Asian American Quality of Life in the United States:

Studying the differences in Asian American economic well-being within Austin, Texas

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Introduction

In this project, we study the impact of cultural differences on economic well-being in the Asian American population within the Austin area. Our objective is to answer the question: do cultural factors affect economic outcomes such as income bracket, employment rate, or quality of life among Asian Americans? We aim to determine how these variables influence each other and to uncover the underlying mechanisms that contribute to economic disparities within the Asian American population. By examining factors, such as ethnicity, education, religion, and belonging, we aspire to discern their interconnectedness with the economic success indicators mentioned.

This research is motivated by the recognition that a one-size-fits-all policy approach overlooks the unique cultural contexts that shape individual experiences. We also want to address the diversity within the Asian American Community. This recognition includes factors such as ethnic and religious differences along with how they are related to socioeconomic status. The visualizations and modeling performed in this study also investigate the relationship between income and factors determining income in the U.S. such as education and English proficiency. These allow us to identify additional disparities among the Asian American community. Lastly, we want to challenge stereotypes and combat discrimination faced by Asian Americans in various aspects of life, such as education or the workplace. By looking at variables such as sense of belonging, we hoped to gain insight into the past experiences of the Asian American community to identify discrimination. We aim to provide a nuanced understanding of our individual hypotheses and consider how the various questions are answered through our data.

Data Description

The dataset we are examining contains survey data on the fastest-growing minority group in the United States, Asian Americans. Within this dataset, the broad term includes individuals with origins in the Far East, Southeast Asia, or the Indian subcontinent. The Final Report of the Asian American Quality of Life (AAQoL) comes from a survey completed by the city of Austin, TX from August 19 to December 12, 2015 (Jang 2016, 12). It includes 2,609 observations each corresponding to an individual survey. There are 231 columns in the dataset, each representing the various questions respondents were asked to fill out when taking the survey.

The dataset is cleaned and prepared for each individual hypothesis in the exploratory analysis due to the large scope of variables included in the dataset. The data cleaning procedures will be detailed under every hypothesis in the Exploratory Analysis section.

Exploratory Analysis

In order to uncover initial insights into the dataset, we will be utilizing R to visualize the AAQoL data. With these visualizations, we hope to uncover relations between economic and cultural factors in the Asian American community. We will explore four main hypotheses:

1. **Income Bracket v.s. Education vs. Ethnicity -** We predict a variation in educational attainment amongst the different types of Asian ethnicities. We also expect to see a positive general relationship between education and income.
2. **Income Bracket v.s. English Proficiency –** We predict that the level of English proficiency in the Asian American population will be positively related with their income bracket.
3. **Income Bracket v.s. Religion** We predict that income brackets will vary based on religion and that individuals identifying as Hindu have the highest percentage of top earners on average.
4. **Employment Status v.s. Sense of Belonging** - We predict that those who are employed full-time will have greater levels of belonging and those who are unemployed will have lower levels of belonging.

Hypothesis 1: Income Bracket v.s. Education v.s. Ethnicity

Overview

Our first hypothesis looks at the relationship between ethnicity and educational attainment. We postulate that varying cultural factors and household standards among different Asian American ethnicities will result in varying levels of education for each group. Figure 1 shows the mean years of education completed for each Asian American ethnicity represented in the study along with the relationship between education and income.

We hypothesize that individuals with higher levels of education will likely have higher earnings on average. This is supported by the theory of human capital. Employers are often willing to pay more for individuals who already possess the skills and educational requirements for a job rather than spend resources on training.

Data Preparation

The variables of interest for this visualization were already tidy within the AAQoL dataset. The only change that needed to be made to the data was filtering. First, we filter out “Other” from the Ethnicity column. The survey included an “Other” option for individuals to choose if they were not Asian Indian, Chinese, Filipino, Korean, or Vietnamese. Since we cannot determine these individuals’ ethnicities, we exclude the “Other” category completely.

Next, we filter out individuals who reported as students, retired, or unemployed. The reasoning is we want to visualize the trends of individuals who are actively earning an income. We remove students because they are still pursuing an education which is one of the variables we are studying. We remove retired individuals because often their only earnings come from retirement savings checks or social security. We remove unemployed individuals because they are not making any income by themselves but could still have a high household income level due to their partner’s earnings. The last step in our data preparation for this visualization is removing any missing observations from the Education, Ethnicity, and Income columns.

Visualizations

Shown below is Figure 1. It plots mean education completed against the household income bracket for each Asian American ethnicity in the data. The error bars represent one standard error above and below the mean for each group.

The graph does not depict a clear general relationship between educational attainment and income. We had hypothesized that no matter the ethnic group, the trend should be positive but this does not seem to be the case. There does appear, however, to be a positive return to additional education for Asian Indian and Vietnamese individuals on average. We also see that the Vietnamese population tended to have the lowest completed education on average and Asian Indians had the highest. One potential reason we may observe this is household education standards. It could be that parents in Asian Indian families in Austin enforce educational attainment for their children more strictly than Vietnamese families do.

Figure 1: Mean Education Completed vs Income Bracket

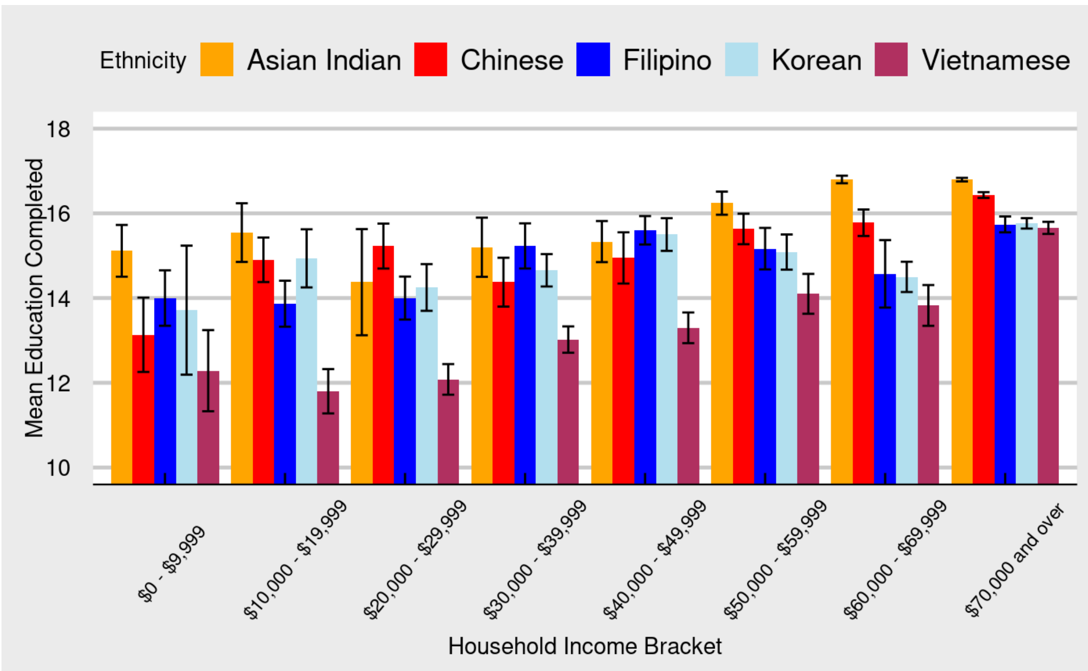


Figure 1 alone cannot be used to determine the return from education. We must consider other factors that influence income. These could be measurable features such as experience, gender, age or they could be unmeasurable such as ability. While we do not see a clear trend showing a positive return to education here, our machine learning model later on in the report does.

Hypothesis 2: Income Bracket v.s. English Proficiency

Overview

This hypothesis seeks to answer whether Asian Immigrants face income discrimination based on their proficiency in English. Two visualizations were made based on this hypothesis. One visualized the percentage difference of levels of proficiencies within different brackets. The other visualized the same relationship but faced the age of the respondents to explore if the relationship remained true through different generations.

Data Preparation

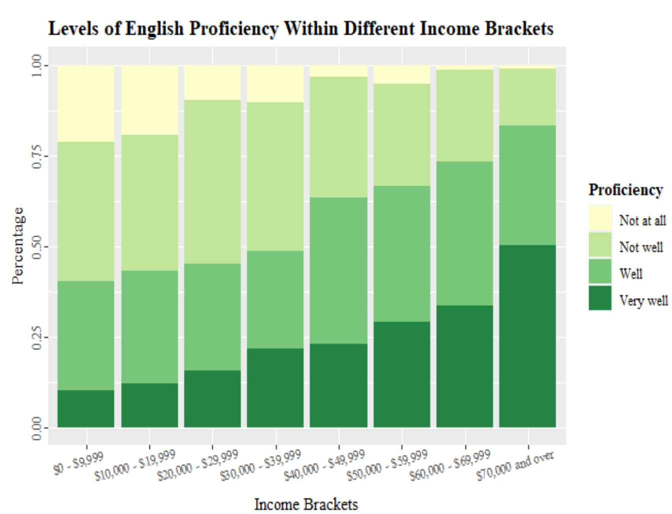
Individuals who were full-time homemakers or full-time students were excluded because their income was not dependent on their English proficiency. The dataset was filtered using R to only include individuals who were not born in the U.S. and were employed full-time, employed part-time, or retired. Individuals who were retired were intentionally included because we wished to explore generational differences in the relationship between income and proficiency.

We also excluded individuals who did not have responses for the relevant variables by selecting those variables and omitting all rows with N/A. This made sure that N/A in other columns did not interfere with the cleaning process. After the filter process, two additional variables were made to assist with the second visualization. The Age variable was categorized into an ordinal categorical variable, AgeCat, in order to facet by age. The Income variable was recoded from 8 categories to 5 categories in the variable Income5, in order to combine categories that had less data and show a clearer trend.

Visualizations

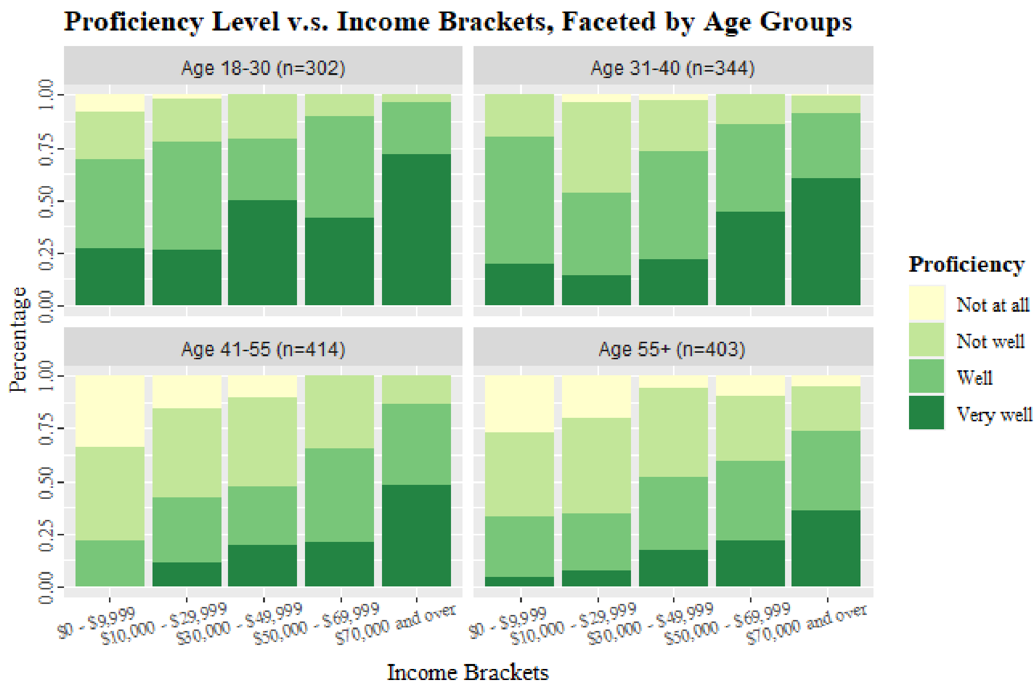
In Figure 2, there is a clear relationship between income bracket and proficiency. As income increased, the English proficiency of the people in that income bracket increased. Less than 50% of the people earning less than $10000 reported their English proficiency as "Well" or above. Meanwhile, More than 75% of the people earning more than $70000 reported their English proficiency as "Well" or "Very Well."

Figure 2: English proficiency vs Income Bracket



A similar trend is observed in all age groups when the data is faceted into groups by age, as seen in Figure 3. Visually, there is no effect of age on the relationship between income levels and English proficiency levels in Asian American populations. However, there is a clear increase in the overall proficiency in English among the younger generation when compared to the older generation. 75% of most income brackets in the 18-30 age group reported “Well” or “Very Well” for proficiency in English. See Figure 3 below.

Figure 3: English Proficiency v.s. Income Bracket, faceted by age

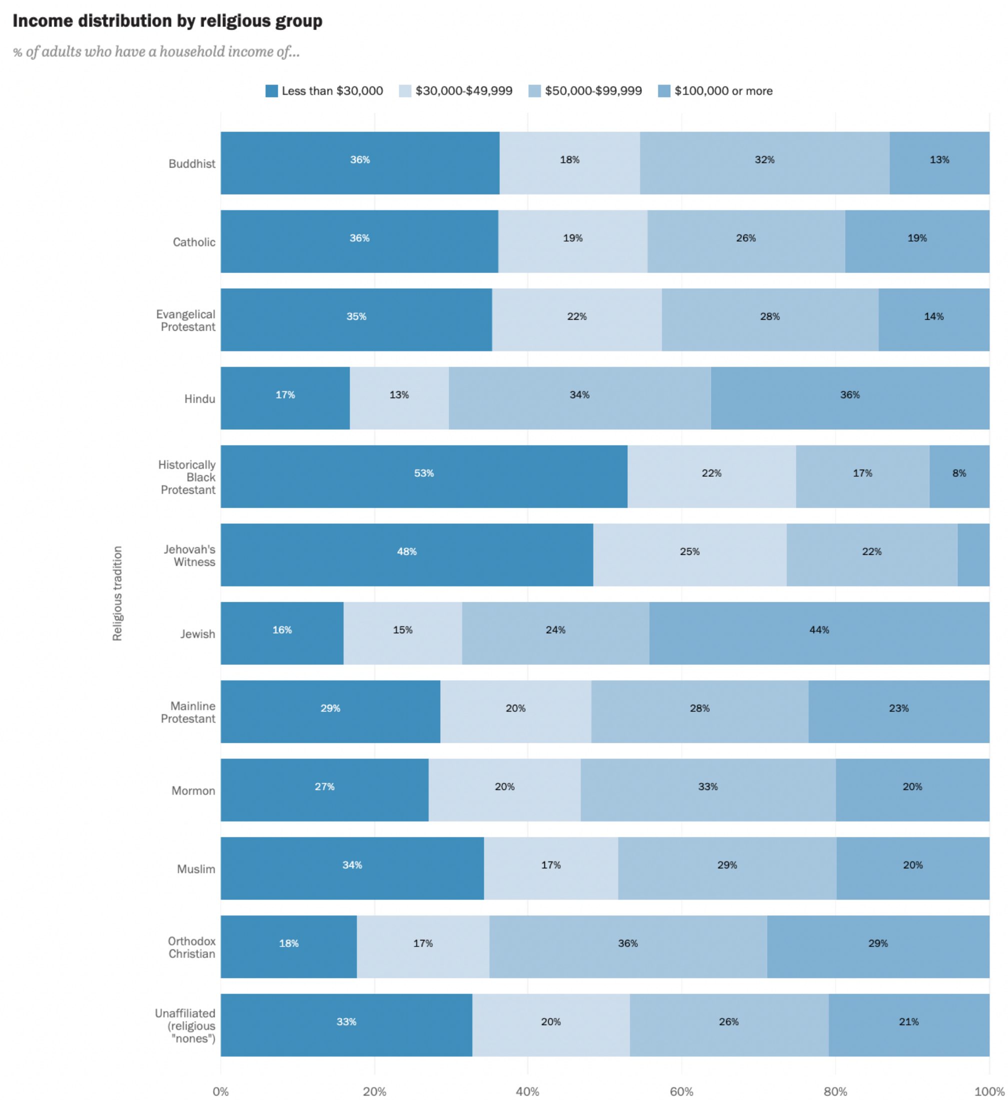


Hypothesis 3: Income Bracket v.s. Religion

Overview

According to Bettendorf and Dijkgraaf's study in low-income countries, religion has a negative effect on income, whereas, in high-income countries like the US, the effect of religion on income is positive (2008). See Figure 4 for a visualization relating income to religious groups (Pew Research Center, 2023).

Figure 4: Religion and income data from the Pew Research Center



Building on the foundation laid by Bettendorf and Dijkgraaf's study in low-income countries, we delved into the relationship between religious affiliation and income in the United States.

Notably, our analysis acknowledges the absence of specific religious groups, such as Jews and Orthodox Christians, in our Asian American Quality of Life dataset. The hypothesis is that religious affiliation significantly shapes income distribution in the U.S., with a particular focus on top earners.

Data Preparation

In this R code, we conducted an analysis on the dataset 'AAQoL' to explore the relationship between income and religion. We began by selecting relevant columns, namely 'Income' and 'Religion,' and filtering out rows with missing values using the na.omit() function. Subsequently, we grouped the data by both 'Income' and 'Religion,' calculating the count of occurrences for each combination.

To provide a comprehensive view, we also computed the total number of responses for each religious group. These total responses were determined by grouping the data solely by 'Religion.' The two sets of summarized data were then merged based on the 'Religion' column.

The final step involved creating a new variable, 'percentage,' representing the percentage of responses for each income level within each religious group. This was calculated by dividing the count of occurrences by the total responses and multiplying by 100.

Visualization

The visualization highlights interesting patterns in income distribution across religious groups. Muslims show a higher percentage in lower income categories, while Hindus are notable for a greater presence in higher income brackets. The data suggests diverse income levels across religions, with Hindus, Catholics, Unaffiliated, and Protestants standing out as top earners. This concise presentation provides a clear snapshot of the nuanced relationship between income and religious identity.

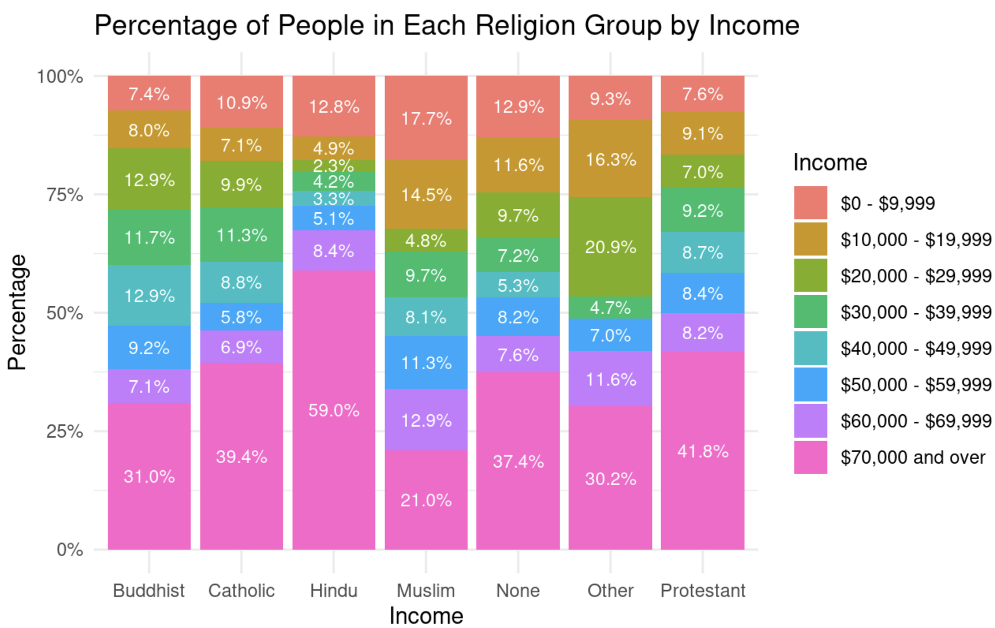
Results

The analysis of the dataset generally aligns with the initial hypothesis, indicating a significant influence of religious affiliation on income distribution in the United States. Hindus emerge as the top earners with 59%, followed by Protestants at 41.8%, and Catholics at 39.4%. However, the absence of Jewish and Orthodox Christian data should be noted. Notably, Muslims deviate from the expected pattern, exhibiting the lowest percentage in the high-income category at 17.7%. This unexpected finding prompts further research opportunities to explore the factors contributing to the unique income dynamics among

Muslims in the U.S., offering a nuanced perspective on the relationship between religious affiliation and income.

(See Figure 5 below.)

Figure 5: Income vs Religious Group



Hypothesis 4: Employment Status v.s. Sense of Belonging

Overview

This hypothesis seeks to answer the relationship between employment and sense of belonging. We predict that those who are employed full-time will have greater levels of belonging and those who are unemployed will have lower levels of belonging. Our reasoning for this is that full-time employees are more likely to spend a significant amount of time in their workplace. With constant interaction with their colleagues and employees, they should have memorable experiences. This fosters a positive and strong work environment which would lead to a sense of belonging at work. These feelings of belonging can then extend beyond work into a broader context.

Data Preparation

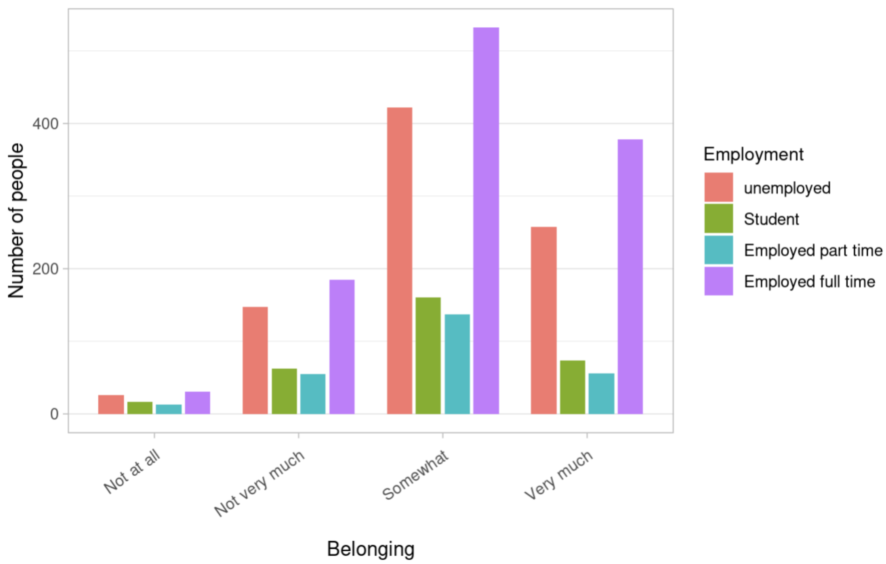
The data preparation involved selecting relevant columns ("Belonging," "Full.Time.Employment," "Part.Time.Employment," "Student," and "Homemaker") from the `Asian American Quality of Life` data frame. Rows with missing values are removed (na.omit), and a new "Employment" variable is created. Unnecessary columns are subsequently excluded, and the data is then grouped by "Belonging" and the newly created "Employment" variable. Filtering out cases where "Employment" is not equal to 0, the code calculates the count (n) for each group.

Another step involves computing the total count of belonging for each unique value of "Belonging." The final step merges the original data frame with the total belonging counts and computes the percentage by dividing the count (n) by the total belonging and multiplying by 100. Based on the resulting data frame ggplot was used to create the plot.

Visualization

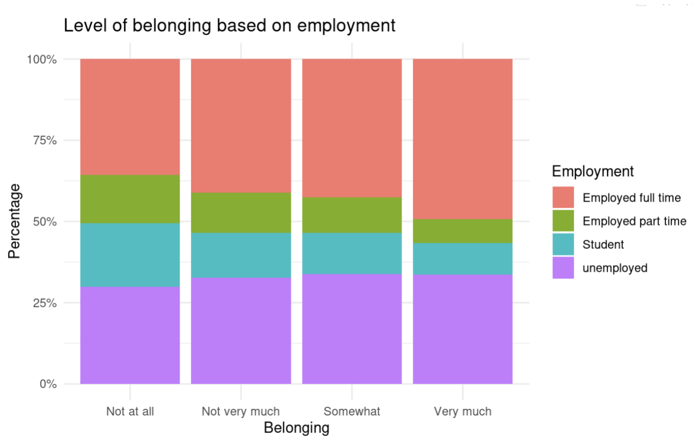
Figure 6 shows there is a trend in the proportion of full-timers and sense of belonging as they feel a greater sense of belonging as the levels increase. As the levels of belonging increase, we see that the proportion of those reporting a greater sense are those employed full-time. When focusing on the last column, more than 65% of those reporting a high sense of belonging are employed full-time. So, full-time employment appears to be a contributing factor to belonging. When looking at the first column, we also see that about 46% of those reporting no sense of belonging are employed full-time. This leads us to believe that there are other factors that lead to a sense of belonging as we did not expect to see a big percentage of full-timers to report no sense of belonging. This could also be dependent on the type of employment. People who hold higher titles and more prestigious positions might be found in the last column. Those with less desirable positions could be found in the first column. There also appears to be a negative relationship between students/part-time employees and the sense of belonging. As we increase the sense of belonging, the percentage of these individuals decreases. Students might face more discrimination at school which could contribute to their lower sense of belonging.

Figure 6: Employment v.s. Sense of Belonging (nominal)



In Figure 7, we see similar results. The number of people reporting a higher sense of belonging are those employed full-time.

Figure 7: Employment v.s. Sense of Belonging (percentage)



Modeling

In our study we had several hypotheses discussing which variables likely impact income. We considered education, religion, ethnicity, English proficiency, gender, and marital status. To model these predictions, we wanted to choose a method where we could interpret the ceteris paribus effect each variable has on income classification. Therefore, the model we use to classify our data is a logistic regression. In a logistic regression we can control for all of the listed variables and interpret each variable's effect on the probability of being placed into a higher household income bracket.

Data

Before performing any regressions, we cleaned our dataset. One of the other reasons why we choose to perform a logistic regression is that our outcome variable is not continuous. In the AAQoL survey, participants chose from a list of income brackets that ranged \$0-9,999 to \$70,000 and over (in \$10,000 increments). In order to have a clearer interpretation of our regression results, we recoded the income brackets as a binary variable. We chose \$60,000 as the cutoff because the US Census Bureau estimated the 2016 median annual household income in Texas to be \$56,565 (Guzman 2017, 3). This corresponds with the year the AAQoL survey was taken. Therefore, the income groups can be classified as approximately above average household income (> \$60,000) and below average household income (< \$60,000).

Similarly the English proficiency variable had to be recoded as a continuous variable. In the AAQoL survey participants chose from a list of phrases to describe their English speaking. We recoded them as follows: Not at all (0), Not well (1), Well (2), and Very Well (3). There could be a potential flaw in recoding English speaking this way because it is unknown if speaking English "Well" is really two times greater than speaking it "Not well," for example. If we had better information we would be able to assign more accurate magnitudes.

Both the religion and ethnicity variables were recoded to individual class-specific binary variables. For religion there is a binary variable for the following categories: None, Other, Buddhist, Catholic, Hindu, Muslim, and Protestant (reference group). Note that Protestant is left out of the regression equation and is the reference group for the other religion variables. For ethnicity there is a binary variable for the following categories: Indian, Korean, Vietnamese, Filipino, Other, Chinese (reference group). Note that Chinese is left out of the regression equation and is the reference group for the other ethnicity variables.

The gender variable was recoded to a binary variable equal to 1 for male and 0 for female. A proxy experience variable was created using the formula Age-education-6. A marriage binary variable was created and is equal to 1 if the individual is married and 0 otherwise. Lastly, the dataset is filtered to include only individuals who classified as having full-time or part-time employment. This is done in an attempt to get a better sense of individual income because an individual can be unemployed but still be in the highest income bracket if their partner earns that amount. Also note this means students, homemakers, and retired individuals are not included. After filtering out observations with missing responses we are left with a total of 1,389 observations. Summary statistics for these observations are provided in Table 1.

Table 1: Logistic regression variables summary statistics

Variable	Mean	Standard Deviation	Maximum	Minimum
Income_binary_dummy	0.560835	0.496285	1.0	0.0
Education Completed	15.434125	2.094118	17.0	2.0
Religion_None_dummy	0.164147	0.370409	1.0	0.0
Religion_Other_dummy	0.020158	0.140542	1.0	0.0
Religion_Buddhist_dummy	0.134629	0.341327	1.0	0.0
Religion_Catholic_dummy	0.215983	0.411502	1.0	0.0
Religion_Hindu_dummy	0.218143	0.412985	1.0	0.0
Religion_Muslim_dummy	0.026638	0.161023	1.0	0.0
Religion_Protestant_dummy	0.215263	0.411005	1.0	0.0
Ethnicity_Asian Indian_dummy	0.259179	0.438184	1.0	0.0
Ethnicity_Korean_dummy	0.138229	0.345140	1.0	0.0
Ethnicity_Vietnamese_dummy	0.229662	0.420615	1.0	0.0
Ethnicity_Filipino_dummy	0.115191	0.319252	1.0	0.0
Ethnicity_Other_dummy	0.058315	0.234339	1.0	0.0
Ethnicity_Chinese_dummy	0.199424	0.399567	1.0	0.0
Numerical English Speaking	2.213103	0.842073	3.0	0.0
Male	0.522678	0.499485	1.0	0.0
Experience	18.098632	13.132801	64.0	-2.0
Married	0.699064	0.458665	1.0	0.0

Regression Equation

Our logistic regression equation is set up as follows:

$$\boldsymbol{Above60k_i = \alpha + \theta Education_i + \sum_{r=1}^{6} \beta_r Religion_i + \sum_{e=7}^{11} \beta_e Ethnicity_i + \gamma English_i}$$
$$\boldsymbol{+ \mu Male_i + \delta Experience_i + \sigma Married_i + e_i}$$

The variable *Above60k*$_i$ is our dependent variable of interest and represents whether a respondent is in the "Above $60,000" or "Below $60,000" income bracket as described in the *Data* section. The independent variables are *Education*$_i$, *Religion*$_i$, *Ethnicity*$_i$, *English*$_i$, *Male*$_i$, *Experience*$_i$, and *Married*$_i$. All of these correspond to the variables explained in the *Data* section.

We split the data into training and test sets within Python. There are 1,041 observations in the training set and 348 in the test set. In Python, we perform the logistic regression by first classifying the model (LogisticRegression()), then fitting the training set to the model (logreg.fit(X_train, Y_train_binary)), and finally classifying outcomes with the test set (logreg.predict(X_test)). To get the slope coefficients we use logreg_fit.coef_[0] and to get the intercept coefficient we use logreg_fit.intercept_[0]. See the regression coefficients in Table 2.

Table 2: Logistic regression output

Intercept: −6.699355898511242

	Feature	Coefficient	P−value
0	Education Completed	0.310496	0.000
1	Religion_None_dummy	−0.162356	0.000
2	Religion_Other_dummy	0.004691	0.270
3	Religion_Buddhist_dummy	−0.467387	0.000
4	Religion_Catholic_dummy	0.191294	0.000
5	Religion_Hindu_dummy	0.016735	0.177
6	Religion_Muslim_dummy	−0.758883	0.000
7	Ethnicity_Asian Indian_dummy	−0.201763	0.000
8	Ethnicity_Korean_dummy	−0.551140	0.000
9	Ethnicity_Vietnamese_dummy	−0.690833	0.000
10	Ethnicity_Filipino_dummy	−0.701122	0.000
11	Ethnicity_Other_dummy	−0.871861	0.000
12	Numerical English Speaking	0.710573	0.000
13	Male	0.342202	0.000
14	Experience	−0.005411	0.989
15	Married	1.439369	0.000

Discussion

Performance

See Table 3 below for performance metrics.

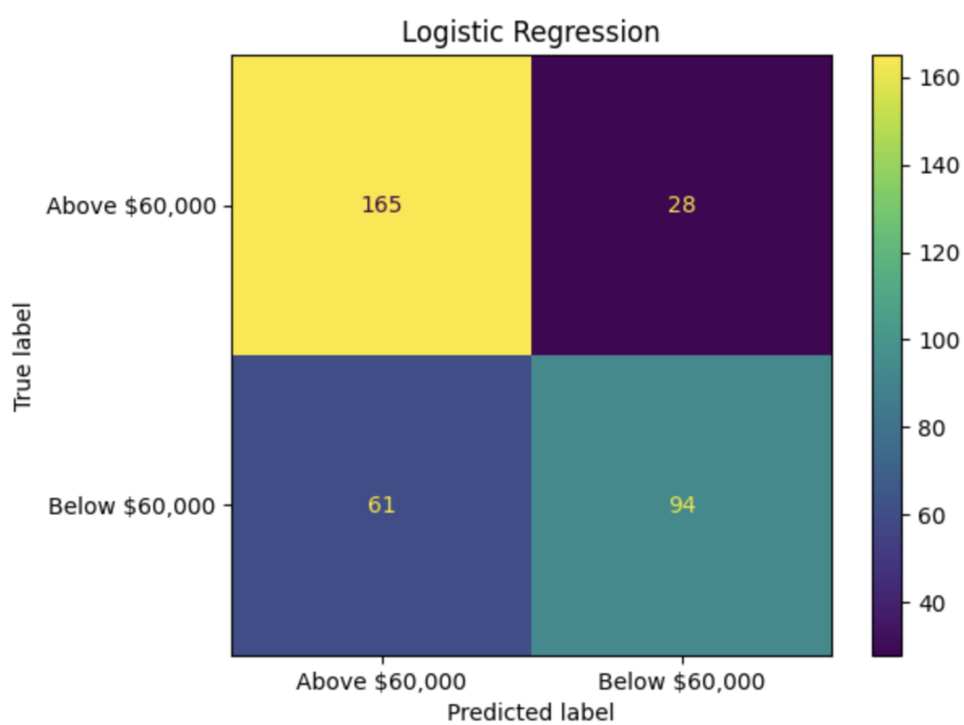
Table 3: Logistic regression performance metrics

Classification Report for Logistic Regression:

	precision	recall	f1-score	support
0	0.77	0.63	0.70	155
1	0.74	0.85	0.79	193
accuracy			0.75	348
macro avg	0.76	0.74	0.74	348
weighted avg	0.76	0.75	0.75	348

As we can see from Table 3, the precision, recall, and accuracy scores all range between .74-.76. An accuracy score of .75 shows that the model is doing a good job at classifying individuals into above average or below average household income groups. These scores are visualized in the confusion matrix as shown below (Figure 8).

Figure 8: Logistic regression confusion matrix



Findings

From the regression coefficients in Table 2 we find some interesting results. First off, the coefficient on education is positive, as expected, and large in magnitude at .310 ($p<.01$). This means that all else equal, one more year of education increases an individual's probability of being classified in the above average household income bracket by 31.0% on average. It should be noted that based on our summary statistics, the mean education in our study is 15.4. In this dataset, 16 years of education resembles an undergraduate degree. Therefore this education effect is likely picking up the impact of completing college and it certainly does not resemble the return to another year of highschool, for example.

Another interesting result from our regression is the coefficient on English proficiency of .711 ($p<.01$). This implies that jumping up an English proficiency classification–as described in the *Data* section–increases an individual's probability of being placed in the above average household income bracket by 71.1% on average. This was one of the effects we were primarily interested in studying. How important is English proficiency in determining income in the United States? Based on the regression results it seems to matter a great deal.

From our ethnicity binary variables, we can get a sense of how ethnicity determines income while controlling for education, experience, and gender. Since all the ethnicity variables in the table have negative coefficients, Chinese individuals are the most likely to be placed in the above average household income bracket. Apart from the Other Ethnicities category, the ethnicity with the lowest probability of being in the above average household income bracket was Filipinos on average. Performing the same analysis with religion shows Catholics are the most likely to be in the above average household income bracket on average. Buddhists are the least likely on average.

Limitations

Our study has a couple limitations found in the data. First, our analysis is limited because income is not reported as a continuous variable, but rather a categorical variable. We are required to perform a logistic regression and cannot test for the direct monetary effects of changes in the various independent variables within our model. Another limitation from the data is that the survey has a small density of individuals with low education. Due to this, we can not state that the education effect on income would apply to all education levels. One solution to this could be a quadratic education term in the model. However, due to the small number of low-education observations, even this would likely not reveal any causal effects.

One limitation in our model is that the logistic regression can give uninterpretable results. For example, in Table 2 the coefficient on *Married* is 1.439. A variable cannot increase the probability of the outcome by more than 100%. A solution to this could be to use a probabilistic model instead. In probabilistic models, slope coefficients greater than 1 can still be approximated by evaluating the model at a specific value.

Ethics

From the AREA Plus (4p) Framework, we will be anticipating the people affected, reflecting on potential unintended consequences, and engaging in potentially under-represented groups in our population.

People Affected

The primary group affected by the outcome of this work would be Asian Americans in the United States. Though the data was taken from Austin specifically, the outcomes of this work could be misused and generalized to Asian Americans as a whole. Indirectly, anyone could be affected by this work if it is used to compare and contrast different ethnicities outside the Asian American group. Additionally, because the dataset did not differentiate between the different South Asian groups, and only specified Asian Indians as the only option given, this could result in other South Asian groups or Asian Indians themselves being misrepresented.

Unintended Consequences

There are many ways that the data from this project could be used to misrepresent or make broad generalizations about groups of people without taking the historical and sociological contexts into consideration. For example, the data from our third hypothesis paints the picture that Asian Americans in the ‘Hindu’ religious group have higher income levels than Asian Americans in the ‘Muslim’ religious group. Though this data is important and accurate, it is crucial to consider the immigration patterns that could have resulted in this disparity, rather than equating correlation with causation and generalizing the characteristics of these groups. If these types of conclusions are made by those viewing this project, it could result in hate and discrimination.

Under-Represented

There are several groups of stakeholders who are overlooked in the dataset itself. The only options for ‘Ethnicity’ to choose from in the survey given are Chinese, Asian Indian, Korean, Vietnamese, Filipino, and Other. This overlooks various groups such as Pakistani, Bangladeshi, Nepalese, and Burmese groups, including many others. Someone taking this survey who falls into a more specific ethnic group could choose to check a broader category. Everyone who falls into the ‘other’ category is excluded from this survey. In our project, it is important to take this into consideration when looking at the data, especially for our first hypothesis.

Conclusion

To conclude this study, there are many key findings that we saw. The first of many findings is that there is are varying levels of education and returns to education for the Asian American ethnic groups studied. While some ethnicities typically had children advance to higher level studies and go to college, some of the averages for other ethnicities corresponded to never graduating high school. This may be due to cultural norms and if certain ethnicities value education more than others. The second finding we acknowledged was that the levels of income varied heavily amongst different religious groups. We observed that Catholics and Protestants are among the top in income while Muslims have a greater percentage with lower income on average. Thirdly, we also saw that there was a positive relationship between a person's proficiency in English and their income level. This might be due to the fact the United States is English dependent and if people can speak English at a higher level, they can work more efficiently and will be paid more as a result. Lastly, we observed that full-time employees and unemployed individuals dominate in the proportion of belonging across the different levels. This helps in showing that employment levels effect the sense of belonging in the United States.We should note that this study has many strengths such as a large data size and visualization tools, but there are some weaknesses. These include social desirability bias and causation versus correlation. To improve such actions and findings, it would be best to incorporate longitudinal data to study changes over time and to capture dynamic processes, and further the research to include more ethnicities.

Acknowledgements

Task	Data Preparation	Graphs	ML	Presentation Prep	Presentation	Report Writing	Website		Total	Contribution
Task %	25	25	15	20	30	15	10		140	
Caleb Abraham	5	0	0	0	10	5	0		20	100
Sree Dharma	5	0	0	5	10	0	0		20	100
Ayush Narayan	0	5	5	5	5	0	0		20	100
Valerie Khaiman	0	10	0	0	5	5	0		20	100
Clover Chen	5	5	0	0	0	0	10		20	100
Orlando Di Leo	5	5	10	0	0	0	0		20	100
Hilario Fraire Jr	5	0	0	10	0	5	0		20	100
Total	25	25	15	20	30	15	10	Total	140	
								Max	20	

Bibliography

Arnold, N. (2023, March 23). *Learning from Asian-American success*. City Journal. https://www.city-journal.org/article/learning-from-asian-american-success

Bettendorf, Leon J.H. and Elbert Dijkgraaf (2008, January 31). *Religion and Income: Heterogeneity between Countries*. Social Science Research Network. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1088980.

Guzman, Gloria G. (2017 September). *Household Income: 2016.* U.S. Census Bureau. https://www.census.gov/content/dam/Census/library/publications/2017/acs/acsbr16-02.pdf.

Kochhar, R. (2018, July 12). *Income inequality in the U.S. is rising most rapidly among Asians*. Pew Research Center's Social & Demographic Trends Project. https://www.pewresearch.org/social-trends/2018/07/12/income-inequality-in-the-u-s-is-rising-most-rapidly-among-asians/

Rohan Carter-Rau, B. O., Nicol Turner Lee, S. B. (2022, March 9). *Asian-American success and the pitfalls of generalization.* Brookings. https://www.brookings.edu/articles/asian-american-success-and-the-pitfalls-of-generalization/

Ruiz, N. G. (2022, August 2). *What it means to be Asian in America. Pew Research Center Race & Ethnicity*. https://www.pewresearch.org/race-ethnicity/2022/08/02/what-it-means-to-be-asian-in-america/.

Pew Research Center (accessed 2023 December 4,). *Income distribution by religious group*. https://www.pewresearch.org/religion/religious-landscape-study/income-distribution/.

Jang, Yuri (2023, October 13) *Asian Americans in Austin: Final Report of the Asian American Quality of Life (AAQoL) Survey.* Asian American Quality of Life. https://data.austintexas.gov/dataset/Final-Report-of-the-Asian-American-Quality-of-Life/hc5t-p62z.