COMPARING MULTILEVEL AND SINGLE-LEVEL NEGATIVE BINOMIAL REGRESSION MODELS OF PERSONAL CRIMES: EVIDENCE FROM THE NATIONAL CRIME VICTIMIZATION SURVEY.

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1. Introduction

Multilevel/hierarchical modeling explicitly accounts for the clustering of the units of analysis in surveys which use multi-stage sampling, such as the National Crime Victimization Survey (NCVS). It thus avoids atomistic or ecological fallacy which occurs when one analyzes such data assuming that they are the product of simple random sampling. In empirical victimization research the clustering of crime incidents within individuals, individuals within households, households within neighborhoods etc. makes multilevel modeling quite attractive. To my knowledge, the only published studies in the field of victimology using hierarchical techniques are Rountree *et al.* (1994) and Rountree and Land (1996) which model the risk of burglary and violent crime in the neighborhoods of Seattle. Neither, however, discusses how its results differ from conventional regression modeling nor does it analyze the implications of random effects.

This study is concerned with comparing the results between estimated single-level and multilevel models of personal crimes drawn from the 1994 NCVS. The main interest here is to find out whether and, if so, how the multilevel specification offers new insights into victimization. Unlike most empirical victimization research this work focuses on personal crime counts or incidence rates rather than risks which ignore the very prevalent phenomenon of crime concentration (Farrell, 1992; Osborn and Tseloni, 1998). The statistical specification employed is the negative binomial regression model which accounts for the population unexplained heterogeneity in cross section analyses (Osborn and Tseloni, 1998: 308).

The next section is an overview of the data set employed. Sections 3 and 4 describe the variables used in this study and give theoretical justification for their selection. Section 5 presents the statistical models and section 6 gives the results. A concluding section 7 discusses the implications of this exercise and offers suggestions for future research.

2. The data

The study employs data from the 1994 NCVS. The NCVS is conducted monthly by the Census Bureau of the U.S. on behalf of the Bureau of Justice Statistics. The sample, in principle, represents the non institutionalized permanent residents of the U.S. 12 years or older. The Address List from the Decennial Census provides the sampling frame for a rotating panel of housing units. The survey collects detailed information about the victimization experiences of each member 12 years or older of the households which live in the selected housing units. The housing units remain in the NCVS sample for three years and their eligible residents are interviewed every six months during that period.

The 1994 NCVS includes information collected during three interviews between January 1994 and June 1995. Therefore it includes information on victimizations which occurred during a period of one and a half years. Being a sample of housing units the NCVS has serious attrition problems since it does not follow (or trace back) the households if they move out (or in) the selected units before the end of the survey.

The sample of this study consists of all the households which occupied the selected housing units at the time of the first interview (January to June 1994) of the 1994 NCVS public use file. Households which moved in after this period have been removed from the data set. Thus the sampling unit of the employed data set is the household (rather than the housing unit) with all its members 12 years or older. Housing units which were occupied by more than one household during the period of the survey are not overcounted here. Another advantage is that most included households (91.3%) had a bounding (or pre-survey) interview. This is very important because it ensures lack of telescoping in crime reporting. The data offer a natural 2 level hierarchy of individuals (level-1 unit) nested within households (level-2 unit). Table 1 presents the distribution of individuals per household in the sample.

3. The response variable

The response variable of this study, Y_{ij}, is a count which gives the number of personal crimes each household member 12 years or older has experienced during a maximum of 18 months prior to the last interview of the NCVS. Personal crimes is a composite variable which includes rape, sexual assault, robbery, assault, threats, pocket-picking and larceny. In particular, Y_{ij} takes on values $y_{ij} = 0, 1, \ldots,$ where i denotes the individual and j his or her household.

Table 1: Number of Individuals 12 years old or older per Household.

Number of Individuals	Frequency
1	27,011
2	89,126
3	42,051
4	26,307
5	8,718
6	2,307
7	681
8	257
9	108
10	52
11	11
Total	196,629

Table 2 presents the empirical frequency distributions of personal victimizations which occurred within 6, 12 or 18 months. The distribution of the total number of personal crimes (last column) is clearly very skewed and the bulk of cases are concentrated around zero events (97.5%). Overdispersion, whereby the variance is greater than the mean, exists in the data. The negative binomial regression model which allows for extra-Poisson variation seems appropriate for modeling personal crimes (Cameron and Trivedi, 1986; McCullagh and Nelder, 1989).

4. The covariates

The empirical modeling of this study follows the routine activities or lifestyle theory of criminal victimization. Proponents of the theory (Hindelang *et al.*, 1978; Cohen and Felson, 1979; Felson, 1998) argue that the demographic and socio-economic characteristics of individuals and their households, as well as their lifestyle patterns and everyday routine activities determine their exposure to crime. With regard to personal crime they do so by determining individuals' vulnerability and their chances of coming into contact with motivated offenders through social and physical proximity in the absence of effective guardians.

To model the number of personal victimizations the characteristics of the individuals and their households, which theory and previous research suggest, are employed here. Similarly to the response variable they are drawn from the 1994 NCVS. The covariates which refer to the person (level-1) include socio-demographic characteristics, such as sex, age, race, marital status, educational level, and employment status, as well as lifestyle factors, namely shopping, evenings out, and use of public transportation. Length of time living at the address is an indicator of guardianship through knowledge of the neighborhood and friendship networks.

Two dummy variables, 6 and 12 months, which are defined at the person level, capture the effect of shorter reference periods for those who moved out before the end of the survey.

The level-2 or household covariates include indicators of affluence, such as number of cars owned, annual family income, tenure, and type of accommodation; household composition, namely number of adults and children in the household; and protection against crime. The last is measured by whether devices against intruders are fitted and participation in neighborhood watch. Place size in terms of population and urban area of residence which are also defined at the household level depict physical proximity to potential offenders.

Table 3 summarizes the descriptive statistics, namely mean, standard deviation (S.D.) where appropriate, and range of values, of the set of covariates used in this study. They are qualitative except for age and number of adults which are discrete. The reference category of each non-binary qualitative covariate is indicated as the *base* in Table 3 and shown in parentheses next to the variable name in Table 4 of modeling results below.

5. The statistical model

5.1. The multilevel Poisson model

Goldstein (1995) describes multilevel models for proportions and presents models for counts as an extension of the former. The negative binomial multilevel model derives as an extension of the Poisson. First I define the Poisson multilevel model.

Let μ_{ij} be the expected number of victimizations. The log link function for the Poisson model with random coefficients is

$$\ln \mu_{ij} = \eta_{ij} = X_{ij}\beta + \Sigma_{\tau=0}^{p} u_{\tau j} z_{\tau ij} + \Sigma_{\tau=p+1}^{r} u_{\tau j} z_{\tau j} \qquad (1)$$

where $\tau=0,1...,\ r$ with r being the total number of random coefficients in the model including the intercept. Note that the coefficients are random at level-2 (household), or higher if there was any. The level-1 (individual) randomness solely defines the probability distribution of the observed response (Goldstein *et al.*, 1998).

X_{ij} is a row vector of K ($K \geq r$) covariates for the ij individual including the intercept, some of which may refer to the individuals' household. $z_{0ij}=1$, $z_{\tau ij} = x_{\tau ij}$ for $\tau=1...,\ p$, are covariates for the ij individual with random effects. $z_{\tau j} = x_{\tau j}$, for $\tau=p+1...,\ r$, refer to the r-p random effects covariates for the j household.

$[u_{\tau j}]$~ N (0, Ω_u) is the random departure from the *j-th* household (Goldstein, 1995).

The probability distribution for Y_{ij} follows the Poisson distribution so that the probability that Y_{ij} takes the specific value y_{ij} is:

$$\Pr(Y_{ij} = y_{ij}) = \frac{\exp(-\mu_{ij})\mu_{ij}^{y_{ij}}}{y_{ij}!}, \; y_{ij}=0,1,..., \quad (2)$$

with the usual property that $E(Y_{ij})=var(Y_{ij})=\mu_{ij}$ which equals to $\exp(\eta_{ij})$ from Eq. (1).

For any given household the exponential of each element which is related to a personal covariate, $\exp(\beta_k)$, of the fixed effects vector β gives the multiplicative effect on the mean number of events μ_{ij} for a unit increase in the corresponding covariate, x_{kij}, assuming that all other covariates are held constant (Goldstein and Rasbash, 1996; Osborn and Tseloni, 1998). In the case of qualitative predictors, it gives the multiplicative effect of being in the specified category compared to the base. If the corresponding covariate is defined at the household level $\exp(\beta_k)$ gives the multiplicative effect on μ_{ij} of each individual in households with a unit increase in the corresponding covariate, x_{kj}.

The level-2 random component, Ω_u, measures the variation of μ_{ij} between level-2 units (Goldstein, 1995), here households. The first element in Ω_u, $var(u_{0j})$, gives the dispersion related to the intercept of the model between households. If the model includes qualitative covariates the intercept represents the joint effect of all their reference categories. In other words, $var(u_{0j})$ gives the between households unexplained heterogeneity of mean personal crimes suffered by the reference individual.

The interpretation of the elements in the remainder of Ω_u depends on the level at which the corresponding covariate is measured. For covariates defined at the person level, $z_{\tau ij} = x_{\tau ij}$, $var(u_{\tau j})$ gives the random variation of the corresponding effect ('slope'), β_τ, between households. Further $cov(u_{0j}, u_{\tau j})$ may be used to calculate the correlation between the intercept and the corresponding 'slope' (Goldstein, 1995).

If $z_{\tau j} = x_{\tau j}$, namely the corresponding covariate refers to households, and both $var(u_{\tau j})$ and $cov(u_{0j}, u_{\tau j})$ are non-zero it can be said that the between households variance of the expected number of events, here personal crimes, is a quadratic function of $x_{\tau j}$, $var(u_{\tau j})x_{\tau j}^2 + 2cov(u_{0j}, u_{\tau j})x_{\tau j} + var(u_{0j})$ (Goldstein, 1995). However, if x_{dj} is a dummy variable $var(u_{dj})$ is restricted to zero for avoiding overspecification in the level-2 random part of the model. In this case the variance of μ_{ij} between households of the base category, $x_{dj} = 0$, is given by $var(u_{0j})$, whereas $var(u_{0j})+2cov(u_{0j},u_{dj})$ gives the between households with $x_{dj} = 1$ variance (Goldstein, 1995). Thus, each household type defined by the dummy variable has different unexplained heterogeneity of personal crimes.

5.2. The multilevel negative binomial model

The multilevel negative binomial model (henceforth MNBM) derives by allowing for between individuals random variation of the expected number of events μ_{ij} in Eq. (2).

$$\ln \mu_{ij} = \eta_{ij} + e_{ij} \quad (3)$$

where $cov(e_{ij},u_{ij})=0$ and $exp(e_{ij})$ follows a gamma probability distribution, $\Gamma(v)$, with mean 1 and variance $\alpha = v^{-1}$. Integrating with respect to e_{ij} (Cameron and Trivedi, 1986) the resulting probability distribution

$$\Pr(Y_{ij} = y_{ij}) = \frac{\exp(-\exp(\eta_{ij}+e_{ij}))\exp(\eta_{ij}+e_{ij})^{y_{ij}}}{y_{ij}!} \quad (4)$$

one version of the MNBM is obtained:

$$\Pr(Y_{ij} = y_{ij}) = \frac{\Gamma(y_{ij}+v)}{y_{ij}!\Gamma(v)} \frac{v^v \mu_{ij}^{*y_{ij}}}{(v+\mu_{ij}^*)^{v+y_{ij}}}, \; y_{ij}=0,1,..., \quad (5)$$

where $E(Y_{ij})=\mu^*_{ij}=exp(\eta_{ij})$, similarly to the multilevel Poisson model, but $var(Y_{ij})=\mu^*_{ij} + \alpha\mu^{*2}_{ij}$.

Since the mean function of the MNBM is identical to the Poisson, the interpretation of the fixed and level-2 random parts of the model given in the previous sub-section applies also here. The extra-Poisson variation at level-1 is defined by α and μ^*_{ij}. Both being positive they allow for overdispersion which is estimated by α. As mentioned, in the models below overdispersion stems from between individuals unexplained heterogeneity (Osborn and Tseloni, 1998).

5.3. The negative binomial model

Cameron and Trivedi (1986) give a detailed discussion of the single-level negative binomial regression model (henceforth NBM). This specification ignores possible clustering of level-1 units within level-2 ones and therefore any random variation between level-2 units, u_j, in Eq. (1) cannot be accommodated in the model. Equation (1) becomes

$$\ln \lambda_i = X_i\beta \quad (6)$$

where λ_i is the mean and variance of the corresponding single-level Poisson model.

The probability distribution of the NBM is given by

$$\Pr(Y_i = y_i) = \frac{\Gamma(y_i+v)}{y_i!\Gamma(v)} \frac{v^v \lambda_i^{*y_i}}{(v+\lambda_i^*)^{v+y_i}} \qquad (7)$$

where λ_i^* is the mean of a random Poisson parameter λ_i, which is defined as $\ln \lambda_i = X_i\beta + e_i$. $\lambda_i^* = E(Y_i) = X_i\beta$, and $var(Y_i) = \lambda_i^* + a\lambda_i^{*2}$ which gives a Negbin 2 specification (Cameron and Trivedi, 1986). All other elements are defined as before. Osborn and Tseloni (1998) discuss the interpretation of this model in an application to property crimes.

6. Results

6.1. Methodology

In the discussion below I compare the results between the NBM and the corresponding fixed effects MNBM of personal victimizations with random intercept. The former has been obtained using maximum likelihood (ML) estimation via the software package LIMDEP (Greene, 1991). The multilevel results have been obtained using iterative generalized least squares (IGLS) estimation with first order marginal quasi-likelihood (MQL) approximation via the software package MLwiN (Goldstein *et al.*, 1998). The estimated models are presented in Table 4. Each one includes all the covariates given in Table 3.

The last part of Table 4 presents a baseline model consisting only of the intercept and its random components (with respect to the MLwiN model). The number of observations used in the analysis and an overall goodness of fit statistic are shown at the end of the table.

Table 4 shows the estimated average number of personal crimes for the reference individual for each model (last row of estimated fixed effects). The reference person is defined by the base attributes of all the qualitative covariates in the models (see section 4 and Table 3). To ease interpretation, she is also assumed to be of average age (42 years old) and live in a two adults household. As seen, the reference individual is estimated to suffer effectively zero personal crimes (0.009) during an 18 months period. Note that the MNBM prediction is unit specific assuming zero random effects.

6.2. The NBM versus the MNBM

Considering the first part of Table 4, the estimated coefficients (fixed effects) and standard errors of the NBM (Model 4.1) and the MNBM with random intercept (Model 4.2.) of personal victimizations are effectively identical. Under the assumption of zero random effects the two models produce the same estimate of the average number of events for the reference person (see section 6.1). Since by definition the NBM overlooks the between households random variation of the expected number of personal crimes the random parts of the two models differ. The estimated overdispersion parameter of Model 4.1 seems very marginally underestimated compared to Model 4.2. When individual and household characteristics are omitted (baseline model) it seems that the NBM estimated unexplained heterogeneity is an underestimate of the combined level-1 and level-2 estimated random variation of the MNBM.

6.3. Unexplained Heterogeneity

As mentioned in the section discussing the MNBM, the level-1 random component consists of the mean (expected) number of personal victimizations, μ^* and the overdispersion parameter, a, which is a measurement of unexplained heterogeneity between individuals with regard to their mean personal victimizations. The level-2 variance in the multilevel specification measures additional random variation of the mean number of personal victimizations. It may be interpreted as between households unexplained heterogeneity.

Comparing the estimated overdispersion parameter between the models of Table 4 and the corresponding baseline models, it is clear that roughly *half* of the original unexplained heterogeneity between individuals is attributed to their personal and household characteristics. However, there remains substantial unexplained heterogeneity and this is true for both models or regardless of the estimation procedure, ML or IGLS. According to results not presented here this is so for fixed effects and random household effects MNBM's. If one allows for random individual effects unexplained heterogeneity decreases further by a crude *fourth*.

Considering the between households random variation, roughly only one fifth seems to be explained by the covariates of the fixed effects models (Model 4.2).

7. Discussion

This paper compares single-level and multilevel negative binomial models of personal victimization counts. Two levels of analysis are used for the latter, individual (level-1) and household (level-2). The negative binomial regression models of this study explicitly account for population unexplained heterogeneity which is estimated by the respective coefficients of overdispersion. While both the NBM and the MNBM estimate the between individuals such heterogeneity the latter accounts for additional unexplained heterogeneity between households. Should higher levels of aggregation be used unexplained heterogeneity could be allocated over various sources of clustering, such as the segment, the Census track or the state.

The similarity of the estimated coefficients and their standard errors between the conventional and the multilevel specification indicates that accounting for the clustering of sampling units does not influence the estimated fixed effects of personal crime covariates. Thus if one is interested only in fixed effects he/she may safely use the less complicated NBM. However the two models offer a different story with regard to the estimated unexplained heterogeneity between individuals. Further the between households unexplained heterogeneity and subsequently any such random effects of covariates are ignored in the NBM specification. This results in different predictions drawn from the NBM and the MNBM, especially when one is interested in population averaging (Goldstein and Rabash, 1996). What's more important the two models offer different interpretation of the personal covariates with significant random effects (see section 5.1 above).

The implications of the between households random coefficients of household and, especially, personal characteristics offer new insights into traditional lifestyle victimization theory which are supported by recent empirical work on repeat and multiple victimization (Farrell, 1992). For instance, according to results not presented here it has been evidenced that the higher the estimated base mean personal crimes the less being male or frequent going out increases personal crimes (Tseloni, 1999). Evidently, such modifications to victimization theory have enormous implications for crime prevention.

Future NCVS based victimization research should disentangle unexplained heterogeneity into all possible clusterings of the lower unit of analysis, such as the household, the segment and the PSU. To this end, pseudo area identifiers are an integral component of the public use NCVS files. Another direction of improvement would be to compare the estimated comparative model (Table 4) across a number of multilevel modeling procedures for testing the robustness of the obtained results. The NCVS panel design, finally, allows for simultaneous estimation of both explanations of repeat/multiple victimization, namely heterogeneity and event dependence, which is the concern of my current research.

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Table 2: Observed Frequency Distributions of Personal Crimes.

	Frequencies			
Number of Crimes	During 6 Months	During 12 Months	During 18 Months	Total
0	124,934	62,479	4,363	191,776
1	2,220	1,724	120	4,064
2	269	249	30	548
3	81	75	6	162
4	32	25	1	58
5	1	9	0	10
6	2	4	0	6
7	0	3	0	3
8	0	2	0	2
Total	127,539	64,570	4,520	196,629

Table 3: Description of Covariates.

Variables	**Mean (S.D.)**	**Values**
Individual Level Covariates		
Age	42.46 (19.32)	12-90
Male	0.473	0-1
Marital Status		
Married (base)	0.546	-
Single	0.284	0-1
Divorced	0.098	0-1
Widowed	0.069	0-1
Race		
White (base)	0.861	-
African-American/ Am. Indian /Aleut /Eskimo	0.110	0-1
Asian /Pacific Islander	0.029	0-1
Educational Attainment		
Primary School or Illiterate (base)	0.120	-
High School	0.464	0-1
College	0.402	0-1
Employment Status		
Working Full Time (base)	0.516	-
Working Part Time	0.034	0-1
No paid work	0.295	0-1
School Pupil	0.073	0-1
Going Shopping		
Never (base)	0.020	-
Daily	0.181	0-1
Once a Week or Less Often	0.706	0-1
Spending Evenings Out		
Never (base)	0.074	-
Daily	0.175	0-1
Once a Week or Less Often	0.657	0-1
Using Public Transportation		
Never (base)	0.720	-
Daily or At least Once a Week	0.065	0-1
Less Often than Once a Week	0.120	0-1

Table 3: Description of Covariates. (ctd.)

Variables	Mean (S.D.)	Values
Length of Time at Address		
Less than Six Months	0.03	0-1
Six to Eleven Months	0.04	0-1
One or Two Years	0.13	0-1
Three to Five Years	0.18	0-1
Six to Ten Years	0.17	0-1
11 Years or Longer (base)	0.34	-
Household Level Covariates (ctd.)		
Children in the Household	0.3	0-1
Number of Adults	2.56 (1.16)	1-11
Number of Cars		
None (base)	0.07	-
One to Three Cars	0.78	0-1
Four or More Cars	0.146	0-1
Household Annual Income		
Less than $10,000	0.104	0-1
$10,000-$49,999 (base)	0.533	-
$50,000 or More	0.235	0-1
Refused to Answer	0.128	0-1
Tenure: Own House /Apartment	0.254	0-1
Type of Accommodation: House /Apartment /Flat	0.939	0-1
Devices Against Intruders	0.650	0-1
Neighborhood Watch Member	0.087	0-1
Urban Area	0.717	0-1
Place Size		
24,999 or Less (base)	0.590	-
25,000-249,999	0.257	0-1
250,000 or More	0.153	0-1
Reference Period		
Six Months	0.649	0-1
Twelve Months	0.328	0-1
Eighteen Months (base)	0.023	-
Number of Cases	196,629	

Note: When the numbers for the categories of the same variable do not add up to 100 it is due to missing values.

Table 4: Comparison of Negative Binomial Models of Personal Victimization.

	Model 4.1	Model 4.2
Estimated Fixed Effects (s.e.)		
Covariate		
Individual Characteristics		
Age	-0.034 (0.002)	-0.034(0.002)
Male	0.352 (0.035)	0.359 (0.036)
Marital Status (Married)		
Single	0.419 (0.052)	0.419 (0.057)
Divorced	0.953 (0.055)	0.941 (0.058)
Widowed	0.371 (0.116)	0.369 (0.124)
Race (White)		
African-American/ A. Indian /Aleut /Eskimo	-0.067 (0.054)	-0.064 (0.058)
Asian /Pacific Islander	-0.475 (0.116)	-0.470 (0.127)
Educational Attainment (Primary School/Illiterate)		
High School	-0.010 (0.072)	-0.005 (0.069)
College	0.112 (0.077)	0.135 (0.077)
Employment Status (Working Full Time)		
Working Part Time	0.334 (0.075)	0.318 (0.078)
No paid work	-0.021 (0.047)	-0.026 (0.050)
School Pupil	0.265 (0.081)	0.251 (0.080)
Individuals' Lifestyle		
Shopping (Never)		
Daily	0.582 (0.167)	0.594 (0.181)
Once a Week or Less Often	0.247 (0.165)	0.265 (0.178)
Evenings Out (Never)		
Daily	0.361 (0.087)	0.353 (0.094)
Once a Week or Less Often	0.036 (0.083)	0.034 (0.089)
Public Transportation (Never)		
Daily or At least Once a Week	0.460 (0.060)	0.450 (0.064)
Less Often than Once a Week	0.289 (0.045)	0.285 (0.049)
Length of Time at Address (11 Years or Longer)		
Less than Six Months	0.892 (0.081)	0.909 (0.086)
Six to Eleven Months	0.479 (0.074)	0.479 (0.081)
One or Two Years	0.207 (0.056)	0.204 (0.061)
Three to Five Years	0.045 (0.051)	0.040 (0.056)
Six to Ten Years	0.084 (0.050)	0.084 (0.056)
Reference Period (18 Months)		
Six Months	-0.784 (0.101)	-0.785 (0.107)
Twelve Months	-0.136 (0.102)	-0.135 (0.107)

Table 4: Comparison of Negative Binomial Models of Personal Victimization (ctd.).

	Model 4.1	Model 4.2
Estimated Fixed Effects (s.e.)		
Covariate		
Household Characteristics		
Children	0.172 (0.038)	0.181 (0.043)
Number of Adults	-0.054 (0.017)	-0.045 (0.019)
Number of Cars (None)		
One to Three Cars	-0.049 (0.075)	-0.075 (0.080)
Four or More Cars	0.211 (0.089)	0.195 (0.096)
Annual Income ($10,000-$49,999)		
Less than $10,000	0.170 (0.060)	0.189 (0.064)
$50,000 or More	-0.067 (0.042)	-0.070 (0.048)
Refused to Answer	-0.062 (0.059)	-0.069 (0.065)
Living in Owned House/Apartment	0.018 (0.042)	0.030 (0.048)
House/Apartment/Flat	-0.066 (0.073)	-0.064 (0.080)
Devices against Intruders	0.180 (0.037)	0.186 (0.041)
Neighborhood Watch	0.131 (0.056)	0.133 (0.061)
Area Characteristics		
Urban	0.201 (0.046)	0.203 (0.051)
Place Size (24,999 or Less)		
25,000-249,999	0.106 (0.043)	0.107 (0.048)
250,000 or More	0.238 (0.053)	0.245 (0.058)
Constant	-3.210 (0.252)	-3.246 (0.269)
Average number of Personal Crimes (reference person)	0.009	0.009
Estimated Random Effects (s.e.)		
Between Individuals: overdispersion (α)	6.584 (0.257)	7.046 (0.170)
Between Households: $\sigma^2_{Constant}$	-	1.999 (0.129)
Log Likelihood Function	-19,432.8	-129,997
Baseline Model		
Constant	-3.489 (0.015)	-3.431 (0.018)
Estimated Random Effects (s.e.)		
Between Individuals: overdispersion (α)	15.561 (0.510)	13.718 (0.214)
Between Households: $\sigma^2_{Constant}$	-	2.546 (0.152)
Log Likelihood Function	-25,647.3	-26,893.9
Number of observations	154,019	154,019