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Economic Fluctuations and Crime: Temporary and Persistent Effects

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Abstract:

Purpose: Since the literature on the effect of the unemployment rate as reflection of economic fluctuations on crime shows an empirically ambiguous effect, this study argues that a new way of modelling the dynamics of unemployment and crime by focusing on the transitory and persistent effect of unemployment on crime helps resolve this ambiguity.

Design: Panel data for US states from 1965-2006 are examined using the Mundlak (1978) methodology to incorporate the dynamic interactions between crime and unemployment into the estimation.

Findings: After decomposing the unemployment effect on crime into a transitory and persistent effect, evidence of a strong positive correlation between unemployment and almost all types of crime-rates is unearthed. This evidence is robust to endogeneity and the controlling for cross-panel correlation and indicators for state imprisonment.

Originality: The paper is the first to examine the dynamics of the interaction of crime and economic fluctuations using the temporary and persistent effects framework of Mundlak (1978). In one set of estimates, one can evaluation both the short- and long-run effects of changes of unemployment on crime.

JEL: K42, J6, C33

Keywords: Crime, Unemployment, Panel models, Hausman-Taylor specification.

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Economic Fluctuations and Crime:

Temporary and Persistent Effects

'Nothing tends so much to corrupt mankind as dependency, while independency …increases honesty of the people. The establishment of commerce and manufactures, which brings about independency, is the best police for preventing crimes.'

Adam Smith, 1763, *Lectures on Justice, Police, Revenue and Arms*, edited by Edwin Cannan (1896).

I. Introduction

On an intuitive level, one should expect a strong relationship between crime and economic fluctuation socio-economic status. During a downturn, income decreases and poverty and unemployment rises leading to social exclusion and deprivation which induces stress and frustration. These make for a frayed social fabric that causes crime to increase. In addition, a sharp change in income and wealth may provide an increasing motivation and growing set of opportunities criminal behavior.

The above conjectures have provoked a substantial body of research starting early in the twentieth century (Bonger, 1916). Thomas (1927) provides evidence of a strong negative correlation between various types of crime rates and the business cycle, and her results were confirmed by Henry and Short (1954). Since then there has been a very large literature on the crime-business cycle relationship, although much of the investigations within the discipline of economics into the relationship have often found that the positive link between unemployment and crime is weak at best and often there are results showing no effect of unemployment rates on crime.

The standard theoretical framework underpinning the crime – unemployment relationship in economics is founded on the work of Becker (1968) and Ehrlich (1973, 1975). In general, these approaches model the supply of criminal offences which is determined on two key factors. The first involves the probability of getting caught and the severity of punishments if convicted of a crime. If these increase, one would expect that individuals will be less likely to try to commit a crime. The second issue is the person's preferences toward criminal activity. While difficult to measure directly, an important aspect of this factor is the alternative to crime – namely, labor market participation. If employment and wages are generally high, the opportunity cost of participating in criminal activity is high. Conversely, if there is substantial unemployment, the opportunity cost of spending time in criminal activity is low and should lead to higher crime rates.[1]

Using this theory as base, a number of economists have attempted to determine empirically the relationship between crime and unemployment. Early comprehensive literature reviews by Tarling (1982), Chiricos (1987), Freeman (1983) and Box (1987) highlight the conclusion that there appears to be only a moderate positive causal link between unemployment and crime. This conclusion is further confirmed in later work by Freeman (1992, 1995, and 1999) who finds that the link between crime and unemployment is fragile at best. In more recent work, Choe (2008), in investigating the effects of inequality on crime, generally finds no statistically significant effect of unemployment on crime rates using a US state-level dataset from 1995-2004 while the positive relationship between unemployment and crime is confirmed by Lin (2008). Gould *et al*. (2002) also report that both wages and unemployment are related to crime, but that wages play a larger role in the crime trends over the last few decades.

Although the above review focuses on the research in the economic discipline of the link between crime and unemployment, discourse in criminology and other social sciences shows other pathways though which unemployment can affect crime. Candor and Land (1985) develop a theoretical model to propose that the aggregate unemployment rate may affect criminal activity by increasing levels of criminal motivation and by influencing the availability and vulnerability of criminal targets and, thus, the number of criminal opportunities.[2] Furthermore, other criminologists focus on the psychological effects of social exclusion on forming individuals' behaviors. Thus, Sampson and Laub (1993), Lemert (1967) and Farrington (1977) suggest that the strength of social bonds can explain participation in criminal activities and that people may become locked into a cycle of offending since if they are caught and punished are deliberately stigmatized by the criminal justice system. Bourguignon (1998) shows that crime rates are positively correlated with income inequality and relative poverty.[3] Furthermore, Rosenfeld and Fornango (2007) propose that consumer sentiment has significant effects on robbery and property crime rates and they find that it significantly affects the crime decline during the 1990s.

In other research, criminality has been found by Sampson and Laub (1993) to be dependent upon social structure and social networks while Warr (2002) finds that influence of peers is also important. Thus, the individual's position in the structure of society influences his or her criminal behavior. However, all of these factors are influenced by unemployment since the strength of social bonds, the level of participation in society and positive self-image and social behavior of peers are determined, at least in part, by the level of deprivation, unemployment and social exclusion which are functions of both the duration and the severity of the economic downturns.

Furthermore, the 2001 special issue of the *Journal of Quantitative Criminology* provides numerous important insights for the theoretical and empirical investigation of crime–unemployment relationship, offering multiple explanations of the fragility of the crime unemployment relationship primarily by drawing attention to the statistical approaches which are used in the literature. For example, Greenberg (2001) uses a cointegration approach to identify the long term relationship between crime and unemployment as reflected in the prevailing lag structure. In contrast, Britt (2001) questions the overall suitability of this particular methodology used by Greenberg (2001).

Later in the same issue of the journal, Levitt (2001) advocates using natural experiments and disaggregated panel estimation which highlights a common theme in the literature by using panel datasets to estimate the unemployment-crime relationship. Doyle *et al*. (1999), Raphael and Winter-Ebmer (2001), Levitt (2004) and Mocan and Bali (2010) use state-level data to find unemployment effects on property crime rates (with moderate or no effects on other crime rates in the cases where they examine other types of crimes). In similar line, Arvanities and DeFina (2006) find that economic downturns affect property crimes and robbery, and Phillips and Land (2012) find a strong and consistent pattern of unemployment on burglary, larceny and motor vehicle theft crime via both opportunity and motivation effects . Interestingly, Andresen (2012) finds that motivation matters in the long run whereas opportunity (guardianship) matters in the short run. Using a quasi – experimental analysis, Bushway, Cook and Phillips (2012) using data over 13 business cycles, investigate the effects of short term fluctuations of unemployment on crime establishing that an economic contraction *causes* an increase in burglary and robbery rates.

Thus, this brief review of the literature suggests several key points. The papers suggest that improving the wider socioeconomic context in which individuals live can reduce crime and decrease crime participation. Hence, it is not only that the poverty or deprivation of individual families leads to crime but it is also the wider context of social stress and disorder caused by unemployment that dissolves the social fabric during the downturns which causes the increase in criminality. In this sense, economic prosperity '*is the best police for preventing crimes'* (Smith, 1793).

Furthermore, the literature also suggests a careful econometric modelling of the relationship between crime and unemployment. While much of the economics literature examines a contemporaneous relationship between crime and unemployment, criminology and other social sciences literatures suggest that other factors are important. In particular, factors such as social exclusion and prolonged deprivation suggest that there may be long run effects that need to be investigated. Even when time is recognized to be a factor (e.g. as in Andresen, 2012), it is useful for policy reasons to distinguish and model simultaneously both the transitory and persistent effects of unemployment on crime. Thus, this paper proposes an econometric methodology that decomposes the unemployment effect on crime into a transitory and persistent effect highlighting the dynamic nature of this relationship for different types of crime namely violent crime, property, murder, rape, robbery, aggravated assault, burglary, larceny theft and vehicle theft. It shows that the standard way of investigating the relationship of using a fixed effects methodology to link crime rates and unemployment rates can be modified to generate the intuitive and theoretical effects between crime and the health of the economy.

Using crime data for US states over a 40 year period, it is found that there is a strong positive relationship between unemployment and a wide range of different crimes. In particular it is also shown that the persistent effect of unemployment rates has a particularly large impact on crime rates, highlighting that the factors that relate to long term unemployment are key policy issues to examine when looking to mitigate crime rates.

II. Data and Descriptive Statistics

In order to examine the issues discussed above, data on crime rates, unemployment rates, and other covariates are collected at the US state level from 1965 to 2006. Several different categories of crime rates per 100,000 people from the Unified Crime Reports are used:[4] violent crime, property crime, murder, rape, robbery, aggravated assault, burglary, larceny theft, and vehicle theft. Unemployment rates, the proportion of a state's population that are in various age ranges, the proportions which are white, African-American, or Hispanic, the proportions with no high school, high school, or college degrees, the proportion of adults who are divorced and the proportion of single female headed households with minors are obtained from the US Bureau of Labor Statistics website (www.bls.gov) or from Flood *et al*. (2015). A quadratic specification of time trends is also used in the regressions.

Table 1 reports descriptive statistics on crime rates. The first column reports the average crime rates across all states and years. The highest crime rates are property crime and larceny theft, and the lowest are rape and murder. To see if there are differences by unemployment rates, the sample is disaggregated in two ways. First, the sample is split by whether the unemployment rate of the specific year is below or above of the overall (unweighted) median unemployment rate for all states and years. For each crime-rate type, the rate is higher when the unemployment rate is above the median, particularly for violent crime, murder, and robbery.

Of course, states vary in their levels of unemployment through time in systematic ways. An alternative comparison is to examine whether there are differences in crime rates if a state's unemployment rate is below or above the state's average unemployment rate over the period 1965-2006. Using this comparison, the average crime rates are reported in the final two columns of Table 1. The differences in crime rates between high and low unemployment rates time periods are much smaller compared to the former comparison but generally confirm the previously described pattern. When actual unemployment is above the average state unemployment rate, the crime rate is higher compared to the case where actual unemployment is below the average state unemployment rate for violent crime, murder, robbery, aggravated assault, and vehicle theft. For the other crime-rate types, crime is (generally slightly) higher during low unemployment times.

III. Methodology and Regression Results

The above evidence relies on averages and ignores the effect of possible confounding factors, such as demographic makeup of the state and measures of the 'social fabric' of the state. In order to control such confounding factors a more rigorous analysis is required. This section describes several different empirical methodologies to investigate whether unemployment is correlated with higher or lower crime rates, *ceteris paribus*. Since this paper utilizes panel data, the estimating equation has the form:

$$C_{jt} = X_{jt}\beta + U_{jt}\gamma + I_{jt}\delta + s_j + \varepsilon_{jt} \tag{1}$$

where for state j and year t, C is (the log of) a crime-rate type, X is a vector of demographic controls for the age, race, educational characteristics of each state and a time trend, U is the unemployment rate approximating the fluctuation of economic fortunes, and I is per capita income in each state. The last two terms, s and ε, are unobserved components of the error term, although the former is specific to a state.

A. Basic Specification

The standard empirical specification with panel data is to assume that the unobserved state-specific component of the error term has a fixed-effect relationship with the dependent variable. Thus, the estimation of equation (1) would imply estimating a set of state-level fixed effects.

The coefficient on the unemployment rate and per capita income (divided by 1000) for each crime type are reported in columns (1) and (2) of Table 2. Interestingly, after controlling for state fixed effects and clustering on the state level panels, most of the coefficients on the unemployment rate turn out to be negative. This indicates that as unemployment rates increase, crime decreases for all crime types except aggravated assault. However, in only a few instances is the coefficient on the unemployment rate statistically significant (property crime, robbery and burglary). Likewise the per capita income results show a negative relationship, indicating that increased income is correlated with decreased crime rates. However, again, it is statistically significant for only a few crime measures – violent crime, property crime, robbery, burglary and vehicle theft. Thus, these results are in line with the overall conclusion of Doyle *et al*. (1999), Raphael and Winter-Ebmer (2001), Levitt (2004), and Mocan and Bali (2010who find similar results for the property crime-unemployment relationship. Furthermore, Phillips and Land (2012), Andresen (2012), and Arvanities and DeFina (2006) find similar relationships for burglary and Andresen (2012) for robbery.

B. Transitory and Persistent Effects of Unemployment on Crime Rates

While the fixed-effects methodology is a standard approach, it exhibits some important and well-known shortcomings. First, it assumes that the state effect is fixed over time, possibly a strong assumption if there had been changes in crime policy at the state level over the time period. Second, any time invariant effect is subsumed into the fixed effect, making the fixed effect economically uninterpretable as it is just the sum of any and all the state specific fixed effects. Although an alternative specification that addresses the shortcomings of the fixed effects estimator would be to model s_j as a random effect, it has problems of its own, namely that it assumes that

$$E(s_j|X_j, U_j, I_j)=0, \tag{2}$$

which is unlikely to be the case.

Mundlak (1978), however, offers a compromise between the two assumptions (also echoed by Greene, 2008, pp. 209-10) by specifying equation (2) as follows:

$$E\left(s_j\middle|X_j,U_j,I_j\right)=\bar{X}_j\beta^m+\bar{U}_j\gamma^m \tag{3}$$

where the bar over the variable vector indicates the mean value of the variable for the state. If one substitutes equation (3) into a random effects form of equation (1), the specification of equation (1) becomes:

$$C_{jt}=X_{jt}\beta+U_{jt}\gamma+I_{jt}\delta+\bar{X}_j\beta^m+\bar{U}_j\gamma^m+\varepsilon_{jt}+(s_j\text{-}E\left(s_j\middle|X_j,U_j,I_j\right))$$

or

$$C_{jt}=X_{jt}\beta+U_{jt}\gamma+I_{jt}\delta+\bar{X}_j\beta^m+\bar{U}_j\gamma^m+\varepsilon_{jt}+u_j. \tag{4}$$

As Greene (2008) states, this retains the random effects specification but should also appropriately deal with the problem of any correlation between the unobserved effects (particularly s_j) and the regressors.[5]

The specification of equation (4) reveals some dynamics of the unemployment – crime relationship without having to specify a lag structure, a problematic issue as pointed out by Greenberg (2001). Interestingly, Egger and Pfaffermayr (2002), using Monte Carlo simulations on the properties of the Mundlak (1978) specification, show that this specification can be viewed as an approximation of a general dynamic autoregressive distributed lag model. Thus, they show that it provides an approximation of the temporary and persistent effects of the decomposed variables, when inference in a dynamic model is not feasible. They report that it is a representation of a model with lagged exogenous variables where the unspecified lag dynamics are fully compensated by the inclusion of the group means.[6] Here to formally model this, equation (4) can be transformed to reveal the dynamics of the effects of the key variable of interest, the unemployment rate, on crime rates. In this transformation, proposed by Van Praag *et al.* (2002), the terms $U_j\gamma + \overline{U}_j\gamma^m$ can be re-specified into $(U_{jt} - \overline{U}_j)\gamma + \overline{U}_j(\gamma + \gamma^m)$. This allows an explicit decomposition of the effect of unemployment into two distinct effects. Differences across states in the average unemployment rate proxy the *persistent* effect (estimated by the coefficient $\gamma+\gamma^m$) and the deviations from the average unemployment rate, $(U_{jt} - \overline{U}_j)$ proxy *temporary* effects (estimated by the coefficient, γ).[7] Note that in this methodology, the relative importance of unemployment on crime rates regarding both a transitory and a persistent effect can be assessed simultaneously in one equation.

What is the economic intuition of this decomposition? Holding per capita income constant, one might expect that the impact of a downturn approximated by an increase in the unemployment rate might be cumulative and the effects of a change in the economic fortunes on crime rates might be felt for many years after the event of the rise of the unemployment rate. This could be the case regardless of the pathway that unemployment impacts crime. For example, because unemployment insurance mitigates the drop in income for at least 26 weeks, long duration unemployment would exhaust these benefits, making the need for income greater. Likewise, it may take time for the social fabric to fray, so temporary changes in unemployment may not have as much of an effect as a more persistent change in the unemployment rate. The effect of an economic downturn on crime may take a long time to manifest itself, and, thus, one should not expect the only effect of unemployment on crime to be of the contemporaneous nature modeled above. It is important to note that this is also consistent with the criminology literature reviewed earlier which stresses the persistent deprivation and inequality effects on crime. These should not be expected to be contemporaneous, but that they play out their impact on crime rates over the long term.

Table 3 contains the results from this Mundlak specification.[8] The results are somewhat different than in the fixed-effects results. For the unemployment coefficients there are fewer estimated negative relationships for the transitory results (that is, the coefficient on the deviation from the state average unemployment rate). Only the transitory effects of unemployment for property crimes and burglary remain negative and statistically significant. Interestingly, the persistent effect of unemployment shows a positive relationship in nearly every case. Specifically in each case where the coefficient is statistically significant, it is positive (e.g. violent crime, murder, robbery, aggravated assault and vehicle theft). Finally, it is important to note that the relative size of the coefficients is much different, with a change in the persistent effect having a larger marginal impact on crime than a transitory change in unemployment effects. The effects of income, as in the fixed effect estimations, continue to indicate a negative correlation where increased income is correlated with falling rates of crime.

While the Mundlak specification attempts to bridge the fixed- and random-effects models, there are still potential problems with this methodology. As Hausman and Taylor (1981) point out, one particular issue might be that the key variables may be correlated with the state-level random effect, u_j. If this is the case, then the results from the previous specifications would be biased because of endogeneity. Fortunately, the Hausman and Taylor (HT) correction is very similar in specification to the Mundlak specification, and so the HT procedure can be used to test whether the results in Table 3 are robust to this type of endogeneity, assuming that the transitory and persistent effects of unemployment and per capita income are the endogenous variables.[9] To establish the exogeneity of the instruments used in the HT method, an overidentification test using a Sargan-Hansen statistic is implemented (Schaffer and Stillman, 2010). The results of this test are given in column (4) of Table 4. In every case, the test statistic is small enough where the exogeneity of the instruments is not rejected at the conventional five percent level. Thus, the HT method is appropriately correcting for endogeneity.

The first three columns of Table 4 contain the results from the HT procedure that assumes that the transitory and persistent effects of unemployment and income are endogenous.[10] In general, the effect is the slight increase of the statistical significance of the transitory effect of unemployment in reducing some crime rates so that these results look similar to the results from the fixed-effects regression reported in Table 2. From Table 3, the transitory unemployment variable is significant only for property , robbery and burglary crimes,. However, when the persistent effects of unemployment on crime corrected for endogeneity, the coefficients are significant and positive for all types of crime except for violent crime and vehicle theft. The important change is the increase in the size of the coefficient – making an already high marginal effect even more pronounced.[11] As before, income is still generally negatively correlated with crime, with highly statistically significant coefficients – violent crime, property crime, rape, robbery, burglary and vehicle theft.

C. Robustness Check 1: Controlling for Cross-panel Correlations

One key assumption of fixed- and random-effects estimation procedures is that there should be no cross-sectional correlations in the data. That is, in terms of equation (1), to obtain efficient estimates, $cov(\varepsilon_{jt},\varepsilon_{is})=0$ for $j\neq i$ and $t\neq s$. If this condition is violated then, while the estimated coefficients will be unbiased the standard errors would not be correct.

To examine this issue, two tests are conducted. First, correlations in the errors ($cov(\varepsilon_{jt},\varepsilon_{is})$) across the 50 states and Washington, DC are estimated. Columns (1) and (2) of Table 5 contain the percentage of correlations that are significant at the 10 and 5 percent level, respectively. It is clear from this table, that the cross-sectional errors are often significantly correlated. At the ten percent level of significance, at least 47 percent of the correlations are statistically significant (up to a high of nearly two-thirds of the correlations for robbery). At the five percent level, at least 40.2 percent of the correlations are statistically significant (up to a high of 60.5 percent for robbery). These are very large numbers of significant correlations indicating cross-panel correlation. Second, a more formal test of the presence of the cross panel correlations comes from Pesaran (2004) who proposes a parametric test of whether the cross panel independence of the data.[12] In each case as shown in column (3), for all crime regressions, the z-statistic from the test has a p-value is less than 0.0001. Given these statistics, it is likely that cross panel correlations need to be taken into account in the estimation procedure.

The most direct way of correcting for the cross panel correlation is to use the Feasible Generalized Least Squares (FGLS) approach, which can be specified to control for cross-panel correlations. Unfortunately, the use of this procedure is not without its problems. On the one hand, Wooldridge (2002, p. 162) indicates that if there is cross-panel correlation, FGLS is more efficient than any other estimator that assumes no correlation (also echoed in Greene, 2000, p. 470ff). On the other hand, coefficient estimates from FGLS may not be the same as those obtained from OLS or fixed effects estimations because the calculation of the coefficients is weighted by an estimated variance-covariance matrix.[13] Thus correcting for the cross panel correlation can lead to better standard errors, but can generate differences in the coefficient estimates.[14]

Table 6 contains the results from the estimated coefficients from this estimation. Interestingly controlling for these correlations explicitly suggests that not only are most of the persistent effects of unemployment positive on crime (except for property crime and larceny theft), but so are the transitory effects. The effects of income are somewhat more mixed, as some correlations are positive (violent crime, murder, rape, robbery, aggravated assault and vehicle theft) while others are negative (e.g. property crime, burglary and larceny theft).

D. Robustness Check 2: Controlling for Imprisonment Effects

The economics literature reviewed earlier suggests that crime rates are partially determined by the severity of punishment. Although punishment may have an independent effect on crime rates, an issue of importance for this study is to examine whether punishment diminishes the effects of unemployment rate on crime. Hence, it is useful to see if the results above are robust to including a measure of punishment. Data on imprisonment rates by state and year from 1965 to 2006 are utilized. These rates are included in the regressions to attempt to control for these effects.[15]

Table 7 below reports the results for two different specifications.[16] For the first row in each crime-rate type, the standard Mundlak regression is reported, while for the second row, results from the FGLS estimation of the Mundlak method are reported. In general, the inclusion of imprisonment rates does not impact the unemployment results in any significant manner. For the Mundlak specification, the results are qualitatively the same as in Table 3 with generally the same variables being statistically significant in both sets of results with the addition of rape(for transitory unemployment effects) and murder and aggravated assault (for income). For the FGLS specification, the results are broadly the same as in Table 6. Transitory unemployment is still estimated to have a positive impact on all crime types (except for larceny theft where it is now statistically insignificant). There is no qualitative difference for the effects of persistent unemployment – it continues to be positive and statistically significant in all cases except for property crime and larceny theft. Finally, the income effect on crime is generally in line with previous results except for the coefficient for rape and aggravated assault is now negative (as in the standard Mundlak regressions). In general, then, the results hold even after an indicator of crime deterrence is included.[17]

IV. Conclusions

On an intuitive level, one should expect a strong relationship between crime and economic fluctuation in socio-economic status. Downturns make for a frail social fabric susceptible to social stress and disorder that causes crime to increase, as well as diminishing the economic resources available to economically vulnerable people. However, the literature on the effect of deteriorating economic fortunes as approximated by the unemployment rate on crime shows a weak relationship at best. Using crime-rate data for US states from 1965-2006, standard fixed effects estimations show few statistically significant effects of unemployment on a variety of crime rates, and when the relationship is statistically significant, it is negative – implying that increases in unemployment rates decrease crime.

However, it is shown that this standard specification is not the correct one. Indeed, re-specifying the empirical relationship does find a positive relationship between crime rates and unemployment. By decomposing the unemployment effect on crime into a transitory and persistent effect this study shows that, in particular, the persistent effect of an increase in unemployment is to increase all types of crime rates in contrast with previous studies which highlighted effects on some of the types of crime. This finding is robust to a number of specifications – including controlling for endogeneity, cross-panel correlations, and crime deterrence. Thus, it appears that, as Adam Smith put it, economic prosperity '*is the best police for preventing crimes*'.

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TABLE 1
Descriptive Statistics for Crime Rate Type

		Unemployment Comparison to			
		Overall Median		State Average	
Crime Type	Overall Sample	Below/Equal	Above	Below/Equal	Above
Violent	398.1	347.7	453.5	394.1	403.0
Property	3770.1	3644.3	3908.3	3772.4	3767.4
Murder	6.9	5.9	8.1	6.9	7.0
Rape	27.8	26.3	29.4	27.9	27.6
Robbery	130.7	110.1	153.3	127.6	134.5
Aggravated Assault	233.3	205.4	263.9	232.0	234.8
Burglary	962.1	910.3	1019.0	962.3	961.8
Larceny Theft	2428.1	2391.1	2468.8	2434.0	2421.0
Vehicle Theft	372.3	338.6	409.3	369.9	375.2

Notes: ‘Crime Types’ are rates per 100,000 people.

TABLE 2
Selected Fixed Effects Regression Results

Crime Type (log)	Unemployment Rate (1)	Per Capita Income/1000 (2)
Violent	-0.002	-0.011*
	(-0.53)	(-1.99)
Property	-0.004**	-0.011**
	(-2.36)	(-2.41)
Murder	-0.002	-0.008
	(-0.85)	(-1.45)
Rape	-0.005	-0.011
	(-1.50)	(-1.64)
Robbery	-0.006*	-0.014**
	(-1.88)	(-2.39)
Aggravated Assault	0.001	-0.007
	(0.14)	(-1.17)
Burglary	-0.005*	-0.011*
	(-1.98)	(-1.94)
Larceny Theft	-0.006	-0.008
	(-0.98)	(-1.65)
Vehicle Theft	-0.004	-0.011*
	(-0.97)	(-1.80)

Notes: Other controls include: proportion of state adult population divorced, proportion of single female headed households with minor children, proportion of state population under 6 years of age, proportion older than 64 years of age, proportion African-American, proportion Hispanic, proportion with no high school diploma, proportion with only a high school diploma, and a trend and its square. Numbers in parentheses are t-statistics based on standard errors clustered by state. *, **, *** indicates 10%, 5%, and 1% statistical significance, respectively.

TABLE 3
Selected Results from Mundlak Specification Results

	Unemployment Rate		Per Capita
	Transitory	Persistent	Income/1000
Crime Type (log)	(1)	(2)	(3)
Violent	0.001	0.133**	-0.011**
	(0.188)	(2.33)	(-1.97)
Property	-0.005***	0.019	-0.016***
	(-2.98)	(0.54)	(-3.39)
Murder	0.001	0.169***	-0.007
	(0.32)	(3.65)	(-0.88)
Rape	-0.004	0.064	-0.011*
	(-1.04)	(1.62)	(-1.65)
Robbery	-0.003	0.188**	-0.013**
	(-0.93)	(2.08)	(-2.18)
Aggravated Assault	0.002	0.119**	-0.009
	(0.53)	(2.22)	(-1.38)
Burglary	-0.006**	0.049	-0.016***
	(-2.22)	(1.36)	(-2.94)
Larceny Theft	-0.005	-0.026	-0.013
	(-0.89)	(-0.82)	(-1.62)
Vehicle Theft	-0.002	0.102*	-0.012*
	(-0.53)	(1.82)	(-1.87)

Notes: Other controls are the same as in Table 2. Numbers in parentheses are z-statistics based on standard errors clustered by state. *, **, *** indicates 10%, 5%, and 1% statistical significance, respectively.

TABLE 4
Hausman-Taylor Specification

Crime Type (log)	Unemployment Transitory (1)	Unemployment Persistent (2)	Per Capita Income/1000 (3)	Sargan-Hansen OverID Test (p-value) (4)
Violent	-0.003	1.346	-0.011**	0.079
	(-0.78)	(1.64)	(-2.15)	(0.779)
Property	-0.007**	0.284**	-0.016***	1.770
	(-2.22)	(2.00)	(-2.89)	(0.183)
Murder	-0.004	1.000**	-0.011	0.405
	(-0.88)	(2.44)	(-1.44)	(0.524)
Rape	-0.007	0.406*	-0.015*	0.065
	(-1.47)	(1.94)	(-1.94)	(0.798)
Robbery	-0.008*	1.257**	-0.019**	0.002
	(-1.66)	(2.38)	(-2.24)	(0.964)
Aggravated Assault	-0.002	0.790**	-0.013	0.008
	(-0.47)	(2.25)	(-1.62)	(0.927)
Burglary	-0.009**	0.387**	-0.017**	2.267
	(-2.09)	(2.15)	(-2.51)	(0.132)
Larceny Theft	-0.009	0.259	-0.014	0.135
	(-1.24)	(1.26)	(-1.15)	(0.714)
Vehicle Theft	-0.005	0.541**	-0.014*	1.339
	(-1.22)	(2.28)	(-1.94)	(0.247)

Notes: Other controls include those listed in Table 2 as well as state mean values for the other independent variables as instruments. The endogenous variables in the equation are transitory and persistent unemployment, income, state divorce rate and state single female headed household rate. Numbers in parentheses are z-statistics based on standard errors clustered by state. *, **, *** indicates 10%, 5%, and 1% statistical significance, respectively.

TABLE 5
Percentages of Significant Correlations by Crime Type

Crime Type	$\rho<0.10$ (1)	<0.05 (2)	Pesaran Test (p-value) (3)
Violent Crime	57.1%	50.5%	36.1 (<0.001)
Property Crime	52.5	45.6	49.8 (<0.001)
Murder	47.5	40.2	32.9 (<0.001)
Rape	57.5	51.2	18.6 (<0.001)
Robbery	66.2	60.5	42.7 (<0.001)
Aggravated Assault	61.3	56.5	19.5 (<0.001)
Burglary	59.6	52.2	66.4 (<0.001)
Larceny Theft	48.3	42.0	43.0 (<0.001)
Vehicle Theft	61.3	54.0	27.9 (<0.001)

TABLE 6
Selected FGLS Results

Crime Type (log)	Unemployment Transitory (1)	Unemployment Persistent (2)	Per Capita Income/1000 (3)
Violent Crime	0.030***	0.056***	0.048***
	(27.26)	(25.57)	(33.25)
Property Crime	0.006***	-0.009***	-0.010***
	(6.63)	(-7.98)	(-13.74)
Murder	0.016***	0.085***	0.032***
	(15.53)	(31.79)	(22.50)
Rape	0.006***	0.022***	0.009***
	(7.69)	(12.23)	(9.76)
Robbery	0.060***	0.087***	0.107***
	(32.25)	(24.56)	(44.55)
Aggravated Assault	0.019***	0.045***	0.020***
	(21.75)	(26.91)	(18.59)
Burglary	0.004***	0.019***	-0.012***
	(5.51)	(14.77)	(-15.04)
Larceny Theft	0.002***	-0.039***	-0.005***
	(2.65)	(-38.41)	(-6.74)
Vehicle Theft	0.036***	0.058***	0.054***
	(30.98)	(25.06)	(39.92)

Notes: Coefficients and standard errors (used to calculate the t-statistics which are in parentheses) are averaged across 500 randomized FGLS regressions where there are no more than 41 states in the regression. All FGLS regressions are estimated controlling for cross-panel correlation and heteroscedasticity. Also controlled for, but not reported, are the list of regressors given in Table 3. *** indicates significance at the 1% level.

TABLE 7
Unemployment Effects Including Imprisonment Rates

Crime Type (log)	Specification	Unemployment Transitory (1)	Unemployment Persistent (2)	Per Capita Income/1000 (3)	Imprisonment Rate (4)
Violent	Mundlak	-0.0004	0.116*	-0.018**	-0.0002
		(-0.12)	(1.85)	(-2.55)	(-1.03)
	FGLS	0.027***	0.063***	0.031***	0.0007***
		(21.50)	(27.53)	(18.33)	(22.87)
Property	Mundlak	-0.006***	0.012	-0.020***	0.0002
		(-3.16)	(0.31)	(-3.99)	(0.79)
	FGLS	0.003***	-0.007***	-0.011***	0.0006***
		(4.58)	(-5.95)	(-13.47)	(37.21)
Murder	Mundlak	0.0003	0.132***	-0.018**	-0.0005**
		(0.01)	(2.69)	(-2.15)	(-2.04)
	FGLS	0.016***	0.083***	0.021***	0.0006***
		(14.20)	(30.59)	(12.75)	(19.68)
Rape	Mundlak	-0.007**	0.040	-0.021***	-0.0010***
		(-2.32)	(0.88)	(-2.64)	(-3.51)
	FGLS	0.002**	0.016***	-0.007***	-0.0001***
		(2.61)	(8.29)	(-6.21)	(-4.99)
Robbery	Mundlak	-0.004	0.183*	-0.019***	0.0001
		(-1.21)	(1.85)	(-2.63)	(0.24)
	FGLS	0.060***	0.116***	0.116***	0.0011***
		(28.81)	(31.29)	(40.32)	(19.21)
Agg assault	Mundlak	0.001	0.098*	-0.016*	0.0001
		(0.33)	(1.75)	(-1.89)	(0.29)
	FGLS	0.015***	0.049***	-0.006***	0.0010***
		(15.05)	(25.69)	(-4.38)	(35.89)
Burglary	Mundlak	-0.007**	0.053	-0.023***	-0.0001
		(-2.37)	(1.32)	(-3.87)	(-0.18)
	FGLS	0.003***	0.028***	-0.019***	0.0005***
		(3.953	(20.1699)	(-19.46)	(28.71)
Larceny theft	Mundlak	-0.006	-0.027	-0.010	0.0006*
		(-0.93)	(-0.82)	(-1.17)	(1.68)
	FGLS	0.0002	-0.036***	-0.005***	0.0008***
		(0.32)	(-34.83)	(-5.61)	(46.33)
Vehicle theft	Mundlak	-0.001	0.096	-0.012	0.0009**
		(-0.11)	(1.60)	(-1.48)	(2.56)
	FGLS	0.036***	0.069***	0.056***	0.0014***
		(28.54)	(28.59)	(33.60)	(42.60)

Notes: Number in parentheses is the t-statistic. Significance: *, **, *** indicate 10, 5, and 1 percent significance. Other variables controlled for are the same as Table 2.

Endnotes

[1] An interesting and recent extension of this work is Engelhardt *et al*. (2008) who employ an optimal search model to investigate the role of anti-crime and anti-unemployment public policy on crime by both the unemployed and employed.
[2] New research in economics by Coon (2015) supports this in the context of crime against illegal immigrants in the US.
[3] Chiu and Madden (1998) use a theoretical model to show that fixed penalties for incarceration lead to a link between inequality and burglary, particularly in poorer areas.
[4] These data originate from the FBI, although these particular data are found at the following website: http://www.disastercenter.com/crime/uscrime.htm.
[5] In the empirical specification below, not all of the elements of $\overline{X}_j\beta^m$ are retained. This is because the Sargan-Hansen overidentification test for the exogeneity of the instruments indicate that the best mix of variables are a subset of the demographic variables. Specifically, in the Mundlak specification, the specification controls for stage-averaged variables of the proportion of the population under five years of age, the proportion over 64, the proportion with no high school degree, and the proportion with only a high school degree.
[6] Notably there is no *a-priori* theory to guide researchers to the appropriate lag structure. Ultimately, the focus of this study is not on the dynamics per se, but on highlighting that there are different transitory and persistent effects of changes in unemployment on crime rates.
[7] This methodology is similar to Friedman (1957) in the study of income and consumption and Gottschalk *et al.* (1994) in the context of decomposing transitory and permanent earnings.
[8] Interestingly, standard random-effects estimation without the Mundlak specification shows that the coefficients on the unemployment rate variable generally follows the pattern of results found with the fixed effects results in Table 2. This is consistent with the idea that while state fixed effects might be important in their own right, excluding them does not change the coefficients of interest in any appreciable way. These results are available from the authors upon request.
[9] Specification tests also suggested that the percentage of adults who are divorced and the percentage of single female headed households with minors were also endogenous, and so these are also considered endogenous in our HT specification.
[10] Satisfying the overidentification test indicated that the independent variables should include all the time varying variables mentioned above, as well as time invariant, state averages of the proportion of the population under 5 years of age, over 64 years of age, with no high school degree, and with only a high school degree.
[11] That the size of the coefficient increases is not particularly surprising since this often happens using predicted regressors from a first stage regression. The key issue here is that the effect is still positive and statistically significant. It is interesting to note that although the temporary effects of unemployment on crime are important for some types of crime, in line with the literature mentioned above, the persistent effects are nearly always important and significant.
[12] The Pesaran (2004) method is used rather than the more standard Breusch and Pagan (1980) Lagrange Multiplier test because there are more cross-sections than years in the dataset. The Stata command of 'xtcsd' is used to implement the Pesaran test.
[13] This is the sigma matrix found, for example, in Wooldridge (2002, p. 158, eq. 7.42)
[14] A further complication identified by Beck and Katz (1995) comes when the number of years is less than the number of panels, which can generate standard errors that are too small. In order to address this, the following procedure is used: a random number generator (based on a uniform distribution) is used to choose a subset of states (any number up to 42) to run a FGLS regression controlling for cross-panel correlations for each crime type. This is done 500 times and the coefficient estimates are averaged over those 500 sets of regressions.
[15] The imprisonment data for 1965 to 1977 come from Langan et al. (1988). The 1978 to 2006 data come from the US Bureau of Justice's Corrections Statistical Analysis Tool at www.bjs.gov.
[16] Other variations are possible namely a dummy variable equal to one starting in 1976, the year the death penalty was legal in the US, a dummy variable equal to one starting in the year of the first execution for the state. Including these variables as alternatives in the relevant regressions does not change the coefficient on the unemployment measure in any specification. These results are available from the authors.
[17] Interestingly, the sign on imprisonment has different signs for different crime types suggesting that when it is positive, incarceration does not have the effect of reducing violent crimes. It is not clear why this is so, although it is

likely that there may be an endogeneity issue between crime and incarceration. However, it is beyond the scope of this paper to investigate this further, although it is an issue that requires further research.