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Demographic Change, Macroeconomic Conditions, and the Murder Rate: The Case of the United States, 1934 to 2006

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DEMOGRAPHIC CHANGE, MACROECONOMIC CONDITIONS, AND THE MURDER RATE: THE CASE OF THE UNITED STATES, 1934 TO 2006

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Fluctuations in aggregate crime rates contrary to recent shifts in the age distribution of the U.S. population have cast doubt on the predictive power of the age-crime hypothesis. By examining a longer time horizon, back to the early 1930s,, we show that the percentage of the young population is a robust predictor of the observed large swings in the U.S. murder rate over time. However, changes in the misery index—the sum of the inflation and unemployment rates—significantly contribute to explaining changes in the murder rate. This applies, in particular, to those changes that are at odds with the long-run trend of the U.S. age distribution, such as the decline in the murder rate in the latter part of the 1970s or its increase starting around the middle of the 1980s.

Key words: murder rate, demographic change, age composition, crime, misery index

JEL Categories: J10, J11

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1. Introduction

A recent econometric study and survey of the literature posits that economists have learned little about criminal behavior, since economic theories do not explain the long-run dynamics of aggregate crime rates (Dills et al. 2008). In this paper, we revisit an old criminological theory and argue that changes in age demographics can explain much more of the variation in aggregate crime rates than has recently been suggested. At the same time, we suggest that any longer run explanation of the aggregate crime rate needs to take into account to what extent society is stressed through a combination of high unemployment and inflation.

While trends in crime rates have long been of interest to scholars, the rapid, unexpected increase in U.S. crime rates in the mid-1980s followed by an unexpected decline in crime rates during the 1990s received an unusual amount of attention. The movements in aggregate crime caused such a stir because the increase in crime during the 1980s was coincident with a dramatic decrease in the percentage of 15-24 year-olds in the population—the age group most likely to commit crime. Because the 15-24 age group has historically had a much higher rate of criminal participation, criminologists believed that changing age demographics could be a powerful predictor of future crime rates. However, the seeming reversal of this trend beginning in the mid-1980s cast serious doubt on the predictive power of the age-crime relationship.

From Figure 1, it is apparent that the murder rate in the U.S. has experienced drastic fluctuations since the 1930s. Against the background of this longer time horizon, the volatility in the murder rate during the 1980s does not appear out of the ordinary. The figure also suggests that fluctuations in the murder rate are tied to predictable changes in the percentage of the population in the 15-29 year-old age group over the long run. Figure 1 indicates that movements in the share of the population in this age group map closely to the murder rate, except during the

1980s. This suggests two conclusions. First, it is important to examine longer time horizons because a focus on the last few decades[1] masks the long-run co-movement of the crime rate and the percentage of the population in the 15-29 year-old age group. Long-run trends cannot be captured with two or three decades of data. Second, Figure 1 also makes it clear that there must be other factors that affect the murder rate, which cannot be left out of an explanation of crime over time. The literature suggests a number of them: unemployment, economic inequality, police effort, increased prison population, drug prohibition, and the crack-cocaine epidemic.[2] In this study, we combine the unemployment rate with the inflation rate" and suggest that this "misery index" can explain those changes in the crime rate that are at odds with those of age demographics (Figure 2).

In this article, we will use the murder rate as a proxy for the overall crime rate. We focus on the murder rate because it is the most violent crime and, therefore, likely the most accurately and consistently measured crime over the long time horizon that we consider (1934 to 2006). To capture the changing age demographics, we focus on the 15-29 age group, as this age group has historically been the most likely to commit murder.

The share of the population in the 15-29 year-old age group turns out to be the variable with by far the largest economic impact on the murder rate. It is the key variable to recreate the large swings in the murder rate over the last 70 years. The misery rate, by contrast, is an essential variable to capture transitory changes in the murder rate around the long-run trend influenced by age demographics.

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[1] Focusing on just the last few decades is very popular because panel data sets are available over this time horizon.

[2] Other more unusual explanations for the drop in crime during the 1990s are abortion legalization (Donohue and Levitt 2001) and a decrease in childhood lead exposure (Reyes 2007).

2. Background Information

Since the seminal work by Becker (1968), economists have studied crime as the outcome of individual, rational choice. Becker derives testable predictions about criminal participation with respect to the probability of apprehension and conviction, severity of punishment if convicted, and subsequent expected return to crime. Becker's model, like most economic models, abstracts from long-run cultural and demographic trends, which could also affect crime rates. As a result, the majority of empirical studies in the economics of crime literature attempt to identify short-run relationships between crime and variables that affect the opportunity cost of crime. To identify these short-run relationships, researchers generally examine differences in crime rates across geographic areas, as there is often substantial variation even within a single city (e.g., see Glaeser et al. 1996). While much can be learned from exploiting short-run variation in crime rates across geographic boundaries, such studies are unlikely to uncover more subtle causal relationships which affect society's propensity for crime in the long run.

Hirschi and Gottfredson (1983) argue that the age distribution of criminality is invariant across time and cultural geography: criminal participation rises dramatically beginning in early adolescence, peaks in the early twenties, and then gradually declines thereafter. The authors cite a voluminous literature covering various countries over the last 150 years to support their claims. The implication of a stable age distribution of crime is that it cannot be explained by social factors, i.e. criminologists do not have observable variables to explain it. Hirschi and Gottfredson's assertions were criticized (e.g., see Greenberg 1985) and damaged by the cycle of crime that began shortly after publication of their seminal paper.[3] In 1985, the crime rate in the

[3] Statistics referenced from O'Brien and Stockard (2009, Fig. 1). Greenberg (1985) emphasizes the importance of cohort effects, as he notes in Table 1 (pp. 4), there are obvious differences in criminal participation rates between the same age groups across different cohorts. Such cohort effects would invalidate an invariant age-crime

U.S. began to rise dramatically at the same time the percentage of the population in the 15-24 year-old age group was declining. Moreover, from 1985 to 1990 the rate of homicide committed by 15-19 year-olds more than doubled to eclipse that of 20-24 and 25-29 year-olds—a clear violation of the invariant age-crime distribution hypothesis. However, Hirschi and Gottfredson (1983) do not claim that the age-crime relationship is completely inflexible, as they mention the possibility of "countervailing social processes" that may temporarily change the age-crime distribution.

A contentious debate surrounds the cause of the steep decline in the rate of violent crime in the United States during the 1990s. Two characteristics of the decline stand out: it was unexpected and it was not specific to any geographic area (Levitt 2004). Levitt (2004) presents four factors that explain the drop in crime in the 1990s: (*i*) waning crack epidemic, (*ii*) increased number of police, (*iii*) increased prison population, and (*iv*) abortion legalization. Levitt (2004) also discusses six other common explanations that he claims do not explain the sudden drop in crime during the 1990s, one of which is fluctuations in age demographics. In his argument against the decrease in the percentage of 15-24 year-olds in the population as a cause of the decline in crime, Levitt cites the increase in the black population between 1990 and 2000 as a counterbalancing effect because blacks have higher offense rates. While Levitt's arguments may be plausible for the 1990s, the factors highlighted by him are less likely to have led to the sharp drop in murder and other crimes during the 1930s through the 1950s. The drop in the murder rate during this time period coincided with the sharp decline in the young population, those in the 15-29 age groups (Figure 1). Likewise, it is plausible that the drop in the young population during the 1990s could explain the concomitant drop in crime. However, Levitt (1999, 2004) argues that

distribution. Grogger (1998) presents evidence that the age-crime relationship can be attributed to differences in economic opportunity amongst different age groups.

changes in the age composition account for only a modest portion of the rise and fall of crime from the 1960s to the 1990s.

Donohue and Levitt (2001) posit that as much as fifty percent of the decline in the violent crime rate during the 1990s can be explained by the legalization of abortion in the 1970s. The first-order effect of abortion legalization is that it lowers the percentage of the age cohort in the population most likely to commit crimes in the future. Donohue and Levitt (2001) offer an even more controversial argument for a second-order effect of abortion legalization: the most likely future criminals are also the most likely to be conceived as an unwanted pregnancy and subsequently aborted. Hence, Donohue and Levitt (2001) argue that abortion legalization should have an even larger effect on aggregate crime rates when the birth cohort who are born during abortion reform reach 18-25 years of age—the age group most likely to commit crime. However, the empirical validity of Donohue and Levitt's abortion-crime hypothesis has been criticized (Joyce 2004, 2006, 2009, Foote and Goetz 2008).[4] Similarly, Dills et al. (2008) examine the abortion-crime relationship at the aggregate level. They suggest that abortion legalization could not have affected crime rates until the late-1980s. However, crime rates began to fluctuate before this time period. This casts further doubt on the robustness of the abortion-crime relationship posited by Donahue and Levitt (2001).[5]

Another hypothesis for the drop in crime during the 1990s is that childhood blood lead levels had dramatically decreased for the cohort most likely to commit crime. Children who are exposed to lead are more likely to exhibit criminal behavior as adults. Reyes (2007), using state-

[4] Donahue and Levitt (2004, 2008) (2004, 2008) (2004, 2008) rebut the papers by Joyce and Foote and Goetz. However, Joyce (2009) is the latest in the debate.

[5] Likewise, Dills et al. (2008) also examine abortion and crime in other countries and find mixed results. In some countries, the Donahue-Levitt hypothesis is supported, while in others it is not. Overall, Dills et al. (2008) conclude that abortion legalization likely had a modest impact on crime.

level data from 1985 to 2002, contends that the phase-out of gasoline lead initiated through the Clean Air Act of 1970 explains 56 percent of the violent crime rate decline in the 1990s.[6] As a result, the 20-29 age cohort in the 1990s would have had lower blood lead levels and thus would have been less prone to commit crimes. Reyes argues further that lead exposure may explain much of the variation in violent crime over a longer period of time in the U.S. While Reyes' story may be largely consistent with the last few decades,[7] this explanation does not suffice over a much longer time horizon. From Dills et al. (2008, Figure 15), it is clear that various measures of lead exposure were on the rise during the dramatic fall of the murder rate during the 1930s through the 1950s. This negative correlation between lead exposure and the murder rate presents inconsistencies in Reyes' hypothesis over a much longer time horizon. In addition, Reyes' predictions suggest that crime will continue to fall until 2020, when the effects of the Clean Air Act of 1970 are complete. However, recent movements in the murder rate cast doubt on this prediction: the murder rate rose in 2003, fell slightly in 2004, and rose in consecutive years from 2005 to 2007.[8]

A recent variable advanced in the literature as a key predictor of crime rates is the misery index (Tang and Lean 2009). The misery index incorporates information from the two macroeconomic variables most likely to affect criminal participation: inflation and

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[6] Reyes (2007) does not find an effect of lead exposure on property crime rates.

[7] Dills et al. (2008) also present a time plot of lead exposure and the murder rate in the U.S. This suggests that the relationship between the murder rate and lead exposure is sensitive to the time period studied, as the relationship exhibits negative, positive, and zero correlation over the last 40-50 years.

[8] Dills et al. (2008) put forward the argument that drug and alcohol prohibition efforts map the homicide rate for much of the 20th century, although they present no formal econometric evidence. However, in Figure 16 of their paper, it is evident that the homicide rate and prohibition expenditure series begin to diverge in the mid-1990s: homicide rates are decreasing, while expenditures on prohibition are rising. This suggests that prohibition efforts may not be strong predictor of future homicide rates, as it may have more transitory effects. We included prohibition expenditures per capita in the model and found no statistical link to the murder rate. We do not present these estimates, because the estimates for the other variables, especially the age-distribution variable, are unaffected by the inclusion of prohibition expenditures in the model.

unemployment (Ralston 2006). Although murder is not necessarily an economically motivated crime, fluctuations in the misery index track the transitory movements in the murder rate reasonably well over time (Figure 2). However, Figure 2 suggests that variables other than the misery index should be included in order to capture changes in the level of the murder rate.

The age-crime relationship has been widely studied, and this literature has yielded mixed results.[9] Against this background, we can identify a robust, positive relationship between the share of 15-29 year-olds in the population and the murder rate if the model is supplemented by the misery index to allow for times of particular stress on society.

3. Data and Estimation Results

We use time-series data from the F.B.I.'s Uniform Crime Report (UCR) on the murder rate in the U.S. from 1934 to 2006. Our two key right-hand-side variables of interest are the percentage of the population in the 15-29 year-old age group and the misery index.

To investigate the long-run relationship between the murder rate and the age-distribution variable, we conduct a test for co-integration. Because the right-hand-side variables that we consider are plausibly exogenous, we stick to the single-equation methodology developed by Engle and Granger (1987), rather than move to the multivariate co-integration methodology advocated by Johansen (2002) and Johansen and Juselius (1990).[10] We use an augmented

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[9] See Table AI, Appendix of Marvell and Moody (1991) for a description of 90 studies—30 of which are time-series studies—that investigate the age-crime relationship. Sixty-seven percent of the 24 time-series studies which examine homicide rates find a "moderate or strong," positive association between homicide and the age distribution of the population (See Table VI of Marvell and Moody (1991)).

[10] As a robustness check, we estimate models of the Johansen type, and include, for that purpose, another endogenous variable, the number of police per capita. As research suggests there is reason to suspect that crime and policing are jointly determined variables (Levitt 1997). The results suggest co-integration among the murder rate, the age variable and police per capita. But the results identify the police variable as weakly exogenous in the vector error correction system constructed for the Johansen approach. This leads us to move to the Engle-Granger methodology.

Dickey-Fuller (ADF) test on the residuals of the co-integrating regression and employ MacKinnon's (1996) significance values for the co-integration tests. We also check our results by running ordinary-least-squares (OLS) regressions with correction for second-order autocorrelation. The results from the OLS regressions are non-spurious to the extent that a common trend can be established among our variables of interest.

A test for first-order co-integration requires that the variables included in the co-integrating equation are integrated of order one. We check the order of integration by conducting augmented Dickey-Fuller tests on the variables used in our analysis. The results of these tests indicate that the null hypothesis of a unit root cannot be rejected for any of the variables considered.[11]

Table 1 presents the results from the Engle-Granger co-integration tests and the OLS regression that corresponds to the co-integrating vector implied by the Engle-Granger tests. Models 1 and 2 include either the misery index or the share of young people in the population as separate variables. Neither model can reject the null hypothesis of no co-integration at conventional levels of statistical significance, although it is apparent that the model with the age distribution variable provides a much closer fit. By contrast, the null of no co-integration is rejected by Model 3, which includes both the age-distribution variable and the misery index. We view this result as credible evidence in favor of a long-run relationship among the murder rate, the share of young people in the population, and the misery index. We come to this conclusion even though the p-value of the test suggests rejection of the null of no-cointegration only at the ten percent level and not at the five percent level. But this evidence needs to be evaluated against the background that the Engle-Granger test is well-known to be sensitive to structural breaks and that we conduct the co-integration test over a period of more than 70 years of data, which

[11] However, the null hypothesis of a unit root for the first differenced variables can be rejected. We, therefore, conclude that all variables are integrated of order one.

includes the years of World War II, without using any observation specific dummy variable. Combining the conclusion of a long-run relationship among the three variables (i.e. the murder rate, the share of young people in the population, and the misery index) with the reasonable assumption that only the murder rate is endogenous, we can conclude that the murder rate is determined in the long run by the age distribution and the misery index.

Model 4 presents the results of a least squares regression with correction for second-order autocorrelation on the variables of Model 3.[12] The parameter estimates from the co-integrating regression (Model 3) and the OLS regression (Model 4) are reasonably similar, although the effect of the misery index on the murder rate is halved in size when estimated by OLS. However, its statistical significance is robust. The size and statistical significance of the age-distribution variable are comparable in both Models 3 and 4.

To make it easier to assess the economic impact of the age distribution and the misery index on the murder rate, we convert the parameter estimates of Models 3 and 4 into elasticity format (evaluated at mean values[13]). The elasticity of the age-distribution variable is 1.2 in Model 3, while it is 1.4 in Model 4. The elasticities are much smaller for the misery index: 0.17 for Model 3 and 0.06 for Model 4. While the elasticity of the misery index is much smaller than the one of the age-distribution variable, the misery rate tends to be more volatile in the short run than the age-distribution variable. Hence, it is better suited than the age variable to pick up sudden changes in the murder rate (Figure 2).

As a next step, we check to what extent the OLS results of Model 4 change as we vary the starting date of the sample. For that purpose, we let each regression sample start one year later.

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[12] The results from the OLS regression generate meaningful estimates because co-integration among the variables considered in Model 3 eliminates concerns that the results are spurious.

[13] For the complete sample and the particular definitions used for the variables, the mean values are 6.74 for the murder rate, 10.64 for the misery index, and 0.236 for the share of the 15 to 29 year old group in the population.

That means, the first sample begins in 1934; the second sample begins in 1935; and this process continues until the last starting year is reached, which we take to be 1976. Each of the regressions ends in 2006, and includes corrections for second-order autocorrelation. The only variables included are the age-distribution variable, the misery index, and a quadratic time trend. Overall, the statistics for the 43 regressions, each with a different *effective* starting date from 1934 to 1976,[14] reveal that the share of young people in the population and the misery index are robust predictors of the murder rate (Table 2).

The coefficient estimates and their t-values vary somewhat for both variables depending on the starting dates of the sample. In particular, starting points between 1944 and the early-1950s generate smaller coefficients for the misery index, while starting points after 1970 generate relatively smaller values for the coefficient for the share of young adults in the 15 to 29 year-old age group. The coefficient for the age-distribution variable is largest when the samples begin between the late-1930s and the early-1950s, and the misery index has its largest impact for samples that begin after 1960. These results are interesting for a number of reasons. First, it shows that the age-distribution variable does not have a statistically significant coefficient when the sample covers only a short time horizon. This is plausible because observations from many years are needed to statistically identify cycles that take many years to evolve, such as changes in age demographics. This simple fact is important because it can explain why panel data studies, which rely on data from the 1960s onwards, cannot identify the long-run impact of demographic change. Second, the increasing importance of the misery index toward the end of the sample suggests that it may be possible to improve the fit of Model 4 by allowing the coefficient of the misery index to vary over the 70 years from the 1930s to the 2000s. A simple alternative

[14] Note that two observations are lost due to correction for autocorrelation.

regression that incorporates a varying coefficient for the misery index is Model 5 of Table 1. The model includes an interaction term between the misery index and a 0/1 indicator variable, I(year $\geq$ 1960), which takes on the value of one from 1960 through the end of the sample. The interaction term allows the coefficient of the misery index to take on two values over the sample, one before 1960 and one after. The value of the coefficient before 1960 is given as 0.017. It is not statistically different from zero, which implies that the misery index had, on average, very little impact on the murder rate before 1960. The value of the misery index from 1960 onwards is given by the sum of the coefficients of the misery index variable and the interaction term, which is 0.1015.[15] This value is statistically indistinguishable from the value of 0.1084 that is estimated for the misery index in Model 3.[16] We note that the estimated coefficient of the age-distribution variable of Model 5 is closer to the one of Model 3 than the coefficient of Model 4. Hence, we can conclude that the estimates of Model 5 are fully consistent with those of Model 3.

According to our estimates, both the misery index and the share of young adults in the 15 to 29 year age group have a positive and statistically significant impact on the murder rate. The misery rate fits quite well to the peaks and troughs of the murder rate for the post-WWII era. The age-distribution variable, by contrast, predicts the overall level of the murder rate during the sample period. Although age demographics and the misery index can jointly explain not only the large swings in the murder rate but also many of its shorter run ups and downs, we want to be clear that other variables may be at work, especially during particular time periods, that contribute to explaining the murder rate. For example, based on the evidence presented, the relatively small elasticity of the misery index makes it impossible to fully explain the 15 percent

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[15] This sum is statistically different from zero at much better than the one-percent level.

[16] The restriction that the sum of the coefficients equals 0.1084 generates a p-value of 0.821.

increase in the murder rate from 1986 to 1991 with the increase in the misery index,[17] even though that increase amounts to a sizable 25 percent over the same years and the timing of the two events match to a large degree.

4. Conclusions

In a seminal article, Hirschi and Gottfredson (1983) claim the relationship between age and crime is largely invariant over time and geography. However, movements in the age distribution of the population that ran counter to the dramatic swings in violent crime of the 1980s and 1990s seriously undermined the invariant age-crime hypothesis. Many new theories for the dramatic increase in crime during the 1980s and the unexpected decrease in crime during the 1990s were put forward. Among these theories, the most provocative were associated with the sudden crime decrease: abortion legalization in the 1970s (Donohue and Levitt 2001) and decreased childhood exposure to lead following the Clean Air Act of 1970 (Reyes 2007). While these theories have empirical support over their respective sample periods, it is unlikely that either can explain crime rates over a longer expanse of time, say back to the 1930s.

We examine the murder rate in the United States for the years 1934-2006 and show a robust, positive, long-run relationship between the murder rate, the percentage of the population aged 15-29 years, and the sum of the inflation and unemployment rates (misery rate). Our estimates indicate that fluctuations in the percentage of those aged 15-29 years explain much of the long-run swings in the level of the murder rate over time. Unfavorable macroeconomic conditions, which we capture by the misery rate, account for much of the short-run variation in the murder rate around the long-run cycle produced by the changing age demographics. We do leave open

[17] The increase in the misery index at the same time will only explain about a quarter of the rise in the murder rate over the time period from 1986 to 1991.

the question whether there may have been other special circumstances at work during the years of the unexpected rise in the murder rate from the middle of the 1980s to the early 1990s.

References

Becker, Gary S. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76, no. 2 (1968): 169-217.

Dills, Angela K., Jeffrey A. Miron, and Garrett Summers. "What Do Economists Know About Crime?" *NBER Working Paper Series,* no. 13759 (2008).

Donohue, John J., and Steven D. Levitt. "Further Evidence that Legalized Abortion Lowered Crime." *Journal of Human Resources* 39, no. 1 (2004): 29-49.

Donohue, John J., and Steven D. Levitt. "Measurement Error, Legalized Abortion, and the Decline in Crime." *Quarterly Journal of Economics* 123, no. 1 (2008): 425-440.

Donohue, John J., and Steven D. Levitt. "The Impact of Legalized Abortion on Crime." *Quarterly Journal of Economics* 116, no. 2 (2001): 379-420.

Foote, Christopher L., and Christopher F. Goetz. "The Impact of Legalized Abortion on Crime: Comment." *Quarterly Journal of Economics* 123, no. 1 (2008): 407–423.

Greenberg, David F. "Age, Crime, and Social Explanation." *American Journal of Sociology* 91, no. 1 (1985): 1-21.

Grogger, Jeffrey T. "Market Wages and Youth Crime." *Journal of Labor Economics* 16, no. 4 (1998): 756-91.

Hirschi, Travis, and Michael Gottfredson. "Age and the Explanation of Crime." *American Journal of Sociology* 89, no. 3 (1983): 552-584.

Johansen, Soren. "A Small Sample Correction of the Test for Cointegrating Rank in the Vector Autoregressive Model." *Econometrica* 70, no. 5 (2002): 1929-1961.

Johansen, Soren, and Katarina Juselius. "Maximum Likelihood Estimation and Inference on Cointegration with Application fo the Demand for Money." *Oxford Bulletin of Economics and Statistics* 52, no. 2 (1990): 169-210.

Joyce, Ted. "A Simple Test of Abortion and Crime." *Review of Economics and Statistics* 91, no. 1 (2009): 112-123.

Joyce, Ted. "Did Legalized Abortion Lower Crime?" *Journal of Human Resources* 39, no. 1 (2004): 1-28.

Joyce, Ted. "Further Tests of Abortion and Crime: A Response to Donohue and Levitt (2001, 2004, 2006)." *NBER Working Paper Series,* no. 12607 (2006).

Juselius, Katarina. *The Cointegrated VAR Model: Methodology and Applications.* Oxford and New York: Oxford University Press, 2006.

Kwiatkoski, Denis, Peter C.B. Phillips, Peter Schmidt, and Yongcheol Shin. "Testing the Null Hypothesis Against the Alternative of a Unit Root." *Journal of Econometrics* 54 (1992): 159-178.

Levitt, Steven D. "The Limited Role of Changing Age Structure in Explaining Aggregate Crime Rates." *Criminology* 37, no. 3 (1999): 581-597.

Levitt, Steven D. "Understanding Why Crime Fell in the 1990s: Four Factors That Explain the Decline and Six That Do Not." *Journal of Economic Perspectives* 18, no. 1 (2004): 163-190.

Levitt, Steven D. "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime." *American Economic Review* 87, no. 3 (1997): 270-290.

Marvell, Thomas B., and Carlisle E. Moody. "Age Structure and Crime Rates: The Conflicting Evidence." *Journal of Quantitative Criminology* 7, no. 3 (1991): 237-273.

O'Brien, Robert M., and Jean Stockard. "Can Cohort Replacement Explain Changes in the Relationship Between Age and Homicide Offending?" *Journal of Quantitative Criminology* 25, no. 1 (2009): 79-101.

Ralston, Roy W. "Economy and Race: Interactive Determinants of Property Crime in the United States, 1958-1995." *American Journal of Economics and Sociology* 58, no. 3 (2006): 405-434.

Reyes, Jessica W. "Environmental Policy as Social Policy? The Impact of Childhood Lead Exposure on Crime." *B.E. Journal of Economic Analysis & Policy* 7, no. 1 (Contributions) (2007).

Tang, Chor Foon, and Hooi Hooi Lean. "New Evidence from the Misery Index in the Crime Funcion." *Economics Letters* 102, no. 2 (2009): 112-115.

Table 1: The Long-Run Relationship Between the Murder Rate, the Share of Young People in the Population, and the Misery Index

Explanatory Variable	Engle-Granger			OLS	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
percent_1529	--	48.3074	34.5508	38.9056	32.7726
				(0.000)	(0.001)
misery	0.2487	--	0.1084	0.0385	0.0167
				(0.036)	(0.385)
*misery*I(year≥1960)*					0.0849
					(0.013)
time	0.1871	0.1406	0.1633	0.2054	0.1515
				(0.000)	(0.006)
$time^2$	-0.0018	-0.0011	-0.0014	-0.0019	-0.0014
				(0.000)	(0.024)
constant	0.3805	-7.8922	-6.1168	-7.2571	-4.9511
				(0.001)	(0.044)
AR Parameters:					
u(-1)				1.2027	1.2324
				(0.000)	(0.000)
u(-2)				-0.4113	-0.4164
				(0.000)	(0.000)
R-squared	0.6805	0.7623	0.7987	0.9601	0.9635
Number of Observations	75	75	75	73	73
Cointegration Tests:					
Lags Included in ADF Test	4	3	4		
Sample Size of ADF Test	70	71	70		
P-value for H0: No-Cointegration	0.5995	0.1665	0.0709		

Notes: p-values are in parentheses. No p-values are reported for the Engle-Granger estimates because they are not statistically reliable. *I(year≥1960)* is an indicator variable that is equal to 1 on and after 1960 and zero before that year.

Table 2: Statistics for 43 OLS Regressions with Varying Starting Dates for the Sample

	Coefficient Estimates		t-values	
Variable	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
percent_1529	1.1476	0.1814	2.2092	0.4390
misery	0.0856	0.0408	2.1739	0.6621

Figure 1: Time Series Plot of the Share of 15-29 Year-Olds and the Murder Rate

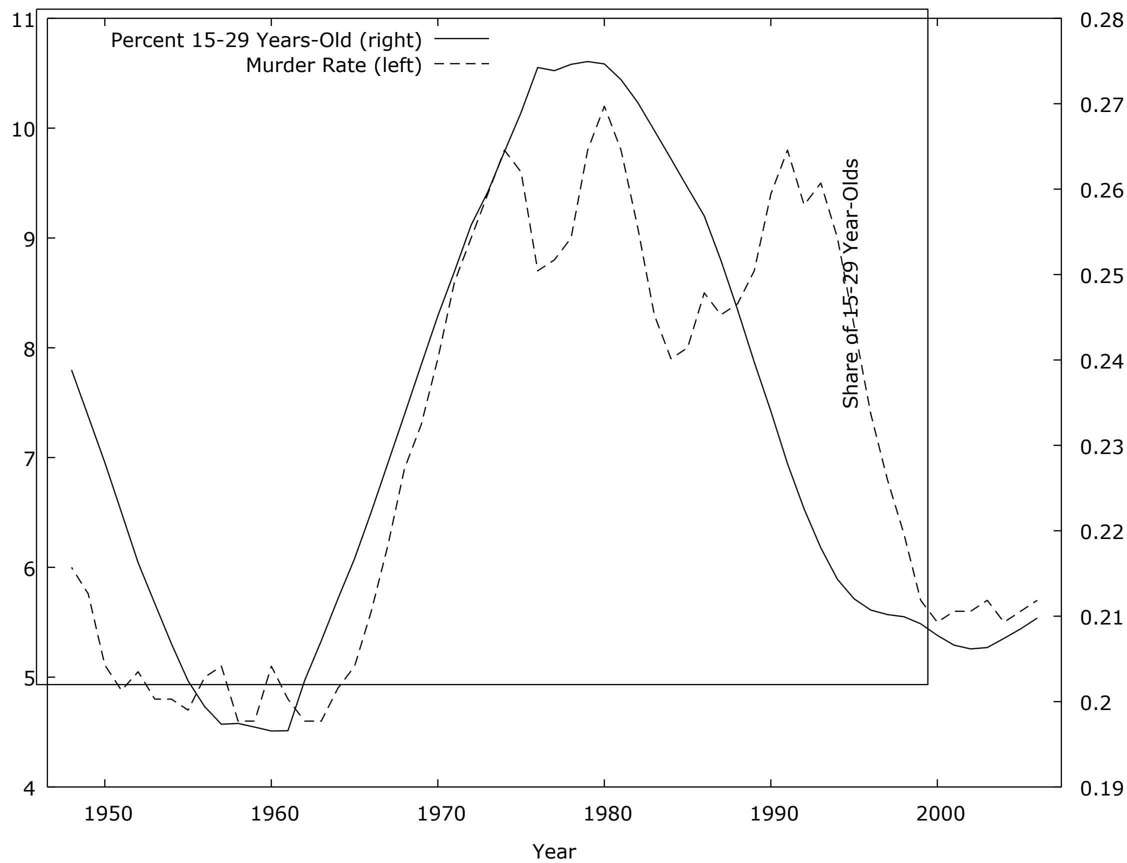

Figure 2: Time Plots of the Misery Index and Murder Rate