Impact of the Speeding Fine Function on Driver Coordination on State Highways

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16. Abstract

This project centers on determining the relationship between the speeding fine function and driver behavior. A large part of this project entails searching all previous literature on speed limits, speeding fine functions, variance of highway speeds, and other forms of driver behavior. Special attention will be focused on how drivers use probability and cost (fines) to decide to drive a particular speed. In addition, simulations and models of driver behavior will be examined. Links between speeding fine functions and driver coordination will be highlighted, and methods of studying these links investigated. The second portion of this study determines a viable means to measure empirically the effects found in this study. Such means will be proposed as potential future studies.

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I.

1. Introduction

The problem of safety on roads is one that has attracted much attention from policymakers, engineers, economists and the press. The number of fatalities on highways has dropped over the past 30 years, though the evidence from increased speed limits and safety is mixed. In general highways have become safer; however, thousands die every year on highways in the United States. A contributing factor in many of these accidents is the relative speeds of the vehicles. While it is nearly impossible to determine the exact cause of most accidents, it is generally agreed that variance in road speeds is a contributor to a large number of these accidents. Thus, one goal of policy should be to limit the variance of speeds on roadways. Governments at all levels enact laws to accomplish this. This study does not look at a new set of laws or enforcement techniques, but examines the most common current law regarding highway behavior--the fine one pays for exceeding the speed limit.

This study examines the potential for using this as a tool to help mitigate the heterogeneity in driver characteristics. Different drivers drive different speeds given the same conditions. Given this, if uniform highway speeds are desirable (and all the evidence on highway accidents shows that this is desirable), then compensating for differing characteristics is necessary. As discussed in Section 2, it may not be desirable to have uniform road speeds; however, the political and fiscal reality is that a more uniform distribution of road speeds may be the only feasible solution to improving highway safety. This study is intended merely as a pilot study to show the potential efficacy of using the speeding fine function to influence driver behavior. The conclusions contain recommendations for a full study to determine the true impact of such policies.

This report is divided into six sections. Section 2 contains the current state of the literature on driver behavior and how to influence this behavior. In addition, this section contains statistics on how drivers currently behave on highways. Section 3 contains theoretical background on the affect of the speeding fine function on driver behavior. Section 4 contains the methodology for the simulations, and Section 5 contains the simulation results. Concluding remarks and recommendations are contained in Section 6. There is an appendix containing the values of the simulation parameters and a few other technical details.

2 Driver Behavior and Highway Safety

There is a large amount of literature on driving behavior and highway safety. The majority of this literature concerns itself with the impact of speed and variance of road speeds on accident rates. This study does not attempt to replicate or refute any of these studies. Instead, this study takes the results of these studies as given and shows how the results support the type of policies examined here. The studies are broken into two categories: 1) the influence of driver behavior on safety, and 2) the influence of policy on driver behavior. The results of the first set of studies show the need for the second set.

2.1 The Impact of Driver Behavior on Highway Safety

The impact of driving behavior on highway safety has been a major focus of research. Much literature exists on the impact of speed limits on accident rates. The literature can be divided into two categories: studies that have looked at the relationship between average speed (and variance of road speeds); and, studies that have examined the benefits and costs of changes in the speed limit.

The most controversial subject in this field is the question of the relationship between average road speed and accident rates. A series of articles in the *American Economic Review* developed the argument. Lave (1985) began the debate with his article where he showed that it was the variance of road speeds that led to higher accident rates and not the average road speed. He showed that there was virtually no relationship between average road speed and the accident rate. However, he did find that the higher the variance of road speeds the higher the accident rate. A series of short pieces responded to this finding. All of them purported to find that higher average road speeds led to higher accident rates.[1] Lave (1989) responds to all of these studies and points out the weaknesses in their approaches.

Scientifically, Lave uses a much more robust and correct specification for his study. By eliminating the affect of differing road conditions, Lave finds that on similar roads with similar characteristics average road speed seems to be an insignificant determinant of highway accident rates. This result has never been contradicted in a study with similar methodology. Other studies find that road speed is important, but these studies do not control for some important characteristics of the roads. Lave estimates accident rates on urban highways, rural interstates, and urban arterials separately. He finds that, in each individual case, the accident rate is not a function of road speed. However, accident rates are much higher on rural interstates for several reasons. Among them: lack of rapid access to emergency and hospital care, higher numbers of car/truck interactions and higher levels of driver fatigue. The other studies do not separate the data between these highway types and thus the results are potentially biased by the aggregation of road types.

The "last word" on this issue went to Rodriguez (1992). Rodriguez found results very similar to Lave. In fact, Rodriguez found a (small) *negative* correlation between average road speed and accident rates. There was a highly significant, and positive, relationship between variance and accident rates. Rodriguez points out that "speed kills" on the individual level is equivalent to "variance kills" on the aggregate level. The fact that there has been no answer to this study implies that no one has found the data to support the other hypothesis. Also, the argument that speed kills and variance kills can be thought of as equivalent may have satisfied some of the polemic detractors of Lave.

It is not the goal of this study to resolve this issue. The guiding principle of this study is that variance is dangerous. All of the studies in this literature have agreed on this fact. The average road speed is virtually ignored in this study. Implicitly, this is an acceptance of the Lave result that average road speed is not a significant contributor to accident rates by itself. However,

[1] The main respondents to Lave's article were: Fowles and Loeb (1989); Levy and Asch (1989) and Snyder (1989).

nothing in the methodology of this study precludes limiting average road speed as one of the policy goals. It would merely require a small change to the objective functions in the study. There is conflicting evidence on the effects of changes in the average road speed on road variance. There are studies that find higher speeds lead to lower variances in road speed and there are a few that find the opposite. We leave this as an open question and merely point out that the speed limit is not a sufficient policy instrument for determining average road speeds and is clearly inadequate for determining the variance of road speeds.

The other part of this literature is the cost of limiting speed on highways.[2] There have been several studies attempting to quantify the benefits and costs of speed limit changes on highways. The results of these studies uniformly conclude that speed limits have higher costs than benefits. This is not surprising in that many government regulations put in place to improve safety carry costs much higher than the value of life imputed in studies. This study does not enter this debate. One of the primary results of this study is that it may be possible to improve safety without increasing the cost of using highways as speed limit restrictions do. Given that average road speed may not influence the accident rate, it is not a given that lowered speed limits improve safety at all.

2.2 The Impact of Policy on Driver Behavior

There has been surprisingly little work on the impact of policy on driving behavior. This stems from the unfortunate concentration on the speed limit as the policy tool by which behavior is influenced. There have been some state-level studies of the impact of the new 65 m.p.h. speed limit, but the results are ambiguous. Some states have found an increase in accident rates and some a decrease in accident rates. One of the larger problems in identifying the accident rates is the compensating action that differential speed limits encourage. When the state speed limit is 55 m.p.h., the speed limit is the same on rural two-lane highways as on divided interstates. This

[2] Examples of this are Castle (1976); Forester, McNown and Singell (1984); Jondrow, Bowes and Levy (1983); Lave and Elias (1997); McNown and Singell (1984); Miller (1984); and Rock (1995). With the exception of Miller, all of these authors find evidence that the costs of the lowered speed limit outweigh the benefits.

makes some drivers choose to cut "cross-country" on the two-lane state highways. These roads are inherently more dangerous than a limited access highway.

When the speed limit is increased to 65 m.p.h. (or more) on the limited access highways (with no corresponding increase on the two-lane state highways), some of these drivers switch back to the interstates. This may increase the accident rate on the interstates for a variety of reasons.[3] However, it should lower the accident rates on the state highways for the converse of these same reasons. Both of these affects must be accounted for in any safety analysis.

These complex issues have made it nearly impossible to determine the net effect of the increase of the speed limit on safety. Most studies have concluded that there has been little affect on the accident rates as a direct result of the speed limit.

One important study must be mentioned here. Polinsky and Shavell (1979) examine the use of fines to deter behavior. Their study is theoretical, but points out the difficulty in obtaining 100% compliance with rules. Their study concentrated on parking fines, but the idea is similar. They find that the optimal policy is not to deter double parking but to limit it. In fact, they point out the difficulty in obtaining total enforcement through the size of the fines required as a function of the probability of being caught. They show that optimal fines need not totally remove the undesirable behavior, nor do they necessarily raise much revenue.

2.3 Current Driver Behavior

The model used to simulate driver behavior for the results presented in this report needs to be calibrated to generate a distribution of road speeds similar to current actual data. Because there is no detailed data available on the distribution of road speeds, certain statistics had to be collected and used in the calibration. The statistics come from a variety of sources. Data was obtained for some states on the percentage of drivers under the speed limit, the mean road speed,

[3] Higher traffic volumes seem to be associated with higher accident rates and this is the first reason why accident rates may increase on rural interstates. Also, the drivers who are switching back to the interstate may have a lower level of risk-aversion than the average driver (and thus be more accident prone drivers). Recall that these drivers were willing to switch to the less safe two-lane highway in the first place.

the 85%tile speed, and any other statistics that were available. Because there have been few studies that are published with detailed information on driver behavior, it is difficult to exactly replicate the distribution of road speeds. With a comprehensive dataset that contains individual road speeds, such a distribution could be constructed and the model calibrated to these figures.

The calibration of the model utilized a combination of data from many different states. The calibration sought the following rough approximations for the road speed distribution under current conditions. In a 65 mile per hour speed zone, the mean road speed was calibrated to be between 70 and 75 miles per hour. Because the fine functions were different in each state, each of the state's fine functions yields a slightly different mean read speed. The variance of road speeds was calibrated to be roughly 25 to 50. Again, the individual state fine functions lead to differences in this figure. Table 1 in the results section contains all of the information about the model's prediction of current behavior.

It is important to note that any differences between actual conditions and the simulated distributions in this study are not due to the inability of the model to predict current conditions; but due to calibration to a different set of values. It was possible to calibrate the model to any set of current conditions. Given this set of conditions, the model can then predict changes in behavior.

2.4 Optimal Distribution and Fines

The largest problem in determining the fine function is what an optimal policy should do. The obvious answer from an economic perspective is to have speeding fines that capture the difference between social and private costs of speeding. The difference in these costs is the difference in the number of lives affected in an accident. The driver may consider the cost to themselves when determining a speed, but they do not consider the cost to other drivers on the road (who may be involved in an accident with the driver being considered). In essence, this would create a tax rate for speeding. The optimal tax rate would merely account for the difference in costs. Unfortunately, this is not how speeding fine functions are used.

In fact, fines greatly exceed the difference between social and private costs of speeding (according to figures from all of the cost-benefit studies cited in this study). Perhaps, the speeding fines can be considered a market for time saving. In this case, elevated prices are a market for time saving. In this case, elevated prices are a market failure in that the socially optimal amount of speed is not purchased. This might be explained by considering a risk aversion rate far greater than neutral for the societal costs. Our society has accepted that sub-optimal levels of speed are used on highways. Given this, there may still be an optimal means of obtaining this level of speed. This is the focus of this study.

There are two concepts that do not seem politically feasible in this country (at least in most states). First, it does not seem possible that optimal levels of speed will be obtained on highways in this country. This would require major revamping of speed limit and speeding fine function laws in a manner that would receive vocal dissension. There are many vocal groups that still want to return to the 55 m.p.h. speed limit. The creation of an "autobahn" style highway system is not feasible in the face of this opposition. The other end of the spectrum is also not feasible. It does not seem likely that harsh fines for speeding will be imposed. A harsh fine would be a major penalty for exceeding the speed limit by only a few miles per hour, making speeding a "real crime" rather than a violation that is punished similar to parking violations (albeit at a higher rate with more consequences).

The study concentrates on distribution of road speeds that are roughly mean preserving. This means that the average road speeds do not change drastically in the optimal fine scenarios. It would be possible to find any mean road speed with some slightly changed objective function.

This report does not make any statement regarding the trade-off between speed traveled and accident rates. It is very possible that the desirable result is not a mean preserving reduction in variance but, rather, a mean increasing reduction in variance. From an economic perspective it might be desirable to see a large increase in average highway speeds at much lower variance than to reduce variance at the current average highway speed. This will be discussed in the result section and examined in a bit more detail in the conclusion section.

3 Speeding Fine Function and Driver Behavior

There are several factors that influence a driver's choice of speed on a highway. These factors can be reduced to two categories: economic factors and non-economic factors. There is a fuzzy boundary between these two categories, but the two are sufficient to label the factors. For the purposes of this study, we will label all factors that are not immediately recognizable as having a cost (or benefit) as non-economic. That means that many factors that may have economic implications will be placed in the non-economic factor category. Which category a factor appears in does not influence how this study treats the factor. In general, this model will only attempt to modify a portion of the drivers' behavior. For all those characteristics that can not be modeled as an economic choice (at least not easily or smoothly), an exogenous upper bound to the speed a driver will choose is utilized. This is termed the exogenous cut-off. This is described in detail below.

3.1 Economic Factors

The economic factors that influence a driver's choice of speed are the factors that we wish to examine in this report. While the non-economic factors are important, the model allows these factors to influence the driver without being able to affect their influence. This might change if fines were imposed for driving below the average speed on the road, but since this does not seem likely in the immediate future, it is not allowed in the model.[4] The most important economic factors are the value of time and the costs of speeding (financial costs).

It would be impossible to include every factor that affected a driver's decision in choosing a highway speed in the model. Instead, this model contains only one parameter that represents the driver's economic characteristics. As such, that one variable will not be able to be named and given a clear interpretation. We will refer to this parameter as the value of the driver's time - but this is misleading. This parameter represents the net value of the driver's time - after all other

[4] Two things should be noted. First, there are fines for driving under the minimum posted speed on highways. These fines are almost never imposed and even when they are they are often for speeds so far under the posted speed limit as to be unimportant for this study. Second, with fines allowed for speeds below the mean road speed, the results of the simulations in this study are dramatically better.

economic costs and benefits of driving are included. As such, it is necessary to discuss some of the other factors that enter this parameter. Most of these factors are costs that may rise with speed, but are difficult to quantify for a particular driver.

The most important economic factor in determining choice of highway speed is the driver's value of time. As the value of the driver's time increases, the driver will choose a higher road speed, *ceteris paribus.* Because it is not possible to know a driver's value of time, a distribution of time values is employed. This value is modified to include many things not captured directly in the model. As such, the parameter that includes the value of the driver's time also includes many other factors and can no longer be interpreted as the value of time.

3.1.1 Insurance Costs

It is widely known that insurance costs are a function of a driver's record. The more tickets and accidents that a driver has (within a certain number of years) the higher the insurance premium paid by the driver. As such, one of the costs of a ticket are the increased insurance costs. Unfortunately there is no uniform relationship for this. Some drivers can get a ticket without their premiums rising, while other drivers face an increase in insurance rates with a ticket. Some of these drivers face a small increase and others a large increase in their insurance rates with a ticket. Still others are in another category, where their insurance may actually be discontinued with a ticket. Another potential cost that is directly linked to this, but not actually an insurance cost, is the possibility that a driver faces action by the state if another ticket is received. Perhaps required driving courses or even more severe, loss of license. We will include these types of costs with insurance costs for brevity.

It may be possible to determine the costs of another ticket to certain drivers. But, it is not feasible to link these costs to a particular car on the road (without some sort of extremely intrusive data gathering methodology). So, we include these costs in the value of time. This means that any potential costs from another ticket will lower the value of time for the driver by the expected value of a ticket at the driver speed (which is the probability of getting a ticket, times the added insurance costs). For those drivers that are in the extreme situation of facing discontinued insurance or loss of license from a ticket, their speed may be controlled by the cut-off speed described in the non-economic factors.

3.1.2 Fuel Costs

For the majority of drivers, fuel costs will also be part of the value of time parameter. It is generally the case that vehicles have higher fuel efficiency at lower speeds. This is not a theoretical necessity, but is generally true at highway speeds for most vehicles. For the majority of drivers, this is a minor consideration in the determination of highway speed. The relationship between highway speed and fuel efficiency is not very steep at most speeds and thus the added fuel costs are quite low for most drivers. What costs there are, however, are included in the value of time parameter as with the insurance costs. For those extremely environmentally conscious drivers that will sacrifice time for reduced fuel consumption (at a rate *much* higher than the value of time lost) this will require the se of the cut-off speed.

3.1.3 Accident Costs

One of the most studied portions of the cost of driving at higher speeds is the increased probability of being involved in an accident. The costs of an accident are usually grouped into three categories: physical damage, injury and death. While this has been studied to a great degree, the actual increased costs from faster driving are not well defined. This is true for several reasons. First, the probability of being in an accident (as a function of speed) is not monotonic. McFarland and Chui, and Rietveld and Shefer (among others) show that the probability of being involved in an accident decreases until a certain speed (somewhere around the 75 - 90%tile speed) and then increases rapidly. Second, the cost of being involved in an accident is hard to determine. The physical damage portion of the costs, and the injury portion of the costs are normally covered by insurance premiums. Thus, there is no internalized cost to these probabilities other than those discussed above in the insurance costs section and the risk aversion a particular driver may have. The value of a life is very difficult to determine. Normally, economic studies use a lifetime earnings method of determining the value of a life. This means that the value of life is greatest for the youngest drivers and less for older drivers. Again, this is impossible to link to a particular road speed without intrusive data gathering methods. These costs will also be incorporated in the value of time parameter. In the case of a strongly risk averse driver, the affect of this cost (and associated risk aversion) will be captured by the cut-off speed.

3.1.4 Ticket Costs

The most obvious component of the cost of driving faster than the speed limit is the potential cost from receiving a ticket. This is explicitly modeled in this study. The expected cost of receiving a ticket is exactly

$$E[C(t)] = P(s) * f(s)$$

Where P(s) represents the probability of receiving a ticket while driving one mile at speed *s*, and f(s) represents the fine associated with a ticket at speed s. It is assumed that drivers are risk neutral concerning tickets. Any risk aversion to tickets will be handled identically to the insurance costs portion of the costs associated with driving.

These costs, are assumed to be internalized by the driver. This means that the drivers understand the two functions and know the values associated with them and the various speeds. While it may seem drastic to assume that drivers know the fine function and the probabilities of being caught at various speeds, this information is known to drivers at some level. Most drivers have a reasonable estimate of the probability of being ticketed at various speeds. In fact, this is the reason that we observe mass points in the density of drivers speeds on highways in real life. The ability of a regulatory body to control, or influence, these mass points is one of the key results of this study.

3.2 Non-economic Factors

The non-economic factors involved in determining the speed a driver will choose are more difficult to describe. These often come under the heading of “human factors”. We will not use this term exclusively here for two reasons. First, some of the reasons fall outside the definition of human factors; and, second, the purpose of this study is to show that some drivers can be influenced by an endogenous choice mechanism. While some drivers will continue to choose their speeds according to a non-economic factor (or factors), we only need that some drivers use the economic criteria in order for this model to work.

The non-economic factors include some of those already discussed above. Namely, if a driver is one ticket away from loss of license, required driving classes or a change in insurance categorization, the driver may choose a speed that avoids this ticket. Other non-economic factors are briefly described here. A driver may choose a speed because of the car they are driving. Some drivers would like to drive much faster than they do, but their car can’t handle the speed for some reason. These reasons could involve the mechanical condition of the car, unfamiliarity with the car or the fact that there are others in the car that cause a drastic change in the risk aversion of the driver (such as children).

A driver may be unfamiliar with the road and reduce their speed for this reason as well. A driver that drives quite fast on familiar roads may slow down considerably on roads that are not familiar. Similar situation such as carrying on an intense conversation in the car, feeling ill or looking for an exit or landmark might cause the driver to slow down from their normal highway speed.

Some drivers are more comfortable in certain conditions than others. For instance, one driver may not mind rolling hills but has difficulty at night. Another driver may not mind darkness but has trouble with rolling hills. These drivers may choose different speeds on different road segments due to these factors.

These are only a few of the conditions that might cause drivers to exogenously determine their road speeds. This study does not model these factors, merely recognizes them and attempts to control for them in the simulations. While it might be possible to study the non-economic factors to influence road speed choice, this does not seem likely to provide much of a return to the study. Understanding how drivers determine road speed can be improved in this fashion, but it is hard to imagine that this will allow policy makers to influence the behavior.

3.3 Political Feasibility

One potential problem with influencing driver behavior is the extreme measures that may be required to do so. It may be possible to stop people from speeding all together (except criminals whose behavior is not being modeled here). But it is not likely to be feasible. Therefore, it is necessary to restrict the parameters of the model to a space that is feasible. Of course, defining feasibility is a difficult process. We will assume that prison terms for violating the speed limit are not feasible. In fact, we will assume that large changes in the fine function itself are not feasible.

The reason for this is that a political body must pass legislation to enforce the speed limit. It is unlikely that any state legislature in this country would pass laws that increased speeding fines drastically. There is no attempt in this study to define what levels of fines would be feasible and what levels would be infeasible. Instead, some broad (and quite restrictive) definitions of feasibility are utilized. The model is severely restricted by these feasibility constraints. In fact, without them, reduction in the variance of road speeds is greatly enhanced. The Zero-Variance/Zero-Revenue results presented below will demonstrate the problems with fine functions that are used to achieve these types of results.

3.4 The Model

The model used to simulate the behavior of drivers is kept parsimonious. The decision of the driver is reduced to a simple binary problem. Drivers are assumed to fall into one of two categories. The first are drivers that minimize the expected costs of driving. The second are drivers that choose their road speed based on exogenous factors (explained above). It is possible for a driver two move between the two groups. An example of this is a driver who will not drive faster than 55 m.p.h. in any conditions. This driver may choose to drive 50 m.p.h. in a 40 m.p.h. zone. This driver, however, will drive 55 m.p.h. in a 65 m.p.h. zone. This means that at highway speeds the driver is in the second group (having exogenously chosen to drive 55 m.p.h.), while in the 40 m.p.h. zone the driver is in the first group (choosing 50 m.p.h. as their desired speed). A more subtle example would be a driver who drives 77 m.p.h. in Virginia and 69 m.p.h. in Maryland. This could well be due to the drivers having an exogenous factor influencing their speed in Maryland.

3.4.1 Cost Minimization

Those drivers that minimize the costs of driving minimize the following function

$$C = \frac{t}{s} + g(s,l,k) * f(s,l)$$

Where: t = value of time parameter, s = speed, l = the speed limit, g is the probability of being caught speeding as a function of the speed traveled, the speed limit, and a vector of enforcement parameters, k is the vector of enforcement parameters, f is the fine as a function of speed traveled and the speed limit. Remember that t constrains much information in addition to the driver's value of time.

Note that in order to minimize the cost of the trip with respect to the speed traveled it is necessary to find the first order condition. Because only a small set of such functions (f and g) will permit closed form solutions, we are required to use numerical maximization techniques to solve the first order condition for each driver. The optimal speed can be defined as

$$s^* = \arg\min\left\{\frac{t}{s} + g(s,l,k) * f(s,l)\right\}$$

So $s*$ is the speed that minimizes the expected costs of highway driving.

3.4.2 Exogenous Cut-Off Speeds

Those drivers that exogenously determine the speed they will drive are modeled separately. Due to the possibility that drivers will switch between groups, the model must allow for this possibility. We begin by assuming that every driver has an exogenous cut-off speed. This is the speed that the driver would travel if there were no speed limits, or if fines were trivially small and add little or no negative repercussions. We model these speeds as follows:

$$s^{-} = \Phi - c^{2}(f_1) - c^{2}(f_2)$$

where **F** , *F i*, and *F 2* are parameters. In the appendix, Figure 2 shows the shape of this curve for the parameters used in the simulations.

Note that some of these cut-off speeds are as high as 150 m.p.h. and others are as low as 55 m.p.h. We assume that individual drivers will drive in this range of speeds unless there are penalties that change the behavior. The upper bound of the cut-off speeds is chosen to be 150 as almost no production cars have top speeds above this speed. So, drivers will be mechanically constrained at 150 m.p.h. in almost all cases. We use 55 m.p.h. as the lower bound of the range. This is somewhat arbitrary. The results would only change in a trivial manner if this were lowered.

3.4.3 Choice of Speed

From the cost minimization procedure, each driver has a speed that minimizes their cost of driving - s_i. From the exogenous cut-off procedure each driver has an upper limit speed that they will not exceed –s_i^-. The driver will drive the lower of these two speeds. The speed that the driver will drive on the highway is then found by

$$s_i = \min\{s_i^*, s_i^-\}$$

This choice is made by each of the drivers on the road. The possibility that the speeds chosen by other drivers enters the decision is not allowed in this model. If this extra factor were added, an even smaller variance of road speeds would be possible. The next section describes the simulation methodology in detail.

3.4.4 The Fine Function

The fine functions used for the base cases in the states examined are of the forms that are currently employed. Some states have a linear fine function, others a complex system of fines that vary for each mile per hour over the limit. In the base cases, the exact fine function for the state is used. The fine functions that are derived from the model can be of any form theoretically. For the purposes of this paper, the fine functions are restricted to be of quadratic form (with the exception of one case discussed below). This is an additional restriction on the fine function that reduces the ability to improve the objective functions. The fine functions are of the form:

$$f = a + b(s-l) + c(s-l)^2$$

where a, b, and c are the parameters of the fine function, s is the speed driven, and l is the speed limit.

It would be possible to further improve the results presented in this study if the fine function were allowed to take a more flexible form.

3.5 Objective Functions

It was necessary to define objective functions for the simulations to optimize. As discussed above, it is not possible to fully describe the feasibility of any particular speeding fine function without detailed information about the legislative process. As such, this study uses constraints that are potentially excessive in their restriction. This means that the results may be understated due to the restrictions imposed. For this study, only two potential objective functions are considered. This means that there are four fine functions studied. The first is the base case fine function - the fine function currently employed in the state of interest. The second fine function is a fine function that would effectively eliminate speeding altogether. The third fine function is a fine function that minimizes the variance of road speed subject to a feasibility constraint, and he final fine function is one that maximizes the revenues raised from speeding tickets. For all of these cases, the level of enforcement is assumed to be constant. While the enforcement level may be increased or decreased with the implementation of any policy such as those studied here, it is of interest to determine the affects of such a policy absent any changes in enforcement. It would be simple to examine the affects of changes in the enforcement level as well as changes in the fine function if specific data were supplied.

3.5.1 Base Fine Function

The drivers are first examined under current fine functions and enforcement levels. This serves two purposes. First, it allows a comparison between the behavior of our simulated drivers and actual drivers on highways. Second, it serves as the base case for the other objective functions. There is no actual objective function in this case. Each driver minimizes their costs (as described in the last section) and the results are examined.

3.5.2 Zero Variance - Zero Revenue Fine Function

This is the case where the possibility of removing speeding altogether is examined. The lowest fine that would result in now speeding is examined. Again here is no objective function in this case either. The fine that will keep all drivers at or under the speed limit is found. This provides a "best-case scenario" for the variance of road speeds. Without implementing severe penalties for driving at speeds just under the speed limit, the variance of road speeds from this case is the lower bound on variance for all other cases.

3.5.3 Minimum Variance Revenue Equivalent Fine Function

This is the objective function that is most closely related to the stated goals of policy toward speed enforcement on highways. It is assumed that minimizing the variance of road speeds is a primary goal of such policies. The literature is quite clear that variance of road speeds is one of the largest contributors to accidents and fatalities on highways. In order to lower the risk of accidents, it is likely that the variance of road speeds must be lowered. This function places no restriction on the average speed on the roadway. It is theoretically possible that mean speeds will drift either higher or lower with the new fine function. In practice, there are no large changes in the average speed on the road from the changes in the fine function initiated here.

The constraint on the optimization is the revenues not change. Rather than a firm constraint, a "loose" constraint is used instead. The revenues are kept constant for two reasons. First, this serves as a simple proxy for feasibility of the fine schedule. Second, this ensures that enforcement levels can remain constant (a pivotal assumption in the process). The feasibility of a fine function is difficult to determine and as such proxies for this must be employed. As such, one possible proxy for feasibility is that revenues not rise with the new fine function (more will be said on this in the result section). It is assumed that enforcement levels do not change as the fine function is altered. It may be possible (though not optimal) that enforcement activities are funded in full or in part by revenues from the activity. If this is the case, it is necessary that revenues not fall in order to maintain the original level of enforcement. Other restrictions and permutations of this equation are possible and some lead to even more improvement in the variance of road speeds.

The objective function for this case is defined as:

$$\Psi = s^{2} + \left(\frac{\max\{R_n, R_b\}}{\min\{R_n, R_b\}} \right)^{t}$$

Where s^2 represents the variance of the road speeds, *Rb* represents the base case revenues raised, *Rn* the revenues raised with the new fine function, and t the precision of the constraint on revenues. When $t = 0$ there is no constraint on revenues and when $t = 8$ the constraint is always perfectly binding. By tightening the relaxing t it is possible to see the impact of funding enforcement levels from ticket revenue on the base objective function (the variance of road speeds). This is not an objective of this study and so t is chosen to be number significantly high to keep revenues within a couple percentage points of the original revenues. The values of t used are presented in the calibration section below. This objective function is minimized in order to find the lowest possible variance of road speeds given the characteristics of the drivers and the constraint on revenues.

3.5.4 Revenue Maximizing Fine Function

The objective function is included as an interesting piece of information. Clearly, maximizing revenues should not be the goal of any speeding fine function. Such a fine function would increase the accident rate, likely decrease overall utility, and is a very inefficient tax. However, if states are using speeding tickets as a tax, it might be possible to identify this by examining the coefficients of this optimization.

The objective function for this case is defined as:

$$\Psi = R_n$$

Where *Rn* are the revenues from the new fine function. This objective function is maximized to obtain the fine function that returns the highest level of revenues.

4 Simulation Methodology

Because no data exists for which to estimate the parameters of the model, simulation techniques must be utilized. In this study, the goal is merely to show that the fine function can be a useful tool in coordinating drivers. As such, the calibration of the model is of less concern than if the model were being used to predict the effects of a policy (such as changing fine functions). More will be said of this in the section with recommendations. The model is calibrated to yield results in the base case similar to actual results on state highways. Due to the lack of detailed data, summary statistics from numerous states are combined to use for the calibration. The results are concerned with the improvement in certain measures, not the nominal speeds or variances. If actual data were obtained, a more detailed analysis could be performed on the effectiveness of the speeding fine function as a policy tool. The methodology employed is detailed in this section.

The process of the simulation is divided into two components. The first is the description of the parameters used in the model. The second is the simulation and optimization of the model. Each part of the process is described here.

4.1 External Parameters

The first part of the simulation was to obtain parameter values for the model that allowed the simulated drives to behave similar to real world drivers. This entailed gathering data on road speeds and the distribution of road speeds and calibrating the parameters to have the distribution of simulated drivers similar to the distribution of real world drivers. Some of the data used are not current, but this has no affect on the model.[5]

Each parameter of the model is calibrated in conjunction with the others to find the base level of the parameters for the simulation. It is important to note that with more complete data, the model could be recalibrated to match any distribution of road speeds. This new calibration would not necessarily yield parameters similar to those used here. Table 5 contains the parameters used in the simulations in this report.

4.1.1 The Value of Time Parameter

The value of time parameter contains information about many economic costs (and even some non-economic costs) incurred by the driver. The value of time is constructed as a normal variable with a lower bound truncation at a value of time of $1 per hour. The value of time is then defined by its mean and standard deviation. We can write the value of time parameter as the following:

$$t \sim \mathrm{N}\left(l , s_{t}^{2}\right)$$

Note that while ? denotes the mean of the normal distribution that *t* is drawn from, it is not the mean of *t* due to the truncation. Figure 1 shows the distribution of value of time used in this model.

[5] Of course calibration to data other than that which reflects the current state on the highways will lead to different results. This difference will merely be quantitative. For any distribution of road speeds with a variance higher than those obtained in our optimized solutions, a decrease in variance is obtainable. There is no suggestion that the fine functions found in this study are those that would be best in any real world situation. For those fine functions to be found, data for the region affected would need to be collected in a detailed fashion and used to calibrate the model properly.

Distribution of the Value of Time Parameter

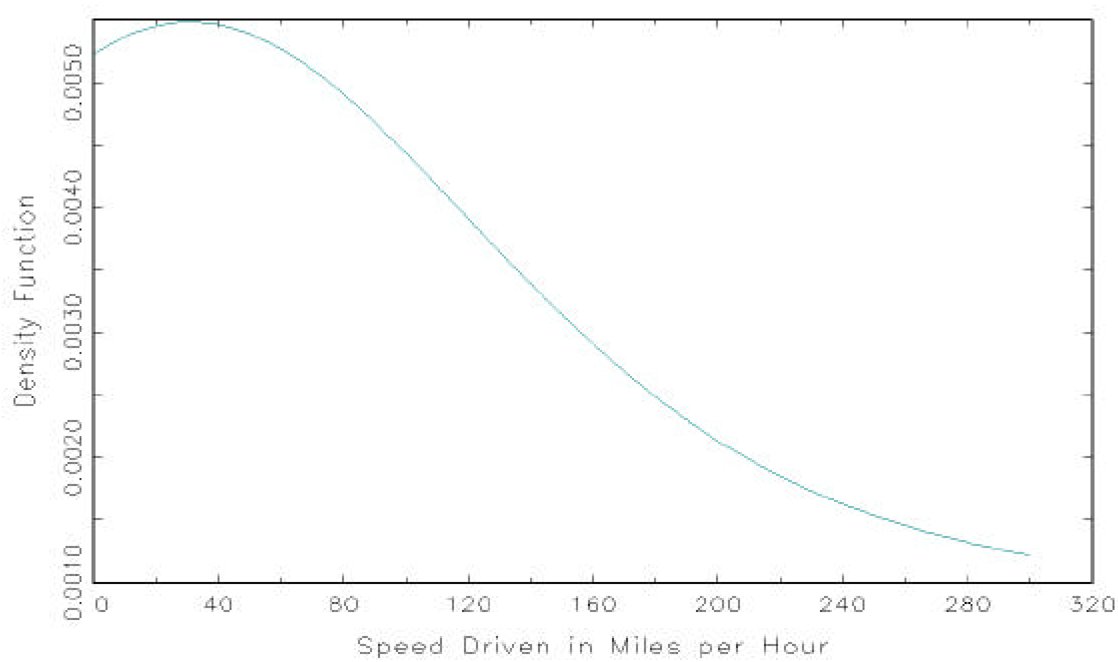

Figure 1

4.1.2 The Exogenous Cut-Off Parameters

The exogenous cut-off describes all of the drivers that cannot be described through the cost function portion of the simulation. The cutoffs are independent of the value of t. Figure 2 shows the distribution of the exogenous cut-off speeds used in this model.

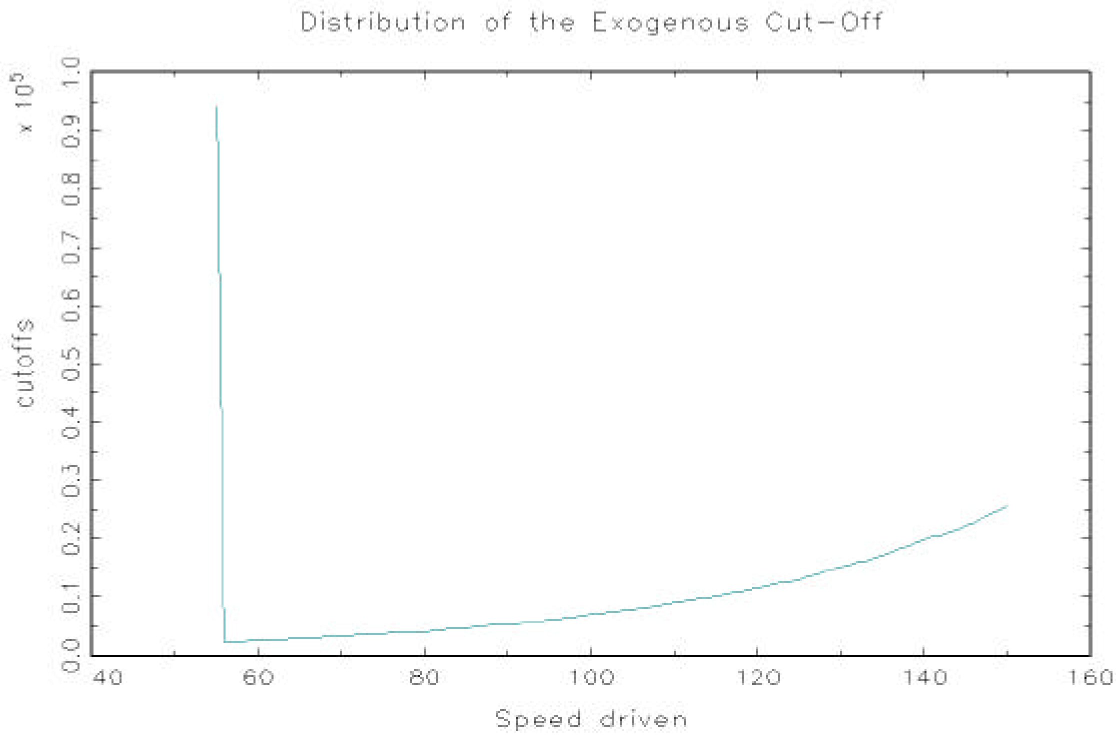

Figure 2

We truncated the cut-off speeds at 55 m.p.h. so that all speeds below this show as part of the mass point at 55 m.p.h.. Again, with actual data, the parameters of the cut-off distribution could be more precisely estimated and other forms could be explored. The use of the "backward" x^2 distribution is used for simplicity and its good fit to the data available. There is no loss of generality from using this distribution because any density function could be employed for this parameter.

This parameter is merely calibrated to allow a good fit to the data obtained. If actual detailed data were available the density function could be fit to the actual number of drivers at every speed below the speed limit and used to capture increases in the desired speed of drivers as conditions (fine functions, speed limits, etc.) changed. Each driver has an exogenous cutoff speed. However, only drivers whose exogenous cutoff speed is less than their optimal speed will drive this speed.

4.1.3 The Probability of Being Ticketed Parameters

Some of the most difficult parameters to calibrate in this model were the enforcement parameters. There were no reliable data concerning the number of tickets written at various speeds. As such, these parameters were used to calibrate the model to reasonable levels rather than actual levels of tickets. More will be said of this in a bit. The form of the probability of being caught speeding was a backward exponential. The function can be written as:

$$g(s,l,k) = 1 - e^{-k(s-l)^h}$$

Figure 3 shows what this function looks like.

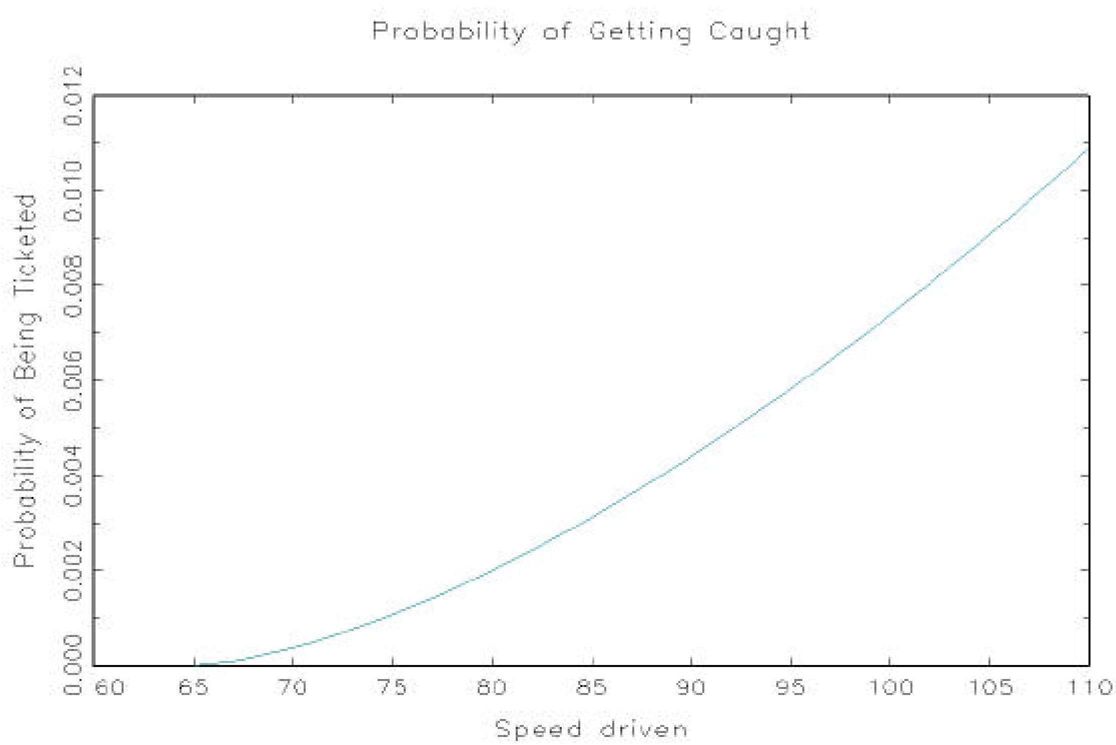

Figure 3

As can be seen, the probability of being written a ticket is 0 for all speeds less than or equal to 65. The probability then begins to rise slowly and eventually the slope becomes more severe. The probability of being ticketed at 70 m.p.h. (in a 65 m.p.h. zone), is approximately .0003. This means that about 3 in 10,000 drivers will be ticketed at this speed.

The probability of being written a ticket peaks (for our range of speeds considered) at approximately 1.1% when the speed is over 105 m.p.h.. This may be a bit too low for rural highways. Basically, we assume that a car traveling at 100 m.p.h. or higher will be ticketed with probability 1 if a police car observes the vehicle at this speed. Thus, the 1.1% probability of being caught implies that there is approximately a 1.1% probability that there is a police vehicle in any one mile of highway traveled. Again, this may be too low - but the results of the paper are not qualitatively affected by this figure.

Combining these two pieces of information, this implies that a car traveling 110m.p.h. is approximately 30 times more likely to receive a ticket than one traveling 70m.p.h. in a 65m.p.h. zone. One thing to note is that it is assumed that the statutory speed limit is the true speed limit. If drivers are given a 5 m.p.h. "buffer", a driver driving 110m.p.h. is 300 times more likely to receive a ticket than a driver driving 71 miles per hour.

The form of this function is also not important for the qualitative results in this study. Functions of linear, quadratic and backward exponential form were all utilized in trial runs of this model. The exact form affects the optimized fines and the exact distribution of the drivers but not the fact that reduced variance is possible with optimized fine functions. With real data for tickets and road speeds, the exact function could be derived and used in the model.

4.2 Speed Choice

Once the parameters are determined, the choice of speed for each driver is easily obtained. Each driver has a value of time and an exogenous cut-off speed. For each driver, the speed that minimizes the cost function is obtained. This is compared to the exogenous cut-off speed and the lower of the two values is selected as the speed that driver chooses. It is possible that a driver utilizes their cost minimizing speed in some cases and the exogenous cut-off speed in others as conditions change. The conditions that change can be the speed limit, the fine function, or the probability of getting caught. The choice of speed for drivers in different situations is given in the results section.

4.3 Objective Function Optimization

For each of the objective functions, the quadratic fine schedule is allowed to vary. Due to the lack of closed-form solutions to any of the problems in this study, a numerical search process is used to determine the optimal fine schedule. In each case, the parameters of the fine function are varied and the objective function re-evaluated at each step. For each change in a parameter of the fine function, each driver's behavior is re-evaluated in order to determine the values of the objective function. For the simulations in this study 100,000 drivers are used to ensure a relatively smooth distribution.

As the number of drivers increases, the precision of the results increases. However, the time it takes to resolve each iteration also increases. For each small change in the fine function parameters, each driver must re-evaluate the speed driven and the objective function must be recalculated. There are potentially thousands of values of the fine function to be examined and thus the number of drivers must be kept to a reasonable level. Some calibration of the model was performed with a small number of drivers (500) and then the final calibration and optimizations were carried out using 1,000,000 drivers.

5 Simulation Results

The results of the model are presented in this section. The results begin with an example that shows why speed limits alone are not enough to guarantee that speed is controlled. While it may seem obvious that speed limits alone are not enough to influence the variance of road speed, the example below shows that speed limits alone are not enough to even control the average speed driven on a highway.

5.1 Base Case Results

The four states used in the simulations are Florida, Massachusetts, Vermont and Washington. These states were chosen because they have a uniform speeding fine function throughout the state and the fine function data was supplied. The four states have very different fine schedules.

The four states' fine schedules are shown in Figure 4. As is evident, the average road speeds from the base cases for each of the four states are close to 70 m.p.h. The variances range from 35 to 48. It should be noted that the same parameters are used in each state and thus the average road speeds and variances cannot be strictly controlled, for individual states, in this study. Obviously, this could be altered in a study with detailed data on all of the relevant statistics and distributions. The 85th percentile speeds are all close to 75 m.p.h., the maximum speeds observed range from 81 to 90 and revenues per highway mile driven range from \$.026 to \$.041.

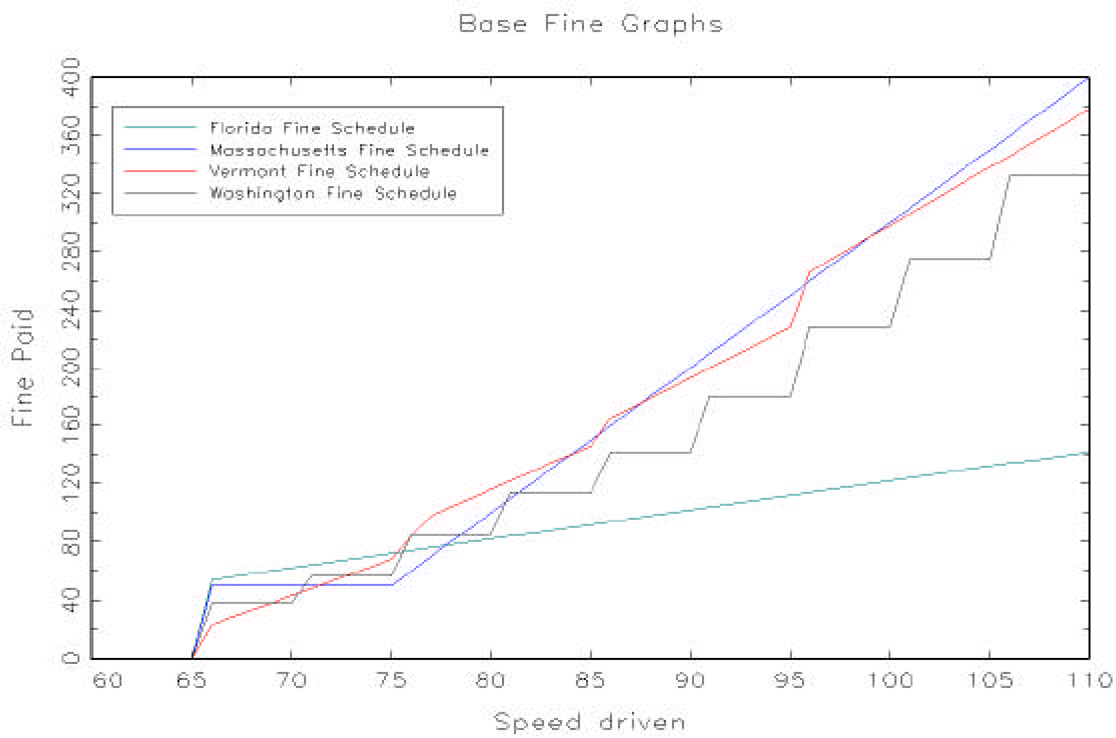

Figure 4

Note that while Florida has the highest fine at 66 m.p.h., it has the lowest fines at high speeds. The base case scenarios are run using the parameters in Table 5. The summary statistics for the base case in each state are provided in Table 1.

Table 1 Results from Base Case					
	Average	**Variance**	**85 %tile**	**Maximum**	**Revenue/Mile**
Florida	69.04	48.45	76.64	90.35	$.0414
Massachusetts	69.14	42.36	75.00	81.11	$.0283
Vermont	68.49	35.04	75.00	82.50	$.0262
Washington	69.05	43.02	75.00	85.00	$.0315

The distributions of road speeds in each state are provided in Figures 5-9. Closer examination of the base results yields some interesting findings. Note that the fine function for Florida is linear but that the rest of the states have inflection points in their fine functions. In each of the states that have infection points in their fine functions, there are mass points of drivers over these speeds. In essence, a fine function with inflection points *intentionally* creates these mass points. The mass point at 55 m.p.h. is an artifact of the lower bound of the exogenous cut-off while the mass point at the speed limit is a result of having fines for speeding. Notice that for Massachusetts (Figure 7) there is a very large mass point at 75 m.p.h. This is true for two reasons: the fine is constant below this speed and there is a major inflection point at this speed. In Vermont (Figure 8) and Washington (Figure 9) there are mass points at 70, 75 and 80 m.p.h. The mass point at 80 m.p.h. is more pronounced for Washington due to the constant fines between the inflection points (similar to Massachusetts below 75 m.p.h.) for this state.

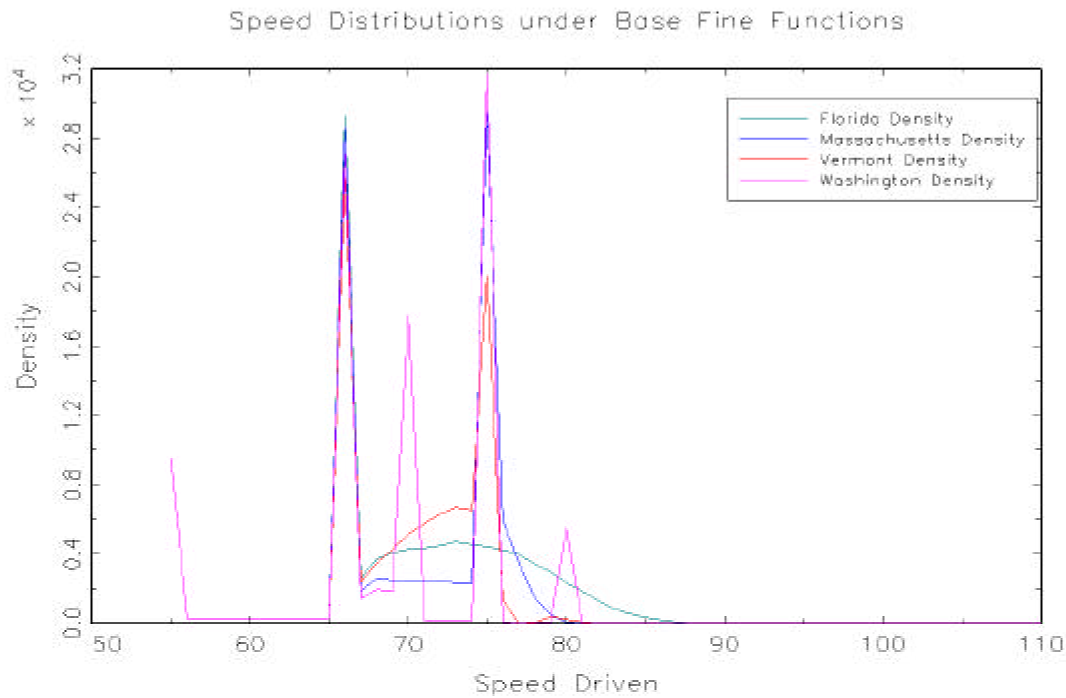

Figure 5

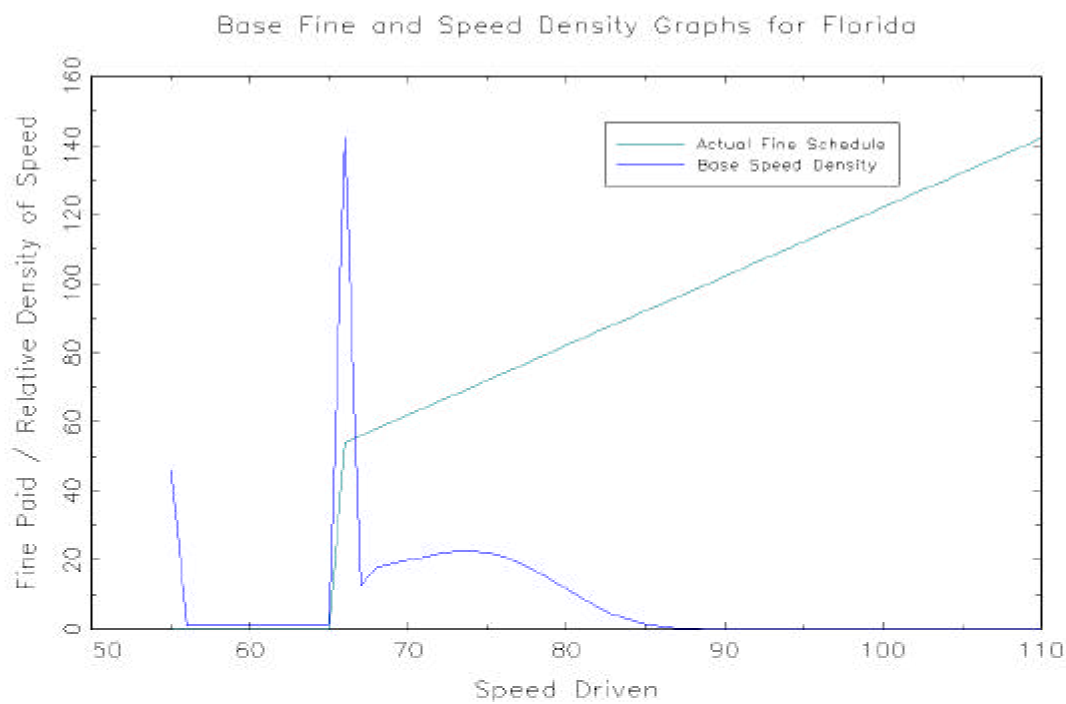

Figure 6

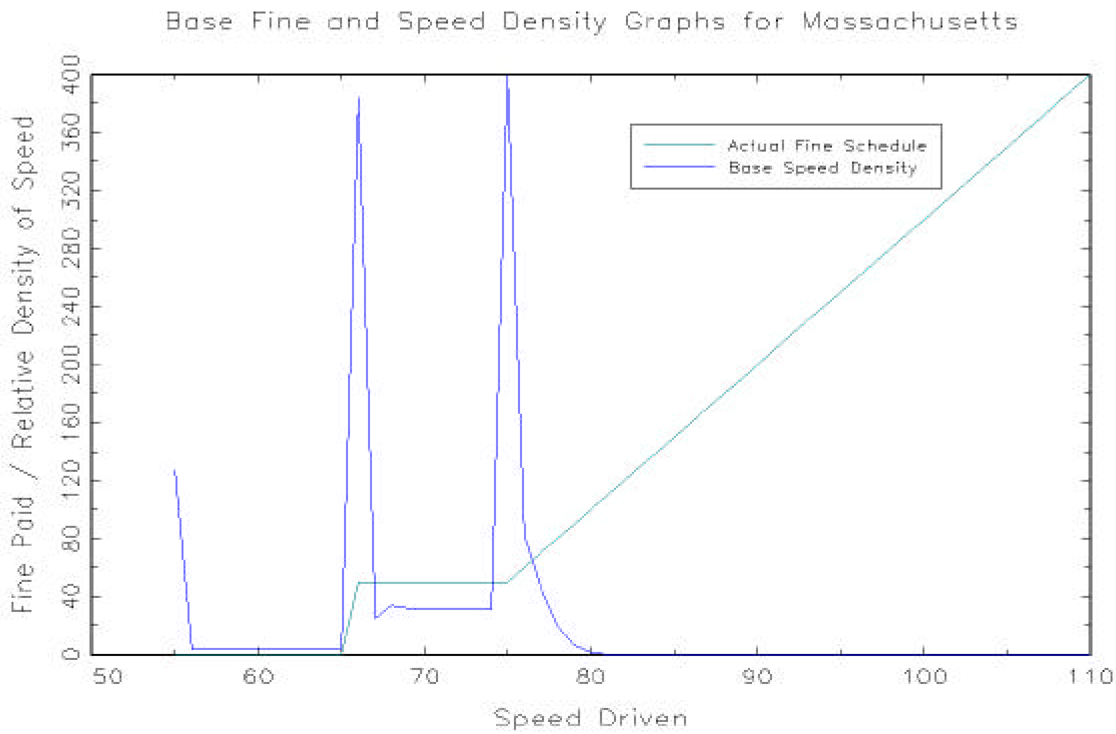

Figure 7

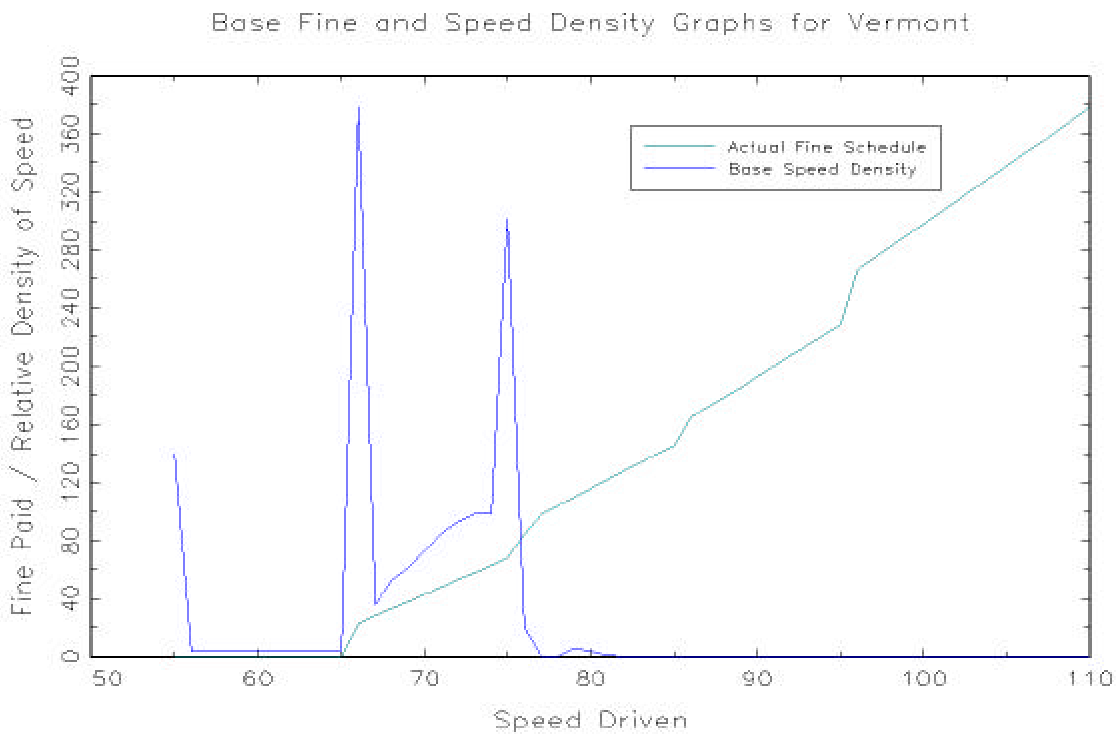

Figure 8

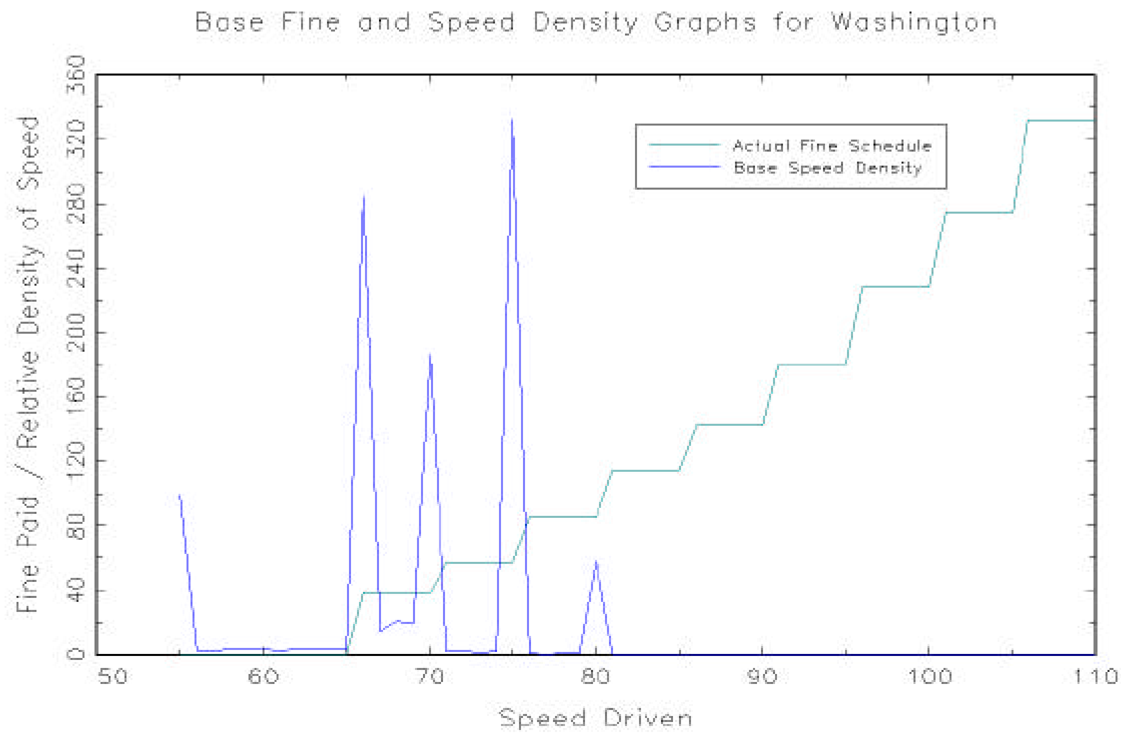

Figure 9

5.2 Simulation Results

The results of the simulations and evaluations are presented in Table 2 with the fine functions presented in Tables 3 and 4. Figures 10-17 also show the results from the simulations. The fine function required to stop all speeding is presented in Table 3. As can be seen, the fines necessary to eliminate speeding approach $2,000. And this is the fine for driving *any* speed over the speed limit. To stop the 85th percentile driver from speeding, the fine would need to be $500-$1,000. This is not likely to be a politically feasible fine for driving 66 in a 65 m.p.h. zone.

Table 2 Results from Simulations					
	Average	**Variance**	**85 %tile**	**Maximum**	**Revenue/Mile**
	Florida				
Revenue Equivalent Case	68.50	42.27	75.54	87.57	$.0389
Revenue Maximizing Case	72.14	85.41	82.45	85.41	$.0461
	Massachusetts				
Revenue Equivalent Case	67.07	26.14	72.09	79.00	$.0271
Revenue Maximizing Case	72.14	85.41	82.45	85.41	$.0461
	Vermont				
Revenue Equivalent Case	66.38	21.83	70.83	78.45	$.0250
Revenue Maximizing Case	72.14	85.41	82.45	85.41	$.0461
	Washington				
Revenue Equivalent Case	68.07	33.19	73.90	80.96	$.0289
Revenue Maximizing Case	72.14	85.41	82.45	85.41	$.0461

The results for the revenue equivalent fines are interesting. Because no restriction was placed on the average road speed, all the average road speeds decreased. This is due to the fact that slow drivers are not penalized in these simulations (and that average speeds were not constrained to be any particular figure). The very fast drivers are slowed and the slow drivers do not change their behavior. The average and 85th percentile speeds are only slightly lowered (one to three m.p.h.). However, the variances are significantly reduced. The variance of road speeds in Florida, the least affected, was reduced by approximately 12%. The variance of road speeds in Vermont and Massachusetts, the greatest reduction, were reduced by approximately 38%.

<table>
<tr><td colspan="7">Table 3 Fine Schedules</td></tr>
<tr><td colspan="2"></td><td colspan="4">Revenue Equivalent Fines</td><td rowspan="2">Revenue Maximizing</td></tr>
<tr><td colspan="2">Quadratic Parameters</td><td>Florida</td><td>Mass.</td><td>Vermont</td><td>Wash.</td></tr>
<tr><td colspan="2">A</td><td>52.068</td><td>48.482</td><td>78.224</td><td>71.691</td><td>33.225</td></tr>
<tr><td colspan="2">B</td><td>1.952</td><td>6.553</td><td>3.078</td><td>1.971</td><td>0.789</td></tr>
<tr><td colspan="2">C</td><td>0.028</td><td>0.278</td><td>0.275</td><td>0.200</td><td>.0006</td></tr>
<tr><td></td><td colspan="6">Zero Variance – Zero Revenue Fines</td></tr>
<tr><td>T</td><td>S(Florida)</td><td colspan="2">S(Mass)</td><td>S(Vermont)</td><td>S(Wash)</td><td>Fine at 66 m.p.h.</td></tr>
<tr><td>25</td><td>68.10</td><td colspan="2">69.33</td><td>69.11</td><td>70.00</td><td>$194.25</td></tr>
<tr><td>50</td><td>71.65</td><td colspan="2">75.00</td><td>71.72</td><td>74.34</td><td>$388.51</td></tr>
<tr><td>75</td><td>74.60</td><td colspan="2">75.00</td><td>73.75</td><td>75.00</td><td>$582.76</td></tr>
<tr><td>100</td><td>77.11</td><td colspan="2">75.00</td><td>75.00</td><td>75.00</td><td>$777.01</td></tr>
<tr><td>125</td><td>79.31</td><td colspan="2">75.76</td><td>75.00</td><td>75.00</td><td>$971.27</td></tr>
<tr><td>150</td><td>81.27</td><td colspan="2">76.68</td><td>75.00</td><td>80.00</td><td>$1,165.52</td></tr>
<tr><td>175</td><td>83.05</td><td colspan="2">77.53</td><td>75.42</td><td>80.00</td><td>$1,359.77</td></tr>
<tr><td>200</td><td>84.69</td><td colspan="2">78.32</td><td>78.88</td><td>80.00</td><td>$1,554.02</td></tr>
<tr><td>225</td><td>86.20</td><td colspan="2">79.05</td><td>79.84</td><td>80.00</td><td>$1,748.28</td></tr>
<tr><td>250</td><td>87.62</td><td colspan="2">79.75</td><td>80.74</td><td>80.00</td><td>$1,942.53</td></tr>
<tr><td>275</td><td>88.95</td><td colspan="2">80.41</td><td>81.60</td><td>85.00</td><td>$2,136.78</td></tr>
<tr><td>300</td><td>90.20</td><td colspan="2">81.04</td><td>82.41</td><td>85.00</td><td>$2,331.04</td></tr>
</table>

Revenues were kept at nearly constant levels with these new fine structures. Revenues fell by 4.5% for Vermont and Massachusetts and by 6% and 8% for Florida and Washington respectively. These reductions could have been avoided with slightly stricter equivalency constraints or more flexible objective function parameters. The “optimal” fine functions are presented in Table 3 and Figure 10. The new road speed distributions are presented in Figures 12-16.

Note that the higher the original revenues, the less the improvement in variance from this procedure. This is because raising revenues is a strong constraint against variance minimization. This clearly points to the fact that effective variance minimizing procedure will result in lower revenues from enforcement (but with a potentially lower enforcement level as well). Also notice that there are no mass points created by these fine schedules above the speed limit. This is due to the quadratic construction of the fines. If inflection points were allowed, mass points could be created that would further reduce variance.

The revenue maximizing fine function is also presented in Table 3. The distribution of drivers under this fine function is presented in Figures 12-15 and Figure 17. Note that revenues rise 12-75% under this fine function. However, variance of road speeds also increase 76-140% over the base cases variances and 100-300% over the revenue equivalent cases. These additional revenues appear to come at a high cost in road variance, which according to all studies of highway safety, translates into a high cost in highway fatalities.

Table 4 Sample Fines for Various Speeds

	Florida		Massachusetts		Vermont		Washington		
Speed	**Base**	**Revenue Equival.**	**Base**	**Revenue Equival.**	**Base**	**Revenue Equival.**	**Base**	**Revenue Equival.**	**Revenue Maximizing**
66	$54	$54.05	$50	$55.31	$23	$81.58	$38	$73.86	$34.01
67	$56	$56.09	$50	$62.70	$28	$85.48	$38	$76.43	$34.81
68	$58	$58.18	$50	$70.64	$33	$89.93	$38	$79.41	$35.60
69	$60	$60.33	$50	$79.15	$38	$94.94	$38	$82.78	$36.39
70	$62	$62.53	$50	$88.20	$43	$100.49	$38	$86.55	$37.19
75	$72	$74.40	$50	$141.84	$68	$136.49	$57	$111.43	$41.18
80	$82	$87.67	$100	$209.40	$116	$186.24	$85	$146.31	$45.20
85	$92	$102.35	$150	$290.88	$146	$249.74	$114	$191.21	$49.25
90	$102	$118.43	$200	$386.27	$193	$326.97	$142	$246.12	$53.34
95	$112	$135.91	$250	$495.58	$228	$417.95	$180	$311.04	$57.45
100	$122	$154.80	$300	$618.82	$298	$522.67	$228	$385.98	$61.60
105	$132	$175.09	$350	$755.96	$338	$641.13	$275	$470.92	$65.78
110	$142	$196.79	$400	$907.03	$378	$773.34	$332	$565.88	$69.99

Table 5 Values of Parameters Used in Simulations

?	s	F	F_1	F_2	k	h	t
40	60	150	15	25	.00003	1.55	8

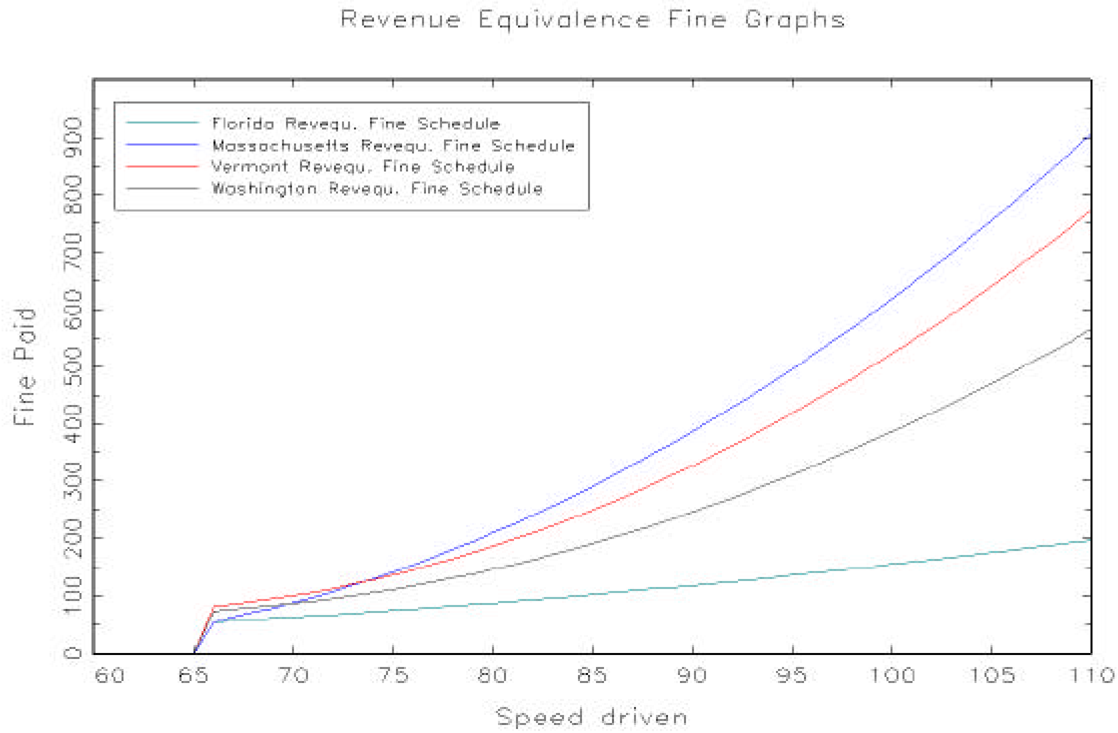

Figure 10

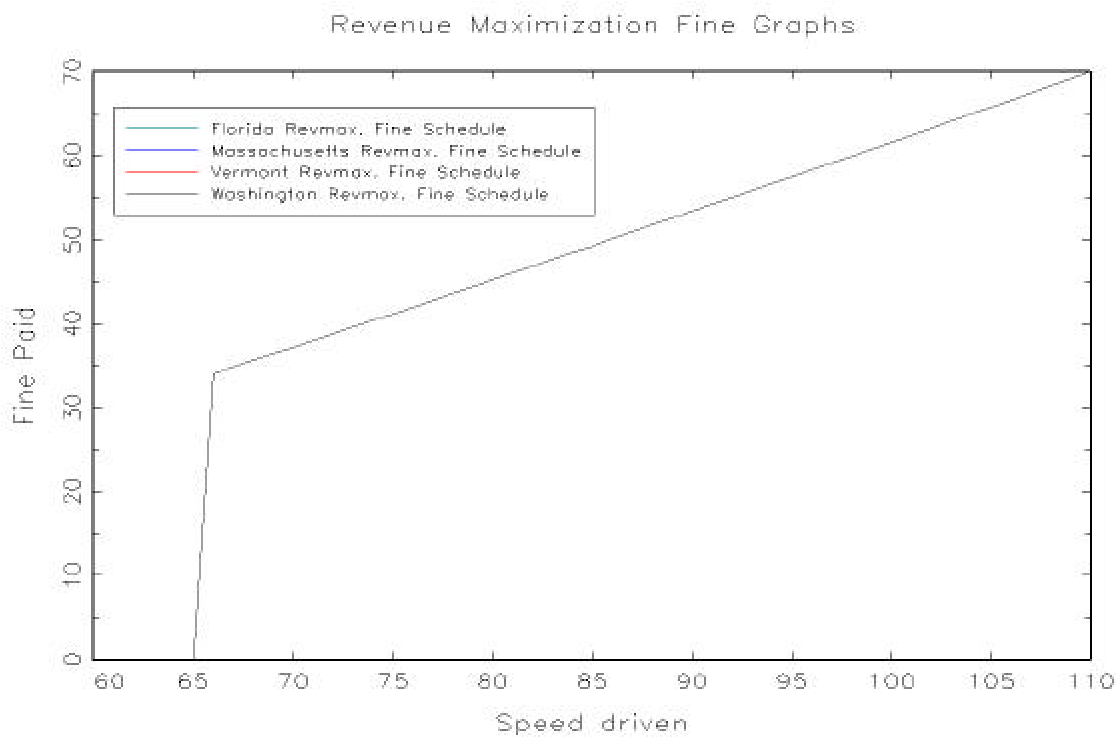

Figure 11

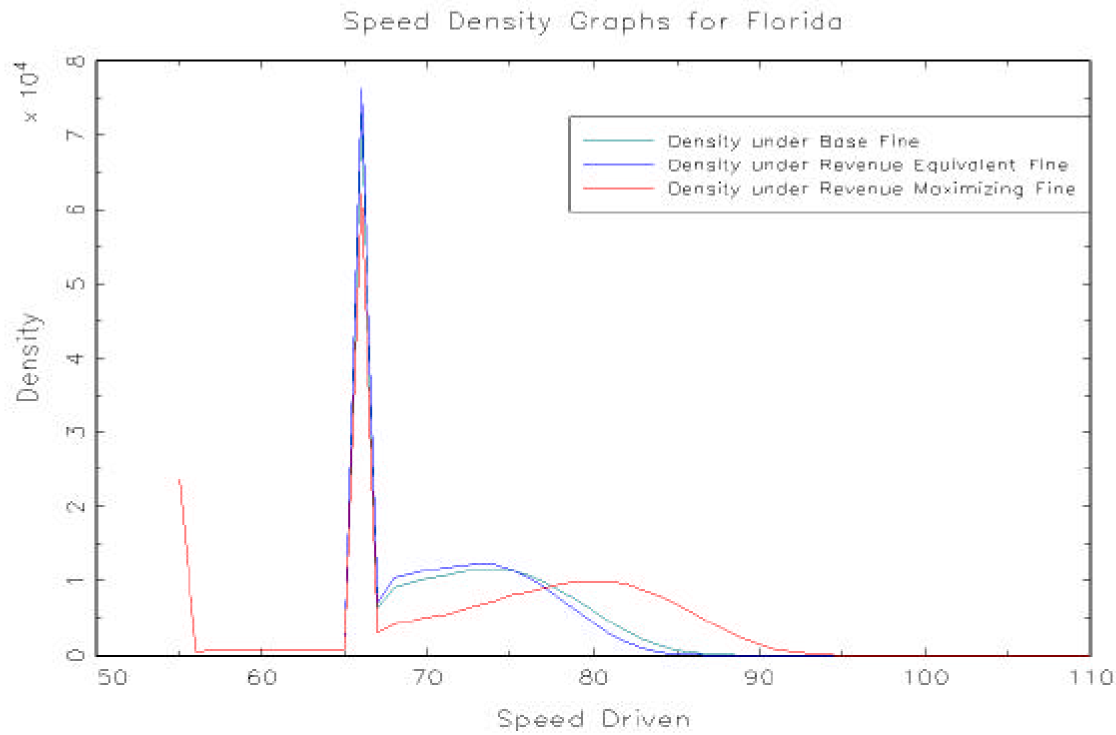

Figure 12

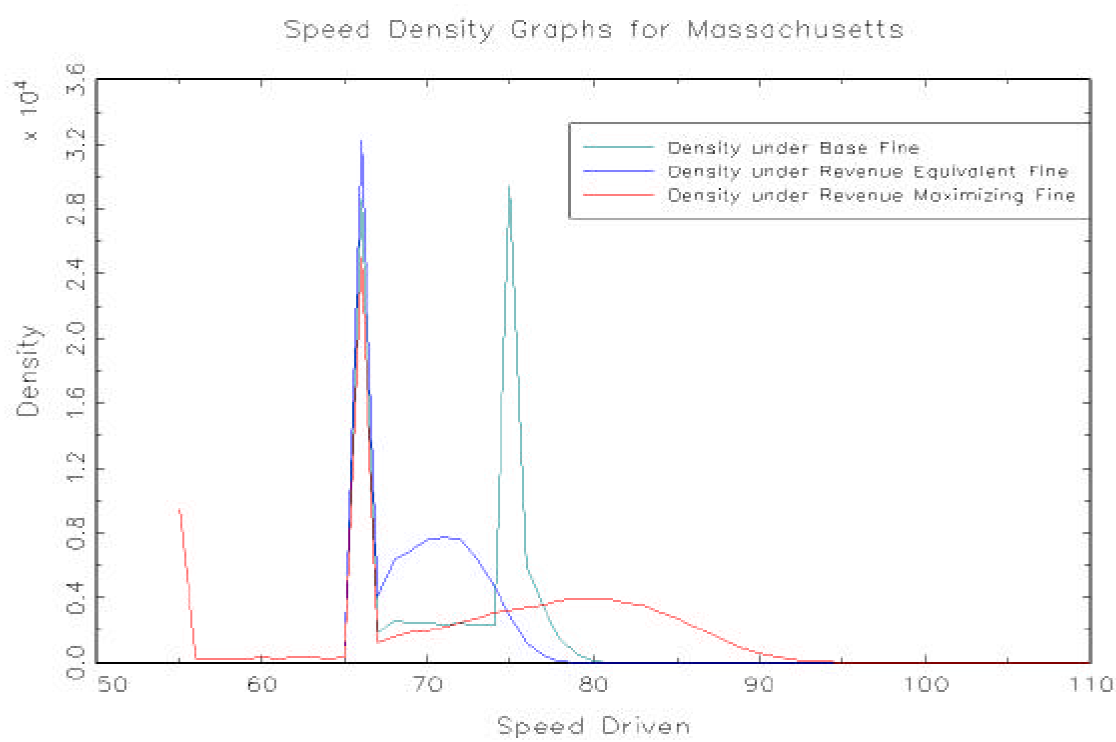

Figure 13

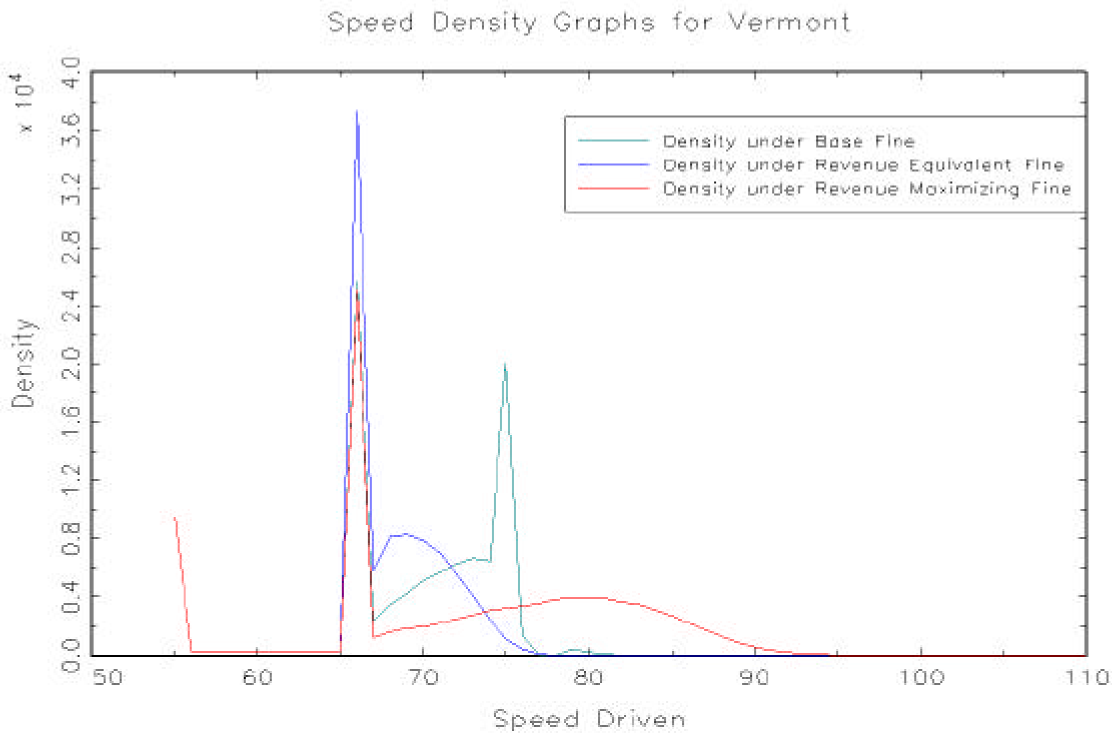

Figure 14

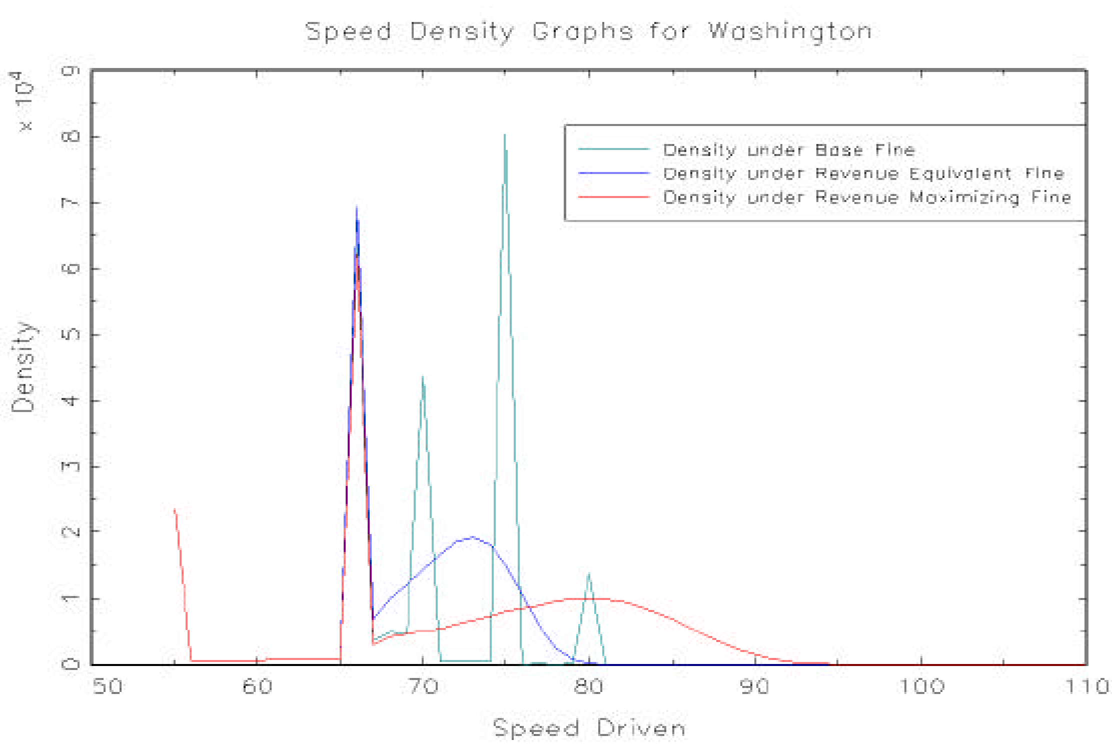

Figure 15

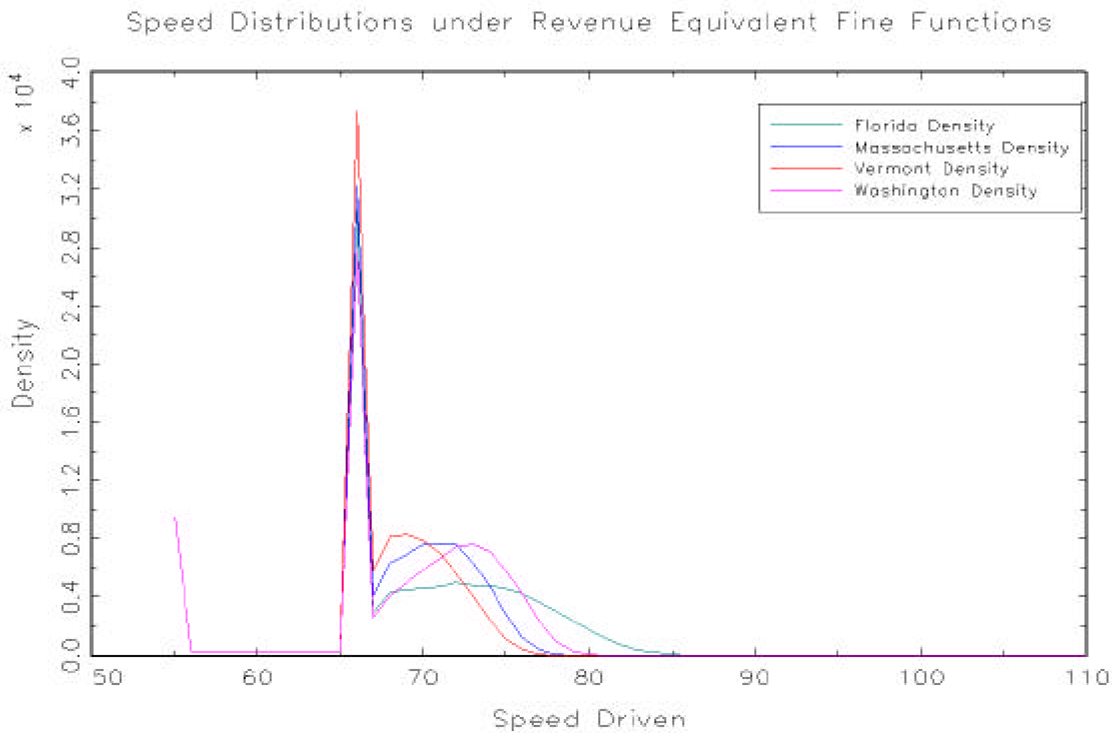

Figure 16

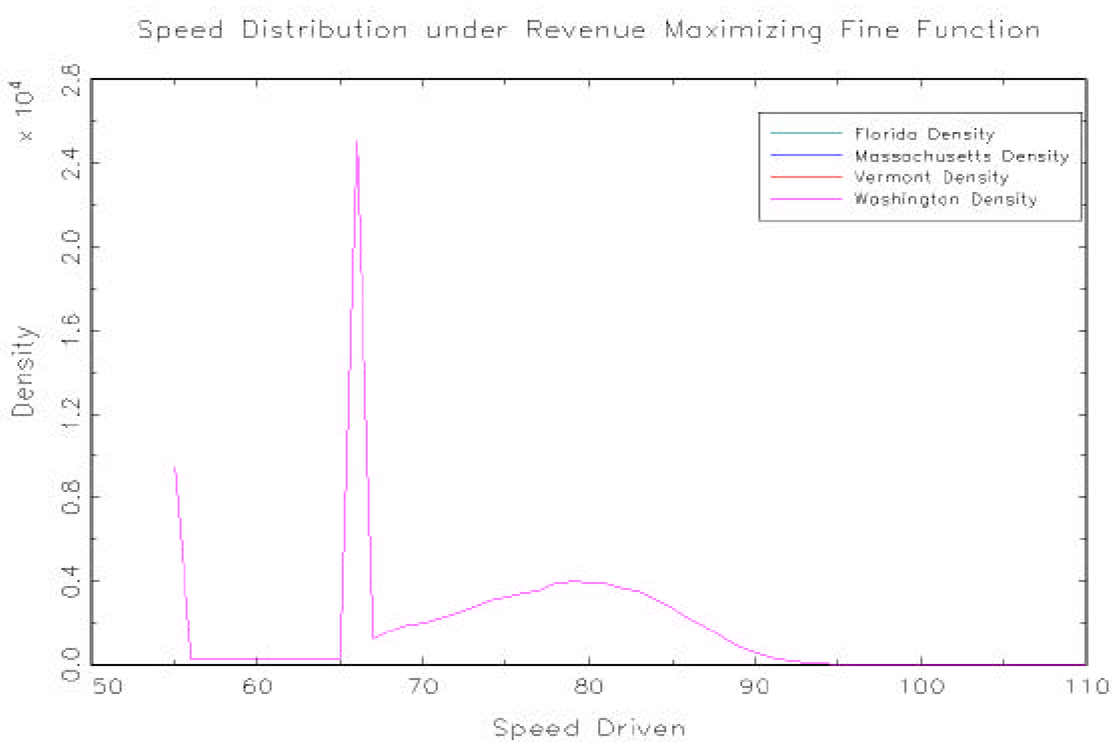

Figure 17

6 CONCLUSIONS

This study presented a methodology for examining the impact of enforcement parameters, particularly the fine schedule, on driver coordination on highways. The chief result of this study is that the variance of road speeds can be reduced when policies are selected with this as an objective.

Recently there has been much press about the new speeding tickets dispensed in Washington, D.C. These tickets appear, to many observers, to serve merely as a revenue source. In fact, a private company projects profits of over $25 million per year from the project. Many organizations that are vocally supportive of safety initiatives, such as the AAA, have come out in opposition to this practice. This vocal opposition to the policy underscores the need for a coherent, rational and effective fine structure.

This study presents results from simulations performed with data that is gathered from a variety of sources and not in the type of detail that is needed to get definitive results from the model. However, the methodology presented can be directly applied to data gathered and the simulations tailored to fit any objective function. In the simulations presented, the variance of road speeds was reduced by 12-38% with new fine functions that reduced revenues by less than 9%. This potential for safety enhancement suggests that collection of data and use of this model could increase the ability of regulating agencies to understand the role of their policies in driver coordination and safety.

This is a powerful tool that can be used to determine the impact of various policies on highway safety parameters (variance of road speeds and, potentially, average road speed). All that is required to calibrate this model properly is a series of observations concerning actual highway speeds on designated portions of highways. Ideally, stretches with differing fine functions and speed limits would be utilized (such as construction zones with doubled fines). In addition, detailed data on the tickets written on these stretches of highway during the data collection period are desired. With this data, the parameters of the model could be calibrated to generate current behavior that exactly matched the data. Changes in enforcement, the speed limit or the fine functions could be examined in detail to determine the effects.

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