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*Jørgen Aasness,
Erling Eide, and Terje Skjerpen*

Criminometrics, Latent Variables, Panel Data, and Different Types of Crime

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Abstract:
A behavioural model of crime is developed and applied to panel data on the number of crimes and clear-ups for the 53 police districts in Norway for the period 1970-78. Data on both total crime and on 12 different types of crime is employed. The model consists of behavioural relations of the offenders and the police, and of measurement relations allowing for random and systematic errors in the registered crimes and clear-ups. A theoretical analysis reveals that the model is identified under certain conditions, and our empirical analysis supports the hypothesis that these conditions are satisfied. Detailed empirical results on deterrence elasticities and other structural parameters are presented.

Keywords: Economics of crime, deterrence, equilibrium models, panel data, latent variables, measurement errors.

JEL classification: C33, C51, K14.

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Address: Jørgen Aasness, Statistics Norway, Research Department,
P.O.Box 8131 Dep., N-0033 Oslo. E-mail: j2a@ssb.no

Terje Skjerpen, Statistics Norway, Research Department. E-mail: tes@ssb.no

Erling Eide, Faculty of Law, University of Oslo, Karl Johansgt. 47, N-0162 Oslo.
E-mail: erling.eide@jus.uio.no

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1. Introduction [1]

Virtually all criminal legislation is pervaded by the belief that punishment has a deterrent effect on crime. This belief was strengthened by a study of Becker (1968) where, in an economic model of crime, it was assumed that crime is a risky business and that people act as rational utility maximizers. When a person considers all benefits and costs of a possible crime, the expected utility of the crime will be reduced when either the probability of being caught and punished or the severity of punishment is increased. Not surprisingly, a reduction in the expected utility of crime will lead to a reduction in the number of crimes.

In the last 20 years the hypothesis of a deterrent effect of punishment has been confirmed by several empirical studies of total crime and of various types of crime, but not by all of them. (See reviews in Blumstein, Cohen and Nagin (1978), Heineke (1978), Bleyleveld (1980), Schmidt and Witte (1984), and Cameron (1988)). Furthermore, methodological problems in the common empirical studies of crime cast doubt on a substantial part of this literature.

Most empirical studies are plagued by substantial underregistration of crime. Registration depends on the attitude of those who discover a crime, on the access to telephone, on insurance, on police routines, etc. If recording differs between police districts (in cross section studies) or over the years (in time series studies), a spurious negative correlation will appear between the crime rate and the proportion of crimes that are cleared up (see e.g. Blumstein et al., 1978). If, on the other hand, an increase in the number of policemen increases the number of crimes that are formally recorded, but not cleared up, there will be a spurious negative correlation between the number of policemen and clear-up proportion. Thus, underreporting and changes in recording will usually introduce a bias in favour of deterrence, but against the hypothesis that the police produces it (Cameron 1988). These spurious correlations impede the evaluation of criminometric studies, that most often confirm that crime increases with a decrease in the clear-up proportion, but that more police does not increase the clear-up proportion. This difficulty has inspired us to deal more explicitly with measurement errors. Especially, we introduce latent variables and employ the maximum likelihood method in estimating the structural relations of a simultaneous model.

Fisher and Nagin (1978) have discussed the serious problem of identification of models of crime. They are reluctant to accept the commonly used procedure in empirical crime studies of identifying models by excluding various socioeconomic variables from the equations. Using panel data we have succeeded in identifying our model by showing that

[1]Paper presented to the Econometric Society European Meeting in Maastricht, Aug. 29 - Sept. 2, 1994. A version of this paper will be published in Eide (forthcoming).

the structural parameters are explicit functions of the theoretical 2. order moments of the log of the crime and clear-up rates.

When designing the model, we have emphasized simplicity in order to focus on some basic theoretical and empirical issues. In particular, we have not included sociodemographic variables explicitly. We include, however, latent police districts effects which summarize the effects of socioeconomic variables on crimes and on clear-ups, and we model the distributions of these latent variables across police districts and over time. The strength of sentences is not included as a variable, because no perceptible difference in this factor seems to exist between police districts and over time in the period studied.

This paper is a continuation of Aasness, Eide and Skjerpen (1992 and 1993). The basic model is essentially the same, but it has been ameliorated on certain points, especially in the more systematic treatment of hypotheses, cf Table 1 below. Whereas our 1992- and 1993-papers employed data on total crime only, we here study 12 different types of crime. For the purpose of comparison, we have included the main results concerning total crime. Section 6, the major empirical part of the paper, contains new results only.

The paper is organized as follows: In section 2 the criminometric model is derived by combining an equilibrium model of the latent number of crimes and clear-ups, based on behavioural relations of the offenders and the police, and measurement relations allowing for random and systematic measurement errors in the registered crimes and clear-ups. Furthermore, submodels and hypotheses are classified. Section 3 presents detailed and subtle identification results within this model class for panel data. Data and inference procedures are presented in section 4, and empirical results using Norwegian data in section 5. In section 6 twelve types of crime are analysed in a similar manner. The main conclusions are summarized in section 7.

2. Model framework and hypotheses

The criminometric model is designed to describe and explain crime and clear-up rates for I (i=1,2,...I) police districts in T (t=1,2,...,T) years. Section 2.1 presents the equilibrium model of crimes and clear-ups based on behavioural relations between the true latent variables. The crime and clear-up tendencies of the police districts are discussed in section 2.2. In section 2.3 we introduce measurement relations connecting the true latent variables with the observed crimes and clear-ups. The criminometric model in final form, derived from the submodels in 2.1, 2.2 and 2.3, is given in section 2.4, and in section 2.5 we define submodels and present hypotheses to be tested. Note that the equations below hold for all relevant i and t.

2.1. An equilibrium model of crimes and clear-ups

The equilibrium model consists of the following three equations:

$$P_{it} = Y_{it}/X_{it}, \tag{1a}$$

$$X_{it} = P_{it}^{b}C_{it}, \tag{1b}$$

$$Y_{it} = X_{it}^{r}U_{it}. \tag{1c}$$

X_{it} is the (true) *crime rate*, i.e. the number of crimes per 1000 inhabitants, in police district i in year t. Y_{it} is the *clear-up rate* defined as the number of clear-ups per 1000 inhabitants. P_{it} is the *clear-up proportion* defined in (1a), i.e. the number of clear-ups as a share of the number of crimes. (In the literature this concept (P_{it}) is sometimes denoted "clear-up rate", while we prefer to use this term to denote the concept symbolized by Y_{it}, treating crimes and clear-ups "symmetrically" throughout the analysis.)

The crime function (1b) says that the crime rate (X_{it}) is a simple power function of the clear-up proportion (P_{it}). It can be interpreted as a behavioural relation for an average offender with rational expectations on the probability of being caught. Furthermore, it can be derived from a utility maximizing model in the tradition of Becker (1968), keeping the severity of punishment constant. For convenience we will call the parameter b the *deterrence elasticity* and the variable C_{it} the *crime tendency* in police district i in year t. The crime tendency (C_{it}) summarizes the effect of the socioeconomic environment and other variables not explicitly modelled. The distribution of these latent crime tendencies across districts and over time will be modelled below.

The clear-up function (1c) says that the clear-up rate (Y_{it}) is a simple power function of the crime rate (X_{it}). It can be interpreted as a behavioural relation of the police. One may also interpret it as a combined relation of the behaviour of the police and the political authorities financing the police force. For convenience we will call the parameter r the *clear-up elasticity*, and the variable U_{it} the *clear-up tendency*.

We will below interpret, exploit, and/or test the following hypotheses on the deterrence elasticity (b) and the clear-up elasticity (r):

$$H_{b0}\text{: } b<0, \quad H_{r0}\text{: } r>0, \quad H_{r1}\text{: } r<1, \quad H_{d0}\text{: } d\equiv 1+b(1-r)>0. \tag{2}$$

The theory of Becker (1968) implies H_{b0}, and most empirical studies support this hypothesis[2]. The various weak aspects of the majority of these studies, however, require further testing of the deterrent effect of the probability of sanctions. Hypothesis H_{r0} seems reasonable because more crimes make it possible to get more cases cleared up. With more crimes, however, less police force would be available per case, thus H_{r1} seems plausible. This hypothesis, too, is (indirectly) supported by several empirical studies, where the probability of sanctions is found to be a decreasing function of the crime rate, see e.g. Vandaele (1978). Restriction H_{d0} secures that there will exist a meaningful and stable solution to our equilibrium model. (The significance of the sign of the "stability parameter" d is discussed below.) Assuming H_{r1}, the restriction H_{d0} is equivalent to $b>-1/(1-r)$, i.e. the deterrence elasticity must not, for a fixed value of r, be too negative. Furthermore, from H_{b0}, H_{r1}, and H_{d0} follows

H_{d1}: $0<d<1$.

The system of equations (1) has three endogenous variables (P_{it}, X_{it}, Y_{it}), and two exogenous variables (C_{it}, U_{it}), with the following solution:

$$P_{it} = C_{it}^{(r-1)/d} U_{it}^{1/d}, \tag{3a}$$

$$X_{it} = C_{it}^{1/d} U_{it}^{b/d}, \tag{3b}$$

$$Y_{it} = C_{it}^{r/d} U_{it}^{(1+b)/d}. \tag{3c}$$

Assuming (2), we obtain clear-cut sign results in five out of six cases: Increased crime tendency (C_{it}) decreases the clear-up proportion (P_{it}), increases the crime rate (X_{it}) and increases the clear-up rate (Y_{it}). Increased clear-up tendency (U_{it}) increases the clear-up proportion (P_{it}), and reduces the crime rate (X_{it}), whereas the sign effect on the clear-up rate depends on the magnitude of the deterrence effect:

$$El_{U_{it}} Y_{it} = (1+b)d \gtreqless 0 \quad \text{iff} \quad b \gtreqless -1. \tag{4}$$

Thus, if the deterrence elasticity is less than -1, an increased clear-up tendency (U_{it}) reduces the number of clear-ups (Y_{it}) due to the strong reduction in the number of crimes.

The question of stability of the equilibrium solution (3) can most easily be discussed by help of Fig. 1, where the crime rate is measured along the horizontal axis, and the clear-up proportion along the vertical one. (For convenience, the subscripts i and t are here

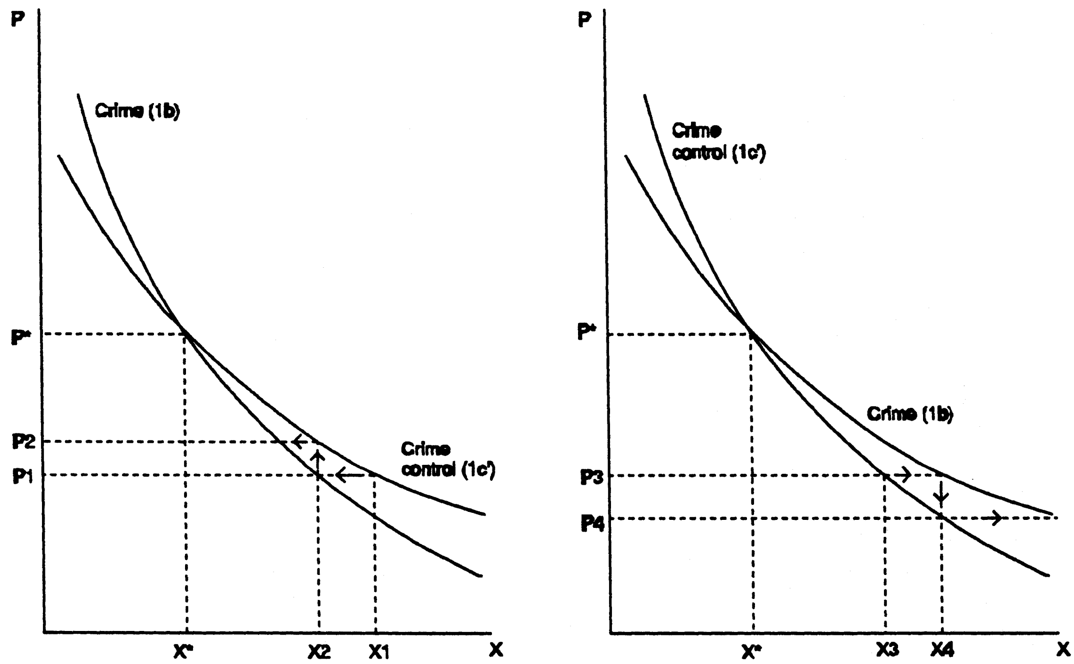
[2]See Eide (forthcoming) for a review.

dropped.) The crime curves illustrate relation (1b) when b<0. The crime control curves are obtained by eliminating the clear-up rate through substitution of (1c) into (1a):

$$P_{it} = X_{it}^{r-1} U_{it} \,, \quad \text{or} \tag{1c'}$$

$$X_{it} = P_{it}^{\frac{1}{r-1}} U_{it}^{\frac{1}{1-r}}. \tag{1c''}$$

Relation (1c') can be interpreted as the crime control function of the society (including the police). The clear-up activity represented by (1c) has been transformed into a function determining the clear-up probability (which again, in interaction with the crime function, determines the equilibrium values of the model).



a) Stable, d>0 (b) Unstable, d<0

Fig. 1 Stability of equilibrium

In Fig. 1 we assume that there exist positive equilibrium values P^* and and X^* of the clear-up proportions and crime rates, respectively, and that H_{b0} and H_{r1} are satisfied. In

Fig. 1 (a) the crime curve is steeper than the crime control curve, which means, cf (1b) and (1c''), that $1/(r-1) < b$, or $1+b(1-r) > 0$, which is the same as restriction H_{d0}. Considering, according to the correspondence-principle of Samuelson (1945), our equilibrium to be the stationary solution to a corresponding dynamic model, where the society (including the police) determines the clear-up probability (cf (1c')), and the potential offenders thereafter determines the number of crimes (cf (1b)), the following mechanism is obtained: If we start out with a hypothetical crime rate X1, the society's crime control (cf (1c')) will result in a clear-up rate P1, a rate at which crime (cf (1b)) will be reduced to X2, which again will result in a higher clear-up rate P2, etc. The crime rate and the clear-up proportion will move towards the equilibrium solution. A similar move towards equilibrium will obtain if we start from a crime rate below its equilibrium value. Thus, restriction $d>0$ is sufficient for a stable equilibrium under the stated conditions. If $d < 0$, we have the situation in Fig. 1 (b). Here, the society's crime control activity will produce, from a hypothetical crime rate X3, say, a clear-up proportion P3, that will result in a higher crime rate X4, which again will produce a lower clear-up proportion P4, etc. The crime rate will explode. Starting with any crime rate below X^*, the clear-up proportion will increase and the crime rate decrease. With our assumptions, we thus find that $d>0$ is also a necessary condition for the equilibrium solution to be stable. (If $d=0$, the two curves merge, and no single equilibrium solution is obtained.) It is straightforward to formally prove stability by analyzing an appropriate difference equation.

2.2. Distribution of crime and clear-up tendencies

The model determines an equilibrium for each police district in every year. By specifying a distribution on the crime and clear-up tendencies (C_{it}, U_{it}) across police districts, and how it varies over time, we obtain a corresponding distribution of crimes and clear-ups (X_{it}, Y_{it}) through the reduced form model (3). Consider the following decomposition:

$$\ln C_{it} = \omega_{0t} + \omega_{1i} + t\omega_{2i}, \tag{5a}$$

$$\ln U_{it} = \lambda_{0t} + \lambda_{1i} + t\lambda_{2i}, \tag{5b}$$

where ω_{0t} and λ_{0t} are deterministic (police district invariant) time trends, and the remaining ωs and λs are time invariant latent district effects. Stochastic specifications are given in (15) below. The assumptions that the covariance matrices, of ωs and λs respectively, are positive semidefinite can be stated as the following hypotheses:

$$H_\omega:\ \sigma_{\omega1\omega1}\geq 0,\ \sigma_{\omega2\omega2}\geq 0,\ \sigma^2_{\omega1\omega2}\leq\sigma_{\omega1\omega1}\sigma_{\omega2\omega2}, \tag{6a}$$
$$H_\lambda:\ \sigma_{\lambda1\lambda1}\geq 0,\ \sigma_{\lambda2\lambda2}\geq 0,\ \sigma^2_{\lambda1\lambda2}\leq\sigma_{\lambda1\lambda1}\sigma_{\lambda2\lambda2}. \tag{6b}$$

These hypotheses will be discussed and tested below.

This structure allows for a restricted evolution over time in the distribution of the crime and clear-up tendencies across police districts. In particular, it follows that

$$\text{var } \ln C_{it} = \sigma_{\omega1\omega1} + 2t\sigma_{\omega1\omega2} + t^2\sigma_{\omega2\omega2}, \tag{7a}$$
$$\text{var } \ln U_{it} = \sigma_{\lambda1\lambda1} + 2t\sigma_{\lambda1\lambda2} + t^2\sigma_{\lambda2\lambda2}. \tag{7b}$$

Note that if $\ln C_{it}$ is assumed to be normally distributed, the coefficient of variation of the crime tendency, $\sqrt{\text{var}C_{it}}/EC_{it}$, will be a simple transformation of var $\ln C_{it}$, cf Aitchison and Brown (1957, p. 8). Thus, dropping the term ω_{2i} implies a constant coefficient of variation of the crime tendency C_{it}.

From (7) it follows that

$$\Delta\text{var } \ln C_{it} = 2\sigma_{\omega1\omega2} + (2t+1)\sigma_{\omega2\omega2}, \tag{8a}$$
$$\Delta\text{var } \ln U_{it} = 2\sigma_{\lambda1\lambda2} + (2t+1)\sigma_{\lambda2\lambda2}, \tag{8b}$$

where Δ denotes the first difference operator. From (8a) we see that the variance of the log of the crime tendency decreases if and only if $\sigma_{\omega1\omega2} < -\sigma_{\omega2\omega2}(2t+1)/2$. Thus, a necessary condition for this to happen, interpreting $\sigma_{\omega2\omega2}$ as a positive variance, is that the covariance between the two components ω_1 and ω_2 is negative.

It should be noted, however, that it is possible to give another interpretation of (7) and (8) above. We may drop (5) and (6) and start with specifying (7). Then we may interpret, say $\sigma_{\omega2\omega2}$, just as a parameter in a relation which describes how var $\ln C_{it}$ evolves over time. With such an interpretation it is meaningful to have a negative value of $\sigma_{\omega2\omega2}$, which implies a time trend towards decreasing spread in the crime tendencies across police districts.

Observe further that our model allows for four different time trends in crime and clear-up tendencies: i) monotonically increasing, ii) monotonically decreasing, iii) first increasing and then decreasing, and iv) first decreasing and then increasing.

We consider the 2. order polynomial in (7a) to be a valid approximation only for a limited time period. In particular, we are interested to test the hypotheses that the derived variances of the crime and clear-up tendencies are positive for a set of time periods, i.e.

$$H_C:\ \text{var } C_{it}>0,\ t=1,2,\ldots,T, \tag{9a}$$
$$H_U:\ \text{var } U_{it}>0,\ t=1,2,\ldots,T. \tag{9b}$$

In our empirical test we shall interpret t=1,2,...,T as the sample period. It may happen that our second order polynomial can make these variances negative for some years, not only outside the sample period, but also within it.

It may occur happen that H_ω is not fulfilled, while H_C is valid, a result which is connected with the interpretation above of (7). Both types of hypotheses will be tested in our empirical analyses.

2.3. Measurement relations

Let x_{it} and y_{it} be the logs of the *registered crime and clear-up rates*, respectively. These are related to the true rates by the following equations:

$$x_{it} = \ln X_{it} + e_t + \varepsilon_{it}, \tag{10a}$$
$$y_{it} = \ln Y_{it} + f_t + \varphi_{it}. \tag{10b}$$

Here, $\exp(e_t)$ and $\exp(f_t)$ represent systematic, multiplicative measurement errors in $\exp(x_{it})$ and $\exp(y_{it})$, respectively. The terms e_t and f_t are police district invariant. They may, however, change over time. They are both deterministic variables. The term e_t takes account of the problem of systematic underreporting (dark number) of crime. The variables ε_{it} and φ_{it} can be interpreted as random measurement errors. Stochastic specifications are given in (15).

The assumption that the covariance matrix of the measurement errors is positive definite, can be stated as the following hypothesis:

$$H_M\text{: } \sigma_{\varepsilon\varepsilon}>0,\ \sigma_{\phi\phi}>0,\ \sigma^2_{\varepsilon\phi}<\sigma_{\varepsilon\varepsilon}\sigma_{\phi\phi}. \tag{11}$$

Note that the random measurement errors (ε_{it} and φ_{it}) are allowed to be correlated. We expect this correlation to be positive: If, in a police district, registration is particularly sloppy, some crimes that elsewhere normally would have resulted in separate files, are only informally recorded. As formal files, including eventual clear-ups, constitute the basis for the production of statistics, both the registered numbers of crimes and the registered number of clear-ups will be lower than in a similar police district with better registration procedures. This underregistration results in a positive correlation between the random measurement errors. The same will happen if some files are forgotten when statistics are produced by the end of the year. We thus state the hypothesis

H_{MC}: $\sigma_{\varepsilon\varphi}>0$. (12)

For convenience we define the following transformed variables:

$$\chi_{it} = \ln X_{it} + e_t, \tag{13a}$$
$$\psi_{it} = \ln Y_{it} + f_t, \tag{13b}$$
$$\pi_{it} = \psi_{it} - \chi_{it}, \tag{13c}$$
$$a_t = \omega_{0t} + (1+b)e_t - bf_t, \tag{13d}$$
$$k_t = \lambda_{0t} - re_t + f_t. \tag{13e}$$

In (13a) we define the log of the *latent crime rate* (χ_{it}) as the sum of the log of the true crime rate (X_{it}) and the systematic measurement error (e_t). The log of the *latent clear-up rate* (ψ_{it}), and the log of the *latent clear-up proportion* (π_{it}) are defined in (13b) and (13c). The parameters a_t and k_t are introduced in order to simplify the criminometric model below. Note that a_t and k_t are composed of the deterministic time trends of (5) and (10). We do not try to identify and estimate these components separately.

2.4. The criminometric model in final form

From (1), (5), (10), and (13) we can now derive the following criminometric model:

$$x_{it} = \chi_{it} + \varepsilon_{it}, \tag{14a}$$
$$y_{it} = \psi_{it} + \varphi_{it}, \tag{14b}$$
$$\pi_{it} = \psi_{it} - \chi_{it}, \tag{14c}$$
$$\chi_{it} = b\pi_{it} + a_t + \omega_{1i} + t\omega_{2i}, \tag{14d}$$
$$\psi_{it} = r\chi_{it} + k_t + \lambda_{1i} + t\lambda_{2i}. \tag{14e}$$

We consider (ε_{it}, φ_{it}, ω_{1i}, ω_{2i}, λ_{1i}, λ_{2i}) as a vector of exogenous, random variables independently drawn from the same distribution, with the following first and second order moments:

$$E\varepsilon_{it}=E\varphi_{it}=E\omega_{1i}=E\omega_{2i}=E\lambda_{1i}=E\lambda_{2i}=0, \tag{15a}$$

$$E\varepsilon_{it}^2=\sigma_{\varepsilon\varepsilon},\quad E\varphi_{it}^2=\sigma_{\varphi\varphi},\quad E\varepsilon_{it}\phi_{it}=\sigma_{\varepsilon\varphi}, \tag{15b}$$

$$E\omega_{1i}^2=\sigma_{\omega1\omega1},\quad E\omega_{2i}^2=\sigma_{\omega2\omega2},\quad E\omega_{1i}\omega_{2i}=\sigma_{\omega1\omega2}, \tag{15c}$$

$E\lambda_{1i}^2=\sigma_{\lambda1\lambda1}, \quad E\lambda_{2i}^2=\sigma_{\lambda2\lambda2}, \quad E\lambda_{1i}\lambda_{2i}=\sigma_{\lambda1\lambda2}.$ (15d)

All other covariances between the exogenous variables (ε,φ, ω, and λ) are assumed to be zero. Note that the assumptions of (15a) are innocent because of the constant terms defined in (5) and (10). The other assumptions are to some degree commented on above. In section 4 we will also exploit and discuss the assumption that the variables are multinormally distributed.

2.5. Hypotheses and model specifications

We have in (2), (6), (9), (11), and (12) formulated various interval hypoteses about the parameters of our model framework. These are restated in Table 1. On the basis of point hypotheses about some of the parameters we have in Table 2 classified various models within our model framework. The assumptions of the models correspond to some of the hypotheses we are interested in testing, especially hypotheses about the correlation of measurement errors, and about the distributions of latent police district effects. Each assumption is given a label, and each model will be denoted by the corresponding combination of labels. (See Aasness, Biørn, and Skjerpen (1993) for a similar framework.) On the basis of the model classification of Table 2 it is possible to specify 2x4x4=32 different models defined by different assumptions in the M-, W- and L-dimensions, where these dimensions refer to correlations of measurement errors (M), correlations of police district effects on crimes (W), and correlations of police district effects on clear-ups (L). All these specific models are estimated and/or tested in the empirical analysis. We could, of course, introduce other specifications, e.g. time trends in the police district invariant terms a_t and k_t, but this is not carried out in the present analysis.

3. Identification

Identification of most of the submodels are proven by showing that the structural parameters are explicit functions of the theoretical 2. order moments of the crime and clear-up rates, cf Appendix B of Aasness, Eide and Skjerpen (1992). The results of our investigation of identification are summarized in Table 3. Here Wi* (i=0,1,2,3) denotes the same assumptions as Wi in Table 2, except that all parameters assumed to be free in Table 2 now are assumed not to be zero. Lj* is defined similarly, and we have, for instance, that W1*L0 corresponds to W1L0, the difference being that $\sigma_{\omega1\omega1}$ can be zero in the latter, but not in the former. Table 3 thus contains a complete set of submodels of W3L3.

Table 1
Interval hypotheses

Name of hyp.	Hypothesis	Explanation	Eq. no.
H_{b0}	$b<0$	Negative deterrence elasticity	2
H_{r0}	$r>0$	Positive clear-up elasticity	
H_{r1}	$r<1$	Clear-ups increase proportionally less than crimes	2
H_{d0}	$d\equiv 1+b(1-r)>0$	Requirement of stable solution to crime model	2
H_{d1}	$0<d<1$	Derived from H_{b0}, H_{r1}, and H_{d0}.	
H_{ω}	$\sigma_{\omega 1\omega 1}\geq 0$, $\sigma_{\omega 2\omega 2}\geq 0$, $\sigma^2_{\omega 1\omega 2}\leq\sigma_{\omega 1\omega 1}\sigma_{\omega 2\omega 2}$	Positive semidefinite covariance matrices for district effects in crime	6a
H_{λ}	$\sigma_{\lambda 1\lambda 1}\geq 0$, $\sigma_{\lambda 2\lambda 2}\geq 0$, $\sigma^2_{\lambda 1\lambda 2}\leq\sigma_{\lambda 1\lambda 1}\sigma_{\lambda 2\lambda 2}$	Positive semidefinite covariance matrices for district effects in clear-ups	6b
H_C	var $C_{it}>0$, $t=1,2,...,T$	Positive variances of crime tendencies for all years in sample period	9a
H_U	var $U_{it}>0$, $t=1,2,...,T$	Positive variances of clear-up tendencies for all years in the sample period	9b
H_M	$\sigma_{\varepsilon\varepsilon}>0$, $\sigma_{\varphi\varphi}>0$, $\sigma^2_{\varepsilon\varphi}<\sigma_{\varepsilon\varepsilon}\sigma_{\varphi\varphi}$	Positive definite covariance matrix of measurement errors	11
H_{MC}	$\sigma_{\varepsilon\varphi}>0$	Positively correlated measurement errors	12

Table 2
Classification of hypotheses and models[a]

Assumptions with respect to correlations of measurement errors

Label	Parameter restriction $\sigma_{\varepsilon\varphi}$	Interpretation
M0	0	No correlation of measurement errors
M1	free	Measurement errors correlated

Assumptions with respect to correlations of police district effects on crimes

Label	Parameter restriction $\sigma_{\omega1\omega1}$	$\sigma_{\omega2\omega2}$	$\sigma_{\omega1\omega2}$	Interpretation
W0	0	0	0	No district effect in crime
W1	free	0	0	Time invariant district effect in crime
W2	free	free	0	Trend in distribution of district effect in crime
W3	free	free	free	Time invariant and trend effects correlated

Assumptions with respect to correlations of police district effects on clear-ups

Label	Parameter restriction $\sigma_{\lambda1\lambda1}$	$\sigma_{\lambda2\lambda2}$	$\sigma_{\lambda1\lambda2}$	Interpretation
L0	0	0	0	No district effect in clear-ups
L1	free	0	0	Time invariant district effect in clear-up
L2	free	free	0	Trend in distribution of district effect in clear-up
L3	free	free	free	Time invariant and trend effects correlated

[a] A model is specified by a combination of 3 labels: e.g. model M0W1L1 is a model where there is no correlation of measurement errors, and no trends in the police district effects on crimes and clear-ups.

A particular problem arises in models $W3^*L3^*$ and $W2^*L2^*$. Here identification of r (or b) requires the solution of a second order equation in this parameter, and we will in general have two different roots, corresponding to two observationally equivalent structures. The model can nevertheless be identified if only one of the two solutions satisfy a priori restrictions on the set of parameter values. The simplest case is to assume H_{d1}, i.e. $0<d<1$, which can be derived from (2), since we have shown (Appendix B, Section B.10 of our 1992 paper) that only one of the two solutions can satisfy this restriction. If one is not willing to use H_{d1} as a maintained assumption, for example because one is interested in testing this hypothesis, or the hypothesis of $b<0$, there are still possibilities for discriminating between the two observationally equivalent structures, combining a priori and empirical information. We will give an example of this, which we will exploit in our empirical analysis below.

Let θ be denote the vector of n=11 structural parameters in our model, and consider first the following set:

$$\Theta_1=\{\theta\in R^n|\sigma_{\varepsilon\varepsilon}\geq 0,\ \sigma_{\varphi\varphi}\geq 0,\ \sigma^2_{\varepsilon\varphi}\leq\sigma_{\varepsilon\varepsilon}\sigma_{\varphi\varphi},\ \text{var}\ \ln C_{it}\geq 0,\ \text{var}\ \ln U_{it}\geq 0,\ t=1,2,...,T\}, \tag{16a}$$

i.e. the parameter values are meaningful with respect to our interpretation with measurement errors and variation in crime tendencies and clear-up tendencies across police

Table 3
Identification of submodels of W3L3[ab]

	$W3^*$	$W2^*$	$W1^*$	$W0^*$
$L3^*$	Identified if assuming H_{d1} or #A=1	Identified	Identified	Not identified[c]
$L2^*$	Identified	Identified if assuming H_{d1} or #A=1	Identified	Not identified[c]
$L1^*$	Identified	Identified	Not identified[e]	Not identified[c]
$L0^*$	Not identified[d]	Not identified[d]	Not identified[d]	Not identified

[a] See section 2.5 and Table 2 for definitions of models. The results hold for both M0 and M1.
[b] $\sigma_{\varepsilon\varepsilon}$, $\sigma_{\varphi\varphi}$, and $\sigma_{\varepsilon\varphi}$ are identified for W3L3 (and for all submodels).
[c] b is identified.
[d] r is identified.
[e] If one of the 4 non-identified parameters is given a fixed value, the remaining ones are identified.

districts. If, say, solution I belongs to Θ_1, while solution II does not, we can discriminate between them, i.e. solution I identifies the structure.

It may happen that both solutions belong to Θ_1. Then we may want to consider further restrictions, say

$$\Theta_2=\{\theta\in R^n|r>0,\ d>0\}, \tag{16b}$$

cf hypotheses H_{r0} and H_{d0} in section 2.1. It turns out that (16b) is all we need in our empirical analysis for total crime in section 5.

In section 6, analyzing various types of crime, we need further restrictions, and we apply

$$\Theta_3=\{\theta\in R^n|b<1,\ r<2\}. \tag{16c}$$

These restrictions are somewhat more arbitrary, but the idea is the following. One may imagine societies with a positive deterrence elasticity b and/or a clear-up elasticity larger than 1, i.e. where hypotheses H_{b0} and H_{r1} are not fulfilled. It seems incredible, however, if these parameters are very high. We have in (16c) chosen limits that are 1 higher than those on which H_{b0} and H_{r1} are based. We denote the corresponding hypotheses H_{b1} and H_{r2}. Restriction (16c) is exploited in our empirical analysis in section 6.

Let $\Sigma(\theta)$ denote the theoretical covariance matrix of the observed variables as a function of the unknown parameters θ of our model. Let

$$A = \{\theta\in R^n|\Sigma(\theta)=\Sigma\} \cap \Theta$$

for an arbitrary value of the covariance matrix Σ, where Θ is a set of parameters, say Θ_1, Θ_2, Θ_3, or a combination of these. If, for a given model, the number of elements in A is equal to one (#A=1), we consider the corresponding solution the only one that can be accepted, conditional on the choice of Θ. The number of elements in A can depend on Σ, and the question of identification of W3*L3* and W2*L2* thus involves empirical issues. In the empirical analysis below we argue that only one of the two solutions of W3*L3* is relevant in our case.

We have demonstrated (in Appendix B (Section B.9) of our 1992 paper) that, Wi*Lj* is observationally equivalent to Wj*Li* for $i\neq j$ and i,j=0,1,2,3. It is also shown, however, that assuming H_{d1} for one such model, the symmetric one is unstable, i.e. d<0. That is, within the set of two symmetric models {Wi*Lj*, Wj*Li*} ($i\neq j$, i,j=1,2,3), we can identify the correct model under assumption H_{d1}. Furthermore, the restrictions in (16) will in our empirical analysis turn out to be sufficient to determine which of two "symmetric" models is relevant or acceptable.

The parameters $\sigma_{\varepsilon\varepsilon}$, $\sigma_{\varphi\varphi}$, and $\sigma_{\varepsilon\varphi}$ are identified for W3L3 as a whole. Six of the submodels are completely identified. Identification of b is further obtained in the three first models of the last column of Table 3, whereas identification of the remaining parameters here requires one supplementary piece of information (e.g. fixing the value of one of them). Similarly, r is identified in the three first models of the last line, and here too one more piece of information is necessary in order to identify the remaining parameters.

4. Data and estimation

The model is estimated by use of data on the number of crimes and clear-ups for 53 police districts in Norway for the period 1970-78, (cf Statistics Norway, annual). Our main reasons for choosing this period is the absence of substantial changes in legal rules or registration practices. The effects on crime and crime registration of such changes being difficult to model, it is convenient to study a period where these problems are negligible or of minor importance. These data are transformed into crime rates and clear-up rates and further into logs of these rates. Finally, the logs are used to calculate a covariance matrix of the log numbers of crime and clear-up rates for the nine years. This covariance matrix (see Appendix) is all the data we use in our econometric analysis of total crime.

Let S be this sample covariance matrix of our observed variables, and

$$F = \ln|\Sigma(\theta)| + \mathrm{tr}(S\Sigma(\theta)^{-1}) - \ln|S| - 2T, \tag{17}$$

where "tr" is the trace operator, i.e. the sum of the diagonal elements of the matrix.

Minimization of F w.r.t. θ is equivalent to maximization of the likelihood function when assuming that all the observed variables (i.e. the lnx's and lny's) are multinormally distributed. (All the first order moments are used to estimate the constant terms a_t and k_t.) We have used the computer program LISREL 7 by Jöreskog and Sörbom (1988) to perform the numerical analysis.

A standard measure of the goodness of fit of the entire model in LISREL is GFI = $1 - \mathrm{tr}[(\Sigma^{-1}S - I)^2]/\mathrm{tr}[(\Sigma^{-1}S)^2]$, where I is the identity matrix; GFI = 1 indicates perfect fit. Standard asymptotic t-values and χ^2- statistics are utilized. We use a significance level of 0.01 as a standard in our test, but report also significance probabilities.

We will test a specific model 0 (the null hypothesis) against a more general model 1 (the maintained hypothesis) by a likelihood ratio test. Let F_0 and F_1 be the minimum of F under model 0 and model 1, respectively, and let s be the difference in the number of parameters of the two models. It can be shown that minus twice the logarithm of the likelihood ratio is equal to $I(F_0 - F_1)$, where I is the number of police districts. According to standard theory this statistic is approximately χ^2 distributed with s degrees of freedom. The χ^2 value for each model, given in Table 4, is defined as IF_0, which can be interpreted as the test statistic above when the alternative hypothesis is an exactly identified model, giving a perfect fit to the sample covariance matrix and accordingly F_1=0. The test statistic $I(F_0 - F_1)$ for an arbitrary pair of models may thus be computed by simply subtracting the corresponding pair of χ^2 values. The significance probability corresponding to the value of a test statistic, i.e. the probability of getting a χ^2 value greater than the value actually obtained given that the null hypothesis is true, is reported in Table 5.

LISREL 7 minimizes the function F without imposing any constraints on the admissible values of the parameter vector θ. Thus the LISREL estimate of a parameter which we interpret as a variance, may well turn out to be negative. This may be considered as a drawback of this computer program. However, if our model and its interpretation is correct, the LISREL estimates should turn out to have the expected signs, apart from sampling errors. Thus, if for a given model the estimates fulfill all the conditions in (16a), we will take this as a confirmation that the model has passed an important test. This in fact happened in our empirical analysis, both for total crime and for the 12 different types of crime.

If one is unwilling to assume normality of the observed variables, the estimators derived from minimizing F above can be labelled quasi maximum likelihood estimators. These estimators will be consistent, but their efficiency and the properties of the test procedures are not so obvious. A large literature on the robustness of these types of estimators and test procedures for departure from normality prevails, see e.g. Jøreskog and Sørbom (1988) for an extensive list of references, with quite different results depending on the assumptions and methods used. A recent and growing literature shows, however, that the estimators and test statistics derived under normality assumptions within LISREL type of models retain their asymptotic properties for wide departures from normality, exploiting assumptions on independently distributed nonnormal latent variables, see e.g. Anderson and Amemiya (1988), Amemiya and Anderson (1990), Browne (1987), and Browne and Shapiro (1988).

The assumption of normality can be tested by use of the (moment coefficient of) skewness $m_3/\sqrt{m_2}^3$ and the (moment coefficient of) kurtosis m_4/m_2^2. In a normal distribution the skewness is equal to zero, and the kurtosis is equal to three. Given that the distribution is normal, the observed skewness and kurtosis are asymptotically independent, and can thus be used for two asymptotically independent tests of normality. Skewness and kurtosis for our samples have been calculated (by SPSS) for the crime and clear-up rates, and for their logs, and are included in Tables A3-A8 of Appendix C in our 1992 paper. In 98% of all samples of size 50 from a normal population we have that the absolute value of skewness is less than 0.787, and the value of kurtosis is within the interval [1.95, 4.88][3]. We find that normality is rejected for the crime rate (Table A3[4]) by the skewness test for all years, and by the kurtosis test for two years. As for the clear-up rate (Table A5), normality is rejected by both tests for all years. The log of crime rates (Table A7) passes the skewness test for all years, but the kurtosis test for none, whereas the log of clear-up rates (Table A8) passes the skewness test in three years, and the kurtosis test also in three years. Obviously, a logarithmic specification of our model is to be preferred to a linear one. The values of the observed kurtosis are low, indicating platykurtic or "flat" distributions. This departure from normality is considered in the χ^2 tests below.

Another approach, based on an assumption of a multivariate elliptical distribution of the observed variables, shows that the likelihood ratio statistics derived under normality are still applicable, by rescaling the test statistics by a factor equal to the inverse of Mardia's coefficient of relative multivariate kurtosis, see Shapiro and Browne (1987). In the present data set of total crime this coefficient is 1.06. This supports our hypothesis that our procedure is robust against deviations from normality, and we do not consider it necessary here to study distributions more in detail.

5. Empirical results, total crime

5.1. Likelihood ratio tests

All 32 models classified in Table 2 have been fitted. Table 4 contains for all models the degrees of freedom (df), the goodness of fit (GFI), and the likelihood ratio χ^2 test statistic for each model against a model with no restriction on the covariance matrix.

First, we have studied the presence of correlation of measurement errors by testing M0 against M1. For all (16) possible combinations of maintained assumptions in the W- and L-dimensions M0 is rejected, even at a level of significance of 10^{-6}

Table 5.1 presents significance probabilities for tests of each of the hypotheses in the W-dimension against a more general hypothesis of the same dimension. These tests are performed for each of the alternative maintained assumptions in the L-dimension. Table 5.2 contains similar tests of the L-dimension. From Tables 5.1 and 5.2 we conclude that the hypotheses of W0, L0, W1, and L1 are rejected. We have further found (not included in

[3]The critical values of skewness and kurtosis can be found in Pearson (1965). A discussion of the present tests of normality is found in White and MacDonald (1980).

[4]The tables referred to in this paragraph are found in Aasness, Eide and Skjerpen (1992).

Table 4
Overview of fitted models

M1-models[a]

District effects on clear-ups		District effects on crime			
		W3	W2	W1	W0
L3	df	160	161	162	163[c]
	χ^2	291.25	291.87	304.69	509.72
	GFI	0.641	0.639	0.632	0.392
L2	df	161	162	163	164[c]
	χ^2	291.87	305.11	309.32	519.03
	GFI	0.639	0.631	0.628	0.386
L1	df	162	163	164[c]	165[c]
	χ^2	304.69	309.32	415.35	620.03
	GFI	0.632	0.628	0.508	0.329
L0	df	163[b]	164[b]	165[b]	166[bc]
	χ^2	509.72	519.03	620.03	1484.8
	GFI	0.392	0.386	0.329	0.185

M0-models[a]

District effects on clear-ups		District effects on crime			
		W3	W2	W1	W0
L3	df	161	162	163	164[c]
	χ^2	600.37	604.21	604.28	704.53
	GFI	0.467	0.460	0.460	0.428
L2	df	162	163	164	165[c]
	χ^2	604.21	622.64	622.65	717.73
	GFI	0.460	0.458	0.458	0.424
L1	df	163	164	165[c]	166[c]
	χ^2	604.28	622.65	742.98	815.16
	GFI	0.460	0.458	0.398	0.387
L0	df	164[b]	165[b]	166[b]	167[bc]
	χ^2	704.53	717.73	815.16	2055
	GFI	0.428	0.424	0.387	0.088

[a] See section 3 regarding the symmetry between WiLj and WjLi (i≠j; i=0,1,2,3).
[b] The model is estimated for a fixed value of b, any b would give the same χ^2.
[c] The model is estimated for a fixed value of r, any r would give the same χ^2.

Table 5
Significance probabilities in likelihood ratio tests[a]

1. Tests of district effects on crimes

Maintained assumptions	W0 against W1	W1 against W2	W2 against W3	W1 against W3
M1L3	0.000000	0.000451	0.442419	0.001581
M1L2	0.000000	0.049156	0.000273	0.000192
M1L1	0.000000	0.000000	0.028295	0.000000
M1L0	0.000000	0.000000	0.002206	0.000000

2. Tests of district effects on clear-ups

Maintained assumptions	L0 against L1	L1 against L2	L2 against L3	L1 against L3
M1W3	0.000000	0.000451	0.442419	0.001581
M1W2	0.000000	0.049156	0.000273	0.000192
M1W1	0.000000	0.000000	0.028295	0.000000
M1W0	0.000000	0.000000	0.002206	0.000000

[a] The equality of the significance probabilities between Tables 5.1 and 5.2 is due to the symmetry between the models WiLj and WjLi, cf Table 4.

Table 5) that W0L0 is rejected against W1L1, W1L1 against W2L2, and W2L2 against W3L3. This leaves us with the general model M1W3L3 and the two non-rejected models M1W3L2 and M1W2L3. The choice between them can be made on the basis of parsimony, and of the acceptability of the estimated parameters. It will be argued below that M1W3L2 is the model to be preferred.

5.2. Evaluation of models not rejected by likelihood ratio tests

As identification of certain parameters in some of our models depends on the solution of a second order equation, there will in general exist two observationally equivalent structures, and correspondingly two global minima to the fit function in (17). Depending on the starting values, LISREL will find one or the other of these two solutions. The second one, which has the same F-value as the first, can be located by choosing appropriate starting values. This is done for the model M1W3L3, where we obtain the solutions I and II, the parameter estimates of which are given in Table 6. Both solutions satisfy restriction (16a), which then cannot distinguish between them.

The two solutions are further characterized in Fig. 2, where the minimum value of F is plotted for various given values of r. The two global minima of F are obtained for those

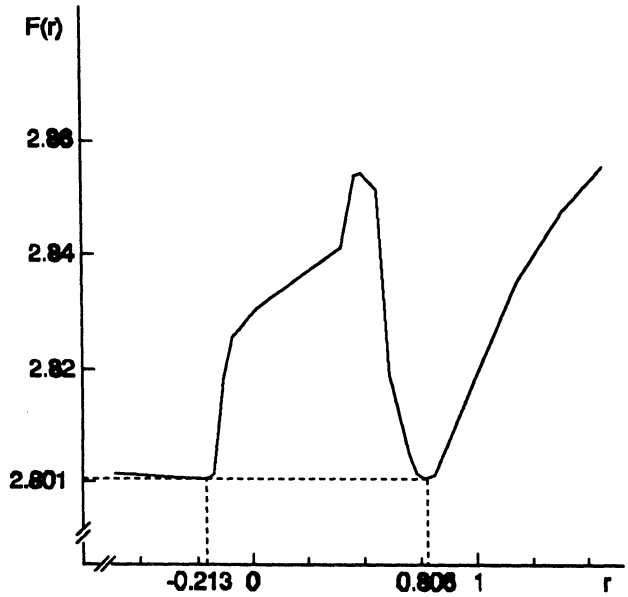


Fig. 2. F-values of M1W3L3 with two solutions

values of r that correspond to the solutions I and II. As a check of our conclusions, the minimum value of F has been calculated for a series of values of r in the interval [-200, 200]. F is decreasing for values of r to the left of the lower solution. For values of r higher than 1.8, F is decreasing, but very slowly, and does not reach lower than 2.829 in the interval studied. Solution II violates restrictions H_{r0} and H_{d0}, cf (16b), whereas all the estimates in solution I seem sensible. Thus, we prefer solution I.

We observe that the estimates of $M1W3L3^{I}$ and $M1W3L3^{II}$ are almost identical with those of M1W3L2 and M1W2L3, respectively. Furthermore, from the estimates of b and r we calculate the value of the stability parameter d to be 0.83 in M1W3L2 and -5.01 in M1W2L3. Thus we prefer the former model to the latter, cf section 3. The final choice is then between $M1W3L3^{I}$ and M1W3L2. Both models have rather similar estimates. The latter being more parsimonious, we consider this model to be the (slightly) preferred one. We focus on this model in sections 5.3 to 5.5, and discuss robustness of results across models in section 5.6.

5.3. The deterrence and clear-up elasticities

The estimate of the deterrence elasticity (b) is significantly negative in our preferred model, and close to -1. The estimate of the clear-up elasticity (r) is about 0.8 in the same model, and the confidence interval is clearly within the boundaries argued a priori, cf (2). These estimates of b and r imply that the estimate of the stability parameter d is 0.8, and the corresponding confidence interval is clearly within the boundaries (0,1), in agreement with our hypothesis H_{d1}.

5.4. Distribution of crime and clear-up tendencies

The estimates of the distribution parameters of the district effects on crime are also given in Table 6. All three are statistically significant. Straightforward calculation shows that for our preferred model the variance of the crime tendency, var $\ln C_{it} = \sigma_{\omega1\omega1} + t^2\sigma_{\omega2\omega2} + 2t\sigma_{\omega1\omega2}$, is estimated to be positive for all years, i.e. for t=1,2,...,9. As this estimate is not restricted to positive values by LISREL, we take the result as a confirmation that our model, and our interpretation of it, has passed an interesting test.

Table 6
Estimates of non-rejected models[ab]

Parameter	M1W3L3[I]	M1W3L2	M1W2L3	M1W3L3[II]
b	-0.824	-0.850	-5.107	-5.157
	(0.353)	(0.308)	(2.144)	(2.487)
r	0.810	0.804	-0.177	-0.213
	(0.094)	(0.082)	(0.426)	(0.519)
$\sigma_{\omega 1 \omega 1}$	0.271	0.268	1.030	1.145
	(0.069)	(0.065)	(1.108)	(1.402)
$\sigma_{\omega 2 \omega 2}$	0.0010	0.0010	0.0093	0.0109
	(0.0004)	(0.0003)	(0.0092)	(0.0125)
$\sigma_{\omega 1 \omega 2}$	-0.0095	-0.0094	0[c]	-0.0194
	(0.0037)	(0.0035)		(0.0364)
$\sigma_{\lambda 1 \lambda 1}$	0.043	0.040	0.371	0.398
	(0.015)	(0.013)	(0.323)	(0.407)
$\sigma_{\lambda 2 \lambda 2}$	0.0004	0.0004	0.0013	0.0014
	(0.0002)	(0.0001)	(0.0012)	(0.0016)
$\sigma_{\lambda 1 \lambda 2}$	-0.0007	0[c]	-0.0131	-0.0139
	(0.0010)		(0.0115)	(0.0145)
$\sigma_{\varepsilon\varepsilon}$	0.028	0.028	0.028	0.028
	(0.002)	(0.002)	(0.002)	(0.002)
$\sigma_{\varphi\varphi}$	0.066	0.066	0.066	0.066
	(0.005)	(0.005)	(0.005)	(0.005)
$\sigma_{\varepsilon\varphi}$	0.032	0.033	0.033	0.032
	(0.003)	(0.003)	(0.003)	(0.003)
d	0.843	0.833	-5.011	-5.255
	(0.044)	(0.045)	(1.609)	(1.725)

[a] See Table 2 for definitions of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

We note that $\sigma_{\omega1\omega2}$ is significantly negative. Furthermore, the estimates indicate a decrease in the variance of the log of the district effects over time. Denoting the first difference operator by Δ, we see in fact that $\Delta \text{var} \ln C_{it} = (2t+1)\sigma_{\omega2\omega2} + 2\sigma_{\omega1\omega2}$ is negative for the whole period. The estimate of var $\ln C_{it}$ is, in this period, reduced from 0.250 to 0.171. The estimate of the variance of the log of the crime tendency is thus substantially reduced during the period.

The estimates of the distribution parameters of the district effects on clear-ups ($\sigma_{\lambda1\lambda1}$ and $\sigma_{\lambda2\lambda2}$) are positive, and significantly different from zero in our preferred model. The variance of the clear-up tendency is increasing during the period from 0.040 to 0.072.

The distribution parameters $\sigma_{\omega i\omega i}$ and $\sigma_{\lambda i\lambda i}$ (i=1,2) are all positive, and interpreting these parameters as variances we find that our model has passed another interesting test.

5.5. Measurement errors

The estimates of the variances and the covariance of the errors of measurement are positive and highly significant. This confirms our hypothesis in section 2.3 of a positive $\sigma_{\varepsilon\varphi}$. Also note that the covariance matrix of the measurement errors (cf section 6.3) is positive definite.

5.6. Robustness of results

Table 7 shows the estimates of all models with two global maxima (solutions I and II). We observe that for all four solutions II the estimates of both r and d are negative. These models are thus rejected according to (16b).

Table 8 contains the estimates of all identified M1-models (solutions II not included). The M0-models are strongly rejected against the corresponding M1-models (details on the M0-models are given in our 1992 paper). Just like in our preferred model, the estimate of b is found to be negative in all but two of the models in Table 8. The two models in question, M1W2L1 and M1W3L1 have not significant estimates of b. They are strongly rejected by the likelihood ratio tests, and have some quite nonsensical estimates. Thus, we do not give them weight as evidence on b. We conclude that the estimated sign of b is robust across models, although the value varies substantially. This result suggests that misspecification in modelling may not hinder the sign of the deterrence elasticity to be correctly determined, but that a reliable estimate of its value requires thorough empirical analysis.

Table 7

Estimates of models with two global maxima[ab]

Parameter	M1W3L3[I]	M1W3L3[II]	M1W2L2[I]	M1W2L2[II]	M0W3L3[I]	M0W3L3[II]	M0W2L2[I]	M0W2L2[II]
b	-0.824	-5.157	-0.890	-4.436	-.920	-4.892	-0.137	-6.312
	(0.353)	(2.487)	(0.541)	(2.356)	(0.296)	(1.591)	(1.028)	(1.060)
r	0.810	-0.213	0.775	-0.124	0.796	-0.087	0.715	-3.503
	(0.094)	(0.519)	(0.120)	(0.684)	(0.067)	(0.350)	(0.086)	(54.9)
$\sigma_{\omega1\omega1}$	0.271	1.145	0.221	0.725	0.271	0.455	0.375	0.434
	(0.069)	(1.402)	(0.079)	(1.010)	(0.063)	(0.559)	(0.240)	(0.301)
$\sigma_{\omega2\omega2}$	0.0010	0.0109	0.0007	0.0072	0.0014	-0.0066	0.0017	-0.0002
	(0.0004)	(0.0125)	(0.0004)	(0.0086)	(0.0003)	(0.0046)	(0.0011)	(0.0020)
$\sigma_{\omega1\omega2}$	-0.0095	-0.0194	0[c]	0[c]	-0.0114	0.0649	0[c]	0[c]
	(0.0037)	(0.0364)			(0.0034)	(0.0422)		
$\sigma_{\lambda1\lambda1}$	0.043	0.398	0.037	0.279	0.0190	0.320	0.0354	20
	(0.0148)	(0.407)	(0.014)	(0.425)	(0.0137)	(0.249)	(0.0095)	(313)
$\sigma_{\lambda2\lambda2}$	0.0004	0.0014	0.0004	0.0008	-0.0003	0.0016	-0.0000	0.089
	(0.0002)	(0.0016)	(0.0001)	(0.0015)	(0.0002)	(0.0011)	(0.0002)	(1.392)
$\sigma_{\lambda1\lambda2}$	-0.0007	-0.0139	0[c]	0[c]	0.0027	-0.0134	0[c]	0[c]
	(0.0010)	(0.0145)			(0.0011)	(0.0094)		
$\sigma_{\varepsilon\varepsilon}$	0.028	0.028	0.028	0.028	0.028	0.028	0.027	0.027
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\sigma_{\varphi\varphi}$	0.066	0.066	0.067	0.067	0.064	0.064	0.064	0.064
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\sigma_{\varepsilon\varphi}$	0.032	0.032	0.033	0.033	0[c]	0[c]	0[c]	0[c]
	(0.003)	(0.003)	(0.003)	(0.003)				
d	0.843	-5.255	0.800	-3.986	0.812	-4.318	0.961	-27.4

[a] See Table 2 for definitions of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.

[b] Standard errors in parentheses.

[c] A priori restriction.

Table 8

Estimates of M1-models[a,b]

Parameter	M1W3L3	M1W3L2	M1W3L1	M1W2L3	M1W2L2	M1W2L1	M1W1L3	M1W1L2
b	-0.824	-0.850	1.764	-5.107	-0.890	230	-2.122	-1.677
	(0.353)	(0.308)	(2.517)	(2.144)	(0.541)	(8815)	(0.447)	(0.273)
r	0.810	0.804	0.529	-0.177	0.775	0.404	1.567	1.004
	(0.094)	(0.082)	(0.099)	(0.426)	(0.120)	(0.097)	(0.809)	(0.167)
$\sigma_{\omega1\omega1}$	0.271	0.268	1.142	1.030	0.221	4201	0.199	0.170
	(0.069)	(0.065)	(1.508)	(1.108)	(0.079)	(319619)	(0.063)	(0.036)
$\sigma_{\omega2\omega2}$	0.0010	0.0010	0.0056	0.0093	0.0007	27.0	0[c]	0[c]
	(0.0004)	(0.0003)	(0.0079)	(0.0092)	(0.0004)	(2055)		
$\sigma_{\omega1\omega2}$	-0.0095	-0.0094	-0.0308	0[c]	0[c]	0[c]	0[c]	0[c]
	(0.0037)	(0.0035)	(0.0446)					
$\sigma_{\lambda1\lambda1}$	0.043	0.040	0.044	0.371	0.037	0.060	0.367	0.079
	(0.0148)	(0.013)	(0.013)	(0.323)	(0.014)	(0.023)	(0.573)	(0.048)
$\sigma_{\lambda2\lambda2}$	0.0004	0.0004	0[c]	0.0013	0.0004	0[c]	0.0018	0.0005
	(0.0002)	(0.0001)		(0.0012)	(0.0001)		(0.0027)	(0.0002)
$\sigma_{\lambda1\lambda2}$	-0.0007	0[c]	0[c]	-0.0131	0[c]	0[c]	-0.0099	0[c]
	(0.0010)			(0.0115)			(0.0152)	
$\sigma_{\varepsilon\varepsilon}$	0.028	0.028	0.028	0.028	0.028	0.029	0.028	0.029
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\sigma_{\varphi\varphi}$	0.066	0.066	0.070	0.066	0.067	0.071	0.070	0.071
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\sigma_{\varepsilon\varphi}$	0.032	0.033	0.034	0.033	0.033	0.035	0.034	0.035
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
d	0.843	0.833	1.831	-5.011	0.800	138	2.203	1.007

[a] See Table 2 for definitions of models. Only solutions I are included; see Table 6 for solutions II.

[b] Standard errors in parentheses.

[c] A priori restriction.

The estimate of r is, as expected, and just as in our preferred model, located in the interval [0,1] for the six models where the estimate is significant. The estimate is negative in M1W2L3. According to Table 5, M1W2L3 is not rejected against M1W3L3. We nevertheless disregard the former model, because the estimated value of d is significantly negative, and because its symmetric counterpart M1W3L2 is perfectly acceptable. Thus, none of the more interesting models have estimates of r that are outside the assumed interval.

For all models the variance of the crime tendency (var $\ln C_{it}$) is found to be positive in all years. We note that $\sigma_{\omega1\omega2}$ is significantly negative for the fitted models where this parameter is not zero a priori (i.e. for the W3-models). Furthermore, the estimates indicate a decrease in the variance of the district effects over time for most models.

The estimates of the variances of the district effects on clear-ups ($\sigma_{\lambda1\lambda1}$ and $\sigma_{\lambda2\lambda2}$) are positive in all models.

The estimates of the variances and the covariance of the errors of measurement are very robust with respect to model specifications.

6. Empirical results, various types of crime

6.1. Overview of procedure

Our model framework has been applied to 12 different types of crime. In section 6.2 we present estimates of the general model W3L3 (solution I) for each of the 12 specific types of crime. In section 6.3 we test for each type of crime the various models within our framework. In particular, we give an empirical investigation of properties related to problems of identification. The estimates for each type of crime, in models not rejected by various criteria, are given in section 6.4. It will be seen that the estimates of most of these models are not very different from those of our general model W3L3 (solution I), which is one reason for presenting the results of the latter model first. We find, however, that for some types of crime there are models more parsimonious than W3L3 that turn out to perform well, whereas some of the rejected models give unreasonable or meaningless results. These results underscores the importance of using a model framework with a class of models, instead of sticking to one particular specification.

Unpublished data from Statistics Norway, which we have used in this study, contains a rather detailed categorization of crime. In order not to have too few observations in some police districts we have chosen to study only those types of offence numbering more than 500 for the whole country in at least some of the years. The following types of crime, which account for more than 95 percent of the total number of crimes, meet this requirement (the numbers being those used to categorize the types of crime in the official crime statistics):

13 Public disorder (incl. burglary).
18 Forgery.
19 Sexual offence.
21 Offence against the personal liberty.
22 Offence of violence against the person.
23 Slander and libel.
24 Embezzlement.
26 Fraud and breach of trust.
28 Offence inflicting damage to property.
40 Aggravated larcenies.
41 Simple larcenies.
43 Theft of motor vehicles.

Our general model has been applied to the 12 different types of crime with data for the period 1972-78. At variance with the study of total crime, data on specific types of crime are not available for the years 1970 and 1971. The covariance matrices of the logs of the crime and clear-up rates for each type of crime are included in the Appendix, Because of the log specification, zero values are treated as missing values. Missing values are then handled by listwise deletion: if data from a police district is missing in one or more years, this district is excluded from the calculation of the covariance matrix of the observed variables.

6.2. Estimates of the general model W3L3

The estimates of our most general model W3L3 are given in Table 11. These are the estimates of solution I, cf section 3 and 5.2. Our analysis which discriminates between solutions I and II is presented in section 6.3, and estimates for both solutions are given in section 6.4.

6.2.1. The deterrence and clear-up elasticities

According to our discussion of rational behaviour in previous chapters we hypothesize that the deterrence elasticity b is negative also for each specific type of offence, even for so-called "expressive crimes", such as sexual abuses, where a precise calculation of costs and benefits hardly is the rule. We find it natural to test whether a lower probability of detection will increase crime also in this case.

The deterrence elasticity (b) is found to be negative for seven of the 12 types of crime, and significantly so in four cases. None of the positive estimates are statistically significant. Thus, we find that H_{b0}, cf Table 1, is not rejected against the alternative hypothesis $b>0$, whereas the latter is rejected against the former in a majority of cases. We conclude that our results give rather strong support to H_{b0}. As one would expect, some of the estimates are higher than the corresponding one obtained for all crimes taken together, and some are lower.

We further expect the clear-up elasticity r to be positive, although one might imagine that the police in certain situations has to use such an amount of their resources on recording an increase in crime that the *number* of those cleared up will decrease.

The estimate of the clear-up elasticity (r) is positive in all cases, and significantly so in 11 of them. Our hypothesis H_{r0} is not rejected against the alternative hypothesis $r<0$, whereas the latter is rejected against the former. We thus conclude that H_{r0} is strongly supported.

In contrast to our expectation in the case of total crime we do not exclude $r>1$ for some types of crime. For a single type of crime the number of clear-ups might increase proportionally more than the number of crimes because the police becomes more efficient in clearing up certain crimes when they are "trained" in solving many cases of a similar type. Within some police districts resources might also be reallocated in order to solve specific types of crime that attract public interest, thus producing a proportionally larger increase in clear-ups than in crimes.

For six types of crime the clear-up elasticity is higher than 1. In most of these cases, however, the estimate of r is less than about one standard error higher than 1. This means that H_{r1} is not rejected against the alternative hypothesis $r>1$, whereas the latter also is not rejected against the former.

Hypothesis H_{d0} of a positive value of the stability parameter d implies that the system of equations have a stable solution. The stability parameter is found to be positive for all types of crime.

6.2.2. Distribution of crime and clear-up tendencies

Hypotheses H_ω and H_λ implies that we interpret the σ parameters of these hypotheses as variances and covariances. The estimates of the distribution parameters of the district effects on crime ($\sigma_{\omega1\omega1}$, $\sigma_{\omega2\omega2}$, and $\sigma_{\omega1\omega2}$) and on clear-ups ($\sigma_{\lambda1\lambda1}$, $\sigma_{\lambda2\lambda2}$, and $\sigma_{\lambda1\lambda2}$) are statistically significant at the 0.05 level according to the *t*-test in 10, 5, 3, 4, 3, and 2 cases, respectively. In all these cases, but one, the sign of the estimates of the variances is in accordance with the hypotheses. The condition $\sigma^2_{\omega1\omega2} \leq \sigma_{\omega1\omega1}\sigma_{\omega2\omega2}$ in H_ω is fulfilled for all types of crime, except forgery, sexual offence, slander and label, and offence against personal liberty. The analogous condition in H_λ is fulfilled for all types of crime, except forgery, embezzlement and fraud. In both cases these exceptions are obtained from non-significant estimates of variances and covariances.

Hypotheses H_C and H_U state that the variances of the log of the crime and clear-up tendencies are positive. These variances, as well as those in the previous paragraph, are not restricted to positive values by LISREL, cf section 4. Straightforward calculation, using these estimates whether they are significant or not, shows that the variance of the log of the crime tendency, var $\ln C_{it} = \sigma_{\omega1\omega1} + t^2\sigma_{\omega2\omega2} + 2t\sigma_{\omega1\omega2}$, is positive for all years, i.e. for $t=1,2,...,7$, for all types of crime, see Table 12. The same holds true for the variance of the log of the clear-up tendency var $\ln U_{it}$, except for an insignificant negative estimate in the first year in the case of embezzlement. Thus, we consider hypoteses H_C and H_U not to be rejected in any of the cases. We take this result as a confirmation that our model framework, and our interpretation of it, has passed another interesting test (in addition to the analogous one for the total number of crimes).

The variance of the log of the crime tendency is decreasing during the period studied for all types of crime, except public disorder, embezzlement, fraud, and slander and libel. In the former three cases there is first a decrease and then an increase, whereas in the latter case there is a steady increase. As a whole there is a general tendency for police districts to become less different as far as crime tendencies are concerned. This is in a relative sense, since the variance of the log of the crime tendency corresponds to the coefficient of variation of the crime tendency, cf comments to (7) in section 2.2.

The variance of the clear-up tendencies develops less uniformly across types of crime. It is

a) increasing for offence against personal liberty, violence against the person, embezzlement, aggravated larcenies, simple larcenies, and thefts of motor vehicles,

b) decreasing for public disorder, slander and libel, and fraud,

c) decreasing and then increasing for sexual abuses and offence inflicting damage to property, and

d) increasing and then decreasing for forgery.

6.2.3. Measurement errors

The estimates of the variances and the covariance of the errors of measurement are all positive and highly significant. We find that hypotheses H_M and H_{MC} are not rejected in any of the cases. Hypothesis H_M states that the covariance matrix of the measurement errors is positive definite. Hypothesis H_{MC} is explained as a result of sloppy registration procedures: for some of the crimes committed the registration of both crimes and clear-ups are lost in the administrative process.

Table 11
Estimates of the general model (W3L3[I])[a] for various types of crime[b]

Parameter	All offence	Public disorder 13	Forgery 18	Sexual offence 19	Offence against personal liberty 21	Violence against the person 22	Slander and libel 23
b	-0.824 (0.353)	0.040 (0.435)	0.048 (0.660)	-0.397 (0.241)	-3.748 (1.718)	-1.060 (0.593)	0.883 (0.485)
r	0.806 (0.094)	0.670 (0.122)	1.018 (0.098)	0.870 (0.199)	1.466 (0.379)	1.072 (0.067)	0.714 (0.244)
$\sigma_{\omega1\omega1}$	0.2707 (0.0693)	0.5256 (0.2015)	0.2469 (0.1015)	0.1939 (0.0839)	1.1520 (1.0205)	0.2861 (0.0751)	0.1515 (0.1235)
$\sigma_{\omega2\omega2}$	0.0010 (0.0004)	0.0075 (0.0034)	-0.0016 (0.0020)	-0.0002 (0.0019)	0.0011 (0.0127)	0.0016 (0.0011)	-0.0014 (0.0038)
$\sigma_{\omega1\omega2}$	-0.0095 (0.0037)	-0.0386 (0.0196)	-0.0051 (0.0123)	-0.0038 (0.0109)	-0.0755 (0.1031)	-0.0113 (0.0073)	0.0240 (0.0216)
$\sigma_{\lambda1\lambda1}$	0.0430 (0.0148)	0.2387 (0.0901)	0.0024 (0.0132)	0.1682 (0.0633)	0.0953 (0.1310)	0.0213 (0.0081)	0.2909 (0.1324)
$\sigma_{\lambda2\lambda2}$	0.0004 (0.0002)	0.0038 (0.0028)	-0.0010 (0.0005)	0.0055 (0.0023)	0.0013 (0.0018)	0.0008 (0.0003)	0 0039 (0.0022)
$\sigma_{\lambda1\lambda2}$	-0.0007 (0.0010)	-0.0282 (0.0149)	0.0047 (0.0021)	-0.0219 (0.0104)	0.0032 (0.0076)	-0.0021 (0.0014)	-0.0260 (0.0159)
$\sigma_{\varepsilon\varepsilon}$	0.028 (0.002)	0.138 (0.013)	0.363 (0.027)	0.198 (0.021)	0.188 (0.024)	0.079 (0.007)	0.177 (0.022)
$\sigma_{\phi\phi}$	0.066 (0.005)	0.349 (0.033)	0.344 (0.035)	0.345 (0.036)	0.251 (0.032)	0.117 (0.010)	0.290 (0.037)
$\sigma_{\varepsilon\phi}$	0.033 (0.003)	0.118 (0.016)	0.267 (0.029)	0.206 (0.024)	0.151 (0.024)	0.085 (0.008)	0.121 (0.023)
d	0.840	1.013	0.999	0.952	2.747	1.076	1.253
χ^2	291.87	155.27	152.36	138.21	179.22	240.17	123.04
GFI	0.639	0.676	0.699	0.682	0.549	0.594	0.649
P	0.000	0.000	0.000	0.002	0.000	0.000	0.024
No.[c]	53	39	38	38	25	53	26

(Cont.)

Table 11 (cont.)
Estimates of the general model (W3L3[I])[a] for various types of crime[b]

Parameter	All offence	Embezzlement 24	Fraud 26	Offence inflicting damage to property 28	Aggravated larcenies 40	Simple larcenies 41	Thefts of motor vehicles 43
b	-0.824 (0.353)	0.055 (0.629)	0.200 (0.758)	-0.502 (0.930)	-2.437 (0.566)	-1.072 (0.193)	-2.679 (0.472)
r	0.806 (0.094)	0.902 (0.070)	0.962 (0.046)	0.901 (0.442)	1.420 (0.419)	1.132 (0.257)	1.608 (0.934)
$\sigma_{\omega1\omega1}$	0.2707 (0.0693)	0.3121 (0.1269)	0.5249 (0.141)	0.3426 (0.1041)	0.7338 (0.3530)	0.3362 (0.0945)	0.7264 (0.2054)
$\sigma_{\omega2\omega2}$	0.0010 (0.0004)	0.0102 (0.0049)	0.0075 (0.0030)	0.0067 (0.0026)	0.0048 (0.0051)	0.0037 (0.0016)	0.0019 (0.0038)
$\sigma_{\omega1\omega2}$	-0.0095 (0.0037)	-0.0355 (0.0214)	-0.0349 (0.0172)	-0.0350 (0.0135)	-0.0463 (0.0388)	-0.0300 (0.0111)	-0.0233 (0.0229)
$\sigma_{\lambda1\lambda1}$	0.0430 (0.0148)	-0.0113 (0.0116)	0.0223 (0.0152)	0.1413 (0.0782)	0.3665 (0.3960)	0.2891 (0.1667)	0.7138 (1.3772)
$\sigma_{\lambda2\lambda2}$	0.0004 (0.0002)	0.0001 (0.0007)	-0.0006 (0.0004)	0.0036 (0.0020)	0.0012 (0.0015)	0.0032 (0.0020)	0.0041 (0.0078)
$\sigma_{\lambda1\lambda2}$	-0.0007 (0.0010)	0.0038 (0.0025)	0.0006 (0.0023)	-0.0155 (0.0096)	-0.0006 (0.0057)	-0.0087 (0.0088)	-0.0094 (0.0216)
$\sigma_{\varepsilon\varepsilon}$	0.028 (0.002)	0.232 (0.026)	0.194 (0.018)	0.096 (0.009)	0.054 (0.005)	0.049 (0.004)	0.070 (0.006)
$\sigma_{\phi\phi}$	0.066 (0.005)	0.272 (0.030)	0.291 (0.027)	0.163 (0.009)	0.198 (0.017)	0.122 (0.011)	0.134 (0.012)
$\sigma_{\varepsilon\phi}$	0.032 (0.003)	0.215 (0.026)	0.210 (0.021)	0.087 (0.010)	0.071 (0.008)	0.044 (0.006)	0.074 (0.006)
d	0.840	0.995	0.992	0.960	2.022	1.142	2.629
χ^2	291.25	141.49	184.22	172.42	181.24	166.43	155.06
GFI	0.641	0.641	0.674	0.684	0.670	0.724	0.682
P	0.000	0.001	0.000	0.000	0.000	0.000	0.000
No.[c]	53	33	47	51	53	52	51

[a] See Table 2 for definition of the model.
[b] Standard errors in parentheses.
[c] Number of police districts after listwise deletion of missing values.

Table 12

Development of crime tendencies (var $\ln C_{it}$) and clear-up tendencies (var $\ln U_{it}$), various types of crime, model W3L3[I]

	t	Public disorder 13	Forgery 18	Sexual abuses 19	Offence against personal liberty 21	Violence against the person 22	Slander and libel 23	Embezzlement 24	Fraud 26	Offence inflict. damage to prop. 28	Aggr. larc. 40	Simple larc. 41	Thefts of motor veh. 43
C	1	0.456	0.235	0.178	1.002	0.265	0.198	0.251	0.463	0.279	0.646	0.310	0.428
R	2	0.401	0.220	0.162	0.861	0.247	0.242	0.211	0.416	0.230	0.568	0.261	0.387
I	3	0.361	0.202	0.145	0.719	0.233	0.282	0.192	0.384	0.193	0.500	0.220	0.350
M	4	0.336	0.181	0.128	0.575	0.222	0.321	0.192	0.367	0.170	0.441	0.186	0.317
E	5	0.326	0.157	0.111	0.431	0.214	0.356	0.214	0.365	0.160	0.392	0.159	0.287
	6	0.332	0.129	0.093	0.285	0.209	0.388	0.255	0.378	0.164	0.352	0.140	0.262
	7	0.351	0.098	0.074	0.139	0.207	0.418	0.318	0.406	0.181	0.323	0.128	0.240
C	1	0.186	0.006	0.130	0.103	0.021	0.243	-0.004	0.023	0.114	0.367	0.275	0.699
L	2	0.141	0.012	0.103	0.113	0.016	0.203	0.004	0.022	0.094	0.369	0.267	0.692
E	3	0.104	0.017	0.086	0.126	0.016	0.170	0.013	0.021	0.081	0.374	0.266	0.694
A	4	0.074	0.019	0.081	0.142	0.018	0.146	0.021	0.019	0.075	0.382	0.271	0.704
R	5	0.052	0.019	0.087	0.160	0.021	0.129	0.030	0.015	0.077	0.392	0.282	0.722
U	6	0.038	0.017	0.104	0.181	0.027	0.120	0.039	0.010	0.086	0.404	0.300	0.748
P	7	0.031	0.013	0.132	0.204	0.033	0.119	0.049	0.004	0.102	0.414	0.324	0.782

6.2.4. Summing up on the W3L3 model

We may thus conclude that solution I of the W3L3 model performs more or less equally well for specific types of crime as for total crime. The estimates have in a large majority of cases the expected signs. The only exceptions are the positive (non-significant) estimates of the deterrence elasticity b for public disorder, slander and libel, forgery, embezzlement, and fraud. (In the next section it will be seen that more parsimonious models give negative estimates of b for the latter three types of crime.)

The change in the variance of the log of the crime tendencies demonstrates a reduction in the relative differences in crime between police districts. The variance of the log of the clear-up tendencies develops differently across types of crime. For nine of the 12 types, however, the variance is higher at the end of the period than at the beginning.

6.3. Tests of model specifications

In order to test various model specifications we present in Table 13 the χ^2-values for various models and in Table 14 the corresponding significance probabilities. Our model framework consists now of a hierarchy of models with W3L3 on the top and W1L1 at the bottom. We have dropped all models with either M0, L0 or W0 in our analysis of different types of crimes in order to save time and space, cf Tables 2-4. Testing of models within this framework by likelihood ratio tests can be performed in various ways. The simplest procedure is to test each model against the general model W3L3. The significance probabilities corresponding to these tests are presented in the first five columns in Table 14. Models rejected by these tests, at a signficance level of 0.01 and 0.05, are marked in Table 15 by $R_{0.01}$ and $R_{0.05}$, respectively.

Another procedure is to start at the top and test each model against the one immediately higher in the hierachy, and if a model is rejected, then all models below in the hierachy are also rejected. Significance probabilities corresponding to such tests can also be found in Table 14. The test results in Table 15 will in our case be the same for both procedures. Other procedures, and other levels of significance, can be applied based on the information in Table 13, but in the following we stick to the test results presented in Table 15. In order to limit our analysis we will give no further consideration of models rejected at a significance level of 0.05.

Since our class of models is not fully identified without restrictions in the parameter space, we also reject models which do not satisfy the restrictions in (16), see section 3. It turns out that restrictions (16a) on the distribution of measurement errors, crime tendencies, and clear-up tendencies, are not binding for any of the models not rejected by the

Table 13

χ^2-values for various types of models and types of crime

Types of crime	Models/Degrees of freedom					
	W3L3	W3L2 W2L3	W3L1 W1L3	W2L2	W2L1 W1L2	W1L1
	94	95	96	96	97	98
Public disorder, 13	155.27	160.10	161.92	171.58	174.13	183.21
Forgery, 18	152.36	155.46	155.64	155.60	155.80	159.09
Sexual offence, 19	138.21	138.67	140.73	149.66	155.16	156.25
Offence against personal liberty, 21	179.22	179.41	181.73	180.60	184.13	186.60
Offence against the person, 22	240.17	243.11	243.23	247.90	248.21	265.32
Slander and libel, 23	123.04	124.45	125.21	128.90	129.00	131.60
Embezzlement, 24	141.49	143.06	148.68	147.88	152.05	159.71
Fraud, 26	184.22	184.29	187.59	190.94	194.51	200.49
Damage to property, 28	172.42	182.77	185.50	206.00	208.34	231.00
Aggravated larcenies, 40	181.24	181.25	185.74	187.01	187.11	211.70
Simple larcenies, 41	166.43	168.47	179.02	190.28	190.39	240.93
Thefts of motor vehicles, 43	155.06	156.03	156.51[a]	157.34	157.63[a]	190.45

[a] The χ^2-value for these models refers to LISREL solutions at a maximum of 300 permitted iterations of the optimization procedure. Convergence has not been obtained.

Table 14
Significance probabilities[a]

Types of crime	W3L2/ W2L3 vs W3L3 DF=1	W3L1/ W1L3 vs W3L3 DF=2	W2L2 vs W3L3 DF=2	W2L1/ W1L2 vs W3L3 DF=3	W1L1 vs W3L3 DF=4	W3L1/ W1L3 vs W3L2/ W2L3 DF=1	W2L2 vs W3L2/ W2L3 DF=1	W2L1/ W1L2 vs W3L2/ W2L3 DF=2	W1L1 vs W3L2/ W2L3 DF=3	W2L1/ W1L2 vs W3L1/ W1L3 DF=1	W1L1 vs W3L1 W1L3 DF=2	W2L1/ W1L2 vs W2L2 DF=1	W1L1 vs W2L2 DF=2	W1L1 vs W2L1/ W1L2 DF=1
	Models/degrees of freedom (DF)													
Public disorder, 13	0.028	0.036	0.000	0.000	0.000	0.177	0.001	0.001	0.000	0.000	0.000	0.110	0.003	0.003
Forgery, 18	0.078	0.194	0.198	0.329	0.151	0.671	0.708	0.844	0.304	0.689	0.178	0.654	0.175	0.070
Sexual offence, 19	0.498	0.284	0.003	0.001	0.001	0.151	0.001	0.000	0.001	0.000	0.000	0.019	0.037	0.296
Off., pers. liberty, 21	0.663	0.285	0.502	0.179	0.117	0.128	0.275	0.094	0.066	0.121	0.088	0.060	0.050	0.116
Off. against person, 22	0.086	0.217	0.021	0.045	0.000	0.729	0.029	0.078	0.000	0.026	0.000	0.578	0.000	0.000
Slander and libel, 23	0.235	0.338	0.053	0.114	0.073	0.383	0.035	0.103	0.067	0.052	0.041	0.752	0.259	0.107
Embezzlement, 24	0.210	0.027	0.041	0.014	0.001	0.018	0.028	0.011	0.001	0.066	0.004	0.041	0.003	0.006
Fraud, 26	0.791	0.185	0.035	0.016	0.003	0.069	0.010	0.006	0.001	0.008	0.001	0.059	0.008	0.014
Damage to property, 28	0.001	0.001	0.000	0.000	0.000	0.098	0.000	0.000	0.000	0.000	0.000	0.126	0.000	0.000
Aggr. larcenies, 40	0.920	0.105	0.056	0.118	0.000	0.034	0.016	0.053	0.000	0.241	0.000	0.752	0.000	0.000
Simple larcenies, 41	0.153	0.002	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.740	0.000	0.000
Thefts, motor veh., 43	0.325	0.484	0.320	0.463	0.000	0.488	0.252	0.449	0.000	0.290	0.000	0.590	0.000	0.000

[a] The significance probabilities are relevant only for nested models. The numbers in col. 6 may e.g. be used to test W3L1 against W3L2, but not against W2L3.

likelihood ratio test. The models with point estimates outside the interval hypotheses in (16b) and (16c) are marked in Table 15 with the names of the hypotheses they contradict, cf Table 1.

Observe first that for each type of crime, one of the solutions of W3L3 is rejected by at least one of our criteria, whereas the other is not. This is a remarkable result, since we could well imagine that both solutions were rejected, or none of them. Thus, in our situation, the identification problem does not seem to be empirically relevant. The solution that is not rejected is denoted solution I, the other solution II. The parameter estimates of both solutions are presented in Tables 17-27. It is seen that the estimates of solution II almost without exceptions are unprecise and rather unreasonable. Our choice of restrictions has clearly separated the appropriate solutions from the non-appropriate ones.

Considering now the less general models in Table 15 we find that quite a few of them satisfy all our criteria. The estimates of these non-rejected models are given in Tables 17-27, and the variances of the crime and clear-up tendencies are given in Table 16. In these tables we find the estimates demonstrating our observation above that the non-rejected models satify (16).

In order not to burden our presentation we have not included the estimates of the rejected models. Our inspection of these have shown, however, that almost all of them perform badly as far as precision and plausibility of estimates are concerned. Thus, our rejection criteria (16) seem to perform quite well. We have further observed that the estimates of these models to a large extent ressemble those of $W3L3^{II}$.

The models that meet all our criteria will on the other hand have estimates rather similar to those of $W3L3^{I}$. For each type of crime parsimony of parameters may guide our choice of model within the group of these reasonable ones.

Table 15
Rejection of models by various criteria

	W3L3^{I}	W3L3^{II}	W3L2	W2L3	W3L1	W1L3	W2L2^{I}	W2L2^{II}	W2L1	W1L2	W1L1
Public disorder,13		H_{r2}	$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$
Forgery, 18		H_{d0},H_{r2},H_{b1}		H_{r0},H_{b1}		H_{r0},H_{b1}		H_{r0},H_{b1}		H_{r0},H_{B1}	
Sexual offence, 19		H_{d0},H_{r0}	H_{d0},H_{r0}		H_{d0},H_{r0}		$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$
Off. pers. liberty, 21		H_{b1}		H_{b1}		H_{b1}	H_{r2}	H_{b1}	H_{r2}		H_{r2}
Off. against person, 22		H_{b1}	H_{b1}		H_{b1}		$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.01}$
Slander and libel, 23		H_{r2}	H_{r2}		H_{r2}	H_{b1}		H_{d0},H_{r2},H_{b1}		H_{r2}	
Embezzlement, 24		H_{r2}		H_{d0},H_{r0}	$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.01}$
Fraud, 26		H_{r2}		H_{r2}		H_{r2},H_{b1}	$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.05}$	$R_{0.01}$
Damage to property, 28		H_{d0},H_{r0}	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$
Aggr. larcenies, 40		H_{b1}		H_{b1}				H_{b1}	H_{b1}		$R_{0.01}$
Simple larcenies, 41		H_{b1}		H_{r0},H_{b1}	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$	$R_{0.01}$
Thefts, motor veh. 43		H_{b1}		H_{b1}	*)	*)		H_{b1}	*)	*)	$R_{0.01}$

[a] $R_{0.01}$: Rejected against W3L3 by a likelihood ratio test at a significance level of 0.01.
$R_{0.05}$: Rejected against W3L3 by a likelihood ratio test at a significance level of 0.05.
H_{d0}: Estimates do not satisfy H_{d0}: $d>0$. H_{r0}: Estimates do not satisfy H_{r0}: $r>0$. H_{r2}: Estimates do not satisfy H_{r2}: $r<2$. H_{b1}: Estimates do not satisfy H_{b1}: $b<1$.
*): No ordinary optimal solution has been found by LISREL7 within a maximum of 300 permitted iterations of the optimization procedure.

Table 16
Development of crime tendencies (var $\ln C_{it}$) and clear-up tendencies (var $\ln U_{it}$), various types of crime, non-rejected models

	t	Forgery, 18				Sexual offence, 19		Offence against personal liberty, 21			Violence against the person, 22		Slander and libel, 23			
		W3L2	W3L1	W2L2^{I}	W2L1	W2L3	W1L3	W3L2	W3L1	W1L2	W2L3	W1L3	W2L3	W2L2^{II}	W2L1	W1L3
Crime tend.	1	0.24	0.24	0.24	0.22	0.143	0.13	1.00	1.89	0.396	0.338	0.24	0.42	0.21	0.21	0.30
	2	0.23	0.22	0.23	0.21	0.139	▪	0.86	1.53	▪	0.239	▪	0.25	0.22	0.22	▪
	3	0.20	0.21	0.22	0.20	0.132	▪	0.72	1.21	▪	0.240	▪	0.26	0.24	0.24	▪
	4	0.19	0.18	0.21	0.18	0.121	▪	0.56	0.91	▪	0.242	▪	0.27	0.26	0.26	▪
	5	0.16	0.16	0.19	0.16	0.108	▪	0.43	0.64	▪	0.245	▪	0.29	0.28	0.28	▪
	6	0.13	0.13	0.16	0.13	0.092	▪	0.28	0.40	▪	0.248	▪	0.31	0.31	0.31	▪
	7	0.10	0.10	0.17	0.10	0.072	▪	0.14	0.19	▪	0.252	▪	0.34	0.34	0.35	▪
Clear-up tend.	1	0.023	0.02	0.013	0.02	0.142	0.141	0.11	0.27	0.038	0.020	0.020	0.22	0.120	0.12	0.23
	2	0.022	▪	0.014	▪	0.112	0.113	0.12	▪	0.037	0.018	0.018	0.19	0.119	▪	0.19
	3	0.021	▪	0.016	▪	0.093	0.095	0.13	▪	0.034	0.018	0.018	0.15	0.117	▪	0.16
	4	0.020	▪	0.019	▪	0.086	0.089	0.14	▪	0.029	0.019	0.019	0.13	0.114	▪	0.14
	5	0.019	▪	0.023	▪	0.090	0.093	0.16	▪	0.023	0.022	0.023	0.11	0.110	▪	0.12
	6	0.018	▪	0.027	▪	0.105	0.108	0.18	▪	0.014	0.028	0.028	0.10	0.105	▪	0.11
	7	0.016	▪	0.032	▪	0.131	0.135	0.20	▪	0.004	0.034	0.034	0.10	0.100	▪	0.11

(Cont.)

Table 16 (cont.)
Development of crime tendencies (var $\ln C_{it}$) and clear-up tendencies (var $\ln U_{it}$), various types of crime, non-rejected models.

	t	Embezzlement, 24	Fraud and breach of trust, 26		Aggravated larcenies, 40					Simple larcenies, 41	Theft of motor vehicles, 43	
		W3L2	W3L2	W3L1	W3L2	W3L1	W1L3	$W2L2^{I}$	W1L2	W3L2	W3L2	$W2L2^{I}$
Crime tend.	1	0.24	0.45	0.46	0.64	0.47	0.39	0.424	0.38	0.31	0.41	0.303
	2	0.20	0.41	0.41	0.56	0.43	•	0.421	•	0.26	0.38	0.300
	3	0.18	0.38	0.37	0.49	0.39	•	0.417	•	0.22	0.34	0.295
	4	0.18	0.36	0.35	0.44	0.37	•	0.410	•	0.19	0.31	0.288
	5	0.20	0.36	0.35	0.39	0.35	•	0.402	•	0.17	0.28	0.279
	6	0.24	0.37	0.36	0.35	0.34	•	0.392	•	0.14	0.26	0.268
	7	0.30	0.39	0.39	0.32	0.34	•	0.380	•	0.13	0.24	0.255
Clear-up tend.	1	0.004	0.029	0.02	0.35	0.14	0.179	0.258	0.14	0.27	0.53	0.258
	2	0.007	0.027	•	0.35	•	0.180	0.261	0.15	0.27	0.54	0.263
	3	0.013	0.023	•	0.36	•	0.183	0.268	0.15	0.27	0.56	0.271
	4	0.021	0.019	•	0.36	•	0.187	0.277	0.16	0.28	0.58	0.282
	5	0.030	0.013	•	0.37	•	0.194	0.288	0.16	0.30	0.61	0.297
	6	0.043	0.005	•	0.39	•	0.202	0.302	0.17	0.32	0.64	0.314
	7	0.057	0.004	•	0.40	•	0.213	0.319	0.18	0.36	0.68	0.335

6.4. Estimates for various types of crime

In this section we present estimates of the models that satisfy restrictions (16).

6.4.1. Public disorder

Most offence within the category of "offence against public order and peace" (here called "public disorder") are burglaries. Table 15 shows that all submodels are rejected against W3L3 by likelihood ratio tests, and that $W3L3^{II}$ is rejected by H_{r2}. The estimates of the two W3L3 solutions are given in Table 17. One observes that several of the estimates of $W3L3^{II}$ are unreasonable and do not satisfy (16). The estimates of $W3L3^{I}$ are mostly statistically significant with expected signs. An exception is the estimate of the deterrence elasticity, which is positive and not statistically significant. There is a decline in the variance of the crime tendency (see Table 12), suggesting a reduction in the differences between police districts for this type of crime. The variance of the log of the clear-up tendency is also decreasing during the period.

Looking at the number of crimes in the various police districts (data not included in this paper) one is surprised to observe how few instances of public disorder are registered in the capital compared to other police districts. One might suspect that in Oslo, and perhaps in other districts, burglaries are not recorded as public disorder. Apparently, there are special problems of recording for this type of crime.

6.4.2. Forgery

In the case of forgery, the estimates of the five models which satisfy the likelihood ratio test, H_{d0}, and H_{r0} are given in Table 18. The estimates of these models are rather similar to each other. The clear-up elasticity r is found to be slightly higher than 1 for all these models. The only notable difference between our general model and the other models is that b is positive in the former and negative in the remaining ones (none of them significant). Our desire for parsimony of parameters points at W2L1 as a good model for forgery. In the case of forgery, too, we note a decrease in the variance of the crime tendency during the period, indicating a shrinking relative difference between police districts in this respect. The clear-up tendency is constant by definition.

6.4.3. Sexual offence

In the case of sexual offence we have three models that are not rejected by the likelihood ratio test, and that also satisfy our restrictions (16). Their estimates are almost identical, see Table 19. With few exceptions the estimates are statistically significant and of expected

Table 17
Public disorder (incl. burglary) 13,
estimates of non-rejected models[ab]

Parameter	$W3L3^{I}$	$W3L3^{II}$
b	0.040	-3.026
	(0.435)	(1.112)
r	0.670	26.267
	(0.122)	(277.4)
$\sigma_{\omega1\omega1}$	0.5256	2.1856
	(0.2015)	(1.7758)
$\sigma_{\omega2\omega2}$	0.0075	-0.035
	(0.0034)	(0.0362)
$\sigma_{\omega1\omega2}$	-0.0386	-0.258
	(0.0196)	(0.2301)
$\sigma_{\lambda1\lambda1}$	0.2387	335.54
	(0.0901)	(7272.5)
$\sigma_{\lambda2\lambda2}$	0.0038	4.776
	(0.0028)	(103.5)
$\sigma_{\lambda1\lambda2}$	-0.0282	-24.12
	(0.0149)	(534.2)
$\sigma_{\varepsilon\varepsilon}$	0.138	0.138
	(0.013)	(0.013)
$\sigma_{\phi\phi}$	0.349	0.349
	(0.033)	(0.033)
$\sigma_{\varepsilon\phi}$	0.118	0.118
	(0.016)	(0.016)
d	1.013	77.9
χ^2	155.27	155.27
GFI	0.676	0.676
P	0.000	0.000

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.

Table 18
Forgery 18, estimates of non-rejected models[ab]

Parameter	W3L3[I]	W3L3[II]	W3L2	W3L1	W2L2[I]	W2L1
b	0.048	56.2	-0.440	-0.359	-0.899	-0.454
	(0.660)	(309)	(2.983)	(1.557)	(3.912)	(1.65)
r	1.018	21.9	1.056	1.048	1.106	1.058
	(0.098)	(289)	(0.322)	(0.165)	(0.430)	(0.177)
$\sigma_{\omega1\omega1}$	0.2469	-7.48	0.2503	0.2493	0.2339	0.2184
	(0.1015)	(90)	(0.1346)	(0.1106)	(0.1916)	(0.0704)
$\sigma_{\omega2\omega2}$	-0.0016	-3.20	-0.0017	-0.0017	-0.0026	-0.0024
	(0.0020)	(35)	(0.0022)	(0.0021)	(0.0026)	(0.0013)
$\sigma_{\omega1\omega2}$	-0.0051	14.7	-0.0048	0.0049	0[c]	0[c]
	(0.0123)	(162)	(0.0129)	(0.0126)		
$\sigma_{\lambda1\lambda1}$	0.0024	108	0.0227	0.0198	0.0245	0.0200
	(0.0132)	(2989)	(0.0111)	(0.0073)	(0.0208)	(0.0077)
$\sigma_{\lambda2\lambda2}$	-0.0010	-0.70	-0.0001	0[c]	-0.0002	0[c]
	(0.0005)	(19)	(0.0003)		(0.0004)	
$\sigma_{\lambda1\lambda2}$	0.0047	-2.21	0[c]	0[c]	0[c]	0[c]
	(0.0021)	(61)				
$\sigma_{\varepsilon\varepsilon}$	0.263	0.263	0.264	0.263	0.267	0.267
	(0.027)	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)
$\sigma_{\phi\phi}$	0.344	0.344	0.341	0.341	0.346	0.346
	(0.035)	(0.035)	(0.034)	(0.034)	(0.033)	(0.033)
$\sigma_{\varepsilon\phi}$	0.267	0.266	0.266	0.266	0.267	0.271
	(0.029))	(0.027)	(0.029)	(0.029)	(0.028)	(0.028)
d	0.999	-1175	1.025	1.017	1.095	1.026
χ^2	152.36	152.36	155.46	155.64	155.60	155.80
GFI	0.699	0.699	0.684	0.683	0.684	0.683
P	0.000	0.000	0.000	0.000	0.000	0.000

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

sign. Thus, we find our model framework to be rather successful for what is often considered to be an expressive crime.

The standard errors of the estimates are as a whole slightly smaller for W2L3 than for the other two models. Only the estimate of $\sigma_{\omega 2 \omega 2}$ is not statistically significant. The estimate of the deterrence elasticity is negative and that of the the clear-up elasticity is positive, and less than 1. The variance of both the crime and clear-up tendencies are decreasing during the period studied, indicating a shrinking relative difference between police districts in both respects. In the more parsimonious model W1L3 the estimate of b is of the same size as in W2L3, but slightly less precise.

6.4.4. Offence against the personal liberty

Table 20 shows that the four non-rejected models for offence against personal liberty divide into two groups: the estimates of W3L3^{I}, W3L2, and W3L1 are very similar to each other, whereas those of W2L3 are more alike those of the rejected W3L3^{II}. In the first group the estimate of the clear-up elasticity is greater than 1, and in the other group smaller than 1. In the first group the estimates of the deterrence elasticity is negative and (for two of the models) statistically significant, whereas they in the second group are positive and non-significant. In the former group the variances of both the crime and the clear-up tendencies are decreasing during the period, indicating also for this type of crime a growing similarity in relative terms between police districts.

6.4.5. Offence of violence against the person

Table 21 contains the estimates of two models, in addition to W3L3, applied to the offence of violence against the person. The estimates of the parameters for W3L3^{I}, W2L3, and W1L3 are very similar. Parsimony of parameters and slightly more precise estimates are arguments for choosing W1L3. All, but one of the estimates are here statistically significant, and of the expected sign. We find a strong deterrent effect of the probability of clear-up. The variance of the crime tendency is constant by definition, and that of the clear-up tendency is increasing. In the W3L3^{I}-model the variance of the crime tendency is decreasing, indicating gradually more similar police district also with respect to this type of crime.

6.4.6. Slander and libel

None of the models applied to slander and label seem to be appropriate, cf. Table 22. The five non-rejected models have positive, but not statistically significant estimates of b, and

Table 19
Sexual offence 19, estimates of non-rejected models[ab]

Parameter	$W3L3^{I}$	$W3L3^{II}$	W2L3	W1L3
b	-0.397	-7.71	-0.495	-0.419
	(0.241)	(11.8)	(0.214)	(0.266)
r	0.870	-1.521	0.933	0.947
	(0.199)	(1.529)	(0.200)	(0.248)
$\sigma_{\omega1\omega1}$	0.1939	10.00	0.1449	0.1265
	(0.0839	(34.2)	(0.0411)	(0.0376)
$\sigma_{\omega2\omega2}$	-0.0002	0.3287	-0.0015	0[c]
	(0.0019)	(1.0270)	(0.0010)	
$\sigma_{\omega1\omega2}$	-0.0038	-1.3034	0[c]	0[c]
	(0.0109)	(4.1200)		
$\sigma_{\lambda1\lambda1}$	0.1682	1.2324	0.1828	0.1807
	(0.0633)	(1.7219)	(0.0681)	(0.0709)
$\sigma_{\lambda2\lambda2}$	0.0055	-0.0014	0.0056	0.0055
	(0.0023)	(0.0017)	(0.0023)	(0.0024)
$\sigma_{\lambda1\lambda2}$	-0.0219	-0.0495	-0.0233	-0.0225
	(0.0104)	(0.1046)	(0.0107)	(0.0109)
$\sigma_{\varepsilon\varepsilon}$	0.198	0.198	0.202	0.195
	(0.021)	(0.021)	(0.020)	(0.019)
$\sigma_{\phi\phi}$	0.345	0.345	0.354	0.345
	(0.036)	(0.036)	(0.035)	(0.033)
$\sigma_{\varepsilon\phi}$	0.206	0.206	0.212	0.204
	(0.024)	(0.024)	(0.024)	(0.022)
d	0.952	-18.44	0.967	0.978
χ^2	138.21	138.21	138.67	140.73
GFI	0.682	0.682	0.687	0.686
P	0.002	0.002	0.002	0.002

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

reasonable positive estimates of r. The most parsimonious model, W2L1, seems to be just as good as the other four. A reason for the rather inconclusive results for this type of crime might be that the offender has some interest in the slander being known, although not that it should be cleared up by the police.

Table 20

Offence against the personal liberty 21, estimates of non-rejected models[ab]

Parameter	W3L3[I]	W3L3[II]	W3L2	W3L1	W1L2
b	-3.748	2.146	-3.806	-5.117	0.755
	(1.718)	(1.744)	(1.829)	(2.770)	(1.026)
r	1.466	0.733	1.479	1.744	0.822
	(0.379)	(0.122)	(0.408)	(0.672)	(0.110)
$\sigma_{\omega1\omega1}$	1.1520	0.4388	1.1429	2.2712	0.3958
	(1.0205)	(0.3045)	(1.0394)	(2.5280)	(0.1809)
$\sigma_{\omega2\omega2}$	0.0011	0.0060	-0.0005	0.0145	0[c]
	(0.0127)	(0.0098)	(0.0122)	(0.0316)	
$\sigma_{\omega1\omega2}$	-0.0755	0.0149	-0.0699	-0.1993	0[c]
	(0.1031)	(0.0366)	(0.0992)	(0.2775)	
$\sigma_{\lambda1\lambda1}$	0.0953	0.0820	0.1144	0.2695	0.0374
	(0.1310)	(0.0478)	(0.1494)	(0.3695)	(0.0182)
$\sigma_{\lambda2\lambda2}$	0.0013	0.0001	0.0018	0[c]	-0.0009
	(0.0018)	(0.0009)	(0.0018)		(0.0005)
$\sigma_{\lambda1\lambda2}$	0.0032	-0.0054	0[c]	0_c	0[c]
	(0.0076)	(0.0059)			
$\sigma_{\varepsilon\varepsilon}$	0.188	0.188	0.186	0.196	0.203
	(0.024)	(0.024)	(0.023)	(0.024)	(0.024)
$\sigma_{\phi\phi}$	0.251	0.251	0.252	0.251	0.274
	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)
$\sigma_{\varepsilon\phi}$	0.151	0.151	0.150	0.156	0.168
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
d	2.75	1.57	2.82	2.81	1.134
χ^2	179.22	179.22	179.41	181.73	184.65
GFI	0.549	0.549	0.549	0.537	0.539
P	0.000	0.000	0.000	0.000	0.000

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.

[b] Standard errors in parentheses.

[c] A priori restriction.

Table 21
Offence of violence against the person 22, estimates of non-rejected models[ab]

Parameter	W3L3[I]	W3L3[II]	W2L3	W1L3
b	-1.060 (0.593)	14.00 (13.05)	-1.459 (0.644)	-1.591 (0.569)
r	1.072 (0.067)	0.057 (0.528)	1.103 (0.071)	1.101 (0.067)
$\sigma_{\omega 1\omega 1}$	0.2861 (0.0751)	4.1629 (7.3936)	0.2375 (0.0629)	0.2436 (0.0587)
$\sigma_{\omega 2\omega 2}$	0.0016 (0.0011)	0.1654 (0.3103)	0.0003 (0.0009)	0[c]
$\sigma_{\omega 1\omega 2}$	-0.0113 (0.0073)	-0.4121 (0.7991)	0[c]	0[c]
$\sigma_{\lambda 1\lambda 1}$	0.0213 (0.0081)	0.2545 (0.2730)	0.0234 (0.0084)	0.0237 (0.0084)
$\sigma_{\lambda 2\lambda 2}$	0.0008 (0.0003)	0.0014 (0.0021)	0.0009 (0.0003)	0.0009 (0.0003)
$\sigma_{\lambda 1\lambda 2}$	-0.0021 (0.0014)	-0.0101 (0.0130)	-0.0023 (0.0014)	-0.0023 (0.0013)
$\sigma_{\epsilon\epsilon}$	0.079 (0.007)	0.079 (0.007)	0.082 (0.007)	0.082 (0.007)
$\sigma_{\phi\phi}$	0.117 (0.010)	0.117 (0.010)	0.122 (0.010)	0.124 (0.010)
$\sigma_{\epsilon\phi}$	0.085 (0.008)	0.085 (0.008)	0.084 (0.008)	0.089 (0.008)
d	1.076	14.2	1.150	1.161
χ^2	240.17	240.17	243.11	243.23
GFI	0.594	0.594	0.601	0.600
P	0.000	0.000	0.000	0.000

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

Table 22
Slander and libel 23, estimates of non-rejected models[ab]

Parameter	W3L3^{I}	W3L3^{II}	W2L3	W1L3	W2L2^{I}	W2L1
b	0.883	-3.493	0.610	0.705	0.201	0.327
	(0.485)	(2.972)	(0.508)	(0.533)	(0.776)	(0.983)
r	0.714	2.132	0.824	0.783	1.026	0.966
	(0.244)	(0.621)	(0.274)	(0.285)	(0.348)	(0.432)
$\sigma_{\omega1\omega1}$	0.1515	3.5493	0.2405	0.2956	0.2121	0.2111
	(0.1235)	(5.4861)	(0.0964)	(0.1149)	(0.0801)	(0.0788)
$\sigma_{\omega2\omega2}$	-0.0014	0.0480	0.0020	0[c]	0.0027	0.0028
	(0.0038)	(0.0861)	(0.0024)		(0.0021)	(0.0024)
$\sigma_{\omega1\omega2}$	0.0240	-0.3172	0[c]	0[c]	0[c]	0[c]
	(0.0216)	(0.5577)				
$\sigma_{\lambda1\lambda1}$	0.2909	0.1942	0.2661	0.2826	0.1204	0.1194
	(0.1324)	(0.2890)	(0.1236)	(0.1326)	(0.0478)	(0.0546)
$\sigma_{\lambda2\lambda2}$	0.0039	-0.0018	0.0035	-0.0041	-0.0004	0[c]
	(0.0022)	(0.0044)	(0.0027)	(0.0028)	(0.0013)	
$\sigma_{\lambda1\lambda2}$	-0.0260	0.0307	-0.0239	-0.0268	0[c]	0[c]
	(0.0159)	(0.0253)	(0.0158)	(0.0163)		
$\sigma_{\varepsilon\varepsilon}$	0.177	0.177	0.172	0.175	0.174	0.174
	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
$\sigma_{\phi\phi}$	0.290	0.290	0.290	0.290	0.315	0.313
	(0.037)	(0.037)	(0.037)	(0.037)	(0.038)	(0.038)
$\sigma_{\varepsilon\phi}$	0.121	0.121	0.120	0.122	0.127	0.127
	(0.023)	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)
d	1.253	4.951	1.107	1.153	0.995	1.011
χ^2	123.04	123.04	124.45	125.21	128.89	129.00
GFI	0.649	0.649	0.641	0.643	0.640	0.639
P	0.024	0.024	0.023	0.024	0.014	0.017

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

6.4.7. *Embezzlement*

In the case of embezzlement only two models satisfy our restrictions (16), cf Table 23. The estimates are not very different from each other. We note, though, that W3L2 is the more parsimonious one, and has a negative, but non-significant estimate of b. Both have first a decreasing, and then an increasing variance of the crime tendency, whereas the variance of the clear-up tendency is increasing for both. This indicates growing differences in relative terms between police districts in both respects in the late seventies.

6.4.8. *Fraud*

Three models satisfy our restrictions (16) in the case of fraud, see Table 24. None of them have statistically significant estimates of b. The one for W3L1 is negative, those for the two others are positive. The variance of the crime tendency is mainly decreasing for all three, with a slight increase at the end of the period. The variance of the clear-up tendency is strongly decreasing. In both respects, then, the differences in relative terms between police districts are reduced.

6.4.9. *Offence inflicting damage to property*

Only $W3L3^{I}$ satisfy our restrictions in the case of offence inflicting damage to property. For this solution the estimate of b is negative (see Table 11), but non-significant. The other estimates have also expected signs, and most of them are statistically significant. The variance of the crime tendency is decreasing, whereas that of the clear-up tendency is first decreasing, and then increasing.

6.4.10. *Aggravated larcenies*

In the case of aggravated larcenies six models satisfy (16). Precision of estimates and parsimony of parameters are arguments for choosing either W3L2 or W1L2 instead of $W3L3^{I}$, cf Table 25. The high negative estimates of the deterrence elasticity indicate that the clear-up probability has a substantial influence on this type of crime. The variance of the crime tendency is decreasing and that of the clear-up tendency increasing for the models allowing for changes in these tendencies. Police districts become less different with respect to aggravated larcenies, and more different with respect to clearing up such crimes, both in relative terms.

Table 23
Embezzlement 24, estimates of non-rejected models[ab]

Parameter	W3L3^{I}	W3L3^{II}	W3L2
b	0.055 (0.629)	-10.21 (7.284)	-0.223 (0.768)
r	0.902 (0.070)	19.1 (205)	0.926 (0.098)
$\sigma_{\omega1\omega1}$	0.3121 (0.1269)	-1.1829 (2.0581)	0.2986 (0.1197)
$\sigma_{\omega2\omega2}$	0.0102 (0.0049)	0.0106 (0.0802)	0.0096 (0.0046)
$\sigma_{\omega1\omega2}$	-0.0355 (0.0214)	0.3963 (0.6160)	-0.0336 (0.0203)
$\sigma_{\lambda1\lambda1}$	-0.0113 (0.0116)	102 (2302)	0.0029 (0.0074)
$\sigma_{\lambda2\lambda2}$	0.0001 (0.0007)	3.34 (75)	0.0011 (0.0005)
$\sigma_{\lambda1\lambda2}$	0.0038 (0.0025)	-11.6 (262)	0[c]
$\sigma_{\epsilon\epsilon}$	0.232 (0.026)	0.232 (0.026)	0.233 (0.026)
$\sigma_{\phi\phi}$	0.272 (0.030)	0.272 (0.030)	0.269 (0.030)
$\sigma_{\epsilon\phi}$	0.215 (0.026)	0.215 (0.026)	0.216 (0.026)
d	0.995	186	0.983
χ^2	141.49	141.49	143.06
GFI	0.641	0.641	0.642
P	0.001	0.001	0.001

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

Table 24
Fraud 26, estimates of non-rejected models[ab]

Parameter	W3L3[I]	W3L3[II]	W3L2	W3L1
b	0.200 (0.758)	-26.23 (31.4)	0.239 (0.793)	-0.795 (2.162)
r	0.962 (0.046)	6.00 (18.9)	0.961 (0.047)	1.005 (0.112)
$\sigma_{\omega1\omega1}$	0.5249 (0.141)	15.34 (38)	0.5256 (0.1418)	0.5218 (0.1468)
$\sigma_{\omega2\omega2}$	0.0075 (0.0030)	-0.3790 (0.9281)	0.0076 (0.0031)	0.0076 (0.0036)
$\sigma_{\omega1\omega2}$	-0.0349 (0.0172)	0.4284 (1.8335)	-0.0348 (0.0172)	-0.0365 (0.0195)
$\sigma_{\lambda1\lambda1}$	0.0223 (0.0152)	13.10 (99)	0.0260 (0.0073)	0.0194 (0.0069)
$\sigma_{\lambda2\lambda2}$	-0.0006 (0.0004)	0.1884 (1.4249)	-0.0004 (0.0002)	0[c]
$\sigma_{\lambda1\lambda2}$	0.0006 (0.0023)	-0.9707 (6.579)	0[c]	0[c]
$\sigma_{\varepsilon\varepsilon}$	0.194 (0.018)	0.194 (0.018)	0.194 (0.018)	0.193 (0.018)
$\sigma_{\phi\phi}$	0.291 (0.027)	0.291 (0.027)	0.290 (0.021)	0.286 (0.026)
$\sigma_{\varepsilon\phi}$	0.210 (0.021)	0.210 (0.021)	0.210 (0.027)	0.208 (0.021)
d	0.992	132	0.991	1.004
χ^2	184.22	184.22	184.29	187.59
GFI	0.674	0.674	0.673	0.668
P	0.000	0.000	0.000	0.000

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

Table 25
Aggravated larcenies 40, estimates of non-rejected models[ab]

Parameter	$W3L3^{I}$	$W3L3^{II}$	W3L2	W3L1	W1L3	$W2L2^{I}$	W1L2
b	-2.437	2.384	-2.408	-1.909	-2.121	-2.363	-2.007
	(0.566)	(2.380)	(0.497)	(0.563)	(1.007)	(1.158)	(0.797)
r	1.420	0.590	1.397	1.065	1.163	1.285	1.102
	(0.419)	(0.095)	(0.353)	(0.190)	(0.491)	(0.773)	(0.337)
$\sigma_{\omega 1\omega 1}$	0.7338	2.083	0.7194	0.5153	0.3910	0.4248	0.3798
	(0.3530)	(2.0056)	(0.3214)	(0.1606)	(0.1345)	(0.2331)	(0.1054)
$\sigma_{\omega 2\omega 2}$	0.0048	0.0070	0.0047	0.0038	0[c]	-0.0009	0[c]
	(0.0051)	(0.0070)	(0.0049)	(0.0031)		(0.0035)	
$\sigma_{\omega 1\omega 2}$	-0.0463	-0.0032	-0.0448	-0.0258	0[c]	0[c]	0[c]
	(0.0388)	(0.0294)	(0.0361)	(0.0187)			
$\sigma_{\lambda 1\lambda 1}$	0.3665	0.1235	0.3433	0.1381	0.1799	0.2562	0.1446
	(0.3960)	(0.0404)	(0.3142)	(0.0940)	(0.2819)	(0.5688)	(0.1696)
$\sigma_{\lambda 2\lambda 2}$	0.0012	0.0008	0.0011	0[c]	0.0009	0.0013	0.0008
	(0.0015)	(0.0007)	(0.0012)		(0.0010)	(0.0023)	(0.0006)
$\sigma_{\lambda 1\lambda 2}$	-0.0006	-0.0078	0[c]	0[c]	-0.0010	0[c]	0[c]
	(0.0057)	(0.0048)			(0.0025)		
$\sigma_{\varepsilon\varepsilon}$	0.054	0.054	0.054	0.054	0.056	0.056	0.056
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\sigma_{\phi\phi}$	0.198	0.198	0.198	0.198	0.206	0.208	0.206
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
$\sigma_{\varepsilon\phi}$	0.071	0.071	0.071	0.070	0.075	0.076	0.075
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
d	2.022	1.977	1.956	1.124	1.346	1.673	1.205
χ^2	181.24	181.24	181.25	185.74	185.74	187.01	187.11
GFI	0.670	0.670	0.670	0.671	0.671	0.657	0.656
P	0.00	0.000	0.00	0.000	0.000	0.071	0.000

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

Table 26
Simple larcenies 41, estimates of non-rejected models[ab]

Parameter	W3L3^{I}	W3L3^{II}	W3L2
b	-1.072	7.583	-0.998
	(0.193)	(14.79)	(0.150)
r	1.132	0.067	1.025
	(0.257)	(0.168)	(0.167)
$\sigma_{\omega 1\omega 1}$	0.3362	16.62	0.3544
	(0.0945)	(56.19)	(0.087)
$\sigma_{\omega 2\omega 2}$	0.0037	0.1850	0.0036
	(0.0016)	(0.6307)	(0.0014)
$\sigma_{\omega 1\omega 2}$	-0.0300	-0.5025	-0.0285
	(0.0111)	(1.6548)	(0.0102)
$\sigma_{\lambda 1\lambda 1}$	0.2891	0.3188	0.2063
	(0.1667)	(0.1182)	(0.0864)
$\sigma_{\lambda 2\lambda 2}$	0.0032	0.0032	0.0022
	(0.0020)	(0.0016)	(0.0011)
$\sigma_{\lambda 1\lambda 2}$	-0.0087	-0.0261	0[c]
	(0.0088)	(0.0112)	
$\sigma_{\varepsilon\varepsilon}$	0.049	0.049	0.049
	(0.004)	(0.004)	(0.004)
$\sigma_{\phi\phi}$	0.122	0.122	0.122
	(0.011)	(0.011)	(0.011)
$\sigma_{\varepsilon\phi}$	0.044	0.044	0.043
	(0.006)	(0.006)	(0.006)
d	1.142	8.07	1.025
χ^2	166.43	166.43	168.47
GFI	0.724	0.724	0.722
P	0.000	0.000	0.000

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

Table 27
Thefts of motor vehicles 43, estimates of non-rejected models[ab]

Parameter	W3L3^{II}	W3L3^{II}	W3L2	W2L2^{I}
b	-2.679	1.645	-2.620	-2.480
	(0.472)	(2.527)	(0.392)	(0.532)
r	1.608	0.627	1.490	1.222
	(0.934)	(0.066)	(0.625)	(0.509)
$\sigma_{\omega1\omega1}$	0.7264	1.9321	0.4524	0.3035
	(0.2054)	(2.2664)	(0.1849)	(0.0997)
$\sigma_{\omega2\omega2}$	0.0019	0.0110	0.0016	-0.0010
	(0.0038)	(0.0135)	(0.0034)	(0.0020)
$\sigma_{\omega1\omega2}$	-0.0233	-0.0255	-0.0021	0^c
	(0.0229)	(0.0379)	(0.0201)	
$\sigma_{\lambda1\lambda1}$	0.7138	0.0659	0.5309	0.2563
	(1.3772)	(0.0234)	(0.7758)	(0.4246)
$\sigma_{\lambda2\lambda2}$	0.0041	0.0003	0.0030	0.0016
	(0.0078)	(0.0005)	(0.0043)	(0.0023)
$\sigma_{\lambda1\lambda2}$	-0.0094	-0.0032	0^c	0^c
	(0.0216)	(0.0030)		
$\sigma_{\varepsilon\varepsilon}$	0.070	0.070	0.071	0.072
	(0.006)	(0.006)	(0.006)	(0.006)
$\sigma_{\phi\phi}$	0.134	0.134	0.134	0.139
	(0.012)	(0.012)	(0.012)	(0.012)
$\sigma_{\varepsilon\phi}$	0.074	0.074	0.074	0.077
	(0.006)	(0.006)	(0.008)	(0.008)
d	2.629	1.614	2.284	1.551
χ^2	155.06	155.06	156.03	157.34
GFI	0.682	0.682	0.683	0.684
P	0.000	0.000	0.000	0.000

[a] See Table 2 for definition of models. Solutions I and II correspond to the two solutions of a second order equation obtained in identifying the model.
[b] Standard errors in parentheses.
[c] A priori restriction.

6.4.11. Simple larcenies

Two of the models applied to simple larcenies, $W3L3^I$ and W3L2 are not rejected. Table 26 shows that their estimates are rather similar, and that those of the latter are statistically significant, and somewhat more precise than those of the former. The estimates are generally almost equal to those of crime at large. This is not surprising considered the large proportion of total crime that consists of simple larcenies. In both models the variance of the crime tendency is decreasing, and that of the clear-up tendency increasing. Both tendencies are typical for most crimes: police districts become less different in crime tendencies and more different in clear-up tendencies, still in relative terms.

6.4.12. Thefts of motor vehicles

Our study of thefts of motor vehicles has not been totally successful, as we for some models have not been able to obtain optimal solutions by using LISREL. The three estimated and non-rejected models of Table 27 exibit rather similar results. Precision and significance of the estimates are arguments for choosing $W2L2^I$. Also for this type of crime the clear-up proportion is found to have a strong negative influence on crime. Here, too, we find a growing similarity in crime between police districts, whereas there is a growing dissimilarity in clear-up.

7. Summing up

A new criminometric model is derived from a theory of criminal and police behaviour, and measurement relations with random and systematic measurement errors. The effects of the socioeconomic environment are summarized by the latent district effects in the crime and clear-up functions, called crime and clear-up tendencies. The distribution of these latent variables across police districts and over time is modelled.

The model has been successfully applied on panel data on the number of crimes and clear-ups for the 53 police districts in Norway for 1970-78, confirming the hypothesis that our approach is fruitful.

The model is not identified if the latent district effects are constant over time, but these submodels are strongly rejected empirically, both for total crime and for 9 out of 12 types of crime. In the general model there will be two observationally equivalent structures, and correspondingly two global maxima in the likelihood function, due to the two solutions of a 2. order equation. However, by reasonable a priori restrictions on the parameter space, only one of the two solutions come out as empirically relevant. It is remarkable that this result was obtained both for total crime and for each of the 12 types of crime.

In our analysis of total crime we find the deterrence elasticity to be significantly negative and close to -1 in our preferred model. The estimate of this elasticity varies considerably between submodels, and illustrates the importance of our systematic approach to classifying, estimating, testing, and evaluating submodels.

Applying our most general model (W3L3) to 12 different types of crime, we find the deterrence elasticity to be negative in seven cases, four of which significantly so. The five positive estimates are mostly rather small and are all statistically non-significant. In three of the five cases the estimates of the deterrence elasticity changes from being positive to being (non-significant) negative, when going to more parsimonious models. Only in the cases of public disorder, and slander and label the deterrence elasticity is found to be positive for all non-rejected models. The clear-up probability has a rather strong negative effect on crime for "simple" economic crimes, such as larcenies and thefts of motor vehicles, whereas more "sofisticated" forms, such as fraud, embezzlement and forgery, are less affected.

The estimate of the clear-up elasticity is for total crime expected to be positive, but less than 1. Presumably, an increase in crime will cet. par. result in a proportionally less increase in clear-ups. In our preferred model it is found to be 0.8. Also for various types of crime we expect a positive estimate, but not necessarily less than 1. Reallocation of police resources within a district might produce a proportionally higher number of clear-ups than of crimes when a specific type of crime is increasing. The estimates are in accordance with this expectation. They are all positive, and for some types of crimes and models they are greater than 1, but not much so.

The variance of the log of the crime tendency for total crime is decreasing for all models (in which a change is allowed) during the period. Except for embezzlement, and slander and label this variance is for all models lower at the end of the period than at the beginning, demonstrating a growing similarity in relative (log) terms among police districts for most types of crime.

The estimates of the variance of the log of the clear-up tendency is increasing for total crime and for half of the specific types of crime. In the remaing cases the development of this tendency is less uniform. For nine of the 12 types of crime, however, our most general model gives a higher variance at the end of the period than at the beginning, indicating a growing dissimilarity among police districts as far as clear-up tendencies are concerned. The more parsimonious models give, with a couple of exceptions, the same result.

The estimates of the variances and the covariance of the errors of measurement are all significantly positive and very robust with respect to model specifications.

Appendix: Data

This Appendix contains the covariance matrices of the logs of the number of crimes and clear-ups for total crime and for 12 types of crime computed on the basis of data from 53 police districts in the period 1972-78. The data on the total number of crimes and clear-ups has been provided by Norsk Samfunnsvitenskapelig Datatjeneste (NSD). All remaining data are unpublished statistics from Statistics Norway.

For convenience, the tables for the various types of crime have been numbered according to the numbers given by Statistics Norway to these various types of crime:

A.13 Offences against public order and peace.
A.18 Forgery.
A.19 Sexual offences.
A.21 Offences against the personal liberty.
A.22 Offences of violence against the person.
A.23 Slander and libel.
A.24 Embezzlement.
A.26 Fraud and breach of trust.
A.28 Offences inflicting damage to property.
A.40 Aggravated larcenies.
A.41 Simple larcenies.
A.43 Thefts of motor vehicles.

A crime is registered by the police for statistical purposes in the year when the investigation is closed. Accordingly, the statistics give information on investigated cases and not about crimes committed in the statistical year. The average period of investigation has for the country as a whole and for all crimes taken together increased from 4 months in 1970-1972 to 4.9 months in the period 1980-1982. Cases shelved for observation are considered closed, but if such cases are subsequently cleared up, a new statistical report is submitted. If this happens the same year, the first report is not included in the statistics, but if it happens in a subsequent year, the crime is registered as a separate crime and clear-up that year.

The only noticeable legal change of some importance to the number of crimes during the studied period, was the decriminalizing of "naskeri" (petty larceny of less than about 50 kr.) by the end of 1972. Until then this crime was included in the group of petty larceny, which accounted for about 30 per cent of total crimes. The number of crimes in this group did not decline from 1972 to 1973.

Table A.1
Covariance matrix of logs of crime rates

Crimes	Crimes 1970	1971	1972	1973	1974	1975	1976	1977	1978
1970	.4019								
1971	.3614	.3695							
1972	.3693	.3673	.3947						
1973	.3714	.3718	.3912	.4187					
1974	.3411	.3367	.3476	.3645	.3660				
1975	.3390	.3402	.3524	.3689	.3505	.3836			
1976	.3107	.3149	.3209	.3390	.3311	.3551	.3475		
1977	.3001	.3070	.3143	.3324	.3151	.3351	.3240	.3331	
1978	.2942	.2894	.2990	.3074	.2973	.3162	.2956	.3017	.3449

Table A.2
Covariance matrix of logs of crime and clear-up rates

Clear-ups	Crimes 1970	1971	1972	1973	1974	1975	1976	1977	1978
1970	.2931	.2590	.2524	.2444	.2302	.2217	.2093	.1957	.1859
1971	.2525	.2622	.2430	.2441	.2144	.2143	.2010	.1918	.1727
1972	.2577	.2670	.2834	.2684	.2386	.2283	.2123	.2053	.1897
1973	.2506	.2713	.2762	.2962	.2458	.2526	.2344	.2242	.1931
1974	.2204	.2334	.2388	.2445	.2533	.2334	.2231	.1993	.1734
1975	.2117	.2205	.2313	.2374	.2222	.2539	.2321	.2056	.1827
1976	.2147	.2286	.2376	.2428	.2366	.2586	.2658	.2250	.1788
1977	.1882	.2062	.2135	.2231	.1911	.2075	.2085	.2231	.1758
1978	.1980	.1998	.2069	.1978	.1883	.1879	.1775	.1803	.2110

Table A.3
Covariance matrix of logs of clear-up rates

Clear-ups	Clear-ups 1970	1971	1972	1973	1974	1975	1976	1977	1978
1970	.2746								
1971	.2279	.2522							
1972	.2165	.2219	.2754						
1973	.1996	.2181	.2350	.2864					
1974	.1796	.1850	.2117	.2210	.2512				
1975	.1642	.1634	.1819	.1997	.1920	.2380			
1976	.1766	.1706	.1969	.2074	.2031	.2060	.2837		
1977	.1499	.1591	.1712	.1903	.1566	.1638	.1830	.2284	
1978	.1672	.1554	.1872	.1605	.1440	.1387	.1582	.1529	.2244

Table A13
Covariance matrix of logs of crime and clear-up rates of offences against public order and peace

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.9201													
R	1973	.4483	.7483												
I	1974	.2827	.3697	.7912											
M	1975	.3116	.3323	.3717	.8589										
E	1976	.2977	.3127	.3480	.3654	.6138									
S	1977	.2953	.2974	.3319	.3171	.3758	.6827								
	1978	.3026	.2307	.3016	.2773	.3249	.3117	.7668							
C	1972	.5617	.2814	.1496	.2425	.2315	.2118	.2548	1.0778						
L	1973	.3994	.4415	.2711	.3003	.2914	.2801	.1932	.4274	.6891					
E	1974	.2260	.1760	.1840	.1758	.2075	.1549	.1164	.2402	.2716	.6883				
A	1975	.2172	.1929	.1889	.2664	.3309	.2420	.1526	.1855	.1968	.2193	.4811			
R	1976	.2085	.1985	.2231	.2883	.4577	.2738	.2630	.2426	.2580	.2332	.3421	.8437		
U	1977	.2228	.2470	.2235	.2171	.2712	.3437	.1989	.2478	.2563	.2152	.1929	.1830	.5699	
P	1978	.3149	.1983	.1810	.1832	.1977	.2105	.3036	.2828	.2194	.1691	.0977	.2000	.2121	.6113

Table A18
Covariance matrix of logs of crime and clear-up rates of forgery

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.4649													
R	1973	.1444	.7114												
I	1974	.2373	.3232	.5455											
M	1975	.1661	.2822	.2935	.5477										
E	1976	.1748	.1743	.1816	.1479	.6444									
S	1977	.0695	.1986	.1526	.1479	.0827	.3051								
	1978	.1934	.2290	.2120	.1612	.1013	.1541	.4911							
C	1972	.3905	.1472	.2385	.1520	.1651	.0823	.2226	.5147						
L	1973	.1217	.5943	.3507	.3364	.1942	.1956	.1977	.1405	.7004					
E	1974	.2881	.3139	.5446	.3014	.2496	.1692	.1874	.2832	.3384	.7412				
A	1975	.1535	.2694	.2598	.5319	.1436	.1508	.1508	.1579	.3291	.2611	.6151			
R	1976	.1400	.1512	.1715	.1436	.4060	.0919	.1023	.1556	.2275	.2481	.1697	.6496		
U	1977	.0544	.1887	.1683	.1683	.0803	.1890	.1532	.0997	.2549	.1893	.1783	.1464	.4050	
P	1978	.2067	.1897	.2290	.1415	.0694	.1482	.4304	.2455	.1689	.2173	.1440	.0915	.1721	.4878

Table A19
Covariance matrix of logs of crime and clear-up rates of sexual offences

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.3291													
R	1973	.1997	.4127												
I	1974	.2294	.2848	.4493											
M	1975	.1240	.1705	.1552	.3848										
E	1976	.1381	.2047	.1413	.1261	.5052									
S	1977	.1812	.2090	.1871	.1673	.0972	.3093								
	1978	.0714	.1420	.1016	.1837	.0466	.0968	.4308							
C	1972	.2549	.0552	.1622	.0827	.0623	.1115	.0634	.4862						
L	1973	.1201	.3580	.1832	.1577	.1484	.1345	.1489	.0910	.4464					
E	1974	.1175	.2214	.3958	.1483	.0556	.1373	.0739	.1876	.2123	.5313				
A	1975	.0369	.1342	.0984	.3214	.0216	.1291	.2577	.0725	.1943	.1906	.5454			
R	1976	.0736	.1442	.1091	.1068	.2689	.0700	.0184	.0826	.1727	.1098	.1021	.5547		
U	1977	.1604	.1979	.2687	.1244	.0808	.2439	.0543	.1331	.1898	.2920	.1640	.2085	.4570	
P	1978	.0074	.0347	.0415	.0780	.0001	.0556	.2661	.0875	.0804	.1418	.2119	.0001	.1437	.4776

Table A21
Covariance matrix of logs of crime and clear-up rates of offence against the personal liberty

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.7165													
R	1973	.2484	.5721												
I	1974	.4518	.2894	.6275											
M	1975	.3400	.2321	.2669	.4500										
E	1976	.2861	.1887	.2632	.2905	.4040									
S	1977	.4311	.2116	.3208	.3940	.3960	.6909								
	1978	.5126	.2022	.3329	.3097	.2505	.4382	.6536							
C	1972	.5864	.1999	.4203	.2552	.1712	.2425	.3712	.7032						
L	1973	.2186	.3691	.3022	.2078	.1580	.2009	.1340	.2132	.6557					
E	1974	.4424	.2981	.4680	.2758	.2666	.3541	.3399	.4462	.3813	.5875				
A	1975	.3525	.2215	.3017	.3844	.2644	.3837	.2812	.3033	.2866	.3936	.5041			
R	1976	.3325	.2125	.2979	.3015	.3237	.4043	.2128	.2380	.2480	.2992	.3214	.5630		
U	1977	.2576	.1238	.1745	.3105	.2578	.4858	.3052	.1677	.1359	.2477	.2969	.2865	.6008	
P	1978	.5277	.1924	.3859	.2593	.2210	.3041	.4827	.4956	.1360	.3342	.2110	.2347	.2182	.5440

Table A22
Covariance matrix of logs of crime and clear-up rates of offence of violence against the person

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.3079													
R	1973	.2347	.2758												
I	1974	.2187	.2145	.2664											
M	1975	.2022	.1863	.2158	.2543										
E	1976	.2312	.2077	.2885	.2890	.4912									
S	1977	.1741	.1551	.1766	.2057	.2831	.2342								
	1978	.1545	.1524	.1587	.1871	.1782	.1429	.2198							
C	1972	.3157	.2316	.2172	.1963	.2131	.1657	.1647	.3708						
L	1973	.2314	.2738	.2044	.1722	.2047	.1505	.1507	.2411	.2985					
E	1974	.2309	.2194	.2695	.2073	.2940	.1753	.1538	.2442	.2304	.3165				
A	1975	.2083	.1873	.2104	.2254	.2577	.1847	.1639	.2199	.1878	.2314	.2402			
R	1976	.2567	.2354	.3207	.2981	.5412	.2929	.1748	.2500	.2423	.3376	.2833	.6371		
U	1977	.1800	.1749	.1716	.1927	.2771	.2299	.1430	.1778	.1895	.1873	.1892	.3060	.2712	
P	1978	.1737	.1660	.1511	.1687	.1797	.1519	.2085	.1931	.1796	.1725	.1630	.1877	.1789	.2705

Table A23
Covariance matrix of logs of crime and clear-up rates of slander and libel

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.5860													
R	1973	.2619	.5529												
I	1974	.2458	.1457	.5357											
M	1975	.2509	.2731	.2568	.3830										
E	1976	.2315	.2469	.2434	.3009	.5459									
S	1977	.2777	.2396	.2529	.3167	.3678	.5397								
	1978	.2131	.2178	.2056	.2142	.2292	.3113	.5702							
C	1972	.3921	.3309	.3138	.2762	.2580	.2150	.1814	.7857						
L	1973	.3414	.3954	.3196	.3266	.2516	.2317	.2269	.5758	.6102					
E	1974	.2339	.1498	.3977	.0976	.2132	.1953	.1639	.4032	.3984	.6911				
A	1975	.2362	.2418	.2037	.4133	.1715	.2282	.1540	.4273	.4829	.2293	.6629			
R	1976	.2770	.3501	.2477	.2758	.3583	.3615	.2254	.3669	.5733	.3350	.4182	.6067		
U	1977	.3086	.2727	.3435	.3771	.3173	.4632	.3177	.3197	.4310	.2677	.3625	.4379	.5574	
P	1978	.3314	.2822	.3051	.1804	.3004	.4378	.4198	.3292	.3958	.3975	.2242	.4251	.4546	.7582

Table A24
Covariance matrix of logs of crime and clear-up rates of embezzlement

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.6134													
R	1973	.2484	.6550												
I	1974	.2687	.1753	.5332											
M	1975	.1001	.1501	.0541	.4445										
E	1976	.1728	.1181	.1813	.1047	.4944									
S	1977	.1370	.1510	.1470	.1592	.3088	.6736								
	1978	.2827	.1540	.1498	.2248	.2831	.2912	.5141							
C	1972	.6019	.1974	.2346	.0949	.1651	.1151	.2305	.4716						
L	1973	.2389	.3282	.1921	.1335	.1096	.1825	.1486	.1961	.6454					
E	1974	.2817	.1740	.4517	.0389	.1816	.1372	.1775	.2529	.2079	.5742				
A	1975	.0742	.1416	.0608	.2915	.0804	.1722	.2230	.0725	.1549	.0543	.4562			
R	1976	.2010	.0979	.1879	.0809	.3994	.2782	.2766	.2022	.1125	.2125	.0944	.5243		
U	1977	.1457	.1421	.0689	.1490	.2327	.3882	.2753	.1190	.1953	.0892	.1917	.2525	.5431	
P	1978	.2088	.1485	.1175	.2090	.2459	.2309	.5046	.1964	.1737	.1424	.2412	.2827	.2474	.5225

Table A26
Covariance matrix of logs of crime and clear-up rates of fraud and breach of trust

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.6535													
R	1973	.3899	.6816												
I	1974	.3918	.4065	.6252											
M	1975	.4175	.4001	.3751	.5308										
E	1976	.3086	.3075	.3307	.3906	.5372									
S	1977	.3872	.2878	.3279	.3493	.3341	.6340								
	1978	.3735	.2423	.2966	.3515	.3512	.4513	.5625							
C	1972	.6877	.3667	.3620	.4168	.2888	.3765	.3553	.7834						
L	1973	.3983	.5140	.3931	.4097	.2635	.2738	.2072	.3943	.5848					
E	1974	.3937	.4014	.6540	.4092	.3406	.3142	.2936	.3641	.4264	.8300				
A	1975	.4089	.3788	.3430	.5086	.3091	.2524	.3049	.4363	.4314	.4123	.6904			
R	1976	.3397	.2743	.3108	.4032	.5536	.3308	.3460	.3334	.2352	.3362	.3485	.6014		
U	1977	.3796	.2564	.2805	.3313	.3002	.5898	.4250	.3800	.2711	.2990	.2705	.3070	.6647	
P	1978	.4069	.2396	.3159	.3764	.3618	.4735	.5981	.3931	.2104	.3174	.3475	.3746	.4577	.6648

Table A28
Covariance matrix of logs of crime and clear-up rates of offence inflictin damage to property

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.4288													
R	1973	.3891	.4904												
I	1974	.1973	.2246	.2694											
M	1975	.2065	.2422	.2299	.2955										
E	1976	.1796	.2134	.1937	.2596	.3123									
S	1977	.1055	.1718	.1351	.2009	.2155	.3430								
	1978	.1934	.2096	.1452	.2000	.2174	.1873	.3193							
C	1972	.3449	.2648	.1461	.1378	.1190	.0602	.1648	.4670						
L	1973	.3099	.3834	.1905	.2220	.1944	.1545	.1758	.3030	.4855					
E	1974	.0994	.0956	.2075	.1601	.1548	.0778	.0525	.1519	.1786	.3326				
A	1975	.1739	.1803	.1599	.2020	.1742	.1298	.0980	.1380	.2364	.2090	.3061			
R	1976	.1423	.1414	.1201	.1889	.2159	.1559	.1048	.1327	.1839	.1681	.2011	.2849		
U	1977	.0503	.1052	.0777	.1346	.1579	.2305	.0996	.0689	.1783	.1216	.1510	.1953	.3776	
P	1978	.1269	.1684	.0946	.1522	.1778	.1691	.2262	.1273	.1930	.0899	.1316	.1383	.1852	.3190

Table A40
Covariance matrix of logs of crime and clear-up rates of aggravated larcenies

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.7134													
R	1973	.6631	.7242												
I	1974	.6529	.6508	.6997											
M	1975	.6802	.6877	.6550	.7331										
E	1976	.6638	.6470	.6601	.6909	.7426									
S	1977	.6695	.6516	.6666	.6885	.7395	.8008								
	1978	.6077	.5914	.6224	.6222	.6433	.6733	.6709							
C	1972	.5606	.5023	.4794	.4891	.4472	.4509	.4233	.6829						
L	1973	.4660	.5734	.4463	.5047	.4269	.4355	.3786	.4489	.6282					
E	1974	.5024	.5027	.5247	.4971	.5158	.4992	.4233	.4337	.4242	.5582				
A	1975	.4921	.5103	.4736	.5435	.5036	.4852	.4331	.3958	.4607	.4171	.5554			
R	1976	.5712	.5620	.5537	.5956	.6280	.5967	.4996	.4730	.4435	.5182	.4804	.7037		
U	1977	.5106	.4976	.4919	.5022	.5914	.6733	.5052	.3620	.3976	.4355	.4216	.4988	.7664	
P	1978	.3841	.3640	.4033	.3558	.3657	.3833	.4137	.3644	.2765	.2919	.3004	.3576	.3435	.4322

Table A41
Covariance matrix of crime and clear-up rates of simple larcenies

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.4819													
R	1973	.4684	.5288												
I	1974	.4098	.4568	.4645											
M	1975	.3911	.4337	.4198	.4767										
E	1976	.3532	.3916	.3864	.4304	.4022									
S	1977	.3495	.3856	.3757	.3990	.3716	.3917								
	1978	.3103	.3438	.3499	.3934	.3488	.3538	.4323							
C	1972	.3008	.2658	.2470	.1795	.1694	.1571	.1130	.4253						
L	1973	.3117	.3314	.2842	.2460	.2409	.2271	.1586	.3176	.4448					
E	1974	.2361	.2211	.2690	.1991	.1944	.1805	.1399	.2679	.2806	.3170				
A	1975	.1458	.1801	.1771	.2290	.1959	.1578	.1346	.1270	.1702	.1502	.2387			
R	1976	.1616	.1686	.1633	.1831	.1908	.1374	.0847	.1776	.2172	.1778	.1720	.3253		
U	1977	.1889	.1998	.1779	.1846	.1752	.1861	.1313	.2112	.2044	.1477	.1398	.1502	.3061	
P	1978	.1552	.1436	.1502	.1528	.1359	.1332	.1688	.1843	.1768	.1254	.1119	.1162	.1817	.2553

Table A43
Covariance matrix of crime and clear-up rates of theft of motor vehicles

		CRIMES							CLEAR-UPS						
		1972	1973	1974	1975	1976	1977	1978	1972	1973	1974	1975	1976	1977	1978
C	1972	.8289													
R	1973	.7845	.8251												
I	1974	.7554	.7660	.8242											
M	1975	.8161	.8083	.8527	.9706										
E	1976	.7641	.7480	.8227	.9296	.9437									
S	1976	.7467	.7186	.7410	.8708	.8338	.8173								
	1978	.7497	.7319	.7371	.8466	.8007	.8023	.9779							
C	1972	.6029	.5173	.5133	.5549	.5552	.5172	.4982	.5689						
L	1973	.5901	.6188	.5708	.5658	.5299	.5146	.5210	.4310	.5730					
E	1974	.5091	.5230	.5886	.5595	.5535	.4845	.4835	.4143	.4521	.5146				
A	1975	.6069	.5992	.6514	.7576	.6815	.6271	.6146	.4466	.4699	.4771	.7301			
R	1976	.5445	.5109	.6017	.6708	.7177	.6098	.5706	.4488	.3825	.4477	.5186	.6272		
U	1977	.5372	.4972	.5048	.6272	.5903	.6136	.5778	.4121	.3766	.3605	.4932	.4705	.5513	
P	1978	.4937	.4726	.4830	.5163	.4881	.4903	.5505	.3627	.3746	.3648	.4190	.3748	.3872	.4463

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Research Department
P.O.B. 8131 Dep.
N-0033 Oslo

Tel.: + 47 - 22 86 45 00
Fax: + 47 - 22 11 12 38

Statistics Norway
Research Department