Municipal Citations, Recidivism, and Deterrence among the Lane County Homeless

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Presented to the Department of Economics at the University of Oregon, in partial fulfillment of the requirement for honors in Economics

June 9th, 2017
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Abstract

Using Lane County Municipal court records we find that homelessness is associated with increased vulnerability to arrest and citations. This study analyzes homelessness in Lane County and looks at the extent a homeless individual is deterred through punitive measures. To study this, we used an economic proportional hazard model to study various covariates effects on the likelihood of recidivism and re-citation. Our results suggest that individuals who experience any sort of extension of homelessness are significantly more likely to receive future citations than those with permanent addresses. Punitive measures such as fines and multiple citations were not associated with an observable deterrent effect among any population. This suggests that the current legal system imposes high costs on the homeless population but fails to deter crime.

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Executive Summary

The proportionate population of homeless individuals in the state of Oregon was .33% of the population in 2015, putting Oregon near double the United States proportionate population. Lane County, specifically, has the second largest population of Homeless individuals versus other Oregon counties. In addition, the largest mainstream cost as a result of homelessness is criminal expenditures. In our study, we examine homelessness and their propensity to commit crimes and recidivism. Based on this propensity we look to evaluate the deterrence effect as it applies to homeless individuals.

Crime and homelessness is a very interesting study because the descriptive statistics provide a lot of relevant information. Researchers have found that the diminishing public expenditure in mental illness has resulted in higher crimes among homeless individuals. Unfortunately, we were unable to find any research relating the deterrence effect and homelessness.

Our hypothesis is: because homeless individuals may be more likely to encounter police officers, commit quality-of-life offenses, and struggle paying fines; they are less likely to be deterred from committing future crimes.

We use a multiple-failure, Andersen-Gill Proportional Hazards (Cox) model to analyze the deterrence effect among homeless individuals and the rest of the population in this dataset. This model provides our study with the probability to commit a crime based on independent covariates. Using this model, we look to determine the demographic characteristics that affect the propensity for homeless individuals to recidivate.

We find that homeless individuals are significantly more likely to recidivate crimes based on their home status. Among homeless individuals, Caucasian males aged 30-35 are the most likely to recidivate. Class C misdemeanors are the most common crimes committed by homeless individuals, which include crimes such as criminal trespass, disorderly conduct, and theft in the 3rd degree. We also find that punitive measures, such as the monetary value of the fine, do not affect an individual's likelihood to recidivate crime, regardless of their home status.

There are several political implications of this analysis. Municipal Courts. We conclude the current model of deterrence for homeless individuals is ineffective. We suggest further research be done in Lane County to find solutions into decreasing the crime rate among homeless individuals.

I. Introduction

The topic of this paper has received much attention and is an important social issue in the city of Eugene. Homelessness is a public issue that pervades the state of Oregon, particularly cities such as Eugene and Portland. Oregon has a high population of homeless individuals. Most of this population comes from the Eugene-Springfield metropolitan area and is the focus of our paper. A distinguishing feature of the homeless population is their vulnerability to arrest. They are exposed to the elements and the scrutiny of the police 24 hours a day. Some of their actions may be considered legal within a private residence, but not outdoors. This vulnerability to arrest for crimes such as consuming alcohol in public or disorderly conduct is a contributing factor to a higher than average crime rate among the homeless demographic. However, the criminal justice system does not serve homeless individuals. The fundamental idea outlining penal theory is that punishment will deter crime. Homeless individuals may not be deterred by punishments associated with the crimes they are likely to commit. A feature of being homeless is a lack of wealth. Therefore, fines levied against a homeless individual are unlikely to be paid and less likely to deter future crime. The purpose of this research is to add to the literature on crime and homelessness by seeing how the characteristics of the homeless affect the number of citations and the likelihood of recidivism.

This paper seeks to fully analyze the issues surrounding homelessness and crime. We first go over the classical model of deterrence originally created by economist Gary Becker. We then analyze the issue of homelessness in Lane County. Next, we address the significant costs of homelessness not just to the individuals, but the costs that burden the county and the greater population. From there we look at the previous literature surrounding homelessness, crime and deterrence. This is when we dive into our own study of the issue with our hypothesis and a discussion of the data we were provided and the data we extrapolated. From these data, we devised a model which we then apply to our data to obtain results. Further analysis of these results leads us to a conclusion accompanied with the policy implications.

I-A. Deterrence

The idea of deterrence is that society can control crime by raising its expected cost. As Gary Becker explained in Crime and Punishment (1974) you can alter the utility value associated with getting caught for committing a crime and the punishment for said crime to lower the rate at which that crime is committed. This comes from Becker's rational choice model. In this model, a rational individual is a utility maximizer. They are trying to maximize their individual utility through the choices they make. When presented with the choice of whether or not to commit crime, a utility maximizing individual will commit crime when the average utility derived from doing so outweighs the utility that could be obtained through legal means. In this model, the utility from crime would represent the potential gains from successfully committing the crime (not getting caught) multiplied by the probability of success minus the probability of getting caught multiplied by the utility lost from getting caught. In this model, the utility lost takes the form of the legal wages forgone in addition to any fines associated with the crime. Mathematically this would be modelled as:

$$Utility_{crime} = (probability * (loot)) – (1\text{-}probability * (wages\ forgone + fines))$$

Thus, from this model, a rational individual will commit crime when the utility of crime outweighs the utility of behaving legally.

Becker then adds social cost as a dimension to his model of crime. Crime incurs a social cost on society through guards, judges, and law enforcement staff that are required to prosecute crime. Lowering crime rates comes at a high cost to society. To lower crime rates you need to alter the utility function of committing crime. Hiring additional law enforcement or prosecuting more crime raises the probability of a criminal getting caught. This higher probability of getting caught thus adds an incentive for an individual to act legally. In this model, there is a socially optimal level of crime. This is where the marginal benefits of a lower crime rate are in equilibrium with the marginal cost of reducing the crime rate. At this equilibrium, society will endure a certain rate of crime as preventing additional crime is too costly. Society would rather tolerate this level of crime than pay for a lower crime rate.

Economists have also made additions to Becker's model. One addition is the idea that not only do sanctions affect crime, but the level of crime also influences sanctions. This addition was made by Oren Bar-Gill and Alon Harel in their article, Crime Rates and Expected Sanctions: The

Economics of Deterrence Revisited, where they hypothesize different scenarios in which higher crime rates can cause self-reinforcing or self-correcting effects on the level of sanction.[1] This is relevant to our study of Lane County's homeless population in suggesting that some of the sanctions associated with specific crimes may not effectively reduce crime.

Despite the many additions to economic models of deterrence, these models still do not apply well to homeless individuals. The model of deterrence created by Becker and expanded upon by other economists assumes that criminals will pay fines when convicted of a lower-level crime. In the case of a homeless individual, they often do not have the ability to pay the fine. If they can't pay a fine, theoretically they will not be deterred from committing future crimes. In turn, if they are not deterred from committing future crimes, the marginal cost to society due to the increased rate of criminal activity increases.

Economists have addressed this issue to a certain extent. In Crime Rates and Expected Sanctions: The Economics of Deterrence Revisited, the authors proposed that the cost of getting arrested has costs outside of homeless individual's freedom and monetary costs. They suggest that individuals also bear a social cost when arrested. In this expanded model of crime, the cost criminals bear when caught committing crime is altered to include this social cost. This social cost comes from the stigma associated with committing certain crimes, with some crimes more stigmatized than others. Drug use may be acceptable within certain social circles, but condemned in others. In these cases the stigma associated with a crime is contextual to an individual's social surroundings. This social cost may deter a potential criminal in some cases, but not all.

[1] Oren Bar-Gill and Alon Harel, "Crime Rates and Expected Sanctions: The Economics of Deterrence Revisited," *The Journal of Legal Studies* 30, no. 2 (2001): 485-501, http://www.jstor.org/stable/10.1086/322055.

Unfortunately, social cost is not something that can be universally quantified, making research into deterrence difficult.

Individual social cost is important in the context of the homeless population because regular fines may not be a deterrent. Homeless individuals may not have the money to pay the fines for the crimes they commit, therefore transferring the cost to society. Typical models of deterrence focus on setting punitive measures high enough to deter potential criminals from committing crime, however this does not apply to homeless individuals.

I-B. Homelessness in Lane County

Point-in-time homeless (PIT) counts are collected by the U.S. Department of Housing and Urban Development (HUD) and presented by Oregon Housing and Community Services. This is the most common method of reporting the homeless population and is presented at the county level. These PIT counts are recorded based on the amount of total homeless individuals in a night in January, regardless of whether they are in a shelter or living on the street. The HUD uses statistics from the Homeless Management Information Systems (HMIS) to develop an estimate for the homeless population. These estimates may not be 100% accurate at any given period of time, but the records are frequently updated to reflect fairly accurate estimates.

Lane County is the 7th highest county for proportional population of homeless individuals at 0.40%.[2] As shown in Figure 1, Lane has a significantly larger proportionate population of

[2] Oregon Housing and Community Services (2015) 2015 Point-In-Time (PIT) Homeless Count [Microsoft Excel Spreadsheet]. Salem, Oregon: Oregon.gov. Available from: https://www.oregon.gov/ohcs/Pages/research-point-in-time-homeless-count-in-oregon.aspx

homeless individuals compared to the rest of Oregon and the United States in general (.33% and .18%). Lane County currently has the second highest homeless population in Oregon with 1,473 homeless individuals, making Lane County home to around 11% of the total population of homeless individuals in Oregon. While heavily overshadowed by Multnomah County which makes up around 29% of the homeless population of Oregon, Lane County still faces a significant problem with homeless individuals.

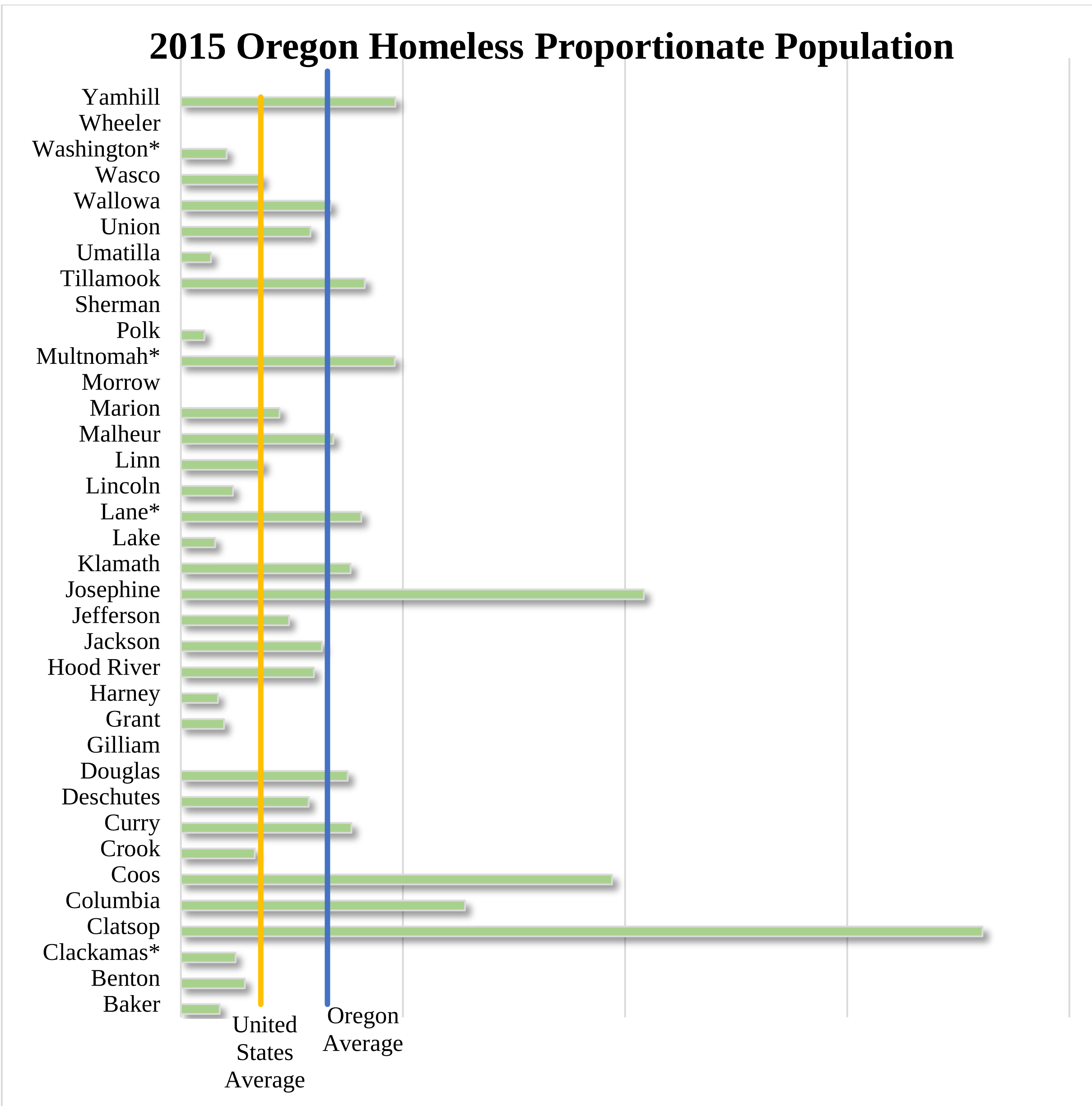

Figure 1

However, in recent years the homeless population in Lane County has been on the decline. As shown in Figure 2, in 2012, the population of homeless in Lane County was 2,057 versus 1,451 in 2016. This is correlated with a decrease in the overall homeless population in Oregon, which has decreased by 2,652 individuals between 2012 and 2016. This may be a result from larger legislation action to end homelessness in the entire state of Oregon and the economic recovery following the great recession. Although Lane County has seen a recent decline, it is still significantly higher than the Oregon and United States average, signaling that efforts to end homelessness should continue.

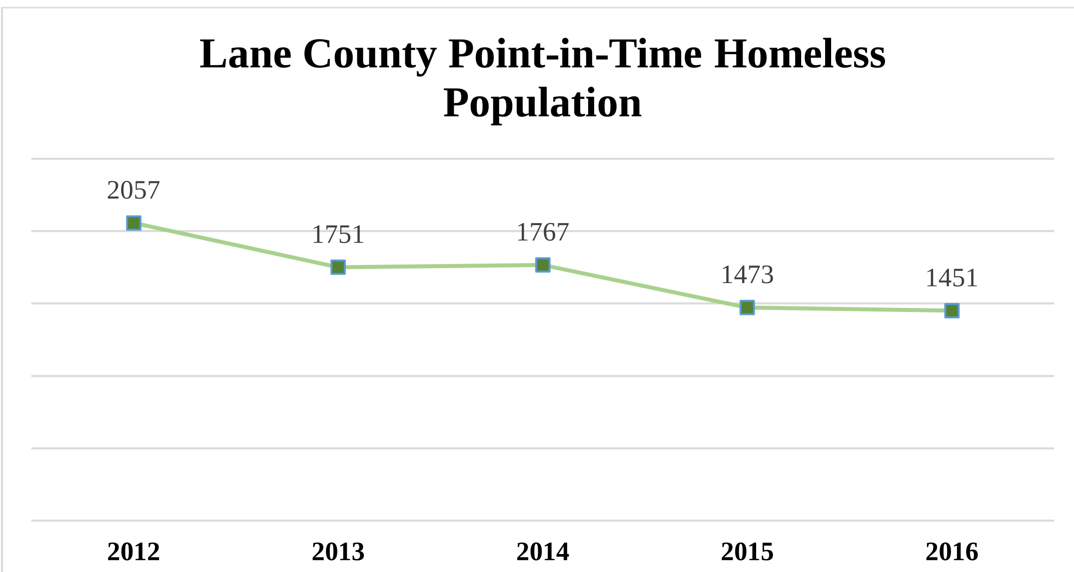

Figure 2[3]

[3] Oregon Housing and Community Services (2015) 2015 Point-In-Time (PIT) Homeless Count [Microsoft Excel Spreadsheet]. Salem, Oregon: Oregon.gov. Available from: https://www.oregon.gov/ohcs/Pages/research-point-in-time-homeless-count-in-oregon.aspx

Oregon Housing and Community Services (2014) 2014 Point-In-Time (PIT) Homeless Count [Microsoft Excel Spreadsheet]. Salem, Oregon: Oregon.gov. Available from: https://www.oregon.gov/ohcs/Pages/research-point-in-time-homeless-count-in-oregon.aspx

Oregon Housing and Community Services (2013) 2013 Point-In-Time (PIT) Homeless Count [Microsoft Excel Spreadsheet]. Salem, Oregon: Oregon.gov. Available from: https://www.oregon.gov/ohcs/Pages/research-point-in-time-homeless-count-in-oregon.aspx

Oregon Housing and Community Services (2012) 2012 Point-In-Time (PIT) Homeless Count [Microsoft Excel Spreadsheet]. Salem, Oregon: Oregon.gov. Available from: https://www.oregon.gov/ohcs/Pages/research-point-in-time-homeless-count-in-oregon.aspx

This is interesting in our data as well, as although we have citation history from 2011 to 2016, most of the data collection did not begin until 2013. In Figure 3 below we can see that similar to the trend reported above, the citations for homeless individuals decreased significantly between 2013 and 2016. This downward trend in homeless citations is roughly proportional to the overall decrease in the homeless population of Lane County.

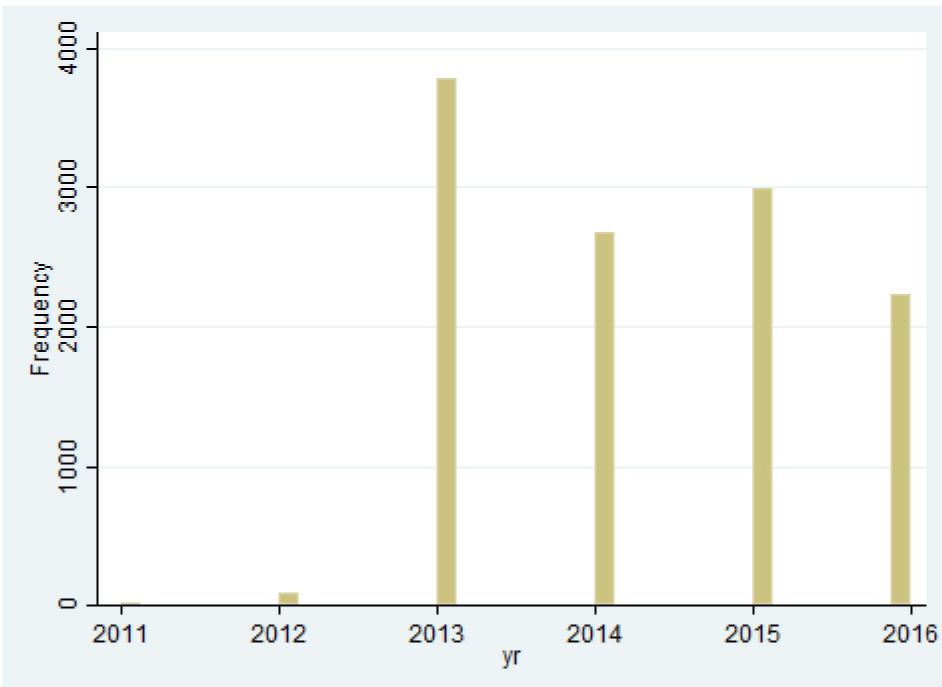

Figure 3

I-C. Cost of Homelessness

Cities incur many social costs from homelessness. These costs usually take the form of a negative externality, which is a result of high homeless rates. Quantifying the cost of an externality is quite difficult, so we will only adhere to definite costs. A study in 2010 by the HUD attempted to define the accounting costs associated with homeless individuals by closely monitoring a cohort of 1,972 first-time homeless individuals in Jacksonville, Florida. During this

18-month monitoring period, the HUD found that the average cost of these individuals to the city of Jacksonville was $2,652. These costs are separated out by whether they are homeless specific, for example: costs to run a shelter or mainstream costs, both of which are expensed by the government or a social program agency. Mainstream costs, while potentially abused by homeless individuals, are costs that any individual could incur regardless of their housing situation. These include income support, physical health, mental health, substance abuse, and criminal justice. On average, this cohort's largest expense were homeless specific costs at $1,634 and combined mainstream costs of $1,018. The largest of these mainstream costs are from criminal justice at the county and city level at $397 per person. While these numbers may seem low in perspective, they add up when distributed over an entire population. In addition, these cost figures do not account for the lost revenue on bad debts, which is a relevant cost for municipal courts and hospitals. For example: criminal costs are defined by the costs of making an arrest at $244.50 per arrest plus a $165 processing fee and $60 for each night's stay. The monetary damages charged to homeless individuals are not taken into account.

These results potentially underestimate the cost of homelessness due to an underrepresented population of individuals and geographic specificities associated with the Jacksonville population. A University of Texas study determined that the average yearly cost of homelessness was $14,480 per each individual, which is largely due to costs incurred from overnight incarceration. While the actual cost of homeless individuals is ambiguous, homelessness does carry an expense to the public. Lane County bares significant costs from homeless individuals, unfortunately we do not have an adequate measure of this exact cost.

II. Literature Review

Homelessness is a commonly explored topic in academic writing that is covered by a variety of disciplines. Although there are many articles discussing the topic of homelessness and crime, we cannot find any economic literature on the subject of deterrence theory and homelessness. The topic of homelessness and crime usually takes focus on mental health and the increased likelihood of committing crime if afflicted with a mental disorder. Other literature discusses the nature of the crimes homeless individuals commit and their legality. Yet nothing has asked the question of to what extent homeless individuals are actually deterred from committing crime. This seems to be an important question with future policy implications that could benefit society as a whole. Although no previous studies have explored the relationship between economic deterrence theory and homelessness, there is a significant amount of literature that helps in understanding deterrence and how it does or does not apply to a homeless individual.

Prior to Gary Becker's piece Crime and Punishment: An Economic Approach (1968), the topic was considered a topic of sociology and outside the realm of economics. Becker applied economic theory to crime with the assumption that individuals who commit crimes are rational utility maximizing individuals. Through this assumption, Becker created an economic model of crime used use to determine an optimal level of crime given different punitive measures and probabilities of getting caught.[4] The model takes as given that you cannot realistically catch and prosecute all instances of crime given the reality of a finite amount of resources. Thus you must

[4] Gary Becker, *Crime and Punishment: An Economic Approach*, vol 1 of the *Essays in the Economics of Crime and Punishment* (National Bureau of Economic Research, 1974)

allocate your resources and set punishments as such to reach an optimal level of crime where the marginal cost of crime to society is equal to the marginal benefit to society of having less crime.

Becker's model has been expanded over time to include the social costs of committing crime and to take into account differing legal frameworks.[5] For example, Crime Rates and Expected Sanctions: The Economics of Deterrence Revisited analyzes the model of crime laid out by Becker and expands on it.[6] In this paper, Oren Bar-Gill and Alon Harel theorize that higher crime rates lead to a lower probability of getting caught. That is, given that the number of police officers, prosecutors, and judges remains constant (at n_1, n_2 and n_3), they can only catch a maximum of X criminals while the prosecutors can only prosecute Y number of criminals and each judge can convict only Z number of criminals. Thus, the justice system can only punish the minimum of $X*n_1$,$Y*n_2$, and $Z*n_3$. The authors also theorize scenarios in which higher crime rates lead to a higher probability of getting caught, mainly public perception and an increased willingness to report crime if it is more widespread. The authors then discuss how sanctions could positively or negatively change with an increased crime rate. The argument for a decreased sanction being that the cost of crime is paid in both punitive measures, such as fines, as well as in stigma and damage to reputation. If an individual has already committed crime, they may be more likely to commit additional crimes due to the reduced social cost regarding stigmatization. The argument for an increased sanction is that an increase in crime prevalence will raise awareness to the public, thus increasing the social condemnation of said crime. In turn, the social costs of committing a crime will increase. This paper adds an important dimension to the

[5] John Harris, "On the Economics of Law and Order," *Journal of Political Economy* 78, no. 1 (1970): 165-74, http://www.jstor.org/stable/1829635.

[6] Oren Bar-Gill and Alon Harel, "Crime Rates and Expected Sanctions: The Economics of Deterrence Revisited," *The Journal of Legal Studies* 30, no. 2 (2001): 485-501, http://www.jstor.org/stable/10.1086/322055.

economic model of crime and helps in understanding that there are unobserved, endogenous, elements present when a criminal decides to commit crime. This is especially applicable to the homeless demographic who have a variety of backgrounds.

One of these backgrounds is mental illness, which is an important element in understanding the full range of the homeless population. In Oregon, approximately 14%[7] of the homeless population in 2015 is afflicted with mental issues, making this a topic of great interest to many academic researchers. Fred Markowitz explores this topic in Psychiatric Hospital Capacity, Homelessness and Crime Arrest Rates, in which he studies diminishing public expenditure on mental health and how it has translated into higher crime rates among the homeless population.[8] Markowitz states that mentally ill individuals are more likely to be homeless and those individuals are much more vulnerable to committing crime. Although our paper cannot determine which homeless individuals in our data set are mentally ill, due to the aforementioned statistic it is a safe bet that mental illness is present. This presents a problem for the classical model of deterrence as these individuals have endogenous factors increasing the likelihood of being subject to recidivism. These endogenous factors are not accounted for by Becker's rational choice model and present an obstacle for the idea of deterrence.

To further understand the homeless population and the crimes they commit, this topic needs to be examined in a legal framework context. Many of the activities that homeless individuals participate in for basic survival are criminalized. David Smith challenges this legal framework in his article A Theoretical and Legal Challenge to Homeless Criminalization as

[7] Oregon Housing and Community Services (2015) 2015 Point-In-Time (PIT) Homeless Count [Microsoft Excel Spreadsheet]. Salem, Oregon: Oregon.gov. Available from: https://www.oregon.gov/ohcs/Pages/research-point-in-time-homeless-count-in-oregon.aspx

[8] Fred E. Markowitz, "Psychiatric Hospital Capacity, Homelessness, and Crime and Arrest Rates," *Criminology* 44, no. 1 (2006): 45-72, Doi: 10.1111/j.1745-9125.2006.00042.x.

Public Policy. This article challenges the criminalizing of many activities that homeless individuals are prone to committing for survival. For example, Smith argues that crimes such as loitering and trespassing should not be criminalized, or at least not to the extent to which they currently are.[9] This article is relevant to our research because the data we used only contains lower level offenses that are typically committed by a homeless individual as a means of survival.

The homeless population of Lane County are far from homogenous and vary in terms of age, race, etc. Each homeless individual's situation differs. These situational factors are the topic of Bill McCarth and John Hagan's paper, Homelessness: A Criminogenic Situation?, which argues that these factors contribute to the individual's propensity to commit a crime. This study focuses on minors who run away from home and live on the streets. It analyzes how the crime rates of this demographic change from living at home to living on the streets.[10] The study found that the longer an individual was homeless the more likely they were to commit crimes. This became increasingly significant when an individual's status as homeless persisted for a year or longer. The authors found this particularly significant across specific crimes such as prostitution and theft. They conclude by suggesting that homelessness and crime should not just be studied through the static condition of homelessness but to the varying extent of their homelessness. Although not completely tangible, the extent of an individual's homelessness can be observed in our data through the frequency at which an individual is arrested. Homeless individuals who are

[9] David Smith, "A Theoretical and Legal Challenge to Homeless Criminalization as Public Policy," *Yale Law and Policy Review* 12, no. 2 (1994): 487-517, http://www.jstor.org/stable/40239428.

[10] Bill McCarthy and John Hagan. "Homelessness: A Criminogenic Situation.," *The British Journal of Criminology* 31, no. 4 (1991): 393-410, http://www.jstor.org/stable/23637690.

arrested at a higher frequency have likely been homeless longer and thus more likely to be arrested again.

III. Hypothesis

The goal of this paper is to compare the deterrent effect of citations among the general population and the homeless. We believe that homeless individuals are more likely to recidivate than an individual with a permanent address. Individuals with residence are more likely to be deterred from crime due to many factors, such as: increased financial stability to pay off fines, more concern about their reputation, etc.

Greater police efforts Against Homeless Individuals

Police are allocating more effort into the homeless population, which is one explanation as to why homeless individuals may be more likely to be cited. This may be based on the specific organization of various policing agencies who may want to deter certain behaviors from homeless individuals, or by policy directives from the city. Another explanation is that homeless individuals are more likely to be caught committing a crime since they do not have their own private residence. For example, a homeless individual who is using illegal substances is much more likely to be caught given they are in public. In this case, the police effort is constant over the amount of citations given.

Monetary Damages not an Adequate Deterrent

For homeless individuals it may be near impossible to pay back large fines. In our dataset, the average presumptive fine is $320.60, which is well over what most homeless individuals can afford. Since there is a large probability these fines will be unpaid, the monetary damages associated with these citations will not be a deterrent to homeless individuals. In San Francisco, Judge Christopher Hite dropped 64,713 outstanding warrants for quality-of-life fines.[11] The reasoning behind this was these specific citations were almost guaranteed to go unpaid, and there was no point dwelling on these uncollectible accounts.

Quality-of-Life Offenses

Certain crimes, like quality-of life-offenses, are committed by homeless individuals because they are necessary. Criminal trespass and public urination are examples of these crimes that homeless individuals would not commit if they had shelter.

IV. Data

Lane County Municipal Court data are used for this analysis and includes many different variables that detail citation information. In this dataset, there are 76,176 citations over the course of 8 years. All entries are citations occurred somewhere within Lane County boundaries. These citations are related to lower level crimes, with the maximum level of crime being a Misdemeanor Class A. Felonies are not included in these data. Records in these data date back as far as 2009, but around 99% of entries are concentrated between years 2013-2016. Within the data are a lot of descriptive statistics in determining what variables will be relevant for a final regression.

[11] Ross, Matier &. "SF Courts Ignoring Thousands of Quality-of-life Citations." San Francisco Chronicle. N.p., 14 Nov. 2016. Web. 08 June 2017.

The data provides useful information, including the address of those who received citations. From this we built a new variable to categorize residency status. Fines were not included in the initial data, but the offense and offense category were. Fines for each of these crimes is publicly available through Lane County and using the data we had on the nature of the offense we were able to build a variable for both presumptive fine and maximum fine. Our data set has been excellent for extrapolating new variables and we have used it to create other variables such as time between offenses and categorical variables for age, fines and residency status. The new variables that we have created from our initial data set will be important in designing a regression to analyze any sort of deterrent effect of crime.

The dependent variable analyzed is a fixed survival-time variable that measures the time between the first citation and future citations. Along with demographic and geographic characteristics regarding each individual stopped and the individuals involved in the legal process, there is data for the result of the citation. For example, someone who did not show up to their hearing is guilty by default. We added several variables in this dataset that were material for this analysis, but not included in the initial dataset. One example of this is maximum fines and presumptive fines for each citation in Lane County.[12] The dataset does not contain information relating to whether or not an individual paid their fine, we can assume that if an individual has been cited an excessive amount of times they either are unaffected by the financial compensation that must be given or they have prolonged making this payment. We will also assume there is a reasonably high probability that a homeless individual who has been cited a large amount of times has not or will not pay their fines.

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[12] *Eugene Municipal Court Fine Schedule* (Eugene, 2016), 23.

Another item withheld from this dataset that is relevant for this analysis is whether the address given for an individual is an actual home address. We split many different addresses from this dataset into residency categories to decipher this exact issue. These categories are: valid home address, homeless, pseudo-homeless (i.e. church address, social services building, etc.), and nonpermanent addresses such as a mobile home park. Many of individuals represented in these variables are certainly going to be homeless, but we cannot guarantee that every single one of them is. As a result of this we generated a new variable to group these individuals together. Grouped together we considered these individuals to be pseudo-homeless. They are neither definitively homeless nor do they definitively have a home. We were able to determine the residency status of our population using the addresses that were provided in our data set.

There is a high potential for human error in the entry of these data. For example, according to the dataset, some individuals received citations while they were 0 years old, which is highly infeasible. We assume our data is accurate and entered into the database without error, but there is a high probability that not all records are completely accurate. However controlling for every single incorrect entry is unlikely. We cannot always gauge the accuracy of an individual's cited address and we don't necessarily want to drop the addresses we have categorized as invalid. This could potentially indicate the lack of a residence, it could also indicate where a homeless individual has taken shelter. It is important to account for this factor when making a conclusion regarding the data.

In addition to the human errors that can occur when entering the data, our own creation of new variables creates some risk of human error. The home category variable was manually created from the addresses provided in our data. These addresses were then categorized into residency statuses based upon their geographical location. For example, a citation which lists the address of a church resulted in the categorizing of that individual's address as a church address. The same was done for commercial, hotel, motel, warehouses, social services, PO boxes, postal service, jail, rehabilitation centers, trailer parks, missions and home addresses. Homelessness was categorized based upon obvious homelessness, typically composed of individuals that provided park addresses or addresses for charity centers. Some addresses that had significant number of citations associated with them were completely invalid. They were in the middle of nowhere with no nearby residences. This all comes with risk as there are likely more homeless records than we have categorized. This is due to the likelihood that many individuals who gave law enforcement officials commercial, postal, warehouse, church, or social service addresses likely could be homeless. Thus we do not expect our results to be exactly 100% accurate, there does exist the possibility that due to human error our results could have bias.

Descriptive Statistics

Our data provides a wealth of information about the population we are observing. For example we can see the distribution of ages across our data set. From table 1 Appendix A, we find that 83% of our data set comes from individuals between the ages of 20 and 45 with 25% being between the ages of 20-25. From this we can further narrow down the distribution of ages to only look at homeless individuals. From table 2, Appendix A we see that homeless individuals within our data set have many more observations from the age range of 40-45 making up almost 25% of the homeless demographic represented in our data.

We can additionally see the number of times an individual is getting stopped with our data. In table 3, Appendix A we restricted the ordercat variable (number of stops) to reach a maximum of 10 stops. Thus we have a larger frequency of 10 stops due to that 10 representing 10 or more stops. From this table out of the 76,176 citations in our data set nearly 20% were composed from individuals who were stopped 10 or more times. 30% of our citations were from individuals only stopped once. Looking at our demographic of interest, the homeless population, we can restrict this table command to just homeless individuals. In table 4, Appendix A we then see that from the citations given to the homeless nearly 50% of citations are given to individuals who have been stopped 10 or more times. Only 10% of the citations are given to non-repeat offenders. There are many ways you can interpret this and one interpretation is that a small group of the homeless population is receiving a significantly greater proportion of the citations than the rest of the population.

Additionally, in table 5, Appendix A, the majority of the homeless population is Caucasian, with the next most represented race being African American. 52% of the homeless individuals cited never had a race recorded during their citation and received a null value for their race. This is a problem throughout our data that leaves us with a huge chunk of missing data.

The types of crimes homeless individuals commit is also interesting in our study. Our data only contains lower level crimes with the most serious being a Class A Misdemeanor which usually carries a maximum sentence of 30 days in jail. From table 6, Appendix A, we can say that out of these offense categories, about 48% of the homeless population is cited for misdemeanors while the rest are cited for lower level violations.

It is reasonable to then suggest that from the crimes homeless individuals are cited for the distribution of such crimes is going to differ from the rest of the data. Homeless individuals are often going to be more vulnerable getting cited for certain crimes such as camping. From table 7,

Appendix A displaying the distribution of individuals cited for camping homeless individuals make up 63% of the citations followed by individuals with homes making up 24% of the camping violations. This is one example where homeless individuals are cited far more for a violation than rest of the individuals in our data.

Our data gives us a variety of variables to work with that tell us a lot about crime in Lane County as well as the distribution of such crimes and how they apply to the homeless individuals represented in our dataset. These descriptive statistics will prompt us to include specific variables in our survival analysis models.

V-A. Survival Analysis

We look to survival analysis as a means of quantifying a possible deterrence effect for the individuals being cited in this dataset. Survival analysis compares side-by-side time and event variables, and estimates the probability that an individual in this model reaches the event in a fixed time interval. The hazard ratio quantifies the relative probability of failure for each covariate. A hazard ratio of 1, for a demographic variable, indicates this demographic is equally as likely as an omitted covariate of failing throughout the duration of our dataset. A hazard ratio greater than 1 signifies this population has a greater likelihood of failure versus an omitted population. A hazard ratio less than 1 signifies the population has a smaller likelihood of failure. For example, if the hazard ratio associated with the homeless dummy variable is greater than one, this is indicative of the homeless population being more likely to recidivate, compared to the omitted population. The omitted population in our model is the population with residence. This model is traditionally used with a single event, typically death in medical statistics, this model can be used with multiple failures. In a multiple failure analysis, we are directly measuring the likelihood of recidivism.

For our regression we are using a Cox Survival model, more specifically an Andersen-Gill Survival Cox model, to describe deterrence levels for demographic variables.[13] The Cox proportional hazards model indicates that multiple covariates have a proportional effect on the hazard rate and that the hazard rate should be adjusted based on the intensity of multiplicative factors. This model is useful for multi-failure events especially as it adjusts for patterns that may have occurred in previous failures.[13]

V-B. Methodology

In our analysis, variables were selected based upon their perceived impact to the research question. Variables, such as the perpetrator's body characteristics, are not beneficial in testing whether there is a deterrence effect for homeless individuals. However we believe variables, such as residency are far more important in determining the likelihood of recidivism.

Other relevant variables do not have enough information to be included in the regression. For example, it may be very beneficial to test whether certain judges are stricter against homeless individuals when it comes to delivering fines. Unfortunately, the actual fine amount is not provided in this dataset. Another issue is almost 50% of citations received by the homeless are guilty by default, meaning homeless individuals do not show up to their court hearings. For these reasons we omit the judge's name from the regression. Variables such as citation officer's

[13] P.K. Andersen and R.D. Gill, *Cox's Regression Model for Counting Processes: A Large Sample Study*, vol 10 of *The Annals of Statisticas*(Institute of Mathematical Statistics, 1982)

characteristics would be very interesting for this regression, but they are not provided in the dataset.

To help answer our research question we use an Andersen-Gill Cox Model to analyze our survival data. We collapse relevant variables from our original data set into a series of means which are uniquely identified by the individual's name id and the time they were stopped by police. This yields a new data set that separates observations into separate stops. However, each name identification has only one observation for each time they were stopped, regardless of the number of citations issued at that stop. The purpose of this model is to allow for multiple failure events by the same individual. For example, once an individual is stopped for an ordinance violation it is still reasonable to assume the possibility they may at some point also be stopped for another ordinance violation, or a different crime.

The variable most likely to indicate deterrence is the presumptive fine. Since we were limited in our knowledge of the delivered fine, we quantified the presumptive fine amount, based on the schedule of fines provided by Lane County Municipal courts.[14] We then add more variables that we believe have an effect on the hazard ratio. Given the discussion on homelessness and increased vulnerability to committing crime, we add in our residency dummy variables to observe the effect of various residency statuses on recidivism.

However, fines and home status are not the only variables affecting an individual's propensity to be stopped. Other exogenous characteristics, such as age and race could play a role. We have several race dummy variables within our data set as well as dummy variables for age ranges that correspond to the US census categorical data. While race variables are included in

[14] *Eugene Municipal Court Fine Schedule* (Eugene, 2016), 23

most regressions, it is important to note the frequent amount of null records may decrease the statistical significance of the data.

In our fully expanded Andersen-Gill Cox Proportional Model, we added in a variable measuring the frequency of citations in a stop. This variable measures the number of citations they received during that stop. We believe receiving more citations during a stop increases the individual's likelihood of being stopped in the future. This may vary depending on the seriousness of the citation. If these crimes included felony level offenses that result in jail time, there may be an incapacitation effect, which prevents the individual from getting stopped within a certain period of time. Due to the nature of our data, which lacks any felony crimes, there is generally no jail time associated with these citations. Thus, in our dataset, there likely is no incapacitation effect and the individual could be more likely to be stopped in the near future.

Seasonal effects and weather could also have a determinant factor on an individual's propensity to commit crime.[15] Thus, we included seasonal dummy variables, omitting winter as the control variable. The reason behind omitting winter is that homeless individuals could be more likely to be cited during the winter. Some resulting crimes could include trespassing, camping and violating park rules. A gender dummy variable was then added to observe whether males or females are more likely to be at risk for repeat-offenses. In addition, we added interaction terms that interact presumptive fine with homelessness as well as with pseudo-homeless. Adding in these additional variables we are left with a bigger model showing broader effects of the included covariates on the hazard ratio associated with additional stops.

[15] Ellen G. Cohn, "Weather and Crime," *The British Journal of Criminology* 30, no. 1 (1990): 51-64, http://www.jstor.org/stable/23638231.

VI. Empirical Specifications and Results

The base model for the specifications is designed to estimate the probability of future failures occurring. We include stop characteristics, housing characteristics, demographics characteristics and seasonal effect to give this base regression a holistic approach to analyzing these data.

Probability of Failure = f (Stop Characteristics, Housing Characteristics, Demographic Characteristics, Seasonal Effects).

In this first regression, we are looking at the effect of a presumptive fine on the hazard ratio of failing. In this model a failure is considered getting stopped again after having previously been stopped.

$$\lambda(t|\textit{Probability of Failure}_i) = \lambda_0(t)\ \exp\ (\beta_1 \textit{Presumptive Fine}_i).\ (1)$$

From the 5,261 subjects we can see that the variable for presumptive fines yields a 1.000411 hazard ratio. What this indicates is that for each dollar increase in the presumptive fine associated with the crime, the likelihood of an individual getting cited again increased 1.000411 times over the duration of our dataset – and this effect is statistically significant. Based on this result we cannot conclude that fines are a reasonable deterrent against crimes. This is a relatively small number and although statistically significant, it does little in telling us about what is causing homeless individuals to be stopped repeatedly.

```
Cox regression -- Efron method for ties

No. of subjects      =        5,261           Number of obs    =     10,968
No. of failures      =       10,968
Time at risk         =  1266599.978
                                              Wald chi2(1)     =      31.54
Log pseudolikelihood =   -87476.712           Prob > chi2      =     0.0000

                            (Std. Err. adjusted for 5,261 clusters in nameid)
```

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
presumptivefine	1.000411	.0000732	5.62	0.000	1.000267	1.000554

The second regression adds homeless and pseudo-homeless dummy variables. We then omitted our home dummy variable to serve as a point of comparison for the other demographics. There are two regressions, one separating out the types of pseudo-homeless variables and one that combines them into a single variable. The first can be seen in Table 1 in Appendix B. For future regressions, we will only use the single pseudo-homeless variable. This regression is meant to assess whether individuals are more likely to commit crime faster in some time interval based on their living situations:

$$\lambda(t|\textit{Probability of Failure}_i) = \lambda_0(t)\ \exp\ (\beta_1 \textit{Presumptive Fine}_i + \beta_2 \textit{Homeless Dummy}_i + \beta_3 \textit{Pseudo-Homeless Dummy}_i).\quad (2)$$

From this regression we can see that individuals classified as homeless are approximately 2.8 times more likely to ‘fail’ than an individual with an address indicating a permanent residence. This hazard ratio is statistically significant at any level of significance. What is interesting about this regression is not just the ratio corresponding to the individuals who have been classified as homeless, but the ratio associated with the pseudo-homeless variable. As a group, they are 2.56 times as likely to have been stopped multiple times as an individual with a home. This number is interestingly quite similar to the ratio associated with the definitely homeless population.

```
Cox regression -- Efron method for ties

No. of subjects      =        5,261           Number of obs    =     10,968
No. of failures      =       10,968
Time at risk         =  1266599.978
                                              Wald chi2(3)     =     634.51
Log pseudolikelihood =   -86283.312           Prob > chi2      =     0.0000

                                (Std. Err. adjusted for 5,261 clusters in nameid)
```

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
presumptivefine	1.000298	.0000793	3.76	0.000	1.000142	1.000453
homelessdum	2.820269	.1319879	22.15	0.000	2.573087	3.091196
pseudohomeless	2.562193	.2066014	11.67	0.000	2.187639	3.000877

The third regression adds demographic characteristics to adjust the coefficients based on race and age and to see if certain races and age ranges are more likely to commit a crime:

$$\lambda(t|\textit{Probability of Failure}_i) = \lambda_0(t)\ \exp\ (\beta_1 \textit{Presumptive Fine}_i + \beta_2 \textit{Homeless Dummy}_i + \beta_3 \textit{Pseudo-Homeless Dummy}_i + \beta_4 \textit{Race}_i + \beta_5 \textit{Age Categories}_i).\ (3)$$

For this regression, we used the Caucasian and 20 to 25 year old dummy variables as controls, because both variables represent the largest proportion of our data set. Adding all of these variables to the model we see that although both of those groups make up the largest proportion of the data that does not mean they are going to have the largest hazard ratios. In this regression we see that Native Americans and African Americans are at greater risk of getting stopped more than once. These hazard ratios associated with the race dummy variables are statistically insignificant, likely a result of missing race data for about half of our observations. From the age dummy variables we see that surprisingly those aged 80 to 85 have the highest hazard ratio. Although statistically significant, this result likely has little meaning as that age range composes a small portion of the data set. Unfortunately, both the age and race dummy variables mostly have higher p-values rendering these variables statistically insignificant, meaning conclusions, likely, should not be drawn from the hazard ratios associated with these variables.

```
Cox regression -- Efron method for ties

No. of subjects      =        5,261           Number of obs    =      10,968
No. of failures      =       10,968
Time at risk         =  1266599.978
                                               Wald chi2(21)    =      852.02
Log pseudolikelihood =   -86200.427           Prob > chi2      =      0.0000

                              (Std. Err. adjusted for 5,261 clusters in nameid)
```

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
presumptivefine	1.000266	.0000801	3.32	0.001	1.000109	1.000423
homelessdum	2.666101	.1281093	20.41	0.000	2.426473	2.929395
pseudohomeless	2.490873	.1968668	11.55	0.000	2.133421	2.908215
AfricanAmerican	1.057947	.0772374	0.77	0.440	.9168969	1.220696
Asian	.8073475	.0701615	-2.46	0.014	.6809072	.9572671
Hispanic	.9389996	.1199954	-0.49	0.622	.7309535	1.20626
NativeAmerican	1.244051	.3151762	0.86	0.389	.7571623	2.04403
age15to20	1.191788	.0946652	2.21	0.027	1.019969	1.392551
age25to30	.9998283	.0468898	-0.00	0.997	.9120231	1.096087
age30to35	1.221718	.0683173	3.58	0.000	1.094895	1.363231
age35to40	1.145275	.0699489	2.22	0.026	1.016065	1.290915
age40to45	1.143124	.0784202	1.95	0.051	.9993079	1.307637
age45to50	1.127836	.1013302	1.34	0.181	.9457358	1.344999
age50to55	1.325479	.1060683	3.52	0.000	1.133072	1.550559
age55to60	1.215466	.1133309	2.09	0.036	1.012456	1.459182
age60to65	.8758422	.0965894	-1.20	0.229	.7055925	1.087171
age65to70	.9310968	.1432641	-0.46	0.643	.6886901	1.258826
age70to75	.6655766	.1198783	-2.26	0.024	.4676129	.9473481
age75to80	.7928554	.2737689	-0.67	0.501	.4029754	1.559946
age80to85	1.813111	.0650365	16.59	0.000	1.690019	1.945168
age85to90	.6692626	.217812	-1.23	0.217	.353649	1.266545

The fourth regression limits the data to only homeless individuals. This allows us to better understand how certain demographic characteristics of homeless individuals may affect their propensity to commit crimes. If we constrain our collapsed data set to only collapse variable values for observations where the individual is homeless we can look at more specific results pertaining to the homeless. In this regression, we additionally included gender as it may have an effect on propensity to commit crime. With this regression from a smaller population we also have to omit the age range from 70 to 90 due to issues of collinearity. We used the Caucasian race and age20to25 variables as the controls just like the previous regression.

$$\lambda(t|Probability\ of\ Failure\ For\ Homeless_i) = \lambda_0(t)\ exp\ (\beta_1 Presumptive\ Fine_i + Age\ Categories_i + \beta_3\ Race_i + \beta_4 Gender_i). \quad (4)$$

We now see that our control variable for race, Caucasian, now is the most likely to have been stopped multiple times. Although insignificant it is still a notable difference between the two regressions. Similar to the previous regression we see that the age range of 30 to 55 in our data set is more likely to have been stopped multiple times. Unlike the previous regression, teenagers are much less likely to have been stopped multiple times. The underlying reason behind the lower hazard ratio could be that younger homeless individuals are less likely to have been homeless for long and as a result may be less likely to engage in illicit activities.[17] Once again none of these hazard ratios are considered statistically significant and conclusions should not be derived from this regression, it does however remain interesting statistical information.

[17] Bill McCarthy and John Hagan. "Homelessness: A Criminogenic Situation.," *The British Journal of Criminology* 31, no. 4 (1991): 393-410, http://www.jstor.org/stable/23637690.

```
Cox regression -- Efron method for ties

No. of subjects      =          790             Number of obs    =      3,205
No. of failures      =        3,205
Time at risk         =  166040.7597
                                                Wald chi2(16)    =      38.36
Log pseudolikelihood =   -19987.219             Prob > chi2      =     0.0013

                                  (Std. Err. adjusted for 790 clusters in nameid)
```

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AfricanAmerican	.9181374	.1556615	-0.50	0.614	.6585588	1.280032
Asian	.7252214	.3437852	-0.68	0.498	.2863951	1.836435
NativeAmerican	.8982707	.4103918	-0.23	0.814	.3668764	2.199351
gender2	1.221608	.1157454	2.11	0.035	1.01457	1.470896
presumptivefine	.9996249	.0001759	-2.13	0.033	.9992803	.9999696
age15to20	.7657111	.2190698	-0.93	0.351	.4370553	1.341509
age25to30	.9496969	.1514295	-0.32	0.746	.6948014	1.298104
age30to35	1.414326	.2078302	2.36	0.018	1.060397	1.886386
age35to40	1.160239	.1712947	1.01	0.314	.8687171	1.54959
age40to45	1.113184	.1719191	0.69	0.488	.8224475	1.506696
age45to50	1.32844	.1982345	1.90	0.057	.9915683	1.779759
age50to55	1.301139	.204321	1.68	0.094	.956439	1.770067
age55to60	1.162217	.2071874	0.84	0.399	.8194912	1.648277
age60to65	.9130186	.1789977	-0.46	0.643	.621729	1.340782
age65to70	.7838223	.2346708	-0.81	0.416	.435887	1.409488
age70to75	.8637615	.2492152	-0.51	0.612	.4906847	1.520496

The fifth regression opens the dataset back to the whole population. We add seasonal effects to test if different seasons affect an individual's likelihood of failure and citation frequency to test the amount of citations one receives in a given stop affects their chance of failure.

$$\lambda(t|\textit{Probability of Failure}_i) = \lambda_0(t)\ \exp\ (\beta_1 \textit{Presumptive Fine}_i + \beta_2 \textit{Homeless Dummy}_i + \beta_3 \textit{Pseudo-Homeless Dummy}_i + \beta_4 \textit{Race}_i + \beta_5 \textit{Age Categories}_i + \beta_6 \textit{Citation Frequency}_i + \beta_7 \textit{Seasonal Effects} + \beta_6 \textit{Gender}_i + \textit{i.Homeless Fines} + \textit{i.Pseudo-Homeless Fines}).\quad (5)$$

Analyzing this regression, we have obtained interesting results. Being a male in our data set is associated with being 1.2 times more likely than a female to be stopped in the future. Not a huge gap in hazard ratios, however it is interesting and may be indicative of men being more likely to be arrested than their female counterparts. Looking at the seasonal dummies it looks like individuals that are cited in the winter are more likely to be cited multiple times than those that are cited in other seasons.

```
Cox regression -- Efron method for ties

No. of subjects      =        5,261          Number of obs    =      10,968
No. of failures      =       10,968
Time at risk         =  1266599.978
                                             Wald chi2(28)    =     1228.39
Log pseudolikelihood =   -85450.632          Prob > chi2      =      0.0000

                                (Std. Err. adjusted for 5,261 clusters in nameid)
```

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender2	1.20134	.0426419	5.17	0.000	1.120604	1.287892
presumptivefine	1.00036	.0000791	4.55	0.000	1.000205	1.000515
citationfreq	1.015677	.0019954	7.92	0.000	1.011773	1.019595
homelessdum	2.766736	.2091631	13.46	0.000	2.385709	3.208617
pseudohomeless	2.944595	.3943139	8.06	0.000	2.264854	3.828344
finehomeless	.9996454	.0001933	-1.83	0.067	.9992667	1.000024
pseudofine	.9993123	.0003008	-2.29	0.022	.9987229	.999902
Spring	.7923186	.0292345	-6.31	0.000	.7370428	.85174
Summer	.7321055	.0268865	-8.49	0.000	.6812608	.7867449
Fall	.8896339	.0375065	-2.77	0.006	.8190776	.9662679
AfricanAmerican	1.06598	.073612	0.93	0.355	.9310407	1.220476
Asian	.8209478	.0679523	-2.38	0.017	.6980058	.965544
Hispanic	.9431006	.1264461	-0.44	0.662	.7251591	1.226543
NativeAmerican	1.216789	.284752	0.84	0.402	.7691615	1.92492
age15to20	1.205451	.0936532	2.41	0.016	1.035186	1.40372
age25to30	1.002167	.0463979	0.05	0.963	.9152324	1.097358
age30to35	1.24071	.0663632	4.03	0.000	1.117226	1.377842
age35to40	1.146988	.0675634	2.33	0.020	1.021925	1.287357
age40to45	1.140119	.0738558	2.02	0.043	1.004177	1.294465
age45to50	1.002735	.0879418	0.03	0.975	.8443722	1.190798
age50to55	1.270696	.0893009	3.41	0.001	1.107189	1.45835
age55to60	1.166426	.1001859	1.79	0.073	.985704	1.380283
age60to65	.8687533	.0895699	-1.36	0.172	.7098002	1.063302
age65to70	.9673252	.1402049	-0.23	0.819	.7281128	1.285128
age70to75	.7026887	.1297355	-1.91	0.056	.4893368	1.009062
age75to80	.8849065	.3004368	-0.36	0.719	.4548874	1.721436
age80to85	1.5551	.0639173	10.74	0.000	1.434737	1.685559
age85to90	.6343743	.1953878	-1.48	0.140	.3468765	1.160156

Finally, the sixth regression adds interaction terms to see if homeless and pseudo-homeless individuals are more likely to commit crimes based on the season and the presumptive fine amount. This is how we came to our final model. In this model we added the interaction terms between the seasons and homeless and pseudo-homeless to see if the hazard ratios would be significantly different than the seasonal dummy variables. We also cut out the age range dummy variables. The effects of specific ages in both the homeless and the whole population have now been well established. As such we cut out the age ranges and replaced them with our initial age variable covering the whole age range.

$$\lambda(t|\mathit{Probability\ of\ Failure}_i) = \lambda_0(t)\ \exp\ (\beta_1 \mathit{Presumptive\ Fine}_i + \beta_2 \mathit{Homeless\ Dummy}_i + \beta_3 \mathit{Pseudo\text{-}Homeless\ Dummy}_i + \beta_4 \mathit{Race}_i + \beta_5 \mathit{Age\ Categories}_i + \beta_6 \mathit{Citation\ Frequency}_i + \beta_7 \mathit{Seasonal\ Effects} + \mathit{i.Homeless\ Fines} + \mathit{i.Pseudo\text{-}Homeless\ Fines} + \mathit{i.Homeless\ Seasonal\ Effects}).\ (6)$$

Unsurprisingly from our final regression, both the homeless and pseudo-homeless variables are associated with large hazard ratios. Both of these are significant and further affirm our hypothesis that homeless individuals are more likely to be repeatedly cited. The hazard ratio associated with citation frequency was greater than 1 suggesting that with each additional citation during a stop you are 1.016 times more at risk to be stopped an additional time in the future. The hazard ratio associated with this was smaller than we might have expected, but does only account for a 1 citation per stop increase. The interaction terms between our seasons and homelessness were not significantly different than the seasonal dummy variables. However the ratios associated with each of these further affirm that those who receive citations in the winter are more likely to be cited at a future date. Lastly our age variable was associated with a hazard ratio just over 1 suggesting age may not have a huge effect on likelihood of future citations. The insignificant p-value of .312 can also be explained by the likelihood that the effects of age on crime vary over time and between the different populations.

```
Cox regression -- Efron method for ties

No. of subjects      =        5,258           Number of obs    =     10,965
No. of failures      =       10,965
Time at risk         =  1266015.478
                                              Wald chi2(21)    =    1065.30
Log pseudolikelihood =   -85464.173           Prob > chi2      =     0.0000

                                 (Std. Err. adjusted for 5,258 clusters in nameid)
```

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
gender2	1.196536	.0427431	5.02	0.000	1.115626	1.283313
presumptivefine	1.000383	.0000788	4.85	0.000	1.000228	1.000537
citationfreq	1.015878	.0020327	7.87	0.000	1.011902	1.01987
homelessdum	3.31154	.3260804	12.16	0.000	2.730323	4.016484
pseudohomeless	3.139293	.5903087	6.08	0.000	2.171566	4.538274
finehomeless	.9996736	.0001934	-1.69	0.091	.9992947	1.000053
pseudofine	.9992849	.0003049	-2.34	0.019	.9986875	.9998826
Spring	.8391442	.0332518	-4.43	0.000	.7764384	.9069142
Summer	.7783396	.0300748	-6.49	0.000	.7215707	.8395747
Fall	.9509431	.042635	-1.12	0.262	.8709462	1.038288
springhomeless	.8698492	.0792108	-1.53	0.126	.7276647	1.039816
summerhomeless	.7920285	.0706675	-2.61	0.009	.6649573	.9433827
fallhomeless	.7796302	.0792784	-2.45	0.014	.638752	.9515792
springpseudo	.8459657	.1273466	-1.11	0.266	.6298222	1.136286
summerpseudo	1.047026	.1623798	0.30	0.767	.7725871	1.418951
fallpseudo	1.007094	.1680754	0.04	0.966	.7261261	1.396781
AfricanAmerican	1.069121	.0724932	0.99	0.324	.9360736	1.221079
Asian	.8083067	.0622036	-2.77	0.006	.6951388	.9398982
Hispanic	.9500588	.126224	-0.39	0.700	.732252	1.232652
NativeAmerican	1.145923	.2730087	0.57	0.568	.7183932	1.827884
age	1.001328	.0013153	1.01	0.312	.9987531	1.003909

VII. Conclusion and Policy Implications

The results obtained in our model can be used to gain a better understanding of the effect of a variety of characteristics on an individual's likelihood of recidivism. The dominating covariate throughout each regression was the residency status. Every other covariate paled in comparison. In our final regression the pseudo-homeless and homeless dummy variables both had hazard ratios greater than 3, meaning they are at least 3 time more likely to recidivate than individuals with a residence. Both of these variables were statistically significant with p-values of .000. Anyone who doesn't have a permanent residence, is at far great risk of recidivism, which is exactly what we hypothesized.

The reasons for greater propensity to receive multiple citations among the homeless and pseudo-homeless population vary. The most notable reason is the greater vulnerability homeless individuals to be cited for acts which may not be illegal if they were to participate in these activities within the privacy of a residency.[19] Homeless individuals spend just about all of their time on the streets, activities such as smoking, finding a place to sleep and drinking are perfectly legal within a residence, but the lack of shelter criminalizes these activities. This is likely one reason that explains recidivism among the homeless population.

Even those who were assumed to be, but not certainly homeless, were much more likely to be at risk of being stopped multiple times. While we believe that a large portion of the demographic that we classified as pseudo-homeless is in fact homeless. What we couldn't always determine is the extent of their homelessness and how it compares to those who were definitively homeless. It is difficult to make a definitive conclusion from the data corresponding to our pseudo-homeless demographic, however, it is very clear from the data that they are more at risk of recidivism than those in homes.

We originally hypothesized that we would observe a clear lack of deterrence among the homeless population. Our hypothesis cannot be accepted from our results. This is due to the difficulty of determining deterrence based on the hazard ratio associated with fines, not

[19] Leon Anderson, Susan G. Baker, and David A. Snow, "Criminality and Homeless Men: An Empirical Assessment," *Social Problems* 36, no. 5 (1989): 532-549, http://www.jstor.org/stable/3096817.

necessarily the hazard ratios from the homeless and pseudo-homeless dummy variables. Classical models of deterrence originally based off of the Becker model suggest that individuals are rational utility maximizing individuals. Thus by setting higher sanctions you will deter crime.[20] In our study if the classical deterrence model were to hold true the hazard ratio corresponding to our presumptive fine variable and the interactions between the homeless and pseudo-homeless populations would be lower than 1. This would mean that the higher the presumptive fine the less likely it would be for an individual to commit additional crimes or receive further citations. In our final model the hazard ratios associated with the interaction terms were slightly under 1 at .999 each. The presumptive fine variable itself contained a hazard ratio of 1.003. These numbers were all arbitrarily close to 1 suggesting that presumptive fines associated with certain offenses and violations do not affect recidivism. The hazard ratios associated with fines are inconclusive in our study, disabling our ability to use the classical model of deterrence Thus, our hypothesis is inconclusive.

Endogenous factors may explain a substantial amount about the results we obtained in our study. The amount of data we had about crime in Lane County tells us a lot about our research question, but it does not explain everything. There are certain unobserved characteristics that we cannot obtain data for. These unobservable characteristics are the endogenous variables that may affect recidivism. An example of this would be mental illness. It has been well documented that individuals that are both homeless and mentally ill are more vulnerable to being cited for crime.[21] Within our data we were able to categorize the residency status of an individual

[20] Gary Becker, *Crime and Punishment: An Economic Approach*, vol 1 of the *Essays in the Economics of Crime and Punishment* (National Bureau of Economic Research, 1974)

[21] *Homeless Mentally Disordered Offenders and Violent Crimes: Preliminary Research Findings*

with a reasonable amount of accuracy. We do not have any way to determine whether or not there are endogenous characteristics associated with that individual that we can measure. There is no categorization for mental illness, and psychological data about every individual would be needed to study this characteristic. Thus, endogeneity does play a role in the results we've obtained.

However, the results observed should signal important policy implications. Homelessness does have a cost. Not just the effect on an individual's life, but on society as a whole. Our results have adequately explained an increased likelihood of homeless individuals to have been stopped multiple times. We do not have data on whether a levied fine was paid by a homeless individual, but the interaction terms in our model do suggest that fines do not have a significant effect on an individual's propensity to receive additional citations. If these fines remain unpaid this comes at significant cost to the taxpayer and society. As such it is a great interest to society to lower the crime rate among the homeless populations.

Since 2011 there have been 12,311 total citations given to homeless individuals in Lane County. Of those citations, 9,374 of them are presumed to be guilty based on the plea data in the municipal court records. The total fine revenue is estimated to be $3.02 million dollars,[22] based on the presumed fines associated with these guilty citations. This value is significantly large and brings an unanswered question on whether any of it will be paid. Given the financial status of most homeless individuals, we assume that the majority of this value will not be collected. This is not an adequate solutions to fixing crime rates among the homeless population.

[22] See Appendix C

Lowering the crime rate among the homeless population is no easy task. The topic is certainly worthy of additional academic exploration across many disciplines. Notably it is very clear that the current legal framework, both within Lane County and elsewhere does not serve homeless individuals. As David Smith discussed in his article, homelessness is largely criminalized through the existing legal framework.[23] Perhaps altering the legal framework to serve the homeless community would better improve the image of Lane County and emphasize the fact that homelessness should not be treated as a criminal issue, rather a social issue.

To summarize, the Andersen-Gill Cox Proportional Hazard Model was used to analyze our data. We collapsed our data based on name identification numbers and separate stops. This analysis shows that the homeless and pseudo-homeless demographics are substantially more prone to recidivism. However, the deterrent effect of fines yielded inconclusive results. The effect of age on recidivism changed depending on both the age and the population of interest. No age variable was significant and varied widely. Among the whole data set those who were categorized as African American or Native American had higher hazard ratios than other races. When limited to just the homeless population, those categorized as Caucasian were at far greater risk than other races in getting cited additional times. Frequency of citations within individual stops did have significant effect on recidivism. Those receiving more citations during a stop were more likely to re-offend later on than those who had fewer citations. Winter was the most notable dummy among the seasonal variables in determining likelihood of future stops, even when narrowed to just the homeless population this did not change. It remains clear that the homeless population is far more likely to be continuously committing lower level crimes than non-

[23] David Smith, "A Theoretical and Legal Challenge to Homeless Criminalization as Public Policy," *Yale Law and Policy Review* 12, no. 2 (1994): 487-517, http://www.jstor.org/stable/40239428.

homeless individuals. Future studies would be useful in exploring methods to reduce the homeless crime rate.

Appendix A- Descriptive Tables

Table 1- Age Categories

```
. tab agecat1
```

agecat1	Freq.	Percent	Cum.
15	1,913	8.33	8.33
20	5,723	24.92	33.25
25	3,433	14.95	48.19
30	2,741	11.93	60.13
35	2,134	9.29	69.42
40	3,242	14.12	83.53
50	1,379	6.00	89.54
55	964	4.20	93.73
60	678	2.95	96.69
65	422	1.84	98.52
70	180	0.78	99.31
75	97	0.42	99.73
80	38	0.17	99.90
85	16	0.07	99.97
90	6	0.03	99.99
95	1	0.00	100.00
100	1	0.00	100.00
Total	22,968	100.00	

Table 2- Age Categories of the Homeless Population

```
. tab agecat1 homelessdum if homelessdum==1, col
```

Key
frequency
column percentage

agecat1	(mean) homelessdum 1	Total
15	40 3.24	40 3.24
20	124 10.06	124 10.06
25	145 11.76	145 11.76
30	160 12.98	160 12.98
35	147 11.92	147 11.92
40	306 24.82	306 24.82
50	141 11.44	141 11.44
55	98 7.95	98 7.95
60	48 3.89	48 3.89
65	17 1.38	17 1.38
70	7 0.57	7 0.57
Total	1,233 100.00	1,233 100.00

```
.
end of do-file

.
```

Table 3- Number of Stops per Individual (Maximum of 10 stops)

10 is indicative of 10 or greater.

```
. tab ordercat
```

ordercat	Freq.	Percent	Cum.
1	23,001	30.19	30.19
2	13,514	17.74	47.94
3	7,550	9.91	57.85
4	5,402	7.09	64.94
5	3,433	4.51	69.44
6	2,983	3.92	73.36
7	2,019	2.65	76.01
8	1,837	2.41	78.42
9	1,414	1.86	80.28
10	15,023	19.72	100.00
Total	76,176	100.00	

Table 4- Number of stops per Homeless Individual (Maximum 10 stops)

10 is indicative of 10 or greater.

```
. tab ordercat if homelessdum==1
```

ordercat	Freq.	Percent	Cum.
1	1,334	11.33	11.33
2	1,012	8.59	19.92
3	794	6.74	26.66
4	674	5.72	32.38
5	534	4.53	36.91
6	489	4.15	41.06
7	395	3.35	44.42
8	379	3.22	47.64
9	327	2.78	50.41
10	5,841	49.59	100.00
Total	11,779	100.00	

Table 5- Race Distribution of Homeless population

```
. tab racecat if homelessdum==1 & nameid != nameid[_n-1]
```

Race	Freq.	Percent	Cum.
AFRICAN AMERICAN	61	4.57	4.57
ASIAN	8	0.60	5.17
CAUCASIAN	547	41.00	46.18
HISPANIC OR LATINO	1	0.07	46.25
NATIVE AMERICAN OR ALASKAN NATIVE	14	1.05	47.30
NULL	700	52.47	99.78
UNKNOWN	3	0.22	100.00
Total	1,334	100.00	

Table 6- Distribution of Offense Levels for the Homeless Population

```
. tab offenselevel2 if homelessdum==1
```

offenselevel2	Freq.	Percent	Cum.
Class A Misdemeanor	513	4.36	4.36
Class A Violation	272	2.31	6.66
Class B Misdemeanor	384	3.26	9.92
Class B Violation	3,421	29.04	38.97
Class C Misdemeanor	4,940	41.94	80.91
Class C Violation	1,276	10.83	91.74
Class D Violation	966	8.20	99.94
Null	7	0.06	100.00
Total	11,779	100.00	

Table 7- Homelessness and Camping

```
. tab homecat camping, col
```

Key: *frequency* / *column percentage*

Home Category	camping 0	camping 1	Total
Church	1,054 1.39	10 1.84	1,064 1.40
Commercial	581 0.77	7 1.29	588 0.77
Health Services	61 0.08	1 0.18	62 0.08
Home	55,243 73.04	133 24.45	55,376 72.69
Homeless	11,434 15.12	345 63.42	11,779 15.46
Hotel	59 0.08	0 0.00	59 0.08
Invalid	667 0.88	3 0.55	670 0.88
Jail	146 0.19	0 0.00	146 0.19
Mission	6 0.01	0 0.00	6 0.01
Motel	101 0.13	0 0.00	101 0.13
NULL	1,547 2.05	9 1.65	1,556 2.04
Null	29 0.04	0 0.00	29 0.04
PO Box	1,670 2.21	19 3.49	1,689 2.22
Postal Services	259 0.34	0 0.00	259 0.34
Rehab	117 0.15	0 0.00	117 0.15
SS Residential	455 0.60	6 1.10	461 0.61
Shelter	18 0.02	0 0.00	18 0.02
Social Services	419 0.55	11 2.02	430 0.56
Trailer	1,740 2.30	0 0.00	1,740 2.28
Warehouse	26 0.03	0 0.00	26 0.03
Total	75,632 100.00	544 100.00	76,176 100.00

Appendix B- Regression

Table 1- Regression 2 for All Dummies

```
Cox regression -- Efron method for ties

No. of subjects      =        5,261           Number of obs    =      10,968
No. of failures      =       10,968
Time at risk         =  1266599.978
                                              Wald chi2(16)    =      714.47
Log pseudolikelihood =   -86188.172           Prob > chi2      =      0.0000

                                 (Std. Err. adjusted for 5,261 clusters in nameid)
```

_t	Haz. Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
presumptivefine	1.000302	.0000795	3.80	0.000	1.000146	1.000458
churchdum	2.473505	.3233985	6.93	0.000	1.914355	3.195973
commercialdum	3.236618	.7191177	5.29	0.000	2.093968	5.002798
healthserdum	2.387389	1.062989	1.95	0.051	.9975257	5.713762
homelessdum	2.84332	.133412	22.27	0.000	2.5935	3.117203
hoteldum	5.113597	3.529658	2.36	0.018	1.321859	19.7819
invaliddum	3.734975	.8066239	6.10	0.000	2.446008	5.703184
jaildum	3.905349	1.398607	3.80	0.000	1.93563	7.879476
moteldum	3.158808	1.542308	2.36	0.018	1.213162	8.224847
podum	1.397122	.2452245	1.91	0.057	.9904455	1.970781
postaldum	3.544996	1.500911	2.99	0.003	1.546061	8.128396
rehabdum	5.762076	2.035278	4.96	0.000	2.883486	11.51437
ssresdum	5.080896	1.395697	5.92	0.000	2.965647	8.704848
shelterdum	1.369321	.3111984	1.38	0.167	.8771159	2.137732
socserdum	2.350364	.5121146	3.92	0.000	1.533448	3.602476
trailerdum	1.378644	.1662191	2.66	0.008	1.088492	1.74614

Appendix C- Calculations

9,374 guilty citations * mean presumptive fine of $322.4376 = $3.02million

```
. tab yr homelessdum
```

yr	homelessdum 0	1	Total
2009	2	0	2
2010	2	0	2
2011	6	2	8
2012	710	86	796
2013	21,374	3,888	25,262
2014	16,795	2,883	19,678
2015	13,525	3,154	16,679
2016	11,451	2,298	13,749
Total	63,865	12,311	76,176

```
. sum presumptivefine if homelessdum==1 & guilt ==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
presumptiv~e	9,374	322.4376	153.5271	40	790

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