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Abstract

Although theory suggests the relationship between crime and wealth is ambiguous, most empirical analyses estimate a monotonic relationship and find that wealth has negative effect on crime. Using two proxies for wealth (median income and poverty rate) and two types of crime (property and violent), we find a quadratic relationship is the best fit for our four crime-wealth groups. In general, the expected negative effect of wealth on crime only applies to wealthier counties. In poorer counties, wealth has an unexpected positive effect on crime. This result may be theoretically consistent, or an unintended byproduct of the Uniform Crime Reports data, which do not include unreported crime.

JEL Classification Codes: J1, K42

Keywords: crime, wealth, Uniform Crime Reports

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Introduction

Economists have long been interested in crime. Becker's (1968) seminal study and its immediate followers (Ehrlich, 1973; Sjoquist, 1973; Block and Heineke, 1975) model the relationship between crime and a variety of covariates, including deterrence, police expenditures, and wealth. Nearly all theoretical approaches model participation in crime as a substitute for legitimate employment. For example, Ehrlich (1996) notes the supply of crime is determined by the expected net return, which equals expected gross return minus forgone wages at a legitimate job and expected punishment. In this setting, it is tempting to assume that an increase in wealth should decrease crime because foregone earnings are increasing. However, if the increase in wealth applies to the individual and his surroundings, then the expected return of crime rises. In this case, the relationship between crime and wealth is ambiguous. In fact, Block and Heineke (1975) note the sign of this relationship is indeterminant in the general case and *positive* assuming risk aversion and the psychic cost of crime is independent of wealth. Nevertheless, the vast majority of empirical research estimates a monotonic function (typically a linear model or log transformation) and finds a negative relationship between wealth and crime.

The increase in data availability allowed many of these early theoretical relationships to be tested, and the most common aggregate data set is the Federal Bureau of Investigation's Uniform Crime Reports (UCR). UCR data are attractive for many reasons. They are available annually, at the county-level, and split crime into eight categories. But UCR data can only count crimes that are reported. Not only does this underestimate the amount of crime, Levitt (1998) notes reporting tendencies and how crimes are classified are not equal across areas. Victimization data alleviate some of these problems, but the most common victimization data set (National Crime Victimization Survey, public release) does not identify a geographical location smaller than four regions of the United States. For this reason, UCR data will likely remain common in the crime literature.

We find an unusual aspect of UCR data when investigating the relationship between crime and wealth at the county level. Using median income and the poverty rate as proxies for wealth, we find a quadratic relationship between wealth and crime fits best. Specifically, the effect of wealth on crime is negative (the expected sign) for rich counties but positive (the unexpected sign) for poor counties. We offer two explanations. First, this result can be considered theoretically consistent. In this scenario, an increase in wealth raises expected returns of crime faster than foregone wages for poor counties, and vice versa for rich counties. Second, the quadratic effect may be the result of using only reported crimes rather than all crimes. For example, an increase in wealth in a poorer county may also raise reporting tendencies because of greater trust of law enforcement by locals or higher police expenditures. Regardless of the cause, researchers should be aware of this aspect of UCR data.

Literature and Methods

As mentioned in the introduction, Becker (1968), Ehrlich (1973), Sjoquist (1973), and Block and Heineke (1975) are widely considered to be the first economic analyses of crime. These studies inspired a number of empirical approaches that test the relationship of crime and a variety of covariates, such as unemployment (Cantor and Land, 1985; Chiricos, 1987; Raphael and Winter-Ebmer, 2001; Gould, Weinberg, and Mustard, 2002), wages (Grogger, 1998; Levitt, 1999; Gould, et al., 2002), poverty (Lee, 2000), education (Sjoquist, 1973; Lochner, 2004; Lochner and Moretti, 2004; Buonanno and Leonida, 2009), inequality (Bourguignon, 2001; Kelly 2000; Fajnzylber, Lederman, and Loayza, 2002), and deterrence (Ehrlich, 1981; Cornwell and Trumbull, 1994; Corman and Mocan, 2000; Liedka, Piehl, and Useem, 2006).

UCR data is the most common data set in empirical analyses of crime. Among the empirical papers mentioned above, Cantor and Land (1985), Chiricos (1987), Levitt (1998), Kelly (2000), Raphael and Winter-Ebmer (2001), Gould, et al. (2002), Lochner (2004), and Liedka, et al. (2006) use UCR data. In addition, Sjoquist (1973) and Lee (2000) use data on reported crimes from the FBI. Although UCR data are available annually at the county-level, its lack of unreported crimes bias the results if the amount of unreported crime is correlated with unemployment, wealth, education, or any of the other key covariates mentioned above.

The logic behind our estimations most closely follows the studies by Isaac Ehrlich (1973, 1977, 1981, and 1996), although similar rationale can found elsewhere. In Ehrlich's 1996 study, he notes the demand for crime comprises the demand for stolen goods and society's tolerance of crime. In comparison, the supply of offenses is determined by the expected net return which equals expected gross return minus forgone wages and expected punishment. This implies a reduced-form model where crime is a function of expected gross return, foregone wages, and punishment. Since UCR data are aggregate at the county level, it is impossible to separate expected gross return and foregone wages, which forces us to simplify the reduced-form model to crime as a function of wealth and punishment. While this simplification is not ideal, it is common in the empirical literature. We also follow the empirical literature by including a variety of demographic controls, such as racial/ethnic, gender, and age distribution to produce a standard empirical model of crime.

Data

UCR data are available annually, at the county-level, and include eight types. We create two broader categories from these eight types of crime. Violent crime is committed with force, and consists of murder/manslaughter, rape, robbery, and assaults. Property crime consists of burglaries, larceny, arson, and motor vehicle theft. The theory is a better match for property crime, since these crimes are more likely to be done for financial gain while the motivations for violent crime are less understood. Nevertheless, we present results for both types.[1] We scaled both types of crime so that each is per 100,000 people to control for differences in population. In addition, many small counties have potentially unreliable data because of fewer reporting agencies, so we use counties with at least 50,000 residents.

All other controls come from the City and County Data Book (CCDB). We use two proxies for wealth at the county-level: median income and poverty rate. Because of limited CCDB data availability, the sample frame for estimations is 2000 to 2004 inclusive. Demographic data consists of racial/ethnicity composition (percent of black, Hispanic, and Asian residents), gender, and age distribution. Because of their unique racial and ethnic compositions, counties in Hawaii or Alaska were omitted. Table 1 presents some summary statistics after making these deletions. We also include fixed effects for each county to capture any persistent differences across counties such as

[1] Our results are similar using separate estimations for each type of crime, although some crimes, such as murder, do not work as well because of considerably lower means.

reporting tendencies. This is one of Levitt's (1998) main concerns with UCR data, which notes reporting tendencies and how crimes are classified are not equal across areas. County-level fixed effects alleviate this concern assuming these problems are time-invariant. Yearly dummy variables are included to account for national trends affecting crime not captured by the other independent variables.

There are separate estimations for property and violent crime using the same explanatory variables. Within each type of crime, there are separate estimations for each proxy of wealth (median income and poverty rate) because of their high correlation. This creates four estimations; one for each crime-wealth combination. Finally, Breusch-Pagan (BP) tests indicate that all four crime-wealth estimations are hetroskedastic. However, the form of hetroskedasticity is too difficult to model with feasible generalized least squares, and the results include the White standard error corrections.

Property Crime Results

Table 2 presents some estimation results for five different model specifications of the property crime-median income model. With the exception of the best fit model presented at Table 4, all other estimates are suppressed for brevity but are available upon request. In general, the specification choice has little impact on the other estimates.

Using the adjusted *r*-squared, the linear, linear-log, and quadratic models have similar explanatory power. However, only the linear and quadratic models produce statistically significant effects of median income. Since the difference between these two models is the statistically significant second-order term, we believe the quadratic provides the best fit for the relationship between property crime and median income.

Based on the estimates, the marginal effect of median income on property crime is

$$\frac{\partial(procrime)}{\partial(medianinc)} = 0.0667 + 2(-8.08*10^{-7})medianinc$$

Setting the above equal to zero, the level of median income where the marginal effect on crime changes from positive to negative is about $41,260. For counties with median income above $41,260 (about 48% of the counties), the marginal effect of median income is negative, which is the sign that is expected from past empirical work. However, the effect of median income on crime is positive for the remaining 52% of the counties. Figure 1 illustrates this relationship.

Table 3 presents model specifications for the property crime-poverty rate model. These results are similar to Table 2. The adjusted *r*-squared again suggests the linear, linear-log, and quadratic models have similar explanatory power. Although none of the estimates are statistically significant, the quadratic has by far the lowest *p*-values.[2] For this reason, we believe the quadratic produces the best fit of the relationship between poverty and property crime.

Although the estimates are outside of what most consider statistically significant, the estimated marginal effect of the poverty rate on property crime is

$$\frac{\partial(procrime)}{\partial(poverty)} = 42.302 + 2(-1.656)poverty$$

Setting the above equal to zero, the level of poverty where the marginal effect changes from positive to negative is about 12.75%. For counties with poverty below 12.75% (about 63% of the counties), the marginal effect of poverty is positive, leaving approximately 37% of counties with higher poverty rates with the opposite sign. Figure 2

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[2] It is not surprising the effect of poverty rates do not fit as well compared to the effect of median income. Most theoretical models motivate the decision to commit crime using income, and the poverty rate is a transformation of the income level.

illustrates this relationship.

Although the percentage of counties with the unexpected effect of wealth is different (52% and 37%), these results are compatible because the relationship between median income and poverty is non-linear. Median income and poverty rates are highly correlated, and the best fit regression of this relationship is linear-log. Below is the result of this estimation, with standard errors in parentheses.

$$medianinc = -\underset{(197.79)}{22{,}867.91}\ln(poverty) + \underset{(476.13)}{97{,}195.01} \tag{1}$$

The *r*-squared of this regression is .7539. At the threshold of poverty rate 12.75% the predicted median income is $38,984, which is close to the median income threshold $41,260. Further, 37% of counties have median income less than $38,984, which is the same percentage of counties below the poverty rate threshold.

Table 4 presents the estimates and standard errors from the quadratic fit of the property crime-median income and property crime-poverty rate estimations. All estimates are included except for the fixed effect controls for each county. Given controls for wealth and dummy variables for each year and county, most of the remaining estimates are statistically insignificant. The main exception is the percent of females in a county, which has a positive and statistically significant effect on property crime.

In general, both of these models indicate the negative effect of wealth that is common in the empirical literature does not apply to poorer counties. In fact, these models predict that an increase in wealth in a poorer county should increase crime. While this is not intuitive, it is consistent with the theoretical literature under a set of assumptions. Using Ehlrich's theoretical models, this unexpected effect of wealth on crime can occur if an increase in wealth raises expected returns to crime faster than foregone wages in poorer counties. Alternatively, this result could also be a byproduct of the UCR data which does not include unreported crimes.

Violent Crime Results

Although the theoretical models are better fit for property crimes than violent crimes, several studies estimate the determinants of violent crime. For example, Kelly (2000) studies the impact of police expenditures and inequality on violent crime and finds "violent crime is little affected by police activity or poverty but strongly affected by inequality, measured either by income or education." Other papers note that some violent crimes are committed for pecuniary gain. Fajnzylber and Lederman (2002) note that "homicides are also committed for profit-seeking motives", and find average income and education attainment have significant and negative effects on violent crime. Although it is difficult to model violent crime, there is established empirical connection between violent crime and wealth.

Table 5 presents some estimation results for five different model specifications of the violent crime-median income model. The linear, linear-log, and quadratic models again provide the highest adjusted *r*-squared values, but the quadratic has by far the lowest *p*-values.

Although the quadratic estimates are statistically insignificant, the estimated marginal effect of median income on violent crime is

$$\frac{\partial(viocrime)}{\partial(medianinc)} = 0.00553 + 2(-4.80 * 10^{-8})medianinc$$

Setting the above equal to zero, the threshold of median income where the marginal effect changes from positive to negative is about $57,556. In other words, counties with median income below $57,556 (about 89% of the counties) have a positive marginal effect of median income. Counties with median income above \$57,556 (about 11% of the counties), have a negative marginal effect of median income. Figure 3 illustrates this relationship.

Table 6 presents the model specification tests for the violent crime-poverty rate model. The results are very similar to the violent crime-median income specification tests in Table 5, except the log-log and quadratic models provide statistically significant effects of the poverty rate. Since the adjusted *r*-squared is higher in the quadratic model, we consider the quadratic to be the best fit.

Based on the estimates, the marginal effect of poverty on violent crime is

$$\frac{\partial(viocrime)}{\partial(poverty)} = 15.267 + 2(-0.583)\,poverty$$

Setting the above equal to zero, the threshold of poverty level of poverty where the marginal effect changes from positive to negative is about 13.09%. For counties with poverty below 13.09% (about 70% of the counties), the marginal effect of poverty is positive. This leaves approximately 30% of counties where higher poverty rates correspond with less violent crime. Figure 4 illustrates this relationship.

Similar to the property crime models, the percent of counties with the unexpected effect of wealth is different (89% and 30%) in the violent crime results. In order to test whether these are compatible, we use the empirical relationship between median income and poverty at equation (1). At the threshold of poverty rate 13.09%, the predicted median income is \$38,360, which is not close to the median income threshold \$57,556. This incompatibility is probably caused by the weaker theoretical relationship between violent crime and wealth. Nevertheless, this does not change our main results that wealth has a quadratic effect on violent crime.

Table 7 presents the estimates and standard errors from the quadratic fit of the violent crime-median income and violent crime-poverty rate estimations. All estimates are included except for the fixed effect controls for each county. As in the property crime models, most of the estimates are statistically insignificant which is probably because wealth, county-specific, and year-specific effects are included in the model. The exceptions are the percent of females and Asians. Females have a positive and statistically significant effect on violent crime, while Asians have a negative and statistically significant effect.

Conclusion

Many social factors affect both property and violent crime. Although theoretical models suggest an ambiguous effect of wealth on crime, the empirical literature usually estimates a monotonic effect. After testing several specifications of the crime-wealth relationship, we find that a quadratic model fits best. This quadratic result exists even in the presence of controls for county-specific fixed effects, year dummies, and controls for age, sex, and race/ethnicity distribution.

In general, wealth has a negative effect on crime for rich counties and a positive effect on crime for poor counties. This means the negative relationship that is typically found in the empirical literature only applies to wealthy counties. In poor counties, the opposite occurs: an increase in wealth in these counties has a positive effect on crime. As stated earlier, this result is consistent with Ehrlich's theory only under a set of restrictive assumptions. Namely an increase in wealth raises expected returns to crime faster than foregone wages in poorer counties and vice versa in wealthy counties. It is difficult to reconcile why this would occur. One possibility is that an increase in median wealth may be coupled with an increase in inequality. An extreme example is when income increases for only the wealthiest in a county, making them more profitable targets while leaving foregone wages for everyone else constant. The other explanation for this result is that UCR data only include reported crime. This aspect of UCR data has been noted in the literature, and our quadratic effect may be another unintended byproduct of omitting unreported crimes. We hope that future research is dedicated to determining whether this quadratic effect is a byproduct of theory (i.e., foregone wages changing at a different rate than expected return) or using only reported crimes.

As the empirical explanations of crime continue to develop, it is likely that UCR data will continue to be the main data set. Our main concern is that the quadratic effect of crime will continue to be ignored which will produce misleading results. This is particularly problematic for those that analyze the effect of crime reduction policies in poorer areas, such as encouraging high school completion. It is likely that such a policy would increase reported crime, which is the opposite of the intended effect.

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Table 1: UCR data summary

Variable	Mean (Standard Deviation)
Violent Crime (per 100,000 people)	355.84 (374.43)
Property Crime (per 100,000 people)	3,178.14 (1,560.68)
Median Income	$42,913 ($10,578)
Poverty Rate	11.61% (4.50%)
% White	85.01%
% Black	10.26%
% Asian	2.14%
% Hispanic	7.97%
% Female	50.78%
% under 14 years old	20.53%
% between 15 and 29 years old	21.10%
% between 30 and 49 years old	29.37%
% older than 50 years old	27.40%

Note: All summary statistics are from 4,635 county-years between 2000 and 2004.

Table 2: Property Crime & Median Income Model Comparison

Model	adjusted *r*-squared	Variable	coefficient (standard error)	*p-value*
linear	0.9123	median income	-0.0211 (0.0097)	0.030
log-linear	0.7955	median income	-5.88e-06 (7.01e-06)	0.402
log-log	0.7954	ln(median income)	-0.0553 (0.3045)	0.856
linear-log	0.9122	ln(median income)	-174.686 (514.752)	0.734
quadratic	0.9125	median income	0.0667 (0.0320)	0.038
		median income squared	-8.08e-07 (2.51e-07)	0.001

Figure 1: Predicted Effect of Median Income on Property Crime

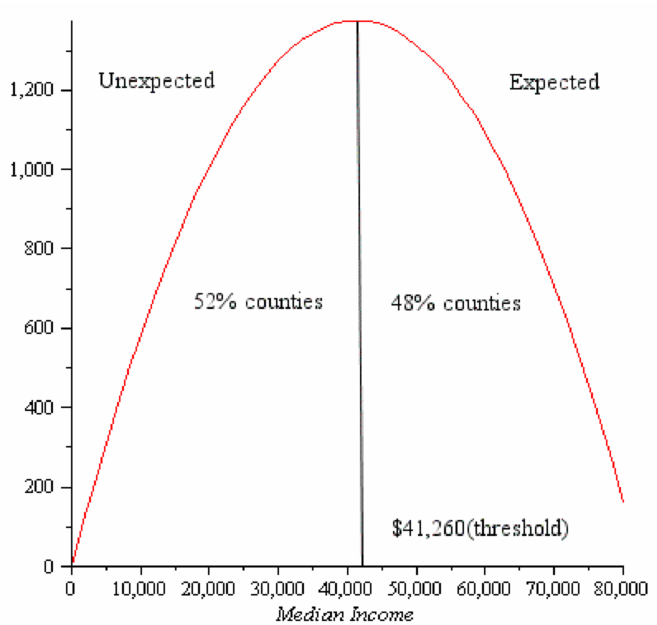

Table 3: Property Crime & Poverty Model Comparison

Model	adjusted *r*-squared	Variable	coefficient (standard error)	*p-value*
linear	0.9122	poverty rate	-7.272 (17.0316)	0.669
log-linear	0.7955	poverty rate	0.00343 (0.00804)	0.670
log-log	0.7955	ln(poverty rate)	0.0786 (0.0857)	0.359
linear-log	0.9122	ln(poverty rate)	5.671 (156.199)	0.971
quadratic	0.9123	poverty rate	42.302 (31.896)	0.185
		poverty rate squared	-1.656 (1.0642)	0.119

Figure 2: Predicted Effect of Poverty Rate on Property Crime

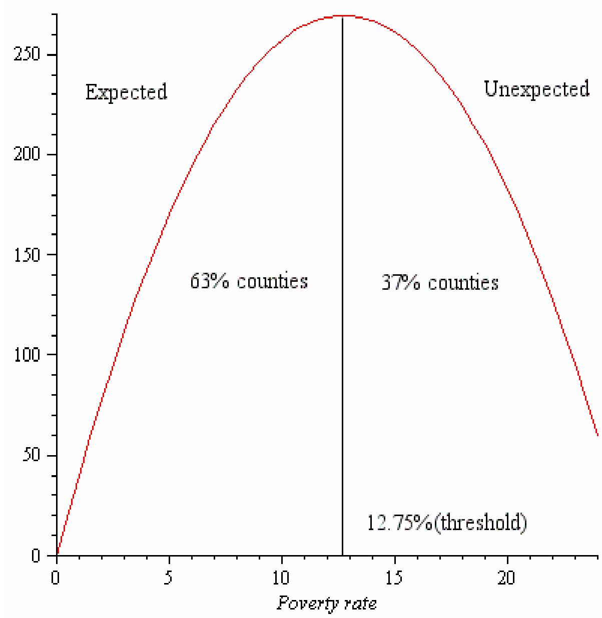

Table 4: Property Crime Quadratic Model

Variable	Coefficient (Standard Error)	*p-value*	Variable	Coefficient (Standard Error)	*p*-value
Median income	0.0667 (0.0320)	0.038	Poverty rate	42.302 (31.896)	0.185
Median income squared	-8.08e-07 (2.51e-07)	0.001	Poverty rate squared	-1.659 (1.064)	0.119
% Black	-18.523 (27.332)	0.498	% Black	-25.463 (27.932)	0.362
% Asian	-61.757 (43.736)	0.158	% Asian	-116.374 (41.621)	0.005
% Hispanic	38.674 (34.673)	0.408	% Hispanic	22.706 (35.935)	0.528
% Female	322.624 (84.270)	<0.001	% Female	291.432 (85.363)	0.001
% between ages 15 and 29	65.642 (32.316)	0.042	% between ages 15 and 29	32.479 (32.004)	0.310
% between ages 30 and 49	91.320 (64.787)	0.159	% between ages 30 and 49	67.811 (65.172)	0.298
% between over age 50	30.543 (40.053)	0.446	% between over age 50	-1.357 (40.240)	0.973
2001 dummy	92.249 (20.444)	<0.001	2001 dummy	100.643 (26.542)	<0.001
2002 dummy	108.816 (33.325)	0.001	2002 dummy	125.029 (34.570)	<0.001
2003 dummy	68.087 (47.568)	0.152	2003 dummy	94.141 (47.207)	0.046
2004 dummy	111.655 (69.281)	0.107	2004 dummy	142.395 (60.447)	0.019
constant	-19,257 (6,052)	0.001	constant	-14,153 6,219	0.023

Table 5: Violent Crime & Median Income Model Comparison

Model	adjusted *r*-squared	Variable	coefficient (standard error)	*p-value*
linear	0.9389	median income	0.000324 (0.00145)	0.828
log-linear	0.8888	median income	-3.02e-06 (6.41e-06)	0.637
log-log	0.8888	ln(median income)	-0.1146 (0.2966)	0.699
linear-log	0.9389	ln(median income)	38.749 (81.248)	0.633
quadratic	0.9389	median income	0.00553 (0.00508)	0.277
		median income squared	-4.80e-08 (3.95e-08)	0.225

Figure 3: Predicted Effect of Median Income on Violent Crime

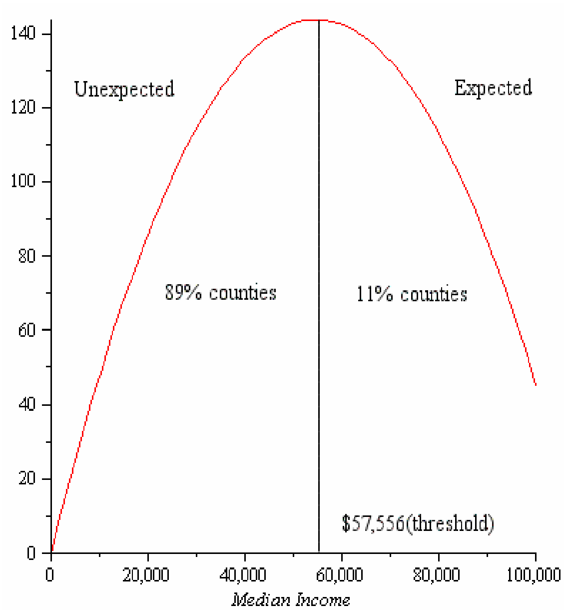

Table 6: Violent Crime & Poverty Model Comparison

Model	adjusted *r*-squared	Variable	coefficient (standard error)	*p-value*
linear	0.9389	poverty rate	-2.196 (2.395)	0.359
log-linear	0.8888	poverty rate	0.000944 (0.00873)	0.914
log-log	0.8889	ln(poverty rate)	0.1637 (0.0929)	0.078
linear-log	0.9389	ln(poverty rate)	26.391 (22.731)	0.246
quadratic	0.9392	poverty rate	15.267 (5.974)	0.011
		poverty rate squared	-0.583 (0.209)	0.005

Figure 4: Predicted Effect of Poverty Rate on Violent Crime

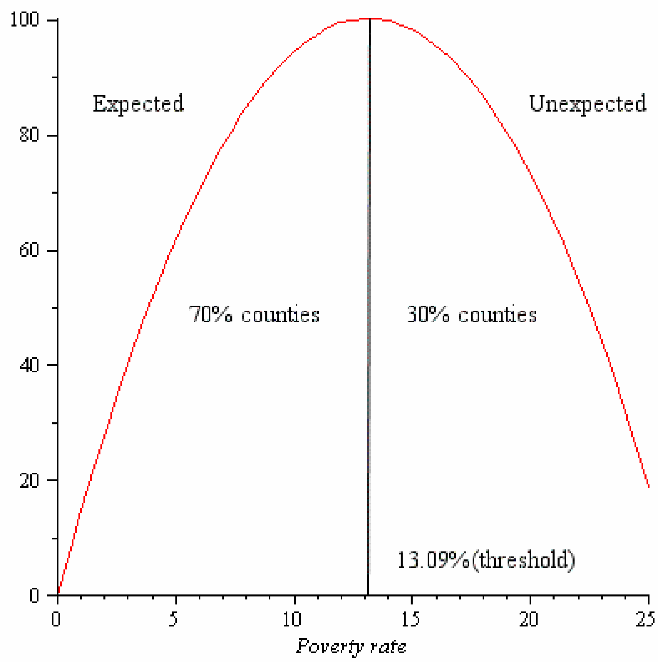

Table 7: Violent Crime Quadratic Model

Variable	Coefficient (Standard Error)	*p-value*	Variable	Coefficient (Standard Error)	*p*-value
Median income	0.00553 (0.00508)	0.277	Poverty rate	15.267 (5.974)	0.011
Median income squared	-4.80e-08 (3.95e-08)	0.225	Poverty rate squared	-0.583 (0.209)	0.005
% Black	3.668 (3.378)	0.278	% Black	2.625 (3.405)	0.441
% Asian	-14.491 (6.028)	0.016	% Asian	-20.161 (5.671)	<0.001
% Hispanic	1.373 (3.903)	0.725	% Hispanic	0.210 (3.923)	0.957
% Female	33.411 (9.673)	0.001	% Female	32.750 (9.814)	0.001
% between ages 15 and 29	2.927 (4.968)	0.556	% between ages 15 and 29	32.479 (32.004)	0.310
% between ages 30 and 49	-4.797 (9.789)	0.624	% between ages 30 and 49	67.811 (65.172)	0.298
% between over age 50	2.952 (6.120)	0.630	% between over age 50	-1.357 (40.240)	0.973
2001 dummy	5.611 (4.136)	0.175	2001 dummy	5.788 (4.111)	0.159
2002 dummy	1.179 (5.144)	0.819	2002 dummy	2.547 (5.168)	0.622
2003 dummy	-18.493 (7.312)	0.011	2003 dummy	-16.028 (7.022)	0.023
2004 dummy	-16.113 (10.415)	0.122	2004 dummy	-10.537 (9.106)	0.247
constant	-1,481 (798)	0.063	constant	-1,136 (789)	0.150