# Safety in Numbers? The Effect of Increasing Numbers of Bicycle Commuters on Bicycle-Automobile Collisions 

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# Safety in Numbers? The Effect of Increasing Numbers of Bicycle Commuters on Bicycle-Automobile Collisions 

## By

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B.S., Northwestern University, Evanston, IL, 2006

Thesis
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Safety in Numbers? The Effect of Increasing Numbers of Bicycle Commuters on BicycleAutomobile Collisions

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The idea that increasing the numbers of bicycle and pedestrians in an area lowers the automobile collision risk for individual cyclists and pedestrians is called the safety in numbers effect. This paper applies the safety in numbers effect to bicycling and pedestrian commuters in California cities from 2005 to 2011. The results indicate that cities with $10 \%$ more bicycle commuters will only see about $6 \%$ more collisions between cyclists and automobiles and thus have a lower average risk to bicycle commuters. These results are similar to those found by Jacobson (2003) although this study uses a multiple regression analysis on an expanded data set.

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## Chapter 1 Introduction

Bicycle commuting is growing rapidly in many cities across the United States, with many places more than doubling the percentage of commuting trips taken by bicycle from 2005 to 2011 (League of American Bicyclists 2011). With more people choosing to bicycle to work the number of bicycle commuters involved in collisions with motor vehicles has also increased. Due to the more exposed nature of cyclists, when involved in a collision they are more than twice as likely as automobile drivers to suffer a severe injury. The debate between lowering injury rates for bicycle commuters mostly focuses on the effect of the environment vs. the effect of the number of bicycle commuters themselves or the "safety in numbers" effect. The safety in numbers effect states that as the number of bicycle commuters increases the risk to each individual bicycle commuter decreases.

Environmental controls for bicycle commuter safety include the constructions of bike paths and lanes, special crossings at intersections, and traffic calming measures in neighborhoods. Bike lanes can be constructed for a relatively low cost during already scheduled times of street reconstruction, or resurfacing and can run from $\$ 5,000$ to $\$ 50,000$ per mile (Pedestrian and Bicycle Information Center 2013). Separated bicycle paths have much higher construction costs and can run from $\$ 40,000$ per mile for a soft surface trail to almost $\$ 1,000,000$ per mile for a paved trail in an urban area (Pedestrian and Bicycle Information Center 2013). As will be discussed in the Literature Review, the construction of bicycle specific infrastructure can have a direct impact on the level of safety experienced by bicycle commuters. Additionally, by
encouraging more individuals to bicycle commute, bicycle infrastructure also contributes to the safety in numbers effect. When increases in bicycle infrastructure result in ridership increases and a higher level of safety among current bicycle commuters the monetary benefits are substantial. An injury to a bicycle commuter amounts to about $\$ 7,600$ in direct medical costs (Lopez, et al. 2012) so if only a couple fewer cyclists are injured per year than the costs to build separated bicycle lanes are more then made up.

This paper follows Jacobson (2003) examining the "safety in numbers" effect while also controlling for demographic and environmental factors. Jacobson (2003) predicted the rate that bicycle injuries in a city would increase in response to increases in the bicycle commuter population. This study adds a number of demographic and environmental factors which have been observed to have an effect on commuter safety. In order to demonstrate the effect of rising bicycle commuter rates on bicycle collisions I employ a model on an unbalanced data set consisting of 69 cities in California from 2005 to 2011. My research utilizes the log of total bicycle collisions as the dependent variable and the log of bicycle commuters as the key independent variable. Following Jacobson (2003) the models are also estimated for bicycle injuries, and pedestrian collisions. I find that as the number of bicycle commuters in a city increases the number of bicycle collisions with automobiles increases at a lower rate, and thus the overall bicycle collision rate decreases. These results confirm the safety in numbers effect observed by Jacobson (2003), however the size of the safety in numbers effect estimated by this study is much smaller than that by Jacobson. Nonetheless, this relationship suggests that methods to increase bicycle commuter rates would have the significant effects on the proportion of bicycle commuters involved in collisions with automobile drivers.

With more people bicycle commuting than at any other time in American history, the safety of bicycle commuters is a substantial concern. The safety in numbers effect suggests that as more individuals start to bicycle commute the level of safety experienced by bicycle commuters will naturally increase. This result holds even after controlling for bicycle-specific infrastructure with the League of American Bicyclists medal variable. Numerous studies suggest that bicycle infrastructure has a substantial impact on both safety, and encouraging individuals to bicycle commute. To reach the levels of bicycle commuting where accident rates drop to the extremely low levels seen in many European cities, bicycle infrastructure construction must increase dramatically.

## Chapter 2 Literature Review

### 2.1 Introduction

Bicycle commuting offers a number of advantages over driving to work both for the individual and society as a whole. Cycling is a low cost and healthy alternative to driving. In dense urban areas cycling is often faster than the alternatives as it allows cyclists to avoid traffic jams and unreliable public transit service (Olde Kalter 2007). For cities cyclists cause less strain on infrastructure and can help raise average health of the public (Olde Kalter 2007).

Even though cycling is a viable transportation option for many commuters and brings a number of benefits, a vast majority of commuters still choose to use other means of transport. Due to the social benefits from increasing the share of bicycle commuters policy makers in a number of cities worldwide are showing increasing interest in encouraging cycling. Paris, Chicago, and Washington DC have all recently introduced systems that provide cheap rental bikes, and many cities are increasing the number of bike lanes (Enserink 2007). In order to understand bicyclist safety it is useful to examine the factors that lead to an individual's decision to commute by bicycle.

### 2.2 Factors that Contribute to an Individuals Decision to Bike Commute

It is often assumed that travel is a "derived demand". This assumes that it is the desirable activity at the destination of the trip which motivates the individual to travel. With bicycle travel this assumption does not always hold true. Bicycling trips could be either recreational,
utilitarian, or both. Recreational trips are for leisure and sport, while utilitarian trips include commuting to work and errands. With recreational trips the motivation is the trip itself, and the benefit that the cyclists receive from the trip. Utilitarian trips fit more closely with the assumptions made for auto and transit trips in that the purpose of the travel is a desired activity at the destination. For this thesis, utilitarian trips are of interest as they are the type of trip where the individual has the choice of different travel modes. The following sections will examine the factors that contribute to an individual's decision to choose cycling for utilitarian trips.

### 2.2.1 Built Environment

An individual's decisions about bicycling are influenced by the built environment in which they live. The built environment can further be divided into two categories: urban form and cycling infrastructure. The measure of urban form of relevance to potential cyclists is distance between destinations. As trip distance increases the share of commuters choosing bicycling decreases (Pucher and Buehler 2006). Non-cyclists also measure distance as a major factor contributing to choosing not to cycle (Dickinson, et al. 2003). Average trip distance on a citywide level is difficult to calculate, but it is reasonable to assume that cities with higher population densities and mixed use neighborhoods have a lower average trip distance. City density (Dill and Voros 2007) and mixed use neighborhoods (Litman, Land Use Impacts on Transport: How Land Use Factors Affect Travel Behavior 2007) are indeed associated with higher levels of bike commuting.

In many studies the existence of bicycle specific infrastructure has been shown to have dramatic effects on the levels of bicycle commuting, both where the infrastructure exists and on a
citywide basis. The presence of bike lanes and paths contribute to both the subjective and objective safety of the bicycle commuters (Klobucar and Fricker 2007). Objective safety is measured in actual bicycle related incidents and will be discussed later. Subjective safety refers to how individuals perceive the safety of their environment. For cyclists subjective safety is highly correlated to the presence of bicycle specific infrastructure (Klobucar and Fricker 2007). If commuters feel the environment is safe for cycling then they will be more likely to choose cycling over other commuting modes. This is especially true for inexperienced and younger cyclists who are more likely to prefer bike lanes and paths to wide curb lanes (Stinson and Bhat 2005). The presence of bicycle lanes (Hunt and Abraham 2007) and paths (Barnes, Thompson and Krizek 2006) have been shown to be associated with higher level of commuting where the infrastructure is built. However in these studies it remains unclear if these infrastructure improvements are increasing the overall number of cyclists, or only modifying the route choice of existing cyclists to take advantage of the cycling specific infrastructure.

The increase in the amount of bicycle infrastructure in a city can increase the number of bicycle commuters. People whom agree that their route is bikeable are about twice as likely to bicycle as those that did not (Titze, et al. 2008). A reveled preference survey found a positive correlation between bicycle commuters rating of the overall quality of bicycle facilities and frequency of bicycle commuting in the area (Sener, Eluru and Bhat 2009). Potential bicycle commuters understand the overall level of the bicycling facilities in their area and are more likely to bicycle when bicycle specific infrastructure is present.

Bicycle lanes are painted bicycle only lanes on existing roads. Not only will current bicycle commuters divert their route to ride on bicycle lanes, but people living near bicycle lanes have also been shown to be more likely to bicycle commute (Krizek and Johnson 2006). The
perception that bicycle lanes are on their route may make a commuter more likely to bicycle (Dill \& Voros, 2007). Not only will an increase bicycle lanes help increase the number of people bicycling to work, but in one study over $40 \%$ of bicycle commuters stated that they would pick a longer route if it included bicycle lanes or paths (Shafizadeh and Niemeier 1997). Since distance has been shown to be a major obstacle for bicycle commuters, increasing the number of bicycle lanes should decrease the amount of re-routing that will be necessary of bicycle commuters. This should have a secondary effect of increasing the overall level of bicycle commuting. Cycle tracks, bicycle lanes that are separated from the road with barriers have long been common in Europe, and are now starting to appear up in many American cities. Surveys conducted in Denmark and Germany reveled that bicycle commuters preferred cycle tracks to simple painted bicycle lanes (Bohle, 2000; Jensen S. U., 2007). In a before and after study in Copenhagen, roads with cycle tracks saw a $20 \%$ increase in bicycle traffic and a $10 \%$ decrease in automobile traffic (Jensen S. U., 2008b). It is possible that these increases in traffic were current commuters modifying their route and not actual increases in the numbers of bicycle commuters.

### 2.2.2 Natural Environment

For motorists and those taking public transit the natural environment is of little importance. Automobiles are able to drive up steep grades in rain or snow, all while keeping their occupants in climate-controlled comfort. Cyclists on the other hand are intimately involved with the natural environment. They are significantly affected by the landscape, weather conditions, and overall climate. The natural environment affects both the individuals' decision to bike commute as well as the route they take.

The presence of steep grades significantly increases the energy that a cyclist has to expend to reach their destination. While recreational and experienced cyclists prefer hilly terrain (Stinson and Bhat 2005), evidence suggests that inexperienced bicycle commuters tend to avoid major hills on their route (Parkin, Wardman and Page 2008). There is some evidence that cities with high average grades have a lower share of bike commuters than flatter areas (Moudon et al. 2005). However in general it appears that hilliness has more to do with route choice within a city than whether or not a given individual chooses to bike commute (Stinson and Bhat, 2005).

Seasonal weather variations have a strong effect on local commuting behavior in a given city. In regions with low winter temperatures cycling rates experience a steep decline in the winter months (Guo, Bhat and Copperman 2007). Not only do fewer people bicycle commute in the winter but the distance that bicycle commuters will travel also decreases (Bergstrom and Magnusson 2003). While seasonal variations in weather have a strong effect on the levels of bicycle commuting, the same relationship does not appear to exist for climate differences. In the United States, three of the top six large cities for bicycle commuting, Portland, Eugene, and Seattle, have over 100 days of rain per year (Dill and Carr 2003). Canadians also bike commute at higher rates than Americans, suggesting that regional climate does not have a large effect on bicycle commuter rates (Pucher and Buehler 2006).

### 2.2.3 Psychological Factors: Attitudes, Social Norms, Habits, and Perceived Safety

Psychological factors can be difficult to measure as they usually rely on stated preference surveys which may introduce bias and limit what can be analyzed. Since cyclists come from all socio-economic backgrounds, psychological factors are one predictor of bicycle commuting.

Attitudes towards cycling, car use and the environment, developed habits, and perceived safety are all excellent psychological predictors of bicycle commuting behavior. In general, car use is seen as more normal behavior than bicycle commuting (Dill and Voros 2007). As expected, bicycle commuters' view cycling as more ordinary behavior than non-cycling commuters, and also place a much higher importance to the health-related benefits of bicycle commuting than non-bicycle commuters (Dill and Voros 2007, Gatersleben and Appleton 2007). Bicycle commuters have a negative perception of the consequences of car use (Stinson and Bhat 2005). Individuals with more deeply held environmental beliefs are also more likely to use nonmotorized transport including cycling (Moudon et al. 2005). While these attitudes are important predictors of cycling behavior, they are not easily observable as demographic characteristics and measuring these attributes requires the use of surveys.

Due to habits many people may not make a rational choice when picking their commuting mode. When behavior becomes repetitive individuals may fail to take every factor into consideration when making a decision (Bamberg and Schmidt 2003). Breaking the habit of automobile commuting can result in a mode reconsideration and possible mode change to bicycle commuting. Experiencing what it is like to commute by bicycle even for a day can persuade some people to change commuting modes (Rose and Marfurt 2007). When recreational cyclists try bicycle commuting they are likely to continue the behavior (Stinson and Bhat 2004). These results suggest that policies to encourage individuals to try bicycle commuting can encourage them to adopt it as their primary commuting mode choice. Non-bicycle commuters' concerns about safety can also be addressed by trying to bicycle at least once.

Bike-to-Work days are becoming increasingly popular in American cities. These events may take place over a day, week, or month and can include free breakfast, giveaways, contests,
and other activities. These events are specifically targeted to help commuters dispel some of the misconceptions that they might have about bicycle commuting. There is evidence that Bike-toWork day's result in ridership increases after the event. In a 2008 study in San Francisco found bicycle counts at a selected intersection were $25 \%$ higher several weeks after a Bike-to-Work day event (LAB 2008). A similar study in Victoria, Australia saw 27\% of first-time riders from Bike-to-Work day were still bicycling to work 5 months after the event (Rose and Marfurt 2007). Bike-to-Work days are an effective means for cities to increase bicycle commuter numbers. While Bike-to-Work days are effective they are not the only means that cities have employed to encourage commuters to try bicycle commute. Bicycle share programs offer shortterm rentals for a nominal fee. Bicycles can be picked up and returned at designated spots around the city and are usually tracked through an automated system. The accessibility of these bicycles ensures that they often might be the fastest and easiest way for a commuter to travel. The placement of these bicycles near transit stations makes them a reasonable choice for mix-mode transport, and also for commuters who may have missed a bus or train. Bicycle share programs and short-term bicycle rentals have been associated with higher levels of bicycle commuting after these programs were instituted (Martens, 2007; Litman, 2009).

Additionally, cities are starting to focus on encouraging students to bicycle or walk to school. This program is called Safe Routes to School and includes education, encouragement, infrastucture and enforcement aimed at increasing the safety and number of students bicycling and walking to school. In the United States the program is funded at the federal level and as of 2012 included over 13,000 schools nationwide (National Center for Safe Routes to School 2013). By encouraging students to bicycle to work it's likely that they will continue to see the potential
of bicycling as their primary commuting mode as they get older, athough as these programs are fairly recent, studies on the long-term effects of Safe Routes to School have not been done.

Ends of trip facilities for bicycle commuters include bicycle parking, showers at workplaces, and bicycle stations. Bicycle parking is usually outdoors, but many workplaces have added indoor parking. Additionally many buildings are adding shower facilities for people that bicycle commute. Bicycle stations are usually built near busy commercial and transit areas and contain secure indoor parking along with a variety of services including showers, repair services, and bicycle rentals. These factors are important concerns for current and potential bicycle commuters.

The availability of secure bicycle parking and showers at work can help raise the perception of the convenience of bicycle commuting and thus raise the likelihood of bicycle commuting (Hunt and Abraham 2007). The impact of indoor secure parking is much greater than the impact of outdoor and unsecured parking. Like secure parking, the availability of shower facilities at work has been shown to have a significant impact on the levels of bicycle commuting among people with access to the facilities (Wardman, Tight and Page 2007). These factors both serve to help normalize bicycle commuting for individuals. Currently the construction of secure bicycle parking and showers at destinations largely falls on employers. Fortunately incentives exist for employers to add these facilities. LEED (Leadership in Energy and Environmental Design) certification is given by the United States Green Building Council. LEED certification comes in four levels from just LEED certification to LEED certification platinum. To get LEED certified a building receives points based on measures from energy efficiency to available bicycle parking. A building receives points for having available bicycle parking, and even more points for having shower facilities available for commuters (US Green Building Council 2005).

LEED certification is a sought after certificate for many new buildings as it helps them attract more environmentally conscious employees. It gives employers an incentive to either construct or choose buildings with available bicycle parking and showers.

While LEED certification is important for private and public buildings, cities can also provide these amenities. Secure bicycle parking at transit stations is available in many American cities and serves to increase the number of commuters for whom bicycling is a reasonable choice. Secure bicycle parking at transit stations has a significant effect both on the levels of bicycle commuting, but also on the levels of transit use (Martens 2007). Bicycle parking at commuter rail stations extends the potential bicycle commuter to many of the people commuting from the suburbs. Several American cities have also been including bicycle stations in their bicycle plans. These stations allow commuters who do not have secure bicycle parking in the workplace a secure place to keep their bicycle, and in many cases a place to shower and do routine repairs as well (CDOT, 2013). So far no studies exist that measure the impacts of bicycle stations on bicycle commuting, but they are presumably positive because bicycle stations are well utilized and offer a number of amenities that have been shown to have a positive impact on bicycle commuting levels.

Safety is often mentioned by non-cyclists as a reason why they do not commute by bicycle. Actual accident rates (objective safety) are certainly important from a societal viewpoint, but how safe bicycle commuters feel (subjective safety) is a more reliable predictor of commuting behavior. As discussed previously individuals are much more likely to commute by bicycle if they feel safe while commuting. This perceived safety has been shown to be highly correlated with the presence of bicycle specific infrastructure. A study in Portland found that even though $7 \%$ of the population already commuted by bicycle, another $60 \%$ would consider it
if they felt that bicycling was safer (Geller 2010). By increasing the level of perceived safety the numbers of bicycle commuters could be dramatically increased.

### 2.3 Factors that Contribute to Objective Bicycle Safety

For this study objective safety is measured as the number of automobile collisions involving bicyclists. This ignores collisions or falls that take place in areas where collisions with motor vehicles are not highly likely, such as bike paths. These incidents are certainly important, but since these are often unreported to the local police or highway patrol it is difficult to measure the levels of these accidents. While the raw number of cyclists involved in fatal collisions is relatively low, the percentage of cyclists involved in collisions of any type is much higher than the percentage of automobile drivers involved in collisions. A number of factors have been shown to increase the level of objective safety experienced by bicycle commuters. These factors widely fit into demographics of the commuters, the urban form including cycling specific infrastructure, and the percentage of bicycle commuters in the overall mode share of the population.

### 2.3.1 Demographics

Demographics play an important role in overall automobile accident rates, although little research has been done on their specific effect on bicycle collisions, the same factors should be present. Age, educational attainment, and marital status are important demographic variables for predicting driving behavior and accident rates.

Age is a strong predictor of automobile accidents. Automobile accidents are one of the main causes of death among 15-to-29 year olds (Ferguson, et al. 2001). Young drivers possess an inflated sense of their driving ability, which may result in undervaluing the risks involved, leading to higher risk taking while driving (Sivak, Soler and Tränkle 1989). Young drivers also perceive traffic laws as less important than do older ones; they use seatbelts less frequently, and tend to drive faster than older drivers (Yagil, 1998; Eby, Vivoda, \& Fordyce, 2002; Shinar, Schechtman, \& Compton, 2001). Likewise older drivers are more likely to be involved in automobile accidents than young people, but for a different set of reasons. Commuters over 75 years of age are over represented in both accident volume and accident injuries (NHTSA 1997). When sleepy the reaction times of the older drivers decrease by more than the rest of the general population (Philip, et al. 1999). Not only are they more likely to be involved in collisions as drivers, but as pedestrians they are also more likely to be hit by an automobile and injured than the rest of the population (Demetriades, et al. 2004). In a population with more teenagers and older drivers we would expect to see a higher number of automobile and bicycle collisions.

Educational levels are a dramatic predictor of involvement in motor vehicle accidents. People with low levels of educational attainment have higher mortality rates per unit of travel, even after controlling for seat-belt use (Braver 2003). Similarly drivers with low levels of educational attainment have a higher probability of being involved in any type of motor vehicle accident, and also of being severely injured in those events (Hasselberg, Vaez and Laflamme 2005). Increasing educational attainment is also highly correlated with speed limit compliance which should result in a lower level of automobile collisions (Hemenway and Solnick 1993). A population with a higher average level of educational attainment would then be expected to have lower levels of automobile and bicycle collisions.

Marital status can be an indicator for automobile collision likelihood. Insurance companies assume that married individuals have a lower accident risk than single individuals and charge them a lower premium rate (Tryfos 1980). A study in New Zealand found that after controlling for age and gender, never married individuals had over twice the risk of being involved in an automobile collision as married individuals (Clark, et al. 2004). Another study looked specifically at work commuting, and driving for work confirmed that married individuals had significantly lower risk both for automobile injury and accidents. (Salminen 2000). A population with a higher percentage of married individuals would then be expected to have a lower level of automobile and bicycle collisions. The next section will discuss how the urban form effects bicycle commuter safety.

### 2.3.2 Urban Form

The urban area in which cyclists commute affects the commuters' safety in a number of ways. Intersections are dangerous for cyclists as they face risk from turning vehicles, inattentive drivers, and pedestrians. Since intersections are risky, for cyclists, a number of studies have focused on the interaction between intersection types and bicycle commuter accident rates (Wang and Nihan 2004; Hels and Orozova-Bekkevold 2007; Gårder, Leden and Pulkkinen 2007; Jensen 2008a). Intersections with more turning lanes and wider medians have been shown to be associated with higher risk of collision for bicycle commuters (Wang and Nihan 2004). Single lane roundabouts are much safer for cyclists than normal traffic stoplights or two lane roundabouts (Hels and Orozova-Bekkevold 2007). Bicycle specific crossings at intersections have been shown to help enhance safety for bicycle commuters. Raised bicycle crossings
(Gårder, Leden and Pulkkinen 2007) and blue marked cycling crossings (Jensen, 2008a) have been shown to decrease the frequency of bicycle and automobile collisions. However Jensen (2008a) found that at intersections with more than four marked bicycle crossings collisions between bicycles and automobiles actually increased. This could be due to a confusing effect on motorists of having many colored lines crossing the intersection.

Bicycle boxes and special phase traffic signals are another way that bicycle commuter safety can be increased at intersections. Bicycle boxes are special bicycle-only boxes where the bicycle commuters are allowed to stop in front of automobiles at intersections. Bicycle boxes do help bicycle commuters to feel safer (Wall, Davies and Crabtree 2003), however they have not been shown to have a significant effect on the safety of bicycle commuters (Allen, Bygrave and Harper 2005). Additionally the bicycle boxes are regularly encroached upon by automobiles and correct usage by all commuters is rare (Wall, Davies, \& Crabtree, 2003; Allen, Bygrave, \& Harper, 2005). The main benefit of bicycle boxes seems to be the feeling of safety that it adds to the bicycle commuters and their addition to intersections is fairly low cost.

A separate traffic signal phase for bicycles is a significantly more expensive addition to an intersection than a bicycle box, but allows the bicycle commuters to cross the intersection without any automobile traffic. These signals are common in European cities but rare in the United States. Davis, CA; New York, NY; and Portland, OR are a few of the American cities that are starting to experiment with bicycle phase traffic signals (Nabti and Ridgeway 2002). In sharp contrast to bicycle boxes, bicycle phase traffic signals have been shown to be highly effective in decreasing the number of collisions between bicycle commuters and motorists. A study done in Davis, CA found automobile-bicycle collisions drop from 10 in the 35 months previous to the installation of the traffic signal to 0 in the 35 months after installation (Korve and

Niemeier 2002). Bicycle phase traffic signals do have a cost in the total volume of traffic that an intersection can handle, although their high level of success suggests that there are significant benefits to bicycle commuter safety by adding them at intersections with high amounts of bicycle traffic.

The type of roadway or path that a cyclist is riding on can have a large influence on the rates of both accidents and severe injury among cyclists. Cyclists might ride on sidewalks, separated bike specific paths, streets with bike lanes and streets. Sidewalks are shown to be the most dangerous place for cyclists to ride with relative risk between 4 and 5 times more dangerous than riding on the road (Aultman-Hall and Kaltenecker 1999; Moritz 1997). This is likely due to cyclists not being seen by cars pulling out of parking spots and alleyways. Studies disagree somewhat on the level of safety on bike and multiuse paths with Rodgers (1997) finding that relative risk on bicycle paths was $60 \%$ that of roads while Aultman-Hall and Kaltenecker (1999) found riding on bicycle paths carried about $150 \%$ more risk than riding on the road. Since many bicycle paths are multiuse the risk of paths with a high volume of runners, pedestrians, pets, and other users would carry more risk than bicycle specific paths.

Bicycle lanes on roads have been shown to be the safest locations for bicycle commuters with risk between $50 \%$ and $60 \%$ of riding on roads without any bicycle facilities (Moritz 1997; Rodgers 1997). This makes intuitive sense as in bike paths the cyclist typically is not sharing the area with pedestrians or any other user group. The effect of cycle tracks, or separated bicycle lanes on safety has not been studied extensively, but given the newly found prevalence of this infrastructure in American cities this would offer an interesting opportunity for future research.

### 2.3.3 Safety in Numbers

The relationship of decreasing collisions with increasing traffic has been well observed in the literature. This phenomenon, dubbed "Smeed's Law" arose when Smeed (1949) found that rates of automobile fatalities were decreasing as the number of drivers rose. This relationship has also been called the safety in numbers effect and has been looked at in a number of studies with both bicycle and pedestrian accident rates. This effect is particularly important to bicycle commuters as they are more likely to be involved in a collision than a motorist, and also more likely to suffer injury as a result of a collision. With respect to bicycle commuters, the safety in numbers effect states that as more people in a city bicycle to work the risk to each individual bicyclist of being involved in a collision will go down.

The majority of studies that have looked at the safety in numbers effect examined the effect at different intersections within one city. Within the city of Lund, Sweden Ekman (1996) found that not only did bicyclist safety increase at intersections with higher cyclist volume, but at intersections with over 50 cyclists per hour the increase in safety was dramatic. By looking at the before and after effect of adding raised crossings in Gothenberg, Sweden, Leden, Gårder and Pulkkinen (2000) found that not only did the raised intersections attract up to $50 \%$ more cyclists than before, but that the relative risk to each cyclist going through the intersection decreased by $24 \%$.

While looking at the frequency of collisions at different intersections within a city is important it does not capture the citywide behavior modification that might arise among automobile commuters as they become more accustomed to sharing the roads with cyclists. Lower accident rates have been found in countries, cities, and towns with higher bicycle
commuter rates (Jacobsen 2003). However Jacobsen (2003) did not use control variables so the relationship found between bicycle commuter rates could be due to other factors.

This study builds on the work done by Jacobsen (2003) to estimate the effect of increasing bicycle commuter rates on the risk to individual bicycle commuters. Jacobsen (2003) used a cross-section of data for California cities in the year 2000, while this paper uses an unbalanced panel data set from 2005-2011. This will allow the analysis to control for city as well as yearly fixed effects, as well as to control for various demographic and commuting characteristic variables. The commuting variables added are population density in thousands and average commute length. As a proxy for the level of bicycle specific infrastructure this study uses the medal awarded by the League of American Bicyclists. The demographic variables added are percentage of population under age 20 , over 65 , married, and with a bachelor's degree or higher. The next section will cover the history of bicycle commuting in the United States and some specific actions that American cities are taking to increase bicycle commuting levels.

## Chapter 3 History and Background

### 3.1 History of Bicycle Commuting in the United States

The bicycle has played a very important role in the history of transportation in the United States. In the 1860s the first pedal driven bicycle was built based on improvements to the foot driven velocipede which looked like a bicycle without pedals. In the early 1890s the invention of pneumatic (air filled) tires allowed lighter and faster bicycles to be built and cycling became popular on (Herlihy 2006). By the end of the 1800s cycling was an extremely common activity for both transportation and recreation. The bicycle offered a lightweight and modern advantage over horse transport. By the end of the 1890s there were more than 25 bicycle manufactures in Chicago alone, including the well-known Arnold, Schwinn and Company (Furness, 2010). During this time the League of American Wheelmen (now called the League of American Bicyclists) lobbied for improved roads (Furness, 2010). Many roads in the country were paved before automobiles even existed. Additionally cities were built with mixed-use in mind and most commutes were short. The bicycle started an unprecedented era of ease of personal transportation. The number of cyclists in the United States increased from 150,000 in 1890 to 4 million in 1896 (Tobin 1974). Access to the bicycle was important to many Americans that had previously been constrained in their mobility. As city cyclists took to the countryside a tourism industry sprang up with inns, hotels and restaurants lining popular routes.

In the early $20^{\text {th }}$ century the rise of the automobile became both a blessing and a curse as urban and rural populations in the United States either embraced the freedom of driving or were forced to adapt to the presence of increasing numbers of automobiles on the roads. Automobile
collisions became a problem soon after they became available for purchase. The very first case of an automobile colliding with a cyclist took place in 1896 in New York when Henry Wells hit a cyclist with his new Duryea automobile only two months after the car was first produced (Mionske 2007).

By 1929 approximately 1 in 4.5 Americans owned an automobile and bicycle commuters were forced to concede right of way to the car (Gudis 2004). Many cyclists moved onto motoring and others simply lost interest. By 1941, 85 percent of bicycles produced in the United States were children's toys (Gudis 2004). Massive postwar expenditures on highway infrastructure cemented the automobile's hold in United States mobility. Cities became more spread out and less pedestrian friendly. The rise of the suburbs made the automobile a necessary part of many people lives.

The energy crises of the 1970s ushered in a period of change. The oil embargo of 1973 created mass fuel shortages across the United States, the tripling of gasoline prices by 1974, and a ripple effect that destabilized international markets (Furness, 2010). The embargo also created the perfect context for bicycle advocates who could speak to the importance of alternative, sustainable modes of transportation. 1973 marked the first year since World War I that bicycles outsold automobiles in the United States (The New York Times 1974). Whereas in previous years the vast majority of bicycles sold were for children, in 1973 adult bicycles accounted for 50 percent of the sales (Kanfer 1975). Most people did not abandon their cars for bicycles, but the prospect of high gas prices allowed cycling to be seen as an attractive option for many city dwellers.

Cycling advocates were able to mobilize support by promoting the environmental benefits of non-motorized transportation as well as tapping into the increasing popularity of
physical fitness. By 1974 approximately $\$ 117$ million was spent on bike projects by all levels of government (Corgel and Floyd 1979). Davis California, Chicago Illinois, and Milwaukee Wisconsin are a few of the cities that instituted bicycle route construction, as well as increased parking and access. The recognition of bicycling as a legitimate mode of transportation indicated a paradigm shift for that time. Unfortunately the increased numbers of cyclists on the roads resulted in increased collisions. 1975 was the worst year on record for cycling fatalities with 1,003 cyclists killed (National Highway Traffic Safety Administration 2007).

The boom in cycling was fairly short lived. With cheap oil flowing Americans flocked back to their cars. Large sports utility vehicles, impractical for urban living, were among the most popular vehicles. Bicycle commuting during this time was repeatedly portrayed in popular culture as a symbol of financial and social failure. A classic example is the 1986 film Quicksilver, which features a stock broker who loses his job and becomes a bike messenger (Donnelly 1986). Given the yuppie lifestyle of the era, bicycling was the opposite of the American Dream. Another example is the film Pee-wee's Big Adventure in which the protagonist, a cyclists, is a childlike social misfit (Burton 1985). In both films bicyclists are presented as debased adults incapable of growing up.

In the early 2000s a number of factors combined to help normalize bicycle commuting for large portions of the American public, and ridership began to increase. The dominance of American cyclist Lance Armstrong in the Tour de France helped renew recreational cycling for fitness. Today recreational and competitive cycling is immensely popular among investment bankers, lawyers, and executives. For many of these executives, "Bicycling is the new golf" (Williams 2005). The high end bicycles purchased by type-A competitors have driven retail growth in bicycles with the sale of high-end road bikes increasing nearly fourfold from 2000 to

2005 (Belkin 2006). These riders support a massive industry with races, events, and high-end tours worldwide even though as a share of the 14 million unit bicycle market, their sales are quite small.

With mainstream acceptance of recreational cycling, the increase in bicycle commuting was not far behind. Rising oil prices, due to the Iraq war incentivized many urban dwellers to consider cycling as their primary mode of transport. Additionally, renewed concerns over climate change and the environmental degradation caused by automobile pollution have helped contribute to bicycles being seen as a normal mode of transport (Furness 2010). By the mid2000s nearly every bicycle manufacturer was offering a line simple cost-effective commuting style bicycles. With so many Americans living in urban areas and making frequent short trips, it's likely that the bicycle could be an ideal solution for large numbers of Americans. Encouraging Americans to ride bikes has been a primary goal of the bicycle advocacy groups in the United States and they appear to be succeeding. From 2000 to 2010 the portion of Americans commuting by bicycle increased by $47 \%$ and bicycle commuters now make up about $0.6 \%$ of all commuters. In major cities this increase was even more significant with an increase of $63 \%$. Bicycle commuters now account for approximately $1 \%$ of all commuters in Americas 70 largest cities (League of American Bicyclists 2011). Cities across the United States are taking measures to encourage bicycle commuting.

### 3.2 Measures to Increase Bicycle Commuting

With the recent growth in bicycle commuting, cities are becoming more aware of the needs and desires of bicycle commuters. As discussed in chapter 2, the addition of bicycle
specific infrastructure has been shown to have a significant effect on the numbers of bicycle commuters. Making people feel safe while on the streets is a crucial element of any bicycle commuting plan. Although there has been some political pushback, many cities are now considering bicycle commuters when they design and make infrastructure improvements. There is a growing acceptance that more people on bicycles leads to fewer automobiles, and thus less strain on the overall transportation infrastructure of cities. Unlike during the cycling boom of the 1970s, planning for bicycle commuters is now a part the transportation planning in most cities across the country. A few of the measures that cities have adopted to encourage increased bicycle commuting include adding separated bicycle lanes and paths, safety measures at intersections, and bicycle share programs combined with well-publicized bicycle to work days.

As discussed previously Portland, Oregon recently conducted a study where they determined that in addition to the $7 \%$ of the population that felt confident riding their bicycle in the existing cycling infrastructure there was an additional $60 \%$ of the city's population that they qualified as "interested but concerned" about bicycling in the city (Geller 2010). This large segment of the population represents potential bicycle commuters and shows just how much potential growth there is for bicycle commuting. They would consider riding their bicycles to work if they felt safer on the roadways. These are the people for who the construction of separated bike lanes and paths is most important. If a large portion of these commuters can be converted to try bicycling to work then some American cities may be able to approach European levels of bicycle ridership. The savings of converting these people would be sustainably lower levels of strain on the current road and public transportation networks.

The construction of on street bicycle lanes in the easiest and most frequently instituted measure utilized to increase the level of bicycle infrastructure in a city; however this is not the
only measure for converting the "interested but concerned" group into regular bicycle commuters. Cycle tracks, common in northern Europe, are now being installed in many American cities. Unlike regular bike lanes, cycle tracks are separated by plastic or metal barriers from automobile traffic. New York was the first American city to introduce cycle tracks, partly as a response to the problem of automobiles blocking and parking in bicycle lanes. As of 2013 there were 16 km of cycle tracks on ten streets in New York City (NYCDOT 2013). Cycle tracks have also started to appear in Washington DC, Portland, and Chicago (DDOT, 2013; City of Portland, 2013; CDOT, 2013).

As discussed in chapter 2, painted bicycle crossings have been shown to help decrease bicycle collisions at intersections. Many cities including New York, Portland, San Francisco, Washington, and Missoula have installed red, blue or green bicycle lanes at intersections (NYCDOT, 2013; City of Portland, 2013; SFMTA, 2013; DDOT, 2013; Weiss, 2012). In addition to painted bicycle lanes at intersections, many cities have been installing bicycle boxes with advanced stop lines for bicycle commuters about 3-5m ahead of the stop line for cars. As with bicycle crossings, New York took the lead with 215 bike boxes installed by 2010, although they have also been installed in San Francisco, Portland, Washington DC and Missoula (SFMTA, 2013; City of Portland, 2013; DDOT, 2013; Weiss, 2012).

Traffic-calmed residential streets can serve as convenient, comfortable and safe bicycle commuting routes, even without any bicycle lanes or other special facilities. Traffic calming measures include traffic circles, speed humps, median islands, curb extensions, diverters, and mid-block street closures with pass-throughs for bikes (Buehler and Pucher 2011). The main goal of these measures is to slow down automobile traffic, and to discourage automobiles from using
residential streets as through routes. Chicago, Portland, and San Francisco all have some traffic calmed residential neighborhoods (CDOT, 2013; City of Portland, 2013; SFMTA, 2013).

As discussed in chapter 2, the existence of bicycle parking at work can have a large effect on how many commuters decide to bicycle. Bicycle commuters have shown a strong preference for secure, sheltered parking to prevent theft and protect bicycles from inclement weather (Hunt and Abraham 2007). Cities have responded to the desires of more bicycle parking in a variety of ways. Sidewalk parking is clearly the most prevalent, but cities are also increasing measures to offer substantial numbers of secure spaces in commercial and population centers. Bike corrals, on-street bicycle parking converted from one or two car parking spaces are becoming popular in Portland and San Francisco (City of Portland, 2013; SFMTA, 2013). These bike-corrals allow between 10-20 bicycles to park in a space that could previously only hold one or two cars. Bikecorrals have proven to be very popular in commercial areas as they dramatically increase the number of potential customers that can park in an area. A number of cities are also instituting laws that require the private provision of bicycle parking in residential and commercial buildings (CDOT, 2013; City of Portland, 2013; SFMTA, 2013). These provisions usually take the form of a minimum number of bicycle spaces according to either the number of car spaces available, or the total floor area available. There are also a number of cities that offer incentives for workplace buildings to provide showers and lockers. These incentives would increase the ability of bicycle commuters to come from further away as longer distance commuters are more likely to need a shower at their destination.

By integrating bicycle commuting with public transit systems cities can encourage more cycling, as well as more public transit use (Brons, Givoni and Rietveld 2009). Cycling extends the area that a given bus or train stop can serve far beyond walking range at a much lower cost
than park and ride stations for automobiles. Public transportation can also be useful to bicycle commuters when they suffer inclement weather and mechanical failures. Many cities have equipped their buses with bicycle racks, as well as allowing bicycle on rail systems (CDOT, 2013; City of Portland, 2013; SFMTA, 2013). Secure bicycle parking at rail stations also allows commuters to participate in multi-modal commuting. Some cities even have constructed bicycle stations adjacent to public transit centers that may include 24 hour security as well as bicycle repair and rental services (CDOT, 2013). By encouraging integration between bicycle and transit commuters, the number of people that can be served by both modes is dramatically increased.

Worldwide bicycle sharing programs have gotten a lot of press and these programs have been expanding to the United States. As discussed in chapter 2, bicycle sharing programs, along with bicycle to work weeks or days have shown to be an effective measure in encouraging individuals to try bicycle commuting. Washington DC, Chicago, and Minneapolis all have bicycle sharing programs that have over 3 million rides per year (DDOT, 2013; CDOT, 2013; City of Minneapolis, 2013). Bike to work weeks often have volunteers and city employees handing out free water bottles as well as encouraging camaraderie and good natured competition between companies. In Chicago, the companies that have the highest percentage of commuters bicycle commute during bike to work week receive small prize packages (CDOT 2013). These measures may prove effective in breaking down the misconceptions that automobile commuters in these cities have about bicycle commuting.

Besides the massive infrastructure improvements, perhaps the biggest difference between the recent bicycle commuting boom and the one in the 1970s is the implementation of comprehensive, long-range bicycle plans in many cities (CDOT, 2013; City of Portland, 2013; SFMTA, 2013). These programs are important for guiding overall strategies to increase cycling
by coordinating a range of programs and infrastructure improvements over time so that they are most effective. Most of these plans set overall long-term goals and have detail about the measures that will be taken to increase cycling. In many cities, planners work with cycling advocacy organizations to determine where infrastructure improvements are most needed, and to understand the local ridership and bicycle injury trends (CDOT, 2013; City of Portland, 2013; SFMTA, 2013).

Chicago, Illinois and Missoula, Montana serve as two interesting case studies on the types of projects currently being undertaken in cities across the country. While drastically different in both population and bicycle commuting rates, both cities have been hard at work in increasing the bicycle commuting rates. They have adopted a number of the measures explained above, and have seen significant increases in bicycle commuting rates.

Chicago Illinois has adopted a large scale program to increase bicycle ridership and safety in the city that takes the insights of the Portland study to heart. This program is currently called the Chicago Streets for Cycling Plan 2020 and includes a number of measurable goals as well as extensive measures to make bicycle commuters feel safe while riding around the city (Klein, 2013). As with Portland the focus is on increasing the level of perceived bicycle safety to increase the percentage of the "interested but concerned" residents that will try bicycle commuting. The plan wants to make it possible that every resident of the city is within two blocks of some sort of bicycle route that links up with the rest of the citywide bicycle network. These networks might be as simple as neighborhood traffic calming measures, or as advanced as barrier protected bicycle lanes. When the current phase of this plan is completed the on-street bicycle network will be over 645 miles long. This will allow resident of the city to get pretty much anywhere with minimal interaction with fast moving automobile traffic. Chicago has even
launched a low cost bicycle share program that allows commuters and tourists to rent bicycles from kiosks around the city (Klein, 2012). While located mostly in the downtown area, this program should help convince many commuters that are on the fence to try bicycle commuting. Additionally the plan is to grow the number of bicycle stations to 400 available from the far north to the south side. Chicago is also among the leaders in advocacy programs with an extremely popular bike-to-work week. The growth of bicycle commuting in Chicago has been substantial with $1.5 \%$ of all commuters now using bicycles. Chicago offers a textbook example of how a large city with extensive financial resources can increase bicycle commuting, and their plan is resulting in increased bicycle ridership in the city.

It is not only large cities that are working hard to increase bicycle commuter rates. Missoula Montana has an extensive plan with the actual stated mission of reducing singleoccupant vehicle use (Weiss 2012). Missoula has utilized a number of measures including traffic calming and an extensive bicycle lane and path network. Missoula also holds an annual Bike Walk Bus week where residents are encouraged to bicycle to work, and receive discounts from retailers around town when they do. Bike-corrals, popular in Portland and San Francisco, are available for cyclists to use in the downtown area. The measures have paid off. Missoula has one of the highest bicycle commuting rates in the country at nearly $6 \%$ of all commuting trips.

The large scale expansion of bicycle infrastructure combined with possible long-term likelihood in increasing oil prices hopefully point to the recent ridership gains being long term and not just part of a short-term boom like in the 1970s. Unlike the boom and bust cycle that bicycle commuting has undergone in the United States, bicycle commuting has long been popular in many European countries. While the United States is currently undergoing a construction boom in bicycle routes and facilities, these have always existed in many European
cities, and construction of them rose with the rise of the automobile. The types of facilities that are being constructed in the United States are mainly based on examples of what proved to be successful in Europe. While it remains to be seen if the current boom in cycling in the United States will be permanent, the radical changes that many cities are undergoing is encouraging, and hopefully more individuals will consider bicycle commuting as a result.

### 3.3 Costs of Bicycle Collisions

As will be discussed in chapter 4, bicycle commuters are at a higher risk for collision than automobile drivers and are more likely than automobile drivers to suffer severe injury or death in the event of a collision. These collisions are not only potentially life altering or deadly for the individuals involved but also have high monetary costs. Additionally the high publicity of cycling deaths may serve as a deterrent for potential bicycle commuters that harbor concerns over safety. Hospitalized bicycle commuters may experience issues including persistent disability, cognitive and behavioral changes, and permanent work disability, and will often require multiple hospital visits and extensive physical therapy to recover (Olkkonen, et al. 1993).

In the United States in 2010, 618 bicyclists were killed and 52,000 were injured after colliding with an automobile (National Highway Traffic Safety Administration 2012). These statistics are based on police reports and likely do not include many bicycle accidents where no automobile was involved as it is unlikely that these would be reported to the police. Total bicycle crashes may exceed police reported bicycle crashes by up to two times (Cercarelli, Rosman and Ryan 1996). Likewise a recent study in San Francisco was able to match only about $45 \%$ of the bicycle injuries that required hospital admission to existing police reports (Lopez, et al. 2012).

Among all injuries that were reported to hospitals $58.5 \%$ were cyclist only injuries but among data that was matched to police reports this number was only $9.1 \%$. This would suggest that injuries to cyclists that do not involve motor vehicles are under reported in police reports. Interestingly almost $81 \%$ of admitted cyclists were not wearing a helmet at the time of the injury.

For a bicycle commuter that is taken to the emergency room following a collision with an automobile there are three possible major direct monetary costs; hospital costs, professional fee costs, and ambulance fee costs. In the San Francisco study, the average medical cost in a bicycle-automobile collision was nearly $\$ 7,600$ of which about $74 \%$ was charged to public funds (Lopez, et al. 2012). However this is only for cyclists that were admitted to the hospital. Bicycle commuters that were only slightly or not-injured and thus were not taken to the hospital were not included. By applying the $\$ 7,600$ to the 52,000 injured cyclists' results in a nationwide total cost of about $\$ 395$ million. Of this about $\$ 292$ million would likely be paid by public funds. This number is an estimate of the direct medical costs of bicycle-automobile collisions, but ignores secondary costs to the American economy and the long-term costs to the bicycle commuters involved in the collisions.

It is possible that significant reductions in medical costs to injured bicycle commuters could be achieved with more commuters riding with helmets. A detailed discussion of mandatory helmet laws is beyond the scope of this paper. Helmet laws may decrease the severe injury rate among cyclists that are involved in a collision. However, helmet laws have also been shown to have a significant negative effect on the numbers of bicycle commuter's (Robinson 2006). This evidence suggests that programs to encourage helmet use may be effective in lowering bicycle commuter injury rates, but the costs and benefits of mandatory helmet laws is an issue which requires further discussion.

Even though the number of fatalities to bicycle commuters is low compared to the raw number of injuries, the costs associated with bicycle fatalities are quite high. Using a Value of Statistical Life equation from the National Highway Traffic Safety Administration, the 2005 study estimated that the average cost for a bicycle death in 2005 was $\$ 1.5$ million (Helmkamp, Aitken and Lawrence 2009). This comes to about $\$ 1.7$ million in 2011 dollars and would put the total economic costs of all the cyclist deaths in that year at $\$ 1.05$ billion. This number represents a substantial loss in human capital in addition to the emotional and psychological tragedy suffered by the families.

## Chapter 4 Empirical Evidence: The Data

### 4.1 Introduction

The data in this study is at the city level for many of the cities with a population above 65,000 people in the state of California from 2005 to 2011. It is an unbalanced panel of 69 cities from 2005-2011 with 337 observations in total when including cities with at least 2 observations. Accident data is provided by the California Highway Patrol and is available at the individual accident level. Demographics are taken from the American Community Survey (ACS) 1-Year data sets released by the US Census Bureau. The ACS estimates are corrected for population, and are not the raw numbers of respondents from the survey. In the models not all cities are included due to some missing values. Table 4.1 shows the locations of the 69 cities. The San

## Figure 4.1-City Locations



Fransico and Los Angelas areas are very well represented, but there are also a number of inland and mountain cities included.

### 4.2 Bicycle Collision Data

The raw number of bicycle collisions in California is on the rise. From 2005 to 2011 the number of collisions involving bicyclists in California grew from 11,600 to around 13,000. The number of fatal bicycle collisions in California has remained fairly constant over the 7 years in the data. In 2005 there were 131 fatal bicycle collisions in California and in 2011 there were 139 fatal bicycle collisions. If bicyclists are involved in a collision their risk of experiencing a fatal collision is around $1 \%$. When involved in a collision bicycle commuters are extremely likely to be injured and the chance of severe injury is also fairly high. In 2011 over $90 \%$ of the bicycle collisions resulted in some sort of injury, and about 7\% resulted in severe injury to the cyclist. Overall bicycle collisions are more likely in the middle of the week with about $50 \%$ of collisions taking place from Tuesday to Thursday. About $22 \%$ of collisions take place on the weekend.

Figure 4.2 - California Total Bicycle Collisions by Year


Figure 4.3 - California Total Fatal Bicycle Collisions by Year


### 4.3 Yearly Commuting Characteristics

The percentage of bicycle commuters varies widely for the 69 cities included in the panel dataset. For a few cities the American Community Survey reports a value of zero for the number of bicycle commuters. This represents two cities in 2006, one in 2007, six in 2008, three in 2009, three in 2010, and one in 2011. These cities are fairly small with an average population of 72,800. Having a zero in the data does not imply that nobody living in these cities commutes by bicycle, just that nobody who filled out the ACS answered that they do. While the ACS scales up the respondents to the population, however if no survey respondents answer that they bicycle commute the city will still receive a 0 for the number of total bicycle commuters. As these cities do have bicycle collisions, including them in the data could skew the results as they would have
an undefined bicycle collision rate, so they are dropped from both the panel and cross sectional models.

Bicycle crash percentage was calculated by dividing the number of collisions involving bicycle commuters by the number of bicycle commuters. Note that this does not denote the exact percentage of bicycle commuters involved in collisions as it is possible that a commuter could be involved in more than one collision, and that recreational cyclists who do not commute by bicycle could be involved in a number of the collisions. However this measure is a good indicator of the collision risk to bicycle commuters in a city in a year. Collisions that took place on the weekend were also deleted from the data as it is more likely that cyclists on the weekend are recreational and not commuting cyclists.

Some statistics for the bicycle commuter and accident activity are presented in Table 4.1. From this table it appears that bicycle commuting is rising and that the percentage of cyclists involved in collisions is decreasing, however since there are different cities involved in each year the trends could be a function of the different cities included each year. The commuter population is slightly different than the total population of the city as it only includes people commuting to work or school. The population density and average commute times have remained fairly constant over the seven years of data. The numbers of cities that have received medals from the League of American Bicyclists has grown substantially in the data. In 2005 not a single city had a medal, and by $201020 \%$ of the cities had a medal. As seen previously the recent investments in bicycle specific infrastructure has been substantial so it is expected that more cities would be deemed "bicycle friendly" communities.

Table 4.1-Yearly Bicycle Summary Statistics

| Year | Freq. | Ave. Commuter <br> Pop. | Bike <br> Commute <br> Pct. | Bike Crash <br> Pct. | Pop. Density <br> (Thousands / <br> Square Mile) | Ave. <br> Commute <br> Time <br> (Minutes) | Medal |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2005 | 14 | 317,318 | $0.88 \%$ | $10 \%$ | 2.81 | 25.3 | $0 \%$ |
| 2006 | 49 | 164,534 | $0.99 \%$ | $10 \%$ | 3.29 | 25.6 | $8 \%$ |
| 2007 | 49 | 142,865 | $1.01 \%$ | $15 \%$ | 2.76 | 25.6 | $8 \%$ |
| 2008 | 56 | 135,933 | $1.21 \%$ | $11 \%$ | 2.85 | 25.5 | $7 \%$ |
| 2009 | 56 | 131,654 | $1.11 \%$ | $13 \%$ | 2.75 | 25.0 | $14 \%$ |
| 2010 | 54 | 131,861 | $1.26 \%$ | $12 \%$ | 2.81 | 25.3 | $20 \%$ |
| 2011 | 59 | 125,810 | $1.35 \%$ | $10 \%$ | 2.81 | 25.5 | $20 \%$ |
| Total | $\mathbf{3 3 7}$ | $\mathbf{1 4 5 , 4 9 9}$ | $\mathbf{1 . 1 5 \%}$ | $\mathbf{1 2 \%}$ | $\mathbf{2 . 8 7}$ | $\mathbf{2 5 . 4}$ | $\mathbf{1 3 \%}$ |

### 4.4 Yearly Demographic Characteristics

The demographic characteristics included in the model do not have as much yearly variation as the commuting and collisions statistics. Table 4.2 shows the averages of the demographic variables that are included in the model. The under 20 variable and the over 65 variable have both remained fairly constant at a little over 7\%. Education high is about $30 \%$ in all years. The married percentage is about $47 \%$. The car crash percentage is decreasing and is not nearly as high as the bicycle crash percentages.

Table 4.2 - Yearly Demographic Characteristics

| Year | Freq. | Age <br> Under 20 <br> Pct. | Age <br> Over 65 <br> Pct. | High <br> Education <br> Pct. | Married <br> Pct. | Car Crash <br> Pct. | Bike <br> Commute <br> Pct. |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2005 | 14 | $7.0 \%$ | $6.8 \%$ | $28 \%$ | $47 \%$ | $4.0 \%$ | $0.88 \%$ |
| 2006 | 49 | $7.3 \%$ | $7.5 \%$ | $32 \%$ | $47 \%$ | $2.8 \%$ | $0.99 \%$ |
| 2007 | 49 | $7.3 \%$ | $7.6 \%$ | $32 \%$ | $47 \%$ | $3.3 \%$ | $1.01 \%$ |
| 2008 | 56 | $7.5 \%$ | $7.4 \%$ | $30 \%$ | $47 \%$ | $2.7 \%$ | $1.21 \%$ |
| 2009 | 56 | $7.0 \%$ | $7.5 \%$ | $31 \%$ | $47 \%$ | $2.8 \%$ | $1.11 \%$ |
| 2010 | 54 | $7.3 \%$ | $7.6 \%$ | $32 \%$ | $46 \%$ | $2.8 \%$ | $1.26 \%$ |
| 2011 | 59 | $7.0 \%$ | $7.5 \%$ | $32 \%$ | $46 \%$ | $2.7 \%$ | $1.35 \%$ |
| Total | $\mathbf{3 3 7}$ | $\mathbf{7 . 2 \%}$ | $\mathbf{7 . 5 \%}$ | $\mathbf{3 1 \%}$ | $\mathbf{4 7 \%}$ | $\mathbf{2 . 8 \%}$ | $\mathbf{1 . 1 5 \%}$ |

### 4.5 Safety in Numbers Trend

There are 21 cities in the data that are available for all years 2005-2011 inclusive. These cities offer an opportunity to study some of the trends in the data and offer preliminary examination of the relationships that are scrutinized in the model. From 2007 to 2011 the number of bicycle commuters in these 21 cities grew from 52,500 to over 74,000. This represents an increase of $41 \%$. Over the same time period the number of bicycle collisions grew from 5,000 to 6,200 or $24 \%$. This represents a substantial decrease in the collision risk to the average bicycle commuter. This relationship is not as apparent for pedestrian commuters even though the numbers of pedestrian collisions are decreasing, the numbers of pedestrian commuters has remained fairly constant. From 2007 to 2011 the number of pedestrian commuters in the 21 cities increased from 189,000 to 191,000 and the number of pedestrian collisions decreased from 5,500 to 4,500 . Due to the small increase in the number of pedestrian commuters it is difficult to tell if the decrease in collisions is due to the statewide effect of the safety in numbers effect.

Figure 4.4 - Selected City Bicycle Commuting Growth


Figure 4.5 - Selected City Bicycle Collision Growth


The safety in numbers effect becomes even more apparent when looking at the percentages. Many of the cities that have a bicycle commuter percentage over $2 \%$ see dramatic decreases in the bicycle crash percentage. Berkeley has two of the lowest values for bicycle crash percentage at $4 \%$ in 2007 and $3.6 \%$ in 2011, and has respectively two of the highest values for

Figure 4.6-Bicycle Commuter Pct. vs. Bicycle Crash Pct. for Selected Cities

bicycle commute percentage at $7 \%$ and $9 \%$ in those years. On the other side of the spectrum is the city of Oceanside, which had bicycle crash percentages of $25 \%$ and $24 \%$ in 2008 and 2010, and had bicycle-commuting rates of $.3 \%$ and $.31 \%$ respectively in those years. Examinations of the simple relationships in the data clearly suggest that safety in numbers is in effect.

### 4.6 Variable Definitions

Table 4.3 and Table 4.4 present the summary statistics for the models. The dependent variable in this study is the $\log$ of the raw number of bicycle collisions in a city. This variable includes only bicycle collisions between bicyclists and automobiles that were reported to the California Department of Highway Patrol. To help capture bicycle-commuters-only collisions that took place during the normal work-week (Monday-Friday). collisions taking place on the weekend were excluded because they are more likely to be recreational cyclists.

The key independent variable is the $\log$ of the number of bicycle commuters in the city. This variable is the American Community Survey estimate of the number of bicycle commuters in a city. The variable population density is the population density in 1000s of people per square mile. This variable is created by taking the total number of people in the city and dividing by the land area in square miles. The average commute time variable is the average daily commuting time for each commuter in the city in minutes. The medal variable is a dummy variable that is 1 if the city has a medal from the League of American Bicyclists in that year. The League of American Bicyclists awards medals to cities that are deemed "Bicycle Friendly." Cities receive these medals by adding bicycle-specific infrastructure, and advocacy programs. For this analysis the medal variable controls for additions in bicycle-specific infrastructure. The under 20 variable is the percentage of the general population that is under the age of 20 and is created by dividing the number of people under the age of 20 by the total population. Likewise, the over 65 variable is the percentage of the general population that is over 65 and is created by dividing the number of people over 65 by the total population. The high education variable is the percentage of the population with at least a bachelor's degree and is created by taking the number of people with at
least a bachelor's degree and dividing by the total population of the city. The married variable is the percentage of the population that is married and is created by taking the number of people that are married by the total population of the city. The car crash probability variable represents the risky drivers in a city and is created by taking the number of collisions between only cars or trucks and dividing by the number of commuters that commute by car or truck.

Following Jacobson (2003), in addition to the bicycle commuting models, additional models are estimated for pedestrian commuters. For these models many of the variables are the same except for the two related specifically to bicycle commuting and accidents. In the pedestrian commuting models the dependent variable is the $\log$ of pedestrian collisions. As with bicycle collisions this includes only weekday collisions between pedestrians and automobiles that are reported to the California Department of Highway Patrol. The main independent variable for the pedestrian models is the log of the number of pedestrian commuters. As with the bicycle commuter numbers, this variable is taken from the American Community Survey and is the estimate of the number of pedestrian commuters in the city.

### 4.7 Variable Summary Statistics

As will be discussed in chapter 6 models are estimated to test the safety in numbers effect for bicycle and pedestrian commuters. The summary statistics for the panel models are presented in Table 4.3. The panel data set is unbalanced with some cities available almost every year, and a few cities available only two of the seven years.

Table 4.3 - Panel Model Summary Statistics

| Model Variables | $\mathbf{N}$ | Mean | Std. Dev. | Min. | Max. |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Log (Bicycle Collisions) | 337 | 4.1 | 1.0 | 1.79 | 7.6 |
| Log (Pedestrian Collisions) | 337 | 4.1 | 1.0 | 2.08 | 7.8 |
| Log (Bicycle Commuters) | 337 | 6.5 | 1.3 | 3.7 | 9.8 |
| Log (Pedestrian Commuters) | 337 | 7.6 | 1.1 | 4.4 | 11.1 |
| Bicycle Collisions | 337 | 114 | 224 | 6 | 1,920 |
| Pedestrian Collisions | 337 | 134 | 340 | 8 | 2,459 |
| Bicycle Commuters | 337 | 1,553 | 2,743 | 39 | 17,957 |
| Pedestrian Commuters | 337 | 4,599 | 10,263 | 85 | 65,719 |
| Pop Density | 337 | 2.9 | 1.7 | .83 | 11.8 |
| Ave. Commute Time | 337 | 25 | 3.6 | 14 | 36 |
| Medal | 337 | 0.13 | 0.33 | 0 | 1 |
| Under 20 | 337 | 7.2 | 1.6 | 3.2 | 12 |
| Over 65 | 337 | 7.5 | 2.0 | 2.7 | 13 |
| High Education | 337 | 31 | 14 | 5 | 70 |
| Married | 337 | 47 | 6 | 28 | 63 |
| Car Crash Probability | 337 | 2.7 | 1.8 | 0.5 | 11 |

For cross sectional comparisons of the cities only one observation from each city is kept as well as eliminating any city with a zero value for bicycle commuters or any of the demographic variables. This comparison has a total of 69 cities with 59 from 2011, 5 from 2010, 2 from 2009, and 3 from 2008, and is used in the cross-sectional regression presented in the model and results section. The cross sectional model summary statistics are presented in Table 4.4.

Table 4.4 - Cross-Section Model Variable Summary Statistics

| Model Variables | $\mathbf{N}$ | Mean | Std. Dev. | Min. | Max. |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Log (Bicycle Collisions) | 80 | 3.8 | 1.0 | 2.08 | 7.5 |
| Log (Pedestrian Collisions) | 80 | 3.7 | 1.0 | 2.08 | 7.6 |
| Log (Bicycle Commuters) | 80 | 6.3 | 1.3 | 3.7 | 9.8 |
| Log (Pedestrian Commuters) | 80 | 7.3 | 1.0 | 4.6 | 11.1 |
| Bicycle Collisions | 80 | 89 | 216 | 8 | 1,844 |
| Pedestrian Collisions | 80 | 81 | 227 | 8 | 1,927 |
| Bicycle Commuters | 80 | 1,315 | 2,745 | 42 | 17,957 |
| Pedestrian Commuters | 80 | 3,258 | 8,799 | 102 | 65,719 |
| Pop Density | 80 | 2.9 | 1.5 | 1.0 | 9.3 |
| Ave. Commute Time | 80 | 26 | 3.8 | 16 | 38 |
| Medal | 80 | 0.17 | 0.37 | 0 | 1.0 |
| Under 20 | 80 | 7.2 | 1.7 | 4.1 | 11 |
| Over 65 | 80 | 7.5 | 2.1 | 3.9 | 14 |
| High Education | 80 | 31 | 15 | 5 | 70 |
| Married | 80 | 46 | 6 | 33 | 61 |
| Car Crash Probability | 80 | 1.8 | 1.0 | 0.7 | 5 |

## Chapter 5 Empirical Model

### 5.1 Safety in Numbers Model

This paper uses a modified version of a model proposed by Jacobson (2003) where the bicycle injuries in city $I$ during time period $t, I_{i t}$, is an exponential function of the number of bicycle commuters, $E_{i t}$. The model proposed by Jacobson (2003) is presented in Equation 5.1 where $a$ and $b$ are the parameters to be estimated.

## Equation 5.1

$$
I_{i t}=a E_{i t}^{b}
$$

In this model $b$ indicates the change in the number of bicycle injuries in response to changes in the number of bicycle commuters. A $b=1$ indicates that as the number of bicycle commuters increases the number of injuries to bicycle commuter's increases at the same rate, $b<$ 1 indicates that bicycle collisions increase at a lower rate than the numbers of bicycle commuters, and $\mathrm{b}<0$ indicates that an increase in the number of bicycle commuters would actually decrease the number of bicycle collisions. Estimating a log-log model for 68 cities in California in 2000, Jacobson (2003) found a $b$ of .31 for bicycling and .41 for pedestrians, indicating that a $10 \%$ increase in the numbers of bicycle and pedestrian commuting would result in increases of $3.1 \%$ for bicycle and $4.1 \%$ for pedestrian collisions. For both bicycle and pedestrian commuters increasing their numbers would result in smaller increases in the number cyclists and pedestrians involved in collisions and thus a lower collision rate for bicycle and pedestrian commuters; confirming the safety in numbers effect.

### 5.2 Empirical Model

This paper uses a similar model but adds a number of urban form and demographic variables. In Jacobson's (2003) model the dependent variable was the number of injuries to bicyclists in a city in year 2000. In this model the dependent variable is the actual number of collisions involving bicycles in a city in a year minus any collisions that take place on the weekends.

## Equation 5.2

## $\log \left(\right.$ BicycleCollisions $\left._{i t}\right)$

$$
\begin{aligned}
& =\beta_{0}+\beta_{1} \log \left(\text { BicycleCommuters }_{i t}\right)+\beta_{2} \text { Pop Density } \\
& i t \\
& +\beta_{3} \text { Ave. Commute Time }_{i t}+\beta_{4} \text { Medal }_{i t}+\beta_{5}{\text { Under } 20_{i t}}+\beta_{6}{\text { Over } 65_{i t}}^{+\beta_{7} \text { High Education }_{i t}+\beta_{8} \text { Married }_{i t}+\beta_{9} \text { Car Crash Probability }_{i t}+\text { City }_{i}} \\
& + \text { Year }_{t}+\varepsilon_{i t}
\end{aligned}
$$

By using the log model $\beta_{1}$ represents the elasticity of additional bicycle commuters to the community. If $\beta_{1}<1$, as expected then a $1 \%$ increase in the number of bicycle commuters in a city would raise the number of bicycle collisions rates by less than $1 \%$ and decrease the average risk to bicycle commuters.

The population density of the city, the average commute time in minutes, and having a medal from the League of American Bicyclists are urban form variables. The urban form includes the layout of the roads, as well the level of bicycle specific infrastructure available to bicycle commuters. The population density of an area can change over time and has been shown to have an impact on the overall safety of bicycle commuters with higher density areas usually
found to be safer for commuters. The expected sign on the population density in thousands per square mile is negative.

It makes intuitive sense that the longer a cyclist is out on the road the more opportunities she has to get into a collision with an automobile. Likewise the longer an automobile driver spends driving to work the more opportunity they have to get involved in an accident with a cyclist. For this study the average commute length of all commuters is available, but not for cyclists specifically. The sign on average commute time is expected to be positive. While the presence of roundabouts, low speed limits, and traffic control devices certainly affects the safety of the bicycle commuters these variables are likely to remain fairly constant within a city over time and are captured with city fixed effect variables. What does change over time in a city is the level of bicycle specific infrastructure. With more people choosing to bicycle commute more cities have chosen to construct bike paths, multi-use paths, and bike lanes. These factors have been shown to have a high impact on bicycle safety. The League of American Bicyclists performs regular audits on city changes in bicycle specific infrastructure and although the raw data is not publicly available they award cities that reach certain improvement guidelines medals. Receiving a medal or moving to a higher medal is representative of an improvement in infrastructure. The sign on the coefficient for medal is expected to be negative.

As discussed in Chapter 2, demographics play an important role in accidents of all types. Both people under 20 and those over 65 are more likely to be involved in an accident than their middle aged counterparts. For this study the under 20 and over 65 variables represent the percentage of the population under 20 and over 65 respectively. Under 20 and over 65 are both expected to have a positive sign. Having at least a bachelor's degree and being married has been shown to decrease an individual's risk for being involved in a collision. For this study these
variables are bachelor's degree percentage, and married percentage. High education and married percentage are expected to negatively impact collisions.

In addition to demographic and social factors there are additional unobserved effects that can affect the overall safety of commuters. These factors include bad weather, infrastructure changes, and any other social factors related to bicycle collisions. These factors are captured as the car crash probability variable. This variable is the probability of automobile drivers of being in a collision with another automobile driver. This variable can be thought of as measuring the level of bad drivers. Car crash probability is expected to have a positive sign. The year fixed effect variables control for year specific factors shared by all cities in a given year.

In addition to the model with city and year fixed effects a number of additional models are estimated. A model with no city fixed effects and a purely cross-sectional model will allow examination if the changes in bicycle collisions are due to changes within a city over time. A very simple model that only examines the effect of bicycle commuters on bicycle collisions with no demographic variables duplicates the work of Jacobson (2003). Additionally the models will be estimated with pedestrian commuters effect on pedestrian collisions. Jacobson (2003) found that the safety in numbers effect held but was smaller for pedestrians.

## Chapter 6 Results

### 6.1 Bicycle Commuting Results

The empirical results confirm the "safety-in numbers" effect for bicycle commuters in California cities. I find that cities with more bicycle commuters have lower rates of bicycle collisions with automobiles.

Table 6.1 presents the estimated panel models of bicycle-automobile collision with year fixed effects included in all models. Model 1 is a pooled OLS model with no city fixed effects, model 2 uses city random effects, and model 3 uses city fixed effects. City and year fixed effects are reported in Table A. 1 in Appendix A. Table 6.2 presents the results as a cross sectional analysis. The cross sectional analysis is presented as the panel results suggests that the observed effects are driven by differences between the cities and not by variation over time within the cities. In cross-sectional models each city has one observation and there are 69 total observations. 59 of the cities come from 2011, 5 come from 2010 and 2 come from 2009, and 3 come from 2008. Additionally all of these models are estimated for bicycle injuries and pedestrian commuters. The panel results explain between $76 \%$ and $98 \%$ of the variation in the log of bicycle collisions by variation in independent variables in the model without and with city fixed effects, respectively. The cross-sectional models explain about $75 \%$ of the variation in the $\log$ of bicycle collisions.

### 6.1.1 Panel Results for Bicycle Collisions

The panel results are represented in Table 6.1. Model 1 is the pooled OLS regression, while models 2 and 3 are the random and fixed effects models respectively. In contrast to random and fixed effects models, pooled OLS method assumes that there is no unobserved

Figure 6.1 - Residuals vs. Pop Density for Bicycle Commuting OLS Panel Model


Hausman test for the random effects assumption that the unobserved effects are uncorrelated with explanatory variables rejects $H_{0}$, implying that the fixed effects model should be used and the random effect coefficients are inconsistent. Likewise an F-test to see if the city fixed effects are significant results in an $\mathrm{F}=38.43$ and a P value $<0.0001$. Among the three panel models the fixed effects model provides the best fit of the data, but in this model nearly all the coefficients are either insignificant, or very near zero. Robust standard errors are presented for all three models as all these models exhibit signs of heteroskedasticity. The population density appears to act as the source of heteroskedasticity for the OLS and fixed effects models and in these models the Breusch-Pagan rejects $H_{0}$ that there is a constant variance $\left(C h i^{2}=3.47\right.$, $\left.\mathrm{P}=0.0624 ; C h i^{2}=16.84, \mathrm{P}<0.0001\right)$.

Model 1 confirms the safety in numbers effect, while model 3 has a statistically insignificant coefficient on the log of bicycle commuters. In model 1 with year fixed effects, but no city fixed effects the coefficient on the log of bicycle commuters is about .6 and this estimate is statistically significant at the $1 \%$ level. Other things being equal, cities with $10 \%$ more bicycle commuters on average have $6 \%$ more bicycle collisions. The coefficient on log of bicycle commuters is clearly different from 0 , but to measure the safety in numbers effect we are most concerned if the coefficient on this variable is less than 1 . In model 1 , at-test to see if $B_{1}$ the coefficient of log of bicycle commuters is different than 1 rejects the null hypothesis that the $B_{1}$ $=1$, strongly supporting the safety in numbers effect $(\mathrm{t}=-8.81, \mathrm{P}<0.001)$. The estimated coefficient is double that of Jacobson (2003) which implies a smaller safety in numbers effect. Jacobson found that as the number of bicycle commuters increased by $10 \%$ the number of injuries to bicyclists would increase by $3 \%$. Unlike this study, Jacobson (2003) did not eliminate injuries that took place on the weekend. Additionally he counted injuries instead of raw collisions, and did not include any control variables.

Table 6.1 - $\log$ (Bicycle Commuting) Panel Results

| Variables | $\begin{gathered} \hline(1) \\ \text { OLS } \end{gathered}$ | (2) Random Effects | (3) Fixed Effects |
| :---: | :---: | :---: | :---: |
| Log (Bicycle Commuters) | $\begin{gathered} 0.621 * * * \\ (0.043) \end{gathered}$ | $\begin{gathered} 0.125 * * * \\ (0.037) \end{gathered}$ | $\begin{gathered} 0.027 \\ (0.020) \end{gathered}$ |
| Pop Density | $\begin{aligned} & -0.003 \\ & (0.022) \end{aligned}$ | $\begin{gathered} 0.030 \\ (0.038) \end{gathered}$ | $\begin{aligned} & -0.037 \\ & (0.032) \end{aligned}$ |
| Ave. Commute Time | $\begin{aligned} & 0.016^{*} \\ & (0.009) \end{aligned}$ | $\begin{aligned} & -0.003 \\ & (0.008) \end{aligned}$ | $\begin{gathered} 0.002 \\ (0.007) \end{gathered}$ |
| Medal | $\begin{gathered} 0.364 * * * \\ (0.087) \end{gathered}$ | $\begin{gathered} 0.197 * * * \\ (0.059) \end{gathered}$ | $\begin{aligned} & 0.086^{*} \\ & (0.046) \end{aligned}$ |
| Under 20 | $\begin{gathered} 0.026 \\ (0.022) \end{gathered}$ | $\begin{aligned} & -0.008 \\ & (0.014) \end{aligned}$ | $\begin{aligned} & -0.017 \\ & (0.012) \end{aligned}$ |
| Over 65 | $\begin{gathered} 0.026 \\ (0.018) \end{gathered}$ | $\begin{aligned} & 0.021^{*} \\ & (0.013) \end{aligned}$ | $\begin{gathered} 0.034^{* *} \\ (0.015) \end{gathered}$ |
| High Education | $\begin{gathered} -0.010^{* * *} \\ (0.002) \end{gathered}$ | $\begin{aligned} & 0.006^{*} \\ & (0.003) \end{aligned}$ | $\begin{gathered} 0.013 * * \\ (0.006) \end{gathered}$ |
| Married | $\begin{aligned} & -0.006 \\ & (0.007) \end{aligned}$ | $\begin{gathered} -0.018 * * * \\ (0.007) \end{gathered}$ | $\begin{aligned} & -0.006 \\ & (0.006) \end{aligned}$ |
| Car Crash Probability | $\begin{gathered} 0.090 * * * \\ (0.018) \end{gathered}$ | $\begin{gathered} 0.099 * * * \\ (0.027) \end{gathered}$ | $\begin{aligned} & 0.041^{*} \\ & (0.022) \end{aligned}$ |
| Constant | $\begin{aligned} & -0.176 \\ & (0.722) \end{aligned}$ | $\begin{gathered} 3.442 * * * \\ (0.475) \end{gathered}$ | $\begin{gathered} 3.247 * * * \\ (0.566) \end{gathered}$ |
| Year Fixed Effects | Y | Y | Y |
| City Fixed Effects | N | N | Y |
| City Random Effects | N | Y | N |
| $H_{0}$ : Log (Bicycle | $\mathrm{t}=-8.81$ | $\mathrm{z}=-23.87$ | $\mathrm{t}=-49.57$ |
| Commuters) $=1$ | $\mathrm{P}<0.001$ | $\mathrm{P}<0.001$ | $\mathrm{P}<0.001$ |
| Breusch-Pagan Test for | Chi ${ }^{2}=3.47$ |  | Chi ${ }^{2}=16.84$ |
| Heteroskedasticity | $\mathrm{P}=0.0624$ |  | $\mathrm{P}<0.0001$ |
| F | 80.87 |  | 247.6 |
| Chi2 |  | 135.2 |  |
| P-value | $<0.0001$ | <0.0001 | < 0.0001 |
| R -squared | 0.758 |  | 0.979 |
| Observations | 337 | 337 | 337 |

Robust standard errors in parentheses
*** $\mathrm{p}<0.01, * * \mathrm{p}<0.05$, * $\mathrm{p}<0.1$

In model 3 the coefficient on the log of bicycle commuters is .027 and is statistically not different from zero. The size of the coefficient implies that cities that grow their numbers of bicycle commuters will see almost no increase in the numbers of bicycle collisions. While it might be attractive to conclude that I have found a very large safety in numbers effect, I believe the small size of this coefficient is driven by insufficient time-series variation to identify the true safety in numbers effect. Additionally, this estimated effect is very different from that found by Jacobson (2003) and in the model with no city fixed effects. In 21 cities with data for all years from 2007-2011 the numbers of bicycle commuters grew from 52,500 to 74,000 or $41 \%$ and the number of bicycle collisions grew from 5,000 to 6,200 or $24 \%$. This would be more in line with the estimate found in model 1 and does show that bicycle collisions are increasing at a much lower rate than the increase in the bicycle commuters. While the average bicycle commuting growth of $40 \%$ in four years is quite significant, a couple cities experience growth rates substantially higher. Alameda almost tripled the number of bicycle commuters and Oakland more than doubled from 2007-2011. Estimating the panel models without Oakland and Alameda offers similar results.

In the panel models the medal variable is the main urban form variable that is statistically significant at any level. Medal is statistically significant with a positive sign in all panel models. Based on the literature the positive sign is unexpected. In model 1 , other things being equal, cities with a medal will have $44 \%$ more bicycle collisions. In model 3 , other things being equal, cities that receive a medal will see an increase of $9 \%$ in the number of bicycle collisions. The number of cities with a medal grew significantly over years in the data with no cities in 2005 having medals and $20 \%$ of them having a medal in 2011. It is possible that the medal variable is not directly related to increases in bicycle infrastructure in this time period, and might not be the
best proxy for bicycle infrastructure. If available, looking at specific increases in bicycle lanes and paths might result in the expected sign. In the following section a cross sectional model that does not include the medal variable will be presented.

The coefficient on over 65 is statistically significant in the city fixed effects model. In this model, other things being equal, cities with a 1 percentage point increase in the percentage of the population over 65 will have an increase in bicycle collisions of $3.4 \%$. Relative to the mean of $7.5 \%$ for over 65 percentage, an increase or decrease of 1 percentage point is fairly large, although not unlikely in the data. For example, Berkeley saw the percentage of the population over 65 go from $6.5 \%$ in 2007 to $9.0 \%$ in 2011 and many other cities experienced year to year changes of over 1 percentage point. The coefficient confirms the theory in the chapter 2 that cities with a higher percentage of the population over 65 will experience an upward pull on collision rates.

The coefficient on the variable car crash probability is statistically significant in models 1 and 3. In model 1 , other things being equal, cities with a 1 percentage point higher car crash probability will have $9 \%$ more bicycle collisions. In model 3, other things being equal, cities with a 1 percentage point increase in car crash probability will on average increase bicycle collisions by $4 \%$.

The panel results in model 1 support the safety in numbers effect for cities adding bicycle commuters, however model 3 offers a better fit of the data. Among the control variables, only the coefficients on population density and medal carry the unexpected sign in models 1 and 3 . The coefficient on population density is not statistically significant at even the $10 \%$ level. The next section will cover the cross sectional model results, one of which duplicates the Jacobson (2003) model.

### 6.1.2 Cross Sectional Results for Bicycle Collisions

In Table 6.2 the cross sectional results are presented. All models have one observation per city. Model 1 has all the control variables, model 2 drops the medal variable, while model 3 follows Jacobson (2003) directly as it includes no control variables and is a regression of the log of bicycle collisions on the log of bicycle commuters. In model 1 the medal variable has the unexpected sign, and some evidence exists that the medals from the League of American Bicyclists are awarded more by lobbying from cities than actual measurable increases in bicycle infrastructure. This variable may not accurately measure increases in bicycle specific infrastructure and is dropped in model 2 to determine its effect on the safety in numbers effect. All three models exhibit signs of heteroskedasticity according to the Breusch-Pagan test. A partial F-test for the 1 vs. model 2 rejects $H_{0}$ that the coefficient on medal $=0(\mathrm{~F}=4.33, \mathrm{P}=$ .0419). A partial F test between models 1 and 3 provides a similar result $(\mathrm{F}=2.66, \mathrm{P}=.0145)$.

The safety in numbers effect is confirmed in all three cross sectional models. In the full model a $10 \%$ increase in bicycle commuters is associated with a $6.3 \%$ increase in bicycle collisions, all else constant. This result is almost identical to the pooled OLS panel model and is about double the coefficient found by Jacobson (2003). In all three cross sectional models the coefficient of the $\log$ of bicycle commuters is significant at the $1 \%$ level. These results confirm the safety in numbers effect as adding bicycle commuters is expected to lower the average rate of bicycle collisions and increase the level of safety enjoyed by the average bicycle commuter. The coefficient on the log of bicycle commuters is less than 1 with P values less than 0.001 for all three models. The deviation from Jacobson (2003) could be due to small differences in the specification of the variables, as well as the updated data set.

Table 6.2- $\log$ (Bicycle Commuting) Cross Sectional Model Results

| Variables | (1) <br> All Controls | (2) <br> No Medal | (3) <br> No Controls |
| :---: | :---: | :---: | :---: |
| Log (Bicycle Commuters) | $\begin{gathered} 0.626 * * * \\ (0.106) \end{gathered}$ | $\begin{gathered} 0.669 * * * \\ (0.088) \end{gathered}$ | $\begin{gathered} 0.628 * * * \\ (0.053) \end{gathered}$ |
| Pop Density (1000s) | $\begin{gathered} 0.040 \\ (0.053) \end{gathered}$ | $\begin{gathered} 0.050 \\ (0.056) \end{gathered}$ |  |
| Ave. Commute Time | $\begin{gathered} 0.025 \\ (0.021) \end{gathered}$ | $\begin{gathered} 0.026 \\ (0.020) \end{gathered}$ |  |
| Medal | $\begin{aligned} & 0.385^{*} \\ & (0.200) \end{aligned}$ |  |  |
| Under 20 | $\begin{gathered} 0.047 \\ (0.066) \end{gathered}$ | $\begin{gathered} 0.042 \\ (0.072) \end{gathered}$ |  |
| Over 65 | $\begin{gathered} 0.032 \\ (0.039) \end{gathered}$ | $\begin{gathered} 0.017 \\ (0.042) \end{gathered}$ |  |
| High Education | $\begin{gathered} -0.012 * * * \\ (0.005) \end{gathered}$ | $\begin{gathered} -0.010^{*} \\ (0.006) \end{gathered}$ |  |
| Married | $\begin{aligned} & -0.001 \\ & (0.017) \end{aligned}$ | $\begin{aligned} & -0.001 \\ & (0.019) \end{aligned}$ |  |
| Car Crash Probability | $\begin{aligned} & 0.129^{*} \\ & (0.073) \end{aligned}$ | $\begin{aligned} & 0.138^{*} \\ & (0.079) \end{aligned}$ |  |
| Constant | $\begin{gathered} -1.272 \\ (1.676) \end{gathered}$ | $\begin{gathered} -1.457 \\ (1.734) \end{gathered}$ | $\begin{aligned} & -0.106 \\ & (0.348) \end{aligned}$ |
| $H_{0}:$ Log (Bicycle | $\mathrm{t}=-5.31$ | $\mathrm{t}=-4.49$ | $\mathrm{t}=-6.99$ |
| Commuters) $=1$ | $\mathrm{P}<0.001$ | $\mathrm{P}<0.001$ | $\mathrm{P}<0.001$ |
| Breusch-Pagan Test for | $C h i^{2}=4.64$ | $C h i^{2}=3.58$ | $C h i^{2}=7.65$ |
| Heteroskedasticity | $\mathrm{P}=0.0312$ | $\mathrm{P}=0.0585$ | $\mathrm{P}=0.0057$ |
| F | 24.02 | 21.39 | 139.0 |
| P -value | < 0.0001 | < 0.0001 | < 0.0001 |
| R -squared | 0.761 | 0.744 | 0.675 |
| Observations | 69 | 69 | 69 |

Robust standard errors in parentheses
*** $\mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05$, * $\mathrm{p}<0.1$

The variable car crash probability is significant at the $10 \%$ level. A 1 percentage point higher car crash probability results in $13 \%$ more bicycle collisions, all else constant. Increases of this level for a city are fairly rare; however this variable can vary significantly between cities. In the cross-sectional data set, the mean of car crash probability is $1.8 \%$ with a minimum of $.7 \%$ and a maximum of 5\%. On the high end, San Bernardino in 2011 had a car crash probability of
$5 \%$ and a bicycle crash probability of $17 \%$, while on the low end, Simi Valley in 2011 had a car crash probability of $.7 \%$ and a bicycle crash probability of only $3 \%$. These results confirm the expected results that cities where drivers are involved in a greater number of automobile collisions will also be cities where drivers are involved in more collisions with bicycle commuters.

Overall the cross sectional models support the safety in numbers effect observed in the pooled OLS panel model. The magnitude of the safety in numbers effect differs from the effect measured by Jacobson (2003). As with the panel models the coefficients on population density and medal have the unexpected signs, however the models estimated without the medal variable maintain the safety in numbers effect. The coefficient on population density is not significant at the $10 \%$ level, and there are a number of possible explanations for the unexpected sign on the coefficient on the medal variable. The increased significance of the bicycle commuting variable suggests that it is differences in bicycle commuting between cities that explains the variation in collision numbers, and not year to year variations of bicycle commuting numbers within cities.

### 6.1.3 Bicycle Injury Results

As discussed previously Jacobson (2003) used injuries to bicyclists as the dependent variable while the previous results presented total collisions involving bicyclists. Appendix Tables B. 1 and B. 2 present the bicycle injury results that follow Jacobson (2003) by regressing the log of injuries to bicycle commuters on the same set of independent variables that are used in the other bicycle commuting models. These results are almost identical to the results presented
above with the log of bicycle collisions as the dependent variable, which makes sense as bicycle injuries and bicycle collisions have a correlation coefficient of .99.

### 6.2 Pedestrian Commuting Results

Although not extensively discussed in the chapters 2 and 3, for many commuters walking to work is a viable mode of transportation, and overall more than twice as many people walk to work as bicycle commute. Even though pedestrian commuting is not seeing the growth that bicycle commuting is, pedestrians benefit from many of the same measures as bicycle commuters. Jacobson (2003) also analyzed the response of pedestrian injuries to increases in pedestrian commuting. The specifications of the pedestrian commuting models are identical to the models estimated for bicycle commuting.

### 6.2.1 Panel Results for Pedestrian Collisions

In Table 6.3 the panel results are presented. Model 1 is a pooled OLS model with no city effects, model 2 has city random effects, and model 3 has city fixed effects. A Hausman test for the random effects assumption that the unobserved effects are uncorrelated with each explanatory variable rejects $H_{0}$, implying that the fixed effects model should be used and the random effect coefficients are biased. A test on the significance of the fixed effects gives a F statistic $=28.48$ and $\mathrm{P}<0.0001$ again rejecting $H_{0}$ that the fixed effects model is equivalent to the pooled OLS model. As in the bicycle commuting results this is problematic as the fixed

Figure 6.2 - -Residuals vs. Pop Density for Pedestrian Commuting OLS Panel Model

effects model contains few
variables that are statistically or practically significant. Under the Breusch-Pagan, test model 1 does not demonstrate heteroskedasticity. Robust standard errors are presented for model 3 as it exhibits signs of heteroskedasticity.

As with the bicycle commuting panel models the population density appears to be a possible cause of the heteroskedasticity.

In model 1 the coefficient on the $\log$ of pedestrian commuters is about .8 and this estimate is statistically significant at the $1 \%$ level. Other things being equal, cities with $10 \%$ more pedestrian commuters will have $8 \%$ more collisions involving pedestrians. $\beta_{1}$ is different from 0 , but to measure the safety in numbers effect we are most concerned if the $\beta_{1}$ less than 1 . In model 1, a t-test on the $\beta_{1}$ results rejects $H_{0}$ that the coefficient $=1$, which confirms the safety in numbers effect. The coefficient is again double that found by Jacobson (2003). He found that as the number of pedestrian commuters increased by $10 \%$ the number of injuries to pedestrians would increase by $4 \%$.

Table 6.3 - $\log$ (Pedestrian Collision) Panel Results

| Variables | (1) <br> Pooled OLS | (2) | (3) <br> Fixed Effects |
| :---: | :---: | :---: | :---: |
| Log (Pedestrian Commuters) | 0.813*** | 0.270*** | 0.073** |
|  | (0.029) | (0.068) | (0.030) |
| Pop Density (1000s) | -0.026 | 0.066** | 0.050** |
|  | (0.019) | (0.030) | (0.022) |
| Ave. Commute Time | 0.010 | -0.009 | -0.011* |
|  | (0.007) | (0.007) | (0.006) |
| Medal | 0.263*** | 0.139** | 0.044 |
|  | (0.082) | (0.057) | (0.040) |
| Under 20 | -0.056*** | -0.031* | -0.017 |
|  | (0.020) | (0.016) | (0.014) |
| Over 65 | 0.037** | 0.010 | 0.009 |
|  | (0.016) | (0.014) | (0.014) |
| High Education | -0.024*** | -0.010*** | -0.008 |
|  | (0.002) | (0.004) | (0.006) |
| Married | -0.008 | -0.016** | -0.004 |
|  | (0.006) | (0.007) | (0.007) |
| Car Crash Probability | 0.059*** | 0.063** | 0.027 |
|  | (0.016) | (0.026) | (0.022) |
| Constant | -0.740 | $3.203 * * *$ | 4.051*** |
|  | (0.588) | (0.619) | (0.573) |
| Year Fixed Effects | Y | Y | Y |
| City Fixed Effects | N | N | Y |
| City Random Effects | N | Y | N |
| $H_{0}: \log$ (Bicycle | $\mathrm{t}=-4.62$ | $\mathrm{z}=-10.75$ | $\mathrm{t}=-30.87$ |
| Commuters) $=1$ | $\mathrm{P}<0.001$ | $\mathrm{P}<0.001$ | $\mathrm{P}<0.001$ |
| Breusch-Pagan Test for Heteroskedasticity | Chi ${ }^{2}=.58$ |  | $C h i^{2}=36.19$ |
|  | $\mathrm{P}=0.4452$ |  | $\mathrm{P}<0.0001$ |
| F | 94.73 |  | 1587 |
| Chi2 |  | 99.12 |  |
| P -value | < 0.0001 | < 0.0001 | < 0.0001 |
| R-squared | 0.826 |  | 0.980 |
| Observations | 337 | 337 | 337 |

Standard errors in parentheses for model 1 and robust standard errors for models 2 and 3

$$
* * * \mathrm{p}<0.01, * * \mathrm{p}<0.05, * \mathrm{p}<0.1
$$

In model 3 with city fixed effects, the coefficient on the log of pedestrian commuters is .073 , and this coefficient is significant at the $5 \%$ level. Other things being equal, cities that increase their numbers of pedestrian commuters by $10 \%$ will only see a $.73 \%$ increase in the
number of collisions involving pedestrians. Although this implies that cities that grow their numbers of pedestrian commuters will see almost no increase in the numbers of pedestrian collisions, like in the bicycle commuting models the estimated coefficient is likely biased. This result is dramatically different than the effect found by Jacobson (2003), and is difficult to isolate simply by looking at trends as pedestrian commuting rates and pedestrian collisions are fairly constant over time. In 21 cities with data for all years from 2007 - 2011 the numbers of pedestrian commuters only increased from 189,000 to 191,000 or about $1 \%$ and the number of pedestrian collisions decreased from 5,500 to 5,200 or 6.5\%.

In contrast with the bicycle commuting panel models, the coefficient on Under 20 carries the negative sign in all pedestrian panel models, and is statistically significant at the $1 \%$ level in the model with no city fixed effects. In model 1 , other things being equal, cities with one standard deviation (1.6 percentage points) more people under 20 will have $9 \%$ fewer collisions involving pedestrians. A one standard deviation change in under 20 percentage year to year is rare, but not unheard of in the data. From 2007 to 2011 Berkeley increased the percentage of people under 20 from about $9 \%$ to almost $12 \%$. Percentage of people under 20 has a different effect on bicycle collisions and pedestrian collisions.

The panel results in model 1 confirm that the safety in numbers effect exists for pedestrian commuters; however this is not the panel model with the best fit of the data. The safety in numbers effect for pedestrians also appears to be less than the effect for bicycle commuters. As with bicycle commuting the results suggest that the unobserved effects between cities are more important than the year to year differences in pedestrian commuting in explaining variations of pedestrian collision numbers within cities.

### 6.2.2 Cross Sectional Results for Pedestrian Collisions

In Table 6.4 the cross sectional results for pedestrian commuting are presented. As in the bicycle commuting results there is one observation per city, and the cities are the exact same as the ones for the bicycle commuting models. Models 1 and 2 have control variables and model 3 estimates the Jacobson (2003) model with the log of pedestrian collisions as a function of the log of pedestrian commuters. Unlike the bicycle commuting cross sectional models, the pedestrian commuting models do not demonstrate any signs of heteroskedasticity. In the Breusch-Pagan tests all three models cannot reject $H_{0}$ of constant variance among the residuals. Unlike in the bicycle commuting models an F-test between models 1 and 2 fails to reject $H_{0}$ that the medal variable is insignificant $(\mathrm{F}=2.60, \mathrm{P}=.1123)$, indicating the model without medal offers as good of fit as the model with all the variables. This makes intuitive sense as the medal variable is ties to increases in bicycle specific infrastructure, which likely does not have the same effect on pedestrian safety that it does on bicycle safety. The remaining control variables are statistically significant. An F-test comparing models 2 and 3 ( $\mathrm{F}=4.64, \mathrm{P}=.0003$ ), indicates that the remaining control variables are jointly significant.

The $\log$ of pedestrian commuters is statistically significant at the $1 \%$ level and has a similar coefficient in all three cross sectional models. A $10 \%$ increase in the number of pedestrian commuters is associated with an $8 \%$ increase in the number of pedestrian collisions, all else constant. This result is about double the $4 \%$ found by Jacobson (2003) in his pedestrian model and almost identical to the results in the panel model with no city fixed effects. In model 2, which drops the medal variable, a $10 \%$ increase in the number of pedestrian commuters is associated with an $8.3 \%$ increase in the number of pedestrian collisions, all else constant. Model

3 replicates Jacobson (2003) and finds a coefficient similar to those found in models 1 and 2. The deviation from Jacobson's (2003) results is possibly due to using more recent data and also different variable specification.

Table $6.4-\log$ (Pedestrian Commuting) Cross Sectional Results

| Variables | $\stackrel{(1)}{\text { All Controls }}$ | (2) <br> No Medal | (3) <br> No Controls |
| :---: | :---: | :---: | :---: |
| Log (Pedestrian Commuters) | $\begin{gathered} 0.790 * * * \\ (0.075) \end{gathered}$ | $\begin{gathered} 0.827 * * * \\ (0.072) \end{gathered}$ | $\begin{gathered} 0.777 * * * \\ (0.068) \end{gathered}$ |
| Pop Density (1000s) | $\begin{aligned} & -0.006 \\ & (0.049) \end{aligned}$ | $\begin{gathered} 0.001 \\ (0.049) \end{gathered}$ |  |
| Ave. Commute Time | $\begin{gathered} 0.019 \\ (0.017) \end{gathered}$ | $\begin{gathered} 0.018 \\ (0.018) \end{gathered}$ |  |
| Medal | $\begin{gathered} 0.282 \\ (0.175) \end{gathered}$ |  |  |
| Under 20 | $\begin{aligned} & -0.025 \\ & (0.050) \end{aligned}$ | $\begin{aligned} & -0.031 \\ & (0.050) \end{aligned}$ |  |
| Over 65 | $\begin{gathered} 0.049 \\ (0.041) \end{gathered}$ | $\begin{gathered} 0.037 \\ (0.041) \end{gathered}$ |  |
| High Education | $\begin{gathered} -0.021 * * * \\ (0.005) \end{gathered}$ | $\begin{gathered} -0.020 * * * \\ (0.005) \end{gathered}$ |  |
| Married | $\begin{aligned} & -0.003 \\ & (0.014) \end{aligned}$ | $\begin{aligned} & -0.003 \\ & (0.014) \end{aligned}$ |  |
| Car Crash Probability | $\begin{gathered} 0.189 * * * \\ (0.067) \end{gathered}$ | $\begin{gathered} 0.198^{* * *} \\ (0.067) \end{gathered}$ |  |
| Constant | $\begin{aligned} & -2.298^{*} \\ & (1.328) \\ & \hline \end{aligned}$ | $\begin{aligned} & -2.455^{*} \\ & (1.342) \\ & \hline \end{aligned}$ | $\begin{gathered} -1.984 * * * \\ (0.508) \end{gathered}$ |
| $H_{0}$ : Log (Bicycle | $\mathrm{t}=-2.80$ | $\mathrm{t}=-2.40$ | $\mathrm{t}=-3.27$ |
| Commuters) $=1$ | $\mathrm{P}=.007$ | $\mathrm{P}=0.020$ | $\mathrm{P}=0.002$ |
| Breusch-Pagan Test for | $C h i^{2}=0.22$ | Chi ${ }^{2}=1.38$ | Chi ${ }^{2}=0.00$ |
| Heteroskedasticity | $\mathrm{P}=0.6375$ | $\mathrm{P}=0.2394$ | $\mathrm{P}=0.9532$ |
| F | 24.45 | 26.47 | 129.9 |
| P -value | < 0.0001 | < 0.0001 | < 0.0001 |
| R-squared | 0.79 | 0.78 | 0.660 |
| Observations | 69 | 69 | 69 |

Standard errors in parentheses
*** $\mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05, * \mathrm{p}<0.1$
As in the bicycle commuting cross sectional model the coefficient on the variable high education is statistically significant at the $1 \%$ level. However for pedestrian collisions this
variable carries nearly double the effect. In the bicycle commuting cross sectional model a 1 percentage point increase in percentage of the population with a bachelor's degree is associated with a $1.2 \%$ decrease in the number of bicycle collisions, all else constant. For the pedestrian cross sectional model a 1 percentage point increase in percentage of the population with a bachelor's degree or higher is associated with a $2.1 \%$ decrease in the number of pedestrian collisions, all else constant. The values for high education are highly variable in the data with cities having between $5 \%$ and $70 \%$ of the population with at least a bachelor's degree. Berkeley in 2011 had a high education percentage of $70 \%$ and a pedestrian collision probability of only $1 \%$, while Compton in 2010 had a high education percentage of only $5 \%$ and one of the highest pedestrian collision probabilities at over $5 \%$.

The cross sectional pedestrian commuting results confirm the results from the first panel model, as well as the results from Jacobson (2003). The safety in numbers effect exists for pedestrian commuters but is not as large as the effect for bicycling commuters. As in the bicycle commuting models the safety in numbers effect is more apparent in models employing variation across cities rather than focusing on time series variation in the fixed effects model.

## Chapter 7 Conclusion

The safety in numbers effect is supported by the results of this study as increasing the number of bicycle and pedestrian commuters has a dramatic effect on the bicycle and pedestrian crash probability in California cities. This suggests measures to encourage more people to commute by bicycle, or to walk to work are an effective means to increase the safety of bicycle and pedestrian commuters. There are many ways to accomplish bicycle commuting increases ranging from the low cost (Bike-to-Work days) to the high cost (safety improvements and workplace showers).

This study employs a panel dataset to expand on Jacobson's (2003) cross-sectional study and to measure the safety in numbers effect in cities that were increasing their numbers of bicycle commuters. However, except for a couple of outliers, bicycle commuting numbers are not extremely variable within cities over time, and isolating the safety in numbers effect from the panel models employing time-series variation alone is problematic. The cross sectional models were estimated to measure the safety in numbers effect as it applies to variations in bicycle commuter numbers between cities. The safety in numbers effect does stand up in the cross sectional models, demonstrating that in cities with higher bicycle commuter rates we would expect to see lower rate of bicycle commuter collisions. The pedestrian models confirm the results found by Jacobson (2003) that the safety in numbers effect also exists for pedestrian commuters.

This paper improves on the model proposed by Jacobson (2003) in a number of ways. The updated data set contains data from 2005 - 2011. The panel models has 364 observations and the cross sectional models have 69 observations while Jacobson (2003) analyzed 68 cities.

Finally the updated models add demographic and environmental variables, which are significant drivers of bicycle commuter safety. The coefficients on bicycle and pedestrian commuters differ from those found by Jacobson (2003) but the confirms the directional effect that adding additional bicycle and pedestrian commuters will increase the level of safety enjoyed by each individual bicycle and pedestrian commuter.

As discussed in the chapter 2 many studies showed that individuals are more likely to start commuting by bicycle after they merely try it once. Many of the concerns they have with cleanliness, speed, and safety are shown to be moot points. Having days where bicycle commuters receive special support or benefits, and having cheap rental bicycles easily available at high traffic locations throughout the city can help get more people to try bike commuting. Safety concerns are high on the list of many potential bicycle commuters. As shown in chapter 2 and this study, the addition of bike lanes and paths (controlled for by American League of Bicyclists medal variable) is not met with widespread gains in actual safety to bicycle commuters. However, these measures often offer a level of perceived safety to potential and current bicycle commuters. If this increase in perceived safety is able to get more people bicycle commuting then safety for the average bicycle commuter will increase as well. This study is only the second study to employ city-level variation to analyze the safety in numbers effect on a citywide basis.

Potential avenues for further research include looking at the specific impacts that recent bicycle infrastructure projects and laws in the United States have had on bicycle commuting growth as well as the effectiveness of specific types of infrastructure improvements have on commuting and collision rates. I would be particularly interested to see the long-term impacts of the Safe Routes to School programs, and the various Bike-to-Work day programs around the
country. Additionally, some cities are adding mandatory helmet laws. It would be interesting to see if the positive effect that these laws have on safety is somewhat negated by the negative effect that they have on ridership levels. If collision data is able to be obtained for more historical years it might also be able to isolate the safety in numbers effect by using bicycle commuting growth within cities. With bicycle commuting rates increasing in the United States it may be tempting to assume that the safety in numbers effect will fix bicycle safety issues, but without the infrastructure and legal protections offered in European cities, we may never see the ridership levels that make cycling an extremely safe option for all commuters.

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## Appendix A - Full Bicycle Commuting Table

Table A. 1 - Full Bicycle Commuting Results

| Variables | (1) $\log ($ Bicycle Collisions) | (2) $\log ($ Bicycle Collisions) | (3) $\log ($ Bicycle Collisions) |
| :---: | :---: | :---: | :---: |
| Log (Bicycle Commuters) | $\begin{gathered} 0.621 * * * \\ (0.043) \end{gathered}$ | $\begin{gathered} 0.125 * * * \\ (0.037) \end{gathered}$ | $\begin{gathered} 0.027 \\ (0.020) \end{gathered}$ |
| Pop Density | $\begin{aligned} & -0.003 \\ & (0.022) \end{aligned}$ | $\begin{gathered} 0.030 \\ (0.038) \end{gathered}$ | $\begin{aligned} & -0.037 \\ & (0.032) \end{aligned}$ |
| Ave. Commute Time | $\begin{aligned} & 0.016^{*} \\ & (0.009) \end{aligned}$ | $\begin{aligned} & -0.003 \\ & (0.008) \end{aligned}$ | $\begin{gathered} 0.002 \\ (0.007) \end{gathered}$ |
| Medal | $\begin{gathered} 0.364 * * * \\ (0.087) \end{gathered}$ | $\begin{gathered} 0.197 * * * \\ (0.059) \end{gathered}$ | $\begin{aligned} & 0.086^{*} \\ & (0.046) \end{aligned}$ |
| Under 20 | $\begin{gathered} 0.026 \\ (0.022) \end{gathered}$ | $\begin{aligned} & -0.008 \\ & (0.014) \end{aligned}$ | $\begin{aligned} & -0.017 \\ & (0.012) \end{aligned}$ |
| Over 65 | $\begin{gathered} 0.026 \\ (0.018) \end{gathered}$ | $\begin{aligned} & 0.021^{*} \\ & (0.013) \end{aligned}$ | $\begin{gathered} 0.034^{* *} \\ (0.015) \end{gathered}$ |
| High Education | $\begin{gathered} -0.010 * * * \\ (0.002) \end{gathered}$ | $\begin{aligned} & 0.006^{*} \\ & (0.003) \end{aligned}$ | $\begin{gathered} 0.013 * * \\ (0.006) \end{gathered}$ |
| Married | $\begin{aligned} & -0.006 \\ & (0.007) \end{aligned}$ | $\begin{gathered} -0.018 * * * \\ (0.007) \end{gathered}$ | $\begin{aligned} & -0.006 \\ & (0.006) \end{aligned}$ |
| Car Crash Probability | $\begin{gathered} 0.090^{* * *} \\ (0.018) \end{gathered}$ | $\begin{gathered} 0.099^{* * *} \\ (0.027) \end{gathered}$ | $\begin{aligned} & 0.041^{*} \\ & (0.022) \end{aligned}$ |
| Constant | $\begin{aligned} & -0.176 \\ & (0.722) \end{aligned}$ | $\begin{gathered} 3.442 * * * \\ (0.475) \end{gathered}$ | $\begin{gathered} 3.247 * * * \\ (0.566) \end{gathered}$ |
| 2006 | $\begin{aligned} & -0.287 \\ & (0.182) \end{aligned}$ | $\begin{gathered} -0.109 * * \\ (0.052) \end{gathered}$ | $\begin{aligned} & -0.019 \\ & (0.058) \end{aligned}$ |
| 2007 | $\begin{aligned} & -0.258 \\ & (0.186) \end{aligned}$ | $\begin{gathered} -0.137 * * * \\ (0.050) \end{gathered}$ | $\begin{aligned} & -0.064 \\ & (0.054) \end{aligned}$ |
| 2008 | $\begin{aligned} & -0.295 \\ & (0.180) \end{aligned}$ | $\begin{aligned} & -0.028 \\ & (0.059) \end{aligned}$ | $\begin{gathered} 0.070 \\ (0.059) \end{gathered}$ |
| 2009 | $\begin{aligned} & -0.181 \\ & (0.183) \end{aligned}$ | $\begin{aligned} & -0.024 \\ & (0.068) \end{aligned}$ | $\begin{gathered} 0.047 \\ (0.063) \end{gathered}$ |
| 2010 | $\begin{aligned} & -0.236 \\ & (0.188) \end{aligned}$ | $\begin{aligned} & -0.031 \\ & (0.060) \end{aligned}$ | $\begin{gathered} 0.052 \\ (0.062) \end{gathered}$ |
| 2011 | $\begin{aligned} & -0.265 \\ & (0.188) \end{aligned}$ | $\begin{gathered} 0.030 \\ (0.087) \end{gathered}$ | $\begin{gathered} 0.067 \\ (0.078) \end{gathered}$ |
| BERKELEY |  |  | $\begin{gathered} 0.672 * * * \\ (0.210) \end{gathered}$ |
| FREMONT |  |  | $\begin{aligned} & -0.251 \\ & (0.237) \end{aligned}$ |
| HAYWARD |  |  | -0.223 |


|  | (0.227) |
| :---: | :---: |
| OAKLAND | 1.011*** |
|  | (0.142) |
| SAN LEANDRO | -1.177*** |
|  | (0.220) |
| UNION CITY | -1.354*** |
|  | (0.268) |
| CHICO | -0.668** |
|  | (0.276) |
| CONCORD | -0.087 |
|  | (0.211) |
| RICHMOND | -0.885*** |
|  | (0.231) |
| FRESNO | 0.998*** |
|  | (0.235) |
| BAKERSFIELD | 0.273 |
|  | (0.266) |
| LOS ANGELES | $3.441 * * *$ |
|  | (0.187) |
| ALHAMBRA | -0.541*** |
|  | (0.175) |
| BURBANK | -0.258 |
|  | (0.195) |
| COMPTON | -0.066 |
|  | (0.288) |
| EL MONTE | 0.481* |
|  | (0.268) |
| GLENDALE | -0.217 |
|  | (0.180) |
| LONG BEACH | 1.575*** |
|  | (0.190) |
| PASADENA | 0.038 |
|  | (0.149) |
| POMONA | 0.290 |
|  | (0.247) |
| SANTA MONICA | 0.333 |
|  | (0.208) |
| TORRANCE | -0.451* |
|  | (0.232) |
| CARSON | -0.894*** |
|  | (0.246) |
| SANTA CLARITA | -0.479** |
|  | (0.243) |
| SALINAS | 0.105 |
|  | (0.303) |
| ORANGE | 0.482*** |


|  | (0.163) |
| :---: | :---: |
| ANAHEIM | 0.844*** |
|  | (0.204) |
| BUENA PARK | $-0.707 * * *$ |
|  | (0.248) |
| COSTA MESA | 0.551*** |
|  | (0.182) |
| FULLERTON | 0.099 |
|  | (0.185) |
| GARDEN GROVE | 0.540** |
|  | (0.223) |
| HUNTINGTON BEACH | 0.849*** |
|  | (0.158) |
| SANTA ANA | 1.443*** |
|  | (0.265) |
| WESTMINSTER | 0.203 |
|  | (0.233) |
| IRVINE | -0.167 |
|  | (0.231) |
| RIVERSIDE | 0.951*** |
|  | (0.188) |
| CORONA | -0.480** |
|  | (0.228) |
| MORENO VALLEY | -0.024 |
|  | (0.281) |
| SACRAMENTO | 1.887*** |
|  | (0.150) |
| ELK GROVE | -0.294 |
|  | (0.238) |
| SAN BERNARDINO | 0.443* |
|  | (0.233) |
| FONTANA | 0.229 |
|  | (0.276) |
| ONTARIO | -0.099 |
|  | (0.235) |
| RANCHO CUCAMONGA | -0.657*** |
|  | (0.219) |
| SAN DIEGO | $2.021^{* * *}$ |
|  | (0.190) |
| CARLSBAD | -0.942*** |
|  | (0.230) |
| CHULA VISTA | -0.018 |
|  | (0.253) |
| EL CAJON | -0.104 |
|  | (0.254) |
| ESCONDIDO | 0.133 |


|  |  |  | (0.254) |
| :---: | :---: | :---: | :---: |
| OCEANSIDE |  |  | -0.153 |
|  |  |  | (0.229) |
| SAN FRANCISCO |  |  | 1.865*** |
|  |  |  | (0.233) |
| STOCKTON |  |  | 1.150*** |
|  |  |  | (0.242) |
| SAN MATEO |  |  | -0.224 |
|  |  |  | (0.161) |
| DALY CITY |  |  | -1.404*** |
|  |  |  | (0.219) |
| REDWOOD CITY |  |  | -0.532** |
|  |  |  | (0.207) |
| SANTA BARBARA |  |  | 0.520*** |
|  |  |  | (0.130) |
| SANTA MARIA |  |  | -0.075 |
|  |  |  | (0.278) |
| SANTA CLARA |  |  | 0.067 |
|  |  |  | (0.143) |
| MOUNTAIN VIEW |  |  | -0.620*** |
|  |  |  | (0.184) |
| SAN JOSE |  |  | 1.736*** |
|  |  |  | (0.190) |
| SUNNYVALE |  |  | -0.258 |
|  |  |  | (0.189) |
| FAIRFIELD |  |  | -0.415 |
|  |  |  | (0.272) |
| VALLEJO |  |  | -0.826*** |
|  |  |  | (0.265) |
| SANTA ROSA |  |  | 0.230 |
|  |  |  | (0.212) |
| MODESTO |  |  | 0.663*** |
|  |  |  | (0.237) |
| VENTURA |  |  | 0.312* |
|  |  |  | (0.165) |
| OXNARD |  |  | 0.530** |
|  |  |  | (0.257) |
| SIMI VALLEY |  |  | -0.448* |
|  |  |  | (0.233) |
| Constant | -0.176 | 3.442*** | 3.247*** |
|  | (0.722) | (0.475) | (0.566) |
| Observations | 337 | 337 | 337 |
| R -squared | 0.758 |  | 0.979 |
| F | 80.87 |  | 247.6 |
| Number of Cities |  | 69 |  |

## Chi2

Robust standard errors in parentheses
*** $\mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05, * \mathrm{p}<0.1$

## Appendix B - Bicycle Injury Tables

Table B.1- Bicycle Injury Panel Results

| Variables | $\mathbf{( 1 )}$ <br> $\mathbf{l o g}(\mathbf{B i c y c l e}$ <br> Injuries) | $\mathbf{( 2 )}$ <br> $\mathbf{l o g}($ Bicycle <br> Injuries) | $\mathbf{( 3 )}$ <br> $\mathbf{l o g}(\mathbf{B i c y c l e}$ <br> Injuries) |
| :--- | :---: | :---: | :---: |
| Log (Bicycle Commuters) | $0.641^{* * *}$ | $0.114^{* * *}$ | 0.007 |
| Pop Density (1000s) | $(0.044)$ | $(0.039)$ | $(0.021)$ |
|  | -0.008 | 0.032 | -0.035 |
| Ave. Commute Time | $(0.023)$ | $(0.039)$ | $(0.032)$ |
|  | 0.014 | -0.003 | 0.002 |
| Medal | $(0.010)$ | $(0.008)$ | $(0.007)$ |
|  | $0.359^{* * *}$ | $0.204^{* * *}$ | $0.087^{*}$ |
| Under 20 | $(0.089)$ | $(0.059)$ | $(0.047)$ |
|  | 0.029 | -0.014 | $-0.022^{*}$ |
| Over 65 | $(0.023)$ | $(0.015)$ | $(0.014)$ |
|  | $0.038^{* *}$ | $0.027^{* *}$ | $0.039^{* * *}$ |
| High Education | $(0.018)$ | $(0.012)$ | $(0.015)$ |
|  | $-0.010^{* * *}$ | $0.007 *$ | 0.009 |
| Married | $(0.002)$ | $(0.004)$ | $(0.006)$ |
| Car Crash Probability | -0.004 | $-0.019^{* * *}$ | -0.005 |
|  | $(0.007)$ | $(0.007)$ | $(0.006)$ |
| Constant | $0.081^{* * *}$ | $0.090^{* * *}$ | 0.028 |
|  | $(0.018)$ | $(0.026)$ | $(0.021)$ |
| Year Fixed Effects | -0.511 | $3.460^{* * *}$ | $3.414^{* * *}$ |
| City Fixed Effects | $(0.745)$ | $(0.471)$ | $(0.567)$ |
| City Random Effects | Y | Y | Y |
| Observations | N | N | Y |
| F | N | Y | N |
| Chi2 | 337 | 337 | 337 |
| R-squared | 73.68 | NA | 346.6 |

Robust standard errors in parentheses
*** $\mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05$, * $\mathrm{p}<0.1$

Table B. 2 - Bicycle Injury Cross-Sectional Results

| Variables | (1) $\log ($ Bicycle Injuries) | $(2)$ $\log ($ Bicycle Injuries) | (3) $\log ($ Bicycle Injuries) |
| :---: | :---: | :---: | :---: |
| Log (Bicycle Commuters) | $\begin{gathered} 0.645 * * * \\ (0.108) \end{gathered}$ | $\begin{gathered} 0.687 * * * \\ (0.089) \end{gathered}$ | $\begin{gathered} 0.643 * * * \\ (0.053) \end{gathered}$ |
| Pop Density (1000s) | $\begin{gathered} 0.036 \\ (0.053) \end{gathered}$ | $\begin{gathered} 0.045 \\ (0.056) \end{gathered}$ |  |
| Ave. Commute Time | $\begin{gathered} 0.024 \\ (0.021) \end{gathered}$ | $\begin{gathered} 0.025 \\ (0.021) \end{gathered}$ |  |
| Medal | $\begin{aligned} & 0.374^{*} \\ & (0.201) \end{aligned}$ |  |  |
| Under 20 | $\begin{gathered} 0.052 \\ (0.067) \end{gathered}$ | $\begin{gathered} 0.047 \\ (0.073) \end{gathered}$ |  |
| Over 65 | $\begin{gathered} 0.046 \\ (0.040) \end{gathered}$ | $\begin{gathered} 0.032 \\ (0.042) \end{gathered}$ |  |
| High Education | $\begin{gathered} -0.012^{* *} \\ (0.005) \end{gathered}$ | $\begin{gathered} -0.010^{*} \\ (0.006) \end{gathered}$ |  |
| Married | $\begin{gathered} 0.003 \\ (0.017) \end{gathered}$ | $\begin{gathered} 0.002 \\ (0.019) \end{gathered}$ |  |
| Car Crash Probability | $\begin{aligned} & 0.130^{*} \\ & (0.073) \end{aligned}$ | $\begin{aligned} & 0.138 * \\ & (0.080) \end{aligned}$ |  |
| Constant | $\begin{aligned} & -1.744 \\ & (1.709) \end{aligned}$ | $\begin{aligned} & -1.924 \\ & (1.763) \end{aligned}$ | $\begin{gathered} -0.275 \\ (0.347) \end{gathered}$ |
| Observations | 69 | 69 | 69 |
| F | 22.99 | 20.69 | 85.80 |
| R-squared | 0.761 | 0.745 | 0.687 |

Robust standard errors in parentheses
*** $\mathrm{p}<0.01, * * \mathrm{p}<0.05, * \mathrm{p}<0.1$

