Does Perceiving a Shorter Life Expectancy Make You More Likely to Commit a Crime?

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1. Introduction

This paper develops an econometric model of crime using cross-sectional data for 2,728 U.S. counties in the year 2000. From the debate over the role of rationality in decisions based on heavy future discounting, I present a theoretical calculation for all costs faced by an individual deciding whether to commit a crime. This definition allows me to suggest a new variable for the economic study of crime, absent from the expansive body of literature available: the number of years an individual is expected to live. I find strong evidence that a higher perceived life expectancy has a negative impact on violent and property crime rates that carries both statistical and economic significance. Facing possible specification and omitted variable biases, I subject my results to robustness checks that provide encouraging results and a foundation for further research into the economic underpinnings of criminal behaviors.

2. Literature Review

In 1930's *Theory of Interest*, Irving Fisher reveals a prejudice regarding human behavior that has persisted in economics ever since. He writes that "poverty bears down heavily on all portions of a man's expected life," and calls the inherent human response to this burden "irrational[1] because the pressure of present needs blinds a person to the needs of the future" (Fisher 1930). To Fisher, the poor are powerless to allocate their preferences between present and future time periods in a rational manner, leading to baffling behavior in the current period. Without assuming a heavy discount on the future, Fisher watches individuals commit actions that defy economic explanation; thus, the formation of their particular time preferences cannot be

[1] Defining an irrational behavior as one that does not stem from logical thought and reasoning is sufficient for understanding Fisher's accusations.

included in any economic framework that seeks to model rational, utility-maximizing behavior.

In this same vein, the prominent discounted-utility model presented by Samuelson (1937) resigns itself to keeping the degree of individual time preferences outside of the model. This penchant for taking the rate of intertemporal choices as given continued in theoretical constructions well into the 20th century. For over seventy years, the issue of whether individual time preferences could be tackled was a one-sided debate: to economists, outright disregard for the future lacked a rational economic motivation. Hence, the behavior it spawned was unpredictable.

This period of disregard ended when Becker and Mulligan (1997) proposed the existence of future-oriented capital[2], an unobservable variable with considerable predictive power. The authors point out that visualizing the future entails a sizeable cost. This cost is especially pronounced if the portrayal is unpleasant. Any time spent trying to envision the future represents time unable to be spent on other utility-generating activities, a significant opportunity cost that certainly merits consideration from rational consumers. Beginning with the fundamental observations that all individuals do not display the same degree of patience and that patient behavior is often associated with rising income and education levels, their model describes how all individuals have the capability to separate their preferences into current and future time periods. The authors take particular care to mention the applicability of this framework to those whose excessive discounts of the future stem from impatience so severe that past economic work has deemed it an irrational and savage aberration.

This proposition of a ubiquitous ability to intertemporally separate utility has an interesting bearing on the realm of criminal behavior. Even society's murderers and thieves, it

[2] Similar to the idea of human capital, future-oriented capital is the stock of resources consumers devote to their weighting of future consumption.

seems, might make their choice to risk imprisonment and the dramatic loss of utility associated with future periods only after a careful cost-benefit analysis. Their decision-making process, in fact, may be a rational utility-maximization strategy merely subject to their specific time preferences.

Empirical economic literature has paid substantial attention to the perpetration of crimes. In a seminal work, Becker (1968) searches for the optimal amount of resources and degree of punishment to allocate in response to criminal activities. The paper also seeks to model the decision made by an individual deciding whether to commit a crime, suggesting that he or she is responsive to the levels of potential cost attached to the action. This research spurred future efforts by econometricians to search for underlying influences on criminal behaviors.

Several factors have been identified as associated with violent and property crime commission. Strain theory, for example, postulates that increased income disparities among a population stimulate criminal behaviors; this result has been tested and demonstrated empirically (Soares 2004) based on a strong theoretical foundation (Freeman 1996). Unemployment rate is also identified as a correlate of criminal activity (Ehlrich 1973; Raphael 2001; Lochner 2004), although the historical evidence has been mixed (Young 1993). In addition, gender is identified as a powerful determinant of violent crime, with men engaging in more violent acts than women, across all cultures and age groups (Levitt & Lochner 2001; Ihlanfeldt 2007). For both sexes, criminal behavior rises with the onset of adolescent and peaks at the age of 18 before a steady decline into young adulthood (Levitt & Lochner 2001), so youths' share of a population has proven a reliable indicator of observed crime prevalence (Freeman 1996).

The long-standing theoretical bias against determinants of time preference also manifests itself in empirical investigations into the determinants of crime. As shown in Table 1, an overview of relevant econometric literature reveals a tendency to ignore factors affecting time preference when looking at the causes of criminal behaviors, with the exception of an individual's income and education. By ignoring additional variables expected under the Becker and Mulligan model to cause patience and affect time preferences, investigating economists run the risk of missing a fundamental influence on the criminal behaviors they study. There exists a gap in the literature where further investigation of the effect of individual time preferences on crime should be.

The present paper is my attempt to fill this void. I will examine a variable with the potential to alter time preference and explain variations across the entire domain of criminal activities: the number of years an individual is expected to live. If this is indeed an elemental factor that is absent from the literature, variations in its level should, *ceteris paribus*, correspond with variations in the proclivity of criminal behaviors.

3. Theoretical Foundation

I begin with the standard economic analysis of choice in terms of the marginal utility (MU) generated from the marginal benefits (MB) and marginal costs (MC) associated with consumption:

$$MU(Consumption) = MB(Consumption) - MC(Consumption)$$

An individual will decide in favor of consumption if its perceived marginal benefits exceed the associated marginal costs. Aligning with prevailing microeconomic theory, I expect consumers to choose their consumption in a way that maximizes the satisfaction they can earn given the limitations of their budget (Pindyck & Rubenfeld 2005).

I further assume that people who engage in criminal behaviors do not require a different fundamental incentive structure than those who do not commit crimes; every individual is expected to allocate his or her time devoted to crime in a way that maximizes utility. This allows me to follow the framework laid by Becker (1968) and extend the standard cost-benefit analysis to an individual deciding whether to commit a crime, giving us:

$$Utility(Crime) = Benefits(Crime) - Costs(Crime)$$

where: (i) An individual commits a crime if and only if $Benefits(Crime) > Costs(Crime)$

(ii) $Costs(crime) = \sum_{t=0}^{T} \beta(s)^t U_t$, the sum of the potential future utility sacrificed (U_t) across all time periods in a person's length of life (T), scaled by $\beta(s)$, the weighting factor on each future period presented by Becker and Mulligan (1997).

A representation of this theoretical structure, along with its utility-maximizing condition, is shown in Figure 1.

Allowing β to be a mutable function of s, the resources spent to envision utility in the future, such as mental energy and imagination, is a departure from the neoclassical approach of treating β as a constant. The $\beta(s)$ function reflects the considerable costs of attempting to visualize the future and will be treated as strictly positive as well as strictly increasing, though expenditure of resources towards this visualization must be subject to diminishing marginal returns, leading to a concave-down function (Becker & Mulligan 1997).

Since a rational individual is never expected to make a decision at the margin that generates negative utility, I further stipulate that the possible sacrifice of utility in every future period (U_t) must have a positive value. This yields the final representation of costs faced by a potential criminal:

(1) $$Costs = \sum_{t=0}^{T} \beta(s)^t U_t, \quad \beta(s) > 0 \;\&\; U_t > 0 \;\; for \; s \geq 0 \;\&\; t = 0, 1, 2, \ldots, T$$

4. Constructing the Linear Regression Equation

I define the crime rate across a population as the number of individuals who decide to commit a crime divided by the total number in a particular area, N, who were faced with the choice:

$$\text{Crime Rate} = \frac{\sum_{i=1}^{N} Crime_i}{N}, \text{ where } \quad \begin{array}{lll} If & Benefits_i > Costs_i & Crime_i = 1 \\ & Otherwise & Crime_i = 0 \end{array}$$

This will be the dependent measure on the left-hand side of the linear regression equation, modeling the crime rate for a particular geographic region. In line with the landmark econometric work by Ehrlich (1973), followed by most researchers since, a distinction will be made between violent crimes and property crimes[3] so that two separate regression-ready equations are formed. Levitt (1998) finds that criminals do not substitute between violent and property crimes, so including one as the dependent variable should not necessitate the presence of the other as an independent variable.

This work classifies all costs for a crime-considering individual at the margin as either opportunity costs of time and resources spent in the current period $(t = 0)$, or potential damages to his or her total level of utility generated in future time periods $(t = 1, 2, \ldots, T)$.

I assume that the primary punishment for crime, incarceration, will drop an individual's level of future utility to zero for the entire length of the prison sentence. Increased emphasis on future utility, then, will lead to a rising degree of potential punishment for a criminal action, in terms of sacrificed utility from a necessarily positive value down to zero, and thus a higher cost in an individual's cost-benefit calculus.

My models for property and violent crime rates begin with the following fundamental

[3] Violent crimes can be murders, negligent manslaughters, forcible rapes, robberies, or aggravated assaults. A property crime is a burglary, larceny, or motor-vehicle theft.

structure, taking as independent variables the factors presented in the existing literature with the theoretical basis to influence the costs as given by Equation (1).

$$CrimeRate_i = \beta_0 + \beta_1 Income_i + \beta_2 Education_i + \beta_3 Inequality_i + \beta_4 Unemployment_i + \beta_5 Chance\,of\ Arrest_i + \beta_6 Youth_i + \beta_7 Males_i + \varepsilon_i \tag{2}$$

Becker and Mulligan (1997) assert that increased income stimulates patient behavior and leads to more thoughtful consideration of future periods. Income thus has a positive relationship with the value of $\beta(s)$ and the level of potential costs associated with a criminal action. The sign of its coefficient in Equation (2) should be negative.

Level of education is also presented as having a positive association with the weight placed on future consumption, $\beta(s)$, in the Becker and Mulligan model (1997). An increased level of education raises the cost of crimes and must decrease the utility generated from their commission. I expect the relationship between education level and observed crime rate to be negative.

Sokoloff (2000) views income inequality as a gauge of the economic opportunities available to the general population in an area; higher income inequality is a signal of reduced access to labor market positions. Hence, increased income inequality lowers an individual's costs for committing a crime; its impact on crime rate should be positive.

Ehrlich (1973) argues that unemployment rate is a proxy for returns to legitimate activities. When an individual becomes unemployed, he or she has more time available to engage in illicit activities. This decreased opportunity cost of time lowers the level of costs associated with committing a time under the theoretical cost structure presented in Equation (1), and creates an incentive for individuals to use their resources outside of the legal sector.

The probability of an individual being arrested for a particular criminal offense has a positive relationship with the expected punishment he or she will be subjected to in future periods (Becker 1968; Ehrlich 1973). An increased chance of arrest contributes to heavier costs faced by a potential criminal, presented in Equation (1), and lower utility offered by an action.

It has been suggested that males are more willing to perpetrate a violent crime than are females (Levitt & Lochner 2000). I expect this to be a result of males' lower opportunity costs for the resources needed to engage in a violent act. The percentage of males in a population should have a positive impact on the area's violent crime rate, and an ambiguous influence on its property crime rate.

The disproportionate number of crimes committed by teenagers and young adults is likely due to the lower emphasis this group places on the future utility levels they risk losing through crime commission. A lower weighting of the future decreases the degree of costs in the utility maximization condition and increases the advertised utility of a criminal behavior. The coefficient on the percentage of youths in an area's population is expected to be positive.

I will add one final variable to Equation (2) that is my addition to the economic study of criminal behavior: the number of years an individual is expected to live. An increased life expectancy will raise a person's potential future utility simply because there will be more future periods in which he or she can consume; i.e., in my notation for the theoretical cost to which an individual actor is exposed, $\sum_{t=0}^{T} \beta(s)^t U_t$, a higher life expectancy raises the value for T, the total number of periods in which a person expects to live, while $\beta(s)$ and U_t are left unchanged. Since $\beta(s)$ is a strictly positive and increasing function, while U_t can never drop to or below 0, this cost calculation will sum across necessarily positive values over a larger number of periods when life expectancy increases.

Now faced with a higher degree of cost for committing a crime, due to larger sacrifices of future utility, the rational consumer with a higher life expectancy (LE) will, *ceteris paribus,* generate less utility from a criminal behavior than another rational consumer with a shorter lifespan. This will lead to an inverse relationship between life expectancy and crime commission; the sign on the coefficient of the life expectancy variable should be negative.

The final theoretical regression equations are given below:

$$
\begin{aligned}
PROPCRIME_i = \beta_0 + \beta_1 LE_i + \beta_2 Income_i + \beta_3 Education_i + \beta_4 Inequality_i + \beta_5 Unemployment_i \\
+ \beta_6 Chance\,of\ Arrest_i + \beta_7 Youth + \zeta_i
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
VIOLENTCRIME_i = \beta_0 + \beta_1 LE_i + \beta_2 Income_i + \beta_3 Education_i + \beta_4 Inequality_i + \beta_5 Unemployment_i \\
+ \beta_6 Chance\,of\ Arrest_i + \beta_7 Youth_i + \beta_8 Males_i + \psi_i
\end{aligned} \tag{4}
$$

5. Summary Statistics

The United States is composed of 3,141 counties or county-equivalents[4] ranging in population size from 67 in Loving County, Texas to 9,519,330 in California's Los Angeles County. County-level data are fitting for studying criminal behavior and its underlying influences because they contain information on crime variability across a domain of geographic divisions that also has measureable variations in a number of demographic characteristics.

All county-by-county data were gathered, for the year 2000, from the 2007 U.S. Census County and City Data Book[5], with the exception of life-expectancy estimates. Analysis was restricted to those counties for which data were available. In all, 413 counties had to be dropped from the data set. The 27 county-equivalents comprising Alaska were omitted because of missing life-expectancy estimates. The 82 counties in Illinois were excluded because the state does not publish its crime rates at the county level. The additional 309 dropped counties were all taken out of the data set because of missing crime-rate data; these were spread out among all states in the

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4 Lousiana has regional subdivisions known as "parishes" and Alaska calls these partitions "boroughs"; the remaining forty-eight states have functioning county governments that operate in the same manner. (http://www.naco.org/Content/NavigationMenu/About_Counties/County_Government/A_Brief_Overview_of_County_Government.htm)

5 The statistics are "a collection of data from the U. S. Census Bureau and other Federal agencies, such as the Bureau of Economic Analysis, the Bureau of Labor Statistics, the Federal Bureau of Investigation, and the Social Security Administration" (http://www.census.gov/prod/www/abs/ccdb07.html).

data set, frequently being those with small populations and likely small police departments. These exclusions left a total of 2,728 observations fit for regression. All inputted crime rates were scaled to result in measures per 100,000 members of the population to give consistent units. The crime rates were also subjected to the log transformation to ease coefficient interpretation and increase the presence of normality in the sample, as suggested by Figure 4.

The ideal life expectancy measure for my analysis would be survey-based individual estimates of their own lifespans, but this was not available at a level that also allowed accurate collection of criminal behaviors and other demographic characteristics deemed important in my guiding theory and the existing literature. Instead, I assume that members of these counties build their own life expectancy estimates based on the average age of death they observe for those around them. This allows me to use life expectancy estimates generated from a 2008 Harvard School of Public Health study that investigated the time trends of life expectancy among all counties in the United States, including its responsiveness to specific diseases. The county level was selected for the study because it is the smallest level for which age-specific mortality data can be found (Ezzati et al. 2008). The most recent estimates described the average age to which individuals in the year 1999 were expected to live; data were available for all counties except those in Alaska, but I accumulated only those for the 2,728 counties that also had published observations of crime rates.

No explicit inequality measure is presented at the county level, so I calculated it as the difference between a county’s logged percentage of households with annual income greater than $75,000 and the logged percentage of households under the poverty line.

Unfortunately, available data also provided no direct measure of the probability of arrest for an individual in a particular county. The first estimator of this variable in an econometric study of crime was the number of offenders imprisoned per known offenses (Ehrlich 1973); those data, however, were gathered at the state level where prison statistics are published by the U.S. Department of Justice, not at a county level at which there is no mandate to publish data on prisoners. I was forced to leave any possible variation accounted for by differences in arrest rate out of the explanatory variables chosen for my final linear regression equations.

Due to the imperfect nature of the substitution for life expectancy and the absence of a measure for probability of arrest, omitted variable bias is a potential problem for later regression results. If the omitted measure is correlated with another included independent variable, it will force existing independent variables into correlation with the error term; this leads to biased coefficients estimates since variation in the omitted measure will by absorbed by existing terms.

After dropping the 49 counties for which the observed violent crime rate in the year 2000 was zero, a potential problem addressed in later robustness checks, the logged form of violent crime rate used in the regression equations ranges from a low of 0.99, in Alabama's Morgan County, to a high of 8.75 in De Baca, New Mexico. The unlogged forms of these observations are 2.7 per 100,000 and 6,294 per 100,000, respectively. The logged form of property crime rate, also used in the final regressions, is presented for all 2,728 observations since there exist no recordings of zero. These observations range from 1.72 to 10.30, corresponding to rates per 100,000 of 5.59 and 29,360.41, respectively. The standard deviations of the logged crime data are 0.94 and 0.83 for violent and property crimes, respectively.

The life expectancy variable shows variation between values of 66.63 in Jackson County, South Dakota and 81.31 in Summit County, Colorado. Centered around a mean of 76.37, these are believable bounds for the measure, with practical variation among the counties. The mean of the sex ratio variable, 98.67 males for 100 females, is consistent with the observation of a female-heavy population in the United States. Since the inequality measure I used is the difference of two logged measures – percentage of households with income exceeding $75,000 and the percentage living under the poverty line – its range from Ziebach County, South Dakota's -2.30, suggestive of very low income inequality, to Douglas County, Maryland's 3.51, indicative of high income inequality, seems reasonable. County unemployment rate has a mean value of 4.24% with the highest observed value belonging to Imperial County, Pennsylvania and the lowest to Loudon, Arkansas.

The final list of variables included in the data set is presented, along with histograms of observed sample distributions and brief variable definitions, in Tables 2 and 3. All of the data were checked for inconsistencies and possible errors in entry, most of which was done manually.

6. Results and Estimation Issues

The ultimate linear regression equations undergoing OLS regression estimation are:

$$\begin{aligned} &\ln VIOLENTCRIME_i = \beta_0 + \beta_1 LE_i + \beta_2 \ln Income_i + \beta_3 \ln HSGradRate_i + \beta_4 Inequality_i \\ &+\beta_5 \ln Unemployment_i + \beta_6 \ln Aged15to24_i + \beta_7 SexRatio_i + \varepsilon_i \end{aligned} \tag{5}$$

$$\begin{aligned} &\ln PROPCRIME_i = \beta_0 + \beta_1 LE_i + \beta_2 \ln Income_i + \beta_3 \ln HSGradRate_i + \beta_4 Inequality_i \\ &+\beta_5 \ln Unemployment_i + \beta_6 \ln Aged15to24_i + \gamma_i \end{aligned} \tag{6}$$

There is an ambiguity in the literature over the ideal specification of an econometric model of crime. Doyle (1999) chooses a double-log form of a crime rate and its proposed explanatory variables that he calls "a fairly standard logarithmic crime equation"; Raphael (2001) also follows this format. Their choice to take the logged form of the dependent crime rate measure is troubling because, when the areas of observation are small enough to yield valid recordings of zero for particular crime rates, perfectly meaningful observations are forced out of the dataset by logarithmic transformations. This can cost the model a good deal of useful information on variability of crime.

This concern is addressed by Ihlanfeldt (2007), who uses a measure of job access, with the ability to take on negative values, in his crime equation. Since the log of a negative number takes on a non-real result, also necessitating a drop from the dataset, this problem is similar to the one I encounter with zero-valued crime rate measures. He notes the superior statistical fit of the linear model to the log-linear form and does not include a logged transformation of the variable in his final regression estimations. Cornwell (1994) and Grogger (1998) also do not use logged forms of their dependent crime rate variables in their concluding models of crime because of their inferior fit as measured by R^2.

Although the final regressions I run settled on the form and interpretation of logged crime rate variables, primarily for their introduction of normality to the sample distributions, I present the results of a linear specification in my robustness checks and compare their characteristics to those of the logged form. This tradeoff introduces potential specification bias that increases the likelihood of impure heteroskedasticity and multicollinearity in my results.

The results of the Variance Inflation Factors (VIF) Test for both regression equations are presented in Table 4. This result is a measure of the degree of variation in each explanatory variable that can be accounted for by other explanatory variables in the equation. The common rule of thumb is that a VIF result in excess of 5 indicates severe multicollinearity; in both VIF tests, only the “difference” variable approaches this level, with values of 4.40 and 4.15. Income inequality is valuable under my guiding theory and, since the value of its VIF coefficient is elevated but still under the prescribed threshold for severe multicollinearity, it will remain in the final regression equations. Due to the theoretical importance of the worrisome variable and the mean VIFs for both equations remaining safely below 5, at 2.24 and 2.32, no action was taken to correct for potential multicollinearity.

My data are likely being affected by pure heteroskedasticity, a non-constant variance across observations of the estimated error term, for two reasons. For one, I am using cross-sectional data at the county level, which has shown a vulnerability to the problem in the past. Second, pure heteroskedasticity often occurs when there is a large discrepancy between the minimum and maximum values of the dependent variable in a regression equation; in the data, logged violent crime rate has a range of 0.99 and 8.75, while logged property crime rate stretches from 1.72 to 10.30, a sizeable distance between the bounds of the measure. Impure heteroskedasticity is also a threat given the possibilities of omitted variable bias and specification error mentioned earlier.

Residual plots of initial regressions run for both crime rates before corrections for heteroskedasticity are given in Figures 2 and 3. The appearance of each suggests the presence of non-constant variance, so I conducted a post-estimation Cook-Weisenburg test for both regressions in Stata 10, seeking evidence to refute its null hypothesis of constant variance in the residuals. The test for both regressions found sufficient evidence to reject the null hypothesis at the 0.05 level of significance: The Chi-squared test statistic for the violent-crime regression had an accompanying p-value of 0.0004; for the property-crime model, the test statistic had a p-value of 0.019. Believing that my sample sizes of 2,679 and 2,728 were sufficient to rely on their large-sample characteristics, I used heteroskedasticity-corrected standard error estimates to reduce the inherent overstating of any t-scores in the regression results. Although these robust standard errors do not fix the problem of heteroskedasticity, they are successful in removing some of the bias in the standard error estimates produced by OLS and do not induce bias in the estimated coefficients.

The final regression results, with both models adjusted for heteroskedasticity, are presented in Table 5. Average life expectancy has coefficients with the expected negative signs and statistically significant t-scores at the .01 level in both the violent-crime and property-crime regressions. The coefficient estimates also have economic significance: A one-year increase in a county's life expectancy, holding other included factors constant, leads to a 15.2% drop in observed violent crime rate and an 9.5% drop in property crime rate.

A county's unemployment rate has coefficients in the anticipated positive direction with significance at the 99% confidence level for both regressions. It is not surprising that the magnitude of this coefficient is larger in the model for property crimes than the one for violent crimes, since its purpose is to proxy the returns to labor in the legitimate sector. For property crimes, whose primary motivation is assumed to be financial, the impact of reduced earning potential in the labor market (shown by an increased unemployment rate) was expected to be larger than the impact on violent crimes, whose motivations are not dominated by monetary concerns. Under this line of reasoning, the significance of a positive coefficient on income inequality found in the property crime regression at the .01 level and lack of significance in the violent crime model makes sense.

It is troubling that the coefficient on high-school diploma attains only moderate significance in the violent-crime model (at the .10 level) and proves insignificant in the property-crime model, since educational attainment was deemed important by the underlying theory. The theory also predicted a positive coefficient for income, but it actually shows significance at the .01 level for both regressions in the positive direction. Although this result is worrisome, the size of its estimated coefficients highlights the important distinction between statistical significance and economic significance. With a value of 0.000005 in the violent-crime model and 0.0000025 in the property-crime model, these estimated coefficients only predict an elevated property-crime rate of .05% and an increased violent-crime rate of .02% for every $1,000 increase in per-capita income; the realistic impact of these estimates is almost negligible. The unfortunate absence of a measure for arrest probability makes it is possible that omitted variable bias is having an effect on all estimated coefficients in the regression that can account for this.

The insignificance of the sex ratio coefficient and its magnitude of 0.01 in the violent crimes regression are also surprising, given historical observations of gender disparity in commission of violent crimes. In both regressions, the percentage of a county's population between the ages of 15 and 24 proves to have a significant positive impact on crime rate. This is consistent with what is known about the demographics of criminals.

7. Robustness Checks

The primary concern over my regression results is the omission of observed crime rates for 49 U.S. counties with no reported violent crimes in 2000, caused by using the log transformation in Equation (5). Since there is valuable information on violent crime variability being lost when these observations are dropped, regressions were also run with the unlogged form of violent crime to contain all 49 observations of zero; these results are presented in the second column of Table 6, with those of the original logged form listed in the first column. The estimated coefficients for all independent variables in column 2 retain their signs from the previous regression. The income inequality and sex ratio variables actually become statistically significant in the unexpected negative direction; this clashes with my guiding theory.

This puzzling occurrence may be the noteworthy result of introducing 49 important observations to the regression, or it may be merely the outcome of a specification that is incompatible with what theory dictates. To check this, I run a third regression that models the non-logged violent crime rate as a function of all independent variables, but only for the 2,679 observations with a non-zero crime rate absorbed by the logged dependent variable in column 1. The results are presented in the third column of Table 6. This specification again changes only the significance of the income inequality and sex ratio variables, pushing the coefficient estimates to directions with statistical significance opposite those prescribed by the underlying theory. It is also worth noting that, although two new variables gain statistical significance with the non-logged form of violent-crime rate, the overall statistical fit of the model, measured by R^2, actually drops from 0.16 to 0.13.

While R^2 maximization is not the goal of econometric research due to flaws in the measurement, these results do seem to indicate an inherently poorer fit for models of crime at the county level using the non-logged form of a violent crime rate than those using logged rates. The gain in significance for variables in the opposite direction deemed by operating theory is the main evidence against the linear form providing a proper fit. Histograms of the distributions of both crime rates in their non-logged forms and logged forms are presented in Figure 4. The increase in normality of these distributions in the logged form supports the idea of their improved fit for OLS regression.

Including a measure for the percentage of minorities in a county's population was not considered relevant under the guiding theory, since it assumed that no inherent psychological or biological differences among individuals would alter their basic responsiveness to a fundamental incentive structure. Empirical tests of crime, however, use this measure with considerable frequency (Ehrlich 1973; Cornwell 1994; Ihlanfeldt 2007; Grogger 1998; Lochner 2004; Raphael 2001). It is available at the county-by-county level from my original data as the population shares of African Americans and Hispanics living in a county, so I added it to my original regression equations as a robustness test. Inspection of a pair-wise correlation matrix suggests no multicollinearity introduced by keeping these two measures separate, so they were treated as distinct variables in both regression equations.

The results are presented in the final two columns of Table 6. The life-expectancy variable remains significant at the .01 tier in both regressions; in fact, the magnitude of its coefficient experiences a slight uptick. Even keeping the percentages of African American and Hispanic residents fixed, a one-year increase in the average life expectancy of a county leads to a 15.3% drop in its observed violent crime rate, and an 11.3% drop in property crime, holding all other included variables constant.

8. Conclusions and Future Research

My paper finds that life expectancy has a significant negative relationship with a county's violent and property crime rates across the entire United States. Holding a county's income, income inequality, unemployment rate, percentage of population aged 15 to 24, number of males per 100 females, and high school graduation rate fixed, a one-year increase in estimated life expectancy leads to a 15.2% drop in the observed violent crime rate. Keeping all of these factors constant except for number of males per 100 females, a one-year jump in life expectancy also leads to a 9.5% drop in property crime rate. An implication of these results is that increased public health spending may be preferable to expenditures on education if a policymaker's goal is to reduce crime, since the effect of education level on criminal activity proved to be ambiguous in both models.

The robustness of my life expectancy measure to an alteration of functional form and the inclusion of a minority rate in both regressions is also quite encouraging. The significance of the coefficients of minority population in both regressions, though, is worrisome because it speaks to a distinct influence of minority status on the likelihood of crime commission, a factor not deemed valid by the developed theory. This is further evidence that an omitted variable bias is present in my equations.

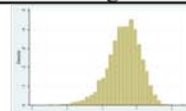
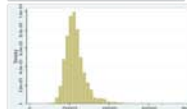
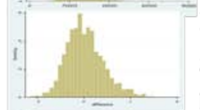
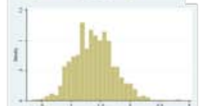
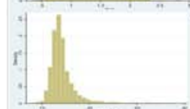
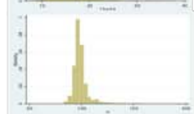
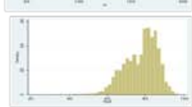
An exciting avenue for future research is determining if differences in life expectancy estimates across a cross section can actually explain some of the disparity between the crime rates of different racial groups. Perhaps with a serviceable proxy for arrest rate, the best choice for a neglected variable in my equations, some interesting discoveries can be made in this area.

Authors	Dependent Variables	Independent Variables	Unique Time Pref.?**
Doyle (1999)	Property and violent crime rates	Amount of police officers, estimated arrest rate, income, inequality measure, percent male, unemployment rate	No
Ihlanfeldt (2007)	Drug crime rate	Age, income, neighborhood employment, percent black, percent men	No
Cornwell & Trumbull (1994)	Total crime rate	Average wages by industry, percent male, percent minority, policy per capita, , urban area	No
Ehrlich (1973)	Total crime rates	Average prison sentence, estimated arrest rate, income, percent men, percent minority, probability of arrest, years of schooling	No
Grogger (1998)	Property crime rates	AFQT score, criminal history, education, marriage status, minority status, union states, urban area	No
Lochner (2004)	7 property and violent crime rates	Age, education, income per worker, metropolitcan area percent black	No
Lochner & Moretti (2004)	Drug sales, property crimes, violent crimes	Age, area of residence, family background, school enrollment, unemployment rate	No
Narayan & Smith (2004)	7 property and violent crime rates	Male youth unemployment, real weekly earnings	No
Raphael (2001)	7 property and violent crime rates	Alcohol consumption, income, military spending, metropolitan area percent black, poverty rate, prison population, unemployment rate	No
Soares (2004)	Property crime rates	Education, GNP, income inequality, income-per-capita growth, urbanization	No

Table 1: Selected Econometric Literature on Criminal Behaviors

** This fourth column indicates whether a study includes a variable, other than income or education with the power to affect time preferenece under the theory presented by Becker and Mulligan (1997)

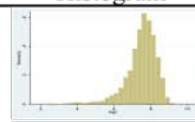
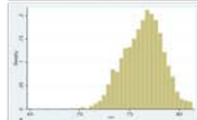
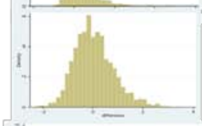
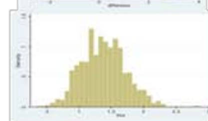
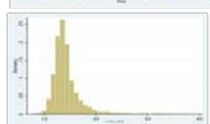
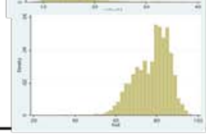
Table 2: Summary Statistics for Violent Crime Regression

Variable	Mean	Std. Dev.	Min	Max	Histogram	Explanation
Ln(violent)	5.27	0.94	0.99	8.75		The logged form of a county's 2000 violent crime rate per 100,000 residents.
Life Expectancy	76.35	1.97	66.63	81.31		The estimated age to which individuals in the year 1999 were expected to live, in years.
Income	23231.19	5696.47	9558	67692		A county's per-capita income in 2000.
Inequality	0.06	0.80	-2.30	3.52		Percentage of households with income greater than $75,000 minus the percentage under the poverty line.
Ln(Unemployment)	1.39	0.35	0.34	2.86		The logged form of a county's unemployment rate for the year 2000.
Ages 15 to 24	14.29	3.00	7.70	37.90		The percentage of a county's residents who were between the ages of 15 and 24 in the year 2000.
Sex Ratio	99.19	9.05	76.20	200.90		The number of men in per 100 females in the population of a county in 2000.
High School Diploma	77.65	8.50	34.70	97		The percentage of a county's residents who, as of 2002, had received a high-scool diploma.

Number of Observations: 2679

Source: U.S. Census County & City Data Book 2007

Table 3: Summary Statistics for Property Crime Regression

Variable	Mean	Std. Dev.	Min	Max	Histogram	Explanation
Ln(property)	7.50	0.84	1.72	10.30		The logged form of a county's 2000 property crime rate per 100,000 residents.
Life Expectancy	76.37	1.97	66.63	81.31		The estimated age to which individuals in the year 1999 were expected to live, in years.
Income	23236.30	5667.93	9558	67692		A county's per-capita income in 2000.
Inequality	0.06	0.80	-2.30	3.52		Percentage of households with income greater than $75,000 minus the percentage under the poverty line.
Ln(Unemployment)	1.38	0.35	0.34	2.86		The logged form of a county's unemployment percent for the year 2000.
Ages 15-24	14.26	2.99	7.70	37.90		The percentage of a county's residents who were between the ages of 15 and 24 in the year 2000.
High School Diploma	77.70	8.46	64.70	97		The percentage of a county's residents who, as of 2002, had received a high-scool diploma.

Number of Observations: 2728

Source: U.S. Census County & City Data Book 2007

Table 4: Variance Inflation Factors Test

	Violent Crime Rate		Property Crime Rate	
Variable	VIF	1/VIF	VIF	1/VIF
Life Expectancy	4.4	0.227413	4.15	0.240892
Income	3.27	0.305855	3.13	0.319904
Ln(Unemployment Rate)	2.5	0.399992	2.3	0.43414
Ages 15-24	1.79	0.557523	1.7	0.588252
High School Diploma	1.61	0.619706	1.6	0.626482
Inequality	1.08	0.925554	1.07	0.936231
Sex Ratio	1.05	0.95047	--	--
Mean VIF	2.24	--	2.32	--

Table 5: Regression Results

	Coefficients	
Variables	Ln(Violent Crimes)	Ln(Property Crimes)
Life Expectancy	-0.152	-0.095
	(12.61)**	(8.63)**
Income	0.000	0.000
	(9.01)**	(4.50)**
Ln(Unemployment Rate)	0.501	0.519
	(8.41)**	(9.02)**
Ages 15-24	0.044	0.049
	(7.69)**	(9.88)**
High School Diploma	-0.006	0.004
	(1.810)	(1.530)
Difference	-0.028	0.244
	(0.620)	(5.81)**
Sex Ratio	-0.001	--
	(0.430)	--
Constant	14.944	12.430
	(17.43)**	(15.87)**
Observations	2679	2728
R-squared	0.16	0.12

Absolute value of t statistics in parentheses

* p-value significant at 5%; ** p-value significant at 1%

Table 6: Robustness Checks

Variables	Regression Coefficients				
	Ln(Violent)	Violent	Violent	Ln(Violent)	Ln(Property)
Life Expectancy	-0.152	-44.636	-43.744	-0.153	-0.113
	(12.61)**	(9.96)**	(9.61)**	(10.65)**	(9.21)**
Income	0.000	0.015	0.016	0.000	0.000
	(9.01)**	(8.93)**	(9.06)**	(5.59)**	(2.65)**
Ln(Unemployment Rate)	0.501	112.136	100.479	0.355	0.416
	(8.41)**	(6.76)**	(5.95)**	(6.16)**	(7.62)**
Ages 15-24	0.044	11.539	10.789	0.014	0.031
	(7.69)**	(7.67)**	(7.16)**	(2.51)*	(5.71)**
High School Diploma	-0.006	-1.184	-1.015	0.021	0.022
	(1.810)	(1.29)	(1.09)	(5.95)**	(6.87)**
Inequality	-0.028	-28.526	-39.107	-0.034	0.241
	(0.620)	(2.14)*	(2.81)**	(0.80)	(6.35)**
Sex Ratio	-0.001	-1.347	-1.293	-0.002	
	(0.430)	(2.63)**	(2.53)*	(1.15)	
Percent Black	--	--	--	0.016	0.007
	--	--	--	(9.51)**	(5.57)**
Percent Hispanic	--	--	--	0.019	0.014
	--	--	--	(13.13)**	(9.97)**
Constant	14.944	3,240.60	3,169.00	13.828	12.892
	(17.43)**	(10.29)**	(9.91)**	(13.39)**	(14.60)**
Adjusted R-Squared	0.16	0.14	0.13	0.23	0.16
Observations	2679	2728	2679	2679	2728

Absolute value of t statistics in parentheses

* p-value is significant at 5%; ** p-value is significant at 1%

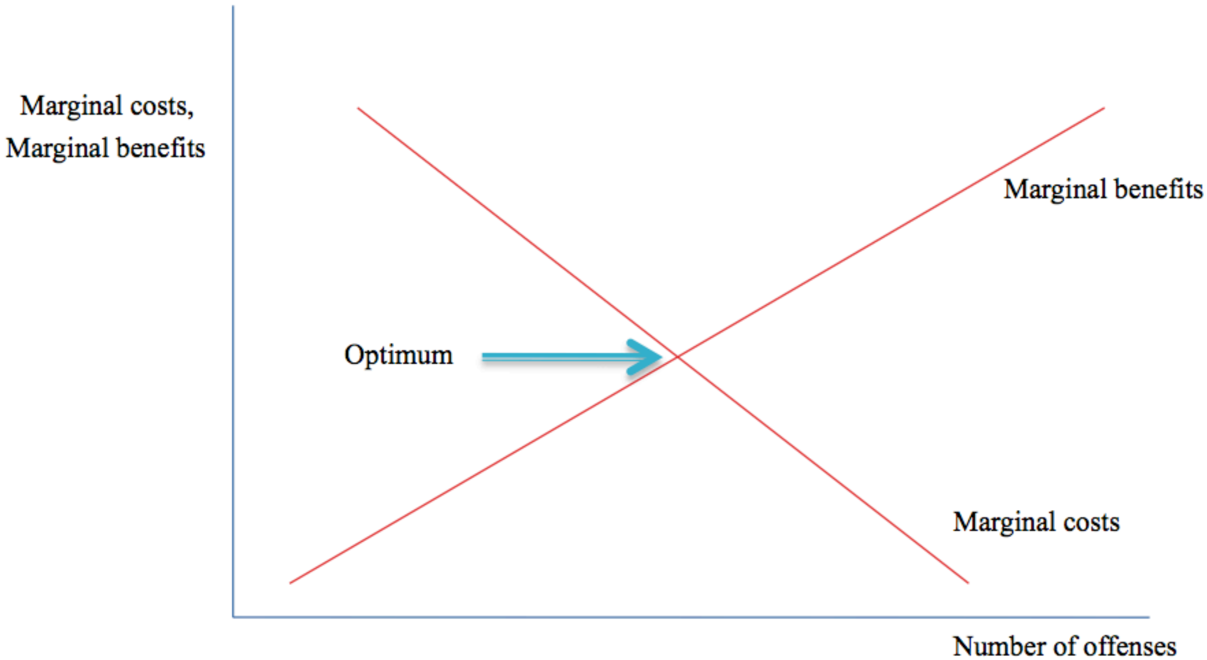


Figure 1: The cost-benefit structure for criminal offenses. The point of intersection indicates the quantity of offenses at which the marginal benefit of committing another crime is equal to its marginal cost. A rational consumer will commit crimes up until this level, and choose not to engage in any more than this quantity.

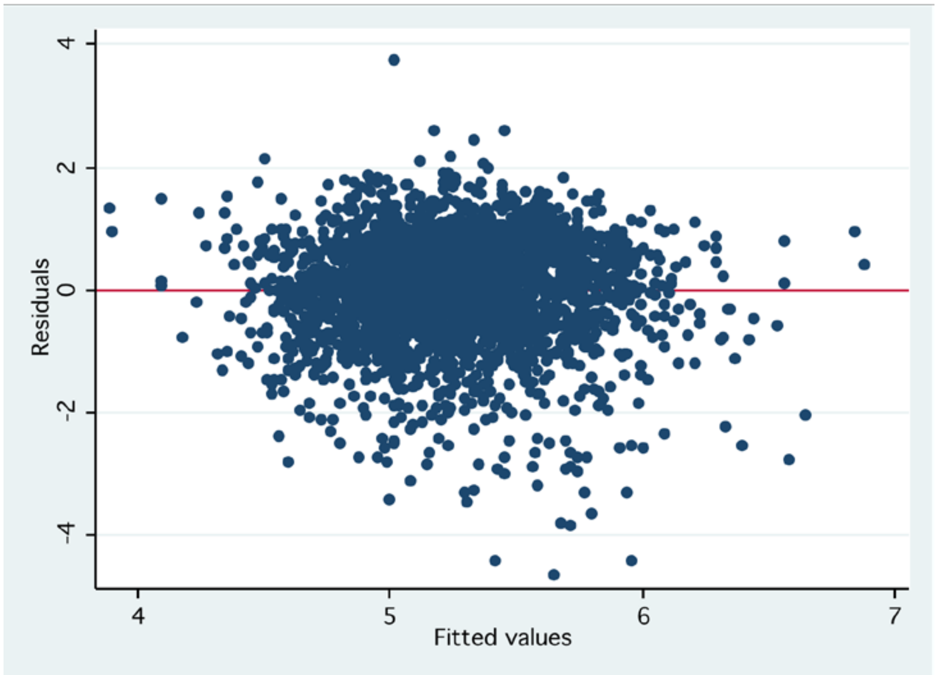


Figure 2: Plot of fitted values generated by the initial violent crimes regression, by the respective sizes of their residuals.

Figure 3: Plot of fitted values generated by the initial property crimes model, by the respective sizes of their residuals

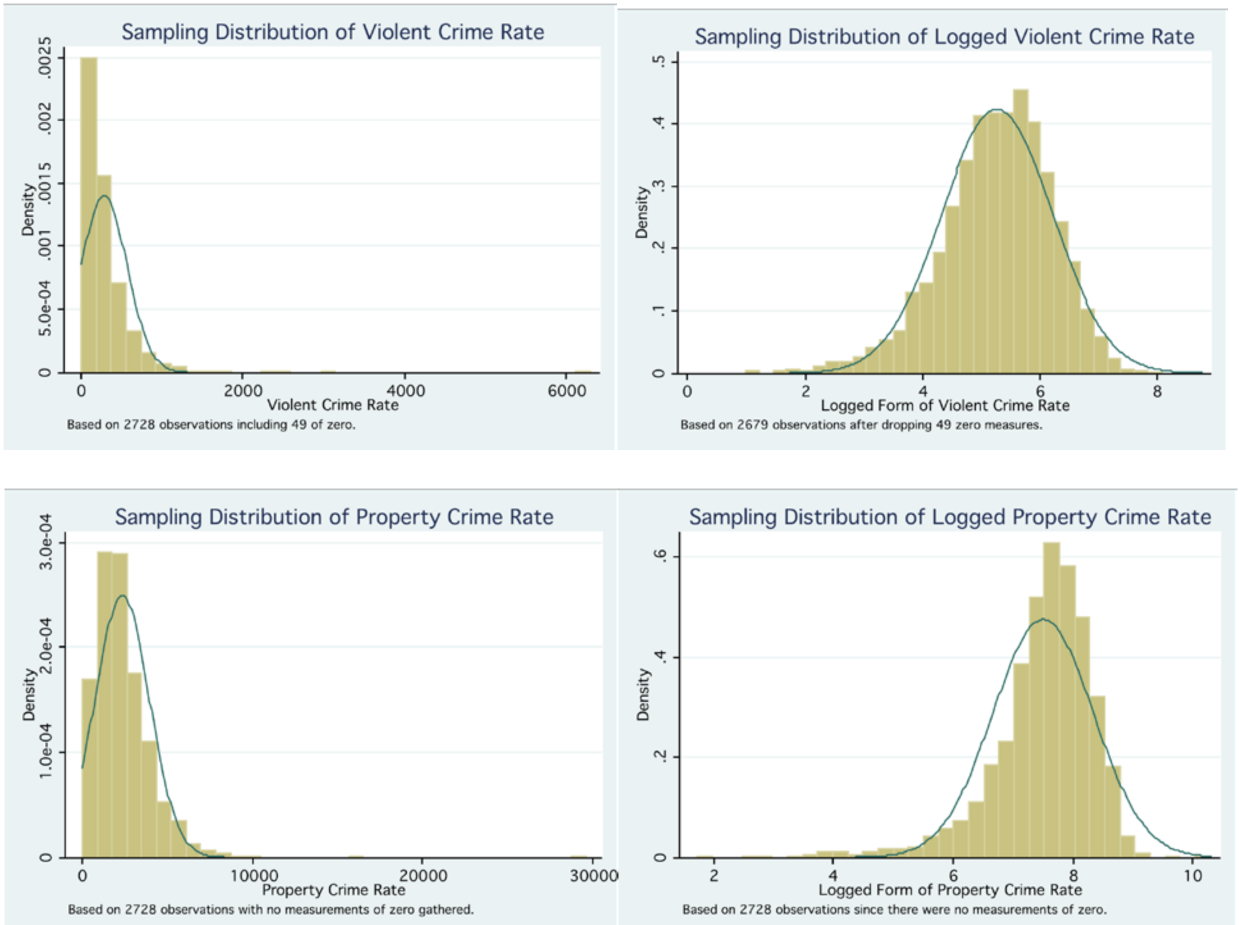


Figure 4: Sampling distributions for both crime rates, in their original and logged forms.

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