

Estimating Deterrence Effects using Crackdowns: Theory and Evidence

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Definition of Crackdown: policing with high intensity. May be focused on specific time periods, on specific geographic areas, or on specific groups

Crackdown is:

1. *arbitrary*: crackdown groups are not different in their propensity to violate the law
2. *publicized* in advance (before violation takes place)

Examples: sobriety checkpoints, announced speeding controls, crackdowns on drug trafficking aimed at particular neighborhoods

How can *announcing* interdiction be efficient with rational agents?

This paper: crackdowns as optimal strategy under rational behavior

Benefit of crackdowns: an example

100 drivers, of two types: 1. half would speed unless they will be caught with certainty; 2. half will never speed

Type is unobservable to the police; Police can only check 50 drivers

1. Equal treatment:

Each citizen has a probability $1/2$ of being checked

All high-propensity citizens speed \Rightarrow speeding rate is $1/2$

2. Crackdown:

Suppose both types are equally distributed over roads A and B and independent of type (no prima facie reason to target one road over the other)

Police control speed only on one road (say road A)

Then no driver on road A speeds \Rightarrow speeding rate is $1/4$ (vs. $1/2$)

Crackdowns may reduce crime rate

In the example, crackdown: 1. breaks population down into two groups (in general, in two at most); 2. is the optimal policing strategy

For future reference: 1. crackdown did not decrease undetected crime; 2. successful controls decrease with a crackdown

Key assumptions:

1. The characteristic (road) is not manipulable in order to avoid interdiction (application: concentrate on highways)
2. Agents behave rationally (application: many users are high frequency users – commuters)

The Deterrence effect

Using crackdowns to compute the deterrence effect of policing, without observing any variation in police resources. Can perform policy experiment in the absence of exogenous variation of resources.

Consider increase in police manpower by 1 check

- Optimal policing scheme: move one person from the non-crackdown group to the crackdown group (from road B to A)
- Expected decrease in speeding rate: from 25% to 24.5% (using average speeding rate in each group)

Policing intensity of groups does not change, only size of groups

Main model

Population of size 1, heterogeneous in the benefit x from exceeding the speed limit

Benefit x not observed by the police, distributed according to cdf F

T is the fine when caught speeding

Let p denote probability that motorist is policed, $p \in [0, \bar{p}]$. A motorist exceeds the speed limit if

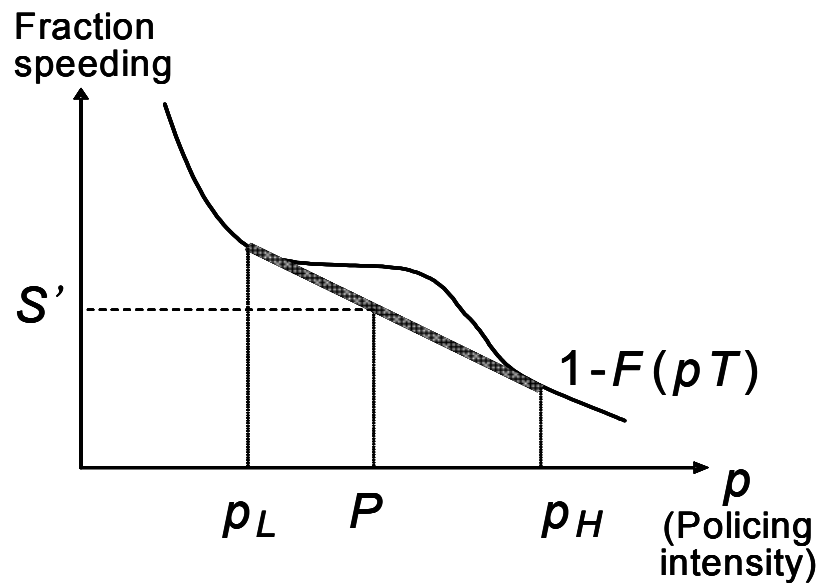
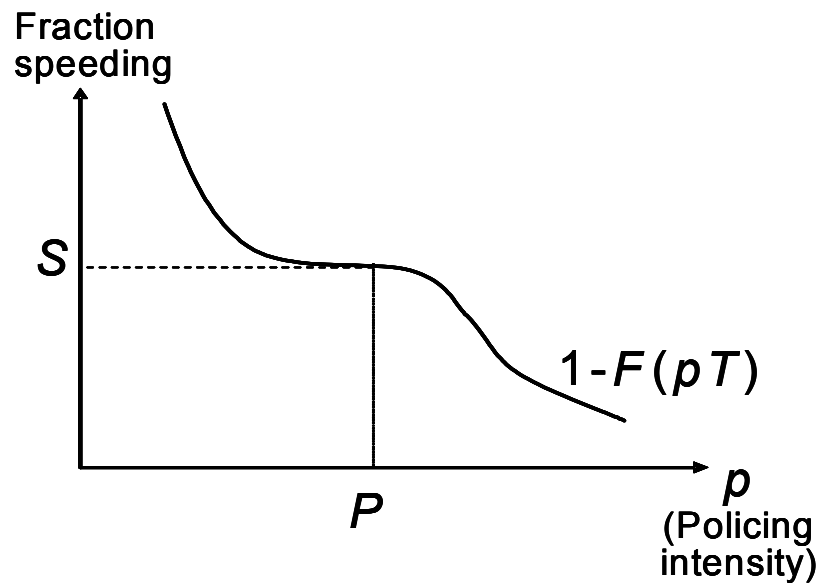
$$x - pT > 0$$

The fraction of speeders $1 - F(pT)$ is decreasing in p

Total resources of P per capita are available for policing. Police minimize number of speeders

Let $\mu(p)$ be the percentage of population policed at intensity p .
Police solves:

$$\min_{\mu} \int_0^1 \mu(p) [1 - F(pT)] dp$$
$$\text{s.t. } \int_0^1 \mu(p) p dp \leq P$$



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The maximum number of different groups is two

Disparate treatment is optimal iff $1 - F(\cdot)$ is non-convex on relevant domain

Increase in P does not change intensity of policing of each group, just size of groups (allows us to compute deterrence effect)

Proposition 1. *The optimal monitoring strategy involves either monitoring everyone at the same rate or dividing the population into at most two groups, monitored at different intensities.*

Denote group size μ_H monitored with intensity p_H , and $\mu_L = 1 - \mu_H$ with intensity p_L

Note: If F is convex on its entire domain, then for any $P \in (0, \bar{p})$ the optimal policing strategy involves monitoring one group of citizens with maximal intensity, and not monitoring the others at all (cf. example)

Proposition 2. *Consider an increase in total police resources to $\tilde{P} \in (P, p_H)$. Then $\tilde{\mu}_H > \mu_H$ and thus $\tilde{\mu}_L < \mu_L$, and p_H, p_L unchanged*

First variant: minimizing undetected crime

Police minimize undetected crime $(1 - p)(1 - F(pT))$. Reasonable, for example, in drugs interdiction.

Police solves:

$$\begin{aligned} \min_{\mu} \int_0^1 \mu(p) (1 - p) (1 - F(pT)) dp \\ \text{s.t. } \int_0^1 \mu(p) p dp \leq P \end{aligned}$$

The same results hold as in the base model.

Proposition 3. *Suppose the police minimizes undetected crime. Then:*

a) Crackdowns may exist (at most two groups)

b) An increase in resources leads to increase in μ_H , and p_H, p_L unchanged

c) There are no crackdowns for any P if the same is true when the police minimizes crime. The converse is not true.

Proof If $1 - F(pT)$ is convex then $(1 - p)(1 - F(pT))$ is convex

Roughly: crackdowns are less likely in variant 1 than in base model

Second variant: constraint on tickets

Police cannot write more than C tickets per capita (where $C < 1$)

Police solves:

$$\begin{aligned} \min_{\mu} \int_0^1 \mu(p) (1 - F(pT)) dp \\ \text{s.t.} \int_0^1 \mu(p) p (1 - F(pT)) dp \leq C \end{aligned}$$

The same results hold as in the base model

If in variant 2 there are no crackdowns for any P then the same is true in the base model. The converse is not true. Roughly: crackdowns are more likely in variant 2 than in base model.

Intuition: with crackdowns, high interdiction group has low crime \Rightarrow cheap in terms of tickets (in the example, under crackdown only $1/4$ tickets written vs. $1/2$)

A third variant: maximizing tickets written. Crackdowns never arise in equilibrium.

The application

Speeding interdiction by radar in Belgium

Police publicize time and location of some interdiction in advance: newspapers, radio, internet

Time and location of announced searches seems to rotate randomly

Key assumptions of the model:

1. Rule out possibility of road switching: restrict analysis to highways
2. Rational agents who have preferences over time of travel: many high frequency users – commuters

The data

Data set from Belgian police: Eastern Flanders province, 2000-2003

Province has 2 major highways (A10, A14) and 1 minor highway (R4)

Radar control machine: 1. counts all cars; 2. records the speed of speeders and takes photographs

5.5 million vehicle observations from 1,238 monitoring events

Data include: date, time, location, whether announced, driving conditions, number of vehicles, number of speeders, number of speeders by 15 km/h, speed, type of car, residence of the speeder

Monitoring policy is to minimize the number of speeder (explicit in Police documents)

Police face annual resource constraint on total number of tickets that can be issued (variant 2 of model is relevant)

Cost of issuing a speeding ticket is the administrative cost of processing the ticket (US \$0.50)

Empirical results

Tables 1-3 and A1-A5

Table 1a
 Number of Vehicles Subject to Announced and Unannounced Monitoring
 by Year

	2000	2001	2002	2003 (first half of year)
announced	266,240	394,540	1,746,340	1,777,977
unannounced	406,941	319,650	526,422	1,139,428
total	673,181	714,190	2,272,762	2,917,405
number of ticketed speeders	33,951	45,264	78,136	48,795

Table 1b
 Number of Announced/Total Monitoring Observations
 by Road and Year

	2000	2001	2002	2003 (first half of year)
A10	18/46	23/52	33/214	125/158
A14	38/138	51/105	156/244	150/218
R4	10/34	1/24	0/5	0/2
Total	66/218	75/181	189/463	275/376

Constructing the monitoring probabilities

Z, m, a : conditioning variables, indicator for monitoring, indicator for announcement

Estimate probability of monitoring and the time spent monitoring (HR) as a fraction of the total hours (T)

On an announcement day,

$$p_H(Z) = \Pr(m = 1|a = 1, Z) \times E\left(\frac{HR}{T} | m = 1, a = 1, Z\right)$$

where $\Pr(m = 1|a = 1, Z) = 1$ (always monitor when announced).
Note that $p_H < 1$.

On an unannounced day,

$$p_L(Z) = \Pr(m = 1|a = 0, Z) \times E\left(\frac{H}{T} | m = 1, a = 0, Z\right)$$

Table A3
 Estimated Logistic Model for the Probability of Monitoring
 when no announcement was made by Year and by Road

	Highway		
	A10	A14	R4
Intercept	-2.50 (0.36)	-2.48 (0.36)	-4.36 (0.58)
quarter 1	0.37 (0.25)	-0.11 (0.44)	0.46 (0.45)
quarter 2	-0.19 (0.28)	0.44 (0.20)	0.55 (0.43)
quarter 3	-1.91 (0.49)	-0.48 (0.22)	0.10 (0.44)
announced last week	0.15 (0.35)	-0.12 (0.20)	0.04 (0.49)
announced yesterday	-0.22 (0.41)	-0.27 (0.23)	...
monitored last week	0.79 (0.40)	2.04 (0.37)	2.10 (0.34)
monitored yesterday	0.37 (0.36)	0.46 (0.19)	-1.21 (0.64)
some announcement same day on any road	0.64 (0.23)	-0.96 (0.21)	-1.36 (0.49)
year 2001	-0.16 (0.29)	-0.67 (0.20)	0.27 (0.34)
year 2002	-0.08 (0.32)	0.30 (0.20)	-0.27 (0.54)
year 2003	-0.01 (0.31)	0.51 (0.25)	...

* All specifications also include fixed effects for day of week.
 The variable “holiday” was not included in the above
 specifications because of too few observations.

Table A4
Average Predicted Probability of Monitoring

Year	Road	no-announcement	no-announcement this road, announced other road	announcement
2000	A10	0.004	0.009	0.27
	A14	0.011	0.003	0.26
	R4	0.009	0.002	0.29
2001	A10	0.004	0.007	0.30
	A14	0.011	0.003	0.30
	R4	0.014	*	0.35
2002	A10	0.008	0.010	0.20
	A14	0.027	0.007	0.25
	R4	0.001	0.001	*
2003	A10	0.011	0.018	0.19
	A14	0.030	0.020	0.23
	R4	*	*	*

* Too few observations in the cell.

Table A5
Can we predict announcements?
Estimated Logistic Model for the Probability of Announcement by Road Conditional on
Day of Week, Month of Year, Announcement/Lagged Monitoring

	Highway		
	A10	A14	R4
intercept	-3.76 (0.36)	-4.94 (0.40)	-3.83 (0.82)
quarter 1	0.08 (0.21)	-0.004 (0.20)	-0.89 (1.18)
quarter 2	0.22 (0.21)	0.02 (0.20)	-0.03 (0.83)
quarter 3	-0.23 (0.22)	-0.01 (0.20)	0.10 (0.79)
holiday	2.23 (0.47)	0.98 (0.27)	...
announced last week	0.34 (0.36)	-0.18 (0.21)	0.13 (0.95)
announced yesterday	-0.52 (0.29)	0.19 (0.21)	...
monitored last week	1.38 (0.41)	2.65 (0.38)	0.88 (0.75)
monitored yesterday	0.25 (0.27)	-0.31 (0.19)	...
year 2001	0.06 (0.03)	0.42 (0.23)	-1.68 (1.08)
year 2002	2.13 (0.30)	1.55 (0.22)	-12.13 (214)
year 2003	2.12 (0.30)	2.16 (0.24)	...
p-value from Score test of joint significance of all covariates except for year indicators	<0.0001	<0.0001	0.7923

*All specifications also include fixed effect for days of week. Some days of week indicators are significant for A10 and A14 in 2000 and for A14 in 2001.

**There is only one announcement day during 2001 on R4.

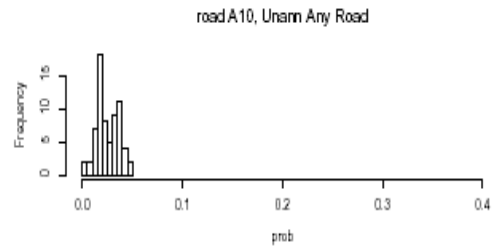
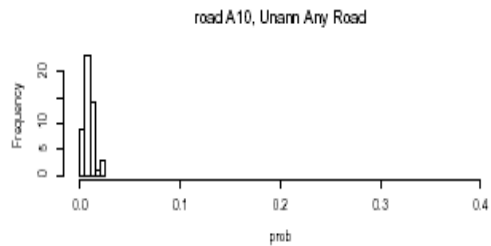
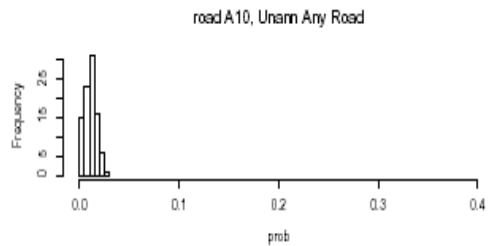
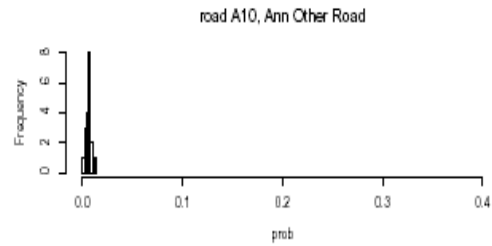
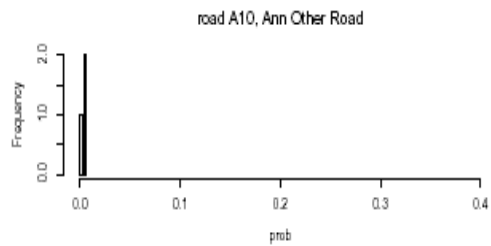
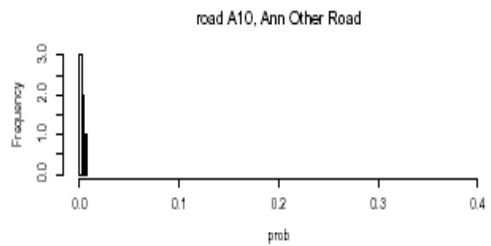
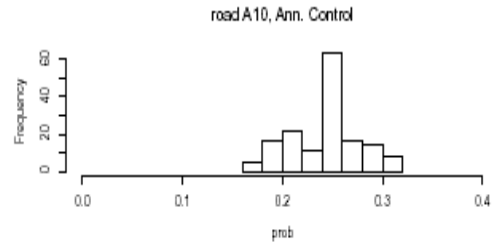
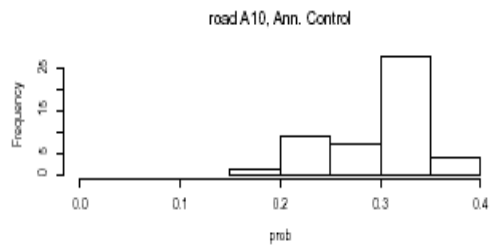
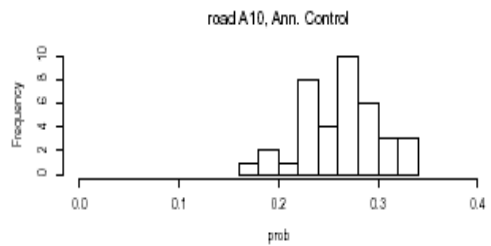


Table 2
 Estimated coefficients from logistic regression of
 probability of speeding
 (Standard errors in parentheses)

	(1)	(2)	(3)	(4)
Intercept	-3.13 (0.006)	-3.26 (0.02)	-3.38 (0.52)	-3.43 (0.01)
indicator for A14	0.34 (0.008)	0.04 (0.007)	0.52 (0.08)	0.23 (0.008)
indicator for R4	0.05 (0.02)	-0.42 (0.02)	0.30 (0.02)	-0.21 (0.02)
announcement A10	-0.61 (0.008)	-0.36 (0.008)
announcement A14	-0.35 (0.005)	-0.12 (0.006)
announcement R4	-0.14 (0.05)	-0.04 (0.05)
prob. of monitoring – A10	-1.17 (0.04)	-0.47 (0.04)
prob. of monitoring – A14	-0.97 (0.02)	-0.40 (0.02)
prob. of monitoring – R4	-0.38 (0.15)	-0.07 (0.15)
density 3	...	-0.09 (0.05)	...	-0.27 (0.06)
density 4	...	0.48 (0.03)	...	0.30 (0.03)
density 5	...	0.29 (0.01)	...	0.24 (0.01)
poor visibility	...	0.92 (0.03)	...	0.97 (0.03)
morning rush hour*weekday	...	-0.47 (0.02)	...	-0.47 (0.02)
evening rush hour*weekday	...	-0.007 (0.006)	...	0.02 (0.006)
Holiday	...	0.49 (0.007)	...	0.51 (0.007)
includes fixed effects for days of week	no	yes	No	yes
includes fixed effects for months of year	no	yes	No	yes
includes fixed effects for year	no	yes	No	yes
p-value from joint test that all coefficients equal 0	<0.0001	<0.0001	<0.0001	<0.0001

Table 3
Decrease in speeding due to crackdown (announcement days)
implied by coefficients from alternative models

Road		Specification			
		(1)	(2)	(3)	(4)
A10	Predicted % speeding above threshold on unannounced days	4.2	3.2	3.3	3.0
phigh= 0.2007 plow= 0.0084	Decrease in speeding on announcement days implied by estimated coefficients	1.88	0.60	0.20	0.25
	Decrease as a % of speeding on unannounced days	44.8%	19.1%	6.1%	8.4%
	Slope of 1-F Effect of increasing number of tickets by 10000	-9.78% -43,686	-3.12% -12,123	-1.04% -3,364	-1.30% -4,746
A14	Average % speeding on unannounced days	5.8	5.0	5.4	5.0
phigh= 0.2441 plow= 0.0167	Decrease in speeding on announcement days implied by estimated coefficients	1.66	0.50	1.01	0.41
	Decrease as a % of speeding on unannounced days	28.5%	10.2%	18.9%	8.4%
	slope of 1-F	-7.30%	-2.20%	-4.44%	-1.80%
	Effect of increasing number of tickets by 10000	-18,168	-4,926	-10,291	-3,954
R4	Average % speeding on unannounced days	4.4	4.3	4.4	4.3
phigh= 0.2576 plow= 0.0091	Decrease in speeding on announcement days implied by estimated coefficients	0.54	0.16	0.38	0.07
	Decrease as a % of speeding on unannounced days	12.21%	3.6%	8.6%	1.6%
	slope of 1-F Effect of increasing number of tickets by 10000	-2.17% -5,679	-0.64% -1,563	-1.53% -3,831	-0.28% -668

Total number of vehicles on each highway for the entire year (Driver Pop) was estimated from the data collecting during monitoring. The estimation was performed by a regression of vehicles per hour on conditioning variables (quarter of the year, day of the week, time of day (morning, afternoon, evening) holiday indicator, and an indicator for holiday*weekend).

Estimating the deterrence effect of increasing tickets

From calculation of crime rate

$$\mu(p_L) \cdot (1 - F(p_L T)) + \mu(p_H) \cdot (1 - F(p_H T))$$

we can calculate the change in the crime rate

$$\begin{aligned} \Delta \text{Crime} &= (\tilde{C} - C) \left[\frac{F(p_L T) - F(p_H T)}{(1 - F(p_H T)) p_H - (1 - F(p_L T)) p_L} \right] \\ &= \Delta C \cdot \left[\frac{(\text{crime rate}|p_H) - (\text{crime rate}|p_L)}{(\text{crime rate}|p_H) \cdot p_H - (\text{crime rate}|p_L) \cdot p_L} \right] \end{aligned}$$

Next steps

Use data on accidents to computing the decreased probability of an accident from an increase in the ticket allowance. Compare with value of life.

Issue: taking speed into account in the empirical analysis (see extension theory)

Issue: in model we assume that everyone is aware of crackdowns. Suppose fraction α is not then our estimates on the elasticity of speeding to increasing ticket allowance are biased downwards

Other applications: Auditing of firms? Allocation of time in political campaigning?

Conclusions

Presented a model in which unbiased policing of identical individuals leads to crackdowns on a subgroup; this policy optimally reduces crime

Compared different incentive models for police in terms of likelihood to give rise to crackdowns

Used the model to estimate deterrence effect of policing in the absence of exogenous variation in police resources (Note: μ and p 's are endogenous); Can perform policy experiments

Extension: continuous crime

Driver's objective function

$$\max_s x(s) - pT(s)$$

maximizer $s^*(p)$ is decreasing in p

Denote $\tilde{F}(s|p)$ the fraction of individuals who choose to travel at or below speed s for given p

Because $s'(p) < 0$, drivers will decrease optimal speed as the probability of being monitored increases. The function $\tilde{F}(s|p)$ is therefore increasing in p .

The police's objective function would be represented by the function

$$D(p) \equiv \int K(s) d\tilde{F}(s|p)$$

where $K(s)$ is a non-decreasing function. Then replace $1 - F(pT)$ by $D(p)$ and same analysis goes through

1. DESCRIPTIVE STATISTICS

Tables 1a, 1b: increase in the number of monitoring events and number of cars monitored over time

2. ESTIMATED PROBABILITY OF MONITORING

Table A3 - estimated coefficients of logit regression from monitoring on non-announcement days: pretty insignificant, expect monitoring on other road (but different signs)

Table A4 - expected probabilities $p(Z)$

Table A5 - are announced monitoring events predictable? Except monitored last week, none other is a predictor of prob of monitoring; Crackdowns are arbitrary

Note: dealing with different trip length: $m_x - m_p > 0$

3. VALIDATING THE MODEL

1. Two groups at most

Histogram and Table A4: even if announced on a different road, no different p_L

p_H 0.2 and 0.3 and p_L between 0.001 and 0.030 (p_H is typically about 25 times bigger than p_L)

2. increase in the number of tickets, implies no change in p_H, p_L (but μ_H increases). In the years 2001 and 2002 there were large and exogenous increases in police resources

See histogram; Table A3: years-fixed effects are not significantly different from zero

Table A5: the coefficients on the year fixed effects are positive and significantly different from zero

3. expected number of successful interdictions per capita is larger in the crackdown group: e.g. A10 0.466% on announced days vs 0.035% on unannounced

THE DETERRENCE EFFECT OF ANNOUNCED MONITORING

THE PROBABILITY OF SPEEDING

Table 2: model (1),(2): announcement fixed effect; (3),(4) announcement probability (as predicted in Table A4) – provides the coefficients of the logistic regression

→ speeding decreases when there is monitoring; robust to inclusion of covariates, but effect is large and significant (poor visibility, traffic density,...)

Table 3: for 4 models, the estimated probabilities of speeding using logistic regression in Table 2;

→ coefficients are smaller when covariates are included: decrease of
8 – 19% on A10 – 8 – 10% on A14 – 1.6 – 3.6% on R4

→ effect of increase in 10,000 tickets