Assessing the Impact of Deterrence on Road Safety due to the Demerit Point System

Chandler, Vincent

Queen's University (Kingston, Canada)

June 2012

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Vincent Chandler [1]
chandlev@econ.queensu.ca

Department of Economics
Dunning Hall, Room 333
94 University Avenue
Queen's University
Kingston, Ontario
K7L 3N6

Abstract

This paper assesses the impact of demerit points on the probability of traffic violation of drivers. To address the heterogeneity of drivers, I use the expiration process of points to compare the behaviour of similar drivers with different demerit points. I find that the threat of losing a driver's license affects only drivers close to the limit, but reduces their probability of violation by 50 to 80 percent.

JEL Codes: K32, K42, Z18

June 2012

[1]The author wishes to thank the SAAQ for providing the data, and especially the help from Francois Tardif. I also acknowledge useful comments from Steve Lehrer, Susumu Imai, Robin Boadway, and the QED Empirical Economics Reading Group. This project was undertaken with the financial support from the Ontario Graduate Scholarship

1 Introduction

In the judicial system, the threat of punishment is used to make sure citizens abide by the law. For drivers, this punishment takes the form of a fine. For drivers in a country implementing a demerit point system, an accumulation of fines leads to a greater punishment: the revocation of their license. Bourgeon and Picard (2007) study theoretically this type of incentive structure, and show that the demerit point system removes bad drivers from the road and reaches a social optimum. Pulido et al. (2010) find that the introduction of demerit points in Spain in 2006 reduced the road-related mortality by 14.5 percent [2]. Dionne et al. (2011) provide some micro-empirical evidence that drivers closer to the limit adopt a safer behaviour and have a lower probability of violation. To do so, they compare the average residual probability of traffic violation of drivers with 7 points with the one of drivers with 9 points, and determine that this risk decreases by 20 percent over the interval. If drivers with 7 and 9 points were homogeneous, then this difference in probability would reflect the impact of an increase in the number of points on the behaviour of drivers. However, since drivers with 7 points are probably safer drivers than those with 9 points, this difference is only a lower bound for the actual impact of deterrence. This heterogeneity problem is omnipresent in the literature on the impact of deterrence (e.g. Helland and Tabarrok, 2007).

The objective of this paper is to address this heteogeneity and assess the impact of demerit points on the behaviour of drivers. To do so, I use the expiration of traffic violations after two years as a quasi-exogenous variation in the number of points: two similar drivers have the same number of points at time "t". Due to the timing of their violations, some points of one driver will expire, while the other driver will keep the same number of points. In that sense, two ex-ante similar drivers now have a different number of demerit points at time "t+1". By comparing the probability of violation of both groups for a given number of demerit points, I can assess the impact of the number of demerit points on the probability of violation. Using this method, I find that for drivers with 10 points a decrease of 3 points leads to an increase of 50 percent in the probability of violation. For drivers with 14 points, a decrease of 3 points increases the probability of violation by 80 percent.

To determine this impact, this paper uses the administrative dataset of

[2]This result could be invalid, because the authors are using ARIMA on a non-stationary time series

the Societe d'Assurance Automobile du Quebec (SAAQ) which contains the records of almost 3 million drivers between 1998 and 2010. Such a large sample size is necessary for this study, because the most interesting drivers are those who are close to the maximum number of points, and they tend to be relatively rare. Dionne et al. (2011), for example, only have 16 drivers (0.04% of a sample of 40 000) with 13-14 points. In comparison, this study can rely on almost 20 000 observations in the same range to produce reliable estimates of the effects of demerit points on driving behaviour.

2 Basic Model

Before discussing the details of the data and the empirical strategy, it is important to present an outline of the theoretical framework. Dionne et al. (2011) develop a model where the driver "i" maximizes her value function using her driving effort (e). An increase in her level of effort decreases her probability of being caught ($q(e)$) and her instantaneous utility. The change in probability is self-explanatory, but the change in instantaneous utility could be more problematic. The idea is that most violations are due to speeding, burning red lights or not stoping at a stop sign (Tardif, 2010). All of these violations allow the offender to arrive faster at destination which increases the instantaneous utility of drivers. If drivers are caught, they pay a fine, and accumulate a demerit point (p). Abstracting from the expiration of points, the general Bellman equation can therefore be expressed as:

$$W_i(p) = max_e\ \phi_i(e) - q(e)fine + q(e)\beta W_i(p+1) + (1-q(e))\beta W_i(p) \quad (1)$$

Dionne et al. (2011) show in a continuous time setting that effort will increase as drivers get closer to the limit. This model provides a testable prediction: drivers with more points should drive more carefully and have a lower probability of violation all things being equal.

3 Data and Methodology

3.1 Dataset

To test this prediction, I use data from the administrative database of the Societe d'Assurance Automobile du Quebec (SAAQ), a public monopoly whose mission is to provide insurance protection against bodily harm for Quebecers. To reduce the number of accidents and claims, the SAAQ introduced a demerit point system in 1978, according to which drivers accumulate points for each traffic violation. The number of points given for a violation is a function of its severity[3]. The system also allows a decumulation of points. After two years, points expire. For example, if a driver is found guilty of a 2-point offense on January 1st 2008, the two points will be removed from the driver's file on January 1st 2010. If a driver accumulates 15 points or more, her driving license is revoked. To regain the right to drive, a driver needs to wait a certain period of time before she can reapply for a license, and attempt the theory and practice exams.

The data set used in this study contains all the traffic violations and license revocations between 1998 and 2010. For each traffic violation, there is a unique identifier for the driver, the number of points lost, the date of the violation and the date of the conviction. The number of violations per year ranged from 563 964 in 2000 to 1 035 031 in 2007. For each license revocation, I have a unique identifier and the date of the revocation. The number of revocations ranged from 11 107 in 2000 to 29 985 in 2009. Finally, the data also contains some limited information on the drivers: their gender and date of birth.

4 Methodology

The traffic violations serve as a proxy for the behaviour of drivers. Similarly to Dionne et al. (2011) I make the assumption that the probability of being caught is a function of the driver's behaviour. If drivers decrease their probability of being caught, I infer that they must have improved their driving behaviour. One could, however, imagine that drivers use tricks to avoid tickets and nullify this relationship as Iyengar (2007) documents for the three-strikes policy in California . Drivers could, for example, avoid major highways and drive on country roads to avoid police control. Since most violations are due to speeding (Tardif, 2010), this strategy would be counterproductive, because it would probably lead to an overall longer commute time. There is therefore no reason to expect this kind of avoidance behaviour. Another strategy would be to let a spouse or a friend drive. If the probability of an accident is reduced by changing the driver, then this strategy is beneficial to society. Whether drivers drive more safely, ask a safer driver to replace them or take public transportation, the result for society is the same: fewer accidents. In that sense, a reduction in the probability of violation is a

[3]Table 1 presents the number of points for the most common violations

valid proxy for the social gains attained through the demerit point system.

To estimate the impact of demerit points on the probability of violation, I use the expiration of points to compare the behaviour of similar drivers with a different number of points. Of the drivers with a given number of points at time "t", some of them have a violation that will expire at time "t+1", and other do not. The number of points of the drivers in the first group (treatment) will therefore decrease in the next period, while the number of points of the second group will stay constant (control). If this variation were exogenous, it would be simple to compare the behaviour of both groups and attribute any difference in the violation probability to the change in the number of points. This variation is, however, not exogenous. Indeed, drivers are not randomly convicted of violations. Only drivers who are in violation of the law when driving can be arrested. The two groups could therefore differ in their driving behaviour and driving pattern.

Dionne et al. (2011) show theoretically that drivers with the same number of points tend to have a similar driving behaviour. In that sense, if both groups of drivers had the same distribution of points at the time of the conviction, they must have had a similar behaviour at that time. Figures 1 and 2 show the distribution for drivers with 3 and 6 points in 2010 respectively. The two graphs show important difference between both types of drivers. Figures 1 to 5 show the same distribution for drivers with 10, 11, 12, 13 and 14 points, respectively. Contrary to figures 1 and 2, the distributions for both groups are very similar. If the distribution of points was the same, then the average behaviour must have been the same. Given the same behaviour, some drivers were randomly arrested and others not. In that sense, condition on a certain number of points at time "t", the difference between the treatment and control groups was random, which speaks for an exogenous variation.

Figures 1 to 7

Drivers may have had the same behaviour, but there could be some seasonality in the number of kilometres driven. If two drivers have the same behaviour, but one drives more than the other, then the latter has a higher probability of being arrested. It could therefore be that drivers who were caught two years before the reference date simply drove more. If, for example, a certain group of drivers always goes on a long car trip in July-August, their probability of having a traffic violation is much higher in July-August.

Furthermore, since the violations are redeemed after exactly two years, their probability of having points redeemed in July-August is also higher. This type of seasonal behaviour would lead to a spurious positive relationship between points expiring and the probability of a violation. The first event does not cause the second; both are caused by a third event, the seasonality of the driving behaviour. Such a phenomenon is unlikely to affect the results, because there is no reason why this kind of behaviour should be more frequent at a certain number of points. Why would drivers with 5 points have this kind of behaviour and drivers with 10 not? In that sense, differences in coefficients across the number of points should eliminate this problem.

If all the drivers in the sample had a valid license throughout the period, these two issues would be the only two empirical challenges. Unfortunately, every month, new licenses are issued. Since the dataset only contains violations, it is impossible to say whether a lack of previous violations is synonymous with a good behaviour or with the fact that a driver did not previously hold a valid license. This ambiguity could affect the comparison between drivers whose points expire and those whose points do not, because the treatment group clearly had a valid license two years ago. The control group, however, might not have had a violation at that time, because they did not have a valid license at the time. If this were the case, the treatment and control groups would be significantly different; the former would have more driving experience than the latter. In such a case, one would expect less experienced drivers (control) to be more prone to dangerous driving than experienced drivers (treatment). Consequently, I would find that treated drivers are less likely to commit a violation, even though they have fewer points. Since I expect the opposite relationship, this empirical issue would only reduce the magnitude of the coefficient and produce more conservative estimates. If this problem is substantial, it will be so for drivers with a small number of points. It is indeed unlikely that many new drivers manage to accumulate enough points in a short period of time to be part of the sample of drivers with more than 10 points who are the focus of the analysis. To prevent this potential problem, I exclude all drivers that lost their license between 2006 and 2010 from the analysis. Furthermore, I remove all drivers aged between 16 and 24 in 2010 from the sample. By removing both groups, I am reducing the chance that treated drivers were different from the control in that the latter were driving in 2008 while the former were not.

The lack of data on the status of drivers does not only reduce the information on past driving, it also affects the information on present driving. No violation could mean that the driver did not commit any violation or it could mean that a driver emigrated or stopped driving. If a driver leaves the province, she will not accumulate any further points on her Quebec driver's license, but she might still have demerit points at a given point in time. If drivers whose points expire have a higher probability of leaving the province, what appears to be a reduction in the probability of violation could simply be an increase in the emigration probability. The only way through which drivers can escape the scrutiny of the SAAQ is by leaving the province. If they do so, they will probably move to another province. In 2008, about 25 000 people left Quebec for another province (Statistics Canada, 2011). This number is small, and there is no reason to believe that the number of demerit points was correlated with the emigration decision, meaning that very few of these people would have many demerit points. In that sense, the impact of emigration on the results is probably minuscule.

The previous discussion has highlighted some potential empirical issues that could jeopardize the comparison between both groups, but none of these challenges actually poses a threat to the validity of the results. To undertake this comparison, I need to calculate the number of points of a driver at a reference date, whether some points are redeemed over a certain period, and whether the driver committed a traffic violation within a certain period. With this information, I can study two situations in which the expiry of points could affect the behaviour of drivers. In the first one, the expiry of points in "t" could affect the driving behaviour in "t+1", in the second one an expected expiry of points in "t+1" could modify the driving behaviour in "t".

Figure 8 shows the timeline of events in the first scenario. To calculate the number of demerit points of a given driver at a reference date "t", I sum the points accumulated through convictions between "t-24" and "t". If a person was convicted of a violation in period "t-24", those points will expire in "t", so I can distinguish between "treated" and "control" drivers. For a given number of points in "t", I then compare the probability of a violation committed in the period "t+1" between both groups. As an example, I calculate the number of points as of April 1st 2010. I then determine the drivers whose points will expire during the month of April, ie the drivers who were convicted of a violation in April 2008. I then compare the probability of violation in May and June 2010 for the two types of drivers.

Figure 8

Figure 9 shows the timeline of events for the second scenario. I calculate the number of points the same way as I did in the first scenario. I then determine which drivers will redeem points in period “t+2” and create both groups. Finally, I compare the behaviour of both groups in “t+1” for a given number of points in , I also study the impact of the expectation of expiry of points on the behavior of drivers. Figure 2 shows the timeline. Now instead of taking the period after the redemption to compare the behaviour of drivers, I consider the period before the redemption. If drivers expect to redeem points, they could change their behaviour before the redemption actually takes place.

Figure 9

Instead of simply comparing the probabilities, I control for certain drivers' characteristics in the following probit regression:

$$\text{Violation} = \beta_0 + \beta_1\text{Treatment} + \beta_2\text{Age Dummies} + \beta_3\text{Male} + u_t \qquad (2)$$

The variables involved in the regression are hereby defined:

- **Violation** is a dummy variable which indicates whether a violation was committed in the two months following (first scenario) or preceding (second scenario) the month of the expiration of points. Since this variable is binary, there is no indication of the severity of the violation through the number of points.

- **Treatment** is a dummy variable, which takes the value of 1 for those drivers who had 3 points expire during the month “t” and takes the value 0 if the driver did not have any point expire in the same month. I chose an expiration of 3 points for two reasons. First, it is has a certain salience for the driver and is therefore more likely to affect the behaviour. Second, a 3-point violation is the most frequent violation (Tardif, 2010) thus providing a large enough sample of drivers with points expiration to reject the null hypothesis.

- **Age Dummies** are created for the following age groups: 25-34, 35-44, 45-54, 55-64 and more than 65. Since younger drivers tend to have a higher probability of violations, it is important to control for age.

- **Male** equals 1 for male and 0 for female. Since males tend to commit more violations, it is important to control for gender.

This probit regression is performed separately for each number of demerit points. One would expect the coefficient for treatment to be larger for drivers with many points than for drivers with few points, because the difference in points probably matters more for drivers closer to the limit than for those further away. This relationship between the value of the coefficient and the number of points of the drivers in the sample will shed some light on the relationship between driving effort and the number of points stated by Dionne et al. (2011). If effort is constant across the number of points, then my results will validate the assumptions from Bourgeon and Picard (2007) according to whom drivers do not change their behaviour as a function of their total number of demerit points.

To increase the power of the rejection tests, I pool reference dates. I calculate the number of points, identify the redeemed and non-redeemed groups, and observe the violation at four reference dates: January 1st, April 1st, July 1st and October 1st 2010. I then pool the observations together, and perform regression (1) for each number of demerit points.

5 Results

Before considering the results of the probit regressions, let us first study the relationship between the number of points and the probability of violation. Without any deterrence, this function should be increasing: the worst drivers accumulate the most points, and they have a higher propensity to commit violations than the ones with few points. With deterrence, drivers tend to be more careful as they approach the limit which reduces their propensity to commit violations. If the deterrence effect is stronger than the self-selection, there could be a decrease in the probability of violation in the neighbourhood of the limit as suggested by Abbring et al. (2003) as moral hazard. Figure 10 shows this relationship. It would seem that there is a positive relationship up to 8 points. Afterwards, the probability of violation remains fairly constant at 9 percent. This graphic would speak for some deterrence starting at 9 points, but it is difficult to determine its magnitude.

Figure 10

The probit regressions offer a more robust analysis of the impact of deterrence on driving behaviour. As mentioned previously, the number of points could have an impact on the driving behaviour at two moments: before and after the variation. Expecting the expiry of points, drivers could become less careful, because they know that their total number of points will soon decrease. Similarly, drivers could become less careful after the expiration when their total number of point has actually decreased.

5.1 Change of Behavior after the Treatment

Table 2 shows the value of the coefficients on the redemption variable. Two results stand out:

First, the coefficient for treatment is positive and significant in the 9 to 14 points range. This coefficient equals 1 when the number of points of drivers decreases, meaning that a reduction in points leads to an increase in the probability of traffic violation for drivers with a total number of points between 9 and 14. Conversely, this result indicates that drivers change their behaviour and drive more carefully when their total number of points exceeds 9 points. To better understand better the magnitude of the results of table 2, let us compare the actual probability of violation for treated and non-treated drivers at different numbers of demerit points. At 10 demerit points, the probability of violation of drivers who were lost 3 points is 12.2 percent (2 377 obs), while the same probability for those who did not lose points is 8.1 percent (40 778 obs). This difference of 4.1 percent is an increase of 50 percent in the probability of violation. At 14 demerit points, this probability of the redeemed drivers is 10.7 percent (719 obs) while it is 5.9 percent (7 682 obs). In this case, the loss of three points leads to an increase of more than 80 percent in the probability of traffic violation. In both cases, the difference in 3 points is far above the 20 percent reported in Dionne et al. (2011).

Second, there seems to be a significant negative coefficient for drivers with 3 to 6 points. It is hard to understand why drivers whose total number of points decreases would drive more carefully. This counter-intuitive effect could be due to the data problem discussed in the methodology. Drivers whose points did not expire (control) might not have been driving at the time of the expiration. In that sense, treated drivers could be more experienced, and therefore less prone to violations. Since this effect is small in comparison to the positive coefficients between 9 and 14 points, we can safely assume that it is due to imprecise data.

Table 2

These results support the model from Dionne et al. (2011). Overall, there seems to be an improvement in the behaviour of drivers. However, this improvement can only be noticed between 9 and 14 points. For drivers with fewer points than 9, there doesn't seem to be an improvement in the driving behaviour as their number of points increase. It could be that the improvement is so small that it is impossible to capture it through regression analysis or it could be that the function linking the number of points to the effort is flat below 9 points. One reason why behaviors could start changing at around 9 points is that the SAAQ sends a letter informing the driver of her number of points when the driver has reached 7 points. A person with 6 points accumulating 3 points would get the letter, and possibly change her behaviour. With fewer than 7 points, drivers might not be aware of their total number of points nor of the consequences of accumulating 15 points. It is, however, important to know that the SAAQ does not send any letter informing the driver of a reduction in the number of points due to an expiration of points. The evidence from table 2 suggests that drivers are not only aware of the expiry of points but also change their behaviour accordingly.

5.2 Change of Behaviour Before the Treatment

Table 3 shows a picture similar to the one of table 2. Again, drivers start changing their behaviour at around 9 points. The magnitude of the coefficients is similar to the ones of the previous table. It may come as a surprise that the coefficients at 13 or 14 points in table 3 are similar to the ones in table 2. In the previous case, the drivers could afford to gain some points, because they had actually lost the points. In this case, however, the points have not be removed yet, so drivers need to stay below the 15 point limit. The problem is that the limit is not perfectly enforced. It is therefore possible for drivers with 14 points to commit a 2-point violation and not lose their license. The next section will discuss the stringency of the limit.

Table 3

5.3 How Rigid is the Limit?

So far we have assumed that the limit is perfectly enforced: a person with 13 points who drives 33km/h above the speed limit and is caught will accumulate two points and thus lose her license. The actual revocation in Quebec is not as stringent, because new points are not added to the total number of points at the time of the violation, but at the time of the conviction. In other words, it is possible for drivers to delay conviction, wait for some points to expire, plead guilty, and avoid revocation. If drivers use this strategy, the deterrence of the point system loses its power, and could explain why the coefficients of table 2 do not increase when going from 10 points to 14 points and why the coefficient at 14 points is significant in table 3.

To study to which extent drivers act strategically to delay their violation, I conduct a regression explaining the delay between violation and conviction. In the first specification, I only include the total number of points and a dummy variable whether the violation would bring the driver to the limit and lead to a revocation. Since the relationship between the number of points and the delay could be non-linear, I consider a model where I only use dummy variables for the number of points. Finally, I add the revocation dummy to the non-linear model. This variable equals 1 when a violation would bring a driver above the maximum. Table 4 provides evidence for the fact that drivers do use the delay strategically. Drivers threatened by a revocation, for example, take on average three to four months longer to be convicted. Since drivers are probably aware of this possibility, they are probably not deterred as much as they would be if the violation date were used instead of the conviction date. At this point it is impossible to know to which extent the possibility to delay violations affects the deterrence and thus the behaviour of drivers.

Table 4

6 Conclusion

The purpose of this paper is to study the impact of a variation in the number of demerit points on the behaviour of drivers. This task is challenging, because drivers with different number of points are probably also different in other ways. In that sense, when comparing their behaviour, it is impossible to say what causes differences in behaviour: self-selection or deterrence. To address this heterogeneity problem, this paper uses the expiration of points after two years as a quasi-experiment: two similar groups of drivers who had the same number of points now have different number of points in the next period. When comparing the probability of violations of both groups, the analysis suggests that a reduction from 10 to 7 points leads to an increase of 50 percent in the probability of violation, and a reduction from 14 to 11 points increases the probability of violation by 80 percent. These effects are much larger than the 20 percent reported in Dionne et al. (2011) without accounting for heterogeneity. This paper also studies to which extent drivers tend to delay the conviction to avoid revocation.

Further research should investigate how differences in the implementation of demerit point system may change the deterrence of such schemes. Delaying the conviction , for example, may reduce the incentives of drivers to change their behaviour. Comparing coefficients across jurisdictions with different policies could suggest avenues to improve the demerit point system.

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Figure 1: Distribution of Points Two years a before the Expiry (3 Points in 2010)

3 points.pdf

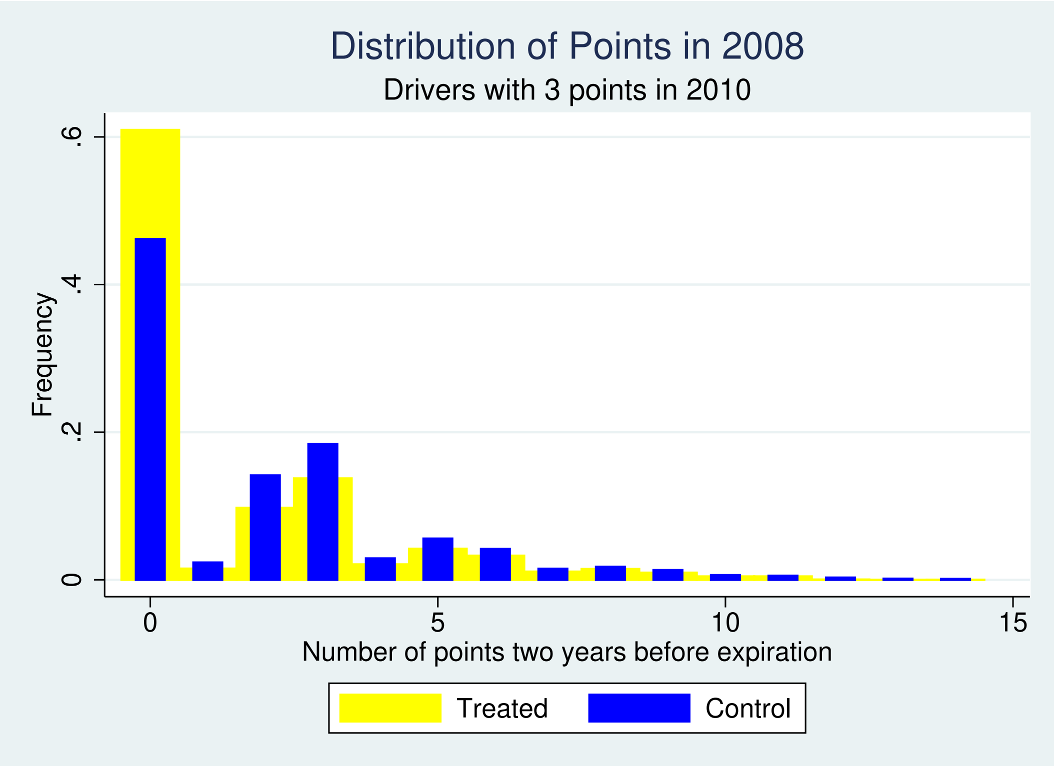

Figure 2: Distribution of Points Two years a before the Expiry (6 Points in 2010)

6 points.pdf

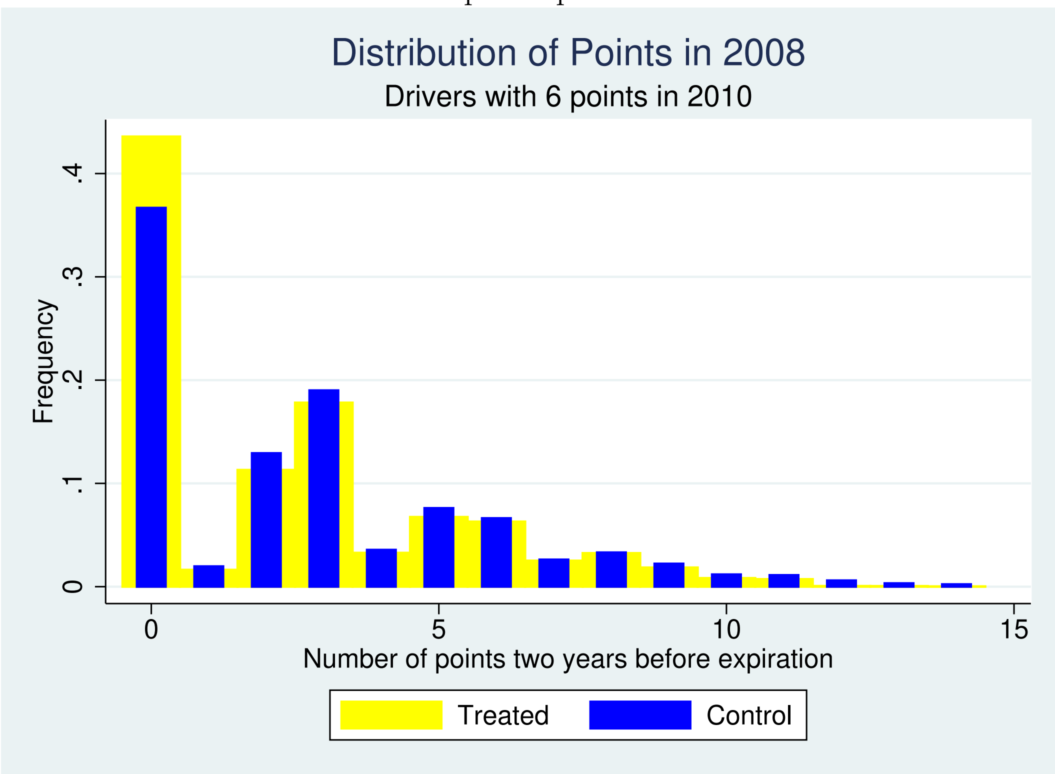

Figure 3: Distribution of Points Two years a before the Expiry (10 Points in 2010)

10 points.pdf

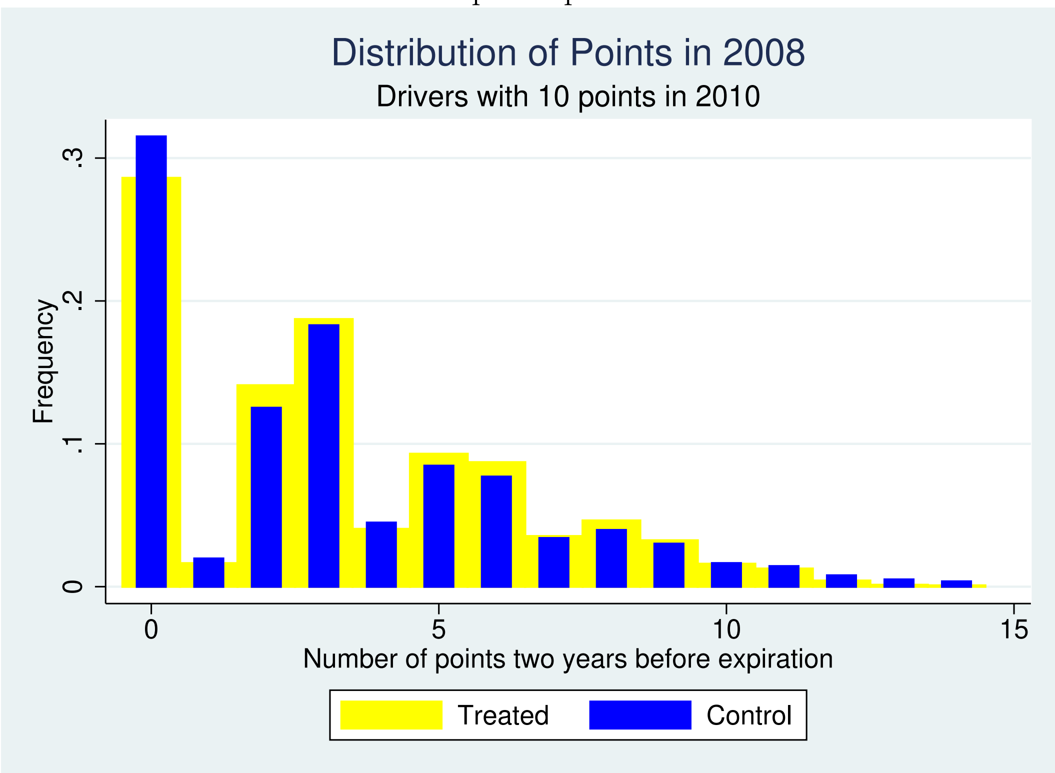

Figure 4: Distribution of Points Two years a before the Expiry (11 Points in 2010)

11 points.pdf

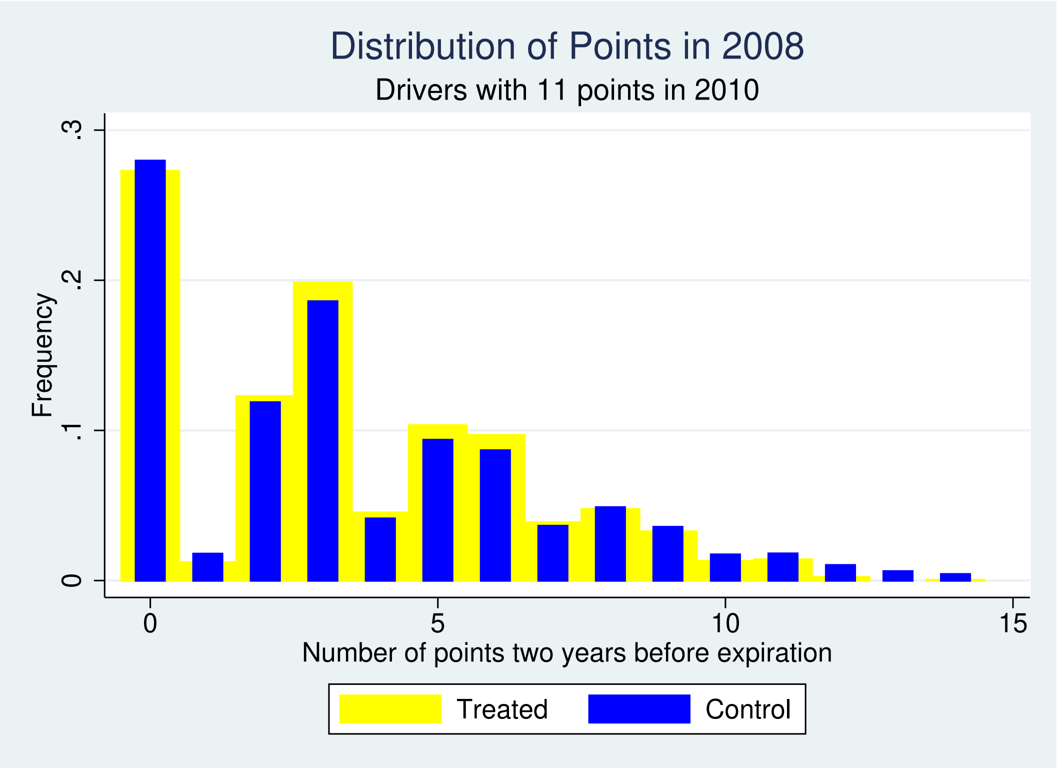

Figure 5: Distribution of Points Two years a before the Expiry (12 Points in 2010)

12 points.pdf

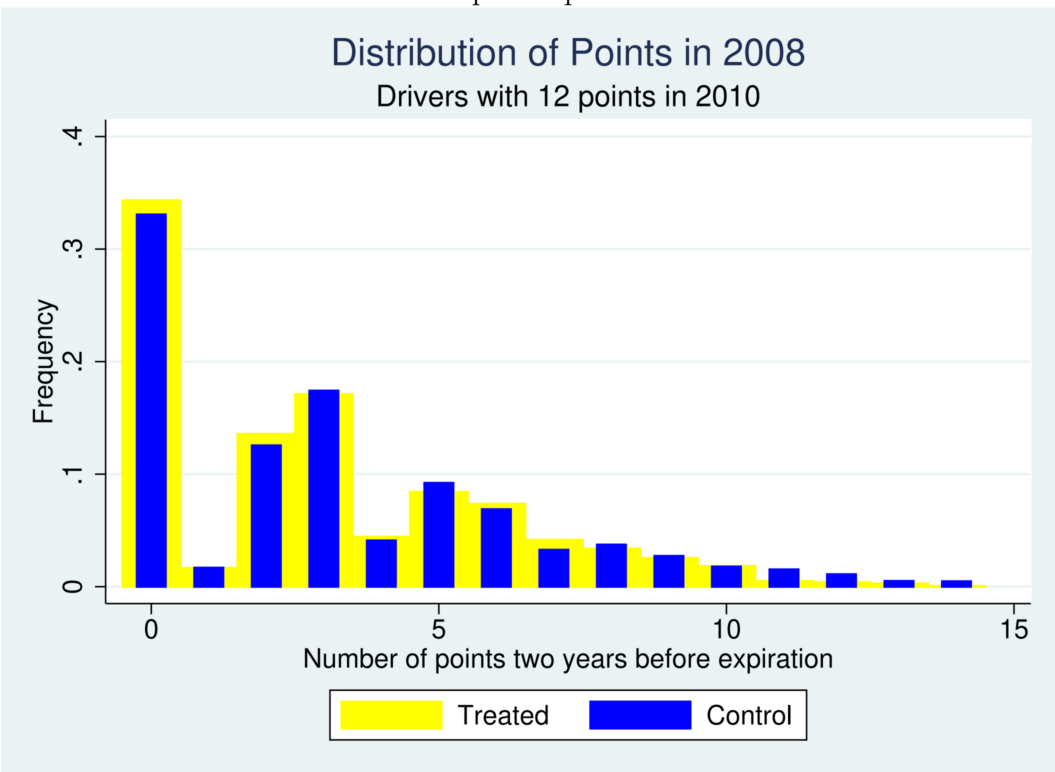

Figure 6: Distribution of Points Two years a before the Expiry (13 Points in 2010)

13 points.pdf

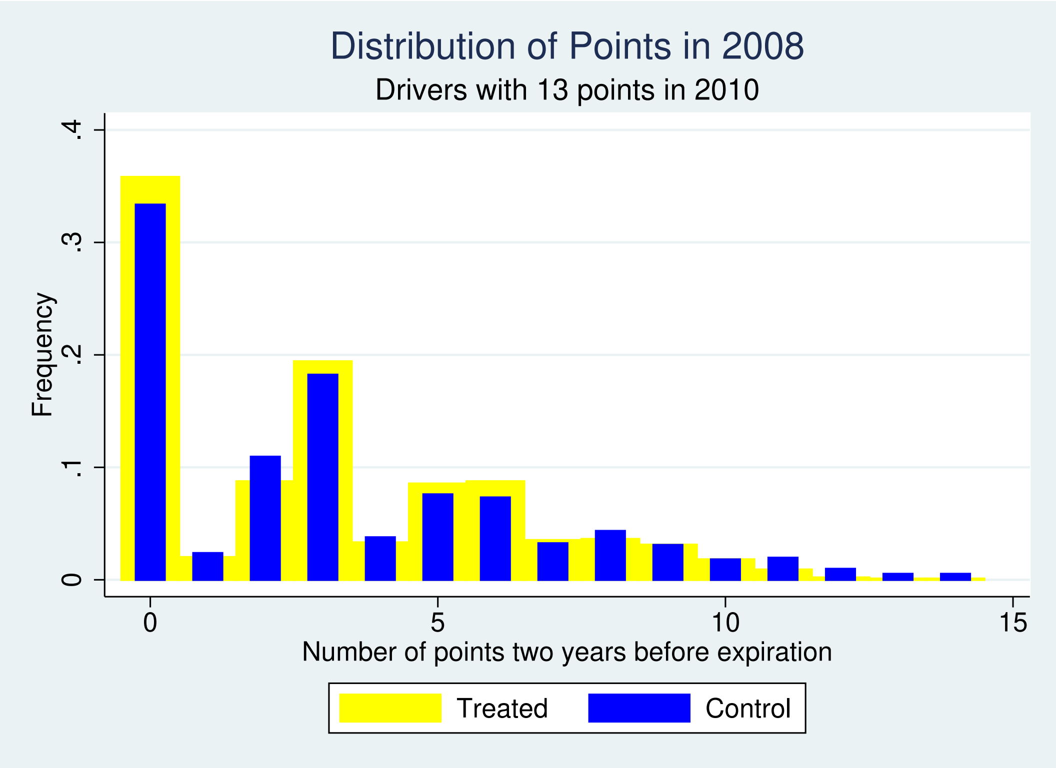

Figure 7: Distribution of Points Two years a before the Expiry (14 Points in 2010)

14 points.pdf

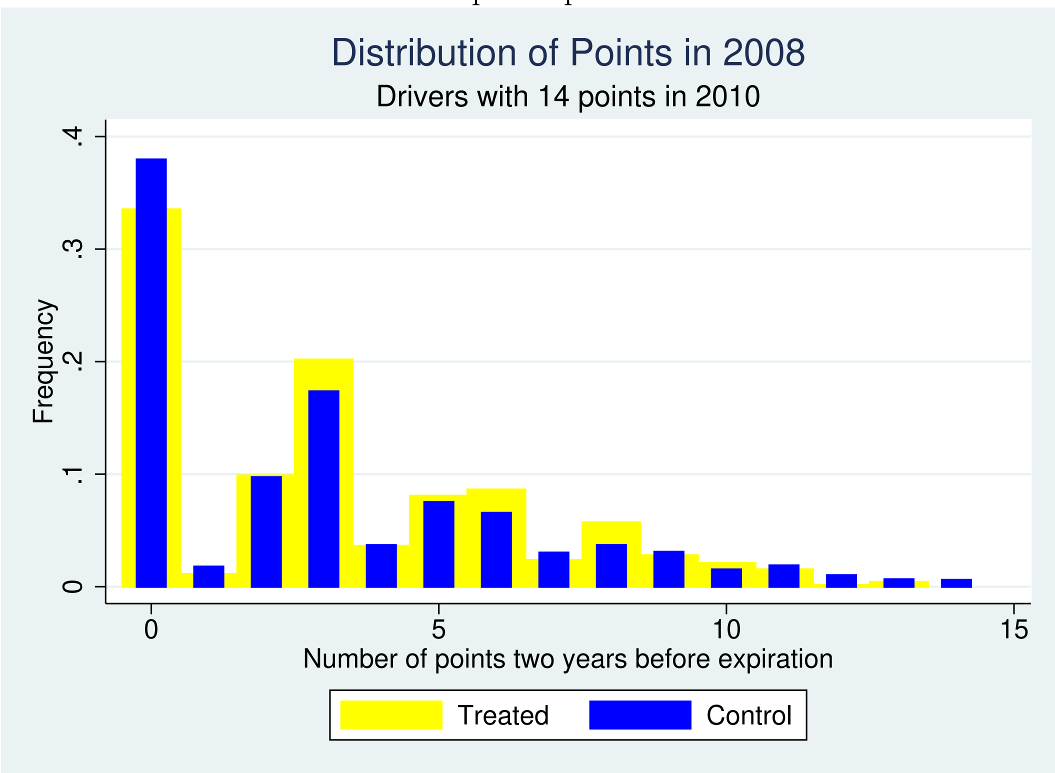

Figure 8: Impact of Treatment on Future Driving Behavior

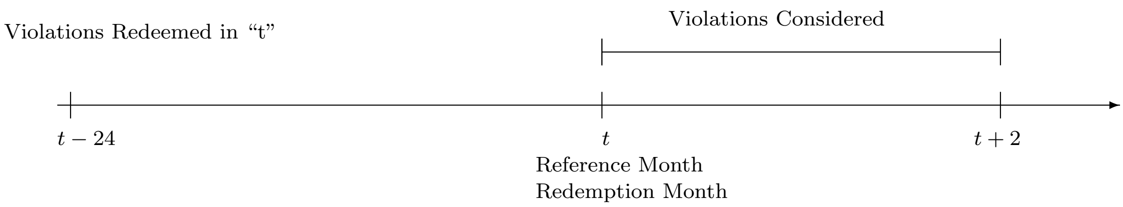

Figure 9: Impact of Expected Treatment on Present Driving Behavior

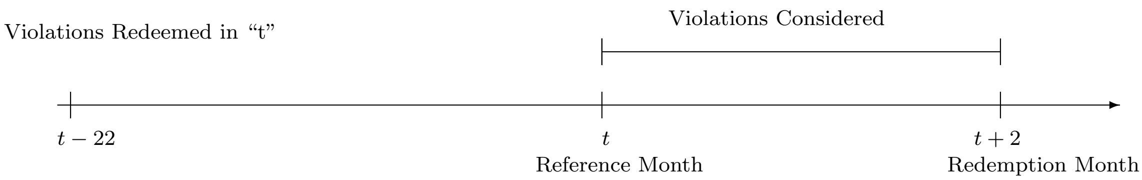

Figure 10: Probability of Violations by the Number of Demerit Points

Violation by Points.pdf

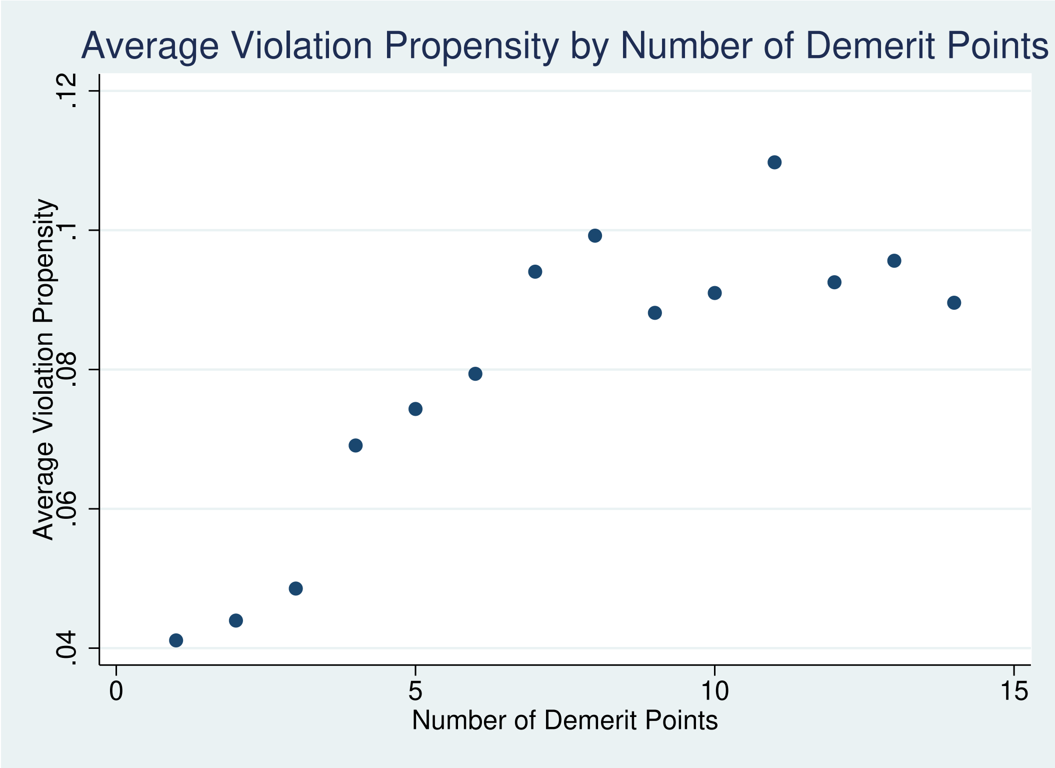

Table 1: Points for Each Violation

Speeding by 11 to 20 km/h	1
Speeding by 21 to 30 km/h	2
Speeding by 31 to 45 km/h	3 or more
Speeding by more than 45 km/h	4 or more
Burning a red light	3
Not stopping at a stop sign	3
Not wearing a seat belt	3

Note: The number of points in the two last categories depend on the speed limit where the driver speeded. For example, a driver speeding by 42 km/h in a 50 km/h zone will have 6 points added to her file.

Table 2: Impact of Redeeming Three Points on the Probability of a Violation in the Following Two Months

Demerit Points	Coefficient on Redemption	t-value	Sample
3	-0.063***	-6.77	1 397 470
4	-0.042	-1.09	243 099
5	-0.040**	-2.42	345 890
6	-0.030**	-2.03	255 385
7	0.002	0.08	92 341
8	-0.009	-0.43	97 177
9	0.109***	4.56	78 468
10	0.238***	6.92	43 155
11	0.081**	2.40	29 446
12	0.149***	3.44	19 899
13	0.24***	4.27	10 825
14	0.314***	4.71	8 401

Note: These numbers are the coefficients on the dummy variable redemption in a probit regression explaining the occurrence of traffic violation (=1) when controlling for age and gender of the driver. * (10 percent), ** (5 percent) and * (1 percent).

Table 3: Impact of Redeeming Three Points on the Probability of a Violation in the Previous Two Months

Demerit Points	Coefficient on Redemption	t-value	Sample
3	-0.037***	-3.59	1 045 302
4	-0.009	-0.20	180 117
5	-0.003	-0.16	257 270
6	-0.008	-0.48	190 025
7	0.012	0.37	68 412
8	-0.028	-1.16	73 385
9	0.115***	4.25	58 339
10	0.198***	4.93	31 891
11	0.109***	2.88	21 820
12	0.246***	5.08	14 604
13	0.142**	2.00	7 879
14	0.331***	4.30	6 221

Note: These numbers are the coefficients on the dummy variable redemption in a probit regression explaining the occurrence of traffic violation (=1) when controlling for age and gender of the driver. * (10 percent), ** (5 percent) and * (1 percent).

Table 4: Evidence of Strategic Behaviour on the Number of Days between Violation and Conviction

	(1)	(2)	(3)
Total Number Points	7.929***		
	(140.95)		
Potential Revocation	108.1***		128.0***
	(61.86)		(46.15)
2 points		11.00***	11.00***
		(23.64)	(23.67)
3 points		20.57***	20.57***
		(48.91)	(48.98)
4 points		28.56***	28.56***
		(31.07)	(31.11)
5 points		30.49***	30.49***
		(45.15)	(45.21)
6 points		41.83***	41.83***
		(54.29)	(54.37)
7 points		57.27***	55.31***
		(49.44)	(47.78)
8 points		62.65***	60.89***
		(58.08)	(56.50)
9 points		82.70***	79.81***
		(64.42)	(62.19)
10 points		111.8***	106.2***
		(65.04)	(61.68)
11 points		122.2***	115.0***
		(68.57)	(64.39)
12 points		150.9***	82.45***
		(66.47)	(30.43)
13 points		181.6***	68.92***
		(62.75)	(18.21)
14 points		195.6***	67.58***
		(59.25)	(15.69)
Constant	57.95***	59.35***	59.35***
	(349.79)	(334.52)	(334.98)
N	760648	760648	760648
r^2	0.042	0.041	0.043

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$