DataHugger

Data Management and Visualization Assignment 4: Creating graphs for Variables relevant to Weekend Effect on Mortality in US Hospitals.-Lewittes

Research Question: Is there a dependence on the mortality rate in the United States on the day of the week? Specifically, my **hypothesis** is that there a higher mortality rate on the Weekends or perhaps Monday that may be due to the reduced level of medical care available on the weekends. To elucidate the dependence of mortality on the day of the week we will need to identify that the place of death was within a hospital or medical facility, and there may be important cross terms of age, sex, race, marital status, and cause of death.

Second Related Research Question: Are deaths in hospitals due to accidental injuries (such as traffic accidents) also subject to a weekend effect? This is made more challenging as the number of accidental injuries themselves may be reasonably be assumed to vary between weekdays and weekends. So these deaths due to accidental injuries will be need to be excluded from the initial research question. However, we may be able to generate a normalization factor to remove the day of accidental injury bias by comparing the number of dead on arrival per day on the weekends, to the dead on arrival per day on the weekdays. The **hypothesis of the second research question** is that there is a higher mortality rate on the weekends due to reduced medical care available for accidental injuries after normalization.

Data set chosen: The 2013 mortality data base distributed by the CDC.(Centers for disease control)

The numerous graphs below will answer both research questions. However, the assignment is to create 2 specific graphs, one univariate and one bivariate graph. The first two graphs will be examples of these along with the code used to generate these graphs.

It was found considering the data that in order to determine if there were an increase in deaths in the US at medical institutions on the weekends (including Mondays in the definition of weekend) that we would have to isolate deaths that would have needed immediate medical care and that the deaths took place in Emergency Rooms rather than in Hospitals. (The death rate in hospitals is skewed to weekdays because they routinely perform elective but dangerous surgery on weekdays only. Emergency Rooms do not have that kind of bias so testing for uniformity of care by day of the week should be possible in ERs.) Furthermore, it was found (as shown near the bottom of this document) that the frequency of accidental deaths (for example from dangerous recreation, or drinking and driving) is skewed to the weekends, so while these require immediate medical care, deaths resulting from accidents were excluded. Included were causes of death such as acute heart attacks, strokes, and other medical conditions that if not attended to immediately would have a high probability of mortality and have no intrinsic bias to the weekend.

The first chart is a count of the deaths by day of the week (Sunday = 1) for medically critical cases in Emergency Rooms. The null hypothesis is that there is no increase in deaths on the weekend, that the death count per day should be uniformly distributed across all days of the week. This graph appears to confirm the null hypothesis. That is good news for the US medical system and is in contrast to the problems uncovered in England. We can take a closer look at this and determine if this is statistically verified. Also the first research question included a look at potential cross terms such as sex, marital status, and race in addition to the location and cause of death that have been considered in obtaining this first chart this first chart.

#import library functions

import pandas

import numpy

import seaborn

import matplotlib.pyplot as plt

#Change variable names into words I can remember

Day = ' DOW_of_Death'

Place = ' Place_Of_Death'

Sex = ' Sex'

Race = ' Race_Recode_3'

Age = ' Age_Recode_12'

Cause = ' Cause_Recode_113'

Married = ' Marital_Status'

```
Sudden = ‘Sudden’

Weekend= 'Weekend’

data = pandas.read_csv('VS13MORTshort.csv’, low_memory=False)

“”“#The variable Sudden is set to one for Causes of death that require immediate

medical intervention to prevent death, such as heart attack, stroke,

meningitis, but not accidents and homicides such as traffic accidents, and

discharge of fire arms etc.  ”“”

data['Sudden’] = ((data[Cause]==9) | (data[Cause]==10) |

            (data[Cause]==50) | (data[Cause]==59) |

            (data[Cause]==60) | (data[Cause]==66) |

            (data[Cause]==70) | (data[Cause]==73) |

            (data[Cause]==80) | (data[Cause]==105) |

            (data[Cause]==106) | (data[Cause]==107)

            ).astype('int’)

# Select only deaths in Emergency Rooms, Place =2.

subER1 =      data[(data[Place] == 2)]

subER = subER1.copy()

subER[Place] = pandas.to_numeric(subER[Place])
```

```
subCriticalER1 = subER1[(subER1[Sudden] == 1)]

subCriticalER = subCriticalER1.copy()

seaborn.countplot(x= Day, data=subCriticalER)

plt.xlabel(“Day of Week”)

plt.suptitle(“# of Deaths for Critical Cases In Emergency Rooms by Day of Week”)

plt.title(“Excluding Accidents”)

seaborn.plt.show()
```

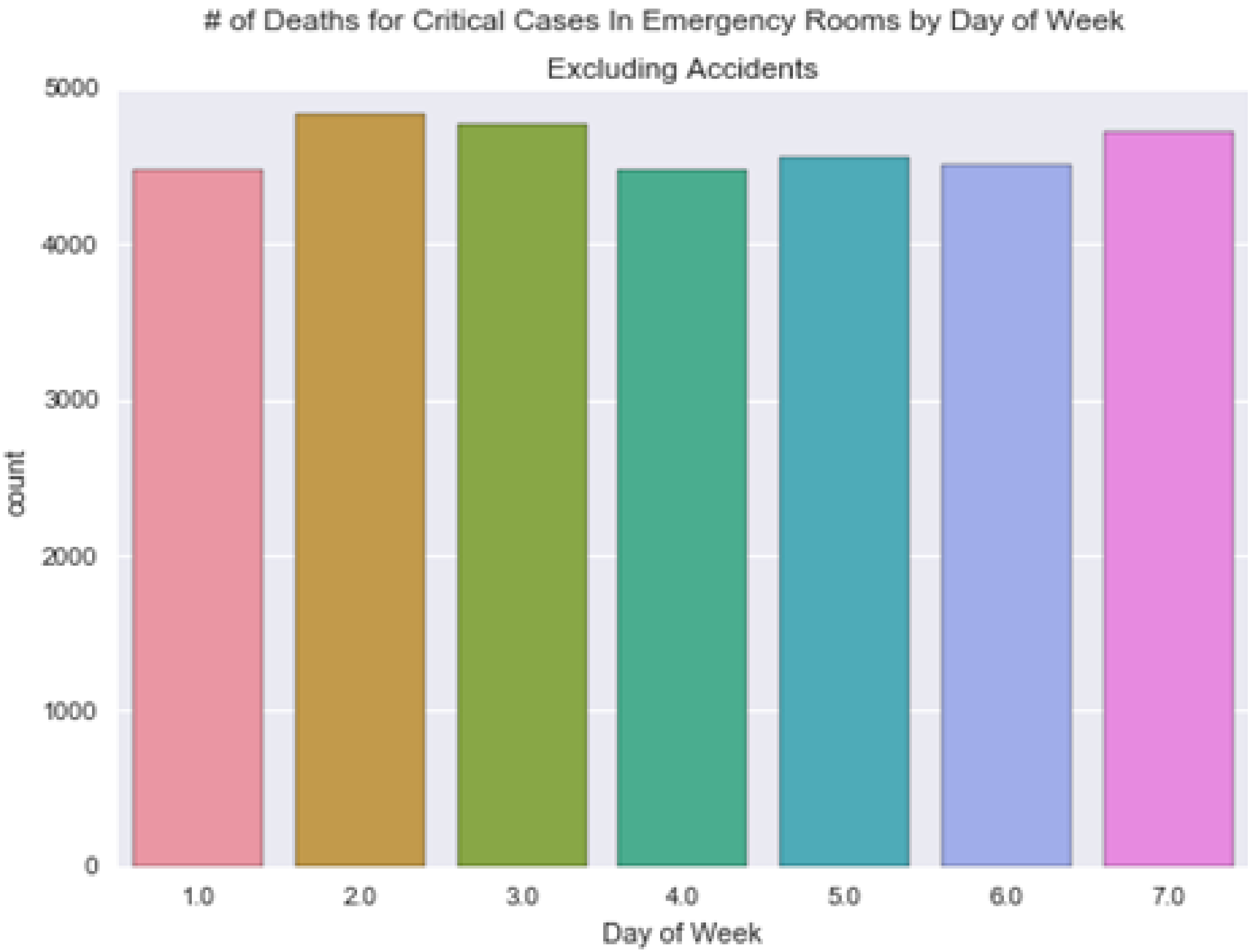


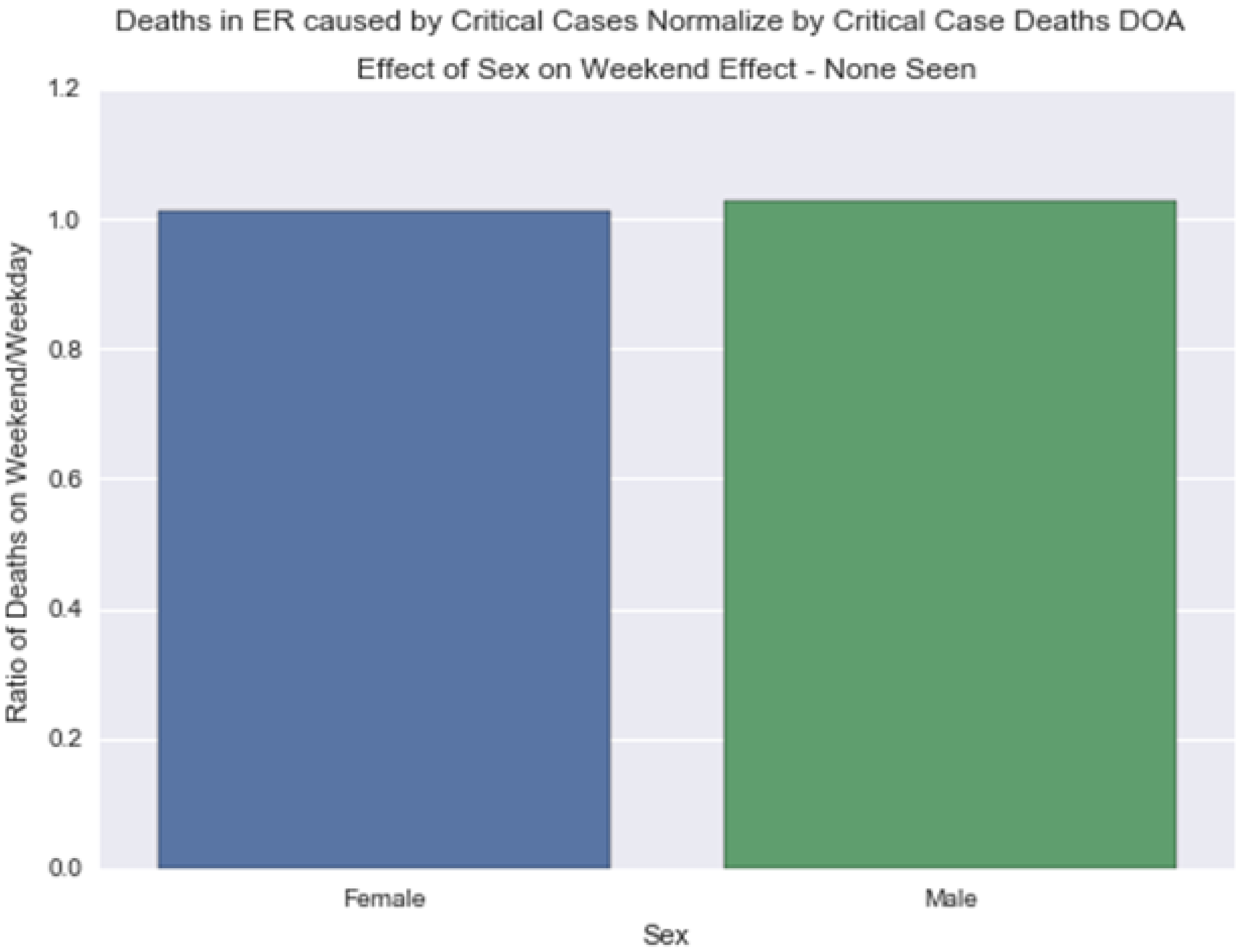
Chart 1: Univariate Example: The distribution appears uniform suggesting that there is no mortality issue in the US medical system supplying adequate medical coverage on the weekends. Sunday = 1. The weekend is considered Saturday, Sunday, and Monday.

We can refine this information by reducing the reducing the day of the week variable to 2 categories from the original 7. We will call the new variable Weekend which combines and codes Saturday, Sunday, and Monday as 1 and the rest of the weekdays as 0. Unfortunately, even though there are only two categories they are not of equal size so that the suggested method of taking an average will over this variable will not produce the percent probability of a death being on a weekend which could be used as y variable in a bivariate plot. To deal with this issue the probability of Weekend being 1 and being 0 is first calculated. These probability values are then normalized by the number of days in each category.   Now on equal footing if the normalized probability of 1 is divided by the probability of 0, then we get a value that is the ratio of the death rate on the weekend to the weekdays. The expected value is exactly 1 if there were no weekend mortality issue. We can combine this variable with other variables such as sex to see if there is a cross term with the Sex variable.

The bivariate bar chart example below shows the ratio of the death rate per day categorized by sex. The values are very close to 1, specifically 1.013 for Females, and 1.029 for Males. We can do error analysis using counting statistics on the original data and use error propagation to obtain error bars for these values. The standard deviation of these values is estimated to be 0.015. Both values are then within 2 standard deviations from the expected value of 1, and within 1 standard deviation of each other. Therefore, one can conclude that there is no weekend effect on mortality in US medical facilities answering the principle part of the first research question, and additionally that there is no significant interaction with sex. Below is the additional code that was required to create the graph. The error analysis code is not shown here.

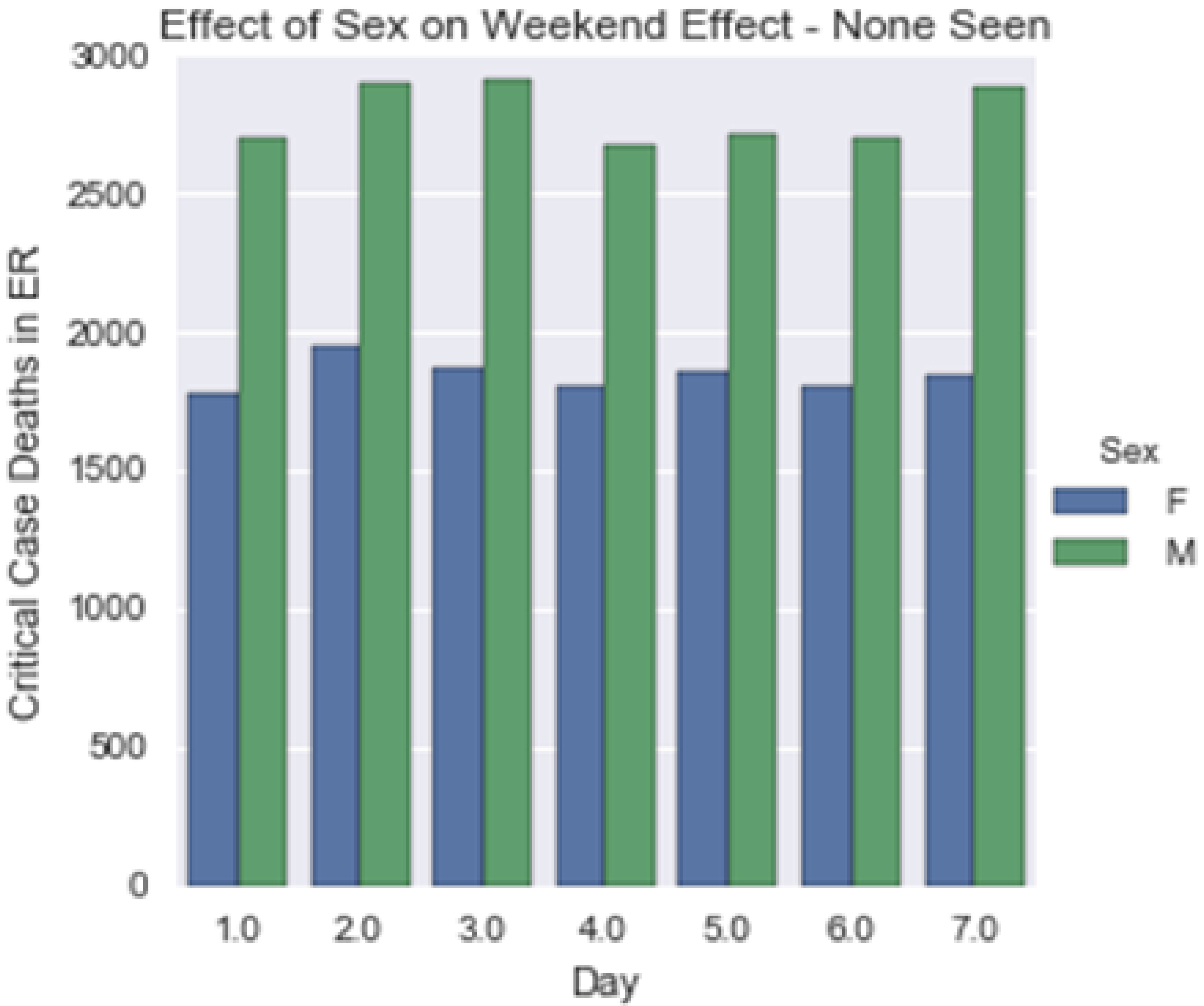
```
data['Weekend’] = ((data[Day]==1) | (data[Day]==2) | (data[Day]==7)).astype('int’)

print ('Percentages of Deaths in Emergency Rooms by by Weekend: Sat+Sun+Mon’)

p111 = 100 * subCriticalER.groupby([Weekend,Sex]).size() / len(subCriticalER)

dn=numpy.asarray(p111/100, dtype=numpy.float)

FractiononWeekend = [(4/3)*dn[2]/dn[0],(4/3)*dn[3]/dn[1]]

FractonWeekend=numpy.asarray(FractiononWeekend, dtype=numpy.float)

MySex=[“Female”, “Male”]
```

```
seaborn.barplot(x=MySex, y = FractonWeekend)

plt.xlabel('Sex’)

plt.ylabel('Ratio of Deaths on Weekend/Weekday’)

plt.title(“Effect of Sex on Weekend Effect - None Seen”)

plt.suptitle(“Deaths in ER caused by Critical Cases Normalize by Critical Case Deaths DOA”)

seaborn.plt.show()
```



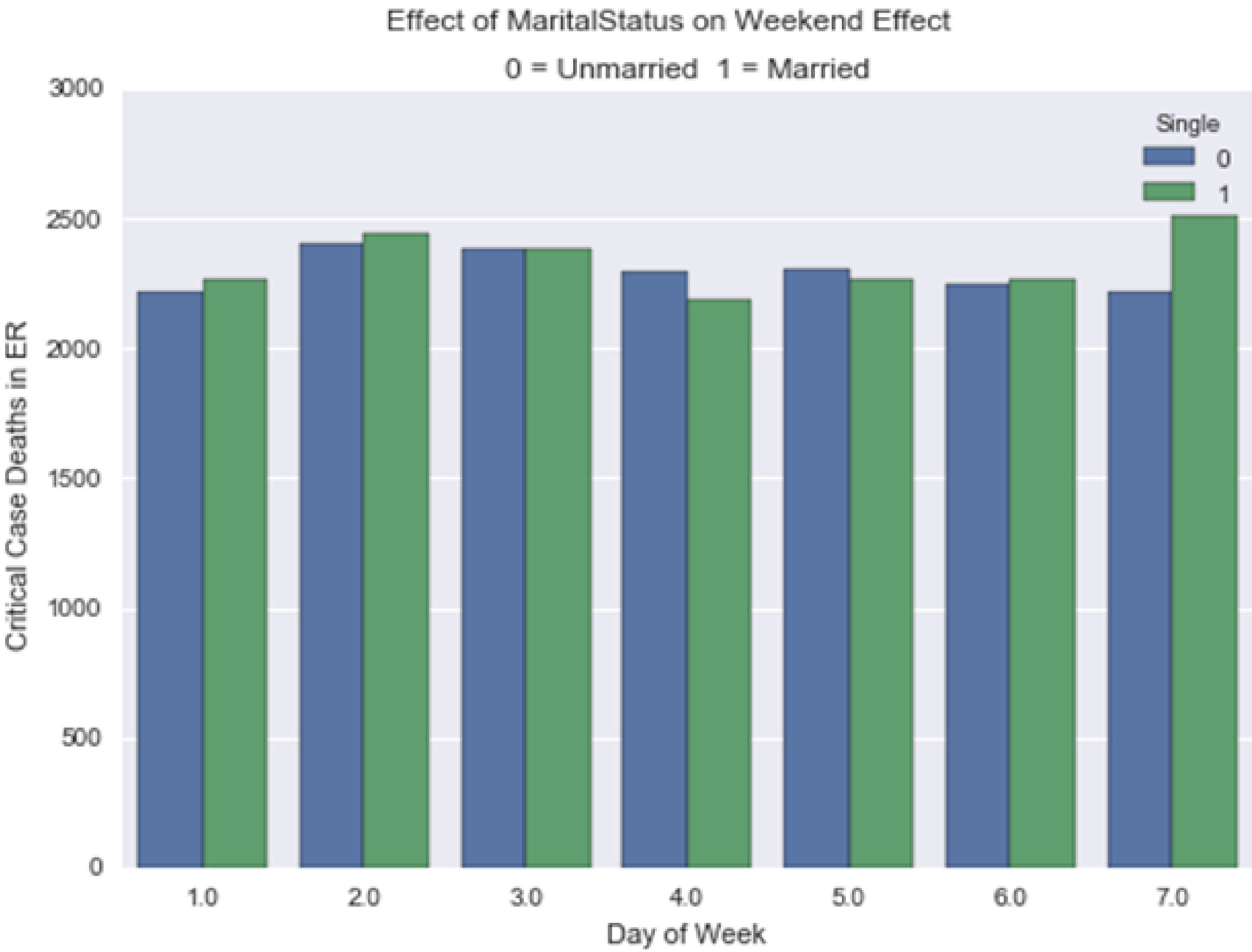
A different style of bivariate graph for two categorical variables is used to show the relationships of cross terms between “day of the week” and the variables sex. marital status, race, and age.

Replotting the Sex variable using the second style of bivariate graphs shows not only that there is no weekend effect based on sex but that there are a lot fewer deaths of females that males in the ER due to critical medical cases such as acute heart attack, and strokes.

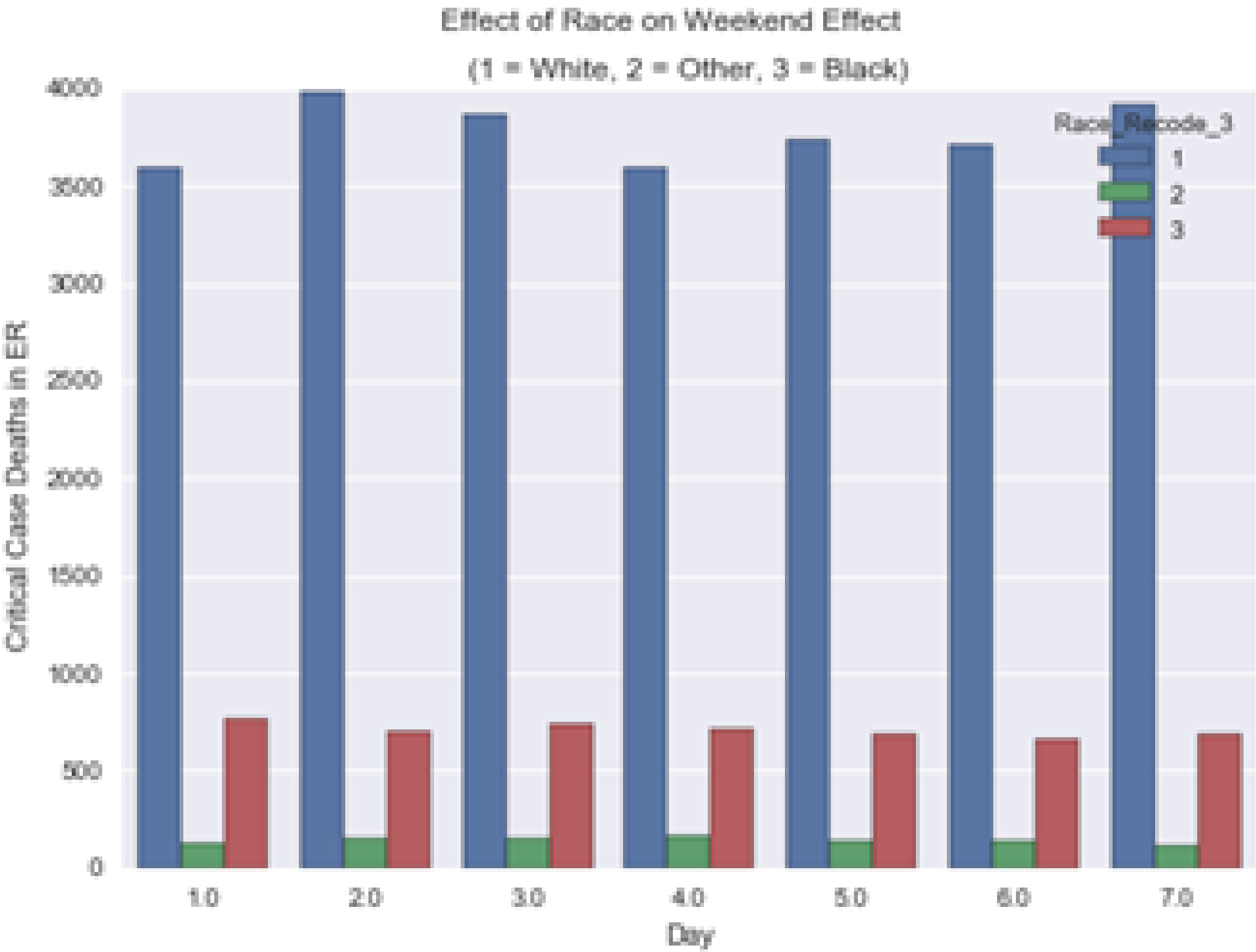


Effect of Sex on Weekend Effect - None Seen
Critical Case Deaths in ER
3000
2500
2000
1500
1000
500
0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
Day
Sex
F
M

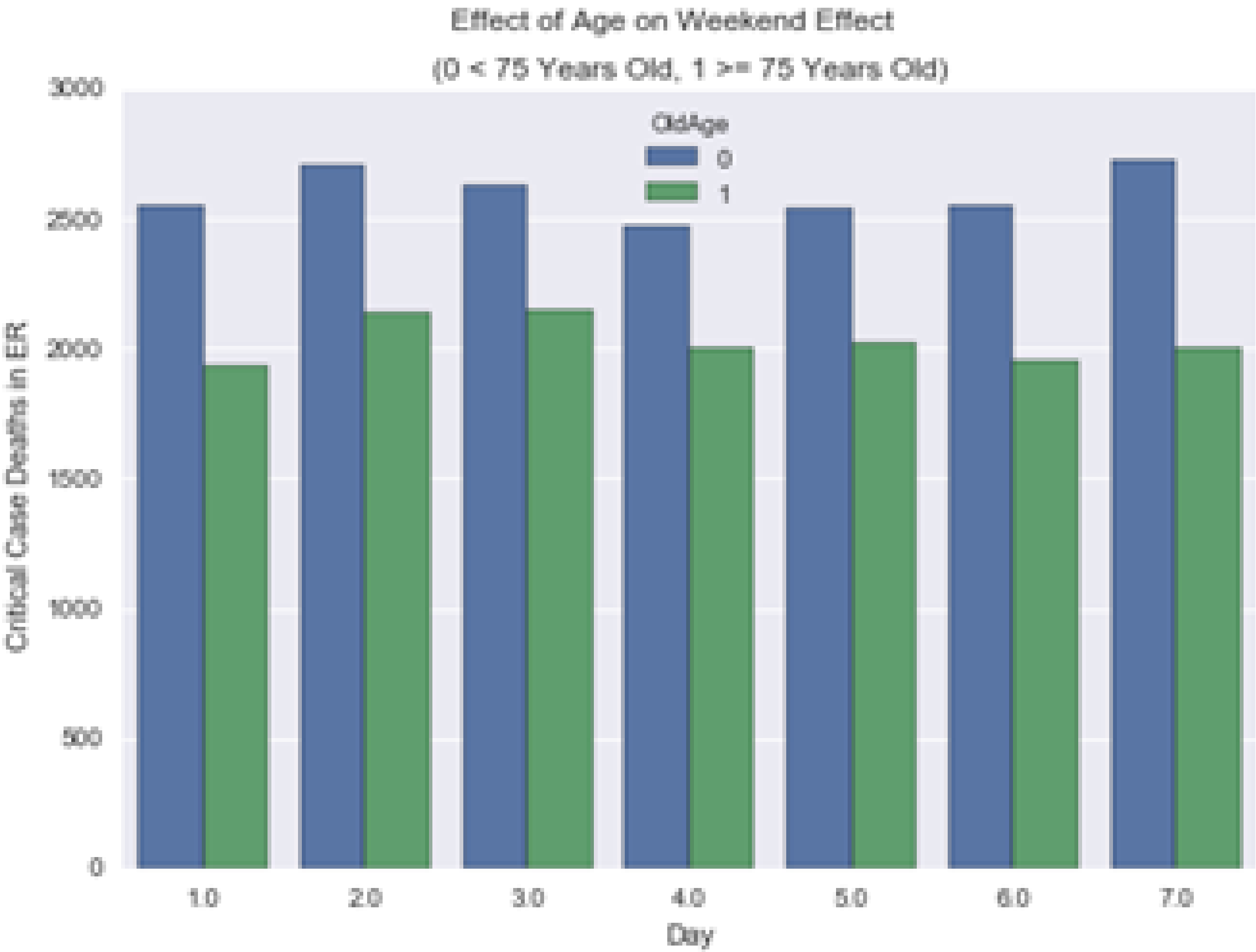
The chart showing the cross term with Marital status shows surprising result. There is a significant greater mortality of married people than single people on Sundays. This is very strange and should be questioned and investigated further to see for instance if this holds in analyzing this data for years other than 2013. But we could speculate that married people (or older married people) engage in a specific activity (with some risk of heart attack or stroke) on Saturdays that single people do not. Note that the Marital status variable combined single, divorced and widowed into the single category of Unmarried.



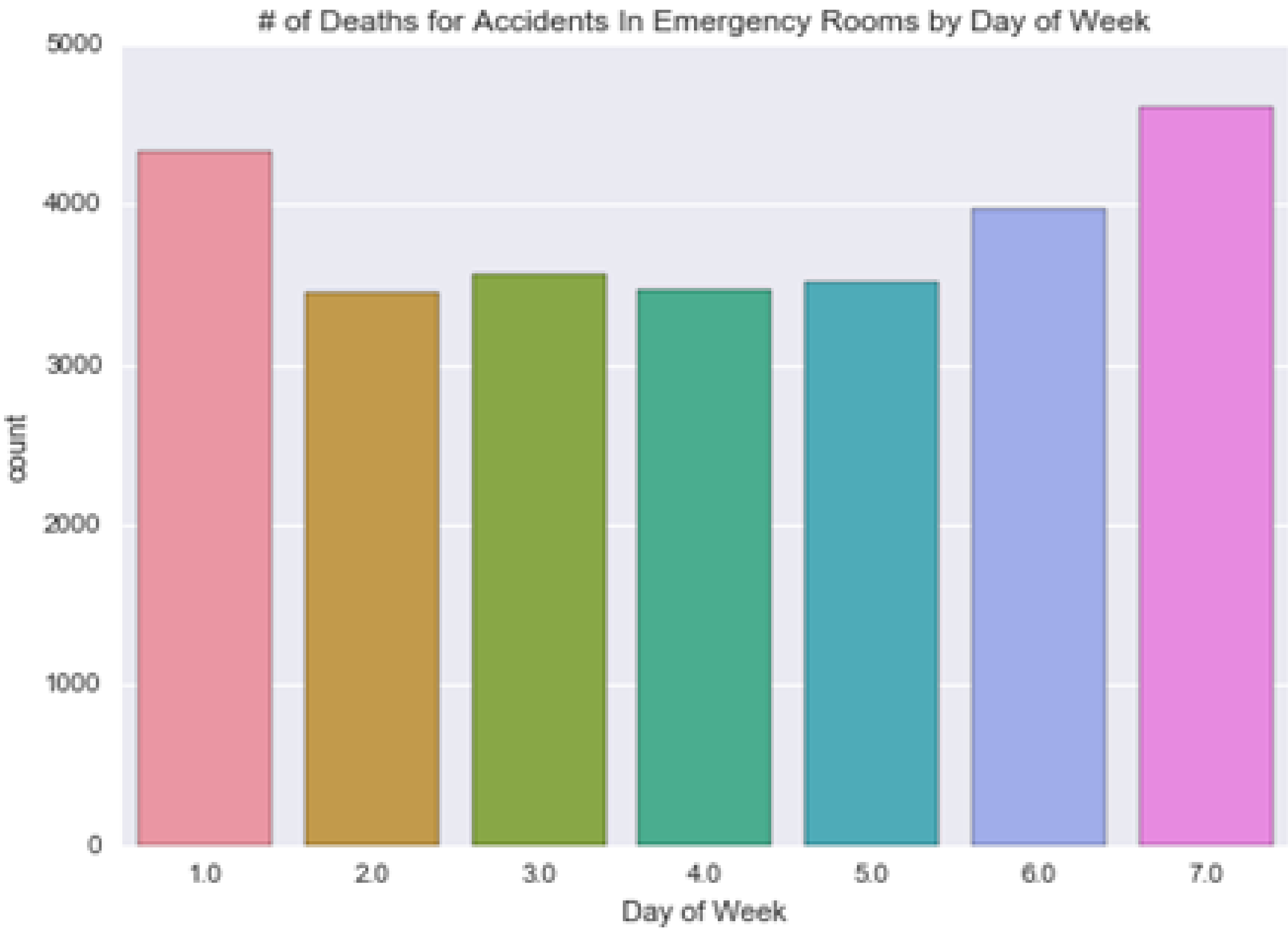
In the following two similar charts for race and age no interesting observations are seen confirming the null hypothesis that race and age do not interact with the mortality rate analyzed by “day of the week”. Note that in the analysis of age people the data was recoded into two categories, less than 75 or greater than or equal to 75. On the assumption that perhaps people greater than 75 years old would be more fragile and represent a more sensitive measure of a potential weekend effect.



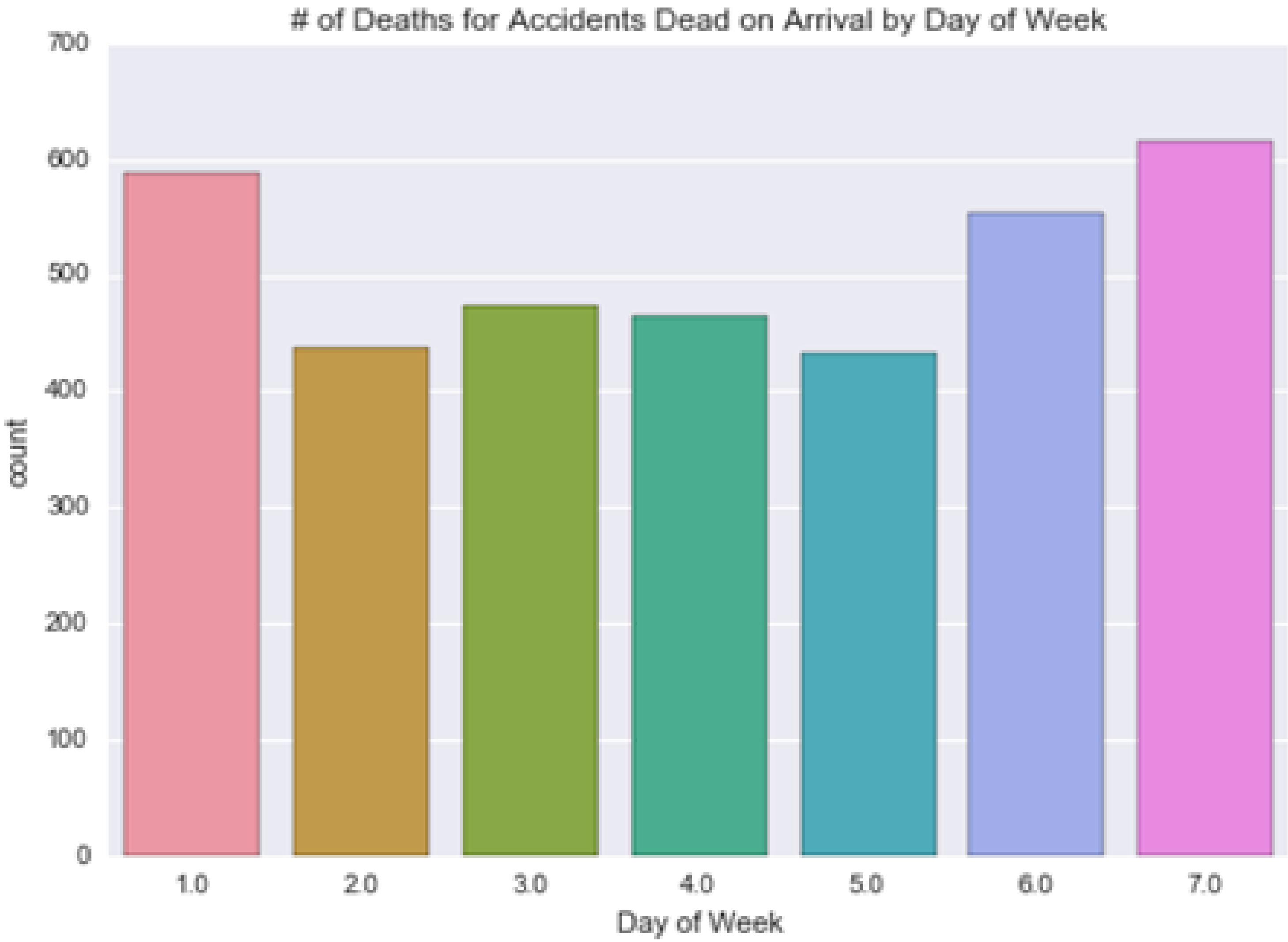
Effect of Race on Weekend Effect
(1 = White, 2 = Other, 3 = Black)
Race_Recode_3
1
2
3
Critical Case Deaths in ER
0
500
1000
1500
2000
2500
3000
3500
4000
1.0
2.0
3.0
4.0
5.0
6.0
7.0
Day



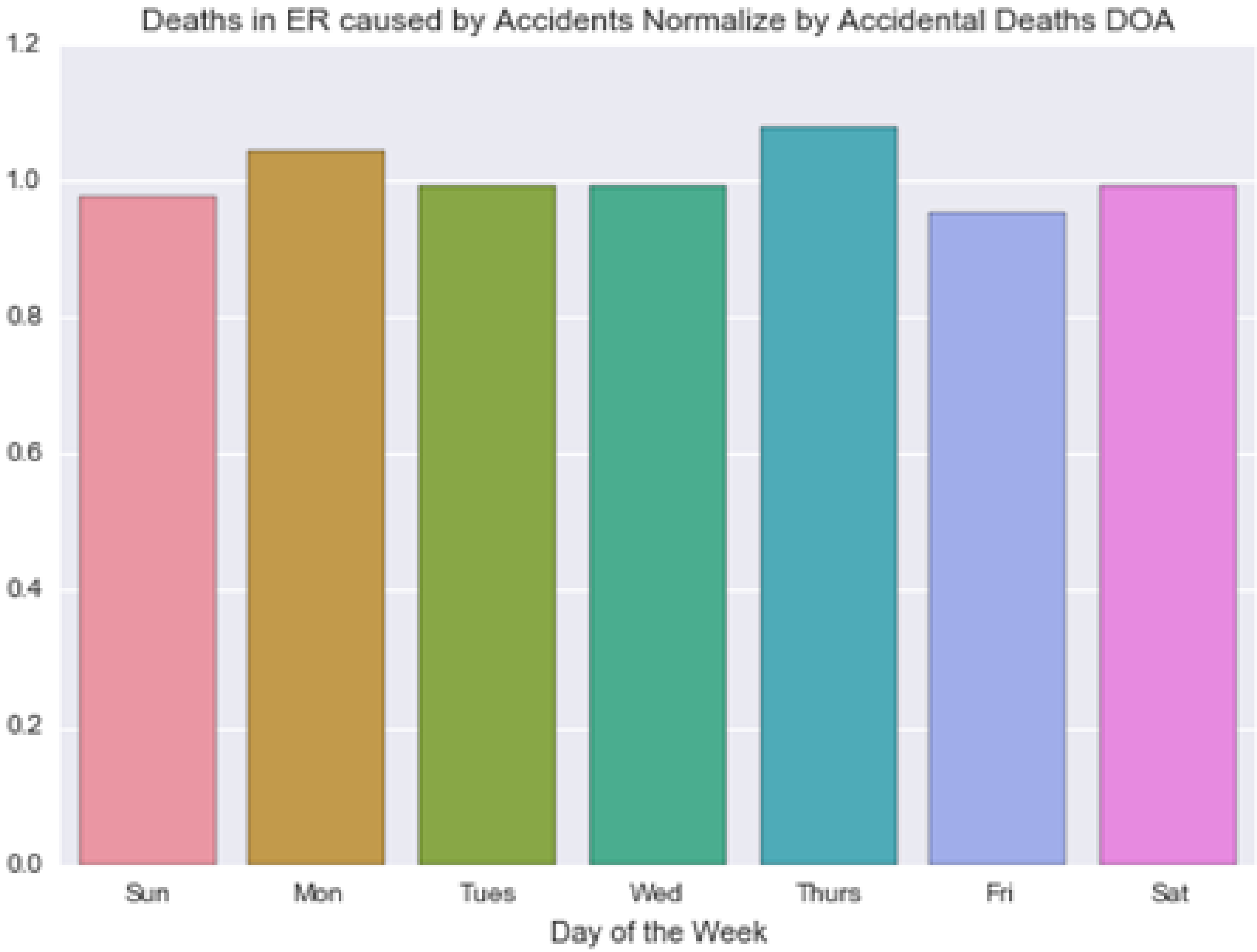
The second related research question will now be addressed. Are deaths in medical facilities due to accidental injuries (such as traffic accidents) also subject to a weekend effect? The next chart appears to show a clear increase in mortality in Emergency Rooms on the weekends. Actually Friday, Saturday, and Sunday. This is suggestive of the possibility that the frequency of accidents on these days is the important criterion here, rather than a failure of the medical care. To determine this, we will need to normalize this data by the frequency of accidents occurring. Fortunately hidden in this data set is the ability to do just that.



We can obtain the counts for deaths due to accidents with the location variable set to “dead on arrival”. This will result in counts per day that are proportional to the frequency of accidents per day and independent of the effectiveness of care in medical facilities. Below is a chart showing the daily counts of accidents that are dead on arrival. Notice that the pattern by day is similar to the chart above.



When the accidental death rate per day in the Emergency Rooms are normalized by the accidental death rates counted as dead on arrival is charted below we see that there is no weekend effect of mortality seen in the Emergency Room answering the second research question. This also confirmed the importance of removing the accidental deaths when we approached the first research question discussed above.



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May 14th, 2016

MORE YOU MIGHT LIKE

Data Management and Visualization Assignment 3 - Lewittes: Data Management of Variables relevant to Weekend Effect on Mortality in US Hospitals.

The CDC 2013 data base on US mortality has 2,601,452 observations (deaths recorded in 2013) and 75 variables. The goal is to analyze this data set to determine if there is a problem with critical medical care on the weekends in the US as there is in the United Kingdom. This assignment is intended to subset the data set, fix

Data Management and Visualization Assignment 2 - Lewittes: Univariate Analysis of Variables relevant to Weekend Effect on Mortality in US Hospitals.

The CDC 2013 data base on US mortality has 2,601,452 observations and 75 variables. Of these 75 variables there are about 9 variables relevant to the study of whether there are excessive numbers of deaths on weekends and perhaps Mondays in our

Data Management and Visualization Assignment 1- Getting Your Research Started Weekend Effect on Mortality in US Hospitals.

Motivation: Both I and my wife have had close encounters with the US medical system recently. It seemed obvious from our experiences that the medical care on the weekends was weak. Weekend care seemed like a holding pattern until the resources became available on Monday.

Data set chosen: I have selected the 2013 mortality data base distributed by the CDC.(Centers for disease control) problems with any of these variables, and create auxiliary variables that will enable the answering of the research question.

There are 10 potentially relevant variables out of the 75 variables in this data set. Since it was taking about 5 minutes every time the data set it was read into the program it was decided to write code that would subset just the relevant variables and save them to the disk in a csv file. As a result, now the reading in process takes seconds rather than minutes. Here is the code used to create the smaller, more tractable, csv file.

```
mydata = data[[Day, Place, Sex, Race, Age, Education, Month, Cause, Married]]

#Save to csv file

mydata.to_csv('VS13MORTshort.csv')
```

The Month variable according to the codebook was to be coded as 1 to 12. But in fact only about 1/3rd of the data was coded 1 to 12 the rest was coded 101 to 112. The values of 101 to 112 medical system. I have performed univariate analysis on these 9 variables and also subdivided the data set based on place of death values and reanalyzed by the day of the week. The most important four analyses are displayed just below. Following this is displayed the 237 lines of code which includes extensive comments, and following that the output of the code in its entirety.

The first variable analysed is day of the week for all deaths in all locations. Each day of the week had about 370,000 deaths, or 14.2%+/-0.2%. In this there does not seem to be more deaths on the weekends than during the rest of the week. The second critical variable to this study is the place of death. For example Hospital inpatient, ER outpatient, dead on arrival, home, etc. We have subdivided the data set by the "place of death" variable and analyzed several of the subsets by "day of the week" to look for a weekend effect for deaths in different locations. The effect we saw for hospital inpatients was actually a decrease in

Research Question : Is there a dependence on the mortality rate in the United States on the day of the week? Specifically my **hypothesis** is that there a higher mortality rate on the Weekends or perhaps Monday that may be due to the reduced level of medical care available on the weekends. To elucidate the dependence of mortality on the day of the week we will need to identify that the place of death was within a hospital or medical facility, and there may be important cross terms of age, sex, race, marital status, and cause of death.

Second Related Research Question : Are deaths in hospitals due to accidental injuries (such as traffic accidents) also subject to a weekend effect? This is made more challenging as the number of accidental injuries themselves may be reasonably be assumed to vary between weekdays and weekends. So these deaths due to accidental injuries will be need to be excluded from the initial research question. However we may be able to were recoded to 1 to 12. Here is the code that accomplished that. Followed by an updated histogram and frequency table of deaths by month. The frequency data shows a spike of deaths in January of about 10% where the rest of the year is closer to 8% per month on average. In point of fact a bar chart (not shown this week) makes it clear that there January is not an individual spike but part of a yearly trend were more people die of influenza, pneumonia, heart attacks (shoveling snow) etc. in the winter time than in the summer.

```
#The variable Month has been coded both 1 to 12 and 1 to 101 to 112

#The following code combines these in a new variable MonthFixed

data[MonthFixed]= ((data[Month]>=100)*(-100)+data[Month]).astype('int')

c14 = data.groupby(MonthFixed, sort = True).size()

print ('# of Deaths by Month')
```

the death rate on the weekends (perhaps due to the reduction in the number of surgeries performed on weekends), but we did see a positive weekend effect in the Emergency Room location were there was an increase in deaths by about .7% comparing the average of Saturday, Sunday and Monday to the rest of the week. This represents about 175 excess deaths per weekend day during the year. These two subdivided analysis are shown in our summery output just below. Both counts and percentages are shown for all univariate analyses performed.

Yet to be seen is whether the weekend differences noted so far are statistically significant. Furthermore there may be other causes for the effects seen rather than lack of staffing. By further subdivision of the data based on cause of death, for example heart attack and age or fragility of the patient, it is hoped to see into this weekend effect with higher fidelity.

generate a normalization factor to remove the day of accidental injury bias by comparing the number of dead on arrival per day on the weekends, to the dead on arrival per day on the weekdays. The **hypothesis of the second research question** is that there is a higher mortality rate on the weekends due to reduced medical care available for accidental injuries after normalization.

Literature Review

Search terms used for literature review were “higher mortality rate on weekends” and “weekend effect”

Summary : Almost all of the references found pertained to the United Kingdom whose health system differs substantially from that in the United States. From the literature review it is seen that in the United Kingdom that there may be as many as 11,000 extra deaths (15%) per year when patients are admitted on a weekend [17]. This effect has been studied for specific medical conditions such as heart attacks[1] and ruptured aortic

```
print ('(1 = January, 12 = December)')

print ("Deaths by month data fixed")

print(c14)

print ()

print ('Percentages of Deaths by
Month')

print ('(1 = January, 12 = December)')

print ("Deaths by month data fixed")

p14 = 100 *
 data.groupby(MonthFixed).size() /
len(data)

print (round(p14,2))

print ()
```

# of Deaths by Month

(1 = January, 12 = December)

Deaths by month data fixed

MonthFixed

1 261504

2 218003

4 Important Univariate Analyses for this Study , The code is below.

# of Deaths by Day of Week: Sunday = 1

1 366342

2 369826

3 376152

4 369304

5 369270

6 375286

7 375141

9 131

Name: DOW_of_Death, dtype: int64

Percentages of Deaths by Day of Week: Sunday = 1

1 14.08

aneurysms[3]. As serious as this sounds it is a political issue as to how to address this problem. There is no great desire on the part of physicians to work weekends. The only low cost method of addressing this problem would be to shift resources from the weekdays to the weekends which would weaken the weekday care. The current practice of forcing junior doctors to work longer hours has been met with protests.[13,14] Only one reference was found that pertained to the USA which focused on acute coronary syndrome over the last decade[18].

References

1.Kostis W.J., Demissie K., Marcella S.W., Shao Y.-H., Wilson A.C., Moreyra A.E. (2007). "Weekend versus weekday admission and mortality from myocardial infarction". *N Engl J Med* **356**: 1099–1109. doi:10.1056/nejmoa063355.

2. Groves EM, Khoshchehreh M, Le C, Malik S (2014). "Effects of weekend admission on the outcomes and

3 233231

4 214119

5 210398

6 200418

7 204931

8 204968

9 199120

10 212081

11 212188

12 230491

dtype: int64

Percentages of Deaths by Month

(1 = January, 12 = December)

Deaths by month data fixed

MonthFixed

1 10.05

2 8.38

3 8.97

2 14.22

3 14.46

4 14.20

5 14.19

6 14.43

7 14.42

9 0.01

Name: DOW_of_Death, dtype: float64

# of Deaths by Place

(1 = Hospital or Medical Center Inpatient

(2 = Hospital, Medical Center or ER - Outpatient)

(3 = Hospital or Medical Center- Dead on Arrival)

(4 = Decedent's home)

(5 = Hospice facility

management of ruptured aortic aneurysms". *J Vasc Surg.* **60**: 318–324. doi:10.1016/j.jvs.2014.02.052.

3.RCP Council (November 2010). "RCP Position Statement Care of Medical Patients Out of Hours" (PDF).

4. Association of Royal Medical Colleges (November 2013). "Seven Day Consultant Present Care Implementation".

5.Flynn, Paul (2013-02-21). "Should the NHS work at weekends as it does in the week? No". *The BMJ* **346**: f622. doi:10.1136/bmj.f622. ISSN 1756-1833.PMID 23430215.

6.Freemantle, Nick; Ray, Daniel; McNulty, David; Rosser, David; Bennett, Simon; Keogh, Bruce E.; Pagano, Domenico (2015-09-05)."Increased mortality associated with weekend hospital admission: a case for expanded seven day services?". *The BMJ* **351**: h4596. doi:10.1136/bmj.h4596. ISSN 1756-1833. PMID 26342923.

4 8.23

5 8.09

6 7.70

7 7.88

8 7.88

9 7.65

10 8.15

11 8.16

12 8.86

dtype: float64

It was found that the number of empty cells in the Education variable data accounted for most of the frequency distribution results. Subsetting the data set on the Education variable has been used to remove the empty and code 99 (no data) values. Here is the code and the improved frequency response. Note that the missing and code 99 values have been eliminated and that 41.8% of the population who died had had a high school education and another ~25% of the population had at

(6 = Nursing home/long term care)

(7 = Other)

(9 = Place of death unknown)

1 795545

2 174722

3 14670

4 752406

5 159514

6 521912

7 181042

9 1641

Name: Place_Of_Death, dtype: int64

Percentages of Deaths by Place

(1 = Hospital or Medical Center Inpatient

(2 = Hospital, Medical Center or ER - Outpatient)

7. "'The weekend effect' means 11,000 extra NHS deaths a year". Retrieved 2015-10-07.

8. Weaver, Matthew; Campbell, Denis. "The Hunt file: doctors' dossier of patients 'put at risk' by health secretary". *the Guardian*. Retrieved 2015-10-07.

9. "Re: Increased mortality associated with weekend hospital admission: a case for expanded seven day services?". *The BMJ*. 2015-10-12.

10. "Contract reform for consultants and doctors and dentists in training – supporting healthcare services seven days a week - Publications - GOV.UK". *www.gov.uk*. Retrieved 2015-10-07.

11. Choices, NHS. "My NHS - NHS Choices". *www.nhs.uk*. Retrieved 2015-10-07.

12. "BMA - DDRB Recommendations - Analysis For Juniors | British Medical Association". *bma.org.uk*. Retrieved 2015-10-07.

least some college education. This is consistent with the education level of 25 year olds in the US in 1960.

```
# Convert Education to numeric

data[Education]=data[Education].conve
rt_objects(convert_numeric=True)

subEducation = (data[(data[Education]
<= 20)])

print ('# of Deaths by Years of
Education ')

print ('(0 = None,17= 5 Years or More of
College, 99 = Not Stated')

c8 =
subEducation.groupby(Education).size(
)

print (c8)

print ()

print ('Percentages of Deaths by Years
of Education')

print ('(0 = None,17= 5 Years or More of
College, 99 = Not Stated')
```

(3 = Hospital or Medical Center- Dead on Arrival)

(4 = Decedent's home)

(5 = Hospice facility

(6 = Nursing home/long term care)

(7 = Other)

(9 = Place of death unknown)

```
1    30.58

2     6.72

3     0.56

4    28.92

5     6.13

6    20.06

7     6.96

9     0.06

Name:  Place_Of_Death, dtype: float64
```


13. "Junior Doctors descend on Westminster in protest at 'unsafe' working contracts". *Express.co.uk*. Retrieved 2015-10-07.

14. "Junior doctors plan protest against "unfair and unsafe" contract shake-up facing colleagues in England". *Herald Scotland*. Retrieved 2015-10-07.

15. "Consultants must work weekends to save lives, Jeremy Hunt says". Retrieved 2015-10-07.

16. "Petition for MPs to debate a vote of no confidence in Jeremy Hunt hits 100,000 in 24 hours". *The Independent*. Retrieved 2015-10-07\

17. Weekend effect on mortality seen in UK reported in the Guardian Magazine. http://www.theguardian.com/society/2015/sep/05/bruce-keogh-hospital-patients-risk-death-admitted-weekends.

18. Khoshchehreh M, Groves EM, Tehrani D3, Amin A, Patel PM, Malik S. (2016). "Changes in mortality on weekend versus weekday admissions for Acute Coronary Syndrome in the

```
p8 = 100 * subEducation.groupby(Education).size() / len(subEducation)

print (round(p8,2))

print ()
```

Percentages of Deaths by Years of Education

(0 = None,17= 5 Years or More of College, 99 = Not Stated

Education

0.000000   1.550000

1.000000   0.090000

2.000000   0.180000

3.000000   0.610000

4.000000   0.550000

5.000000   0.720000

6.000000   2.050000

7.000000   1.690000

8.000000   5.640000

9.000000   3.140000

# of Deaths in Hospitals by Day of Week: Sunday = 1

DOW_of_Death

1   108923

2   113558

3   117877

4   114480

5   114318

6   115459

7   110925

9   5

dtype: int64

Percentages of Deaths in Hospitals by Day of Week: Sunday = 1

DOW_of_Death

1   13.69

2   14.27

3   14.82

United States over the past decade url =”. *Int J Cardiol* **210**: 164–172. doi:10.1016/j.ijcard.2016.02.087.

Code Book

Day of Week of Death

1 … Sunday

2 … Monday

3 … Tuesday

4 … Wednesday

5 … Thursday

6 … Friday

7 … Saturday

9 … Unknown

Place of Death and Decedent’s Status

1 … Hospital, clinic or Medical Center

- Inpatient

10.000000   4.800000

11.000000   4.570000

12.000000   41.810000

13.000000   3.880000

14.000000   10.290000

15.000000   1.730000

16.000000   9.800000

17.000000   6.900000

In the variable used for the cause of death there are 135 categories. To elucidate whether there is a weekend effect for deaths in the hospital or emergency rooms in the US it was felt that if there were an effect it would be amplified by only including people who died from a cause that would have required immediate and intense medical intervention. So a variable was created where its value was 1 for causes that would have had the patient in critical condition as they entered the medical system, and 0 for other causes of

4   14.39

5   14.37

6   14.51

7   13.94

9   0.00

dtype: float64

# of Deaths in Emergency Rooms by Day of Week: Sunday = 1

DOW_of_Death

1   25298

2   25852

3   25114

4   24249

5   23817

6   24468

7   25923

2 … Hospital, Clinic or Medical Center

  - Outpatient or admitted to Emergency Room

3 … Hospital, Clinic or Medical Center

- Dead on Arrival

4 … Decedent’s home

5 … Hospice facility

6 … Nursing home/long term care

7 … Other

9 … Place of death unknown

Sex

M … Male

F … Female

Race Recode 3

1 … White

2 … Races other than White or Black

death. Causes of death such as acute heat attack, stroke, traffic accidents, gunshot victims etc. were coded in the “Sudden” variable as 1. A subset of a subset was selected based on location of death (ER or Hospital separately) and the Sudden variable. The code for these two sets of counts and frequencies is below followed by the tables generated.   Concentrating on the frequency data we can see that in the Emergency Rooms there may in fact be a measurable weekend effect. The average frequency of death /day on the weekend in the ER for critical cases is 15.3% where the average per day for weekdays is 13.9%. This same trend is not seen in the Hospital Environment. The weekend average in the Hospital is 13.9% where the week day rate of deaths is higher at 14.4%. It is speculated that the cause of this trend in the hospital is because procedures are scheduled for the weekdays. This is not the case in the ER environment. One concern is that the rate of accidents may be higher on the weekends that weekdays and this will need to be explored before a

9   1

dtype: int64

Percentages of Deaths in Emergency Rooms by Day of Week: Sunday = 1

DOW_of_Death

1   14.48

2   14.80

3   14.37

4   13.88

5   13.63

6   14.00

7   14.84

9   0.00

dtype: float64

Code

3 … Black

Age Recode 12

01 … Under 1 year (includes not stated infant ages)

02 … 1 - 4 years

03 … 5 - 14 years

04 … 15 - 24 years

05 … 25 - 34 years

06 … 35 - 44 years

07 … 45 - 54 years

08 … 55 - 64 years

09 … 65 - 74 years

10 … 75 - 84 years

11 … 85 years and over

12 … Age not stated

conclusion can be reached regarding the increased rate of deaths on the weekends in the Emergency Rooms.

```
#new Sudden variable

“““#The variable Sudden is set to one for Causes of death that require immediate

medical intervention to prevent death, such as heart attack, stroke,

meningitis, and accidents and homicides such as traffic accidents, and

discharge of fire arms etc.  ”“”

data['Sudden’] = ((data[Cause]==9) | (data[Cause]==10) |

              (data[Cause]==50) | (data[Cause]==59) |

              (data[Cause]==60) | (data[Cause]==66) |

              (data[Cause]==70) | (data[Cause]==73) |
```

```
# -*- coding: utf-8 -*-
“““
Spyder Editor
Mark Lewittes
Mortality study to determine if there is a weekend effect in the USA
medical system.
”“”
#import library functions
import pandas
import numpy
# any additional libraries would be imported here
#Read in data set
data =
pandas.read_csv(‘VS13MORT.csv’, low_memory=False)
print (“# of observations”)
print (len(data)) #number of observations (rows)
print (“# of variables”)
print (len(data.columns)) # number of variables (columns)
#print a list of the variable names
print (“variable names”)
print (data.columns)
print()
# main program starts here
```

Education (1989 revision)

00 … No formal education

01-08 … Years of elementary school

09 … 1 year of high school

10 … 2 years of high school

11 … 3 years of high school

12 … 4 years of high school

13 … 1 year of college

14 … 2 years of college

15 … 3 years of college

16 … 4 years of college

17 … 5 or more years of college

99 … Not stated

Month of Death

01 … January

```
            (data[Cause]==80) |
(data[Cause]==105) |

            (data[Cause]==106) |
(data[Cause]==107) |

            ((data[Cause]>=113) &
(data[Cause]<=129)) |

            (data[Cause]==132) |
(data[Cause]==133)

            ).astype('int')

c5 = data.groupby("Sudden").size()

print ("Sudden Deaths")

print (c5)

subHospital1 = data[(data[Place] == 1)]

subER1 =      data[(data[Place] == 2)]

subCriticalER1 =
subER1[(subER1[Sudden] == 1)]

subNotCriticalER1 =
subER1[(subER1[Sudden] == 0)]

print ('# of Deaths for Critical Cases in
Emergency Rooms by Day of Week:
Sunday = 1')
```

```
#Change variable names into words I
can remember
Day = ' DOW_of_Death'
Place = ' Place_Of_Death'
Sex = ' Sex'
Race = ' Race_Recode_3'
Age = ' Age_Recode_12'
Education =' Education'
Month = ' Month_Of_Death'
Cause = ' Cause_Recode_113'
Married = ' Marital_Status'

#setting variables you will be working
with to numeric
#The Education variable has some bad
data and cannot be converted to
numeric
data[Day] =
pandas.to_numeric(data[Day])
data[Place] =
pandas.to_numeric(data[Place])
data[Race] =
pandas.to_numeric(data[Race])
data[Age] =
pandas.to_numeric(data[Age])
#Education data is already numeric so
it cannot be converted to numeric
#sub2[Education] =
pandas.to_numeric(sub2[Education])
```

02 … February

03 … March

04 … April

05 … May

06 … June

07 … July

08 … August

09 … September

10 … October

11 … November

12 … December

Tenth Revision 39 Selected Causes of Death Adapted for use by DVS

113 Cause Recode

```
c11 =
subCriticalER.groupby(Day).size()

print (c11)

print ()

print ('Percentages of Deaths for
Critical Cases in Emergency Rooms by
Day of Week: Sunday = 1')

p11 = 100 *
 subCriticalER.groupby(Day).size() /
len(subCriticalER)

print (round(p11,2))

print ()

subCriticalHospital1 =
subHospital[(subHospital[Sudden] ==
1)]

subCriticalHospital =
subCriticalHospital1.copy()

#groupby command ordered the output
more logically than .value_counts

print ('# of Deaths for Critical Cases in
Hospitals by Day of Week: Sunday =
1')
```

```
data[Month] =
pandas.to_numeric(data[Month])
data[Cause] =
pandas.to_numeric(data[Cause])

#counts and percentages (i.e.
frequency distributions) for each
variable

print ('# of Deaths by Day of Week:
Sunday = 1')
c1 =
data[Day].value_counts(sort=False)
print (c1)
print ()

print ('Percentages of Deaths by Day of
Week: Sunday = 1')
p1 = 100 *
data[Day].value_counts(sort=False,
normalize=True)
print (round(p1,2))
print ()

print ('# of Deaths by Race')
print ('(1 = White, 2 = Other, 4 =
Black)')
c2 =
data[Race].value_counts(sort=False)
print (c2)
print ()
```

A recode of the ICD cause code into 113 groups for NCHS publications. Further back in this document is a complete list of recodes and the causes included.

001-135 … Code range (not inclusive)

ST: 1 = Subtotal Limited: Sex: 1 = Males; 2 = Females Age: 1 = 5 and over; 2 = 10-54; 3 = 28 days and over; 4 = Under 1 year; 5 = 1-4 years; 6 = 1 year and over; 7 = 10 years and over ***** Cause Subtotals are not identified in this file ***** 113 S Limited Recode T Sex Age Cause Title and ICD-10 Codes Included

001 Salmonella infections (A01-A02)

002 Shigellosis and amebiasis (A03,A06)

003 Certain other intestinal infections (A04,A07-A09)

004 1 Tuberculosis (A16-A19)

```
c11 =
subCriticalHospital.groupby(Day).size()

print (c11)

print ()

print ('Percentages of Deaths for
Critical Cases in Hospitals by Day of
Week: Sunday = 1')

p11 = 100 *
 subCriticalHospital.groupby(Day).size(
) / len(subCriticalHospital)

print (round(p11,2))

print ()
```

# of Deaths for Critical Cases in Emergency Rooms by Day of Week: Sunday = 1

DOW_of_Death

1.000000   8812

2.000000   8295

3.000000   8327

4.000000   7952

```
print ('Percentages of Deaths by Race')
print ('(1 = White, 2 = Other, 4 =
Black)')
p2 = 100 *
data[Race].value_counts(sort=False,
normalize=True)
print (round(p2,2))
print ()

print ('# of Deaths by Age Catagory')
print ('(1 = Under 1, 8 = 55 to 64, 11 =
Over 85)')
c3 =
data[Age].value_counts(sort=False)
print (c3)
print ()

print ('Percentages of Deaths by Age
Catagory')
print ('(1 = Under 1, 8 = 55 to 64, 11 =
Over 85)')
p3 = 100 *
data[Age].value_counts(sort=False,
normalize=True)
print (round(p3,2))
print ()

print ('# of Deaths by Marital Status')
print ('(U = unknown , M = married, D =
divorsed, S = single, W = widowed)')
```

005 Respiratory tuberculosis (A16)

006 Other tuberculosis (A17-A19)

007 Whooping cough (A37)

008 Scarlet fever and erysipelas (A38,A46)

009 Meningococcal infection (A39)

010 3 Septicemia (A40-A41)

011 Syphilis (A50-A53)

012 Acute poliomyelitis (A80)

013 Arthropod-borne viral encephalitis (A83-A84,A85.2)

014 Measles (B05)

015 Viral hepatitis (B15-B19)

016 Human immunodeficiency virus (HIV) disease (B20-B24)

017 Malaria (B50-B54)

018 Other and unspecified infectious and parasitic diseases and their sequelae (A00,A05,A20-A36,A42-

5.000000 8086

6.000000 8487

7.000000 9331

dtype: int64

Percentages of Deaths for Critical Cases in Emergency Rooms by Day of Week: Sunday = 1

DOW_of_Death

1.000000 14.860000

2.000000 13.990000

3.000000 14.040000

4.000000 13.410000

5.000000 13.640000

6.000000 14.310000

7.000000 15.740000

dtype: float64

```
c4 =
data[Married].value_counts(sort=False)
print (c4)
print ()

print ('Percentages of Deaths by Marital
Status’)
print (’(U = unknown , M = married, D =
divorsed, S = single, W = widowed)’)
p4 = 100 *
data[Married].value_counts(sort=False,
normalize=True)
print (round(p4,2))
print ()

print (’# of Deaths by Sexual Identity’)
print (’(M = Male, F = Female’)
c5 =
data[Sex].value_counts(sort=False)
print (c5)
print ()

print ('Percentages of Deaths by
Sexual Identy’)
print (’(M = Male, F = Female’)
p5 = 100 *
data[Sex].value_counts(sort=False,
normalize=True)
print (round(p5,2))
print ()
```

A44,A48-A49,A54-A79,A81-A82,A85.0-A85.1,A85.8, A86-B04,B06-B09,B25-B49,B55-B99)

019 1 Malignant neoplasms (C00-C97)

020 Malignant neoplasms of lip, oral cavity and pharynx (C00-C14)

021 Malignant neoplasm of esophagus (C15)

022 Malignant neoplasm of stomach (C16)

023 Malignant neoplasms of colon, rectum and anus (C18-C21)

024 Malignant neoplasms of liver and intrahepatic bile ducts (C22)

025 Malignant neoplasm of pancreas (C25)

026 Malignant neoplasm of larynx (C32)

027 Malignant neoplasms of trachea, bronchus and lung (C33-C34)

028 Malignant melanoma of skin (C43)

029 Malignant neoplasm of breast (C50)

# of Deaths for Critical Cases in Hospitals by Day of Week: Sunday = 1

DOW_of_Death

1.000000   23937

2.000000   24662

3.000000   25646

4.000000   24702

5.000000   24759

6.000000   24982

7.000000   24092

dtype: int64

Percentages of Deaths for Critical Cases in Hospitals by Day of Week: Sunday = 1

DOW_of_Death

1.000000   13.850000

2.000000   14.270000

3.000000   14.840000

4.000000   14.300000

```
#Used subsetting to remove the empty values of Month
sub1=data[(data[Month]<13)]
print ('# of Deaths by Month')
print ('(1 = January, 12 = December)')
c6 = sub1[Month].value_counts(sort=False)
print (c6)
print ()

print ('Percentages of Deaths by Month')
print ('(1 = January, 12 = December)')
p6 = 100 * sub1[Month].value_counts(sort=False, normalize=True)
print (round(p6,2))
print ()

print ('# of Deaths by Cause')
print ('( 46=Atherosclerosis, 52= Other Circulatory Deseases, 59=Bronchitis,)')
print ('(63= Gastritis/duodenitis,  70= Perinatal problems, 111= All other Deseases)')
c7 = data.groupby(Cause).size()
print (c7)
print ()
```

030 2 Malignant neoplasm of cervix uteri (C53)

031 2 Malignant neoplasms of corpus uteri and uterus, part unspecified (C54-C55)

032 2 Malignant neoplasm of ovary (C56)

033 1 Malignant neoplasm of prostate (C61)

034 Malignant neoplasms of kidney and renal pelvis (C64-C65)

035 Malignant neoplasm of bladder (C67)

036 Malignant neoplasms of meninges, brain and other parts of central nervous system (C70-C72)

037 1 Malignant neoplasms of lymphoid, hematopoietic and related tissue (C81-C96)

038 Hodgkin's disease (C81)

039 Non-Hodgkin's lymphoma (C82-C85)

040 Leukemia (C91-C95)

```
5.000000   14.330000

6.000000   14.460000

7.000000   13.940000

dtype: float64
```

```
print ('Percentages of Deaths by Cause')
print ('( 46=Atherosclerosis, 52= Other Circulatory Deseases, 59=Bronchitis,)')
print ('(63= Gastritis/duodenitis,  70= Perinatal problems, 111= All other Deseases)')
p7 = 100 * data.groupby(Cause).size()/ len(data)
print (round(p7,2))
print ()

print ('# of Deaths by Years of Education ')
print ('(0 = None,17= 5 Years or More of College, 99 = Not Stated')
c8 = data.groupby(Education).size()
print (c8)
print ()

print ('Percentages of Deaths by Years of Education')
print ('(0 = None,17= 5 Years or More of College, 99 = Not Stated')
p8 = 100 * data.groupby(Education).size() / len(data)
print (round(p8,2))
print ()
```

041 Multiple myeloma and immunoproliferative neoplasms (C88,C90)

042 Other and unspecified malignant neoplasms of lymphoid, hematopoietic and related tissue (C96)

043 All other and unspecified malignant neoplasms (C17,C23-C24,C26-C31,C37-C41, C44-C49,C51-C52,C57-C60,C62-C63,C66,C68-C69,C73-C80,C97)

044 In situ neoplasms, benign neoplasms and neoplasms of uncertain or unknown behavior (D00-D48)

045 Anemias (D50-D64)

046 3 Diabetes mellitus (E10-E14)

047 Nutritional deficiencies (E40-E64)

048 Malnutrition (E40-E46)

049 Other nutritional deficiencies (E50-E64)

050 Meningitis (G00,G03)

051 Parkinson’s disease (G20-G21)

```
print ('# of Deaths by Place')
print ('(1 = Hospital or Medical Center Inpatient')
print ('(2 = Hospital, Medical Center or ER - Outpatient)')
print ('(3 = Hospital or Medical Center-Dead on Arrival)')
print ('(4 = Decedent's home)')
print ('(5 = Hospice facility')
print ('(6 = Nursing home/long term care)')
print ('(7 = Other)')
print ('(9 = Place of death unknown)')
c9 =
data[Place].value_counts(sort=False)
print (c9)
print ()

print ('Percentages of Deaths by Place')
print ('(1 = Hospital or Medical Center Inpatient')
print ('(2 = Hospital, Medical Center or ER - Outpatient)')
print ('(3 = Hospital or Medical Center-Dead on Arrival)')
print ('(4 = Decedent's home)')
print ('(5 = Hospice facility')
print ('(6 = Nursing home/long term
```

052 Alzheimer's disease (G30)

053 1 Major cardiovascular diseases (I00-I78)

054 1 Diseases of heart (I00-I09,I11,I13,I20-I51)

055 Acute rheumatic fever and chronic rheumatic heart diseases (I00-I09)

056 Hypertensive heart disease (I11)

057 Hypertensive heart and renal disease (I13)

058 1 Ischemic heart diseases (I20-I25)

059 Acute myocardial infarction (I21-I22)

060 Other acute ischemic heart diseases (I24)

061 1 Other forms of chronic ischemic heart disease (I20,I25)

062 Atherosclerotic cardiovascular disease, so described (I25.0)

063 All other forms of chronic ischemic heart disease (I20,I25.1-I25.9)

064 1 Other heart diseases (I26-I51)

```
care)’)
print (’(7 = Other)’)
print (’(9 = Place of death unknown)’)
p9 = 100 *
data[Place].value_counts(sort=False,
normalize=True)
print (round(p9,2))
print ()
print ()

subHospital1 = data[(data[Place] == 1)]
subER1 =      data[(data[Place] == 2)]
subNursing1 = data[(data[Place] == 6)]
subHospice1 = data[(data[Place] == 5)]

subHospital = subHospital1.copy()
subER = subER1.copy()
subNursing = subNursing1.copy()
subHospice = subHospice1.copy()

subHospital[Place] =
pandas.to_numeric(subHospital[Place])
subER[Place] =
pandas.to_numeric(subER[Place])
subNursing[Place] =
pandas.to_numeric(subNursing[Place])
subHospice[Place] =
pandas.to_numeric(subHospice[Place])
```

065 Acute and subacute endocarditis (I33)

066 Diseases of pericardium and acute myocarditis (I30-I31,I40)

067 Heart failure (I50)

068 All other forms of heart disease (I26-I28,I34-I38,I42-I49,I51)

069 Essential (primary) hypertension and hypertensive renal disease (I10,I12,I15)

070 Cerebrovascular diseases (I60-I69)

071 Atherosclerosis (I70)

072 1 Other diseases of circulatory system (I71-I78)

073 Aortic aneurysm and dissection (I71)

074 Other diseases of arteries, arterioles and capillaries (I72-I78)

075 Other disorders of circulatory system (I80-I99)

```
print ('# of Deaths in Hospitals by Day of Week: Sunday = 1')
c10 = subHospital.groupby(Day).size()
print (c10)
print ()

print ('Percentages of Deaths in Hospitals by Day of Week: Sunday = 1')
p10 = 100 *
subHospital.groupby(Day).size() /
len(subHospital)
print (round(p10,2))
print ()
print ()

#groupby command ordered the output more logically than .value_counts
print ('# of Deaths in Emergency Rooms by Day of Week: Sunday = 1')
c11 = subER.groupby(Day).size()
print (c11)
print ()

print ('Percentages of Deaths in Emergency Rooms by Day of Week: Sunday = 1')
p11 = 100 *
 subER.groupby(Day).size() /
len(subER)
```

076 1 Influenza and pneumonia (J09-J18)

077 Influenza (J09-J11)

078 Pneumonia (J12-J18)

079 1 Other acute lower respiratory infections (J20-J22,U04)

080 Acute bronchitis and bronchiolitis (J20-J21)

081 Other and unspecified acute lower respiratory infection (J22,U04)

082 1 Chronic lower respiratory diseases (J40-J47)

083 Bronchitis, chronic and unspecified (J40-J42)

084 3 Emphysema (J43)

085 Asthma (J45-J46)

086 Other chronic lower respiratory diseases (J44,J47)

087 Pneumoconioses and chemical effects (J60-J66,J68)

088 Pneumonitis due to solids and liquids (J69)

```
print (round(p11,2))
print ()
print ()

print ('# of Deaths in Nursing Homes by Day of Week: Sunday = 1')
c12 = subNursing.groupby(Day).size()
print (c12)
print ()

print ('Percentages of Deaths Nursing Homes by Day of Week: Sunday = 1')
p12 = 100 * subNursing.groupby(Day).size() / len(subNursing)
print (round(p12,2))
print ()
print ()

print ('# of Deaths in Hospice by Day of Week: Sunday = 1')
c13 = subHospice.groupby(Day).size()
print (c13)
print ()

print ('Percentages of Deaths Hospice by Day of Week: Sunday = 1')
p13 = 100 * subHospice.groupby(Day).size() / len
```

089 Other diseases of respiratory system (J00-J06,J30-J39,J67,J70-J98)

090 Peptic ulcer (K25-K28)

091 Diseases of appendix (K35-K38)

092 Hernia (K40-K46)

093 1 Chronic liver disease and cirrhosis (K70,K73-K74)

094 Alcoholic liver disease (K70)

095 Other chronic liver disease and cirrhosis (K73-K74)

096 Cholelithiasis and other disorders of gallbladder (K80-K82)

097 1 Nephritis, nephrotic syndrome and nephrosis (N00-N07,N17-N19,N25-N27)

098 Acute and rapidly progressive nephritic and nephrotic syndrome (N00-N01,N04)

099 Chronic glomerulonephritis, nephritis and nephropathy not specified as acute or chronic, and renal sclerosis unspecified (N02-N03,N05-N07,N26)

(subHospice)
print (round(p13,2))
print ()

Complete Output from code

# of observations

2601452

# of variables

75

variable names

Index(['Resident_Status', ' Education', ' Month_Of_Death', ' Sex', ' Age_Key',

' Age_Value', ' Age_Sub_Flag', ' Age_Recode_52', ' Age_Recode_27',

' Age_Recode_12', ' Infant_Age_Recode_22', ' Place_Of_Death',

' Marital_Status', ' DOW_of_Death', ' Data_Year', ' Injured_At_Work',

100 Renal failure (N17-N19)

101 Other disorders of kidney (N25,N27)

102 Infections of kidney (N10-N12,N13.6,N15.1)

103 1 Hyperplasia of prostate (N40)

104 2 Inflammatory diseases of female pelvic organs (N70-N76)

105 1 2 7 Pregnancy, childbirth and the puerperium (O00-O99)

106 2 7 Pregnancy with abortive outcome (O00-O07)

107 2 7 Other complications of pregnancy, childbirth and the puerperium (O10-O99)

108 Certain conditions originating in the perinatal period (P00-P96)

109 Congenital malformations, deformations and chromosomal abnormalities (Q00-Q99)

110 Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified (R00-R99)

’ Manner_Of_Death’, ’ Method_Of_Disposition’, ’ Autopsy’,

’ Activity_Code’, ’ Place_Of_Causal_Injury’, ’ ICD10’,

’ Cause_Recode_358’, ’ Cause_Recode_113’, ’ Infant_Cause_Recode_130’,

’ Cause_Recode_39’, ’ Entity_Axis_Conditions’, ’ EAC1’, ’ EAC2’,

’ EAC3’, ’ EAC4’, ’ EAC5’, ’ EAC6’, ’ EAC7’, ’ EAC8’, ’ EAC9’, ’ EAC10’,

’ EAC11’, ’ EAC12’, ’ EAC13’, ’ EAC14’, ’ EAC15’, ’ EAC16’, ’ EAC17’,

’ EAC18’, ’ EAC19’, ’ EAC20’, ’ Record_Axis_Conditions’, ’ RA1’, ’ RA2’,

’ RA3’, ’ RA4’, ’ RA5’, ’ RA6’, ’ RA7’, ’ RA8’, ’ RA9’, ’ RA10’,

’ RA11’, ’ RA12’, ’ RA13’, ’ RA14’, ’ RA15’, ’ RA16’, ’ RA17’, ’ RA18’,

’ RA19’, ’ RA20’, ’ Race’, ’ Race_Bridged’, ’ Race_Imputation’,

111 All other diseases (Residual) (D65-E07,E15-E34,E65-F99,G04-G14,G23-G25,G31-H93,

K00-K22,K29-K31,K50-K66,K71-K72,K75-K76,K83-M99, N13.0-N13.5,N13.7-N13.9, N14,N15.0,N15.8-N15.9,N20-N23,N28-N39,N41-N64,N80-N98)

112 1 Accidents (unintentional injuries) (V01-X59,Y85-Y86)

113 1 Transport accidents (V01-V99,Y85)

114 Motor vehicle accidents (V02-V04,V09.0,V09.2,V12-V14,V19.0-V19.2,

V19.4-V19.6,V20-V79,V80.3-V80.5,V81.0-V81.1,V82.0-V82.1,V83-V86, V87.0-V87.8,V88.0-V88.8,V89.0,V89.2

115 Other land transport accidents (V01,V05-V06,V09.1,V09.3-V09.9, V10-V11,

V15-V18,V19.3,V19.8-V19.9,V80.0-V80.2,V80.6-V80.9,V81.2-V81.9,

’ Race_Recode_3’, ’ Race_Recode_5’, ’ Hispanic_Origin’,

’ Hispanic_Origin_Recode’],

dtype='object’)

# of Deaths by Day of Week: Sunday = 1

1	366342
2	369826
3	376152
4	369304
5	369270
6	375286
7	375141
9	131

Name: DOW_of_Death, dtype: int64

Percentages of Deaths by Day of Week: Sunday = 1

V82.2-V82.9,V87.9,V88.9,V89.1,V89.3,V89.9)

116 Water, air and space, and other and unspecified transport accidents and their sequelae (V90-V99,Y85)

117 1 Nontransport accidents (W00-X59,Y86)

118 Falls (W00-W19)

119 Accidental discharge of firearms (W32-W34)

120 Accidental drowning and submersion (W65-W74)

121 Accidental exposure to smoke, fire and flames (X00-X09)

122 Accidental poisoning and exposure to noxious substances (X40-X49)

123 Other and unspecified nontransport accidents and their sequelae (W20-W31,W35-W64,W75-W99,X10-X39,X50-X59,Y86)

124 1 1 Intentional self-harm (suicide) (*U03,X60-X84,Y87.0)

1   14.08

2   14.22

3   14.46

4   14.20

5   14.19

6   14.43

7   14.42

9   0.01

Name: DOW_of_Death, dtype: float64

# of Deaths by Race

(1 = White, 2 = Other, 4 = Black)

1   2220602

2   77389

3   303461

Name: Race_Recode_3, dtype: int64

Percentages of Deaths by Race

125 1 Intentional self-harm (suicide) by discharge of firearms (X72-X74)

126 1 Intentional self-harm (suicide) by other and unspecified means and their sequelae (*U03,X60-X71,X75-X84,Y87.0)

127 1 Assault (homicide) (*U01-*U02,X85-Y09,Y87.1)

128 Assault (homicide) by discharge of firearms (*U01.4,X93-X95)

129 Assault (homicide) by other and unspecified means and their sequelae (*U01.0-*U01.3,*U01.5-*U01.9,*U02,X85-X92,X96-Y09,Y87.1)

130 Legal intervention (Y35,Y89.0)

131 1 Events of undetermined intent (Y10-Y34,Y87.2,Y89.9)

132 Discharge of firearms, undetermined intent (Y22-Y24)

133 Other and unspecified events of undetermined intent and their sequelae (Y10-Y21,Y25-Y34,Y87.2,Y89.9)

(1 = White, 2 = Other, 4 = Black)

1   85.36

2   2.97

3   11.67

Name: Race_Recode_3, dtype: float64

# of Deaths by Age Catagory

(1 = Under 1, 8 = 55 to 64, 11 = Over 85)

1   23497

2   4088

3   5381

4   28680

5   45710

6   69901

7   178311

8   338984

9   455322

134 Operations of war and their sequelae (Y36,Y89.1)

135 Complications of medical and surgical care (Y40-Y84,Y88)

10   625668

11   825557

12   353

Name: Age_Recode_12, dtype: int64

Percentages of Deaths by Age Catagory

(1 = Under 1, 8 = 55 to 64, 11 = Over 85)

1   0.90

2   0.16

3   0.21

4   1.10

5   1.76

6   2.69

7   6.85

8   13.03

9   17.50

10   24.05

11   31.73

12   0.01

Name: Age_Recode_12, dtype: float64

# of Deaths by Marital Status

(U = unknown , M = married, D = divorced, S = single, W = widowed)

W   903757

M   969061

S   324270

U   17444

D   386920

Name: Marital_Status, dtype: int64

Percentages of Deaths by Marital Status

(U = unknown , M = married, D = divorced, S = single, W = widowed)

W   34.74

M   37.25

S   12.46

U   0.67

D   14.87

Name: Marital_Status, dtype: float64

# of Deaths by Sexual Identity

(M = Male, F = Female

F   1292382

M   1309070

Name: Sex, dtype: int64

Percentages of Deaths by Sexual Identy

(M = Male, F = Female

F   49.68

M   50.32

Name: Sex, dtype: float64

# of Deaths by Month

(1 = January, 12 = December)

1	41810
2	34351
3	36902
4	34256
5	33795
6	32083
7	30237
8	28968
9	28506
10	30135
11	30020
12	32229

Name: Month_Of_Death, dtype: int64

Percentages of Deaths by Month

(1 = January, 12 = December)

1	10.63
2	8.73
3	9.38
4	8.71
5	8.59
6	8.16
7	7.69
8	7.37
9	7.25
10	7.66
11	7.63
12	8.19

Name: Month_Of_Death, dtype: float64

# of Deaths by Cause

(46=Atherosclerosis, 52= Other Circulatory Deseases, 59=Bronchitis,)

(63= Gastritis/duodenitis, 70= Perinatal problems, 111= All other Deseases)

Cause_Recode_113

1	41
2	6
3	10601
5	410
6	151
7	12
8	1
9	59
10	38209
11	49
13	4
15	8174
16	6999
17	12
18	6025

20	8859
21	14709
22	11280
23	52305
24	24074
25	39033
26	3732
27	156369
28	9403
29	41371
30	4225
31	9334
32	14296
33	27706
34	13919
…	
99	254
100	46463

101	34
102	641
103	560
104	129
106	27
107	1115
108	12123
109	9605
110	38021
111	320369
114	35650
115	1014
116	1591
118	30288
119	506
120	3496
121	2770
122	38997

123	17057
125	21190
126	20056
128	11230
129	4957
130	518
132	282
133	4337
134	15
135	2773

dtype: int64

Percentages of Deaths by Cause

(46=Atherosclerosis, 52= Other Circulatory Deseases, 59=Bronchitis,)

(63= Gastritis/duodenitis, 70= Perinatal problems, 111= All other Deseases)

Cause_Recode_113

1	0.00

2	0.00
3	0.41
5	0.02
6	0.01
7	0.00
8	0.00
9	0.00
10	1.47
11	0.00
13	0.00
15	0.31
16	0.27
17	0.00
18	0.23
20	0.34
21	0.57
22	0.43
23	2.01

24	0.93
25	1.50
26	0.14
27	6.01
28	0.36
29	1.59
30	0.16
31	0.36
32	0.55
33	1.07
34	0.54
…	
99	0.01
100	1.79
101	0.00
102	0.02
103	0.02
104	0.00

106	0.00
107	0.04
108	0.47
109	0.37
110	1.46
111	12.32
114	1.37
115	0.04
116	0.06
118	1.16
119	0.02
120	0.13
121	0.11
122	1.50
123	0.66
125	0.81
126	0.77
128	0.43

129 0.19

130 0.02

132 0.01

133 0.17

134 0.00

135 0.11

dtype: float64

# of Deaths by Years of Education

(0 = None,17= 5 Years or More of College, 99 = Not Stated

Education

2208160

00 6034

01 338

02 714

03 2360

04 2120

05	2785
06	7952
07	6571
08	21933
09	12207
10	18670
11	17751
12	162483
13	15073
14	40003
15	6706
16	38076
17	26824
99	4692

dtype: int64

Percentages of Deaths by Years of Education

(0 = None,17= 5 Years or More of College, 99 = Not Stated

Education

	84.88
00	0.23
01	0.01
02	0.03
03	0.09
04	0.08
05	0.11
06	0.31
07	0.25
08	0.84
09	0.47
10	0.72
11	0.68
12	6.25
13	0.58

14	1.54
15	0.26
16	1.46
17	1.03
99	0.18

dtype: float64

# of Deaths by Place

(1 = Hospital or Medical Center Inpatient

(2 = Hospital, Medical Center or ER - Outpatient)

(3 = Hospital or Medical Center- Dead on Arrival)

(4 = Decedent’s home)

(5 = Hospice facility

(6 = Nursing home/long term care)

(7 = Other)

(9 = Place of death unknown)

1   795545

2   174722

3   14670

4   752406

5   159514

6   521912

7   181042

9   1641

Name: Place_Of_Death, dtype: int64

Percentages of Deaths by Place

(1 = Hospital or Medical Center Inpatient

(2 = Hospital, Medical Center or ER - Outpatient)

(3 = Hospital or Medical Center- Dead on Arrival)

(4 = Decedent’s home)

(5 = Hospice facility

(6 = Nursing home/long term care)

(7 = Other)

(9 = Place of death unknown)

1   30.58

2   6.72

3   0.56

4   28.92

5   6.13

6   20.06

7   6.96

9   0.06

Name: Place_Of_Death, dtype: float64

# of Deaths in Hospitals by Day of Week: Sunday = 1

DOW_of_Death

1   108923

2   113558

3   117877

4   114480

5   114318

6   115459

7   110925

9   5

dtype: int64

Percentages of Deaths in Hospitals by Day of Week: Sunday = 1

DOW_of_Death

1   13.69

2   14.27

3   14.82

4   14.39

5   14.37

6   14.51

7   13.94

9   0.00

dtype: float64

# of Deaths in Emergency Rooms by Day of Week: Sunday = 1

DOW_of_Death

1   25298

2   25852

3   25114

4   24249

5   23817

6   24468

7   25923

9   1

dtype: int64

Percentages of Deaths in Emergency Rooms by Day of Week: Sunday = 1

```
DOW_of_Death

1    14.48

2    14.80

3    14.37

4    13.88

5    13.63

6    14.00

7    14.84

9     0.00

dtype: float64
```

# of Deaths in Nursing Homes by Day of Week: Sunday = 1

```
DOW_of_Death

1    74812

2    73475
```

3 73778

4 73375

5 73864

6 75694

7 76906

9 8

dtype: int64

Percentages of Deaths Nursing Homes by Day of Week: Sunday = 1

DOW_of_Death

1 14.33

2 14.08

3 14.14

4 14.06

5 14.15

6 14.50

7 14.74

9   0.00

dtype: float64

# of Deaths in Hospice by Day of Week: Sunday = 1

DOW_of_Death

1   22157

2   21181

3   22658

4   22892

5   23252

6   23711

Show more

7   23659

9   4

dtype: int64

Percentages of Deaths Hospice by Day of Week: Sunday = 1

```
DOW_of_Death
1    13.89
2    13.28
3    14.20
4    14.35
5    14.58
6    14.86
7    14.83
9     0.00
dtype: float64
```