ASSIGNMENT TWO

Can the use of Australian census income data indicate whether or not there needs to be stricter controls on credit card applications for young Australians under 21?

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2.1 PROBLEM STATEMENT

Can the use of Australian census income data indicate whether or not there needs to be stricter controls on credit card applications for young Australians under 21?

2.2 BACKGROUND

This study will investigate personal income and employment data from the 2016 Australian Census to identify any distinct characteristics with age groups and determine if there should be a prohibition on applying for credit cards under the age of 21 without a co-signer nor written proof of stable income like in the United States according to Schwartz [1].

The current legal age in Australia to apply for a credit card is 18. Cooke [2] claims that unsteady income is a significant factor in having a credit card application rejected. According to CreditCard.com.au [3] the minimum annual income required is typically $35,000 per year. However according to the same site and McMullen et al [4] Australians can get low income credit cards with a minimum annual income of $15,000, albeit with lesser privileges.

A survey in November 2020 reported by Granwal [5] revealed that 18 to 25 years olds have the highest average value of personal debt over other age demographics, around $3800.

2.3 INPUT DATA

A data pack was downloaded from https://datapacks.censusdata.abs.gov.au/datapacks/ [6]. The tables were part of the 2017 ABS release of the 2016 Census for the Australian population. The datasets are tabular data, in CSV format. They are static, only showing the results from the 2016 Census survey. Three tables will be used and according to the ABS [6] [7] [8] [9] are titled as follows:

G17A and G17B: Total Personal Income (weekly) by Age by Sex
G43B: Labour Force Status by Age by Sex

All the attributes are categorical. The ages are grouped into age groups, the incomes grouped into intervals and the labour force status is categorical. The income attribute is most important but employment status information (full time, part time and unemployment) will be utilised because they are useful indicators of income stability. All tables have one row and each attribute represents a particular gender, age group and income range and the count of persons within it. Only all persons data (P) will be considered from both tables. From G17B and G17C the following attributes will be used: P_Neg_Nil_income_x_y_yrs, P_Neg_Nil_income_Tot, P_a_b_x_y_yrs, P_a_b_Tot and P_Tot_Tot. So therefore the attributes showing income from $a to $b and negative or nil income for each age bracket x years to y years, and the total population of each age group.

From G43B, the attributes showing the full time and part time employed persons count and the unemployed persons count for all age brackets (e.g. P_Emp_FullT_x_y, P_Emp_PartT_x_y and P_Tot_Unemp_x_y) as well as total populations for each category, age group will be utilised. The other attributes for 43B are as follows: Employed but away from work (Emp_awy_f_wrk), Hours Worked Not Stated (Hours_wkd_NS), Unemployed but looking for full time work (Unem_look_FTW), Unemployed but looking for part time work (Unem_look_PTW), Total Persons in Labour Force (Tot_LF), Total Persons Not In Labour Force (Not_in_LF) and Labour Force Status Not Stated (LF_NS). The Total Persons in Labour Force was later used post analysis to explain unusual employment rates.

Age Categories	*Income Categories*	*Employment Categories*
15 to 19 years	Negative to nil income	Full time
20 to 24 years	$1-149	Part time
25 to 34 years	$150-299	Unemployed
35 to 44 years	$300-399	
45 to 54 years	$400-499	
55 to 64 years	$500-649	
65 to 74 years	$650-749	
75 to 84 years	$800-999	
> 85 years	$1000-1249	
	$1250-1499	
	$1500-1749	
	$1750-1999	
	$2000-2999	
	Over $3000	

Table 1: *Summary of the age, income and employment categories used in Census data for this study.*

3.1 BUSINESS REQUIREMENTS
The main aim of this study is to identify any notable characteristics in income with regards to income requirements for credit card applications with age demographics to identify the need for restrictions for under 21 year olds.

In this process it is possible that trends with other age groups with income and employment status can be identified and become the subject of debate for whether or not there should be restrictions on them. This may be the case for those post retirement.

Bertram in 2020 [10] suggested that big data is very useful for financial and banking organisations in that it efficiently enhances the ways they can risk manage, provide better and faster responses in the system and better overall risk coverage. This study on personal income and employment by age category will be a useful resource in improving risk management. Banks can identify how risky a potential customer is from their age if that age is likely to be associated with poor income and employment. It will improve the process of approving and rejecting. Risk management is essential when dealing with people with more vulnerable employment and income situations.

Using Census data does have restrictions. It is not quite up to date and can be vague in representing every age group and personal income by all individuals in detail. The numbers for age and income is grouped into categories. Banks may want more detail on a particular individual's income and work status in certain circumstances.

This study can be useful for the federal government in the situation they consider tighter laws for credit cards and other financial loans based on age demographics, such as in the United States with the CARD Act.

This is a short study that has taken a few weeks to complete with some fairly intensive data wrangling. It forms the basis for future data science projects that can more accurately identify financial issues and improve operations.

3.2 BUSINESS APPLICATION AREAS.
The use of population data is important in the banking and lending sector. Bhargava [11] suggests that it is very useful for identifying a customer's financial behaviour and the types of services they want and understand customers in order to effectively hit target markets. Bhargava also suggests the income level and stability is important in optimising an offer to a customer. This study identifies any importance in Census data in whether targeting age groups to sell and to avoid selling to is a good idea based on age specific income and employment information.

The intent of this study is to identify any distinctive age characteristics with credit card ineligibility based on personal income. The base of this study can also be used to determine the eligibility of other banking products to consumers based on age such as mortgages, personal and car loans and even types of insurance. If there are notable patterns with age groups and credit card ineligibility banks and other financial institutions can use this study as a means to reduce losses from unpaid debt and improve efficiency in credit card lending. The identification of links between employment type and income will provide other reliable criteria for credit card approvals. In challenging economic times due to Covid and government responses and high levels of debt it is important that banking services focus on reducing losses and one tactic is to improve their standards for lending money to prospect customers.

The data wrangling process provided a good basis for the development of programs that can meddle complex Census datasets into simple tables. Future data wrangling work will focus on the development of a program that can automate the process of wrangling these datasets into easy to read, understand and use tables. This is also of significant benefit to businesses that want to undertake their own data analysis activities using Census data.

3.3 CHALLENGES

There are a few significant challenges in this study. Income is not the sole determinant for approving credit cards. Employment status and credit history other factors in approving credit cards for example. The income values in ranges, no exact income details for people. In the eyes of some businesses the results may be a little vague.

For the data for personal income and employment status, the age values are shown in ranges. There are no exact age values. This is a potential problem when using 15 to 19 years plus 20 to 24 years to look at characteristics specific to under 21s. For personal income and employment details the Census data groups these age groups together. Table G04 in the 2016 Census is age by sex [12]. Obtaining data for the total count of persons for each age from 15 to 19 yields these results

Attribute	Count	Percentage of 15 to 19 year group
Age_yr_15_P	278837	19.61
Age_yr_16_P	282097	19.84
Age_yr_17_P	282478	19.87
Age_yr_18_P	284249	20
Age_yr_19_P	293937	20.68

Approximately 40.68 percent of this group is 18 years old and over and legally able to apply for a credit card. 100 percent of all other ages in this study are allowed by law to apply for a credit card.

The datasets are large with a lot of values. For each table there is only one row, representing the entire Australian set. There are many columns, each representing one attribute and one value per attribute. This can present challenges with the data wrangling process, including the unintentional creation of errors and subsequent error propagation as the process continues. The process for data wrangling to modify both datasets into the required attributes and categorical values was lengthy and complex, requiring many lines of code.

Finally the data is from the 2016 Census, the results of essentially a survey undertaken by every household in Australia during a night in 2016. The data on employment and income is accurate as that night in 2016. It was five years ago. Things may have changed significantly since then. MacroTrends [13] reports the 2016 unemployment rate in Australia as 5.71 percent. This figure increased to 6.61 percent in 2020. The ABS [14] reported the national unemployment rate as 5.8 percent in February 2021, which can be seen as a minor change from the 2016 figure. The ABS [15] also reported changes in median income for Australians in 2017/2018 from 2016/2017, a 3 percent increase. It is possible that there have been further changes over the last few financial years. These examples suggest that weekly income and employment status statistics could be different in the 2021 Census, which will be released in 2022 and for that reason cannot be used unfortunately for this study.

4.1 DATA ANALYSIS

4.1.1 Software

Python was used for the data analysis. Python has features and modules are simple to learn and use and is already the most popular programming language for data science. To back that up a survey conducted by KDnuggets found 65.8 percent of 1800 participants use Python for data science according to Piatesky in 2019 [16] . The modules numpy, pandas and matplotlib have been used for the data extraction and wrangling and visualisations. Python IDLE was employed as the main platform to develop and run the code, and Anaconda was utilised to visualise the pandas data frames and numpy arrays. Excel as utilised to test the accuracy of the mathematical operations constructed. It is important to test code before it is deployed to eliminate errors and prevent significant error propagation.

4.1.2 Procedure Summary

The data process can be summarised as follows

1. Download the data pack from the Census 2016 website.
2. Extract the tables 17b, 17c and 43b for the whole Australian population set.
3. Discard any unwanted columns from 17b and merge with 17c. Discard any unwanted columns in 43b.
3. Check the data frames for 17 and 43 for any missing and non-numerical values.
4. Wrangle the data frames using numpy into arrays where each column represents an age group and each row represents an attribute (of income for 17 and employment status for 43) and save into new csv file.
5. Use modified data frame in 17 to calculate eligibility for both low income and normal income credit cards in terms of both population count and percentage of population for each age category.
6. Calculate percentages of full time employed, unemployed and total employed in 43 for each age category.
7. Group age categories into under 25 ,25 and over, under 20, 20 and over, under 25, 25 to 64 years , under 20 v 20 to 64 years and calculate attributes in income, credit card eligibility and employment status for these age categories.
8. Use matplotlib to bar graph credit card eligibility categories and employment categories for all age groups, then compare credit card eligibility and employment type for the new age categories (under 25 v 25 and over, under 20 v 20 and over, under 25 v 25 to 64 years, under 20 v 20 to 64 years).
9. Create scatter plots and correlation matrices for the following:
    - low income credit card eligibility v total employed
    - normal income credit card eligibility v full time employed
    - credit card ineligibility v total unemployed

Three separate python files were constructed. One to create the data frames in a comprehensive data wrangling process, one to create all the bar graphs and one to create the scatter plots and correlation matrices.

A full 2016 Census data pack was downloaded as a zip folder from the 2016 Census website and extracted. The tables G17B, G17C and G43B were taken and used for this study. . All the female specific attributes from G43B were also eliminated. This project only deals with attributes for all persons, nothing gender specific. The resulting data frames were named Data frame 17b and Data frame 43b.

The row and column attributes representing the totals were checked for Data frame 17b using Python. It was noted that the values representing the total for each age group and each income interval did not match the actual calculated values in Python. A screenshot is shown below.

```
Number of columns in DataFrame 17: 161
Number of numerical values in DataFrame 17: 161
There are no missing values nor erraneous values in the income by age dataframe
Number of columns in DataFrame 43: 121
Number of numerical values in DataFrame 43: 121
There are no missing values nor erraneous values in the employment status by age dataframe
The number of values match the number of columns like in the dataframe 17b
The number of values match the number of columns like in the dataframe 43b
The total value reported in the Census is 1421595. The calculated total of the column values are actually 1421599
The total value reported in the Census is 1566793. The calculated total of the column values are actually 1566807
The total value reported in the Census is 3368449. The calculated total of the column values are actually 3368457
The total value reported in the Census is 3144935. The calculated total of the column values are actually 3144949
The total value reported in the Census is 3105007. The calculated total of the column values are actually 3105014
The total value reported in the Census is 2753734. The calculated total of the column values are actually 2753738
The total value reported in the Census is 2076707. The calculated total of the column values are actually 2076714
The total value reported in the Census is 1113209. The calculated total of the column values are actually 1113231
The total value reported in the Census is 486842. The calculated total of the column values are actually 486849
The total value reported in the Census is 19037277. The calculated total of the column values are actually 19037279
```

Figure 1: *The Output From Python showing no missing data and also showing that the Census reported totals and calculated totals disagree for Data frame 17 very slightly.*

This could be due to how Census forms were filled out. It is possible that a minority of people may have made errors in their forms including filling out more than one income bracket. The mathematical totals were calculated but the totals reported by the Census are likely to be more realistic and accurate population totals, so were kept as the totals. This was also the case for Dataframe43b where some employment categories were definitely not mutually exclusive.

Income levels were categorised into two sets of categories based on credit card application research in Australia. According to creditcard.com.au [3] and McMullen et al [4] a typical threshold for a normal credit card is a minimum income of $35,000 annually and for special low rate credit cards $15,000 annually. Pay Calculator [17] estimates the weekly pay after tax for both annual incomes to be $600/week and $288/week receptively. If the lowest vale in the income range falls below the threshold, that income bracket will be classified 'ineligible' for a credit card, otherwise the income bracket will be classified as 'eligible'. This information will be added to the table. In this study this implies that in order to be eligible for a low income credit card, the income bracket an individual should be in is the $300 to $399/week or higher. Anything less was considered ineligible. In order to be eligible for a normal income limit credit card, the income bracket an individual should be in is the $650 to $749/week or higher. Anything less was considered ineligible, even though a person may have income between $600 and $649. As there are only income categories the exact incomes of people were unknown.

The Data frame 17b was manipulated to calculate the count of persons considered both eligible and ineligible for both the low income ($15000/year) and normal income ($35000/year) credit cards by summing up the appropriate income bracket counts within each category. These rows were added to the data frame, and this data frame was exported to CSV for backup. These characteristics were then calculated as percentages of the age group population. When calculating these percentages the figures for personal income not stated were subtracted from the total, so consequently not all eligible and ineligible pairs will add up to 100. the purpose was to calculate a more accurate percentage of those eligible as only the reported incomes were considered. The final table shows the total for all people regardless of whether or not they stated their income.

N(eligible low income CC)	= N(Total) – N($150-299/week) – N($1-149/week) – N(negative/no income)
N(eligible CC with $35K/year income)	= N(Total) - N($500-649/week) – N($400-499/week) + N($300-399/week) - N($150-299/week) – N($1-149/week) – N(negative/no income)
N(ineligible low income CC)	= N($150-299/week) + N($1-149/week) + N(negative/no income)
N(ineligible CC with $35K/year income)	= N(ineligible low income CC) + N($500-649/week) + N($400-499/week) + N($300-399/week)
PC (eligibility)	= (N(eligibility)/N(Total))x100
Employment Rate	= (N(Total Employed)/N(Total))x100
Unemployment Rate	= (N(Total Unemployed)/N(Total))x100
FT Employment Rate	= (N(Employed Full Time)/N(Total))x100

Figure 2: *Equations of Calculations Used To Wrangle Data From Census Tables*

Matplotlib and pyplot was used to produce bar graphs. The pyplot sub module of matplotlib was utilised (import matplotlib.pyplot as plt) using the function plt.bar along with associated editing and styling functions to plot the bar graphs. The following graphs were produced

- Number of persons by age group that earn more than $300/week and likely to be eligible for a low income credit card.
- Number of persons by age group that earn more than $650/week and likely to be eligible for a normal credit card.
- For both levels the ineligibility by number of persons for each age group.
- Eligibility and ineligibility for both levels as percentages of the population counts for each age group, using numpy mathematical operations to calculate these percentages.
- Total employment rate for each age group
- Total unemployment rate for each age group
- Full time employment rate for each age group

Matplotlib and pyplot was also used to create bar graphs to compare percentage characteristics of credit card eligibility, ineligibility, total employment, unemployment and full time employment between the following age groups

- Under 25 years old versus over 25 years old
- Under 20 years old versus over 20 years old
- Under 25 years old versus those aged from 25 to 64
- Under 20 years old versus those aged from 20 to 64

Under 25 years	Ages 15 to 19 + Ages 20 to 24
25 years and over	Ages 25 to 34 + Ages 35 to 44 + Ages 45 to 54 + Ages 55 to 64 + Ages 65 to 74 + Ages 75 to 84 + Ages 85 and over
20 years and over	Ages 20 to 24 + Ages 25 to 34 + Ages 35 to 44 + Ages 45 to 54 + Ages 55 to 64 + Ages 65 to 74 + Ages 75 to 84 + Ages 85 and over
25 to 64 years	Ages 25 to 34 + Ages 35 to 44 + Ages 45 to 54 + Ages 55 to 64
20 to 64 years	Ages 20 to 24 + Ages 25 to 34 + Ages 35 to 44 + Ages 45 to 54 + Ages 55 to 64

Figure 3: *How the new age groups were created using Census age groups.*

The 64 age limit was chosen because according to the Australian Department Of Social Services [18] the minimum age to be eligible for an aged pension prior to 1 July 2017 was 65 years. This study assumes that those under 65 are more likely to be not working and could have lower incomes than other adults over 25 but their financial situation is more complex than under 25 year olds (e.g. presence of savings).

Scatter plots were constructed to visualise any relationship between full time employment percentages and eligibility for normal credit card percentages, total employment percentages and eligibility for low income credit card percentages and total unemployment percentages and ineligibility for low income credit card percentages. Linear regression was employed to analyse the relationship between credit card eligibility based on income and work status. The command plt.scatter(x,y) can be used to create scatter plots using x and y values. The command df.corr() can be used to create a correlation matrix. Ranjan [19] claims that he general function from pandas dataframe.corr() is used to find the pairwise correlation of all columns in the data frame. Any non numeric values are automatically excluded. The standard Pearson coefficient is the default method.

The final tables as csv files along with the python codes are attached as separate files.

Attribute	Type
Eligible CC $15000/yr income minimum	Integer (population count)
Ineligible CC $15000/yr income minimum	Integer (population count)
Eligible CC $35000/yr income minimum	Integer (population count)
Ineligible CC $35000/yr income minimum	Integer (population count)
PC Eligible CC $15000/yr income minimum	Float (percentage of total minus undeclared income count)
PC Ineligible CC $15000/yr income minimum	Float (percentage of total minus undeclared income count)
PC Eligible CC $35000/yr income minimum	Float (percentage of total minus undeclared income count)Float (percentage of total minus undeclared income count)
PC Ineligible CC $35000/yr income minimum	Float (percentage of total minus undeclared income count)
Employed Full Time	Integer (population count)
Total Employed	Integer (population count)
Total Unemployed	Integer (population count)
PC Employed Full Time	Float (percentage of total)
PC Employed	Float (percentage of total)
PC Unemployed	Float (percentage of total)
Total	Integer (total count)

Figure 4: *Attributes in the final table for credit card eligibility and employment status*

4.2 ANALYSIS RESULTS

The bar graphs depicted in Figure 5 to 8 show the population counts for all Census age groups for the following categories: eligible for a low income credit card, ineligible for a low income credit card, eligible for a credit card with a minimum income of $35000/year and ineligible for such a credit card. For each age group covering the ages 25 to 64 more than two million in each category are eligible for a low income credit card. In contrast less than 500000 of those ages 15 to 19 and those aged over 85 are eligible for a low income credit card. More than 1 million of those aged from 15 to 19 are ineligible for a low income credit card, almost twice the count of the age group with the second highest number. The percentage of eligibility for a low income credit card is notably low for the 15 to 19 age group, with just 16.09 percent eligible for a low income credit card, compared to every other age group where the same figure is over 60 percent. The 20 to 24 age group is the only other group with a figure less than 79 percent (65.94%). Ineligibility for a low income credit card is 83.91 percent for the 15 to 19 age group, with the 20 to 24 age group having the next highest, less than half this figure (34.06%). All other age groups have ineligibility rates less than 21 percent.

The number of people aged under 25 years old of 65 years old that earn $35,000 a year and over and are eligible for a credit card with such a requirement is notably lower than the other age groups, with figures nearly a third or less of the age groups covering the 25 to 64 year olds. There is no notable pattern with age for ineligibility, with the highest count being in the 65 to 74 age group and the lowest count being the 85 years and over group. Only 3.89 percent of 15 to 19 year olds can get a credit card with a $35,000 minimum income requirement, compared to 19.79 percent and 19.97 percent for the 75 to 85 age group and the 85 and over age groups respectively (close to six times the figure for the 15 to 19 group), 30.22 percent for 55 to 64 year olds and 37.28 for 20 to 24 year olds. All over age groups have eligibility rates over 50 percent.

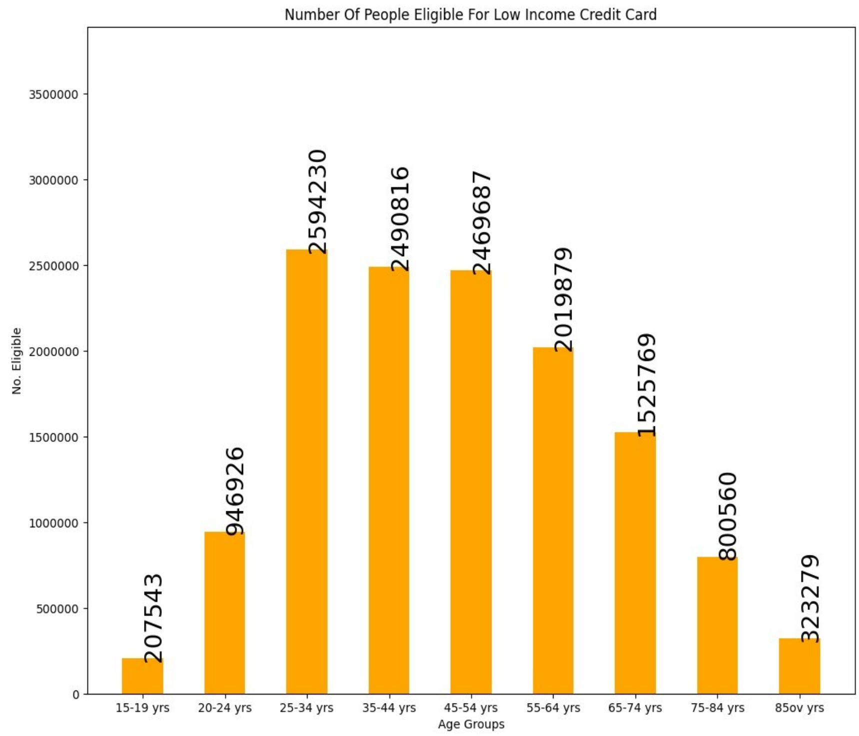


Figure 5: *Number of persons in each age group eligible for a low income credit card.*

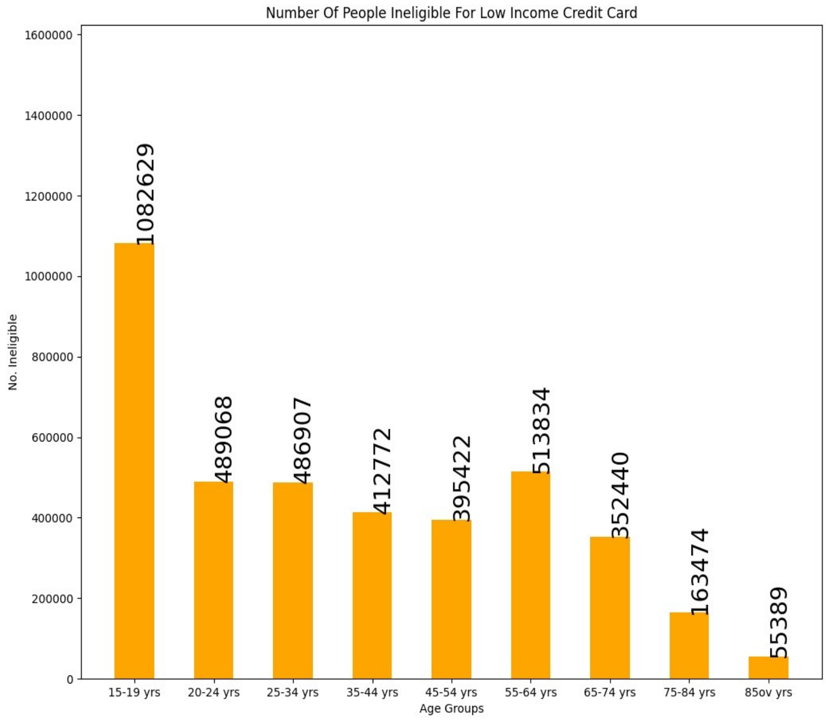


Figure 6*: Number of persons in each age group ineligible for a low income credit card.*

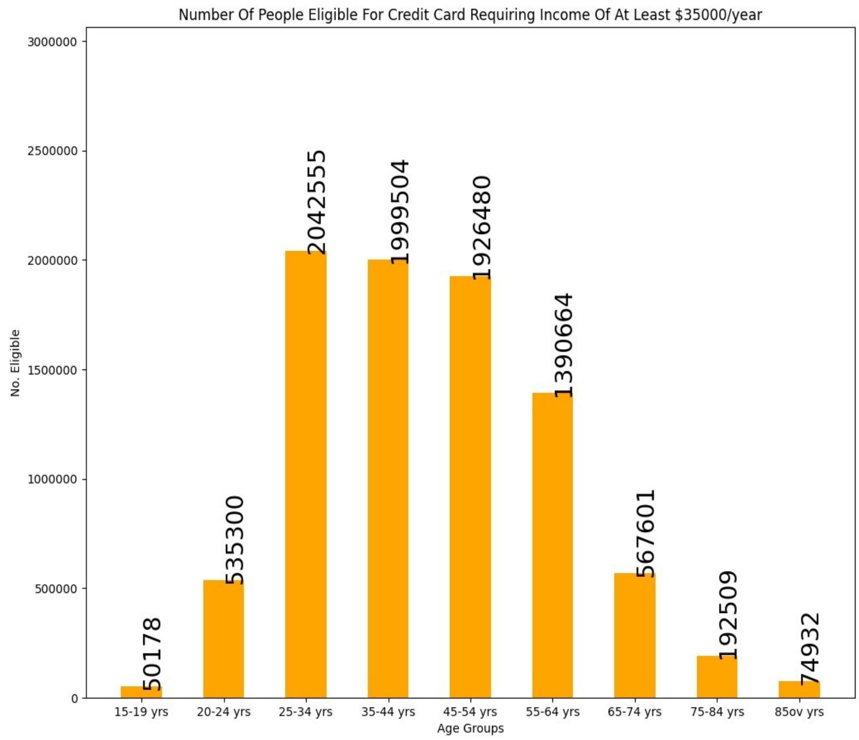


Figure 7 *Number of persons in each age group eligible for a credit card that requires earning at least $35000/year.*

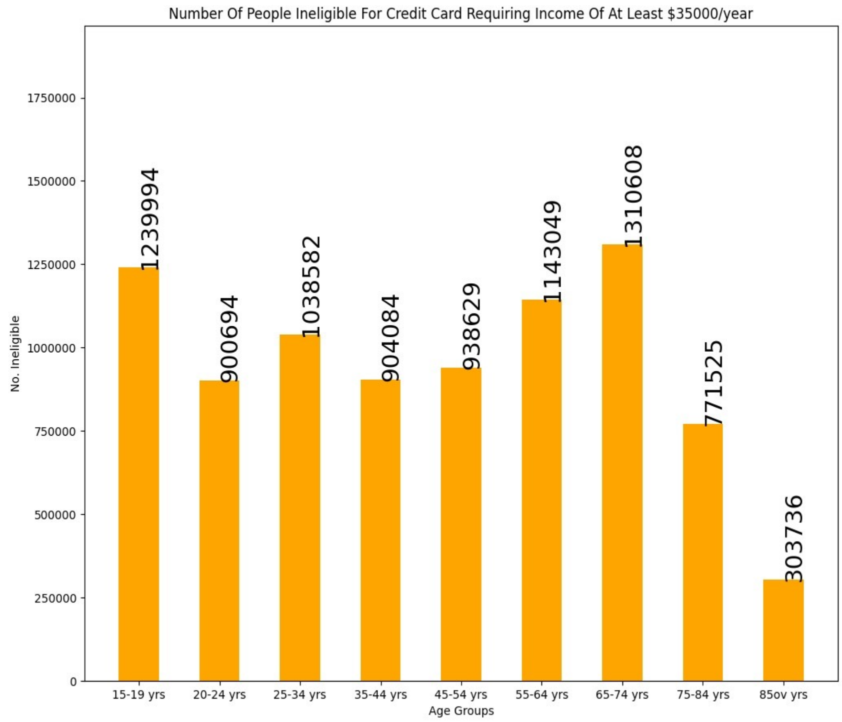


Figure 8 *Number of persons in each age group ineligible for a credit card that requires a minimum annual income of $35000/year.*

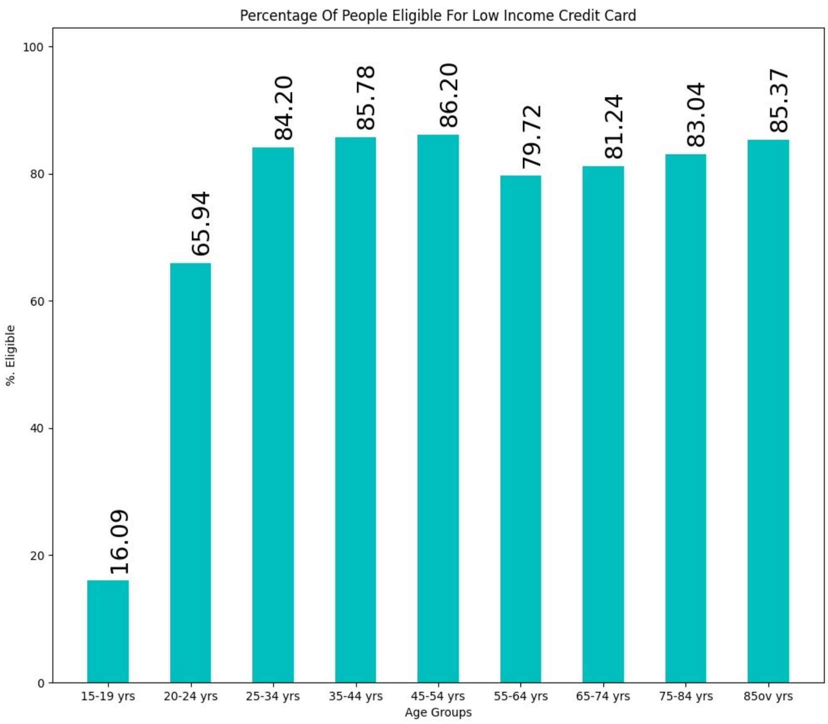


Figure 9: *Percentage of people in each age group eligible for a low income credit card.*

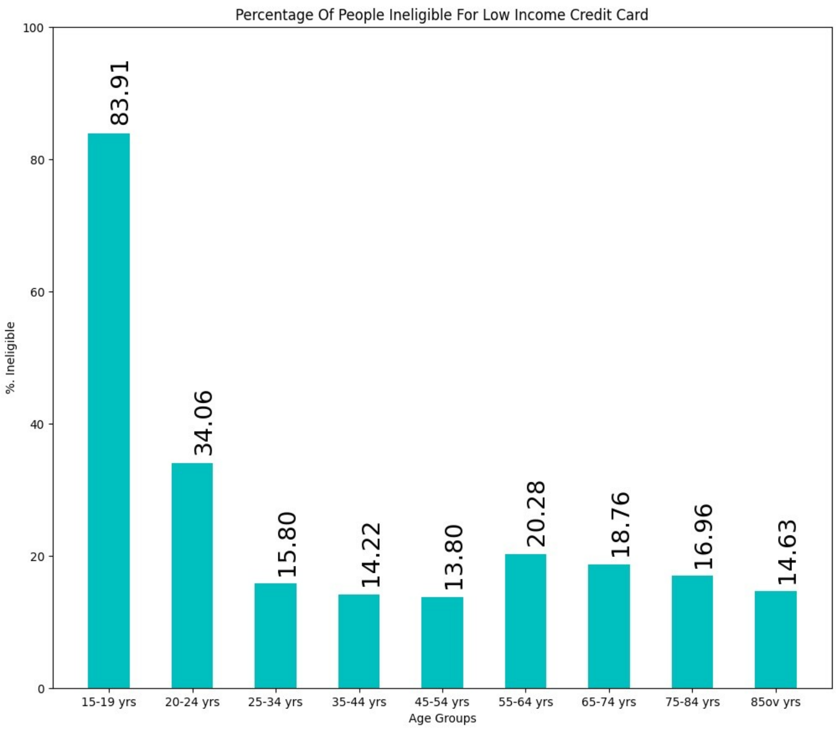


Figure 10: *Percentage of people in each age group not eligible for a low income credit card.*

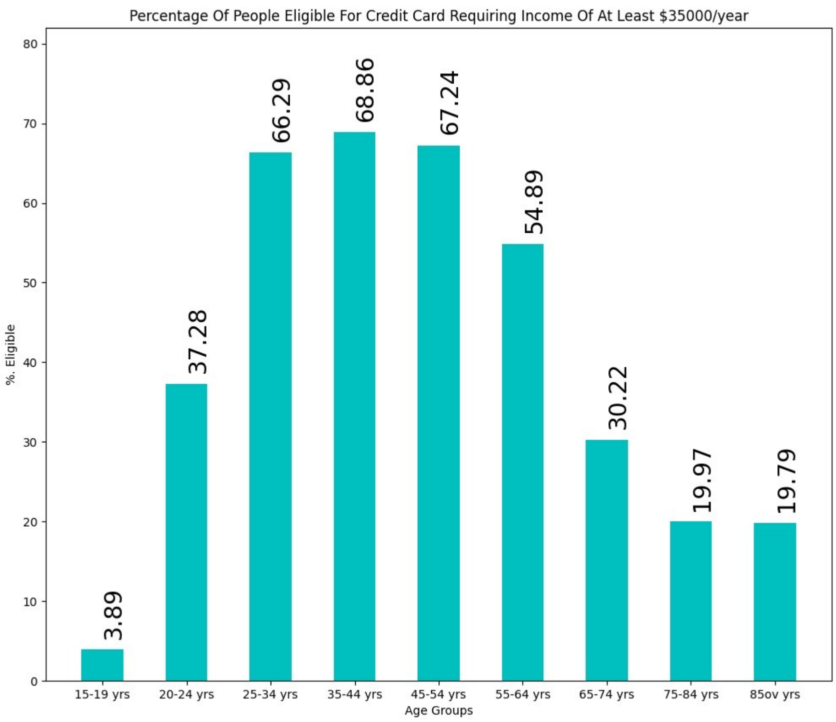


Figure 11: *Percentage of people in each age group eligible for a credit card requiring minimum income of $35000/year.*

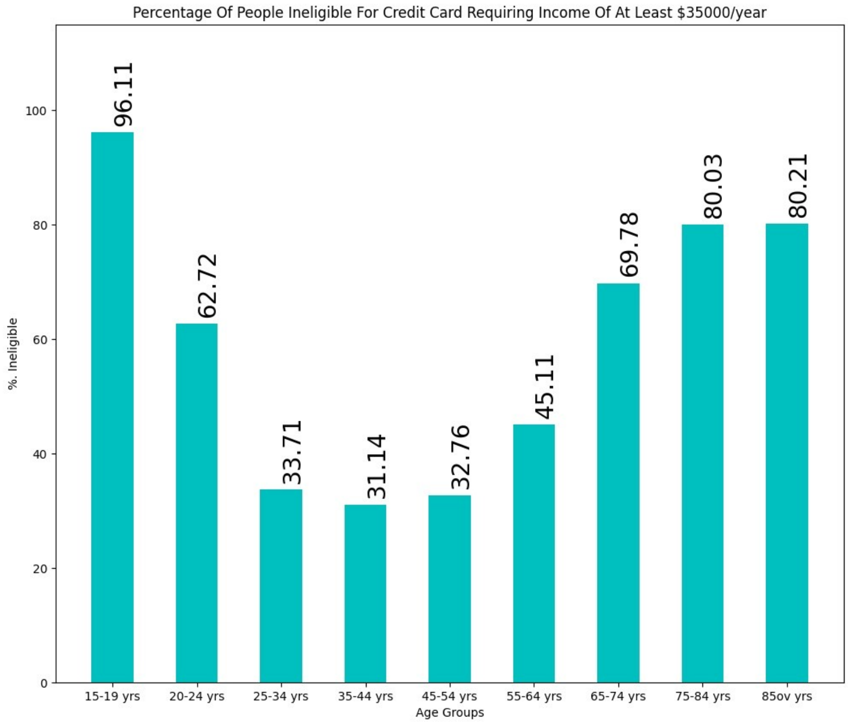


Figure 12: *Percentage of people in each age group not eligible for a credit card due to not having an income at $35000/year or more.*

Figures 13, 14 and 15 display results for full time employment, total employment and unemployment as percentages of population for each age group. Less than 10 percent of 15 to 19 year olds work full time, less than 33 percent of 20 to 24 year olds work full time and for age groups 55 and over the figures are less than 36 percent with figures less than 10 percent for ages 65 and up. All other age groups are above 50 percent full time employment. The rates of employment are under 38 percent for 15 to 19 year olds but under 20 percent for those in age groups 65 and over. All other age groups are above 58 percent with the three age groups covering 25 to 54 year olds all over 70 percent employment. The unemployment rate is notable higher amongst the 15 to 19 and 20 to 24 age groups with figures of 9.44 percent and 8.6 percent respectively. The unemployment rates are notably very low for all age groups above 65 years old, all under 1 percent.

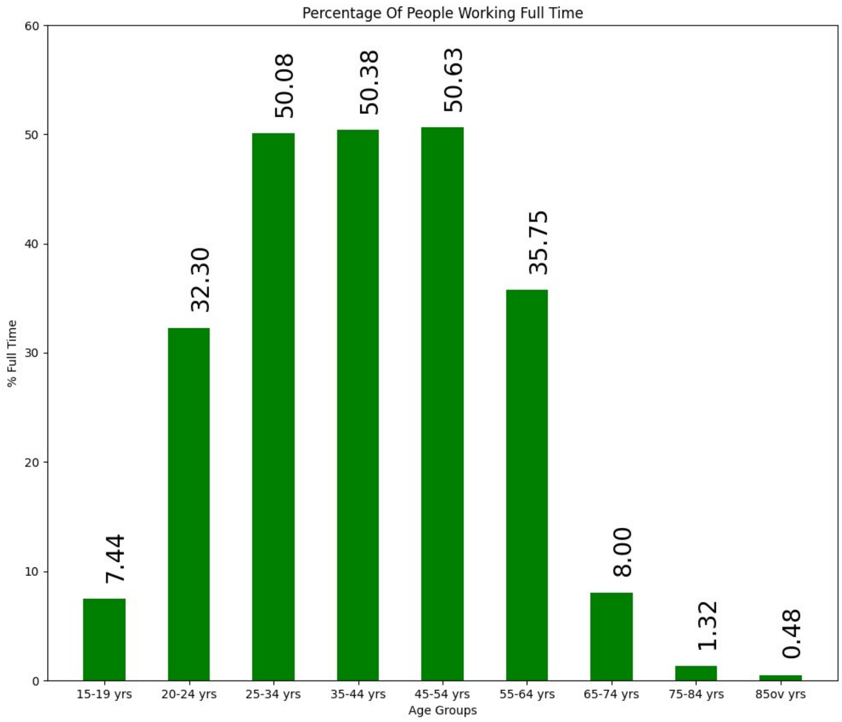


Figure 13: *Percentage of each group in full time employment*

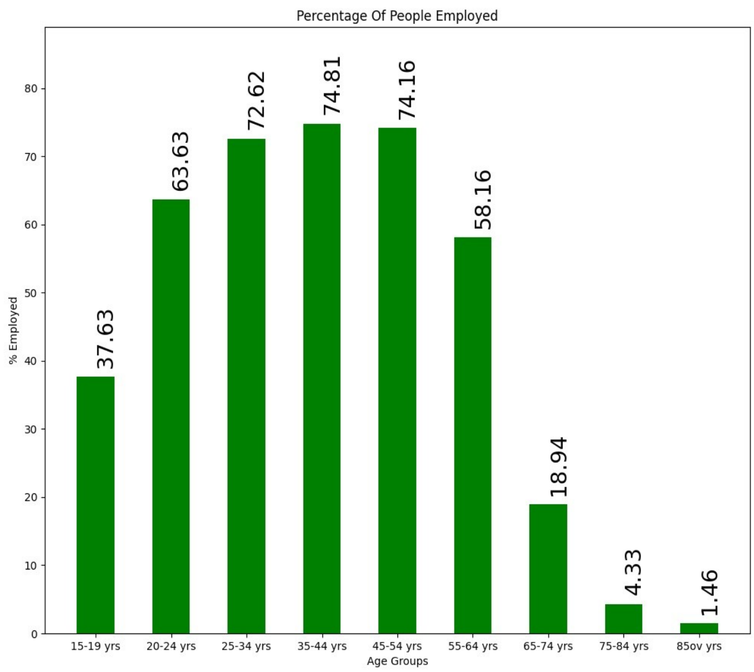


Figure 14: *Employment rate of each age group*

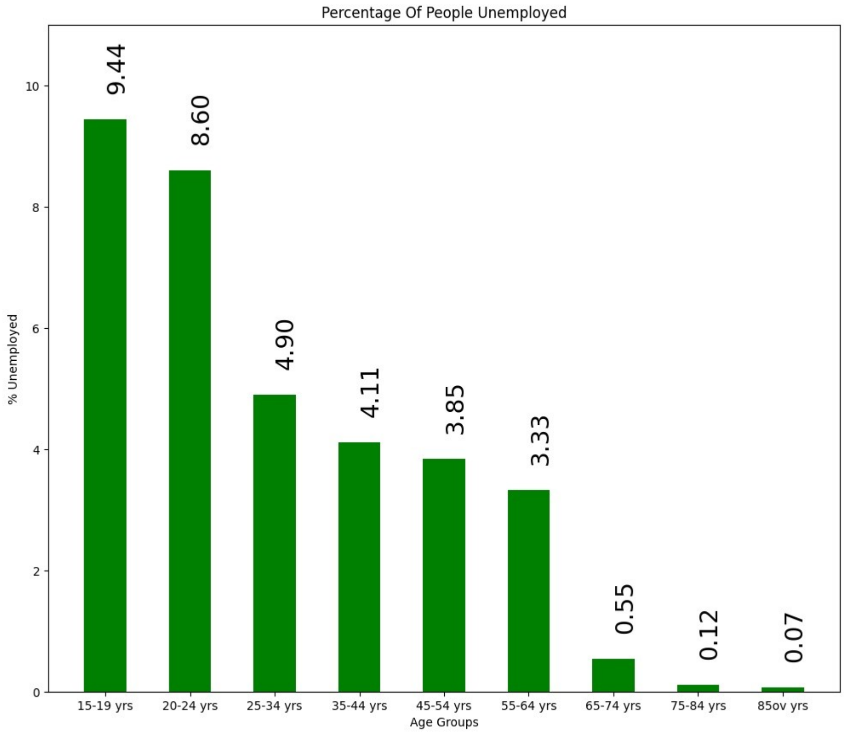


Figure 15: *Unemployment rate by age group*

4.2.1 Under 25 Year Olds v 25 Year Olds and Over

The percentage of under 25 year olds eligible for a low income credit card (38.6 percent) is about half that of 25 years and over (76.2 percent). Those under the age of 25 (52.6 percent) are about three and a half times as likely to be ineligible for a low income credit card than those 25 and over (14.8 percent). Those over the age of 25 are more than 2.5 times as likely to be eligible for a credit card (51.1 percent eligibility) whilst earning $35,000/year and more than those under the age of 25 (19.6 percent eligibility). 71.6 percent of under 25s are ineligible for a credit card with those minimum income conditions compared to 39.9 percent of those 25 years and over.

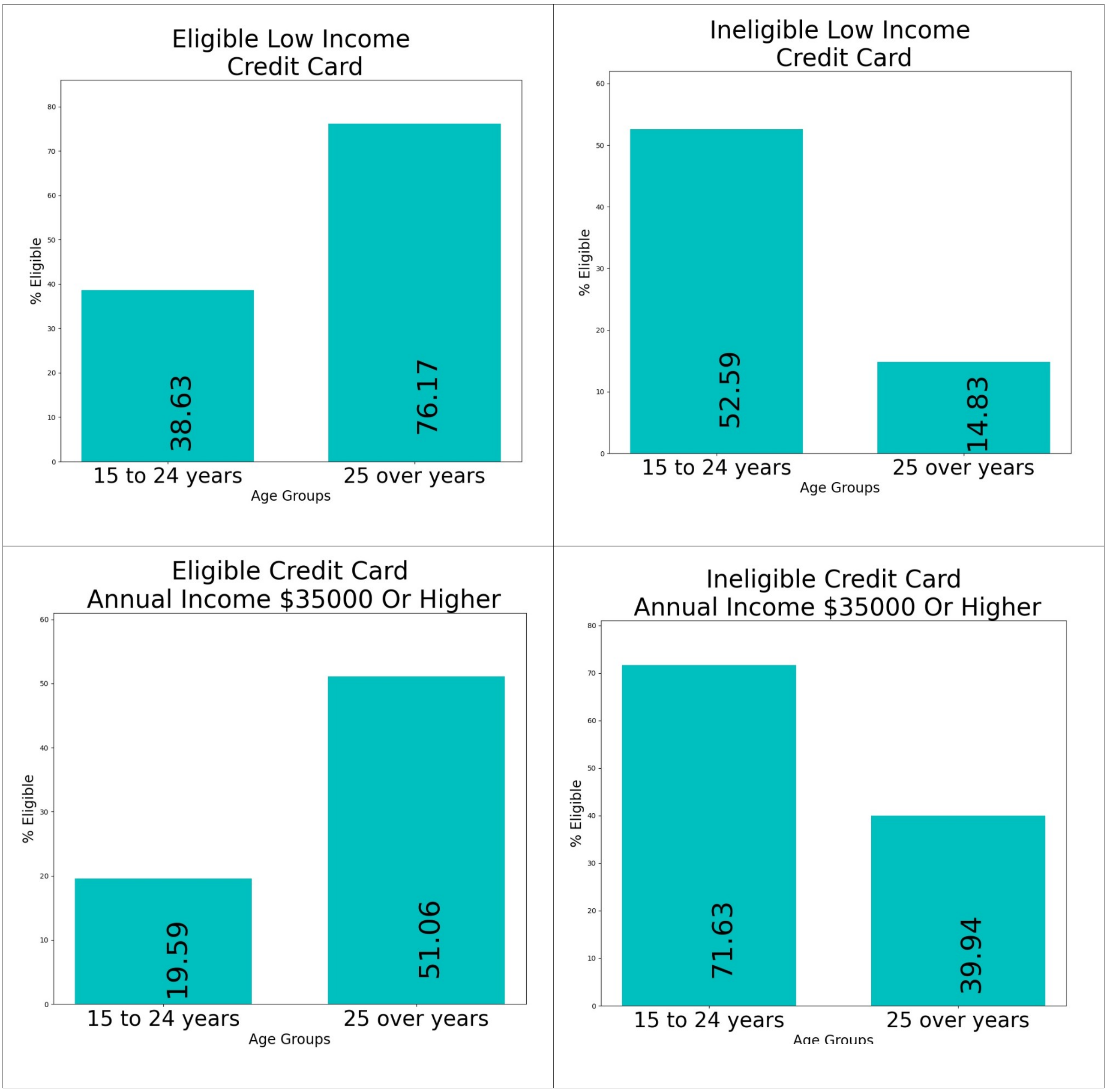
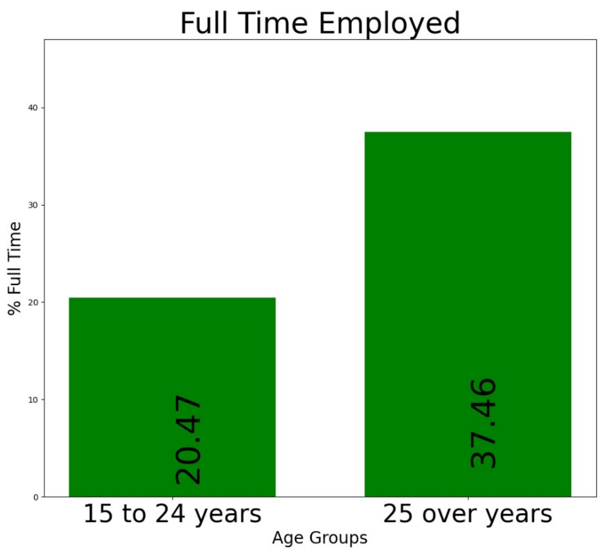


Figure 16: *Eligibility and ineligibility for under 25s v 25s and over.*



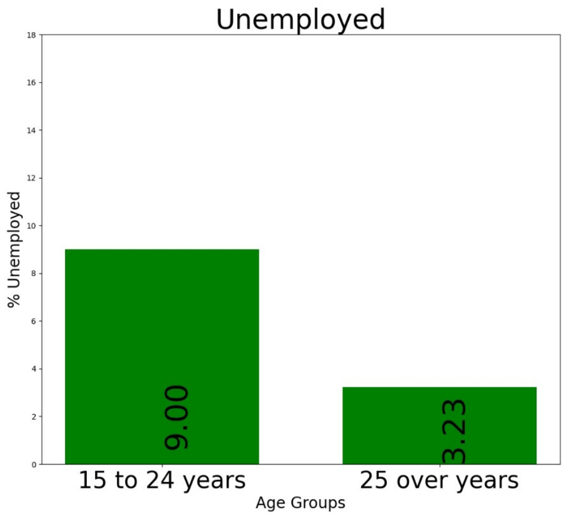
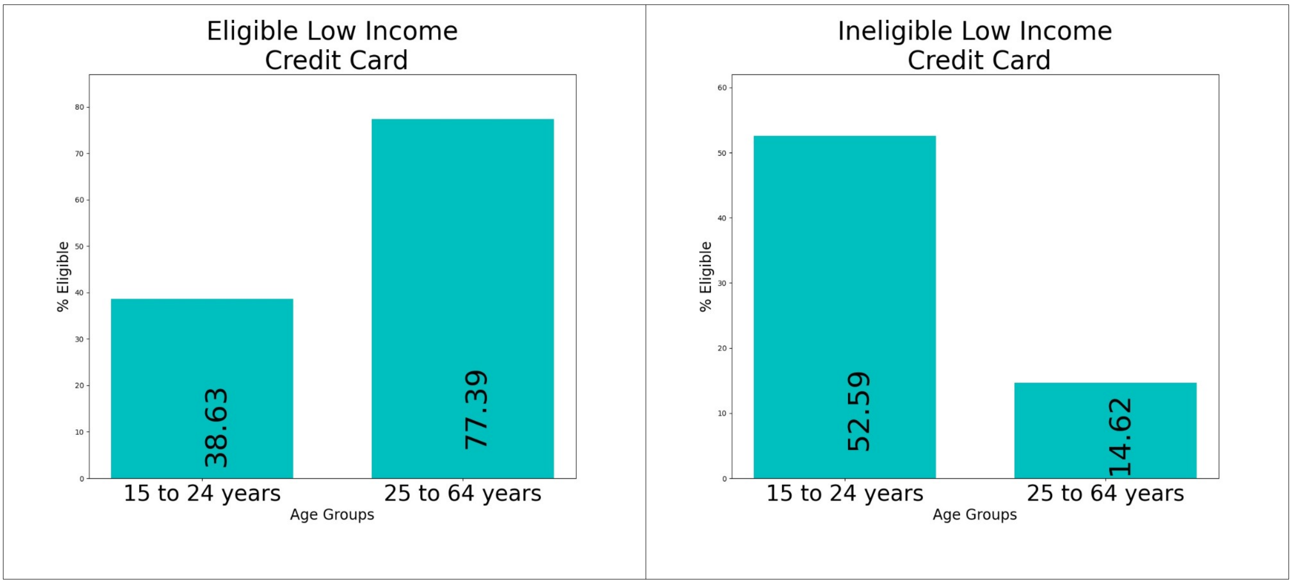


Figure 17: *Employment status percentages under 25s v 25s and over.*

The full time employment rate for those 25 years and over (37.46 percent) is nearly double that of those under 25 year olds (20.47 percent). There is only a 6 percent different in employment rate between the two age categories but the unemployment rate for under 25 year olds is nearly triple that of those 25 years and over.

4.2.2 Under 25 Year Olds v 25 to 64 Year Olds.

Removing the age groups from 65 years and over results in the figure for over 25 year olds for low income credit card eligibility increasing very slightly (1.2 percent increase) but a more notable increase in eligibility for a credit card requiring a minimum annual income of $35000 (8.4 percent increase). The ineligibility for such a credit card decreases by 7.4 percent. The figure for full time employment is 47.1 percent for 25 to 64 year olds with the employment rate going to above 70 percent when ignoring those over 'retirement age'. There is a slightly higher figure for unemployment (4.1 percent).



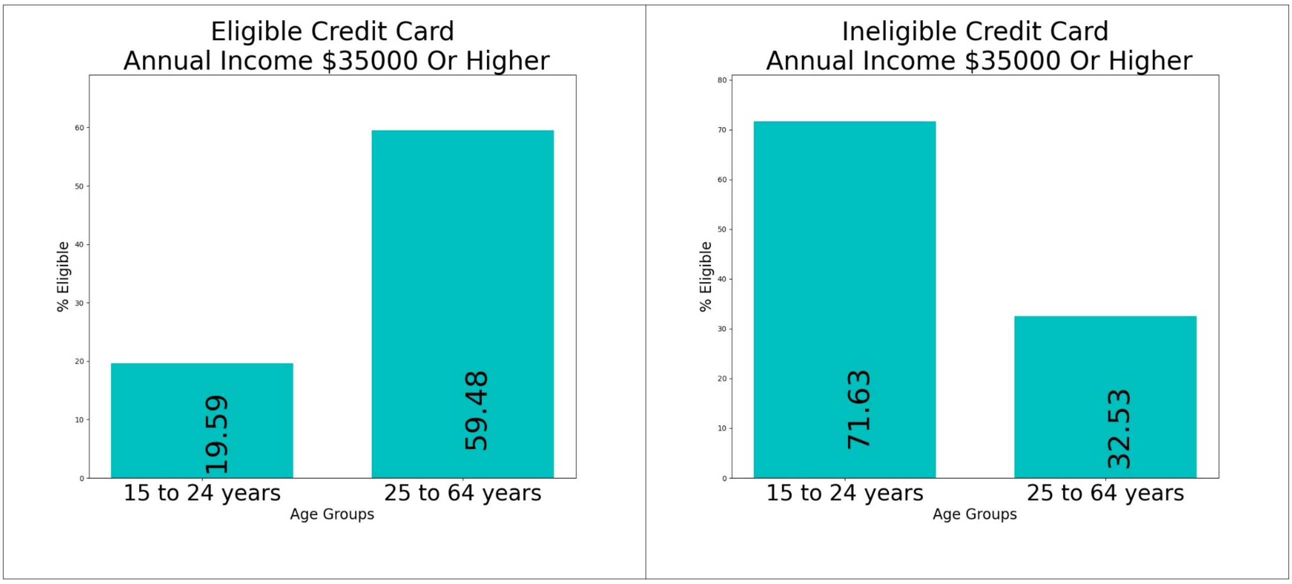


Figure 18: *Credit card eligibility and eligibility 15 to 24 years v 25 to 64 years*

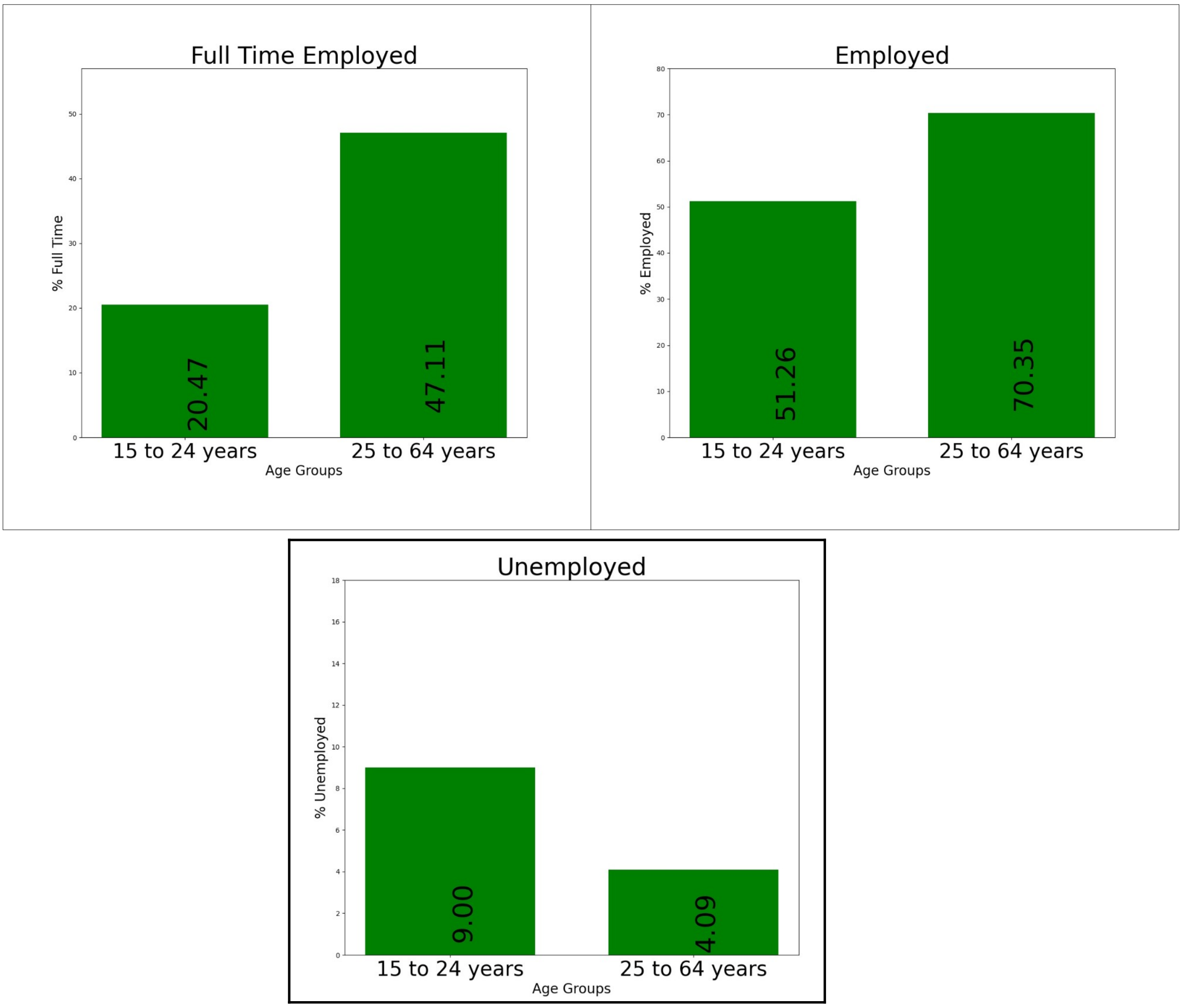


Figure 19: *Employment status 15 to 24 years v 25 to 64 years*

4.2.3. Under 20 Year Olds v 20 Years And Over.

Now comparing just those in the 15 to 19 year old age group to the rest (20 years and over) yields substantial differences in the eligibility for a low income credit card, where those over the age of 20 are more than 4.5 times as likely to be eligible for one as the eligibility rate for under 20 year olds is under 20 percent. More than double the percentage of 15 to 19 year olds would be considered ineligible for a credit card with a $35,000/year income requirement. In fact it is 96.1 percent ineligibility compared to just 41.5 percent for those aged 20 and over. More than four times the percentage of over 20s work full time (37 percent) than under 20s and their employment rate is 20 percent higher than 15 to 19 year olds (57.6 percent). Only 3.7 percent of over 20s are unemployed.

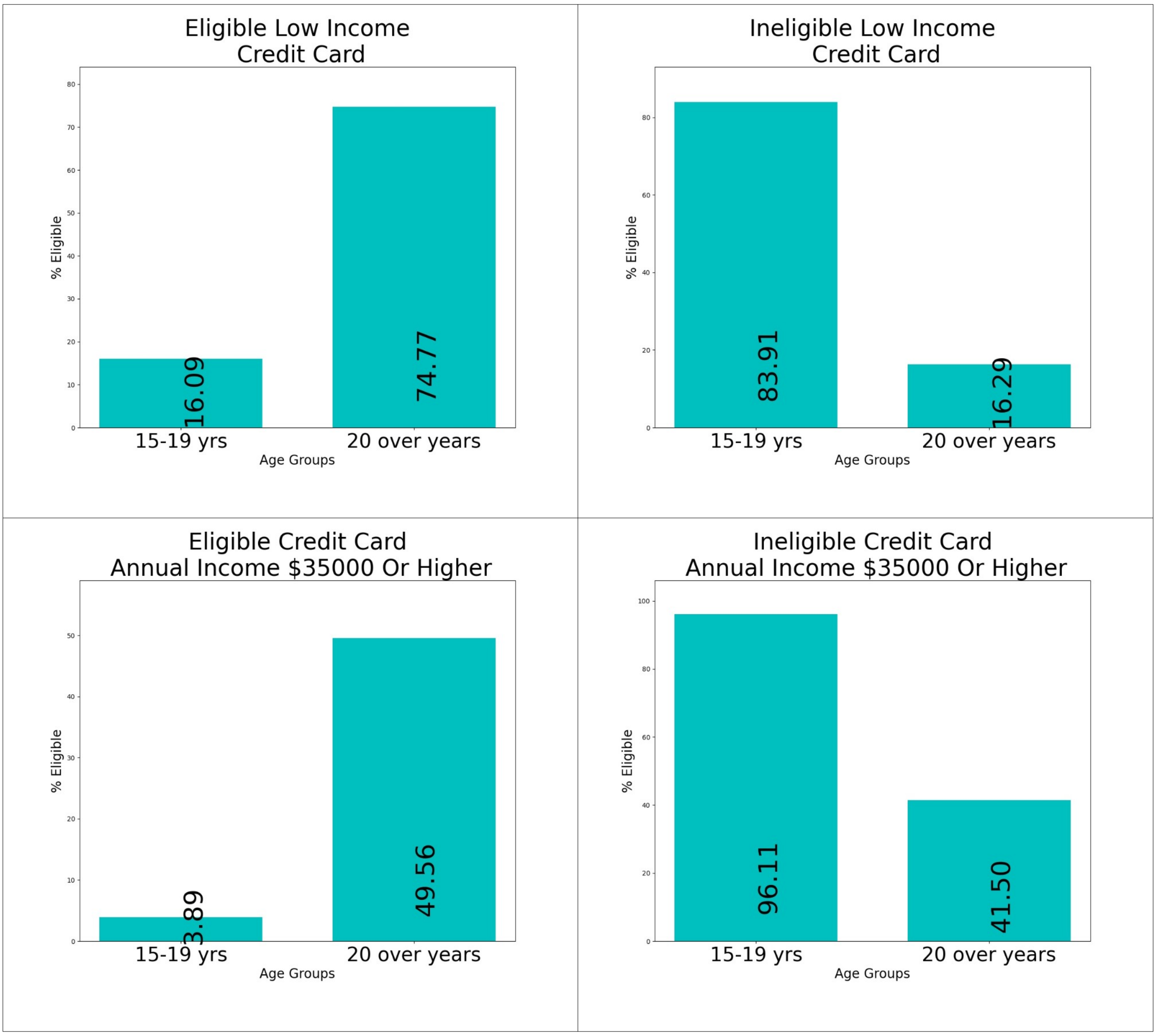


Figure 20: *Eligibility and ineligibility 15 to 19 years v 20 years and over.*

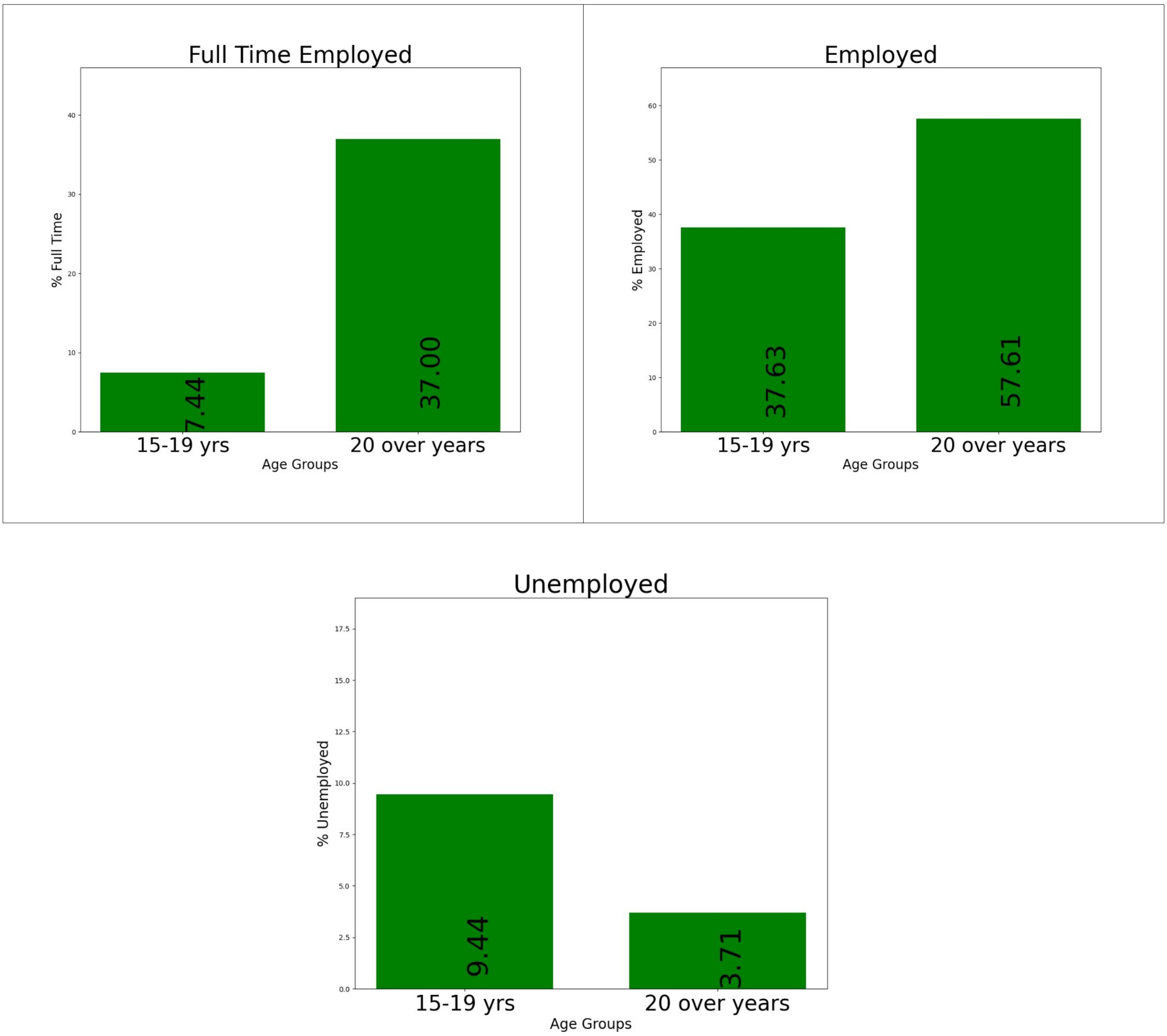


Figure 21: *Employment status 15 to 19 years v 20 years and over*

<u>4.2.4. Under 20 Year Olds v 20 to 64 Year Olds</u>

Eliminating the people aged 65 years and over from the 20 years and over group results in a slight increase in the percentage of low income credit card eligibility (75.5 percent) and a notable increase in the percentage of people earning $35,000/year or more (up to 56.6 percent eligibility for such a credit card requirement with 35.3 percent ineligibility). The full time employment rate increases to 45.4 percent and the overall employment rate increases to 69.6 percent.

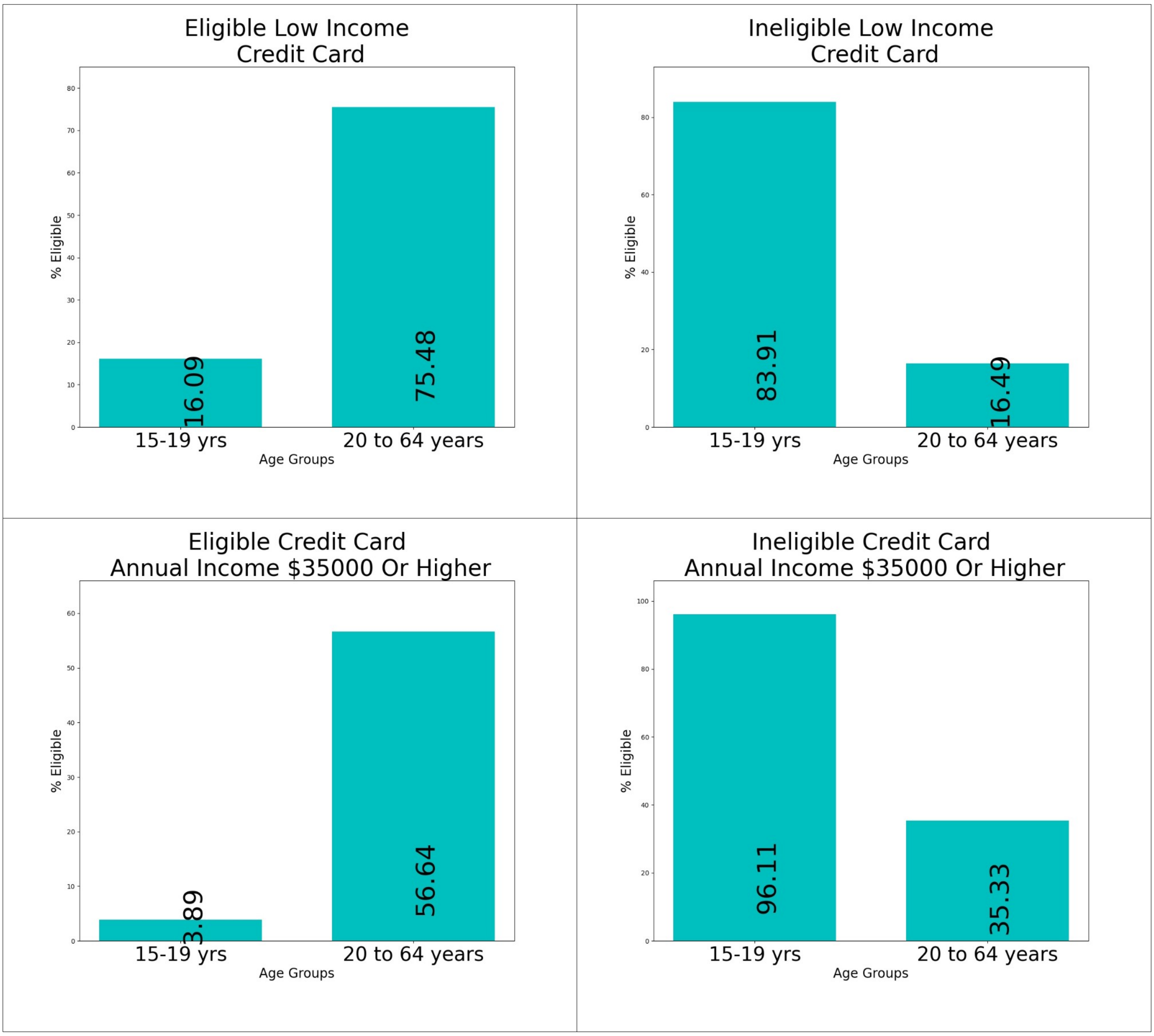


Figure 22: *Eligibility and ineligibility 15 to 19 years v 20 to 64 years.*

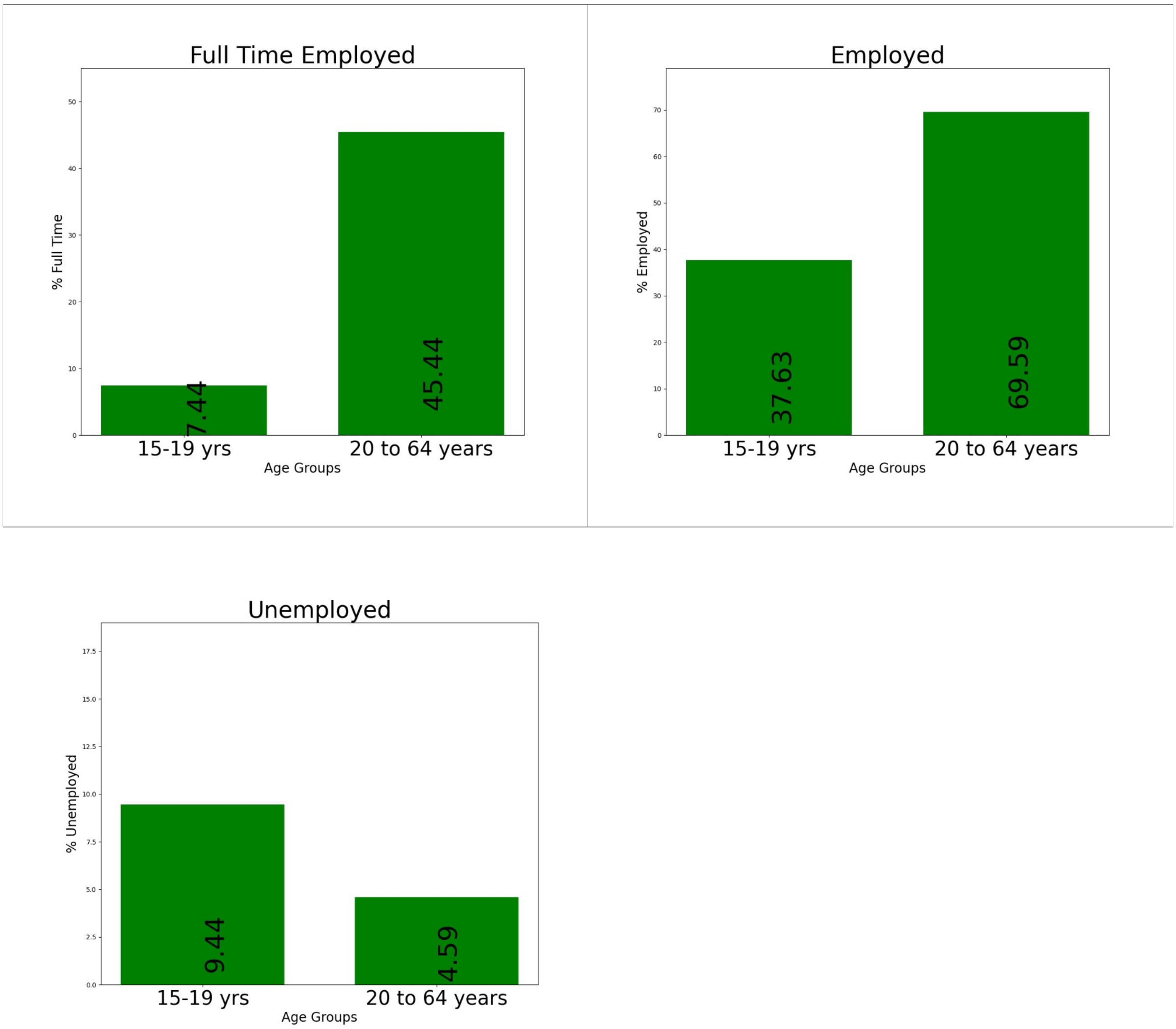


Figure 23: *Employment status 15 to 19 years v 20 to 64 years*

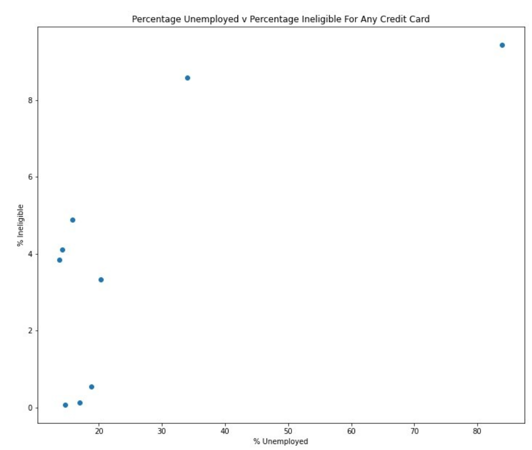
<u>4.2.5 Results Summary</u>

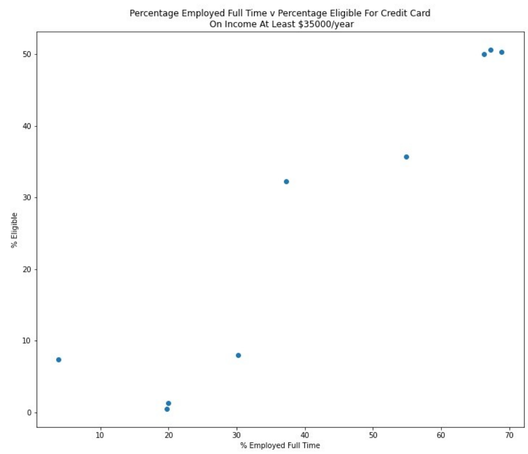
From the percentages it can be claimed that those under the age of 20 are around five times more likely to be ineligible for a low income credit card than those aged 20 and over, including and not including those 65 years and over. They are over 95 percent ineligibility for a credit card requiring a minimum income of $35,000 , more than twice as likely to be ineligible than those 20 years and over. They eligibility for such a credit card is extremely low. The 15 to 24 age group is 3.7 times more likely to be ineligible for a low income credit card than those aged 25 and over and twice as likely to be ineligible for a credit card requiring an income of at least $35,000 a year. The eligibility for a low rate credit card is significantly higher than just the 15 to 19 year olds alone but the eligibility for a credit card and having an income of at least $35,000 a year is less than 20 percent.

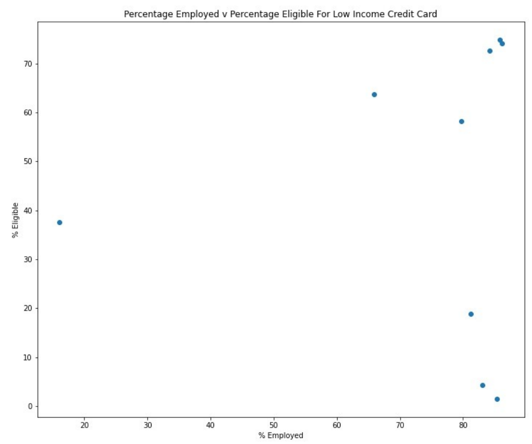
As stated earlier percentages do not add up to 100 due to those in the Census refusing to state their income.

4.2.6 Scatter plots and linear correlation.

According to Profillidis and Botzoris in 2018 [20] values of the linear correlation coefficient indicate strong positive correlation when the value is between 0.8 and 1.0 and moderate positive correlation when the values are from 0.3 to 0.6. The scatter plots and linear correlation coefficient shows a fairly strong positive correlation of 0.939 between the percentage of people in each age group employed full time and earning a minimal income of $35000 a year for credit card eligibility. That means that age groups with higher full time employment rates are more likely to be earning the $35000 a year minimum income to obtain a normal credit card. There is a moderate positive correlation between the employment rate and the percentage of those eligible for a low income credit card (0.527) and a fairly strong positive correlation between the unemployment rate and the percentage of those in each age group that are ineligible for any credit card (0.726). We can conclude that employment status is a factor in determining the amount of weekly income people earn and therefore the likelihood of eligibility to obtain a credit card.







	% Eligible CC $15000/year	% Employed
% Eligible CC $15000/year	1.000000	0.052741
% Employed	0.052741	1.000000

	% Eligible CC $35000/year	% FT Employed
% Eligible CC $35000/year	1.00000	0.93903
% FT Employed	0.93903	1.00000

	% Ineligible CC	% Unemployed
% Ineligible CC	1.000000	0.726092
% Unemployed	0.726092	1.000000

Figure 24: *Scatter Plots Showing Correlation Between Employment And Eligibility Based On Income*

4.2.7. Labour Force Data

As discussed earlier challenge with utilising this study is the use of the 15 to 19 year old age category. If we were to assume that all the 16.1 percent of eligible low income credit card holders were in this 40 percent the figure still looks significantly lower than all the other age groups, but still less than 50 percent.

A quick Python pandas code was created to check the percentage of each Census age group in the labour force. The labour force category was ignored in the main data analysis process, but it may explain the low values of eligibility and employment amongst the older age groups. As shown below less than 20 percent of those ages from 65 to 74 were in the labour force in 2016 and less than five percent of those in the age groups 75 and above were in the labour force. As the eligibility age for the aged pension was 65 in 2016 and the retirement age was such the low values are consistent with these facts and can provide good reasoning for the lower personal incomes and credit card eligibility based on personal income amongst those aged 65 and over. The percentage of 15 to 19 year olds is significantly higher than these older age groups (47 percent).

	Age Group	PC In Labour Force
0	15-19 yrs	47.071494
1	20-24 yrs	72.230856
2	25-34 yrs	77.520158
3	35-44 yrs	78.925447
4	45-54 yrs	78.006909
5	55-64 yrs	61.490689
6	65-74 yrs	19.483057
7	75-84 yrs	4.453342
8	85ov yrs	1.526779
9	Total	60.257010
10	15 to 24 years	60.262389
11	25 over years	60.255938
12	20 over years	61.321025
13	20 to 64 years	74.184374
14	25 to 64 years	74.431765

Figure 25: *Percentage of Each Age Group In The Labour Force (Output From Jupyter Notebook)*

5. CONCLUSIONS AND RECOMMENDATIONS

The study has found that credit card eligibility is significantly lower amongst under 25 year olds than 25 year olds and over and the gulf between under 20 year olds and over 20 year olds is larger. When considering over 25s and over 20s taking away those over the age of 64 increased these differences. Eligibility for any credit card is notably very low amongst 15 to 19 year olds and eligibility for a credit card whilst boasting a personal income of $35000/year and over is significantly lower for ages under 25 and ages 65 and above. There is a strong correlation between the percentages of eligibility for a credit card due to having a minimal income of $35000/over and the percentage in full time employment, showing that employment type definitely has influence in personal income and therefore meeting credit card application criteria.

The Python library including the pandas, numpy and matplotlib modules have been very useful tools in the wrangling of the datasets from Census tables 17 and 43 into easy to read tables and data visualisations with bar graphs, scatter plots and linear correlation. The work done with Python will form the basis for future data programming work using Census data.

Based on the credit card eligibility percentages for each age group used in this data analysis the following recommendations can be made

- The credit card application age limit should stay at 18 years and should not be decreased, as indicated by characteristics amongst 15 to 19 year olds for credit card eligibility.
- All age groups 18 and over should be allowed to apply for a low income credit card provided they meet the income requirements
- Due to substantially low percentages of people earning under $35,000 a year under the age of 25, the idea of implementing laws for under 21 year olds to require parent or guardian consent and proof of income beyond reasonable doubt according to the CARD Act in the United States has significant merit. Less than 15 percent of under 25 year olds declared an annual income of at least $35000. Only about 20 percent of this age group declared they were working in a full time job. They are significantly lower figures than those 25 years old and over.
- Those on the aged pension and in retirement must provide proof of income and financial assets to get a credit card normally allowed for those with an income of at least $35,000/year.

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