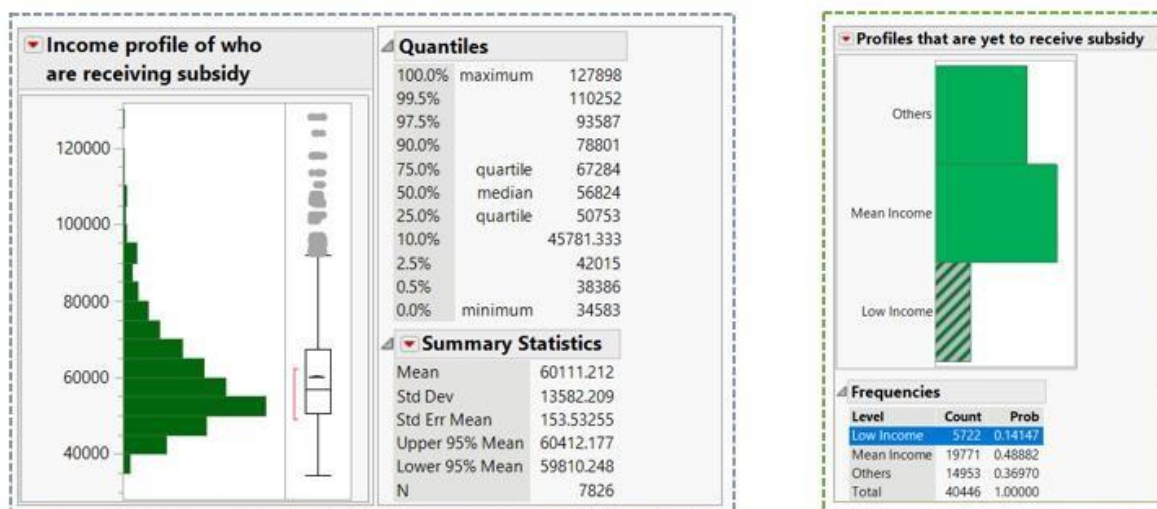
**Figure 24: Members who are receiving and yet to receive subsidy**

6.1.3 Neighborhood

Numerous epidemiological studies have found that there is a strong link between living environment and physical health[5]. Living environment which strengthens social and health inequalities includes the remoteness of living, the size of the city, the safety of the community, the cleanliness of the community and other factors. According to our research, geographic location, mental illness, HIV, digestive diseases and CT scan are important factors that prompt house insecurity.

Geographic

Many cities throughout the world are experiencing challenges in areas such as housing quality and informal settlements, transportation planning, food systems and dietary patterns, all of which have the potential to impact health, health risk factors, and health behaviors.

According to our data, it can be observed that in mega cities (1-Metro) and the most remote small towns (9-Nonmetro), the proportion of people with insecure housing is relatively high. In densely populated areas, members with insecure housing have higher health risk scores.
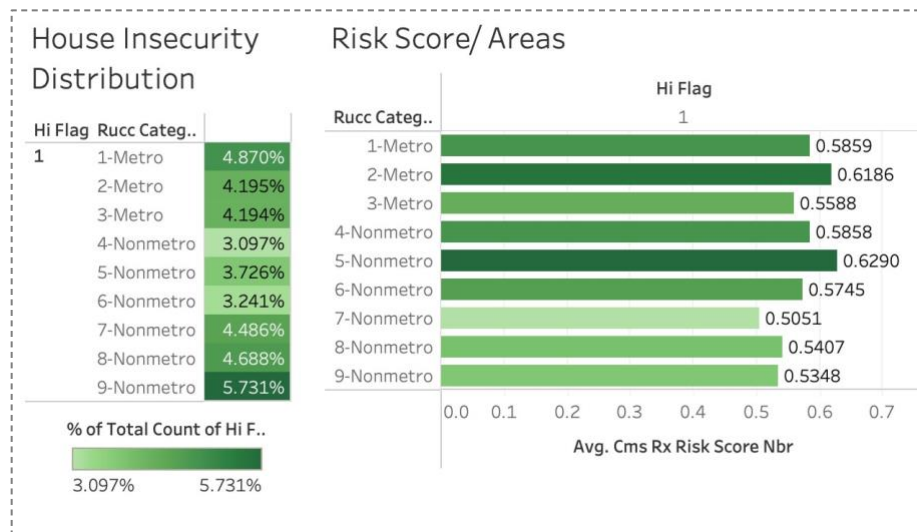
Figure 25

Safety
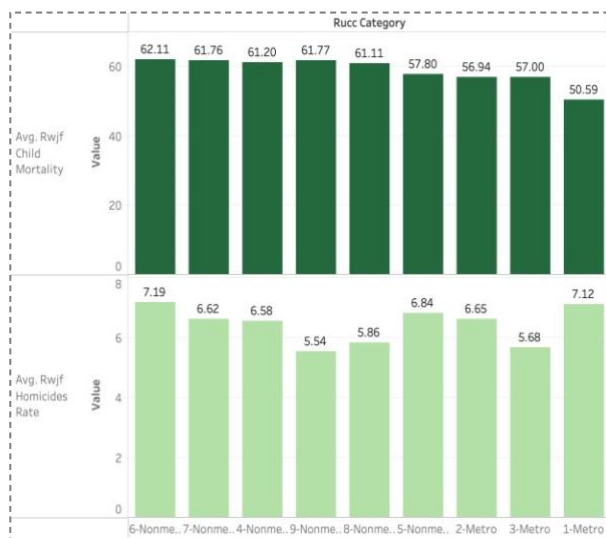
Figure 26

Violent crime impairs the health and development of victims, family members and entire communities. And violent crime is geographically concentrated in specific neighborhoods and more localized areas, known as hotspots.[c] In addition to the death, disability and other injuries that can result from violent crimes, they can also cause physical and mental pain and suffering to survivors.

From the graph on the right, we can observe that small cities with populations of 2,500 to 20,000 (6-Nonmetro) have the highest homicide rate and infant mortality rate. Therefore, housing insecurity due to community insecurity may be one of the major factors in such areas.

Diseases

Poor mental health was highly prevalent in people with housing insecurity and was exacerbated by the coexistence of life insecurities[6] HIV infection rate is also highly correlated with crime rate and unclean living conditions have been linked to digestive diseases, such as having unclean food or water.
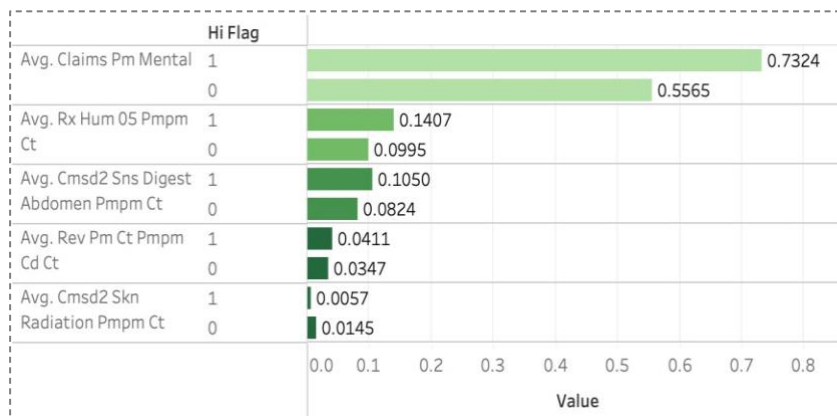
Figure 27

As can be seen from the figure below, mental illness is a high incidence disease in the whole group. The average number of insurance claims of members with insecure housing is 31.6% higher than that of members with secure housing. In HIV, digestive diseases and CT examinations, the average number of insurance claims or prescription claims of members with unsafe housing is 41.4%, 27.4% and 18.4% higher than that of members with safe housing. On the contrary, the average number of insurance claims for skin diseases is higher in the group with safe housing.

In terms of city size, the incidence of such diseases is higher among the housing insecure groups living in medium-sized cities with a population of more than 20000. Digestive diseases are more significant in remote areas with a population of less than 2500.
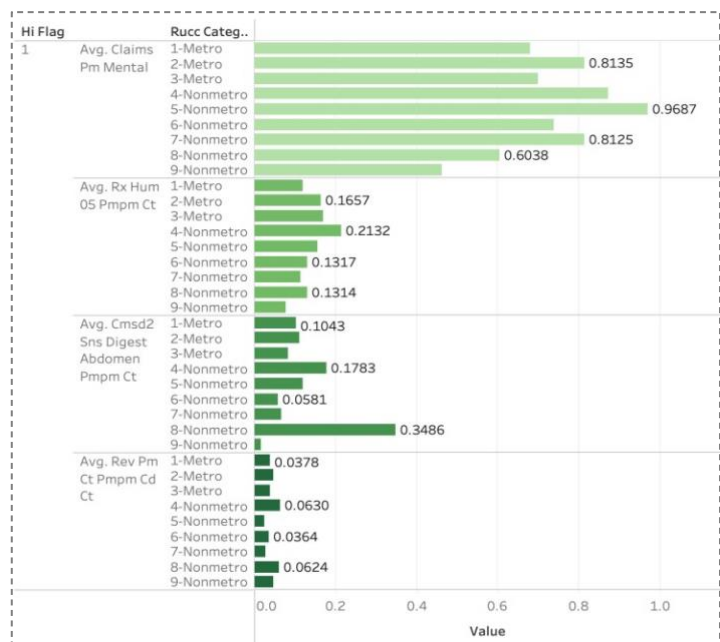
Figure 28: distribution of prescription cost of Asthma and rucc category

6.2 What Humana is doing?

Humana has conducted several surveys of Humana members to identify the housing insecurity and are continuously researching and already working on this issue to diminish health harming conditions which are the results of housing related social needs[8]. Humana has:

1) Developed strategic partnership with nonprofit organizations such as Volunteers of America
2) Implemented Bold Goal population health strategy which includes programs like Family Scholar House and Kinsley House
3) Raised $25 million investment through CREA, LLC, PNC to increase affordable housing capacity using low-income housing tax credits
4) Established a dedicated team of employees to work exclusively on the Community of Opportunity effort, by partnering and supporting Blackowned businesses and organizations that serve the Black community in Louisville.

6.3 Proposing Solutions and its Implementations

In addition to what Humana is doing, they can follow the analyses similar to this report and implement our recommendations explained in the following sections:

6.3.1 Ensuring Quality And Safety Of Houses

a) For group A in 4 - Non metro areas Humana can invest in structural home modifications to make it accessible to elderly people. These modifications can include replacing small door knobs with pull handles, reconstructing and widening hallways, replacing normal stairs with wheelchair ramp etc. which improves the accessibility of elderly people.

Humana can partner with nonprofit organizations and local organizations in these areas to work on home improvements, repairs and modifications which will help elderly people to avoid fall hazards. Rebuilding Together, Inc.[18] is a national volunteer organization which works on ensuring safe and healthy housing. They assist low-income seniors with the help of their local affiliated organizations. Humana can be a strategic partner with them as well.

Older American Act[17] provides modification and repair funds[16]. Humana can partner with them to distribute these funds.

b) For group B, in 9 - Non metro areas Humana can invest in sanitization on a community basis which includes pest control, damp control, carpet cleaning. They can use a variety of methods to enhance housing, including creating and enforcing housing regulations and standards, conducting **"Healthy Homes"**[20] initiatives to enhance indoor air quality, evaluating the state of existing housing, and campaigning for safe, affordable housing.

c) Humana is already researching human migration and social change[20]. It is also conducting surveys to identify the members who are migrating. For group C in states in the Southern part of the US, especially in the 1- Metro area, Humana can help these people find homes with subsidized rents.

They can form a strategic partnership with the local companies that do so and invest in them.

6.3.2 Building Stable, Affordable And Safer Neighborhoods:

One way to reduce the Black homeownership gap is to re-visit the policies of banking services. Till now, it has been a practice to consider past credit history in issuing mortgages. However, given there is huge wealth disparity it is impossible to reduce this bias with existing credit policies. To achieve true racial equality one of recommendations would be to put a soft boundary over credit policies for firsttime home buyers. Not just that, variable down payment options based on salary slab would be beneficial for the home buyers and would inhibit them from spending 30% of their monthly salary.

Even when down payment assistance is available, unaffordable home prices remain a major obstacle to homeownership in many communities. In addition to Humana's current efforts to build sustainable houses, we would recommend building lasting, sustainable homeownership opportunities with the help of federal, state, and local agencies.

Our recommendation would be to build affordable gated communities with TINY houses. Below we have come up with a sample community plan where we include several units for the stability of lowincome households.

Following are features of the community plan.

1)   Tiny houses

3)   Health Care Clinic

4)   Regional Community Bank

5)   Park

6)   Solar enabled electricity unit.

WHY TINY HOMES?

Cost Savings:
80-90% cheaper than traditional housing

Reduced Carbon Footprint:
Uses 7% of the energy that a traditional house does.

.

Tiny houses are cost-effective and leave less carbon footprint and can be built faster than others. The Tiny Homes industry market size is expected to increase by $3.57 billion between 2021-2016 with a CAGR of 4.45%. The increase growth is due to environmental concerns and housing concerns. There are several private investors who are specifically interested in building these houses.

We can also provide houses with several cost options based on land area. There are many private LLC's who are working towards this, we have identified few LLC, who are aiming to build houses at $25000 for 153 Sq ft and $44192 for 400 sq ft. Making contracts with upcoming construction companies would be beneficial in terms of cost and quality.

For a better livelihood apart from housing, it is important to have access to basic essential amenities. Banks are important in providing specific and subsidized services to people in that community, these community regional banks should also focus on providing basic awareness on implications of maintaining good credit score, several laws that are beneficial for the community.

Health is another major implication resulting from housing insecurity among people below the poverty line. We also observe HIV, Depression and Child Mortality rate are higher in case of racial communities. Hence, we recommend an in-house health care clinic. Apart from medical services, it is important for this clinic to conduct awareness training on maintaining hygiene, sanitation etc.

Cleaner environment is equally important for sustainable living. Community parks should be encouraged to be part of this gated community, as we observed elevated and alarming claim rate with respect to respiratory diseases.

Solar energy units are one-time investments and are a great way to offset energy costs and reduce environmental impact of houses in the long run. There are several polices which support and encourage installation of these units. For example, Federal Investment Tax Credit (ITC) which provided a tax benefit for installing residential, commercial, and utility scale solar, Public Utilities Regulatory Act (PURPA) which can mandate the utilities purchase energy from solar and other qualifying facilities.

Implementation Plan:
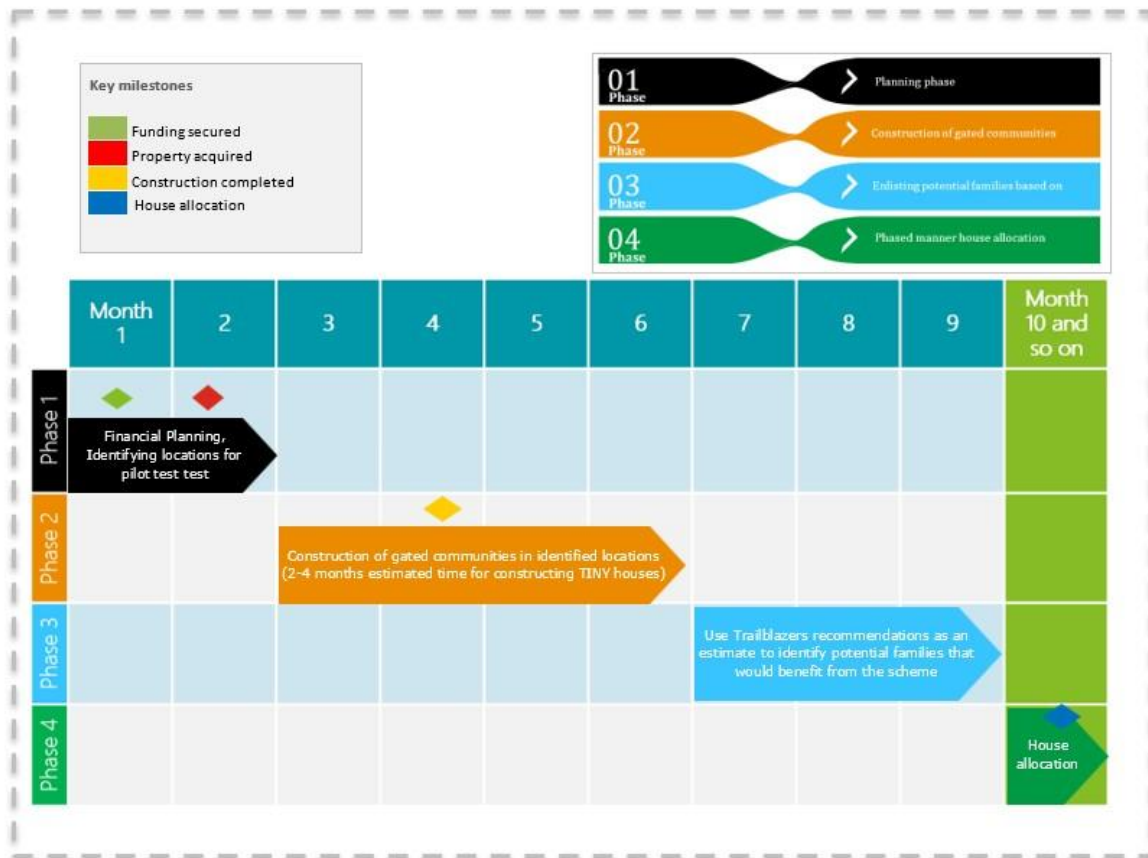
We plan to execute our project in four phases

1) In phase 1, our focus on securing funding, where our recommendation would be to coalesce funding from several federal and state governments along with private investors. In this phase we would also identify potential region where this planning would be successful. We identified Non-Metro regions 4,8 are best in terms of Housing insecurity problem

2) In phase 2, construction of gated societies, as mentioned earlier TINY homes are affordable, and they are estimated to construct within 3 months.

3) In phase 3, we recommend using our recommendation in identifying potential families that would benefit for the scheme.

4) Final phase 4, would be house allocation phase.

If pilot is successful our suggestion is to expand the scope of Humana Healthy Horizons, which includes house assistance benefits in Florida and Southern California.

6.4 Expected Value For Humana

For implementation of "Healthy Homes" we did the Cost Benefit Analysis for 1 county in the 9-Nonmetro area. We see from figure xx that North Dakota is having many 9-Nonmetro counties. So we pick 1 county in North Dakota to see what would be the expenditure for building healthier homes.

Cost of creating Healthier Home: $378 M

Cost Of Creating A Healthier Home		
No. of Household Units in 1 9-Non Metro County [1]	87247	
Activities [2]	Approximation Unit Cost (in $)[2]	Total Cost
Keep It Dry	544	47462368
Keep It Clean	42	3664374
Keep It Ventilated	225	19630575
Keep It Contaminant-Free	1235	107750045
Keep it Pest Free	180	15704460
Keep It Safe	532	46415404
Keep it Maintained	791	69012377
Keep It Thermally Controlled/ Energy Efficient	785	68488895
	Total amount	378128498

Benefit(Reimburse amount saved) : $ 266M

Total Humana members in 1 county(approx) - 10000		
	Humana's Total Expenditure	**378128498**
Mean Cost per month of prescription related to Asthma (From Data) each person (in $)	23.42	
Population in 1 county [1]	186562	
No. of Humana members in 9-Nonmetro (From Data)	349	
Total asthma cost per person (in $)	8173.58	
Max Asthma cost in 1 county (in $)	0	
Other costs related to clinical per county (in $)	30000000	
Total cost of Humana (in $)	30000000	
Total saving	348128498	~ $ 266M

[1] https://www.census.gov/quickfacts/fact/table/casscountynorthdakota,ND/BZA210220

[2] https://nchh.org/resource-library/costs-for-creating-a-healthier-home_english.pdf

On implementation of affordable, and safer neighborhoods,

Location: Non-Metro 6	
County	**Claiborne County, Mississippi**
General statistics	
% of black population	80%
Total population	11,240
Average Income	$32,268
house occupancy rate (%)	75%
Number of houses	3000
Housing in requirement	4,000
Health related claims	
% of people not insured	28.50%
Avg number of health-related claims in Non-Metro (Source: Humana MAPD data)	15.4
Number of people who claimed per month	500
Average paid claims for Mississippi Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2690178/	$352.00
Total claim amount born by Humana	$176,000.00
Post implementation	
Average number of people who claimed (Assumption)	200
Average paid claims for Mississippi	$70,400.00
Total reimbursed	$105,600.00

7. Conclusion and Future Work

In conclusion we can say that Humana can expand their strategy of Bold Goal Population Health Strategy for Social Determinants of Health [21] by using our analyses and

recommendations. They can reach out to the targeted segments of population recommended by us and help them with housing issues. They can hold campaigns in the areas that has been identified by us and spread awareness of their programs. The Accountable Health Communities Health-Related Social Needs Screening Tool made by CMS and CMMI [22] is a very efficient tool to examine if the mitigations of conditions related to health related social needs is actually benefitting the Medicare and Medicaid beneficiaries in terms of healthcare costs and improving their health. Housing instability is a major component of that tool. It has been observed that this tool has lowered emergency department utilization in fee for service Medicare by 9% [23]. Humana can conduct surveys based on this tool to get more information of their members so that they can discover the needs of their members in a more detailed manner. In this way Humana can achieve its goal around social determinants of health and especially Health related social needs (HRSNs) issues.

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https://innovation.cms.gov/innovationmodels/ahcm

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9. Acknowledgement

As a last thought, we would like to express our sincere appreciation to Humana and the Mays Business School departments for conducting, hosting, and facilitating the chance to explore this intriguing dataset. It helped us to identify this social issue and learn a lot about it. It gave us the opportunity to make recommendations for issues with such a huge impact on society.