Estimating police effectiveness with individual victimization data

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Abstract

In this paper, we present evidence on the effect of greater numbers of police personnel on victimization of crime and experience of nuisance. We make use of individual data from a Dutch victimization survey unique in its size, duration and scope. By using individual victimization data we provide evidence on the effects of police on nuisance rather than 'hard crime' only, we circumvent measurement error common to police statistics, and we are able to control for both individual and municipality characteristics. We find significantly negative effects of higher police levels on property crime, violent crime and nuisance. The estimated elasticities are in line with the literature based on police statistics. Urban police forces are more effective than rural police forces for most types of crime and nuisance. Additionally, we find experience of nuisance mostly to be a characteristic of the municipality in which someone lives, with little variation across individuals in a municipality, whereas victimization of violent crime varies across individuals rather than municipalities. For property crime, individual and municipality characteristics are about equally important. Finally, we provide evidence that greater police protection allows people to move around more freely, which is an additional benefit of higher police levels not reflected in a decline in victimization rates.

JEL Classification: K4 – Legal procedure, the Legal System, and Illegal Behavior, C23 – Models with Panel Data.
Key words: police, crime, nuisance, effectiveness, victimization survey

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1 Introduction

Methodological advances and the crime drop of the 1990s observed in many countries have spurred a renewed interest in identifying the causal effect of police on crime. New research designs are employed to break through the simultaneity between police and crime levels and to address omitted variable bias. Di Tella and Schargrodsky (2004) and Klick and Tabarrok (2005) use shocks to police presence related to terrorist attacks and terrorist alerts to identify police effectiveness. Corman and Mocan (2000, 2005) use high frequency data to escape the (slow) adjustment in allocation of police resources to crime rates. Levitt (2002) employs an instrumental variable design to identify changes in police levels that are not related to changes in crime rates. These recent studies consistently find a substantial negative effect of police on crime recorded by the police.

So far, the literature is exclusively based on police statistics as source of crime data. In this paper, we switch the perspective from offenders to victims of crime, using data from the Dutch Victimization Survey. Using individual victimization data has a number of advantages. First, whereas recorded crime statistics indicate the formal aspects of police performance over time and across jurisdictions, the victimization survey also reflects police activities that primarily rely on informal policing methods. The survey includes many dimensions of 'quality of life' in the neighborhood not covered in police statistics, including experience of nuisances like vandalism, littering and graffiti. By using victimization data, we provide evidence on the effects of police on people's experience of quality of life rather than the incidence of 'hard crime' only.

Additionally, we circumvent several types of measurement error common to police statistics that may result in biased estimates. Recorded crime statistics are subject to changes in reporting and recording behavior that are hard to control for with cross-sectional and time-series dummy variables (Dryden Witte and Witt, 2001). The effect of more police officers on the percentage of crimes reported may be limited (Levitt, 1998), but there are many other factors that may bias both cross-section and time-series analysis based on recorded crime. Sources of bias in recorded crime include changes in policing priorities and administrative practices, the introduction of new information technology within the police organization, and changes in citizen concerns about specific crimes (Wittebrood and Junger, 2002). Only studies analyzing the effect of police for a short period of time in a single city are not likely to suffer as much from measurement error in police statistics (DiTella and Schardgrodsky, 2004 and Klick and Tabarrok, 2005).

The victimization survey also includes a rich and easily accessible source of individual background characteristics of respondents (both victims and non-victims). When using data on offenders, individual characteristics can only be collected through painstaking efforts related to combining police statistics with sources such as school records and draft registration records.

Because of the costs related to such data collection, the resulting data tend to be limited to one locality, such as the Philadelphia cohort of young men studied by Tauchen et al. (1994). As we will show in the analysis, individual characteristics are particularly important for explaining violent crime.

We employ an estimation procedure that deviates from the usual fixed effects approach in the literature on police effectiveness. To obtain consistent estimates of the effect of police, we need to control for municipality specific effects that are correlated with police personnel. One way to solve this issue is to exploit the panel character of the data – by merging repeated cross sections of the survey – and use municipality specific fixed effects (FE). The main shortcoming of this approach is that for periods of many years the assumption that municipality effects are constant over time is likely to be too restrictive. As an alternative, we use the modified Random Effects (RE) framework proposed by Mundlak (1978). We model the correlation between the municipality effect and time varying observables as a function of municipality specific averages per survey wave. Under mild assumptions, these RE estimates are consistent. In contrast to FE estimation, we are able to model municipality specific effects that vary over time. As we will discuss later, the Mundlak approach is related to the literature on cluster and peer effects (see Manski, 1993).

The rest of the paper is organized as follows. Section 2 describes our data. In section 3, we discuss the empirical strategy. Section 4 presents the estimation results. Section 5 concludes.

2 Data

For our analysis, we use the Dutch Victimization Survey (PMB). The PMB is a repeated cross-section telephone survey that is unique in its sampling size (about 80,000 yearly respondents; about two percent of the Dutch population) and its broad scope.

The PMB contains detailed information on victimization of crime and experience of nuisance and preventative measures. For every survey wave, respondents have been selected at random from the total population over 15 years of age. Per police region (and sometimes smaller areas), the interviewers used stratified sampling. A minimum of 1,000 respondents were interviewed in each of the 25 police regions.

All victimization is observed at the individual level, only victimization of bicycle theft, burglary, car theft, theft from cars and one preventative measure are measured at the household level. Respondents are interviewed in the first ten weeks in the year a survey is held, with the victimization reflecting the twelve months preceding the interview date. This means that a substantial part of the observed victimization occurs in the year preceding the interview year.

Table 2.1 PMB Sample statistics (1995-2003)

Individual characteristics	Mean	Standard deviation of mean
Male	0.54	0.0008
Age	46.7	0.0270
Education level: low	0.25	0.0007
Education level: medium	0.47	0.0008
Education level: high	0.29	0.0007
Employed	0.56	0.0008
Student	0.055	0.0004
Housewife	0.22	0.0007
Immigrant	0.038	0.0003
Single household	0.21	0.0006
Children[a]	0.34	0.0004
Terraced house	0.58	0.0008
Detached house	0.15	0.0006
Apartment / else	0.27	0.0007
Crime and nuisance[b]		
Victimization of bicycle theft (per household)	0.11	0.0005
Victimization of theft from car (per household)	0.076	0.0004
Victimization of theft of car (per household)	0.010	0.0001
Victimization of burglary (per household)	0.069	0.0004
Victimization of threat	0.048	0.0003
Victimization of robbery with violence	0.0035	0.0001
Victimization of assault	0.0081	0.0001
Nuisance from littering	0.29	0.0007
Nuisance from graffiti	0.15	0.0006
Nuisance from youth in public spaces	0.12	0.0005
Nuisance from harassment in public spaces	0.034	0.0003
Nuisance from public intoxication	0.078	0.0004
Nuisance from vandalism	0.19	0.0006
Nuisance from drug users	0.070	0.0004
Police		
Police personnel per 100,000 inhabitants	256.2	0.015
Preventative measures[c]		
Drive or walk round	0.11	0.0005
Leaving valuable properties at home	0.18	0.0006
Not allowing children to go out (per household)	0.17	0.0011

Notes: (a) Defined as the share of children in the total number of people within a household. (b) On nuisance: respondents are asked whether they consider a certain type of nuisance to be a frequently occurring event in their neighborhood. The figures indicate the proportion of people who answered the question affirmative. (c) Share of respondents that frequently take such preventative measures.

In addition to the PMB, data on police resources were obtained from the Dutch Interior Department. Historical series of police levels from 1994 to 2003 are only available at the regional level. For all 25 police regions, growth in police personnel outstripped growth in population in this period. The total number of police personnel in full time equivalents increased from 38,429 in 1994 to 47,964 in 2002.

We have pooled PMB data for the years 1995-2003. During this period, the PMB survey was conducted every odd year. Table 2.1 summarizes the key variables we use for the empirical analysis. Background characteristics include age, gender, education level, ethnicity, housing type, household size, and income status (employed, student, housewife, or else).

Table 2.2 Distribution of respondents across municipalities (1995-2003)

Number of individual respondents per municipality	Percent of municipalities (cumulative)	Percent of respondents (cumulative)
1 – 10	1.3	0.0
11 – 25	4.7	0.1
25 – 50	9.9	0.5
51 – 100	22.4	2.0
101 – 150	34.8	4.6
151 – 200	44.0	7.4
200 – 300	56.9	12.9
300 – 500	70.4	22.1
500 – 1000	90.1	46.2
> 1000	100.0	100.0
Total number	686	402,463

We estimate the effect of police on victimization of crime and experience of nuisance at the level of individual respondents, taking into account municipality specific effects. In the pooled sample, we have 686 municipalities, with 585 individual observations on average. For separate years in the sample, the average yearly number of individual observations per municipality equals 115. Table 2.2 shows the distribution of individual observations over municipalities. For the vast majority of municipalities, we have sufficient individual observations to obtain reliable municipality specific effects.

3 Research design

3.1 Fixed or random effects?

We start off by modeling the chance of becoming victim of crime or experiencing nuisance y as follows:

$$(1) \qquad \Pr(y_{ijt} = 1 \mid \boldsymbol{\alpha}, \boldsymbol{X}) = \alpha_j + \boldsymbol{X}_{ijt}\boldsymbol{\beta} + \gamma\, lnp_{jt-1} + \varepsilon_{ijt}$$

In this Linear Probability Model (LPM), α_j indicates an effect on y that is specific for municipality j. $\boldsymbol{X}_{ijt}$ is a matrix representing the characteristics of individual i that is inhabitant of municipality j at time t, with $\boldsymbol{\beta}$ as a vector describing the effects of $\boldsymbol{X}$. lnp_{jt-1} represents the logarithmic value of the number of police personnel per capita in municipality j at time $t-1$, and

γ is a parameter describing the effect of *lnp*. For ease of exposition, we initially assume that the number of police personnel per capita is observed at the level of municipalities. We return to this issue in Section 3.3. Finally, ε_{ijt} is the error term of the LPM model. Initially, we assume this error term to be identically and independent distributed, with mean zero.

We include individual characteristics $\boldsymbol{X}_{ijt}$ to prevent estimation bias through (observable) variables that affect both police and victimization levels, either by chance or by deliberate policy. For instance, one of the control variables is the state of the economy. If growth of police is concentrated in areas with lagging job opportunities, then – without proper controls for the state of the economy – we are likely to underestimate the effect of police (omitted variable bias). We discuss the issue of simultaneity in the next section.

Given the size of the data set, we expect the LPM to provide consistent estimates of the partial effects for the average values of $\boldsymbol{X}$ and *lnp*, provided that estimation techniques are robust to heteroskedasticy. The advantage of using an LPM specification rather than a binary model is that fixed effect (FE) estimation is subject to the incidental parameters problem (see Wooldridge, 2002). Moreover, the estimation of municipality specific effects is computationally far more complex in a non-linear setting.

When estimating equation (1) using a conventional GLS model, we may expect the coefficient estimate of γ to be biased, as $\boldsymbol{\alpha}$ and *lnp* are likely to be correlated. The default option to solve this problem is to use FE or first-difference estimation, using municipality fixed effects. If we assume that the error term is identically and independent distributed, then this approach yields consistent estimates of $\boldsymbol{\beta}$ and γ. Within the context of our panel however, the assumption that the municipality specific effect is constant over time is likely to be too restrictive. In particular, individual victimization of crime and nuisance is not only affected by individual characteristics, but also by the composition of inhabitants within a municipality. In the time period under investigation (8 years), the composition of each municipality will change and the changes in one municipality will be different from changes observed in other municipalities – which contrasts with the assumption that $\boldsymbol{\alpha}$ is constant over time. Consequently, if the number of police is linked to these trends, the effect of police personnel per capita, γ tends to be underestimated.

In order to make the FE approach more flexible, an obvious solution is to specify municipality specific effects for separate years. However, this comes at a price. First, the number of parameters to be estimated increases dramatically, which may result in inefficiency problems (especially since we have a small number of observations for some municipalities, which creates problems for crimes with low victimization rates). Second, by allowing the coefficients to vary both over time and for each municipality, the parameter estimate of γ can no longer be identified. Alternatively, we use a modified random effects (RE) framework proposed by

Mundlak (1978).[1] Within this approach, the correlation between the municipality effect and the time varying observables is specified as a linear function of municipality averages per year:

$$(2) \qquad \Pr(y_{ijt} = 1) \quad = \quad \alpha_{jt} + \boldsymbol{X}_{ijt}\boldsymbol{\beta} + \gamma\, lnp_{jt-1} + \varepsilon_{ijt}$$

with the auxiliary regression

$$(3) \qquad \alpha_{jt} \quad = \quad \boldsymbol{\delta_1}\, \boldsymbol{X}_{\cdot jt} + \boldsymbol{\delta_2}\, lnp_{j.} + \eta_{jt}$$

where $\boldsymbol{X}_{\cdot jt}$ equals the average value of individual characteristics per municipality j per year t, and $\boldsymbol{\delta_1}$ describes the effect of these characteristics on $\boldsymbol{\alpha}$. $lnp_{j.}$ is the average value of lnp_{jt} per municipality across time t. η_{jt} represents the remaining yearly municipality effect. Again, we assume this variable to be independent and identically distributed.

By adding average values of $\boldsymbol{X}$ and *lnp* as a set of controls for unobserved heterogeneity, we disentangle the well known "within" from the "between" estimators of both coefficients. Thus the coefficient estimates are identified from variation of $\boldsymbol{X}$ and *lnp*, holding the averages constant. Under mild assumptions, the modified RE estimators are identical to the FE estimators. Within the context of equations (2-3) however, the computation of municipality averages is somewhat different from the (conventional) Mundlak approach. In particular, municipality averages are obtained by averaging $\boldsymbol{X}$ over each municipality per year, rather than averaging over time only. Thus, municipality effects are allowed to vary over time, without substantial loss of degrees of freedom.

In contrast to variables like level of education, there is no variation in police personnel per capita at the individual level for a given year (*lnp* itself is already a municipality average). Therefore, we take the average value of *lnp* over time for each municipality. Under the assumption that averaged *lnp* is uncorrelated with the (time-varying) municipality effect, the modified RE and FE estimates of γ are identical. This assumption might be too restrictive, however – that is, the number of police per municipality might be driven by time trends in $\boldsymbol{X}$. We test the validity of this assumption by comparing the modified RE and the FE estimates for γ in section 4.2.

Modifying the RE model along the lines suggested by Mundlak is related to the empirical literature on cluster or peer effects (see e.g. Manski, 1993). In this literature, adding group averages has been used to estimate the importance of cluster effects – that is, the effect of the

[1] Another reason not to exclusively rely on an FE approach is that within our data set variance between regional police levels accounts for 95 percent of total variance in police levels. Thus, when using the RE approach, the impact of police on crime is identified almost exclusively from cross-section variation.

behavior of other people in a reference group on the behavior of an individual (so-called 'endogenous effects'). Within the context of our model, however, the interpretation of cluster effects is different. The coefficients for individual characteristics reflect the effect of an individual's behavior on the risk of victimization. The coefficients for the municipality averages reflect both cluster and sorting effects. Cluster effects occur if reference group behavior affects the individual risk of victimization.[2] Think of nuisances like littering and graffiti that indiscriminately affect people living in a certain municipality. Sorting effects stem from individuals with similar characteristics concentrating into municipalities with an *a priori* higher risk of victimization.

3.2 Simultaneity

So far, we have assumed that there is no feedback from crime (or nuisance) to current police levels (strict exogeneity). For our estimates of police effectiveness to be consistent, two-year changes in police personnel should not be correlated with local trends in crime. Simultaneity is not a major hurdle in estimating our model for three reasons. First, police budgeting was not targeted at following local crime trends. The police budget is distributed by means of a budgeting formula that includes a number of municipality-specific characteristics.[3] Of all variables in the budgeting formula only one is related to *trends* in local crime (the number of non-western immigrants), and, most importantly, the variables have not been updated on a frequent basis (the variables are currently 5 to 12 years old). Second, we are able to control for the single variable in the formula that is supposed to follow crime trends: we include the number immigrants within every municipality as a control variable. Third, even when there is a policy response to diverging local crime trends through the impaired working of the formula that we are not able to control for, budgeting decisions should lead to changes in police personnel *within one year* to create simultaneity problems – because of the one-year lag in the causal effect of police on crime in our model. As it turns out, it takes at least two years to hire and train new police personnel.

Simultaneity may still occur indirectly if shocks to crime rates carry over to other years. The policy response to diverging crime trends may be delayed, but if the shocks have an effect over multiple years, we may still have a simultaneity problem. In the case changes in police personnel are correlated with delayed shocks in crime rates, the estimated effect of police on crime is biased towards zero. To control for this type of 'indirect simultaneity', we redefine the residual municipality specific effect η in an additional auxiliary regression that allows for serial correlation:

[2] Thus, the interpretation of cluster effects is different from endogenous effects – that is, individual behavior that is affected by the behavior of the reference group (Manski, 1993).

[3] The budget formula includes the following variables: population, number of residences, number of shops, number of moves, number of non-western second generation immigrants, length of roadways and housing density.

$$(4) \qquad \eta_{jt} = \rho\, \eta_{j,t-1} + u_{jt}$$

where ρ represents the degree of serial correlation and the error term u is assumed to be independent and identically distributed.[4]

3.3 Measurement error

Both for the FE and modified RE model specification, we have used municipalities as the relevant geographical or reference unit, so as to control for cluster and sorting effects of crime and nuisance as discussed in section 3.1. Thus far, we have abstracted from the fact that police personnel per capita is measured with error – that is, we observe police personnel per capita for 25 regions, instead of 686 municipalities. Now suppose we define the natural logarithm of police personnel per capita as the sum of a regional component and a municipality specific component. Furthermore, we assume the municipality specific component to have an expected value of zero and to be independent and identically distributed. Then, in order to obtain consistent estimates, the municipality specific component should not be correlated with the regional component. This assumption is common for various applications of stratified sampling, where units in the sample are represented with different frequencies than they are in the population.[5]

Measurement error may also arise with respect to the averages of the other independent variables in our model. Suppose that these variables would be averaged across regions instead of municipalities, then – using similar arguments as in the case of police personnel – consistency is still achieved. This is not an argument to estimate the model using regions as reference groups for all independent variables. Given the number of independent variables in our model, the number of regions is very limited, casting doubts on the efficiency of the estimated parameters of the averaged variables.[6] This is also likely to affect the efficiency of the estimated effect of police on crime. Thus, although we do not observe police personnel at the level of municipalities, this is no reason to switch to regions as cluster groups for the other independent variables as well.

[4] We do not model serial correlation for more than one year given the small number of years in our sample (5).

[5] This contrasts to situations where the classical errors in variables (CEV) assumption applies. In that case, measurement errors are (fully) correlated with the observed variable, causing estimates to be biased to zero (attenuation bias).

[6] See Wooldridge (2002), who discusses the importance of a high number of clusters (in our model: yearly observations of municipalities) to be able to apply panel data methods.

4 Estimation results

In this section, we present the estimation results for various model specifications. We start by presenting the estimation results of the modified RE approach with an autoregressive structure as defined by equations (2), (3) and (4): the 'preferred model'. In order to determine the importance of various sources of endogeneity, we compare these results with other model versions, using FE estimation and/or ignoring the possibility of serial correlation. Then, we go into control variables at the individual versus the municipality level. We also estimate the effect of police on preventative behavior. Furthermore, we re-estimate the preferred model using specifications that allow the effect op police personnel to vary across groups of regions.

4.1 Effect of police on crime and nuisance

Table 4.1 presents the estimation results based on the preferred model.[7] When analyzing property crime, we find the police to be effective in reducing bicycle theft, burglary and theft from cars. Only the effect of police on victimization of car theft is not statistically significant. This result is due to low victimization rates (1 percent of households) and correspondingly high standard errors. In contrast to police statistics, a victimization survey provides less precise figures for relatively rare types of crimes.

Table 4.1 Effect of police on crime and nuisance - implied elasticities

Property crime			**Violent crime**			**Nuisance**		
Burglary	– 0.49***	(0.18)	Threat	– 0.54**	(0.22)	Littering	– 0.39***	(0.076)
Car theft	– 0.70	(0.52)	Assault	– 0.74	(0.56)	Graffiti	– 0.52***	(0.12)
Theft from car	– 1.02***	(0.18)	Robbery with			Youth nuisance	– 0.41***	(0.14)
Bicycle theft	– 0.41***	(0.14)	violence	– 0.47	(0.85)	Harassment	– 0.67**	(0.27)
						Public intoxication	– 0.45***	(0.17)
						Vandalism	– 0.01	(0.11)
						Drug nuisance	– 0.38**	(0.18)

Notes: Estimation results for all other variables are included in the appendix. Standard errors are between parentheses. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.

We estimate a one percent increase in police personnel to result in a decrease in threat of 0.54 percentage point. We also find a negative effect on assault and robbery with violence, but the effect is not statistically significant. Victimization of both types of crimes occurs even less frequently than victimization of car theft, which results in high standard errors.

We select seven measures of nuisance included in the survey that are available for each wave, including littering, graffiti, youth nuisance, harassment, public intoxication, vandalism and drug

[7] The elasticities are computed as follows: estimated coefficient for *lnp* (as in appendix) divided by the average value of that specific type of crime or nuisance (as in summary statistics).

nuisance. We find the effect of police to be negative and statistically significant for all of these types of nuisance except vandalism. The estimated elasticities for littering, graffiti, youth nuisance, harassment, public intoxication and drug nuisance are – 0.39, – 0.52, – 0.41, – 0.67, – 0.45 and – 0.38, respectively.

Comparison with other studies

Table 4.2 shows that our estimated elasticities for property and violent crime are in line with recent studies based on police statistics (we only include estimates statistically significant at the 10-percent level or better). For reasons of comparability, we have lumped together several types of property crimes and violent crimes. The overview shows that reliable estimates of the effect of police on violent crime are relatively rare. Measurement error in police statistics on violent crime is a primary reason for the lack of empirical evidence.

Table 4.2 Point estimates for effect of police on property and violent crime

	Unit of analysis	Property crime	Burglary	Car theft and theft from cars	Violent crime
This study	Dutch municipalities	– 0.67***[a]	– 0.49***	– 0.94***	– 0.53***[b]
Marvell & Moody, 1996	Major US cities		– 0.32**	– 0.85**[c]	
Corman & Mocan, 2002	New York City		– 0.42***		
Kovandzic & Sloan, 2002	Florida counties		– 0.19**		
Levitt, 2002	Major US cities	– 0.50**			– 0.44*
DiTella & Schargrodsky, 2004	Buenos Aires neighborhoods			– 0.33***[c, d]	
Klick & Tabarrok, 2005	Washington D.C. city districts		– 0.30*	– 0.86**	
Corman & Mocan, 2005	New York City			– 0.56**[c]	

Notes: (a) Includes burglary, car theft, theft from car and bicycle theft. (b) Includes threat, assault and robbery with violence. (c) Excludes theft from cars. (d) Deterrence effects only. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.

The Netherlands is no exception. Whereas Dutch victimization data and police statistics for property crime show similar trends, Wittebrood and Junger (2002) find very different trends for violent crime. Police records on violent crime have improved considerably, because police reports are made for an increasing number of notified crimes and more police reports are finding their way into the official records. The discrepancy between victimization data and police statistics, the so-called 'dark number', is becoming smaller. The precise trends in recorded violent crime differ from police force to police force, however, leading to major measurement error. Thus, particularly in the case of violent crime, Dutch police statistics do not provide for a reliable alternative source of crime data.

Although the Netherlands may provide a different setting than the US or Argentina, the results do not suggest that the use of a victimization survey as alternative source of crime data greatly

affects the estimated effect of police on crime. If anything, our point estimates are somewhat higher. Thus, our results confirm the existing evidence using a different source of crime data and a different estimation method.

4.2 Robustness and endogeneity

Consistent estimation of the effectiveness of police personnel requires proper controls for omitted variables, as well as for the possibility of (indirect) simultaneity. To assess the importance of these potential sources of endogeneity and to validate the robustness of our results, we have re-estimated the model using various other specifications. We have estimated model versions without an autoregressive structure. The comparison of specifications with and without the inclusion of lagged residuals can be considered as a test on strict exogeneity of the police personnel parameter – that is, a test whether police personnel remains unaffected by past realizations of crime and nuisance. Additionally, we have re-estimated the model using FE estimation instead of the modified RE approach. Comparing the FE and RE estimates of police effectiveness can also be interpreted as a test on strict exogeneity, i.e. whether we are able to capture variation in municipality specific time trends by our controls.

Table 4.3 shows the implied elasticities of the effect of police personnel on crime and nuisance, using the four alternative model specifications – with the preferred model as our benchmark. Again, it should be noted that all these models are estimated using an LPM specification, enabling us to apply conventional FE estimation.[8] Generally, we find the estimated effect of police personnel in specification (i) to exceed the effect estimated in specifications (ii-iv). This finding suggests that the role of endogeneity is important, both originating from (lagged) time trends that are unobserved, as well as time trends that are captured by our control variables.

Comparing the elasticity estimates for the various specifications, we find the number of police personnel to respond to (lagged) changes in crime and nuisance for almost all variables. As most types of crime and nuisance are serially correlated over time as well, not controlling for serial correlation yields a bias towards zero in our elasticity estimates. For property crime and violent crime, the bias of RE and FE estimates is similar. For nuisance our results are mixed. In particular, drugs nuisance shows a reverse causality bias for the modified RE model. Apparently, police personnel is negatively correlated with victimization of drug nuisance.[9]

[8] The estimation results are robust to the choice between LPM and Probit as well as Logit.

[9] This finding is in line with the negative sign of the estimated coefficient for the average level of police personnel in the modified RE model in the case of drug nuisance, i.e. police personnel is negatively correlated with this type of nuisance.

Table 4.3 Effect of police on crime and nuisance – implied elasticities for various model specifications

	Specification (i) Preferred model		Specification (ii)		Specification (iii)		Specification (iv)	
Estimation approach	Modified Random Effects (Mundlak)		Modified Random Effects (Mundlak)		Fixed Effects		Fixed Effects	
AR- term included	Yes		No		Yes		No	
Property crime								
Burglary	– 0.49***	(0.18)	0.37***	(0.15)	0.11	(0.24)	0.79***	(0.18)
Car theft	– 0.70	(0.52)	– 0.31	(0.47)	– 0.55	(0.64)	– 0.11	(0.52)
Theft from car	– 1.02***	(0.18)	– 0.36**	(0.16)	– 0.49**	(0.23)	0.17	(0.18)
Bicycle theft	– 0.41***	(0.14)	– 0.21*	(0.11)	0.24	(0.17)	0.35***	(0.13)
Violent crime								
Threat	– 0.54**	(0.22)	– 0.41**	(0.18)	– 0.37	(0.27)	– 0.36*	(0.21)
Robbery with violence	– 0.47	(0.85)	– 0.18	(0.71)	0.95	(1.08)	0.41	(0.80)
Assault	– 0.74	(0.56)	– 0.31	(0.44)	– 0.69	(0.68)	– 0.11	(0.52)
Nuisance								
Littering	– 0.39***	(0.076)	– 0.33***	(0.061)	– 0.14	(0.094)	0.061	(0.071)
Graffiti	– 0.52***	(0.12)	– 0.43***	(0.094)	– 0.48***	(0.14)	0.0048	(0.11)
Youth nuisance	– 0.41***	(0.14)	– 0.18*	(0.11)	– 0.58***	(0.17)	– 0.082	(0.13)
Harassment	– 0.67**	(0.27)	0.090	(0.22)	– 0.044	(0.37)	1.79***	(0.25)
Public intoxication	– 0.45***	(0.17)	– 0.15	(0.14)	– 0.19	(0.22)	0.68***	(0.16)
Vandalism	– 0.01	(0.11)	– 0.36***	(0.088)	– 0.36***	(0.13)	0.14	(0.098)
Drug nuisance	– 0.38**	(0.18)	– 0.69***	(0.17)	0.085	(0.22)	0.11	(0.21)

Notes: Standard errors are between parentheses. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.

A comparison between RE and FE estimation results shows that trends in municipality specific effects are correlated with police personnel per capita. In the FE models, differences between municipalities are specified as an effect that is constant over time. Generally, we find this assumption to be too restrictive. Our modified RE estimation results show that ignoring time trends due to changes at the level of municipalities leads to an estimation bias towards zero, with youth and noise nuisance as the exceptions.

The various model specifications illustrate the importance of proper controls for the estimation of police effectiveness – both for lagged effects in the residual terms, as well as time trends that are captured by the municipality averages. One may argue that not all relevant variables are captured in our municipality averaged values, still leaving our estimates inconsistent.[10] However, it is likely that the size of the remaining endogeneity bias is small. In particular, omitted variable bias only occurs when the distribution of police personnel at the regional level is related to omitted variables. All variables that are included in the budgeting formula (see

[10] In terms of our preferred model, this concerns the orthogonality constraint between the residual η in equation (4) and lnp .

section 3.2) are included in our municipality averages. Thus, our modified RE estimates are close to consistency.

4.3 Victimization: is it the individual or the municipality?

Since we use individual victimization data, we are able to control for background characteristics both at the level of the individual and of the municipality. The estimation results for the control variables allow us to analyze whether victimization of crime and experience of nuisance is dominated by individual characteristics or by factors at the level of the municipality. Individual characteristics can reflect the extent to which people are willing to take risks for instance. But higher victimization rates may also be related to the place in which someone lives. In that case, people experience crime and nuisance regardless of their individual background.

Table 4.4 Variance decomposition for crime and nuisance rates

	R-squared	Proportion due to individual effects	Proportion due to municipality effects
Property crime			
Bicycle theft	0.071	0.687	0.313
Burglary	0.015	0.321	0.679
Car theft	0.0040	0.379	0.621
Theft from car	0.036	0.407	0.593
Violent crime			
Threat	0.030	0.787	0.213
Robbery with violence	0.0022	0.166	0.834
Assault	0.0073	0.841	0.158
Nuisance			
Littering	0.074	0.170	0.830
Graffiti	0.059	0.160	0.840
Youth nuisance	0.020	0.396	0.604
Harassment	0.023	0.164	0.836
Public intoxication	0.043	0.538	0.417
Vandalism	0.038	0.306	0.694
Drug nuisance	0.049	0.196	0.804

To see whether individual or municipality factors dominate, we decompose the explained variance in crime and nuisance rates into two parts: the proportion of the explained variance due to differences in background characteristics of individual respondents and the proportion due to differences in characteristics of municipalities (all estimates are based on the preferred model). Table 4.4 presents the results of the variance decomposition.

Factors at the level of the municipality seem to be particularly important when explaining experience of nuisance. This result makes intuitive sense: there is not much an individual can do to avoid experiencing problems like littering, graffiti and drug nuisance. Nuisance rates are high in municipalities with a young, low educated, immigrant population outside the labor force living in apartment buildings (tables A.3 and A.4). Nuisance is simply part of living in municipalities with these characteristics.

In the case of violent crime, individual effects dominate, with robbery with violence as the exception. Apparently, victimization of threat and assault is something that varies across individuals rather than across municipalities. Thus, compared to nuisance, threat and assault are not as likely to be a characteristic of a municipality. Victimization of violent crime decreases with age, increases with education level, and is particularly high among females, immigrants, and people living in apartment buildings (table A.2).

For victimization of property crime, we find mixed results, indicating that both individual and municipality characteristics are important. These findings underline the importance of controlling for individual background characteristics, especially in the case of violent crime.

4.4 Police protection and preventative behavior

With a higher level of police protection, citizens are able to take fewer self-protective measures such as not venturing out at night or installing a burglar alarm. A relaxation in preventative behavior is an additional gain of higher police levels not reflected in lower victimization rates.[11]

Using the same modified RE approach as before, we test whether precautionary measures are affected by increases in police personnel. The victimization survey includes data on preventative measures. We focus on three measures in the survey that people can easily alter according to local safety conditions: drive or walk round to avoid unsafe places, leaving valuable properties at home to prevent theft, and not allowing children to go out because of safety reasons. These are also measures people decide for themselves, as against measures like additional hinges and locks on doors and windows that the police might advise about.[12] Just like the one-year lag between the effect of police on crime, we assume a one-year lag between higher police presence and changes in preventative behavior. We assume that when making a decision on whether to avoid a certain street for instance, potential victims treat public expenditures on crime control as exogenous. After all, as discussed in section 3.2, our

[11] We do not consider the optimal balance between the two forms of protection.

[12] In the case the police advise citizens on appropriate preventative measures, more police could lead to more private prevention. We focus on measures that are most likely to be individual decisions affected by the degree of police protection rather than by advice from the police.

estimation approach addresses simultaneity between police and crime, therefore, we also deal with simultaneity between police and preventative measures related to crime levels.

Table 4.5 Effect of police on preventative behavior, estimated elasticities

Drive or walk round to avoid unsafe places	– 0.58***	(0.15)
Leaving valuable properties at home to prevent theft	– 0.48***	(0.12)
Not allowing children to go out because of safety reasons	– 0.47**	(0.20)

Notes: Estimation results for all other variables are included in the appendix. Standard error between parentheses. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.

Table 4.5 provides the estimated elasticities. As expected, more police leads to fewer self-protective measures. A one percent increase in police levels leads to a 0.6 percent decrease in people who frequently drive or walk round to avoid unsafe places and a 0.5 percent decrease in people who frequently leave valuable properties at home to prevent theft and frequently tell their children not to go out because of safety reasons. Thus, we provide evidence that there is an additional effect of police on preventative behavior, next to the effect of police on victimization rates most frequently reported in the literature.[13]

4.5 Police effectiveness and degree of urbanization

Intuitively, we expect the police to be most effective in fighting crime and nuisance in urban regions. After all, a police officer in a densely populated region can control more people than a police officer in a sparsely population region. To test the difference in effectiveness between urban and rural regions, we include an interaction term for police levels and average police levels in the four most urbanized 'Randstad' regions in the preferred model.[14] We assume that the impact of all other explanatory variables in our model is equal for regions with a high and low degree of urbanization.

Table 4.6 presents the estimated elasticities for the two types of regions. The results indicate that urban police forces are more effective in bringing down burglary, car theft, graffiti and youth nuisance than rural police forces. We find the opposite result for drug nuisance, however.

[13] Philipson and Posner (1996) argue that a decline in preventative behavior due to better police protection partially offsets the effect of police on crime. An increase in the level of public protection, as by hiring more police, will cause the crime rate to fall and thus will lower the demand for private prevention – which will cause the crime rate to rise again, partially undoing the effect of the increase in public protection. Based on state level data for 1985-1994, they provide empirical evidence for the effect of the burglary rate on having an alarm system. They also find a negative effect of police levels on the presence of burglar alarms, but the effect is not statistically significant. Because of same-year simultaneity between crime and preventative behavior, we are not able to test whether fewer preventative measures in response to better police protection lead to higher victimization rates than in the case of no behavioral response.

[14] The most urbanized regions include: Amsterdam-Amstelland, Rotterdam-Rijnmond, Haaglanden and Utrecht.

Although urban police forces tend to be more effective than rural police forces for most types of crime and nuisance, we do not find that urban police forces are more effective across the board, which is in line with findings reported by Kovandzic and Sloan (2002, p. 73).

Table 4.6 Effect of police on crime in regions with a high and a low degree of urbanization

	High degree of urbanization		Low degree of urbanization		Difference	
Property crime						
Bicycle theft	– 0.36	(0.26)	– 0.44**	(0.15)	0.080	(0.30)
Burglary	– 1.90**	(0.32)	– 0.51**	(0.20)	– 1.39**	(0.38)
Car theft	– 2.91**	(0.86)	– 0.96	(0.60)	– 1.95*	(1.05)
Theft from car	– 1.16**	(0.29)	– 1.24**	(0.23)	0.080	(0.37)
Violent crime						
Threat	0.20	(0.40)	– 0.57**	(0.25)	0.77	(0.47)
Robbery with violence	– 0.21	(0.44)	– 0.62	(1.18)	0.41	(1.26)
Assault	– 0.39	(0.93)	– 0.82	(0.63)	0.43	(1.12)
Nuisance						
Littering	– 0.62**	(0.13)	– 0.47**	(0.087)	0.15	(0.16)
Graffiti	– 2.76**	(0.18)	– 0.88**	(0.14)	– 1.88**	(0.23)
Youth nuisance	– 1.24**	(0.25)	– 0.52**	(0.15)	– 0.72**	(0.29)
Harassment	– 0.48	(0.36)	– 0.91**	(0.36)	0.43	(0.51)
Public intoxication	– 0.43***	(0.13)	– 0.50***	(0.18)	– 0.070	(0.22)
Vandalism	0.00	(0.093)	0.066	(0.11)	– 0.066	(0.14)
Drug nuisance	0.30	(0.28)	– 0.48*	(0.22)	0.78**	(0.36)

Notes: Standard errors are between parentheses. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.

5 Conclusions

The literature on police effectiveness relies exclusively on police statistics as source of crime data. In this paper, we switch the perspective from offenders to victims of crime, using data from the Dutch Victimization Survey. This data set covers a wide range of crimes and also nuisances for a range of years and provides a great number of individual background characteristics of respondents. When estimating police effectiveness, the survey data allows us to control for both municipality effects and individual characteristics of victims.

We find significantly negative effects of higher police levels on property crime and violent crime. The estimated elasticities for a number of crime categories range from – 0.4 to – 1. Using a different source of data and a different estimation method, we confirm the existing empirical evidence – and extend it to the experience of nuisance. We find the police to have a similar impact on several types of nuisance not included in previous studies: littering, graffiti, youth nuisance, harassment, public intoxication and drug nuisance. Urban police forces tend to be more effective than rural police forces for most types of crime and nuisance.

Comparing estimates from different model specifications and different estimation techniques, we show the importance of controlling for two sources of endogeneity. First, we find police levels to respond to lagged changes in crime and nuisance rates. Second, police levels are correlated to year-on-year changes in municipality specific characteristics. This effect would not have been picked up in a fixed effects estimation approach. Ignoring both sources of endogeneity would lead to underestimation of the effect of police.

We find experience of nuisance mostly to be a characteristic of the municipality in which someone lives, with little variation across individuals in a municipality, whereas victimization of violent crime varies across individuals rather than municipalities. For property crime, individual and municipality characteristics are about equally important. These findings underline the importance of controlling for individual background characteristics, especially in the case of violent crime.

Finally, we provide evidence that greater police protection leads to fewer preventative measures, which is an additional benefit of higher police levels not reflected in a decline in victimization rates.

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Appendix

Table A.1 Effect of police on victimization of property crime - the modified RE model

	Burglary		Bicycle theft		Car theft		Theft from car	
Ln (police) (t-1)	– 0.032***	(0.012)	– 0.047***	(0.016)	– 0.0069	(0.0051)	– 0.077***	(0.014)
AR-term	0.23***	(0.016)	0.28***	(0.016)	0.13***	(0.025)	0.33***	(0.019)
Individual characteristics								
Male	– 0.0047***	(0.0010)	0.0042***	(0.0014)	– 0.0022***	(0.0005)	– 0.0059***	(0.0012)
25 < age < 35	– 0.015***	(0.0024)	– 0.10***	(0.0035)	– 0.0024**	(0.0011)	– 0.0071**	(0.0030)
35 < age < 45	– 0.015***	(0.0024)	– 0.086***	(0.0036)	– 0.0042***	(0.0011)	– 0.028***	(0.0030)
45 < age < 55	– 0.016***	(0.0024)	– 0.069***	(0.0036)	– 0.0044***	(0.0011)	– 0.034***	(0.0029)
55 < age < 65	– 0.022***	(0.0026)	– 0.12***	(0.0037)	– 0.0059***	(0.0012)	– 0.057***	(0.0031)
Age > 65	– 0.039***	(0.0026)	– 0.14***	(0.0038)	– 0.0080***	(0.0012)	– 0.083***	(0.0032)
Education level 2	– 0.0006	(0.0016)	– 0.0077***	(0.0020)	– 0.0007	(0.0008)	– 0.0064***	(0.0020)
Education level 3	0.0060***	(0.0017)	0.0023	(0.0021)	– 0.0002	(0.0008)	– 0.0032	(0.0020)
Education level 4	0.0068***	(0.0017)	– 0.0001	(0.0021)	– 0.0004	(0.0008)	– 0.0015	(0.0020)
Education level 5	0.011***	(0.0021)	0.0085***	(0.0028)	0.0000	(0.0010)	0.0075***	(0.0025)
Education level 6	0.016***	(0.0018)	0.023***	(0.0022)	0.0002	(0.0008)	0.012***	(0.0021)
Education level 7	0.021***	(0.0023)	0.038***	(0.0029)	– 0.0002	(0.0011)	0.018***	(0.0028)
Employee	– 0.0003	(0.0013)	0.013***	(0.0018)	0.0016***	(0.0006)	0.0098***	(0.0015)
Student	– 0.0016	(0.0030)	0.060***	(0.0048)	– 0.0009	(0.0014)	– 0.019***	(0.0036)
House wife	– 0.0061***	(0.0013)	– 0.0072***	(0.0017)	0.0003	(0.0006)	– 0.0020	(0.0015)
Immigrant	0.0034	(0.0025)	0.020***	(0.0037)	0.0067***	(0.0014)	0.019***	(0.0033)
2 person househ.	– 0.0037***	(0.0012)	0.0035**	(0.0015)	0.0004	(0.0006)	0.0078***	(0.0016)
3/4 persons	– 0.0064***	(0.0018)	0.070***	(0.0025)	0.0004***	(0.0008)	0.023***	(0.0022)
> 4 persons	– 0.0049*	(0.0026)	0.14***	(0.0039)	0.0055***	(0.0012)	0.033***	(0.0030)
Children	0.0021	(0.0035)	– 0.079***	(0.0053)	– 0.0059***	(0.0016)	– 0.056***	(0.0041)
Terraced house	0.0029**	(0.0012)	– 0.027***	(0.0016)	– 0.0043***	(0.0006)	– 0.019***	(0.0016)
Detached house	0.022***	(0.0017)	– 0.036***	(0.0021)	– 0.0030***	(0.0007)	– 0.014***	(0.0019)
Municipality averages								
Ln (police) (t-1)	0.031***	(0.011)	0.023	(0.015)	0.0051*	(0.0050)	0.078***	(0.014)
Male	0.029	(0.023)	– 0.025	(0.030)	– 0.0086	(0.010)	0.040	(0.026)
25 < age < 35	– 0.078*	(0.047)	– 0.15**	(0.061)	– 0.0032	(0.019)	0.038	(0.052)
35 < age < 45	– 0.0098	(0.045)	– 0.073	(0.058)	0.022	(0.018)	0.10**	(0.049)
45 < age < 55	– 0.10**	(0.046)	– 0.17***	(0.059)	– 0.026	(0.019)	– 0.0084	(0.051)
55 < age < 65	– 0.077*	(0.045)	– 0.11**	(0.059)	– 0.016	(0.018)	0.068	(0.049)
Age > 65	– 0.073	(0.047)	– 0.35	(0.061)	– 0.012	(0.019)	– 0.034	(0.051)
Education level 2	0.11***	(0.037)	0.073	(0.047)	0.012	(0.015)	– 0.030	(0.040)
Education level 3	0.092***	(0.035)	0.11***	(0.044)	0.0050	(0.014)	– 0.12***	(0.038)
Education level 4	– 0.090***	(0.030)	0.010	(0.038)	– 0.016	(0.012)	– 0.26***	(0.033)
Education level 5	– 0.085**	(0.039)	– 0.31***	(0.050)	– 0.032**	(0.016)	– 0.12***	(0.043)
Education level 6	0.15***	(0.029)	0.17***	(0.037)	0.035***	(0.012)	0.067**	(0.032)
Education level 7	0.0024	(0.029)	0.074**	(0.037)	0.0042	(0.012)	– 0.18***	(0.032)
Employee	0.0010	(0.023)	– 0.053*	(0.031)	– 0.0029	(0.010)	0.042	(0.026)
Student	– 0.14**	(0.060)	– 0.054	(0.078)	– 0.054**	((0.023)	– 0.0088	(0.066)
House wife	– 0.040	(0.031)	– 0.18***	(0.040)	0.023*	(0.014)	0.050	(0.035)
Immigrant	0.13***	(0.036)	0.037	(0.047)	0.054***	(0.015)	0.43***	(0.041)

Table A.1 Effect of police on victimization of property crime - the modified RE model (continued)

	Burglary		Bicycle theft		Car theft		Theft from car	
2 person househ.	– 0.0037***	(0.0012)	0.0035**	(0.0015)	0.0004	(0.0006)	0.0078***	(0.0016)
3/4 persons	– 0.0064***	(0.0018)	0.070***	(0.0025)	0.0004***	(0.0008)	0.023***	(0.0022)
> 4 persons	– 0.0049*	(0.0026)	0.14***	(0.0039)	0.0055***	(0.0012)	0.033***	(0.0030)
Children	– 0.42***	(0.062)	– 0.17**	(0.080)	– 0.17***	(0.026)	– 0.64***	(0.066)
Terraced house	0.0088	(0.0073)	0.006	(0.010)	– 0.0011	(0.0030)	– 0.066***	(0.0085)
Detached house	– 0.064***	(0.0083)	– 0.078***	(0.011)	– 0.0082**	(0.0034)	– 0.13***	(0.0098)
Number of obs.	308,445		285,654		256,754		256,748	

Notes: Results for year fixed effects are not reported. Standard errors are between parentheses. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.

Table A.2 Effect of police on victimization of violent crime – the modified RE model

	Assault		Threat		Robbery with violence	
Ln (police) (t-1)	– 0.0060	(0.0045)	– 0.026**	(0.011)	– 0.0017	(0.0030)
AR-term	0.014	(0.017)	0.076***	(0.019)	0.034*	(0.020)
Individual characteristics						
Male	– 0.0035***	(0.0004)	– 0.035***	(0.0009)	– 0.00011	(0.00025)
25 < age < 35	– 0.015***	(0.0013)	– 0.045***	(0.0025)	– 0.0030***	(0.00062)
35 < age < 45	– 0.016***	(0.0013)	– 0.050***	(0.0025)	– 0.0028***	(0.00063)
45 < age < 55	– 0.019***	(0.013)	– 0.059***	(0.0025)	– 0.0028***	(0.00064)
55 < age < 65	– 0.022***	(0.0013)	– 0.074***	(0.0026)	– 0.0025***	(0.00069)
Age > 65	– 0.025***	(0.0013)	– 0.093***	(0.0026)	– 0.0026***	(0.00072)
Education level 2	– 0.0012**	(0.0005)	– 0.0058***	(0.0012)	– 0.00065	(0.00046)
Education level 3	– 0.0008	(0.0006)	– 0.0030**	(0.0012)	– 0.00024	(0.00048)
Education level 4	– 0.0005	(0.0006)	– 0.0047***	(0.0013)	– 0.00043	(0.00047)
Education level 5	– 0.0002	(0.0008)	0.012***	(0.0018)	0.00040	(0.00060)
Education level 6	– 0.0010*	(0.0006)	0.015***	(0.0014)	0.00043	(0.00050)
Education level 7	– 0.0018**	(0.0008)	0.015***	(0.0019)	0.00039	(0.00062)
Employee	– 0.0013**	(0.0006)	0.0009	(0.0012)	0.00018	(0.00035)
Student	0.0035**	(0.0018)	0.0035	(0.0033)	0.00031	(0.00083)
House wife	– 0.0006	(0.0004)	– 0.0003	(0.0010)	0.00044	(0.00035)
Immigrant	0.0020**	(0.0010)	– 0.015***	(0.0021)	0.0010***	(0.00072)
Terraced house	– 0.0023***	(0.0005)	– 0.013***	(0.0011)	– 0.00097***	(0.00030)
Detached house	– 0.0022***	(0.0006)	– 0.015***	(0.0014)	– 0.0011	(0.00036)
Municipality averages						
Ln (police) (t-1)	0.0042	(0.0044)	0.018*	(0.010)	0.0025	(0.0028)
Male	0.0035	(0.0083)	– 0.0040	(0.020)	0.0018	(0.0050)
25 < age < 35	0.022	(0.017)	– 0.0092	(0.041)	– 0.00048	(0.0086)
35 < age < 45	0.0043	(0.015)	– 0.017	(0.035)	– 0.00041	(0.0075)
45 < age < 55	0.027*	(0.016)	0.0019	(0.037)	0.00091	(0.0075)
55 < age < 65	0.013	(0.016)	– 0.042	(0.037)	0.0011	(0.0087)
Age > 65	– 0.0056	(0.017)	– 0.11***	(0.041)	– 0.015	(0.0090)
Education level 2	– 0.038***	(0.014)	– 0.094***	(0.031)	0.0096	(0.0075)
Education level 3	– 0.043***	(0.013)	– 0.089***	(0.030)	– 0.0092	(0.0072)
Education level 4	– 0.036***	(0.011)	– 0.11***	(0.025)	– 0.0085	(0.0056)
Education level 5	– 0.0060	(0.013)	– 0.053*	(0.031)	-0.013*	(0.0079)
Education level 6	– 0.022**	(0.011)	– 0.012	(0.025)	0.016***	(0.0059)
Education level 7	– 0.032***	(0.011)	– 0.073***	(0.025)	– 0.0063	(0.0057)
Employee	– 0.011	(0.0083)	– 0.062***	(0.020)	– 0.0084*	(0.0048)
Student	– 0.018	(0.023)	– 0.12**	(0.054)	– 0.0046	(0.012)
House wife	– 0.014	(0.010)	– 0.075***	(0.024)	– 0.0081	(0.0059)
Immigrant	0.029**	(0.013)	0.20***	(0.031)	0.041***	(0.0085)
Terraced house	– 0.0055***	(0.0022)	– 0.023***	(0.0056)	– 0.0039***	(0.0014)
Detached house	– 0.010***	(0.0028)	– 0.047***	(0.0067)	– 0.0052***	(0.0017)
Number of observations	308,445		308,445		308,445	

Notes: Results for year fixed effects are not reported. Standard errors are between parentheses. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.

Table A.3 Effect of police on experience of nuisance (1) – the modified RE model

	Littering		Graffiti		Youth nuisance	
Ln (police) (t-1)	– 0.11***	(0.022)	– 0.076***	(0.017)	– 0.049***	(0.016)
AR-term	0.42***	(0.014)	0.46***	(0.013)	0.27***	(0.013)
Individual characteristics						
Male	0.033***	(0.0018)	0.0079***	(0.0014)	0.010***	(0.0014)
25 < age < 35	– 0.017***	(0.0038)	– 0.036***	(0.0031)	– 0.034***	(0.0031)
35 < age < 45	0.0014	(0.0038)	– 0.023***	(0.0032)	– 0.033***	(0.0031)
45 < age < 55	0.012***	(0.0039)	– 0.014***	(0.0032)	– 0.039***	(0.0032)
55 < age < 65	0.023***	(0.0043)	– 0.0054	(0.0035)	– 0.045***	(0.0034)
Age > 65	– 0.030***	(0.0050)	– 0.038***	(0.0037)	– 0.082***	(0.0035)
Education level 2	0.021***	(0.0036)	0.014***	(0.0027)	0.0065**	(0.0026)
Education level 3	0.028***	(0.0036)	0.028***	(0.0027)	0.0043*	(0.0026)
Education level 4	0.032***	(0.0035)	0.026***	(0.0027)	0.0028	(0.0026)
Education level 5	0.028***	(0.0042)	0.033***	(0.0033)	– 0.0031	(0.0030)
Education level 6	0.034***	(0.0036)	0.031***	(0.0028)	– 0.0068***	(0.0026)
Education level 7	0.012***	(0.0042)	0.019***	(0.0033)	– 0.026***	(0.0030)
Employee	– 0.030***	(0.0024)	– 0.0087***	(0.0019)	– 0.015***	(0.0019)
Student	0.042***	(0.0050)	0.031***	(0.0042)	0.0059	(0.0040)
House wife	– 0.0037	(0.0026)	– 0.0064***	(0.0020)	– 0.0089***	(0.0019)
Immigrant	– 0.049***	(0.0042)	– 0.036***	(0.0034)	0.012***	(0.0033)
Terraced house	– 0.10***	(0.0022)	– 0.070***	(0.0018)	– 0.050***	(0.0017)
Detached house	– 0.12***	(0.0029)	– 0.091***	(0.0022)	– 0.067***	(0.0021)
Municipality averages						
Ln (police) (t-1)	0.0093	(0.021)	0.053***	(0.017)	0.0041	(0.016)
Male	0.011	(0.044)	– 0.16***	(0.031)	– 0.089***	(0.033)
25 < age < 35	– 0.14	(0.087)	– 0.040	(0.062)	– 0.016	(0.063)
35 < age < 45	– 0.085	(0.077)	– 0.13**	(0.055)	0.12**	(0.055)
45 < age < 55	– 0.31***	(0.082)	– 0.061	(0.056)	0.096*	(0.058)
55 < age < 65	– 0.56***	(0.081)	– 0.32***	(0.057)	– 0.0009	(0.063)
Age > 65	– 0.48***	(0.088)	– 0.41***	(0.063)	– 0.23***	(0.063)
Education level 2	– 0.42***	(0.068)	– 0.23***	(0.048)	– 0.24***	(0.051)
Education level 3	– 0.26***	(0.063)	– 0.011	(0.045)	– 0.13***	(0.046)
Education level 4	– 0.63***	(0.053)	– 0.24***	(0.038)	– 0.43***	(0.039)
Education level 5	– 0.77***	(0.065)	– 0.30***	(0.047)	– 0.42***	(0.049)
Education level 6	– 0.48***	(0.053)	– 0.034	(0.038)	– 0.22***	(0.039)
Education level 7	– 0.45***	(0.053)	– 0.13***	(0.038)	– 0.34***	(0.038)
Employee	– 0.085*	(0.043)	– 0.10***	(0.032)	– 0.025	(0.032)
Student	– 0.54***	(0.11)	– 0.19**	(0.083)	– 0.36***	(0.082)
House wife	– 0.41***	(0.051)	– 0.11***	(0.038)	– 0.13***	(0.038)
Immigrant	1.34***	(0.066)	0.90***	(0.050)	0.22***	(0.048)
Terraced house	– 0.16***	(0.012)	– 0.083***	(0.0089)	– 0.052***	(0.0086)
Detached house	– 0.47***	(0.014)	– 0.25***	(0.010)	– 0.2***	(0.010)
Number of observations	308,445		308,445		308,445	

Notes: Results for year fixed effects are not reported. Standard errors are between parentheses. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.

Table A.4 Effect of police on nuisance (2) - the modified RE model

	Harassment		Drug nuisance		Public intoxication		Vandalism	
Ln (police) (t-1)	– 0.023**	(0.0091)	– 0.027**	(0.012)	– 0.034***	(0.013)	– 0.0024	(0.020)
AR-term	0.34***	(0.017)	0.41***	(0.015)	0.43***	(0.015)	0.64***	(0.0096)
Individual characteristics								
Male	0.0048***	(0.0008)	– 0.0000	(0.0011)	0.0022*	(0.0011)	0.013***	(0.0016)
25 < age < 35	– 0.017***	(0.0018)	– 0.018***	(0.0025)	– 0.050***	(0.0030)	– 0.056***	(0.0034)
35 < age < 45	– 0.016***	(0.0018)	– 0.011***	(0.0025)	– 0.069***	(0.0030)	– 0.024***	(0.0035)
45 < age < 55	– 0.015***	(0.0018)	– 0.010***	(0.0025)	– 0.075***	(0.0030)	– 0.0052	(0.0036)
55 < age < 65	– 0.018***	(0.0020)	– 0.024***	(0.0027)	– 0.094***	(0.0031)	– 0.0098***	(0.0039)
Age > 65	– 0.026***	(0.0021)	– 0.067***	(0.0028)	– 0.13***	(0.0032)	– 0.063***	(0.0041)
Education level 2	– 0.0048***	(0.0015)	– 0.0006	(0.0021)	– 0.0037*	(0.0019)	0.015***	(0.0032)
Education level 3	– 0.0069***	(0.0015)	– 0.0077***	(0.0021)	– 0.0083***	(0.0019)	0.012***	(0.0032)
Education level 4	– 0.0074***	(0.0015)	– 0.011***	(0.0020)	– 0.0078***	(0.0019)	0.011***	(0.0031)
Education level 5	– 0.010***	(0.0018)	– 0.019***	(0.0024)	– 0.0091***	(0.0024)	– 0.0051	(0.0037)
Education level 6	– 0.0086***	(0.0016)	– 0.017***	(0.0021)	0.0021	(0.0020)	– 0.012***	(0.0032)
Education level 7	– 0.015***	(0.0018)	– 0.021***	(0.0025)	0.016***	(0.0025)	– 0.050***	(0.0036)
Employee	– 0.0053***	(0.0010)	– 0.013***	(0.0015)	– 0.0030**	(0.0015)	– 0.0063**	(0.0022)
Student	– 0.0029	(0.0024)	– 0.010***	(0.0031)	– 0.0030	(0.0039)	0.013**	(0.0045)
House wife	– 0.0026**	(0.0010)	– 0.0060***	(0.0014)	– 0.0066***	(0.0014)	– 0.0063**	(0.0022)
Immigrant	– 0.0027	(0.0019)	0.021***	(0.0030)	– 0.000	(0.0028)	– 0.015***	(0.0037)
Terraced house	– 0.023***	(0.0010)	– 0.050***	(0.0014)	– 0.062***	(0.0014)	– 0.0075***	(0.0019)
Detached house	– 0.023***	(0.0011)	– 0.054***	(0.0016)	– 0.060***	(0.0018)	– 0.043***	(0.0025)
Municipality averages								
Ln (police) (t-1)	0.012	(0.0088)	– 0.014	(0.012)	0.012	(0.0013)	– 0.040**	(0.020)
Male	– 0.0017	(0.014)	– 0.075***	(0.023)	0.10***	(0.026)	– 0.078**	(0.039)
25 < age < 35	– 0.066**	(0.027)	0.0026	(0.043)	– 0.081	(0.051)	– 0.44***	(0.078)
35 < age < 45	– 0.067***	(0.025)	– 0.091**	(0.040)	– 0.40***	(0.046)	0.15**	(0.069)
45 < age < 55	0.0005	(0.024)	– 0.21***	(0.040)	– 0.26***	(0.048)	– 0.010	(0.073)
55 < age < 65	– 0.057**	(0.026)	– 0.11***	(0.041)	– 0.17***	(0.048)	– 0.37***	(0.072)
Age > 65	– 0.16***	(0.028)	– 0.43***	(0.045)	– 0.41***	(0.051)	– 0.90***	(0.079)
Education level 2	– 0.094***	(0.021)	– 0.36***	(0.034)	– 0.33***	(0.041)	– 0.37***	(0.062)
Education level 3	– 0.21***	(0.020)	– 0.54***	(0.032)	– 0.28***	(0.038)	0.15***	(0.057)
Education level 4	– 0.16***	(0.016)	– 0.59***	(0.027)	– 0.33***	(0.032)	– 0.51***	(0.048)
Education level 5	– 0.27***	(0.022)	– 0.97***	(0.034)	– 0.50***	(0.039)	– 0.45***	(0.059)
Education level 6	– 0.033**	(0.017)	– 0.22***	(0.026)	– 0.15***	(0.032)	– 0.46***	(0.048)
Education level 7	– 0.16***	(0.017)	– 0.54***	(0.026)	– 0.22***	(0.031)	– 0.28***	(0.047)
Employee	– 0.079***	(0.015)	– 0.39***	(0.023)	– 0.049*	(0.026)	– 0.57***	(0.040)
Student	– 0.046	(0.039)	– 0.11*	(0.061)	– 0.58***	(0.067)	– 0.21**	(0.10)
House wife	– 0.095***	(0.018)	– 0.34***	(0.026)	– 0.22***	(0.030)	– 0.49***	(0.047)
Immigrant	0.38***	(0.025)	1.16***	(0.039)	0.38	(0.037)	0.79***	(0.057)
Terraced house	– 0.037***	(0.0042)	– 0.027***	(0.0063)	– 0.057***	(0.0068)	0.087***	(0.010)
Detached house	– 0.080***	(0.0048)	– 0.11***	(0.0074)	– 0.040***	(0.008)	– 0.22***	(0.012)
Number of obs.	308,445		302,679		304,780		299,840	

Notes: Results for year fixed effects are not reported. Standard errors are between parentheses. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.

Table A.5 Effect of police on preventative measures – the modified RE model

	Drive or walk around		Leaving properties at home		Forbidding children to go out	
Ln (police) (t-1)	– 0.059***	(0.015)	– 0.077***	(0.019)	– 0.080**	(0.034)
AR-term	0.53***	(0.015)	0.28***	(0.015)	0.43***	(0.051)
Individual characteristics						
Male	0.085***	(0.0013)	0.051***	(0.0015)	0.062***	(0.0029)
25 < age < 35	– 0.016***	(0.0027)	0.0013	(0.0030)	0.061***	(0.0057)
35 < age < 45	0.0023	(0.0028)	0.029***	(0.0031)	0.13***	(0.0058)
45 < age < 55	0.018***	(0.0028)	0.055***	(0.0031)	0.17***	(0.070)
55 < age < 65	0.023***	(0.0031)	0.087***	(0.0035)	0.18***	(0.020)
Age > 65	0.0031	(0.0033)	0.099***	(0.0038)	0.088**	(0.038)
Education level 2	0.011***	(0.0025)	0.014***	(0.0032)	– 0.024*	(0.013)
Education level 3	0.020***	(0.0026)	0.021***	(0.0033)	– 0.038***	(0.013)
Education level 4	0.025***	(0.0025)	0.024***	(0.0032)	– 0.049***	(0.012)
Education level 5	0.025***	(0.0030)	0.017***	(0.0037)	– 0.063***	(0.013)
Education level 6	0.028***	(0.0025)	0.022***	(0.0032)	– 0.064***	(0.012)
Education level 7	0.018***	(0.0030)	– 0.00074	(0.0037)	– 0.088***	(0.013)
Employee	– 0.016***	(0.0018)	– 0.016***	(0.0021)	– 0.017***	(0.0042)
Student	– 0.0070**	(0.0035)	– 0.014***	(0.0038)	– 0.033***	(0.0068)
House wife	– 0.018***	(0.0019)	– 0.0072***	(0.0023)	0.0019	(0.0045)
Immigrant	0.024	(0.0032)	0.016***	(0.0037)	0.054***	(0.0068)
Children	0.015***	(0.0043)	– 0.019***	(0.0050)	0.26***	(0.012)
Terraced house	– 0.012***	(0.0016)	– 0.023***	(0.0020)	– 0.013***	(0.0048)
Detached house	– 0.022***	(0.0020)	– 0.026***	(0.0026)	– 0.0096*	(0.0058)
Municipality averages						
Ln (police) (t-1)	0.0088	(0.015)	0.073***	(0.018)	0.043	(0.034)
Male	– 0.17***	(0.028)	– 0.038	(0.038)	– 0.19***	(0.068)
25 < age < 35	– 0.32***	(0.054)	– 0.15**	(0.074)	– 0.63***	(0.14)
35 < age < 45	– 0.21***	(0.053)	0.061	(0.070)	– 0.51***	(0.13)
45 < age < 55	– 0.37***	(0.053)	– 0.19***	(0.073)	– 0.65***	(0.13)
55 < age < 65	– 0.50***	(0.053)	– 0.19***	(0.072)	– 0.82***	(0.13)
Age > 65	– 0.51***	(0.055)	– 0.19**	(0.075)	– 0.91***	(0.14)
Education level 2	– 0.021	(0.042)	0.17***	(0.058)	– 0.12	(0.10)
Education level 3	– 0.033	(0.039)	– 0.098*	(0.054)	– 0.0074	(0.097)
Education level 4	– 0.24***	(0.034)	– 0.20***	(0.047)	– 0.18**	(0.084)
Education level 5	– 0.48***	(0.046)	– 0.096	(0.061)	– 0.41	(0.11)
Education level 6	0.13***	(0.033)	0.23***	(0.045)	0.40***	(0.080)
Education level 7	– 0.30***	(0.033)	– 0.13***	(0.045)	– 0.11	(0.082)
Employee	– 0.21***	(0.028)	– 0.076**	(0.038)	– 0.57***	(0.069)
Student	0.0098	(0.072)	– 0.077	(0.095)	– 0.67***	(0.17)
House wife	– 0.12***	(0.037)	– 0.0034	(0.050)	– 0.31***	(0.089)
Immigrant	0.62***	(0.045)	0.39***	(0.058)	0.81***	(0.11)
Children	– 0.26***	(0.073)	– 0.73***	(0.098)	– 0.78***	(0.18)
Terraced house	– 0.040***	(0.089)	– 0.068***	(0.012)	– 0.092***	(0.022)
Detached house	– 0.19***	(0.010)	– 0.23***	(0.014)	– 0.29***	(0.027)
Number of observations	306,945		306,986		87,793	

Notes: Results for year fixed effects as well as the number of people in the household are not reported. Standard errors are between parentheses. * Statistically significant at the 10-percent level. ** Statistically significant at the 5-percent level. *** Statistically significant at the 1-percent level.