Economics Bulletin

Volume 36, Issue 3

A dynamic panel data study of the unemployment-crime relationship: the case of Pennsylvania

Sarah A. Frederick
Indiana University of Pennsylvania

James J. Jozefowicz
Indiana University of Pennsylvania

Zackary T. Nelson
Indiana University of Pennsylvania

Abstract

The present study analyzes the unemployment-crime (U-C) relationship in Pennsylvania using a balanced panel data set of the 67 counties over the period from 1990 to 2009. A dynamic panel data model is estimated by Generalized Method of Moments to account for endogeneity, measurement error, heteroskedasticity, and serial correlation. This estimation methodology overcomes several econometric problems ignored in previous analyses of the U-C relationship. Explicitly accounting for the dynamics of crime isolates criminal inertia from potential criminal motivation effects. The results suggest a statistically significant impact of previous criminal activity on future crimes, but a statistically insignificant relationship between the unemployment rate and the crime rate. Although these results run counter to the Cantor and Land (1985) hypothesis, they indicate that specifying a dynamic model of crime and addressing the econometric shortcomings of OLS regression analysis may yield more precise results.

Corresponding Author: james.jozefowicz@iup.edu. We appreciate helpful suggestions and insightful advice from Stephanie Brewer, Todd Potts, Yaya Sissoko, and Brian Sloboda. We especially are indebted to an anonymous reviewer whose recommendations significantly improved this paper. We gratefully acknowledge Debbie Bacco for her superb editorial assistance and Kelsey Altman for her excellent research assistance. The usual disclaimer applies.
Citation: Sarah A. Frederick and James J. Jozefowicz and Zackary T. Nelson, (2016) "A dynamic panel data study of the unemployment-crime relationship: the case of Pennsylvania", *Economics Bulletin*, Volume 36, Issue 3, pages 1497-1507
Contact: Sarah A. Frederick - S.A.Frederick@live.iup.edu, James J. Jozefowicz - James.Jozefowicz@iup.edu, Zackary T. Nelson - Z.T.Nelson@live.iup.edu.
Submitted: August 22, 2015. **Published:** August 03, 2016.

1. Introduction

Research on the determinants of crime is ongoing, because as Teles (2004) points out, crime is a perplexing problem for which there exists no consensus on a solution. In that vein, Lee and Holoviak (2006) argue for a two-fold approach whereby effective crime-fighting policies need to address underlying labor market conditions rather than solely funding police and deterrence efforts. However, this assertion assumes that there is a meaningful relationship between the unemployment rate as a measure of economic activity and crime rates. Arvanities and DeFina (2006) argue that the paper by Cantor and Land (1985) is the "seminal work" in the analysis of the unemployment-crime (U-C) relationship. When the unemployment rate increases, Cantor and Land (1985) identify two countervailing effects on crime. Criminal opportunity will decline as fewer commuters mean fewer potential victims, and unemployed individuals remain at home guarding their belongings. Alternatively, criminal motivation will increase as people resort to crime due to the hardship of ongoing unemployment (Phillips and Land 2012). Empirically, Cantor and Land (1985), analyzing United States time-series data from 1946 to 1982 to test their hypotheses, determine that criminal opportunity has a negative effect while criminal motivation has a positive effect on crime consistent with the predictions of their model.

Andresen (2013) notes that Cantor and Land (1985) has served as a launch point for extensive inquiry into the question. Testing the Cantor and Land (1985) predictions in Canadian provinces, Andresen (2013) finds the expected negative and positive effects for the unemployment variables. Phillips and Land (2012) estimate the Cantor and Land (1985) model using a sample of 400 large (populations in excess of 100,000) United States counties and also obtain the expected signs in most instances.

However, the aforementioned U-C studies among others (e.g., Choe 2008 and Patalinghug 2011) employ static models, and Saridakis and Spengler (2012) suggest that dynamic models are more appropriate for analyzing crime rates. Buonanno and Montolio (2008) emphasize the "persistence" effects of crime stemming from the declining costs to offenders of committing illegal activities due to acquired experience and expertise, not to mention a lack of legitimate employment opportunities and lower expected wages for convicted criminals. Furthermore, Saridakis and Spengler (2012) assert that criminals will persist in illegal activities *regardless* of improvements that may occur in their economic circumstances. Thus, a failure to account for what Speziale (2014) refers to as "criminal inertia" in the analysis risks overstating the impact of unemployment on crime, because variation in crime that actually stems from an individual's proclivity to continue illegal conduct may be attributed to changes in their economic circumstances. Similarly, Andresen (2013) emphasizes that while individuals encountering elevated unemployment and poor economic prospects may experience an increased motivation toward criminal activity, ignoring the persistence effects of crime mistakenly implies that a significant segment of the overall population fluctuates in and out of illegal behavior with the vagaries of economic activity. Intuitively, this implication seems to be an exaggeration of reality.

Econometrically, estimating static models of the U-C relationship may suffer from shortcomings, which calls the veracity of their findings into question (Andresen 2013). In particular, OLS estimates are biased in the face of endogenous regressors and measurement error in addition to unobserved heterogeneity (Buonanno and Montolio 2008). While some crime studies have employed dynamic models, they typically have analyzed data samples from other countries (e.g., Buonanno and Montolio 2008, Saridakis and Spengler 2012, and Speziale 2014) and/or focused on other determinants of crime (e.g., Choe 2008).

This article contributes to the existing empirical literature in four ways. First, it exploits the advantages of a county-level panel in analyzing the U-C relationship over a 20-year period for a novel sample of Pennsylvania data.[1] Buonanno and Montolio (2008) stress that crime is related to the features of a specific geographic area, and Jenkins (2014) observes that crime deterrence efforts are implemented locally in the United States, so focusing on counties within a single state is appropriate. Second, it improves on the methodology employed by other U-C analyses by estimating a dynamic model with GMM to address endogeneity, measurement error, heteroskedasticity, and serial correlation. Third, the inclusion of the lagged dependent variable in the model demonstrates whether and to what degree past criminal behavior promotes additional criminal acts. Fourth, the lagged crime rate also separates the criminal motivation effect of unemployment rates from criminal inertia effects that may bias other U-C findings.

The remainder of the article is as follows. The next section offers the variables and the empirical model. The third section discusses the findings. The final section provides the conclusions.

2. The Model and Data

The data sample is a balanced panel of the 67 Pennsylvania counties from 1990 to 2009. Witt, Clarke, and Fielding (1998), Buonanno and Montolio (2008), Choe (2008), Phillips and Land (2012), Saridakis and Spengler (2012), Speziale (2014), and Bandyopadhyay, Bhattacharya, and Sensarma (2015) similarly utilize panel data in their analyses. Like Arvanities and DeFina (2006) and Phillips and Land (2012), the dependent variable is the number of reported Part I crimes per 100,000 people (*ONECRIME*). It includes murder, nonnegligent manslaughter, forcible rape, robbery, assault, burglary, larceny-theft, motor vehicle theft, and arson. Grugan (2014) notes that Part I offenses offer a more accurate representation of crime trends, because they are reported to police at a higher rate than other infractions. Data was collected from the United States Census Bureau and Pennsylvania State Police Uniform Crime Reports.

2.1 Control Variables

Although Cantor and Land (1985) point out that there exists no agreement on a "complete" list of variables, the controls utilized here to mitigate omitted variable bias are similar to those used by other empirical tests of the Cantor and Land (1985) model of the U-C relationship (Arvanities and DeFina 2006, Phillips and Land 2012). *NONWHITE* is the percent of the population that is not Caucasian, and *YOUNG* is the percent of the population between 18 and 24 years old. *POVERTY* measures the percent of the population below the poverty line. *POPDENSITY* is the population density. Deterrence variables include: *ARREST* which represents the number of Part I crime arrests, *CLEARANCE* which is the number of crimes cleared by charges being filed

[1]Counties as units of observation offer advantages including greater homogeneity since they are smaller than states, which results in less variation in structural factors over time and reduced aggregation biases, and counties' boundaries do not change over time in contrast to the borders of Metropolitan Statistical Areas (MSAs) (Arvanities and DeFina 2006, Choe 2008, and Phillips and Land 2012).

divided by the number of Part I crimes reported, and *POLICE* which is the total number of police officers divided by the population. Table I provides variable definitions and descriptive statistics.

Table I. Variable Definitions and Descriptive Statistics

Variable name	Mean	Std. Dev.	Minimum	Maximum	Definition
ONECRIME	2,252.52	1,021.19	456.10	7,377.60	Part I crime rate per 100,000 people
UNEMP	6.23	1.99	2.60	17.30	Unemployment rate
NONWHITE	4.99	6.94	0.18	57.50	Percent of population that is not Caucasian
YOUNG	13.36	3.16	6.50	34.17	Percent of population between the ages of 18 and 24
POVERTY	11.53	3.54	1.50	30.69	Percent of population below the poverty threshold
POPDENSITY	454.44	1,423.19	11.20	11,745.00	Population density
ARREST	1,294.88	3,072.50	13.00	29,904.00	Number of arrests for Part I crimes
CLEARANCE	30.99	11.11	9.70	315.40	Number of crimes cleared by charges being filed divided by the total number of Part I crimes recorded
POLICE	0.0018	0.001	0.00	0.011	Number of police officers divided by the population

2.2 Empirical Model

Similar to Buonanno and Montolio (2008) and Saridakis and Spengler (2012), the U-C relationship for county *i* at year *t* is estimated using the following dynamic empirical model:

$$Log(ONECRIME_{it}) = \alpha + \beta_1 Log(ONECRIME_{it-1}) + \beta_2 Log(UNEMP_{it}) + \beta_3 X_{it} + \eta_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where $i = 1\ldots N$ and $t = 1\ldots T$ denote the county and time dimensions of the panel data set, respectively, α is the constant, X_{it} is the set of control variables, η_i is a county-specific effect, λ_t represents a time-specific effect, and ε_{it} is the error term.

While *UNEMP* is assumed to be exogenous as argued by Saridakis and Spengler (2012), the deterrence variables (*ARREST*, *CLEARANCE*, and *POLICE*) are considered to be endogenous consistent with Lin (2009) and Saridakis and Spengler (2012). In order to address endogeneity, measurement error bias, heteroskedasticity, and serial correlation, the generalized method of moments (GMM) technique with the first-difference transformation introduced by Arellano and Bond (1991) is employed to obtain efficient estimates. Buonanno and Montolio (2008), Saridakis and Spengler (2012), and Speziale (2014) similarly utilize a GMM framework.

In accordance with Choe (2008), Patalinghug (2011), Saridakis and Spengler (2012), and Andresen (2013), all variables are transformed into natural logarithms. Choe (2008) and Patalinghug (2011) enumerate the advantages of logarithms in decreasing the range of the data and ameliorating reporting biases in crime data. The double log specification yields coefficients that can be interpreted as elasticities. Furthermore, according to Buonanno and Montolio (2008) and Saridakis and Spengler (2012), the estimated coefficients from the model capture the short-run impact of a 1% change in a regressor on the crime rate *ceteris paribus* due to the inclusion of the lagged dependent variable (i.e., short-run elasticity). Saridakis and Spengler (2012) explain that a long-run elasticity can be calculated by dividing an estimated coefficient by one minus the coefficient of *CRIME(-1)*. It measures the long-run change in crime across all years resulting from a permanent change in a given explanatory variable (Saridakis and Spengler 2012).

3. Empirical Results

Table II presents the estimation results. Model 1 is a static pooled OLS regression in accordance with Buonanno and Montolio (2008) and Patalinghug (2011). The adjusted R^2 is 0.41. *UNEMP* bears a positive coefficient that is statistically different from zero at the 10% level (Speziale 2014 and Bandyopadhyay *et al.* 2015). Thus, a 10% increase in the unemployment rate increases the crime rate by 1.2%, all else equal, in Pennsylvania counties. The deterrence variables *ARREST*, *CLEARANCE*, and *POLICE* are individually significant at the 1% level. *NONWHITE*, *YOUNG*, *POPDENSITY* and *POVERTY* have statistically insignificant coefficients.

In Model 2, consistent with expectations, GMM estimation reveals the coefficient on *CRIME(-1)* to be positive and significant at the 1% level with an estimated elasticity of 0.25. This indicates “criminal inertia” in Pennsylvania counties (Speziale 2014). Notably, *UNEMP*, in contrast to Model 1, is not statistically different from zero once the dynamics of the crime rate are taken into account (Buonanno and Montolio 2008). Thus, unemployment does not affect an individual’s decision to commit a crime in Pennsylvania (Saridakis and Spengler 2012). As predicted by Andresen (2013), the magnitude of the coefficient on *UNEMP* considerably declines from 0.119 in Model 1 to 0.02 in Model 2, which is indicative of the bias in the static model results.

The remainder of the results of Model 2 are consistent with those of Model 1 except *POPDENSITY* and *POVERTY* become significant at the 1% level with negative and positive coefficients, respectively. The positive estimate on *POVERTY* is consistent with Choe (2008) and indicates short-run and long-run elasticities of 0.11 and 0.15, respectively, for Pennsylvania counties. The positive coefficient on *ARREST* and the negative coefficient on *CLEARANCE* mirror the findings of Buonanno and Montolio (2008) and Nelson and Jozefowicz (2015). Andresen (2013) also obtains a positive coefficient on the *POLICE* variable.

3.1 Deterrence Variables and Endogeneity Concerns

Reilly and Witt (1996), Levitt (1997), Lin (2009), and Saridakis and Spengler (2012) note the possibility of an endogeneity problem between crime and the deterrence covariates. Thus, Models 3-5 account for the endogeneity of the *ARREST*, *CLEARANCE*, and *POLICE* variables, respectively, within the GMM framework. The findings for *CRIME(-1)*, *CLEARANCE*, *POLICE*, *POPDENSITY*, and *POVERTY* are robust in sign and significance across these models. The elasticities for *CRIME(-1)* range from 0.21 to 0.27. Importantly, *UNEMP* continues to lack significance at conventional levels throughout Models 3-5.

Notably, *ARREST* experiences a change of sign from positive to negative while remaining significant in Model 3, which is consistent with Levitt (1997). Its short-run elasticity is -0.03 which implies a long-run elasticity of -0.04. *CLEARANCE* exhibits a short-run elasticity of -0.18 and a corresponding long-run elasticity of -0.24 in Model 4. As Reilly and Witt (1996) note, crime is more sensitive to deterrence variables in the long run than in the short run, and these short-run and long-run elasticities for *ARREST* and *CLEARANCE* support this assertion. Comparing the absolute values of these elasticities indicates that *CLEARANCE* reduces crime to a greater degree than *ARREST* in Pennsylvania counties. The *CLEARANCE* regressor proxies for police aggressiveness, and it represents reduced rewards and increased opportunity costs of committing crimes, which results in fewer motivated offenders (Nelson and Jozefowicz 2015).

Although *POLICE* retains a positive sign after controlling for its potential endogeneity in Model 5, Levitt (1997) explains that the Uniform Crime Report dependent variable may suffer from reporting bias due to differences between *reported* crimes and *actual* crimes in addition to the reality that police devote one-half of their time to non-crime-related activities. Thus, the effectiveness of *POLICE* in Pennsylvania may be understated. Alternatively, Andresen (2013) suggests that this positive correlation may reflect a structural crime problem in the state.

Table II. Regression Estimates

Variables	Model 1	Model 2[a]	Model 3[b]	Model 4[c]	Model 5[d]
	Pooled OLS	GMM	GMM	GMM	GMM
Constant	9.42***	N/A	N/A	N/A	N/A
	(28.63)	N/A	N/A	N/A	N/A
Log(CRIME(-1))	N/A	0.25***	0.27***	0.25***	0.21***
	N/A	(6.19)	(10.62)	(8.92)	(8.60)
Log(UNEMP)	0.119*	0.02	-0.04	0.04	-0.06
	(1.68)	(0.34)	(-1.01)	(0.88)	(-1.23)

Log(ARREST)	0.168***	0.08***	-0.03***	0.09***	0.09***
	(3.14)	(5.79)	(-4.13)	(7.60)	(8.05)
Log(CLEARANCE)	-0.324***	-0.09***	-0.09***	-0.18***	-0.14***
	(-7.26)	(-2.64)	(-4.38)	(-4.66)	(-5.23)
Log(POLICE)	0.237***	0.11***	0.13***	0.09***	0.04**
	(19.84)	(4.03)	(6.94)	(4.73)	(2.54)
Log(NONWHITE)	0.018	0.01	0.04**	0.02	0.03
	(0.760)	(0.15)	(1.98)	(0.59)	(0.95)
Log(YOUNG)	-0.052	-0.001	-0.16	-0.27**	0.17
	(-1.14)	(-0.01)	(-1.05)	(-2.10)	(0.82)
Log(POPDENSITY)	-0.054	-0.69***	-0.76***	-0.54***	-0.92***
	(-0.880)	(-3.45)	(-6.41)	(-3.74)	(-6.39)
Log(POVERTY)	-0.005	0.11***	0.11***	0.11***	0.09***
	(-0.090)	(2.94)	(3.54)	(3.35)	(3.30)
Wald Test		100.91***	483.72***	168.56***	405.95***
Specification tests					
Sargan J-test		21.00	39.14	37.79	47.39
Prob(J-test)		0.226	0.250	0.300	0.063
Serial correlation					
First order		-4.63***	-4.31***	-3.93***	-4.31***
Second order		1.35	1.28	1.11	0.779
$\overline{R}^2$	0.41				

Notes: t-statistics in parentheses are based on standard errors robust to heteroskedasticity and serial correlation. ***, **, * denote coefficient significant at 1%, 5%, and 10% levels, respectively. GMM models employ the first-difference transformation.

[a] *CRIME(-1)* is instrumented by lagged own values.
[b] *CRIME(-1)* and *ARREST* are instrumented by lagged own values.
[c] *CRIME(-1)*and *CLEARANCE* are instrumented by lagged own values.
[d] *CRIME(-1)* and *POLICE* are instrumented by lagged own values.

3.2 GMM Specification Tests

Wald test results reject the null hypothesis that all estimated coefficients are jointly zero at the 1% level for Models 2-5. The importance of specification tests for GMM models is emphasized by Buonanno and Montolio (2008), and two such tests are suggested by Arellano and Bond (1991) and Arellano and Bover (1995). The Sargan J-test results do not reject the null hypothesis of valid overidentifying restrictions in support of the overall validity of the instruments for all GMM models (i.e., the instrument is uncorrelated with the error term), which mirrors the findings of Buonanno and Montolio (2008) and Saridakis and Spengler (2012). As anticipated, Arellano-Bond serial correlation tests indicate the presence of first order serial correlation, but the absence of second order autocorrelation, which Buonanno and Montolio (2008) cite as evidence of correctly specified moment conditions in Models 2-5.

4. Conclusion

This study examines the U-C relationship in Pennsylvania using a panel data set encompassing 20 years of crime and unemployment rates and deterrence variables for its 67 counties. The findings provide evidence that specifying a dynamic model and controlling for endogeneity, measurement error, heteroskedasticity, and serial correlation within a GMM framework mitigates potential bias in the U-C results. The static model indicates a positive and statistically significant impact of unemployment rates on crime rates. However, the dynamic model reveals no effect of unemployment on criminal activity, but persistence of crime over time in Pennsylvania counties.

The criminal inertia revealed in this study conveys the degree to which previous criminal acts encourage the commitment of future crimes in Pennsylvania counties. The recidivism rate provides a rough approximation of the persistence effects of crime (Pew Center on the States 2011). In contrast to the United States 3-year recidivism rate of 43.3%, the Pennsylvania 3-year recidivism rate has hovered around 60% for the last decade, which speaks to the seriousness of the issue (Pew Center on the States 2011 and Pennsylvania Department of Corrections 2013).

Notably, the unemployment rate does not impact the crime rate in Pennsylvania counties. Cantor and Land (1985) explain that the deleterious effects of unemployment during recessions may be mitigated by institutional and social support structures, and the financial and moral support of communities, families, and charities. Since the period of study encompasses recessions in 1990-1991, 2001, and the Great Recession from late 2007 until mid-2009, it is conceivable that unemployment benefits, which may be extended in instances of ongoing economic hardship, and other social safety nets served to ameliorate the hardships of unemployment. Consequently, the criminal motivation effect of joblessness in Pennsylvania counties may have been neutralized. However, it is beyond the scope of the present study to unequivocally make that claim.

Among the deterrence measures, the clearance and arrest rates offer crime-fighting potential in Pennsylvania counties. Although the typical municipality in Pennsylvania devotes one-third of its budget to law enforcement expenditures, which is among its largest outlays, the effectiveness of police in reducing criminal activity may be understated by this analysis (Jenkins 2014). This may be because Pennsylvania has more police departments than the rest of the states with 1,117 state and local police departments having exclusive jurisdiction in the state (Jenkins 2014). Alternatively, this finding may be indicative of a structural crime problem in Pennsylvania.

From a policy perspective, Lee and Holoviak (2006) argue that alleviating crime requires addressing labor market conditions, and Freeman (1996) states, "it is difficult to see any long-term solution to crime that does not include some improvement in labor market conditions."
However, based on the current analysis, it appears that intervention that breaks the cycle of criminal hysteresis in conjunction with some conventional deterrence approaches offers hope in the fight against crime in Pennsylvania counties. Commonwealth of Pennsylvania Governor Tom Wolfe stated, "We want to intervene more effectively early on in the process so that we're not creating a criminal system that actually creates more crime, that we're actually reducing crime" (Langley 2016). Consistent with this study's focus on county-level data, Turner (2015) quotes Pennsylvania Department of Corrections Secretary John Wetzel as saying, "Counties play a bigger role in reducing recidivism than the state. The average state prison inmate has already been arrested seven or eight times. Those entering county facilities have a less extensive [criminal] history and can be taken off the track of crime and put back." The stakes are high, because the Pennsylvania Department of Corrections, with roughly 1 in 200 adult Pennsylvanians incarcerated, has a budget of approximately $2 billion and ranks among the most

expensive state agencies (Worden 2013). Eisen and Bowling (2015) report, “As state budgets grow tighter, government should invest in policies that achieve their intended goals. Prioritizing modern, evidence-based criminal justice policies with record of success…seems to be the best way forward in Pennsylvania…” Thus, the outcomes of this analysis, using Pennsylvania as an example, may provide useful guidance for state-level decision makers as they develop and implement crime-fighting policy measures in the future.

References

Andresen, M. A. (2013) “Unemployment, Business, Cycles, Crime, and the Canadian Provinces” *Journal of Criminal Justice* **41**, 220-227.

Arellano, M. and S. Bond (1991) “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations” *Review of Economic Studies* **58**, 277-297.

Arellano, M. and O. Bover (1995) “Another Look at the Instrumental-Variable Estimation of Error Components Models” *Journal of Econometrics* **68**, 29-52.

Arvanities, T. M. and R. H. DeFina (2006) “Business Cycles and Street Crime” *Criminology* **44**, 139-164.

Bandyopadhyay, S., S. Bhattacharya, and R. Sensarma (2015) “An Analysis of the Factors Determining Crime in England and Wales: A Quantile Regression Approach” *Economics Bulletin* **35**, 665-679.

Buonanno, P. and D. Montolio (2008) “Identifying the Socio-economic and Demographic Determinants of Crime across Spanish Provinces” *International Review of Law and Economics* **28**, 89-97.

Cantor, D. and K. C. Land (1985) “Unemployment and Crime Rates in the Post-World War II United States: A Theoretical and Empirical Analysis” *American Sociological Review* **50**, 317-332.

Choe, J. (2008) “Income Inequality and Crime in the United States” *Economics Letters* **101**, 31-33.

Eisen, L.-B. and J. Bowling (2015) “Pennsylvania Fact Sheet: What Caused the Crime Decline?” The Brennan Center for Justice at New York University School of Law. Available at https://www.brennancenter.org/analysis/pennsylvania-fact-sheet-what-caused-crime-decline (Accessed 24 May 2016).

Freeman, R. B. (1996) “Why Do So Many Young American Men Commit Crimes and What Might We Do About It?” *Journal of Economic Perspectives* **10**, 25-42.

Grugan, S. T. (2014) “Crime Trends in Pennsylvania” in *Pennsylvania’s Criminal Justice System* by M. P. Brewster and H. R. Dammer, Eds., Carolina Academic Press: Durham, 3-30.

Jenkins, M. J. (2014) “Law Enforcement in Pennsylvania” in *Pennsylvania’s Criminal Justice System* by M. P. Brewster and H. R. Dammer, Eds., Carolina Academic Press: Durham, 89-110.

Langley, K. (2016) “Bipartisan Group to Study Pa. Criminal Justice System” *Pittsburgh Post-Gazette* February 19, 2016. Available at http://www.post-gazette.com/news/state/2016/02/19/State-officials-announce-bipartisan-effort-to-review-state-criminal-justice-system/stories/201602190090 (Accessed 24 May 2016).

Lee, D. Y. and S. J. Holoviak (2006) “Unemployment and Crime: An Empirical Investigation” *Applied Economics Letters* **13**, 805-810.

Levitt, S. D. (1997) “Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime” *American Economic Review* **87**, 270-290.

Lin, M.-J. (2009) “More Police, Less Crime: Evidence from US State Data” *International Review of Law and Economics* **29**, 73-80.

Nelson, Z. T. and J. J. Jozefowicz (2015) “’Keystone Kops’ and Crime Theories: A Panel Data Analysis of Pennsylvania County Crime Rates” *Pennsylvania Economic Review* **22**, 1-23.

Patalinghug, E. E. (2011) “Crime Rates and Labor Market Opportunities in the Philippines: 1970-2008” *Economics Letters* **113**, 160-164.

Pennsylvania Department of Corrections (2013) “Recidivism Report 2013: Recidivism in Pennsylvania” Available at http://www.nationalcia.org/wp-content/uploads/2013-PA-DOC-Recidivism-Report.pdf (Accessed 24 May 2016).

Pew Center on the States (2011) “State of Recidivism: The Revolving Door of America’s Prisons” Washington, DC: The Pew Charitable Trusts. Available at http://www.pewtrusts.org/~/media/legacy/uploadedfiles/wwwpewtrustsorg/reports/sentencing_and_corrections/staterecidivismrevolvingdooramericaprisons20pdf.pdf (Accessed 24 May 2016).

Phillips, J. and K. C. Land (2012) “The Link between Unemployment and Crime Rate Fluctuations: An Analysis at the County, State, and National Levels” *Social Science Research* **41**, 681-694.

Reilly, B. and R. Witt (1996) “Crime, Deterrence and Unemployment in England and Wales: An Empirical Analysis” *Bulletin of Economic Research* **48**, 137-159.

Saridakis, G. and H. Spengler (2012) “Crime, Deterrence and Unemployment in Greece: A Panel Data Approach” *Social Science Journal* **49**, 167-174.

Speziale, N. (2014) “Does Unemployment Increase Crime? Evidence from Italian Provinces” *Applied Economics Letters* **21**, 1083-1089.

Teles, V. K. (2004) “The Effects of Macroeconomic Policies on Crime” *Economics Bulletin* **11**, 1-9.

Turner, F. (2015) “Pa. Crime and Prison Population Down Despite Repeat Offender Stats” *Reading Eagle* May 9, 2015. Available at http://www.correctionsone.com/corrections/articles/8544583-Pa-crime-and-prison-population-down-despite-repeat-offender-stats/ (Accessed 24 May 2016).

Witt, R., A. Clarke, and N. Fielding (1998) “Crime, Earnings Inequality and Unemployment in England and Wales” *Applied Economics Letters* **5**, 265-267.

Worden, A. (2013) “Study Finds High Recidivism Rate Among Pa. Offenders” *Philadelphia Inquirer* March 5, 2013. Available at http://articles.philly.com/2013-03-05/news/37473296_1_recidivism-state-inmates-state-prison-populations (Accessed 24 May 2016).