Healthcare is expensive

& it is getting more expensive

Singapore's healthcare spending is likely to continue rising; targeted support needed: Gan

FRI, MAR 05, 2021 - 4:13 PM | UPDATED FRI, MAR 05, 2021 - 4:17 PM

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SINGAPORE'S spending on healthcare has grown every year and is likely to continue rising, which is why the country needs to be prudent and ensure support is targeted at those in greater need, Health Minister Gan Kim Yong said on Friday.

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HOW MUCH DOES THE UNITED STATES SPEND ON HEALTHCARE?

States has one of the highest costs of healthcare in the world. In ...nited States spent about $3.6 trillion on healthcare, which averages ...1,000 per person. Relative to the size of the economy, healthcare ...creased over the past few decades, from 5 percent of gross ...oduct (GDP) in 1960 to 18 percent in 2018. The Centers for Medicare ...d Services (CMS) project that by 2028, such costs will climb to $6.2 ...bout $18,000 per person, and will represent about 20 percent of ...er, those projections do not take into account the impacts of the

FROM THE BLOG

- How Does the U.S. Healthcare System Compare to Other Countries?

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MANAGING HEALTHCARE COST INCREASES

2ND NOV 2020

Name and Constituency of Member of Parliament
Ms Ng Ling Ling
MP for Ang Mo Kio GRC

Question No. 264

To ask the Mi... announced ra...

Answer

1. Several f... more medical... was 6.9 days, ... healthcare. A...

THE EFFECTS OF RISING HEALTHCARE COSTS ON THE US ECONOMY

THE EFFECTS OF RISING HEALTHCARE COSTS ON THE US ECONOMY

Author(s): Elena Toader
Subject(s): Health and medicine and law
Published by: Addleton Academic Publishers
Keywords: healthcare cost growth; US economy; reform;
Summary/Abstract: In this paper I am particularly interested in exploring the extremely decentralized character of healthcare decision-making in the ... and the expenditures and ... pending growth, the cost- ... ng-term consequences of

Rising healthcare costs and universal health coverage in India: an analysis of national sample surveys, 1986-2014

Tools

GUMBER, Anil, LALITHA, N and DHAK, Biplab (2017). *Rising healthcare costs and universa... surveys, 1986-2014.* Working Paper. India, Gujarat Institute of Development Research, Ahm...

Rising pressure of healthcare cost

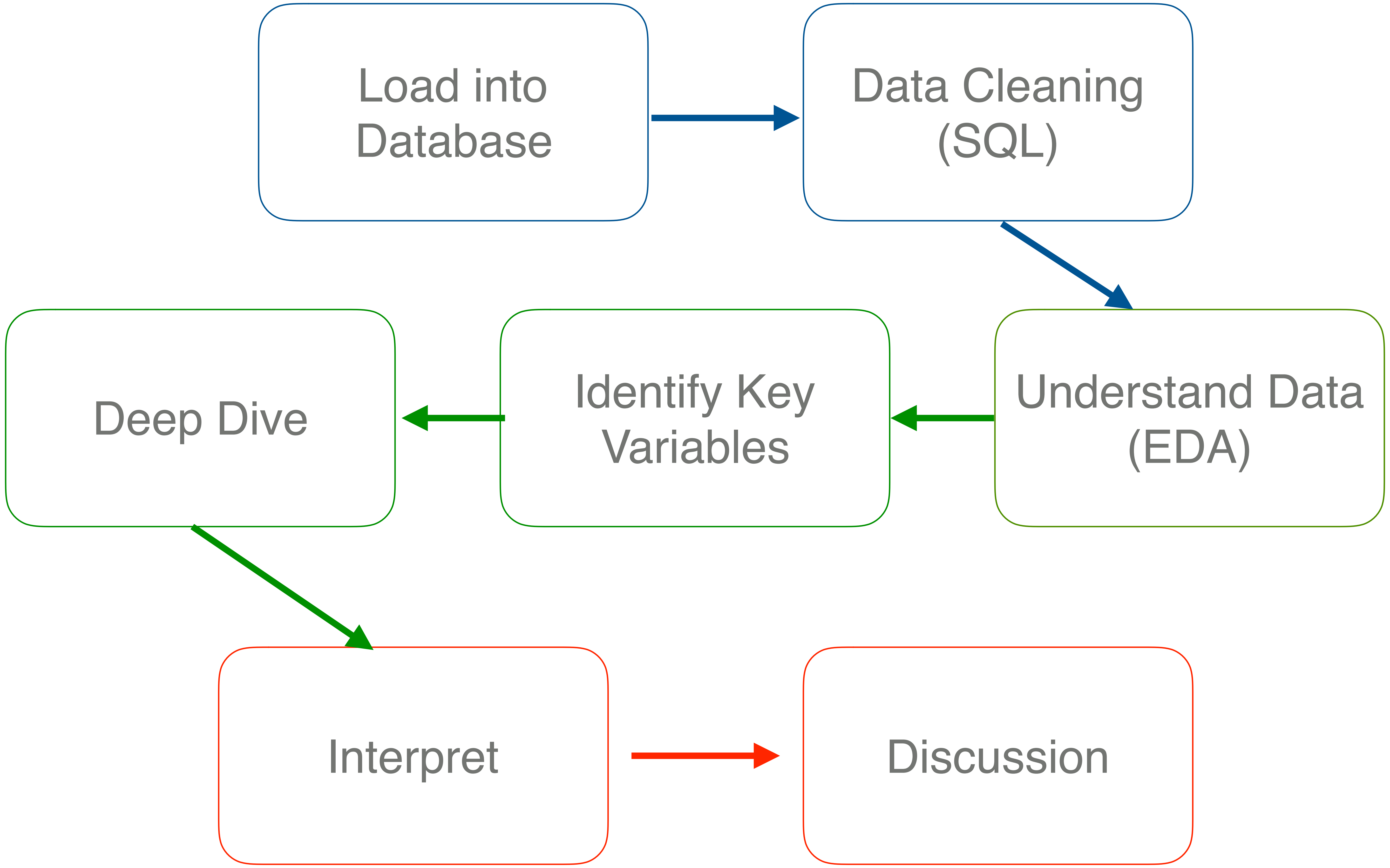
By CECILIA KOK

Increases in medical bills are outpacing the general inflation rate each year. That raises the question whether healthcare is reserved only for those who can afford it

"I got the bill for my surgery. Now I know what those doctors were wearing masks for"
– American bureaucrat, James H. Boren (1925)

Assessing key cost drivers associated with inpatient admission of patients with condition X

Project Flow



Contents

Our Data

A summary of our dataset .

Our Data

- Clinical and financial data of patients hospitalised for a certain (X) condition
- 3,400 inpatient admission
- 3,000 unique patients
- 5 year data (2011 - 2015)
- Per row per inpatient admission

Clinical (Admission)

- Date of admission/discharge
- Pre-Op Medication
- Symptoms
- Lab Results
- Weight / Height

Patient

- Demographics
- Medical History

Financial

- Total Bill per admission

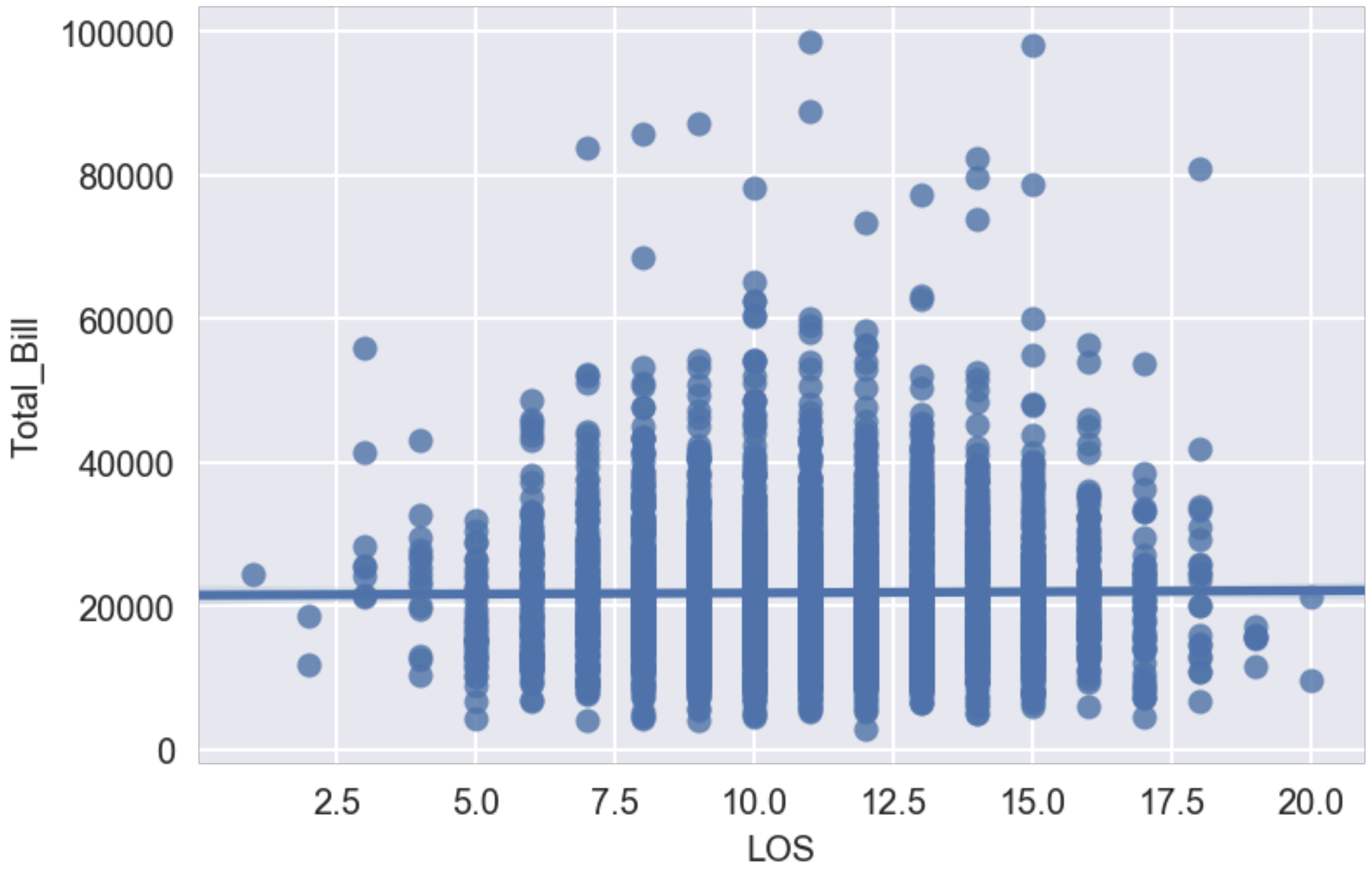
New Variables

- Number of encounter per patient (in 5 years)
- Length of Stay
- Age
- BMI
- BMI Risk Level
- Year / Quarter of admission
- 30 Days Readmission
- Number of Medical History
- Number of Symptoms
- Number of Pre-Op Medications

Clean-Up

- Standardising strings
- Converting into numeric
- Imputing null values

Length of Stay



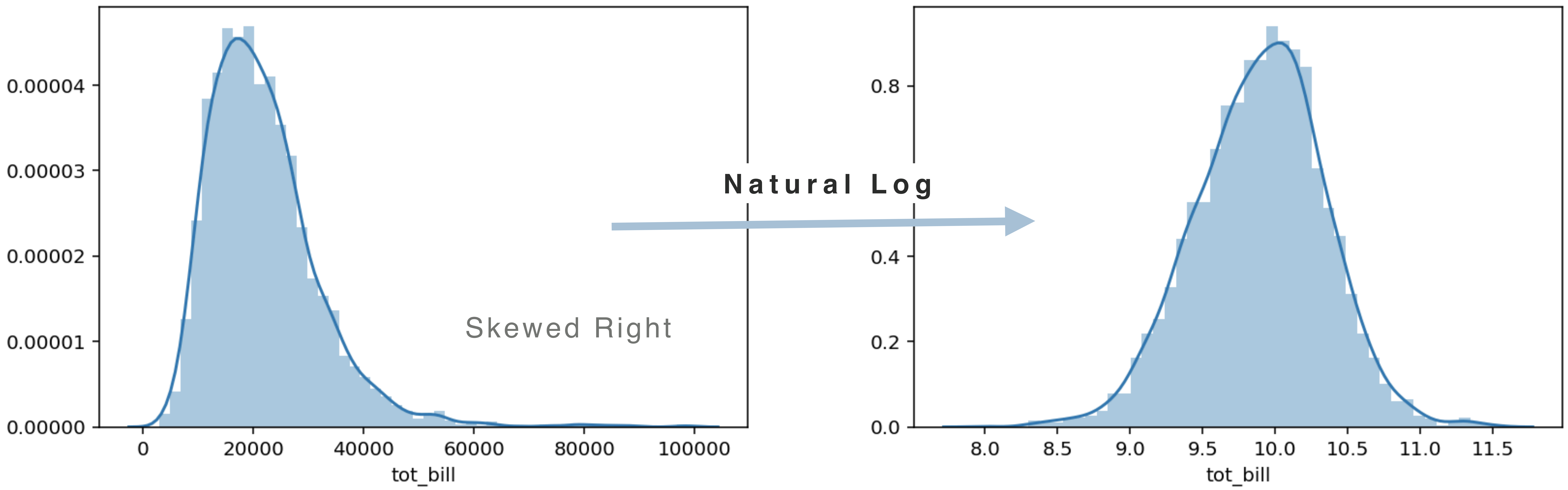
Pearson Correlation Coefficient

R = 0.0090

P-value = 0.5996

Target Variable

Distribution



Total Bill **Total Bill (Log)**

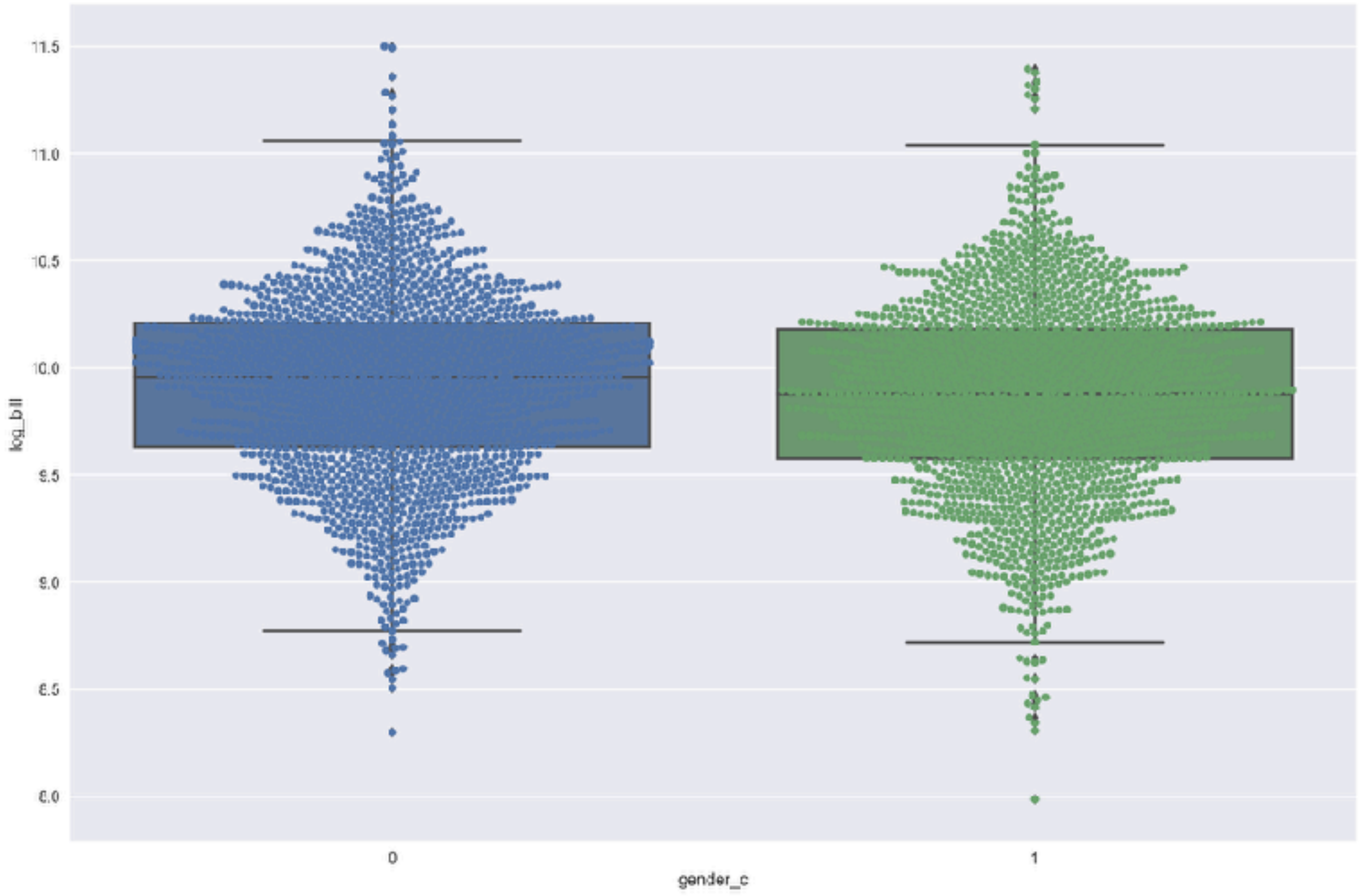
To ensure approximate normality

Demographics

		Count (per patient)	Total Bill (per adm)	
			Mean	P-Value
Total		**3,000**	**21,859**	
Gender	Female (1)	1,497	21,273	**<0.01***
	Male (0)	1,503	22,446	
Resident Status	Singaporean (0)	2,392	20,211	**<0.01***
	PR (1)	465	24,370	
	Foreigner (2)	143	41,704	
Race	Indian (1)	295	23,682	**<0.01***
	Chinese (2)	1,915	19,118	
	Malay (3)	629	29,506	
	Others (4)	161	21,320	
Age	< 55	1,755	19,334	**<0.01***
	> 55	1,252	25,398	

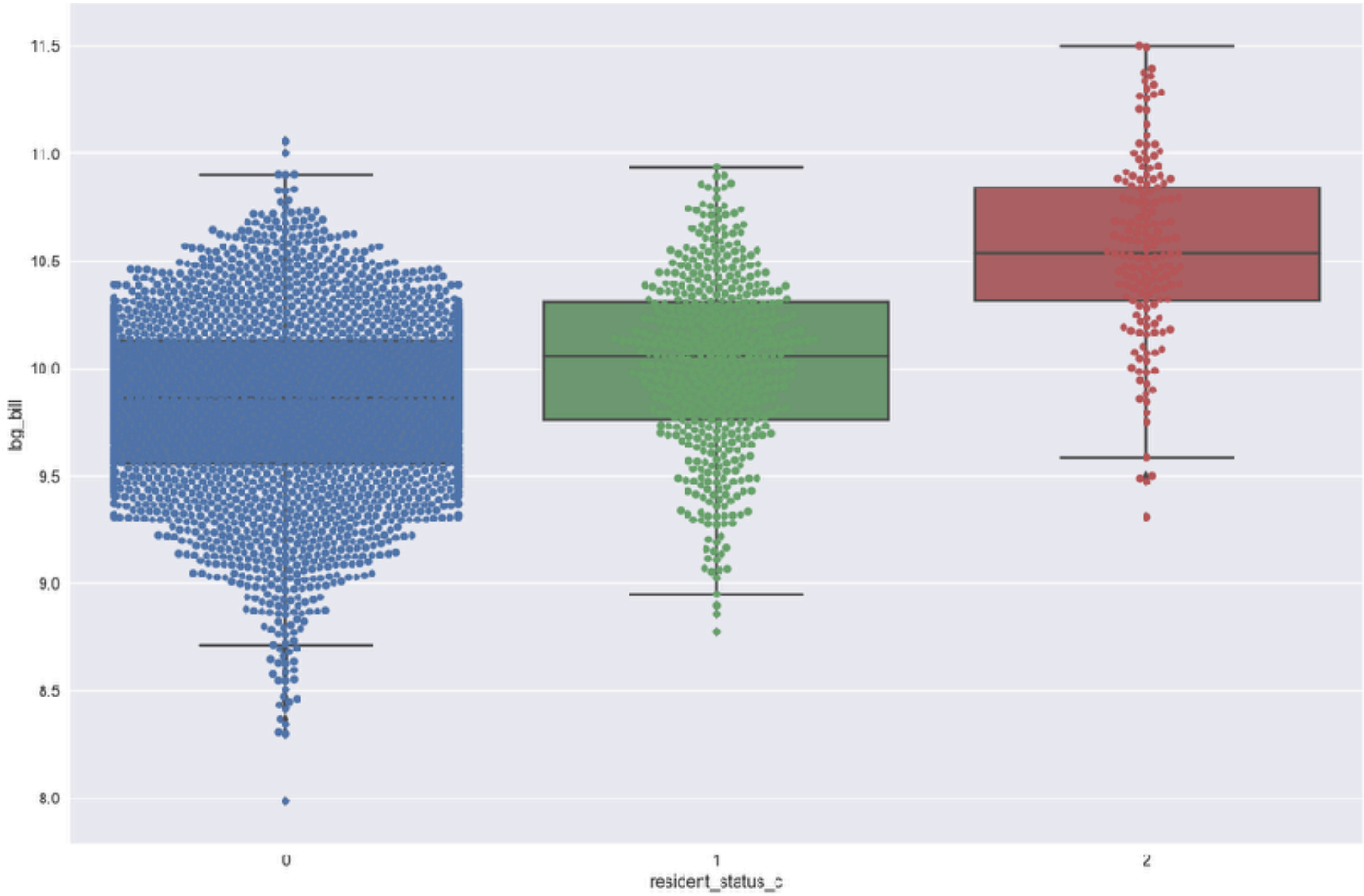
* Not tested for homogeneity and normality assumptions due to time constraint. One-way ANOVA is used

Gender



Male Female

Resident Status

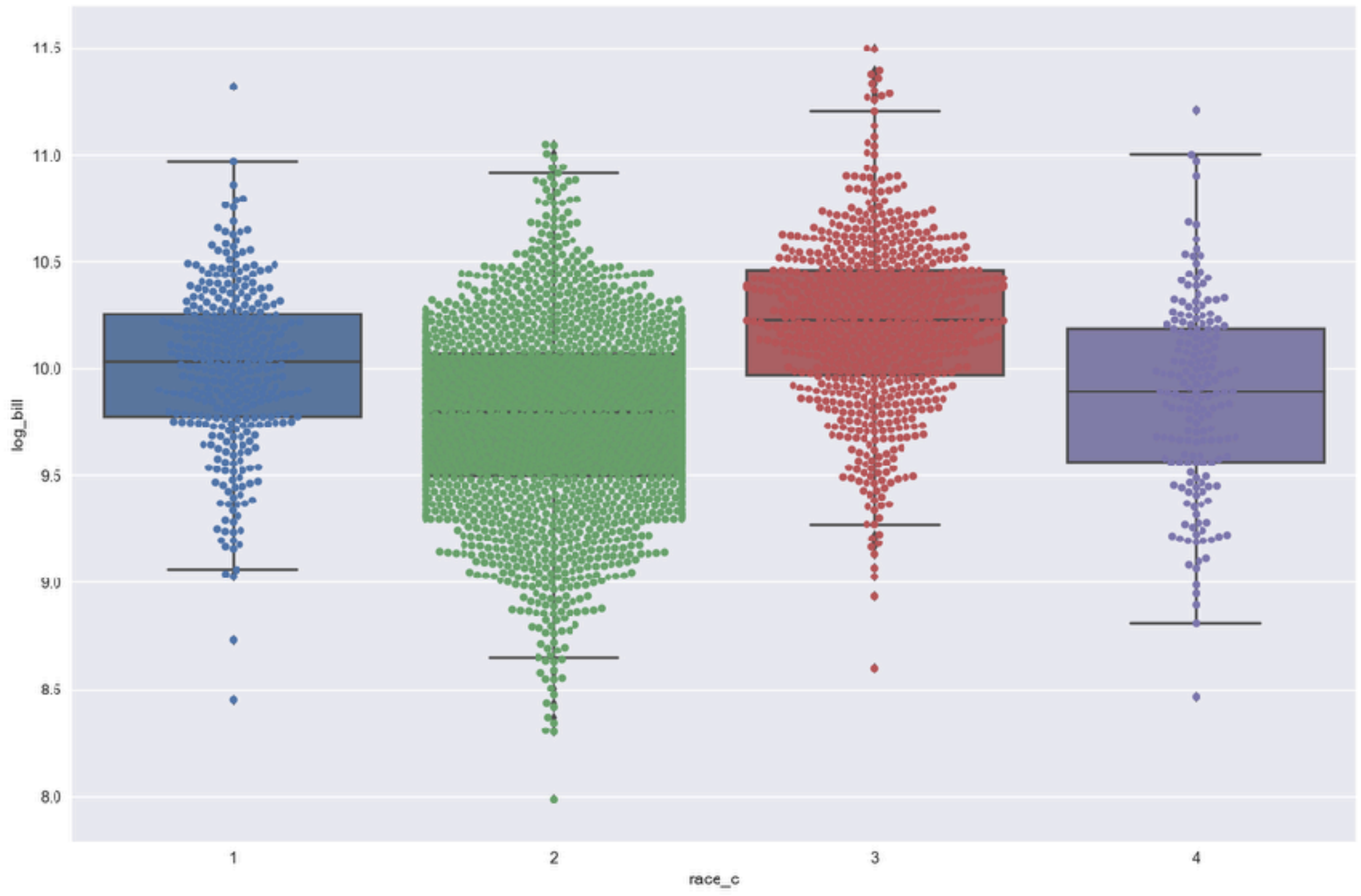


Singaporean Permanent Resident Foreigners

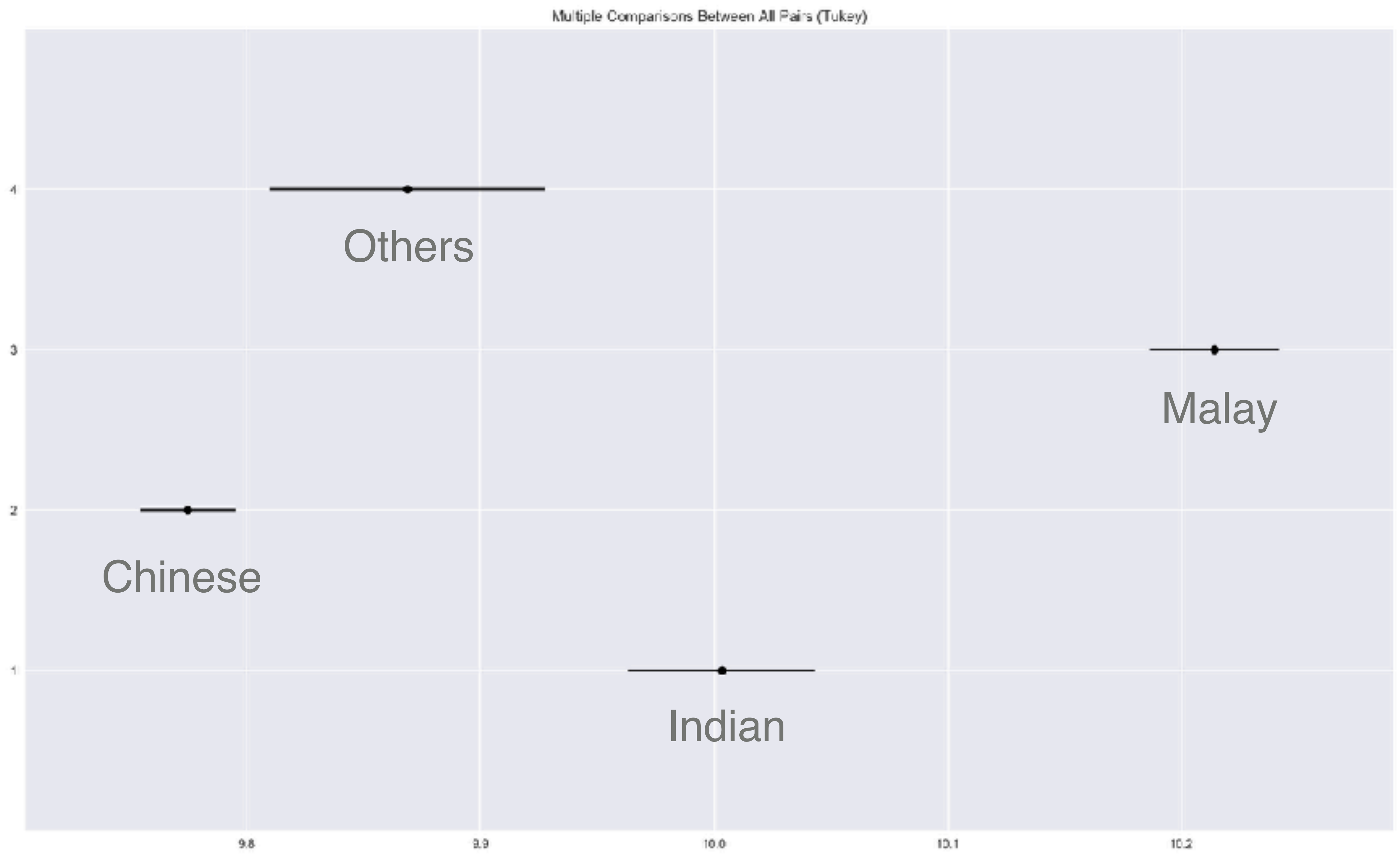
- Almost equal representation between male and female
- Male having 5.5% higher mean than female

- Singaporean have higher subsidies than PR and foreigners

Race



Indian Chinese Malay Others



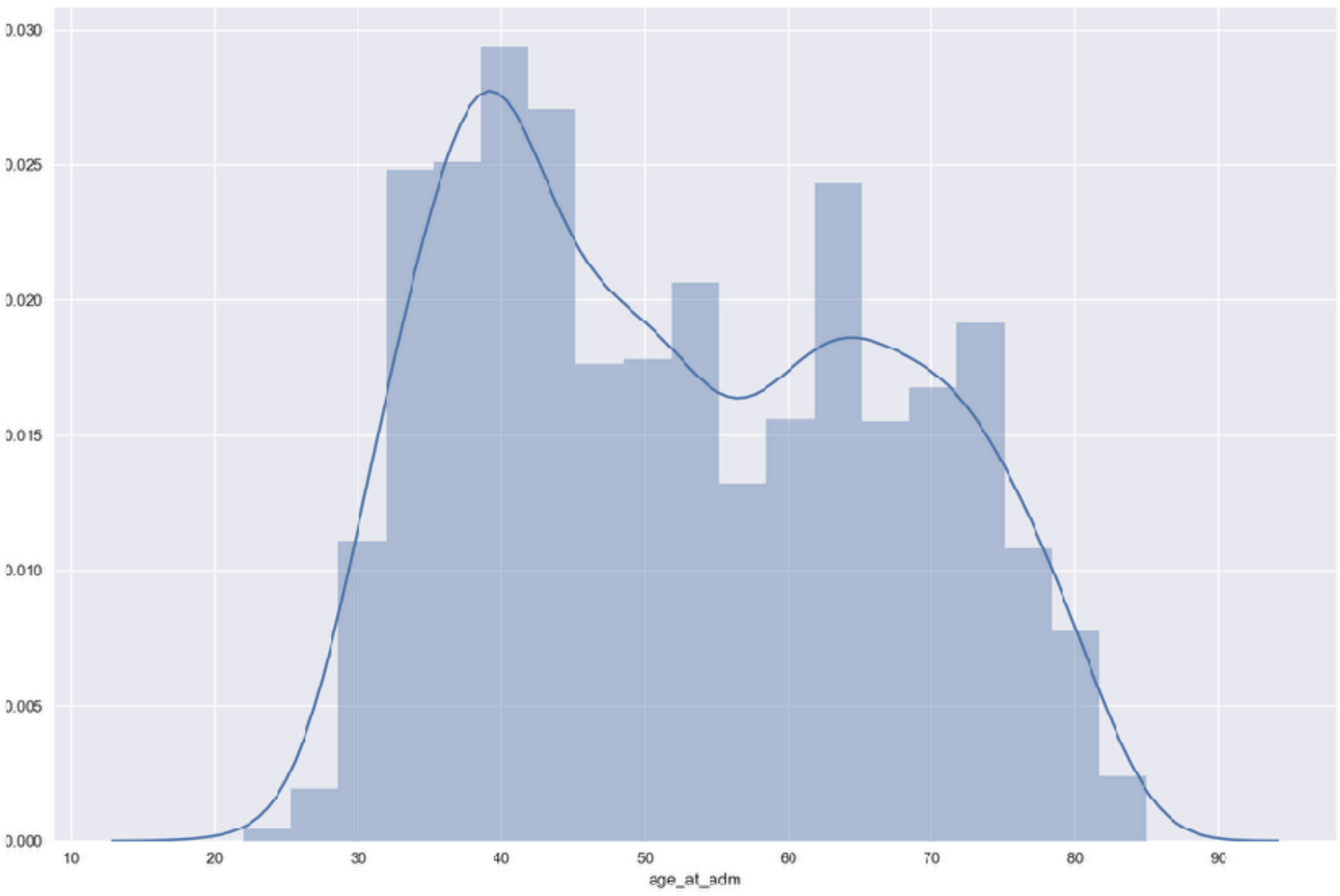
Multiple Comparison of Means - Tukey HSD,FWER=0.05

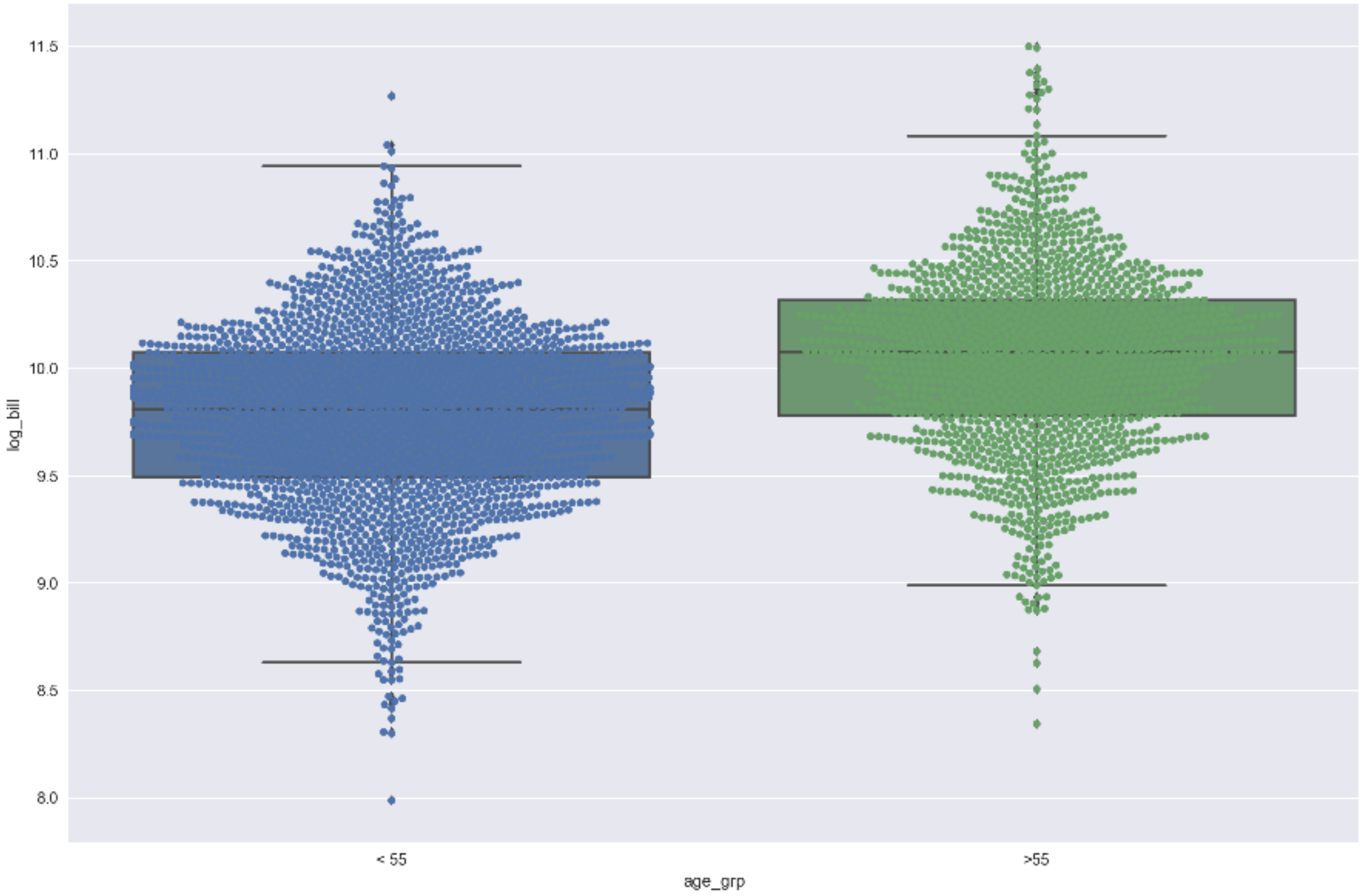
group1	group2	meandiff	lower	upper	reject
1	2	-0.2285	-0.2896	-0.1673	True
1	3	0.2108	0.1415	0.2801	True
1	4	-0.1343	-0.2308	-0.0379	True
2	3	0.4393	0.3936	0.4849	True
2	4	0.0941	0.013	0.1753	True
3	4	-0.3451	-0.4325	-0.2577	True

- There are more Chinese represented in our data
- Malays have the highest mean out of all races

• Not tested for homogeneity assumptions due to time constraint. Tukey's Honestly Significant Difference

Age





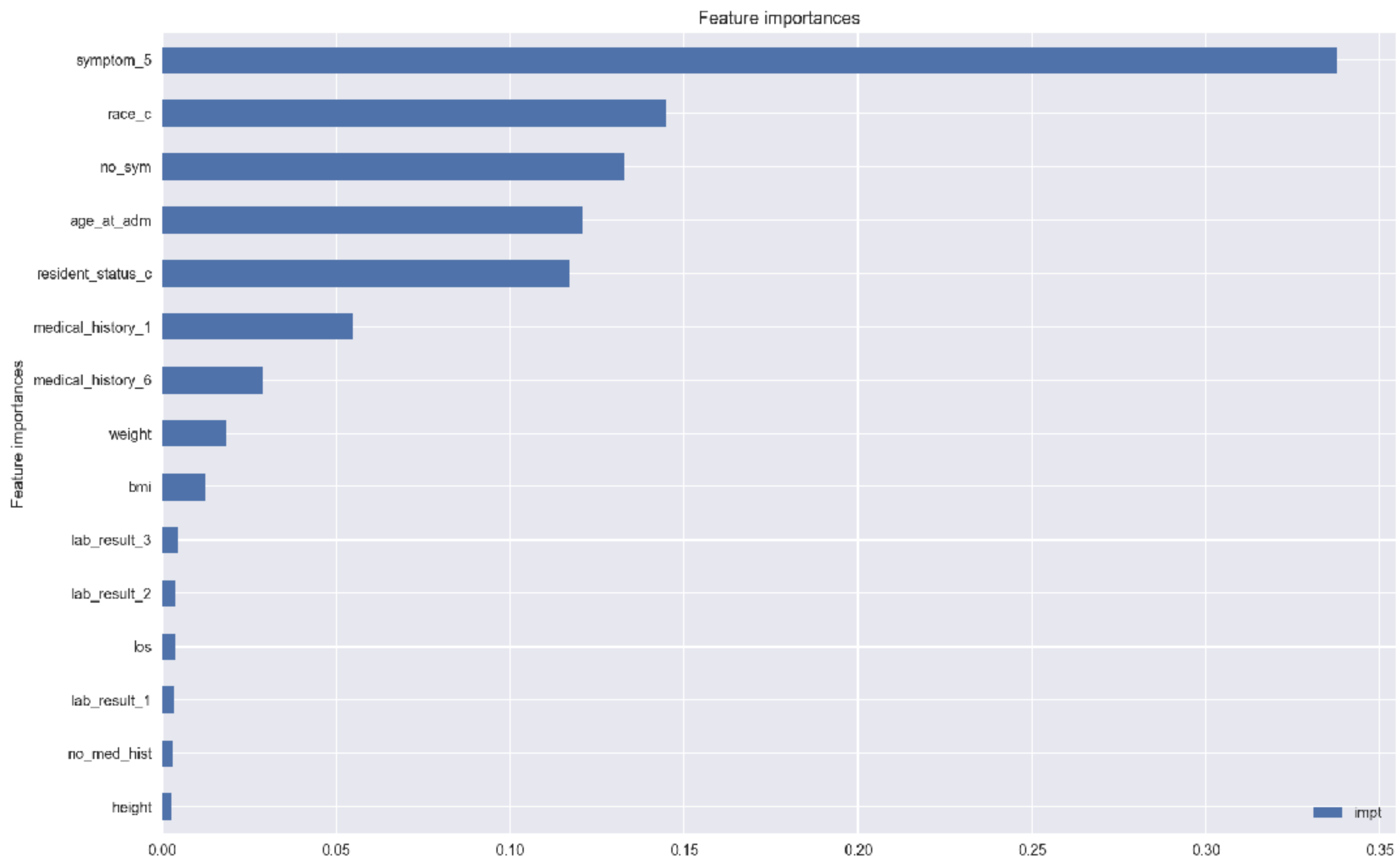
- Bimodal Distribution - We have 2 groups - above 55 and below 55
- Patients > 55 years old have ~31% higher mean total bill than those < 55

Which variable matters?

A quick way to help us focus on what matters .

Decision Tree

A quick dirty way to help zoom into important variables

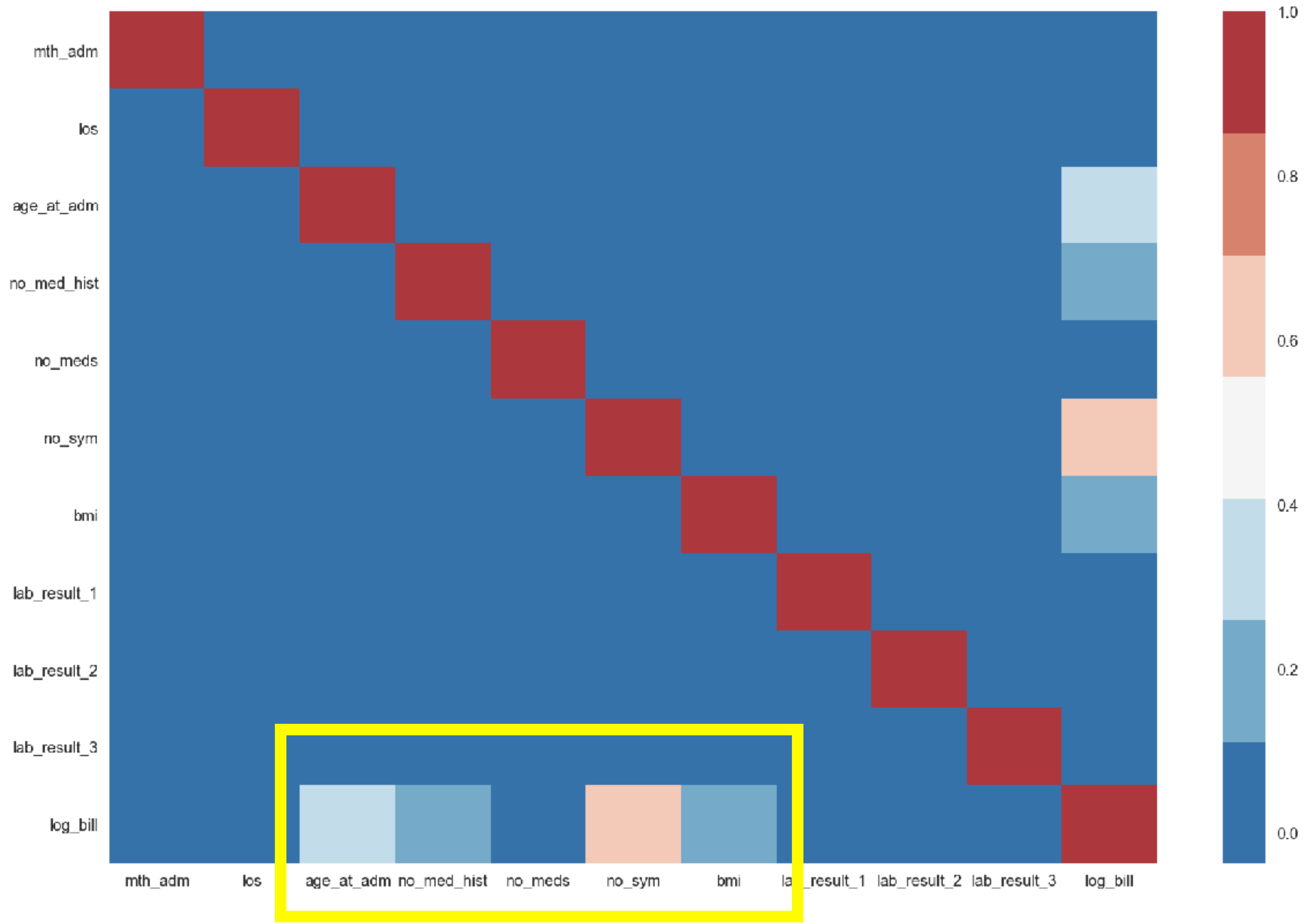


Top 10

1. Symptom 5
2. Race
3. Number of Symptoms
4. Age
5. Resident Status
6. Medical History 1
7. Medical History 6
8. BMI (Height & Weight)
9. Lab Result 3
10. Lab Result 2

Correlation Coefficient Matrix

On continuous variables



Some positive correlation

- Age
- Number of medical history
- Number of symptoms
- BMI

Patient Level vs Admission Level

It depends on what we want to achieve .

Patient

- Race
- Age
- Resident Status
- BMI
- Number of Medical History
- Medical History 1
- Medical History 6

Clinical (Admission)

- Symptom 5
- Number of Symptoms
- Lab Result 3
- Lab Result 2

Patient

- Race
- Age
- Resident Status
- BMI
- Number of Medical History
- Medical History 1
- Medical History 6

Clinical (Admission)

- Symptom 5
- Number of Symptoms
- Lab Result 3
- Lab Result 2

Our Data

- Clinical and financial data of patients hospitalised for a certain (X) condition
- Per row per patient's total bill per year
- 3,314 rows
- 3,000 unique patients
- 5 year data (2011 - 2015)

Variables

- **Number of encounter per year** (*continuous*)
- **Readmission (> 1 encounter per year)** (*binary*)
- **Age** (*continuous*)
- **Age (<55, >55)** (*categorical*)
- **BMI** (*continuous*)
- **BMI Risk Level** (*categorical*) (*healthhub.sg*)
- **Number of Medical History** (*continuous*)
- **Medical History 1 through 7** (*binary*)

Target Variable

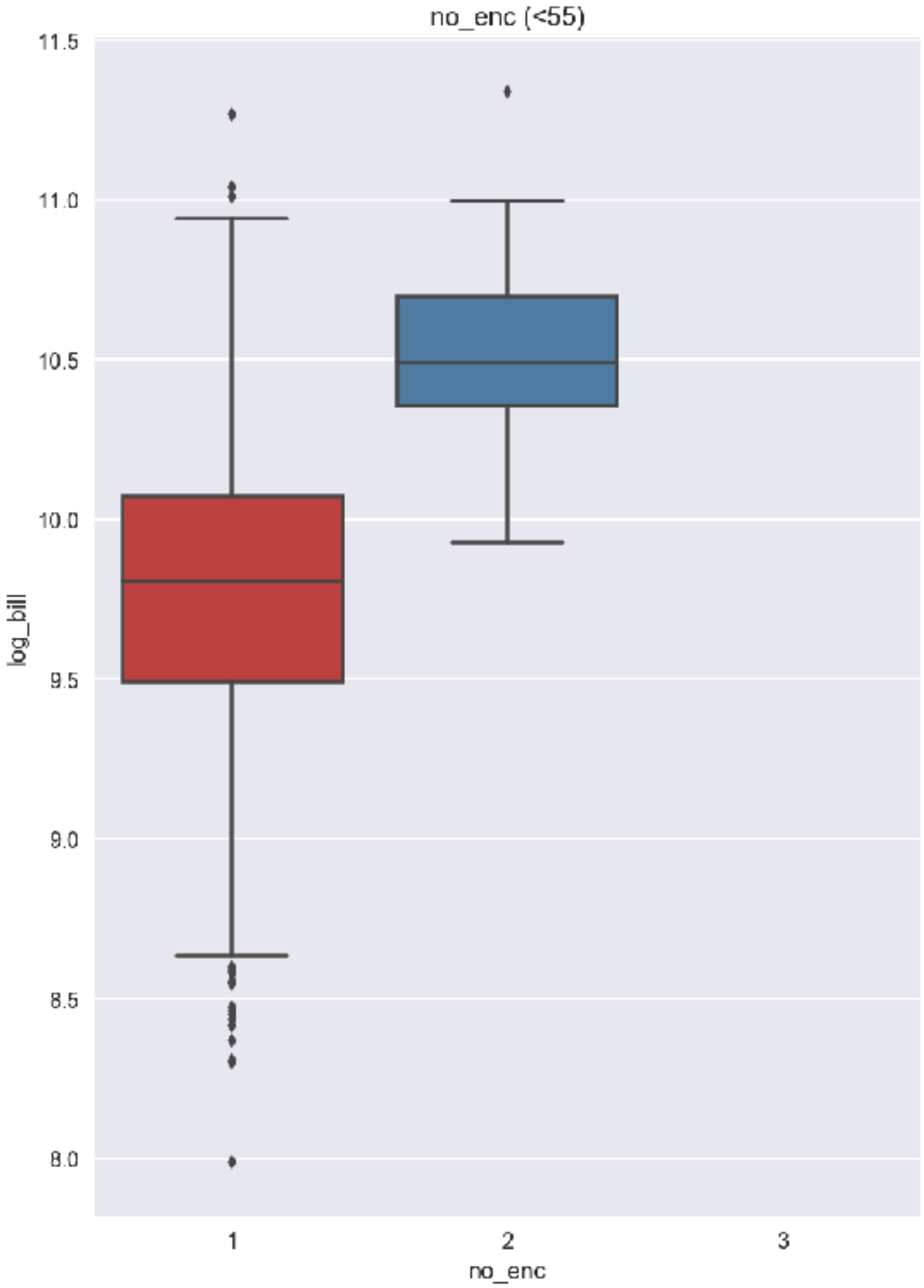
- **Patient's total bill per year**

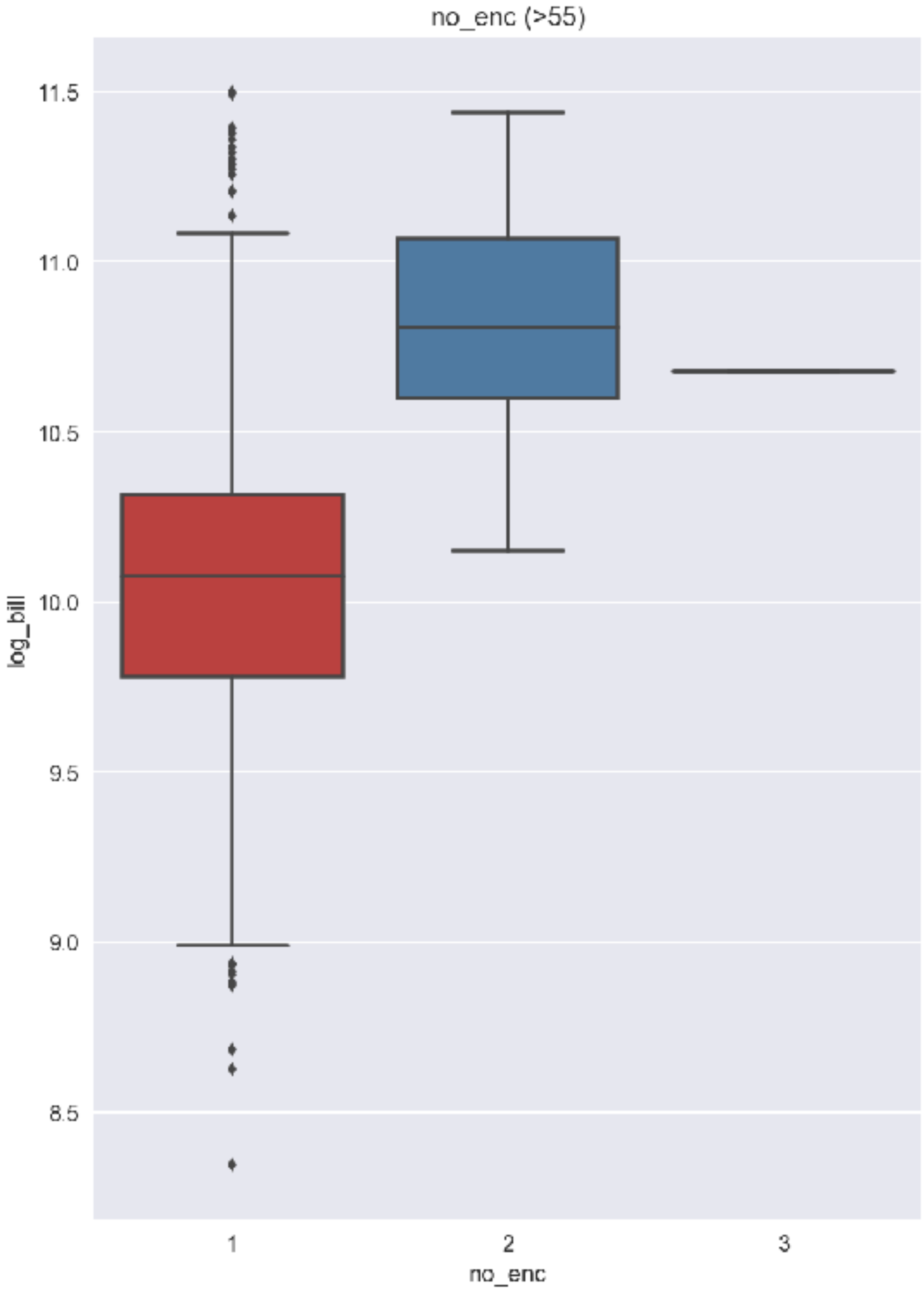
Number of Encounters/Year

		Count	Total Bill (per yr)	
			Mean	P-Value
Total		3,314		
Number of Encounter / Year	1	2,928	21,828	**<0.01***
	2	84	45,140	
	3	1	43,490	

• Not tested for homogeneity and normality assumptions due to time constraint. One-way ANOVA is used

Number of Encounters / Year

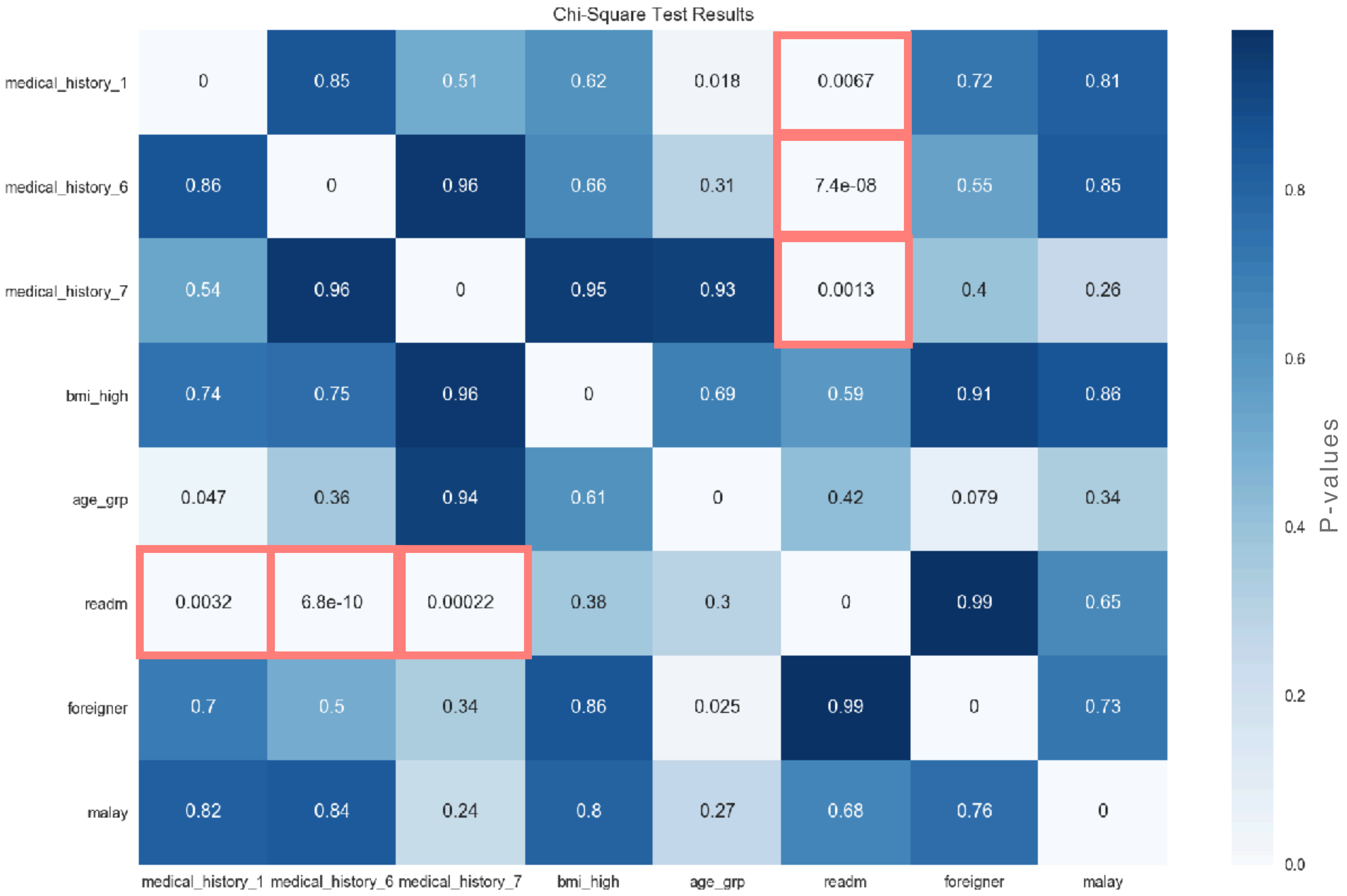




- P-Value < 0.01 for both age groups

- Not tested for homogeneity and normality assumptions due to time constraint. One-way ANOVA is used

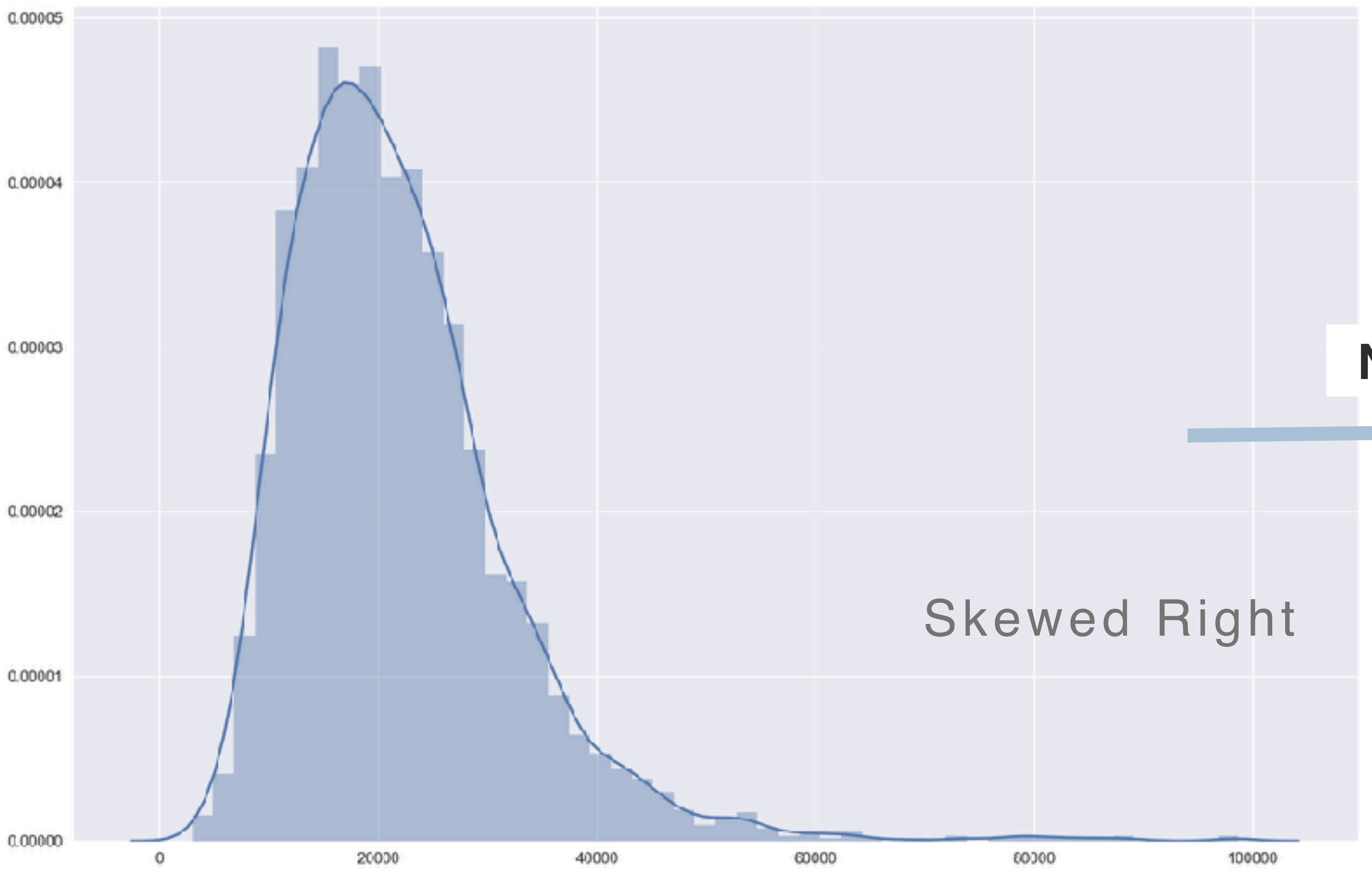
CHI-Square Test



- The presence of medical history 1, 6 and 7 have high correlation with > 1 encounter per year
- P-values < 0.01

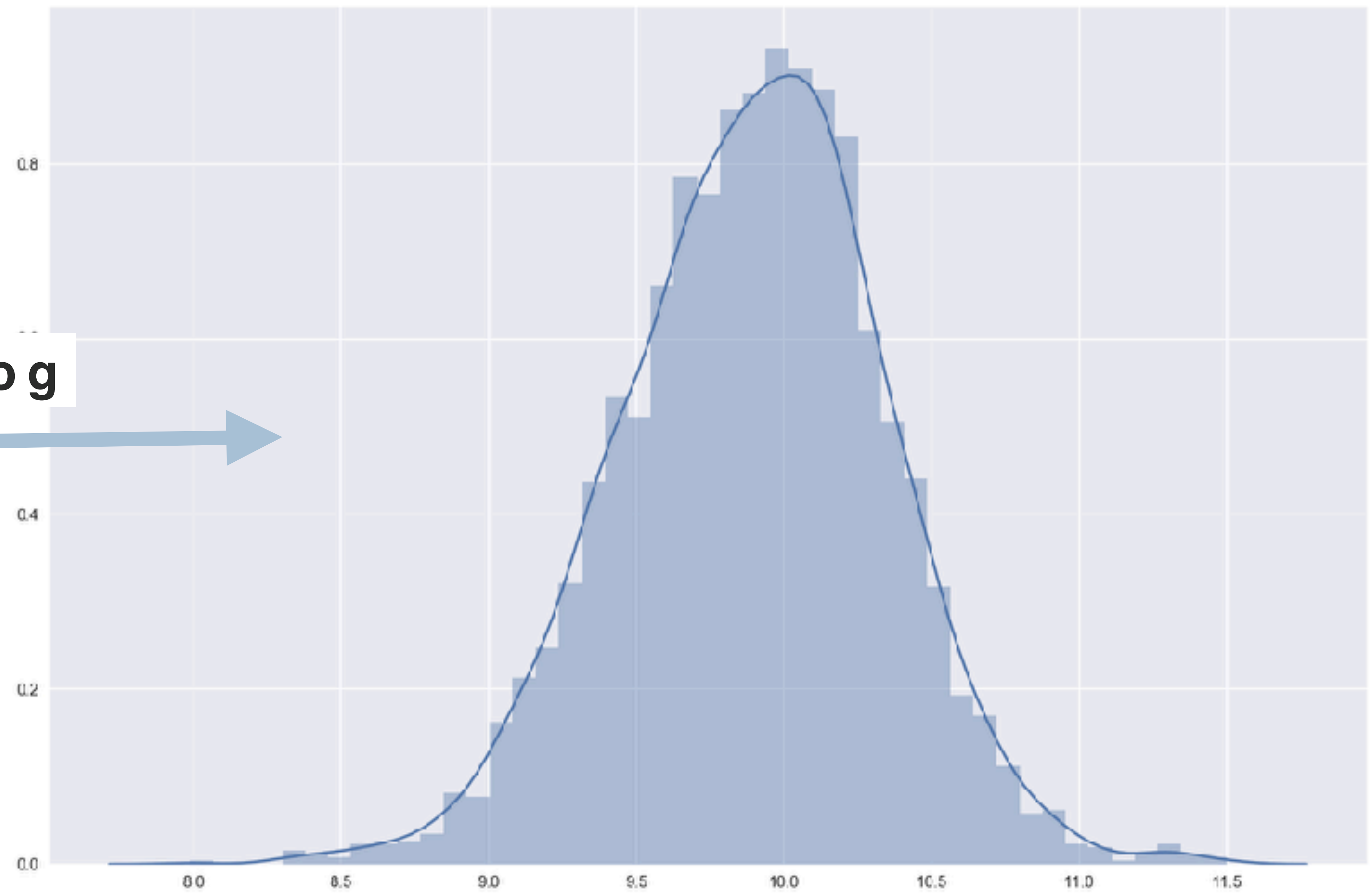
Target Variable

Distribution



$$\frac{\text{Total Bill / year}}{\text{Number of Encounters / year}}$$

Natural Log



$$\frac{\text{Total Bill / year}}{\text{Number of Encounters / year}} \text{ (Log)}$$

To ensure approximate normality

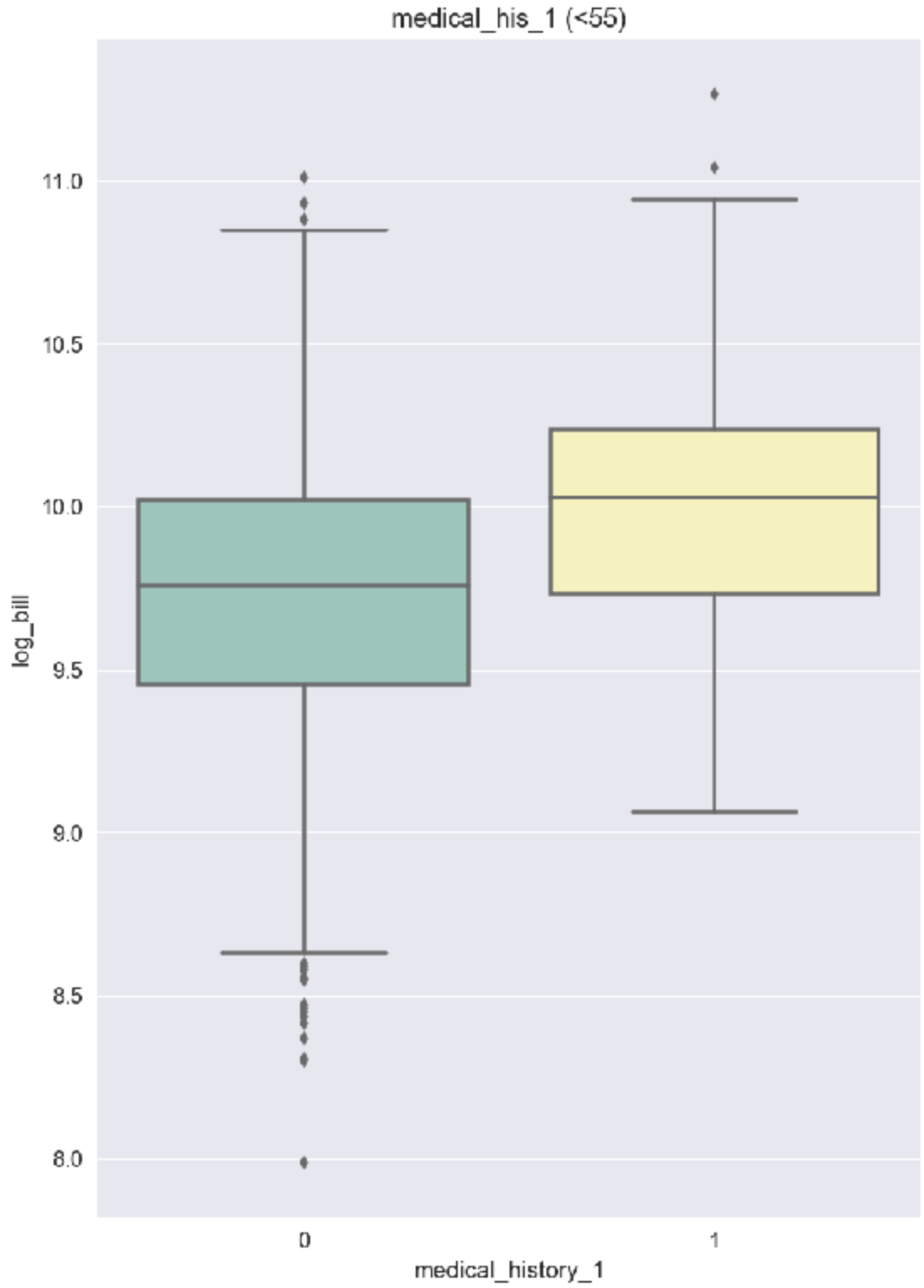
Medical History

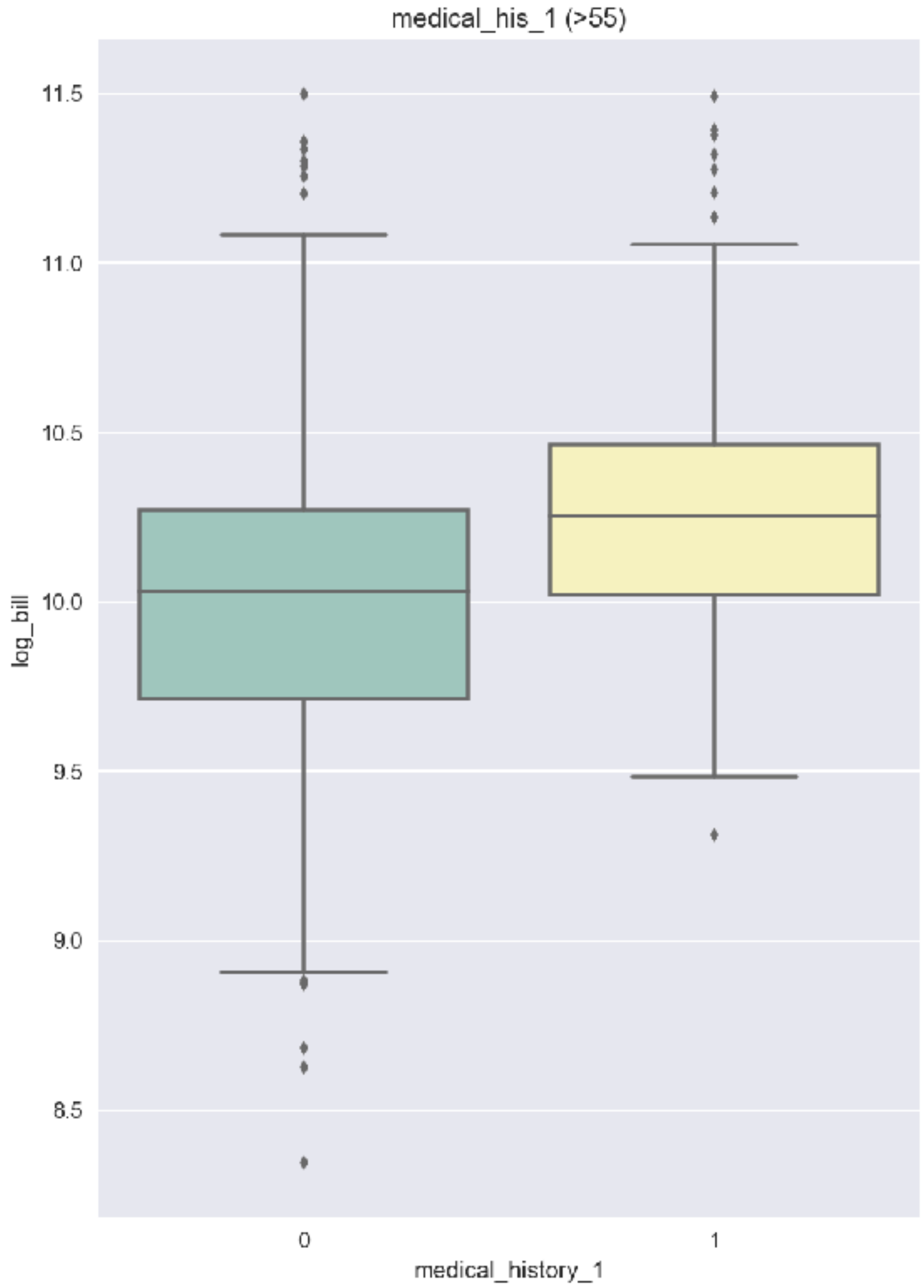
		Count	Avg Total Bill (per enc per yr)	
			Mean	P-Value
Total		3,314		
Number of Med History	0	795	19,497	**<0.01***
	1	1,258	21,463	
	2	800	24,696	
	3	310	26,532	
	4	47	31,191	
	5	7	36,853	
Med Hist 1		**562**	26,850	**<0.01***
Med Hist 2		953	22,357	0.086
Med Hist 3		459	22,205	0.023
Med Hist 4		175	21,480	0.943
Med Hist 5		196	23,129	0.018
Med Hist 6		**839**	24,175	**<0.01***
Med Hist 7		842	22,484	0.040

- Not tested for homogeneity and normality assumptions due to time constraint. One-way ANOVA is used

Medical History 1

Total Count: 562 / 3,000 (18.7%)



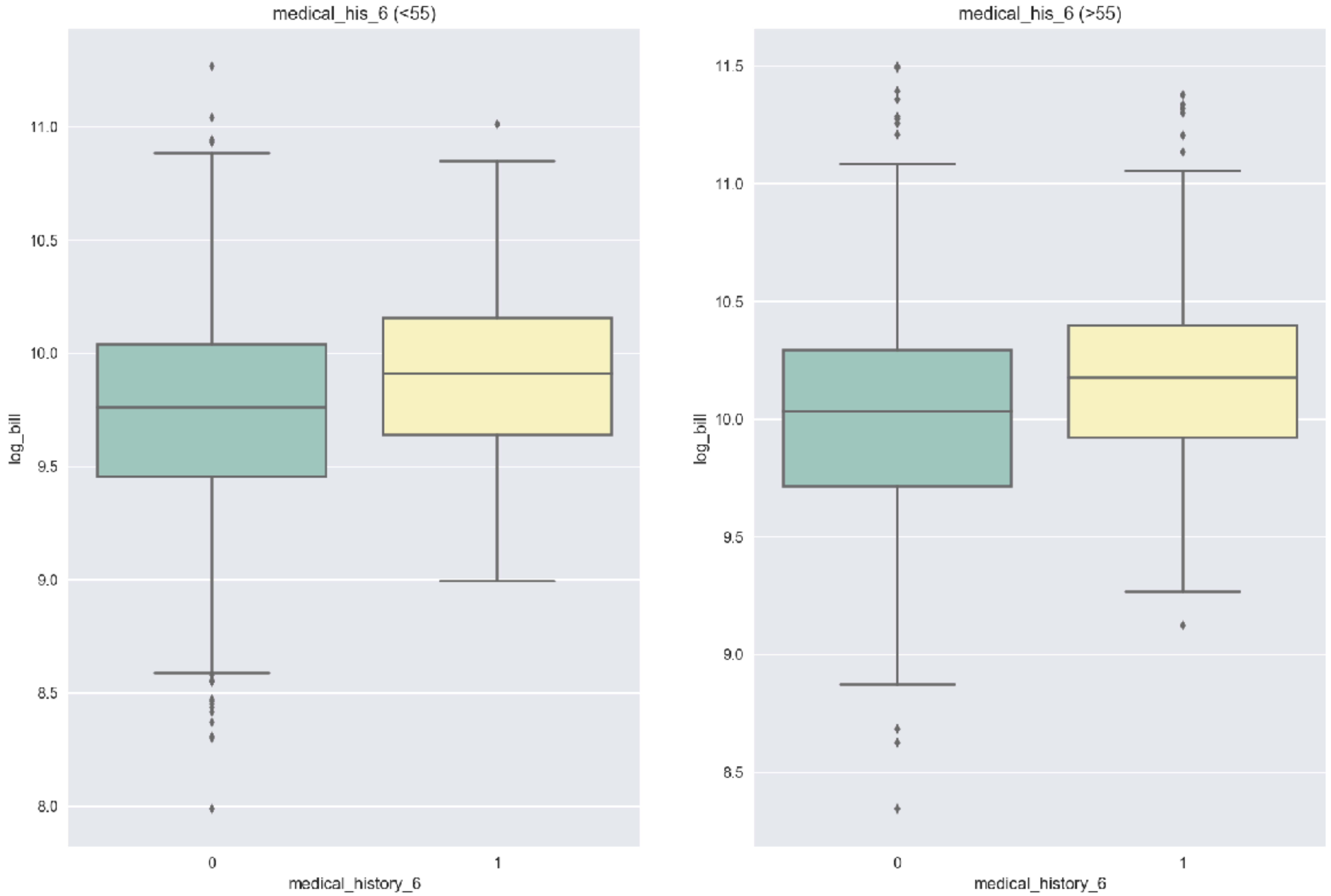


- 18.7% of patients with medical history 1 contributes 21.7% of the avg total bills.
- P-Value < 0.01 for both age groups

- Not tested for homogeneity and normality assumptions due to time constraint. One-way ANOVA is used

Medical History 6

Count: 839/ 3,000 (28.0%)

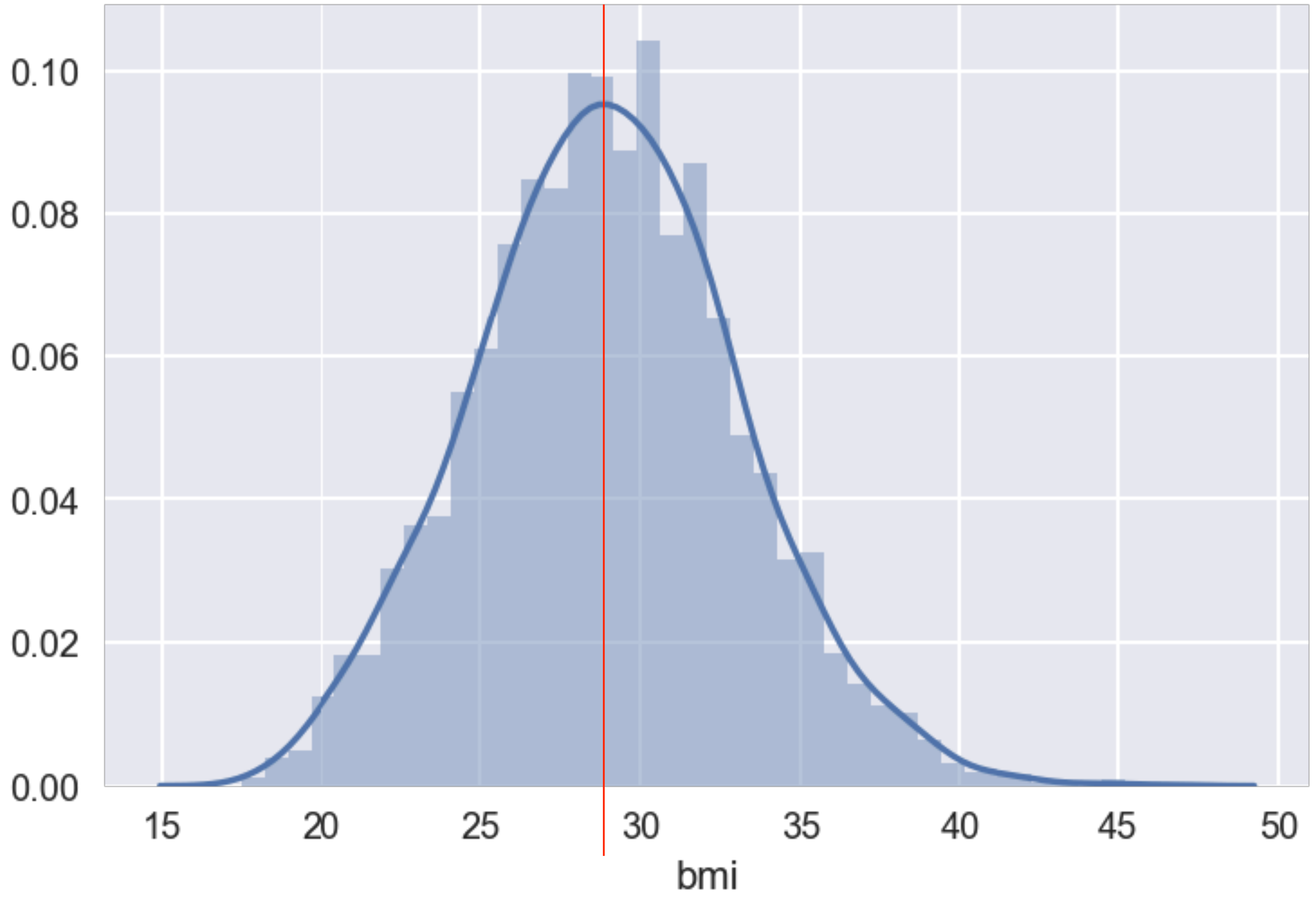


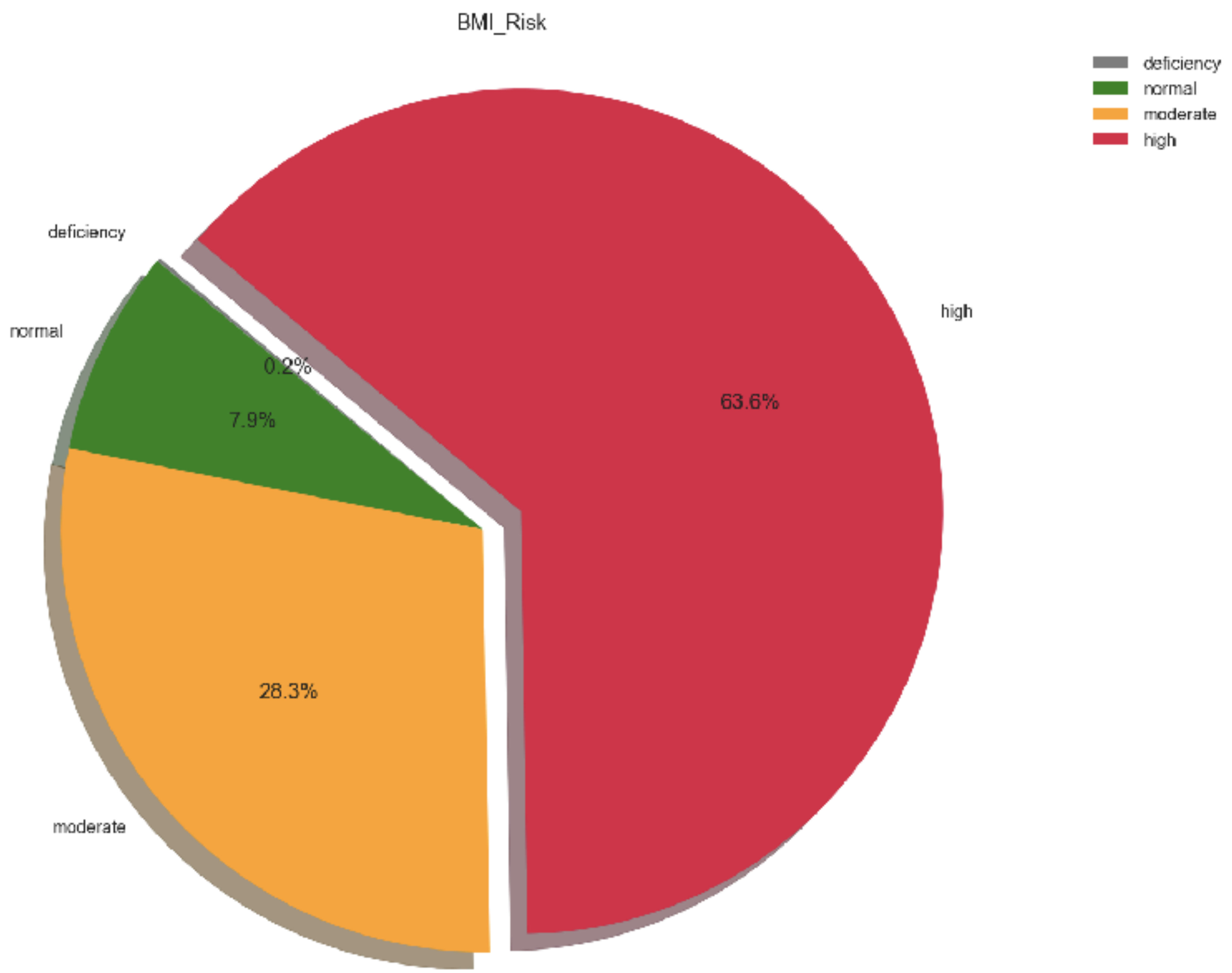
- 28% of patients with medical history 6 contributes 29.44% of the avg total bills.
- P-Value < 0.01 for both age groups

• Not tested for homogeneity and normality assumptions due to time constraint. One-way ANOVA is used

Body Mass Index (BMI)

$$BMI = \frac{Weight\,(kg)}{[Height(m)]^2}$$



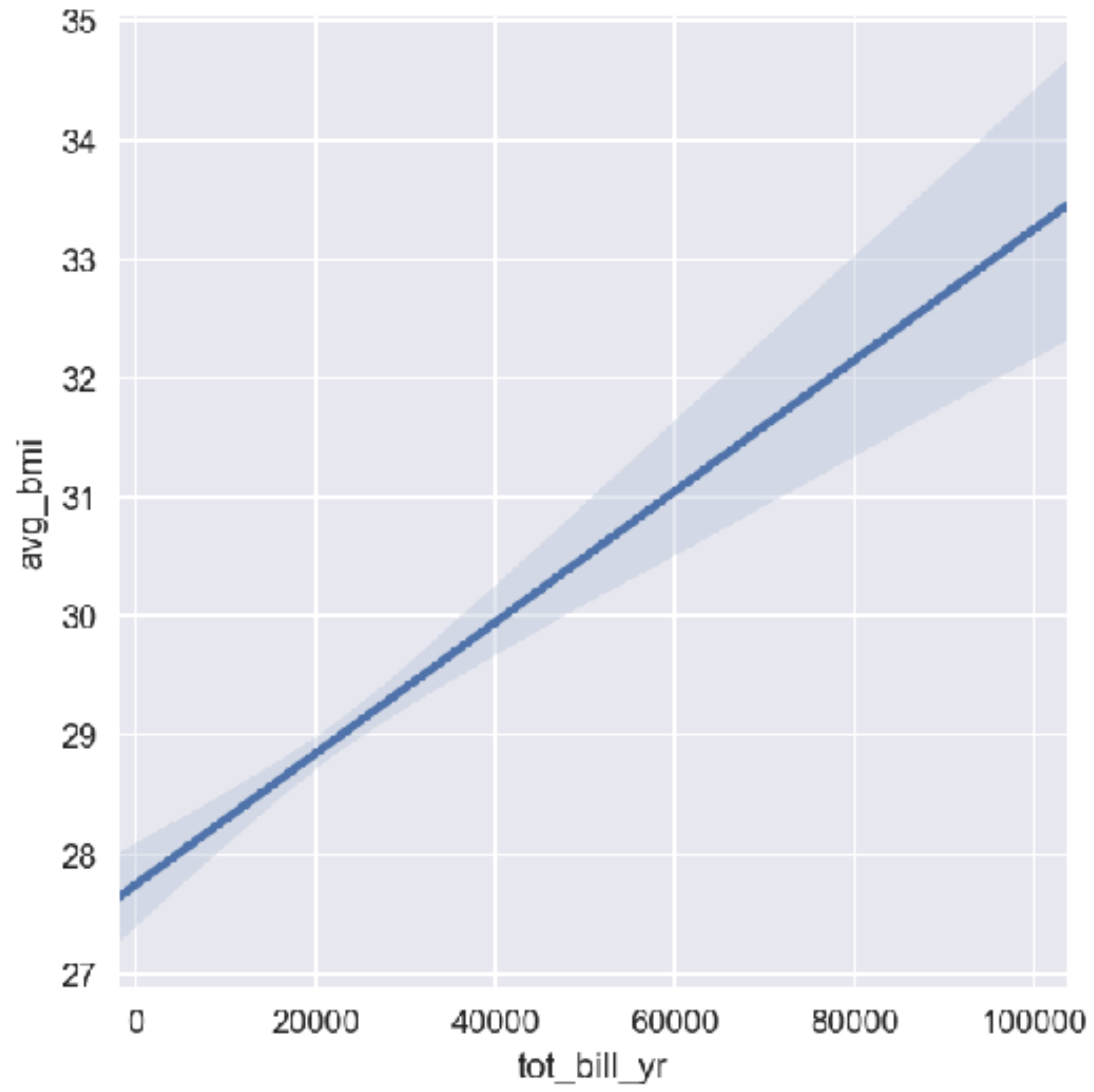


- Mean BMI = 28.95 (high risk)
- **63.6**% patient population have high BMI risk

Body Mass Index (BMI)

$$BMI = \frac{Weight\,(kg)}{[Height(m)]^2}$$

		Total Bill (/enc/yr)	
		Mean	**P-Value**
BMI Risk Level	Deficiency	11,200	**<0.01***
	Normal	19,389	
	Moderate	20,774	
	High	22,651	



R: 0.140, P-value: <0.01*

- There is significance between BMI Risk and Avg total bill per year at 0.01 significance level
- Positive correlation between BMI and avg total bill

- Not tested for homogeneity and normality assumptions due to time constraint. One-way ANOVA is used

Model & Interpretation

Explainability matters .

Variance Inflation Factor

To check for multicollinearity between variables

	VIF Factor	features
0	1.0	medical_history_1
1	1.0	medical_history_6
2	2.0	bmi_high
3	1.0	age_grp
4	1.0	foreigner
5	1.0	malay

No variables have a VIF of more than 5

Linear Regression Model

$Y = \beta 0 + \beta 1$ medical history 1 $+ \beta 2$ medical history 6 $+ \beta 3$ high bmi risk

$+ \beta 4$ age > 55 $+ \beta 5$ foreigner $+ \beta 6$ malay

	Parameter	**Estimate**	**Standard Error**	**P-Value**
Model 2	Intercept	9.51	0.012	<0.01*
	Medical History 1	0.26	0.016	<0.01*
	Medical History 6	0.17	0.014	<0.01*
	High BMI risk	0.11	0.012	<0.01*
	Age > 55	0.25	0.012	<0.01*
	Foreigner	0.68	0.028	<0.01*
	Malay	0.40	0.015	<0.01*

R-squared = 0.415

- Not tested for homogeneity and normality assumptions due to time constraint. One-way ANOVA is used

Linear Regression Model

Y = β0 + β1 medical history 1 + β2 medical history 6 + β3 high bmi risk

+ β4 age > 55 + β5 foreigner + β6 malay

Interpretation:

Average total bill per year for patients with condition X and have/is

- medical history 1 is **~ 29.11 %** higher when compared to patients without
- medical history 6 is **~ 18.71 %** higher when compared to patients without

- high BMI risk is **~ 11.37 %** higher when compared to patients doesn't
- age > 55 years old is **~ 27.86 %** higher when compared to patients < 55

- a foreigner is **~ 96.83 %** higher when compared to patients who are Singaporeans or PR
- malay is **~ 49.05 %** higher when compared to patients of other races

Use Case Discussion

Identify patient population at risk of higher admission cost for condition X for intervention

Findings suggest that admission cost per year are significantly affected by

1. Number of admitted encounters,
2. Medical history,
3. Body Mass Index
4. Age
5. Demographics

Use Case Discussion

Identify patient population at risk of higher admission cost for condition X for intervention

Findings suggest that admission cost per year are significantly affected by

1. Number of admitted encounters
2. Medical history
3. Body Mass Index
4. Age
5. Demographics

- Cost per year increases with frequent admissions
- Highly correlated to medical history
- Consider continuity of care for these patients after discharge to prevent readmission

Use Case Discussion

Identify patient population at risk of <u>higher</u> admission cost for condition X <u>for intervention</u>

Findings suggest that admission cost per year are significantly affected by

1. Number of admitted encounters
2. Medical history
3. Body Mass Index
4. Age
5. Demographics

- Increases complexity, more complications, more need for healthcare attention
- Preventive care for patients without existing conditions through regular screenings
- Medical History 1 and 6 have bigger impact than others
- Not enough information

Use Case Discussion

Identify patient population at risk of <u>higher</u> admission cost for condition X <u>for intervention</u>

Findings suggest that admission cost per year are significantly affected by

1. Number of admitted encounters
2. Medical history
3. Body Mass Index
4. Age
5. Demographics

- Not surprising that patients with high health risk to have more complications and require more interventions
- Better manage patient's BMI by encouraging them to participate in health programmes
- Frequent health screenings

Use Case Discussion

Identify patient population at risk of <u>higher</u> admission cost for condition X <u>for intervention</u>

Findings suggest that admission cost per year are significantly affected by

1. Number of admitted encounters
2. Medical history
3. Body Mass Index
4. Age
5. Demographics

- Expected that elderly patients would need more medical attention than younger population
- Non-Singaporeans have less subsidies
- Non-modifiable variables, but allows healthcare providers/ministry of health to target population for policy planning and interventions

Given more time…

- Adjusted for confounders (demographics group) rather than using it as a factor
- Test for homogeneity and normality assumptions
- Look into admission level data for more use cases
  - Symptoms affect cost per admission
  - Useful for pharmaceutical companies
- Interactive dashboards to show how each variable varies
- Improve on visualisation and story-telling