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Catching or Fining Speeders

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Inhoudstafel

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Gebruikte afkortingen

EU	European Union
vkm	Vehicle kilometer

Samenvatting

De verwachte boete die iemand kan krijgen voor een verkeersovertreding is gelijk aan het product van de pakkans en de hoogte van de boete. Omdat het uitvoeren van wegcontroles vaak veel duurder is dan het opleggen van de sanctie zelf, is de combinatie van een lage pakkans en een hoge boete te verkiezen vanuit kosteffectiviteitsoverwegingen. In deze bijdrage onderzoeken we of, en hoe, de keuze tussen pakkans en boete beïnvloed wordt door de aanwezigheid van bepaalde belangengroepen. Via een 'political economy' model bekijken we de impact van twee belangengroepen: één die opkomt voor de belangen van kwetsbare weggebruikers zoals fietsers en voetgangers en één die opkomt voor de belangen van autobestuurders. Wanneer enkel kwetsbare weggebruikers actief lobbyen, vinden we dat de verwachte boete hoger is dan wanneer enkel de belangen van autobestuurders in rekening worden gebracht. Wanneer we focussen op de keuze tussen pakkans en boete voor eenzelfde verwachte boete, dan zien we dat kwetsbare weggebruikers een voorkeur hebben voor een boete die hoger is dan maatschappelijk optimaal (en dus de pakkans lager is dan optimaal). Het omgekeerde resultaat geldt wanneer vooral autobestuurders een impact zouden hebben op het beleid.

We testen deze voorspellingen voor de handhaving van snelheidsovertredingen in de EU. We baseren ons hierbij op gegevens over de aandelen van kwetsbare weggebruikers en autobestuurders, ongevalsrisico's en het handhavingsbeleid in de Europese lidstaten. De test leidt ons tot drie observaties. Ten eerste is er erg veel variatie in handhavingsstrategieën in de EU. Ten tweede zijn er aanwijzingen dat de pakkans inderdaad stijgt, wanneer de boetebedragen dalen. Dit komt overeen met de klassieke handhavingsmodellen. Ten derde vinden we geen aanwijzingen van de invloed van belangengroepen op de keuze van pakkans versus boete, maar zien we wel een stijging van de verwachte boete in landen waar de zwakke weggebruikers een groter aandeel van het wegverkeer innemen. Het gebrek aan duidelijke resultaten is het gevolg van de gebrekkige gegevens die over dit onderwerp beschikbaar zijn. De indicatoren verschillen van land tot land en worden op een niet-systematische wijze verzameld. Dit zorgt voor een slechte onderlinge vergelijkbaarheid en kan ook verklaren waarom we het effect van belangengroepen slechts gedeeltelijk terugvinden.

1 Introduction

In order to increase road safety, several monitoring and enforcement strategies can be selected in order to put speed limitations into effect. In general, the public debate emphasizes raising the probability of detecting speed violations rather than increasing the fines. This observation conflicts with economic theory that prefers maximum fines and minimal (costly) monitoring efforts (see, for example, Becker 1968, Polinsky and Shavell 1979 and Shavell 2004). In Europe, we see at present large variations in the magnitude of speeding fines and in fines for drunk driving (section 4) and in the probability of detection. To better understand these variations, we look at the determinants of monitoring and enforcement decisions for speeding and we model public policy as the outcome of a political process that is influenced by lobbying efforts of different interest groups. Moreover, a first attempt is made to empirically test this model for speeding enforcement in de EU.

Many previous studies investigating road safety compliance enhancement have followed a schematic and descriptive approach in creating a traffic law compliance model: for example, both the study by Mäkinen et al. (2003) and that by the European Transport Safety Council (ETSC, 2011) used a graphical scheme to present the different forces driving compliance, while Zaal (1994) used a verbal description of the contributing factors. Earlier, Solomon (1988) specified the three E's of traffic calming as three ways that can be used to achieve adherence to traffic laws: engineering, education and enforcement. This concept of 3E's has since been the dominant approach in traffic engineering. A notable exception is the formal model used by Bjornskau and Elvik (1992) to investigate the impact of formal enforcement (monitoring and sanctioning) on speed compliance. We contribute to this literature by including lobby pressure as a possible explanatory factor for current levels of traffic safety enforcement. To this end, we focus on monitoring and fining decisions, and take engineering and education-based policy measures as a given.

In many policy settings, several principals (i.e. lobbyists) simultaneously try to control the actions of an agent (i.e. the policy maker) by promising contributions in return for policy favors. Dixit et al. (1997) apply such a common agency model model[1] to income taxation, while Aidt (1998) uses the model to analyze environmental policy. Beside interest group pressure, there may also be other reasons why policy makers opt for high monitoring efforts and low fine levels rather than the theoretically optimal high fines and low monitoring probabilities. Recently, Makowsky and Stratmann (2009) study the political economy determinants of traffic fines. They empirically estimate the influence of the incentives faced by police officers and their vote maximizing principals on speeding tickets. They find indeed that the size of the violation is not the sole determinant of the fine and that it is also determined by the police officers' objective functions.

In this paper, we use the common agency model of Dixit et al. (1997) to understand the influence of different lobby groups. We only take two categories of individual agents into account: vulnerable road users, such as pedestrians and cyclists, and strong road users, such as car and truck drivers. Each individual acts as a vulnerable road user as well as a strong road user for a certain proportion of their trips. First, we analyze the preferred expected fine, which is the optimal combination of the probability of detection and the magnitude of the fine. The socially optimal combinations serve as a benchmark. This benchmark is then compared to two lobbying equilibriums: first, when the vulnerable road users form the only effective lobby group and, secondly, when the strong road users get all the lobbying weight. We argue that vulnerable road users opt for a higher expected fine than is socially optimal because, in our model, they bear all the accident losses. The strong road users, on the other hand, prefer a very low expected fine since they have to pay the fines and see little of the benefits associated with an increase in traffic safety. Next, we determine numerically the optimal combination of the detection and fine parameters when the expected fine is kept fixed. In that case, we find that vulnerable road users opt for high fines and a low probability of detection, while strong road users prefer a high probability of detection and low fines. The main explanation for these findings is that increasing the detection probability is costly for society as a whole, while increasing the fine has no social costs and only affects the strong road users that violate the speed limit.

Our contribution to the existing literature is threefold. First, we use lobbying theory to understand the level of the expected fine as well as the choice between the detection probability and the level of the

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[1] This model is based on the common agency model of Bernheim and Winston (1986). Grossman and Helpman (2001) provide an excellent introduction to the theoretical literature on interest group politics.

fine. Second, we incorporate imperfect compliance into the lobbying model. Third, we provide a first attempt to empirically verify theoretical predictions with observed enforcement policies for reducing speed violations.

2 Model

The model under consideration focuses on enforcement policy, more particularly on the trade-off between higher fines and a higher probability of detection. The same approach can also be used to analyze, for instance, road safety investments. We examine different combinations of detection probabilities and fines, and use the political weight of different interest groups to explain the variations in the monitoring and enforcement policy that is selected by the policy makers.

2.1 Assumptions

We assume that there are two types of economic agents: the government and road users. The government decides on the enforcement policy associated with speed regulations while taking account of the social costs of accidents, the private costs of driving, the revenues from fines and the costs of enforcement. We distinguish two types of road users: 1) vulnerable road users that walk or cycle and 2) strong road users that drive a car or a truck. Further we assume that pedestrians and bicyclists are homogenous. However, car or truck drivers differ with respect to their valuation of time when selecting their speed so as to maximize their utility. They prefer higher speeds to lower ones, *ceteris paribus*. Overall, the population consist of N individuals who each perform j trips. Thus the total number of trips is $J = jN$. For each individual, we assume that a number j_v of these journeys involve vulnerable road use and that this number is uniformly distributed between 0 and j. The number of journeys per individual as a strong road user is then $j_c=j- j_v$ and also uniformly distributed. For the population[2] the total number of trips as walker or cyclist is equal to $J_v=J/4$ and the total number of trips as car or truck driver is $J_c=3J/4$.

Car and truck drivers are subject to an exogenously given speed limit $\overline{s}$. As Graves et al. (1989) show, raising the level of policing is likely to have a lower social cost, at the margin, than lowering the speed limits. Thus we focus on selecting the appropriate monitoring and enforcement strategy and take the speed limits as given. Strong road users drive at the speed s that maximizes their utility. If drivers exceed the speed limit, they are caught with probability π. This probability of detection does not depend on the magnitude of the violation or on the probability of having an accident[3]. As a case in point, speed cameras, both manned and unmanned, are not more likely to film a driver at 120 km/h than one driving at 100 km/h.[4] The costs of enforcement consist of a fixed enforcement cost C_E^F (for example, the cost of installing a speed camera) and a variable enforcement cost C_E^V (for example, the administrative cost of writing a notice of violation). The total enforcement cost is thus an increasing and convex function of the probability of detection and the number of violators.

Once violators are caught, they face a fine $F\left(s\right) = f + v(s - \overline{s})$ with f the fixed fine, v the variable fine, $\overline{s}$ the speed limit and $\begin{cases} F\left(s\right) = 0 \; if \, s \leq \overline{s} \\ F\left(s\right) > 0 \; if \, s > \overline{s} \end{cases}$ with $F'\left(s\right) > 0$ and $F''\left(s\right) = 0$.

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[2] Thus we assume that the expected proportion of vulnerable road use per individual is 25%. This corresponds with practice in Belgium (Toint et al. 2001). Taking a different distribution between vulnerable and strong road use into account would, however, not significantly influence the main insights from our model.

[3] It would be more correct to use $\tilde{\pi} \equiv \left(1 - p(s)\right)\left[\pi\right] + p\left(s\right) = \left[\pi + p(s)(1-\pi)\right]$ instead of π. $\tilde{\pi}$ means that if a car driver is not involved in an accident with probability $\left(1 - p\left(s\right)\right)$ and he is speeding, he has to pay a fine with probability π and if he has an accident with probability p(s) and he is speeding, the probability of a fine equals one.

[4] A counterexample would be speedguns which are less frequently used especially in Europe.

This linear fine[5] contains a gravity component, directly related to the degree of non-compliance; and also a non-gravity part, which considers extra elements such as the economic impact of the penalty on the violator, the economic benefits of non-compliance such as illegal profits or the costs associated with catching speeders.

2.2 Modeling agents' behavior

In this section we discuss the behavior of the two agents: the road users who are utility maximizers and the government who maximizes a weighted welfare function. First, we model the road users' reaction to the selected monitoring and enforcement policy using backward induction. Next, we determine the government's preferred monitoring and enforcement strategy for a given level of lobbying activity and the reaction functions of the road users.

2.2.1 Road users

First we discuss the utility of the road users and then we turn to the speed selected by the strong road users.

2.2.1.1 Road users' utility function

The utility of the average road user consists of two parts: one part depending on the vulnerable road use as pedestrian or cyclist, and one part depending on the strong road use as car or truck driver. We assume that the utility of the average road user is quasi-linear and determined by the spending on consumption goods[6], the number of trips as a vulnerable road user $\left(j_v\right)$ and as a strong road user $\left(j_c\right)$, the expected accident costs, $p\left(s\right)h$, with $p\left(s\right)$ the probability per trip of having an accident and *h* the harm caused by the accident[7] and, for strong road users, the time cost of making the trip $C_T\left(t,s\right)$ (with $\frac{\partial C_T}{\partial t}>0, \frac{\partial C_T}{\partial s}<0, \frac{\partial^2 C_T}{\partial t^2}=0$ and $\frac{\partial^2 C_T}{\partial s^2}>0$). As mentioned before, strong road users differ in their value of time $t\in\left[t_1,t_2\right]$ and hence will drive at different speeds. We assume that the value of time is continuously and uniformly distributed with probability density $\frac{1}{t_2-t_1}$ and cumulative distribution $\frac{t-t_1}{t_2-t_1}$.

Further, we assume that utility is additive in consumption and in both types of trips, with a constant marginal utility γ_v per trip for vulnerable road usage and γ_c per trip for strong road usage. We assume that road users maximize their utility while taking into account their budget constraint: the amount spend on consumption goods, on private monetary costs of driving $C_M\left(s\right)$ and – when applicable – paying speeding tickets should not exceed the sum of the exogenously given income *Y* and the lump sum transfer L[8]. We assume that the private monetary costs[9] of driving $C_M\left(s\right)$ are a

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[5] In practice, for example in Belgium, linear fines are often used for speed violations because they are easy to communicate and to implement.

[6] The price of this consumption good is normalized to one.

[7] For derivational ease, we include the speed-dependent nature of the harm function into the accident probability function. This does not qualitatively change our results, since the expected harm function depends on the speed level. Also, assuming that vulnerable road users are risk averse to harm does not change the results qualitatively.

[8] We normalise the cost of taking a trip as a vulnerable road user to zero.

[9] Private accident losses could be incorporated in the C_M function and this would influence private speed decisions. However, given the focus of the paper and the clarity of the exposition, we opt to leave them out. Including private accident losses would make the results less pronounced, but in essence the same. This assumption can be considered as a normalisation since in accidents between strong and vulnerable road users, the losses of the strong road user will be smaller than those of the vulnerable road users.

function of the speed s that the driver selects and include the resource cost and the fuel cost with $\frac{\partial C_M}{\partial s}{}^{\wedge}$ 0 and $\frac{\partial^2 C_M}{\partial s^2} \geq 0$.

This gives us the expression for the indirect utility V of an average road user:

$$V = Y + L + j_v\left[\gamma_v - p(s)h\right] + j_c\left[\gamma_c - C_T(t,s) - C_M(s) - \pi R\big(F(s)\big)\right] \quad (1)$$

where $R\big(F(s)\big) \equiv \alpha_c F(s) + \frac{\beta_c}{2} F(s)^2$ represents the disutility per trip of incurring the risk of having to pay a fine. For later use, we define the utility per trip generated by vulnerable and strong road use respectively as:

$$V_v = \gamma_v - p(s)h$$
$$V_c = \gamma_c - C_T(t,s) - C_M(s) - \pi R\big(F(s)\big)$$

To implement the model of Dixit et al. (1997), a quasi-linear utility function is assumed and the strong road users are risk averse with respect to the fine payments. Polinsky and Shavell (1979) discuss the impact of risk aversion on the trade-off between the optimal detection probability and the level of the fine[10]. Contrary to Becker (1968), the optimal fine level is shown to be lower than the maximal fine in the presence of risk averse individuals and measurement errors. Assuming risk aversion imposes two conditions on the parameters α_c and β_c [11]:

$$r = -\frac{V''}{V'} = -\frac{\beta_c}{\alpha_c + \beta_c F(s)} > 0 \qquad \Rightarrow \qquad \beta_c < 0 \quad and \quad \frac{\alpha_c}{-\beta_c} > F(s) \quad (2)$$

We also know that, if car drivers are risk averse, they prefer a high probability of detection combined with a lower fine to a lower probability and a higher fine with the same expected value (Rothschild and Stiglitz, 1970 and 1971).

2.2.1.2 Speed decision

For each trip the strong road user chooses his speed *s* in order to minimize the costs associated with the speed regulation:

$$\min_s \left\{C_T(t,s) + C_M(s) + \pi R\big(F(s)\big)\right\} \qquad (3)$$

Thus the optimal strategy is to comply when the marginal expected penalty for non-compliance is larger than the marginal costs savings of exceeding the standard; that is, when $\pi \frac{\partial R\big(F(s)\big)}{\partial s} \geq -\frac{\partial C_T(t,s)}{\partial s} - \frac{\partial C_M(s)}{\partial s}$. In that case, the optimal strategy is to comply and to drive the private optimal speed: $s = s^o(t)$ with $s^o(t)$ defined by $\frac{\partial C_T(t,s^o)}{\partial s} + \frac{\partial C_M(s^o)}{\partial s} = 0$. However, the optimal strategy is to exceed the speed limit if the marginal expected penalty is below the marginal cost savings at the limit. In that case, we have $s > \bar{s}$ and

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[10] For example, Bar-Ilan (2000) also considered the risk attitude of road users so as to analyse the behaviour of red light runners. In this study, red light runners included in the sample are shown to be risk lovers and this explains why they are not deterred by the high expected damages (injuries or even death) combined with low probabilities of having these damages.

[11] We use the Arrow-Pratt measure of risk aversion. Moreover, we assume that the second condition can be met since, in practice, speed has an upper limit and therefore the possible fine that can be imposed is also limited.

$$-\frac{\partial C_T\left(t,s\right)}{\partial s}-\frac{\partial C_M\left(s\right)}{\partial s}=\pi\frac{\partial R\left(F\left(s\right)\right)}{\partial s} \qquad (4)$$

This is the familiar result that, for an interior solution, marginal costs of driving faster equal the marginal expected disutility of the fine. Individual speeding decisions are assumed to be independent between road users and thus roads are assumed to be uncongested.

There exists a certain value of time $\tilde{t}$ for which drivers are indifferent between speeding or not and this indifference point is a function of π and $F\left(s\right)$. Given that the value of time is uniformly distributed, it follows from the model that road users will comply with the speed limit during a proportion $\frac{\tilde{t}-t_1}{t_2-t_1}$ of the J_c trips and that in a proportion $\frac{t_2-\tilde{t}}{t_2-t_1}$ of the trips they will speed.

2.2.2 Government

The government receives the net fine revenues (probability of detection times the fine times the number of offences minus the cost of enforcement) and uses this revenue to give a lump sum *L* to all road users *N*.

$$\pi\frac{J_c}{t_2-t_1}\int_{\tilde{t}}^{t_2}\left(F\left(s(t)\right)-C_E^V\right)dt-C_E^F=L\,N \qquad (5)$$

Hence, the lump sum transfer depends on the detection probability and the fine imposed: $L\left(\pi,F\left(s\right)\right)$. For this reason the transfer is determined by the number of speeders as well as by the extent of speeding. Note that individual road users do not take the individual effect of their speeding decision on the size of the transfer into account. However, collectively as a lobby group they do take the aggregate effect of speeding decisions on the lump sum transfer into account.

Thus we assume that road users join lobbying groups in order to try to influence regulatory decisions: one lobby group is defending the interests of all vulnerable road users and another group is dedicated to the interests of all strong road users. We assume that an individual joins the group defending the interests of vulnerable road users when his vulnerable road use is more frequent than average ($j_v \geq \frac{j}{4}$) and that he joins the group defending the interests of strong road users when his strong road use is more frequent than average ($j_v > \frac{3j}{4}$).

Following Dixit et al. (1997), we assume that the outcome of the lobbying 4 can be represented by the maximum of a function that equals a weighted sum of a social welfare function *SWF* (representing the pure political process before lobbying) and the utility functions of the lobbying groups.

$$OBJ\left(\theta,\lambda\right)=\theta SWF+\left(1-\theta\right)\left[N\left[Y+L\right]+\lambda J_vV_v+\left[1-\lambda\right]J_cV_c\right] \qquad (6)$$

The weights $\left(\theta \text{ and } \lambda\right)$ are determined by the lobbying game. If $\theta=1$, lobbying has no influence on the policy decision and the regulator selects the monitoring and enforcement strategy that maximizes social welfare. If $\theta=0$, only lobbies matter and then the parameter λ determines the relative power of each lobby group. In this paper we assume that the outcome of the purely political process (SWF) corresponds to the maximum of an additive utilitarian social welfare function[12].

In the next section, we determine analytically the optimal probability of detection and the associated fine function for the case with and without lobbying. This is then the point of departure for the following

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[12] We can take other assumptions but this would require us to model more finely the working of the political process itself.

section, where we explore empirical evidence for the possible influence of lobby groups on monitoring and enforcement of road safety policies in European countries.

3 The optimal fine function and probability of detection

We first consider the benchmark case, where the government simply maximizes the objective function (6) with respect to the probability of detection π, the fixed fine *f* and the variable fine *v* in the absence of any lobby groups $(\theta = 1)$. Next, we examine two extreme lobbying equilibriums: one where vulnerable road users have all the lobbying weight $(\theta = 0,\ \lambda = 1)$ and one where strong road users dominate the political process $(\theta = 0,\ \lambda = 0)$. We show how interest groups would want to influence the monitoring and enforcement strategy.

3.1 Benchmark: $\boldsymbol{\theta = 1}$

In the benchmark, there are no lobby groups and we assume that this results into the maximization of an additive utilitarian social welfare function:

$$SWF = N\,V = N\,Y + N\,L + J_v V_v + \frac{J_c}{t_2 - t_1}\left[\int_{t_1}^{\tilde{t}} V_c\left(comply\right)dt + \int_{\tilde{t}}^{t_2} V_c\left(speed\right)dt\right] \qquad (7)$$

Now we calculate the derivatives of social welfare with respect to π, *f* and *v*. These first order conditions form a system of three equations and three unknowns (see appendix), which solve for the optimal level of detection probability, and the optimal fixed and variable fine. It is more instructive to discuss the different drivers of these three parameters one by one.

The socially optimal probability of detection is determined by equating the marginal increase in the disutility of fines associated with increasing the monitoring frequency to the associated marginal decrease in accident costs corrected for the impact on government revenues. Thus the marginal cost of a higher probability equals the marginal benefit in the optimum. If the probability increases, the speed on the roads decreases, for a given fine function, and thus the expected accident costs decrease. However, the change in government revenue is uncertain because two opposite effects play. Firstly, due to the relative increase in the expected fine, there are fewer speeders, the chosen speed is lower and the variable enforcement costs are higher. Hence government revenue decreases (a cost). On the other hand, additional revenue is created because the expected fine is higher and, because there are fewer speeders, the variable enforcement costs decrease (a benefit).

Next, we discuss the fixed component of the fine, which is determined by the expression $\frac{dSWF}{df} = 0$ (see appendix). Hence, the socially optimal fixed fine is determined by equating the change in government revenue to the decrease in accident costs. The socially optimal variable fine *v* is determined in a similar way as the fixed fine *f* (see appendix) and equates the change in government revenues to the change in accident costs.

In summary, the three monitoring and enforcement parameters (*v*, *f* and π) are determined by equating the marginal costs to the marginal benefits. The exact magnitudes of the parameters depend on the way the speed decisions react to the change in the probability of detection, the change in the fixed fine or the change in the variable fine. These reactions depend crucially on the degree of risk aversion. We cannot guarantee a unique solution since several combinations of *v*, *f* and π will have the same effect on drivers' compliance and are therefore indistinguishable. It is after all the expected fine that influences road users' behavior and not the level of its constituent parts as such. Consider, for instance, the extreme case where all drivers comply with the speed regulations. Such fully compliant behavior could be obtained by inspecting everyone and imposing a sufficiently high fine, but it could also be obtained by halving the probability of detection and doubling the fine.

3.2 $\theta = 0$ and only the vulnerable road users lobby counts: $\lambda = 1$

When the government decision making is only influenced by the lobby group of vulnerable road users, the objective function equals

$$OBJ(0,1) = N\left[Y + L\right] + J_v V_v \quad (8)$$

The optimal probability of detection is then determined by

$$\frac{dOBJ(0,1)}{d\pi} = 0 \qquad \Rightarrow \qquad N\frac{dL}{d\pi} + J_v\left[-\frac{dp(s)}{d\pi}h\right] = 0 \qquad (9)$$

For the vulnerable road user lobby, the marginal benefits of improved monitoring are the reduction in accident costs and the (possible) increase in fine revenues of which its members receives a share. The vulnerable road user lobby does not take any effects on the private cost of the strong road use into account. So the marginal costs of increased control include only the higher monitoring costs.

Secondly, the fixed fine that is preferred by the vulnerable road user lobby is determined by $\frac{dOBJ(0,1)}{df} = 0$ (see appendix). This expression is identical to the social optimum. Further, the variable fine in this scenario is found by solving $\frac{dOBJ(0,1)}{dv} = 0$ (see appendix). Again we find an identical expression as for the social optimum.

3.3 $\theta = 0$ and only the strong road users lobby counts: $\lambda = 0$

In this scenario, the government is only influenced by the strong road user lobby. The objective function then equals

$$OBJ(0,0) = N\left[Y + L\right] + J_c V_c \qquad (10)$$

The optimal probability of detection is derived from $\frac{dOBJ(0,0)}{d\pi} = 0$. The possible benefit to the strong road users of more monitoring is the change in government revenue, while the cost consists of the disutility of the fine. The strong road user lobby does not take any effect on the accident costs into account and it only considers part of the enforcement cost and the government revenues. To determine the fine parameters, *f* and *v*, the lobby group only looks at the change in government revenue and ignores the potential harm to vulnerable road users. The exact expression for the first order conditions for the fixed and variable fine parameters can be found in appendix.

3.4 Discussion

We now compare the solutions preferred by the vulnerable and strong road user lobby groups with respect to the probability of detection and the level of the fine. Both lobby groups account for the impact on government revenue in an identical way. They balance the additional cost of increased enforcement with the additional benefit of increased fine revenues. However, the impact on accident costs and the disutility of facing a fine are treated differently by the lobby groups.

Firstly, looking at the probability of detection, we find that the value preferred by the vulnerable road user lobby is higher than the socially optimal probability of detection, since the vulnerable road user lobby ignores the increase in the disutility of facing a fine by the strong road users. On the other hand, the probability preferred by the strong road user lobby is lower than the socially optimal probability of detection, since this lobby group ignores the reduction in accident costs associated with higher detection probabilities.

Secondly, looking at the fixed and variable fines, we find that the values preferred by the vulnerable road user lobby are identical to the socially optimal fine levels, since the same balancing of costs and benefits is made in both instances. However, the fine values preferred by the strong road user lobby are lower than the socially optimal fine levels, since again the impact on accident costs is ignored.

4 Empirical illustration

We illustrate the theoretical analysis by means of empirical data collected for several European countries. The goal is to investigate whether the possible impact of lobbying activity is reflected on the actual monitoring and enforcement policies for speed limitations in the European Union.

4.1 Description of the dataset

We start by discussing the available empirical data with respect to the share of vulnerable road users, accident rates, enforcement of speeding across different EU countries.

First, given the analysis above, we make a distinction between countries with a large share of vulnerable road users and countries with a lower share. We opted to focus on the use of bicycles compared to the use of cars. There are different ways to measure this. Table 1 shows a comparison of the number of vehicle kilometers (vkm) per inhabitant per year by car and by bicycle; the bicycle and car shares in all journeys; whether the main mode of transport is car or bicycle; and the relative number of km travelled cycling compared to the European average.

For consistency reasons, we decided to show data for the year 2008, even if for some indicators more recent data were available. Still, for some indicators, we had to rely on older data. The numbers of vkm by car per inhabitant per year are taken from the ERSAP project[13]. Unfortunately, there is no consistent data source for the annual number of vkm for all EU countries. Within the ERSAP project, data on vkm from Eurostat, ITF (2009) and TREMOVE were compared and combined into one dataset. The number of inhabitants for each country was taken from the Eurostat website. Recent data on cycling km covering several European countries are scarce. The bicycle vkm are based on ECMT (2004) who report the number of vkm by bicycle per day for several countries and on Dekoster & Schollaert (1999). The car share is taken from Eurostat. The bicycle share is based on a report of the Ministerie van Verkeer en Waterstaat and Fietsberaad (2009). The data on the main mode of transport come from the EC (2011) report, which was a survey on the current means of transport that EU citizens use to get around on a daily basis. Hence the reported shares are the result of a questionnaire and are not based on observed behavior. In each country about 1.000 interviews were conducted. The relative number of km travelled by bicycle compared to the EU average is taken from Eurostat (2007).

Table 1 shows that the countries with the highest bicycle shares are the Netherlands (26%), Denmark (19%), Germany (10%), Austria (9%) and Belgium (8%). These are also the countries with a relatively high number of bicycle km per inhabitant per year and with high shares of respondents indicating the bicycle as their main mode of transport. Also Hungary, Slovakia, Finland and Sweden report relatively high shares of bicycle as the main mode of transport, while these countries are usually not really seen as cycling countries, using the indicators for cycling share.

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[13] http://www.tmleuven.be/project/ersap/home.htm

Table 1: Share of vulnerable road users across the EU

	Car (vkm/inhabitant /year)	Bicycle vkm (km/inhabitant /year)	Bicycle share all journeys	Car share all journeys	Main mode transport = bicycle	Main mode transport =car	Relative nr of km travelled by VRU compared to EU average
BE	9166	327	8%	78%	13%	61%	1.23
BG	232			75%	2%	33%	
CZ	5329		3%	76%	7%	36%	
DK	8857	958	19%	82%	19%	63%	
DE	8634	300	10%	86%	13%	61%	1.16
EE	5717			81%	5%	37%	
IE	6657	228	3%	84%	3%	68%	
EL	7175	91		81%	3%	47%	0.67
ES	8480	24		80%	2%	47%	0.70
FR	7558	87	5%	84%	3%	64%	0.82
IT	9768	168	5%	83%	5%	54%	1.00
CY	3387			81%	0%	89%	
LV	6570			88%	8%	29%	
LT	7231			91%	5%	49%	
LU	18398	40		84%	2%	64%	
HU	5982			60%	19%	28%	
MT	2013			81%	0%	65%	
NL	7466	1019	26%	87%	31%	49%	2.07
AT	6663	154	9%	79%	8%	61%	1.02
PL	3853			86%	9%	43%	
PT	6984	35		85%	2%	53%	0.76
RO	2029			77%	5%	30%	
SI	8689			86%	7%	68%	
SK	495			73%	10%	32%	
FI	10261	282	7%	85%	13%	62%	
SE	8498	300	7%	83%	17%	52%	
UK	8316	81	2%	88%	2%	57%	
NO			6%				
CH			9%				

Source: own data collection and own calculations using ITF, Eurostat, TREMOVE, Fietsberaad (2009), ECMT (2004), Dekoster & Schollaert (1999), EC (2011)

Next we approximate the level of harm caused by road accidents. Table 2 shows the total number of accidents, the total number of people killed and injured, as well as the total number of cyclist killed and injured (CARE database and Delhaye & Akkermans 2010). Using these data and the data on the number of vkm travelled from table 1, we calculated the accident rate (total number of accidents/vkm), the accident rate for cyclists (total number of cyclists killed and injured/vkm car), and the share of cyclists killed in road fatalities (number of cyclists killed/total killed). The average accident rate for Europe is 0.538 accidents per million vkm. This number is highly skewed by the very high accident rates of Bulgaria and Slovakia who have an accident rate of almost 3 accidents per million vkm. Without those two countries, the average accident rate drops to 0.311. Compared to this average accident rate, Denmark, Finland, Luxembourg and the Netherlands have much lower accident rates, while Cyprus, Austria, Portugal, Romania and Slovenia have relatively higher accident rates. The accident rate for cyclists is on average 0.024 – much lower than the total accident rate – reflecting the much lower modal share. Comparing the national figures with this average, we see that Belgium, the

Netherlands, Austria and the Czech Republic are relatively safe for cyclists. When we consider the relative importance of cyclists killed in the total number of road fatalities, the average is about 7% in Europe. When we compare this number with the shares of people indicating the bicycle as the main mode of transport from table 1, we see that there is not a perfect one-to-one relationship. For Belgium, Denmark, Germany, Hungary and the Netherlands, the share of cyclists killed is lower than the share of road users for which cycling is the main mode of transport. For the Netherlands, cyclists count for 26% of the people killed in traffic, while they have a higher share in traffic (31% state that cycling is the main mode of transport). Among the “non-cycling” countries, we see that Estonia, the UK, Lithuania, Luxembourg, Portugal and Slovenia are relatively unsafe for cyclists.

Table 2: Accident rates across Europe

	total accidents (2008)	killed (2010)	injured (2008)	killed cyclist (2009-2010-2011)	injured cyclist	all accidents /1 mio vkm	bicycle accidents (injured+killed) /car vkm	share killed cyclists
BE	39306	812	64315	68	6384	0.402	0.066	8%
BG	6610	776	9951	0		3.726	0.000	0%
CZ	19676	802	28501	63	2931	0.356	0.054	8%
DK	3498	255	5923	26	1061	0.072	0.022	10%
DE	288297	3648	407859	399		0.406	0.001	11%
EE	1347	78	2398	7	139	0.176	0.019	9%
IE	6615	212	7806	5	300	0.226	0.010	2%
EL	15032	1258	18796	13	206	0.187	0.003	1%
ES	85503	2479	130947	67	2567	0.223	0.007	3%
FR	67288	3992	93798	141	4636	0.139	0.010	4%
IT	211404	4090	309027	263	14535	0.363	0.025	6%
CY	1197	60	1963	2		0.448	0.001	3%
LV	3193	218	5408	15	273	0.214	0.019	7%
LT	3625	300	5940	30		0.149	0.001	10%
LU	787	32	1139	2	29	0.088	0.003	6%
HU	16308	740	25369	92	2980	0.271	0.051	12%
MT	753	15	1172	0	4	0.912	0.005	0%
NL	10778	537	27525	138	7967	0.088	0.066	26%
AT	35348	552	50521	42	5559	0.638	0.101	8%
PL	38832	3908	62097	314	5564	0.264	0.040	8%
PT	35426	937	43933	45	1384	0.478	0.019	5%
RO	25995	2377	36177	140	1645	0.595	0.041	6%
SI	7659	138	12741	17		0.438	0.001	12%
SK	8119	371	11040	27		3.036	0.010	7%
FI	6072	272	8513	19	1003	0.112	0.019	7%
SE	16504	266	26248	20	2317	0.212	0.030	8%
UK	160080	1905	237790	111	16277	0.315	0.032	6%
average						0.538	0.024	7%

*BE: 2006, IE: 2002, LU and PL: 2005
Source: Eurostat pocketbook (2012), CARE database (2013), Delhaye ea (2009), own calculations

Table 3: Enforcement of speeding across Europe

	speed limit							% speeding (cars and vans)		
	built-up area	outside build up areas	motor-ways	point system	liability system	number of speed tickets per 1000 inhabitants - 2008	minimum fine speeding (euro)	urban roads	rural roads	motor-ways
BE	30-50	90-120	120	no		255	50	93%-60%°	50%-30%°	40%°
BG	50	90	130	yes		20	10			
CZ	50	90	130	yes	strict liability	17	19	20.9%*	17%*	
DK	50	80	110-130	yes	strict liability (contributory negligence)	45	134	61%**	72%**	70%**
DE	30-50	100	130*	yes	strict liability (contributory negligence)	103	15			
EE	50	90-110	110	no			15		24.9%-	
IE	50	80-100	120	yes	fault based	40	80+2 points	54.9%**	21%-	15%**
EL	50	90-110	130	yes		31	40			
ES	50	90-100	120	yes	strict liability	44	100			35.3%*
FR	50	80-110	110-130	yes	strict liability (contributory negligence)	138	135+1 point	45.7%*	20%	25.9%-41.2%*
IT	50	90-110	130-150	yes	strict liability (contributory negligence)	24	35			
CY	50	80	100	yes	fault based	137	5		55%***	
LV	50	90	110	yes		49	30 + 1 point		42%*	
LT	50	70-90	110-130	yes		10	12		35%**	17.4%*
LU	50	90	130	yes		42	49	43%***		5%***
HU	50	90-110	130	yes	strict liability	29	102	53.4%**	60%-	31.6%*
MT	50	60-80	-	yes	fault based		25			
NL	30-50-70	80-100	100-120	no	strict liability (contributory negligence)	558	30			41.0%-36.0%***
AT	30-50	100	130	yes	strict liability (contributory negligence)	456	21	71.2%***-51%**	20%**	19%**
PL	50-60	90-110	130	yes	strict liability	34	14,75	81%**	70%**	
PT	50	90-100	120	no			60	38%	74%	
RO	50	90-100	130	yes	fault based	51	92			
SI	30-50	90-100	130	no	strict liability	24	250	85%		17%*
SK	50	90	130	yes		72	10			
FI	40-50	80-100	100-120	no		50	130		60.91-51.53%**	
SE	30-50	70-90	100-120	no	strict liability	25	215	53.3%	55.1%-50.2%	
UK	32-48	96-112	112	yes	fault based	28	90+3 points	49%**	10%-	49%**

[2] assuming 5 km/h too fast

° 2010 / * 2009 / ** 2008 / *** 2006 / ****2005

In Germany some motorways do not have a speed limit, but an advised speed of 130 km/h. About half of the motorways in Germany have a speed limit of 120 km/h or lower.

Source: www.logitravel.com, Best Point Project (2011) Deliverable 1, Vlaminck (2012), PIN Flash 16, www.guardian.co.uk, www.anwb.nl, www.novinite.com, justlanded.com, www.politsei.ee, www.news.cyprusdriving.net, ETSC Country Report Latvia, www.fyidenmark.com, www.Trafficfines.eu

Next we focus on the monitoring and enforcement of speeding offenses (table 3). We report the speed limit for different road types, whether there is a drivers' license point system in place, the type of liability system, the number of speed tickets per 1000 inhabitants (both police checks and camera)[14] and the percentage of people speeding[15]. Only 7 countries have no point system in place (Belgium, Estonia, the Netherlands, Portugal, Slovenia, Finland and Sweden). Of the 17 countries of which the liability system is well-documented, only 5 have a fault based system, while 12 have a strict liability rule. As systems differ very much between countries, we opted to show only the fine for minor offenses – without taking into account differences in definition for these minor offenses[16].

The speed limit in built up areas is mostly 50 km/ h or lower in special zones (inside cities, near schools, etc.). On motorways the speed limit varies between 100 and 130 km/h, with a slight dominance of the 130 km/h regime. For the regional roads the variance is much higher – between 60 and 110 km/h, although the 90-100 occurs most frequently. Our indicator for the probability of detection (the number of speed tickets per 1000 inhabitants) is on average 95 tickets per 1000 inhabitants. The lowest number of speed tickets is found in Latvia (10), and the highest number in the Netherlands (558). Given the number of people speeding, we assume that the number of speed tickets is positively correlated with the number of checks and hence an indicator for the level of monitoring. Most speeding takes place in the built-up areas. In addition, we have to take into account that often points are subtracted as well. If we disregard the point system, the average minimum fine for speeding is 65 euro; the lowest fine is 5 euro in Cyprus, the highest fine is given in Slovenia with 250 euro for minor speeding offenses.

4.2 Estimation results

The goal of gathering these data was to see whether our theoretical findings are reflected in reality. To investigate this issue, we estimate a simple two stage least square model.

In the first stage, we estimate the minimum fine as a function of the percentage reporting bicycles as their main mode of transport, the percentage reporting cars as their main mode of transport, the total number of accidents per vkm and the presence of a point system:

$$\text{Fine} = b_0 + b_1(\text{bicycle main mode}) + b_2(\text{car main mode}) + b_3(\text{accident rate}) + b_4(\text{point system}) + e_1$$

Next, in the second stage, we use the predicted minimum fine from the first stage to estimate the detection probability in combination with the percentage reporting bicycles as their main mode of transport, the percentage reporting cars as their main mode of transport and the total number of accidents per vkm:

$$\text{Detection probability} = b_0 + b_1(\text{bicycle main mode}) + b_2(\text{car main mode}) + b_3(\text{accident rate}) + b_4(\text{predicted fine}) + e_2$$

Due to the limited number of observations, the estimation results should be carefully interpreted. We have selected the model with the highest R^2 value and with an F-test significant at the 10% level. Thus the results provide an first attempt to identify the relationships highlighted in the theoretical model.

First, we find that the minimum fine level for speeding is negatively influenced by the presence of point system in a particular country. Thus countries with a point system tend to have lower minimum fine levels. Further, in our dataset we do not observe a statistically significant effect of the accident rate and the relative presence of cyclists and car drivers on the minimum fine level.

Secondly, looking at the detection probability, we find that both the presence of cyclists and the presence of car drivers have a statistically significant positive effect on the probability of detection, while the other explanatory variables are statistically insignificant. The observation that the probability

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[14] For most countries the data are taken from PIN Flash 16 background tables. For Belgium the source is Vlamink (2012), for the UK the website of the Guardian (2008) and for Germany we made an estimation using the data from Kraftfahrt-Bundesamt (2012) on the number of offences above 20 km/h and assuming that this represents 1/3 of all offences.

[15] Source: PIN Flash 16 background tables

[16] For most countries the source is either www.logitravel.com or www.anwb.nl. For BG www.novinite.com, for CZ www.justlanded.com, for EE www.politsei.ee, for CY www.news.cyprusdriving.net, for Latvia the ETSC country report, for DK www.fyidenmark.com, for AT and LUX www.trafficfines.eu. If the fines were reported in the national currency, they were converted using www.xe.com (December 2012).

of detection increases with the importance of cycling is not what we expected based on the model's predictions. We expected a higher fine and a lower probability of detection, for a given expected fine, in countries with more vulnerable road users – reflected by the share of people stating that biking is their main mode of transport. One likely explanation would be that the expected fine is not comparable in the different countries. Finally, the observation that the detection probability increases with the relative importance of care drivers is in line with the model's predictions, at least for a given expected fine.

Table 4: Estimation results

First stage	Dependent variable **= Minimum fine**		
	Coefficient	Standard error	p-value
Bicycle main mode	-209.41	216.39	0.352
Car main mode	-19.29	95.56	0.842
Accident rate	-18.18	15.37	0.251
Point system	-97.63	37.94	0.019
	Number of obs. = 24 F(4,19) = 2.51 Prob>F = 0.0763 R-squared = 0.3455 Adj R-squared = 0.2077		
Second stage	Dependent variable **= Detection probability**		
	Coefficient	Standard error	p-value
Bicycle main mode	1099.17	324.92	0.001
Car main mode	314.22	167.75	0.061
Accident rate	19.59	29.60	0.508
Predicted minimum fine	-0.1775	0.7002	0.800
	Number of obs. = 24 F(4,19) = 13.36 Prob>F = 0.0096 R-squared = 0.3910		

5 Conclusions

In the context of road safety and more specifically speed limits, we developed a model that represents the preferences of different lobby groups. In the model, the lobby groups can select different combinations of the detection probability and the fine level. We showed that, in general, vulnerable road users (cyclists, pedestrians) prefer a higher expected fine than strong road users (car and truck drivers). If we focused on the choice between the magnitude of the fine and the detection probability for a given fixed expected fine, we found that the vulnerable road users prefer a higher fine and a lower detection frequency than the strong road users. This model cannot only be used to explain current policy in one country, but it could also serve to clarify differences in policy between countries or regions.

Therefore, we made a first attempt to investigate the differences in monitoring and enforcement strategy in the European Union for speeding offenses. To study the variation in policies, we looked at the shares of vulnerable and strong road users, the accident probabilities and the type of enforcement policy in place. We can make three observations. Firstly, there is a lot of variation in the enforcement strategies. Secondly, as theory suggests, the level of the fine decreases, as the probability of detection increases. Thirdly, we do not find evidence of the influence of interest groups on the choice of detection probabilities versus fine levels. However, we do observe an increase in the expected fine in countries in which vulnerable road users occupy a large share of road use.

Furthermore, the analysis is not restricted to the setting of fines and probability of detection for speeding, nor is it limited to vulnerable versus strong road users. Other types of (road) users such as freight versus passenger transport, pedestrians versus cyclists, etc. can be discussed as long as their objective functions can be clearly defined. It can also provide additional insights into the political processes that determine the monitoring and enforcement strategies for, for example, environmental legislation.

Note that we did not discuss the political process behind the objective function of the government as this is beyond the scope of this paper. Furthermore, we did not take into account any equity effects the enforcement policy may have; nor did we consider the case where all users are – to some extent – risk averse. Finally, we assumed that the fine revenues were redistributed in a lump sum fashion. In reality, these revenues are often earmarked. If, for example, all revenue is used for investments in traffic safety, this lowers the general accident risk and hence creates an additional incentive for the vulnerable road users to set the expected fine at revenue maximizing levels.

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Bijlagen - Appendix

1. Benchmark

Social welfare equals:

$$
\begin{aligned}
SWF &= NV = NY + NL + J_v V_v + \frac{J_c}{t_2 - t_1}\left[\int_{t_1}^{\tilde{t}} V_c\left(comply\right)dt + \int_{\tilde{t}}^{t_2} V_c\left(speed\right)dt\right] \\
&= NY + NL + J_V\left[\gamma_v - p\left(s\right)h\right] + \frac{J_c}{t_2 - t_1}\int_{t_1}^{\tilde{t}}\left[\gamma_c - C_T\left(t,s\right) - C_M\left(s\right)\right]dt \\
&+ \frac{J_c}{t_2 - t_1}\int_{\tilde{t}}^{t_2}\left[\gamma_c - C_T\left(t,s\right) - C_M\left(s\right) - \pi R\left(F\left(s\right)\right)\right]dt
\end{aligned}
$$

The first order condition for the detection probability is:

$$
\frac{dSWF}{d\pi} = \left[\begin{array}{l}
\underbrace{J_v\left[-\frac{dp\left(s\right)}{d\pi}h\right]}_{\text{decreased accident cost}} + \underbrace{\frac{J_c}{t_2 - t_1}\left(\int_{\tilde{t}}^{t_2}\left[\left(f + v\left(s - \bar{s}\right)\right) + \pi v\frac{ds}{d\pi} - C^V_E\right]dt - \pi C^V_E\frac{d\tilde{t}}{d\pi}\right)}_{\text{change in government revenues from fines}} \\
\underbrace{+\frac{J_c}{t_2 - t_1}\int_{\tilde{t}}^{t_2}\left[\begin{array}{l} -\frac{dC_T(t,s)}{d\pi} - \frac{dC_M\left(s\right)}{d\pi} - \pi\left[\alpha + \beta\left(f + v\left(s - \bar{s}\right)\right)v\frac{ds}{d\pi}\right] \\ -\left[\alpha\left(f + v\left(s - \bar{s}\right)\right) + \frac{\beta}{2}\left(f + v\left(s - \bar{s}\right)\right)^2\right]\end{array}\right]dt}_{\text{change trip costs}}
\end{array}\right] = 0
$$

Replacing the expression for the lump sum transfer *L*, we have:

$$
\left[\begin{array}{l}
\underbrace{J_v\left[-\frac{dp\left(s\right)}{d\pi}h\right]}_{\text{decreased accident cost}} + \underbrace{\frac{J_c}{t_2 - t_1}\int_{\tilde{t}}^{t_2}\left[-\left[\alpha\left(f + v\left(s - \bar{s}\right)\right) + \frac{\beta}{2}\left(f + v\left(s - \bar{s}\right)\right)^2\right]\right]dt}_{\text{disutility fine}} \\
\underbrace{+\frac{J_c}{t_2 - t_1}\left(\int_{\tilde{t}}^{t_2}\left[\left(f + v\left(s - \bar{s}\right)\right) + \pi v\frac{ds}{d\pi} - C^V_E\right]dt - \pi C^V_E\frac{d\tilde{t}}{d\pi}\right)}_{\text{change in government revenues from fines}}
\end{array}\right] = 0 \qquad \forall s \geq \bar{s}
$$

Next, the fixed fine is determined by the following expression:

$$
\frac{dSWF}{df} = \left[\begin{array}{l}
\underbrace{J_v\left[-\frac{dp\left(s\right)}{df}h\right]}_{\text{decreased accident cost}} + \underbrace{\pi\frac{J_c}{t_2 - t_1}\left[t_2 - \tilde{t} - C^V_E\frac{d\tilde{t}}{df}\right]}_{\text{change in government revenues from fines}} \\
\underbrace{+\frac{J_c}{t_2 - t_1}\int_{\tilde{t}}^{t_2}\left[-\frac{dC_T(t,s)}{df} - \frac{dC_M\left(s\right)}{df} - \pi\left[\alpha + \beta\left(f + v\left(s - \bar{s}\right)\right)v\frac{ds}{df}\right]\right]dt}_{\text{change in trip costs}}
\end{array}\right] = 0
$$

Hence, using equation (4), the socially optimal *f* is determined by equating the change in government revenues to the decrease in accident costs.

$$\underbrace{J_v\left[-\frac{dp(s)}{df}h\right]}_{\text{decreased accident cost}}+\underbrace{\pi\frac{J_c}{t_2-t_1}\left[t_2-\tilde{t}-C_E^V\frac{d\tilde{t}}{df}\right]}_{\text{change in government revenues from fines}}=0 \qquad \forall s\geq\overline{s}$$

The socially optimal variable fine *v* is determined in a similar way as the fixed fine *f.*

$$\frac{dSWF}{dv}=\underbrace{J_v\left[-\frac{dp(s)}{dv}h\right]}_{\text{decreased accident cost}}+\underbrace{\pi\frac{J_c}{t_2-t_1}\left[\int_{\tilde{t}}^{t_2}\left(s-\overline{s}\right)dt-C_E^V\frac{d\tilde{t}}{dv}\right]}_{\text{change in government revenues from fines}}=0 \quad \forall s\geq\overline{s}$$

2. Vulnerable road user lobby

The detection probability is determined by:

$$\underbrace{J_v\left[-\frac{dp(s)}{d\pi}h\right]}_{\text{decreased accident cost}}+\underbrace{\frac{J_c}{t_2-t_1}\left(\int_{\tilde{t}}^{t_2}\left[\left(f+v\left(s-\overline{s}\right)\right)+\pi v\frac{ds}{d\pi}-C_E^V\right]dt-\pi C_E^V\frac{d\tilde{t}}{d\pi}\right)}_{\text{change in government revenues from fines}}=0$$

The fixed fine that is preferred by the vulnerable road user lobby is determined by:

$$\frac{dOBJ(0,1)}{df}=\underbrace{J_v\left[-\frac{dp(s)}{df}h\right]}_{\text{decreased accident cost}}+\underbrace{\pi\frac{J_c}{t_2-t_1}\left[t_2-\tilde{t}-C_E^V\frac{d\tilde{t}}{df}\right]}_{\text{change in government revenues from fines}}=0 \qquad \forall s\geq\overline{s}$$

The variable fine in this scenario is found by solving:

$$\frac{dOBJ\left(0,1\right)}{dv}=\underbrace{J_v\left[-\frac{dp(s)}{dv}h\right]}_{\text{decreased accident cost}}+\underbrace{\pi\frac{J_c}{t_2-t_1}\left[\int_{\tilde{t}}^{t_2}\left(s-\overline{s}\right)dt-C_E^V\frac{d\tilde{t}}{dv}\right]}_{\text{change in government revenues from fines}}=0 \qquad \forall s\geq\overline{s}$$

3. Strong road user lobby

The optimal detection frequency is derived from:

$$\left[\begin{array}{l}\underbrace{\frac{J_c}{t_2-t_1}\int_{\tilde{t}}^{t_2}\left[-\left[\alpha\left(f+v\left(s-\overline{s}\right)\right)+\frac{\beta}{2}\left(f+v\left(s-\overline{s}\right)\right)^2\right]\right]dt}_{\text{distutility fine}}\\ +\underbrace{\frac{J_c}{t_2-t_1}\left(\int_{\tilde{t}}^{t_2}\left[\left(f+v\left(s-\overline{s}\right)\right)+\pi v\frac{ds}{d\pi}-C_E^V\right]dt-\pi C_E^V\frac{d\tilde{t}}{d\pi}\right)}_{\text{change in government revenues from fines}}\end{array}\right]=0 \quad \forall s\geq\overline{s}$$

The first order conditions for the fixed and variable fine parameters are:

$$\frac{dOBJ(0,0)}{df}=\underbrace{\pi\frac{J_c}{t_2-t_1}\left[t_2-\tilde{t}-C_E^V\frac{d\tilde{t}}{df}\right]}_{\text{change in government revenues from fines}}=0 \quad \forall s\geq\overline{s}$$

$$\frac{dOBJ(0,0)}{dv}=\underbrace{\pi\frac{J_c}{t_2-t_1}\left[\int_{\tilde{t}}^{t_2}\left(s-\overline{s}\right)dt-C_E^V\frac{d\tilde{t}}{dv}\right]}_{\text{change in government revenues from fines}}=0 \quad \forall s\geq\overline{s}$$

Het Steunpunt Verkeersveiligheid 2012-2015 is een samenwerkingsverband tussen de volgende partners: