Economics Thesis

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Systematic Differences between Bicyclists and Motor-Vehicle Operators

Abstract

Using accident data from the Oregon Trauma Registry Report, this paper examines characteristics of the individuals that get into bicycling and car accidents, and provides some insight as to how different traits prior to the accident might affect the outcome. I estimate a variety of linear regression models and find that the claimed health benefits of bicycling have a tangible impact on accident outcome. An in depth analysis of hospital charges accrued is provided, using a log-linear model containing various elements from the accident. I find that bicyclists and motor-vehicle operators differ on multiple fronts, which cause statistically significant distortions in the hospital bills accrued by each group.

Keywords: Oregon Trauma Registry, ISS, Pre-existing Condtion, Accident Type, Linear Probability Model

Acknowledgments: I would like to thank my advisor, Ralph Mastromonaco for his endless insight and help putting this paper together along with Andrew Schopieray for pushing me in my studies of mathematics. I would also like to thank my family and friends for their tireless support of my endeavors. Lastly, I would like to thank Donald Au of the Oregon Health Department for helping me obtain the data used in this project.

Ralph Mastromonaco, Advisor

1 Introduction

Transportation is one of the most prominent and reccurring decisions an individual faces in his or her daily life. Everyday, individuals decide how they would like to get from one location to another. Motor-vehicles and their human-powered counterpart, bicycles, are two popular methods of transportation. Many of us are familiar with these choices. While this observation seems mundane, it's the foundation for many behavioral, economic, and political discussions. If transportation is viewed as a *decision*, then there is a broad range of economic questions that could be studied. Driving, bicycling, and walking can be considered substitutes for each other, and thus reveal certain aspects of the particular individuals' preferences.

There are inherent risks affiliated with transportation decisions. Although these might not be conceptualized during decision making, consequences include: death, injury, and hospital expenses incurred by the individual. It is important to note that each mode of transportation has a unique bundle of risks. Of particular interest are the different risks associated with bicycling and driving.

There are various advantages to driving or bicycling over walking, such as personal utility from each mode, as well as an inherent efficiency gain over walking. One of the largest advantages to bicycling compared to driving is the health benefits received from the exercise. According to one study (The Better Health Channel, 2016), an individual must bicycle only 2-4 hours per week to start improving health. This means that at a minimum, one must ride 20 minutes a day, 6 days a week. The benefits include: decreased body fat levels, improved joint mobility, increased cardiovascular fitness, strengthened bones, and decreased stress levels.

Darren Warburton, in *Health Benefits of Physical Activity: The Evidence*, summarizes the benefits of exercising in general by stating, "There appears to be a linear relation between physical activity and health status, such that a further increase in physical activity and fitness will lead to additional improvements in health status." These studies support the view that bicyclists are healthier than the average individual. However, health alone does not capture the differences in trauma costs between accident types. The average cost of getting into a bicycling cost in Oregon is $24,610, whereas a motor-vehicle accident costs $34,570 on average. Clearly, there is a large difference between hospital charges.[1]

[1] These charges denote charges *accrued* by the individual, not the charges paid. This distinction is important and will be discussed in depth further in the paper.

Injury Severity Score (abbreviated ISS) is a useful variable for quantifying physical severity of an injury because it is independent of accident type. According to Trauma.org, "Injury Severity Score is an anatomical scoring system that provides an overall score for patients with multiple injuries. Each injury is assigned an Abbreviated Injury Scale (AIS) score and is allocated to one of six body regions (Head, Face, Chest, Abdomen, Extremities (including Pelvis), External). Only the highest AIS score in each body region is used. The 3 most severely injured body regions have their score squared and added together to produce the ISS score."[2] Hospital charges should not be a function of accident type, if injury severity is controlled for, since they are independent. Interestingly, even after controlling for ISS, hospital charges for motor-vehicle accidents are still 20% more expensive, which suggests that bicyclists are different in some way that is not captured by injury severity.

This paper aims to identify any systematic differences between bicyclists and drivers, and examine how the variations impact hospital charges accrued by an individual following an accident. I explore the possibility that variation in charges between accident types is caused by race, gender, and ethnicity propensities to use a particular mode of transportation. I then exploit the possibility that these demographic variables are acting as a proxy for different health and behavioral preferences prior to the accident. To study the health of each group of individuals, I examine the top 10 most frequently occurring pre-existing conditions in the dataset of individuals whom only have one condition. Additionally, I study various illicit substances prior to crashes, and safety equipment usage. I estimate the difference in total hospital charges amongst the groups while controlling for these confounding factors.

The difference in means suggests that bicycling accidents are roughly 20% less expensive in regards to hospital charges than motor vehicle accidents. However, these groups are different on various fronts which causes this number to be misleading. I find that bicyclists are on average slightly healthier than motor-vehicle operators prior to their respective accident. I also find that this difference in health likely has a real effect on the hospital charges accrued by the individual. After controlling for all of these factors, I find that bicycling accidents are roughly 10% cheaper, indicating that these factors account for 10% of the accidents cost.

[2] Also according to Trauma.org: "Injuries are ranked on a scale of 1 to 6, with 1 being minor, 5 severe and 6 an unsurvivable injury. This represents the 'threat to life' associated with an injury and is not meant to represent a comprehensive measure of severity."

2 Data

The data used in this analysis comes from the Oregon Trauma Registry, which is a branch of the Oregon Health Authority. The objectives of the registrar are: "to monitor and provide information necessary to evaluate trauma patient outcome, assess compliance of prehospital care providers and hospitals with state standards, provide and review data for injury prevention programs, research and education and produce annual and biennial statistical reports." The data set analyzed contains information regarding individuals that have been checked into an Oregon Trauma Center between the years of 2003-2014 for either a bicycling or motor-vehicle accident. According to The Oregon Trauma Registry Report, a "Trauma Center" is "a system of health care delivery that combines prehospital Emergency Medical Services (EMS) resources and hospital resources to optimize the care and the outcome of traumatically injured patients."

The dataset contains various demographic information such as age, ethnicity and gender. It also lists an individuals insurance situation, as well as previous health conditions prior to the accident, along with safety equipment used, and any illicit substances consumed prior to the accident. It is important to note that all of the pre-existing conditions, safety equipment, and illicit substance variables only capture the extensive margin.

ISS, death, and hospital charges will be the primary accident outcomes studied in this paper. For all of the models estimated, I use $ln(Th_i)$, because the distribution of hospital charges is skewed to the right. As mentioned in the introduction, the difference in mean hospital charges between cyclists and motor-vehicle operators is statistically significant. The density plots of hospital charges, and the logarithm of charges can be found in the Appendix. Variations amongst all elements of accident outcome suggest omitted variable bias.

There are a few interesting relationships between the accident outcome variables. One might think that an accident with more severe injuries would result in higher hospital charges. If total hospital charges is thought of as a function of quantity of medical services provided to an individual, it is reasonable to think that a worse accident requires more medical attention. Thus as ISS increases (indicating a more severe accident), it should be the case that total hospital charges increase as well. The following scatterplot provides a visualization of this relationship:

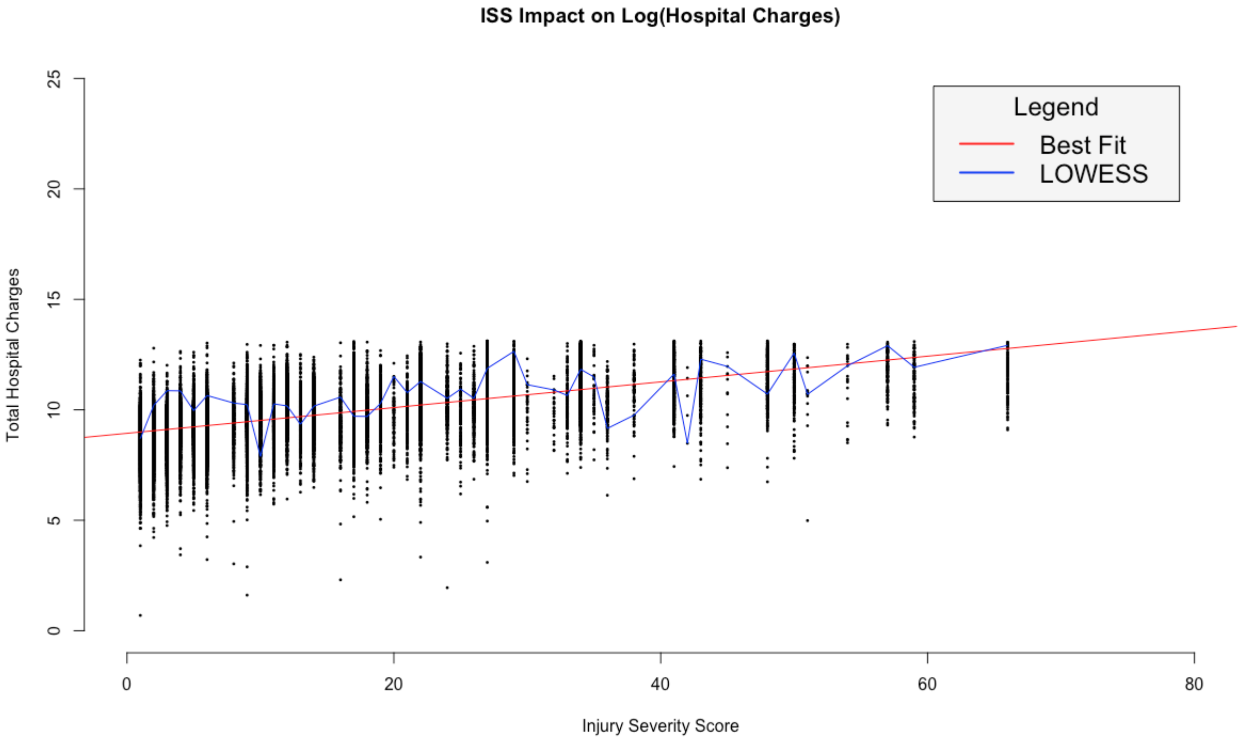

Figure 1: Adjusted $R^2 = 0.3268$.

These results seem reasonable, as one might think that a more severe injury would require more hospital services to repair. Since the calculation of ISS is independent from mode of transportation, it should be the case that a constant ISS k, for accident type x, results in the same amount of hospital charges for all accident types x. A simple linear regression model indicates whether or not this is indeed the case. The regression is specified below (Table 1) , where T is dummy variable which indicates a bicycling accident. The omitted group in this regression is motor-vehicle accidents.

$$ln(TH_i) = \beta_0 + \beta_1 T_i + \beta_2 ISS_i + \epsilon_i$$

	Dependent variable:
T	−0.206***
	(0.016)
ISS	0.053***
	(0.001)
Constant	9.033***
	(0.009)
Observations	25,581
R^2	0.347
Adjusted R^2	0.347
Residual Std. Error	0.915 (df = 25,578)
F Statistic	6,788.477*** (df = 2; 25,578)
Note: Robust standard errors in parenthesis	*p<0.1; **p<0.05; ***p<0.01

Table 1: Simple Regression

The coefficient on T_i is surprising because, intuitively, this number should be zero. This is not the case which implies that there omitted variables bias present. The presence of omitted variables in this simple model further suggests there are systematic differences between bicyclists and drivers, which I argue is a function of demographics, insurance, health, safety equipment, and illicit drug use prior to the accident.

ISS explains a reasonable portion of total hospital charges; but, either hospital malpractice is rampant, or ISS is not the best indicator of the quantity of medical services provided. For example, certain groups of individuals could need less medical services provided at the same injury severity. There is an interesting relationship between death and hospital charges as well. The data suggests that dying is substantially cheaper than surviving an accident. Most individuals in this dataset survive their respective accidents, the following figures illustrates this:

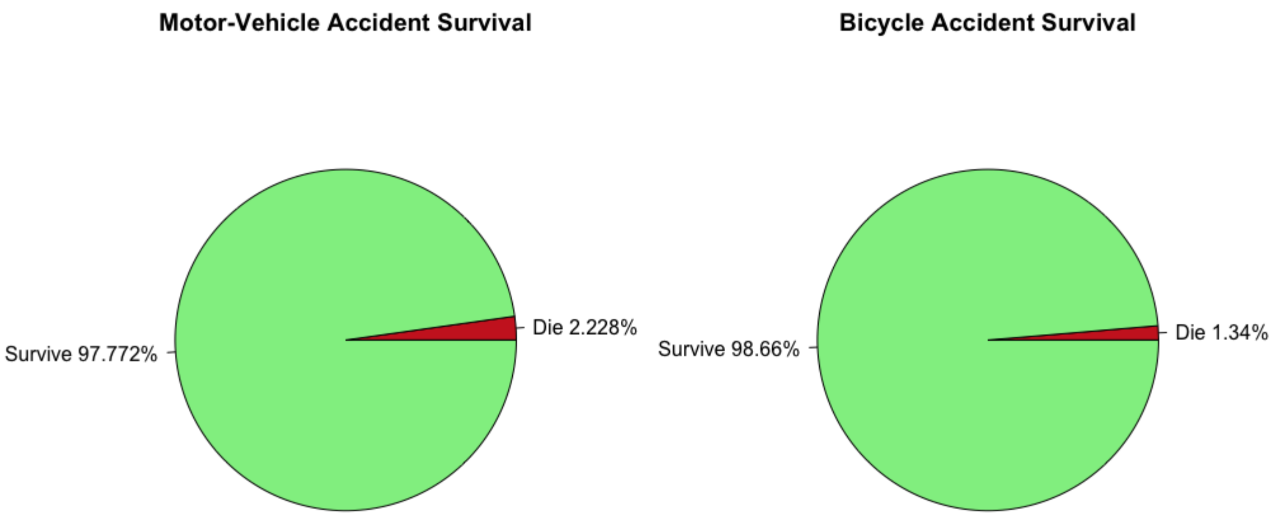

Figure 2

2.1 The Pedestrian

In the context of this dataset, it is very difficult to illustrate that both operating a motor-vehicle and riding a bicycle is costlier than walking. The analysis of pedestrians in this dataset is much less clear than bicyclists or motor-vehicle operators. Behavioral traits of pedestrians that are hit by bicycles or cars cannot be deduced because the individual pedestrian is not causing the damage. There are cases where pedestrians would cause harm to themselves, but I will ignore those instances this paper. The following example illustrates the reason any conclusion based on pedestrian behavior would be muddled is given: it is fairly certain that when an individual chooses to consume alcohol and drive, they are aware of their decision and thus what they are doing is by choice, which speaks to their preferences and thus some conclusions can be made. However, a pedestrian that gets hit by a drunk driver says little about the pedestrian other than that they were unlucky. This goes under the assumption that pedestrians that get hit are hit randomly. There might be a certain behavior of a pedestrian (such as being intoxicated themselves) that would make them more or less likely to be hit by a bicycle or car, but this would be difficult to conclude.

2.2 Data Summary

Pooled proportion testing points (Tables 13-17) to differences in propensity for insurance, illicit drug use prior to accident, and rates of pre-existing conditions occurring. These differences are convincing evidence that there is something different about cyclists that causes their hospital bills to be less expensive, despite having a higher ISS. Since this coefficient in non-zero, I argue that the following is occuring within the simple model:

$$cov(T_i, \epsilon_i) > 0$$
$$cov(TH_i, \epsilon_i) > 0$$

This indicates that there is something different about bicyclists causing the difference in means, which cannot be explained by accident severity alone. Although dying in an accident is cheaper than surviving, one would expect that this would make car accidents cheaper than bike accidents. More motor-vehicle operators die in accidents, but hospital charges are higher despite this.

3 Differences between Bicyclicists and Drivers

3.1 Motorvehicle Accidents Overview

As mentioned above, motor-vehicle accidents are quite costly on average. In the State of Oregon, from 2003 and 2014, there were 37,139 motor-vehicle accidents resulting in traumatic injury, or 3,381 accidents per year.[3] There is a tremendous cost associated with these accidents, the total hospital charges for medical bills accrued by individuals involved in motor-vehicle accidents was \$2,324,120,788. This averages out to approximately \$211,283,708 dollars per year. Of these accidents, roughly 2% die. Motor-vehicle accident victims are assumed to be represantative of the average population of Oregon. This assumption is made so that conclusions about bicyclists can be made relative to the average individual. Of course, this assumption likely isn't entirely true, as some groups and people will have a higher propensity to get into an accident.

[3] This is grossly underestimated because many accidents that *do not* result in an individual going to a trauma system does not show up in this dataset.

3.2 Bicycling Accidents Overview

There have been 4,645 accidents involving bicycling only, and 2,226 involving bicyclists and cars from 2003-2014. There is a large cost associated with all of these as well, the total amount paid for bicycling accidents during this time period is $117,047,067. Bicycling accidents cost less on average than car accidents and have a lower death rate (only 1.34%). Bicyclists also have a lower propensity drugs such as cannabis and cocaine compared to motorvehicle operators.[4]

There is a subtle distinction that needs to be made when examining the samples. A "bicycling accident" is an ambiguous term; for example, it could mean a bicyclist hit a pedestrian and both individuals went to the hospital, or it could indicate a car hit a bicyclist and only the bicyclist went to the hospital. In order to avoid any confusion on what individual goes to the hospital following an accident, I classify the accident type by the victims transportation choice. If a pedestrian gets hit by a bicycle, it would fall under a "pedestrian accident." This distinction is important because it allows for a clearer analysis of each respective sample.

One particularly interesting observation is that bicyclists have a slightly higher ISS than motor-vehicle operators. The average ISS of a bicycling accident is 13.91, compared to 12.78 for motor-vehicle operators. This seems surprising, given that more motor-vehicle operators die. A higher ISS increases the probability of death since an ISS of 75 indicates the individual died. The difference between accident types is statistically significant, as seen in Table 3 below.

	Test	Results
1	Welch Two Sample t-test:	$t(9526.45) = 9.15$, $p < .001$, $d = NA$

Table 2: Welches T-test for difference in ISS means.

This seems strange as motor-vehicles have a higher hospital bill, and ISS is a *decent* predictor of hospital charges. This disparity further points to differences in the groups that are not explained by ISS. Bicyclists, like motorvehicle operators, mostly use their vehicle for transportation. Research by Dill (2016) finds that in a sample of 166 bicyclists in Portland, only 5% used their bicycle for exercise. This allows for the assumption to hold that the bicyclists in this dataset use their bicycles for transit.

[4]See Table 13 for pooled proportion testing of different substances between accident types.

3.3 Demographics

The most natural place to start the examination is to study the demographics of the different accident types. There are differences in the propensity of each racial/ethnic group to use a certain mode of transportation The differences in proportions of a particular race are the following : cyclists are 6% more White than motor-vehicle drivers, 4.5% less Hispanic, and .8% less Native American. To examine the importance of each particular demographic variable, I specify three models that examine the significance of demographic characteristics. These models use White individuals as the omitted group; hence, all of the coefficients reflect the marginal effect relative to White individuals. An example of the functional form of the model is found below, along with the results in Table 3.

$$ISS_i = \beta_0 + \beta Age_i + \alpha M_i + \lambda_n race_i + \delta T_i + \epsilon_i$$

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
Constant	9.227***	10.403***	−0.004**
	(0.017)	(0.179)	(0.002)
T	0.016	1.420***	−0.008***
	(0.016)	(0.184)	(0.002)
Age.in.Years	0.009***	0.046***	0.001***
	(0.0003)	(0.003)	(0.00005)
Male	0.053***	1.172***	0.006***
	(0.013)	(0.140)	(0.002)
Asian	0.116**	0.475	0.002
	(0.046)	(0.570)	(0.006)
African American	0.298***	−1.841***	−0.007*
	(0.038)	(0.472)	(0.004)
Hispanic	−0.048**	−1.136***	−0.004**
	(0.021)	(0.230)	(0.002)
Native American	−0.087	0.184	0.006
	(0.063)	(0.624)	(0.007)
Other	0.138***	−0.353	−0.001
	(0.047)	(0.541)	(0.005)
Pacific Islander	0.367**	0.750	0.021
	(0.172)	(1.994)	(0.024)
Observations	37,282		
R^2	0.027		
Adjusted R^2	0.027		
Residual Std. Error	1.212 (df = 37272)		
F Statistic	114.758*** (df = 9; 37272)		
Notes: Robust standard errors in parenthesis			*p<0.1; **p<0.05; ***p<0.01

Table 3: Demographics Regressions

These coefficients indicate that demographics potentially impact accident outcome. Precisely why demographics have an effect on an accident outcome is difficult to answer. It is well documented that there are income disparities amongst different racial groups. In a study done by the Pew Research Center (Kocharr & Fry, 2014), various income gaps between different racial groups were noted, which suggests that race and socioeconomic status are correlated. However, (Kawacih et al.,2005) point out that using race as a proxy for class is problematic because it acts as a very rough proxy. They state "that any analysis of racial differences that adjusts for class could be viewed as statistically overcontrolling for a large portion of the causal effect of race on health." The distribution of ethnicities is given below:

Type	A	AFA	H	NAT	OTH	PI	W
B	1.45%	1.74%	6.64%	.52%	1.5%	.135%	88%
C	.178%	1.91%	11.2%	1.394%	1.68%	.153%	81.89%

Table 4: Proportions of Ethnic Groups

Clearly, there are a disproportionate amount of White individuals in the sample, which is consistent with the population of Oregon.[5] Regardless of which group is healthier, if health impacts accident outcome, then health is omitted from the naive regression (Table 1) which would cause the coefficient on the accident type variable to be biased. It could also be the case that these demographic variables are proxying for other behavioral traits, such as propensity to use drugs and safety equipment prior to an accident.

3.4 Insurance

An individuals insurance situation prior to an accident could potentially affect how much they are billed. Various papers[6] support this notion, and thus it seems pertinent to examine the propensities of bicyclists and motor-vehicle operators to use insurance. Pooled proportion testing indicates that there are indeed differences in each group to own a particular form of insurance. To gain further insight as to how the different insurance types affect accident outcome, I estimate a set of linear regression models in which the dependent variables are primary insurers of the individual. Since many individuals have an additional insurer, I include a dummy variable, $P2D$, that is set to 1 if an individual has a secondary payor, and 0 if not. Short descriptions of each variable used can be found in Table 12 in the Appendix. The functional form of the model is below along with the regression results in Tables 5 and 6.

$$ln(Th_i) = \beta_0 + \theta_n Payor1_i + \Gamma P2D_i + \phi_n(Payor1_i * P2D_i) + \delta T_i + \alpha T_i \epsilon_i$$

[5]According to oregonlive.com, as of 2010, Oregon is 78% White, 12% Hispanic, 2% African American, 4% Asian, and 2.1% Native American, and 2.9% other racial groups.

[6]See *Insurer Competition in Health Care Markets*, (Ho,Lee 2013)

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
Constant	9.214***	10.302***	
	(0.021)	(0.222)	
Self			0.017***
			(0.002)
Blue	−0.362***	0.119	0.002**
	(0.083)	(1.046)	(0.001)
Car	−0.013	−0.563**	0.018***
	(0.024)	(0.251)	(0.001)
Charity	−0.056	1.076*	0.018***
	(0.052)	(0.583)	(0.006)
Comm	0.296***	2.220***	0.010***
	(0.033)	(0.357)	(0.002)
HMO	−0.244**	−0.640	0.015*
	(0.096)	(0.745)	(0.009)
Medicaid	0.466***	2.795***	0.014***
	(0.042)	(0.451)	(0.003)
Medicare	0.419***	3.583***	0.057***
	(0.070)	(0.773)	(0.013)
Other	−0.027	0.120	0.012***
	(0.039)	(0.381)	(0.003)
Ward	0.073	−2.958*	0.001
	(0.222)	(1.709)	(0.0005)
Work	0.110*	−0.096	0.012**
	(0.061)	(0.573)	(0.005)
T	0.078***	1.679***	−0.004**
	(0.017)	(0.193)	(0.002)
Observations	43,413		
R^2	0.054		
Adjusted R^2	0.054		
Residual Std. Error	1.193 (df = 43390)		
F Statistic	113.512*** (df = 22; 43390)		
Notes: Robust standard errors in parenthesis			*p<0.1; **p<0.05; ***p<0.01

Table 5: Insurance Regressions

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
P2D	0.266***	0.492	−0.004
	(0.039)	(0.400)	(0.004)
Blue*P2D	0.285**	2.098	0.009
	(0.121)	(1.507)	(0.006)
Car*P2D	0.383***	3.866***	0.012***
	(0.042)	(0.429)	(0.004)
Charity*P2D	0.310	1.958	−0.012*
	(0.220)	(3.209)	(0.007)
Comm*P2D	−0.174***	0.459	0.009*
	(0.058)	(0.611)	(0.006)
HMO*P2D	0.239*	3.035**	0.007
	(0.139)	(1.544)	(0.015)
Medicaid*P2D	−0.192***	1.143	0.009
	(0.070)	(0.768)	(0.007)
Medicare*P2D	−0.148	−0.190	−0.015
	(0.092)	(0.993)	(0.015)
Other*P2D	0.106	2.278***	0.007
	(0.065)	(0.648)	(0.006)
Ward*P2D	−0.811**	−1.670	0.003
	(0.325)	(2.421)	(0.004)
Work*P2D	0.273***	2.736***	0.004
	(0.085)	(0.842)	(0.008)
Observations	43,413		
R^2	0.054		
Adjusted R^2	0.054		
Residual Std. Error	1.193 (df = 43390)		
F Statistic	113.512*** (df = 22; 43390)		
Notes: Robust standard errors in parenthesis	*p<0.1; **p<0.05; ***p<0.01		

Table 6: Insurance Regressions: interaction terms.

Models (1) and (2) use individuals with no insurance as the omitted group. This means that the coefficients for these models are the marginal effect of the particular insurance type *relative* to those with no insurance. There are some stark differences between insurance types compared to not being insured. The model predicts that having Medicare makes an individuals hospital charges 41.9% more expensive over having no insurance. Model (2) predicts that those with Medicare also have a 21.839 higher ISS score than those with no insurance, which hints at moral hazard. The differences in the propensity to use insurance seems to be contributing to the variation in hospital charges across accident types.

3.5 Health

An individual's health dictates a large part of what they can do and how efficiently they can do it. There are various studies regarding this and I do not need to convince anyone that being healthy usually makes an individual better off than being unhealthy. Perhaps less healthy individuals have bodies on average that are slightly more frail and less resistant to impact, or maybe it is the case that there is a behavioral difference amongst those that have a pre-existing condition which causes them to value their health more. Such a value may influence their behaviour to act safer. Regardless of the direction of the impact, any differences in health of each group could potentially explain some of the variation in hospital charges between them.

In this paper, the term "health" will be refer to the pre-existing conditions an individual has prior to the accident. Fortunately, the dataset contains different conditions individuals have prior to the accident. I examine the top 10 most occurring conditions for individuals that only have *one* condition. There is no way of knowing how much an individual rides his or her bicycle, but given the multitude of proposed health benefits, it should be the case that bicyclists have less of the conditions that the act claims to alleviate. Below is a set of bar charts that give the relative proportions of the pre-existing conditions for each group.[7]

[7] "B," "'C," "P," denote bicycles, cars, and pedestrians, respectively. The proportions for these can be found in Table 2.

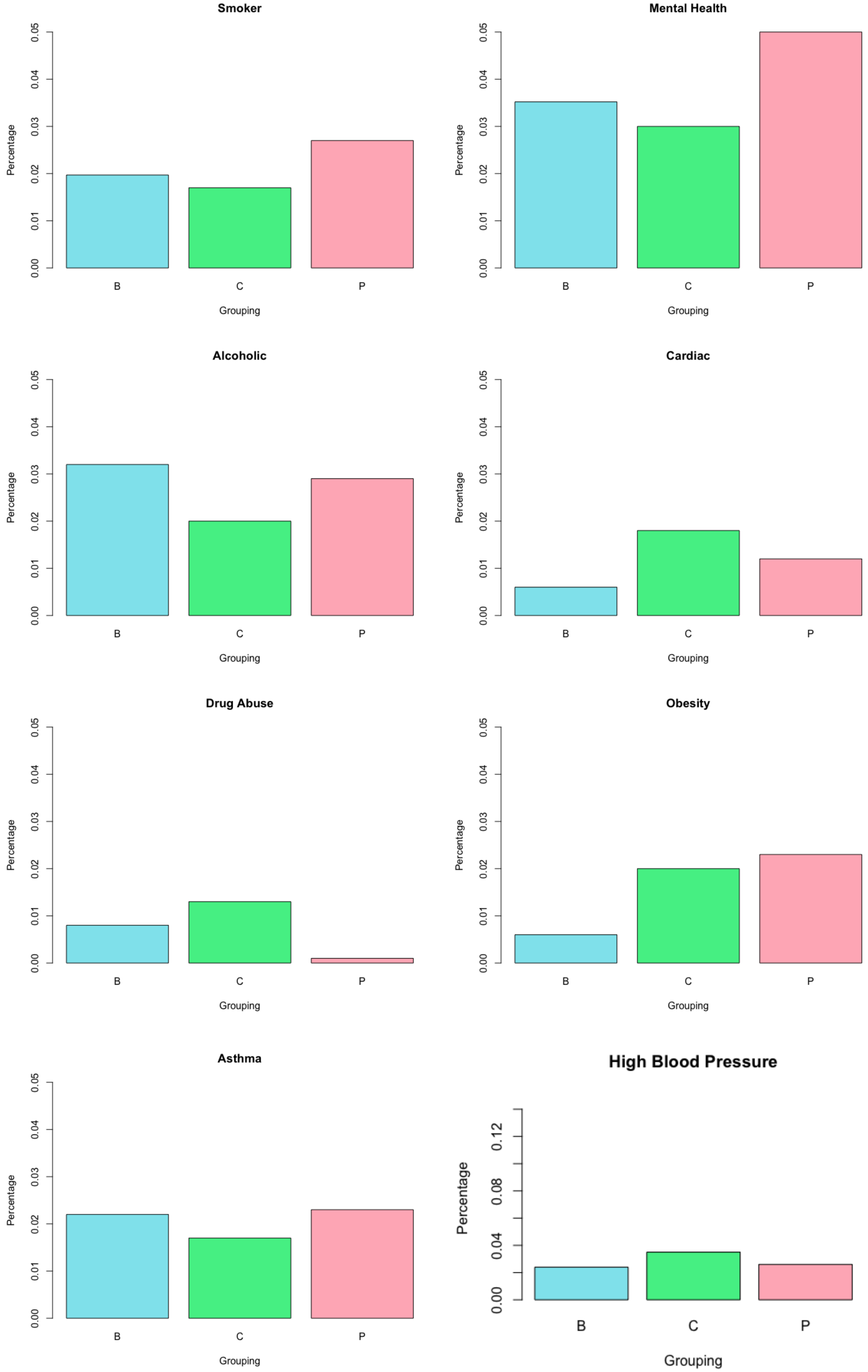
Smoker
Mental Health
Alcoholic
Cardiac
Drug Abuse
Obesity
Asthma
High Blood Pressure
Percentage
Grouping
B
C
P
0.00
0.01
0.02
0.03
0.04
0.05
0.04
0.08
0.12

Figure 3

Pooled proportion testing (Table 11 in the Appendix) verifies that most of the differences in pre-existing conditions between accident types are statistically significant. The differences motivate an analysis of the relative health of each group. Interestingly, the claimed health benefits of bicycling seem to have a real impact on the proportion of bicyclists with those preexisting conditions. Bicyclists have less cardiac issues, less obesity, and less mental health issues than the other groups, which is precisely what is expected.

While the proportion of individuals with health issues might be indicative of the health benefits from physical activity, it suggests nothing about how this affects accident outcome. Furthermore, this data set contains no information about the severity of each condition. Specifically, is no way to distinguish between two people with the same set of pre-existing conditions in terms of what an individuals' condition severity was prior to an accident. Since there is no way to distinguish the severity of each condition from the data, I specify a linear probability model in order to rank the conditions in terms of their impact on accident fatality rates. The ranking is derived from the magnititude of the coefficients. The difference in proportions is statistically significant for all pre-existing conditions listed, with the notable exception drug use.

3.6 Ranking the Prexisting Conditions

To gain insight into how health affects accident fatality rates, I specify a linear probability model in which the dependent variable, D_i, is set to 1 if the ith individual dies in a bicycling or car accident, and 0 if they survive. The dependent variables consists of the top 10 most occurring single prexisting conditions. Short descriptions of each variable can be found in the Appendix. The model is specified in the following manner, with coefficients estimates in Table 1:

$$D_i = \beta_0 + \beta_n Comorbidity_i + \delta T_i + \epsilon_i$$

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
Constant	9.599***	12.539***	
	(0.100)	(0.100)	
Alcoholic	0.318	0.299	0.020***
	(0.477)	(0.477)	(0.005)
Asthma	0.015	−1.023*	0.004*
	(0.534)	(0.534)	(0.002)
Cardiac	0.455	2.751***	0.041***
	(0.619)	(0.619)	(0.009)
Drug Abuse	0.417	1.017	0.021***
	(0.725)	(0.725)	(0.008)
HTN	0.092	0.397	0.014***
	(0.390)	(0.390)	(0.004)
Diabetes	0.042	−0.750	0.022**
	(0.804)	(0.804)	(0.010)
None			0.016***
			(0.001)
Obesity	0.154	1.491**	0.019**
	(0.736)	(0.736)	(0.008)
Other	0.422*	1.145***	0.016***
	(0.232)	(0.232)	(0.002)
Mental Health	0.378	−0.144	0.012***
	(0.443)	(0.443)	(0.003)
Smoker	0.400	1.625***	0.004*
	(0.603)	(0.603)	(0.002)
T	−0.128	1.190***	−0.011***
	(0.206)	(0.206)	(0.001)
Observations	27,705		
R^2	0.024		
Adjusted R^2	0.024		
Residual Std. Error	1.120 (df = 27693)		
F Statistic	63.172*** (df = 11; 27693)		
Notes: Robust standard errors in parenthesis.	*p<0.1; **p<0.05; ***p<0.01		

Table 7: Comorbidity Regressions

While it is tempting to interpret the coefficients on model (3) in Table 7, as the marginal effects of a particular pre-existing condition on the probability of surviving an accident, that is not the case. These coefficient on this model indicates the accident survival rate relative to an individual choosen at *random* from our sample, regardless of their health status. The purpose of this model is to be able to rank the conditions against themselves, and illustrate that they have some effect on accident outcome. Most individuals survive their respective accidents as shown in Figure 1, so as a result, the coefficients should be very small.

The coefficients on model (3) with the greatest significance level are "Drug Abuse," "Alcoholism," "Other," "Mental Health," and " Cardiac". Ranking the coefficients from highest to lowest provides some indication of which comorbid factors have a greater impact on accident fatality rates. The ranking is as follows:

1) Cardiac
2) Diabetes
3) Drug Abuse
4) Obesity
5) Alcoholism
6) Other
7) High blood pressure
8) Mental Health
9) Smoker
10) Asthma

These results are important because they allow for a distinction between the two groups in terms of health. Bicyclists on average have less of the conditions that have a signficant impact on the marginal probability of death in an accident, which suggests that health is one of the omitted variables in the original model specified in the introduction. No conclusions can be made about how these conditions affect accident outcome relative to healthy individuals thus far. The next step in the analysis will be examining how these conditions impact accident outcome compared to people that are healthy.

3.7 Relative Health

To approach the question of examining these conditions relative to healthy individuals, I examine how severe of accidents individuals with poor health get into. Model (2) in Table 6 uses ISS as the independent variable, and the same pre-exisiting conditions as specified in the previous model are used as the independent variables. This model is different because the omitted group consists of those with no comorbididty. The model is specified in the following manner:

$$ISS_i = \beta_0 + \beta_n Comorbidity_i + \delta T_i + \epsilon_i$$

The model's ouputs can be found in Table 7. Since the omitted group is individuals that are healthy, the coefficients, $\{\beta_1 ... \beta_9\}$, can be interpreted as the marginal effects of having that condition on accident severity *relative* to a healthy individual. All of these coefficients suggest that having a condition prior to an accident increases the severity of the accident on average, over a healthy individual. Some of these conditions appear to be associated with increased accident severity, including fatality risk.

3.8 Substance Abuse

The Oregon DMV claims that roughly 40% of all motor-vehicle accidents deaths in the State of Oregon involve some type of alcohol.[8]Unfortunately, people have found more substances than just alcohol to intoxicate themselves with before they drive or bicycle. Since my data only indicates whether a particular drug was present, not how much was present, I can only study the extensive margin. To examine the effect of a drugs' impact on accident outcome, I specify a new set of models. These models use various toxic substances as regressors, as well as a variable for sobriety. The reference group, is those that are legally drunk.[9]The general form of the new model can be found below, along with the results of the regression.

$$ISS_i = \beta_0 + \delta_n Drug_i + \lambda T_i + \gamma Sober_i + \epsilon_i$$

[8]See Oregon DMV 2014-2015 Drivers Manual.
[9]By Federal law, this is defined as having a BAC >.08

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
Sober	−0.0001	0.613***	0.005***
	(0.011)	(0.149)	(0.001)
T	−0.083***	1.334***	−0.012***
	(0.014)	(0.175)	(0.001)
Amphet	0.381***	2.491***	0.011***
	(0.033)	(0.471)	(0.004)
Barb	0.412***	6.332*	0.046
	(0.150)	(3.331)	(0.049)
Benz	0.521***	4.070***	0.009**
	(0.046)	(0.612)	(0.004)
Cann	0.401***	2.326***	0.011***
	(0.024)	(0.328)	(0.003)
Coc	0.381***	0.659	0.006
	(0.058)	(0.753)	(0.005)
Meth	0.556***	2.538***	0.020*
	(0.081)	(0.943)	(0.011)
None	0.355***	2.164***	0.012***
	(0.012)	(0.157)	(0.001)
Opiat	0.185***	0.565	0.009**
	(0.032)	(0.382)	(0.004)
Other	−0.058	−2.737**	−0.003***
	(0.086)	(1.090)	(0.001)
PCP	−1.199***	−10.626***	−0.003
	(0.201)	(0.166)	(0.002)
Constant	9.636***	11.819***	
	(0.011)	(0.146)	
Observations	44,185		
R^2	0.028		
Adjusted R^2	0.028		
Residual Std. Error	1.079 (df = 44,169)		
F Statistic	84.837*** (df = 15; 44,169)		
Note: Robust standard errors in parenthesis.		*p<0.1; **p<0.05; ***p<0.01	

Table 8: Toxic Substances Regressions

The coefficients here represent the marginal effect of the particular substance *relative* to being legally drunk. For example, the interpretation of the coefficient on opiates for model 1 is that using opiates increases expected hospital charges by 18.5% over being legally drunk. As seen from the regression, many of the drugs are correlated with an increase in accident severity, hospital charges, and probability of death.

Perhaps the most interesting insight that can be gleaned from this model is that consuming cannabis prior to an accident increases the severity of the accident, on every front. This is increasingly relevant as marijuana is legalized throughout the United States. This result is even more pertinent for the State of Oregon due to the drugs' recent legalization. The coefficients suggest that marijuana impairs driving ability at least as much as alcohol. As seen from the pooled proportion testing, the propensity of bicyclists and drivers to use drugs prior to operating their vehicle is different. Specifically, bicyclists use less toxic substances than drivers on average. Since the majority of the coefficients in the models presented in this section are statistically significant, I conclude that drug use prior to an accident has a significant effect on the outcome. This conclusion points to another systematic difference amongst bicyclists and drivers that may be causing the variation in total hospital charges.

3.9 Safety Equipment

Oregon law mandates that all individuals in a motor-vehicle wear a seatbelt. It also dictates that all individuals under the age of 16 wear a helmet when riding a bicycle. For this analysis, I specifiy two different sets of models: one for bicyclists and one for motor-vehicles. I justify using different models because the sample is now individuals using only one piece of safety equipment. Since the safety equipment used by each group is different,[10] so thus one model uses only motor-vehicle accidents, and the other uses bicycling accidents. The general form of the new model is the following:

$$D_i = \beta_0 + \alpha_n Safety_i + \epsilon_i$$

Oregon law also mandates that "Children over forty pounds or who have reached the upper weight limit for their forward-facing car seat must use boosters to 4'9" tall or age eight and the adult belt fits correctly." Since almost all children use the child's seat, the "child seat" variable works as a near perfect proxy for children as well, therefore no interaction term will be used. The results of the regression can be found in Tables 9 and 10 below.

[10]No bicyclists were found to wear a seatbelt or utilize and airbag

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
None			0.025***
			(0.002)
Airbag	0.040	−2.064***	0.028***
	(0.042)	(0.565)	(0.006)
Belt	−0.496***	−5.223***	0.010***
	(0.022)	(0.243)	(0.001)
Child	−1.033***	−5.597***	0.010**
	(0.066)	(0.725)	(0.005)
Helm	−0.230**	−2.452**	0.038**
	(0.091)	(1.073)	(0.019)
Constant	9.889***	15.805***	
	(0.015)	(0.191)	
Observations	13,151		
R^2	0.054		
Adjusted R^2	0.054		
Residual Std. Error	1.178 (df = 13146)		
F Statistic	187.286*** (df = 4; 13146)		
Notes: Robust standard errors in parenthesis			*p<0.1; **p<0.05; ***p<0.01

Table 9: Safety Equipment: Motor-vehicles only

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
None			0.006***
			(0.002)
Helmet	0.046	0.274	0.004**
	(0.033)	(0.377)	(0.002)
Constant	9.544***	13.810***	
	(0.021)	(0.255)	
Observations	3,343		
R^2	0.0002		
Adjusted R^2	−0.0001		
Residual Std. Error	10.934 (df = 3341)		
F Statistic	0.503 (df = 1; 3341)		
Notes: Robust standard errors in parenthesis			*p<0.1; **p<0.05; ***p<0.01

Table 10: Safety Equipment: Bicycles only

It is clear from these regression results that safety equipment has some impact on accident outcome. Some of the coefficients on these models lend themselves to the conclusion that safety equipment has an important impact on accident outcome. This is yet another set of regressors that could cause differences in hospital bills accrued by each group regardless of ISS scores.

4 Accident Outcome

I have provided an in-depth analysis of the characteristics of individuals that get into car and bicycling accidents. I have studied how abusing substances, using safety equipment, and health prior to accident all affect the outcome of the accident. Now, I will conduct an analysis that studies the impact of these traits upon the total hospital charges accrued by the individual following their accident. By modeling accident cost as a function of many different variables, I am able to gain some understanding as to these systematic differences cause variation in the hospital charges.

4.1 The Accident Cost Model

As I have discussed throughout the preceeding sections, there are significant differences in the health of the groups of individuals. Amongst other factors, the transportation mode choice variable acts as a proxy for many of these differences such as health, drugs consumed, safety equipment used, etc. Bicyclists have better health status, a lower propensity to consume drugs, and different uses of safety equipment prior to their accidents compared to motorvehicle operators. For hospital charges in particular, leaving these notable variables out of the model causes omitted variable bias.

I will specify a new model that uses $ln(Th_i)$ as the independent variable. To capture the entire cost of the accident, I include regressors that have an important part in explaining the outcome. To account for differences in safety equipment usage, I use a variable "EQ1" that is set to 1 if an individual had any safety equipment used in an accident, and 0 if not. I include an interaction between accident type and "EQ1" to account for the different uses. I also include an interaction term for being legally drunk and accident type as I suspect there will be a different effect for being drunk for bicyclists and motor-vehicle operators. Short descriptions of each variable used can be found in Table 12 in the Appendix. The other regressors are pre-existing condtions, various drugs and demographic information, all of which were shown to have a significant impact on the accident's outcome. These models use sober, White individuals with no pre-existing conditions their accident as the reference category. The general form of the new model is specified below, and the results of the regression can be found in the Appendix (Tables 17-21).

$$ln(Th_i) = \beta_0 + \beta_n Comorbidity_i + \delta_n Drugs_i + \alpha EQ_i + \lambda_n Demographics_i + \phi_n(Payor1_i * P2D_i) + \zeta(Drunk_i * T_i) + \chi Drunk_i + \psi T_i + \tau(T_i * EQ_i) + \theta_n Payor1_i + \Sigma P2D_i + \epsilon_i$$

As examined earlier in the paper, bicyclists are on average slightly healthier than motor vehicle operators. Table 12 shows that some of the conditions that bicyclists frequently have less of, indeed have a significant impact on accident cost outcome. For example, the coefficient on 'card' from Table 11 is .147. This indicates that having a cardiac issue will lead to a 14.7% increase in total hospital charges, on average. Similarly, having a mental health condition, drug abuse history, or alcoholism increases expected hospital charges of the ith individual by 25.3%, 33.1%, and 16.9%, respectively. The most feasible explanation seems to be that these health factors have a real impact on accident outcome, and something about having one of the pre-existing conditions prior to the accident causes an individual's body to be more frail in some way, causing the body to need more medical attention relative to those that didn't have them. Since bicyclists have less of these conditions, it seems as if they are slightly more robust to accident severity in terms of charges. Another possible explanation for this is that having better health prior to an accident makes the individual respond better to treatment, which could then make the accident cheaper. Regardless of the underlying reason as to what causes the distortion in charges, the difference in health between bicyclists and motorvehicle operators accounts for some of the variation.

The coefficients related to insurance are also fascinating. Based on the results of the regression, there are some discrepancies in the charges across different insurance types. For example, having Medicaid over no insurance increases total hospital charges by 31.3%. While hospital charges for insured invividuals may be higher, this does not necessarily indicate a higher cost to the individual. Since we have no information about how much an individual *actually* pays, it is difficult to say if this increased cost from insurance actually makes the accident more expensive to the individual.

Notice the coefficient on T_i is $-.107$ and is statistically significant at the 1% level. This is substantially closer to 0 than the coefficient on the naive regression,[11] which suggests that the variables this regression controlled for have a significant impact on hospital charges. After including various confounding factors such as health, ethnicity, drug usage, and insurance, bicyclists have hospital charges that are roughly 10% less expensive than motor-vehicle accidents. This suggests that the confounding variables studied in this paper account for roughly 10% of the variation in hospital charges. Moreover, because these various factors influence hospital charges, I conclude that they were omitted from the naive regression (Table 1) introduced early in the paper.

5 Conclusion

If total hospital charges is viewed as a good proxy ISS, a higher bill indicates a worse injury. Though there is a lack of empirical evidence on this, extrapolating, there is relationship between ISS and "recovery time" where recovery time is the amount of days that it takes an individual to return to a normal level of productivity. It seems reasonable to think that a worse injury (higher ISS) has a longer recovery time. This entails that a higher ISS causes the unobservable costs to be even higher. For example, a worse injury could lead to more days off work, taking time off work has an opportunity cost that is the individuals wage. Since an individuals health prior to an accident has a real effect on the accidents outcome in terms of ISS, the implication is now that not only does health impact the observable cost of an accident, but it *likely* also effects the unmeasurable cost of the accident. Additionally, it seems to be the case that bicyclists, despite getting into slightly worse accidents on average in terms of ISS, have lower hospital bills. There is also evidence that health affects probability of dying in an accident. Since bicyclists are on average "healthier," this likely contributes to explaining why less bicyclists die in accidents.

Perhaps the most interesting implication from this study is that if we consider the health benefits obtained from bicycling, and how these affects the outcome of an accident, then the cost of riding a bicycle over driving becomes less expensive relative to its alternatives such as driving. Furthermore, despite being a slower method of transportation, the cost of time lost in the short run from bicycling is likely overestimated by many individuals when deciding what

[11]See Table 1

mode of transportation to chose.

This paper uses various models to examine the multitude of factors that go into an accidents outcome. The outcome of the accident can be decomposed into a few different factors: probability of death, injury severity, and bill to the individual. I have shown that demographics have some effect on the accident outcome in terms of both physical severity and total hospital charges. Using a linear probability model, and standard linear regression models I show that health prior to an accident affects all three of these factors. Using pooled proportion testing, I was able to estimate that people getting into bicycling accidents are on average slightly healthier than those getting into motor vehicle accidents and thus the average population. Finally, taking all of the important accident elements, I created a log-linear model that estimated hospital costs among bicyclists and motor vehicle operators. This model provides more insight into what affects an accidents outcome, and the respective magnitude of each element. I find that, after controlling for all of these confounding factors, motor-vehicle accidents are 9.9% more expensive on average than bicycling accidents. I conclude that the cost of bicycling is likely underestimated when individuals are making transportation decisions. This is likely due to a lack of information, and perhaps a stronger preference for the utility gained from time saved in the short-run at the expense of the long-run health benefits of cycling.

6 Appendix

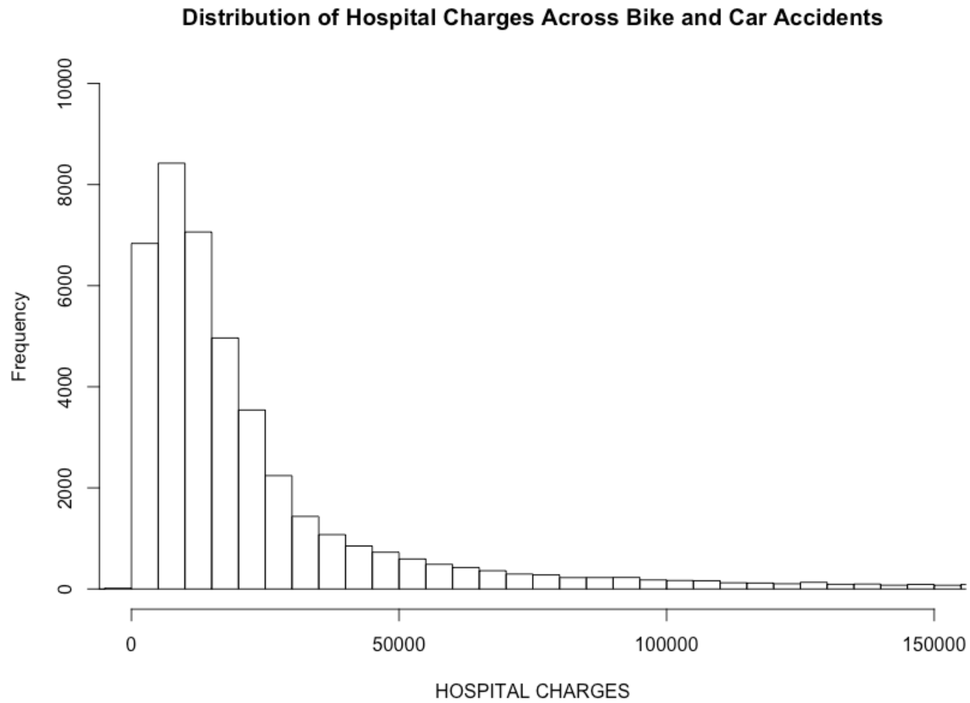

Figure 4

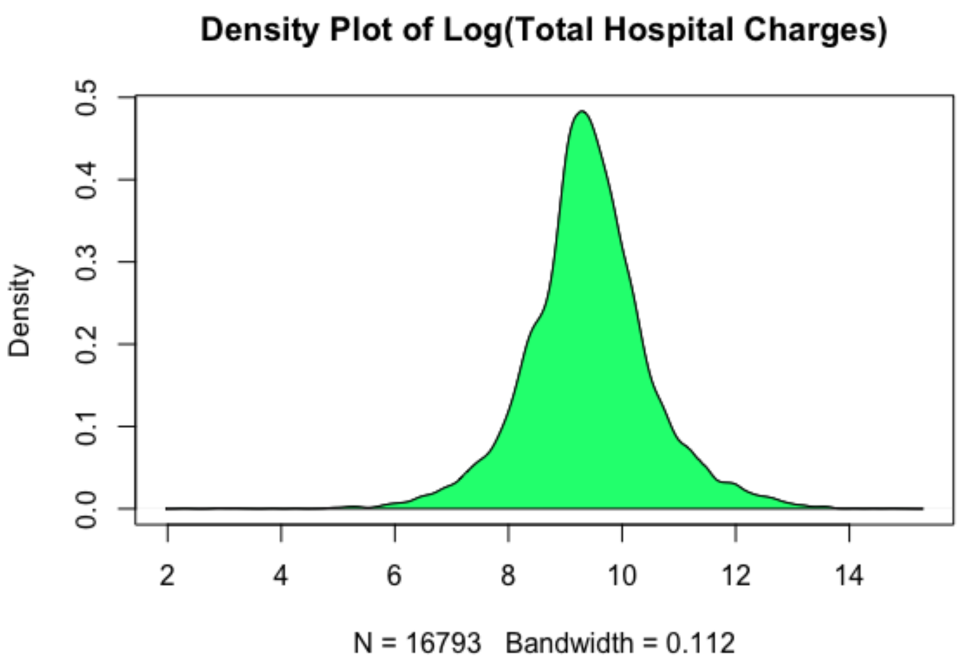

Figure 5

Panel A: Full Sample					
	Mean	Median	St. Dev.	Min	Max
Age	37.26	33.0	20.6344	0	250.00
Alcohol Level	0.063	0	0.107	0	.99
ISS	13.35	9.00	13.00	0	75
Total Hospital Charges	33290	15160	74736.62	0	3158000
MV.Speed	45.66	45	29.850	0	800
Panel B: Motor Vehicles Only					
	Mean	Median	St.Dev.	Min	Max
Age	34.02	29	18.951	0	96
Alcohol Level	0.065	0	0.1048	0	.98
ISS	12.78	9.00	11.70702	0	75
Total Hospital Charges	34570	15310	75541.7	0	2766000
MV.Speed	50.52	50.00	28.163	0	600
Panel C: Bicylists Only					
	Mean	Median	St.Dev.	Min	Max
Age	33.17	31	18.551	6.25	93.00
Alcohol Level	0.0744	0	.1176	0.00	.62
ISS	13.91	11	11.01	1	75
Total Hospital Charges	24610	14260	68412.15	25	3158000
MV.Speed	29.3	25	25.4	0.00	200
Panel D: Pedestrians Only					
	Mean	Median	St.Dev.	Min	Max
Age	36.42	34.	21.84	0	117
Alcohol Level	0.0728	0	0.121	0	.71
ISS	17.28	12	15.93	1	75
Total Hospital Charges	52030	20310	94733.95	0	1257000
MV.Speed	27.86	30.00	15.914	0	350

Table 11: Summary Statistics

Variable	Description
ISS	Injury Severity Score
A	Ethnic Group: Asian
Age	Age in years
AFA	Ethnic Group: African American
M	Gender:Male
H	Ethnic Group: Hawaiian
W	Ethnic Group: White
None	Indicates no information recorded
PI	Pacific Islander ethnicity
NAT	Ethnic Group: Native American
Mvs	Vehicle speed
T	Bicycling Accident
LDN	Dummy Variable:Death
Coc	Toxic Substance: Cocaine
Cann	Toxic Substance: Cannabis
Amphet	Toxic Substance: Amphetamine
Benz	Toxic Substance: Benzodiazepines
Drunk	Dummy Variable: BAC >.08
PCP	Toxic Substance: Phencyclidine
Other	Toxic Substance: Unspecified
HTN	Comorbidity: High Blood Pressure
Cardiac	Comorbidity: General Heart issues
Psych	Comorbidity: General Mental Health
NIDD	Comorbidity: Diabetes
Belt	Safety Equipment: Seatbelt
Child	Safety Equipment: Childseat
Helm	Safety Equipment: Helmet
EQ1	Safety Equipment: Any 1 safety equipment used
HMO	Insurance type: Health Maintenance Organization
Blue	Insurer: Blue Cross Blue Shield
Car	Insurance type: private car insurance
Comm	Insurance type: Commerical
Ward	Insurer: Ward Insurance Inc.
Work	Insurance type: generic work insurance
Self	No insurance
P2D	Secondary Insurer

Table 12: Short Variable Descriptions

Proportion Testing for Pre-exisiting Conditions			
Condition	$\boldsymbol{\rho_b - \rho_c}$	$\boldsymbol{\chi^2}$	**P-Value**
Alcoholism	0.0116	20.037	7.594e-06
Asthma	0.00492	4.3637	0.03671
Cardiac	-0.01236	28.858	7.786e-08
Drug Abuse	-0.00484	6.0654	0.01379
Hyptertension	-0.01061	10.835	0.0001
None	0.04432	28.565	9.061e-08
Obesity	-0.01395	34.532	4.192e-09
Other	-0.01275	4.428	0.03535
Smoker	0.00244	1.0849	0.2976
Psych	0.00486	2.4612	0.1167

Table 13

Proportion Testing for Illicit Substances			
Drug	$\rho_b - \rho_c$	χ^2	**P-Value**
Amphet	-0.004671361	10.349	0.001296
Barb	-0.0008591038	3.7252	0.0536
Benz	-0.004875268	16.568	4.695e-05
Cannabis	-0.01312806	21.146	4.256e-06
Cocaine	-0.001431559	3.4115	0.06474
Meth	-0.000253554	0.06299	0.8018
Opiates	-0.01110973	51.183	8.415e-13
None	-0.0831749	248.59	<2.2e-16
PCP	-0.0001077035	0.7457	0.3878

Table 14

Proportion Testing for Ethnic Groups			
Ethnicity	$\rho_b - \rho_c$	χ^2	**P-Value**
Asian	-0.00329508	3.1767,	0.0747
African American	-0.00166307	0.7458	0.3878
Hispanic	-0.04537404	109.39	<2.2e-16
Native American	-0.008708132	30.413	3.492e-08
Other	-0.00180064	0.99084	0.3195
Pacific Islander	-0.000176168	0.10309	0.7482
White	0.0610172	130.49	<2.2e-16

Table 15

Proportion Testing for Insurance Types			
Insurer	$\rho_b - \rho_c$	χ^2	**P-Value**
Blue	0.02677951	497.99	<2.2e-16
Car	-0.5430648	7674.3	<2.2e-16
Charity	0.01201779	74.421	<2.2e-16
Community	0.2033679	3691.4	<2.2e-16
Medicaid	0.1023159	1235.1	<2.2e-16
Medicare	0.03776879	374.76	<2.2e-16
Other	0.0777657	744.04	<2.2e-16
Self	0.08869047	563.11	<2.2e-16
Ward	-0.000181558	0.16219	0.6871
Work	-0.02584531	168.9	<2.2e-16

Table 16

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
New.ISS	0.048***		0.003***
	(0.001)		(0.0002)
LDN	−0.812***	33.383***	
	(0.085)	(1.375)	
T	−0.107***	−1.551**	−0.010**
	(0.039)	(0.629)	(0.005)
EQ1	−0.023	−3.906***	0.002
	(0.017)	(0.275)	(0.003)
Drunk	−0.038**	−1.095***	−0.003
	(0.017)	(0.254)	(0.002)
T*EQ1	0.119***	3.403***	−0.008
	(0.046)	(0.756)	(0.005)
Asian	0.099**	0.043	−0.009
	(0.045)	(0.744)	(0.006)
African American	0.210***	−2.827***	0.007
	(0.039)	(0.610)	(0.007)
Hispanic	0.093***	−0.648**	−0.005**
	(0.019)	(0.316)	(0.002)
Native American	0.055	−1.292	0.012
	(0.069)	(1.003)	(0.011)
Other	0.067	−1.185	0.001
	(0.048)	(0.745)	(0.007)
Pacifc Islander	0.200	−1.257	−0.010
	(0.191)	(2.242)	(0.008)
Age	0.004***	0.014**	0.0003***
	(0.0005)	(0.007)	(0.0001)
Male	−0.007	1.101***	−0.001
	(0.014)	(0.221)	(0.002)
Observations	14,177		
R^2	0.413		
Adjusted R^2	0.410		
Residual Std. Error	0.794 (df = 14119)		
F Statistic	174.167*** (df = 57; 14119)		
Notes: Robust standard errors in parenthesis			*p<0.1; **p<0.05; ***p<0.01

Table 17: Main Regression: Misc. Coefficients

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
Alcoholic	0.169***	−0.580	0.003
	(0.041)	(0.540)	(0.006)
Asthma	0.116**	−0.233	−0.009**
	(0.047)	(0.778)	(0.005)
Cardiac	0.147**	0.510	−0.006
	(0.063)	(0.939)	(0.012)
Drugs	0.331***	−1.222	0.007
	(0.067)	(1.205)	(0.012)
Hypertension	−0.005	0.252	−0.017***
	(0.043)	(0.596)	(0.006)
Diabetes	0.008	−2.000*	0.015
	(0.084)	(1.132)	(0.017)
Obesity	0.114*	2.412**	−0.005
	(0.066)	(0.999)	(0.011)
Other	0.206***	0.006	−0.001
	(0.019)	(0.304)	(0.003)
Psych	0.253***	−0.604	−0.008**
	(0.031)	(0.567)	(0.004)
Smoker	0.126***	1.033	−0.018***
	(0.036)	(0.657)	(0.003)
Observations	14,177		
R^2	0.413		
Adjusted R^2	0.410		
Residual Std. Error	0.794 (df = 14119)		
F Statistic	174.167*** (df = 57; 14119)		

Notes: Robust standard errors in parenthesis — *p<0.1; **p<0.05; ***p<0.01

Table 18: Main Regression: Pre-existing conditions

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
Amphet	0.057	1.695**	−0.005
	(0.051)	(0.810)	(0.008)
Barb	−0.490	5.929	−0.041*
	(0.342)	(6.379)	(0.022)
Benz	0.156*	4.543***	−0.020*
	(0.081)	(1.205)	(0.011)
Cannabis	0.097***	0.984***	−0.004
	(0.023)	(0.373)	(0.003)
Cocaine	0.166**	−0.247	−0.001
	(0.073)	(1.087)	(0.010)
Meth	0.311***	1.206	0.003
	(0.115)	(1.568)	(0.019)
Opiat	−0.039	−0.490	−0.006
	(0.047)	(0.569)	(0.005)
Other	−0.145**	−2.460*	−0.007
	(0.073)	(1.317)	(0.005)
PCP	−0.838***	−14.422***	0.020***
	(0.027)	(0.444)	(0.004)
Observations	14,177		
R^2	0.413		
Adjusted R^2	0.410		
Residual Std. Error	0.794 (df = 14119)		
F Statistic	174.167*** (df = 57; 14119)		
Notes: Robust standard errors in parenthesis			*p<0.1; **p<0.05; ***p<0.01

Table 19: Main Regression: Toxic Substances

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
Blue	−0.020	−1.235	−0.008
	(0.211)	(2.366)	(0.008)
Car	0.029	−0.038	0.001
	(0.035)	(0.439)	(0.004)
Charity	−0.289***	0.389	−0.0003
	(0.054)	(0.870)	(0.007)
Community	0.115**	3.020***	−0.013***
	(0.046)	(0.642)	(0.004)
HMO	0.227	−3.154*	−0.001
	(0.147)	(1.757)	(0.006)
Medicaid	0.313***	2.577***	−0.002
	(0.051)	(0.762)	(0.007)
Medicare	0.249*	2.950	0.064*
	(0.140)	(1.844)	(0.036)
Other	−0.047	0.230	−0.003
	(0.059)	(0.710)	(0.007)
Ward	0.013	−6.718***	0.012
	(0.249)	(1.395)	(0.008)
Work	0.144*	−1.351	−0.011**
	(0.077)	(0.925)	(0.005)
P2D	0.137***	1.009	−0.009**
	(0.045)	(0.656)	(0.004)
Observations	14,177		
R^2	0.413		
Adjusted R^2	0.410		
Residual Std. Error	0.794 (df = 14119)		
F Statistic	174.167*** (df = 57; 14119)		

Notes: Robust standard errors in parenthesis — *p<0.1; **p<0.05; ***p<0.01

Table 20: Main Regression: Insurance types

	Dependent variable:		
	Hospital Charges	ISS	Live/Die
	(1)	(2)	(3)
P2D	0.137***	1.009	−0.009**
	(0.045)	(0.656)	(0.004)
BlueP2D	0.148	4.614	−0.004
	(0.234)	(3.047)	(0.010)
CarP2D	0.144***	2.782***	0.004
	(0.049)	(0.703)	(0.005)
CharityP2D	0.296***	4.805	−0.022
	(0.071)	(6.911)	(0.026)
Comm*P2D	−0.066	−0.640	0.011
	(0.070)	(1.092)	(0.007)
HMO*P2D	−0.205	2.823	−0.002
	(0.192)	(2.630)	(0.009)
Medicaid*P2D	−0.233***	1.904	−0.006
	(0.080)	(1.366)	(0.009)
Medicare*P2D	−0.352**	−2.146	−0.054
	(0.173)	(2.303)	(0.039)
Other*P2D	0.145*	2.993***	−0.001
	(0.081)	(1.120)	(0.009)
Ward*P2D	−0.783**	−0.013	−0.003
	(0.356)	(2.806)	(0.011)
Work*P2D	0.064	3.042**	0.018*
	(0.099)	(1.332)	(0.011)
T*Drunk	−0.078*	0.635	−0.00003
	(0.046)	(0.748)	(0.005)
Constant	8.909***	12.760***	−0.031***
	(0.039)	(0.526)	(0.005)
Observations	14,177		
R^2	0.413		
Adjusted R^2	0.410		
Residual Std. Error	0.794 (df = 14119)		
F Statistic	174.167*** (df = 57; 14119)		
Notes: Robust standard errors in parenthesis		*p<0.1; **p<0.05; ***p<0.01	

Table 21: Main Regression: Interactions

7 References

1. Dill, Jennifer. "Bicycling for Transportation and Health: The Role of Infrastructure." J Public Health Pol 30 (2000): S95-100. Palgrave Macmillan. Web. 25 Apr. 2016.

2. Kawachi, I., Daniels, N., & Robinson, D. E. (n.d.). Health Disparities By Race And Class: Why Both Matter.
Retrieved June 01, 2016, from http://content.healthaffairs.org/content/24/2/343.full

3. Kochhar, R., & Fry, R. (2014). Wealth inequality has widened along racial, ethnic lines since end of Great Recession. Retrieved June 01, 2016, from http://www.pewresearch.org/fact-tank/2014/12/12/racial-wealth-gaps-great-recession/

4. Lehrfeld, David, Dana Selover, Candace Hamilton, Phyllis Lebo, Phillip Engle, Stella Rausch-Scott, Lisa Millet, Dagan Wright, and Nathan Jarret. Oregon Trauma Registry Report. Rep. N.p., Dec. 2014. Web. 28 Apr. 2016.

5. Levine, Robert V., and Ara Norenzayan. The Pace of Life in 31 Countries. Rep. N.p.: n.p., n.d. Print.

6. Warburton, Darren E.R., Crystal Whitney Nicol, and Shannon S.D. Bredin. "Health Benefits of Physical Activity: The Evidence." CMAJ: Canadian Medical Association Journal 174.6 (2006): 801809. PMC. Web. 28 Apr. 2016.

7. "Cycling - Health Benefits." - Better Health Channel. N.p., n.d. Web. 28 Apr. 2016.

8. "TRAUMA.ORG: Trauma Scoring: Injury Severity Score." TRAUMA.ORG: Trauma Scoring: Injury Severity Score. N.p., n.d. Web. 28 Apr. 2016.

9. "Benzodiazepines Drug Class: Side Effects, Types & Uses."RxList. N.p., n.d. Web. 09 May 2016.

10. Ho, K., & Lee, R. S. (2016, April 29). Insurer Competition in Health Care Markets (Rep.). Retrieved June 1, 2016, from Harvard website: http://www.people.fas.harvard.edu/ robin-lee/papers/InsurerComp.pdf