ABSTRACT

Title of Thesis:	CONTROL, LEARNING, AND VULNERABILITY: AN INTERACTIONAL APPROACH TO ENGAGEMENT IN VIOLENT EXTREMISM
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In criminological research, scholars present learning and social control theories as competing explanations for criminal behavior. While this has extended to specific offenses and analogous behaviors, it has less frequently been related to ideologically-motivated extremist behavior. This study considers the explanatory power of these two schools of criminological thought as they predict individual participation in violent ideologically motivated extremist behaviors using a recently collected individual-level dataset. A combination of Multivariate Imputation through Chained Equations (MICE), Exploratory Factor Analysis, and logistic regression is used to examine the relationship between theoretical measures and the probability of violent extremist behavior. Ultimately, this thesis finds: (1) having stronger social bonds is associated with a lower probability of violent ideologically motivated behavior, (2) the social learning of violence is associated with a higher probability of violent

ideologically motivated behavior, and (3) these relationships depend somewhat upon the ideological milieu of the individual.

CONTROL, LEARNING, AND VULNERABILITY: AN INTERACTIONAL APPROACH TO ENGAGEMENT IN VIOLENT EXTREMISM

by

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Dedication

This work is dedicated to my dear friends and colleagues. Without their collective love, support, and encouragement, this thesis would likely never have come to pass.

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I would like to thank my committee for their support and encouragement through the learning process of this master's thesis: Dr. Laura Dugan, my committee chair; Dr. Gary LaFree; and Dr. Terence Thornberry.

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Chapter 1: Introduction

Since the founding of the United States, the free expression of unpopular opinions has long been hailed as a cornerstone of democratic development and free society (Bill of Rights Institute, 2017). The peaceful expression of divergent opinions, seen notably in the women's suffrage movement of the early 20th century, and civil rights era of the 1950s and 1960s perhaps best exemplify the importance of such expression, and it has accordingly been given great renown in the history of the United States. This right is enshrined in the national self-image and mythology, and remains a constitutionally protected right to citizens to this day. It is not to say, however that this right to express oneself is without limits; indeed, there are restrictions, namely in terms of expressing one's own opinion and pursuing one's own cause at the expense of another's well-being or health. Deviant or extreme viewpoints, in and of themselves, while perhaps troubling to democratic governments are quite clearly distinct from the violent expression of such viewpoints. Recently, forms of non-violent expression have become subject to further legal limitation, particularly when associated with dangerously disruptive acts or violent action. This line in the sand between legitimate constitutionally protected expression and dangerously disruptive or violent action remains one that can serve as a dichotomy when examining contemporary issues in political violence. In short, this thesis examines how one can go from holding an anti-government, deviant, or extreme viewpoint to potentially expressing it violently.

In the extant literature on terrorism and political violence, some common themes have been identified among those who engage in violent extremism, or choose to cross this line in the sand. Often, however this takes the form of a risk factors approach, particularly when examined from a multidisciplinary lens such as discussed by Horgan (2008). Although a risk factor approach is an important first step, the bare representation of correlates of extremism does little to integrate the work into more well-developed scholarly fields and theories. For instance, specific psychological and social preconditions for extremist violence include factors such as emotional vulnerability, dissatisfaction with the status quo, identification with victimized groups, and belief that violence against the state may not be inherently immoral (Horgan, 2008). It is disheartening however to consider these risk factors absent any coherent theoretical binds such as can often be found in scholarly works examining more common types of criminal and deviant behavior.

Criminology offers a solution to this and as a multidisciplinary field of study examining deviant and criminal human behavior, violent extremism falls well within its scope. In the body of criminological research, scholars have presented theoretical explanations to the problem of violent extremism and in some cases, have had success. That is not to say that all criminological theory may be suited to this problem. As is discussed below, certain theories hold more promise for the topic at hand, and indeed may provide a conceptual framework for expanding this primarily risk-factors approach. In short, by considering the range of contemporary criminological theories, I address the following question: Under what conditions do individuals who espouse extremist ideologies become ideologically violent?

Beginning with theories of deterrence and rational choice, explaining the emergence of violent extremism proves exceptionally difficult due to an emphasis on the role of formal punishment and sanctions, rather than the genesis of violence (Beccaria, 1764; Bentham, 1776). Distinct from its deterrence predecessors, rational choice explanations struggle when ascribing subjective utility structures (a necessary component for understanding engagement in extremist interpretations of ideologies) to individuals with largely incomplete information (Cornish & Clarke, 2014). Turning next to Social Disorganization and Collective Efficacy (Sampson, Raudenbush, & Earls, 1997; Shaw & McKay, 1942), a unit of analysis problem emerges – by construction, individual level motivation remains outside of the scope of the neighborhood-based theories. Contrastingly, strain theory, as outlined most recently by Robert Agnew (1992) generally adheres to an individual unit of analysis, but suffers from an absence of subjective measures and data tied to small and distinguishable temporal units – the lynchpin for the causal mechanism. On the other hand, theories of opportunity often make an explicit assumption of motivation, and still others treat the radicalization toward violence as a vestigial concern by construction. Due to the multitude of circumstances from which extremist behavior could emerge, and the issue of defining a specific situation resembling the nebulous nature of much non-violent extremism, theories of criminal opportunity appear inappropriate for explaining both the empirically supported risk factors for extremism, and more pointedly, providing a framework for predicting violent extremism.

In short, while there is a growing body of scholarly criminological literature that has developed a theory-informed view of the study of terrorism (Agnew, 2010; Akers & Silverman, 2004; Kirby, 2007), explaining the entry to terrorism and radicalization still eludes many. Indeed, the aforementioned selections may not be the best ways to conceptually organize or understand the phenomenon of non-violent or violent extremist behavior as it emerges. Thus, this thesis capitalizes on this gap in the literature and explores potential alternative theoretical frameworks for this social phenomenon.

Returning to known risk factors for radicalization and extremist behavior suggested by Horgan (2008), it is apparent that many of the constructs outlined may resonate with the control theory school of thought. Accordingly, this presents an excellent starting point for considering engagement in ideologically motivated behavior. Often presented as a radical change in thought from other conceptualizations of criminal behavior, proponents for control theories interrupt the sea of those asking, “why do people partake in deviant and criminal acts?”, with the marked reframing of the question – simply “what prevents people from doing so?” (Reiss, 1951; Toby, 1957; Hirschi, 1969; Hirschi & Gottfredson, 1983).

While not the first to invoke this question, Travis Hirschi’s Social Bond theory has regularly found support when predicting both criminality and other acts of deviance (Hirschi, 1969; Hindelang, 1973; McQuillan, Berdahl, & Chapple, 2005). This theory suggests that four dimensions of informal bonds restrain individuals from offending or deviating from social norms, indicating a relative risk when comparing bond levels across individuals. Specifically, these four bonds are identified as attachment, involvement, commitment, and belief (Hirschi, 1969). Specific operationalizations of these constructs are discussed later, including an outline of the degree to which they have been robust predictors of delinquency in criminological work. As the theory would suggest, when an individual's bonds to traditional social norms weaken, one would anticipate an increase in the probability of offending. Although methodologically critiqued over the decades since its genesis, this theory remains a potent figure in the individual-level framing of behavior and thus merits exploration under the framework of violent extremism (Giordano, Cernkovich, & Pugh, 1986; Pleydon & Schner, 2001). In fact, this theory is well-suited to the problem at-hand due to the broad conceptualization of these bonds to society; while initially conceptualized around an adolescent sample, the strength of bonds should also vary throughout the life and can be represented by indicators such as are described below.

Notably, this theory has been applied to explaining crime and deviance in a general population – focusing primarily on delinquency in adolescents, however the premise remains the same in considering the atypical population and behavior of interest in this thesis. While the relationship of social bonds and radicalization has been examined nominally using case studies (Kirby, 2007), due to the absence of large sample data at the individual level, this theory has yet to be tested or seriously considered in this context to date. Due to the stark qualitative distinction between violent and non-violent acts, this framework lends itself well to considering involvement and the decision to partake in violent extremism as contrasted with non-violent acts. In short, despite the dearth of work addressing this approach within violent extremism, the theoretical constructs alone suggest that there is much promise in this theory. To parallel an approach that has been done countless times in criminological literature, I turn next to the school of thought dominated by learning theories as a competing explanation for violent extremism.

Learning theories, whose genesis can be credited largely to the psychological literature, provide a natural counterpoint to control theories. Encapsulated best perhaps by Edwin Sutherland, learning theories suggest that crime (and therefore deviance) is a learned behavior and is learned through the same processes as normative and prosocial behaviors (Sutherland, 1947). As can be seen in many well-regarded works in criminology, this often places the theory in direct competition with the view of control theories, resulting in much debate (Akers, Krohn, Lanza-Kaduce, & Radosevich, 1979; Matsueda & Heimer, 1987; Wright, Caspi, Moffitt, & Silva, 1999). Of the learning theories, the most recent and well regarded is Ron Akers' Social Learning Theory (Akers, 1998). This theory, expanding upon Sutherland's differential association, provides four mechanisms for learning, namely differential association, imitation, differential reinforcement, and definitions. Again, to be detailed later, these constructs have had success in predicting both criminal and deviant behavior, and allow for a more robust consideration of some peer effects (Akers & Lee, 1996; Akers & Jensen, 2006). Similar to social bonds however, social learning theory specifically, and indeed learning theories as a whole appear to be largely underrepresented in empirical literature on terrorism and violent extremism. That is not to say that the constructs would be ill-suited, but rather this, again stems from the absence of large datasets with theoretically appropriate measures. Conceptually, the inclusion of social learning theory in an explanatory model for engagement in violent extremism should be quite informative as it addresses the two major theoretical concerns of unit of analysis, and a temporal ordering that includes the engagement phase of radicalization. While learning and control are often posed in competition to one another, recent scholars have developed integrated theories which account for the reciprocal and interrelated independent effects of control and learning constructs.

Thornberry's (1987) interactional theory serves as an excellent example of a modern integrated theoretical approach, bridging this perceived gap between learning and control schools of thought. The theory, in short, suggests that the fragility of socializing bonds to society permits individuals to be exposed to social learning mechanisms that contribute to antisocial behaviors. Specifically, Thornberry accounts for the reciprocal feedback loops of deviance and the weakening of social bonds over time. Although it has been critiqued for strong temporal ordering assumptions accredited to these mechanisms, the theory provides a harmonious marriage of control and learning constructs. Despite the difficulty in addressing these assumptions (particularly within the study of extremist violence), this theory exhibits, more broadly the successful combination of these seemingly at-odds schools of thought - suggesting that it need not be a dichotomous query.

With this theoretical grounding, the risk factors discussed by Horgan (2008) can be adapted to a more constructive framework. Control theory allows us to contextualize the risk factor of how *belief that violence against the state may not be perceived to be inherently immoral*. Contrastingly, risk factors related to social learning theory include *the appreciation of the significance of membership in the movement* and *identification with victims of political or politicized violence*. Utilizing the integrated framework as suggested by Thornberry, the *kinship and social ties to those experiencing or who have experienced political or politicized violence* and *the dissatisfaction with the status quo* and *belief that direct action is necessary* can be housed under the umbrellas of criminological thought. In that the theoretical and conceptual overlap between these risk factors and criminological constructs is easily identifiable, it behooves researchers to consider theoretical framing within these extant schools of thought.

Finally, we are left with *emotional vulnerability* as a correlate of extremist violence. While none of the three frameworks appears most suited to encompass this final construct, it speaks to one of the many oft-cited sources of unobservable variation within the population of potential extremists (Nagin & Paternoster, 2000; Jensen & LaFree, 2016; Victoroff, 2005). Like how criminal propensity may be primed; an individual's emotional vulnerability toward radicalization and violent extremism likely exists outside of the realm of empirical measurement. This vulnerability could, however be primed by certain life experiences to lead some down this path, suggesting that it may represent a latent variable or construct. While admittedly a rough transposition of these risk factors onto extant criminological theory, credence emerges to considering both learning and control theories as potential contributory factors to the engagement of violent extremism.

This thesis seeks to determine if both learning and control theories can provide independent contributions to the explanation of violent extremism, whether an integrated theoretical approach can better inform the process of engagement in violent extremism, and if the effects of learning and control vary across ideological milieu. These questions are addressed with a quantitative approach using data from a new and unique source. This source, as provided by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) is the first open-source large sample database of violent extremists who radicalized primarily within the United States and went on to commit either violent or non-violent ideologically motivated acts.

The next chapter provides a theoretical backdrop for violent extremism as an outcome analogous to serious crime and delinquency. The theories discussed are drawn principally from criminology, though are applied to the unique set of behaviors represented by violent extremism. The third chapter outlines the data source and method. The fourth chapter reviews the results, and the thesis ends with a discussion of the implications of the findings, limitations, and next steps.

Chapter 2: Theoretical Background

Violent Extremism as an Outcome Analogous to Crime and Delinquency

Social learning theory, social bonds theory, and Thornberry's interactional theory can help explain the relationship between known risk factors of extremism, commonly studied criminological constructs, and extremist violence. All three theoretical perspectives draw on the psychological and social context of individuals who become exposed to violent extremist ideologies. Indeed, researchers have argued that engagement in violent extremism is one of multiple outcomes of a radicalization process, and that while pathways to this potential outcome may diverge; common elements in the socialization toward violence and non-violence may exist. Insofar as the process of engagement in violent radicalization is dynamic and phasic, by construction the theories to explain it must allow for both violent and non-violent extremism, de-radicalization, and disengagement from extremist ideologies, all of which are satisfied by the three selected theories. Combined, by examining the preconditions of violence, these theories focus on why certain individuals are more, or less inclined toward violent extremist acts.

Before advancing to a theoretical discussion of engagement in violent and non-violent extremist behavior, the benefit of going beyond a risk-factors approach must be addressed. As outlined above, a risk factor approach often provides a meaningful first step to understanding potential correlates of specific outcomes and guiding inquiry and assessment in the study of crime and delinquency (Bushway & Reuter, n.d.; Pressman, 2016). These are often first informed by readily observable patterns in data and available theory; however, they may produce discord or logical inconsistency when brought together across foundational theoretical assumptions. Beyond potential internal inconsistencies, limiting analysis and prediction to the use of risk factors is inherently restrictive and provides little direction for future evaluation of a given phenomenon. By adhering to theoretical frameworks on the other hand, natural avenues exist for prediction, and importantly, the potential underlying mechanisms that produce a given behavior. This allows, if supported, more plausible direction for potential interventions to encourage desirable behavior, or reduce the incidence of problematic behaviors. Not only that, a theoretical approach could inform the possible negative externalities of a proposed intervention, whereas a risk factor approach may not encompass such detail. Finally, in the present case the use of theory would potentially allow for the distinction between some commonly observed risk factors (e.g.: gender, age, and previous criminality) and those which may be more strongly indicative of future violent or non-violent extremist behavior among radicalized individuals.

Social Bonds

Social Bonds theory was first introduced by Travis Hirschi in 1969. As contrasted with the extant literature on the causes of crime that focused upon theories of deterrence and the adaptive nature of crime and delinquency, Hirschi's (1969) application of social control focuses on the forces that bind individuals to conventional society and social norms. In short, social bonds theory answers the question "Why *do* men obey the rules of society?"[emphasis in original] (Hirschi, 1969, p.10). Hirschi, much like the control theorists before him, sought to distinguish the role of informal social controls and socialization (such as those produced by the family and career aspirations) with that of formal social controls and sanctions (e.g. threats of state action). In this way, social bonds theory is representative of control theories and indeed fits the purpose of the study at hand (Toby, 1957; Sykes & Matza, 1957; Reckless, 1961; Gottfredson & Hirschi, 1990). The mechanism of the theory, as articulated by Hirschi, outlines four distinct classes of bonds, reflecting four (potentially overlapping) sources of informal social control. If an individual has weak bonds across each of the dimensions (*attachment*, *involvement*, *commitment*, and *belief*), they likely have little inhibition from deviance or crime, whereas increasing strengths of bonds indicates stronger adherence to social norms. Importantly, Hirschi did not propose a specific threshold for which individuals would be safe or at risk to deviance – the overall strength of bonds was seen as a relative risk within and across individuals. Below, the bonds are articulated as they were originally conceptualized, followed by a note on the diversity of the application of the theory, and concluding with the overall merit for the application to the present project.

According to Hirschi, *attachment* represents an emotional closeness to parents and intimate peer groups (1969). This was measured with questions such as "Do your parents seem to understand you?"(Hirschi, 1969, p. 282). As an affective bond, an individual high on attachment would seek to avoid disappointing and alienating parents and intimate prosocial others, and thus would likely be inhibited from crime and delinquency. Thus, those who are low on scales of attachment are more willing to risk disappointing others due to a weak bond to these individuals or a lack of those to whom they should be bonded.

Involvement is a measure of how individuals spend their time. Those with more time dedicated to prosocial or conventional activities would simply have less opportunity to engage in delinquency or crime. As has been expanded by Osgood and Anderson (2004), while the specific qualitative characteristics of free time are important, it remains true that absent free time, one is restrained from delinquency. This construct was measured with an inventory of an individual's free time, specifically with questions such as "How many hours a week do you spend playing a team game (such as football, basketball, or baseball)?"(Hirschi, 1969, p.261). Hirschi specifically cites Matza and Sykes as evidence of the general predisposition of youth to attitudes found in the leisure class, wherein the values appear to promote delinquency when left unattended.

As a rational component of bonds to society, *commitment* represented an individual's investment in their own prosocial trajectory. This logical bond signifies an individual's consideration of the potential future costs of deviant behavior. Hirschi argued that this was best observed through one's commitment to educational and occupational careers, which would necessarily be jeopardized by involvement with delinquency, crime, and the criminal justice system. Reminiscent of Jackson Toby's "Stakes in Conformity" (1957), this construct was measured with questions like "How important do you think grades are for getting the kind of job you want when you finish school?"(Hirschi, 1969, p.250).

Finally, Hirschi's bond of *belief*, while assuming a universal value system within societies, represents the relative importance of conventional norms to individuals. The bond is discussed as the degree to which individuals ascribe to the moral and legal codes, and would be controlled by such beliefs. It is inherently distinct from Sykes and Matza's Techniques of Neutralization (1957) in that belief may only exist in terms of a restraining force from delinquency, rather than a bidirectional force, which could justify deviant behavior. Belief was measured with questions such as asking the degree to which a respondent agreed or disagreed with the statement "It is alright to get around the law if you can get away with it" (Hirschi, 1969, p. 258).

Of note, Hirschi (1969) presents what is considered a population heterogeneity argument toward the role of peer groups and group processes (Nagin & Paternoster, 2000). The theory addresses the role of groups and organizations by suggesting that individuals who share similar characteristics (namely relative levels of social bonds) will coalesce into groups and organizations with one another. This argument extended so far as to suggest those with insufficient attachment bonds were incapable of warm affective relationships with peers or deviant others – a point of critique in later testing of the theory (Pleydon & Schner, 2001; Thornberry, Krohn, Lizotte, & Chard-Wierschem, 1993).

Although the theory was originally proposed using survey data from high school students and has been traditionally applied to delinquency (as suggested by the name of the original publication – "Causes of Delinquency"), it has regularly been expanded to address various offenses and behaviors in the Criminological literature. Indeed, scholars have applied this theoretical structure to such diverse locales and fields as the study of the life course (Sampson & Laub, 1990), illicit substance use (Stewart, 2003), violence (McQuillan, Berdahl, & Chapple, 2005), school misbehavior (Stewart, 2003) and the use of internet pornography (Stack, Wasserman, & Kern, 2004). Lending credence to the validity of the theoretical constructs, the diversity of topics researched suggests a universality of constructs.

While this theory has been criticized for its inability to account for the certain temporal effects, it has remained a prominent fixture in the modern study of crime and delinquency, even outside of the scope of the original research. Of note, Hirschi intended specifically to explain delinquency in an adolescent population, and thus the bonds reflect ties to conventional society that would be especially pertinent to adolescents. This is not to say however that the bonds, and ultimately the ability to predict deviant and antisocial behavior could not be conceptualized within older populations, or with more serious types of offending. Fundamentally, bonds to conventional society, while perhaps most at risk in later adolescence, need not remain intact in later life. As the observable manifestations of the conceptual magnitude of bonds increases, from adhering to school rules, to seeking advanced education and getting married, so too may the forms of deviance and crime when bonds are weakest. Thus, extending this theory to the study of radicalization, and specifically extremist violence, is not a stretch. In fact, as outlined above, certain behavioral, contextual, and social correlates of violent extremism appear to fit neatly within the extant theoretical structure. In the context of this thesis and consistent with prior literature on the theory, one would anticipate those with weaker bonds to conventional society to be less restrained from engaging in acts of violent extremism.

Social Learning Theory

Social Learning Theory (SLT), in its modern form, was introduced by Akers and colleagues in 1979 (Akers, Krohn, Lanza-Kaduce, & Radosevich, 1979). As an extension and clarification of Burgess and Akers' Differential Association-Reinforcement Theory (1966), , SLT emerged and has remained at the forefront of learning theories in criminology. Dating back to Sutherland (1947), these theories contend that certain processes govern learning of both prosocial and criminal behavior. Holding true to the tradition of the learning school, Akers assumes that learning is an adaptive process by which individuals are exposed to specific stimuli and form responses. Specifically, Akers outlines four principal constructs of learning, namely: *differential associations, definitions, imitation*, and *differential reinforcement* (1998). With each construct emerging from a distinct philosophy of learning, Akers joined the works of Sutherland (1947), Bandura (1962), Skinner (1963), and Sykes and Matza (1957) to describe how individuals interpret and integrate stimuli that may lead to delinquency or crime, through the same mechanisms as one would learn to ride a bicycle. Below, the constructs are articulated, followed by a note on the diversity of the application of this theory of crime and delinquency, and concluding with the overall merit for the application to this thesis.

Differential association draws upon how intimate social groups (especially peer groups, family members, and more) are associated with the behaviors and the learning. As suggested by Akers and colleagues (1979), *differential association* occurs first in the learning process within which subsequent learning can take place. More specifically, the normative definitions and attitudes of those with whom one associates are more likely to influence their own stance on prosocial or anti-social behaviors and activities.

Definitions, as the construct most closely adapted from Sutherland's original work, reflect "the values, orientations, and attitudes toward criminal/deviant or conforming behavior held by individuals" (Sutherland, 1947). As discussed by Sutherland, these definitions are formed as favorable or unfavorable to the commission of antisocial behaviors or crime. When an individual has an excess of definitions favorable to the commission of crime relative to definitions unfavorable, they will be more likely to offend. Akers integrated this construct by suggesting that these norms, attitudes, and orientations represent specific cognitive or verbal behaviors that serve as discriminative stimuli in viewing the world. As an individual comes to define specific behaviors as good, or justified (Sykes & Matza, 1957), the more likely they are to engage in such behaviors. This construct has been measured explicitly using the number and frequency of Sykes and Matza's neutralizations, self-reported approval or disapproval of use, and general attitudes of violating or abiding by laws (Akers et al., 1979).

The construct of *imitation* "refers to the engagement in behavior after the observation of similar behavior in others" (Akers R. L., 2013, p. 144). Drawn from work by Albert Bandura (1962), imitation suggests that observation (in-person or otherwise) contributes to the learning process, and this may differentially affect learners depending on to the extent to which they identify with the models. While likely apparent, there was not a perfect correlation between behavior observed and behavior exhibited, indicating that an element of choice is involved, and thus the consequences of behaviors observed may influence the probability of imitation. As represented by Akers, imitation is a potential process through which individuals could be exposed to definitions and reinforcement. To measure this, authors have summed the total of admired 'models' who respondents report having participated in a given behavior (Akers, Krohn, Lanza-Kaduce, & Radosevich, 1979).

The primary mechanism of learning identified by Akers in SLT is operant conditioning, or as it was reframed *differential reinforcement.* Analogous to B.F. Skinner's *operant conditioning*, *differential reinforcement* has been operationalized to suggest that the likelihood of events is influenced by past, present and anticipated future rewards and punishments for any given action. In its most basic form, differential reinforcement encompasses two distinct dimensions of responses to behaviors – amounting to four potential classifications. The responses can be produced by the introduction (positive) or removal (negative) of a positive or negative stimulus. The second dimension relates to the desired change in probability of behavior; reinforcement is designed to increase the behavior whereas punishment is designed to reduce its probability. For example, when a stimulus is introduced with the goal of increasing the probability of a given behavior, this is labeled positive reinforcement. Of note, these constructs have been expanded to discuss vicarious reinforcement and behavioral updating (Warr & Stafford, 1991). This construct has been measured using indicators of praise or punishment for engaging in certain behaviors, experience with informal or formal deterrence, and the specific reactions of friends (Akers, Krohn, Lanza-Kaduce, & Radosevich, 1979).

It is important to note the significance of groups under social learning theory. In fact, it categorically rejects the notion put forth by Hirschi's Social Bonds that peers have no causal impact on behavior. Due to the dynamic process outlined by the theory, it represents a state-based process in which group processes and group members themselves shape individuals over time. Like how social bonds theory has been used to address various types of offending and delinquency, SLT was originally designed to explain traditional forms of delinquency and crime. Having said that, the theory has seen a very diverse application in the Criminological literature to date. Scholars have applied this structure to drug offending (Akers R. L., 1992), gang membership (Winfree Jr., Backstrom, & Mays, 1994), white-collar crime, and nominally, terrorism (Akers & Silverman, 2004).

Since the theory is able to explain a wide berth of offending and the significance of group processes it seems reasonable to extend the theory to violent extremism. Like Hirschi's social bonds, Akers' SLT was originally framed around explaining the incidence of delinquent behaviors among an adolescent population (Akers, 1998). Again however, this is not to say that an extension of these constructs to account for learning that occurs beyond adolescence and toward more serious forms of deviance and violence is without support. Indeed, unlike in the case of a theory which presents a taxonomical strategy – the agnostic approach provided by Akers permits extension to understanding the social and group processes of all forms of learning – and particularly the learning of deviance. Thus, while admittedly outside the typical range of behaviors, the theory is within its scope to explain how peers can shape the opportunities to violent extremism and limit or expand the potential actions of individuals. While the theory has not been formally applied to the topic, reflections of SLT emerge when examining the narrative works provided by Marc Sageman (2004), and Aidan Kirby (2007) on group relations within Islamist cells. Thus returning to the context of this thesis, evidence of the social learning of violence, or violent extremism through any of the proposed constructs of SLT should be predictive of violence, whereas the absence of such indicators should more strongly predict non-violent, albeit ideologically extreme, behavior.

Interactional Theory

While both learning and social bonds hold high esteem in the criminological literature, the mutual exclusivity of the causal mechanisms is troubling when seeking to account for the diverse realm of human behavior. Since much offending and extremist violence occurs in the context of peers and organizations, it makes sense that group processes must be thoroughly considered (Crenshaw, 1987; Sageman, 2004). Social learning theory suggests that individuals may join groups for a number of reasons, importantly - group membership has a causal effect on the learning of behaviors, controlling for predisposition to offend and previous learned behavior. Contrastingly, social bonds theory rests on an argument that individuals with similar levels of social bonds will inherently come together and any outcomes are a product of their inherent propensity toward offending (as moderated by bonds) rather than group processes. Because the theories provide conflicting theses of how and why groups form (and indeed their causal impact if any), it may be that an alternative approach that does not is more appropriate. Thornberry and Krohn’s (2005) interactional theory provides such an alternative.

To its core, interactional theory reflects an age-graded understanding of bi-directional relationships among constructs and the proportionality of cause and effect. More simply, the theory rests on the primacy of informal social controls as a mechanism of preventing crime and delinquency, but departs from Hirschi's social bonds in stating that once control has been weakened sufficiently, learning mechanisms take hold. Specifically, interactional theory draws on Hirschi (1969) to address three principal social bonds to conventional middle-class society: *attachment to parents*, *commitment to school*, and *belief in conventional values*. When these bonds are weakened, freedom to engage in antisocial behavior expands. This behavior however emerges through interacting with delinquent peers (*differential associations*) and the formation of delinquent values (or definitions) as consistent with Akers' social learning theory (1998).

As these constructs were reviewed above, repetition is unnecessary; however, a brief review of the logic for the theoretical model merits exploration. In its initial formulation, Thornberry (1987) explicitly outlines the bidirectional causal links between the constructs in the model. Take for example the negative relationship between attachment to parents and association with delinquent peers. This causal structure necessarily suggests that increases in attachment to parents should predict a decrease in association with delinquent peers. Since this relationship is reciprocal, increases in associations with delinquent peers should also independently decrease the strength of attachment to parents. Absent the reciprocal structure, it is clear that simply accounting for the impact of a stable attachment to parents insufficiently address what is a qualitatively reciprocal relationship.

Beyond positing the importance of such reciprocal relationships, Thornberry (1987) embraces the age-graded nature of socialization. In doing so, Thornberry clarifies the modeling of delinquent behavior as it relates to the various forms of social control and social learning. The initial reciprocal model considers the original five predictive constructs and the outcome of delinquent (or antisocial) behavior. These relationships all appear as predicted by the more traditional control and learning literature, with increases in control and decreases in association with delinquent peers and delinquent values predicting lower delinquent behavior – and vice versa. In middle adolescence, the importance of attachment to parents in predicting delinquency is less robust and due to the increased independence of youth, delinquent values that are formed and unchecked are more strongly predictive of delinquent behaviors. Turning to later adolescence (18-20 years of age), commitment to conventional activities and commitment to families enter the model – the first adopting much of the significance of the commitment to school and the second expanding the importance of attachment and commitment to the possible formation of nuclear families of their own. Worth noting, the age-graded nature of the models adds a layer of complexity and the specific ages ascribed to each period somewhat restrict the predictive capacity of the theory when such relationships occur out of the presumed sequence.

Since the theory adopts some of the same constructs as social bonds and social learning theory, it is fair to suggest that a translation to explaining violent extremism is a plausible extension of the scope. Indeed, since the theory is structured to account for the importance of age-graded sources and weights of social bonds, it may be more suited than the source-agnostic form provided by Hirschi (1969). Further, in accounting for the varying potential forms of learning over the life course and sources of learning, while maintaining a grasp on the traditional constructs, it provides an age-graded consideration of these learning facets as well. Thus, it well may be that interactional theory is best suited to explain the complex pattern of behavior and social interaction that produces violent extremism.

While Thornberry and Krohn (2005) present an appealing alternative to the exclusive meaning of groups outlined in social bonds and social learning theory, the theory does make explicit claims for reciprocal and chronologically specific relationships. This constraint, while informative and cognitively appealing in addressing delinquency, makes testing of the theory in its original form difficult. Accordingly, there has been little work on integrated theory outside of the original context. This is not to say that the theory is untestable, but rather a specific type and granularity of data are necessary for a formal test of the theory (Rochester Youth Development Study, 1991) – and thus it is well outside the scope of the present research to do so. With this in mind, the framework provided by this theory should inform the processes by which already radical individuals are severed from agents and institutions of informal social control and through mechanisms of social learning the separation is cemented. Thus, the transition to violence is a learned step even among those who are unbounded by conventional prosocial norms and engaged with extremist ideologies. In short, I expect that the theoretical process of reciprocal relationships between decreased social bonds and socially learned violence should explain the means by which non-violent individuals, even within radicalized groups, become violent.

Radicalization

Similar to explanations of criminality and delinquency, researchers tend to agree that engagement in violent extremism, or indeed ascribing to an extremist ideology is a multi-stage process (Horgan, 2008; Kruglanski A. W., et al., 2014; Gill, 2015; Jensen & LaFree, 2016). In fact, while the literature tends to focus on the aforementioned risk factors, these risk factors are discussed as stage-graded, wherein the importance of certain elements wax and wane across increasing levels of involvement. This processual understanding of engagement suggests that static factors may be limited in explaining the phenomenon and thus processes that involve recursive or developmental components may be more fit to describing how individuals engage in violent extremism. Furthermore, as the development and deployment of de-radicalization programs has proliferated over the past decade, the understanding that this process of engagement and radicalization is either permanent or monotonic over time has been refuted. Accordingly, theoretical explanations must account for adaptive and dynamic change in behavior, both toward and away from further involvement. In this vein, the capacity of interactional theory to address the recursive and dynamic relationships that produce change and continuity in delinquency and crime should fit these processes well.

In examining what is known about radicalization across scholarly fields, three primary units of analysis emerge. These processes and causes of radicalization have been proposed at individual, meso (group), and macro (state and society) levels

(Kruglanski A. W., et al., 2014; Sageman, 2004; Agnew, 2010). While likely intuitive due to the relationship with more traditional crime, at the individual level, gender and age commonly serve as predictors of violent extremism (Laqueur, 1977; Bakker, 2006; Klausen, Morrill, & Libretti, 2016). Specifically, authors have found that men participate in violent extremism far more frequently than women (Bakker, 2006), however distinct from traditional crime, the most frequent age of offenders in political violence was in the mid-20s, a marked departure from the peak of what is commonly referred to as the age-crime curve (Klausen, Morrill, & Libretti, 2016; Pape, 2005; McCaluley & Segal, 1987). Another notably different predictor from traditional criminality is a high prevalence of marriage as observed by Sageman (2004) in his study of Islamist terrorists.

Radicalization is not solely situated in the realm of individuals however. In light of changes in the political environment, internal dynamics of leadership, and group dynamics, law-abiding organizations may depart from licit means of resistance and choose to engage in illegal ideologically motivated behavior. Meso, or group-level effects have been proposed, and find support in explaining general patterns of terrorist organizations, but also in entry to, and engagement in violent extremism. Sageman (2008) outlined the process by which close groups of friends became affiliated with al Qa'ida through a reciprocally insular environment of one-upsmanship, producing a fierce adherence to each other and the group at large. The social nature of this process should be emphasized, as absent the reinforcement by the close friend group, it is unlikely that such a fervent belief would have developed – a phenomenon viewed in social psychology as well, analogous to cohesion advancing practices (Sidanius, 1993). Thus, as described in Akers (1998) and Thornberry (1987), the associations that one has with violent or otherwise radicalized individuals should contribute to the probability of violent extremist behavior. Contrastingly, prosocial interactions such as proposed in Hirschi should constrain individuals from engaging with violent or extremist others, inhibiting these group effects.

Finally, research on macro, or state levels have indicated certain societal attributes that could predict the emergence of violent extremism. Briefly, factors such as perceptions of state illegitimacy (Engene, 1998; Lipset, 1963), political regime characteristics (Przeworski, 1995), historical tradition of resistance (Crenshaw, 1990), rapid economic growth (Gurr, 1972; Huntington, 1968), and economic inequality (Muller, Seligson, & Midlarsky, 1989) all appear to be associated with higher prevalence of violent extremism domestically and internationally. These factors, while important in the general understanding of the phenomenon of violent extremism, are generally addressed as fairly coarse-grained explanations only able to account for a small proportion of variation in terrorism and are outside of the focus of this thesis (LaFree & Bersani, 2014).

As discussed above, any theoretical treatment of violent extremism ought to include the following: dynamic and evolving processes of engagement, the possibility of de-radicalization, and the impact of social interaction as either a protective or an exacerbating force across individuals. With these factors in mind, social bonds, social learning theory, and interactional theory serve as a strong theoretical basis from which the problem can be addressed.

Moving forward, it is important to consider the following: do these factors describe a homogeneous group? While often espousing their own specific goals, individuals and groups in the United States have been categorized loosely as far left, far right, single issue, or Islamist, depending upon the characteristics of the ideology espoused. For decades in fact, there has been consensus that all terrorism and violent extremism may not be alike, and indeed may follow distinct mechanisms of entry (Rapoport, 2004; Crenshaw, 1990; LaFree & Dugan, 2009). Accordingly, given the variation in groups, it would be naïve to suggest that the factors that have been identified and could be proposed have homogeneous effects on these individuals. This noted divergence in ideological focus could then inform a theoretical framework for understanding the heterogeneity of engagement in extremist violence.

An understanding of correlates of radicalization does not necessarily prove insightful with respect to the process by which it occurs. This is particularly the case with respect to the temporal ordering of factors. As suggested above, expanding known theoretical frameworks to the radicalization process (first by examining the overlap between theory and empirical patterns, such as is explored here) should allow for a more directed and coherent examination of these processes. While a formal literature surrounding the phenomenon of radicalization to violent extremism is still emerging, for decades authors have considered this path in distinct ways. Early conceptualizations of radicalization treated it as a discrete trait (a person was either radicalized or not), but over time a process-based understanding has evolved in the theoretical literature (Horgan, 2005; Horgan, 2008; Kruglanski, Chen, Dechesne, Fishman, & Orehek, 2009; Kruglanski A. W., et al., 2014; Kruglanski A. W., et al., 2016). Modern theories of radicalization tend to emerge from qualitative interviews or case studies of violent individuals; however, it is clear that similar processes should exist for non-violent individuals, and indeed this may be the gap that criminological theory can help fill.

As an example of a process-based approach, Horgan (2005) presents a three-stage process model of radicalization wherein terrorism as a more global construct is broken down into the phases of "'becoming' a terrorist, 'being' a terrorist… and disengaging from terrorism" (p.81). Notably, this theory points out the importance of flexibility in identifying the motivational, structural, and social components that may encourage, sustain, and inhibit violent extremism across all three stages. Indeed, Horgan (2005) suggests that while some factors may overlap, understanding the characteristics and context of one stage may have little bearing on explanations of other components of the model.

Beyond Horgan's three-stage model, other authors have provided alternative processes while examining psychological explanations of violent radicalization. For example, Kruglanski et al. (2009) explore the "quest for significance". In an examination of suicide terrorism, the authors note that heterogeneous factors produce what would otherwise appear to be similar behavioral end-points (Kruglanski et al., 2009). Focusing on this, they emphasize the role that the perception of events and the shaping of self-perception has on suicide bombers. This theory is articulated more formally in Kruglanski et al. (2014) when the authors specify three principal components to the model – *motivation* of the individual, *ideological framework* that the individual operates within, and the *social processes* into and within the group. In short, the core principal of this perspective is that within all individuals is a "fundamental desire to matter, to be someone, to have respect…" (Kruglanski et al., 2014, p.73). As a well-established principle in the psychological literature, the process of how demonstrating agency and volition serves as a framework for understanding violent extremism. Distinct from Horgan's (2005) approach, Kruglanski et al. (2014) focus specifically on the individual experience and precursors to radicalization. Further, they describe the various potential degrees of radicalization as the "extent of imbalance between the focal goal served by the extreme behavior and other common ends that people have…" (p.72). Thus, radicalization as a construct represents a deviation from otherwise normative behavior and is indicated by specific behavioral patterns. At the end of the spectrum of behaviors indicative of radicalization are the perpetration of ideologically motivated acts of violent extremism.

Kruglanski's (2014) model puts forth that radicalization emerges under three preconditions: the arousal of the goal of significance, identification of violence as an appropriate means to achieve significance, and a commitment shift from non-violent or non-radical goals to the goal of significance. These are identified to be sequential insofar as the quest for significance must be initiated before adherence to violence can emerge. The goal of significance becomes aroused when an individual experiences a loss of significance, anticipates a potential significance loss, or perceives an opportunity for significance gain. While individuals may need to accept that violence is an appropriate means to achieve significance, it does not necessarily require that all individuals perpetrate such violence, but rather that the group which they represent utilizes it as a tactic. It can be said then, that even among those who are radicalized, the perpetration of violence is yet another step into group engagement.

Notably, the criminological explanations examined herein would also suggest a process-based model of radicalization. As addressed above, from the perspective of a social bonds approach, bonds must be weakened to the point of allowing for such action to take place. Naturally, these bonds under the appropriate conditions could regain strength through a newfound prosocial family connection, a meaningful prosocial long-term goal, or perhaps most pertinently, action by the government which would restore belief in the moral authority of social institutions. Similarly, when evaluated form a social learning approach, adherence to and entrenchment in an ideological system must occur over time, based upon the tenets of the system and often the specific benefits of membership must be presented or realized as a reinforcement structure to potential initiates. Further, those who would disengage could similarly have more prosocial models of behavior presented to them by a long-time associate, or the prospective punishments of any activity within a group could come to vastly outweigh further action – adjusting the differential reinforcement structure that a current member experiences.

Importantly, and like the criminologically inspired descriptions above, both Kruglanski and Horgan suggest that their models should not be interpreted to suggest a uniform pathway toward, through, and out of violent extremism, but rather that variation occurs across individuals, and the ideological milieu embraced. Thus, examining the phenomenon from a theoretically informed stance should consider this source of variation as well.

Given the clear overlap between extant psychological explanations of radicalization and their sociogenic counterparts in the criminological literature, I expect that constructs described in both social learning and social bonds should be predictive of violent extremism. Furthermore, I expect that the patterns of behavior outlined by Thornberry's interactional theory will emerge upon closer inspection of the processes leading to violent extremism. Broadly, this research examines the capacity of criminological theories to explain variation in violent extremism among already radicalized individuals. It is important to note that as discussed in the radicalization literature, some variation in processes should also exist across the ideology of groups or movements and thus the ideology of each individual is treated as a control. The methods and data I will use to test my hypotheses and explore my research questions about these relationships will discussed in the following sections.

Hypotheses

Focusing on the theoretical explanations of violent extremist behavior, the following hypotheses emerge:

1. Levels of *social bonds* to conventional society and participation in violent extremist behaviors should have a negative and statistically significant relationship.
2. The *social learning* of violence or violent extremism and participation in violent extremist behaviors should have a positive and statistically significant relationship.

Chapter 3: Data and Methodology

I used individual-level data drawn from a new and unique source to test the hypotheses. This source, the Profiles of Individual Radicalization in the United States (PIRUS) database is a cross-sectional, quantitative dataset of 1,473 individuals in the United States who radicalized to the point of violent or non-violent ideologically motivated criminal activity, or ideologically motivated association with a foreign or domestic extremist organization from 1948 until 2013 (except for two cases from 2014). These data, described in detail below, will provide an examination of the associations between these criminological constructs and the potential outcome of violent ideologically motivated behavior. The next sections provide a description of the data source, followed by an account of the strengths and limitations of PIRUS and similar open-source data in the analysis of terrorism and political violence.

Data – Profiles of Individual Radicalization in the United States (PIRUS)

This thesis uses PIRUS, a newly released and ostensibly unique data source collected by the National Consortium for the Study of Terrorism and Responses to Terrorism (START). The PIRUS database includes individuals representing far right, far left, Islamist, and single issue ideologies who radicalized primarily within the United States and have been linked to ideologically motivated crime or violence. The PIRUS dataset, while not alone in examining the phenomenon, is best suited for these questions due to the individual level focus and emphasis on precursors to the ideologically motivated behavior. This is contrasted with the Extremist Crime Database (ECDB) and American Terrorism Study (ATS) databases which, while considered highly among researchers, focus more on the incident and criminal justice procedural outcomes respectively.

According to Jensen & LaFree (2016), these data were collected and coded in several stages involving multiple waves of coding. First, researchers used open-sources and extant START research products to collect a list of names and preliminary background information on around 3,900 individuals from various ideological milieus and time frames for possible inclusion in the dataset. The publicly available sources considered at this stage included newspaper articles, websites (e.g., government, terrorist group, watchdog groups, research institutes, personal information finder sites), secondary datasets, peer-reviewed academic articles, journalistic accounts including books and documentaries, court records, police reports, witness transcribed interviews, psychological evaluations/reports, and information credited to the individual being researched (verified personal websites, autobiographies, social media accounts).[1] Many of the sources used in this initial collection are listed in Appendix A.

Second, researchers coded each of these observations to determine whether the individuals should be included in the dataset using the inclusion criteria (detailed below). Third, researchers coded the relevant background, contextual, and ideological

[1] To date, I have reached out to researchers currently working on the PIRUS database team at START to specify the data collection procedure including the full list of sources used for the original name generation and any search terms used on LexisNexis (and other search engines). As the original team had left following the initial collection, the current data collection and management team has attempted to reconstruct their procedure however the process was not documented in such a way as to allow a definitive list.

information for a final random sample of 1,473 individuals who met the inclusion criteria for the dataset. [2]

To be included individuals must meet at least one of the following five criteria:

1) The individual was arrested;
2) The individual was indicted of a crime;
3) The individual was killed because of his or her ideological activities;
4) The individual is/was a member of a designated terrorist organization; or
5) The individual was associated with an extremist organization whose leader(s) or founder(s) has/have been indicted of an ideologically motivated offense.

Further, each individual must have been radicalized in the United States, have espoused (or currently espouses) ideological motives, and show evidence of a link between their behaviors and the ideological motive that they espouse. For example, leaving a suicide note citing group ideology, harboring a fellow member of a group, or taking part in a Sovereign Citizen tax-evasion rally before defrauding IRS on taxes would constitute ideological consistency with behaviors. After an individual had been determined to meet the inclusion criteria, they were coded on various demographic, social, and individual attributes by trained research assistants, and quality controlled

[2] According to personal communication with researchers currently on the PIRUS database team at START, the 1,473 included were the result of a simple random sample of qualifying cases based on limited resources. Since the initial coding, the project staff have gone back and are coding the remaining individuals who qualified for a version of PIRUS which has not yet been released.

by full-time project staff. To ensure reliability, a 10% random sample of cases were coded a second time by separate coders, which resulted in an average Krippendorff's alpha of 0.76 – above the common standard of 0.70 used in social science research (Pyrooz, LaFree, Decker, & James, 2017).

Strengths and Limitations of PIRUS

While PIRUS represents a significant movement toward the "big data" study of individual radicalization and terrorism, it has its limitations. Insofar as PIRUS was produced through open-source collection and investigation, it remains vulnerable to the typical biases therein. Perhaps the most notable of these concerns are the sampling procedure for how individuals enter the dataset and the missingness of data among those included.

Of note, since these data are a product of open-sources, two additional criteria are tacitly included for an individual to enter the dataset. First, for any of the explicit inclusion criteria to be met, an individual's activities must first come to the attention of law enforcement or the media. As a fundamental step, if an individual is not exposed in any fashion (even unidentified), their behaviors, affiliations, and crimes cannot constitute inclusion into the dataset, nor would merit efforts to identify. This substantially reduces the probability of entry into PIRUS for those who are successful at maintaining operational security or try and fail to engage in any of the proscribed behaviors. Similarly, for inclusion into the dataset an exposed individual must be identified. Again, a straightforward requirement, however as has been well-documented in the Global Terrorism Database (National Consortium for the Study of Terrorism and Responses to Terrorism (START), 2016), a substantial proportion of attacks (which would arguably be more easily detected than non-violent behavior) go unclaimed and the perpetrators unidentified. Fortunately, the proportion of unidentified and unattributed attacks in the United States is smaller than in many other countries, however the concern of exposure as a selection mechanism remains. Interestingly, an analog within the criminological discourse exists in databases of ‘cleared’ cases by police departments.

In a similar fashion, these databases represent those who law enforcement are reasonably sure are responsible for some illegal act – regardless of being in custody. To extend the analogy, while findings may be generalizable to those who have contact with law enforcement and produce an official record, generalizing findings to those who remain on the street offending covertly or engaging in status offenses without a formal sanction is inappropriate. The characteristics of these explicitly covert or otherwise undetected offenders is often a topic of speculation, however absent a reliable self-reporting of such behaviors, a picture of these offenders remains elusive. In the present case, the findings from PIRUS should be interpreted with care, and any generalization must be restricted to individuals who are already radicalized and have engaged in detected, ideologically-motivated behavior.

Referring to some of the sampling limitations, the PIRUS team also notes that “the sample likely reflects news reporting trends over time. That is, as reporters shift their primary focus from one ideology or movement to another, it becomes increasingly easier to identify individuals who are associated with the groups that are under intense media scrutiny, and increasingly harder to identify those who are not” (National Consortium for the Study of Terrorism and Responses to Terrorism, 2017). Furthermore, the availability of digital historical sources was limited, resulting in a likely absence of individuals from 1948 through the 1980s (START, 2017).

These sampling limitations are exacerbated by the prevalence of missing information within the database. Due to the open-sourced nature of the PIRUS data, key theoretical variables experience an exceedingly high degree of missingness (summarized later). This may be because violent and non-violent extremists regularly conceal or misrepresent their explanations and observable behaviors. In the language of internal validity, the capacity to estimate the effects of these variables on the dependent variable accurately is stunted by a selection bias when applying modeling techniques. In the present thesis, careful use of imputation techniques is exercised to remedy this absence to a moderate degree, however despite statistical techniques to estimate the nature of this missingness, the character of these details remains ostensibly unidentified. This is not to say that imputation resolves the fundamentally troubling degree of missingness in many variables, but rather that it will allow for an accounting of patterns in the data which would otherwise be obfuscated by limited sample sizes. Taking a step back however and acknowledging the state of research on radicalization to ideologically motivated behavior, PIRUS remains a strong step forward.

Insofar as accomplishing the goal of identifying all radicalized individuals in a specific period, the data fall short, however the PIRUS database clearly represents an extension of extant police or other administrative records to approximate the profile of radicalized individuals in the United States. Indeed, as suggested in Pyrooz et al. (2017), the PIRUS dataset is exemplary in that it is one of the most comprehensive current attempts to gather systematic individual-level data on domestic extremists in the United States to date. While other official sources, collected and utilized internally by federal authorities may be more complete in some respects, they are often restricted in their release or the level of detail due to the sensitivity of the topic and individual privacies. Since such limited glimpses have been used in the past to inform our perceptions of radicalization and radicalized individuals, the depth of information available in the PIRUS dataset helps to fill the gaps of knowledge in a meaningful way that is not accessible by other commonly-used research methodologies (LaFree, Jensen, James, & Safer-Lichtenstein, Forthcoming).

Measures of Interest

Outcome Measure

The dependent variable of interest in this thesis is the dichotomous measure, *Violent*. This measure represents whether an individual actively participated in an ideologically motivated operation that resulted in casualties or was clearly intended to result in injury or death but failed. This measure also coded any cases of conspiracy to kill or injure where a law enforcement or other interdiction occurred during the plotting phase as violent.[3] Having consulted with one of the Principal Investigators for the PIRUS project, it is the "rare case" where an individual's exposure event chronologically preceded information used to code another variable. Accordingly,

[3] In some cases, it may be possible that individuals included in the database acted together (and thus the data may not be independent) – this is explored through efforts to match the dates of exposure, affiliated groups, and other pertinent details whenever possible.

concerns of the temporal ordering of this outcome measure and the independent variables listed below are assuaged.

Naturally, this distinction of violent and non-violent behaviors begs an explanation as to what constitutes a non-violent act of ideologically motivated extremism. Examples of such acts include the destruction of property and vandalism, to inciting others toward violence, possession of illegal weapons without operational plans for violence, and still more indirect forms such as filing false liens and engaging in tax fraud. In light of the covert nature of many processes (such as how attacks can be disrupted), ideally the cases of law enforcement interdiction pre-attack would be recoded as non-violent. Unfortunately, a meaningful way of discerning which of the cases in the sample would satisfy these limited criteria for violence is unavailable and indeed little is known about the heterogeneity among cases that would have been affected. To accommodate this, I estimate the effect of any biases produced by cases that might be miscoded as non-violent (or violent) when they were in fact violent (or non-violent).

Independent Variables

A summary of the measures used to operationalize the theoretically pertinent constructs follows. To acknowledge the theoretical structure of Social Bonds and SLT as reflecting the relative strength of informal social control and learning in producing a criminal (or violent extremist) outcome, factor analysis is performed on the following lists of variables to measure the respective influences of each of these theories on predicting violent extremism. Provided that the measures reflect the theoretical constructs, factor loadings should serve to consolidate the respective effects of social bonds and social learning in predicting violence.

Many of these variables are assessed as of the time of their exposure to law enforcement rather than in a given period before any ideologically motivated behavior. While this limits the conclusions that can be drawn from some measures, in many cases the mere presence of certain factors (such as a marriage or employment) at a given time should be sufficient to indicate the theoretical constructs in question. Furthermore, as the variables available within the PIRUS dataset represent an overlapping and distal relationship with the constructs outlined in these theories, allowing these to coalesce into factors should most closely approximate the relationship between observed manifestations of control and learning and the constructs of interest. In turn, the variables included in each index of control and learning are explained below.

Social Bonds Variables

As presented above, the overall observed strength of social bonds should include variables indicative of an individual's *attachment*, *involvement*, *commitment*, and *belief*. Since the constructs of attachment and belief are relatively distinct phenomena, these may be operationalized more explicitly, however the behavioral overlap in manifestations of involvement and commitment belie a deeper entanglement of the constructs. Thus, these variables together approximate the overall evidence of positive social bonds, in lieu of a by-bond series of measures.

First examining indicators of attachment, two variables (*Abuse Child* and *Close Family*) from the extant PIRUS codebook are included to contribute toward the construct. The *Abuse Child* variable is a categorical measure recoded to signify if the individual was ever abused by a family member as a child.[4] While an overall rare occurrence, the presence of abuse by a family member (to be recoded as 1) would be clear manifestation of a weak bond of attachment. The absence of such abuse is an indication of stronger attachment (recoded as 0). Although these variables represent a rough approximation of attachment, this operationalization is limited since it is unable to tap into the closeness that individuals had to these intimate others, solely their mere presence and whether their relationship to them may have been damaged by abuse.

The *Close Family* variable, which was originally coded on an ordinal (and dichotomous) scale (0 = distant, 1 = close) has also been included as-is to indicate the construct of attachment. Close attachment would naturally signify a strong emotional bond of attachment with an individual's family – and is like some of the original questions used by Hirschi. This variable indicates to what degree individuals interact with more family members, attend family gatherings on a regular basis, or celebrates holidays with their family.

Next, five variables (*Work History, Unstructured Time, Student*, *Military,* and *Aspirations*) have been included to indicate the influence of bonds of involvement and commitment. As explained above, the behavioral manifestations of these constructs – particularly in adulthood – permit the grouping in this context.

First, *Work History* is included as an ordinal reflection of the individual's employment prior to their date of exposure. Presently, this variable ranges from 0 =

[4] This involves combining the current 2 and 3 codes which account for evidence of abuse solely by family members or by family and non-family members.

Long-term unemployed to 3 = Regularly employed with intermediate values for Underemployed = 1 and Serially Employed = 2. This range of values will serve to indicate the strength of commitment and involvement adult social bonds.

Second, and consistent with more common operationalizations of *involvement*, *Unstructured Time* is an indicator of individuals who are not thoroughly involved with prosocial activities. As exemplified in the PIRUS codebook, an “unemployed person who is not actively seeking employment, is not a student, and is not engaged in the community” would qualify (START, 2017, p. 40). The variable *Unstructured Time* is already coded as dichotomous with those who “have a lot of unstructured time that was not taken up by activities”=1, and those who do not=0. This is reverse-coded to indicate the presence of involvement in the absence of unstructured time.

Third, the *Student* variable is included as-is and captures if the individual was a student at the time of their radicalization of beliefs or behaviors (1), or not (0). Pursuing educational goals has long been conceived of as an indication of prosocial trajectories, and thus even later in life, and perhaps particularly so, student status should reflect bonds of involvement in conventional society.

Fourth, the *Military* variable is included to represent if the individual was in the US military. This is recoded from the original categorical coding to indicate if the individual was active duty at the time of radicalization (2), ever (1) in the US military, but inactive at the time of their radicalization, or never in the US military (0). Similar to the nature of the marital status variable, the role of membership in the military has been supported to be a source of informal social control – particularly in Sampson and Laub’s age-graded theory of informal social control. This would be strongly indicative of bonds of involvement and commitment. In the present case, some heterogeneity of the original coding is abandoned in light of the primary dependent variable of interest – violence. Since the key temporal ordering is solely that the individual was in the US military at some point before the potential outcome of violence, whether they were deployed or experienced active combat at the time of their reported radicalization becomes immaterial[5].

Finally, the *Aspirations* variable is included as indicative of the construct of commitment; the absence of strong commitment is a commonly cited strong predictor of later criminal behavior. The *Aspirations* variable is ordinally coded to answer the question of if the individual had clear educational or career aspirations. The original coding will remain intact, with the strongest evidence of commitment being demonstrated by those who achieved aspirations prior to public exposure (3), followed by those who had aspirations, tried, and failed to achieve them (2), and those who had clear aspirations, but did not attempt to achieve them (1). Finally, the absence of aspirations (0) would suggest that an individual was not reported to have discussed future career or educational goals.

To assess the force of the social bond of belief in conventional norms, two variables (*Angry US* and *Radical Beliefs*) are included. The *Angry US* variable in the extant codebook measures if there were (1 = yes) any signs that the individual was angry with US society, or did not accept the moral validity of the American social value system, or not (0 = no).

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[5] This point has been discussed with current project managers and investigators working on the PIRUS team, and as above with the temporal ordering of the dependent variable occurring after the independent variables, this remains the case.

Finally, the *Radical Beliefs* variable is included as a measure of relative belief in conventional norms. This variable is ordinally coded to assess the maximum extent of radicalization apparent in the individual's beliefs (0 = Ideological system but no evidence of belief in radical versions of ideology, 1 = Evidence of exposure to radical ideology, 2 = Pursues further information on radical ideology, 3 = Full knowledge of tenets of radical ideology, 4 = Shares many of the beliefs of radical ideology, 5 = Deep commitment to radical ideological beliefs). Importantly, maintaining the ordinal structure of the variable maximizes the observable variation in belief across individuals in the dataset.

In summary, the nine items constituting the aggregate level of social bonds represent the relative overall strength that social bonds exert on these individuals to conventional society. As articulated above, having relatively lower levels of adult social bonds should be predictive of having a less strict social cost for engaging in violent extremist behavior, rather than non-violent ideologically motivated behavior, and thus be positively associated with the violent outcomes.

Social Learning Variables

Contrastingly, the items representing the observed influence of social learning include variables for the constructs of *differential association*, *imitation*, *differential reinforcement*, and *definitions.* These responses, when aggregated reflect the cumulative learning processes, which contributed to the individuals engaging in violent ideologically motivated extremist behaviors. Insofar as social learning theory would suggest that the learning process is cumulative – with differential association as a necessary precursor to imitation, reinforcement, and the formation of definitions over time – the behaviors indicative of these constructs need not be a clinical manifestation of each individual learning component. As follows, the items that are included, and their recodings are identified – with a brief mention of the theoretical constructs that they approximate.

First, the *Group Membership* variable, as a proxy for the differential association process, is included. This variable, originally coded categorically (0 = Not a member of a group, 1 = Member of an informal group of fellow extremists, 2 = Member of a formal extremist organization or an extremist movement, 3 = Member of an above-ground political movement or activist group) was recoded to indicate if the individual was (1) or was not (0) a member of an extremist group of any variety (1 or 2). Those who were members of above-ground political movements (3) yet did not associate with other extremists are not considered as having differentially associated with those who would contribute to the learning of violent extremist behaviors.

Next, the *Recruiter* variable which represents who, if known, actively recruited the individual, was recoded from the categorical original coding (0 = Associate(s) or member(s) of a terrorist or violent extremist group, 1 = Family Member, 2 = Friend, 3 = Other) to a series of binary indicators, one for each of the four categorical outcomes. These various items collectively approximate the construct of definitions and when coded positively (indicating the presence of any of these recruiters) signify a lower barrier to entry into these groups due to a presumably stronger association and reinforcement. Further, as the formation of definitions unfavorable to obeying the law is a product of (among other things) closeness to the role model, an extant strong relationship, such as observed in Family Members and Friends should differentially contribute to the adherence to violent ideologies and thus violence as a member of the group.

The *Actively Connect* variable is recoded to a dichotomous measure of if the individual actively reached out to an extremist group prior to ideologically motivated radical behaviors (1) or not (0) from its original ordinal coding (0 = No, 1 = Yes, prior to ideologically motivated radical behaviors, 2 = Yes, after ideologically motivated radical behaviors). This will capture a temporally critical nature of group processes; for learning processes to occur and be a product of group association and membership, the ideologically motivated behavior must not occur before group membership.

The *Clique Radicalize,* originally coded ordinally, (0 = No, not a member of a clique, 1 = No, radicalization began prior to clique membership, 2 = Yes, onset of radicalization coincided with clique membership) has been included as-is. This will reflect the constructs of differential association, imitation, and differential reinforcement or simply, the exposure to a close-knit group of intimate peers as they contribute to the learning process of radicalization.

Relatedly, the *Gang* variable is included as a means of assessing if there is evidence that the individual was involved in a street gang, an organized criminal group, or both prior to their date of exposure[6]. The presence of gang membership

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[6] This assumes that any information about gang membership would be detected and reported on by the media or other sources pooled in the PIRUS data collection process. While this will naturally not always be the case, these data have been justifiably analyzed by Pyrooz and colleagues (2017) under an assumption that this represents an outwardly active subset of members, or those who would have been detected and sanctioned specifically for their gang-related behavior. So while this may not reflect all gang members, it ought to include any who were particularly criminally active – encompassing the

would be indicative of the entire social learning process at play – from differential association with violent others, to imitation and reinforcement, and definitions unfavorable to obeying the law. The original coding of the variable is categorical (0 = No, 1 = Yes, street gang, 2 = Yes, organized criminal group, 3 = Yes, both street gang and organized criminal group), however this is recoded as dichotomous to reflect if there is evidence that the individual was ever a member of either type of gang (1) or not (0).

Next, the *Radical Friend,* variable –which uses an ordinal coding to address if one of the individual's friends was involved in radical activities (0 = No, 1 = Yes, but only known to have engaged in legal activities, 2 = Yes, but only known to have engaged in non-violent illegal activities, 3 = Yes, known to have engaged in extremist violence) is included. This will approximate a component of the individual's differential association to influences of violent, or illegal radical actions through peers. As peers are a well-established source of definitions in criminological research, in this case higher values will represent more definitions unfavorable to conventional norms and a model for the imitation of possibly violent ideologically motivated behavior.

Finally, both the *Beliefs Trajectory* and *Behaviors Trajectory* variables have been reverse coded from their current dichotomous coding (0 = Gradual, 1 = Key moments) to reflect the gradual learning process (1) or otherwise (0). These each reflect the development of definitions and reinforcement over time – a key temporal

subsection of interest to those who may go on and become ideologically violent. Importantly, and as is discussed in the limitations of this paper, this measurement error produces two empirical limitations.

dimension of the learning processes. Importantly, while learning theories can accommodate varying speeds of learning, the process should not be driven by a specific event or a key moment – but rather incrementally as the reinforcement of behaviors occurs. Even in the case of the imitation of violent (or non-violent) ideologically motivated behavior, one would first need to be socially engaged with a prospective behavioral model, or have some sympathetic perspective toward the beliefs and behaviors modeled. In instances when beliefs and behavior appears to be driven by key moments, other social processes, or the response to the breakdown of normative expectations, may be occurring. In these data, over 90% of those identified as having experienced key moments in these items were also coded as having had a specific event as influential to their radicalization in behaviors or beliefs on a separate PIRUS variable – *Event Influence*. This is important because some events accounted for in *Event Influence* include the September 11 terrorist attacks, the Vietnam War, the Ruby Ridge/Waco incident, which would all serve as an exogenous shift in the individuals' trajectory, rather than a social learning process at work. Accordingly, the absence of these – and evidence of gradual radicalization of behaviors or beliefs would be stronger indications of such a social learning of violent ideologically motivated behaviors.

In summary, the eleven items constituting the social learning constructs when taken together represent the relative cumulative evidence of social learning processes that these individuals experienced leading them toward violent extremist behaviors. Thus, stronger evidence of these learning constructs as they are manifest here should predict a higher probability of violent ideologically motivated behavior.

Control Variables

Since both sets of theoretical items benefit from the inclusion of the *Previous Criminal Activity* variable (albeit for theoretically distinct reasons), it has been included separately as a control. This approximation of an individual's criminal history is included ordinally (0 = No previous criminal activity 1 = Previous (non-violent) minor criminal, activity (e.g., convicted of a misdemeanor crime), 2 = Previous (non-violent) serious criminal activity (e.g., convicted of a felony crime), 3 = Previous violent crime) to maintain the granularity of this well-known indicator of future offending. Since both the weakness of social bonds and the social learning of crime would have occurred prior to events which would have produced an earlier criminal history, including this variable allows the theoretical scales to remain agnostic to prior offending. Also, as there exists no theoretical justification to anticipate different levels of associations between the theoretical variables (or loadings) and the probability of violence across the ideological milieu of the those in the dataset, each of the four ideological binary variables (*Radicalization Far Right*, *Radicalization Far Left*, *Radicalization Islamist*, and *Radicalization Single Issue*) has been included as control variables.

Further, due to known differences in the rates of violent offending and notable variation in the social controls and learning processes that men and women experience the gender of the individual is included as a control. This should allow for a cleaner estimate of the relationship between the theoretical scales and the outcome. In the current dataset this is included as the *Gender* variable. This has been recoded to an indicator of *Male*, (1 = Male, 0 = Female). Finally, due to the known relationship between age and offending in the criminological literature, the PIRUS code *Age* is included to account for the plausible overlap into this related realm of study. This is currently coded as the age of the individual at the time of exposure, which again typically refers to the date of the incident or the date of arrest.

Analytic Plan

Analyses begin with a descriptive examination of the theoretical and control variables. Next, this is followed by a thorough examination of the degree of missingness across the variables that form the pushes and pulls of the theoretical constructs. If, for example it would be problematic if one or more variables representing a given construct exhibits a substantially higher degree of missingness and was the only item to characterize a critical theoretical construct. Further, a cursory inspection of the distribution of values across each of these measures indicates that among an already radicalized population, there exists variation on these key constructs.

Addressing Missing Data

In light of the missingness of data on key independent variables (as summarized in Table 1), a plan to allow for robust quantitative analysis is executed. To more aptly demonstrate the gravity of the missing data across the theoretical items, a trimmed analytical model (including only 10 of the 22 theoretical predictors) naively estimated would be based on only **7** observations. To help account for this striking missingness, multivariate imputation by chained equations (MICE) is applied to these data. While MICE is not the only potential remedy to missingness in observational data, this strategy applied allows for a more meaningful interpretation under the circumstances.

Briefly, the core assumption about the nature of the missing data can be classified as one of the following: data are missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR). In the case of data MCAR, the probability of missing data on a dependent measure is unrelated to the value of the dependent measure itself, or to the value of any other variables in the model. Often a heroic assumption, missingness completely at random is the default when naïve models are performed in most commonly used statistical packages (STATA 14.0, SPSS, etc.) when they encounter missing data. In the present case, due to the data generating process of open-source collection and coding, this assumption of missingness being completely at random is untenable.

Considering the strength of the MCAR assumption, missingness at random (MAR), is a more likely scenario. MAR represents the case in which the probability of a variable being unobserved (i.e.: a missing value) is unrelated to the value of said variable, conditional on the remaining variables in the analysis. Simply put, after controlling for what we know, remaining missingness is assumed to be random. Insofar as the PIRUS dataset has a rich depth of variables upon which to condition, with careful interpretation of findings to abstain from extending beyond the support of the data, this assumption is defensible. Under the MAR assumption, a MICE procedure is applied here.

Table 1 – Missing Data on Dependent Variable, Controls and Theoretical Variables

Variable Name	**Valid N**	**Missing N**	**Total**	**% Missing**			
Social Learning Scale							
Group_Membership	1473	0	1473	0			
Actively_Recruited	629	844	1473	0.572980312			
Recruiter	613	860	1473	0.583842498			
Actively_Connect	556	917	1473	0.622539036			
Gang				1473	0	1473	0
Clique_Radicalize	693	780	1473	0.529531568			
Radical_Friend	708	765	1473	0.519348269			
Radical_Family	295	1178	1473	0.799728445			
Radical_Signif_Other	347	1126	1473	0.764426341			
Family_Ideology	244	1229	1473	0.834351663			
Kicked_Out	206	1267	1473	0.860149355			
Radicalization_Place	459	1014	1473	0.688391039			
Beliefs_Trajectory	547	926	1473	0.628649016			
Behaviors_Trajectory	588	885	1473	0.600814664			
Social Bonds *Scale*							
Absent_Parent	274	1199	1473	0.813985064			
Abuse_Child	1465	8	1473	0.005431093			
Abuse_Adult	1465	8	1473	0.005431093			
Close_Family	289	1184	1473	0.803801765			

Marital_Status	723	750	1473	0.509164969
Employment_Status	624	849	1473	0.576374745
Work_History	619	854	1473	0.579769179
Unstructured_Time	546	927	1473	0.629327902
Education	519	954	1473	0.647657841
Student	789	684	1473	0.464358452
Military	856	617	1473	0.418873048
Aspirations	153	1320	1473	0.896130346
Angry_US	905	568	1473	0.385607604
US_Govt_Leader	793	680	1473	0.461642906
Radical_Beliefs	1357	116	1473	0.078750849
Contol Variables				
Age	1395	78	1473	0.052953157
Male	1473	0	1473	0
Previous_Criminal_Activity	678	795	1473	0.539714868
Ideological Milieu				
Full Sample	1473	0	1473	0
Radicalization_Far_Right	641	0	641	0
Radicalization_Far_Left	305	0	305	0
Radicalization_Islamist	222	0	222	0

Radicalization_Single_Issue	305	0	305	0

In MICE, a series of regression models are estimated for each variable with missing data being modeled conditional upon the known variables in the dataset. This process is repeated iteratively until convergence, or stable estimates of the distribution of the parameters governing the imputation process, is achieved and a final imputed dataset is formed. Once this procedure has been completed, the entire imputation process is repeated until sufficient datasets have been formed to properly account for the imputed nature of these new values and their respective standard errors. Of note, the MICE procedure can be used within software packages to simultaneously estimate imputation datasets with distinct estimation procedures based upon differing distributional assumptions, from OLS (standard linear regression) to Negative Binomial and Maximum Likelihood Estimation (logit, ologit, and mlogit). Ultimately, these imputed data can be assessed by comparing them to the non-imputed observations and evaluating the distributions produced (see Table 5).

While under the conditions of MAR, the MICE procedure is a reliable and precise approach for addressing the issue of missing data, it does have certain drawbacks (Graham, 2008; Graham, Cumsille, & Elek-Fisk, 2003; Graham, Olchowski, & Gilreath, 2007). Specifically, extant work on the proper application of the MICE procedure is unclear as to the number of datasets necessary for imputation, only detailing that at least 40 imputations are recommended when 50% missing information is present to mitigate losses of statistical power due to necessarily increased standard errors from using this procedure (Graham et al., 2007). Despite this concern by the authors who developed these procedures, advances in computing power allow this thesis to perform 100 imputations of the missing data – a computationally demanding, but analytically satisfactory solution.

Typically, the MICE procedure is strengthened by variables in the dataset which allow for more precise and efficient estimation of missing values, which over the various iterations converge on a stable estimate (Graham, 2009). Briefly, the more variables included in the specification model, the more precise the estimate, and the more iterations and complete information included, the more efficient the estimate. Accordingly, MICE specifications often employ, or seek to employ all other variables available, however in the present case this was not feasible due to missingness on non-theoretical covariates which would break down the estimation processes. To address this and strategically maximize the precision and efficiency of imputed values, I perform an iterative process, first including variables with complete information and non-theoretical variables with less than 10% missingness, imputing only one theoretical variable. When this first iteration was successful, I proceed by attempting to impute more theoretical variables of progressively higher proportions of missingness, beginning with those count variables, followed by dichotomous variables, and finally including ordinal items. When the estimation process broke down due to failure to converge on stable estimates, I revert to the previous successful imputation and added more, less-complete covariates from the dataset. If this alternative process remains unsuccessful, I remove less complete non-theoretical variables one at a time and resumed the estimation procedure. Ultimately, 100 imputed datasets are successfully estimated for the theoretical items listed above using the variables presented in Table 2.

Finally, missingness not at random (MNAR) is defined as when missingness in each variable depends on the value of the unobserved data, independent of variation in other observed data. Briefly, even knowing the value of observable characteristics, there remains a selection process in what values of the missing data are and are not observed. This is often considered particularly problematic when naïve models are estimated, since parameter estimates are likely to be biased in ways that cannot be reliably diagnosed (Graham, 2009). While the threat of MNAR may be present, it is unlikely, and this thesis does not address it analytically as others have (Safer-Lichtenstein, LaFree, & Loughran, 2017).

Table 2: Final Imputation Model

Predictors		Imputed Values		
Complete	**Incomplete**	**Negative Binomial**	**Logit**	**Ordinal Logit**
Violent	Abuse Child	Age	Beliefs Trajectory	Actively Connect
Radicalization Far Right	Abuse Adult		Unstructured Time	Clique Radicalize
Radicalization Far Left	Absent Parent		Angry US	Aspirations
Radicalization Single Issue	Actively Connect		Behaviors Trajectory	Close Family
Radicalization Islamist	Age		Student	Radical Friend
Gender	Angry US		Military Ordinal	Previous Criminal Activity
Group Membership	Aspirations		Abuse Child	Work History
Ideological_Sub_Category1	Behaviors Trajectory		Recruit Family	Radical Beliefs
Gang	Beliefs Trajectory		Recruit Friend	
Subject ID	Clique Radicalize		Recruit Member	
	Close Family		Recruit Other	
	Employment Status			
	Family Ideology			
	Kicked Out			
	Marital Status			
	Military			
	Previous Criminal Activity			
	Radical Beliefs			
	Abuse Sexual			
	Residency Status			
	Radical Family			

Radical Friend	
Radical Significant Other	
Radicalization Place	
Recruit Family	
Recruit Friend	
Recruit Member	
Recruit Other	
Student	
Unstructured Time	
US Govt Leader	
Work History	
Criminal Severity	
Plot_Target1	
Extent Plot	
Radical Behaviors	
Immigrant Generation	
Abuse Emotional	
Abuse Other Physical	

Exploratory Factor Analysis

Next, to address the hypotheses analytically, this thesis first performs preliminary logistic regressions using the theoretically inspired sets of variables to predict the violent outcome. This is followed by an application of exploratory factor analysis for each set, and ends with a series of logistic regression models to estimate the impact of the factor loadings on the probability of engaging in violent extremist behavior. Briefly, factor analysis is used to identify relationships among items, and from these relationships produce a set of common ‘factors’ (Grice, 2001, 2007). These common factors are unobserved latent relationships or constructs and may hold some theoretical importance (Grice, 2001, 2007; Porter & Fabrigar, 2007). Briefly, there are two core types of factor analysis: Confirmatory Factor Analysis (CFA) and Exploratory Factor Analysis (EFA). CFA is often used to test hypotheses on the relationships between observable items and existing underlying latent constructs. Given the modest match between the theories utilized in this thesis and the specific items coded to measure them, the more rigid CFA technique is not an appropriate choice.

Alternatively, EFA explores the underlying structure of related items without imposing any specific restrictions on the outcome (Child, 1990). Simply put, researchers conducting EFA set no expectations on the nature of the items and the number of underlying latent constructs, and thus EFA is often used when there is no a priori theoretical operationalization for a specific measurement model. Insofar as the PIRUS dataset was not necessarily designed for testing the theories of Social Learning or Social Bonds, and accordingly the theoretical clarity of such variables that were coded is unclear, no comprehensive theoretical understanding of how these items may relate to one another exists. This lends credence in the present case to the use of EFA, and thus this study uses EFA to identify interrelationships and ultimately factors related to the perpetration of violent ideologically motivated behavior.

Moving forward, exploratory factor analysis is performed on each set of variables (social bonds and social learning) and logit models run both (1) by substituting the items which load heavily onto the produced factors with their factor loadings and (2) by including those heavily loading items individually. Using the control and learning constructs individually, factor analysis allows this study to identify any unobserved theoretical binds between existing items, and in the first series of models to create a factor loading score representing the relative levels of these aggregate theoretical influences on individuals.

Prior to extracting factors, it is necessary to assess whether the data themselves are suitable for the factor analysis procedure. Factor analysis requires large samples to ensure that the correlations among variables are reliable estimates. Similarly, it is also preferable that the ratio of subjects-to-variables is large. While there is no specific lower limit on the minimum acceptable sample size, having 150 units or more and subject-to-variable ratio of 10 to 1 is generally accepted (Beavers et al., 2013). This study's sample size (n=1473) and subject-to-variable ratio (≈52:1) meet these criteria. Furthermore, as factor analysis is driven by the covariation of measures, a marked absence of data on any of the measures critically inhibits the application of the method. Thus, the imputation the technique discussed above is applied here before the factor analysis procedure to ensure that factors produced are based upon the most complete view of PIRUS.

The present study used EFA to assess the covariation across connected theoretical items. Shown in Tables 15 and 16 (see Appendix B), the bivariate correlation matrices of the control and learning items lend surficial support to relationships of theoretical items, however the factor analysis approach allows for multivariate covariances to be examined analytically. Establishing the basis for relationships between the items, I estimated the bivariate polychoric correlations. While Pearson correlation matrices are commonly used to assess these relationships, due to the presence of a number of ordinal variables among the theoretical items, it is not suitable (as it assumes an interval or ratio scale between values). Like the Pearson correlations, the polychoric correlation matrix produces a statistic between -1 and 1. Since several items exhibit reasonably strong polychoric correlations, the data appear suitable for factor analysis.

Next, I conducted a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy test on each of the sets of items. The KMO test provides a statistic ranging from 0 to 1, reflecting the proportion of the variance among the variables that is shared or common. This study's KMO test yielded a statistic of 0.6842 and 0.5112 for the social bonds and social learning variable sets respectively (and collectively 0.5966) – suggesting that each set of items shares a modest amount of variance. While this falls short of the often targeted 0.80 KMO statistic, in acknowledging the potential downward biases of the open source data collection used in the creation of PIRUS and the overall data-generating process, the produced statistics are (while not ideal) acceptable.

I then selected an extraction method to determine the number of underlying latent factors. EFA extraction methods are iterative processes that rely on matrix algebra to create linear combinations of items that explain the maximum amount of variance between items (Beavers et al., 2013). The first extraction in this process is based off the assumption that each linear combination is independent (Beavers et al., 2013). These linear combinations represent factors. This iterative process continues until all of the sample's variance is accounted for (Suhr, 2006). With this in mind, I applied EFA individually to the set of control items and the set of learning items.

There are several criteria for identifying the appropriate number of factors. For EFA, these include identifying differences in eigenvalues, and accounting for the cumulative percent of variance extracted by each factor. Tables 17 and 18 (see Appendix B) display the eigenvalues and differences between eigenvalues for the potential factors. Eigenvalues represent the maximum amount of variance that has not been accounted for by previous factors (Suhr, 2006). They are produced by the determined extraction method, and since extraction is performed iteratively to determine eigenvalues, the first factor often represents the greatest variance among items. In factor analysis, factors with high eigenvalues (one or larger) are typically retained, however this is a heuristic tool and decisions on the number of factors may be made based upon jumps in the magnitude of eigenvalues – as illustrated in the right columns of Tables 17 and 18. As shown by the difference between the first and second eigenvalues in Table 17, and the second and third eigenvalues in Table 18, the control variables have one factor, whereas the learning factors have two factors. These differences are depicted visually in what is called a scree plot in Figure 2 and 3 for the control and learning items respectively (see Appendix B).

Table 3: Social Bonds Factor Loading

Variable	Factor 1 Loading
Abuse Child	-0.103
Close Family	0.266
Work History	0.303
Unstructured Time	-0.355
Student	-0.017
Military	-0.033
Aspirations	0.129
Angry US	0.027
Radical Beliefs	-0.023

Table 4: Social Learning Two Factor Loadings

Variable	Factor 1 Loading	Factor 2 Loading
Group Membership	-0.1208	0.11316
Recruit Family	-0.01131	0.04663
Recruit Friend	0.03808	0.13615
Recruit Member	0.00319	0.13401

Recruit Other	0.01777	0.12835
Actively Connect	-0.02234	0.21837
Gang	0.00213	0.01268
Clique Radicalize	0.04065	0.40967
Radical Friend	-0.00404	-0.08821
Beliefs Trajectory	0.38467	-0.01824
Behaviors Trajectory	0.40215	0.01746

I then created the factor scores for the one factor and two factor solutions using a least squares regression approach. Each individual received a factor score that represented the overall impact of sources of social bonds on their life, as well as two factor scores to depict the cumulative social learning forces that they experienced. In the case of the learning items, due to the presence of two factors and to maximize variation across the two produced factor scores, an orthogonal rotation was performed. Orthogonal factor rotation allows for solutions to be more clearly identified when items load onto more than one potential factor and does not assume factors to be correlated – whereas oblique factor rotation makes this assumption. The loadings for each of the items to these scores are depicted in Tables 3 and 4. Ultimately, the produced scores ranged from -4.364 to 0.532 for the control factor, -0.716 to 1.987 for the first learning factor, and -0.713 to 3.301 for the second learning factor.

Finally, a logistic regression (logit) model is estimated using various combinations of the learning and control items, the produced factor scores, and the control variables. A logit model is most appropriate in this case due to the binary nature of the dependent variable (*Violent*) and the ease of interpretation of the produced coefficient estimates.

$$P(Violent = 1) = \frac{Exp(ControlFactor + EngagementProcess + LearningTrajectory)}{1 + Exp(ControlFactor + EngagementProcess + LearningTrajectory)} \quad (1)$$

Chapter 4: Results

To review, this study used a combination of Factor Analysis and Logistic Regression to examine the relationship between control and learning factors and the potential outcome of violent ideologically motivated behavior. Specifically, this study evaluated two hypotheses: (1) levels of social bonds and participation in violent extremist behaviors have a negative and statistically significant relationship, and (2) the social learning of violence or violent extremism and participation in violent extremist behaviors should have a positive and statistically significant relationship. Each hypothesis was investigated first with each item coded individually. Next, the models were estimated using the individual items for both theories. Third, factor analysis was performed on the groupings of theoretical variables, resulting in factors and factor loadings (which were estimated and substituted for variables loaded heavily)[7]. Fourth, factor loading driven models were estimated for each theoretical stance individually. Fifth, factor models were estimated including both theories, and finally, the models were estimated including identified covariates from the itemized models which did not load heavily onto the factors.

Descriptive Statistics

Table 5 provides the summary statistics for the variables of interest, both before, and after imputations were performed. Comparing the items reflecting theoretical constructs across the two datasets, among social bonds items there existed

[7] This was based upon the factor loadings of component items for each of the theoretical perspectives. Factor loadings constituting inclusion following orthogonal factor rotation were, as an initial and low bar, those above 0.10.

significant differences across *Close Family*, *Work History*, *Unstructured Time*, *Military*, and *Angry US*. Additionally, marginally significant differences were observed in the *Student* and *Aspirations* variables. Generally, however, these differences appeared to follow similar distributions and the variances were markedly smaller (see Figure 1 in Appendix B for distributional comparisons of all non-dichotomous items). This pattern was similar among social learning items, with all *Recruiter* variables, *Actively Connect*, *Clique Radicalize*, *Radical Friend*, *Behaviors Trajectory*, and *Beliefs Trajectory* significant differing between pre and post-imputation estimates. Again, while the point estimates changed by an average 21.7% in magnitude, the most notable difference observed following the imputation was a reduction in the standard deviations by 25.15%.

Beginning first with the dependent variable of interest – *Violent*, just over half of the individuals in the dataset (52.8%) were coded as having engaged in some form of violent ideologically motivated behavior. Among the sample, 90% of the individuals were male, with a mean age just over 34 years at the time of exposure. Across ideologies, the modal category ascribed to a Far Right ideology (43.5%), followed by Far Left and Single Issue (20.7% each) and Islamists (15.1%). Notably, these individuals often did not have any reported prior criminal activity (71.49%). This minority with a criminal record were divided across non-violent minor crime (12.97%), non-violent felonies (5.77%), and a previous violent crime (9.78%). In broad strokes moving forward, the following notable patterns emerged when examining the remaining variables of interest – first in social bonds, and then in social learning items.

Table 5: Descriptive Statistics

	Original			Imputed		
Variable Name	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Violent	1473	0.528	0.499	1,473	0.528	0.499
Abuse_Child	1465	0.019	0.137	1,473	0.019	0.137
Close_Family	289	0.799	0.401	1,473	0.933	0.249
Work_History	565	2.501	0.874	1,473	2.764	0.662
Unstructured_Time	546	0.201	0.401	1,473	0.1	0.3
Student	789	0.257	0.437	1,473	0.223	0.417
Military	856	0.231	0.517	1,473	0.16	0.431
Aspirations	153	1.647	1.15	1,473	1.826	1.212
Angry_US	905	0.854	0.353	1,473	0.908	0.29
Radical_Beliefs	1357	4.064	1.468	1,473	4.138	1.432
Group_Membership	1473	1.496	0.829	1,473	1.496	0.829
Recruit_Family	613	0.054	0.226	1,473	0.022	0.148
Recruit_Friend	613	0.069	0.253	1,473	0.029	0.168
Recruit_Member	613	0.109	0.312	1,473	0.045	0.208
Recruit_Other	613	0.064	0.244	1,473	0.027	0.163
Actively_Connect	556	0.55	0.676	1,473	0.277	0.526
Gang	1473	0.064	0.276	1,473	0.064	0.276
Clique_Radicalize	693	0.602	0.757	1,473	0.335	0.635
Radical_Friend	698	2.38	0.837	1,473	2.678	0.683
Beliefs_Trajectory	547	0.296	0.457	1,473	0.158	0.364
Behaviors_Trajectory	588	0.381	0.486	1,473	0.253	0.435
Gender	1473	0.9	0.3	1,473	0.9	0.3
Age	1395	34.182	13.216	1,473	34.204	12.897
Previous_Criminal_Activity	678	1.013	1.129	1,473	0.538	0.975
Radicalization_Far_Right	1473	0.435	0.496	1,473	0.435	0.496
Radicalization_Far_Left	1473	0.207	0.405	1,473	0.207	0.405
Radicalization_Islamist	1473	0.151	0.358	1,473	0.151	0.358
Radicalization_Single_Issue	1473	0.207	0.405	1,473	0.207	0.405

Perhaps surprisingly, in the imputed data, the "average" perpetrator of ideologically motivated behavior does not appear to have experienced, or exhibit many indicators of weak social bonds. In the imputed dataset, only 0.2% of individuals were reported to have experienced abuse as a child and over 93% reportedly had close family relationships. Similarly, the average score for work history of individuals in the dataset was 2.764 – suggesting that most were regularly employed, with few representing the serially-employed, under-employed, and unemployed categories.

This is supported by *Unstructured Time*, which was found only in 10% of individuals. Perhaps begging an explanation of where this time is allocated however, only 22.3% of individuals reported being a student at the time of inclusion in the dataset, and the modal individual had never been in the US military (86.63%) – regardless of timing relative to their radicalization. Turning next to the beliefs and aspirations of the sample, almost all indicated some sense of anger toward the US government (90.8%), and an average score on the radical belief scale was 4.138 – suggesting an overall strong adherence to extremist interpretations of group ideologies. Finally, with respect to the aspirations of these individuals, the modal coding was 3 (38.7%) – suggesting generally speaking these individuals had clear educational or career aspirations, which they had achieved by the time of their public exposure.

Turning next to those items indicative of social learning processes, most individuals in the sample were a member of some form of group or organization (85%), with 27.29% owing membership to an informal group of fellow extremists, and 50.85% being members of a formal extremist organization or movement. Next, there was little indication of the presence of former gang members in the sample, with only 5.57% being reportedly a member of any kind of gang – with most of those being former or current street gang members (4.75%).

Moving on to other specific indicators of group processes, perhaps surprisingly, there was a relatively low incidence of explicit recruitment from family members (2.2%), friends (2.9%), current members of the organization (4.5%), or other individuals (2.7%). Contrastingly, in fully 20.10% of the individuals, there was an active attempt to connect to groups prior to reported radicalization, with 3.8% of individuals actively connecting after their radicalization. As for the radicalization process among intimate groups, or cliques, 24.44% of individuals experienced some part of their pre-exposure time with a clique, with 15.41% exhibiting clique membership after the beginning of their radicalization and the remaining 9.03% being reported as having the beginning of their radicalization coincide with clique membership. Interestingly, individuals in this sample were broadly reported to have close friends who were involved in radical activities (97.71%), with 58.88% being reported to have close friends who engaged in extremist violence. Regarding the pace of radicalization and movement toward ideologically motivated behaviors, the individuals in the sample on whole are generally reported as having had gradual radicalization in both behaviors (56.5%) and beliefs (63.6%) over time, as contrasted with specific key moments driving their radicalization.

Taken together, the sample exhibits indicators of social bonds and some evidence of the social learning of violence or extremist behavior. Naturally, this does not differentiate the prevalence solely among those who ultimately engaged in violent or non-violent ideologically motivated behavior, and thus these relationships are addressed with respect to their ability to predict the outcome of interest below.

Moving next to the relationships among the sets of theoretical items and broadly across the scope of the project, Table 6 shows the Pearson bivariate correlations for the social bonds, and social learning items. Considering first the social bonds items (upper-left quadrant of Table 6), as anticipated, there is a high degree of correlation present - particularly those which are suggested to measure similar constructs. This is most evident in the *Work History* and *Unstructured Time* and variables, however high correlations are present in other item pairs such as between *Unstructured Time* and *Close Family* ($\rho = -0.547$) and *Aspirations* and *Work History* ($\rho = 0.317$) that would not necessarily be directly tied.

Next, in evaluating the social learning items (lower-right quadrant), relationships among variables appear to be less common, however the Clique Radicalize variable retains modest correlations with a number of the recruitment-oriented variables (*Recruit Family*, *Recruit Friend*, *Recruit Member*, *Recruit Other*, and *Actively Connect*). Similarly, the *Beliefs Trajectory* and *Behaviors Trajectory* variables exhibit a strong correlation ($\rho = 0.487$). Finally, as the control and learning items relate to each other (lower-left), there do not appear to be any relationships with a magnitude in excess of $\rho = 0.244$ (*Behaviors Trajectory* and *Radical Beliefs*). Indeed with the exception of this pairing, relationships between control and learning items are generally below $\rho = 0.150$ in magnitude.

The presence of high correlations within theoretical item sets, while promising in a confirmatory sense for the proposed theoretical relationships, are analytically concerning. Termed multicollinearity, this concern is manifest when multiple items that co-vary with one another are used to predict an outcome variable. More mechanically, the variation in co-varying regressors is divided across the items, and thus standard errors are upwardly biased – artificially increasing the probability of Type II error. To account for the probability of itemized predictions experiencing multicollinearity in the context of regressions, I perform diagnostic iterative removal and addition of highly correlated predictors, monitoring the standard errors most likely to be suffering from Type-II error. Importantly for the primary method applied here, using a factor analysis approach takes advantage of the extant covariation among variables, and instead of significant relationships being obfuscated by multicollinearity, latent factors (manifest by the covariation) serve as items which can collectively predict the outcome of interest.

Logistic Regression Models

This study conducted logistic regression in two stages to test its hypotheses. The first stage of analysis examined the relationships between theoretical items and the *Violent* outcome (Models 1, 2, and 3 in Table 7), while the second stage evaluated these relationships and substitutes the factor loadings for the individual items (Models 4, 5, 6, and 7 in Table 8). The following analyses are organized by stage (itemized and factor) and by the specific hypothesis being addressed.

Table 6: Bivariate Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1) Violent	1.000																				
2) Abuse_Child	0.042	1.000																			
3) Close_Family	-0.094	**-0.242**	1.000																		
4) Work_History	-0.106	**-0.251**	0.415	1.000																	
5) Unstructured_Time	0.079	**0.219**	-0.547	-0.545	1.000																
6) Student	-0.052	-0.015	0.045	-0.019	0.012	1.000															
7) Military	0.038	-0.005	-0.104	-0.073	0.129	-0.096	1.000														
8) Aspirations	-0.093	-0.095	0.196	0.317	-0.186	**-0.263**	-0.018	1.000													
9) Angry_US	-0.006	-0.110	0.047	0.039	-0.035	0.025	0.026	0.043	1.000												
10) Radical_Beliefs	0.045	-0.003	-0.045	-0.034	-0.015	0.006	0.026	-0.139	-0.032	1.000											
11) Group_Membership	-0.147	-0.059	0.058	0.051	-0.120	0.055	-0.067	0.026	-0.019	0.125	1.000										
12) Recruit_Family	0.005	0.046	-0.015	-0.036	-0.005	0.051	-0.024	0.094	-0.031	0.037	0.048	1.000									
13) Recruit_Friend	0.002	-0.024	-0.067	-0.103	0.010	0.014	-0.017	-0.108	-0.112	0.014	0.013	0.028	1.000								
14) Recruit_Member	0.056	0.017	-0.073	-0.109	0.058	0.047	-0.020	-0.125	-0.054	-0.085	0.050	0.011	0.020	1.000							
15) Recruit_Other	0.024	-0.023	0.028	0.009	0.014	0.061	0.016	-0.066	-0.004	-0.077	0.041	-0.025	-0.004	-0.037	1.000						
16) Actively_Connect	-0.027	0.031	-0.113	-0.115	0.014	0.139	0.045	-0.003	-0.024	0.117	0.121	-0.001	0.062	0.077	0.039	1.000					
17) Gang	0.130	0.058	-0.086	-0.026	0.022	-0.047	-0.034	0.009	-0.020	-0.017	0.031	-0.002	-0.011	0.020	-0.008	-0.010	1.000				
18) Clique_Radicalize	0.078	-0.026	-0.035	-0.037	-0.015	0.082	-0.039	-0.027	0.028	-0.066	0.020	0.086	**0.239**	**0.208**	**0.247**	**0.231**	0.022	1.000			
19) Radical_Friend	0.032	-0.124	0.034	0.026	-0.135	-0.126	-0.035	-0.089	-0.041	0.039	-0.002	0.004	-0.019	-0.031	-0.019	-0.158	-0.024	-0.055	1.000		
20) Beliefs_Trajectory	0.039	0.117	-0.064	-0.077	0.043	-0.066	0.086	0.064	0.003	-0.147	-0.121	0.023	0.069	0.022	0.054	0.056	0.015	0.039	-0.058	1.000	
21) Behaviors_Trajectory	0.033	0.045	-0.039	-0.062	0.031	-0.068	0.093	0.052	0.040	**-0.244**	-0.129	-0.014	0.085	0.068	0.057	0.024	0.013	0.161	0.002	0.487	1.000

Note: Item pairs where $|\rho| > 0.20$ are bolded and items above $|\rho| > 0.4$ are underlined.

Stage 1: Itemized Theoretical Models

Hypothesis 1: Social Bonds and Violent Extremism are Negatively Related

Table 7 displays the logistic regression results for the itemized theoretical predictors of a violent extremist behavioral outcome. Absent controls of social learning variables, only one of the social bonds items was significantly associated with the violent behavior (see Model 1). Specifically, holding all else constant, a one-unit increase on the ordinal *Radical Beliefs* measure was associated with a 0.093 increase in the probability of violent ideologically motivated behavior. This is in line with hypothesis 1, as higher values of the *Radical Beliefs* measure, as addressed above, are suggestive of a weaker bond of belief in conventional norms.

Considering Model 3, when controlling for social learning items, indicators of social bonds were collectively found to be more predictive of the outcome than taken in isolation. The *Work History* variable became marginally significant and negative, and the coefficient of the *Radical Beliefs* measure remained positive and increased in magnitude. More directly, consistent with the tenets of social bonding theory, individuals with a more stable work history were marginally less likely to engage in a violent ideologically motivated behavior and individuals with more entrenched and firmly held radicalized beliefs were more likely to engage in violent acts. Of note, in both Models 1 and 3, as predicted in above there was evidence of possible Type-II error – with standard errors for the *Work History* and *Aspirations* items being inflated due to co-variation across theoretical predictors.

Hypothesis 2: Social Learning of Violence and Violent Extremist Behaviors are Positively Related

Turning attention to Hypothesis 2, Table 7 again shows the logistic regression results for the itemized estimation of the probability of violent outcomes. Without accounting for the social bonds items, four of the social learning variables were statistically significantly related to the outcome. First, when controlling for all else, the *Group Membership* variable was significantly negatively related to the violent outcome. This is in stark contrast to the hypothesized relationship of a strongly positively association between the two. Perhaps less surprisingly, when controlling for all else, there was a significant positive relationship between the *Gang* and *Clique Radicalize* variables and the outcome, and a marginally significant relationship between the *Radical Friend* variable and probability of violent extremist behavior.

When accounting for the presence of social bonds items in Model 3, these findings remain relatively stable. As in Model 2, *Group Membership* was found to be significantly negatively related to the *Violent* outcome. Similarly, the *Gang* and *Clique Radicalize* variables remained significantly positively associated with the violent outcome. Notably, the *Gang* variable was estimated to be the largest in magnitude in Model 3. The *Radical Friend* variable, however, was no longer marginally significant, with both the magnitude of the coefficient decreasing and the robust standard error increasing. On the whole, Model 3 suggests that some social learning factors relate to whether or not an individual comes to engage in violent extremist behavior. Like in the case of the social bonds variables, there was evidence of multicollinearity inflating the estimated standard errors of the measures in Models 2 and 3. This was particularly the case for the *Behaviors* and *Beliefs Trajectory* items, though diagnostics suggest that the inflation unlikely results in Type-II error. Accounting for the evidence of potential multicollinearity in both hypotheses, I proceed to the factor models.

Table 7: Logistic Regression Models

Variable Name	Model 1		Model 2		Model 3	
	$\hat{\beta}$	Std. Err.	$\hat{\beta}$	Std. Err.	$\hat{\beta}$	Std. Err.
Abuse Child	0.077	0.421			-0.012	0.436
Close Family	-0.064	0.248			-0.071	0.259
Work History	-0.119	0.092			-0.159†	0.095
Unstructured Time	0.217	0.208			0.154	0.217
Student	-0.184	0.149			-0.134	0.154
Military	0.027	0.144			0.034	0.150
Aspirations	-0.076	0.057			-0.058	0.062
Angry US	0.118	0.184			0.070	0.189
Radical Beliefs	0.093*	0.037			0.138**	0.041
Group Membership			-0.295**	0.065	-0.292**	0.069
Recruit Family			0.211	0.371	0.197	0.375
Recruit Friend			-0.130	0.344	-0.295	0.348
Recruit Member			0.452	0.294	0.449	0.307
Recruit Other			0.222	0.352	0.267	0.359
Actively Connect			-0.070	0.111	-0.140	0.115
Gang			0.852**	0.283	0.876**	0.281
Clique Radicalize			0.220*	0.100	0.260**	0.101
Radical Friend			0.121†	0.064	0.113	0.077
Beliefs Trajectory			0.116	0.181	0.138	0.184
Behaviors Trajectory			-0.003	0.151	0.072	0.160
Male	0.348 †	0.186	0.344*	0.170	0.325†	0.193
Age	-0.013*	0.005	-0.012**	0.004	-0.011†	0.006
Previous Criminal Activity	0.250**	0.061	0.243**	0.061	0.199**	0.063
Radicalization Far Right	0.509**	0.144	0.375**	0.144	0.383**	0.148
Radicalization Far Left	-0.557**	0.172	-0.515**	0.163	-0.527**	0.176
Radicalization Islamist	0.296 †	0.176	0.046	0.186	0.074	0.191

Note: Robust standard errors used. † indicates $p<0.10$, * indicates $p<0.05$, ** indicates $p<0.01$

Stage 2: Factor Analysis Models

Hypothesis 1: Social Bonds and Violent Extremist Behaviors are Negatively Related

Presented in Table 8, the factor analysis models give a second examination of the relationship between social bonds and violent behaviors – accounting for multicollinearity in measures. Taken in isolation, in Model 4, the latent control factor loading produced for each individual (*ControlFactor*) was found to be significantly negatively related with the probability of a violent behavioral outcome.[8]

Next, Model 6 demonstrates the relationship of the social bonds composite factor when controlling for the presence of learning factors. Specifically, when controlling for all else in the model, the ControlFactor remains significantly negatively associated with the violent behavioral outcome, thus individuals having higher values on this factor were less likely to engage in the violent ideologically motivated behavior. This model did not, however, account for all previously significant relationships with the outcome of interest. For this, we move on to Model 7.

Neither Model 4, nor Model 6 accounted well for the observed relationship between the *Radical Beliefs* measure and the *Violent* outcome (as observed in Models 1 and 3) due to the factor loadings. Accordingly, this, and the Social Learning significant predictor counterpart of gang membership (*Gang*), was included in Model 7. In Model 7, the control factor variable remains relatively unchanged, staying significantly negatively associated with the violent outcome. Indeed, the robust standard error from model-to-model was nearly identical across models 4, 6, and 7 and the magnitude of the coefficient decreased by less than 10%, suggesting a fairly stable relationship. Furthermore, the radical beliefs item, when re-introduced to the

[8] This factor was based largely on the control items *Abuse Child*, *Close Family*, *Work History*, *Unstructured Time*, and *Aspirations*, which loaded onto the first factor with a magnitude greater than 0.100.

model was found to be statistically significant and positively related with the violent outcome, much as before.

<u>Hypothesis 2:</u> Social Learning of Violence and Violent Extremist Behaviors are Positively Related

In evaluating the factor models for Hypothesis 2, as discussed above the social learning items loaded best onto two separate factors (*LearningTrajectory* and *EngagementProcess*).[9] In Table 8, the logistic regression models show the relationship between these factors and the probability of a violent outcome. Model 5 indicates that *LearningTrajectory* was found to be significantly positively related to the probability of violent ideologically motivated behavior. Curiously, *EngagementProcess*, which included the previously significant item of *Clique Radicalize*, was not found to be significant in either direction.

Moving next to Model 6, when controlling for social bonds factors, *LearningTrajectory* remained significant, with only a slight decrease in the magnitude of the coefficient. As in Model 5, *EngagementProcess* was not found to be significant, and indeed the coefficient decreased in magnitude. Of note, the *Gang* variable, which had previously been significantly positively related to the violent outcome did not load heavily onto either learning factor. Accordingly, when Model 7, included this item individually. In Model 7, as with models 5 and 6, when controlling for all else, *LearningTrajectory* was found to be significant and positively related to the violent outcome. Like before, *EngagementProcess* was not significant in either

[9] When orthogonal rotation was performed, *LearningTrajectory* was based primarily on *Beliefs Trajectory* and *Behaviors Trajectory*, while *EngagementProcess* was based upon *Recruit Friend*, *Recruit Member*, *Recruit Other*, *Actively Connect*, and *Clique Radicalize*. As with the control items, items with a loading with a magnitude over 0.100 were considered substantially contributing.

direction, with the magnitude of the coefficient dropping yet again. Lending more support to the learning argument however, the *Gang* item was significantly and positively related to the violent outcome – again with the highest magnitude in the model.

Table 8: Factor Analysis Models

Variable Name	**Model 4**		**Model 5**		**Model 6**		**Model 7**	
	$\hat{\beta}$	**Std Err.**	$\hat{\beta}$	**Std Err.**	$\hat{\beta}$	**Std Err.**	$\hat{\beta}$	**Std Err.**
ControlFactor	-0.248**	0.072			-0.240**	0.073	-0.227**	0.074
LearnFactor1			0.170*	0.078	0.156*	0.078	0.083*	0.035
LearnFactor2			0.063	0.087	0.057	0.087	0.196	0.081
Radical Beliefs							0.037*	0.088
Gang							0.775**	0.275
Age	-0.013**	0.004	-0.014**	0.004	-0.012**	0.004	-0.015**	0.004
Male	0.324*	0.142	0.343*	0.142	0.328*	0.142	0.123	0.157
Previous Criminal History	0.253**	0.060	0.288**	0.060	0.249**	0.061	0.219**	0.062
Radicalization Far Left	-0.602**	0.150	-0.572**	0.152	-0.606**	0.152	-0.713**	0.159
Radicalization Far Right	0.489**	0.139	0.508**	0.140	0.490**	0.140	0.407**	0.142
Radicalization Islamist	0.217	0.170	0.185	0.176	0.145	0.177	0.104	0.178

Note: Robust standard errors used. † indicates p<0.10, * indicates p<0.05, ** indicates p<0.01

The Influence of Control Variables

Overall, the control variables included in the analysis showed a comparably robust relationship with the dependent variable. Taken in turn below, *Male*, *Age*, *Previous Criminal Activity*, and the Radicalization Ideological Milieu will be discussed.

One of the most commonly cited concerns in the criminological literature, and indeed one of the most persistent predictors of crime, gender was expected to be positively associated with violent ideologically motivated behavior. In the present analysis, this relationship is exhibited, though with mixed results, with four of seven models showing a significant relationship. In Models 2, 4, 5, and 6, there is, as expected, a positive and significant relationship between being male and the probability of engaging in violent extremist behaviors. Across these models, the coefficient remains relatively stable around 0.340. In Models 1 and 3 however, being male is only marginally significantly associated with an increased probability of engaging in violent ideologically motivated behaviors. Further, in the final of the seven models, the gender variable becomes not significant, with the point estimate having dropped precipitously to 0.123 solely by including the previously significant items of *Radical Beliefs* and *Gangs*. In the present models overall, there exists mixed support for the notion of maleness being related to violent outcomes, even when controlling for theoretical constructs.

Contrasted with the gender variable, the *Age* variable was anticipated to be negatively related to the outcome, and found strong support in the present models. In all but one of the models presented (Model 3), there was found to be a statistically significant and negative relationship between the age of the perpetrator at the time of exposure and the probability of having engaged in a violent offense, when controlling for all else.

Third, the *Previous Criminal History* ordinal measure was expected, perhaps understandably, to have a positive relationship with the outcome of interest. Not surprisingly, higher values on this measure were found to be significantly and positively related to the probability of violent ideologically-motivated behavior.[10]

[10] In all seven models, previous criminal history was significant at a p-value of less than 0.01.

Finally, the dichotomous items included for the various ideological milieu (Far Left, Far Right, and Islamist) found some support in distinguishing the probability of engaging in violent ideologically motivated behaviors. Perhaps most importantly to note, these are all in reference to the omitted category of *Radicalization Single Issue*. In all models, compared to individuals identified as adhering to a *"Single Issue"* ideology, those identified as radicalizing to a *Far Left* ideology variable were less likely to engage in of violent behavior, whereas those *Far Right* ideologies were more likely to engage in violent behaviors. Perhaps most intriguingly, there was no observed significant relationship between espousing an *Islamist* ideology and engaging in violent or non-violent offenses, when compared with *Single Issue* individuals. While not the focus of this study, these models were also estimated based upon the other potential reference categories (Far Right, Far Left, and Islamist), see Tables 9-14 (in Appendix B) for the results of these various estimations. Taken together, these figures show that Far Right inspired individuals are the most likely to be violent, followed by Islamists and Single Issue inspired actors (with no significant difference between these probabilities), followed by Far Left inspired individuals who are least likely to be violent.

Summary of Results

Overall, the above results indicate weak support for the first hypothesis and modest support for the second hypothesis – however these findings appear robust to the inclusion of identified covariates as in Model 7. These findings are generally consistent when looking across ideologies – however the variation in coefficients across ideology bears further scrutiny.

Chapter 5: Discussion

The above analyses are an important first step in understanding the relationship between established theoretical constructs in Criminology and ideologically motivated violent behavior. While the methods used fall short in establishing causal identification between the theoretical predictors and the outcome, the results strongly suggest that both social bonds and social learning can provide insight into which radicalized individuals turn violent. This is one of the first studies to examine these theoretical relationships within terrorism research using quantitative data. In doing so, it offers theoretical, practical, and policy contributions. Each contribution is addressed in more depth below, followed by an accounting of the research limitations. I conclude with a brief summary and directions for future research.

Theoretical Contribution

This thesis lends support to the application criminological theory to explaining violent and non-violent extremist behavior, namely with social bonds and social learning theories. Often, proponents of social bonds and social learning claim that each theory can explain away the influence of the other. In the results presented above however, both theories remained significant predictors of violent ideologically motivated behavior despite the inclusion of the other predictors. Of note, this could represent the presence of both control and learning processes at work, as suggested by Interactional (Thornberry, 1987). In Interactional Theory, the reciprocity of social bonds and social learning would suggest that both forces should be observed to have a relationship with criminal offending, and indeed in the present analyses this is the case. In light of this, I propose that as demonstrated here, Interactional Theory should be considered as an integrated approach to understanding violent and non-violent ideologically motivated behavior among radicalized individuals. To best understand the fit of Interactional Theory however, the granularity of data presented here remains too coarse. Indeed, as discussed in Thornberry (1987) the use of richly detailed, longitudinal data is necessary assess the time-ordered propositions in the theory. Finally, this thesis successfully extends the principles of social bonds and social learning theory to later stages in the life-course and also to the decision to engage in violence by already radicalized individuals.

Practical Contributions

Next, this thesis lends to three principal practical contributions in the study of ideologically motivated behavior, namely serving as an example of the careful use of open-source data, the application of the MICE procedure to the PIRUS data, and the use of the Exploratory Factor Analysis method – addressed in turn below.

The Use of PIRUS in Studying Extremist Behavior

In a world of ideal measurement, looking at the decision among radicalized individuals to engage in violent behaviors would begin with the population of radicalized individuals in the United States who have engaged in either violent or non-violent ideologically motivated behavior. This group would then be interviewed, assessing relevant sociological, psychological, community, geographic, and demographic information using a life history calendar (Caspi & Amell, 1994; Horney, Osgood, & Marshall, 1995). Next, these individuals would be followed prospectively, with repeated interviews occurring at six-month periods, coding the same attributes over time with a life-history calendar. Further, to ensure the veracity of these interview data, observations would be corroborated between the provided self-reports with peer or family reports, workplace reports, and any official administrative records. This would ensure the accuracy and completeness of these data, and allow for bystander impressions to inform theoretical measurements. Practically, this would be a titanic undertaking, costing millions of dollars and years of data collection before any findings could be assessed.

While such a retrospective-prospective dataset may be the best strategy to assess ideologically motivated behavior, PIRUS has many similar characteristics for a fraction of the cost and absent many of the potential logistical concerns. Due to the comprehensiveness of news coverage in the United States and the salience of extremist acts as a topic of journalism, the PIRUS sampling, driven by open-source collection of names and extremist acts approximates a population of these radicalized individuals. Similarly, the corroboration of news sources and the systematic coding of cases serves as a transparent and well-accounted for set of attributes on individuals in the dataset. In fact, in the area of community and geographic information, where PIRUS stands well in the shadow of these idealized retrospective and prospective data, investigators have recently begun appending all extant cases and an expanded set with such information for future use. Thus, despite the noted areas in which the data are limited, the PIRUS dataset remains a promising source of insight for exploring ideologically motivated behavior in the United States.

Application of MICE to PIRUS and High-Missingness Imputation

Often, the presence of missing observations or values in datasets is a concerning for researchers, limiting the number of observations upon which analyses can be run or biasing results in unpredictable ways. In the face of large amounts of missing data, this thesis outlines a detailed approach to accounting for this concern, and allows for the rich dataset to inform the analysis on all individuals in the sample. Contrasted with naïve treatments of these data based upon a missing completely at random (MCAR) assumption, the application of MICE allows for an assessment of the PIRUS data under the more plausible MAR assumption. As discussed above, the MAR depends upon conditionally random missingness of observations or values. While to date there exist no formal tests to ascertain if missingness is conditionally random, the wealth of covariates used in the prediction of missing values as applied in the MICE procedure here gives strong footing for the defense of this assumption, and stands in stark contrast to the simple mean-imputation or by-subgroup mean-imputation procedure which has been suggested elsewhere (Graham et al., 2003).

Beyond the assumptions incumbent to the MICE procedure, the broader idea of imputing large portions of data often raises concern – with good reason. Typically, heuristics for missing data suggest simply omitting variables with over a certain proportion missing, as the already-crucial importance of missingness assumptions increases exponentially with the proportion of values missing. This thesis has demonstrated that even in the case of over 80% missingness on certain theoretical variables, stable values can be efficiently imputed when a substantial quantity of multivariate imputation datasets are generated (100 datasets here). Broadening the scope of this lesson to the application of imputation techniques in Criminology, a transparent application of the procedures and limitations should allow for the best use of large and incomplete (and open-source) datasets such as PIRUS and others.

Factor Analysis and Theoretical Scales in PIRUS

In considering the contribution of this project beyond support for the hypotheses, the novel application of Exploratory Factor Analysis to these data merits an independent discussion. Previously, studies examining the PIRUS data have largely explored the itemized contributions of predictors in a regression context (Jasko, LaFree, & Kruglanski, 2017; Jensen & LaFree, 2016; Safer-Lichtenstein et al., 2017). As demonstrated above, itemized predictions – particularly those which may co-vary for theoretical or practical purposes – are observed to afflict models with multicollinearity, increasing the probability of a type-II error. While the application of an itemized logistic regression to these data would have uncovered some support for the hypotheses, the correlation among predictors (see Table 6) masked the explanatory power of the theoretical sets. Coopting this property of the data as an analytic boon however, the application of EFA in this study found robust relationships in predicting the probability of a violent outcome across the methods applied.

It is interesting to note that when applying the EFA method to the social bonds and social learning variables a one-factor and two-factor solution (respectively) emerged. As the Hirschi's theory of social bonds would typically suggest the presence of four distinct sets of bonds (Hirschi, 1969), the presence of only one factor does not lend strong support to this notion. Indeed, others evaluating social bonds have found a similar disparity in the number of bonds predicted and the latent factors

(Agnew, 1985). Although this disparity is somewhat discouraging, in the present context, the social control factor was largely driven by the *Close Family* variable and *Work History* variable – two indicators of largely distinct types of bonds. This suggests that although the factor analysis procedure was only able to detect the presence of a single latent factor for social bonds, the bind within the factor does seem to be theoretically consistent.

Turning next to the Social Learning Theory factors, while the expectation of a four-factor solution should be mitigated due to the theoretical confluence of constructs as learning progresses, the theory would still likely suggest some distinct loading patterns to be present (Akers, 1998). Accordingly, it is remains encouraging to see two fairly distinct factors emerge, with one accounting primarily for the learning trajectory (driven by beliefs and behaviors trajectories), and the other accounting for the engagement process itself – from recruitment to association with those seeking involvement in extremist organizations. Of note, absent a factor analysis approach such as was applied here, both the precision and efficiency of revealing these relationships would have been sacrificed needlessly.

Policy Implications

In considering the policy implications for this thesis, while cautioning as to the specific role that learning and social bonds may have on the probability of violent behavior, it is clear that both seem to matter. Thus, when examining the role that de-radicalization programs may have on encouraging the desistance of individuals engaged with extremist ideologies, attention should be paid to 1) encouraging prosocial relationships and outcomes, and 2) limiting access to those who would promote violent behaviors.

Stronger social bonds to conventional society, as discussed in Hirschi (1969) and operationalized here, appear to be associated with a reduced probability of engaging in various forms of offending (including ideologically motivated extremist behavior). Accordingly, promoting the development of these bonds in vulnerable communities through educational initiatives and procedural justice in policing and official actions may build resistance to ideologically motivated violence. Similarly, helping to reestablish these bonds among those who already espouse extremist ideologies may contribute positively to the reduction of violent behaviors. Contrastingly, the learning processes addressed by Akers (1998) and operationalized here are associated with an increased probability of violent behavioral outcomes. Thus, promoting the learning of non-violent (and non-criminal) means of effecting political change should be considered within the scope of de-radicalization efforts and building resistance to vulnerable communities – ultimately substituting the learning processes of violence for those which may produce similar political outcomes absent the loss of life or property.

Limitations

There are several limitations to this thesis, largely driven by the data available for analysis. As the findings presented relate to the impact that proposed learning and control mechanisms may have on the probability of violent or non-violent ideologically motivated behavior, the match between theoretical constructs and the items used to measure them is relatively weak. Since both Hirschi's social bonds and

Akers' social learning theory both have established scales for measurement, the use of weak proxies, albeit by necessity, bears a critical consideration (Akers, 1998; Hirschi, 1969). In the case of the attachment, for example, the most proximate measures were an affirmative dichotomous assertion that the individual had a close relationship with their family and the absence of physical, emotional, or sexual abuse. Naturally, this does not capture the full dimension of an affective relationship between the individual and prosocial intimate others.

Similarly, the absence of perceptual measures and self-report by these radicalized individuals distinguishes these findings from prior theoretical manifestations of these constructs. Indeed, without knowing how an individual valued a given "radical friend", or the relationship one had with their "clique", it is difficult to consider the impact that these sources would have had on their decision to engage in violent or non-violent behavior. Fortunately, these relationships, as crude measures, should be seen globally as producing a minimum impact on later offending decisions, and thus the coefficients addressed above should be treated as downwardly biased. In short, the impact of these theoretical constructs on predicting violent ideologically motivated behavior may be higher than presented here.

Considering next the methodological and analytical limitations of this project, as highlighted above, the use of open-source data on violent extremism necessarily focuses on what news media and other official outlets believe to be pertinent in terms of events and details. Accordingly, the most frequently available data on those individuals included in the analysis will likely be related to the extremist acts, or when details are particularly shocking in light of the potential violent outcome.

Similarly, before the advent of mass media on the internet, the availability and veracity of sources is limited, likely biasing conclusion about these processes and individuals to those who were active in more recent years. Further, the non-random nature of the sample used in the PIRUS data restricts conclusions that can be made about violent extremism generally. Indeed, as highlighted above, any findings from this thesis should not be generalized beyond individuals who have already radicalized in the United States and have been identified as having engaged in some form of detected, ideologically motivated behavior. Broadly, a well-defined and theoretically appropriate "control group" for making more general conclusions is absent in much of the current terrorism research (Jensen & LaFree, 2016). In this thesis, the analytical comparisons contrast radicalized persons who all have broken the law or are members of a terrorist organization. This ignores the early stages of engagement with extremist ideologies where illegal behavior is not yet present. Thus, this thesis does not represent a test of the theories used, as theoretical predictions are often restricted to predicting if crime would occur, rather than the severity of criminality. Bearing this caution in mind however, these data are the first of this kind to obtain such granular level data on a radicalized set of individuals. Indeed, the ability to earnestly examine the factors that may precede violent extremism, and the ability to explore theoretical explanations for this problem – as is done here – is a substantial step forward in the field and in producing solutions.

Further, it should be noted that some of the coding decisions in the PIRUS database are founded upon assumptions that bear further scrutiny. Specifically, in certain codes (e.g. *Gang*, and *Abuse Child*), coders were instructed to code the absence of information as an attribute not being present, rather than an indication of missing information on that attribute. For example, unless there was affirmative evidence that an individual was a member of a gang, the individual was coded as a zero for *Gang* or that they were not a member. This may be a reasonable assumption in certain cases with a wealth of information that would support a negative coding of the *Gang* attribute, however because the quality of reporting varies across cases, we cannot know how many of these zeros are truly ones. As suggested above, this measurement error can produce bias in the form imputed values and coefficient estimates. Considering first the impact on the imputation procedure, when using MICE, the accuracy of imputed values is necessarily a function of the accurate coding of the predictor variables. Since the *Gang* variable (among others) is likely biased toward reporting non-membership (or toward zero), the imputation of values for incomplete variables will experience imputation error. This may increase the variability in the estimates for those coded as non-gang, and artificially increase the precision of those coded as gang members (as with the other variables). Encouragingly however, in other analyses of these data, researchers using similar logistic regression models and varying methods of accounting for the missing data produced convergent estimates of the predictors on the *Violent* outcome (Jasko et al., 2017; Safer-Lichtenstein et al., 2017).

Next, regarding the measurement error, the coefficient estimates reported in the logistic regression models for the *Gang*, *Abuse Child*, and *Abuse Adult* should be taken with caution since it is likely that the information which would be confirmatory of these variables would be differentially available depending on the nature of the individual's behavior. Due to journalistic bias toward more thorough reporting on dramatic cases, when a violent act was performed it is more likely that the coded value reflects the true value of that attribute. Alternatively, when non-violent actions were undertaken, there would be less focus on antecedent traits and relationships for the accused. Thus, when a non-violent act was undertaken, the individual is more likely, regardless of their actual gang membership or childhood abuse, to be coded as not being a member or abused – even when it may be the case. Accordingly, the estimates reported are likely inflated due this coding convention. However, due to the observed magnitude of the *Gang* variable, it is likely that the significance of this relationship would remain intact.

Finally, the analyses applied in this project are limited in their capacity to form causal identification or fully explore the nuance of these relationships. In order to understand the potential interactions between learning, social bonds, and violent behavior, longitudinal models capable of accounting for reciprocal causality, time lags, selection, and endogenous forces would be necessary, along with the requisite longitudinal and representative data. Ultimately however, the goal of this project was to assess the presence of relationships between the theoretical constructs and the probability of violent behavior among radicalized individuals in the United States. To this end, the application of logistic regression on the extracted factor loadings, non-loading covariates, and statistical controls succeeded.

Summary and Directions for Future Research

As anticipated, I found a relationship between both learning and control constructs and violent extremism. Thus, there appears to be support for the contention that criminological explanations of behavior can, and perhaps ought to be applied to terrorism as a parallel field of study. Further, open-source data can continue to provide a meaningful first step to examining this phenomenon. As access to individuals who engage in non-violent and violent extremist behaviors remains exceptionally limited, we can appreciate the capacity of open-source evidence to examine these and other relationships of interest. Overall, the findings herein inform future inquiry into the processes observed in violent extremism and provide a methodological contribution toward the handling of missing data experience more in the study of terrorism and responses to terrorism and violent extremism more broadly.

Future research on this topic should explore three primary avenues. First, authors should continue to capitalize on the PIRUS data – examining the capacity of other criminological theories to explain ideologically motivated behavior. Second, while often computationally demanding, the use of advanced imputation and analytic techniques should continue to be considered in applying quantitative methods to terrorism research. Finally, quantitative analysis should be supplemented with a qualitative examination of the lived experiences of radicalized individuals through primary data collection or the assessment of narrative life histories of radicalized and individuals could shed light on the perceived importance of various theoretical mechanisms at work. With such information, researchers could better understand the line in the sand of violence in pursuit of ideologically motivated goals.

Appendix A: PIRUS Source List

Source Name
National Consortium for the Study of Terrorism and Responses to Terrorism Global Terrorism Database
Southern Poverty Law Center (SPLC) Intelligence Reports
Animal Liberation Front Website
No Compromise Website
Bite Back Website
Animal Liberation Press Office
The Guardian
Komo News
United States of America Department of Justice Press Releases
Daily Mail Website
Green is the New Red Website
Animal Liberation Front Supporters Group Website
North American Animal Liberation Press Office Website
The Associated Press Website
States News Service
News Wire
The Globe and Mail (Canada)
The Christian Science Monitor
The Washington Times
The New York Times
The Washington Post
USA Today
Toronto Star
Highbeam
United States District Court Eastern District of California
The Sunday Times (London)
Anti-Defamation League
The Observer
United States Federal Bureau of Investigation Website
United States Senate Hearing Statements
United States Senate Committee on Environment and Public Works Hearing Statements
The Independent
United States Court of Appeals of California, Fourth Appellate District
The Philadelphia Inquirer
Western Daily Press
The Times (London)
The Financial Times (London)
The Daily Telegraph

Agence France Presse
Builder
Sunday Herald
US District Court for Western District of Wisconsin
US District Court for Western District of Michigan
The Evening Standard
The Express
The News of the World
US Federal News
The Seattle Times
St. Petersburg Times
The Mirror
The Gazette
PR Newswire
Salon.com
The Scotsman
Automotive News
The Irish Times
Adweek
The Australian
San Mateo County Times
San Jose Mercury News
Alameda Times Star
Contra Costa Times
Reuters
Federal Document Clearing House
Seattle Weekly
Wall Street Journal
Newsweek
Washington State Government
United States District Court Western District of Washington at Seattle
The General Assembly Pennsylvania
Daily Star
United Press International
The Dallas Morning News
De Standard
Birmingham Post
Deseret Morning News
Deutsche Press Agentur
University Wire
US Court of Appeals for the Ninth Circuit
Court of Criminal Appeals of Tennessee

Het Finanieele Dagblad
Canberra Times
Arkansas Democrat – Gazette
Salon Media Group
National Post
Joint inquiry into intelligence community activities before and after the terrorist attacks of September 11, 2001
Leaving Guantanamo: Policies, pressures, and detainees returning to the fight
America’s culture of terrorism: Violence, capitalism, and the written word
Right-Wing Violence in North America
Women and Organized Radical Terrorism in the United States
Radical violence in the United States
Responding to terrorism victims: Oklahoma City and beyond
Right-wing resurgence : how a domestic terrorist threat is being ignored
Prison radicalization : are terrorist cells forming in U.S. cell blocks? : hearing before the Committee on Homeland Security and Governmental Affairs, United States Senate, One Hundred Ninth Congress
Compilation of hearings on Islamist radicalization. : Vol. I hearings before the Committee on Homeland Security, House of Representatives, One Hundred Twelfth Congress, first session, March 10, June 15, and July 27, 2011.
The spectacular few : prisoner radicalization and the evolving terrorist threat
Why youth join al-Qaeda
Hate groups in America: a record of bigotry and violence
Terrorism Since 9/11: The American Cases
Bringing the War Home
Terrorism in the United States (Counterterrorism Threat Assessment and Warning Unit, National Security Division) 1996-1998
American extremists: militias, supremacists, klansmen, communists & others
FALN: Threat to America
A Force Upon The Plan: The American Milita Movement and the Politics of Hate
The Anti-Abortion Movement and the Rise of the Religious Right
Terror in the Night: The Klan's Campaign Against the Jews
Terrorism in America: Pipe Bombs and Pipe Dreams
Cuban Exile Website
Slate News
The Militia Threat: Terrorist Among Us
ProChoice.org Website
Freakoutnation.com Website
Southernstudies.org Website
WomensENews.org Website
Indy Week website
MH/CHAOS: The CIA’s Campaign Against the Radical New Left and the Black Panthers
Guys and Guns Amok: Domestic Terrorism and School Shootings from the Oklahoma

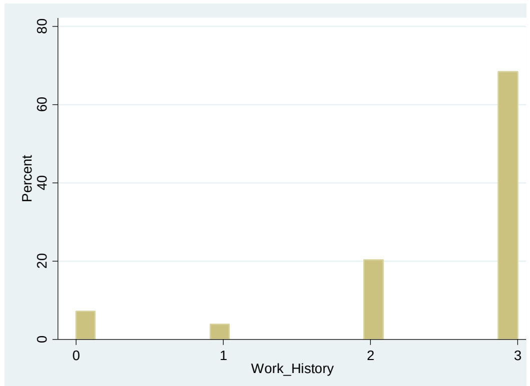
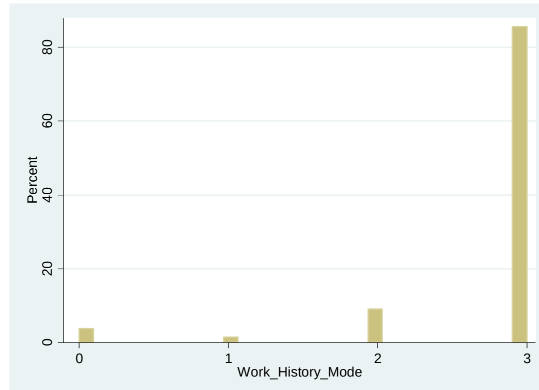
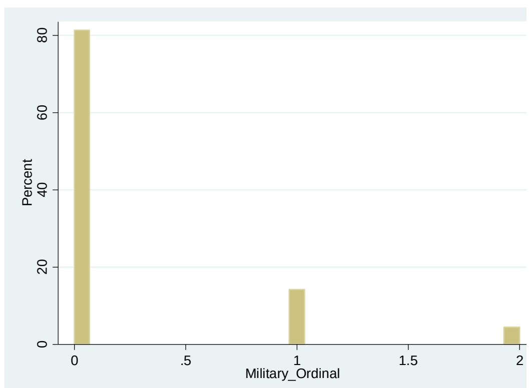
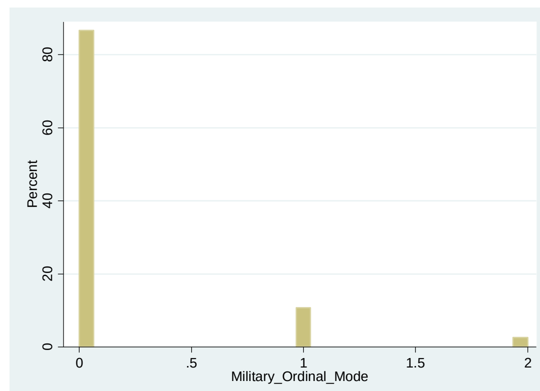
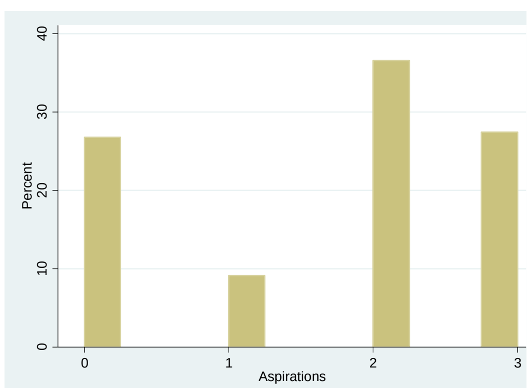
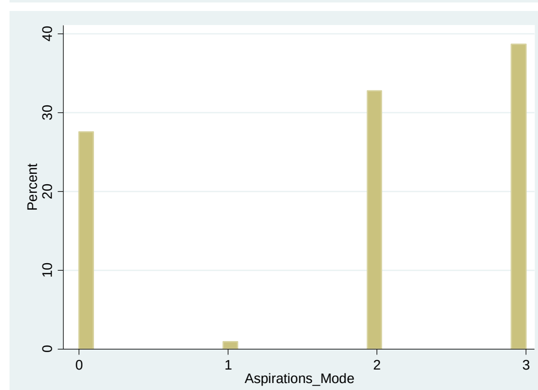
City Bombing to the Virginia Tech Massacre
"All-American Monster" The Unauthorized Biography of Timothy McVeigh
The Ku Klux Klan; an encyclopedia
Encyclopedia of White Power: a Sourcebook on the Radical Racist Right
Religion and the Racist Right: The Origins of the Christian Identity Movement
Contemporary Voices of White Nationalism in America
Tabernacle of Hate: Seduction into Right-Wing Extremism
My Awakening
Who Was Who in America, with World Notables, v. 10: 1989-1993
Public Broadcasting Station
Let My People Go!: The Miracle of the Montgomery Bus Boycott
Time Magazine
Sixties Radicals, Then and Now: Candid Conversations With Those Who Shaped the Era
National Young Lords Website
Chicago Tribune
History.com Archives
The Encyclopedia of Arkansas History & Culture
Let Nobody Turn Us Around: Voices of Resistance, Reform, and Renewal: an African American Anthology
Imprisoned Intellectuals: America's Political Prisoners Write on Life, Liberation and Rebellion
Democracy Now! Website
Lewiston Daily Sun
truTV.com Website
Philadelphia City Paper
Far Left of Center
Outlaws of America: The Weather Underground and the Politics of Solidarity
Denver Anarchist Black Cross Blog
Los Angeles Times
Latinopia.com Website
CNN.com Website
American Fuehrer
Milwaukeemag.com Website
The New York Post
The New York Press
Star Tribune
AlJazeera
NBC News
Frontpage Magazine
CBS News
World Socialist Web Site
The New American
The Miami Herald

The Jerusalem Post
American Terrorist: Timothy McVeigh and the Oklahoma City Bombing
Terrorism in America
The Courier Mail (Australia)
The Elkhart Truth
The Ku Klux Klan and Related American Racialist and Antisemitic Organizations: A History and Analysis
The Victoria Advocate
From Selma to Sorrow: The Life and Death of Viola Liuzzo
WRAL Raleigh/Durham/Fayetteville Website
Indianapolis Star
United Press International
The Awful Grace of God
The Jihad Next Door
The Enemy of My Enemy: The Alarming Convergence of Militant Islam and the Extreme Right
Gathering Storm: America's Militia Threat
AnnArbor.com Website
The Delta Discovery
NewsObserver.com
Alaska Public Media
ABC World News
Fox News
America’s Most Wanted
The Daily Inter Lake
LA News
Fairbanks Daily News-Miner
BND Marine
The Decature Daily
Cleveland.com Website
The Republican
TribLive
The Press-Enterprise
The Huffington Post
Canada Free Press
Pittsburgh Post-Gazette
AnimalRights.net Website
The Boston Globe
Valley News
Free Republic
The Standard-Examiner
Eugene Weekly
Memphis Flyer

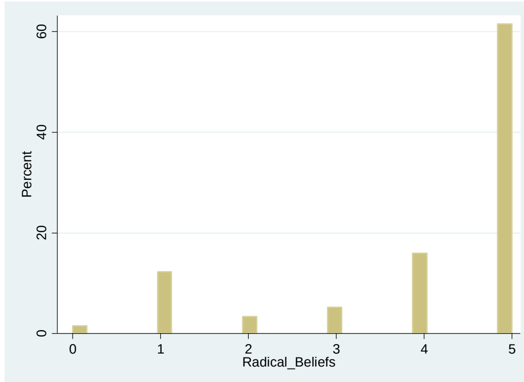
The Alaska Dispatch
WTNH
The Blaze
The Straights Times (Singapore)
Jane's Terrorism & Security Monitor
San Francisco Chronicle
Political Violence and Terrorism in Modern America: A Chronology
The Way the Wind Blew: A History of the Weather Underground
Weatherman
Mother Jones
Daily News (New York)

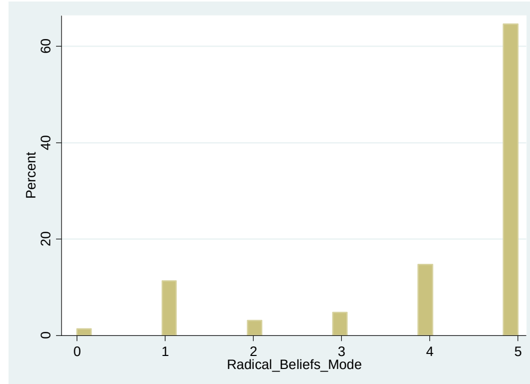
Appendix B: Supplemental Figures and Tables

Figure 1: Imputed vs. Observed Distributional Comparisons

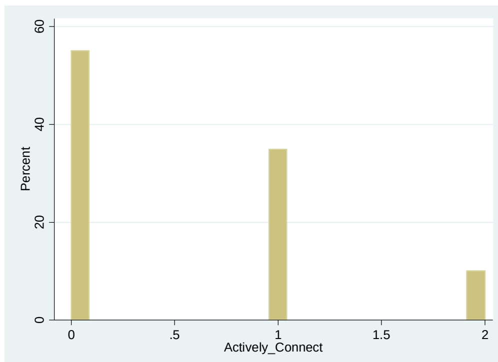
Variable	Observed Values	Imputed Values
Work History		
Military		
Aspirations		

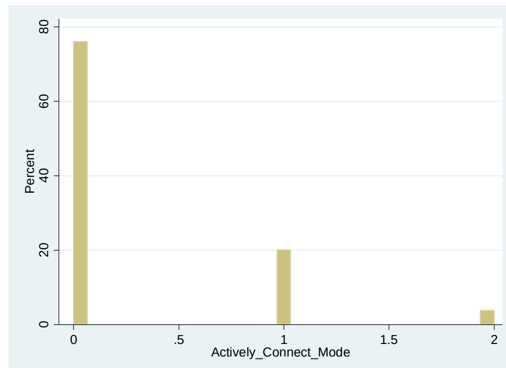
Radical Beliefs



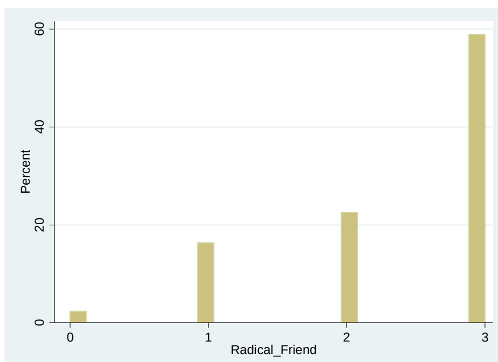


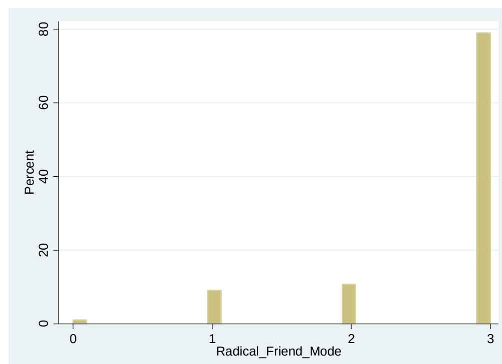
Actively Connect



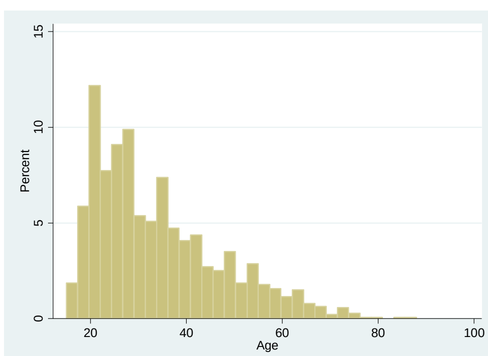


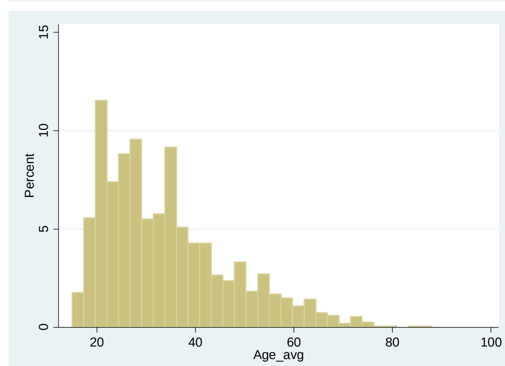
Radical Friend



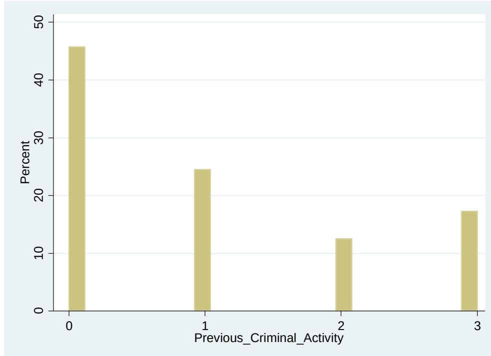


Age





Previous Criminal Activity



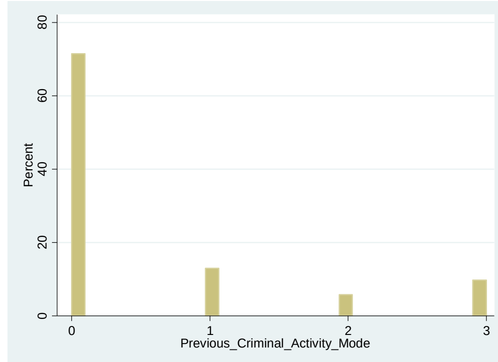


Table 9: Far Right Reference - Logistic Regression Models

Variable Name	**Model 1**		**Model 2**		**Model 3**	
	$\hat{\beta}$	**Std. Err.**	$\hat{\beta}$	**Std. Err.**	$\hat{\beta}$	**Std. Err.**
Abuse Child	0.152	0.424			0.045	0.435
Close Family	0.055	0.246			0.002	0.256
Work History	-0.070	0.091			-0.128	0.094
Unstructured Time	0.325	0.209			0.227	0.218
Student	-0.168	0.148			-0.122	0.154
Military	0.019	0.143			0.031	0.150
Aspirations	-0.083	0.057			-0.062	0.062
Angry US	0.176	0.183			0.106	0.188
Radical Beliefs	0.102**	0.037			0.143**	0.041
Group Membership			-0.279**	0.066	-0.288**	0.069
Recruit Family			0.238	0.373	0.212	0.375
Recruit Friend			-0.128	0.343	-0.275	0.349
Recruit Member			0.458	0.296	0.458	0.306
Recruit Other			0.230	0.350	0.260	0.359
Actively Connect			-0.059	0.111	-0.129	0.115
Gang			0.878**	0.282	0.895**	0.280
Clique Radicalize			0.230*	0.100	0.265**	0.101
Radical Friend			0.170**	0.065	0.134†	0.077
Beliefs Trajectory			0.115	0.181	0.138	0.184
Behaviors Trajectory			0.011	0.151	0.081	0.160
Male	0.409*	0.186	0.448**	0.169	0.361†	0.193
Age	-0.011*	0.005	-0.010*	0.004	-0.010†	0.006
Previous Criminal Activity	0.257**	0.060	0.242**	0.061	0.201**	0.063
Radicalization Single Issue	-0.426**	0.144	-0.316*	0.145	-0.326*	0.148
Radicalization Far Left	-1.011**	0.157	-0.826**	0.154	-0.876**	0.165
Radicalization Islamist	-0.157	0.158	-0.279	0.170	-0.275	0.174

Note: Robust standard errors used. † indicates p<0.10, * indicates p<0.05, ** indicates p<0.01

Table 10: Far Right Reference - Factor Analysis Models

Variable Name	**Model 4**		**Model 5**		**Model 6**		**Model 7**	
	$\hat{\beta}$	**Std Err.**	$\hat{\beta}$	**Std Err.**	$\hat{\beta}$	**Std Err.**	$\hat{\beta}$	**Std Err.**
ControlFactor	-0.253**	0.072			-0.244**	0.073	-0.224**	0.074
LearnFactor1			0.167*	0.078	0.153*	0.078	0.209**	0.081
LearnFactor2			0.076	0.087	0.068	0.087	0.040	0.088
Radical Beliefs							0.111**	0.035
Gang							0.799**	0.276
Previous Criminal Activity	0.255*	0.060	0.291**	0.059	0.251**	0.060	0.218**	0.061
Age	-0.007**	0.003	-0.009*	0.003	-0.007*	0.003	-0.012**	0.004
Gender	0.567**	0.138	0.596**	0.139	0.572**	0.139	0.280†	0.154
Radicalization Far Left	-0.941**	0.139	-0.928**	0.140	-0.949**	0.140	-1.050**	0.149
Radicalization Single Issue	-0.377**	0.138	-0.390**	0.138	-0.379**	0.139	-0.424**	0.141
Radicalization Islamist	-0.174	0.155	-0.226	0.160	-0.253	0.161	-0.262	0.164

Note: Robust standard errors used. † indicates p<0.10, * indicates p<0.05, ** indicates p<0.01

Table 11: Far Left Reference - Logistic Regression Models

Variable Name	**Model 1**		**Model 2**		**Model 3**	
	$\widehat{\beta}$	**Std. Err.**	$\widehat{\beta}$	**Std. Err.**	$\widehat{\beta}$	**Std. Err.**
Abuse Child	-0.014	0.420			-0.096	0.437
Close Family	-0.223	0.251			-0.186	0.261
Work History	-0.183*	0.093			-0.207*	0.096
Unstructured Time	0.084	0.206			0.045	0.215
Student	-0.203	0.148			-0.154	0.153
Military	0.041	0.146			0.042	0.151
Aspirations	-0.069	0.057			-0.055	0.062
Angry US	0.048	0.184			0.018	0.189
Radical Beliefs	0.080*	0.037			0.130**	0.041
Group Membership			-0.330**	0.064	-0.302**	0.069
Recruit Family			0.175	0.369	0.182	0.377
Recruit Friend			-0.136	0.345	-0.329	0.349
Recruit Member			0.449	0.291	0.433	0.306
Recruit Other			0.209	0.355	0.267	0.358
Actively Connect			-0.088	0.110	-0.152	0.115
Gang			0.836**	0.282	0.861**	0.281
Clique Radicalize			0.210*	0.100	0.260**	0.101
Radical Friend			0.042	0.063	0.079	0.077
Beliefs Trajectory			0.113	0.180	0.135	0.184
Behaviors Trajectory	0.279		-0.032	0.151	0.051	0.159
Male	0.245	0.187	0.204	0.172	0.276	0.194
Age	1.107**	0.005	-0.015**	0.004	-0.013*	0.006
Previous Criminal Activity	0.634**	0.061	0.246**	0.061	0.197**	0.064
Radicalization Far Right	0.867**	0.160	0.893**	0.162	0.938**	0.167
Radicalization Single Issue	-0.014**	0.174	0.536**	0.174	0.586**	0.177
Radicalization Islamist	-0.223**	0.183	0.534**	0.193	0.611**	0.196

Note: Robust standard errors used. † indicates p<0.10, * indicates p<0.05, ** indicates p<0.01

Table 12: Far Left Reference - Factor Analysis Models

Variable Name	**Model 4**		**Model 5**		**Model 6**		**Model 7**	
	$\widehat{\beta}$	**Std Err.**	$\widehat{\beta}$	**Std Err.**	$\widehat{\beta}$	**Std Err.**	$\widehat{\beta}$	**Std Err.**
ControlFactor	-0.239**	0.072			-0.230**	0.073	-0.226**	0.074
LearnFactor1			0.175*	0.078	0.162*	0.078	0.176*	0.080
LearnFactor2			0.038	0.086	0.031	0.086	0.013	0.087
Radical Beliefs							0.027	0.033
Gang							0.758**	0.273
Previous Criminal Activity	0.248**	0.060	0.283**	0.060	0.245**	0.061	0.215**	0.062
Age	-0.019**	0.004	-0.021**	0.004	-0.019**	0.004	-0.020**	0.004
Gender	-0.008	0.143	0.025	0.142	-0.004	0.143	-0.093	0.161
Radicalization Single Issue	0.564**	0.169	0.538**	0.169	0.560**	0.170	0.527**	0.170
Radicalization Far Right	1.071**	0.157	1.063**	0.157	1.072**	0.158	1.007**	0.160
Radicalization Islamist	0.747**	0.181	0.701**	0.183	0.686**	0.184	0.675**	0.184

Note: Robust standard errors used. † indicates p<0.10, * indicates p<0.05, ** indicates p<0.01

Table 13: Islamist Reference - Logistic Regression Models

Variable Name	Model 1		Model 2		Model 3	
	$\widehat{\beta}$	Std. Err.	$\widehat{\beta}$	Std. Err.	$\widehat{\beta}$	Std. Err.
Abuse Child	0.120	0.423			-0.005	0.436
Close Family	-0.005	0.247			-0.065	0.258
Work History	-0.097	0.092			-0.158	0.095
Unstructured Time	0.276	0.207			0.162	0.217
Student	-0.170	0.148			-0.133	0.154
Military	0.021	0.144			0.032	0.150
Aspirations	-0.076	0.057			-0.057	0.062
Angry US	0.146	0.184			0.072	0.189
Radical Beliefs	0.097**	0.037			0.138**	0.041
Group Membership			-0.298**	0.067	-0.297**	0.070
Recruit Family			0.216	0.371	0.203	0.376
Recruit Friend			-0.125	0.344	-0.286	0.348
Recruit Member			0.459	0.294	0.459	0.306
Recruit Other			0.238	0.350	0.290	0.359
Actively Connect			-0.063	0.110	-0.130	0.114
Gang			0.852**	0.283	0.875**	0.281
Clique Radicalize			0.225*	0.100	0.266**	0.101
Radical Friend			0.121†	0.067	0.113	0.078
Beliefs Trajectory			0.118	0.181	0.141	0.184
Behaviors Trajectory			-0.004	0.151	0.070	0.160
Male	0.387*	0.184	0.353*	0.165	0.336†	0.192
Age	-0.012*	0.005	-0.012**	0.004	-0.011†	0.006
Previous Criminal Activity	0.253**	0.061	0.243**	0.061	0.198**	0.063
Radicalization Far Right	0.286†	0.161	0.371*	0.171	0.367*	0.177
Radicalization Far Left	-0.773**	0.184	-0.519**	0.184	-0.543**	0.198
Radicalization Single Issue	-0.177	0.179	0.020	0.190	0.017	0.195

Note: Robust standard errors used. † indicates p<0.10, * indicates p<0.05, ** indicates p<0.01

Table 14: Islamist Reference - Factor Analysis Models

Variable Name	Model 4		Model 5		Model 6		Model 7	
	$\widehat{\beta}$	Std Err.	$\widehat{\beta}$	Std Err.	$\widehat{\beta}$	Std Err.	$\widehat{\beta}$	Std Err.
ControlFactor	-0.253**	0.072			-0.242**	0.073	-0.225**	0.074
LearnFactor1			0.174*	0.078	0.159*	0.078	0.200*	0.080
LearnFactor2			0.081	0.085	0.071	0.086	0.032	0.087
Radical Beliefs							0.094	0.035
Gang							0.784**	0.277
Previous Criminal Activity	0.253**	0.060	0.288**	0.060	0.248**	0.061	0.219**	0.062
Age	-0.011**	0.004	-0.013**	0.004	-0.011**	0.004	-0.014**	0.004
Gender	0.419**	0.138	0.417**	0.138	0.384**	0.138	0.176**	0.153
Radicalization Far Right	0.346*	0.153	0.398*	0.156	0.408**	0.157	0.257	0.162
Radicalization Single Issue	-0.109	0.167	-0.075	0.170	-0.052	0.170	-0.190	0.174
Radicalization Far Left	-0.715**	0.158	-0.662**	0.158	-0.673**	0.158	-0.839**	0.168

Note: Robust standard errors used. † indicates p<0.10, * indicates p<0.05, ** indicates p<0.01

Table 15: Polychoric Correlation Matrix – Social Bonds Variables

Variable Name									
	1	2	3	4	5	6	7	8	9
1) Abuse Child	1.000								
2) Close Family	-0.618	1.000							
3) Work History	-0.603	0.688	1.000						
4) Unstructured Time	0.589	-0.847	-0.791	1.000					
5) Student	-0.065	0.131	-0.013	0.028	1.000				
6) Military	-0.007	-0.239	-0.248	0.277	-0.258	1.000			
7) Aspirations	-0.316	0.409	0.521	-0.345	-0.413	0.001	1.000		
8) Angry US	-0.366	0.138	0.094	-0.096	0.062	0.079	0.078	1.000	
9) Radical Beliefs	0.040	-0.126	-0.069	-0.056	-0.042	0.025	-0.203	-0.075	1.000

Table 16: Polychoric Correlation Matrix – Social Learning Variables

Variable Name											
	1	2	3	4	5	6	7	8	9	10	11
1) Group Membership	1.000										
2) Recruit Family	0.143	1.000									
3) Recruit Friend	0.018	0.151	1.000								
4) Recruit Member	0.109	0.060	0.096	1.000							
5) Recruit Other	0.109	-0.025	-0.029	-0.893	1.000						
6) Actively Connect	0.179	-0.013	0.171	0.187	0.136	1.000					
7) Gang	0.059	0.005	-0.049	0.077	-0.034	-0.035	1.000				
8) Clique Radicalize	0.005	0.256	0.562	0.454	0.583	0.357	0.059	1.000			
9) Radical Friend	-0.025	0.040	-0.084	-0.095	-0.058	-0.291	-0.061	-0.111	1.000		
10) Beliefs Trajectory	-0.186	0.088	0.219	0.068	0.181	0.113	0.022	0.073	-0.096	1.000	
11) Behaviors Trajectory	-0.189	-0.055	0.256	0.184	0.181	0.035	0.019	0.267	0.019	0.752	1.000

Table 17 – Social Bonds Eigenvalues

Factor	Eigenvalue	Difference
Factor 1	**1.65746**	**1.25407**
Factor 2	0.40338	0.28056
Factor 3	0.12282	0.0348
Factor 4	0.08803	0.14772
Factor 5	-0.05969	0.01048
Factor 6	-0.07017	0.02611
Factor 7	-0.09628	0.08025
Factor 8	-0.17653	0.0964
Factor 9	-0.27293	.

Table 18 – Social Learning Eigenvalues

Factor	Eigenvalue	Difference
Factor 1	**0.93914**	**0.35684**
Factor 2	**0.5823**	**0.42687**
Factor 3	0.15543	0.03618
Factor 4	0.11925	0.06774
Factor 5	0.05152	0.01957
Factor 6	0.03195	0.0358
Factor 7	-0.00385	0.02257
Factor 8	-0.02642	0.10933
Factor 9	-0.13575	0.09604
Factor 10	-0.23179	0.10462
Factor 11	-0.33641	.

Figure 2: Scree plot of Eigenvalues for Social Bonds Items

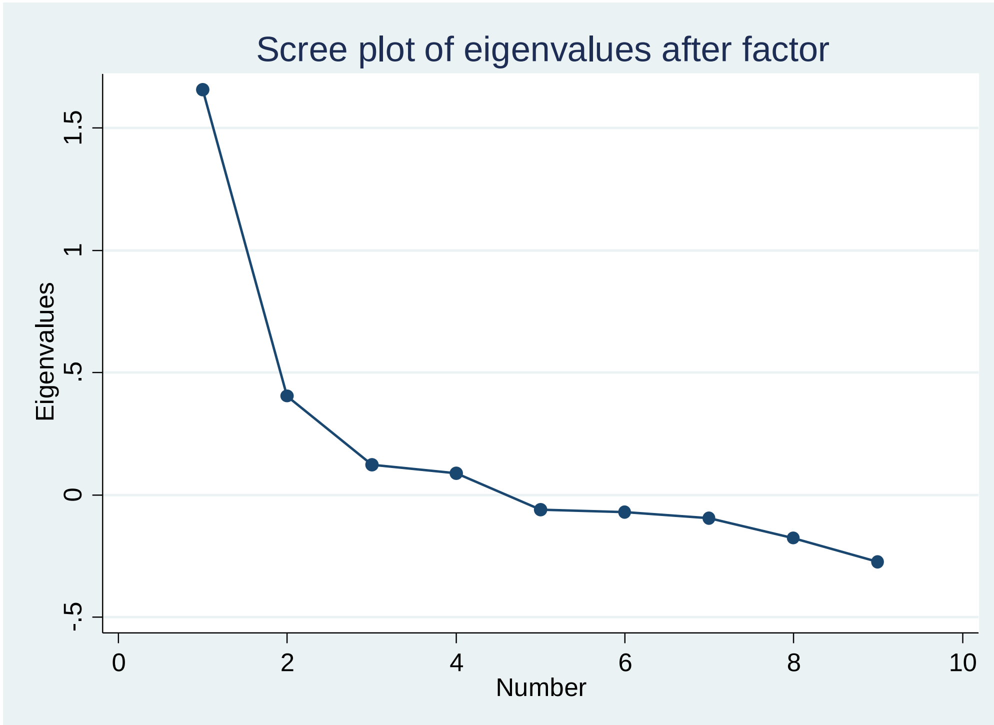
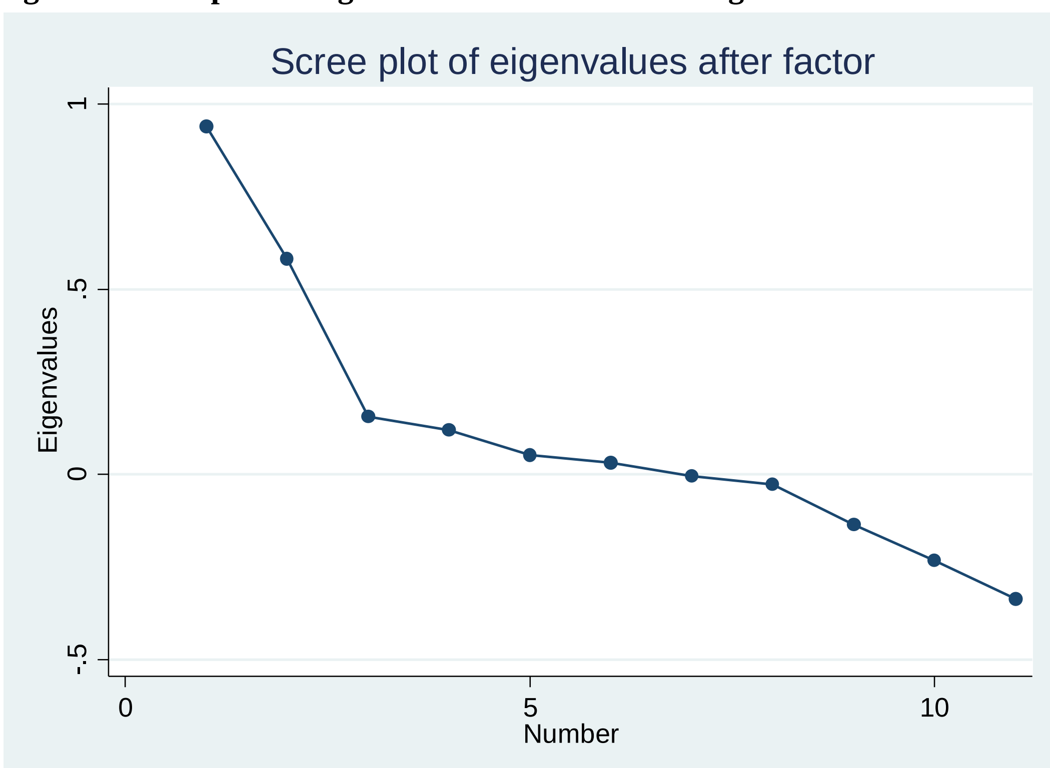


Figure 3: Scree plot of Eigenvalues for Social Learning Items



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