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by

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Abstract: The purpose of this research is to test the economic model of crime for the existence of substitution among property crimes using aggregate data from North Carolina counties in 1983. Two models were estimated using weighted least squares. The first model tests the deterrent effect of four criminal justice variables on the rate of four property crimes. The second model tests for substitution cross effects among the crimes. While deterrent effects for individual crimes are apparent, the estimated elasticities do not support the notion that substitution among property crimes exist.

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I. Introduction

Through the application of economic theory, economists have contributed greatly to criminology. Ongoing research continues to develop the economic model of crime and increase our understanding of the individual criminal. Economic theories of consumer choice provide a useful structure and a systematic framework for analyzing criminal activity and creating testable models. A criticism of economic models of criminal behavior is that they hold constant the social and personal background which determines an individual's attitude toward the law, as well as other behavioral characteristics that are possible determinants of criminality. However, these models are based on characteristics that are common to large classes of economic agents. Criminals respond to incentives in the same way a non-criminal would. The criminal reaches the decision to commit a crime through a personal cost-benefit analysis. The criminal's choices are likely to change as the costs and benefits associated with an illegal activity change. This analysis of crime has provided policy makers with a better understanding of criminal behavior, thereby aiding in the creation of more effective crime legislation.

The objective of this research is to test a particular version of the economic model of crime by creating a model concerned with the effects of changes in deterrence variables, i.e., arrest, conviction and imprisonment rates and sentence lengths, on the rate of a specific property crime. Then, in an effort to more accurately depict the factors influencing a criminal's choice, the possibility of substitution between property crimes is introduced into the model.

II. Review of Previous Work

The concept of deterrence is central to economic models of crime. Empirical studies have generally established the negative correlation between punishment for a crime and that crime's offense rate. However, according to Levitt's (1995) argument, effective deterrence in the real world is subject to several impediments. The most formidable of these obstacles are: (1) the likelihood that the criminal lacks information about the "price" of committing a crime and/or the criminal's overestimation of his/her own abilities; (2) the substantial lag in the administration of punishment versus the immediate accrual of benefits from an offense, which lessens the deterrent effect of even severe punishments; and (3) the fact that serving time in prison is sometimes favorably looked upon as a rite of passage among certain groups. Levitt goes on to argue that reductions in crime are reached through two channels; deterrence and incapacitation, but concludes that deterrence is empirically more important than incapacitation.

In past empirical work much emphasis has been placed on the criminal's choice between legal and illegal activities. Economic theories of consumer choice, however, suggest that opportunities for substitution among illegal activities should be included in the model, reflecting the criminal's ability to choose between crimes. Some empirical work has addressed the need to consider possible crime substitution.

Holtmann and Yap (1978) used cross-sectional data for 43 U.S. states in 1970 with burglary, larceny, and robbery expressed in *per capita* terms. Estimations of double-log equations were done using two-staged least squares. The 2SLS method was used under the assumption that the offense rate and probability of imprisonment are determined simultaneously. Their explanatory variables are income, poverty, and race with generally all positive and significant coefficients. Deterrence variables include the average sentence lengths and the percentage of offenders imprisoned for each crime. The own effects, i.e., the effects of deterrence variables for the particular crime, for larceny and robbery are not significant for either variable. The cross-crime effects, i.e. the effects of deterrence variables for one crime on another, proved statistically insignificant in the case of the sentence length but an increase in the probability of imprisonment variable has a significant positive cross effect on all three crimes.

Using 401 municipalities in New Jersey in 1970, Hakim, *et. al*. (1984) tested for substitution among vehicle theft, larceny, robbery, and burglary. The model assumes that all property crimes and criminal justice measures are directly or indirectly interrelated. For this reason a ten equation system including offense and arrest rates was estimated using three-stage least squares. Offenses are measured in total as opposed to per capita terms. All own effects are negative and mostly significant positive cross effects exist among the crimes. Both the Holtmann and Yap and Hakim, *et.al*. studies fail to include population age/sex composition and population density variables, which are traditionally included in criminological work.

Cameron (1987) criticizes the common assumption that a simultaneous specification is the "correct" one. If tests for specification error due to simultaneity bias rejects its presence, then a single equation may be used. Cameron uses data from 41 police force areas in England and Wales to do OLS estimations of single robbery, larceny, and burglary offense equations. Substitution is measured by each crime rate's response to differential arrest probabilities. Variables measuring population density and percent young male are included in the model along with an unemployment variable. Only robbery's own effect is significantly negative. Cameron finds all positive cross effects except for the probability of being arrested for larceny having a deterrent effect on robbery, about which he argues that “ a high rate of catching larcenists may indicate a rapid rate of removal of criminals from the bottom of the career ladder.”

Although they do not address the crime substitution issue, three other studies are of relevance to this research given their use on North Carolina county data.. Trumbull (1989) estimated total crime rates using OLS on 1981 data for North Carolina counties. Included criminal justice variables were the probabilities of arrest, conviction and imprisonment and the severity of punishment. The deterrent effects of the criminal justice variables, most notably sentence length, were negative and significant.

Cornwell and Trumbull (1994) tested for the presence of simultaneous effects on the criminal justice variables and rejected them for the North Carolina counties. Sorenson and Trumbull (1996) use the same 1983 data set employed in this study to test for spatial autocorrelation in crime rates for North Carolina counties. They conclude that critical to the specification of an economic model of crime using aggregate data is the careful consideration of spatial variation, including weighting proportions observations largely along the lines of spatial variation in population.

III. The Model

The thrust of this research is to extend the economic analysis of crime substitution by estimating the crime rate equations for two sets of crimes: (1) robbery, burglary and larceny and (2) vehicle theft, burglary and larceny. For each individual crime two models are estimated -- a traditional model and an augmented one that tests for cross effects. The traditional model testing for own effects and the influence of the control variables is:

Crime Rate = f (density, unemployment, % minority, % young male, arrest ratio, conviction ratio, imprisonment ratio, sentence length, *error*)

The augmented model expands the traditional model to test for cross-crime effects by adding to the equation the conviction ratios, imprisonment ratios, and sentence lengths variables for the remaining two substitute crimes in the particular grouping.

Table 1 gives definitions of the four crimes used. The crimes were chosen because they involve stolen property and can be intuitively considered substitutes. Several reasons justify replacing robbery with vehicle theft in the second model. First, by definition robbery involves using or threatening the use of force. Larcenists and burglars would most likely substitute into another non-violent property crime like vehicle theft. Secondly, only three crimes were included in each group to minimize the loss of degrees of freedom. Thirdly, the grouping together of larceny, burglary, and robbery facilitates comparison to past studies that used the same three crimes. Lastly, vehicle thefts were more numerous than robberies which, when combined with the above reasons, made vehicle theft a desirable variable.

The data shows that a hierarchy among the crimes exists, with robbery at the top, followed by burglary, vehicle theft, and larceny. The order stems from: (1) the relative risks involved and the skills needed to perform each crime and (2) the severity of each crime as judged by society (reflected in the sentence length).

Only four control variables are included in order to minimize the loss of degrees of freedom. Population density captures the effects of the increased opportunities in urban areas to commit crimes (i.e. more targets and hiding places) and to band together with other criminals. An age/sex variable is included to reflect the fact that, for these crimes, young males 15-24 are the main offenders. The other two measures are unemployment, included to measure legitimate activity opportunities, and the proportion that is minority or nonwhite. The coefficients on these variables are hypothesized to be positive.

The variables reflecting the consequences of illegitimate activities are the arrest, conviction, and imprisonment ratios, and the sentence length. Making the economic assumption that as the expected return to an illegitimate activity falls the individual will do less of it, the hypothesized sign is negative for the own effects of all the criminal justice variables. Assuming that the property crimes being tested are possible substitutes for one another, the cross effect coefficients are expected to be positive.

IV. Data

The data are compiled from 1983 FBI and North Carolina Department of Correction sources for that state's counties. Ideally, individual level data would be used but such data would be difficult and costly to obtain. Aggregated data are also useful because the unit of observation is a political jurisdiction that has control over the criminal justice measures it employs, allowing the researcher to compare the effects of these measures across units of observation. Aggregation does, however, introduce bias and other difficulties, some of which may be accounted for econometrically. Aggregations may mask variation within a jurisdiction. Lacking individual data the best alternative is to utilize the lowest, feasible level of aggregated data available (Sorenson and Trumbull 1996). County level data may be the ideal level of aggregation, being finer than state level, yet not prone to suffer from spatial modeling problems to the extent that municipal level data does.

The basic distributional characteristics of the 1983 crime data are summarized in Table 2. Not all counties have been included because several counties reported very few property crimes during the observation period, which is evident in the small individual crime rates. In fact, several counties reported zero robberies. To correct for the low (and unreliable) robbery ratios, counties with less than ten offenses were excluded in the first set of equations, resulting in a sample size of 48. Similarly, counties with less than ten vehicle thefts were excluded in the second set of equations, leaving a sample size of 55. The descriptive statistics illustrate some of the problems of merging the FBI and NCDOC data sets. In the FBI data, lags exist between the reporting of the offense and the arrest for that offense. The NCDOC conviction and sentencing data are based on the actual date of conviction and sentencing. This merger sometimes produces rates (i.e., arrest to conviction) greater than one. Another data peculiarity is that an offender committing a crime during any period may not be arrested, convicted, or imprisoned during that period. Also, plea bargaining may cause the recorded crime to differ from the offense committed.

There are clear differences between crimes and among counties. The mean arrest rate is substantially higher for robbery, with the other three means being close to one another. This is possibly a reflection of the relative severity of robbery. The mean arrest rates follow the property crime hierarchy (robbery, burglary, vehicle theft, larceny), as do the mean conviction rates. Robbery has the highest mean conviction rate also. The imprisonment rates follow suit with the exception of vehicle theft being ranked above burglary. The hierarchy is best seen in the mean sentence lengths, which reflect society's valuation of the deserved punishment for each crime. Overall, the data exhibit much variation which should enhance the estimations.

V. Modeling and Results

The estimation was done using double-log models and weighted least squares, with all variables weighted by the BEA estimated county populations for 1983. WLS was used to avoid heteroskedasticity problems arising from large variations in population across counties, which would generate larger error variances in smaller counties.

The results of the first set of crime rate estimations, those for the grouping robbery, burglary, larceny, are shown in Tables 3-5. The F-tests for overall fit were significant at the 1% level for each set of models. For the robbery traditional equation the percent minority and population density coefficients are positive and significant, the unemployment coefficient is negative but insignificant, and the percent young male coefficient is positive but insignificant. The positive and significant own effect of the robbery arrest rate was certainly unexpected and contrary to the theoretical model. The other three own effects have the expected negative signs. In the augmented model the robbery arrest rate was also unexpectedly positive and significant. All the cross effects for robbery had an unexpected sign or was insignificant, showing no signs of larceny and burglary being substitutes for robbery.

The traditional burglary model behaved as expected. All control, own, and cross effects coefficients have the expected signs, with the burglary arrest rate having a strong own effect. The augmented model, like that of robbery, shows no significant signs of substitution among the crimes.

The traditional larceny model has negative coefficients for unemployment and an unexpected significant negative coefficient on the percentage young male variable. The youthful nature of theft would certainly lead one to expect this variable to have a positive effect. The own effect variables behaved well. The augmented model exhibits more positive cross effects than the previous two, but none are significant.

Noteworthy is the declining magnitude (in the order: arrest, conviction, imprisonment, and sentence) of the own effects coefficients in both the traditional and augmented models. Theory dictates that this should occur, reflecting the influence of the more immediate consequences of committing an offense (Cameron, 1987). The magnitudes of the elasticities represent the potential payoffs to different law enforcement strategies.

Turning to the second set of crime rate estimations, those for the burglary, larceny, and vehicle theft group (Tables 6-8), the traditional burglary and larceny models (n = 48) behaved very similar to the burglary and larceny models of the first set of crimes (n = 55). The traditional and augmented vehicle theft models acted much the same. The own effects are negative as expected. No significant positive cross effects were found. In comparison to the robbery models, the vehicle theft arrest rate demonstrated a deterrent effect on that crime's rate, although it is not statistically significant. In general, the second set of estimated equations have similar adjusted R-square values and have equally significant F-test results when compared to the first set. As in the first set, all the own effects coefficients decline in magnitude from arrest rate to mean sentence length.

Considering the control variables for all crime rates estimated, population density, as hypothesized, seems to have the greatest effect on robbery. Percent minority was positive and significant in every instance, unemployment was generally positive, and percent young male was only significant when negative.

As an additional test of the substitution possibility F-tests were performed on each augmented model to evaluate the relevance of the cross effects variables. Tests indicated that adding the variables did not improve the model, leaving one to conclude that the traditional models are superior in "goodness of fit."

There is strong evidence of the existence of multicollinearity based on high correlation coefficients between several pairs of variables and high condition indexes (>30). A significant source of confounding multicollinearity may be that a county with high rates of arrest, conviction, etc. for one crime will likely have similarly high values in other crimes, possibly due to local law enforcement priorities or tough judges.

VI. Conclusions

This research is unique in its use of less than state level data and the employment of several different criminal justice variables. The augmented models estimated in this study failed to produce the hypothesized results concerning substitution among property crimes and are contrary to the findings of other like studies. The traditional, simpler models, however, do reinforce the empirical findings of others by demonstrating the general deterrent effect of criminal justice measures on crime rates.

Econometric difficulties may be causing the lack of significant substitution effects in this research. Perhaps a simpler model using only the arrest rate variable is in order (Cameron 1987). The inclusion of the conviction, imprisonment, and sentence length variables may be theoretically irrelevant due to their small influence on the under-informed criminal's choice to commit an offense. Having so many criminal justice variables may also make it difficult for any of them to be significant. The need for more observations is a concern. The reliability of the data is also questionable for reasons mentioned above.

Further improvements to the model may include the addition of law enforcement variables like the number of policemen per capita or law enforcement spending per capita. Such variables may introduce simultaneity. Two-stage least squares could be run and endogeneity tests performed. Spatial econometric techniques could also be employed to control for spatial problems common with aggregate data.

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Table 1. Definitions of the Uniform Crime Reports Crime Categories

Robbery:

The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force, or threat of force, or violence, and/or by putting the victim in fear.

Burglary:

The unlawful entry of a structure to commit a felony or a theft. Attempted forcible entry is included.

Larceny:

The unlawful taking of property from the possession of another. Examples are thefts of bicycles or automobile accessories, shoplifting, pocket-picking, or the stealing of any property or article which is not taken by force and violence or by fraud. Attempted larcenies are included. Embezzlement, "con" games, forgery, and worthless checks are excluded.

Motor Vehicle Theft

The theft or attempted theft of a motor vehicle**.**

Taken from: Levitt (1995).

Table 2. Variables and Descriptive Statistics

Variable	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Crime Rates (# of crimes / population of reporting jurisdictions):				
ROBORATE-robbery	0.0003	0.0001	0.0001	0.0006
BURORATE-burglary	0.0104	0.0041	0.0037	0.0228
VEHORATE-vehicle theft	0.0014	0.0007	0.0004	0.0036
LARORATE-larceny	0.0205	0.0102	0.0052	0.0481
Arrest Rates (# of arrests / # of crimes):				
ROBAROF-robbery	0.5433	0.2431	0.2200	1.3125
BURAROF-burglary	0.2391	0.0947	0.0969	0.6437
VEHAROF-vehicle theft	0.2493	0.1264	0.0725	0.6667
LARAROF-larceny	0.2123	0.0675	0.1125	0.4176
Conviction Rates (# of convictions / # of arrests):				
ROBTOA2-robbery	0.5093	0.2920	0.0476	1.3333
BURTOA2-burglary	0.4601	0.1234	0.2467	0.8409
VEHTOA2-vehicle theft	0.4436	0.2747	0.0488	1.0000
LARTOA2-larceny	0.3620	0.1645	0.1019	0.7385
Imprisonment Rates (# of imprisonments / # of convictions):				
ROBPSPRO-robbery	0.8649	0.1269	0.6000	1.0000
BURPSPRO-burglary	0.5419	0.0850	0.3091	0.6774
VEHPSPRO-vehicle theft	0.5904	0.2196	0.2222	1.0000
LARPSPRO-larceny	0.3635	0.1010	0.0667	0.5725
Mean Sentence Lengths (days):				
ROBMEAN-robbery	3422.1	1057.6	1096.0	6666.0
BURMEAN-burglary	1119.3	281.3	653.3	2086.3
VEHMEAN-vehicle theft	629.7	261.4	212.4	1497.6
LARMEAN-larceny	603.6	178.1	281.3	1390.8
Control Variables (population density, unemployment rate, % minority, % young male):				
DENSITY	173.2052	160.8094	35.0410	786.8050
UNEMP	9.5982	2.5063	3.9000	15.2000
PCMIN	0.2395	0.1484	0.0096	0.6153
PCYNGML	0.0940	0.0280	0.0739	0.2636

Table 3. Robbery Models

(BURGLARY, ROBBERY, LARCENY GROUP)

	Traditional		Augmented	
adjusted r-square	0.7741		0.7877	
F-test	21.1290	***	11.901	***
F-test for joint significance			1.3137	

Coefficients and t-statistics:

	Traditional		Augmented	
LDENSITY	0.519145	***	0.368389	***
	7.092		*3.545*	
LUNEMP	-0.172115		0.113012	
	-0.997		*0.541*	
LPCMIN	0.383564	***	0.388967	***
	5.011		*4.483*	
LPCYNGML	0.335871		0.341031	
	1.665		*1.495*	
LROBAROF	0.366474	***	0.530053	***
	3.121		*3.707*	
LBURAROF			-0.68494	**
			-2.48	
LLARAROF			0.370346	
			1.45	
LROBTOA2	-0.224776	***	-0.067556	
	-2.894		*-0.624*	
LBURTOA2			-0.544215	**
			-2.258	
LLARTOA2			-0.141393	
			-1.048	
LROBPPRO	-0.085955		0.046248	
	-0.248		*0.13*	
LBURPPRO			-0.096013	
			-0.221	
LLARPPRO			-0.085154	
			-0.434	
LROBMEAN	-0.033821		-0.01599	
	-0.241		*-0.096*	
LBURMEAN			-0.151773	
			-0.596	
LLARMEAN			-0.105253	
			-0.383	

Level of Significance: *** 1% ** 5% * 10%
t-scores in italics

Table 4. Burglary Models

(BURGLARY, ROBBERY, LARCENY GROUP)

	Traditional		Augmented	
adjusted r-square	0.8205		0.8179	
F-test	27.851	***	14.192	***
F-test for joint significance			0.9304	
Coefficients and t-statistics:				
LDENSITY	0.175737	***	0.129387	*
	3.7		*1.977*	
LUNEMP	0.240798	**	0.221365	
	2.108		*1.682*	
LPCMIN	0.212328	***	0.216062	***
	4.627		*3.955*	
LPCYNGML	0.02121		-0.008263	
	0.18		*-0.058*	
LBURAROF	-0.586488	***	-0.553188	***
	-5.446		*-3.181*	
LROBAROF			0.003517	
			0.039	
LLARAROF			-0.123526	
			-0.768	
LBURTOA2	-0.478724	***	-0.496237	***
	-4.303		*-3.27*	
LROBTOA2			0.07945	
			1.166	
LLARTOA2			-0.124533	
			-1.465	
LBURPPRO	-0.163987		-0.003765	
	-0.843		*-0.014*	
LROBPPRO			0.23127	
			1.034	
LLARPPRO			-0.228302	*
			-1.847	
LBURMEAN	-0.062003		0.023508	
	-0.512		*0.147*	
LROBMEAN			0.050467	
			0.479	
LLARMEAN			-0.204144	
			-1.179	

Level of Significance: *** 1% ** 5% * 10%
t-scores in italics

Table 5. Larceny Models

(BURGLARY, ROBBERY, LARCENY GROUP)

	Traditional		Augmented	
adjusted R-square	0.8704		0.8728	
F-test	40.454	***	21.152	***
F-test for joint significance			1.0914	
Coefficients and t-statistics:				
LDENSITY	0.278251	***	0.246276	***
	6.517		*4.026*	
LUNEMP	-0.039098		0.001258	
	-0.368		*0.01*	
LPCMIN	0.255853	***	0.222052	***
	5.927		*4.348*	
LPCYNGML	-0.241485	**	-0.120264	
	-2.104		*-0.896*	
LLARAROF	-0.465803	***	-0.221741	
	-4.608		*-1.475*	
LROBAROF			-0.036126	
			-0.429	
LBURAROF			-0.275876	*
			-1.697	
LLARTOA2	-0.284885	***	-0.284358	***
	-3.712		*-3.579*	
LROBTOA2			0.014798	
			0.232	
LBURTOA2			-0.125669	
			-0.886	
LLARPPRO	-0.21138	**	-0.232054	*
	-2.286		*-2.008*	
LROBPPRO			0.331497	
			1.585	
LBURPPRO			0.250032	
			0.979	
LLARMEAN	-0.176797		-0.151091	
	-1.486		*-0.934*	
LROBMEAN			0.002728	
			0.028	
LBURMEAN			-0.078068	
			-0.521	

Level of Significance: *** 1% ** 5% * 10%

t-scores in italics

Table 6. Burglary Models

(BURGLARY, VEHICLE THEFT, LARCENY GROUP)

	Traditional		***Augmented***	
adjusted R-square	0.8292		0.8246	
F-test	33.76	***	16.87	***
F-test for joint significance			0.8509	
Coefficients and t-statistics:				
LDENSITY	0.1638	***	0.1267	**
	3.7440		*2.3300*	
LUNEMP	0.3152	***	0.3838	**
	2.6950		*2.6480*	
LPCMIN	0.1611	***	0.1861	***
	4.5350		*4.4160*	
LPCYNGML	0.0082		0.0187	
	0.0580		*0.1150*	
LBURAROF	-0.6808	***	-0.5735	***
	-6.7550		*-3.8080*	
LVEHAROF			-0.0059	
			-0.0760	
LLARAROF			-0.2173	
			-1.4520	
LBURTOA2	-0.4836	***	-0.4747	***
	-3.8960		*-3.2530*	
LVEHTOA2			-0.0393	
			-0.7280	
LLARTOA2			-0.1238	
			-1.5250	
LBURPPRO	-0.1500		-0.0555	
	-0.8510		*-0.2440*	
LVEHPPRO			0.0157	
			0.1700	
LLARPPRO			-0.1116	
			-1.0790	
LBURMEAN	-0.0313		-0.0567	
	-0.2790		*-0.4120*	
LVEHMEAN			-0.0098	
			-0.1080	
LLARMEAN			0.0227	
			0.1630	

Level of Significance: * 1% ** 5% * 10%**
t-scores in italics

Table 7. Vehicle Theft Models *(BURGLARY, VEHICLE THEFT, LARCENY GROUP)*

	Traditional		***Augmented***	
adjusted R-square	0.6858		0.7186	
F-test	15.7350	***	9.6180	***
F-test for joint significance			1.6692	
Coefficients and t-statistics:				
LDENSITY	0.3976	***	0.2589	***
	5.9620		*3.0390*	
LUNEMP	0.0288		0.2799	
	0.1560		*1.2340*	
LPCMIN	0.1435	**	0.1748	**
	2.4340		*2.6490*	
LPCYNGML	-0.0927		0.0408	
	-0.3890		*0.1600*	
LVEHAROF	-0.1764		-0.1241	
	-1.6020		*-1.0270*	
LBURAROF			-0.1822	
			-0.7720	
LLARAROF			-0.3887	
			-1.6580	
LVEHTOA2	-0.0409		-0.0049	
	-0.5100		*-0.0580*	
LBURTOA2			-0.2915	
			-1.2760	
LLARTOA2			-0.2424	*
			-1.9080	
LVEHPPRO	-0.3461	**	-0.1907	
	-2.4640		*-1.3130*	
LBURPPRO			0.3994	
			1.1210	
LLARPPRO			-0.2510	
			-1.5490	
LVEHMEAN	-0.1200		-0.1864	
	-0.9270		*-1.3190*	
LBURMEAN			0.1399	
			0.6500	
LLARMEAN			-0.0566	
			-0.2590	

Level of Significance: * 1% ** 5% * 10%**

t-scores in italics

Table 8. Larceny Models

(BURGLARY, VEHICLE THEFT, LARCENY GROUP)

	Traditional		Augmented	
adjusted R-square	0.8494		0.8610	
F-test	39.069	***	21.902	***
F-test for joint significance			1.4791	
Coefficients and t-statistics:				
LDENSITY	0.357913	***	0.275305	***
	7.571		*4.595*	
LUNEMP	0.105886		0.328369	**
	0.795		*2.057*	
LPCMIN	0.220354	***	0.217305	***
	5.301		*4.681*	
LPCYNGML	-0.020357		0.259245	
	-0.134		*1.445*	
LLARAROF	-0.571969	***	-0.538821	***
	-4.668		*-3.268*	
LVEHAROF			0.028333	
			0.333	
LBURAROF			-0.293776	*
			-1.771	
LLARTOA2	-0.26387	***	-0.231407	**
	-3.072		*-2.59*	
LVEHTOA2			-0.049856	
			-0.839	
LBURTOA2			-0.456214	***
			-2.838	
LLARPPRO	-0.062009		-0.000497	
	-0.693		*-0.004*	
LVEHPPRO			0.077304	
			0.757	
LBURPPRO			0.172264	
			0.688	
LLARMEAN	0.008375		0.069973	
	0.064		*0.456*	
LVEHMEAN			-0.100854	
			-1.015	
LBURMEAN			0.061787	
			0.408	

Level of Significance: * 1% ** 5% * 10%**

t-scores in italics