

ABSTRACT

Title of Document: CO-OFFENDING IN CONTEXT: THE ROLE OF ECONOMIC HARDSHIP

Zachary Rowan, Doctor of Philosophy, 2017

Directed By: Jean M. McGloin, Department of Criminology and Criminal Justice

The group nature of crime is one of its better-known features. Over the past few decades, empirical work on group crime has been dominated by an offender-based perspective. Yet scholars have argued that the emergence of group crime is contextually dependent on the availability, proximity, and convergence of suitable co-offenders. It is unlikely that these conditions are equally distributed across space and time; instead, they are likely influenced by socio-structural factors, such as economic hardship. This dissertation hypothesizes that the relationship between economic hardship and co-offending operates through both long-and short-term impacts. In particular, long-term effects of economic hardship associated with increasing criminal motivation are expected to be positively related to the rate of co-offending and the proportion of crimes that are co-offenses. Economic hardship is expected to lead to more contemporaneous increases in the levels of guardianship and a reduction in the quality of criminal targets. This short-term effect is expected to have an overall null relationship with the rate of co-offending, but should be positively related to the proportion of crimes that are co-offenses. I further hypothesize that these relationships will vary across instrumental and expressive crimes.

Using incident-level data from the National Crime Victimization Survey (NCVS) that has been aggregated to the Metropolitan Statistical Level (MSA), I evaluate the macro-level relationship between economic hardship and co-offending utilizing a hybrid modeling strategy that combines fixed and random effects estimators. The results from these analyses suggest that the long-term effect associated with increases in economic hardship are positively and strongly related to the rate and proportion of instrumental and expressive crimes that are co-offenses. There is mixed evidence in support of the hypothesized relationships relating the short-term effect associated with economic hardship and the rate/proportion of instrumental and expressive crimes that are co-offenses. Across these results, there is variation in the extent to which the age-distribution of an MSA moderates the relationship between economic hardship and group crime. The theoretical implications and limitations of this dissertation are discussed in the context of the broader literature interested in studying group offending.

CO-OFFENDING IN CONTEXT: THE ROLE OF ECONOMIC HARDSHIP

Zachary R. Rowan

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree for
Doctor of Philosophy
2017

Advisory Committee:

Professor Jean McGloin, Chair
Professor James Lynch
Assistant Professor Lauren Porter
Associate Professor Min Xie
Professor Jeffrey Lucas (Dean's Representative)

© Copyright by
Zachary R. Rowan
2017

ACKNOWLEDGMENTS

In many ways, this dissertation reflects the culmination of the last ten years of my time spent at the University of Maryland as an undergraduate and graduate student. I would be remiss not to thank those who have provided guidance and have helped shape me into the person I am today. Without question, I must thank my chair, mentor, and friend, Jean McGloin for her unwavering support, unparalleled feedback, and dedication to making me a better scholar. The past ten years have been an amazing experience and I am so grateful for all of the time and effort you have placed into me as a student. You are irreplaceable and invaluable. To my committee members, Jim Lynch, Min Xie, Lauren Porter, and Jeff Lucas – thank you for your thoughtful feedback that has helped make this dissertation better scholarship. I would also like to thank John Laub for being instrumental in providing support and encouraging my intellectual and political development during these last few years as a graduate student. Lastly, to all of my friends and family, both within and outside the walls of LeFrak, thank you for your endless supply of patience, advice, invitations to happy hour, and companionship.

TABLE OF CONTENTS

ACKNOWLEDGMENTS.....	ii
TABLE OF CONTENTS.....	iii
LIST OF TABLES	iv
CHAPTER 1: INTRODUCTION.....	1
CHAPTER 2: LITERATURE REVIEW	11
The Role of Economic Hardship in Explaining Co-offending.....	18
Motivation and Co-offending	31
Opportunity and Co-offending.....	34
Economic Hardship and Co-offending by Crime Type	37
Variation in the Impact of Economic Hardship on Group Crime across MSA Age-Profiles.....	44
CHAPTER 3: DATA & METHODS.....	47
Measures.....	60
Dependent Variables.....	60
Independent Variables	64
Control Variables	70
CHAPTER 4: RESULTS	75
Rate of Co-offending Results	75
Proportion of Co-offending Results.....	87
CHAPTER 5: DISCUSSION.....	102
Limitations and Future Directions	110
APPENDIX	116
REFERENCES.....	137

LIST OF TABLES

Table 1: Descriptive Statistics for Variables	73
Table 2: Hybrid Model for Overall Rate of Co-offending, Unemployment Rate N=540.....	76
Table 3: Hybrid Model for Overall Rate of Co-offending, Percent Poverty N=540.....	77
Table 4: Hybrid Model for Rate of Household Property Co-offending, Unemployment Rate N=474	79
Table 5: Hybrid Model for Rate of Household Property Co-offending, Percent Poverty N=474..	80
Table 6: Hybrid Model for Rate of Personal Instrumental Co-offending, Unemployment Rate N=533	82
Table 7: Hybrid Model for Rate of Personal Instrumental Co-offending, Percent Poverty N=533	83
Table 8: Hybrid Model for the Rate of Expressive Co-offending, Unemployment Rate N=450 ..	85
Table 9: Hybrid Model for Rate of Expressive Co-offending, Percent Poverty N=450.....	86
Table 10: Hybrid Model for Overall Proportion of Crimes that are Co-offenses, Unemployment Rate N=540.....	88
Table 11: Hybrid Model for Overall Proportion of Crimes that are Co-offenses, Unemployment Rate N=540.....	89
Table 12: Hybrid Model for Proportion of Household Property Crimes that are Co-offenses, Unemployment Rate N=474.....	90
Table 13: Hybrid Model for Proportion of Household Property Crimes that are Co-offenses, Percent Poverty N=533	91
Table 14: Hybrid Model for Proportion of Personal Instrumental Crimes that are Co-offenses, Unemployment Rate N=533	92
Table 15: Hybrid Model for Proportion of Personal Instrumental Crimes that are Co-offenses, Percent Poverty N=474	94
Table 16: Hybrid Model for Proportion of Expressive Crimes that are Co-offenses, Unemployment Rate N=450	95
Table 17: Hybrid Model for Proportion of Expressive Crimes that are Co-offenses, Percent Poverty N=450	96
Table 18: Summary of Results.....	100
Table 19: Supplemental Analyses, Overall Proportion of Crimes that are Co-offenses – Unemployment Rate N=540	117
Table 20: Supplemental Analyses, Overall Proportion of Crimes that are Co-offenses - Percent Poverty N=540	118
Table 21: Supplemental Analyses, Proportion of Household Property Crimes that are Co-offenses – Unemployment Rate N=474	119
Table 22: Supplemental Analyses, Proportion of Household Property Crimes that are Co-offenses - Percent Poverty N=474	120
Table 23: Supplemental Analyses, Proportion of Personal Instrumental Crimes that are Co- offenses – Unemployment Rate N=533	121
Table 24: Supplemental Analyses, Proportion of Personal Instrumental Crimes that are Co- offenses - Percent Poverty N=533.....	122

Table 25: Supplemental Analyses, Proportion of Expressive Crimes that are Co-offenses – Unemployment Rate N=450	123
Table 26: Supplemental Analyses, Proportion of Expressive Crimes that are Co-offenses - Percent Poverty N=450	124
Table 27: Pooled Supplemental Analyses, Rate of Household Property Co-offending - Unemployment Rate	125
Table 28: Pooled Supplemental Analyses, Rate of Household Property Co-offending – Percent Poverty	126
Table 29: Pooled Supplemental Analyses, Rate of Personal Instrumental Co-offending – Unemployment Rate	127
Table 30: Pooled Supplemental Analyses, Rate of Personal Instrumental Co-offending Groups – Percent Poverty	128
Table 31: Pooled Supplemental Analyses, Rate of Expressive Crime Committed in Groups - Unemployment Rate	129
Table 32: Pooled Supplemental Analyses, Rate of Personal Instrumental Co-offending – Percent Poverty	130
Table 33: Pooled Supplemental Analyses, Proportion of Household Property Crimes that are Co-offenses - Unemployment Rate	131
Table 34: Pooled Supplemental Analyses, Proportion of Household Property Crimes that are Co-offenses – Percent Poverty	132
Table 35: Pooled Supplemental Analyses, Proportion of Personal Instrumental Crimes that are Co-offenses - Unemployment Rate	133
Table 36: Pooled Supplemental Analyses, Proportion of Personal Instrumental Crimes that are Co-offenses – Percent Poverty	134
Table 37: Pooled Supplemental Analyses, Proportion of Expressive Crimes that are Co-offenses - Unemployment Rate	135
Table 38: Pooled Supplemental Analyses, Proportion of Expressive Crimes that are Co-offenses – Percent Poverty.....	136

LIST OF FIGURES

Figure 1: Count of Co-offending Incidents by MSA, N=594 62
Figure 2: Unweighted Proportion of Co-offenses by MSA, N=594..... 64
Figure 3: Unemployment Rate by MSA, N=600 67
Figure 4: Percent of Poverty by MSA, N=600..... 69

CHAPTER 1: INTRODUCTION

Scholars have long recognized the group nature of crime. More than a century ago, Breckenridge and Abbott (1912: 35) argued that “there is scarcely a type of delinquent boy who is not associated with others in his wrongdoing” and subsequent work has confirmed the high prevalence of co-offending (Carrington, 2009; McCarthy, Hagan, & Lawrence, 1998; McGloin & Nguyen, 2012; Warr, 2002; Wright & Decker, 1994). Still, co-offending or group crime (i.e., when two or more people commit crime together) has often been overlooked and relegated to a mere descriptive feature of crime and offending, which has resulted in relatively limited research on the process and impact of criminal cooperation. More recent research has sought to make sense of the regularity of co-offending and found it has important implications for a variety of behavioral outcomes. For instance, scholars observe that co-offending experience leads to an increase in the likelihood of recidivism, engaging in more serious criminal behavior, and further embeddedness in criminal networks (Alarid, Burton, & Hochstetler, 2009; Bouchard & Nguyen, 2010; Carrington, 2009; Conway & McCord 2002; Felson, 2009; McGloin & Piquero, 2010; Stolzenberg & D’Alessio, 2008). Despite the growth in co-offending research over the past two decades, our understanding of group crime is still in its nascent stages and there remain a number of challenges that need to be addressed to advance the field. Perhaps most notably, there has been a nearly exclusive focus on individual-level analyses of co-offending. Individual level analyses are undeniably important, but research has generally failed to consider complementary units of analysis that have proven valuable in advancing the broader offending literature.

The focus on individual-level analyses of co-offending has been driven in part by a limited supply of data that hinders evaluating co-offending from different perspectives. Existing research has primarily relied on surveys or narrative data among select samples of offenders and largely relied on offender perceptions of the value of criminal accomplices (e.g., Clarke & Cornish, 1985; Jacobs & Wright, 2010; Hochstetler, 2001; McCarthy et al., 1998; Wright & Decker, 1997). Prior work on co-offending is also affected by a range of other limitations. Given the nature of narrative or survey data among offenders, an offender's post-hoc interpretation of co-offending experiences may affect responses about the value and role of co-offenders. Additionally, the scope of much prior work has been limited to juvenile delinquency, has been largely gender-specific, and often has been limited to a single or small range of offenses (see discussion in van Mastrigt & Farrington, 2009). Several studies have used official records (e.g., McCord & Conway, 2002; McGloin & Piquero, 2010; Ouellet, Boivin, Leclerc, & Morselli, 2013; Reiss & Farrington, 1991), but they suffer from limitations due to the underreporting of criminal acts and questions about how accurately events that involve more than one offender are identified (e.g., Schaefer et al., 2014; Tillyer & Tillyer, 2015). For instance, Tillyer and Tillyer (2015) evaluated robbery incidents using NIBRS and acknowledged that in addition to issues related to reporting compliance with NIBRS, roughly 40% of robberies in the United States are not reported to law enforcement (see also Baumer & Lauritsen, 2010). The limitations associated with both the type of data and methods used to capture and understand co-offending likely underestimate the extent of co-offending and present a potentially narrow view on the implications of co-offending.

Even among studies that examine similar research questions, differences in conclusions have emerged, raising concerns over the extent to which the current co-offending literature provides enough consistent evidence to generalize findings about the nature of co-offending. For instance, McCarthy et al. (1998) found that, despite the inherent risks associated with co-offending among street youth, experiencing adversity (e.g., failure to find safe shelter, nutritional sustenance) led to a greater willingness to co-offend. In an extension of this work, Nguyen and McGloin (2013) evaluated the adversity hypothesis among two samples of incarcerated offenders and found less consistent evidence. These divergent findings may be due to differences in the sample (street youth vs. incarcerated offenders) and measures used (i.e., perceptions of adversity vs. objective measures of adversity). In any case, they are reflective of the fragmented depictions of co-offending provided by individual-level studies. In lieu of continuing the status quo in co-offending research, perhaps by turning to largely underexplored hypotheses at a unit of analysis other than at the level of individual offenders, we can expand upon our understanding of the emergence of co-offending and provide additional evidence to help contextualize conclusions drawn from existing co-offending research.

Theoretical and empirical work examining the processes associated with engaging in group crime have resided in individual-level explanations. However, there is reason to believe that this process is also situated within a broader context (e.g., Felson, 2003; Tremblay, 1993). It is hypothesized that the emergence of group crime is conditioned by the availability, proximity, and convergence of potentially 'suitable' co-offenders (Felson, 2003; Tremblay, 1993). The identification of individuals willing to cooperate and deemed suitable accomplices may be an arduous process for some offenders, as research has

demonstrated the brevity of co-offending relationships and the immense uncertainty that accompanies taking on criminal accomplices (McCarthy et al., 1998; McGloin et al. 2008; Weerman, 2003). Indeed, Wright and Decker's (1997) interviews with burglars highlighted the ever-present threat of duplicity that accompanies taking on a co-offender. One burglar summarized this potential risk by stating, "[My co-offenders] would probably tell on me, but, to be honest, I'd probably tell on them too" (Wright & Decker, 1997: 154). Still, criminal cooperation occurs with regularity despite the potential hazards associated in doing so (Bruinsma & Bernasco, 2004; Coleman, 1990; Lin 1999; McCarthy et al., 1998).

Despite the uncertainties associated with co-offending, certain social conditions experienced by offenders actually may facilitate mutual collaboration and trust between offenders (McCarthy et al., 1998; Shover, 1991; Tremblay, 1993). For instance, McCarthy et al. (1998) found evidence supporting the hypothesis that under conditions of adversity or desperation, individuals were more willing to collaborate with others. Individual experiences of adversity are likely conditioned by the socio-structural conditions that an individual belongs to, as factors that produce adversity are not equally distributed throughout society. This suggests that access to individuals who are willing to engage in cooperative criminal action is also conditioned by the surrounding context (e.g., D'Alessio & Stolzenberg, 2010; Schaefer et al., 2014). Ultimately, variation in the prevalence of co-offending and overall proportion of crime that is committed in groups may be influenced by broader contextual factors that facilitate the convergence of conditions necessary for this type of behavior to occur and increase the motivation to take on accomplices (Alarid et al., 2009; Hochstetler, 2001; McGloin et al., 2008; Warr, 1996, 2001).

Tremblay (1993) speculates that economic hardship, as measured by macro-level unemployment, should influence the emergence of co-offending. Because of the increased leisure time due to unemployment, there should be an increase in the availability, proximity, and convergence of potential offenders. As more individuals become unemployed, crime may be viewed as a viable option to make ends meet and to the extent that finding a suitable co-offender takes time, unemployment increases the amount of leisure time that may be used to search for co-offenders (Tremblay, 1993). If the density and concentration of motivated offenders is a function of unemployment, this may lead to an increased interaction between offenders and commission of criminal opportunities among multiple offenders. Determining whether offenders actually engage in more co-offenses as a result of the effect of unemployment is an empirical question that will be tested by this dissertation.

Economic hardship may also result in a reduction in the quantity or quality of criminal opportunities, leading some offenders to consider working together to target more lucrative opportunities generally or to leverage criminal connections to facilitate access to opportunities (e.g., Cohen & Felson, 1979; Tremblay, 1993). Consistent with hypotheses derived from routine activity theory, unemployment alters the criminal 'target backcloth' by increasing levels of guardianship and altering the spatial opportunity structure of suitable targets (Brantingham & Brantingham, 1993; Cohen & Felson, 1979). Collaboration with co-offenders can expand awareness spaces of more suitable criminal opportunities, provide access to criminal networks, and allow offenders to share the practical demands associated with committing a crime (Andresen & Felson, 2010, 2012). Additionally, the incentives derived from co-offending may help overcome the increased

risks, fear, and costs attributed to heightened guardianship (Cusson, 1993; McGloin & Thomas, 2016). Thus, the contextual influence of economic hardship may generate behavioral settings that promote co-offending as a viable ‘action alternative’ (Wikström, 2006; Wikström & Svensson, 2010).

Still, Tremblay’s (1993) arguments rest on relatively underspecified assumptions about the precise mechanisms that characterize the relationship between unemployment and co-offending. Extant literature analyzing the impact of unemployment on crime offers some guidance for fully exploring how it might be related to co-offending (Andresen, 2015; Arvanites & Defina, 2006; Cantor & Land, 1985; Chiricos, 1987; Levitt, 2001; Raphael & Winter-Ebmer, 2001). Cantor and Land (1985) specified that some of the weak or non-significant results observed in studies evaluating the relationship between unemployment and crime occurred because two processes that comprised the total effect canceled themselves out. Specifically, Cantor and Land (1985) argued that the two mechanisms through which unemployment impacted crime were: 1) a system activity or “motivation” effect, and 2) a guardianship effect. These scholars argued that whereas the lagged effect of economic hardship on motivation increased crime, the contemporaneous influence of increased guardianship generated by unemployment led to a reduction in crime (Cantor & Land, 1985). Thus, to fully specify the crime (and group crime) relationship with economic hardship, it is necessary to tease apart processes that are temporally and substantively distinct.

The relationship between crime and economic hardship further varies across important socio-structural characteristics and the crime type examined. First, consistent with Cantor and Land’s (1985) argument that conditions of unemployment affect both

those who become unemployed and those who experience an economic downturn, the age-distribution of a geographic area may moderate the impact of economic hardship. Prior work has suggested that the impact of economic hardship and crime may be most prominently experienced by younger individuals seeking to enter adult labor opportunities, but fail to do so because of the decline in jobs (Britt, 1997). Given the concentration of co-offending in adolescence and the declining prevalence of co-offending among individuals over time, it is possible that patterns of co-offending across macro-level areas may be similarly tied to the age distribution of an area. Further, Cantor and Land (1985) utilized unemployment as one possible measure of economic hardship and hypothesized that because that measure was reflective of the general state of the economy, it tapped into the experience of adversity relevant for explaining the motivation and opportunity to commit crime. As such, the hypothesized processes relating economic hardship to co-offending are not specific to unemployment, but rather should emerge across other operationalizations of economic hardship. Additionally, prior work suggests that economic hardship may be more salient for property crime compared to violent crime because of the potential for monetary gain attached to forms of property crime (e.g., Britt, 1997; Cantor & Land, 1985; Phillips & Land, 2012; Raphael & Winter, 2001). Therefore, it will be important to consider the relationship between co-offending and more than one indicator of economic hardship, across crime types, and to investigate whether the impact of economic hardship is moderated by the age-profile of an area.

This model has not been used to evaluate the relationship between economic hardship and co-offending, but serves as a useful guide to elucidate the processes that can explain the emergence of co-offending. There are several additional challenges associated

with integrating literatures on crime, co-offending, and economic hardship. Tremblay (1993) suggests that because there is variability in how both motivation and opportunity are related to co-offending, there is a need to consider how these mechanisms are related to both *rates* of co-offending and the *proportion* of crimes that are co-offenses. The motivation to engage in crime derived from increases in economic hardship should increase both the *rate* and *proportion* of co-offending. Co-offending is a form of criminal activity that is also driven by the experience of adversity and economic hardship. Past research has demonstrated a positive association between experiencing adversity and a willingness to take on criminal accomplices, therefore the relationship between motivation and the *rate* of co-offending is expected to be positive (McCarthy et al., 1998; Tremblay, 1993). As more potential offenders have an expanded willingness to view co-offending as a viable action alternative and are situated within contexts conducive to form such relationships, this suggests that economic hardship may have a unique and additive relationship on co-offending. Increased motivation derived from economic hardship would therefore be expected to lead to a higher proportion of crime being classified as a co-offense.

In contrast, the viability of criminal opportunities for crime are expected to be diminished by economic hardship due to shifts in the level of guardianship and availability of valued goods. Despite the observed negative relationship between opportunity/guardianship and crime generally (e.g., Andresen, 2012; Cantor & Land, 1985), the practical advantages offered by accomplices and the increased convergence of potential co-offenders may produce more opportunities and a greater willingness to engage in co-offending to overcome the changing landscape of criminal targets. Thus, even with a decline in overall criminal opportunities, the proportion of co-offenses relative to all crime

that is committed is expected to increase in areas with increasing levels of economic hardship. Specifying the relationship between the short-term effects associated with increases in economic hardship and the rate of co-offending is a bit more complex. The expected reduction in the availability of targets and increased presence of more effective guardians may uniformly depress the volume of all potential opportunities, regardless of whether an offender engages in crime alone or with others. This would suggest that there is a negative relationship between the short-term effect of economic hardship and the rate of co-offending. Still, the advantages and influence of accomplices that may be particularly salient during times of economic hardship could lead offenders to consider co-offending as a viable and preferred criminal action. Under this scenario, the rate of co-offenses may be positively related to the short-term impact attributable to economic hardship. These conflicting processes suggest that there is likely an inconsistent or null relationship between the short-term effects of opportunity on the rate of co-offending. Ultimately, the Cantor and Land (1985) model provides a useful framework to evaluate the nuances in the relationship between co-offending and economic hardship.

To evaluate the extent to which conditions of economic hardship are related to co-offending, macro level data are needed. The National Crime Victimization Survey (NCVS) offers the opportunity to consider criminal events that involve more than one offender, yet it has rarely been leveraged to further our understanding of co-offending. Indeed, only four studies have focused on the co-offending measures in the NCVS (Clark, 1992; Lynch, 2002; Oudekerk & Morgan, 2016; Reiss, 1988). Although the NCVS was clearly designed to capture information related to victimization experiences, the unique data structure and rich detail on these victimization experiences has also been extended to develop a research

agenda that incorporates a contextual framework (e.g., Xie, Heimer, & Lauritsen, 2012). The Bureau of Justice Statistics and the Census Bureau have created a macro-level NCVS data file at the metropolitan statistical area level between the years of 1979-2004 that provides the opportunity to associate aggregated victim reports of multiple-offender criminal incidents to 40 of the largest MSAs across the United States¹. Consistent with these broader research efforts, this type of data offers an opportunity to study co-offending at the macro-level and forms the basis for the research agenda of this dissertation.

Ultimately, the purpose of this dissertation is to 1) move beyond individual-level analyses of co-offending and provide a macro-level evaluation of co-offending that also demonstrates the utility of using victimization data, 2) evaluate the extent to which economic hardship is related to the emergence of co-offending through a modeling strategy that provides estimates of the impact of both the long-and short-term processes of motivation and opportunity/guardianships, 3) determine more precisely how economic hardship is related to co-offending by evaluating the hypothesized relationships across different types of group crime, and 4) evaluate the robustness of these findings through the implementation of alternative methodological specifications.

¹ As discussed in the Data and Methods section below, due to the lack of MSA-level unemployment information between 1979 and 1989, the proposed dissertation will only be able to utilize victimization data between 1990 and 2004.

CHAPTER 2: LITERATURE REVIEW

The group nature of crime is one of the most well-documented characteristics of criminal behavior. Shaw and McKay (1942) observed that approximately 80% of juveniles in the Cook County Juvenile Court were suspected of committing crimes with other offenders. Co-offending typically referred to as “the perpetration of an offence by more than one person” (Weerman, 2003: 398)². By this definition, co-offending refers to criminal events where more than one offender is actively engaged in the commission of the crime (i.e., it does not consider the role of offenders beyond the immediate criminal event). In other words, co-offending is not equivalent to having deviant peers. To aid in understanding the distinction, first consider that an individual may have friends who socialize and pressure him towards deviance, but still commits crime alone. Second, deviant peers may be part of the potential pool of criminal accomplices, but co-offenders may include people other than friends (e.g., McGloin & Nguyen, 2013; Warr, 2002). For instance, potential accomplices may be identified in behavioral settings where offenders happen to converge or could be drawn from highly organized criminal groups – both of which may not overlap with traditionally defined measures of deviant peers (Felson, 2003; McGloin & Nguyen, 2013).

Scholarly research on co-offending has generally lagged behind the broader criminological research agenda, as the majority of the existing inquiries on co-offending are largely descriptive in nature and exclusively focus on individual-level patterns of co-offending (e.g., van Mastrigt & Farrington, 2009; Weerman, 2003). These analyses

² Tremblay (1993) has extended the definition of co-offending to include all individuals that help plan or identify a particular criminal opportunity but may not partake in the actual offense. Other than studies on which he is an author, however, the co-offending literature does not embrace this definition. Instead, it focuses on events when individuals commit crime together.

represent early efforts to consider co-offending as an important dimension of criminal behavior. Reiss' (1988: 117) work represents the first explicit argument that co-offending is worthy of its own research agenda: "understanding co-offending is central to understanding the etiology of crime and effects of intervention strategies." To demonstrate this point, Reiss (1988) used incident-level data from the National Crime Survey (NCS, now known as the National Crime Victimization Survey) to evaluate how various social and demographic characteristics of co-offending relationships explained differences in patterns to co-offending across the criminal career. Ultimately, Reiss (1988) illuminated many of the basic features of co-offending and paved the way for a growing research area.

Recent research on co-offending has sought to understand the motivations associated with engaging in group crime (e.g., McCarthy et al., 1998; Weerman, 2003), the roles individuals occupy in co-offending relationships (McGloin & Nguyen, 2012), and the effect that experience with co-offending has on promoting criminal outcomes (Conway & McCord, 2002; Rowan et al, 2016). Unfortunately, van Mastricht and Farrington (2009: 555) framed this literature by stating, "when taken together, they paint a fragmented and confusing picture of co-offending." This is due in part to the limited supply of data used to understand co-offending, which has generated conclusions from small-scale studies that focus on juvenile delinquency, that are gender specific, and that reflect a small range of offense types (see discussion in van Mastricht & Farrington, 2009). In order to bring new insight into the study of co-offending and to expand existing findings, the proposed dissertation will use a large-scale data set, the National Crime Victimization Survey (NCVS), to address a notably understudied issue in the study of co-offending. Specifically,

this dissertation investigates co-offending from a macro-level perspective by evaluating the extent to which economic hardship facilitates the emergence of co-offending.

Why Study Co-offending at the Macro-Level?

There is a sizeable literature examining how patterns of offending and victimization can be explained by social and structural patterns at the macro-level, dating back to Shaw and McKay's (1942) study of social disorganization (e.g., Bursik, 1988; Cohen & Felson, 1979; Sampson and Groves, 1989; Wilson, 1987). This literature has further demonstrated that crime is not randomly distributed across space or time (e.g., Kubrin & Weitzer, 2003; Weisburd, Groff, & Yang, 2012). With some exceptions (e.g., Cloward & Ohlin, 1960), most of these macro-level perspectives largely overlook or completely discount the impact of socio-structural conditions on the *form* of offending and whether there are multiple offenders involved. Interestingly, despite the lack of empirical attention towards co-offending, these theoretical perspectives often acknowledge the important role that a very specific type of group has on facilitating the persistence of deviant behavior across neighborhoods. Specifically, recognition that gangs or delinquent subcultures exerted significant influence on behavior in interstitial areas or neighborhoods was a primary area of interest for many of these scholars.

Thrasher (1927) argued that gangs were a critical component of the urban ecological system that emerged as a result of the instability and lack of control over immigrant youth. Short and Strodtbeck (1965) also acknowledged that because of the structural differentiation across neighborhoods, involvement in peer-groups such as gangs became an extremely important source of status, respect, and a means of overcoming failures attached to the goals of larger society. The social interactions within and with other

gangs served as one of the major contributors to explaining violence among the boys studied (Short & Strodtbeck, 1965). Consistent with this argument, Shaw and McKay (1942) described how the concentration of delinquency and its persistence over time were a function of the continued contact that individuals have with other offenders (i.e., gangs). Specifically, Shaw and McKay (1942) argued that, because of the increased concentration of delinquency in certain areas, there was a higher probability of contact with other delinquent boys – and older offenders – that perpetuated the reinforcement of criminal activity and sanctioning of non-conformity to deviant norms. Cloward and Ohlin (1960) similarly detailed the importance of delinquent subcultures by arguing that criminal behavior that was supported by these delinquent subcultures was likely to recur, access to a successful criminal career was often dependent on participant in the delinquent subculture, and the delinquent subculture generated a sense of stability and resistance to legitimate society by requiring delinquent involvement to maintain one's social standing. Of note, Cloward and Ohlin (1960) distinguished between solitary offenders and offenders who were part of a delinquent subculture. This distinction delineated the offending patterns of those delinquents who offended alone and those who offended with others – or were at least part of a delinquent subculture – and suggested that macro-conditions that produced these subcultures imparted substantially higher social and moral costs onto society because of the more serious offending of those who participated in delinquent subcultures.

In many ways, co-offending serves as one of the linchpins to the observations and theoretical strides made by these early macro-level perspectives. Although invoking gangs or deviant subcultures was the primary focus, each of these perspectives explicitly reinforced the idea that engaging in crime with others facilitated group-formation and was

a consequence of variation in social conditions and opportunity structures across geographic areas. If, as Short and Strotbeck (1965) argued, the criminal group represented the intersection of both individual and macro-level factors, scholars must attend to understanding *both* sets of factors to more completely understand co-offending. As mentioned, a much larger literature has investigated the individual-level factors associated with participation in co-offending, yet a void remains with regard to the macro-level factors that facilitate co-offending. Further, by extending our understanding of groups beyond that of gangs, we can understand how processes at the macro-level are related to another kind of criminal “group” and how they contextualize the interdependent nature of criminal activity.

Viewing crime as an interdependent event is not a new proposition, as several existing criminological theories explicitly attempt to specify the conditions that facilitate the emergence of crime. For instance, nearly all criminological theories assume opportunity to be a necessary condition for crime to occur, however, routine activities theory more specifically theorizes how such criminal opportunities are generated (Cohen & Felson, 1979). Routine activities perspectives argue that crime requires a motivated offender capable of committing a crime, a suitable target for the offender, and the absence of capable guardians (Cohen & Felson, 1979). Importantly though, Cohen and Felson (1979) argued that structural changes at the macro-level altered routine activity patterns among individuals and in turn affected the convergence of the conditions necessary for crime to occur (Cohen & Felson, 1979). These arguments have been theorized at the micro-level in the sense that differences in individual lifestyles, which expose individuals to motivated offenders, are protected by guardians, and interact with attractive targets influence the

extent to which individuals are likely to be victimized (e.g., Hindelang et al., 1978; Miethe & Meier, 1994). While these theoretical arguments have advanced our understanding of offending and victimization patterns, there is limited consideration for how these patterns may also be related to co-offending. Indeed, Cohen and Felson (1979, p.589) explicitly stated that “[they] do not examine why individuals or groups are inclined criminally, but rather we take criminal inclination as a given...” Such an approach arguably discounts the potential for the presence of an additional offender to directly impact the conditions necessary for crime to occur.

As mentioned, prior research has supported the notion that co-offenders can facilitate criminal inclination among others, help identify criminal opportunities, and ameliorate the role of potential guardians (e.g., Andresen & Felson, 2010; Weerman, 2003; Wright & Decker, 1997). Warr (2001: 79) further suggested crime “depend[s] not on the behavior of any one individual, but on the intersections between the criminal careers of numerous offenders. Viewed that way, opportunity is not only temporally and spatially structured, but socially structured as well.” This is not to argue that incorporating co-offending into a routine activities framework resolves limitations of the theory, but rather illustrates how criminal activity may be dependent on the presence of multiple offenders. In fact, Felson and Cohen (1980, p. 403) acknowledged that the theory might benefit from investigating offender dynamics and alluded to the potential role of peers, writing:

However, the routine activity approach might in the future be applied to the analysis of offenders and their inclinations as well. For example, the structure of primary group activity may affect the likelihood that cultural transmission or social control of criminal inclinations will occur, while the structure of the community may influence the extent of peer group activity influencing crime. We also expect that circumstances favorable for carrying out violations may contribute to criminal inclinations in the long run by rewarding these inclinations.

Consistent with prior evidence demonstrating how the presence of peers alters risk perceptions and criminal inclinations (e.g., Chein et al., 2011; Gardner & Steinberg, 2005; McGloin & Thomas, 2016; O'Brien et al., 2011; Warr 2001), it is likely the case that the presence of other offenders may be one of the more important “circumstances favorable for carrying out violations.” Accordingly, changes in routine activities or other social conditions would be hypothesized to impact both crime generally and patterns of co-offending. Tremblay (1993: 17) argued that whether an individual co-offends should not just be a way to classify offenders, but needs to be viewed as an “intelligible outcome of a pattern of individually reasoned choices and constraints that vary across settings, across crimes, and over a given offender’s life cycle”. Thus, it would seem important to consider whether macro-level socio-structural changes influence the likelihood of crime being committed by more than one individual.

Tremblay (1993) hypothesized that social conditions facilitated the distribution, access to, and the search for suitable co-offenders and suggested that this process can be framed by routine activities theory (Cohen & Felson, 1979). Subsequent scholars interested in co-offending have further speculated and in some instances empirically tested how macro-level factors were related to co-offending, however have been limited by cross-sectional analyses, data constraints, and underspecified hypotheses. (D'Alessio & Stolzenberg, 2010; Felson, 2003; Schaefer et al., 2014; Tremblay, 1993). Felson (2003) argued that prior explanations for the emergence of co-offending simply did not have enough empirical regularity to explain the process of taking on accomplices: gangs were too amorphous, social networks were unbounded, and accomplices tended to be unstable over time. To reconcile the limitations of prior work, Felson (2003) suggested that we

should explore the role of offender convergence settings as stable structures that can be used to understand processes associated with co-offending. Perhaps if we are able to identify macro-level conditions that facilitate the likelihood of offender convergence settings and the desire to take on criminal accomplices, we can gain a better understanding of the conditions that generate co-offending. To build upon this prior literature, this dissertation evaluates of the role of a well-known macro-level factor – economic hardship - and the emergence of co-offending.

The Role of Economic Hardship in Explaining Co-offending

Scholars across several disciplines have sought to empirically test the relationship between economic hardship and crime (e.g., Becker, 1968; Bonger, 1916; Cantor & Land 1985; Hale & Sabbagh, 1991; Parker & Horwitz, 1986). The mechanisms that explain this relationship largely fall under either motivational or an opportunity framework. With respect to motivation, difficulty obtaining or maintaining employment challenges the ability of individuals to fulfill basic needs, which may lead individuals to be more likely to commit crime (Cloward & Ohlin, 1960; Merton, 1938). Alternatively, rational choice scholars suggest that the decision-making calculus of potential offenders is affected by unemployment such that unemployed or underemployed individuals view the perceived costs of committing crime to be lower relative to the potential gains (e.g., Becker, 1968; Block & Heineke, 1975). Thus, for these individuals, the potential monetary gain (or utility) derived from committing crime is weighted more heavily than the costs of being caught and convicted. In contrast, employed individuals have significantly more to lose and face higher opportunity costs associated with deciding whether to engage in crime.

In contrast, criminal opportunity theories posit a negative relationship between economic hardship and crime (e.g., Cohen, Felson, & Land, 1980; Cohen & Felson, 1979; Cook & Zarkin, 1985). This perspective argues that crime requires a motivated offender who has the ability to carry out a crime, a person or object that serves as a suitable target for the offender, and the absence of capable guardians (Cohen & Felson, 1979). As mentioned, criminal acts can be viewed as incidents that are tied to the convergence of the routines of offenders, victims, and capable guardians. Fluctuations or changes in economic activity disrupt the conditions that facilitate the emergence of crime, resulting in the reduction of criminal opportunities (particularly for property crime). For example, increases in unemployment leads more individuals to remain at home instead of at work, resulting in an increase in the guardianship over their property and general surroundings (Cohen & Felson, 1979). Additionally, economic hardship reduces spending power for the purchase of valued goods, which affects the availability and attractiveness of potential targets of crime. In total, the changing opportunity structure for crimes results in a reduction in criminal activity (Cohen & Felson, 1979).

Empirical work largely suggests that there is a moderate to inconsistent relationship between unemployment and crime. Among the earliest reviews of this relationship, Freeman (1983) and Chiricos (1987) generally concluded that there was a small positive effect of unemployment on crime that often was inconsistent across studies and generally fell short of the magnitude of the relationships between other factors and crime. In response to these inconsistent findings, Chiricos (1987) stated that the early “consensus of doubt” regarding this relationship challenged scholars to further investigate explanations for the inconsistent findings and improve upon methodological limitations. Perhaps most

importantly, Cantor and Land (1985: 319) explicitly argued that, “a complete structural explanation of the effects of unemployment on crime must incorporate both the impact on criminal motivation and the situational impact on the likelihood of motivated offenders interacting with ineffectively guarded, suitable targets.” Cantor and Land (1985) argued that the relationship between these two components and crime rates were in opposite directions. For motivation, they expected that unemployment would have a positive lagged effect because the experience of economic hardship would be temporarily buffered by social safety nets and other resources. Individuals therefore would not be immediately motivated to engage in illegal activity, but over time dwindling access to resources and an inability to substantially improve economic stability may lead individuals to become motivated to commit crime. With regard to guardianship, increases in unemployment would more immediately impact the relative frequency and duration that individuals were in their homes, as opposed to at work or in other leisure spaces, and would result in an increase in the level of guardianship against criminal activity. Thus, the more contemporaneous effect of the guardianship component attributed to unemployment should be negative.

Tremblay (1993) adopted a routine activities framework to articulate hypotheses about how changes in broader structural factors (e.g., unemployment, housing arrangements, incarceration) could alter the prevalence of motivated co-offenders and the quality of criminal opportunities. Specifically, increases in the level of unemployment would increase the concentration of potential offenders and the amount of leisure time these motivated offenders have to search for co-offenders. As Felson (2003: 157) argued, finding co-offenders was not just about the availability or proximity to other offenders, but was

influenced by whether individuals were “likely co-offenders, without outside interference, and with substantial time available to socialize.” Increases in unemployment may produce a larger number of offender convergence settings that facilitate the ‘mutual discovery process’ associated with identifying co-offenders. Cohen and Felson’s (1979) routine activities theory assumed offender motivation to be a given, but acknowledged the capacity of structural factors to facilitate opportunities for interaction among offenders and targets. For instance, Cohen and Felson (1979, p.589) wrote:

....the convergence in time and space of suitable targets and the absences of capable guardians may even lead to large increases in crime without necessarily requiring any increase in the structural conditions that motivate individuals to engage in crime. That is, if the proportion of motivated offenders or even suitable targets were to remain stable in a community, changes in routine activities could nonetheless alter the likelihood of their convergence in space and time, thereby creating more opportunities for crimes to occur.

This statement acknowledges that shifts in structural conditions generate convergence settings ripe for crime, but falls short of explicitly stating that such settings would facilitate the interaction of offenders. In turn, these theoretical frameworks have been viewed through the lens of assuming that ‘motivated offenders’ are isolated from one another. The extent to which there are motivated offenders is partly a function of the extent to which individuals interact with other potential offenders and may be willing to engage in crime because of the presence and involvement of other offenders. If increases in unemployment generate offender convergence settings, it would likely follow that there would be more offenders not just motivated to commit crime, but also a greater likelihood of considering engaging in crime with others.

Changes in economic hardship also impacts the “target backcloth” or distribution of suitable targets (Brantingham & Brantingham, 1993). Across the board, increases in

guardianship may reduce the total number of available opportunities, but also may incentivize individuals to be more willing to offend with others in order to overcome the reduction in target vulnerability. As one of the burglars interviewed by Wright and Decker (1997: 150) stated:

[I]t's almost always a little safer to have someone else with you...Because if you got someone outside, they can always give a little signal and let you know when someone's coming or whatever. If you're alone, you can't hear these things.

Similarly, Wright and Decker (1997) concluded from interviews that co-offenders served to provide assistance if there was unanticipated resistance from guardians and also increased the perceived odds that at least one offender could escape if law enforcement was encountered. In the face of a potentially different and a more difficult landscape of criminal opportunities, support from co-offenders could facilitate an expansion of awareness spaces of more suitable criminal opportunities, provide access to criminal networks, and share in the practical demands associated with the commission of crime. Such a resource may prove to be a highly valuable particularly individuals are experiencing the effects of economic instability.

In addition to the practical advantages co-offenders may provide in the completion of criminal acts, certain social conditions experienced by offenders may facilitate mutual collaboration and trust between offenders (McCarthy et al., 1998; Shover, 1991; Tremblay, 1993). McCarthy et al. (1998) first formalized a theory for understanding why individuals would be motivated to take on criminal accomplices in the face of the uncertainty and risk associated with co-offending. McCarthy et al. (1998) argued that individuals in states of desperation would be more likely to believe that achieving one's own interests may only be fulfilled by involving other individuals. These scholars found that despite the inherent risks associated co-offending among street youth, experiencing adversity (e.g., failure to

find safe shelter, nutritional sustenance) led to a greater willingness to co-offend. In an extension of this work, Nguyen and McGloin (2013) evaluated the adversity hypothesis among two samples of incarcerated offenders using indicators of more objective experiences of adversity, including unemployment. Interestingly, Nguyen and McGloin (2013) found less consistent evidence for adversity increasing the likelihood of reported co-offending, even among those offenders who reported experiencing unemployment. While such results are somewhat conflicting in nature, it is important to recognize that both reflect individual-level reported experiences of adversity and neglect to consider the broader context that may influence the availability of *other* potential co-offenders and their willingness to co-offend. Specifically, although an individual offender may report experiencing an economic downturn, unless that individual is embedded within an area that also can be characterized as experiencing higher levels of economic hardship there may simply be less opportunity to find other potential motivated offenders and less of a motivational shift in the likelihood that people would be willing to take on a co-offender in the first place (i.e., McCarthy et al., 1998). Thus, to the extent that exposure to conditions of adversity is not equally distributed across space and time, access to individuals who might also be motivated to engage in cooperative criminal action will be affected.

For instance, the positive relationship between experiences of adversity and a greater willingness to co-offend among McCarthy et al.'s (1998) sample of street youth may be influenced by the fact that these youth were from similar neighborhoods and experiencing the same macro-level social conditions. Because the experience of adversity was arguably relatively uniform among the sample, so too were the processes that facilitated motivation and the opportunities to identify co-offenders. In contrast, the null

or inconsistent relationships observed among the samples of incarcerated offenders used by Nguyen and McGloin (2013) may be explained because these offenders came from different contexts with conditions that did not necessarily facilitate co-offending. If macro-level factors matter in affecting the distribution of motivated offenders and the availability of convergence spaces, a sample of inmates drawn from various communities and areas are more likely to be differentially exposed to conditions that may or may not be conducive to co-offending. Ultimately, variation in the prevalence of co-offenses may be influenced by broader contextual factors that facilitate the convergence of conditions conducive for co-offending (Alarid et al., 2009; Hochstetler, 2001; McGloin et al., 2008; Warr, 1996, 2001).

Still, if changes in socio-structural factors reduce the availability of opportunities to engage in crime, individuals could potentially become less cooperative. Human ecology scholars point out that shocks to society and communities may lead individuals to compete over available natural resources (e.g., Hawley, 1986; Park, 1936; Wirth, 1945). In Park's (1936) discussion of human ecology, he argued that the existence of a community depended on several factors including: 1) a population that was territorially organized, (2) was more or less completely rooted in the soil it occupies, (3) its' individual units lived in a relationship of mutual interdependence and that through competition the symbiotic character of a community was maintained. Therefore, competition among individuals may increase because socio-structural changes affect the availability of natural resources and relations among members in a community. When applied to the discussion of criminal opportunities as a resource, changing socio-structural conditions that diminish the availability of criminal opportunities could lead to a scenario where competition trumps co-operation among potential offenders.

Further, under conditions of economic adversity, changes to the availability of suitable targets also affects the potential returns to crime that are an important function of the decision to engage in crime. Raphael and Winter (2001) argued that a rational offender should compare the returns to time use in legal and illegal activities to determine whether to partake in criminal activity. Among those individuals affected by unemployment, securing the optimal return to criminal activity in lieu of engaging in licit opportunities may be achieved by engaging in crime alone. One of the main drawbacks to engaging in co-offending is the potential splitting of any profits that would minimize the total monetary utility associated with any one criminal act. Perhaps, as criminal opportunities considered to be low hanging fruit dwindled (i.e., less risky, available, and unguarded targets), criminal cooperation would become viewed as an increasingly viable option (e.g., Raphael & Winter, 2001). This delayed willingness to take on criminal accomplices is potentially consistent with the long-term buildup of motivation to engage in crime associated with increases in economic hardship (Cantor & Land, 1985). Ultimately however, hypotheses suggesting increasing economic hardship leads to criminal competition are not entirely consistent with evidence in support individuals recognizing that one's own prosocial or illegal goals/interests can only be achieved through cooperation (e.g., Coleman, 1990; McCarthy et al., 1998). Therefore, this dissertation empirically evaluates the extent to which economic hardship actually promotes criminal cooperation.

Two prior studies have considered whether variation in neighborhood and city-level demographic and social characteristics influence rates of co-offending (D'Alessio & Stolzenberg, 2010; Schaefer et al., 2014). In an effort to disentangle the relationship between urbanicity and offending, D'Alessio and Stolzenberg (2010) utilized NIBRS

incident-level data to tease apart competing mechanisms that could explain this relationship. Specifically, areas with reduced collective efficacy, or social breakdown as D'Alessio and Stolzenberg (2010: 713) referred to it, may reduce "the development of friendship networks necessary to induce the occurrence of co-offending crime." In contrast, subcultural theories suggest that areas of high urbanicity are characterized by more extensive deviant subcultures that facilitate group based offending. D'Alessio and Stolzenberg (2010) found that consistent with social breakdown theory urbanization reduced co-offending, however, there was also was no relationship between the rate of unemployment and co-offending.

In a theoretical and empirical complement to the aforementioned study, Schaefer et al. (2014) argued that neighborhoods low in social disorganization promoted trust (or collective efficacy) among residents and facilitated connections to social networks that generated a context conducive to co-offending. Using delinquency records from Maricopa County, Arizona, Schaefer et al. (2014) reported that although collective efficacy was found to reduce crime, areas characterized by low disadvantage, residential stability, and demographic homogeneity actually exhibited more co-offending. Schaefer et al. (2014) concluded that a byproduct of the higher degree of collective efficacy among social networks in these areas was the ability to trust other potential offenders. A case could also be made that these same areas may exhibited a high degree of guardianship, consistent with Sampson et al.'s (1997) finding that areas high in collective efficacy demonstrated a higher degree of residents' willingness to intervene on behalf of some common good. Although increased guardianship generated from unemployment and collective efficacy may be driven by two distinct processes, both macro-level conditions similarly affect the quality

and viability of criminal opportunities that may lead individuals to be more willing to take on criminal accomplices in order to overcome the added risks involved in such an endeavor. Thus, it may also be possible that the changing opportunity structure for crime in these areas promoted criminal cooperation because of the fact that the inherent risks and difficulty associated with crime increased.

Although Schaefer et al. (2014) and D'Alessio and Stolzenberg (2010) recognized the vital role that neighborhood and contextual factors played in generating the conditions conducive to co-offending, these studies face several limitations that impede the strength of the conclusions. First, these studies are limited by the fact that both use official police statistics that may not capture the full range of co-offending events. As mentioned earlier, official statistics drastically underreport the number of crimes that are committed – including co-offenses - and may not be able to identify whether crimes involved multiple offenders. Contextual variation in disadvantage has also been linked to victim willingness to report crimes to police, therefore, relying on official records to assess how different contexts facilitate co-offending ignores the systematic differences in rates of reporting (Baumer, 2002; Kirk & Matsuda, 2011).

These studies also only considered whether co-offending was cross-sectionally associated with socio-structural conditions. Co-offending research broadly has only evaluated the cross-sectional relationship between states of adversity and the likelihood (or willingness) of co-offending, yet research at the macro level suggests that changes in social conditions likely have both immediate effects on criminal opportunities and longer lasting shifts in motivation to engage in crime (e.g., Cohen & Land, 1985; Kubrin & Weitzer, 2003). In order to detect both types of processes, longitudinal data are required (e.g., Cohen

& Felson, 1979; Kubrin & Weitzer, 2003). Lastly, there has not yet been a complete consideration of the distinction between the rate of co-offending and proportion of crimes that are co-offenses. Understanding how macro-level conditions are related to these two substantively different outcomes may provide insight into the nuances in how offenders respond to social-structural conditions. Ultimately, this prior work has not yet specifically theorized and rigorously considered how increases in economic hardship has implications for understanding the emergence of co-offending.

Specifying the Relationship between Co-offending and Economic Hardship

In Tremblay's (1993) discussion of the relationship between economic hardship and co-offending, he referenced prior work by Cantor and Land (1985) that developed a well-known model for estimating the relationship between economic hardship and crime. Cantor and Land (1985) argued that there were essentially two mechanisms through which economic hardship, as measured by unemployment, impacted crime: 1) a system activity or "motivation" effect, and 2) a guardianship effect. The system activity effect represents the motivation to engage in crime, whereas the guardianship effect reflects the level of protection provided to potential criminal targets or opportunities. Cantor and Land (1985: 319) explicitly argued that, "a complete structural explanation of the effects of unemployment on crime must incorporate both the impact on criminal motivation and the situational impact on the likelihood of motivated offenders interacting with ineffectively guarded, suitable targets." They suggested that the relationship between these two components and crime rates would be in opposite directions. For the system activity effect, they expected that unemployment would exhibit a positive lagged effect because economic hardship would be temporally buffered by social safety nets and other resources.

Individuals therefore would not be immediately motivated to engage in illegal activity, but over time dwindling access to resources and an inability to substantially improve economic stability may lead individuals to be motivated to turn to crime. With regard to the guardianship effect, shifts in employment should impact the relative frequency and duration that individuals are in their homes, as opposed to at work, or other in leisure spaces and therefore would result in an increase in the level of guardianship against criminal activity. Thus, the contemporaneous effect of the guardianship component in the model should be negative.

Consistent with the expectations of the model, Cantor and Land (1985) found that the motivational component was positive, particularly for property crime, and the guardianship effect was negative. More recent work on the relationship between economic hardship and crime has offered mixed results, however (e.g., Andresen, 2012, 2016; Arvanities & DeFina, 2006; Greenberg, 2001). Even so, the Cantor and Land (1985) model provides a useful framework to evaluate the nuances in the relationship between co-offending and economic hardship. Still, there are several challenges to integrating literatures on crime, co-offending, and economic hardship. Perhaps most notably, whereas the outcome is straightforward for studies focused on crime rates, the theoretical arguments regarding the potential relationship between unemployment and co-offending highlight the potential relevance of two related, yet distinct, outcomes. Specifically, Tremblay's (1993) theoretical view suggested that, because there was variability in how motivation and opportunity were related to co-offending, there was a need to consider both *rates* of co-offending and the *proportion* of crimes that are co-offenses as dependent variables. Thinking about both outcomes provides more nuanced insight on how macro-level contexts

might facilitate conditions that make co-offending more likely to occur (i.e., rates) and also a viable action alternative for offenders (i.e., proportion) (Weerman, 2003).

Drawing on Tremblay's (1993) work and extensions of it, there is reason to believe that economic hardship will lead to an increase in the occurrence or volume of co-offending as a result of the increased concentration of motivated (co)offenders who are more willing to take on accomplices to meet their goals. As many theoretical perspectives suggest (Becker, 1968; Bongor, 1916; Cloward & Ohlin, 1960; Cohen, 1955; Hughes & Carter, 1981), difficult economic circumstances should increase individuals' motivation for crime. Above and beyond that general increase in criminal motivation, however, there may be a greater willingness to engage in group crime, despite the added risks it entails (e.g., incompetent co-offenders, snitching). Indeed, past findings indicate that individuals exposed to adverse economic conditions were more likely to express a willingness to cooperate with others and take on the risks that accompany co-offending because the potential gains were so attractive during a state of adversity (McCarthy et al., 1998; Tremblay, 1993).

With regard to the other mechanism, the reduction of suitable criminal opportunities during higher levels of unemployment may prompt offenders to adapt their behavior by shifting away from solo crime towards co-offending. In the face of an economic slowdown, opportunities for crime are reduced because targets may become less suitable and guardianship increases, which should depress the overall crime rate (e.g., Cantor & Land, 1985; Cohen & Felson, 1979). Under such circumstances, taking on accomplices may provide a number of practical advantages (e.g., Weerman, 2003; Wright & Decker, 1994). Not only might co-offenders offer aid during the actual criminal event

(e.g., serve as a lookout), but they may provide access to information that could open up more viable criminal opportunities (e.g., broaden awareness spaces and criminal skills). Moreover, Tremblay (1993) argued that one consequence of increases in unemployment was an increased concentration of potential (co)offenders in primary group leisure spaces (see also Felson, 2003). Scholars have noted that one of the most important precursors of co-offending is the availability of accomplices (Weerman, 2003). Thus, offenders may not only see the advantages of turning to group crime but also may simply have greater access to a pool of potential co-offenders who may provide such advantages. Thus, even as the short-term “guardianship” component of economic hardship effect reduces crime rates, the total *proportion* of crimes that are co-offenses may increase. Thinking more carefully about the relationship between co-offending and the processes associated with unemployment requires a thorough consideration of the expected impact that motivation and opportunity will have on both outcomes of group crime.

Motivation and Co-offending

Motivation derived from economic hardship is expected to increase an individual’s willingness to not only offend, but also partake in crime with other offenders. Cantor and Land (1985: 319) described how “an increase in the unemployment rate produces a shift in the density distribution of the population along [a motivation continuum] towards its higher end.” Further, they argued that the shift in the density distribution was not entirely due to changes in motivation to commit crime among those who become unemployed, but rather was also influenced by individuals who were still employed but were negatively affected by the economic climate. One could argue that parallel to the distribution of motivation to offend is a similar continuum indicative of a willingness to engage in co-offending. Indeed,

McCarthy et al. (1998) found evidence for the fact that under conditions of adversity individuals were more willing to take on criminal accomplices. Despite the inherent uncertainties associated with co-offending, conditions of economic hardship may generate a context in which there is an expanded motivation to co-offend.

Thus, it may be the case that not only does the pool of motivated offenders grow larger, but the degree to which these offenders are willing to co-offend expands as well. Similar to the fact that economic hardship impacts both those who are unemployed and underemployed, the motivation to engage in co-offending also applies to a range of potential offenders. Offenders could be crudely categorized into individuals who previously have committed crime or actively consider crime as part of their behavioral repertoire and those individuals who have limited to no experience with criminal behavior. Among both types of offenders, co-offending may become viewed as a viable action alternative as a result of experiencing economic hardship (e.g., McCarthy et al., 1998; Nguyen & McGloin, 2013; Weerman, 2003). Experienced offenders recognize the risks involved with shifting criminal opportunities and taking on criminal accomplices, however, may reconcile these challenges with the potential benefits derived from co-offending (e.g., McCarthy et al., 1998). Alternatively, uninitiated individuals that previously did not view crime as an option, may take comfort in committing crime in the company of others because of the anonymity, diffusion of responsibility, and mitigation of risk involved with co-offending (e.g., McGloin & Piquero 2009, Warr, 2002). Thus, even though participation in delinquent and risky behavior may be inconsistent with an individual's long-term preferences or beliefs, the presence of others may offer the necessary incentives and confidence to engage in risky behavior (Granovetter, 1978; Matza, 1964; McGloin & Rowan, 2015; Thomas &

McGloin, 2016). As a result of the fact that the experience of economic hardship would be anticipated to facilitate greater motivation to engage in co-offending among both of these types of potential offenders, there would be an expected increase in the *rate* of co-offending. Therefore, the dissertation hypothesizes:

Hypothesis 1: There will be a positive relationship between economic hardship and the rate of co-offending in the long-term.

The increased viability of engaging in crime with others among a wide range of potential offenders suggests that the overall distribution of crime that is committed by more than one offender would shift. Tremblay (1993) introduced the notion that increases in unemployment would be related to the proportion of crimes that involved co-offending, unfortunately, he did not fully specify his predictions. While he provided a rationale for the relationship between motivation and the rate of co-offending and opportunity/guardianship and the ratio of co-offenses to total offenses, he left unanswered how motivation was related to the ratio of co-offenses to total offenses and how opportunity/guardianship was related to the rate of co-offending. As previously mentioned, shifts in unemployment contribute to conditions that facilitate individuals being more willing to cooperate with others (e.g., McCarthy et al., 1998). Consistent with the fact that changes in motivation to engage in co-offending are a function of both individuals previously inclined to engage in crime and individuals uninitiated into the criminal world that now view co-offending as a viable choice, it would also be expected that the total proportion of crimes that are co-offenses logically increases. As more potential offenders have an expanded willingness to view co-offending as a viable action alternative and are situated in contexts conducive to forming such relationships, this suggests that economic

hardship may have a unique and additive relationship on the likelihood that an offense involves more than one offender. Stated differently, if the rate at which individuals are opting to engage in crime with other offenders surpasses that of engaging in crime alone, the distribution of crime committed in an area would shift towards co-offending. Increased motivation derived from economic hardship would therefore be expected to lead to a higher *proportion* of crimes being classified as a co-offense. Thus, it is hypothesized that:

Hypothesis 2: There will be a positive relationship between economic hardship and the proportion of crimes that are co-offenses in the long-term.

Opportunity and Co-offending

As previously mentioned, increases in economic hardship are expected to lead to a lower convergence of the conditions that produce criminal acts, resulting in an overall reduction in crime (e.g., Cohen & Felson, 1979; Cantor & Land, 1985). Previously employed individuals are more likely to spend time in primary locations (i.e., homes, neighborhoods), leading to an increased concentration of guardians. Additionally, because of the depressed economic conditions, individuals have less purchasing power for valuable goods and also spend less time in job-related and other leisure travel. Consistent with the fact that a significant amount of personal property crime occurs when individuals are outside of their homes, these changes in the vulnerability and distribution of available targets results in potentially more difficult and risky criminal opportunities (e.g., Cohen & Felson, 1979). Nonetheless, co-offenders may be particularly apt to take on less suitable targets, as they not only provide a number of practical advantages but also shift preferences towards more risky endeavors (e.g., Gardner & Steinberg, 2005; Weerman, 2003).

As Wright and Decker (1997) found in their interviews with burglars, co-offenders provided a number of tactical advantages in managing victims, facilitated the transfer of goods, and shared the demands of completing a crime. Further, it may be expected that offenders need to capitalize on co-offenders' awareness space, criminal skillset, or criminal network to identify available opportunities or overcome the challenges presented by increased guardianship. Collectively, this suggests that offenders may engage in adaptive behavior as a result of changes in the distribution and quality of criminal opportunities. Additionally, because potential co-offenders are more likely to be concentrated and accessible during times of increased economic hardship, this facilitates an increase in the number of convergent settings for offenders to find suitable co-offenders (e.g., Cantor & Land, 1985; Felson, 2003). Thus, despite the decline in crime associated with increases in unemployment found in prior research, the total *proportion* of crimes that are co-offenses would be expected to increase because of the advantages and accessibility of co-offenders. Therefore, this dissertation hypothesizes:

Hypothesis 3: There will be a positive relationship between economic hardship and the proportion of crimes that are co-offenses in the short-term.

To judiciously consider the full implications of how opportunity/guardianship is related to co-offending, it is necessary to consider how it might also be related to the rate of co-offending. The reduction in the availability of targets and increased presence of more effective guardians may have a relatively uniform suppression on the volume of all criminal opportunities. Given that prior work generally finds a negative relationship between the contemporaneous effects of opportunity/guardianship on crime, this could be considered evidence indicative of the overall reduction in criminal opportunities – regardless of

whether an offender engages in the act alone or with others (e.g., Cantor & Land, 1985; Phillips & Land, 2012). Nonetheless, several studies have found that the negative short-term effect of opportunity on crime varies depending on the type of crime considered (e.g., Andresen, 2015; Aravanites & DeFina, 2006; Rosenfeld & Fornango, 2007). For instance, Andresen (2015) found that the short-run effects of unemployment were positively related to shoplifting and theft. He interpreted this finding as offenders shifting towards committing less serious property crime. Although speculative, an association between co-offending and property crime may help explain the presence of a positive short-run relationship to these crime types. If offenders engage in adaptive behavior, such that they are more likely to engage in group crime to overcome the difficulty attached to more guarded and difficult criminal opportunities, Andresen's (2015) finding may be suggestive of an increased volume of offenders involved that have opted to co-offend.

The extent to which a reduction in suitable criminal opportunities differentially deters offenders may explain the rate of both co-offending and solo crimes. Consistent with the previous discussion of opportunity, co-offenders may be particularly suited to meet the demands of more difficult and less suitable criminal opportunities. Because of the instrumental advantages offered by co-offenders and the mechanisms that produce a sense of anonymity and shared responsibility, co-offending may be viewed as both a viable and preferred option during conditions of economic hardship. As Clarke argued (2009), according to a rational choice perspective potential offenders will attempt to continue to offend even when faced with blocked or more difficult opportunities. Weisburd et al. (2006) found some qualitative evidence suggesting that prostitutes and individuals selling drugs engaged in method displacement, which involved engaging in strategies to avoid

being detected or arrested. To be sure, this does not speak to a shift in the form of offending, but does provide evidence that offenders may engage in adaptive behavior that reduces risks associated with changes in opportunities. The decision to take on accomplices, may similarly be viewed as a way to mitigate the risks involved with less tenable opportunities. Still, the overwhelming evidence suggests that the deterrence processes associated with police interventions overwhelmingly discourages most forms of displacement (e.g., Weisburd et al., 2006). The competing forces surrounding the availability and adaptations to criminal opportunities suggest that there is likely an inconsistent or null relationship between the short-term effects of opportunity on the *rate* of co-offending. As such, this dissertation proposes the following hypothesis:

Hypothesis 4: There will be a null relationship between economic hardship and the rate of co-offending in the short-term.

Economic Hardship and Co-offending by Crime Type

The impact of economic hardship on crime and co-offending is arguably not monolithic. Within the co-offending literature there tends to be an empirical interest or discussion of the role of co-offenders across different types of crime (e.g., Cromwell et al., 1991; McGloin & Rowan, 2015). Co-offending is often discussed as a highly instrumental process (i.e., crime was planned ahead, or the co-offender was selected based on some attribute) where there is an explicit ‘exchange’ of skills or knowledge about a particular criminal opportunity (e.g., Andresen & Felson, 2010; Weerman, 2003). Still, co-offending also involves criminal incidents characterized by more primordial or spontaneous convergence of multiple offenders that does not involve pre-planned deliberation to solicit the assistance of other offenders (e.g., Felson, 2009; McGloin & Rowan, 2015). The theoretical arguments laid forth in this dissertation to support the relationship between

economic hardship and the emergence of co-offending are applicable to both types of criminal incidents. The increased concentration of potentially motivated offenders in space in time due to increases in economic hardship, may lead to simply more convergence settings that facilitate minimally planned criminal activity that could be substantively different from highly organized criminal activity. Alternatively, if the quality and quantity of criminal opportunities decline with increases in economic hardship, leveraging criminal connections to identify and seek out more lucrative targets could become a more probable feature of instrumental criminal decision-making. Although it would be theoretically informative to understand whether changes in macro-level conditions induce changes in the type of co-offending, without data to measure differences in the specific motivations behind incidents of co-offending it is beyond the scope of this dissertation.

Nonetheless, evaluating these relationships across different crime types can provide some insight and serve as a proxy solution to understanding how economic hardship may be related to instrumental and primordial criminal acts (e.g., Britt, 1997; Cantor & Land, 1985; Phillips & Land, 2012; Raphael & Winter, 2001). Property crimes, such as robbery, theft, and burglary, are qualitatively different from more violent or expressive crimes because they may be viewed as a means to compensate for economic needs that are impacted by increasing levels of economic hardship. With respect to co-offending, much of the discussion about the exchange processes associated with taking on criminal accomplices and the role that co-offenders have on altering offender awareness spaces tends to also more closely align with instrumental crimes (e.g., Hochstelter, 2001; Weerman, 2003). If co-offenders facilitate an increase in awareness spaces for criminal

opportunities, it is likely because they are helping offenders identify viable or lucrative criminal targets that have some extrinsic benefit attached to it.

Prior work has also suggested that the presence of others can facilitate more expressive or violent types of criminal activity because they obviate concern for the risks attached to engaging in more serious types of crime (e.g., McGloin & Rowan, 2015; McGloin & Thomas, 2016). Due to the seriousness of engaging in violent crime, it may be that the having other offenders present reduces a sense of responsibility and anonymity that help persuade individuals who may not otherwise engage in violent behavior choose to engage in such crime (e.g., LeBon, 1960; McGloin & Piquero, 2009). If there is an increase in the convergence of potential offenders in space and time due to increases in economic hardship, violent collective behavior may also be expected to increase. In thinking about how the relationship between economic hardship and co-offending varies by crime type, this raises a few additional issues over the direction of the relationship between measures of economic hardship and the rate and the proportion outcomes for each type of co-offending.

Prior research indicates that impact of economic hardship may be more salient for instrumental crimes that result in monetary gains (e.g., Britt, 1997; Cantor & Land, 1985; Phillips & Land, 2012; Raphael & Winter, 2001). Part of this explanation is driven by the fact that individuals may become more motivated to engage in such crimes because of the potential reward attached to successful instrumental crimes. As a result, it would be expected that increases in motivation driven by economic hardship in the long-term (Hypothesis 1) would lead offenders to become more motivated to engage in instrumental co-offenses, as opposed to other violent or expressive forms of co-offenses. Consistent with

this argument, it would be expected that because of the motivating pull of instrumental forms of crimes coupled with the increased willingness of individuals to take on co-offenders, there would be an increase in the proportion of instrumental crimes that are classified as co-offenses (Hypothesis 2). There is little reason to expect that increases in economic hardship will lead individuals to become more motivated to engage in expressive or violent co-offenses (e.g., simple or aggravated assault). Thus, the long-term effect of increased motivation would not be expected to be related to the overall rate of expressive co-offending or proportion of expressive crimes that are co-offenses. This leads to several additional sub-hypotheses by crime type:

Hypothesis 1a: There will be a positive relationship between economic hardship and the rate of instrumental co-offending in the long-term.

Hypothesis 1b: There will be a null relationship economic hardship and the rate of expressive co-offending in the long-term.

Hypothesis 2a: There will be a positive relationship between economic hardship and the proportion of instrumental crimes that are co-offenses in the long-term.

Hypothesis 2b: There will be a null relationship between economic hardship and the proportion of expressive crimes that are co-offenses in the long-term.

With respect to the relationship between opportunity/guardianship and the rate and proportion of crimes that are co-offenses (Hypothesis 3 & Hypothesis 4), it would be expected that there would be some similar implications for both instrumental and expressive forms of co-offending. As argued by Cantor and Land (1985), increased levels of economic hardship alter the opportunity structures for crime by increasing the presence of unemployed guardians in homes and diminishing the quality and quantity of targets

because individuals have reduced spending power. This shift in guardianship and the overall distribution of available (and valuable) targets, may lead individuals to consider taking on criminal accomplices for instrumental crimes to overcome the added risks associated with targeting more guarded or lucrative criminal opportunities (e.g., Wright and Decker, 1997). Still, the overall suppression of criminal opportunities as a result of changes in the opportunity structure of crime may universally impact both crimes that would be committed alone and with other offenders. As a result, the competing forces on criminal opportunities suggest that there is likely an inconsistent or null relationship between the short-term effects of opportunity on the rate of instrumental co-offending (Hypothesis 3).

In contrast, although it is likely the case that the overall rate of instrumental co-offending is negatively related to the short-term opportunity/guardianship effect, it is hypothesized that the proportion of instrumental crimes are co-offenses is expected to increase. Potential co-offenders are more likely to be concentrated and accessible during times of increased economic hardship, which increases the availability of behavioral convergent settings for individuals to identify and find suitable co-offenders (e.g., Felson, 2003; Tremblay, 1993). In addition to the increase in these types of settings, the adaptive utility of taking on criminal accomplices may be paramount during times of economic hardship. As mentioned, co-offenders may facilitate an expansion of offenders' awareness spaces, provide criminal skills, or have knowledge of identifying criminal opportunities or targets (Hochstetler, 2001; Weerman, 2003). This could contribute to viewing co-offending for instrumental crimes as both a viable and preferred option when economic hardship increases. Because this suggests that offenders would engage in adaptive behavior away

from solo-offending and towards co-offending for instrumental crimes, there would be an expected positive relationship between the short-term effects of economic hardship and the proportion of instrumental crimes that are co-offenses.

If increases in economic hardship generate more accessible and stable behavioral convergence settings, it would also be anticipated that the rate and the proportion of expressive crimes that are co-offenses would increase. Cantor and Land (1985) posited that increases in economic hardship would lead to an increase in the concentration of leisure activities within primary group locations (i.e., homes, neighborhoods, community). They further claimed that this would lead to lower rates of violent crime because most violent acts were committed by casual acquaintances or strangers, which would be less prevalent within primary-group locations. While empirical evidence has provided evidence in support of this claim, it overlooked the fact that an increased convergence of offenders in primary-group locations also facilitates access to and interaction with other potential co-offenders (Cantor & Land, 1985; Tremblay, 1993).

This has important implications for expressive criminal behavior, because of the potentially salient role that the presence of others plays in facilitating violent behavior. McGloin and Piquero (2009: 339) argued that processes tied to group involvement, including anonymity and the diffusion of responsibility, facilitate individuals to “move past some restraint threshold for offending.” If expressive or violent behavior requires more situational inducement to partake in, the increased concentration and availability of potential offenders due to economic hardship may facilitate a particularly important situational inducement – a co-offender (McGloin & Rowan, 2015). Indeed, McGloin and Piquero (2009) observed that violent criminal behavior was characterized as having more

offenders involved – independent of these accomplices prior involvement in violence - when compared to nonviolent crimes. This provides some support for how the presence of other offenders can contribute towards a greater likelihood of violent behavior. Thus, the saliency of group processes in altering perceptions of risks/costs associated with expressive crime and the hypothesized increase in convergence settings would translate to an expected positive relationship between the opportunity/guardianship effect and the rate of expressive co-offending. McCord and Conway (2002) also observed a relationship between group offending and violent behavior, finding that individuals were more likely to engage in violent behavior after being exposed to a co-offender who had previously engaged in violent crime. This suggests that economic hardship may also produce behavioral convergent settings that facilitate socialization and contact among offenders with varied histories of violent and expressive behavior. Collectively, there would be an expected positive relationship between the short-term effects of opportunity/guardianship and the proportion of expressive crimes that are co-offenses. This results in the following sub-hypotheses:

Hypothesis 3a: There will be a positive relationship between economic hardship and the proportion of instrumental crimes that are co-offenses in the short-term.

Hypothesis 3b: There will be a positive relationship between economic hardship and the proportion of expressive crimes that are co-offenses in the short-term.

Hypothesis 4a: There will be a null relationship between economic hardship and the rate of instrumental co-offending in the short-term.

Hypothesis 4b: There will be a positive relationship between economic hardship and the rate of expressive co-offending in the short-term.

Variation in the Impact of Economic Hardship on Co-offending across MSA Age-Profiles

In addition to the potential for these relationships to vary across crime type, Cantor and Land (1985) argued that the impact of economic hardship, as measured through the unemployment rate, impacted those individuals who were unemployed, underemployed, and others experiencing economic instability. This point was part of a well-known debate between Cantor and Land (2001) and Greenberg (2001), to which Cantor and Land (2001: 331) clarified their original argument by stating, "...we postulated both a direct effect of an increase in the aggregate unemployment rate on the criminal motivation of the specific individuals who become unemployed and a contextual effect on the criminal motivation of others in the population." This point has two major implications for understanding the relationship between co-offending and economic hardship. First, consistent with Cantor and Land's (1985) argument that conditions of unemployment (economic hardship) affected both those who become unemployed and those who experienced an economic downturn, the age-distribution of a geographic area may moderate the impact of economic hardship. Prior work has suggested that the impact of economic hardship and crime was most prominently experienced by younger individuals seeking to enter adult labor opportunities, but failed to do so because of the decline in available jobs (Britt, 1997). Given the concentration of co-offending in adolescence and the declining prevalence of co-offending among individuals over time, it is possible that patterns of co-offending across macro-level areas may be similarly tied to the age distribution of an area

It also may be the case that among older individuals who are actively part of the labor market, changes in economic conditions may directly impact their willingness to engage in group crime and the opportunity structure for crime. Britt (1997) also found that

unemployment had a greater motivational effect among adults for homicide and aggravated assault. Crutchfield (1989) study on labor stratification and violent crime provided some context to this finding by claiming that neighborhoods with higher levels of unemployment or underemployment in secondary labor markets generated a “situation of company” context. Specifically, there is an influx of individuals who are idle and not participating in school, work, or the local labor market. This increases the number of potential victims, offenders, and arguably co-offenders in a given area. As such, if changes in the state of the economy are most salient for the adult segment of the population most attached to the labor market, the impact of economic hardship on co-offending may be moderated by the prevalence of this adult population. In order to take a first step towards understanding how the age-distribution of an MSA moderates the impact of economic hardship on outcomes associated with co-offending, the following hypothesis is proposed:

Hypothesis 5: Of the relationships between economic hardship and co-offending outcomes where a positive relationship is predicted, it is expected that this relationship will be positively moderated by the distribution of the age-profile of an MSA.

The NCVS offers the unique opportunity to utilize a longitudinal dataset in order to assess how macro-level conditions influence the emergence of co-offending. The Bureau of Justice Statistics and the Census Bureau have created an aggregate level NCVS data file at the MSA-level between the years of 1990-2004 that would provide the opportunity to associate aggregated victim reports of multiple-offender criminal incidents to a number of large MSAs across the United States. Leveraging this unique dataset will also provide

substantial advancements into scholarly research interested in co-offending. Scholars have argued for some time that the convergence of offenders and offenders' willingness to cooperate are influenced by socio-structural conditions, yet without data that enables this type of analysis these hypotheses remain untested (Felson, 2003; Tremblay, 1993). Further, given the differences in the expected effects of motivation and opportunity on co-offending and across crime type, this research will illuminate how changes in macro-level economic hardship influences the emergence of behavioral convergence settings that are conducive to co-offending. Not only does this provide a contextualized understanding of collective criminal behavior, but subsequently underscores the fact that purely instrumental or rational models of criminal behavior often overlook how the self-interest of offenders may be achieved by collaborative efforts with other offenders when faced with categorical changes in opportunity structures and sources of motivation (McCarthy et al., 1998; Schaefer et al., 2014). Ultimately, this research question provides an empirical template for further inquiry into understanding the socio-structural conditions that differentiate offending patterns and opportunities related to co-offending.

CHAPTER 3: DATA & METHODS

This dissertation uses data from the National Crime Victimization Survey (NCVS), which is the largest nationally representative source of information on criminal victimization in the United States. The NCVS is administered to a nationally representative sample of households by the United States Census Bureau and is sponsored by the Bureau of Justice Statistics (BJS). In total, the NCVS is a collection of individual interviews conducted with the residents of households sampled and include approximately 90,000 housing units and 160,000 individuals that are interviewed twice each year for three years. The NCVS has been collecting information on personal and household victimization since 1972, however, the survey underwent a significant redesign in 1992. The survey was developed by BJS with four goals in mind: “(1) to develop detailed information about the victims and consequences of crime; (2) to estimate the numbers and types of crimes not reported to the police; (3) to provide uniform measures of selected types of crimes, and; (4) to permit comparisons over time and types of areas” (Bureau of Justice Statistics, 2014:1). The NCVS collects information through self-reports of individuals age 12 or older on nonfatal personal crimes (rape or sexual assault, robbery, aggravated and simple assault, personal larceny) and household property crime (burglary, motor vehicle theft, and other theft).

The NCVS has a series of strengths that address the existing limitations in co-offending research that relies on individual-level, offender based analyses or official records. First, the NCVS (formerly NCS) has used a nationally representative sampling frame to gather information on victimization experiences. At a minimum, these data will provide macro-level estimates for co-offending among offenses where individuals were

able to report whether or not more than one offender was involved in the victimization. Prior work has largely relied on samples of incarcerated offenders, street youth, or in some instances official records among juveniles or specific types of offenders (i.e., burglars, males). This approach limits the generalizability of the findings to the select sample used and often is based on cross-sectional analyses that inhibit an assessment of temporal ordering of many of the proposed hypotheses. The NCVS does not restrict which offenders are included in reports of victimization, except insofar as victimizations of those potential respondents under the age of 12 or those who decline to participate in the survey are excluded. Importantly, person-level response rates have been extremely high, ranging from 96% in 1973 to 87% in 2014 (Truman & Langton, 2015).

Second, the NCVS has been used to capture the dark figure of crime or crime that is not reported to the police and used in official statistics. It has been well established that a non-random portion of crimes are unreported to police. Most recently in 2014, 46% of violent victimizations and 37% of property victimizations were reported to the police, leaving a relatively large percentage of crimes that may involve co-offenders missing from official records (Truman & Langton, 2015). It may also be possible that all of the co-offenders involved in particular crime escape detection and, even when captured, offenders maintain a sense of loyalty by not ‘snitching’ on their partners (e.g., Anderson, 1999; Rosenfeld, Jacobs, & Wright, 2003). This gap in reporting is further compounded by the fact that there are a variety of reasons that explain why individuals do not report being victimized, which may or may not be associated with whether individuals were victimized by more than one offender. Although, there is some evidence suggesting that victimizations by more than one offender are more likely to be reported to the police than victimizations

by a single offender (Baumer & Lauritsen, 2010). Among cases with valid information on whether more than one offender was involved in a reported victimization, approximately 56% of criminal incidents that involve more than one offender were reported to the police, whereas 41% of criminal incidents that involve a single offender were reported to the police. This confirms prior evidence suggesting that group crime was more likely to come to the attention of law enforcement, however, still nearly 44% of crimes involving multiple offenders were not reported to the police. As a result, past research that has attempted to assess whether macro-level factors influenced the likelihood of co-offending and have relied on official records may be poorly estimating these relationships due to the significant and systematic variation in the likelihood that crimes involving more than one offender were reported to the police. Additionally, the few studies that have used official records have several limitations that preclude firm conclusions on the relationship between macro-level factors and co-offending. Tillyer and Tillyer (2015) focused exclusively on robbery which tends to have higher likelihood of being reported to the police and implicates many of the key processes related to the instrumental decision to take on criminal accomplices. D'Alessio and Stolzenberg (2010) only included 184 cities that reported NIBRS data for all 12 months during the year 2000 and had a population of 25,000 or more. Although they acknowledged that NIBRS data represented a small percentage of the U.S. population, this study is further limited by not considering the longitudinal impacts associated with economic hardship. The NCVS includes a range of criminal incidents – reported or otherwise – and enables a longitudinal analysis.

Thus, the NCVS offers an opportunity to utilize victimization data to substantively contribute to the discussion on co-offending. Hough (1987: 366) argued (using the British

Crime Survey) that relying on victim surveys can actually provide insight into the offender decision making process and may actually serve as a “counterweight to the picture of [crime] in popular mythology.” While most scholars have not necessarily answered this call to action, victimization surveys such as the BCS and NCVS offer insight into criminal events and offending that are clearly not captured by official records. Ultimately, the goal of this dissertation is to utilize the relatively rich level of incident-level information and the ability to situate co-offenses into context in order to advance our understanding of co-offending.

BJS and the Census Bureau have created an aggregate level NCVS-NCS data file at the MSA-level (1990-2004), which provides the opportunity to associate aggregate victim reports of criminal incidents that involve more than one offender to a number of MSAs across the United States. This data file contains both a weighted person-based file, and a weighted incident-based file, which contain the "core" counties within the top 40 Metropolitan Statistical Areas (MSAs) (See Appendix A for full list). According to ICPSR/BJS, the core counties were defined as those self-representing primary sampling units that are common to the MSA definitions determined by the Office of Management and Budget. Collectively, the core counties represent nearly 40 percent of the U.S. population. The incident-based file contains select incident-level factors variables, including whether more than one offender was involved in the victimization from January 1990 through December 2004. The total number of MSA-period observations was also reduced because three MSAs were missing incident-level information for the years 1991 and 1992. There is a total MSA-period sample size of N=594.

The NCVS MSA-data provides sub-national and longitudinal estimates of co-offending. MSAs have been utilized in past research across a number of disciplines and has been argued to be a relevant unit of analysis for considering the role of labor, housing, education, and other social institutions (e.g., Bound & Holzer, 2000; Laeven & Popov, 2016; McCall, 2001). The reach and impact of many of these social institutions often surpass city and even county boundaries, suggesting a need to consider a slightly broader geographic coverage (e.g., Burr et al., 1992; Crutchfield et al., 1982). Still, recent advances in hotspots and place-based criminology have argued for the saliency of micro-places in explaining variation in crime and risks to crime (e.g. Weisburd, Groff, & Yang, 2012). These efforts have provided significant advances in understanding the identification of hot spots and the crime prevention strategies. While it would be ideal to evaluate these relationships at lower levels of aggregation (i.e., block level), the current analyses are limited to evaluating the relationship between economic hardship and co-offending at the level of MSAs. Further, the theoretical expectations for the research question investigating the relationship between economic hardship and crime do not demand a micro-level evaluation (e.g., Tremblay, 1993). If changes in economic hardship are related to co-offending at the MSA-level, one could further argue for narrowing the unit of analysis to have a more precise understanding of the spatial distribution of co-offenses. The proposed dissertation seeks to contribute to the relative void in co-offending literature on the role of macro-level contexts in facilitating criminal cooperation.

As mentioned, beginning in 1992 the NCVS (NCS) underwent a significant redesign to incorporate new questions and integrate newer survey methodology techniques. The primary impetus of this redesign was based on criticisms that the NCVS did not do an

adequately capture intimate-partner violence. Comparisons of the NCVS and NCS indicated that a much larger number of rapes, aggravated assaults, simple assaults, and nonstranger violence were captured with the NCVS (Kindermann, Lynch, & Cantor, 1997). Because the MSA-level data file includes years prior to and after the redesign, crime estimates from years before 1992 need to be adjusted in order to produce comparable rates to those generated from the NCVS. Kindermann, Lynch, and Cantor (1997) developed crime ratios for each crime type so that the victimization rates from the years prior to 1992 can be weighted to enable comparisons of crime trends over time. Specifically, estimates for crime rates in the NCS were adjusted such that estimates for aggravated assault were multiplied by 1.23, 1.75 for simple assault, and 1.0 for robbery. An additional concern with the estimating rates of victimization is that both the NCS and NCVS classified incidents as a 'series victimization' if there more than three incidents of the same type for the NCS and six or more incidents were the same type for the NCVS. As noted by Xie et al. (2012), only 3% of incidents in the years 1980-2004 were classified as series incidents and the MSA-level data do not contain information about the number of times the same type of incident occurred. Therefore, series incidents are included in the MSA-level data and are counted as a single incident.

Analytic Plan

Cantor and Land (1985) developed a model of the effect of economic hardship on crime and separated the total effect into motivational and opportunity components. Specifically, Cantor and Land (1985) argued that the effect of economic hardship on motivation emerged over time, whereas the effect on opportunity occurred immediately. The development of this model has led to the proliferation of research interested in the

relationship between economic hardship and crime, but also triggered a significant challenge of Cantor and Land's (1985) empirical specification of this relationship (e.g., Greenberg, 2001; Hale & Sabbagh, 1991; Phillips & Land, 2012). Greenberg (2001) raised several issues with the Cantor and Land (1985) model, including modeling of theoretical statements, statistical misspecification, and the identification of units of analysis. A full review of the details of the debate that has occurred over the past few decades is beyond the scope of this dissertation, however, the proposed dissertation intends to leverage some of the responses to the criticisms of this debate in order to test the relationship between economic hardship and co-offending. In particular, emphasis is placed on ensuring that the hypothesized predictions are appropriately specified in the model and care is taken to consider the implications of working with time-series panel data that are being used in the proposed analyses. Andresen (2012, 2015) has developed a hybrid-model that addressed several of the criticisms levied against the Cantor and Land model. In particular, the model includes empirical corollaries for the long-and-short term effects of economic hardship on crime that are consistent with the theoretical predictions and also accounts for the non-stationary nature of crime and measures of economic hardship.

The theoretical model put forth by Cantor and Land (1985), which specifies that the lagged or long-term effect of motivation and the contemporaneous or short-term effect of opportunity should have opposite directions on the overall crime rate can be specified as follows, using the unemployment rate as the measure of economic hardship:

$$C_t = \alpha + \beta_1 Unemploy_t + B_2 \Delta Unemploy_t + \gamma Z_t + \varepsilon_t \quad (1)$$

where C_t is the crime rate at time t , α is the intercept, $Unemploy_t$ is the unemployment rate at time t , β_1 is the estimated parameter for contemporaneous

unemployment, $\Delta Unemploy_t$ is the difference operator, B_2 is the estimated parameter for lagged unemployment. Andresen (2012) illustrated that Cantor and Land (1985) specified the motivational effect on crime as the difference in crime between time t and time t_{t-1} ($B_2 Unemploy_t - B_2 Unemploy_{t-1}$). The motivational effect is not necessarily a lagged term as described by Cantor and Land (1985) and Andresen (2012) argued that the parameters used by Cantor and Land (1985) do not enable the effects of the long and short run processes to be properly identified.

Andresen (2012) stated that in order to identify the motivational effect of unemployment on crime a statistical method that captures long term relationships must be implemented. An ecological cross-sectional term is used to account for this long term relationship, as individuals who are embedded within areas with levels of economic hardship that are on average higher than other areas are anticipated to have greater motivation for crime. Thus, in any given year these individuals are expected to be “further along a continuum according to their levels of motivation for criminal behavior” (Andresen, 2012: 1617). In order to also model the effect of opportunity, Andresen (2012) employed a fixed effects estimation strategy that was able to identify the contemporaneous effect of unemployment on crime. Levitt (2001: 382) has argued that by using a fixed-effects estimation approach in panel data, “only the short-term relationships between the variables will be reflected in the parameter estimates.”

In developing a model that accommodates both long-and-short term effects of economic hardship, which are consistent with how economic hardship affects motivation and opportunity for crime, Andresen (2012) specified a hybrid or decomposition model that enabled the simultaneous estimation of these different effects:

$$Y_{jt} = \alpha + \beta \bar{X}_j + \gamma (X_{jk} - \bar{X}_j) + \varepsilon \quad (2)$$

where Y_{jt} is the logarithm of a crime rate in a geographic area j at time t , α is the common intercept, β is the estimated parameter for the motivational or long-run effect of variable \bar{X}_j , γ is the estimated parameter for the opportunity or short-run effect of variable X that is conceptualized as the deviation from its average value over the entire time frame of the data. Andresen (2012) evaluated this hybrid model using data from census tracts in the Vancouver Census Metropolitan Area and found results consistent with those originally hypothesized by Cantor and Land (1985). Specifically, the long-run impact of unemployment on property and violent crimes was statistically significant and positive. The short-run effect was consistently negative for all crime types, but, was only statistically significant for property crime. Subsequent work by Andresen (2013, 2015) has generated similar consistency in the findings and the validity of this model across other levels of aggregation.

This model provides a number of benefits because it incorporates the major theoretical predictions originally proposed by Cantor and Land (1985), but further introduces statistical methods that enable the complexity of their arguments to be appropriately modeled. In particular, this model integrates statistical methods to evaluate both the long-term effects of motivation and more short-term effects of opportunity that are intimately tied to the nature of co-offending. The model developed by Andresen (2012) will be utilized in order to specify the impact that economic hardship has on co-offending utilizing the NCVS MSA-level data from 1990-2004. As stated in the proposed hypotheses, the decomposed effect of economic hardship on co-offending is expected to operate somewhat differently across crime types and by the outcome of co-offending. Therefore,

the hybrid model will have to be repeated several times in order to accommodate the different outcomes.

One additional challenge associated with the analytic plan is that the proportion of total crime that is committed by more than one offender is a limited dependent variable that violates some of the assumptions of ordinary linear regression. In particular, because the proportion of total crime that is committed in groups is bounded between 0 and 1, OLS approaches could predict outcomes that are below 0 and above 1 and result in severely biased estimates of explanatory terms. Further, it assumes that the processes which generate variation in the outcome are constant throughout the entire distribution of the outcome. Papke and Wooldridge (1996) recently referred to these types of variables as fractional response variables. A number of solutions to this issue have been proposed. Scholars have proposed first presenting descriptive information on the occurrence of the bounded values (0, 1) and then modeling the continuous component of the outcome using the beta distribution (e.g., Paolino, 2001). These two-step modeling approaches essentially discount or exclude the contribution of values at the bounds, which may be problematic depending on the dependent variable under study (Cook et al., 2008). Alternatively, scholars have utilized a logistic transformation of the proportion outcome because it ensures that the predictive values remain between 0 and 1 and approximates a linearization of the outcome. In particular, there is nearly a linear transformation of proportions between .20 and .80, whereas values close to 0 and 1 are spread out at an increasing rate. One drawback to this approach is that values that fall on the bounds of 0 and 1 are inherently excluded unless these values are transformed by the addition of a small constant (Cook et al., 2008).

More advanced analytical approaches have been developed to address these limitations, which require the specification of the nonlinear functional form of the proportion outcome. Papke and Wooldridge (1996) proposed the use of a quasi-maximum likelihood estimators to estimate models that utilize proportion outcomes without implementing a transformation of the outcome. This modeling strategy is considered to be an extension of the general linear model and is able to simultaneously account for the bounded nature of the dependent variable and ensures that predicted values remain within the limits of the variable. One of the main limitations of this modeling approach is that because it explicitly accounts for the non-linear nature of the model, interpretation of the point estimates is restricted and require the calculation of average marginal effects. Proponents of this approach argue that this enables a consideration of the average effects at different percentiles of the distribution of the outcome, which may be informative in understanding whether the impact of certain covariates is constant across variation in the outcome (e.g., Papke and Wooldridge, 1996). However, for the purposes of the hybrid modeling strategy utilized in this dissertation, the calculation of marginal effects becomes problematic (Schunck, 2013). The inclusion of both a between-and within unit estimator into a model raises the questions of whether the predicted values derived from marginal effects should be based on the between or within components of the model and what values each of the covariates should be set to. More specifically, each of the between and within components of the covariates in the model are comprised either fully or in part by their mean value over the study period, which is often used to estimate the average marginal effects of covariates. Given the relative nascence of the hybrid modeling strategy and limited methodological testing for how it might be integrated into a fractional response

framework, fractional response models would result in providing uninterpretable results that would inhibit an understanding of the magnitude of the estimates.

In order to evaluate the relationship between the short and long term effects of economic hardship and the proportion of group crime, such that each hypothesis can be tested and discussed in relation to the rate of group crime, this dissertation opts to utilize a logistic transformation of the proportion outcome. As discussed, this approach has been previously used to accommodate a proportion outcome and also generates interpretable estimates (Baum, 2008; McDowell & Cox, 2001). In doing so, the analytic model is able to retain the specifications associated with the hybrid model and provide point estimates for the long and short term effects of economic hardship. To address the fact that a logistic transformation of a proportion outcome excludes values at the bounds $[0, 1]$, a small constant value that is defined by the lowest proportion of group crime for each crime type is added to the lower bound and subtracted from the upper bound.³ Additionally, because of the fact that heteroskedastic errors are often observed in proportion dependent variables, robust standard errors are calculated for each of these models. Given the analytical challenges associated with a dependent variable that is a proportion, the robustness of the findings were confirmed with the inclusion of sensitivity analyses. These analyses are presented in an Appendix and include modeling the proportion outcome in an OLS regression, beta regression, and also in a fractional response model (see Appendix 2).

³ It is important to note that the bounds present in the proportion outcome may represent distorted values that are derived from the sampling procedure utilized in the NCVS to generate aggregate-level estimates of victimization experiences. If an MSA is estimated to have zero group crime in a given year, this may be driven by the fact that among the relatively small number of households interviewed – and that had valid data on whether or not more than one offender was involved in a victimization experience – there were no incidents of reported group crime. One could argue that it would be unreasonable to expect that in a given year there would be zero incidents of group crime in an entire MSA. Still, this low estimate of group crime may still signal that an MSA experienced a non-negligible, but small amount of group crime. Therefore, observations at the bounds are retained to ensure a robust sample size.

Importantly, although the magnitude of the estimates vary across the modeling strategy, the direction and statistical significance of the main predictor variables are largely consistent.

Lastly, there is an important data constraint that raises some concerns over the generalizability and validity of the results. The MSA-level data captures core-counties within the overall NCVS survey. Although these counties represent nearly 40% of the US population once the sampling design is accounted for, the number of respondents and reported incidents within some MSAs that are used to estimate MSA-level victimization rates are relatively small. This raises concerns over a lack of statistical power to produce aggregate estimates of co-offending. Solutions to this concern generate tension between maintaining construct validity of the theoretical concepts (i.e., motivation and opportunity) and specifying a robust empirical model. One possible approach to addressing the small sample sizes within each MSA in any given year would be to pool the MSA data over time. Cantor and Land (1985, 2001) cited evidence suggesting that recovery from economic recessions may occur over two-year business cycle, which might provide support for pooling the available data across two years of data. Most recently, Xie et al. (2012) pooled the MSA-level NCVS data across five-year intervals to address both the small sample size and to account for fluctuations around unemployment and crime trends. Still, Cantor and Land (1985) and their critics convincingly argue that the delayed effect of unemployment on crime beyond a year would be illogical because of the inconsistent evidence in a one-year lagged effect (Greenberg, 2001).

Thus, pooling data across years could lead to a distortion in the construct validity for both processes in the model. Scholars generally agree that the effects of unemployment

on crime (and co-offending) can be categorized into long and short-term components. If data are pooled together over a number of years, the construct validity of what is considered a short-term opportunity effect or a long-term motivation effect is weakened. Cantor and Land's (1985) initial formulation of the opportunity effect specifically made quite clear that the timing was contemporaneous with shifts in the economic business cycle. Even pooling data across two to three years raises questions about the distinction between the two components of the unemployment and crime model. Nonetheless, one must grapple with the fact that some MSAs do not contain many cases (e.g., West Palm Beach-Boca Baton, FL contains 416 cases across all the 14 years of data). In order to balance maintaining the specified theoretical arguments and developing a robust empirical model, several sets of analyses will be conducted in order to assess the consistency of the results. Consistent with past research that has used annual estimates, the analyses will first proceed with a model that evaluates the impact of economic hardship on group crime in a single year. Subsequent analyses will continue to increase the number of years that are pooled until three years of data are pooled.

Measures

Dependent Variables

Consistent with the hypotheses, it is expected that there will be differences in the relationship between economic hardship and co-offending across instrumental and expressive crime types. The NCVS collects information on nonfatal personal crimes (rape or sexual assault, robbery, aggravated and simple assault, personal larceny) and household property crime (burglary, motor vehicle theft, and other theft). Instrumental crimes, or crimes that involve the potential for monetary gain, include the following offenses:

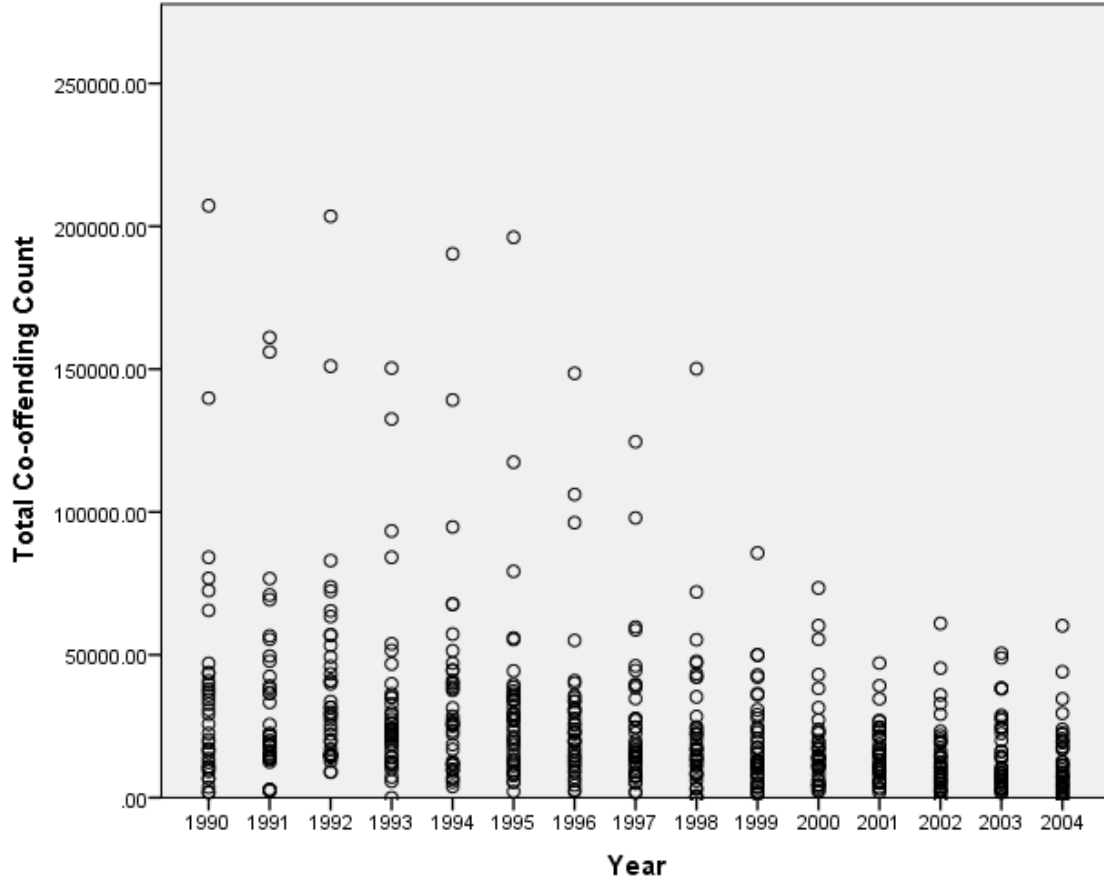
robbery, personal larceny, burglary, motor vehicle theft, and other theft. One important distinction to make across these crime categories is the unit of analysis. Among the personal crimes (i.e., robbery, personal larceny) the unit of analysis is the individual respondent, whereas for household instrumental crimes (i.e., burglary, motor vehicle theft, other theft) the unit of analysis is the entire household. As a result of this difference, instrumental crimes that involve more than one offender will be divided into personal and household based instrumental crimes. Expressive crimes will include person based aggravated and simple assaults. Because of the relatively low prevalence of rape or sexual assault and the substantively different nature of this type of crime as it may relate to co-offending, it is excluded from the construction of expressive crimes for this dissertation. It is important to note that the delineation between instrumental and expressive crimes is not meant to reify these crime categories, but rather is consistent with prior work evaluating the relationship between economic hardship and unemployment and can provide insight into the potentially unique implications co-offending has across various crime types (i.e., McCord & Conway, 2002; Weerman, 2003).

Rate of Co-offending. Consistent with the hypothesized relationships between economic hardship and co-offending, across certain crime types there is an expectation that the overall volume of co-offending would change. For instance, economic hardship is expected to be positively related to the rate of instrumental co-offending in the long-term because motivation to engage in co-offenses that involves monetary gain takes time to develop and experiencing adversity leads offenders to become more willing to take on accomplices. Figure 1 shows the trends in time of the weighted count of co-offending incidents across MSAs. Because of the NCVS re-design, two formulas were used to

calculate estimates of the rate of co-offending. Annual estimates for each MSA from 1993 to 2004 will be calculated based on the following formula:

$$\text{Rate of Cooffending}_t = \frac{\text{Number of Cooffenses}_t}{\text{Number of respondents aged 12 years or older}_t / 1000}$$

Figure 1: Count of Co-offending Incidents by MSA, N=594



Annual estimates for MSAs between 1979 and 1992 will be calculated based on the following formula, where w_c is the weight for each crime type:

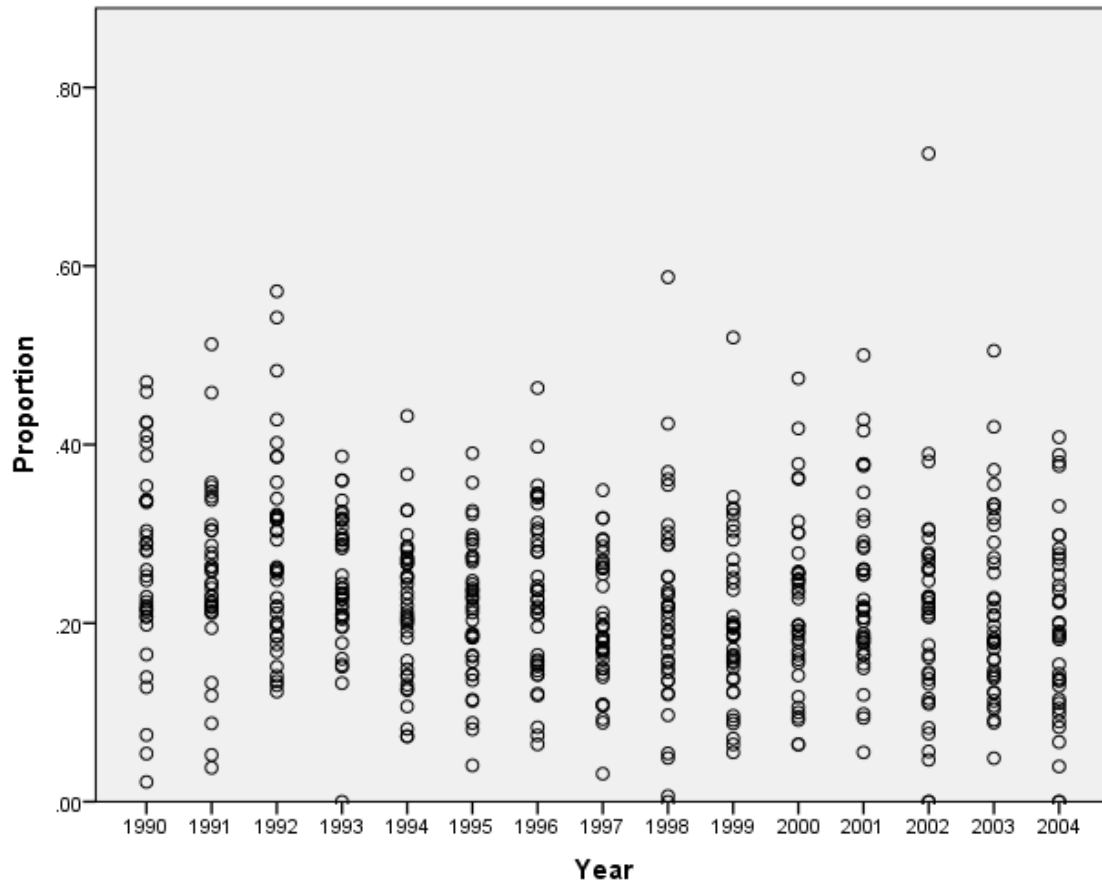
$$\text{Rate of Cooffending}_t = \frac{w_c * \text{Number of Cooffenses}_{ct}}{\text{Number of respondents aged 12 years or older}_t / 1000}$$

Proportion of Co-offending. Under conditions of economic adversity the advantages and shift in preferences associated with co-offending is expected to affect the *proportion* of co-offenses committed. For each MSA, the incident records will also be used to generate an estimated proportion of offenses that involved multiple offenders. Figure 2 shows the trends over time of the weighted proportion of co-offending incidents. For all of the years in the dataset, the proportion of offenses that are co-offenses will be calculated by the following formula⁴:

$$\textit{Proportion of Cooffending}_t = \frac{\textit{Number of Cooffenses}_t}{\textit{Total Number of Incidents}_t}$$

⁴ In the calculation of a proportion of co-offenses, the weighting procedure used to provide comparable estimates of crimes before and after 1992 would be applied to both the numerator and the denominator. As a result, it is not necessary to apply weights to account for change in methodology across the NCS and NCVS.

Figure 2: Proportion of Co-offenses by MSA, N=594



Independent Variables

Economic Hardship. Over the past decade, there has been a relatively expansive growth in empirical analyses that seek to understand the role of economic hardship and crime. Primarily, much of this research relies on the unemployment rate as a measure of the state of the economy. This decision is largely guided by the fact that scholars have continued to test and refine Cantor and Land’s (1985) original model, which argued in support of the use of the unemployment rate. Still, a number of additional studies have questioned the use of the unemployment rate and have replaced this measure with alternatives, including: 1) the gross state product or gross domestic product (Arvanites & DeFina, 2006; Rosenfeld & Fornango, 2007), 2) consumer sentiment (Rosenfeld &

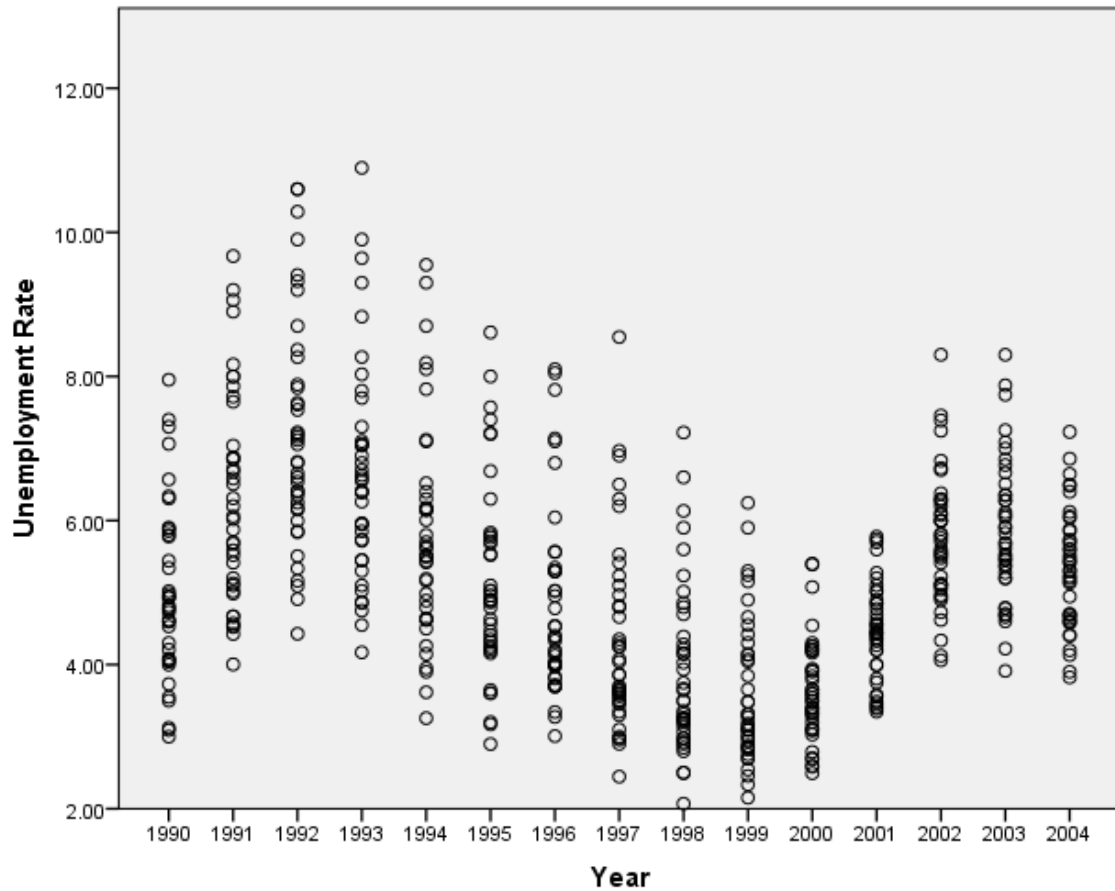
Fornango, 2007), 3) average wages (Yearwood & Koinis, 2011), and measures of low income (e.g., Andresen & Linning, 2015). Use of measures other than the rate of unemployment are largely based on the argument that there are a number of limitations attached to this measure and it does not accurately capture the state of the economy and overlooks segments of the population that may turn to crime in the face of hardship.

As defined by the Bureau of Labor Statistics (2014: 10), unemployed individuals include “All those [individuals] who did not have a job at all during the survey reference week, made at least one specific active effort to find a job during the prior 4 weeks, and were available for work (unless temporarily ill). All those who were not working and were waiting to be called back to a job from which they had been laid off.” Greenberg (2001) suggests that this definition excludes a number individuals, including: 1) those who become discouraged because they have given up on finding a job or never sought to obtain employment in the first place, 2) stay at home parents or students who are not working or looking for a job, 3) workers who make extremely low wages or may be involved in the secondary labor market. Exclusion of these segments of the population are important for understanding the relationship between economic hardship and crime because individuals within these categories may be most likely to turn to crime to meet the demands of living expenditures. Cantor and Land (1985, 2001) argue that it is still a valid proxy for the overall state of the economic system. Additionally, as originally suggested by Tremblay (1993), using unemployment aligns with the theoretical predictions for the model with co-offending as an outcome. In order to address the limitations of a single measure of economic hardship, multiple alternative measures will be used including the unemployment rate and the percent of poverty in an area. Each of these measures attempt

to provide an indicator of the strength of the state of the economy in an area and have been used in prior research to understand the relationship with crime.

Annual unemployment information for each of the MSAs between the years of 1990-2004 was obtained from the Bureau of Labor Statistics (BLS). The government conducts a monthly survey titled, the Current Population Survey (CPS), to capture the level of unemployment in the country. Approximately 60,000 households are eligible to be included in the sample and these households are selected to be representative of the entire population of the United States. Census Bureau employees contact the eligible sample members and inquire about labor force activities and non-labor force status of members of the household. BLS defines the unemployment rates as a percentage of the labor force that is considered unemployed. Figure 3 shows the trends over time in the unemployment rate.

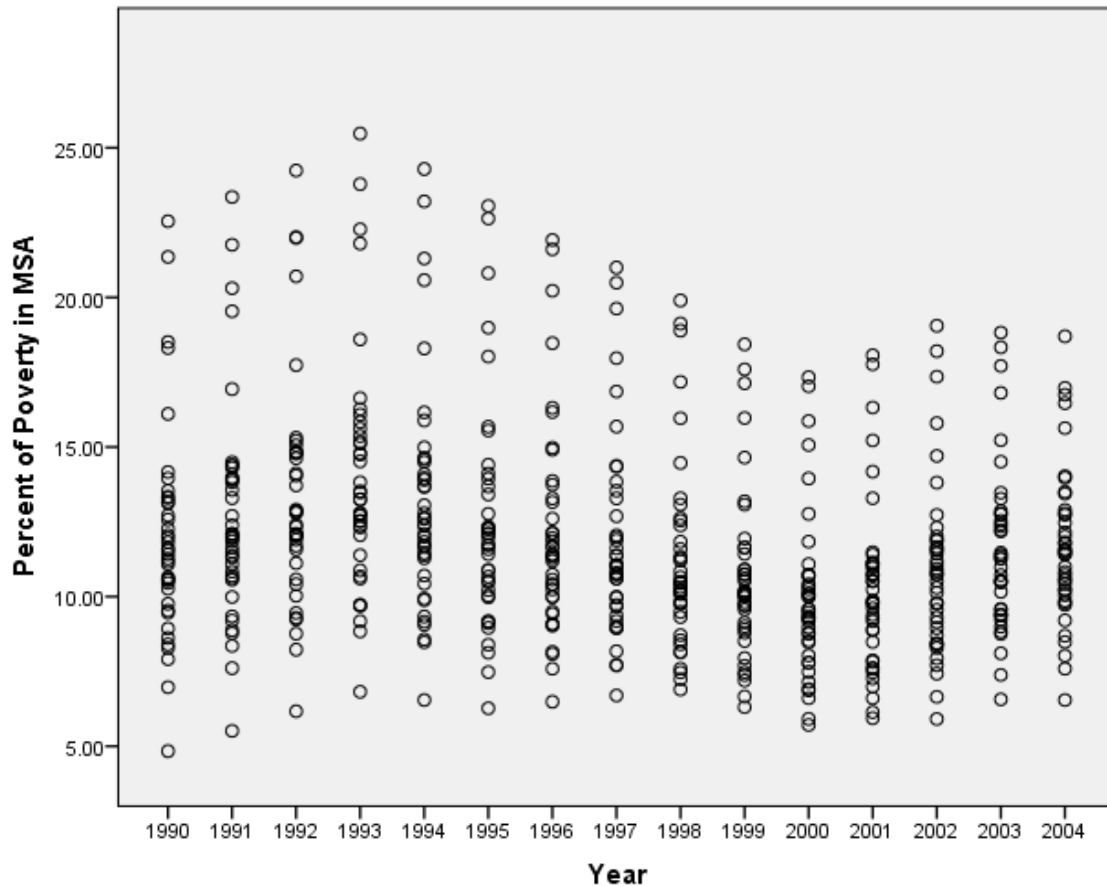
Figure 3: Unemployment Rate by MSA, N=600



To overcome some of the limitations of the measure of unemployment as an indicator for economic hardship, a measure capturing the percentage of poverty in an MSA is also included. Poverty status is defined by comparing pre-tax cash income to a threshold that is determined by the U.S. Census Bureau and is approximately three times the cost of a minimum food diet. Whereas individuals experiencing poverty may be unemployed or included in the unemployment rate, poverty levels also capture those individuals that are discouraged from the labor market or participate in the secondary labor market and are excluded from the labor force totals used to calculate the employment rate. As such, a measure of poverty arguably captures a wider range of economic hardship that may be particularly salient in tapping into the experience of

adversity that alters both motivation and opportunities for crime (and criminal cooperation). Indeed, Vold and Bernard (1986: 138) state that it is “the lack of some fixed level of material goods necessary for survival and minimum well-being” that generates conditions conducive to crime. The measure of the percentage of poverty is derived from data collected through the American Community Survey (ACS) conducted by the Census Bureau. Specifically, the Small Area Income and Poverty Estimates program utilizes a combination of indicators including ACS data, federal income tax returns, SNAP benefits, decennial census data, postcensal population estimates, Supplemental Security income reciprocity, and economic data from the Bureau of Economic Analysis (BEA) to generate model-based estimates of poverty levels at the county-level. These estimates were combined to match the core counties utilized in the MSA-NCVS data file to create indicators for the percentage of the population in an area that are below the poverty threshold. Figure 4 portrays the changes in percentage of poverty across the MSAs used in the analysis over the course of the 14 year time period.

Figure 4: Percent of Poverty by MSA, N=600



The use of multiple measures of economic hardship enables a consideration of its relationship to co-offending that addresses concerns over the limitations of both measures. While each measure taps into the construct of economic hardship, differences in the unemployment rates and the percentage of poverty may not be without consequence. Specifically, any observed differences in the results could be driven by the fact that each measure may be differentially related to long-term processes associated with motivation and short-term processes attributable to changes in the opportunity structure for crime. For instance, Cantor and Land (1985) explicitly described how the short-term effect of opportunity/guardianship was associated with the unemployment rate because as more people become unemployed they are more likely to spend time in home guarding their property and neighborhood. This association is inextricably tied to people

becoming unemployed, therefore the contemporaneous impact of rising unemployment on opportunity/guardianship may be most salient for this measure of economic hardship. It is likely the case that poverty levels in an MSA also capture the extent to which people are unemployed or underemployed and spending time at home, however, the conceptual link between the short-term changes in guardianship articulated by Cantor and Land (1985) is not as immediately associated with increasing poverty levels. Similar arguments can be made with respect to thinking about the long-term effects associated with motivation. Both the unemployment rate and the percentage of poverty arguably serve as indicators of the extent of adversity experienced in an area that may lead individuals to become more motivated to engage in criminal activity.

If, as Cantor and Land (1985) argued, more than just those who become unemployed experience adverse consequences of a declining economy, the percentage of poverty may capture a deeper sense of adversity beyond that of the unemployment rate. One of the major limitations of the unemployment rate was that it inherently excludes individuals (i.e., those discouraged from the labor market) that may be most relevant for understanding patterns of criminal activity. To be sure, at a global level, the correlation between the unemployment rate and the percentage of poverty within an MSA is .548 ($p < .001$), which suggests that there is a fairly strong relationship between these two measures. Nonetheless, observed differences in the findings across measures of economic hardship may reflect how these different measures uniquely tap into processes related to motivation and opportunity.

Control Variables

Ecological Controls. Consistent with past research that has sought to evaluate the relationship between unemployment and crime, it is important to control for several area-

level factors that may be related to rates of co-offending and criminal activity generally. Age is not only strongly correlated with criminal behavior, but also has been demonstrated to be related to the likelihood of co-offending (e.g., Farrington, 1986; Gottfredson & Hirschi, 1990; McCord & Conway, 2002). In order to account for this, measures of the percentage of the population between the ages of 15 and 24 years of age were included as a control. It is also hypothesized that the short-and long-term processes associated with increases in economic hardship may be moderated by the age-distribution of an MSA. As a result, two interaction terms are included in the analyses. The first interacts the between- and within-measures of economic hardship with the percentage of the MSA that is between the ages of 15 and 24 years old, which is consistent with prior arguments suggesting that the impact of economic hardship may be most salient among those seeking to enter the adult labor market. Alternatively, the between-and within-measures of economic hardship are interacted with the percentage of the MSA that is between the ages of 25 and 44 years old to evaluate whether these processes may be more important among those most likely to be in the adult labor market and responsible for their own financial well-being. Although this is a relatively crude distinction in the age-profile of an MSA, there is limited variation in smaller categories of age over time within the MSA, which diminishes the ability to detect within-MSA changes in the potential moderating relationship. Some evidence suggests that black individuals are more likely to engage in co-offending, therefore the percentage of the population in an MSA that is black will be controlled for (Andresen &

Felson, 2010; Lynch, 2002; McCord & Conway, 2002). Data for these control variables will be obtained by the U.S. Census Bureau⁵.

Trend Variables. One of the major criticisms levied against Cantor and Land (1985) was that they did not adequately address the fact that they did not address trends in crime rates (e.g., Greenberg, 2001). In order to account for the trends in both unemployment and crime data, a linear and quadratic time trend variables will be included as controls (Andresen, 2015; Raphael & Winter-Ebmer, 2001).

Single Offender Crime Rate. In order to discern the independent effect of unemployment on co-offending from crime generally, it is necessary to also account for the crime rate. This also provides a control for any year to year fluctuations in crime rate trends that can cause specification issues in time-series panel data (e.g., Greenberg, 2001; Hale & Sabbagh, 1991). Still, because group crime is part of the overall crime committed in an area, including a measure of the overall crime rate would essentially be including the major dependent variable as part of an independent variable. To address this and attempt to isolate the role that macro-level conditions of economic hardship have in explaining group crime, the total single-offender offense rate will be included as a control variable. In order to calculate the single-offender crime rates in each MSA, a similar formula used to calculate the rate of co-offending victimization will be used. This single-offender crime rate will only include offenses that also enables a victim-offender interaction to be

⁵ While it would be ideal to include a wide range of control variables, it is difficult to identify control variables that are essentially available at the county-level that are related to the outcomes of interest. Because the MSAs created by the NCVS may differ from the MSA categorization used by the Census Bureau, existing data may not necessarily correspond to the configuration of an MSA in the NCVS. In addition, the single-offender crime rate in some of the models serves as a relatively strong control for many of the processes that would also be related to group crime.

consistent with the rate of co-offending. This essentially only excludes intimate partner violence or other sexual assaults. Additionally, consistent with the fact that the analyses will be divided by crime type, the single-offender crime rate will also correspond to the same group crime outcome. This control variable will also only be included in the rate of group crime models because the numerator of the single-offender crime rate is inherently part of the denominator of the proportion outcome. Because the denominator of the proportion outcome is comprised of the total number of solo-and group based offenses, the outcome would inherently be a function of this control variable.

$$\text{Single Offender Crime Rate}_t$$

$$= \frac{\text{Number of Single Offender Offenses}_t}{\text{Number of respondents aged 12 years or older}_t / 1000}$$

Table 1: Descriptive Statistics for Variables⁶

<i>Variable</i>	N	Mean	Standard Deviation
Logged Overall Group Crime Rate	540	2.28	.65
Logged Overall Solo Crime Rate	540	10.95	.72
Logged Group Household Property Crime Rate	474	1.09	.66
Logged Solo Household Property Crime Rate	474	2.20	.48
Logged Group Personal Instrumental Crime Rate	533	1.15	.71
Logged Solo Personal Instrumental Crime	533	1.46	.67
Logged Group Expressive Crime Rate	450	1.70	.71
Logged Solo Expressive Crime Rate	450	3.03	.53
Overall Proportion of Group Crime	540	.24	.10

⁶ Missing data was handled through listwise deletion. All of the missing data occurs because for certain MSAs there were either too few a number of respondents with valid data or respondents which reported zero victimizations of certain crime types.

Proportion of Group Household Crime	474	.22	.14
Proportion of Group Personal Instrumental Crime	533	.41	.27
Proportion of Group Expressive Crime	450	.20	.11
Percentage of Poverty	600	11.87	3.49
Rate of Unemployment	600	5.20	1.59
Percent 15 to 24	600	13.40	1.31
Percent 25 to 44	600	32.80	2.50
Percent Black	600	14.99	8.76
Percent Male	600	48.89	.85

CHAPTER 4: RESULTS

The presentation of the results proceeds first by examining the set of models that focus on evaluating the relationship between economic hardship and the overall rate of co-offending and is followed by the set of models examining the relationship between economic hardship and the overall proportion of crime that is committed by more than one offender. As previously mentioned, there is reason to believe that the short-and long-term processes associated with economic hardship are differentially related to various crime types⁷. Therefore, the results are first examined by looking at the rate of overall co-offending and the proportion of overall crimes that are co-offenses, followed by models that are divided by crime type. Each of these models also are tested across several measures of economic hardship (i.e., unemployment rate, percent of poverty) and are evaluated to determine whether the age-distribution of an MSA moderates the short- and long-term processes associated with economic hardship.⁸

Rate of Co-offending Results

Table 2 presents the results for the model using the overall rate of co-offending as an outcome. Across the models, the short-and long-term relationship between unemployment and the overall rate of co-offending is not statistically significant. Thus, there is limited support for the overall hypotheses that suggest there will be a positive relationship between the long-term impact associated with motivation (Hypothesis 1) and a positive relationship between the short-term impact associated with

⁷ Consistent with Cantor and Land's (1985) theoretical arguments, the long-term effect of economic hardship refers to a motivational influence and the short-term effect refers to the influence of opportunity.

⁸ Each of the models presented were tested for serial auto-correlation and heteroskedastic errors. There was no evidence to suggest that these factors impacted the results of the analyses. Additionally, the time trend variables are excluded from the presentation of the results as they do not substantively affect the interpretation of the findings and are meant to account for trends in the data.

opportunity/guardianship (Hypothesis 2) and rate of co-offending. Interestingly, the only statistically significant predictor is the decomposed relationship between the overall rate of solo-crime and the rate of co-offending. In essence, this suggests that MSAs that on average have higher rates of solo crime also have higher rates of co-offending and those MSAs that experience short-run increases in the rate of solo-crime also experience positive increases in the rate of co-offending. This is not totally surprising, as it implies that conditions that lead to increases in solo-offending are simultaneously related to conditions that produce co-offending. The lack of statistically significant findings for the overall rate of co-offending further suggests that the processes triggered by economic hardship may be differentially related to certain crime types.

**Table 2: Hybrid Model for Overall Rate of Co-offending, Unemployment Rate
N=540**

	Baseline Model (2a)		Interaction Model with Age Profile 15-24 (2b)		Interaction Model with Age Profile 25-44 (2c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Unemployment Rate	.013 (.028)	.019 (.019)	.471 (.381)	-.228 (.172)	.285 (.637)	-.057 (.259)
Solo-Offense Rate	.194*** (.049)	.395*** (.074)	.239*** (.073)	.397*** (.063)	.226** (.020)	.400*** (.064)
Percent Aged 15-24	.019 (.030)	-.097 (.092)	.204 (.157)	-.189* (.089)		
Percent Male	.012 (.056)	.012 (.144)	.008 (.056)	-.030 (.142)	.066 (.069)	-.055 (.138)
Percent Black	.004 (.004)		.003 (.005)	.032 (.033)	.007 (.005)	.041 (.034)
Percent Aged 25-44					.024 (.096)	-.012 (.068)
Unemployment Rate X Percent Aged 15-24			-.035 (.029)	.019 (.013)		
Unemployment Rate X Percent Aged 25-44					-.009 (.020)	.003 (.008)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Table 3 presents a similar set of results when using the percentage of the MSA that is at or below the poverty level as an indicator of economic hardship. The decomposed relationship between the rate of solo-offending and the rate of co-offending is statistically significant across all of the models, indicating a strong relationship between these forms of arguably interdependent behaviors. Of note, in the baseline model 3a the short-term effect of poverty is statistically significant and positively related to the overall rate of co-offending. For every one-unit increase in short-term increases in the percentage of poverty, the expected rate of co-offending increases by nearly 5.4% ($\exp^{.053}$). This suggests that within-MSA increases in the percentage of poverty induces short term increase in the rate of co-offending, which is consistent with the expectation that there would be a more contemporaneous demand for co-offending given the decline in the quality of criminal opportunities and an increased convergence of offenders in space in time (Hypothesis 3).

Table 3: Hybrid Model for Overall Rate of Co-offending, Percent Poverty N=540

	Baseline Model (3a)		Interaction Model with Age Profile 15-24 (3b)		Interaction Model with Age Profile 25-44 (3c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Percent Poverty	.015 (.009)	.053** (.021)	.159 (.172)	-.002 (.134)	.107 (.222)	-.176 (.176)
Solo-Offense Rate	.184*** (.047)	.383*** (.077)	.181** (.063)	.383 (.063)	.191** (.065)	.391*** (.063)
Percent Aged 15-24	-.002 (.036)	-.059 (.082)	.122 (.152)	-.103 (.123)		
Percent Male	.031 (.055)	.035 (.139)	.036 (.059)	.024 (.033)	.045 (.065)	-.034 (.139)
Percent Black	.004 (.004)	.024 (.036)	.004 (.005)	.022 (.140)	.005 (.005)	.015 (.034)
Percent Aged 25-44					.024 (.073)	-.065 (.073)
Percent Poverty X Percent Aged 15-24			-.010 (.012)	.004 (.010)		

Percent Poverty X Percent Aged 25-44						-.003 (.007)	.007 (.005)
---	--	--	--	--	--	-----------------	----------------

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

The next set of results separate out the long-and short-term relationship between each indicator of economic hardship and three types of co-offending – household property crime, personal instrumental crime, and expressive crime. Table 4 presents the results for household property co-offending and the unemployment rate as an indicator of economic hardship. As a reminder, the long-term effect captured by a between-unit estimator represents the motivation effect devised by Cantor and Land (1985), and the short-term effect captured by a within-unit estimator represents the opportunity effect. As can be seen in Model 4a, consistent with Hypothesis 1a changes in long-term motivation due to increase in economic hardship are statistically significant and positively related to the rate of household property co-offending. An interpretation of the long term impact of higher levels of unemployment suggests that for every 1% increase in the average unemployment level of a MSA over the period, the rate of household property co-offending increases by 7.4% ($\exp^{.071}$). Additionally, as hypothesized by Hypothesis 3a, there is not a statistically significant relationship between the unemployment rate and the rate of household property co-offending. Models 4b and 4c evaluate whether or not the impact of unemployment on the rate of household property co-offending interacts with the age-distribution of an area. The results from Model 4b indicates that there is small, but statically significant and positive moderating impact of the percentage of the MSA between the ages 15-24, such that a one-unit increase in the within-MSA deviation of this age profile increases the expected impact of increases in the short-term effect of unemployment by 4.4%. The only other consistently statistically significant control variable is the short-term impact of the

rate of single-offender crimes. This positive relationship suggests that areas whose rate of single-offender crimes in a given year is higher than its average over the 14 year time period also have a substantive increase in the rate of household property co-offending.

Table 4: Hybrid Model for Rate of Household Property Co-offending, Unemployment Rate N=474

	Baseline Model (4a)		Interaction Model with Age Profile 15-24 (4b)		Interaction Model with Age Profile 25-44 (4c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Unemployment Rate	.071* (.035)	.015 (.028)	.064 (.368)	-.557* (.267)	.548 (.642)	-.602 (.376)
Solo-Offense Rate	.092 (.174)	.258*** (.070)	.111 (.157)	.267*** (.070)	.112 (.162)	.269*** (.071)
Percent Aged 15-24	.039 (.038)	-.097 (.087)	.036 (.146)	-.296* (.127)		
Percent Male	.019 (.062)	.318 (.200)	.020 (.055)	.221 (.206)	.091 (.069)	.193 (.196)
Percent Black	-.003 (.006)	.031 (.049)	-.003 (.005)	.018 (.050)	-.001 (.006)	.022 (.052)
Percent Aged 25-44					.051 (.096)	-.013 (.089)
Unemployment Rate X Percent Aged 15-24			.001 (.027)	.043* (.020)		
Unemployment Rate X Percent Aged 25-44					-.015 (.019)	.019 (.011)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Table 5 presents models using percent of poverty in the MSA as the indicator for economic hardship. Interestingly, some different results emerge. As seen in the baseline model, both the long term motivation effect and the short term effect of opportunity/guardianship are both statistically significant and positively related to the rate of household property co-offending. Consistent with Hypothesis 1a, the long term effect of motivation indicates that for every one-unit increase in the average percentage of poverty of an area, there is nearly 3.3% increase in the average rate of household property co-

offending. In contrast to the hypothesized null relationship in Hypothesis 3a, a 1% increase in within-MSA percentage of poverty leads to an increase in the rate of household property co-offending by about 6.9%. This finding suggests that perhaps the percentage of poverty captures a differential set of short-term processes related to co-offending and indicates that under increasingly adverse conditions of poverty, changing opportunity structures for crime leads co-offending to be seen as a more viable option. The interactions between the percentage of poverty and age distribution of an MSA suggest that there is not a moderating impact of the age distribution on the rate of household property co-offending. As observed in Model 5a, within-MSA increases in the percentage of male residents was marginally significant and positively related to the rate of household property co-offending, which aligns with the fact that crime is typically committed by males.

Table 5: Hybrid Model for Rate of Household Property Co-offending, Percent Poverty N=474

	Baseline Model (5a)		Interaction Model with Age Profile 15-24 (5b)		Interaction Model with Age Profile 25-44 (5c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Percent Poverty	.033** (.012)	.067** (.026)	.090 (.167)	.083 (.184)	.188 (.239)	-.107 (.238)
Solo-Offense Rate	.048 (.159)	.250*** (.069)	.038 (.165)	.249*** (.059)	.018 (.166)	.244*** (.069)
Percent Aged 15-24	-.009 (.040)	-.038 (.088)	.040 (.151)	-.025 (.171)		
Percent Male	.057 (.059)	.330† (.195)	.058 (.061)	.335† (.199)	.083 (.070)	.247 (.195)
Percent Black	-.002 (.005)	.016 (.049)	-.002 (.005)	.017 (.049)	-.001 (.006)	.017 (.052)
Percent Aged 25-44					.037 (.080)	.010 (.096)
Percent Poverty X Percent Aged 15-24			-.004 (.012)	-.001 (.013)		
Percent Poverty X Percent Aged 25-44					-.005 (.007)	.005 (.007)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Table 6 presents the results for the rate of personal instrumental co-offending and the unemployment rate as the indicator for economic hardship. Examining the coefficients for the long term and short term effects of unemployment on the rate of personal instrumental co-offending indicates that neither of the relationships are statistically significant by traditional standards, however, both are marginally significant. Consistent with Hypothesis 1a, a 1% increase in the average level of unemployment in an MSA is associated with a marginally significant 6.8% increase in the rate of personal instrumental co-offending. In contrast to the null relationship hypothesized by Hypothesis 3a, there is also a marginally significant and positive relationship between the short term effect of unemployment associated with opportunity/guardianship and the rate of personal instrumental co-offending. Specifically, a 1% increase in within-MSA unemployment is associated with a 4.7% increase in the rate of personal instrumental co-offending. Again, perhaps this positive relationship suggests that macro-level conditions triggered by more short term changes associated with unemployment generate convergence settings or opportunities that are conducive to co-offending despite increases in the level of guardianship. Consistent with several of the models of household property co-offending, the unemployment rate is not consistently moderated by the age distribution of an MSA in the explanation of the rate of personal instrumental co-offending. Across each of the models, MSAs that have on average a higher percentage of the population that is black have a statistically higher rate of personal instrumental co-offending.

Table 6: Hybrid Model for Rate of Personal Instrumental Co-offending, Unemployment Rate N=533

	Baseline Model (6a)		Interaction Model with Age Profile 15-24 (6b)		Interaction Model with Age Profile 25-44 (6c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Unemployment Rate	.066† (.039)	.046† (.025)	-.076 (.355)	-.211 (.220)	.123 (.615)	.097 (.324)
Solo-Offense Rate	.466** (.167)	-.015 (.045)	.442* (.177)	-.023 (.045)	.387* (.174)	-.014 (.045)
Percent Aged 15-24	-.006 (.038)	-.008 (.082)	-.065 (.151)	-.100 (.113)		
Percent Male	-.006 (.062)	.055 (.174)	-.004 (.062)	.012 (.179)	-.102 (.073)	.078 (.170)
Percent Black	.015** (.006)	-.001 (.042)	.015** (.006)	-.007 (.042)	.010† (.006)	-.001 (.043)
Percent Aged 25-44					.054 (.093)	-.038 (.084)
Unemployment Rate X Percent Aged 15-24			.011 (.027)	.019 (.017)		
Unemployment Rate X Percent Aged 25-44					-.001 (.019)	-.002 (.010)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Table 7 reports the results for the relationship between the percent of poverty in an MSA and the rate of personal instrumental co-offending. Consistent with Hypothesis 1a, there is a statistically significant and positive relationship between the long-term effect of poverty associated with motivation and the rate of personal instrumental co-offending. Specifically, a 1% increase in the average percent of poverty across MSAs is expected to lead to a 2.9% increase in the rate of personal instrumental co-offending. Inconsistent with Hypothesis 3b, there is also a statistically significant and positive relationship between the short-term effect of changes in the percentage of poverty and rate of personal instrumental co-offending. Specifically, a 1% increase in within-MSA poverty is expected to lead to a nearly 8.7% increase in the rate of personal instrumental co-offending net of other controls.

The emerging pattern of positive and statistically significant relationships in the short term with the rate of co-offending outcomes continues to suggest that there are processes which are facilitating increases in the volume of co-offending despite changes in the level of guardianship and opportunities for crime. The results for the interaction between the age profile of an MSA and the percent of poverty in an MSA indicate that the percentage of the MSA that is between the ages 15 and 24 moderates the relationship between poverty and the rate of personal instrumental co-offending. In particular, the interaction term is positive and statistically significant indicating that a one-unit increase in the average percentage of the MSA between the ages 15-24 increases the expected impact of increasing levels of poverty on the rate of personal instrumental co-offending by nearly 3.5%.

Table 7: Hybrid Model for Rate of Personal Instrumental Co-offending, Percent Poverty N=533

	Baseline Model (7a)		Interaction Model with Age Profile 15-24 (7b)		Interaction Model with Age Profile 25-44 (7c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Percent Poverty	.029* (.015)	.084*** (.024)	-.435* (.170)	-.023 (.167)	-.078 (.253)	.024 (.221)
Solo-Offense Rate	.395* (.176)	-.025 (.045)	.425** (.158)	-.027 (.045)	.369* (.137)	-.027 (.045)
Percent Aged 15-24	-.051 (.042)	.037 (.082)	-.449** (.151)	-.045 (.154)		
Percent Male	.027 (.065)	.107 (.170)	.009 (.059)	.077 (.145)	-.100 (.075)	.158 (.171)
Percent Black	.016** (.006)	-.022 (.042)	.018*** (.005)	-.024 (.042)	.010† (.006)	-.026 (.043)
Percent Aged 25-44					.004 (.086)	-.077 (.090)
Percent Poverty X Percent Aged 15-24			.034** (.0123)	.008 (.012)		
Percent Poverty X Percent Aged 25-44					.003 (.008)	.002 (.007)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

These last set of results for the rate of co-offending pertain to the relationship between indicators of economic hardship and the rate of expressive co-offending. As a reminder, in formulating the hypotheses by crime type it was expected that there may be differences in the expected direction or presence of relationships for expressive co-offending. Table 8 presents the results using the unemployment rate as the indicator of economic hardship. Consistent with the specification of Hypothesis 1b for expressive crime, there is a null relationship between the long term effect associated with unemployment and the rate of expressive co-offending. As argued, there is little reason to expect that increases in unemployment would lead individuals to become more motivated to engage in expressive crime and the results provide support for this claim. There is also marginal support for a positive relationship between the short term effect associated with unemployment and the rate of expressive co-offending (Hypothesis 3b). Specifically, a 1% increase in within-MSA unemployment rates is expected to lead to a 5.9% increase in the rate of expressive co-offending. This increase was hypothesized to be attributable to the increased concentration of available and potentially motivated offenders in space and time. There were also positive and statistically significant relationships in the long and short term effects of the rate of single-offender expressive crimes. There is no evidence in support of a moderating relationship of the age-profile of the MSA across each of the specifications in Models 8b and 8c.

Table 8: Hybrid Model for the Rate of Expressive Co-offending, Unemployment Rate N=450

	Baseline Model (8a)		Interaction Model with Age Profile 15-24 (8b)		Interaction Model with Age Profile 25-44 (8c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Unemployment Rate	.003 (.033)	.058* (.030)	.158 (.365)	-.161 (.283)	-.645 (.566)	.049 (.394)
Solo-Offense Rate	.240† (.137)	.341*** (.088)	.231† (.139)	.345*** (.088)	.257* (.131)	.273*** (.090)
Percent Aged 15-24	.021 (.034)	-.037 (.092)	.082 (.147)	-.117 (.136)		
Percent Male	.050 (.053)	-.037 (.223)	.051 (.052)	-.074 (.228)	.105† (.059)	-.161 (.214)
Percent Black	-.001 (.005)	-.047 (.054)	-.001 (.005)	-.051 (.055)	.001 (.005)	-.006 (.057)
Percent Aged 25-44					-.118 (.085)	.205* (.089)
Unemployment Rate X Percent Aged 15-24			-.012 (.027)	.016 (.021)		
Unemployment Rate X Percent Aged 25-44					.019 (.017)	.001 (.012)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Table 9 presents the results for the relationship between the long and short term effects associated with percent of poverty in an MSA and the rate of expressive co-offending. Consistent with the specification of Hypothesis 2b, there is a null relationship between the long term impact associated with motivation and the rate of expressive co-offending. Additionally, the statistically significant and positive relationship between the short term effects associated with opportunity/guardianship provides support for Hypothesis 3b. Specifically, a 1% increase in within-MSA percent poverty is expected to lead to an 8.4% increase in the rate of expressive co-offending. Of note, the interaction model that includes an interaction term between the percentage of the MSA that is between the ages 15 to 24 and the percentage of poverty suggests that there is a moderating

relationship. An interpretation of the long term interaction term suggests that as the percentage of people aged 15 to 24 increases by one-unit, the slope for the impact of poverty is negatively related to the rate of expressive co-offending by about 3%.

Table 9: Hybrid Model for Rate of Expressive Co-offending, Percent Poverty N=450

	Baseline Model (9a)		Interaction Model with Age Profile 15-24 (9b)		Interaction Model with Age Profile 25-44 (9c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Percent Poverty	.002 (.011)	.081** (.028)	.418** (.142)	-.256 (.199)	-.010 (.201)	-.364 (.255)
Solo-Offense Rate	.244† (.127)	.348*** (.087)	.189 (.121)	.363*** (.087)	.271* (.119)	.290*** (.088)
Percent Aged 15-24	.017 (.039)	-.004 (.093)	.379** (.130)	-.276 (.184)		
Percent Male	.053 (.054)	.076 (.218)	.073 (.051)	.006 (.221)	.099† (.058)	-.093 (.215)
Percent Black	-.001 (.005)	-.063 (.054)	-.004 (.004)	-.074 (.054)	.001 (.005)	-.057 (.058)
Percent Aged 25-44					-.024 (.069)	.064 (.100)
Percent Poverty X Percent Aged 15-24			-.030** (.010)	.024† (.014)		
Percent Poverty X Percent Aged 25-44					.001 (.006)	.013† (.007)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

As previously mentioned, there is an important limitation of the data that required additional attention with respect to determining the robustness of the results. In particular, for the some of the MSAs there are a small number of incidents included within the MSA that are used to generate estimates of MSA-level co-offending rates. This raises the risk of statistical power in producing national estimates of co-offending, particularly when evaluating changes in these rates or proportions over time. In order to address some of the small sample sizes within each MSA in any given year, pooled analyses were conducted across 2 and 3 year increments replicating each of the models generated in the results

above. Of note, the substantive findings found in the analyses utilizing annual estimates were almost entirely replicated for each of the crime types and for each type of indicator of economic hardship. The only major difference that emerged was the level of statistical significance increased for the long and short term coefficients that were statistically significant in the models presented above. The replication of these findings ameliorate concerns that the results reported above were hampered or drastically impacted by instances of small sample size for certain MSAs. While these pooled results reflect the same substantive results, it becomes more difficult to interpret the meaning of long and short term effects when the time periods associated with these effects now extend to 2 and 3 year intervals. These results are not presented and are included as Appendix 3.

Proportion of Co-offending Results

The following section presents the results for each of the models examining the proportion of co-offending as an outcome. Table 10 presents the results for the decomposed relationship between unemployment and the overall proportion of crimes that are co-offenses. As can be seen in the table, the only statistically significant relationship with the proportion crimes that are co-offenses is the long term effect associated with motivation. This is consistent with Hypothesis 2 that argued that individuals – both those previously initiated into criminal behavior and those who previously did not view crime as a viable option - who are embedded in MSAs with on average higher levels of economic hardship would become more motivated to co-offend. It is expected that for every one-unit increase in the rate of unemployment, the proportion of crimes that are co-offenses is expected to increase by 13.7% ($e^{.128}$). There is limited support for Hypothesis 4, which argued that

in the short-term there would be a positive relationship between economic hardship and the proportion of crimes that are co-offenses.

Table 10: Hybrid Model for Overall Proportion of Crimes that are Co-offenses, Unemployment Rate N=540

	Baseline Model (10a)		Interaction Model with Age Profile 15-24 (10b)		Interaction Model with Age Profile 25-44 (10c)	
	Long Term Effect	Short Term Effect	Long Term Effect	Short Term Effect	Long Term Effect	Short Term Effect
Independent Variables						
Unemployment Rate	.128** (.042)	-.015 (.027)	.276 (.469)	-.36 (.236)	.140 (.744)	-.232 (.345)
Percent Aged 15-24	.014 (.041)	-.063 (.088)	.064 (.304)	-.009 (.417)		
Percent Male	-.082 (.069)	-.023 (.187)	-.012 (.196)	-.222 (.376)	-.063 (.086)	-.081 (.185)
Percent Black	.004 (.006)	.050 (.044)	-.015 (.057)	.052 (.097)	.005 (.007)	.047 (.045)
Percent Aged 25-44					.001 (.115)	-.018 (.091)
Unemployment Rate X Percent Aged 15-24			-.010 (.035)	.026 (.018)		
Unemployment Rate X Percent Aged 25-44					-.001 (.023)	.007 (.010)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Table 11 presents the results for the model evaluating the relationship between the long and short term effects associated with percent of poverty in an MSA and the overall proportion of crimes that are co-offenses. As observed in the baseline model (11a), there are positive and statistically significant relationships between the long-and short-term effects associated with changes in the percentage of poverty. In particular, on average MSAs with higher levels of poverty experience a 4.3% increase in the proportion of crimes that are co-offenses. This is consistent with Hypothesis 2, which argued that long-term processes associated with motivation would be positively related to the proportion of crimes that are co-offenses. A one-unit increase in the average percent of poverty in an MSA is associated with a 4.3% increase in the expected proportion of crimes that are co-

offenses. There is marginal support for Hypothesis 4 as evidenced by the marginally significant and positive short-term effect of the percent poverty. Specifically, for every one-unit increase in within-MSA changes in the percentage of poverty there is an expected increase in the proportion of crimes that are co-offenses by 4.1%.

Table 11: Hybrid Model for Overall Proportion of Crimes that are Co-offenses, Unemployment Rate N=540

	Baseline Model (11a)		Interaction Model with Age Profile 15-24 (11b)		Interaction Model with Age Profile 25-44 (11c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Percent Poverty	.042** (.015)	.040† (.023)	-.107 (.238)	-.035 (.138)	-.192 (.261)	-.146 (.196)
Percent Aged 15-24	-.053 (.048)	-.008 (.097)	-.181 (.207)	-.067 (.160)		
Percent Male	-.036 (.084)	-.042 (.131)	-.041 (.087)	-.062 (.137)	-.059 (.937)	-.087 (.144)
Percent Black	.007 (.006)	.041 (.037)	.008 (.007)	.040 (.037)	.005 (.008)	.034 (.039)
Percent Aged 25-44					-.090 (.90)	-.034 (.078)
Percent Poverty X Percent Aged 15-24			.011 (.017)	.005 (.010)		
Percent Poverty X Percent Aged 25-44					.007 (.008)	.006 (.006)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

The next set of tables present the results for the proportion of crimes that are co-offenses by crime type. Table 12 presents the results for the proportion of household property crimes that are co-offenses and uses the unemployment rate as a measure of economic hardship. Consistent with Hypothesis 2a, there is a positive and statistically significant relationship between the long-term processes associated with motivation and the proportion of household property crimes that are co-offenses. Specifically, for every one-unit increase in the average unemployment rate there is an 11% expected increase in

the proportion of household property crimes that are co-offenses. In contrast to Hypothesis 4a, there is not a positive relationship between the short-term effects associated with unemployment and the proportion of household property crimes that are co-offenses. Of note, there is only one other set of statistically significant relationships across the models presented in Table 12. There is evidence to suggest that the short-term effects associated with opportunity/guardianship is moderated by the percentage of the MSA that is between the ages 25 to 44. Specifically, for every one-unit increase in within-MSA deviations in this age demographic, the expected slope for the impact of the short-term effect of unemployment is expected to increase by approximately 3.7% ($e^{.037}$). Given that a moderating relationship has yet to emerge across most of the previously discussed models, this relationship is viewed tentatively. Nonetheless, it suggests that perhaps the more contemporaneous impact of increases in unemployment is most salient in contributing to individuals in this older age category view co-offending as a viable option or are more likely to be associated with convergent spaces that expose individuals to the opportunity to identify suitable co-offenders.

Table 12: Hybrid Model for Proportion of Household Property Crimes that are Co-offenses, Unemployment Rate N=474

	Baseline Model (13a)		Interaction Model with Age Profile 15-24 (13b)		Interaction Model with Age Profile 25-44 (13c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Unemployment Rate	.101** (.038)	-.005 (.047)	-.089 (.338)	-.714 (.480)	.759 (.741)	-1.22* (.605)
Percent Aged 15-24	.001 (.042)	-.097 (.099)	-.070 (.145)	-.339 (.209)		
Percent Male	.003 (.075)	.382† (.214)	.004 (.075)	.260 (.227)	.013 (.077)	.290 (.206)
Percent Black	-.006 (.006)	.012 (.065)	-.006 (.006)	-.001 (.075)	-.006 (.006)	-.023 (.082)

Percent Aged 25-44					.092 (.113)	-.155 (.139)
Unemployment Rate X Percent Aged 15-24			.014 (.026)	.053 (.035)		
Unemployment Rate X Percent Aged 25-44					-.020 (.022)	.037* (.018)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Table 13 presents the results for the proportion of household property crimes that are co-offenses using the percentage of poverty in an MSA as the measure of economic hardship. Consistent with Hypothesis 2a, there is a positive and statistically significant relationship between the long-term processes associated with motivation and the proportion of household property crimes that are co-offenses. Specifically, for every one-unit increase in the average unemployment rate there is a 4.2% expected increase in the proportion of household property crimes that are co-offenses. There is marginal support for Hypothesis 4a, as there is a marginally significant and positive relationship between the short-term effects associated with poverty and the proportion of household property crimes that are co-offenses. This finding is consistent with the expectation that in the short-term, increase in economic hardship increase the convergence of motivated offenders in space and time and facilitate the identification of suitable targets. None of the other control variables are statistically significant and there does not appear to be a moderating relationship between poverty and the age-distribution of an MSA.

Table 13: Hybrid Model for Proportion of Household Property Crimes that are Co-offenses, Percent Poverty N=533

	Baseline Model (14a)		Interaction Model with Age Profile 15-24 (14b)		Interaction Model with Age Profile 25-44 (14c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Percent Poverty	.041** (.016)	.079† (.042)	-.012 (.235)	.083 (.286)	-.147 (.314)	-.176 (.304)

Percent Aged 15-24	-.056 (.048)	-.003 (.106)	-.101 (.207)	-.001 (.264)		
Percent Male	.039 (.078)	.354 (.228)	.038 (.081)	.354 (.224)	-.007 (.073)	.338 (.225)
Percent Black	-.005 (.006)	-.003 (.067)	-.005 (.006)	-.003 (.069)	-.007 (.005)	-.011 (.077)
Percent Aged 25-44					-.065 (.108)	-.087 (.124)
Percent Poverty X Percent Aged 15-24			.004 (.017)	-.001 (.021)		
Percent Poverty X Percent Aged 25-44					.005 (.009)	.007 (.009)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Table 14 presents the results for the proportion of personal instrumental crimes that are co-offenses using the unemployment rate as the measure of economic hardship. Inconsistent with the expected relationships hypothesized in Hypothesis 2a and 4a, there are no statistically significant relationships between the long-and short-term effects associated with increases in the unemployment rate and the proportion of personal instrumental crimes that are co-offenses. It is possible that certain types of crime, such as household property crime, tend to involve multiple offenders for reasons that are not observed in personal instrumental crimes, such as robbery. Of note, the percentage of an MSA that is black emerges as a consistently positive and significant predictor of the proportion of personal instrumental crimes that are co-offenses.

Table 14: Hybrid Model for Proportion of Personal Instrumental Crimes that are Co-offenses, Unemployment Rate N=533

	Baseline Model (15a)		Interaction Model with Age Profile 15-24 (15b)		Interaction Model with Age Profile 25-44 (15c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Unemployment Rate	.051 (.091)	.005 (.072)	.093 (.528)	.072 (.600)	.709 (.709)	.536 (.722)
Percent Aged 15-24	-.065 (.097)	.147 (.249)	.049 (.221)	-.003 (.322)		
Percent Male	-.040	.183	.075	-.317	.095	-.254

	(.179)	(.374)	(.150)	(.478)	(.212)	(.419)
Percent Black	.028* (.012)	.011 (.128)	.032* (.013)	-.099 (.094)	.034* (.018)	-.103 (.101)
Percent Aged 25-44					.097 (.143)	-.078 (.240)
Unemployment Rate X Percent Aged 15-24			-.006 (.040)	-.006 (.047)		
Unemployment Rate X Percent Aged 25-44					-.021 (.022)	-.016 (.021)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Table 15 presents the results for the proportion of personal instrumental crimes that are co-offenses using the percentage of poverty in an MSA as the measure of economic hardship. Again, inconsistent with the expected relationships hypothesized in Hypothesis 2a and 4a, there are no statistically significant relationships between the long- and short-term effects associated with increases in the unemployment rate and the proportion of personal instrumental crimes that are co-offenses for the baseline model. In the moderating models, there appears to be a moderating relationship between the percentage of the MSA that is between the ages 15 and 24 and the percentage of poverty. In particular, across MSAs a one-unit increase in the percentage of an MSA that is between the ages 15 and 24 leads to an approximately 4.1% increase in the slope of the impact of the long-term effect of poverty. Consistent with the prior model, the percent Black in an MSA is also statistically significant and positively related to the proportion of personal instrumental crimes that are co-offenses.

Table 15: Hybrid Model for Proportion of Personal Instrumental Crimes that are Co-offenses, Percent Poverty N=474

	Baseline Model (16a)		Interaction Model with Age Profile 15-24 (16b)		Interaction Model with Age Profile 25-44 (16c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Percent Poverty	.013 (.032)	.051 (.055)	-.550* (.261)	-.494 (.342)	-.126 (.632)	-.003 (.427)
Percent Aged 15-24	-.099 (.112)	.193 (.239)	-.457* (.215)	-.415 (.394)		
Percent Male	-.026 (.184)	.188 (.362)	.062 (.149)	-.448 (.444)	.105 (.213)	-.269 (.372)
Percent Black	.029* (.012)	.002 (.125)	.035** (.013)	-.124 (.104)	.034* (.017)	-.122 (.106)
Percent Aged 25-44					-.046 (.234)	-.149 (.236)
Percent Poverty X Percent Aged 15-24			.040* (.018)	.037 (.024)		
Percent Poverty X Percent Aged 25-44					.004 (.019)	.001 (.013)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

The final set of results present the models that evaluate the relationship between the measures of economic hardship and the proportion of expressive crimes that are co-offenses. Table 16 presents the results for the proportion of expressive crimes that are co-offenses using the unemployment rate as the measure of economic hardship. Consistent with Hypothesis 2b, there is a null relationship between the long-term effect associated with motivation and the proportion of expressive crimes that are co-offenses. There was no reason to expect that there would be an increase in the motivation to commit expressive co-offending that would lead to a substantive shift in an offender's willingness to take on co-offenders resulting in an increase in the proportion of these crimes committed in groups. In contrast to the expected positive relationship between the short-term effect associated with unemployment and the proportion of expressive crimes that are co-offenses (Hypothesis 4b), there is not a statistically significant relationship in the

baseline model. Of note, the percentage of the MSA that is between the ages 25 and 44 appears to moderate the relationship between the unemployment rate and the proportion of expressive crimes that are co-offenses. Across MSAs, a one-unit increase in the average percentage of an MSA-population between the ages 25 to 44 is associated with a 4.4% increase in the expected slope of the long-term effect of unemployment on the proportion of expressive crimes that are co-offenses. None of the other control variables exhibit statistically significant relationships with the outcome.

Table 16: Hybrid Model for Proportion of Expressive Crimes that are Co-offenses, Unemployment Rate N=450

	Baseline Model (17a)		Interaction Model with Age Profile 15-24 (17b)		Interaction Model with Age Profile 25-44 (17c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Unemployment Rate	.060 (.055)	.046 (.039)	-.271 (.550)	-.329 (.451)	-1.35* (.675)	.195 (.612)
Percent Aged 15-24	.015 (.078)	-.057 (.197)	-.119 (.248)	-.181 (.262)		
Percent Male	.039 (.101)	-.153 (.439)	.038 (.099)	-.227 (.423)	.052 (.089)	-.319 (.413)
Percent Black	.002 (.009)	-.052 (.088)	.003 (.009)	-.059 (.082)	.003 (.008)	-.017 (.092)
Percent Aged 25-44					-.218† (.113)	.208 (.142)
Unemployment Rate X Percent Aged 15-24			.025 (.042)	.028 (.033)		
Unemployment Rate X Percent Aged 25-44					.043* (.021)	-.004 (.018)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

Lastly, Table 17 presents the results for the models examining the relationship between the long-and short-term effects of poverty on the proportion of expressive crimes that are co-offenses. Consistent with Hypothesis 2b, there is a null relationship between the long-term effect associated with motivation and the proportion of expressive crimes

that are co-offenses. Additionally, there is a positive and statistically significant relationship in the expected direction for the impact of the short-term effect associated with poverty and the proportion of expressive crimes that are co-offenses. Specifically, for every one-unit increase in the within-MSA percentage of poverty there is an expected 10% increase in the proportion of expressive crimes that are co-offenses. There does not appear to be any moderating relationships between the age-distribution of the MSA and the percentage of poverty in an MSA on the outcome.

Table 17: Hybrid Model for Proportion of Expressive Crimes that are Co-offenses, Percent Poverty N=450

	Baseline Model (18a)		Interaction Model with Age Profile 15-24 (18b)		Interaction Model with Age Profile 25-44 (18c)	
	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>	<i>Long Term Effect</i>	<i>Short Term Effect</i>
Independent Variables						
Percent Poverty	.010 (.018)	.099* (.042)	.430 (.321)	.504 (.345)	-.293 (.325)	-.424 (.371)
Percent Aged 15-24	.002 (.069)	-.002 (.173)	.368 (.282)	-.488 (.379)		
Percent Male	.040 (.093)	-.050 (.370)	.051 (.084)	-.169 (.357)	.071 (.100)	-.227 (.372)
Percent Black	.003 (.009)	-.069 (.083)	.001 (.007)	-.088 (.084)	.003 (.009)	-.082 (.095)
Percent Aged 25-44					-.122 (.112)	-.05 (.136)
Percent Poverty X Percent Aged 15-24			-.030 (.024)	.044† (.025)		
Percent Poverty X Percent Aged 25-44					.009 (.010)	.015 (.011)

p<.001***, p<.01**, p<.05*, p<.10†

*Time trends are included in the models, however are not presented in the results.

As mentioned with the models evaluating the relationship between economic hardship and the rate of co-offending, in order to address some of the small sample sizes within each MSA in any given year, pooled analyses were conducted across 2 and 3 year increments replicating each of the models generated in the results above. Of note, the substantive findings found in the analyses utilizing annual estimates were almost entirely

replicated for each of the crime types and for each type of indicator of economic hardship. The replication of these findings address concerns that the results reported above were hampered or drastically impacted by instances of small sample size for certain MSAs. While these pooled results generally reflect the same substantive results, it becomes more difficult to interpret the meaning of long and short term effects when the time periods associated with these effects now extend to 2 and 3 year intervals. As a result, these results are not presented and are included as Appendix 3.

Table 18 presents an overall summary of whether empirical support is observed for each of the hypotheses of the current study across each indicator of economic hardship and whether the relationships are moderated by the age-distribution of the MSA. Because there are two categories of instrumental crime (i.e., household property, personal instrumental), Table 18 also denotes whether empirical support is observed for each of these crime types by specifying these crime types in parentheses. As a reminder, it was also hypothesized that the moderating relationship would only be observed in instances where there was an expected positive and statistically significant relationship between economic hardship and the crime type outcome. Thus, for several hypotheses whether the relationship between economic hardship and co-offending was moderated by the age-distribution of an MSA is not applicable and is denoted as such by 'NA'.⁹ Still, in a few cases statistically significant relationships emerged for certain crime types and are therefore reported in parentheses.

⁹ Although it was hypothesized that the age-profile of an MSA would not moderate all of the relationships between economic hardship and co-offending, for the purpose of providing consistent results across models these moderating relationships were included in the results. Additionally, it is possible for moderating relationships to occur even when main effects of certain covariates on an outcome do not emerge. The moderating relationships that are statistically significant provide a foundation for future work to consider the extent to which processes related to economic hardship matter differently across unique social and demographic contexts of a geographic area.

Across both measures of economic hardship, several general conclusions can be drawn. Consistent with the expectation that there would be a positive relationship between economic hardship and instrumental crimes in the long term, there tends to be consistent evidence to indicate that the long-term effects of economic hardship led to a higher rate of instrumental forms of co-offending and in one instance (i.e., household property co-offending) a higher proportion of crimes that were co-offenses. This is supportive of the expected drive that experiencing economic hardship has on committing crimes with potential monetary gains that can supplement reduced or lost income (e.g., Cantor & Land, 1985). The fact that there was a long-term positive relationship between economic hardship and the proportion of household property crimes that were co-offenses is also demonstrative of the potential shift in the distribution of individuals willing to engage in household property crime with the added utility of additional accomplices. As expected, there were null relationships between economic hardship and the rate and proportion outcomes for expressive co-offending in the long-term. There was limited reason to expect that more offenders would become motivated over time to engage in expressive co-offending because of experiencing economic hardship.

The overall findings for the relationship between the short-term effect of economic hardship and the co-offending outcomes provided some inconsistent evidence with the hypotheses. In general, there tended to be a strong positive relationship between economic hardship and the rate of instrumental and expressive co-offending in the short-term. While this relationship was expected for expressive crimes due to the hypothesized increase in behavioral convergent spaces in the short-run, these results contrast the original hypotheses for instrumental crimes. In particular, it was expected that there

would be countervailing influences in the short-run that suppressed opportunities for all forms of instrumental crimes despite the added utility of taking on a co-offender in the face of a changing criminal target backcloth. The observed positive relationship in the short-run for the rate of both forms of instrumental crimes suggests that there may be a strong lure to engaging in instrumental crimes with other offenders that is acted on when offenders occupy spaces that provide concentrated accessibility to other accomplices. Lastly in the short-term, positive relationships between economic hardship and the proportion of household property crimes and expressive crimes that were co-offenses also emerged. Among instrumental crimes, this is consistent with the theoretical arguments that short-term changes in the opportunity structure for crime may lead offenders to engage in adaptive behavior towards co-offending to overcome the added risks and difficulties associated with increased guardianship and the reduction in the circulation of targets. As a result, there is a positive shift in the distribution of offenders engaging in household property co-offending relative to those engaging in this type of crime alone. The positive relationship in the short-term with the proportion of expressive crimes that were co-offenses is in line with the expectation that the increased availability of convergent spaces driven by the short-term changes of economic hardship would generate more opportunities for engaging in expressive forms of crimes with other offenders. In total, these findings provide supportive evidence for how long and short-term processes associated with economic hardship facilitates the emergence of co-offending.

Table 18: Summary of Results

Hypotheses	Measure of Economic Hardship	Empirical Support (Y/N)	Moderated by Age Distribution 15-24 (Y/N)	Moderated by Age Distribution 25-44 (Y/N)
(1) There will be a positive relationship between economic hardship and the rate of co-offending in the long-term.	Unemployment Rate	No	No	No
	Percent Poverty	No	No	No
(1a) There will be a positive relationship between economic hardship and the rate of instrumental co-offending in the long-term.	Unemployment Rate	Yes (Household Property, Personal Instrumental)	Yes (Household Property)	No
	Percent Poverty	Yes (Household Property, Personal Instrumental)	Yes (Personal Instrumental)	No
(1b) There will be a null relationship economic hardship and the rate of expressive co-offending in the long-term.	Unemployment Rate	Yes	NA	NA (Expressive Crime statistically significant)
	Percent Poverty	Yes	NA (Expressive Crime statistically significant)	NA
(2) There will be a positive relationship between economic hardship and the proportion of crimes that are co-offenses in the long-term.	Unemployment Rate	Yes	No	No
	Percent Poverty	Yes	No	No
(2a) There will be a positive relationship between economic hardship and the proportion of instrumental crimes that are co-offenses in the long-term.	Unemployment Rate	Yes (Household Property)	No	No
	Percent Poverty	Yes (Household Property)	Yes (Personal Instrumental)	No
(2b) There will be a null relationship between economic hardship and the proportion of expressive crimes that are co-offenses in the long-term.	Unemployment Rate	Yes	NA	NA (Expressive Crime statistically significant)
	Percent Poverty	Yes	NA	NA

(3) There will be a positive relationship between economic hardship and the proportion of crimes that are co-offenses in the short-term.	Unemployment Rate	No	No	No
	Percent Poverty	Yes	No	No
(3a) There will be a positive relationship between economic hardship and the proportion of instrumental crimes that are co-offenses in the short-term.	Unemployment Rate	No	No	Yes (Household Property)
	Percent Poverty	Yes (Household Property)	No	No
(3b) There will be a positive relationship between economic hardship and the proportion of expressive crimes that are co-offenses in the short-term.	Unemployment Rate	No	No	No
	Percent Poverty	Yes	Yes	No
(4) There will be a null relationship between economic hardship and the rate of co-offending in the short-term.	Unemployment Rate	Yes	NA	NA
	Percent Poverty	No	NA	NA
(4a) There will be a null relationship between economic hardship and the rate of instrumental co-offending in the short-term.	Unemployment Rate	No (Personal Instrumental statistically significant)	NA (Household Property statistically significant)	NA
	Percent Poverty	No (Household Property, Personal Instrumental statistically significant)	NA	NA
(4b) There will be a positive relationship between economic hardship and the rate of expressive co-offending in the short-term.	Unemployment Rate	Yes	No	No
	Percent Poverty	Yes	Yes	Yes

CHAPTER 5: DISCUSSION

The notion that crime occurs within a social structure and context is arguably one of the most important tenants of criminological theory and research (e.g., Shaw & McKay, 1942; Thrasher, 1927). To explain how social conditions facilitated criminal behavior, many theoretical perspectives elevated the role of criminal groups or subcultures and demonstrably stated that engaging in crime with others was essential to the acquisition of delinquent norms or behavior that maintained the concentration of crime in urban areas (e.g., Cloward & Ohlin, 1960; Cohen, 1955; Short & Strodtbeck, 1965). Despite the fact that this early theoretical work suggested that socio-structural factors generated conditions conducive to offending with others, co-offending research was ultimately spearheaded by scholars most interested in understanding individual-level experiences of criminal cooperation and how involvement in co-offending impacted elements of a criminal career (e.g., Reiss, 1986, 1988). To advance the co-offending literature beyond an individual-level framework, this dissertation re-situated co-offending into context by examining how economic hardship was related to the emergence of co-offending.

Specifically, this dissertation integrated the conceptual arguments proposed by Tremblay (1993) and Felson (2003) to develop an empirical model that tested how economic hardship facilitated aggregate level shifts in the motivation to engage in co-offending and influenced opportunity structures for crime that make taking on accomplices a more viable option. Tremblay (1993) and Felson (2003) both identified the challenges associated with specifying consistent and stable explanations for the emergence of co-offending. Felson (2003) contended that the unstable nature of gangs, unwieldy and unbounded nature of social friendship networks, and rapidly changing offender networks

cannot consistently explain how and why group offending occurs with such regularity. Collectively, these scholars suggested that macro-level conditions facilitated motivation to engage in crime with others and generated behavioral convergent settings that enabled paths towards identifying suitable co-offenders. In line with a much broader empirical background, Tremblay (1993) hypothesized explicitly that economic hardship - as measured by unemployment - generated an increased concentration of motivated offenders and altered the opportunity structure for crime such that engaging in crime with others was both more practical and viable for offenders. To evaluate these premises, this dissertation used aggregated victimization incidents at the MSA-level from the NCVS to understand how economic hardship, measured by both the unemployment rate and the percent of poverty in an MSA, were related to two outcomes - the rate of co-offending and the proportion of crimes that are co-offenses.

The first conclusion from this dissertation is that both the long-and short-term processes associated with economic hardship were more likely to predict increases consistent with the proposed hypotheses for the rate of co-offending as opposed to the proportion of crimes that are co-offenses. As expected, motivation derived from the long-term impact of increases in economic hardship tended to be consistently associated with increasing rates of instrumental forms of co-offending. The fact that offenders were more likely to engage in instrumental forms of co-offending continues to suggest that individuals respond to economic hardship by engaging in illegal activity to supplement or replace lost income and make ends meet (e.g., Cantor & Land, 1985). Perhaps more importantly though, this finding extends Cantor and Land's (1985) argument that the long-term impact of economic hardship shifts the density of the distribution of motivation to commit crime

among a population by further recognizing that this distribution is interdependently tied to a willingness to engage in crime with others. Prior co-offending work has explicitly argued that despite the inherent risks associated with taking on co-offending, the uncertainties surrounding changing conditions of economic or social adversity may directly impact the likelihood that individuals are motivated to engage in crime by incorporating an accomplice into the offending equation (e.g., McCarthy et al., 1998; Nguyen & McGloin, 2013). The positive relationship between economic hardship and the rates of instrumental co-offending demonstrated that the overall volume of criminal incidents within an MSA increased relative to its population and suggested that economic hardship impacted the decision to co-offend for a relatively broad segment of the population. Although it is possible that a small percentage of the population increased the frequency that they co-offended, prior work would suggest that the increased motivation impacted both individuals already motivated to engage in crime and those who would not normally do so but decide to engage in crime (e.g., McGloin and Rowan, 2015; Warr, 2002).

Thus, motivational forces to engage in crime are not necessarily tied solely to an individual offender's experience of adversity, but rather are a function of the interdependent experience of offenders being embedded within the same context. This argument is particularly important if we consider the relatively static view of motivation among prior theoretical perspectives that largely assume motivation to be a given or narrowly discussed as a construct among offenders who only ever engage in crime alone. The findings from this dissertation addressed Felson and Cohen's (1980) call to consider how offender inclinations may be impacted by other offenders by underscoring the role

that macro-level conditions have in facilitating not just motivation to commit crime generally – but motivation that is explicitly tied to engaging in crime with others.

The findings from this dissertation also provided insight into our understanding of the interplay between co-offending and opportunity structures for crime (Cohen and Felson, 1979). Despite prior evidence suggesting that a decline in criminal opportunities in the short-term was driven by added risks and reduced potential rewards associated with a changing criminal landscape, results from this dissertation demonstrated a positive increase in both instrumental and expressive rates of group crime (Cantor & Land, 1985; Phillips & Land, 2012). Although this is the first study to evaluate these relationships, it provided some important considerations to our understanding of offender responses to changing opportunity structures to crime. Specifically, while Cantor and Land (1985) argued that the contemporaneous impact of economic hardship increased the level of guardianship and reduced the circulation of quality goods, the observed short-term positive relationship for instrumental crimes suggests that the advantages in taking on co-offenders during times of economic hardship may provide added utility in the decision-making process to engage in crime. Further, the utility of taking on co-offenders is also accompanied in the short-run by an expected increase in the availability of behavioral convergent settings for individuals to identify and find a suitable co-offender. As Crutchfield (1989: 491) argued, areas characterized by high involvement in unstable secondary labor markets and high levels of unemployment generate conditions that leave many people “frequently idle in a ‘situation of company’” that is conducive to crime. Although Crutchfield (1989) did not explicitly argue that the influx of situations of company may facilitate co-offending, his argument is consistent with the expectation that economic hardship increases the concentration of

potentially motivated criminal accomplices (Tremblay, 1993). This increased concentration among potential offenders can also explain the positive short-term effect of economic hardship on the rate of expressive group crime, as the presence of others has been demonstrated to provide the situational inducements necessary to enable individuals to be more likely to engage in expressive or violent crime (e.g., McGloin & Piquero, 2009; McGloin & Thomas, 2016).

Still, it is important to note that offender adaptation to changing economic conditions at the macro-level did not consistently translate into a shift in the overall proportion of crime that was committed by more than one offender. If the experience of economic hardship generated motivation and opportunities conducive to committing crime with others at a higher rate than among individuals committing crime alone, we would have observed significant increases in the proportion of crime committed by multiple offenders. This only emerged for household property crime, suggesting that a willingness to work with others may be particularly important for criminal acts where increased guardianship may be most likely to occur. Indeed, D'Alessio, Eitle, and Stolzenberg (2012) demonstrated that increasing levels of unemployment resulted in a contemporaneous decline in residential burglaries that occurred during normal working hours, when individuals previously spent time away from home. Qualitative evidence from Wright and Decker's (1997) interviews with active residential burglars provided some support for the importance of co-offenders by serving as look-outs and assisting if unanticipated resistance from guardians occurred. Thus, the positive relationships that emerged for household property co-offending may be reflective of offenders leveraging co-offenders as resources to overcome the added risks associated with household property crime. The overall lack of

statistically significant relationships to the proportion of crimes that are co-offenses for other crime types may further reflect the dynamic relationship between economic hardship and all forms of crime – solo and group – that is not readily captured in one year time periods (e.g., Greenberg, 2001). Shifts in the proportion of crime that are co-offenses may be more responsive to immediate changes in the opportunity structure for crime that may not be readily captured by using annual estimates of the state of economic conditions.

The second major conclusion from this dissertation concerns the extent to which the methodological and conceptual specification of the analytic approach used in this dissertation extends our understanding of the macro-level relationship between economic hardship and co-offending. Since Cantor and Land's (1985) seminal article, scholars have often misinterpreted their study as a relationship between the unemployment and crime (e.g., Greenberg, 2001); however, Cantor and Land (2001: 332) explicitly argued that the "unemployment rate represents changes to macroeconomic conditions" and was meant to serve as a proxy of the state of the economy. In support of this claim, this dissertation continued the trend of scholarly work to evaluate the proposed relationships utilizing multiple indicators of economic hardship (e.g., Arvanites & Defina, 2006). The percentage of poverty within an MSA was chosen in part because it captures families whose financial income was likely a function of poor or lack of employment status, but also served as a measure of economic hardship that was not dependent on being categorized as belonging to the labor force. Interestingly, many of the relationships described earlier were driven by the long-and short-term effects associated with increases in poverty and were often not observed in the models utilizing unemployment rate as a measure of economic hardship. This should not lead to the conclusion that the unemployment rate cannot explain the

emergence of group crime, but rather illustrates that the experience of economic hardship may be most salient for promoting a willingness to cooperate and for generating conditions that make group crime a seemingly practical decision. For instance, McCarthy et al.'s (1998) conclusion that adversity led to an increased willingness to engage in crime with others was based on a scale of adversity that included 1) going a whole day without eating, or 2) going a whole day without sleeping in or on a bus, restaurant, park, or street. Although unemployment may be highly correlated with these experiences, the fact that the unemployment rate does not include individuals who have essentially become discouraged or 'dropped out' of the labor market may not be capturing the true extent of experiencing economic hardship that is more likely to promote criminal cooperation (BLS, 2014). The differences in the findings across the measures of economic hardship suggest that future work should continue to consider how criminal cooperation may be dependent on the type of adversity that potential offenders experience.

Relatedly, the reification of the unemployment rate as *the* measure of economic hardship has also led to significant debate over understanding the segment of the population that such a measure applies to (Cantor and Land, 2001; Greenberg, 2001). To evaluate the extent to which macroeconomic changes captured by the unemployment rate and percentage of poverty in an MSA have an impact on more than just those individuals or families that become unemployed or are under the poverty level threshold, tests for whether the age-distribution of an MSA moderated these relationships were conducted. This arguably improves upon prior work which has only explicitly looked at whether rates of unemployment by age-groups are related to crime because it attempts to evaluate whether measures of economic hardship interact with the segments of the population that

theoretically would be subject to the experience of an economic downturn. Although the results from this dissertation demonstrated mixed findings with respect to when the age-distribution of an MSA moderated the relationship of economic hardship, there was more consistent evidence for MSAs with greater percentages of individuals between the ages of 15 to 24 years old to have a stronger impact of economic hardship on both rates of co-offending and in some instances the proportion of crimes that are co-offenses. This finding is consistent with prior research indicating that the prevalence of co-offending peaked during adolescence and declines in adulthood (e.g., Reiss & Farrington, 1991) and research that suggested the impact of unemployment was most salient among young adults who were denied entry into the adult labor market. While speculative, these findings provide preliminary support for the fact that MSAs with more of-crime aged individuals (and arguably more prone to be involved in group crime) are most responsive to changing economic conditions that motivate individuals to take on co-offenders and generate conditions that make co-offending a viable option. There was some evidence that the relationship between economic hardship and expressive group crime was moderated by the percent of the MSA that was between the ages of 25 and 44 years old, which may be consistent with Crutchfield (1989) and Tremblay's (1993) arguments that the influx of people most likely to be involved in the labor market are now unemployed and concentrated in space and time. This concentration, in addition to the strained experience due to economic hardship, may facilitate an increase in expressive or violent crime given the impact that the presence of others have on providing the necessary inducements to engage in violent crime (e.g., McGloin and Piquero, 2009).

Limitations and Future Directions

Despite the strengths of this dissertation, there are several limitations worth consideration. As with any dataset, the use of NCVS carries several analytical and conceptual issues. In order to capture incidents of group crime within the NCVS, the sampling strategy required the use of respondents who had valid data on whether or not they saw offender. This additional layer of sample selection further reduced the number of actual respondents within an MSA that could be used to generate MSA-level estimates of the rate of group crime and proportion of group crime incidents, which may limit the accuracy of the estimates and generalizability of the findings. To provide robustness checks for the analyses, pooled regression models for two and three year intervals were conducted to essentially increase the number of observations within each MSA. Findings from these supplemental analyses confirmed the results from the main models using annual estimates. Additionally, although the NCVS captures crimes unreported to the police that are excluded from studies using official data, the NCVS does not include estimates of several crime types including homicide and crime at commercial businesses. To the extent that differences in the likelihood that these crime types are more likely to be committed by more than one offender as a result of changing economic conditions, the results within this dissertation may vary when compared to studies that utilize official police records. It is also the case that the NCVS utilizes a hierarchy rule, such that if a victimization incident could be classified as more than one type of crime there is an ordered decision process to determine the final crime classification. For example, if a victimization involved both burglary and assault it would be classified as an assault. Thus, the substantive distinction

between instrumental and expressive crimes becomes a bit blurred and may lead to an overestimation of the rate and proportion of expressive crimes that are co-offenses.

Lastly, the examination of co-offending in this dissertation was devised by a relatively crude distinction of whether or not a victim reported seeing one or more than one offender. This was chosen because there is substantial missing data in the follow-up survey questions asked of respondents regarding the number of offenders, demographic characteristics about the offender, whether the offender(s) appeared to be using drugs, and whether the victim knew the offender. While it would be ideal to understand the extent to which the relationship between economic hardship and group crime was driven by certain types of offenders or characteristics about offenders, to avoid the ability to make reasonable inferences about the nature of co-offending in these victimization experiences this dissertation only examined the binary distinction of whether or not more than one offender was involved. In an effort to try to contextualize the findings in terms of differences in the form of co-offending that may be related to variation in offender motivation, models using different crime type outcomes were used.

Recent work within criminology that examines the role of place in explaining crime has demonstrated the importance of smaller units of micro-places (e.g., Eck & Weisburd, 1995; Groff, Weisburd, & Yang, 2010). In general, the concentration of crime and persistence of crime that occurs at the micro-level (e.g., block, street segment) suggests that the processes which facilitate criminal behavior are localized and systematically related to the opportunity structures defined at the micro-level. This dissertation utilized MSA-level data, which arguably may be too broad of a geographic unit to capture how economic hardship alters the interaction among offenders and target backcloth that would

facilitate group offending. While this is an obvious limitation, the fact that statistically significant relationships emerged at the MSA-level suggests that future work that is consistent with efforts that refine the geographic unit of analysis to lower levels of aggregation may be warranted to better understand the nature of localized processes relevant for explaining group crime.

Relatedly, the current analyses did not explicitly have measures of motivation to engage in group crime or opportunity structures for crime. Instead, it adopted a statistical method that distinguished differences in long-and short-term effects that were expected to be related to increases in economic hardship and hypothesized to be related to the concepts of motivation and opportunity (e.g., Andresen, 2012). This approach has been utilized in prior evaluations of the relationship between crime and economic hardship, however, clearly overlooks the possibility that these short-and long-term effects are capturing factors other than motivation or opportunity (e.g., Andresen, 2012, 2015; Andresen & Linning, 2015). Although this is a potential challenge associated with most macro-level research that utilizes aggregate level data (i.e., socioeconomic status, racial heterogeneity) to tap into processes that are theoretically associated with such measures, it may be worth exploring whether there are measures that are more strongly tied to the constructs of motivation and opportunity.

Beyond these limitations, this dissertation serves to help substantively advance our understanding of co-offending and offers a number of avenues for future research. Among the few studies that have been conducted that consider group crime at the macro-level, analytical and substantive flaws limit the ability of the studies to draw completely valid conclusions on the relationship between certain macro-level factors and group crime. The

results further reinforce that long-and short-term processes attributed to increases in economic hardship are not only related to crime, but also facilitates co-offending among offenders. Thus, prior research examining the relationship between economic hardship and crime may be missing a key substantive distinction in the outcome of crime that actually lead to in some instances different conclusions about the relationship between motivation for and opportunity structures to commit group crime.

Further, this dissertation demonstrated the utility of using victimization data to study co-offending and can be viewed as an example for additional work to consider a macro-level evaluation of group crime that addresses many of the limitations of official records. The limited availability of data that capture group crime must lead scholars interested in this form of criminal behavior to adopt creative approaches to studying co-offending. The NCVS offers a potential resource as a widely available dataset for scholar's to promote a co-offending research agenda. Lastly, this analytic strategy adopted in this dissertation provides an extension of Cantor and Land's (1985) original crime-unemployment model through the utilization of a hybrid modeling strategy proposed by Andresen (2012) to specifically consider multiple outcomes of group crime.

This dissertation should contribute to developing a future research agenda that continues to explore how co-offending is embedded into context and also more generally understand the process of co-offending. The main macro-level condition that was focused on in this dissertation was economic hardship, which while theoretically and empirically grounded in prior research is not the only macro-level condition that likely affects the emergence of group crime. For instance, Schaefer et al. (2014) provided some evidence to suggest that while collective efficacy is generally related to a reduction in crime, it has the

inadvertent effect of promoting trust among individuals within social networks that facilitates co-offending relationships. Identifying other constructs related to the formation of trust, including measures of collective efficacy or measures of trust found in the General Social Survey, and merging them into the NCVS may prove to demonstrate the unintended consequences of a traditionally crime-reducing macro-level factor. Additionally, research interested in understanding the nexus between crime rates and immigration have demonstrated that areas that experience an increased concentration of immigrants tend to actually report lower rates of crime (e.g., Martinez, Jr., Stowell, & Lee, 2010; Stowell, Messner, McGeever, & Raffalovich, 2009; Wadsworth, 2010). Perhaps the strong network and families ties associated with a new wave of immigrants into an area similarly promote trust among informal networks that inadvertently promote group offending (e.g., Portes et al., 2009; Portes & Zhou, 1993). By examining the relationship between dimensions of immigration concentration across areas, this may explain some of the systematic differences in the emergence of group crime and could provide additional context to understanding the development of offending patterns among immigrants.

In addition to exploring multiple measures of macro-level factors that may help explain the emergence of co-offending, multi-level approaches that integrate an understanding of both the contextual and individual level factors that facilitate co-offending among potential offenders would also be beneficial. The complex process by which offenders take on accomplices is arguably driven by both individual and contextual level explanatory factors. For instance, it may be the case that individuals who experience adversity or become unemployed may be more willing to co-offend (e.g., McCarthy et al., 1998), however, systematic differences in economic hardship across various contexts may

differentiate accessibility and availability to the conditions that facilitate co-offending. Short and Strotbeck (1965) alluded to this type of argument early on by stating that the criminal group represented the intersection of both individual and macro-level factors, therefore, it is prudent for scholars to identify or collect data that enable a multi-level framework to develop theoretical explanations and empirical tests for the study of co-offending.

One of the major premises of this dissertation and of the work that inspired it is that behavioral convergent settings offer stable contexts for which offenders can use to identify and socialize with suitable co-offenders (e.g., Felson, 2003). This dissertation begins to place bounds on understanding how macro-level factors generate conditions more favorable to group crime, however, does not address how offenders identify these convergent settings. One direction for future research may be to consider the domain or location that multiple offender victimizations occur. For example, Bichler, Malm, and Enriquez (2014) utilize network analysis among a sample of delinquent youth to identify self-nominated ‘magnetic’ hangout spaces that promote the concentration of youth in space that are conducive to crime. It will be important as scholars continue to understand how behavioral convergent settings emerge, where these settings are and how they evolve under changing socio-structural conditions. Alternatively, if convergent settings are generated through the routines and patterns of individuals, utilizing street-network or connectivity data would provide an opportunity to explore both where concentration of likely offenders is most probable and the ease in which offenders would be able converge in space. It is my hope that scholars continue to investigate how context matters for understanding the process of co-offending.

APPENDIX

Appendix A: List of MSAs included in NCVS Data

Anaheim-Santa Ana, CA
Atlanta, GA
Baltimore, MD
Boston, MA-NH
Charlotte-Gastonia-Rock Hill, NC-SC
Chicago, IL
Cincinnati, OH-KY-IN
Cleveland, Lorain, Elyria, OH
Columbus, OH
Dallas, TX
Denver, CO
Detroit, MI
Fort Lauderdale, FL
Fort Worth-Arlington, TX
Houston, TX
Kansas City, MO-KS
Los Angeles-Long Beach, CA
Miami, FL
Minneapolis-St. Paul, MN-WI
Nassau-Suffolk, NY
New York, NY
Newark, NJ
Norfolk-Virginia Beach-Newport News, VA-NC
Oakland, CA
Orlando, FL
Philadelphia, PA-NJ
Phoenix-Mesa, AZ
Pittsburgh, PA
Portland-Vancouver, OR-WA
Riverside-San Bernardino, CA
Sacramento, CA
St. Louis, MO-IL
San Antonio, TX
San Diego, CA
San Francisco, CA
San Jose, CA
Seattle-Bellevue-Everett, WA
Tampa-St. Petersburg-Clearwater, FL
Washington, DC-MD-VA-WV
West Palm Beach-Boca Raton, FL

Appendix B: Supplemental Analyses

Alternative Specifications of Proportion Outcomes

Table 19: Supplemental Analyses, Overall Proportion of Crimes that are Co-offenses – Unemployment Rate N=540

	Untransformed Continuous Outcome			Fractional Response Model		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.022*** (.006)	.063 (.050)	.057 (.109)	.118*** (.030)	.311 (.257)	.274 (.346)
Percent Aged 15-24	.001 (.005)	.017 (.024)		.005 (.029)	.086 (.127)	
Percent Male	-.007 (.011)	-.008 (.011)	-.007 (.013)	-.039 (.058)	-.041 (.005)	
Percent Black	.001 (.001)	.001 (.001)	.001 (.001)	.004 (.005)	.004 (.005)	
Percent Aged 25-44			.005 (.017)			.024 (.056)
Unemployment Rate X Percent Aged 15-24		-.003 (.004)			-.015 (.021)	
Unemployment Rate X Percent Aged 25-44			-.001 (.003)			-.005 (.011)
<i>Short Term Effect</i>						
Unemployment Rate	-.001 (.003)	-.065* (.028)	-.064 (.050)	-.003 (.019)	-.337* (.140)	-.344 (.314)
Percent Aged 15-24	-.002 (.0169)	-.025 (.019)		-.012 (.091)	-.133 (.104)	
Percent Male	.008 (.025)	-.003 (.024)	.009 (.027)	.034 (.136)	-.024 (.129)	.033 (.141)
Percent Black	.008 (.007)	.005 (.006)	.005 (.007)	.038 (.036)	.026 (.033)	.028 (.036)
Percent Aged 25-44			-.017 (.013)			-.080 (.073)
Unemployment Rate X Percent Aged 15-24		.005* (.006)			.025* (.011)	
Unemployment Rate X Percent Aged 25-44			.002 (.002)			

p<.001***, p<.01**, p<.05*, p<.10†

Table 20: Supplemental Analyses, Overall Proportion of Crimes that are Co-offenses - Percent Poverty N=540

	Untransformed Continuous Outcome			Fractional Response Model		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.007** (.003)	-.019 (.038)	-.012 (.046)	.037** (.013)	-.106 (.198)	-.066 (.233)
Percent Aged 15-24	-.010 (.008)	-.033 (.033)		-.055 (.041)	-.179 (.174)	
Percent Male	.001 (.012)	-.001 (.012)	-.004 (.013)	.002 (.063)	-.003 (.066)	-.021 (.065)
Percent Black	.001 (.001)	.001 (.001)	.001 (.001)	.007 (.005)	.008 (.005)	.006 (.006)
Percent Aged 25-44			-.008 (.015)			-.048 (.079)
Percent Poverty X Percent Aged 15-24		.002 (.003)			.010 (.014)	
Percent Poverty X Percent Aged 25-44			.001 (.001)			.003 (.007)
<i>Short Term Effect</i>						
Percent Poverty	.008* (.003)	-.011 (.024)	-.045 (.032)	.042* (.017)	-.053 (.128)	-.232 (.177)
Percent Aged 15-24	.006 (.015)	-.009 (.027)		.033 (.082)	-.041 (.147)	
Percent Male	.007 (.022)	.002 (.022)	.007 (.024)	.035 (.119)	.008 (.122)	.024 (.135)
Percent Black	.005 (.006)	.005 (.006)	.003 (.007)	.026 (.034)	.024 (.034)	.015 (.037)
Percent Aged 25-44			-.022 (.014)			-.105 (.076)
Percent Poverty X Percent Aged 15-24		.001 (.002)			.007 (.009)	
Percent Poverty X Percent Aged 25-44			.002 (.001)			.008 (.005)

p<.001***, p<.01**, p<.05*, p<.10†

Table 21: Supplemental Analyses, Proportion of Household Property Crimes that are Co-offenses – Unemployment Rate N=474

	Untransformed Continuous Outcome			Fractional Response Model		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.015* (.007)	-.008 (.057)	.147 (.132)	.087* (.040)	-.033 (.303)	.830 (.719)
Percent Aged 15-24	-.001 (.007)	-.009 (.022)		-.003 (.039)	-.053 (.129)	
Percent Male	-.002 (.013)	-.002 (.013)	-.001 (.015)	-.014 (.076)	-.015 (.075)	-.012 (.090)
Percent Black	-.001 (.001)	-.001 (.001)	-.001 (.001)	-.007 (.006)	-.007 (.006)	-.007 (.007)
Percent Aged 25-44			.019 (.020)			
Unemployment Rate X Percent Aged 15-24		.002 (.004)			.009 (.023)	
Unemployment Rate X Percent Aged 25-44			-.004 (.004)			-.023 (.022)
<i>Short Term Effect</i>						
Unemployment Rate	.001 (.008)	-.102 (.075)	-.209* (.094)	.011 (.044)	-.567 (.442)	-1.23* (.540)
Percent Aged 15-24	-.016 (.018)	-.051 (.033)		-.092 (.102)	-.292 (.193)	
Percent Male	.060 (.038)	.042 (.041)	.048 (.037)	.342 (.220)	.249 (.224)	.261 (.215)
Percent Black	.002 (.011)	-.001 (.013)	-.006 (.015)	.004 (.065)	-.008 (.074)	-.038 (.086)
Percent Aged 25-44			-.034 (.023)			-.187 (.130)
Unemployment Rate X Percent Aged 15-24		.008 (.006)			.043 (.033)	
Unemployment Rate X Percent Aged 25-44			.006* (.003)			.037* (.016)

p<.001***, p<.01**, p<.05*, p<.10†

Table 22: Supplemental Analyses, Proportion of Household Property Crimes that are Co-offenses - Percent Poverty N=474

	Untransformed Continuous Outcome			Fractional Response Model		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.007* (.003)	-.001 (.039)	-.009 (.057)	.038* (.017)	.012 (.221)	-.059 (.318)
Percent Aged 15-24	-.010 (.008)	-.016 (.033)		-.062 (.049)	-.085 (.192)	
Percent Male	.005 (.014)	.004 (.014)	-.004 (.014)	.026 (.083)	.025 (.084)	-.028 (.082)
Percent Black	-.001 (.001)	-.001 (.001)	-.001 (.001)	-.005 (.006)	-.005 (.006)	-.008 (.007)
Percent Aged 25-44			-.005 (.020)			-.030 (.111)
Percent Poverty X Percent Aged 15-24		.001 (.003)			.002 (.016)	
Percent Poverty X Percent Aged 25-44			.001 (.002)			.003 (.009)
<i>Short Term Effect</i>						
Percent Poverty	.012† (.007)	.011 (.046)	-.024 (.051)	.074† (.040)	.099 (.263)	-.106 (.304)
Percent Aged 15-24	-.003 (.019)	-.004 (.043)		-.020 (.105)	.001 (.245)	
Percent Male	.058 (.040)	.058 (.040)	.057 (.040)	.355 (.236)	.360 (.229)	.326 (.230)
Percent Black	-.001 (.012)	-.001 (.012)	-.003 (.014)	-.014 (.067)	-.014 (.069)	-.026 (.082)
Percent Aged 25-44			-.018 (.021)			-.082 (.127)
Percent Poverty X Percent Aged 15-24		.001 (.003)			-.002 (.019)	
Percent Poverty X Percent Aged 25-44			.001 (.001)			.005 (.009)

p<.001***, p<.01**, p<.05*, p<.10†

Table 23: Supplemental Analyses, Proportion of Personal Instrumental Crimes that are Co-offenses – Unemployment Rate N=533

	Untransformed Continuous Outcome			Fractional Response Model		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.006 (.014)	-.008 (.087)	.049 (.109)	.026 (.060)	-.057 (.366)	.206 (.460)
Percent Aged 15-24	-.008 (.015)	.003 (.037)		-.029 (.062)	.002 (.155)	
Percent Male	-.009 (.025)	.006 (.021)	.006 (.031)	-.041 (.106)	.025 (.087)	.023 (.129)
Percent Black	.004* (.002)	.004* (.002)	.004† (.002)	.017* (.008)	.018* (.008)	.019† (.011)
Percent Aged 25-44			.009 (.022)			.039 (.092)
Unemployment Rate X Percent Aged 15-24		.001 (.001)			.004 (.028)	
Unemployment Rate X Percent Aged 25-44			-.001 (.003)			-.006 (.014)
<i>Short Term Effect</i>						
Unemployment Rate	-.002 (.011)	-.006 (.101)	.028 (.109)	-.007 (.047)	-.051 (.420)	.113 (.459)
Percent Aged 15-24	.027 (.039)	-.001 (.052)		.115 (.163)	-.017 (.219)	
Percent Male	.026 (.060)	-.050 (.073)	-.032 (.068)	.113 (.254)	-.223 (.307)	-.147 (.286)
Percent Black	.003 (.020)	-.017 (.014)	-.019 (.015)	.015 (.081)	-.069 (.059)	-.079 (.064)
Percent Aged 25-44			-.024 (.035)			-.101 (.147)
Unemployment Rate X Percent Aged 15-24		.001 (.008)			.003 (.033)	
Unemployment Rate X Percent Aged 25-44			-.001 (.003)			-.004 (.014)

p<.001***, p<.01**, p<.05*, p<.10†

Table 24: Supplemental Analyses, Proportion of Personal Instrumental Crimes that are Co-offenses - Percent Poverty N=533

	Untransformed Continuous Outcome			Fractional Response Model		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.001 (.005)	-.091* (.041)	-.031 (.097)	.006 (.021)	-.415* (.177)	-.149 (.405)
Percent Aged 15-24	-.010 (.017)	-.073* (.034)		-.039 (.069)	-.337* (.149)	
Percent Male	-.007 (.027)	.004 (.020)	.007 (.031)	-.036 (.110)	.014 (.084)	.024 (.126)
Percent Black	.004* (.002)	.005** (.002)	.004† (.003)	.017* (.008)	.020* (.008)	.018† (.011)
Percent Aged 25-44			-.008 (.035)			-.038 (.147)
Percent Poverty X Percent Aged 15-24		.007* (.003)			.030* (.013)	
Percent Poverty X Percent Aged 25-44			.001 (.003)			.005 (.012)
<i>Short Term Effect</i>						
Percent Poverty	.004 (.009)	-.075 (.053)	-.009 (.066)	.017 (.037)	-.369† (.223)	-.054 (.275)
Percent Aged 15-24	.033 (.037)	-.058 (.061)		.138 (.157)	-.289 (.259)	
Percent Male	.024 (.059)	-.068 (.070)	-.040 (.062)	.105 (.248)	.014 (.084)	-.185 (.262)
Percent Black	.002 (.019)	-.020 (.015)	-.020 (.016)	.013 (.078)	.020* (.008)	-.083 (.065)
Percent Aged 25-44			-.027 (.035)			-.110 (.147)
Percent Poverty X Percent Aged 15-24		.005 (.004)			.026† (.016)	
Percent Poverty X Percent Aged 25-44			.001 (.002)			.002 (.008)

p<.001***, p<.01**, p<.05*, p<.10†

Table 25: Supplemental Analyses, Proportion of Expressive Crimes that are Co-offenses – Unemployment Rate N=450

	Untransformed Continuous Outcome			Fractional Response Model		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.009† (.006)	-.031 (.059)	-.202** (.078)	.066* (.030)	-.144 (.396)	-1.196* (.540)
Percent Aged 15-24	.005 (.008)	-.011 (.027)		.032 (.050)	-.050 (.170)	
Percent Male	.006 (.011)	.006 (.011)	.008 (.011)	.032 (.065)	.032 (.065)	.048 (.059)
Percent Black	.001 (.001)	.001 (.001)	.001 (.001)	.003 (.006)	.003 (.006)	.004 (.005)
Percent Aged 25-44			-.032* (.013)			-.187* (.086)
Unemployment Rate X Percent Aged 15-24		.003 (.004)			.016 (.030)	
Unemployment Rate X Percent Aged 25-44			.006** (.002)			.038* (.016)
<i>Short Term Effect</i>						
Unemployment Rate	.001 (.005)	-.035 (.059)	.088 (.080)	.014 (.031)	-.209 (.364)	.557 (.502)
Percent Aged 15-24	-.009 (.023)	-.020 (.032)		-.033 (.138)	-.110 (.200)	
Percent Male	-.003 (.053)	-.010 (.051)	-.012 (.049)	-.068 (.313)	-.105 (.302)	-.123 (.296)
Percent Black	-.001 (.012)	-.001 (.011)	.004 (.013)	-.011 (.072)	-.015 (.069)	.024 (.076)
Percent Aged 25-44			.019 (.020)			.150 (.117)
Unemployment Rate X Percent Aged 15-24		.003 (.004)			.017 (.026)	
Unemployment Rate X Percent Aged 25-44			-.003 (.002)			-.016 (.015)

p<.001***, p<.01**, p<.05*, p<.10†

Table 26: Supplemental Analyses, Proportion of Expressive Crimes that are Co-offenses - Percent Poverty N=450

	Untransformed Continuous Outcome			Fractional Response Model		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.003 (.002)	.062* (.031)	-.005 (.042)	.020† (.010)	.392* (.209)	.007 (.233)
Percent Aged 15-24	.001 (.008)	.053† (.028)		.006 (.048)	.322† (.184)	
Percent Male	.009 (.011)	.010 (.010)	.011 (.011)	.047 (.064)	.058 (.058)	.062 (.061)
Percent Black	.001 (.001)	.001 (.001)	.001 (.001)	.004 (.006)	.002 (.005)	.004 (.005)
Percent Aged 25-44			-.004 (.014)			-.011 (.080)
Percent Poverty X Percent Aged 15-24		-.004† (.002)			-.026† (.016)	
Percent Poverty X Percent Aged 25-44			.001 (.001)			.001 (.007)
<i>Short Term Effect</i>						
Percent Poverty	.009† (.005)	-.059 (.043)	-.041 (.047)	.059* (.029)	-.359 (.281)	-.246 (.282)
Percent Aged 15-24	-.001 (.020)	-.056 (.046)		.010 (.121)	-.337 (.303)	
Percent Male	.001 (.047)	-.013 (.045)	-.011 (.047)	-.029 (.280)	-.095 (.271)	-.104 (.286)
Percent Black	-.002 (.012)	-.004 (.011)	-.005 (.013)	-.020 (.069)	-.032 (.069)	-.031 (.079)
Percent Aged 25-44			-.009 (.019)			-.033 (.114)
Percent Poverty X Percent Aged 15-24		.005 (.003)			.030 (.020)	
Percent Poverty X Percent Aged 25-44			.001 (.001)			.009 (.008)

p<.001***, p<.01**, p<.05*, p<.10†

Table 27: Pooled Supplemental Analyses, Rate of Household Property Co-offending - Unemployment Rate

	2-Year Pooled (N=275)			3-Year Pooled (N=200)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.062† (.034)	.334 (.357)	.248 (.553)	.043 (.035)	.307 (.367)	.2326 (.609)
Solo-Offense Rate	.487** (.144)	.503*** (.150)	.508*** (.143)	.400** (.134)	.407** (.137)	.399** (.139)
Percent Aged 15-24	.036 (.032)	.146 (.146)		.044 (.032)	.150 (.150)	
Percent Male	-.005 (.056)	-.009 (.058)	.104 (.065)	-.005 (.056)	-.009 (.057)	.093 (.067)
Percent Black	-.002 (.005)	-.002 (.005)	.004 (.005)	-.002 (.0050)	-.003 (.005)	.003 (.005)
Percent Aged 25-44			-.008 (.086)			.002 (.096)
Unemployment Rate X Percent Aged 15-24		-.020 (.027)			-.020 (.027)	
Unemployment Rate X Percent Aged 25-44			-.007 (.017)			-.007 (.018)
<i>Short Term Effect</i>						
Unemployment Rate	.058* (.029)	-.285 (.232)	-.048 (.364)	.076* (.034)	-.357 (.243)	.133 (.379)
Solo-Offense Rate	.245** (.080)	.247** (.079)	.249** (.081)	.204* (.081)	.208** (.080)	.201* (.083)
Percent Aged 15-24	.005 (.091)	-.121 (.124)		.056 (.082)	-.113 (.125)	
Percent Male	.049 (.180)	-.018 (.184)	.070 (.181)	.059 (.166)	-.026 (.171)	.139 (.170)
Percent Black	.080† (.045)	.068 (.046)	.077† (.047)	.115** (.038)	.100** (.039)	.118** (.039)
Percent Aged 25-44			-.045 (.099)			-.047 (.093)
Unemployment Rate X Percent Aged 15-24		.026 (.017)			.033† (.018)	
Unemployment Rate X Percent Aged 25-44			.003 (.011)			-.002 (.012)

p<.001***, p<.01**, p<.05*, p<.10†

Table 28: Pooled Supplemental Analyses, Rate of Household Property Co-offending – Percent Poverty

	2-Year Pooled (N=275)			3-Year Pooled (N=200)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.028** (.010)	.024 (.154)	-.017 (.191)	.022* (.011)	-.003 (.167)	-.018 (.205)
Solo-Offense Rate	.464*** (.127)	.464*** (.131)	.475*** (.129)	.385** (.127)	.386** (.130)	.385** (.126)
Percent Aged 15-24	-.006 (.032)	-.009 (.136)		.012 (.034)	-.010 (.145)	
Percent Male	.028 (.052)	.028 (.054)	.088 (.060)	.019 (.055)	.018 (.057)	.073 (.063)
Percent Black	-.001 (.004)	-.001 (.004)	.002 (.005)	-.002 (.004)	-.002 (.005)	.001 (.005)
Percent Aged 25-44			-.046 (.064)			-.035 (.069)
Percent Poverty X Percent Aged 15-24		.001 (.011)			.002 (.012)	
Percent Poverty X Percent Aged 25-44			.001 (.006)			.001 (.006)
<i>Short Term Effect</i>						
Percent Poverty	.049† (.029)	.064 (.191)	-.121 (.262)	.066* (.027)	.221 (.183)	.149 (.239)
Solo-Offense Rate	.255** (.080)	.254** (.080)	.258 (.080)	.208** (.081)	.207** (.080)	.205* (.081)
Percent Aged 15-24	-.006 (.092)	.006 (.172)		.053 (.081)	.175 (.164)	
Percent Male	.113 (.180)	.118 (.188)	.105 (.185)	.126 (.162)	.169 (.170)	.215 (.172)
Percent Black	.057 (.046)	.057 (.046)	.052 (.047)	.085* (.039)	.085* (.039)	.093* (.039)
Percent Aged 25-44			-.082 (.108)			-.043 (.095)
Percent Poverty X Percent Aged 15-24		-.001 (.013)			-.011 (.013)	
Percent Poverty X Percent Aged 25-44			.005 (.008)			-.003 (.007)

p<.001***, p<.01**, p<.05*, p<.10†

Table 29: Pooled Supplemental Analyses, Rate of Personal Instrumental Co-offending – Unemployment Rate

	2-Year Pooled (N=276)			3-Year Pooled (N=197)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.077* (.033)	.032 (.361)	.359 (.567)	.069* (.034)	-.092 (.333)	.282 (.549)
Solo-Offense Rate	.415** (.142)	.407** (.158)	.341* (.153)	.444*** (.139)	.423** (.144)	.362** (.140)
Percent Aged 15-24	-.020 (.033)	-.038 (.147)		-.017 (.031)	-.082 (.137)	
Percent Male	.001 (.053)	.001 (.054)	-.088 (.064)	-.020 (.052)	-.017 (.051)	-.114* (.058)
Percent Black	.014** (.005)	.015** (.005)	.010* (.005)	.012** (.005)	.013** (.005)	.009† (.005)
Percent Aged 25-44			.074 (.085)			.072 (.084)
Unemployment Rate X Percent Aged 15-24		.003 (.027)			.012 (.025)	
Unemployment Rate X Percent Aged 25-44			-.008 (.017)			-.005 (.017)
<i>Short Term Effect</i>						
Unemployment Rate	.015 (.028)	-.079 (.230)	.221 (.342)	-.021 (.034)	-.214 (.251)	.052 (.369)
Solo-Offense Rate	.214*** (.062)	.212*** (.062)	.209*** (.062)	.235** (.077)	.236** (.078)	.233** (.076)
Percent Aged 15-24	.035 (.088)	.001 (.122)		-.003 (.085)	-.076 (.128)	
Percent Male	-.015 (.177)	-.032 (.183)	.077 (.177)	.232 (.168)	.193 (.177)	.340* (.169)
Percent Black	.002 (.044)	-.001 (.044)	.007 (.044)	.003 (.038)	-.002 (.039)	.008 (.038)
Percent Aged 25-44			-.063 (.092)			-.131 (.089)
Unemployment Rate X Percent Aged 15-24		.007 (.017)			.015 (.019)	
Unemployment Rate X Percent Aged 25-44			-.006 (.010)			-.003 (.011)

p<.001***, p<.01**, p<.05*, p<.10†

Table 30: Pooled Supplemental Analyses, Rate of Personal Instrumental Co-offending Groups – Percent Poverty

	2-Year Pooled (N=276)			3-Year Pooled (N=197)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.032** (.011)	-.445*** (.132)	.015 (.209)	.025* (.012)	-.484*** (.136)	-.068 (.201)
Solo-Offense Rate	.368** (.141)	.430*** (.119)	.275† (.162)	.409** (.145)	.479*** (.122)	.348* (.150)
Percent Aged 15-24	-.065* (.034)	-.473*** (.116)		-.054 (.034)	-.482*** (.118)	
Percent Male	.039 (.053)	.020 (.045)	-.075 (.067)	.004 (.054)	-.021 (.045)	-.114† (.060)
Percent Black	.016*** (.005)	.018*** (.004)	.011* (.005)	.014** (.005)	.015*** (.004)	.008† (.005)
Percent Aged 25-44			.021 (.071)			.005 (.068)
Percent Poverty X Percent Aged 15-24		.035*** (.010)			.037*** (.010)	
Percent Poverty X Percent Aged 25-44			.001 (.006)			.003 (.006)
<i>Short Term Effect</i>						
Percent Poverty	.084** (.027)	-.008 (.180)	.018 (.246)	.052† (.027)	-.119 (.183)	.001 (.235)
Solo-Offense Rate	.191** (.061)	.189** (.061)	.182** (.061)	.210** (.077)	.200** (.078)	.198** (.077)
Percent Aged 15-24	.083 (.086)	.017 (.163)		.049 (.083)	-.084 (.165)	
Percent Male	.009 (.172)	-.022 (.179)	.103 (.178)	.204 (.163)	.154 (.174)	.309† (.172)
Percent Black	-.021 (.043)	-.023 (.043)	-.021 (.044)	-.010 (.038)	-.009 (.039)	-.004 (.039)
Percent Aged 25-44			-.110 (.101)			-.141 (.093)
Percent Poverty X Percent Aged 15-24		.007 (.013)			.012 (.013)	
Percent Poverty X Percent Aged 25-44			.002 (.007)			.001 (.007)

p<.001***, p<.01**, p<.05*, p<.10†

Table 31: Pooled Supplemental Analyses, Rate of Expressive Crime Committed in Groups - Unemployment Rate

	2-Year Pooled (N=276)			3-Year Pooled (N=197)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.022 (.041)	-.665† (.378)	-.968 (.646)	.034 (.038)	-.479 (.365)	-.778 (.608)
Solo-Offense Rate	.589*** (.132)	.569*** (.127)	.571*** (.133)	.611*** (.055)	.597*** (.115)	.597*** (.116)
Percent Aged 15-24	.031 (.037)	-.245 (.155)		.033 (.032)	-.173 (.149)	
Percent Male	-.023 (.063)	-.015 (.060)	-.036 (.075)	-.016 (.055)	-.009 (.056)	-.016 (.066)
Percent Black	-.001 (.005)	.001 (.005)	-.001 (.006)	-.001 (.005)	.001 (.005)	-.001 (.005)
Percent Aged 25-44			-.129 (.101)			-.109 (.095)
Unemployment Rate X Percent Aged 15-24		.051† (.028)			.038 (.027)	
Unemployment Rate X Percent Aged 25-44			.031 (.020)			.025 (.018)
<i>Short Term Effect</i>						
Unemployment Rate	.018 (.030)	.332 (.243)	.113 (.370)	-.055 (.038)	.153 (.272)	.342 (.417)
Solo-Offense Rate	.212* (.098)	.211* (.098)	.202* (.098)	.420*** (.120)	.410*** (.120)	.428*** (.121)
Percent Aged 15-24	-.137 (.094)	-.019 (.130)		-.202* (.091)	-.121 (.139)	
Percent Male	.198 (.186)	.257 (.192)	.066 (.188)	.286 (.184)	.328† (.192)	.151 (.190)
Percent Black	.030 (.047)	.041 (.047)	.036 (.048)	.030 (.042)	.036 (.043)	.039 (.044)
Percent Aged 25-44			.086 (.102)			.092 (.103)
Unemployment Rate X Percent Aged 15-24		-.023 (.018)			-.016 (.021)	
Unemployment Rate X Percent Aged 25-44			-.002 (.011)			-.011 (.013)

p<.001***, p<.01**, p<.05*, p<.10†

Table 32: Pooled Supplemental Analyses, Rate of Personal Instrumental Co-offending – Percent Poverty

	2-Year Pooled (N=276)			3-Year Pooled (N=197)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.017 (.013)	.322† (.193)	-.082 (.240)	.018 (.012)	.294† (.172)	-.059 (.207)
Solo-Offense Rate	.604*** (.124)	.556*** (.129)	.588*** (.124)	.609*** (.108)	.572*** (.110)	.604*** (.103)
Percent Aged 15-24	.006 (.041)	.271 (.173)		.008 (.036)	.244 (.151)	
Percent Male	-.003 (.064)	.009 (.064)	-.052 (.074)	.002 (.056)	.015 (.057)	-.032 (.062)
Percent Black	.001 (.005)	-.002 (.006)	-.003 (.006)	-.001 (.005)	-.002 (.005)	-.002 (.005)
Percent Aged 25-44			-.006 (.081)			-.007 (.070)
Percent Poverty X Percent Aged 15-24		-.022 (.014)				
Percent Poverty X Percent Aged 25-44			.003 (.007)		-.020 (.013)	.002 (.006)
<i>Short Term Effect</i>						
Percent Poverty	.052† (.029)	.037 (.194)	-.281 (.268)	.023 (.030)	-.158 (.202)	-.48 (.268)
Solo-Offense Rate	.213* (.096)	.212* (.096)	.220* (.096)	.426*** (.120)	.430*** (.120)	.457*** (.121)
Percent Aged 15-24	-.113 (.092)	-.126 (.176)		-.139 (.090)	-.281 (.182)	
Percent Male	.218 (.182)	.216 (.190)	.046 (.191)	.228 (.181)	.177 (.189)	.044 (.193)
Percent Black	.015 (.047)	.015 (.047)	.002 (.048)	.030 (.043)	.030 (.043)	.010 (.044)
Percent Aged 25-44			-.015 (.111)			-.062 (.107)
Percent Poverty X Percent Aged 15-24		.001 (.014)			.013 (.014)	
Percent Poverty X Percent Aged 25-44			.010 (.008)			.013 (.008)

p<.001***, p<.01**, p<.05*, p<.10†

Table 33: Pooled Supplemental Analyses, Proportion of Household Property Crimes that are Co-offenses - Unemployment Rate

	2-Year Pooled (N=275)			3-Year Pooled (N=197)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.097* (.046)	.445 (.407)	.563 (.625)	.088* (.041)	.798** (.280)	.507 (.611)
Percent Aged 15-24	.028 (.045)	.169 (.187)		.035 (.044)	.321* (.127)	
Percent Male	-.037 (.087)	-.039 (.085)	.010 (.110)	-.040 (.079)	-.047 (.078)	.057 (.107)
Percent Black	-.004 (.008)	-.005 (.008)	.004 (.010)	-.006 (.008)	-.008 (.007)	-.001 (.009)
Percent Aged 25-44			.010 (.110)			.034 (.109)
Unemployment Rate X Percent Aged 15-24		-.026 (.031)			-.053* (.022)	
Unemployment Rate X Percent Aged 25-44			-.016 (.019)			-.014 (.019)
<i>Short Term Effect</i>						
Unemployment Rate	.028 (.064)	-.513 (.342)	-.267 (.775)	.066 (.055)	-.338 (.341)	-.868 (.550)
Percent Aged 15-24	.094 (.148)	-.106 (.204)		-.077 (.119)	-.235 (.185)	
Percent Male	.080 (.376)	-.025 (.394)	.238 (.328)	.107 (.284)	.027 (.301)	.071 (.273)
Percent Black	.061 (.092)	.043 (.093)	.052 (.097)	.030 (.052)	.016 (.058)	.010 (.058)
Percent Aged 25-44			-.199 (.183)			-.186 (.135)
Unemployment Rate X Percent Aged 15-24		.041 (.027)			.031 (.027)	
Unemployment Rate X Percent Aged 25-44			.009 (.024)			.029 (.017)

p<.001***, p<.01**, p<.05*, p<.10†

Table 34: Pooled Supplemental Analyses, Proportion of Household Property Crimes that are Co-offenses – Percent Poverty

	2-Year Pooled (N=275)			3-Year Pooled (N=197)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.039* (.016)	-.048 (.244)	-.210 (.222)	.032* (.014)	.137 (.166)	-.114 (.182)
Percent Aged 15-24	-.031 (.056)	-.105 (.222)		-.012 (.060)	.078 (.169)	
Percent Male	.006 (.098)	.003 (.099)	.093 (.117)	-.012 (.095)	-.007 (.092)	.040 (.101)
Percent Black	-.002 (.009)	-.002 (.009)	.001 (.009)	-.005 (.008)	-.006 (.008)	-.003 (.008)
Percent Aged 25-44			-.139† (.075)			.078 (.064)
Percent Poverty X Percent Aged 15-24		.006 (.018)			-.008 (.012)	
Percent Poverty X Percent Aged 25-44			.007 (.007)			.004 (.006)
<i>Short Term Effect</i>						
Percent Poverty	.033 (.050)	-.062 (.279)	-.273 (.402)	.036 (.040)	.175 (.280)	-.345 (.101)
Percent Aged 15-24	.095 (.140)	.022 (.280)		-.098 (.118)	.011 (.279)	
Percent Male	.111 (.369)	.084 (.384)	.219 (.344)	.167 (.283)	.206 (.287)	.099 (.283)
Percent Black	.048 (.091)	.047 (.092)	.041 (.097)	.010 (.054)	.010 (.053)	-.002 (.057)
Percent Aged 25-44			-.239 (.216)			-.161 (.155)
Percent Poverty X Percent Aged 15-24		.007 (.021)			-.010 (.020)	
Percent Poverty X Percent Aged 25-44			.009 (.012)			.012 (.010)

p<.001***, p<.01**, p<.05*, p<.10†

Table 35: Pooled Supplemental Analyses, Proportion of Personal Instrumental Crimes that are Co-offenses - Unemployment Rate

	2-Year Pooled (N=271)			3-Year Pooled (N=197)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.140† (.080)	1.81* (.817)	3.22* (1.50)	.078 (.077)	.963 (.823)	2.54* (1.27)
Percent Aged 15-24	-.129 (.126)	.548 (.352)		-.080 (.085)	.269 (.332)	
Percent Male	-.018 (.190)	-.029 (.182)	.027 (.150)	-.110 (.148)	-.120 (.146)	-.221* (.113)
Percent Black	.038 (.119)	.021 (.013)	.023† (.012)	.014 (.009)	.012 (.009)	.007 (.009)
Percent Aged 25-44			.393† (.221)			.390* (.197)
Unemployment Rate X Percent Aged 15-24		-.125* (.062)			-.066	
Unemployment Rate X Percent Aged 25-44			-.095* (.045)			-.074† (.039)
<i>Short Term Effect</i>						
Unemployment Rate	-.071 (.062)	.439 (.609)	.927 (.860)	-.162* (.083)	-.314 (1.11)	.399 (1.36)
Percent Aged 15-24	.226 (.227)	.408 (.329)		.123 (.193)	.060 (.455)	
Percent Male	.072 (.287)	.160 (.319)	.203 (.327)	.982** (.359)	.950* (.407)	1.23*** (.380)
Percent Black	.038 (.119)	.052 (.122)	.050 (.122)	.011 (.081)	.004 (.082)	.023 (.096)
Percent Aged 25-44			.196 (.250)			-.132 (.279)
Unemployment Rate X Percent Aged 15-24		-.039 (.046)			.011 (.083)	
Unemployment Rate X Percent Aged 25-44			-.031 (.026)			-.018 (.042)

p<.001***, p<.01**, p<.05*, p<.10†

Table 36: Pooled Supplemental Analyses, Proportion of Personal Instrumental Crimes that are Co-offenses – Percent Poverty

	2-Year Pooled (N=275)			3-Year Pooled (N=197)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.057† (.030)	-1.14*** (.323)	.116 (.511)	.018 (.027)	-1.15*** (.232)	-.333 (.462)
Percent Aged 15-24	-.216† (.130)	-1.24*** (.318)		-.117 (.091)	-.1.11*** (.241)	
Percent Male	.049 (.166)	.006 (.141)	.049 (.156)	-.098 (.147)	-.145 (.135)	-.219† (.121)
Percent Black	.026* (.013)	.031** (.010)	.027* (.012)	.015† (.009)	.020** (.008)	.008 (.009)
Percent Aged 25-44			-.064 (.182)			-.107 (.163)
Percent Poverty X Percent Aged 15-24		.087*** (.024)			.085*** (.017)	
Percent Poverty X Percent Aged 25-44			-.003 (.016)			.010 (.014)
<i>Short Term Effect</i>						
Percent Poverty	.035 (.065)	.140 (.350)	.430 (.402)	-.033 (.055)	.183 (.417)	.574 (.479)
Percent Aged 15-24	.312 (.227)	.406 (.317)		.213 (.197)	.386 (.328)	
Percent Male	-.001 (.290)	.018 (.294)	.223 (.337)	.833* (.354)	.902* (.390)	1.19*** (.373)
Percent Black	.041 (.116)	.042 (.116)	.053 (.122)	.039 (.083)	.043 (.082)	.072 (.101)
Percent Aged 25-44			.130 (.237)			-.042 (.245)
Percent Poverty X Percent Aged 15-24		-.007 (.024)			-.016 (.029)	
Percent Poverty X Percent Aged 25-44			-.012 (.011)			-.019 (.014)

p<.001***, p<.01**, p<.05*, p<.10†

Table 37: Pooled Supplemental Analyses, Proportion of Expressive Crimes that are Co-offenses - Unemployment Rate

	2-Year Pooled (N=276)			3-Year Pooled (N=200)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Unemployment Rate	.037 (.067)	-1.86** (.603)	-2.38* (1.02)	.074† (.043)	-.800† (.428)	-1.04† (.572)
Percent Aged 15-24	.061 (.096)	-.707* (.286)		.041 (.054)	-.311 (.215)	
Percent Male	-.081 (.108)	-.058 (.091)	-.143 (.131)	-.061 (.070)	-.052 (.065)	-.074 (.081)
Percent Black	.001 (.011)	.005 (.010)	-.002 (.012)	-.001 (.008)	.002 (.007)	-.001 (.008)
Percent Aged 25-44			-.313* (.151)			-.147 (.092)
Unemployment Rate X Percent Aged 15-24		.142** (.046)			.065† (.034)	
Unemployment Rate X Percent Aged 25-44			.075* (.030)			.034* (.017)
<i>Short Term Effect</i>						
Unemployment Rate	-.027 (.071)	1.01 (.615)	.232 (1.31)	-.082 (.057)	.276 (.432)	.490 (.766)
Percent Aged 15-24	-.295 (.225)	.097 (.335)		-.278 (.170)	-.137 (.224)	
Percent Male	.280 (.351)	.476 (.416)	.107 (.415)	.371 (.241)	.442 (.287)	.215 (.248)
Percent Black	.009 (.079)	.048 (.101)	.022 (.085)	.025 (.058)	.037 (.063)	.039 (.055)
Percent Aged 25-44			.035 (.284)			.094 (.165)
Unemployment Rate X Percent Aged 15-24		-.079† (.045)			-.027 (.033)	
Unemployment Rate X Percent Aged 25-44			-.007 (.038)			-.016 (.023)

p<.001***, p<.01**, p<.05*, p<.10†

Table 38: Pooled Supplemental Analyses, Proportion of Expressive Crimes that are Co-offenses – Percent Poverty

	2-Year Pooled (N=275)			3-Year Pooled (N=197)		
	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44	Baseline Model	Interaction Model with Age Profile 15-24	Interaction Model with Age Profile 25-44
Independent Variables						
<i>Long Term Effect</i>						
Percent Poverty	.025 (.024)	.396 (.438)	-.213 (.441)	.029† (.017)	.260 (.335)	-.109 (.335)
Percent Aged 15-24	.025 (.107)	.340 (.385)		-.001 (.056)	.195 (.278)	
Percent Male	-.053 (.105)	-.039 (.103)	-.175 (.129)	-.034 (.070)	-.025 (.070)	-.090 (.083)
Percent Black	.001 (.012)	-.001 (.010)	-.006 (.012)	.001 (.008)	-.001 (.007)	-.003 (.008)
Percent Aged 25-44			-.014 (.147)			-.021 (.109)
Percent Poverty X Percent Aged 15-24		-.027 (.032)			-.017 (.025)	
Percent Poverty X Percent Aged 25-44			.008 (.013)			.004 (.010)
<i>Short Term Effect</i>						
Percent Poverty	.041 (.056)	-.005 (.528)	-.562 (.699)	.034 (.031)	-.171 (.246)	-.599 (.388)
Percent Aged 15-24	-.240 (.204)	-.276 (.492)		-.184 (.151)		
Percent Male	.250 (.322)	.238 (.357)	.011 (.409)	.286 (.220)	.229 (.245)	.059 (.241)
Percent Black	.003 (.078)	.002 (.078)	-.020 (.077)	.024 (.056)	.024 (.056)	-.004 (.048)
Percent Aged 25-44			-.160 (.247)			-.129 (.143)
Percent Poverty X Percent Aged 15-24		.003 (.036)			.015 (.018)	
Percent Poverty X Percent Aged 25-44			.018 (.020)			-.129 (.143)

p<.001***, p<.01**, p<.05*, p<.10†

REFERENCES

- Alarid, L. F., Burton, V. S., & Hochstetler, A. L. (2009). Group and solo robberies: Do accomplices shape criminal form? *Journal of Criminal Justice*, 37(1), 1-9.
- Anderson, E. (1999). *Code of the Street*. New York: Norton.
- Andresen, M. A. (2012). Unemployment and crime: A neighborhood level panel data approach. *Social Science Research*, 41(6), 1615-1628.
- Andresen, M. A. (2015). Unemployment, GDP, and crime: The importance of multiple measurements of the economy. *Canadian Journal of Criminology and Criminal Justice*, 57(1), 35-58.
- Andresen, M.A., & Felson, M. (2010). Situational crime prevention and co-offending. *Crime Patterns and Analysis. ECCA Journal*, 3(1).
- Andresen, M. A., & Felson, M. (2012). Co-offending and the diversification of crime types. *International Journal of Offender Therapy and Comparative Criminology*, 56(5), 811-829.
- Andresen, M.A., & Linning, S.J. (2015). Unemployment, business cycles, and crime specialization: Canadian provinces, 1981-2009. *Australian & New Zealand Journal of Criminology*, 0(0), 1-19.
- Arvanites, T. M., and Defina, R. H. (2006). Business cycles and street crime. *Criminology*, 44(1), 139-164.
- Baum, C.F. (2008). Modeling proportions. *The Stata Journal*, 8(2), 299-303.
- Baumer, E. P. (2002). Neighborhood disadvantage and police notification by victims of violence. *Criminology*, 40(3), 579-616.
- Baumer, E. P., & Lauritsen, J. L. (2010). Reporting crime to the police, 1973–2005: a multivariate analysis of long-term trends in the National Crime Survey (NCS) and National Crime Victimization Survey (NCVS). *Criminology*, 48(1), 131-185.
- Becker, G. S. (1968). Crime and punishment: An economic approach. In *The Economic Dimensions of Crime* (pp. 13-68). Palgrave Macmillan UK.
- Berk, R. A. (1974). A gaming approach to crowd behavior. *American Sociological Review*, 355-373.

- Bernasco, W. (2006). Co-offending and the choice of target areas in burglary. *Journal of Investigative Psychology and Offender Profiling*, 3(3), 139-155.
- Bernasco, W. (2010). A sentimental journey to crime: Effects of residential history on crime location choice. *Criminology*, 48(2), 389-416.
- Bichler, G., Malm, A., & Enriquez, J. (2014). Magnetic facilities: Identifying the convergence settings of juvenile delinquents. *Crime & Delinquency*, 60(7), 971-998.
- Birkbeck, C., & LaFree, G. (1993). The situational analysis of crime and deviance. *Annual Review of Sociology*, 113-137.
- Block, C. R., & Block, R. (1993). *Street Gang Crime in Chicago*. Washington DC: US Department of Justice, Office of Justice Programs, National Institute of Justice.
- Bonger, W. A. (1916). *Criminality and Economic Conditions*. Boston: Little, Brown.
- Bouchard, M., & Nguyen, H. (2010). Is it who you know, or how many that counts? Criminal networks and cost avoidance in a sample of young offenders. *Justice Quarterly*, 27(1), 130-158.
- Bound, J., & Holzer, H. J. (2000). Demand shifts, population adjustments, and labor market outcomes during the 1980s. *Journal of Labor Economics*, 18(1), 20-54.
- Brantingham, P. J., & Brantingham, P. L. (Eds.). (1981). *Environmental Criminology*. Beverly Hills, CA: Sage Publications.
- Brantingham, P. J., & Brantingham, P. L. (1993). Environment, routine and situation: Toward a pattern theory of crime. *Advances in Criminological Theory*, 5, 259-294.
- Breckinridge, S. P., & Abbott, E. (1912). *The Delinquent Child and the Home*. New York: Charities Publication Committee.
- Britt, C. L. (1997). Reconsidering the unemployment and crime relationship: Variation by age group and historical period. *Journal of Quantitative Criminology*, 13(4), 405-428.
- Bruinsma, G., & Bernasco, W. (2004). Criminal groups and transnational illegal markets. *Crime, Law and Social Change*, 41(1), 79-94.
- Bureau of Justice Statistics. (2014). *National Crime Victimization Survey: Technical documentation*. Washington, DC: The U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics.
- Bureau of Labor Statistics. (2014). *How the Government Measures Unemployment*. Washington, DC: The U.S. Department of Labor, Bureau of Labor Statistics.

- Burr, J. A., Potter, L.B., Galle, O.R., Fossett, M.A. (1992). Migration and metropolitan opportunity structures: A demographic response to racial inequality. *Social Science Research*, 21, 380–405.
- Bursik, R. J. (1988). Social disorganization and theories of crime and delinquency: Problems and prospects. *Criminology*, 26(4), 519-552.
- Cantor, D., & Land, K. C. (1985). Unemployment and crime rates in the post-World War II United States: A theoretical and empirical analysis. *American Sociological Review*, 317-332.
- Cantor, D., & Land, K. C. (2001). Unemployment and crime rate fluctuations: A comment on Greenberg. *Journal of Quantitative Criminology*, 17(4), 329-342.
- Carrington, P. J. (2009). Co-offending and the development of the delinquent career. *Criminology*, 47(4), 1295-1329.
- Chein, J., Albert, D., O'Brien, L., Uckert, K., & Steinberg, L. (2011). Peers increase adolescent risk taking by enhancing activity in the brain's reward circuitry. *Developmental Science*, 14(2), F1-F10.
- Chiricos, T. G. (1987). Rates of crime and unemployment: An analysis of aggregate research evidence. *Social Problems*, 34(2), 187-212.
- Clark, R.D. (1992). Companions in crime: An analysis of co-offending among juveniles. Ph.D. Dissertation, State University of New York at Albany. Ann Arbor, MI: University Microfilms.
- Clarke, R. V. (2009). Situational crime prevention: Theoretical background and current practice. In *Handbook on Crime and Deviance* (pp. 259-276). Springer New York.
- Clarke, R. V., & Cornish, D. B. (1985). Modeling offenders' decisions: A framework for research and policy. *Crime and Justice*, 147-185.
- Cloward, R. A., & Ohlin, L. E. (1960). *Delinquency and Opportunity: A Study of Delinquent Gangs*. Glencoe, Ill: Free Press.
- Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, 588-608.
- Cohen, L. E., Felson, M., & Land, K. C. (1980). Property crime rates in the United States: A macrodynamic analysis, 1947-1977; With ex ante forecasts for the mid-1980s. *American Journal of Sociology*, 86(1), 90-118.
- Cohen, A. K. (1955). *Delinquent Boys: The Subculture of the Gang*. London: Collier-Macmillan.

- Coleman, J. S. (1990). *Foundations of Social Capital Theory*. Cambridge, Mass: Belknap.
- Conway, K. P., & McCord, J. (2002). A longitudinal examination of the relation between co-offending with violent accomplices and violent crime. *Aggressive Behavior*, 28(2), 97-108.
- Cook, P. J., & Zarkin, G. A. (1985). Crime and the business cycle. *The Journal of Legal Studies*, 14(1), 115-128.
- Cook, D. O., Kieschnick, R., & McCullough, B. D. (2008). Regression analysis of proportions in finance with self-selection. *Journal of Empirical Finance*, 15(5), 860-867.
- Cromwell, P. F., Olson, J. N., & D'Aunn Wester Avary. (1991). *Breaking and Entering: An Ethnographic Analysis of Burglary*. Newbury Park, CA: Sage.
- Crutchfield, R. D. (1989). Labor stratification and violent crime. *Social Forces*, 68(2), 489-512.
- Crutchfield, R. D., Geerken, M. R., & Gove, W. R. (1982). Crime rate and social integration: The impact of metropolitan mobility. *Criminology*, 20(3-4), 467-478.
- Cusson, M. (1993). Situational deterrence: Fear during the criminal event. *Crime Prevention Studies*, 1, 55-68.
- D'Alessio, S. J., & Stolzenberg, L. (2010). Do cities influence co-offending? *Journal of Criminal Justice*, 38(4), 711-719.
- D'Alessio, S.J., Eitle, D., & Stolzenberg, L. (2012). Unemployment, guardianship, and weekday residential burglary. *Justice Quarterly*, 29(6), 919-932.
- Farrington, D. P. (1986). Age and crime. *Crime and Justice*, 189-250.
- Felson, M. (2003). The process of co-offending. In *Theory for Practice in Situational Crime Prevention*. *Crime Prevention Studies* Vol. 16, eds. Martha J. Smith and Derek B. Cornish. Monsey, NY: Criminal Justice Press.
- Felson, M. (2009). The natural history of extended co-offending. *Trends in Organized Crime*, 12(2), 159-165.
- Felson, M., & Cohen, L.E. (1980). Human ecology and crime: A routine activity approach. *Human Ecology*, 8(4), 389-406.
- Freeman, R. B. (1983). Crime and unemployment. In James Q. Wilson (Ed), *Crime and Public Policy*. San Francisco: Institute for Contemporary Studies Press.

- Freud, S. (1960). *The Ego and the Id*. New York and London: W, W, Norton and Company.
- Gardner, M., & Steinberg, L. (2005). Peer influence on risk taking, risk preference, and risky decision making in adolescence and adulthood: an experimental study. *Developmental Psychology*, 41(4), 625.
- Gottfredson, M. R., & Hirschi, T. (1990). *A General Theory of Crime*. Stanford University Press.
- Granovetter, M. (1978). Threshold models of collective behavior. *The American Journal of Sociology*, 83(6), 1420-1443.
- Greenberg, D. F. (2001). Time series analysis of crime rates. *Journal of Quantitative Criminology*, 17(4), 291-327.
- Hale, C., & Sabbagh, D. (1991). Testing the relationship between unemployment and crime: A methodological comment and empirical analysis using time series data from England and Wales. *Journal of Research in Crime and Delinquency*, 28(4), 400-417.
- Hawley, A. H. (1986). *Human Ecology: A Theoretical Essay*. Chicago, IL: The University of Chicago Press.
- Hindelang, M., Gottfredson, M., & Garoalo, J. (1978). *Victims of Personal Crime*. Cambridge, Mass: Ballinger.
- Hochstetler, A. (2001). Opportunities and decisions: interactional dynamics in robbery and burglary groups. *Criminology*, 39(3), 737-764.
- Hough, M. (1987). Offenders' choice of target: Findings from victim surveys. *Journal of Quantitative Criminology*, 3(4), 355-369.
- Hughes, M., & Carter, T. J. (1981). A declining economy and sociological theories of crime: Predictions and explications. In Wright, Kevin (Ed.) *Crime and Criminal Justice in a Declining Economy*. Cambridge: Oelgeschlager, Gunn & Hain.
- Jacobs, B. A., & Wright, R. (2010). Bounded rationality, retaliation, and the spread of urban violence. *Journal of Interpersonal Violence*, 25(10), 1739-1766.
- Kelly, M. (2000). Inequality and crime. *Review of Economics and Statistics*, 82(4), 530-539.
- Kindermann, C., Lynch, J., & Cantor, D. (1997). Effects of the redesign on victimization estimates (p. 2). Washington, DC: US Department of Justice, Bureau of Justice Statistics.

- Kirk, D. S., & Matsuda, M. (2011). Legal cynicism, collective efficacy, and the ecology of arrest. *Criminology*, 49(2), 443-472.
- Kubrin, C. E., & Weitzer, R. (2003). New directions in social disorganization theory. *Journal of Research in Crime and Delinquency*, 40(4), 374-402.
- Laeven, L., & Popov, A. (2016). A lost generation? Education decisions and employment outcomes during the US housing boom-bust cycle of the 2000s. *The American Economic Review*, 106(5), 630-635.
- Le Bon, G. (1960). *The Mind of the Crowd*. New York: Viking.
- Levitt, S. D. (2001). Alternative strategies for identifying the link between unemployment and crime. *Journal of Quantitative Criminology*, 17(4), 377-390.
- Lin, N. (1999). Building a network theory of social capital. *Connections* 22, 28–51.
- Lynch, J. P. (2002). *Trends in Juvenile Violent Offending: An analysis of Victim Survey Data*. Washington, DC: US Department of Justice, Office of Justice Programs, Office of Juvenile Justice and Delinquency Prevention.
- Martinez Jr., R. (1996). Latinos and lethal violence: The impact of poverty and inequality. *Social Problems*, 43(2), 131-146.
- Martinez Jr., R., Stowell, J. I., & Lee, M. T. (2010). Immigration and crime in an era of transformation: A longitudinal analysis of homicides in San Diego neighborhoods, 1980-2000. *Criminology*, 48(3), 797-829.
- Matza, D. (1964). *Delinquency and Drift*. New York, NY: John Wiley and Sons, Inc.
- McCall, L. (2001). Sources of racial wage inequality in metropolitan labor markets: Racial, ethnic, and gender differences. *American Sociological Review*, 520-541.
- McCarthy, B., Hagan, J., & Cohen, L. E. (1998). Uncertainty, cooperation, and crime: Understanding the decision to co-offend. *Social Forces*, 77(1), 155-184.
- McCord, J., & Conway, K. P. (2002). Patterns of juvenile delinquency and co-offending. In *Crime and social organization* (Vol. 10, pp. 15-30). New Brunswick, NJ: Transaction Publishers.
- McDowell, A., & Cox, N. J. (2001). FAQ: How do you fit a model when the dependent variable is a proportion? <http://www.stata.com/support/faqs/stat/logit.html>.
- McGloin, J., Sullivan, C. J., Piquero, A. R., & Bacon, S. (2008). Investigating the stability of co-offending and co-offenders among a sample of youthful offenders. *Criminology*, 46(1), 155-188.

McGloin, J. M., & Piquero, A. R. (2009). 'I Wasn't Alone': Collective Behaviour and Violent Delinquency. *Australian & New Zealand Journal of Criminology*, 42(3), 336-353.

McGloin, J. M., & Piquero, A. R. (2010). On the relationship between co-offending network redundancy and offending versatility. *Journal of Research in Crime and Delinquency*, 47, 63-90.

McGloin, J. M., & Nguyen, H. (2012). It was my idea: Considering the instigation of co-offending. *Criminology*, 50(2), 463-494.

McGloin, J.M., & Rowan, Z. R. (2015). A threshold model of collective crime. *Criminology*, 53(3), 484-512.

McGloin, J.M., & Thomas, K. J. (2016). Incentives for Collective Deviance: Group Size and Changes in Perceived Risk, Cost, and Reward. *Criminology*.

Miethe, T. D., & Meier, R. F. (1994). *Crime and its Social Context: Toward an Integrated Theory of Offenders, Victims, and Situations*. Suny Press.

Nguyen, H., & McGloin, J.M. (2013). Does economic adversity breed criminal cooperation? Considering the motivation behind group crime. *Criminology*, 51(4), 833-870.

O'Brien, L., Albert, D., Chein, J., & Steinberg, L. (2011). Adolescents prefer more immediate rewards when in the presence of their peers. *Journal of Research on Adolescence*, 21(4), 747-753.

Oudekerk, B., & Morgan, R. (2016). *Co-offending Among Adolescents in Violent Victimization, 2004-2013*. The U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics. Washington, DC.

Ouellet, F., Boivin, R., Leclerc, C., & Morselli, C. (2013). Friends with (out) benefits: co-offending and re-arrest. *Global Crime*, 14(2-3), 141-154.

Paolino, P. (2001). Maximum likelihood estimation of models with beta-distributed dependent variables. *Political Analysis*, 9(4), 325-346

Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics*, 11(6), 619-632.

Park, R. E. (1936). Human ecology. *American Journal of Sociology*, 42(1), 1-15.

- Parker, R. N. (1989). Poverty, subculture of violence, and type of homicide. *Social Forces*, 67(4), 983-1007.
- Parker, R. N., & Horwitz, A. V. (1986). Unemployment, crime, and imprisonment: A panel approach. *Criminology*, 24(4), 751-773.
- Phillips, J. & Land, K. C. (2012). The link between unemployment and crime rate fluctuations: An analysis at the county, state, and national levels. *Social Science Research*, 41(3), 681-694.
- Portes, A., & Zhou, M. The new second generation: Segmented assimilation and its variants. *The Annals of the American Academy of Political and Social Science*, 530(1), 74-96.
- Portes, A., Fernandez-Kelly, P., Haller, W. (2009). The adaptation of the immigrant second generation in America: A theoretical overview and recent evidence. *Journal of Ethnic and Migration Studies*, 35(7), 1077-1104.
- Pridemore, W. A. (2011). Poverty matters: A reassessment of the inequality-homicide relationship in cross-national studies. *British Journal of Criminology*, 51(5), 739-772.
- Raphael, S., & Winter-Ebmer, R. (2001). Identifying the effect of unemployment on crime. *Journal of Law and Economics*, 44(1), 259-283.
- Reiss, A. J., Jr. (1986). Co-offender influences on criminal careers. In A. Blumstein, J. Cohen, J.A. Roth, & C.A. Visher (Eds.) *Criminal Careers and Career Criminals*, pp. 121-160. Washington, DC: National Academy Press.
- Reilly, B., & Witt, R. Crime, deterrence, and unemployment in England and Wales: An empirical analysis. *Bulletin of Economic Research*, 48(2), 137-159.
- Reiss, A. J., Jr. (1988). Co-offending and criminal careers. In N. Morris, & M. Tonry (Eds.), *Crime and Justice*, pp. 117-170. Chicago: University of Chicago Press.
- Reiss, A. J., & Farrington, D. P. (1991). Advancing knowledge about co-offending: Results from a prospective longitudinal survey of London males. *The Journal of Criminal Law and Criminology*, 82(2), 360-395.
- Rosenfeld, R., & Fornango, R. (2007). The impact of economic conditions on robbery and property crime: the role of consumer sentiment. *Criminology*, 45(4), 735-769.
- Rosenfeld, R., Jacobs, B. A., & Wright, R. (2003). Snitching and the code of the street. *British Journal of Criminology*, 43(2), 291-309.

- Rowan, Z. R., McGloin, J.M., & Nguyen, H. (2016). Capitalizing on criminal accomplices: Considering the relationship between co-offending and illegal earnings. *Under Review*.
- Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology*, 774-802.
- Sampson, R. J., Raudenbush, S.W., Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective Efficacy. *Science*, 227, 918-923.
- Schaefer, D. R., Rodriguez, N., & Decker, S. H. (2014). The role of neighborhood context in youth co-offending. *Criminology*, 52(1), 117-139.
- Schunck, R. (2013). Within and between estimates in random-effects models: Advantages and drawbacks of correlated random effects and hybrid models. *The Stata Journal*, 13(1), 65-76.
- Shaw, C.R., & McKay, H.D. (1942). *Juvenile Delinquency and Urban Areas*. Chicago, IL: University of Chicago Press.
- Short, J. F., & Strodtbeck, F. (1965). *Group Process and Gang Delinquency*. Chicago, IL: University of Chicago Press.
- Shover, N. (1991). Burglary. *Crime and Justice*, 14, 73-113.
- Stolzenberg, L., & D'Alessio, S. J. (2008). Co-offending and the age-crime curve. *Journal of Research in Crime and Delinquency*, 45(1), 65-86.
- Thrasher, F. M. (1927). *The Gang: A Study of 1,313 Gangs in Chicago*. Chicago, IL: The University of Chicago Press.
- Tillyer, M. S., & Tillyer, R. (2015). Maybe I should do this alone: A comparison of solo and co-offending robbery outcomes. *Justice Quarterly*, 32(6), 1064-1088.
- Tremblay, P. (1993). Searching for suitable co-offenders. In *Advances in Criminological Theory*. Vol.5, *Routine Activity and Rational Choice*, eds. R. V. Clarke and M. Felson, pp. 17-36. New Brunswick, NJ: Transaction Publishers.
- Truman, J.L., & Langton, L. (2015). *Criminal Victimization, 2014*. Washington DC: US Department of Justice, Office of Justice Programs, National Institute of Justice.
- van Mastrigt, S.B., Farrington, D.P. (2009). Co-offending, age, gender, and crime type: Implications for criminal justice policy. *The British Journal of Criminology*, 49(4), 552-573.

- Wadsworth, T. (2010). Is immigration responsible for the crime drop? An assessment of the influence of immigration on changes in violent crime between 1990 and 2000. *Social Science Quarterly*, 91(2), 531-553.
- Warr, M. (1996). Organization and instigation in delinquent groups. *Criminology*, 34(1), 11-37.
- Warr, M. (2001). Crime and opportunity: A theoretical essay. In Meier, Robert, Leslie Kennedy and Vincent Sacco (Eds), *The Process and Structure of Crime: Criminal Events and Crime Analysis*. New Brunswick, N.J.: Transaction Publishers.
- Warr, M. (2002). *Companions in crime: The social aspects of criminal conduct*. Cambridge University Press.
- Weerman, F. M. (2003). Co-offending as Social Exchange. Explaining Characteristics of Co-offending. *British Journal of Criminology*, 43(2), 398-416.
- Weisburd, D., Wyckoff, L.A., Ready, J., Eck, J.E., Hinkle, J.C., Gajewski, F. (2006). Does crime just move around the corner? A controlled study of spatial displacement and diffusion of crime control benefits. *Criminology*, 44(3), 549-592.
- Weisburd, D., Groff, E. R., & Yang, S. M. (2012). *The Criminology of Place: Street Segments and Our Understanding of the Crime Problem*. Oxford University Press.
- Wikström, P.-O. H. (2006). Individuals, settings, and acts of crime: Situational mechanisms and the explanation of crime. In P.-O. H. Wikstrom & R. J. Sampson (Eds.), *The Explanation of Crime: Context, Mechanisms, and Development* (pp. 61-107). Cambridge: Cambridge University Press.
- Wikström, P. O. H., & Svensson, R. (2010). When does self-control matter? The interaction between morality and self-control in crime causation. *European Journal of Criminology*, 7(5), 395-410.
- Wilson, W. J. (1987). *The Truly Disadvantaged*. Chicago, IL: The University of Chicago Press.
- Wirth, L. (1945). Human Ecology. *American Journal of Sociology*, 50(6), 483-488.
- Wright, R.T., & Decker, S. (1994) *Burglars on the Job: Streetlife and Residential Break-ins*. Boston, Mass.: Northeastern University Press.
- Wright, R.T., & Decker, S. (1997). *Armed Robbers in Action*. Boston, Mass.: Northeastern University Press.

Xie, M., Lauritsen, J. L., & Heimer, K. (2012). Intimate partner violence in US Metropolitan areas: The contextual influences of police and social services. *Criminology*, 50(4), 961-992.

Yearwood, D. L., & Koinis, G. (2011). Revisiting property crime and economic conditions: An exploratory study to identify predictors beyond unemployment rates. *The Social Science Journal*, 48(1), 145-158.