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An Analysis of the Relationship Between Employment and Crime

Deepak Mallubhotla '13
Illinois Wesleyan University, hmallubh@iwu.edu

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Abstract
The relationship between aggregate unemployment rates and the incidence of crime has been frequently analyzed (Cantor and Land, 1985; Bennett, 1991; Bushway, 2011). However, the result of this analysis has been inconsistent. This discrepancy could be related to the inconsistent application of both economic and sociological theory, as well as several methodological issues with previous research and literature (Bennett, 1991). Becker's 1968 paper describes crime as an individual decision made based on potential loss and gain. However, many prior analyses examine aggregate data, masking changes in individuals' situations behind aggregate numbers.

The importance of predicting crime for law enforcement and public policy can have a large significance and magnitude on informed decisions. This can both reduce the cost of law enforcement and increase the efficiency of anti-crime measures.

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I. INTRODUCTION

The relationship between aggregate unemployment rates and the incidence of crime has been frequently analyzed (Cantor and Land, 1985; Bennett, 1991; Bushway, 2011). However, the result of this analysis has been inconsistent. This discrepancy could be related to the inconsistent application of both economic and sociological theory, as well as several methodological issues with previous research and literature (Bennett, 1991). Becker's 1968 paper describes crime as an individual decision made based on potential loss and gain. However, many prior analyses examine aggregate data, masking changes in individuals' situations behind aggregate numbers.

The importance of predicting crime for law enforcement and public policy can have a large significance and magnitude on informed decisions. This can both reduce the cost of law enforcement and increase the efficiency of anti-crime measures.

Potential criminals include their own situations in their decision-making processes. In order to examine how changes in situation affect changes in crime rates, it is necessary to look at time series data to see the subject's response to changes. The longitudinal nature of time series analysis also allows for comparison between individuals. As a result, it is possible to make general statements about responses to economic conditions.

NLSY97 data was examined to see whether employment variables predict crime, with employment represented by both income and the number of weeks worked. Theory predicts that there are lagged effects of employment on crime, which is why both lagged and unlagged cases are examined. In order to validate the assumption that changes in employment cause changes in crime, rather than the other way around, the impact of lagged crime on employment variables is also tested. Employment is found to have a significant effect on crime, although the theory fails to explain the lagged effects of employment measures.

II. THEORY & LITERATURE REVIEW

Many of the economic theories of criminal activity draw from Becker's 1968 paper, analyzing crime as the result of rational choice. In his model, individuals consider the expected benefit of crime, taking into account the chance of success and the possible monetary gain. If the expected benefit is greater than the expected cost, which takes into account the chance of failure and the cost of being punished, the individual will commit a crime.

The expected benefit of crime depends on a variety of factors. For crimes such as theft or burglary, there is usually a clear monetary gain. However, the utility gained from many types of violent crime, including rape and murder, is usually not measurable. The expected benefit of crime should also depend on income and wealth; money has diminishing marginal effects on utility, so people with higher wealth or income benefit comparatively less from the same amount of capital.

The costs of crime offer a more direct relationship between employment status and crime. In general, the cost of crime is its punishment and depends on the chance of being caught. The costs include any fines for the crime and the opportunity cost incurred by imprisonment. While in jail, a person cannot earn the wages they would have earned if not in jail. There may also be a loss in future wages. With a conviction on record, it is harder to find higher paying jobs, which means that past crimes can lead to lost wages well into the future (Barak, 2009). Often included in other studies is a measurement of the utility gained by being honest or the cost of being dishonest. Many individuals associate immorality with crime, and incur a "moral cost" by committing a crime (Bourguignon, 2003).

If unemployed, a person earns no wages, and so loses no wages if in jail. This decreases the opportunity cost of committing crime. Additionally, if a person's wealth decreases while unemployed, the same financial benefit from a crime will have greater relative value. Both effects lead to a higher chance of committing crime.

Cohen and Felson (1979) predict additional effects on crime from unemployment. They base their theory around the idea that individuals tend to fall into routines. According to them, individuals who have fallen into routines while employed tend to stay in their routines immediately after losing employment. According to the routine activities theory, routines take a certain amount of time to change. Instead of changing their habits, Cohen and Felson claim that they the recently unemployed will tend to draw on savings for a short period of time to perpetuate their old routines while first unemployed, without changing their behavior. If conditions while unemployed are favorable for committing crimes, individuals will commit crimes only after taking time to break routines. Routine activities theory thus suggests that there is a lagged effect of unemployment on crime.

Christenson and Thornberry (1984) point out that it is important to also consider reciprocal effects. As mentioned above, committing a crime can make it more difficult to procure employment in the future. This not only increases the expected cost of current crime, decreasing crime rates, but also leads to lagged effects of crime on employment. Without testing for reciprocal effects, conclusions assuming the changes in crime could occur before changes in employment are invalid.

Theory predicts that both the number of weeks worked and income should correlate negatively to the probability that an individual commits a crime. Routine activities theory predicts that this correlation should be lagged. It is important to separately test for reciprocal effects, as they influence the validity of the forward relationship between employment measures and crime.

III. EMPIRICAL MODEL

By using longitudinal data, we can account for each individual's characteristics by looking at the likelihood of committing a crime changes over time. The NLSY97 has longitudinal data for a many individuals that include self-reported crimes and information about employment. In order to simplify the analysis, only three types of crime are examined: destruction of property, theft both above and below 50 dollars, and assault. The survey question about assault focuses on fights, which are more likely to offer a financial benefit than other types of violent crime, such as murder or rape. As Land (1985) finds, purely violent crimes such as murder or rape respond differently to changes in economic variables than other types of crime, partly because these crimes usually offer a psychological benefit, rather than a financial one. As a result, no other violent crimes are analyzed.

Self-reported crime data tends to underestimate the number of crimes committed (Mosher, et. al, 2002). Minor offenses are particularly liable to being under-reported; the inclusion of thefts below 50 dollars could skew the data. This problem is difficult to avoid for longitudinal data, as surveys rely on self-reported information.

When analyzing the chance of an individual committing a crime based on their current economic situation, the total number of crimes isn't as relevant as whether or not a crime was committed at all. If conditions make crime favorable, individuals should commit crimes as long as they continue to offer a net benefit. As a result, we look solely at whether or not an individual committed a crime in the survey year. This leads to a binary dependent variable. Although subjects tend to underestimate the number of crimes committed, they are more likely to accurately answer binary questions about crime (Mosher, et. al, 2002).

Income per week is included to take into account the potential opportunity cost of time in prison, as well as the lower relative benefit from committing crimes. Both effects should lead to a negative correlation between income and crime. The amount of employment is measured by the number of weeks worked each year. This doesn't discriminate between full-time and part-time workers. However, the amount of work per week is reflected in weekly income. These variables collectively represent employment.

Several other variables can also impact crime rates and are important to control for. As many authors have shown (Shelley, 1981), age has a strong negative impact on crime rates, an effect that is separate from correlations between age and other variables. Because age is known to have non-linear effects on crime (Shelley, 1981), age squared is included as well. Education is also measured. The subject's highest degree is used to

measure education, even if the survey year is before the subject obtained the degree. In these cases, the highest degree variable serves as a proxy for educational achievement, ranging from a high school education to a PhD, omitting the case of no high school or high school equivalent degree.

Because the dependent variable is a binary variable, a logistic regression model is used. The relationship is assumed to be multiplicative, as in Equation 1.

$$P = Emp*Income*ß$$

Here, P represents the odds of an individual committing a crime, Emp is the number of weeks employed and Income is income per week. The variable ß represents the product of other factors. Taking the logarithm, the following regression equation is created, Equation 2.

$$\ln P = \alpha\_0 + \alpha\_1 \ln Emp + \alpha\_2 \ln Income + \alpha\_3 Age + \alpha\_4 Age^2 + \alpha\_4 Female + \sum_i y_k HighestDegree_i$$

Here, the α_k represent the coefficients for the different variables. The y_k represents the coefficients for the collection of education dummy variables Highest $Degree_i$.

The logarithmic nature of Equation 2 makes the equation focus on the multiplicative assumption in Equation 1, which is equivalent to the assumption that the equation is linear in the proportional changes of the variables. This suggests that Equation 2 measures the individuals' responses to changes in variables. As a result, dummy variables are unnecessary for each individual in Equation 2.

Some survey questions are phrased in terms of the calendar year before the interview, while others are based on the duration since the last interview. Subjects who missed survey years are likely to report data with different scopes, making the data meaningless. In order to avoid these errors, all missing years and cases following missing years are excluded from the analysis.

In order to measure the lagged effect of employment variables on crime, another regression is run. According to the routine activities theory mentioned above, there should be a lagged effect of income and weeks worked on crime. As Thornberry and Christenson mention (1984), there are also reciprocal effects to consider. However, using unlagged crime rate variables to test such effects is mathematically a re-arrangement of the regression in Equation 2. In order to measure the reciprocal effects, regressions are run to measure the impact of crime on future economic variables by lagging the crime variable. Equation 3 shows the regression equation for the number of weeks worked.

$$WeeksWorked = [(\alpha+ß)]\_0 LagCrimeInYear + ß\_1 Age + ß\_2 Age^2 + ß\_3 Income + ß\_4 Gender + \sum\_i y\_i HighestDegree\_i + ß\_5 LagWeeksWorked$$

These regressions are simple linear regressions. They are run for both the length of employment and weekly income. The other variables are included for the same reason as in the first set of regressions. Income and WeeksWorked are lagged in their own regressions, and unlagged in the others. Including a lagged dependent variable as an independent variable for time-series data reduces autocorrelation. Along with variables like education and age, income can be seen as a measure of productivity, which influences the length an individual, is hired. If productivity is taken to explain the length of employment, then the length of employment cannot be used in the regression for productivity, as it gives no new information. Equation 4 shows the income regression.

$$Income = [(\alpha+ß)]\_0 LagCrimeInYear + ß\_1 Age + ß\_2 Age^2 + ß\_3 Gender + \sum\_i y\_i HighestDegree\_i + ß\_4 LagIncome$$

Table 1 gives some descriptive statistics for the data. The ages range from 13 to 30, with every subject within a couple years of the same age. For both WeeksWorked and income earned, the means are decreased by the number of cases with no reported employment.

IV. RESULTS

Table 2 presents the results of the unlagged crime regression. The coefficients are the log odds ratios for each independent variable. As expected, both the number of weeks worked and employment show a significant negative relationship with the likelihood of committing a crime. Because the regression is run in log terms, the magnitudes of the coefficients represent the powers of the terms multiplied. More importantly, the significance of the coefficients points to a multiplicative relationship between these independent variables and crime rates. To interpret the log odds ratio, the coefficient is exponentiated, yielding the odds ratio,

which is then converted to a probability.

The odds ratio for number of WeeksWorked means that for an increase by a factor of e in the number of weeks worked, the odds of committing a crime decrease by 10 percent, meaning that the individual is 2.4 percent less likely to commit a crime. Similarly, when income increases by a factor of e, the individual's chance of committing a crime decreases by around 2.2 percent compared to even odds. This comparison to even odds represents the exponentiation of the odds ratio mentioned earlier. However, the change in probability for a given change in odds is nonlinear, and so the comparison to even odds serves only as an illustrative tool.

Because there is a finite number of weeks in a year, there is a limit to how low weeks worked can decrease the odds ratio for committing a crime. Compared to an identical individual with no employment in a year, an individual with 52 weeks worked will be around 10 percent less likely to commit a crime. Given the cost required to employ someone throughout the year, this is a relatively small decrease in crime rates.

The education dummy variables are generally as expected, with more education leading to lower crime, with two exceptions. The variables range from a GED, the first case, to a professional degree, the seventh case, which omits the case of no GED and no high school. Subjects with a PhD and subjects with a GED show a higher chance of committing a crime than those without degrees, which contradicts the hypothesis that education leads to higher crime. The result for doctorates is small and very insignificant, which makes sense given that there are very few individuals in the study with a highest degree of a PhD. However, the results for GEDs are significant to the .05 level. There are many possible explanations for this: individuals who took the time to get a GED could be the same individuals who are more willing to take risks for economic gain, for instance. For the other education levels, the results make sense: as education level rises, the chance of committing crime drops.

The age results also support Shelley's empirical findings (1981). As discussed above, age should have a negative, but diminishing, effect on crime rates. The results show a strong negative impact of age on crime; however, age squared shows a slight, but significant, positive correlation with the chance of committing crime. This nonlinear term, although small, significantly reduces the marginal effect of age for the ranges of ages in the study. Theoretically, the turning point at which the nonlinear effects dominate and higher age leads to more crime is around 26 with the data given. However, this is unreliable simply because of the limited age range of the study. With a highest age of 30, there are too few points above the age of 26 to make a claim about a turning point; however, it is notable that a turning point was seen at all, and gives opportunity for further analysis with larger data sets.

Gender also has a significant coefficient, showing that women are less likely to commit crimes. Compared to even odds, the probability of committing a crime decreases by more than .13 for women, an effect that supports other criminological research (Shelley, 1981).

Table 3 contains the regression results for the model with only lagged employment variables included. Most of the coefficients are similar to those obtained from the first regression. However, the lagged income and lagged number of WeeksWorked variables both correlate positively to crime. As mentioned by Shelley (1981) and Cohen and Felson (1979), this could be because individuals compare their current position to past positions, and once an individual has been more successful, they are willing to take greater risks to continue their success.

Table 4 summarizes the regression with both the lagged and non-lagged cases. The same patterns seen earlier are seen here as well. The impact of age on crime is much larger, while the coefficient for gender is smaller.

Compared to the first and second regressions, the coefficients for the employment variables are greater in magnitude. This can be interpreted in a variety of ways. The positive sign of the lagged variables suggests that to a certain extent, the amount that an individual's income or employment has improved within a year plays a role in determining when to commit crime.

The results for the reciprocal effects are summarized in Tables 5 and 6. For the regression with only lagged crime rate, we see that most coefficients have the expected sign. As expected, as age increases the number of weeks worked increases as well. Diminishing returns for age suggest that age squared should reduce the impact of age, with a coefficient with the opposite sign. Age squared here has a slight but significant negative effect, as expected. The education dummy variables all have positive effects, but interestingly, higher education

has less of a positive impact than an associate degree or junior college.

As can be seen, lagged crime rates have a negative impact on the number of weeks worked. However, this effect is both small, and statistically insignificant. This suggests that crime does not have a strong lagged effect on employment.

Table 6 summarizes the results for the income regression. For income per week, crime has an even smaller, statistically insignificant effect. The same is true for unlagged crime: the effect is relatively small and insignificant. This suggests that the result obtained by Thornberry needs to be revisited, as the effects of crime on employment and wages are small.

V. CONCLUSIONS

As expected, employment correlates negatively to crime. Assuming that this relationship is a causal relationship, this suggests that increasing employment leads to lower crime rates. Because the relationship is logarithmic, the effect has diminishing marginal returns, meaning that increasing employment is most effective for individuals who are unemployed or have little employment. The same is true for income.

The results support Becker's rational choice theory. However, for the lagged variables, the effect is positive, and fails to show evidence for routine activities theory, which claims that Becker's predicted negative effect would be lagged. The positive effect observed is statistically significant. Moreover, the effect's magnitude increases when the unlagged variables are included as well, suggesting that, to a certain degree, the difference between current and past employment status is an important determinant of crime. This could be because of the importance of comparison for individuals: the routine activities theory describes a necessary lag in time for routines to be broken, but, rather than the change of routine, the change in lifestyle necessitated by changes in employment may be more relevant.

For the reciprocal effects described by Thornberry (1984), the results are mixed. The effects of crime on the number of weeks worked and on weekly income are both small and statistically insignificant. This suggests that the relationship is more complex than the description of either routine activities theory or the reciprocal effect theory.

Shelley (1981) mentions that given the complexity of the causes of crime, it is impossible to come up with coherent prediction. However, Becker's rational choice theory remains well supported by the evidence, which justifies its continued use (Levitt and Miles, 2006) in analyzing crime.

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VII. APPENDIX

Table 1: Descriptive Statistics

	Minimum	Maximum	Mean	Std. Deviation
AnyCrimesinYear	0	1	.19	.389
WeeksWorked	0	60	24.84	21.035
IncomePerWeek	0.00	44091.00	223.6962	814.42017
HighestDegree	0	7	2.21	1.375
Gender	1	2	1.47	.499

Table 2: Unlagged Employment

B	S.E.	Wald	df	Sig.	Exp(B)	
LnWeeksWorked	-.159	.025	39.649	1	.000	.853
LnIncomePerWeek	-.063	.016	14.608	1	.000	.939
HighestDegree			140.047	7	.000	
HighestDegree(1)	.196	.075	6.735	1	.009	1.216
HighestDegree(2)	-.165	.065	6.344	1	.012	.848
HighestDegree(3)	-.180	.089	4.065	1	.044	.835
HighestDegree(4)	-.468	.073	41.508	1	.000	.626
HighestDegree(5)	-.540	.117	21.127	1	.000	.583
HighestDegree(6)	.059	.389	.023	1	.879	1.061
HighestDegree(7)	-.728	.229	10.089	1	.001	.483
Age	-.744	.062	144.518	1	.000	.475
Gender(1)	-.470	.038	156.780	1	.000	.625
AgeSquared	.014	.001	94.939	1	.000	1.014
CrimeLastYear	1.414	.038	1361.635	1	.000	4.111
Constant	8.400	.615	186.763	1	.000	4445.093

a. Variable(s) entered on step 1: LnWeeksWorked, LnIncomePerWeek, HighestDegree, Age, Gender, AgeSquared, CrimesLastYear.

Table 3: Lagged Employment						
B	S.E.	Wald	df	Sig.	Exp(B)	
LagLnWeeksWorked	.180	.023	60.543	1	.000	1.198
LagLnIncomePerWeek	.213	.013	254.126	1	.000	1.237
HighestDegree			154.125	7	.000	
HighestDegree(1)	.141	.075	3.559	1	.059	1.151
HighestDegree(2)	-.284	.064	19.885	1	.000	.753
HighestDegree(3)	-.365	.090	16.555	1	.000	.694
HighestDegree(4)	-.522	.072	53.331	1	.000	.593
HighestDegree(5)	-.737	.121	37.354	1	.000	.478
HighestDegree(6)	-.355	.475	.559	1	.455	.701
HighestDegree(7)	-.638	.221	8.365	1	.004	.528
Age	-1.084	.054	403.658	1	.000	.338
Gender(1)	-.373	.038	97.190	1	.000	.689
AgeSquared	.020	.001	228.190	1	.000	1.020
CrimeLastYear	1.688	.043	1561.462	1	.000	5.411
Constant	10.326	.578	319.232	1	.000	30524.587
a. Variable(s) entered on step 1: LagLnWeeksWorked, LagLnIncomePerWeek, HighestDegree, Age, Gender, AgeSquared, CrimeLastYear.						

Table 4: Unlagged and Lagged Employment						
B	S.E.	Wald	df	Sig.	Exp(B)	
LagLnWeeeksWorked	.259	.036	52.845	1	.000	1.296
LagLnIncomePerWeek	.261	.020	173.035	1	.000	1.298
LnWeeksWorked	-.300	.039	60.439	1	.000	.741
LnIncomePerWeek	-.186	.025	53.755	1	.000	.830
HighestDegree			85.394	7	.000	
HighestDegree(1)	.002	.106	.000	1	.985	1.002
HighestDegree(2)	-.377	.091	17.180	1	.000	.686
HighestDegree(3)	-.496	.122	16.540	1	.000	.609
HighestDegree(4)	-.602	.099	36.586	1	.000	.548
HighestDegree(5)	-.755	.156	23.561	1	.000	.470
HighestDegree(6)	-.587	.578	1.031	1	.310	.556
HighestDegree(7)	-1.136	.311	13.325	1	.000	.321
Age	-.970	.088	121.764	1	.000	.379
Gender(1)	-.355	.051	48.502	1	.000	.701
AgeSquared	.018	.002	81.550	1	.000	1.018
CrimeLastYear	1.742	.053	1096.264	1	.000	5.710
Constant	10.327	.904	130.507	1	.000	30551.427
a. Variable(s) entered on step 1: LagLnWeeksWorked, LagLnIncomePerWeek, LnWeeksWorked, LnIncomePerWeek, HighestDegree, Age, Gender, AgeSquared, CrimeLastYear.						

Table 5

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-69.281	2.500		-27.715	.000
	CrimeLastYear	-.257	.190	-.006	-1.351	.177
	AgeSquared	-.148	.005	-1.325	-27.898	.000
	IncomePerWeek	-.003	.000	-.140	-32.567	.000
	Age	7.763	.233	1.593	33.386	.000
	KEY!SEX(SYMBOL)1997	-.288	.145	-.008	-1.992	.046
	GED	1.218	.297	.024	4.106	.000
	High School	4.826	.248	.142	19.422	.000
	Associate/Junior College	6.348	.355	.094	17.875	.000
	Bachelor's	4.719	.277	.112	17.064	.000
	Master's	4.110	.441	.045	9.322	.000
	PhD	2.060	1.923	.004	1.072	.284
	Professional Degree	1.028	.844	.005	1.218	.223
	LagWeeksWorked	.175	.003	.278	62.440	.000

a. Dependent Variable: Weeks Worked

Table 6

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-837.039	146.285		-5.722	.000
	CrimeLastYear	-2.329	11.394	-.001	-.204	.838
	AgeSquared	-.084	.306	-.015	-.273	.785
	WeeksWorked	-8.097	.266	-.157	-30.497	.000
	Age	68.495	13.539	.282	5.059	.000
	KEY!SEX(SYMBOL)1997	-68.853	8.368	-.041	-8.228	.000
	GED	46.472	17.255	.019	2.693	.007
	High School	106.984	14.594	.064	7.331	.000
	Associate/Junior College	156.113	20.653	.047	7.559	.000
	Bachelor's	99.585	16.192	.048	6.150	.000
	Master's	68.071	25.593	.015	2.660	.008
	PhD	91.678	107.206	.004	.855	.392
	Professional Degree	16.854	49.480	.002	.341	.733
	LagIncomePerWeek	.047	.005	.043	8.592	.000

a. Dependent Variable: IncomePerWeek