Document Title:	Consequences of Childhood Exposure to Intimate Partner Violence
Author(s):	Clifton R. Emery
Document No.:	215347
Date Received:	August 2006
Award Number:	2005-WG-BX-0001

Final Technical Report

Consequences of Childhood Exposure to Intimate Partner Violence

by Clifton R. Emery

This project was supported by Grant No. (2005-WG-BX-0001) awarded by the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice. Points of view in this document are those of the author and do not necessarily represent the official position or policies of the U.S. Department of Justice.

Chapter 1[1]: Introduction

There is no dearth of literature on the subject of deleterious consequences of partner violence on children. While claims that children are the "forgotten victims" (Susi, 1998) of domestic violence may have been true once, these statements can no longer be made by a dispassionate and informed observer. In the last ten years, there has been a veritable explosion[2] of research on the impact on children of exposure to partner violence. Review articles (Edleson, 1999; Holtzworth-Munroe, Smutzler and Sandin, 1997) and meta-analyses (Wolfe et al., 2003; Kitzmann et al., 2003) of the subject evaluate scores of studies at a clip. The range of child outcomes examined has also been extremely broad.[3] Thus, research on the effects of exposure to intimate partner violence on children is not new in terms of studying a hitherto ignored subject, nor is it likely to be unique in terms of the types of effects examined.

The problem of domestic violence and its attendant consequences for children is a perennial one for human society, and pays little heed to national boundaries. A man's prerogative to use violence against his wife was ensconced in the twelve tables that

[1] This project was supported by Grant No. (2005-WG-BX-0001) awarded by the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice. Points of view in this document are those of the author and do not necessarily represent the official position or policies of the U.S. Department of Justice.

[2] A search on the subject of "domestic violence" from 1984-2004 in the Social Science Citation Index and the Science Citation Index produced 2,903 hits. Of these, 114 involved the study of effects of exposure to intimate partner violence on children. While this is not a huge percentage of the total, 77% of the articles on exposure were published within the last five years.

[3] A review of the 114 articles described in the previous footnote identified more than 50 different child outcomes that had been studied.

formed the cornerstone of ancient Roman law (Lewis and Reinhold, 60). While domestic violence was outlawed by the Koryo dynasty in ancient Korea (Koryo-sa, circa 936 AD), Hamel asserts in 17th century Korea that a husband who killed his wife went free if any extenuating circumstances were pleaded (Hamel, 58). It is found throughout the world from New Guinea (Knauft, 409) to New England (Groves, 2001) and everywhere in between (Fishbach and Herbert, 1997). Thus, the most common justifications for research; the novelty of the subject or the sudden appearance of an acute problem, do not apply in this case. This necessitates a more thorough argument in support of the potential contribution of this paper.

For this purposes of this paper, *I limit the definition of domestic violence to the use of physical force (e.g. forcible restraint, slapping, shoving, throwing objects at, hitting, kicking, throwing objects at, biting, burning, sexual assault, murder) or threat of the same against an intimate partner*.[4] This problem is both chronic and common. Conservative estimates of domestic violence range from 1,036,340 per year (Bureau of Justice Statistics) to nearly 16 percent of married and cohabiting couples per year in the United States (Straus and Gelles, 1990; 118). Many of these couples have children. Research on the impact of domestic violence on the children of one or both of the parents is of theoretical import to at least three bodies of literature.

Because theories of child and human development posit the existence of different primary maturation tasks and constraints at different stages of the life course (Piaget, 1965; Erikson, 1963; Bowlby, 1982; Freud 1975), developmental theory can be drawn upon to create sets of empirically verifiable propositions about the nature of the

[4] By intimate partner, I mean someone with whom the perpetrator is involved in a romantic or sexual relationship of some duration, say at least a month.

consequences at different stages. These propositions should be limited to those logically implied by or at least consistent with the theory. The use of data to test these propositions then has relevance not only for the propositions themselves, but bears on the viability of the theory as well. Theories of delinquency, deviance and aggression (Hirschi, 2002; Matza, 1990; Cloward & Ohlin, 1960; Becker, 1973; Bandura, 1973; Gould, 1987) explicate conditions under which children and adolescents will violate social and legal norms, and are thus also implicated by research on the impact of domestic violence on children. Theories of duress (Herman, 1992, Lazarus & Folkman, 1984) study how individuals handle stressful situations, and for this reason are also relevant. Finally, many theories of family violence attempt to describe and explain patterns of perpetration in terms of individual, couple or family relational characteristics (Gelles & Straus, 1989; Giles-Sims, 1983; Dobash & Dobash, 1979; Walker, 1979; Holtzworth-Munroe, 1994), and are thus similarly implicated by research on consequences for the children.

Language increases potential through a commitment to reduction in complexity (Luhman, 1976)[5]. Theory has a similar function, organizing one's understanding of existing knowledge, thereby solving an infinity problem. It sorts out questions of cause versus correlation and makes meaningful predictions about the consequences of domestic violence for children and the circumstances in which those consequences will be manifest. It is thus unfortunate that more than two-thirds of the research uncovered by my literature review of consequences of childhood exposure to domestic violence would

[5] Luhmann argues that "any determination of action requires a simplification, a reduction of complexity" (Luhman, 1995; 166).

be characterized by the Parsonian tradition as empiricist[6] (Parsons, 1968; 10). The first contribution I propose to make with this paper is that of theory-driven research.

The second contribution this study will make is to do research that is practical. Social work in many respects attempts to fulfill the role of the conscience of society in action, using the Rawlsian principle of distributive justice (Wakefield, 1988) to promote the interests of the disenfranchised and empower the powerless. This is, perhaps, why so many social workers practice with children, who are in most respects at the mercy of their parents. Better information about whether there are deleterious consequences for children from exposure to domestic violence, what they are, and when and under what circumstances they will occur can help both practitioners and policy makers to intervene and channel resources appropriately. Intervention with the children may also work to decrease the prevalence of domestic violence in the long term via the curtailing of intergenerational effects (see Widom, 1989; and Ehrensaft et al., 2003 for a nice review of this literature).

A third contribution made by this research is to strike a balance between the resolution of measurement problems and the examination of concrete outcomes. Psychologists recognize the importance of ascertaining the reliability and validity of the theoretical constructs they employ in research, and have created an elaborate process for establishing this. They argue that questions like "how many times did you get into a fight" are too idiosyncratic to reliably capture a construct like aggression. Sociologists often counter that elaborate scales such as those used to measure aggression are too far

---

[6] Through its failure to make explicit reference to the body of theory which guides the generation of its research hypotheses, empiricist research minimizes its own contribution to the construction of knowledge. This is not to be confused with empirical research, which involves the study of those portions of the experienced world that are inter-subjectively knowable.

removed from real world activity and thus have questionable use in the discussion of overt phenomena. While nearly all of the existing literature falls into either one camp or the other, I propose a balanced approach. Some of the outcomes I examine will be scales which I will subject to the usual rigorous psychometric assessment of reliability and validity, while others will be relevant and easily recognized concrete outcomes.

The fourth contribution I propose to make with this study is the use of high quality data and advanced statistical techniques to adjudicate between conflicting findings in existing literature. The current literature is plagued with threats to validity resulting from poor data quality and the failure to implement appropriate analytic techniques. Most of the studies I have reviewed (see a list of brief descriptions in Appendix I) use data that cannot be reasonably construed to represent any region or identifiable group of people. Since clinical and policy interventions operate after the fact within real world boundaries, this makes generalizing findings to intervention-relevant populations problematic. This study will make use of data from the Project on Human Development in Chicago Neighborhoods, which is representative of a specific set of Chicago districts. Most studies I have reviewed use cross-sectional data. This compounds the cause versus correlation problem inherent in all research, in this case, particularly with respect to questions like: does exposure to domestic violence really have negative consequences for children, or do findings of effects really result from some sort of status effect (e.g. stigma experienced by battered women or low social status associated with domestic violence)? The longitudinal data employed by this study will allow for the use of fixed effects models which, by relying on certain assumptions, can answer this question. Current research often fails to make use of appropriate statistical techniques. Quantitative research on multiple outcomes which uses neither Bonferroni corrections nor multivariate techniques bears an increased risk of false positives.[7] Failure to properly deal with missing data bears the risk of biased estimates of effects (in the case of listwise deletion) or biased inferences (in the case of multiple imputation with regression). Failure to select an appropriate statistical tool for an analysis at best limits the potential contribution of the research, and at worst destroys it. This research will use multivariate techniques to handle the threat to validity posed by the study of multiple outcomes, it will use Data Augmentation[8] and the E.M. algorithm to deal with missing data, and it will make use of logistic regression and other techniques as appropriate. Finally, any form of data analysis is predicated on a set of assumptions which, if violated, have serious implications for the validity of conclusions. While most of the existing literature ignores these assumptions, this paper will thoroughly test all assumptions for which this is feasible, and provide arguments for those for which it is not.

In this, the first chapter, I hope that I have provided a persuasive argument for the value of this study. The second chapter will map out the empirical research literature, providing a picture of knowledge on the subject as it stands today. The third chapter will provide an overview of pertinent theory (developmental, deviance and duress), use and synthesize this theory to organize known facts and provide a theoretical model for the impact of domestic violence on children. The fourth chapter will introduce the data. The fifth chapter will operationalize the model in steps, starting with the most basic assumptions. The sixth chapter will deal with the implementation of missing data

[7] They risk finding evidence of an effect when there really isn't one.
[8] Both of which have similarly unbiased outcomes if the data are Missing at Random.

analysis. Chapter 7 will provide the theoretical results of the analysis and chapter 8 will draw theoretically relevant and empirically supported conclusions from the study..

Chapter 2: The State of the Subject

> "John started having severe behavior problems, very resistant, defiant...John would be having a temper tantrum and kicking and his arms would be going, and I would just be restraining him, and saying, 'You can't hit, you'll get hurt, I'll stay with you as long as you want, you're ok, you're safe right here'" (*a battered woman talking about her son*, Stephens, 1999; 740).

> "So what really hit hard, then, was when my daughter at my preschool…was getting in an argument with a little boy who was a year younger than she and he was putting her down, and she was sitting down on the floor like this [she huddles into herself, head bowed] and I thought, 'Oh, my god, this is me and her dad.' I mean, I just, that's what did it. I said, 'I've got to get out of this. I am teaching these girls totally wrong. I am not doing them any good by staying in this marriage" (Stephens, 1999; 738).

As the quotations above indicate, both experience and common sense, as well as theory, tell us that exposure to domestic violence has deleterious consequences for children. This chapter will provide a picture of the empirical research literature as it is currently, as yet making use of only the broadest theoretical strokes to organize the material. It will point out contradictions in the literature[9], but it will not attempt to resolve all of them. The most basic element by which the material can be broken down is by age. If developmental theory has any relevance whatsoever to this problem, age must effect the ways in which the impact of exposure to domestic violence is manifested.

[9] This chapter reviews research literature on the effects of domestic violence exposure to children dating from 1984 to 2004. A twenty year search of the Science Citation Index and the Social Science Citation Index was conducted for the term "domestic violence". Articles related to child outcomes were then selected manually.

Because breaking down studies by years, months and days of age would be both tedious and counterproductive, I will, for the moment without any rationalization, group ages into 0-1, 2-6, 7-12, 13-18, and adults. The remainder of the classifications used in this chapter must be in some respects arbitrary, because I am not yet attempting to organize the material according to strict theoretical criteria. In many cases I use taxonomy employed by the literature itself. I also attempt to use the categories to reflect where the preponderance of the literature on child outcomes lies. Categories are not, however, mutually exclusive. They are: externalizing[10], internalizing, relationships[11], physical health/well-being, drug/alcohol use, intergenerational effects[12], anxiety[13] and cognitive-emotional development.

Externalizing[14]

[Ages 0-1]

Externalization at ages 0-1 is difficult to measure. Still, a few studies have investigated this relationship for this age group. DeVoe and Smith (2002) find an

[10] The Penguin Dictionary of Psychology notes that while this term is used in many disparate areas of psychology to mean different things, all meanings "share the underlying notion that some 'thing' initially internal of 'inside' gets represented, projected or manifested in the external world" (Reber & Reber, 2001). Thus, in this case, externalizing behaviors can be conceived of as those stemming from attributions which relegate the source of psychological distress to the outside world, while internalizing behaviors can be conceived of as those behaviors stemming from attributions which relegate the source of psychological distress to something within the individual experiencing it. Thus, crying and depression are typically associated with internalizing, while fighting is typically associated with externalizing. Convenience as much as theory dictates the use of the internalization/externalization distinction here, since a great deal of the research employs Achenbach's Child Behavior Checklist as an outcome, which can be so subdivided.

[11] Ranging from social competence to relationships with peers to attachment.

[12] These may seem to be more appropriately grouped into internalization and externalization categories for victims and perpetrators respectively. However, the intergenerational transmission of domestic violence is such an important part of this literature that I have created an individual category.

[13] Some might argue that this is more appropriately grouped into the internalizing camp (this is debatable). However, the category accommodates the large number of studies on Post Traumatic Stress Disorder as an outcome.

[14] The externalizing scale on Achenbach's CBCL contains items like: argues a lot, cruel to animals, cruelty to others/bullying, destroys his/her own things, destroys things belonging to others, disobedient at home, disobedient at school, doesn't feel guilty after misbehaving, gets in many fights, lying or cheating, physically attacks people, threatens people, vandalism, steals and sets fires.

important relationship between exposure to domestic violence and externalizing behavior for 1-6 year olds. Kitzmann et al. (2003) find a statistically significant[15] relationship between exposure to domestic violence and externalizing behavior in a meta-analysis for all age ranges. McFarlane et al. (2003), using Achenbach's Child Behavior Checklist (CBCL), find no effect for children from 18 months to five years, while Yates et al. (2003) also using the checklist find a positive association between exposure to domestic violence in pre-school and externalizing behaviors at age 16[16]. These results are quite contradictory, particularly considering DeVoe and Smith's work is a qualitative study of children in a battered women's shelter while Kitzmann et al. do a meta-analysis which lumps together all ages. McFarlane et al. have a larger sample, but with case control subjects and fewer statistical controls than Yates et al. Both McFarlane et al. and Yates et al. have samples from agencies, which are thus not reflective of any general population. Theory and more empirical work are necessary to untangle this confusion.

[Ages 2-6]

There are many studies of externalization for this age group. These are more easily comprehended in tabular form, rather than via a description. The results appear in Table 1. A '0' indicates no effect, while '+' indicates a positive effect significant at the $p<0.05$ level, and '-' indicates a similarly significant negative association.

Table 1. Externalization for Ages 2-6

Externalizing	Study	Effect
CBCL	Jaffee et al. (2002)	+

[15] $p<0.05$

[16] The work of Yates brings up an interesting confound in the literature, namely, whether the research looks for effects that are concurrent with exposure to domestic violence, or looks for effects later. In order to increase precision and get a better understanding of what findings mean, future research should, at a minimum, distinguish age at time of study from age at time of exposure, and indicate whether exposure was ongoing or terminated.

	Litrownik et al. (2003)	+
	Kernick et al. (2003)	+
	Dubowitz et al. (2003)	+
	McFarlane et al. (2003)	0
	Hughes et al. (1989)	0
	Levendosky et al (2003)	0
	Morrel et al. (2003)	+ for Mother Report, 0 for Teacher
	Yates et al. (2003)	+ (teacher report)
	DeVoe and Smith (2002)	+
	Kitzmann et al. (2003)	+
Aggression	McCloskey & Lichter 2003)	+
Passive Aggression	Onyskiw & Hayduk (2001)	+
Fighting	Onyskiw & Hayduk (2001)	+
Juvenile Court Referral for Violent Offense	Herrera & McCloskey (2001)	+

The findings for this age group are somewhat contradictory. Most of the studies are based on mother report, and indicate a positive relationship. On the other hand, Morrel et al. (2003) find a positive relationship when mother is reporting child behavior, but no relationship when the teacher is reporting the behavior. Since the previous studies all used mother's report, it is unclear whether the association seen between exposure and externalizing is a true effect, or is an artifact of an effect of domestic violence on the mother's world view. Still, Yates et al. (2003) used teacher report of CBCL and found a positive effect. With regard to studies using the CBCL, Jaffee et al., and Dubowitz et al. have the best sampling technique here, none of the other studies are representative of any geographic area. Among the other studies, the research by Onyskiw & Hayduk also uses a very good representative sample. The methodologically superior approach of these studies inclines me to give more weight to their findings, which support the idea of an effect, at least when the mother is reporting.

[Ages 7-12]

Table 2 shows current literature findings for externalization for 7-12 year olds. There are more contradictions here. There are many possible sources for the discrepancies. First, from a purely statistical standpoint, enough studies of the same subject will eventually find significant results even if there is no relationship, unless Bonferroni corrections are made. Further, many of the samples employed are not

Table 2: Externalizing for Ages 7-12

Externalizing	Study	Effect
	Kitzmann et al. (2003)	+
	DeVoe and Smith (2002)	+
CBCL	Hughes et al. (1989)	0
	Graham-Bermann (1996)	0
	Jaffee et al. (2002)	+
	Kernic et al. (2003)	+
	McFarlane et al. (2003)	+
	Dubowitz et al. (2001)	+
	Raviv et al. (2001)	+
	Yates et al. (2003)	+
Fighting	Onyskiw & Hayduk (2001)	+
Passive Aggression	Onyskiw & Hayduk (2001)	+
Aggression	McCloskey & Lichter 2003)	+
Juvenile Court Referral for Violent Offense	Herrera & McCloskey (2001)	+
Bullying	Baldry, (2003)	+

representative, introducing the possibility of bias. Finally, many of these studies have different controls, which obviously influences whether an effect is found. This last is a more theoretical issue, however, and will be dealt with in chapter 3. Still, almost all of the studies seem to point to a relationship between exposure and externalizing behaviors for this age group. In addition, both Hughes et al. and Graham-Bermann (the two studies which found no effects) were using convenience samples rather than representative samples, while Jaffee et al., Dubowitz et al., Raviv et al., Onyskiw & Hayduk and Baldry all used representative samples and found positive effects. The existence of a real relationship seems likely for this age group.

[Ages 13-18]

Presented below are current literature findings for externalizing in the thirteen through eighteen age bracket. As usual, the preponderance of the studies seem to find effects of domestic violence exposure on externalizing behavior. There are two null

Table 3: Externalizing for Ages 13-18

Externalizing	Study	Effect
	DeVoe and Smith (2002)	+
	Kitzmann et al. (2003)	+
CBCL	Kernic et al. (2003)	+
	McFarlane et al. (2003)	+
	Muller et al. (2000)	0
	Yates et al. (2003)	+
Criminal Behavior	Eitle & Turner (2002)	0
Juvenile Court Referral for Violent Offense	Herrera & McCloskey (2001)	+
Bullying	Baldry, (2003)	+
Aggression	McCloskey & Lichter 2003)	+

findings. Muller et al. use a sample representative of psychiatric inpatients (n=65) and find no effects for the CBCL. Statistical power may be an issue in this case, as well as the number of statistical controls employed. Thus, the question here seems to be less whether there is an effect, and more, what explains it? Interestingly, Eitle & Turner found no effect of domestic violence exposure on criminal behavior (robbing, burglary, vandalism, auto theft, theft, carrying a gun and fighting) for this age group, using a representative sample of schools in several counties. Crime tends to be a rare event with a very non-normal distribution, which makes the hierarchical regression employed by the researchers inappropriate. However, fighting is so uncommon an event (and thus it should have a less skewed distribution). They employed a large number of statistical controls however, so again, the question may be one of mediation rather than of no effect.

[Adults]

Presented below are findings from current research on the relationship between domestic violence exposure and externalizing behaviors among adults. Many of these studies are retrospective, examining current recall of exposure in childhood and using this to predict effects in adulthood. Whether some of the activities here truly belong in an

Table 4: Externalizing for Adults

Externalizing	Study	Effect
Teen Pregnancy	Hillis et al. (2004)	+
Impregnating a Teenager	Anda et al. (2001)	+
50> intercourse Partners	Felitti et al. (1998)	+
Criminal Behavior	Eitle & Turner (2002)	0
Fear of Inability to Control Anger	Hillis et al. (2004)	+
Aggression	McCloskey & Lichter 2003)	+

externalizing category is open to debate. It is in fact questionable whether the category itself makes much sense for this age group. In any case, there certainly do seem to be effects here. With the exception of the Eitle and Turner study described previously, all of these studies found effects. In addition, the sample quality was generally a bit better for this group. Anda et al., Felitti et al. and Hillis et al. all use random sampling techniques, although all of the random samples are from an H.M.O. This last fact makes generalization of findings problematic. There is an additional confound here, in that age of exposure cannot be at all estimated for this group.

Of overall interest here to me is the greater number of null findings in the 2-6 age range than in the 7-12 age range. This is more thought provoking when one also considers the fact that studies finding null results are less likely to be published. This difference may be evidence in support of a fundamental developmental shift in the 5-7 age range (see Sameroff & Marshall, 1996). Based on the literature, it seems likely that exposure to domestic violence is associated with an increase in externalizing behaviors at all age ranges. It may still, however, be the case that exposure in one range will be associated with a greater increase than in the others (this can be tested via an interaction effect). If this is not the case, it would seem that theories of child development are of little relevance in explaining the relationship between externalizing behavior and exposure to domestic violence.

Internalizing[17]

[Ages 0-1]

While it may be easier to measure internalizing for this age group than externalizing behaviors, the meaning of measurements here still seems somewhat difficult to interpret. Below is a table presenting the findings on internalization for this group in the current literature. As can be seen in the table, very few studies have looked

Table 5: Internalizing for Ages 0-1

Internalizing	Study	Effect
CBCL	McFarlane et al. (2003)	0
	Yates et al. (2003)	+ (teacher report)
	Kitzmann et al. (2003)	+

at this outcome for this age group, somewhat understandably, since determining whether a newborn is internalizing would be very difficult. Both Kitzmann et al. and Yates et al. look at age ranges extending far beyond the range here, which increases the probability that found effects are confounded with other factors and effects at other ages. This leaves the McFarlane study, which finds no results. This study has some methodological problems, but a large number of subjects. The problem is then unlikely to be one of statistical power. It does seem possible that the effect of exposure to domestic violence

[17] The internalizing scale on Achenbach's CBCL includes items like: clings to adults, cries a lot, deliberately harms self/attempts suicide, feels that no one love him/her, feels worthless or inferior, feels too guilty and unhappy, sad or depressed.

here is so broad (since so poorly understood by children at this age) that it resembles almost any other traumatic exposure, and thus gets lost because of sample heterogeneity.

[Ages 2-6]

Below is a table summarizing existing research on the relationship between domestic violence exposure and internalization. Since both the Morrel study and Hughes

Table 6: Internalizing for Ages 2-6

Internalizing	Study	Effect
CBCL	Jaffee et al. (2002)	+
	Litrownik et al. (2003)	+
	Kernick et al. (2003)	0
	Dubowitz et al. (2003)	+
	McFarlane et al. (2003)	0 for 2-5, + for 6
	Hughes et al. (1989)	0
	Morrel et al. (2003)	0 for Mom & Teacher
	Yates et al. (2003)	+ (teacher report)
	Kitzmann et al. (2003)	+
<u>Depression</u>		
Preschool Symptom Self Report	Morrel et al. (2003)	0
Children's Depression Inventory	Hughes et al. (1989)	0

were done with few if any statistical controls, with respect to the literature, there seems to be no indication of a relationship between exposure and depression for this age group. The sample quality for these two studies is not of the best. Still, this is an interesting finding. As with the findings for externalization on the CBCL for ages 2-6, findings of effects are here again spotty. This is in part probably because many of the findings here are products of the same studies as the externalization research. However, if anything findings are more conflicting here than before. If the meta-analysis is excluded because it confounds all age groups, there are more null findings than findings of effects. However, none of the studies finding null effects had very good sampling techniques (all were convenience samples). On the other hand Jaffee et al. and Dubowitz et al. both use random sampling. Additional research may shed more light on this matter. In my opinion, the most likely scenario here is that a weak effect exists which the smaller studies lack the power to detect.

[Ages 7-12]

The table below presents the findings of recent research on the relationship between domestic violence exposure and internalizing among children aged 7-12. Some

Table 7: Internalizing for Ages 7-12

Internalizing	Study	Effect
	Kitzmann et al. (2003)	+
CBCL	Hughes et al. (1989)	0
	Graham-Bermann (1996)	+
	Jaffee et al. (2002)	+
	Kernic et al. (2003)	0
	McFarlane et al. (2003)	+
	Dubowitz et al. (2001)	+
	Raviv et al. (2001)	0
	Yates et al. (2003)	+
Depression		
Simple Question	Luster et al., (2002)	+
Children's Depression Inventory	Hughes et al. (1989)	0
	Levendosky et al. (2001)	0
Distress (Levonn Scale)	Raviv et al., (2001)	+
Bullying Victimization	Baldry (2003)	+

categories here (distress, bullying victimization) are not clearly within the internalizing category. They are not clearly not internalizing behaviors either. They are presented here for convenience. Luster et al. found an effect for depression. While they had a much better sample (both in terms of size and random probability) than Hughes et al. or Levendosky et al., their measurement of depression was relatively simple. If anything, a weak effect seems most likely for exposure and depression in this age group, with none but the most statistically powerful studies able to detect it. The effects for internalizing in this age range seem more ambiguous than those for externalizing in the same age range.

The studies with a random sample of a geographic area and a relatively large number of subjects were Jaffee et al and Raviv et al, Jaffee having the largest study. Since findings in these studies conflict, better sampling technique and more statistical power do not solve the contradictory findings here. It is possible that the difference in findings occurs from differences in statistical controls used (and is hence a problem for theory). More theoretical work followed by more research is needed.

[Ages 13-18]

The table below presents recent research on effects of domestic violence exposure on internalizing in the thirteen through eighteen year old age group. Initially at least,

Table 8: Internalizing for Ages 13-18

Internalizing	Study	Effect
	Kitzmann et al. (2003)	+
CBCL	Muller et al., (2000)	0
	Kernic et al. (2003)	0
	McFarlane et al. (2003)	+
	Yates et al. (2003)	+
Depression		
Simple Question	Luster et al., (2002)	+
Children's Depression Inventory	Levendosky et al., (2002)	+
Attempted Suicide	Ragin et al., 2002	0
Suicidal Cognition	Baldry & Winkel (2003)	0
Bullying Victimization	Baldry (2003)	+

the literature seems to indicate that there is no relationship between suicide and domestic violence exposure in this age group. The fact that suicide attempts are relatively rare (indicating a skewed distribution) and that the Ragin study is small and non-representative renders the null finding for that study unsurprising. However, suicidal cognition is much more common than suicide itself, making for a more normal distribution. In addition, the Baldry & Winkel study is large and representative of school children in a city, making the null finding less likely if a real effect exists within the population. It is possible that, as opposed to depression, suicidal cognition may have a strong genetic component. Still, Baldry and Winkel employ a large number of statistical controls. More theoretically driver research is needed on this topic. The Luster study is described in the previous section, and the finding of an effect for depression is now supported by Levendosky et al. Finally, findings for internalization on the CBCL are split down the middle. None of the studies involving the CBCL for this age group are representative of any area. In addition, Yates et al. and McFarlane et al. are both studying long term effects of exposure in childhood. Stronger research methods and theoretically driven research are necessary to resolve this conflict.

[Adults]

The table below presents findings for ‘internalizing’ behaviors among adults. The category here may have less meaning, and is perhaps best broken into constituent parts (e.g. depression) than looked at as a whole. Both Felitti et al. and Dube et al. contradict

Table 9: Internalizing for Adults

Internalizing	Study	Effect
	Kitzmann et al. (2003)	+
Depression		
	Felitti et al., (1998)	+
Simple Question	Luster et al., (2002)	+
CES-D/DIS	Anda et al., (2002)	+
Attempted Suicide	Ragin et al., 2002	0
	Felitti et al. (1998)	+
	Dube et al., (2001)	+
Suicidal Cognition	Baldry & Winkel (2003)	0

Ragin’s finding of no effect on suicide for this group, although this is less surprising when one realizes that Felitti et al. and Dube et al. both use the same HMO data. The relationship here is still unclear, but seems to lean more in the direction of a weak positive effect, perhaps because the sample size for the HMO study was much larger than the Ragin study. The literature seems to clearly indicate that exposure to domestic violence in childhood is associated with depression in adulthood. It is the work of theory to elucidate this relationship.

Cognitive-Emotional Development

[Ages 0-1]

A great deal of research has been done in this area, particularly the relationship between domestic violence exposure and IQ. Emotional development issues as well as school performance are also included in this category. I was unable to locate any studies which looked at cognitive-emotional development for the 0-1 age group. The closest type of research would be the attachment literature, but I have put this in the category of relationships.

[Ages 2-6]

The table below presents the findings of recent literature which studies the relationship between domestic violence exposure and cognitive-emotional development.

Table 10: Cognitive-Emotional Development for Ages 2-6.

Cognitive	Study	Effect
Wechsler Scale of Intelligence	Dubowtiz et al. (2001)	0
	Koenen et al. (2003)	-
	Morrel et al. (2003)	0
	Huth-Bocks et al. (2001)	0 (but mediated)
Peabody's Picture Vocabulary Test	Huth-Bocks et al. (2001)	0 (but mediated)
Emotional Development	English et al., (2001)	0
Academic Problems	Kitzman et al. (2003)	+

As can be seen by comparing this table with previous tables, the Child Behavior Checklist (CBCL) is by far the most popular instrument for measuring effects of exposure to domestic violence. The findings with respect to the effect of exposure on IQ are ambiguous. Only the Koenen study finds a significant (negative) effect of exposure on IQ (as measured by the Wechsler Scale). However, Huth-Bocks et al. find no direct effects but do find an effect mediated by mother's depression. However, the Koenen study is by far the largest and the best methodologically, making use of a census of twins born in England from 1994-1995. It also uses extensive controls. All of the other studies of IQ are not representative samples of any region, and they are substantially smaller. A weak association thus seems likely here. The English et al. study does not have a random sample, but the number of subjects is large and the study seems otherwise rigorous. The results of Kitzman et al. are from a meta-analysis. Thus, there seems to be some evidence of academic problems associated with exposure for this age group, but no evidence for an association with emotional development and very weak evidence for a weak association with vocabulary. More research using better methods is clearly needed in this area.

[Ages 7-12]

Below is a table indicating the literature findings on the association between domestic violence exposure and cognitive-emotional development for the 7-12 age group.

Table 11: Cognitive-Emotional Development for Ages 7-12.

Cognitive	Study	Effect
Wechsler Scale of Intelligence	Dubowtiz et al. (2001)	0
Autobiographical Memory	Orbach et al. (2001)	0
Grade Point Average	Luster et al. (2002)	+
Academic Problems	Kitzman et al. (2003)	+

As is clear from the table, there is a dearth of literature on these outcomes for this age group. This dearth will be even clearer to the reader when I point out that the Dubowitz et al. and Luster et al. studies only overlap with this age range by one year each (7 and 12 respectively), with the rest of their subjects falling outside the age range. Further, the

Kitzman article is a meta-analysis covering the age range from infant to adult, and the Orbach study is so poorly described as to be nearly irrelevant. A clear need exists for more research on the relationship between cognitive-emotional development and domestic violence exposure for this age range. I am hesitant to draw conclusions from these results, given their limited number and for some also because of weak methodology. The Luster study had the best sample for this group and a fairly sophisticated analytic approach.

[Ages 13-Adult]

The table below presents cognitive emotional development effects for the 13-Adult age range. None of the studies was either uniquely in the Adult age range or the 13-18 age range, so the chart presenting the results is combined. The dearth of research on this age group (one would think research on IQ or academic problems at least would be more popular) is even more striking than for the previous group. The only new study for this group is the one by Hodgins et al, which uses a convenience sample of university students to examine deficits in reading non-verbal cues and finds an association between domestic violence exposure and inability to read happiness cues. The need for more research in this area and age range is obvious.

Table 12: Cognitive-Emotional Development for Ages 13-Adult.

Cognitive	Study	Effect
Deficit in Reading Non-Verbal Cues	Hodgins et al. (2000)	+
Grade Point Average	Luster et al. (2002)	+
Academic Problems	Kitzman et al. (2003)	+

Anxiety

[Ages 0-1]

This category comprises measures of all forms of anxiety, but the research on the subject is dominated by studies of Post Traumatic Stress Disorder (P.T.S.D). This is difficult to measure among 0 and 1 year olds. Only two studies (DeVoe et al. 2002 and Wolfe et al. (2003) as part of a meta-analysis of all ages) examined the age range at all. The DeVoe study found a positive association between exposure to domestic violence and P.T.S.D for the 1-6 age range. The meta-analysis found positive results for the 1-adult age range.

[Ages 2-6]

The table below presents the research findings in the current literature on the relationship between domestic violence exposure and anxiety for the 2-6 age group.

Table 13: Anxiety for Ages 2-6

Anxiety	Study	Effect
Revised Child Manifest Anxiety Scale (RCMAS)	Hughes et al. (1989)	0
P.T.S.D.		
Trauma Symptom Checklist	Briere et al. (2001)	+
	Kilpatrick & Williams (1998)	+
	Silva, et al. (2000)	+
	DeVoe et al. (2002)	+
	Wolfe et al. (2003)	+

The studies presented here unanimously found a positive association between domestic violence exposure and Post Traumatic Stress Disorder. All of them used small N convenience samples. Under the circumstances, a strong effect of exposure on P.T.S.D. seems likely in this case. Greater methodological sophistication could, however, make better estimates for the effect size in the general population. Since these samples are in fact clinical, a better designed study would also allow for more reliable generalization of the finding of an effect.

[Ages 7-12]

The table below presents findings regarding the relationship between anxiety and domestic violence exposure among 7-12 year olds. The only new study here is the one by Graham-Berman which examines the relationship between exposure and family worries. More research is needed to examine the possibility of differing effects in the 2-6 and 7-12 age groups.

Table 14: Anxiety for Ages 7-12

Anxiety	Study	Effect
Revised Child Manifest Anxiety Scale (RCMAS)	Hughes et al. (1989)	0
Family Worries	Graham-Bermann, (1996)	+
P.T.S.D.		
Trauma Symptom Checklist	Briere et al. (2001)	+
	Kilpatrick & Williams (1998)	+
	Silva, et al. (2000)	+
	Wolfe et al. (2003)	+

[Ages 13-18]

The table below represents the state of the literature which examines the relationship between exposure and P.T.S.D. for 13-18 year olds. It was difficult to decide whether the Hillis study belonged in externalizing outcomes or anxiety outcomes. In the end, it seemed possible that people who have serious difficulty controlling anger

Table 14: Anxiety for Ages 7-12

Anxiety	Study	Effect
Fear of Inability to Control Anger	Hillis et al. (2004)	+
P.T.S.D.		
Trauma Symptom Checklist	Levendosky et al. (2002)	+ (interaction with maternal psychological functioning)
	Muller et al. (2000)	0
	Silva, et al. (2000)	+
	Feerick & Haugaard, (1999)	+
	Wolfe et al. (2003)	+

might not worry about it so much. The Muller study finds no relationship between exposure and P.T.S.D., but this may be a result of statistical power problems. None of the studies here were very large, and all have serious methodological problems with their samples with respect to external validity.

[Adults]

The only studies which examined the effects of childhood exposure to domestic violence on Post Traumatic Stress Disorder as an adult were the Feerick study and Wolfe et al., the results of which can be seen above. The Hillis study (also above) also studied adults. There is clearly a dearth of research (particularly methodologically strong research) in this area.

Relationships

[0-1]

This is a broad category which consists of research on the relationship between domestic violence exposure and social competence, peer relationships, attachment, trust and more general prosocial behavior. Probably some items categorized as externalizing (e.g. bullying) could also be added to this category. The only studies of this topic for the 0-1 age group are those of Kitzmann et al. (2003), which is a meta-analysis of all ages which finds a positive relationship between social problems and exposure, and DeVoe & Smith (2002), which finds a positive relationship between social problems and exposure. It is possible to measure attachment for this age range. Clearly, a study of this is needed. Likewise, more research is needed, and, given DeVoe and Smith's convenience sample, more methodologically rigorous research.

[2-6]

The table below presents research results from investigations of the relationship between exposure and relationships for 2-6 year olds. The results here are rather

Table 15: Relationships for Ages 2-6

Relationships	Study	Effect
Child's Positive Behavior	Levendosky et al. (2003)	0
Attachment	Levendosky et al. (2003)	+
<u>Social Competence/Problems</u>		
	Kitzmann et al. (2003)	+
	DeVoe & Smith (2002)	+
Pictorial Scale of Perceived Competence and Social Acceptance (CBCL)	Morrel et al. (2003)	0
	Kernic et al. (2003)	0
	Hughes et al. (1989)	0

contradictory. No effects are found for positive social behavior or the perceived scale of competence and social acceptance. The only effects are found for Kitzmann (a meta-analysis) and DeVoe & Smith. Thus, the results on social competence lean towards an indication of no effect for this age group. This is puzzling, but thought provoking. More puzzling still is Levendosky's finding of a significantly *positive* relationship between exposure and secure attachment. There is a dearth of research on this topic for this age range. If there are any effects however, it seems likely that they will be too small to be detected by small samples of the type used in these studies, since statistical controls employed here are also minimal.

[Ages 7-12]

The table below presents the findings on the relationship between exposure and child relationships for 7-12 year olds. None of these studies are different from those

Table 16: Relationships for Ages 7-12

Relationships	Study	Effect
<u>Social Competence/Problems</u>		
	Kitzmann et al. (2003)	+
Pictorial Scale of Perceived	Kernic et al. (2003)	0

Competence and Social Acceptance (CBCL)	Hughes et al. (1989)	0

shown in Table 15. There is an unacceptable lack of research on relationships for this age range.

[Ages 13-18]

Below is the table showing findings for the relationships/exposure relationship for 13-18 year olds. The sudden increase in studies of relationships for this age group

Table 17: Relationships for Ages 13-18

Relationships	Study	Effect
<u>Adjustment</u> (Hopkins Symptom Checklist)	Feerick & Haugaard, (1999)	0
Social Avoidance and Distress	Feerick & Haugaard, (1999)	0
Peer Relationships	Levendosky et al. (2002)	- (interaction with social support)
Attachment to Adults	Levendosky et al. (2002)	-
Relationship Questionnaire	Feerick & Haugaard, (1999)	0
Trust Scale	Feerick & Haugaard, (1999)	-
<u>Social Competence/Problems</u>		
	Kitzmann et al. (2003)	+
Pictorial Scale of Perceived Competence and Social Acceptance (CBCL)	Kernic et al. (2003)	0

probably represents, at least in part, a theoretically derived bias. Many theories of development (e.g Erikson, 1963; Galatzer-Levy et al., 1993) argue that adolescence is a period of social experimentation and development. Logically then, family disruption could potentially interfere with this development. However, studying a particular age range because theory leads one to believe an effect will be found for this age range puts the cart before the horse. Research is first needed to confirm that the effect on social relationships is indeed different, and more severe, for this age group before concluding that the theory is correct. The relationship effects found for this age group are conflicting. Studies which set out more explicitly to test theory and which have greater methodological rigor (these are all convenience samples) are needed to untangle this confusion.

[Adults]

The same results in table 17 apply to adults, with the exception that the Levendosky et al. and Kernic et al. studies do not sample adult populations. Clearly, more research is needed on effects for this group.

Physical Health/Well-Being

[Ages 0-1]

There are a myriad of potential causal routes between childhood exposure to domestic violence and physical well-being. These mediating mechanisms range from in utero exposure resulting in birth defects to genetics to disorganized attachment (see Lyongs-Ruth & Jacobovitz in Cassidy & Shaver, 1999) leading to high risk health behavior. Perry argues, however, that "experience, not genetics results in the critical neurobiological factors associated with violence" (Osofsky**, 125**). There are a number of studies of the association between physical well-being and domestic violence exposure for the 0-1 age group, which then drop off in childhood. This is probably because physical outcomes are among the easiest to measure and study in infants. I have also included the child's risk of child abuse in this category. Below is a table presenting relationships found by recent research between exposure and physical well-being. The studies here for the most part seem to indicate a relationship between

Table 18: Physical Well-Being for Ages 0-1

Physical Well Being	Study	Effect
Birth Weight	Neggers et al. (2004)	-

	Kearney et al. (2004)	0
Gestational Age at Birth	Neggers et al. (2004)	-
Miscarriage	Nelson et al. (2003)	0
Child Abuse (Physical, Sexual & Neglect)	McGruigan et al. (2001)	+
	Cox et al. (2003)	+
	Bowen, (2000)	0

negative birth outcomes and domestic violence exposure, as well as between exposure and child abuse and neglect. Bowen finds no relationship between exposure and sexual abuse, but her sample is from a sexual abuse evaluation clinic. The disparate findings between the Neggers and Kearney studies are more difficult to sort out. Both are large studies drawn from hospital populations. The Kearney study however, uses more controls, which may mediate an association between birth weight and exposure. It is possible that Nelson et al.'s null finding is the consequence of a mediated relationship, since that study controlled for drug use and prior miscarriage statistically.

[Ages 2-6]

The table below presents findings in the literature on the relation between exposure and physical well-being for the 2-6 age group. As described previously, there is less research for this age group. The only new study here is by Dubowitz et al. Their study is neither small nor large (n=419), and their methods are neither excellent nor poor (random sample within various agencies). A measurement problem is possible (this is a Likert scale), but it is also possible that serious physical health problems are simply rare in this age group.

Table 19: Physical Well-Being for Ages 2-6

Physical Well Being	Study	Effect
Child Physical Health	Dubowitz et al. (2001)	0
Child Abuse (Physical, Sexual & Neglect)	McGruigan et al. (2001)	+
	Cox et al. (2003)	+
	Bowen, (2000)	0

[Ages 7-18]

The only studies of exposure and physical well-being for the 7-12 age group are the Cox et al., Bowen and Dubowitz et al. studies, the results of which are presented above. Mitchell et al. (2001) studied the relationship between exposure and crime victimization for 12-17 year olds and found a positive association. The only onther research which included the 13-18 age range was the Bowen study. More research is clearly needed for both of these age groups.

[Adults]

There was an increase in the number of studies of the relationship between childhood domestic violence exposure and physical well-being in the adult age group. The table below presents findings from the literature. The research is unanimous in finding a relationship between adult health outcomes and childhood exposure to domestic violence. Most of this work is empiricist however.

Table 20: Physical Well-Being for Adults

Physical Well Being	Study	Effect
Obesity	Felitti et al. (1998)	+
No Exercise	Felitti et al. (1998)	+
Ever had a Sexually Transmitted Disease	Felitti et al. (1998)	+
	Hillis et al. (2000)	+
Death of Infant born to D.V. Witness Mother	Hillis, et al. (2004)	+

Drug & Alcohol Use

[0-18]

A dearth in the literature is somewhat understandable for the 0-12 age group. It is less than desirable, however, for the latter portion of that age group (9-12 year olds). While most of us would like to believe that nine year olds are not drinking or using drugs, these beliefs are certainly not realistic in all circumstances. There is only one study for this age group, which included 12 year olds in its sample. Luster et al. (2002) reported a relationship between d.v. exposure and binge drinking in a random probability county sample of 12-19 year olds. The lack of additional studies on d.v. exposure and substance use in teenagers is a serious problem.

[Adults]

Below are findings from recent literature on the relationship between childhood exposure to domestic violence and adult substance abuse. Almost all of these results

Table 21: Drug & Alcohol Use for Adults

Drugs and Alcohol	Study	Effect
Smokes	Felitti et al. (1998)	+
Illicit Drugs	Felitti et al. (1998)	+
Alcoholic	Felitti et al. (1998)	+
	Anda et al. (2002)	+
Injected Drugs	Felitti et al. (1998)	+

come from a single study, and all of them come from the same data. Thus, while they are unanimous in finding a relationship between childhood exposure to domestic violence and drug and alcohol use in adulthood, the findings cannot be facilely generalized to the larger population. Thus, more work is needed across all ages on the relationship between substance use and domestic violence exposure.

Intergenerational Effects

Studies of intergenerational transmission of domestic violence are somewhat classic in the literature. The first major study was carried out by Kalmuss in 1984. She found a relationship between exposure to domestic violence in childhood and perpetration in adulthood. The idea was, however, popular long before that, because it resonates with our cultural intuition. Phrases such as ‘like father like son’ and ‘chip off the old block’ capture the popular notion of this relationship. If anything, the common bias is probably to over-estimate this effect. Kalmuss (1984) finds intergenerational patterns of marital aggression to be “consistent but weak” (18), which means that exposure to violence certainly does not predestine the child. It is to be expected that the literature on these effects will focus on adolescents and adults. The table below presents studies of intergenerational effects for 13-18 year olds. The findings for the intergenerational

Table 22: Intergenerational Effects for Ages 13-18

Intergenerational Effects	Study	Effect
Domestic Violence Perpetration	Whitefield et al. (2003)	+
	Erensaft et al. (2003)	0
Domestic Violence Victimization	Whitefield et al. (2003)	+
	Erensaft et al. (2003)	0
Dating Violence Perpetration	Jankowski et al. (1999)	+
	Carr et al. (2002)	+
Dating Violence Victimization	Jankowski et al. (1999)	+
Sexual Assault Perpetration	Carr et al. (2002)	0

transmission of domestic violence here are reflective of the findings in the field overall. It seems that about half of the time researchers find a significant relationship, and about half of the time they find nothing. The most likely cause of this is the presence of a weak effect, which disappears with some statistical controls.

[Adults]

In addition to the research above, three additional studies were found on the adult population. The studies of both Cappell & Heiner and Kesner & McKenry (1998) found no relationship between exposure and domestic violence perpetration. On the other hand, MacEwen (1994), did find a relationship between exposure and dating violence perpetration. These contradictory findings remain a problem for the field.

Limitations of current empirical research.

There are a number of limitations of the current research on the relationship between exposure to domestic violence and child outcomes. Perhaps most striking is the considerable disregard for issues of external validity. Studies which use a random probability sample to examine outcomes are few and far between, and studies in which the sampling frame represents a geographic area are rarer still. There are also substantial holes in the study of certain outcomes across age ranges. I said in chapter one that there is no dearth of research on this topic. While this is in pure numbers of articles true, given the difficulties involved in studying this topic, theoretically driven methodologically rigorous research is comparatively rare.

Longitudinal studies are expensive, difficult and lengthy to carry out. Thus, nearly all of the studies are cross-sectional, which compounds the problem of omitted variable bias. Even those studies which are longitudinal did not make use of fixed effects models to control for potential confounds between status effects (poverty, lack of education, social stigma) and the effect of exposure to domestic violence. In addition, none of the studies were able to take advantage of recent developments in statistics regarding the handling of missing data. In fact, most studies did not mention how missing data were handled. The typical practices for handling missing data can seriously bias conclusions. In addition, the studies I reviewed do not test or argue in support of the assumptions made by the analytical tools they employ. The potential for selection bias, omitted variable bias and biased inferences makes it difficult to synthesize previous research on the relationship between child exposure to domestic violence and cognitive and behavioral outcomes. Thus, it is unclear whether a causal relationship exists between exposure and these outcomes and, if one does exist, by what mechanism the effects are transmitted.

Further, few of the studies examined the mechanisms by which effects might be transmitted. Most of the studies used only basic controls (e.g. parent's education, socio-economic status and child abuse). There is some evidence that social support and the child's worrying about the family and mother's psychological functioning may mediate the effects of domestic violence exposure on child behavior (Muller et al., 2000; Graham-Bermann, 1996; Levendosky et al., 2001; Street et al., 2003). Based on the literature cited above, there seems to be some support for maternal psychological functioning as an explanatory mechanism for the relationship between domestic violence exposure and child behavior problems. However, there is little or no research on deviance theory, the child's anxiety, the parent-child relationship or age as potential explanatory mechanisms. An understanding of the mechanisms behind the effects would allow social service agencies and governments to better serve victims by suggesting appropriate targets for intervention. I hope to shed further light on these mechanisms in this project.

Chapter 3: Theorizing Exposure and its Consequences

Definitions

Because it is very easy for disagreement to ensue from a misunderstanding of the nature of the phenomenon under discussion, any sensible argument must provide its readers with the common ground of a definition prior to any explication of the subject. I have already provided a definition of domestic violence in the first chapter. Holden (2003) argues that current research on exposure to domestic violence is conceptually ill-defined, and develops a set of 10 different taxonomical classes of exposure.[18] While I agree that the problem is ill-defined in the literature, and generally favor honing theoretical constructs into homogeneous classes, I think there are at least two problems with Holden's classification system.

First, the categories intervenes, victimized, participates, ostensibly unaware and experiences the aftermath present theories employing them with a real threat of tautology,

[18] These are: child is exposed prenatally, child intervenes, child is victimized, child participates, child is an eyewitness, child overhears, child observes initial effects, child experiences life changes as a consequence, child hears about it, child is ostensibly unaware (Holden, 2003).

because these potentially (and in the case of aftermath, definitely) confound exposure to domestic violence with its consequences.[19] It is the purpose of theory, not taxonomy, to posit and explicate the relationship between cause and effect.

Second, it is not clear that the field is ready for such fine distinctions as the difference between overhears and is an eyewitness. Theoretical distinctions are of little use if they have no connection to real world distinctions. Thus, it would be necessary to show that the distinction between overhearing and being an eyewitness is associated with some difference in child outcomes before any research could reasonably limit its definition of exposure to eyewitnesses. Further, the different theories which abound on domestic violence exposure have different mechanisms explaining the relationship between exposure and child outcomes. These mechanisms make different demands of the definition of exposure. Thus, a broader definition accommodates the as yet heterogeneous body of theory on the topic, while constraining exposure to a narrower definition will prematurely limit the number and type of theories which can be tested.

I hold that the primary claim that exposure to domestic violence has to any unique ontological status (as opposed to simply witnessing a violent act between strangers or on television) is the unique (in both terms of quality and proximity) relationship the child exposed has to the victim(s) and/or perpetrator(s) of the violence. For this reason, I define exposure to domestic violence as cohabitation with a primary caregiver[20] who is a *perpetrator or victim* of domestic violence. I hold childhood to expire at about the time that most people graduate from high school and enter the world of work or tertiary

[19] Since this research investigates what effects, if any, intimate partner violence has on children, to classify types of exposure into the effects on children would assume in advance the results of the study.
[20] Generally a parent. The involvement of the primary caregiver in the violence is important because I argue that it is the unique relationship between the care-giver and the child that makes exposure to intimate partner violence a category which can be meaningfully distinguished from exposure to other types of violence.

education. To include most of those still in high school, my definition of childhood includes ages zero through eighteen.

Selection of Outcomes

Ideally, research should examine outcomes which are not only of theoretical and empirical but also of practical interest. For this reason, this dissertation studies the effect of domestic violence exposure on not only externalizing, internalizing, and total behavior problems, academic and cognitive ability, but also truancy, grade repetition, and drug use. This study will not only work to confirm trends and resolve contradictions in the literature, but will also allow for a test of several theories as applied to domestic violence. Thus I hope not only to look at empirical effects, but to further elucidate the general understanding of how those effects occur (or do not occur) ultimately providing some guidance as to which theories can be usefully applied to this subject.

Achenbach & Edelbrock (1983) define externalizing as “aggressive, antisocial under-controlled behavior” (31) and internalizing as “fearful, inhibited, over-controlled behavior” (ibid). I will retain these definitions. By academic ability I mean the child’s capacity to do well in school. By intellectual ability I mean the child’s “overall capacity to…understand and cope with the world around him” (Wechsler, 5). Thus, I see intellectual ability as a necessary but insufficient condition of academic ability.   By truancy (skipping school), grades, grade repetition and drug use I mean the common sense understanding native speakers of English have of these terms. In the theoretical discussion, I will group academic and intellectual ability, grades and grade repetition into a cognitive impact group and truancy, drug use, and externalizing into an externalization group.

Theoretical Assumptions

Some common theoretical ground should be established before moving on to describe the concepts and implications of the varied theories this research will use and test. These assumptions will be tested prior to testing of specific theories. First, all of the theories here assume a bivariate association between exposure to domestic violence and the outcomes of interest here. This was by and large supported by the empirical literature, as seen in chapter 2. Second, the theories I examine assume that the relationship between exposure and outcomes cannot be explained away by some status effect (e.g. poverty or genetics). Third, the theories as I have extended them assume that the relationship between exposure and outcomes is not the result of a confound with child abuse. Fourth, by definition, developmental theories assume that age matters. Before arguing in support of developmental theory (or even testing it) one should ascertain that the relationship between domestic violence exposure and the outcomes is affected by age.[21]

Relevant Theories

I divide the theories pertinent to the impact of exposure to domestic violence into three classes. Theories of duress attempt to explain how people react to difficult situations. Theories of trauma and the stress and coping literature are included in this category. Theories of development explain the physical, cognitive and social changes associated with human maturation and aging. Theories of this type include attachment

[21] At the level of analysis, if these assumptions hold, one would expect to see (1) baseline correlations between exposure to domestic violence and all outcomes (2) regression coefficients resulting from the regression of outcomes on domestic violence variables remain significant when fixed effects controls are introduced (3) the relationship between partner violence and the outcomes remains statistically significant when child abuse is controlled for and (4) Age should significantly predict the outcomes in O.L.S. models and age x domestic violence interaction terms should be jointly significant predictors of the outcomes in fixed effects models.

and Piagetian theory. Finally theories of deviance explain why people or groups violate social and legal norms. Theories of this type have little to say about any of the outcomes except externalization, truancy and drug use. Among theories of this type are those of Cloward & Ohlin (1960), Matza (1990), Hirschi (1969, 2002) and Gould (1987). This section goes over each of the theories I plan to examine, summarizes it, and presents theoretically driven predictions for the outcomes.

Duress

The broadest type of duress theory is the stress and coping literature, initiated by Lazarus & Folkman (1984). They define stress as "a relationship between the person and the environment that is appraised by the person as taxing or exceeding his or her resources and endangering his or her well-being" (21). Appraisals are the cognitive processes that intervene between an encounter and a reaction. These are most importantly impacted by a person's commitments and beliefs. Coping is the state of "constantly changing cognitive and behavioral efforts to manage specific external and/or internal demands that are appraised as…[stressful]" (141). There are two types of coping. Problem based coping involves managing the problem by attempting to alter environmental causes of stress. Emotion focused coping involves regulating the emotional response to the problem. Laumakis, Margolin & John (1998) employ stress and coping theory to suggest that exposure to domestic violence generates extreme affective reactions (1) which restrict the child's ability for cognitive processing (2). They found support for the first hypothesis, but do not really test the second. They also use hypotheses about gender roles to suggest that boys exposed to domestic violence are likely to implement problem focused coping, while girls are more likely to implement emotion focused coping. They find some support for this.

This suggests that there will be independent effects of exposure to domestic violence on academic and intellectual ability (via cognitive processing). It also suggests that effect on behavior problems (internalizing and externalizing) may be partially mediated by academic and intellectual ability.

Theory on trauma is arguably a subcategory of stress and coping, but much literature exists on it as a separate topic. Trauma is "psychological injury caused by some extreme emotional assault" Reber & Reber, (2001). Herman (1992) says that traumatic experience is characterized by terror and a sense of helplessness in the face of overwhelming force. She argues that the consequences of exposure to trauma are hyperarousal, intrusion and constriction. Intrusion involves re-experiencing the event in a vivid way which interferes with daily functioning, while constriction represents a narrowing of the consciousness to avoid the possibility of intrusion. Flashbacks are a well known intrusive symptom, dissociation a well known constrictive symptom. The disruptive effects of these symptoms and the sense of loss of security resulting from trauma result in a sense of disconnection from others. Herman also notes the possibility of indentification with the abuser (an insidious brainwashing in which the victim initially attempts to understand the abuser for the purpose of self-preservation, but which backfires as the victim validates the abuser's opinions) and the fact that children may engage in traumatic re-enactment (acting out the event over and over in an effort to gain a sense of control). Rossman (1998) states that the state of hyperarousal is associated with the production of hormones which, in large amounts, are associated with the death of cells in the hippocampus. She argues that this can then permanently interfere with memory processing. In cases in which these symptoms cause clinically significant distress, an individual may be diagnosed with an anxiety disorder; Acute Stress Disorder in the short term and Post-Traumatic Stress Disorder in the long term (DSM IV, 1994).

This theory suggests that there will be both direct effects on and difficulty in accurately measuring intellectual ability. The effect of hyperarousal on memory processing could directly affect intellectual ability, while the distractions posed by hyperarousal and intrusive symptoms would make accurate measurement of intellectual ability next to impossible (the child would not be able to pay full attention to the task). There would be a similar effect on academic performance. Externalizing symptoms could result as a consequence of identification with the abuser. These would particularly involve aggression rather than other types of crime. Internalizing behaviors could be part of Posttraumatic Stress Disorder itself. Finally, the theory suggests full mediation of the effect of exposure on all outcomes by symptoms of an anxiety disorder.

Development

Attachment theory was originally developed by John Bowlby (1982) in his studies of the effects of maternal deprivation on evacuees in England during World War II. The attachment bond refers to an affective tie that is persistent, person-specific, emotionally significant, and which results in the infant wishing to remain in proximity with the care-giver and feeling distress at involuntary separation (Cassidy & Shaver, 1999). Additional research was able to characterize the quality of attachment into two types, secure and insecure attachment. Secure attachment is characterized by a little clinging and crying when the mother (care-giver) returns after a separation, which subsides into normal play after a few minutes. Insecure attachment was subdivided into resistant and avoidant types. The resistant type is characterized by a long lasting over-reaction of crying and clinging to the mother when she returns. The avoidant type simply ignores her when she returns. These bonds, formed in infancy, are supposed to form or constitute internal working models (Cassidy & Shaver, 1999) which are used as a template for all future relationships.

A third type of insecure attachment is postulated by Lyons-Ruth & Jacobovitz (Cassidy & Shaver, 1999). They argue that this type, 'attachment disorganization', occurs when the caregiver arouses a contradictory response in the infant (one of both comfort and alarm). This evokes contradictory movements and expressions vis a vis the caretaker. The classic example of this is an approach towards the caretaker which results not in actual contact but in moving past in a tangential fashion. Other characteristics include sequential or simultaneous display of contradictory behaviors, undirected, misdirected incomplete or interrupted movements, stereotyped, asymmetrical or mistimed movements, anomalous postures, freezing, stilling and slowed movements, direct indicators of apprehension of parent, disorientation, confusion and mood lability (Cassidy & Shaver, 522). Research has consistently linked both avoidant and disorganized attachment with aggressive behavior, while resistant attachment has been linked to victimization (ibid). Lyons-Ruth & Jacobovitz suggest that disorganized and avoidant children often learn to cope with the insecurity evoked by the primary caretaker by trying to control the caretaker. Resistant children may be more vulnerable to victimization if the template formed with the caretaker is to cling to the other regardless of his or her actions.

Attachment theory implies that the primary impact of exposure to domestic violence is relational. Children acquire a flawed internal working model for relationships. The fact that primary relationships are experienced as threatening results in poor future relationships and precipitates externalizing and internalizing behaviors. Intellectual ability will not be affected, but academic performance may be, as the attempt to locate a secure attachment figure preempts goals which are less fundamental for well being. According to this theory, the parent-child relationship should fully mediate the relationship between exposure and child outcomes. Likewise, a close relationship with another adult besides the parents may act as a surrogate attachment relationship and thus buffer the negative effects of exposure. Attachment theory also suggests that the earlier the exposure to domestic violence, the worse the impact.

Piaget's theory postulates stage sequential development (Piaget, 1965). In the first stage, objects are assimilated to motor stages, and no abstract set of rules exists (Piaget, 32). For children in stage 2, rules exist, but right and wrong depend on consequences (Sameroff et al., 1996; 6). For children in stage 3 (ages 7-10), these rules are determined by parental authority. It is at this stage that arguments between children are fought with the phrases: 'my mom says…..' and 'well, that can't be right, because my dad says….'. This is in part because at this stage children have not mastered the rules (of games or anything else). On the other hand, at later stages, the rules are mastered and children are aware of them as a permanent social agreement.

If extended logically beyond its original topic to include exposure to domestic violence, Piaget's theory of moral development does not have anything to say about relationships between exposure and intellectual ability, academic ability or internalizing.

However, it does suggest that the critical period for learning rules is stage 3. This implies that exposure to domestic violence in stage 3 is likely to result in externalization, as children at this stage will internalize aggressive actions as part of the rules by which they live. This theory contradicts attachment theory's prediction of the worst effects at the youngest ages. Holding constant the duration and severity of exposure, Piagetian theory implies the relationship between exposure and externalizing behavior will be strongest for exposure between ages 7-10, while attachment theory postulates the worst consequences (and hence strongest link between exposure and externalizing) for exposure in the earliest years of life.

Deviance

Deviance refers to a "pattern of norm violation" (Marshall, 1998) which, when recognized, results in social stigma. Most of the literature on deviance and delinquency does not deal with age or child development, except as an implicit assumption that adolescence is for some reason characterized by an increase in deviance (Gottfredson & Hirschi, 2001).[22] This literature has nothing to say about internalizing or intellectual ability. Its primary focus is on externalizing behaviors that violate legal norms. It speaks to academic ability only insofar as this is disrupted by deviant behavior.

Matza (1964, 1990) argues that delinquents are characterized by a "simmering" sense of injustice (Matza, 101). This assists them in extending existing legal provisions and norms to rationalize illegitimate ends. The existing legal norms are adhered to, but simply suspended under certain circumstances by a neutralizing belief. So, for example,

[22] The authors discuss in this article the invariability of the age-crime curve over time and across cultures. Specifically, delinquent acts remain relatively low in childhood, begin to increase in the teen years, peak in the middle teens and then decline over the rest of life. The authors argue that the absolute lack of variability in this phenomenon leaves social scientists with nothing to explain.

members of a gang may extend the legal excuse for assault (self defense) to cover pre-emptive assaults against other gangs which invade their turf. Matza's image of the delinquent has in common with that of Hirschi (2002) no special motivation or commitment to delinquent action. Delinquents are in a state of drift, "midway between freedom and control" (Matza, 28). A subculture of delinquency (in which the commission of delinquency is common knowledge and which is characterized by mutual misunderstanding –each thinks he must commit delinquent acts in order to be accepted by the others--), the negation of offense (the neutralizing belief), and a sense of injustice are sufficient to propel the adolescent into a state of drift.

While Matza does not consider domestic violence at all, the implications of his theory for the relationship between exposure to domestic violence and child externalizing behaviors can be considered. It seems likely that the exposure could fuel the child's sense of injustice, both towards himself or herself and towards the abused parent. It is also likely that witnessing violent behavior by influential others (parents) will make it easier for the child to develop a neutralizing belief, that violence is ok in more circumstances than are generally accepted by society. If the child's friendships tend to be homophilic, then s/he will be drawn to friends with a similar sense of injustice. This group of friends could then fulfill the conditions for a subculture of deviance, resulting in Matza's three conditions being met and producing deviance from a state of drift. If Matza's theory and the inferences I have drawn are correct, then the relationship between exposure to domestic violence and externalizing behavior should be mediated by the type of friends with whom the child associates.

Cloward & Ohlin (1960) argue that deviance occurs when pathways to social success via legitimate methods are effectively blocked (a lack of opportunity) and the potential deviant has access to a deviant subculture, which inculcates both the norms which support acts of deviance and the techniques for commission. Thus, while Matza's subculture of deviance is not characterized by commitments to deviant action, Cloward & Ohlin's deviant subculture is. They conceive of the deviant subculture at the neighborhood level, and describe three hierarchically ordered types of subculture. A criminal subculture is characterized by illegal activity in pursuit of material gain (thus robbery, theft and the like), and is the most desirable to a potentially deviant actor. A conflict subculture (characterized by gang violence) is formed when groups denied legitimate opportunity also lack access to a criminal subculture. Finally, a retreatist subculture (characterized by drug use) occurs when potentially deviant actors have access to neither the criminal subculture nor gangs.

The most logical extension of Cloward & Ohlin's theory to explain a relationship between domestic violence exposure and externalizing behavior is an argument that the relationship exists because both parents and children are part of the same deviant subculture. While they did not intend the conflict subculture to explain domestic violence, and conceived of the subculture as expiring when deviant actors aged out of it, it also seems possible that deviant actors in a conflict subculture in some sense graduate from gang violence to domestic violence. If Cloward & Ohlin's theory and its extension are correct, the socio-economic characteristics of the neighborhood that families inhabit should mediate the relationship between domestic violence exposure and externalizing behavior.

Unlike the first two theories of deviance described above, Hirschi's (2002) is not a subcultural theory, but a control theory of deviance. In contrast to subcultural theories of deviance, "control theories assume that delinquent acts result when an individual's bond to society is weak or broken" (Hirschi, 2002; 16). Hirschi's theory posits that a weakening of attachment[23] to parents, commitment to conventional lines of action, involvement in conventional activities and belief in the moral validity of norms results in deviance. With respect to attachment, Hirschi writes:

> "The process of becoming alienated from others often involves or is based on active interpersonal conflict. Such conflict could easily supply a reservoir of socially derived hostility sufficient to account for the aggressiveness of those whose attachments to others have been weakened" (18).

Nonetheless, in accordance with social control theory, Hirschi's characterization of problematic attachment to parents is principally a claim of a lack of restraint. Children are "emotionally free" (83) and thus more likely to be exposed to criminogenic influences.

With respect to intimate partner violence, Hirschi's theory implies that exposure disrupts the bond with parents, increasing child deviance. This may occur in several ways. The chaos produced by domestic violence may decrease the parents' ability to monitor the child and prevent deviant acts. Alternately, the actions of the perpetrator and/or the helplessness of the victim may impinge on the parents' credibility with the child, undermining authority and the child's belief in the moral validity of norms

[23] While Hirschi's use of the term attachment is different from that invoked in the literature on attachment theory (and is characterized more by the presence or absence of monitoring rather than the presence or absence of an affective bond which preserves felt security), the use of the term is not coincidental. Both Hirschi's work and attachment theory imply that the quality of parenting has critical influence on child outcomes, including deviance.

espoused by the parents. Finally, the stress produced by the violence may interfere with the parent's ability effectively structure the child's life, resulting in detrimentally harsh or overly lax parenting. Some combination of the three seems likely. Whatever the combination may be, this theory, like attachment theory, invokes the parent-child relationship and implies that the parent-child relationship should mediate the relationship between domestic violence and externalizing behavior.

A systematic restatement (in the form of a table) of the assumptions and predictions of the theories presented follows. The columns represent the theories, while

Theoretical Assumptions and Predictions

Question	**Duress**	**Development**		**Deviance**		
	Stress/Anxiety	**Attachment**	**Piaget**	**Matza**	**Cloward & Ohlin**	**Hirschi**
Theoretical Assumptions						
Baseline Correlations Between Domestic Violence & Outcomes	Y	Y	Y	Y	Y	Y
Correlation Remains when Fixed Effects are Controlled	Y	Y	Y	Y		Y
Effects Remain when Child Abuse is Controlled	Y	Y	Y	Y	Y	Y
Effect of Domestic Violence Varies by Age		Y	Y			
Predictions						
Mediation of all effects by Anxiety?	Y					
Mediation of all effects by parent-child relationship?		Y				Y
Mediation of effects on externalizing by age 7-10 exposure?			Y			
Mediation of effects on externalizing by delinquent peers?				Y		
Mediation of					Y	

effects on externalizing by neighborhood?						
Early Exposure = worst impact?		Y	N			
Exposure between ages 7-10 = worst externalizing		N	Y			
Exposure effects intellectual ability?	Y					
Effect on externalizing varies by child sex?	Y					

the rows indicate questions. Y’s and N’s in the cells stand for yes or no. Thus, this table indicates what answers to which questions support which theories. Basic assumptions are presented first, followed by predictions. The next chapter presents the data and elucidates how these assumptions will be tested.

Chapter 4: Data, Measurement & Methods

Data

The Project on Human Development in Chicago Neighborhoods[24] (P.H.D.C.N.) is a longitudinal study of a representative random probability sample of 6,228 children and their primary caretakers (e.g. mothers) in Chicago. It began in 1994, ended in 2001 and was intended for use in the study of delinquency and crime, substance abuse and violence (Murray Research Center 2005). While interviews were carried out at 3 different time periods (1994, 1997 & 2000), only data from the first two time periods are available at this time. The P.H.D.C.N longitudinal data sample was drawn from a 3 stage cross-sectional stratified cluster sample of Chicago neighborhoods. The sample was stratified by seven levels of racial-ethnic composition and three socio-economic levels (Murray Research Center, 2005). First, 343 neighborhood clusters were created from Chicago's 825 census tracts on the basis of their socio-economic and ethnic homogeneity as well as within-neighborhood similarities in family structure and housing density (ibid). Eighty-three of these neighborhoods, stratified by income and ethnicity,[25] were randomly

[24] Supported in part by the National Institute of Justice

[25] In detail, all of Chicago's 847 populated census tracts were used to create 343 neighborhood clusters, each containing about 8,000 people (Schoua-Glusberg, 2002). These 343 neighborhood clusters were then stratified (using census data) into 21 cells based on income and ethnicity. Some of the cells were empty.

selected into the longitudinal study.[26] Blocks within the neighborhood cluster were then sampled using simple random sampling. Finally, housing units within blocks were sampled.

The 80 neighborhood clusters selected for the longitudinal study contained a total of approximately 40,000 dwelling units. These were screened via in person interviews for eligibility. To be eligible, the dwelling had to be occupied by a family which had a child in at least one of 7 age cohorts (ages 0, 3, 6, 9, 12, 15, 18). The screening had a response rate of 80% and produced 8,347 participants. The first wave of the longitudinal study had a response rate of 75%, which resulted in a sample of 6,228 participants. Response rates were 85.94% and 78.19% of those interviewed in the previous wave in the second and third waves respectively. Data collection began in 1994. Follow-ups were conducted in 1997 and 2000.

The data are incredibly rich, and present opportunities ranging from the option to study community effects via linked census data to the possibility of studying interviewer-participant interaction via video-taped interviews. The data also include a vast array of variables on family structure, parent-child relationships, parent discipline styles, family mental health, and family history of crime and drug use.

The use of high quality longitudinal data representative of neighborhoods in Chicago allows for the correction of many of the problems in previous empirical research shown in chapter 2. The representative quality of sample frame alleviates the external validity problems prevalent in prior research. The large sample size allows for more

---

For example, there were no high income Latino neighborhoods, nor were there low income white neighborhoods. Once the 343 neighborhood clusters were divided amongst the 21 cells, a simple random sample was employed in each of the cells to select a total of 80 neighborhood clusters into the longitudinal sample (Schoua-Glusberg, 2005).

[26] Because the sample frame of 343 neighborhood clusters contained all the Chicago census tracts, the 80 randomly selected neighborhood clusters are representative of the city of Chicago.

sophisticated techniques and makes it less likely that large effects will be overlooked by statistical analysis. The longitudinal quality allows the same child to be compared at different ages. This means that fixed effects models can be used to test for the possibility that selection effects result in omitted variable bias in the relationship between domestic violence exposure and child outcomes. Very few of the studies reviewed in chapter two used data of this caliber. Estimates generated by this data are thus likely to be more reliable.

Independent Variables

The P.H.D.C.N. contains a large number of standardized scales, one of which is Straus & Gelles' (1990) Conflict Tactics Scale (C.T.S.) for the child's mother and her partner. I will use this scale to measure domestic violence exposure.[27] The Conflict Tactics Scale has face validity (it does measure acts of domestic violence as I have defined it), and has been found to have construct validity (see Straus & Gelles, 1990). It is also fairly reliable[28] (in the P.H.D.C.N. data Cronbach's alpha=0.822).[29] Thus, on the whole, the scale is a useful and also widely used measure of domestic violence. The C.T.S. does not perfectly capture domestic violence however. It does not cover the span of all possible violent acts, and thus assumes that perpetrators do not specialize in one particular type of violent act. Further, it does not cover the entire span of lethality of violence. There is no measure of murder on the C.T.S. The data also contain a measure of parent to child violence (the parent-child Conflict Tactics Scale), which will be used as

[27] Children who have lived with a caregiver at a time during which the caregiver either perpetrated or was victimized by domestic violence as measured by the C.T.S. will be judged to have been exposed to domestic violence.
[28] Cronbach's alpha for husband to wife violence was 0.83 for the Straus and Gelles study (ibid).
[29] This is the average Cronbach's alpha for primary caregiver as perpetrator and partner as perpetrator. Individually, the two alphas were 0.8166 and 0.8279 respectively. This includes the 7 physical violence items I use in this study, but not other items on the scale.

a control variable. Change in family income is also used as a control variable.[30] Tables of the dependent, independent and potentially mediating variables, along with the scales used to measure them, are found in the appendix at the end of this paper.

Dependent Variables

The dependent variables (child outcomes) will be measured as follows. The child's score on the Wechsler Intelligence Scale for Children (W.I.S.C.) Vocabulary Test and the child's grades will measure the impact of exposure on the child's cognitive functioning. The W.I.S.C. is designed to assess intelligence (I.Q.) for 6-16 year olds. The reliability of the test is "among the highest of any psychometric measures" (Mental Measurements Yearbook, Volume 12). I will use Achenbach's (1983) Child Behavior Checklist (C.B.C.L.) and questions about child truancy, grade repetition and drug use to assess the behavioral impact of exposure to domestic violence. The C.B.C.L. "combines a 113-item behavior problems checklist with a seven-part social competency checklist" (Mental Measurements Yearbook, Volume 13). The behaviors on the list are in clusters similar to symptoms of psychological disorders in the D.S.M. IV. The instrument's range is children from ages 2-18. The reliability of the C.B.C.L. behavior scales is reported to be "exemplary with internal consistency and one-week test-retest coefficients above .89" (ibid).

Mediating Variables

Stress

[30] This analysis will use fixed effects models. This obviates the need for many control variables because variables which do not change over time (like child's innate learning ability) and variables which do change over time but do so uniformly throughout the data (like child's age) are implicitly controlled for in the model.

The idea that exposure to intimate partner violence causes an anxiety disorder in the child which then causes negative outcomes implies mediation (Baron & Kenny, 1986). Anxiety can best be measured in these data by the anxiety sub-scale of the Child Behavior Checklist. Thus, using the Baron & Kenny test for mediation, if intimate partner exposure significantly predicts the anxiety sub-scale, and significantly predicts negative cognitive and behavioral outcomes, but ceases to significantly predict outcomes when anxiety is added to the model, a mediated relationship is supported. Such a finding would support stress theory as an explanation of the relationship between exposure and outcomes.

Development

If developmental theory is relevant, effects of exposure on outcomes should vary by age. This will be tested by age*exposure interaction effects in logit and regression models. The parent-child relationship will be measured by selected questions from the HOME scale. This scale has questions like whether the primary caregiver is involved in a child organization, whether the primary caregiver discusses television, current events, and what to do in a health emergency with the child. If I find that the relationship mediates (Barron & Kenny, 1986) the effects of exposure to intimate partner violence, I conclude that the data support the theories implicating the relationship (attachment theory and Hirschi's theory of delinquency). I test the Piagetian contention that deviance caused by exposure will be highest in the 7-10 age group with an interaction effect. If a significant positive effect of an ages 7-10 times exposure to intimate partner violence interaction on deviant behavior (externalizing behavior from the Child Behavior Checklist, truancy, grade repetition) is found, I conclude that Piagetian theory is supported. This is a rigorous test because the ages of children in the data range from 0-18. Gottfredson and Hirschi (2001) have found that there is almost invariably a higher rate of delinquency among teenagers than children.

Deviance

Matza's (1990) theory regarding deviant peers will be tested using the Deviance of Peers scale of the P.H.D.C.N. This scale includes questions like how many of the child's friends got into trouble at school or at home, and how often they pressured the child to use drugs. Matza's theory is supported if deviance of peers is found to mediate the effects of exposure to intimate partner violence on externalizing behavior, truancy, grade repetition and drug use (deviant behaviors). Cloward & Ohlin's (1960) theory regarding neighborhood effects is supported if dummy variables for the neighborhood's socio-economic status are found to cause the relationship between exposure and deviant behaviors.

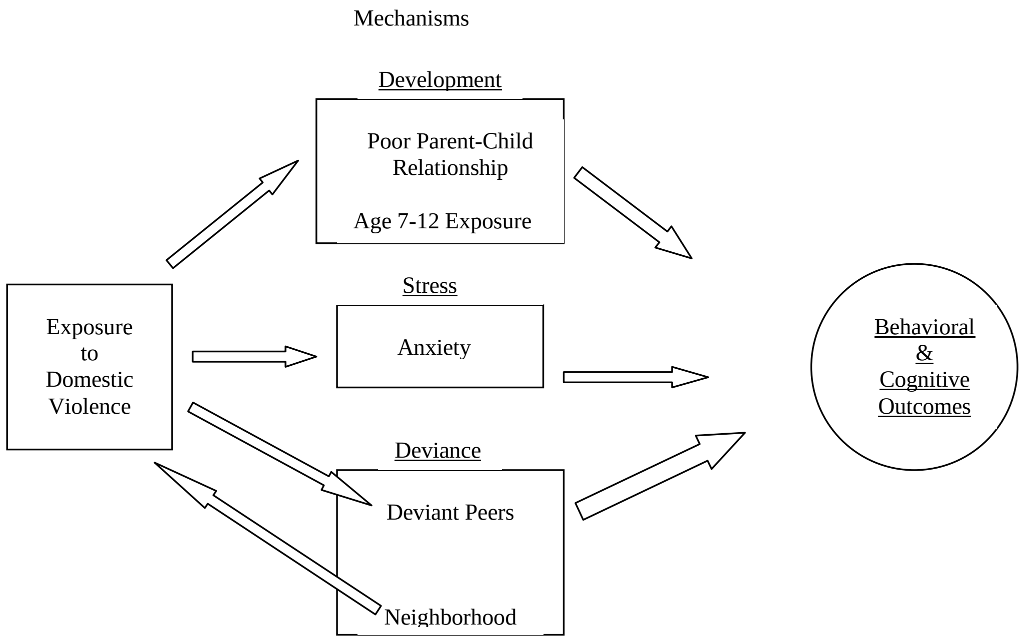
Details of the Analysis

I use the STATA and R programs to analyze the data from the P.H.D.C.N. I run fixed effects regression and logit models. The existence of multiple data points for each child allows for the use of fixed effects models. These models simultaneously eliminate correlation in the error terms and bias from any unobserved variable which does not change over time. Fixed effects models essentially measure the impact that a change in an independent variable has on the change in the dependent variable, controlling for an overall time effect. Any variable in the model (measured or unmeasured) which does not change over time is eliminated from a fixed effects model because each individual's average score is subtracted from both time periods for all variables (dependent and independent) included in a fixed effects model. Subtracting the individual averages for each variable implicitly does the same subtraction to the error term. Since for variables which do not change over the time periods the individual scores at both times will be the same as the average, the net change will be zero, and any unmeasured variables (all of which are in the error term) which do not change over time will drop out of the analysis. Clearly, this means that all variables (dependent, independent and mediating variables) in the fixed effects models must be measured both at time one and time two. Fortunately, this was done in the P.H.D.C.N. data. Cluster weights are used to handle potential autocorrelation from subjects taken from the same household.

I first test for baseline effects of exposure to intimate partner violence on the dependent variables. Including both the cases in which the child is not exposed to domestic violence in time one and is exposed in time two, and the reverse, allows for a test of both the detrimental effects of exposure to violence and the benefits of ending it. The fixed effects models will then be re-estimated including each of the mediating variables in turn. Those variables which, when added to the model produce significant change in the coefficient for intimate partner violence will be judged to significantly mediate the relationship between exposure to intimate partner violence and the dependent variables.[31] A depiction of the conceptual mediation model follows. Mediators are in the center, and arrows indicate the theoretical direction of causality.

[31] Since Hirschi's theory includes two variables, one of which is also used to capture the concept of attachment, I will test both how much better Hirschi's theory does over attachment theory, (by testing the additional variance explained by after school activities) and how much better Hirschi's theory does overall (the combined contribution to the R-square made by attachment to parents and after school activities).

Figure 1: The Model[32]



More detail on model testing is given below:

Let y be any one of the dependent variables. Let z be any of the variables measuring stress, development or deviance.

[32] The name of the theoretical construct is written on top of each figure, while the empirical realization of the theoretical construct is written inside each figure.

Continuous dependent variables: Regression. Dichotomous dependent variables: Logit.

$\Delta y = \beta_0 + \beta_1(\Delta\text{Partner Violence}) + \beta_2(\Delta\text{Child Abuse}) + \beta_3(\Delta\text{Income}) + \varepsilon$

$\text{logit}(\pi_{\Delta y}) = \beta_0 + \beta_1(\Delta\text{Partner Violence}) + \beta_2(\Delta\text{Child Abuse}) + \beta_3(\Delta\text{Income}) + \varepsilon$

(1) Test whether the β_1 coefficient is significantly different from 0. This tests the baseline model, whether poverty and unmeasured background characteristics account for the relationship between exposure to intimate partner violence and poor child outcomes (if so, then β_1=0, otherwise the relationship is not completely explained by fixed effects). Then run the models with the z variable.

$\Delta y = \beta_0 + \beta_1(\Delta\text{Partner Violence}) + \beta_2(\Delta\text{Child Abuse}) + \beta_3(\Delta\text{Income}) + \beta_5(\Delta z) + \varepsilon$

$\text{logit}(\pi_{\Delta y}) = \beta_0 + \beta_1(\Delta\text{Partner Violence}) + \beta_2(\Delta\text{Child Abuse}) + \beta_3(\Delta\text{Income}) + \beta_5(\Delta z) + \varepsilon.$

(2) Test for a significant decrease in the size of the β_1 coefficient. Do this for all combinations of y and z variables. Models in which adding the z variable produces a significant decrease in β_1 support the hypothesis that the theory represented by z is a mechanism that explains the relationship between exposure to intimate partner violence and poor child outcomes.

(3) Finally, I will test which theory best explains the data. This theory should most strongly predict the data controlling for all other variables in the analysis. This is to say that the most powerful theory should produce the largest increase in R-square or Log-Likelihood. Let z_- be any combination of all but one of the variables representing the theoretical mechanisms. Let z_+ be the variable not included in z_-. Then get the difference in R square or log-likelihood between:

$\Delta y = \beta_0 + \beta_1(\Delta\text{Partner Violence}) + \beta_2(\Delta\text{Child Abuse}) + \beta_3(\Delta\text{Income}) + \beta_{5\text{-}zn\text{-}1}(\Delta z_-) + \varepsilon.$

and

$\Delta y=\beta_0+\beta_1(\Delta\text{Partner Violence})+\beta_2(\Delta\text{Child Abuse})+\beta_3(\Delta\text{Income})+\beta_{5\text{-}zn\text{-}1}(\Delta z_{-})+\beta_{zn}(\Delta z_{+})+\varepsilon$

The theory for which z_{+} produces the largest increase in R square or log-likelihood is the one with the most explanatory power in the data.

A common problem in research is the absence of sufficient statistical power to conduct a reasonable test of the research hypothesis. While 6,228 cases seems like more than a reasonable number to insure the power to look for effects of any consequence, I investigated whether this is in fact the case. The findings of the power analysis are that I have at least 80% power to test all of my research hypotheses. More details can be found in the addendum on statistical power.

The sample design of this study is not a simple random sample, but involves stratified cluster sampling. In these circumstances, variances calculated using formulas derived for simple random samples (which is what nearly all computer statistical packages do) will be too small, producing biased inferences (Cochran, 1977). For this reason, when appropriate my analysis calculates and uses the design effect to estimate variance. The next chapter details how the E.M. algorithm and data augmentation were used to handle item non-response.

Chapter 5: Item Non-Response in the Project on Human Development in Chicago Neighborhoods

Introduction

This chapter examines the effect of the use of data augmentation algorithms on means, standard errors and relationships among the variables from the P.H.D.C.N. data used in this paper, as compared with list-wise deletion techniques. It considers, in particular, variables measuring intimate partner[33] violence, child abuse, and child behavior problems; compares how estimates of the prevalence of these problems differ when using different techniques for dealing with item non-response.

Background on Item Non-Response

Methodological Importance of Non-Response

The treatment of missing data is an important branch of statistics perhaps mainly because of the non-trivial consequences of missing data problems for scientific research.

[33] By intimate partner, I mean someone with whom the perpetrator is involved in a romantic or sexual relationship of some duration, say at least a month.

Research has shown that unless the missingness mechanism is constant[34], simple complete case estimates[35] (list-wise deletion) will be biased (Schafer, 25). If the data are not missing completely at random (M.C.A.R.) but are missing at random[36] (M.A.R.), maximum likelihood techniques for handling missing data, such as the E.M.[37] algorithm, produce unbiased estimates (ibid). Even when the missingness mechanism is not ignorable[38] maximum likelihood estimation techniques produce estimates substantially less biased than complete case techniques if the missingness is at least partially explained by observed variables in the data (Schafer, 27). Further, as the strength of the correlation between the observed data and the missingness mechanism increased the bias decreased. Thus, even when the full assumptions for more sophisticated missing data techniques (E.M. or data augmentation) are not met, these techniques still perform better than complete case estimation. They also perform better than mean or regression imputation, both of which bias standard errors downwards, resulting in an increased probability of type I inference errors.

Substantive Importance of Non-Response for Domestic Violence

[34] That is to say missing completely at random. This means that the cause or reason for the data being missing is not related to values of the missing cases or to the values of other variables inside or outside the data.

[35] Complete case estimates are obtained by using only observed values of the data to produce estimates. In other words, any rows with missing cases are deleted from the data when estimates involving variables are calculated.

[36] For the data to be missing at random the cause of missingness must be completely explicable in terms of the observed values of other variables in the data. Controlling for those observed values, the missingness mechanism must not be related to values of the missing cases. For example, it may be the case that people with higher income may find questions about partner violence in their relationships offensive, resulting in a linear relationship between income and the log odds of non-response to the partner violence question. If income is observed in the data, then the missingness mechanism is classified as Missing at Random (M.A.R.).

[37] Expectation-Maximization. For a full treatment, see Schafer, 1997.

[38] Ignorability is the assumption justified for data which are M.A.R., meaning that the missingness of a particular variable is completely explained by other variables observed in the data.

Solutions to item non-response missing data problems are of critical practical and theoretical significance in the study of domestic violence. The sensitive nature of the subject makes the prospect of an M.C.A.R. missingness mechanism extremely improbable. Because of the stigma associated with domestic violence, the fact that it is an illegal activity and the very real fear of potential retribution from a violent partner, respondents perpetrating or being victimized by domestic violence are less likely to answer questions about domestic violence than those who are not. However, the existence of a well-established empirical literature on predictors of domestic violence lends itself to the hope that for a relatively large and well-constructed data set the missingness mechanism may be at least partially ignorable. This suggests that techniques like data augmentation may be used to at least partially correct underestimates of domestic violence produced by complete case techniques.

Correcting these underestimates is of practical policy importance because local, state and federal governments and social service agencies use these estimates to determine necessary policy responses to victims and perpetrators and as a basis for allocating funding. Bias reduction has theoretical interest because of contentious debates about the use of survey techniques to study domestic violence. Contention stems principally from conflicting accounts from qualitative research (Dobash & Dobash, 1979; Walker, 1984), which finds women to be much less violent than men in relationships, and quantitative research (Straus & Gelles, 1990), which finds men and women to perpetrate similar amounts of violence in relationships. Johnson (1995) attempts to synthesize the two positions, arguing that the contention is the result of a missing data problem. Johnson argues that there are two types of intimate partner violence against women.

Patriarchal terrorism is characterized by the systematic terrorization of the female partner by the male partner. This is the picture of domestic violence familiar to any domestic violence advocate; a physically, psychologically, emotionally abusive man who completely controls and brainwashes a passive female victim. Common couple violence is the scenario more familiar to family therapists; a couple gets into an argument which escalates into acts of violence by both parties. Johnson claims that victims and perpetrators of patriarchal terrorism are less likely to both agree to be in a quantitative survey and to respond to survey questions on violence than couples involved in common couple violence. At the same time, victims of patriarchal terrorism are likely to be sought out for qualitative feminist research. The result is an overstatement of the difference between male and female violence in qualitative research and an underestimate of the difference between male and female violence in quantitative research. Correction of item-non response bias may support Johnson's claim if higher levels of male perpetration[39] are found using imputed data. For this hypothesis to be supported, estimates of male violence would have to increase and/or female violence decrease such that the new female rate was lower than the male rate. Correction of item non-response bias is also crucial in estimating the relationship between exposure to partner violence and child cognitive and behavioral outcomes. If the prevalence of domestic violence is under-estimated, research findings may understate the strength of the relationship between exposure and child outcomes.

Appropriate Statistical Techniques for Item Non-Response

There are two widely accepted techniques for handling missing data. Both E.M. and data augmentation solve "difficult incomplete-data problem[s] by repeatedly solving

[39] Ideally a larger difference between rates of male and female perpetration.

tractable complete-data problems" (Schafer, 33). Let Y be the matrix of both observed and missing values in the data, and Y_{miss} be the subset of Y composed of the missing cases. The E.M. algorithm works by estimating a parameter θ using the observed values of the data matrix Y, filling in Y_{miss} using the initial estimate of θ, recalculating θ from the combined observed and imputed data and iterating until the estimates of θ converge (ibid). Schafer shows that for any incomplete data problem the distribution of the Y data matrix can be factored as follows[40]:

(1) $P(Y|\theta) = P(Y_{observed}|\theta)*P(Y_{miss}|Y_{obs}, \theta)$

The log-likelihood of θ is then:

(2) $\ell(\theta|Y) = \ell(\theta|Y_{obs}) + \log P(Y_{miss}|Y_{obs}, \theta) + c$

in which $P(Y_{miss}|Y_{obs}, \theta)$ is the "predictive distribution of the missing data given θ" (Schafer, 38) and c is a constant. Since $\log P(Y_{miss}|Y_{obs}, \theta)$ can't be calculated[41], in the expectation step, the complete-data loglikelihood ($\ell(\theta|Y)$) is averaged over $\log P(Y_{miss}|Y_{obs}, \theta)$ (Schafer, 29). This gives:

(3) $Q(\theta|\theta^{(t)}) = \ell(\theta|Y_{obs}) + I \log P(Y_{miss}|Y_{obs}, \theta)P(Y_{miss}|Y_{obs}, \theta^{(t)})dY_{miss}$.

In the maximization step $Q(\theta|\theta^{(t)})$ is maximized to find $\theta^{(t+1)}$. When problems are well behaved, the E.M. algorithm converges to a global maximum and results in a unique maximum likelihood estimate of θ. This procedure can be somewhat simplified when dealing with regular exponential families.

---

[40] See Schafer, page 38.
[41] We don't know Y_{miss} (ibid).

Data Augmentation is a Bayesian[42] technique which makes use of an initial hypothesis about the distribution of the data (the prior distribution) and the data itself to produce a posterior distribution (which can be viewed as a weighted average of the prior distribution and the data). The posterior distribution becomes the new prior distribution, and is combined again with the data to produce a second posterior. This process iterates, producing a Markov Chain Monte Carlo simulation which can, after a suitable burn in period, be used to estimate the true posterior distribution of the data. For large samples, the obtained posterior distribution produces estimates consistent with maximum likelihood techniques (i.e. E.M.) (Tanner & Wong, 529). The logic of Tanner and Wong's algorithm is as follows[43]:

> Given observed data y, missing data z and a parameter vector θ (where θ constitutes the sufficient statistics for the distribution), the desired quantity is the posterior density of the parameter given the observed data $p(\theta|y)$[44]. But this density must take into account the missing data. Since the missing values are not observed, one obtains the joint density of θ and z given y ($p(\theta,z|y)$) and integrates over all z.

(4) $p(\theta|y) = \int p(\theta|z,y)\, p(z|y)dz$

> However, the probability distribution function of z given y ($p(z|y)$), while unknown, can be estimated using the p.d.f. of z given y and a preliminary estimate of the parameters and the likelihood function of the preliminary parameters given

[42] Bayesian techniques make use of Bayes' Theorem. This theorem makes use of an (often subjective) belief about the probability distribution function of a variable, combined with actual data, to obtain an improved (updated) estimate of the probability distribution. For continuous variables, Bayes' theorem is $f(x|y) = f(y|x)*f(x)/ \int f(y|x)*f(x)dx$. In this formula, f(x) is the prior distribution, while parameter values for $f(y|x)$ are obtained from the data.
[43] See Tanner & Wong, page 530.
[44] Note that once the posterior distribution of the parameter(s) is obtained it can be used to impute multiple sets of data for the missing cases.

y as shown in equation (5):

(5) $p(z|y) = Ip(z|\varphi,y)\, p(\varphi\, |y)d\varphi$

where φ is an initial estimate of the parameter vector. Changing the order of integration and substituting (5) into (4) gives:

(6) $p(\theta|y) = Ip(\varphi\, |y)[Ip(\theta|z,y)\, p(z|\varphi,y)dz]\, d\varphi$

Letting T be the integral transformation which transforms 6 into another integrable function, ($Tf(\theta) = If(\varphi)[Ip(\theta|z,y)\, p(z|\varphi,y)dz]\, d\varphi$). The substitution of (5) into (4) suggests that $p(\theta|y)$ can be calculated iteratively. Specifically, start with an initial approximation of $p(\theta|y)$, call it $p(\theta|y)_i$, plug it in equation (6) for $p(\varphi\, |y)$, and iterate getting:

(7) $p(\theta|y)_{i+1} = Tf(\theta)_i$

Since the integral in $Tf(\theta)_i$ is usually difficult if not impossible to evaluate analytically, Tanner and Wang suggest the use of Markov Chain Monte Carlo. Namely, the researcher should:

a. generate multiple samples of the missing data $z^{(1)},\ldots..z^{(m)}$ using the current approximation of $p(\theta|y)$.

b. update the current approximation of $p(\theta|y)$ by calculating:

(8) $p(\theta|y)_{i+1} = m^{-1}\Sigma p(\theta|z^{(j)}, y)$ over all $z^{(j)}$.

Imputed data is obtained by calculating θ_{i+1} from $p(\theta|y)_{i+1}$, then imputing the missing data from its posterior distribution by substituting θ_{i+1} for φ in $p(z|\varphi,y)$. The process then repeats. Schafer (pages 71-73) notes that the mixing of the conditionals does not provide much practical benefit in speeding the convergence to the posterior distribution of the missing data, making it practical to simply iterate using m=1.[45] The series of imputed data sets created using Markov Chain Monte Carlo simulation represents the posterior distribution of the missing data. The number of imputed data sets required can then be chosen. If 1000 iterations of the algorithm have been run, the 200th, 400th, 600th, 800th, and 1000th sets may be saved for analysis. More data sets should be saved when larger percentages of the data are missing (see Rubin, 18).

A third, unfortunately common method of handling data is to simply eliminate the cases for which an item is missing. This is known as both complete-case analysis and list-wise deletion. As described above, Schafer (1997) has shown that this technique usually produces biased estimates. One advantage of using data augmentation is that it provides estimates of the bias produced when list-wise deletion is used to calculate rates of domestic violence and child behavior problems. Second, substantively, for both theoretical and policy purposes, better estimates of the rate of domestic violence and the relationship between domestic violence and child cognitive ability and behavior are desirable.

Predictors for Data Augmentation

A total of 46 variables were involved in the data augmentation, 42 of which had some missing cases. The Child Behavior Checklist accounted for 4 of these variables (internalizing, externalizing, anxiety/depression and total behavior problems), child abuse accounted for 2 (minor abuse and severe abuse) and domestic (partner) violence accounted for 4 (minor violence by the female partner, severe violence by the female, minor violence by the male and severe violence by the male). Family income accounted for 1 variable. This leaves 35 variables. The three with no missing cases were cohort

[45] Making this a special case of the Gibbs sampler.

(child was 0, 3, 6, 9, 12, 15 or 18 years old in the first wave of the study), child's sex and wave of the data. The remaining 32 variables were selected as predictors for data augmentation because theory predicts they will be related to domestic violence and child behavior and for reasons of theoretical interest. The remaining predictors included:

<u>Family Demographic Characteristics</u>
- Marital Status of the Primary Caregiver (married vs. not)
- Education Level of the Primary Caregiver (henceforth P.C.)
- Age of the P.C.
- Employment Status of the P.C. (employed vs. not)
- Family Size
- Neighborhood Socio-Economic Status (high, middle or low).

<u>Child Characteristics</u>
- Child's Age
- Child's Score on the Wechsler Intelligence Vocabulary Test (WISC)

<u>Parent-Child Relationship Indicators</u>
- Whether the P.C. participates in a child organization (e.g. PTA)
- Does the child have a curfew
- Does the P.C. have rules for child's behavior with peers
- Has the P.C. taught the child how to deal with a health emergency
- Has the P.C. discussed t.v. programs with child in past 2 weeks
- Has the P.C. discussed current events with child in past 2 weeks
- Has the P.C. lost her temper with the child in the past week > 1 time
- P.C. has discussed dangers of alcohol with child in the past year
- P.C. denies child access to alcohol in the home

<u>Deviance of Child's Peers Indicators</u>
- Number of peers involved in non-sport school activity (none, some, all)
- Number who obeyed school rules
- Number who have gotten into trouble at school
- Number who use tobacco
- Number who use marijuana
- Number who use alcohol
- How often asked you to go drinking
- How often offered you marijuana
- Number who have engaged in criminal acts (vandalism, theft, assault)

<u>Problems of the Child</u>
- Ever smoked
- Ever drank alcohol
- Ever used marijuana

Child has been truant in the past year
Child has repeated a grade
Child has problems with school work

Implementation Issues

Difficulty with categorical R model

It should be clear from the description of the data above that it is entirely categorical. Even the measurement of income is an ordinal variable measured increments of $10,000 up to $50,000, the last category being simply >$50,000. While a few ordinal variables have so many levels as to necessitate approximation by the normal distribution (e.g. 226 categories for Child Behavior Checklist Total score), most do not. J.L. Schafer (1999) has written a program for precisely this type of data in R (the R Project, 2005). The general location model is proposed for use with data which has both categorical and continuous variables. While this model would be perfectly adequate for smaller data sets, the problem in this case is that it uses a log-linear model for the categorical data. The default option for this is a full interaction model, which would model an effect for every possible combination of categorical cells. In my data this would entail modeling approximately 10^{11} different effects. While the program does allow for different specifications, putting structural 0's (a structural zero occurs when for logical reasons a case should be missing, e.g. it was deliberately not measured or a value is logically impossible for that case) in cells which one does not wish to model, this would again entail putting in 0's for a vector with a length on the order of 10^{11}.

Thus, I found myself in the position of not being able to use the program as it was intended. Under the circumstances, I sought to write my own data augmentation program. Unfortunately, after a substantial amount of work, this approach proved impractical. The logic of the program was to do parameter simulation (see Schafer, pg.

90), then use the parameters from various iterations to produce imputed data. Thus, depending on the type of variable, the other 44 variables were used to predict it using regression, logistic regression, ordinal or multinomial logits. The coefficients from all of these analyses were assumed to be distributed normally, with the covariance matrix of the parameters being drawn from an inverted Wishart distribution. The result was a multivariate normal distribution with a vector of 2,620 coefficients from various types of analyses and a 2,620 x 2,620 covariance matrix for these parameters. There were two problems with this approach. First, it was unrealistic to assume that the covariances of the parameters would be zero, necessitating the estimation of covariances. Having spoken with Professor Peter McCullagh (an expert in generalized linear models at the University of Chicago), I was advised that determining an analytic formula for these covariances between regression, logit, ordinal logit and multinomial logit coefficients would be quite difficult. The best means then, for getting covariances between parameters is a non-parametric bootstrap. However, using the bootstrap, obtaining a single estimate of the 2620 x 2620 covariance matrix took approximately 2 weeks on a Pentium IV machine. Running a single iteration of the data augmentation algorithm could then be expected to take about 2 weeks. While it is possible to use multiple machines to increase the speed of iterations, the length of time required to run the algorithm was still impractical. The second problem was that specifying 3,429,580 (2620x2620/2 – 2620) linear relationships for the relationships between 45 variables produced a computationally singular covariance matrix, which could not be inverted. This problem could in theory be fixed so that the algorithm could be used (if the lengthy duration of computation were not a concern). This would entail diagnosing and compensating for the singularity. Namely, one could determine which vectors of bootstrapped coefficients were responsible for the singularity, run regressions on these to obtain the appropriate linear transformation, reduce the dimensionality of the covariance matrix appropriately, sample it from the inverted Wishart distribution, then construct a new covariance matrix of the original dimensions using the linear transformations from the regressions to insert covariances for coefficients not included in the sampled covariance matrix. That covariance matrix could then be used with the vector of 2,620 coefficients to produce a sample vector of coefficients from the multivariate normal. That sample vector of coefficients could then be used to produce an imputed data set. This correction is beyond the scope of this research. I will therefore reserve it for future endeavors. I concluded that the best reasonable approach would be to make the best possible use of the available R programs. This meant using Schafer's general location model for mixed data in R, treating as many variables as categorical as was practical and treating the rest as normal. The general location model combines the normal and multinomial likelihood functions into one likelihood function for the data.

Difficulty with structural zeros

The R function for augmenting data with the general location model was much easier to use if one ran the E.M. algorithm on the data first. This is because the data augmentation program requires a large set of vectors which provide information about the data and stating values for the parameters. The E.M. algorithm in R produced this information configured such that it could be immediately plugged into the data augmentation program. Thus, data parameter values were first calculated running the

E.M. algorithm.[46] These parameters were then used as starting values for data augmentation. Once the R function for data augmentation (da.mix) was selected for use, the problem of structural zeros in the data surfaced. Most variables were intentionally not measured for all children/families in the data. In some cases, this was the only sensible approach (it would be ludicrous to measure drug use, grade repetition or truancy for 3 year olds). In other cases the researchers' failure to collect information was frustrating (for example, family size was only measured in wave 1). This means that if one wants to use family size as one of the variables to augment domestic violence, one can only use it for missing cases of domestic violence in the first wave, and must use a separate model for wave two. I created a 16 step program to work around the problem of the structural zeros.[47] Five thousand iterations of data augmentation were run, imputed data were drawn from the 500th, 1000th, 2000th, 3000th, 4000th and 5000th iterations. Neighborhood S.E.S., cohort, wave child's age and child's sex could be (and were) used to predict everything else. Cohort, wave, child's sex and neighborhood s.e.s. were treated as categorical variables, all others had to be approximated as continuous. Rounding was later used to correct for continuous value imputations for categorical variables. The details of this program can be found in the appendix.

Dependence in the Data

[46] There is some cause for concern because many of the variables failed to converge after 1,000 iterations for E.M. However, since data augmentation in and of itself is a sufficient technique for handling missing data, even if initial estimates are quite removed from the true value, and since the E.M. parameter estimates were not particularly far from the list-wise deletion estimates; the E.M. estimates were still used as initial estimates for the data augmentation algorithm.

[47] Thus, creating the imputed data set from the 500th iteration of the data augmentation actually required running the data augmentation algorithm to the 500th iteration 16 different times, always setting the random seed to the same value to insure that the same values were produced. For example, I wanted to use as many variables as possible to predict domestic violence. However, some of the variables I wished to use were not measured (had structural zeros) for some cohorts of the domestic violence variables. For this reason, I had to use smaller models for domestic violence when some of the predictors had structural zeros. Then, I supplemented this data with imputed data from the larger model for cases in which those predictors did not have structural zeros.

A third, more theoretical implementation problem involves dependence in the P.H.D.C.N. data. Two types of dependence co-exist. First, since the data is composed of two waves of the same individuals, measurements for each individual in the second wave can be presumed to be related to measurements for the same individual in the first wave. Second, since the data are drawn from a cluster sample, dependence within neighborhoods is also to be expected. While a program does exist to produce augmented data for panel data, that program is only available for continuous data. While these facts do pose potential problems with respect to the reliability of the estimates produced, there are some mitigating circumstances. First, inserting neighborhood S.E.S. as a variable should help to control for dependence by neighborhood. Second, for such cases of model failure, Schafer (1997) recommends the use of multiple imputation (of which data augmentation is a subspecies) to ameliorate the problem (Schafer, 30-31).[48]

Missing Data Models

The E.M. and data augmentation algorithms described in the previous section and used for correcting the missing P.H.D.C.N. data were developed by J.L. Schafer (1997). The likelihood function of this model combines normal and multinomial likelihoods. Considering the complete data Y to be divided into submatrices of categorical (W) and normally distributed (Z) data, having categorical parameters π and normal parameters μ and Σ, the complete likelihood is proportional to (see Schafer pg. 336 for formulas 9-11):

(9) $L(\theta|Y) \% \; L(\pi|W)L(\mu, \Sigma|W, Z).$

The categorical portion of the likelihood is proportional to:

---

[48] Another way to get around the dependence problem for panel data is to reshape the data set so that each variable in the data is inserted as 2 variables, once for each wave. There are then twice as many variables in the data to be augmented, but the dependence problem will be completely eliminated, for both neighborhood and individual dependence. This work is reserved for future endeavor.

(10) $L(\pi|W) \% \ \Pi_{d=1}^{D} \pi_{(d)}^{xd}$.

The continuous portion of the likelihood is proportional to:

(11) $L(\mu, \Sigma|W, Z) \% \ |\Sigma|^{-n/2} \exp\{-1/2\ \Sigma_{d=1}^{D} \Sigma_{i0Bd}(z_i - \mu_d)^T \Sigma^{-1}(z_i - \mu_d)\}$.

B_d indicates all of the cases falling into cell d. Schafer (336) demonstrates that the sufficient statistics for the complete loglikelihood are linear in relation to each other, indicating that the general location model is a member of the exponential family of distributions. Ordinary maximum likelihood estimates are thus used for π, ($\pi = x_d/n$), and regression maximum likelihood estimates are used for μ and Σ (Schafer, 336-337). For data augmentation, an algorithm with a Dirichlet prior for the categorical data ($\pi \sim D(\alpha)$ resulting in a posterior of $\pi \sim D(\alpha+x)$) is used. The algorithm uses a uniform prior for μ and an inverted Wishart prior for Σ, resulting in multivariate normal and inverted Wishart posteriors, respectively (Schafer, 339-341). The predictive distributions of various combinations of variables given the others are given in Schafer page 348-351.

E.M.

The M-step simply calculates estimates of the parameters using the expected versions of the sufficient statistics. A subscript ‘e’ denotes ‘estimate’.

$\pi_e = E(n^{-1}x)$

$\mu_e = E((U^TU)^{-1}U^TZ)$

$\Sigma_e = E(n^{-1}(Z^TZ - (U^TZ)^T(U^TU)^{-1}(U^TZ)))$

The E-step for this algorithm (obtaining the conditional expected values for the sufficient statistics given the observed data and an assumed value for the parameter matrix θ) is the most difficult (Schafer, 352). It is necessary to obtain conditional expectations for the sufficient statistics Z^TZ, U^TZ and U^TU.[49] Another way of writing U^TU is diag(x), since the two are equivalent. Since x is the vector of total counts for all the cells in the contingency table of categorical variables,

(12) $x = {}_{i=1}\Sigma^n(u_i)$ (Schafer, 352).

The, cells of u_i are Bernoulli. Their expectation is calculated by:

(a) use sweep operator (see Schafer, pgs 148-163)[50] to sweep the parameter matrix θ on positions corresponding to the observed continuous variables ($z_{i(obs)}$) to obtain a transformed parameter matrix θ*, (Schafer, 352).

(b) Use $z_{i(obs)}$ and θ* to calculate the following function for all possible cells[51] w:

(13) $\delta^*_{w,i} = \log(\pi_w^*) + \Sigma_{(j0Oi)}\ \mu^*_{w,j}z_{i,j}$.[52]

(c) The new expected value for the predictive probabilities for all cells in the contingency table of categorical variables is then:

(14) $\pi_{w,i}^* = \exp(\delta^*_{w,i}) / \Sigma_{(Mi(w))} \exp(\delta^*_{w,i})$.[53]

---

[49] U is an n x D matrix in where n is the number of observations and D is the number of cells in a contingency table combining all the categorical variables in the data. The rows of U are composed entirely of zeros except for one column, which will have a '1', indicating the appropriate cell for the observation in question. These rows are denoted u_i. See Schafer, pg 334.

[50] Given a symmetric pxp matrix G with elements g_{ij}, the sweep operator SWP[k] operates on G by replacing it with another pxp symmetric matrix (Schafer calls it H). The elements of H are given by:

$h_{kk} = -1/g_{kk}$, $h_{jk}=h_{kj}= g_{jk}/g_{kk}$ for j□k, and $h_{jl}=h_{lj} = g_{jl} - g_{jk}g_{kl}/g_{kk}$ for j□k and l□k

Note that k is a value set by the sweep operator. Thus, if k is a single number, h_{kk}, h_{jk}, and h_{kj} will only be one element each, while most of the matrix will be h_{jl} or h_{lj}. See Schafer, pg 159. The resulting matrix is said to have been "swept on position k" (ibid). The particular sweep operator in discussion here sweeps on *all* observed positions in succession. This is to say that the resulting matrix is the product sum of all of the swept matrices (see Schafer, 159-160).

[51] Since we are using all possible combinations of cells, when data for all categorical variables are missing, all cells will be possible, but if some categorical variables are non-missing, some cells will be ruled out. For example, for two categorical variables sex and wave, if sex were missing but wave = 2 for a particular case, the cells corresponding to wave=1 would not be in the range of possible cells.

[52] Here j0Oi indicates j includes all of the observed cases in the continuous data ($z_{i(obs)}$). M_i indicates all of the missing components in the categorical data.

[53] Which is to say, for the denominator, sum the exponentiated deltas over all possible missing cells in the categorical data for that row (i).

Each row (w) of U^TZ is ${}_{i=1}\Sigma^n(u_{w,i}z^T_{w,i})$. $u_{w,i}$ is Bernoulli with values depending on whether the observation falls into cell w for row i of the data. For all possible cells the expected value of each row of U^TZ is (353):

(15) $E(u_{w,i}z_{w,i}|Y_{obs}, \theta) = \pi_{w,i}{}^*Hz^*_{w,i}$.

in which "$z^*_{w,i}$ is the predicted mean of z_i given the observed values in $z_{i(obs)}$ and given that unit i falls into cell w" (353). Thus, $z^*_{w,i}$ is the average of $z^*_{w,i,j}$ over all j in which:

(16) $z^*_{w,i,j} = \{\overset{zij}{\mu^*_{w,j}} + \overset{\text{if j is observed}}{\Sigma_{(j0Oi)}\sigma^*_{jk}z_{ik}}$ if j is missing (ibid).

Finally, $Z^TZ = {}_{(i=1)}\Sigma^{n(}z_iz_i^T)$. Since a single element of the matrix $z_{ij}z_{ik}$ can be written as $\Sigma_{(w)}\ \mu^*_{w,i}\ z_{ij}z_{ik}$, the expectation of each element of the matrix is:

(17) $E(z_{ij}z_{ik}|\ Y_{obs}, \theta) = \Sigma_{(Mi(w))}\ \pi_{w,i}{}^*\ E(z_{ij}z_{ik}|\ Y_{obs}, \theta, \mu_{w,i}=1)$ over all missing cases.[54]

Once the expected sufficient statistics have been calculated, the M step described previously can be used to give the new estimate of the parameters. Thus, for example, getting the new estimate for π_e would involve summing the expected counts over all n cases (actual counts when cases are observed, expected counts ($\pi_{w,i}{}^*$), when missing) and dividing the sum by n. The E and M steps are repeated iteratively until suitable convergence of estimates is achieved.

Data Augmentation[55]

The Imputation step (draw $Y_{miss}{}^{t+1}\sim P(Y_{miss}|Y_{obs}, \theta^t)$) first creates a random draw of the u_i, which indicates which categorical cell observation i fills. It then draws a sample from the predictive distribution of $z_{i(miss)}|\ u_i$. Drawing the u_i simply involves a multinomial trial (only for all possible cells, see footnote 27) using the cell probabilities

---

[54] If $z_{ij}z_{ik}$ are both observed, $E(z_{ij}z_{ik}|\ Y_{obs}, \theta, \mu_{w,i}=1) = z_{ij}z_{ik}$. If z_{ij} is observed but z_{ik} is missing, $E(z_{ij}z_{ik}|\ Y_{obs}, \theta, \mu_{w,i}=1) = z_{ij}z^*_{w,ik}$. If both are missing, $E(z_{ij}z_{ik}|\ Y_{obs}, \theta, \mu_{w,i}=1) = z^*_{w\ ij}z^*_{w,ik} + \sigma^*_{jk}$. See Schafer, pages 353-54.

[55] This illustration is drawn from Schafer pgs. 355-356.

given in equation (14). Once the algorithm has assigned the categorical cell for a particular row of data, a draw from the predictive distribution of the missing continuous variables can be made. For a particular missing case for a continuous variable $z_{i(mis)}$, the regression prediction is:

(18) $z^*_{w,i,j} = \mu^*_{w,j} + \Sigma_{(j0Oi)}\sigma^*_{jk}z_{ik}$ (see equation 16)

However, to that prediction must be added "simulated residuals drawn from a multivariate normal distribution" (355). Effectively, this means that a draw of a simulated residual must be made based on the covariances among the variables in the data, given the observed data and the assumed parameters.[56] Schafer (182, 355) suggests a Cholesky factorization of the subsection of the Σ^* matrix pertaining only to the missing data elements for the row. Once the simulated residuals have been added to the $z^*_{w,i,j}$, the algorithm has produced draws from the predictive distribution of both the categorical and continuous variables, and the I-step is complete.

The Posterior step (draw θ^{t+1}~$P(\theta|Y_{obs}, Y_{mis}{}^{t+1})$ uses the improper prior (356):

(19)[57] $P(\pi,\mu,\Sigma)$ %$(\Pi_w \pi_w{}^{\alpha w-1}) |\Sigma|^{-(q+1)/2}$.

Given this prior, the complete data posterior is (ibid):

(20) $\pi|Y \sim \text{Dirichlet}(\alpha+x)$

(21) $\Sigma|\pi,Y \sim \text{Wishart}^{-1}(n-D, (\varepsilon^T\varepsilon)^{-1})$

(22) $\mu|\pi,\Sigma,Y \sim \text{Normal}(\mu_{w(e)}, x_w{}^{-1}\Sigma)$

---

[56] In other words, missing cases covary. Thus, the residuals for the regression predictions should not be independent for a particular row of data. Rather, the residuals for one missing z variable should be related to the residuals for another missing z variable in the same row of data. Thus, if two z variables were missing in a particular row, the residuals for each prediction would have to be drawn from the appropriate bivariate normal distribution.

[57] α is an array of specified hyper-parameters

where $\varepsilon^T\varepsilon$ is $Z^TZ - (U^TZ)^T(U^TU)^{-1}(U^TZ))$. In this step, one simply draws from the distributions in turn. So, for example, (20) would use all old (t) parameters for the draw. On the other hand, (21) would use the new π^{t+1} for the draw of Σ, and (22) would use π^{t+1} and Σ^{t+1} to draw the new t+1 μ. While Schafer makes some suggestions as to how to draw from these distributions (356), the R program already has routines to draw from them. Detailing this thus seems unnecessary. The algorithm then uses the new parameters to create a new draw of missing data, which is combined with the observed data to calculate new parameters which are then used as MLE's to create a new draw of sample parameters and so on.

I ran the E.M. algorithm for 1,000 iterations, followed by 5,000 iterations of the data augmentation algorithm described. Sets of imputed data were drawn for the 500th iteration and for every thousand iterations, resulting in 6 imputed data sets. Following Rubin (21), means and coefficients were then averaged from estimates produced by analyses of the 6 data sets. Variances were then calculated using the average of the within-data variances plus $(1+m^{-1})$ H (estimated variance between estimates).[58] For this case, since six data sets were imputed, m=6. I have run the program to solve the problem of item non-response, but not attrition in wave 2 (the attrition rate was 14.06%). This is left for future research.

Descriptive Statistics of Variables

Table 1, shown below, provides counts of the observed cases and the percentage missing for each type of family violence and compares means and standard errors

[58] For a particular coefficient B, the total variance is:
$(1/6)*(var(B_1)+var(B_2)+\ldots+var(B_6)) + (7/6)*(1/5)*sum(B_i-B_m)^2$
where numeric subscripts indicate which set of imputed data the parameter came from and the m subscript indicates the parameter averaged across all 6 data sets.

calculated using list-wise deletion versus using augmented data. Because this is a longitudinal study, observations in these data are not independent. To correct for this I calculated the intra-cluster correlation coefficient (ρ) for each variable and used this to calculate the design effect. Since each cluster has 2 cases (individuals were measured twice), the design effect is simply $1+\rho$. Corrected variances are obtained by multiplying the simple random sample variance by the design effect. The standard errors given below were corrected using this technique.[59] The rates of item non-response for partner violence are strikingly high with respect to violence against the child. This fact may represent an overall trend of respondents having less comfort with describing violence between adults to a researcher than violence against children. The greater amount of non-response for partner violence also means that more change in estimates is possible when data augmentation is used.

Table 1: Domestic Violence[60]

Variable	n	% missing	List-wise Deletion		Data Augmentation	
Total	9910	15.61%	Mean	S.E.	Mean	S.E.
Minor Violence[61] Female	5491	36.51%	0.006	0	0.020*	0.00102
Severe Violence	6212	28.17%	0.136	0.005495	0.158*	0.004396

[59] The data was, however, collected via a three stage cluster sample. For this reason, one can expect clustering within neighborhoods as well as within individuals. Within individual measurement clustering is a potentially more serious problem (because of higher correlations) and was corrected. Corrections for neighborhood clustering were impractical at the time of writing, but will be made in future work. While including neighborhood S.E.S. in the data augmentation algorithm should work to correct for model failure in the algorithm, neighborhood S.E.S. is not used in the calculation of standard errors for means and is thus not corrected here. Correction will involve calculating the serial correlation coefficient for neighborhood, using this to calculate the design effect and multiplying the standard errors by the design effect.

[60] * indicates $p<0.05$ for a difference in means between list-wise deletion and data augmentation.

[61] Minor and severe violence for both men and women are constructed as mutually exclusive variables. Thus, the minor violence female variable indicates the presence of minor violence by the female *only*. On the other hand, the severe violence variables include both severe violence alone, and severe violence combined with minor violence. Given the very low mean for minor violence by the female, it would appear that when women in the data do use minor violence it is very often combined with severe violence, and thus not reflected in this statistic. Males, on the other hand, seem to perpetrate a fair amount of minor violence without severe violence.

Female						
Minor Violence Male	6192	28.40%	0.111	0.004222	0.138*	0.005277
Severe Violence Male	6137	29.04%	0.102	0.004341	0.123*	0.004341
Minor Violence Against the Child	7809	9.70%	0.549	0.006619	0.536	0.005516
Severe Violence Against the Child	7732	10.59%	0.224	0.005511	0.224	0.005511

All of the estimates for partner violence have increased, which generally supports the under-reporting hypothesis.[62] All of these changes are significant at the 0.05 level, suggesting that item non-response does account for some under-reporting. On the other hand, data augmentation did not result in an increase in the estimate of violence against children. It may be that, given the impetus of western traditions of corporal punishment of children, violence against children is still considered more acceptable than violence against intimate partners.

What is particularly striking is that severe male violence rose by just over 2 percentage points. If one were trying to generalize these estimates to predict the amount of woman battering in Chicago, (a city of 2.8 million) this corresponds to an undercount of 56,000 victims. While the basic underreporting hypothesis is supported by this change, Johnson's (1995) hypothesis regarding the patriarchal terrorism/common couple violence was not. The estimates of severe male and female violence still have women perpetrating as much or more severe violence as men. Further, the difference between women and men did not change. With respect to severe violence as estimated using complete case analysis, women's rates were 3.4 percentage points higher than men's. When data augmentation was used, women's rates were 3.5 percentage points higher than men's.

[62] Of some statistical interest here are the standard errors. While one might expect that multiple imputation would decrease standard errors by adding more cases, the result of the routine appears to have increased variability in the data at the same time, resulting in little difference between complete case and augmented data standard errors. It seems that the decrease in variance resulting from added cases was counter-balanced by less precision (greater uncertainty) in the distribution of the missing cases.

The C.T.S. measure of violence is crude, both in the limited categories measured, the lack of indicators for self defense and in particular the lack of indicators for injury. Straus & Gelles (1990) show that when injuries and hospital visits are examined, women are found to suffer far more from intimate partner violence than men. Thus, the results here do not (and cannot) resolve the debate described by Johnson in favor of the common couple violence side. Nor do the results disprove Johnson's hypothesis, since the hypothesis entailed both item non-response and total non-response (a much harder problem to resolve) on the part of victims of patriarchal terrorism. What these data do show is that Johnson's hypothesis cannot be supported using item non-response techniques for these data. Based on these results, it also seems improbable that missing data fixes for other probability samples will produce evidence to support a simultaneous increase in estimates of male partner severe violence and decrease in estimates of female partner severe violence.

Table 2 shows list-wise deletion and augmented data means for child behavior problems as measured by the Child Behavior Checklist. Externalizing behavior focuses on problem behaviors in which attribution for distress is directed outwards. Thus, an upset child with externalizing problems may break things, scream, hit and so on. Internalizing results from attributions for distress directed inwards. A child with internalizing problems may blame him or her self for distress and feel worthless, depressed, anxious, etc. The estimates for child behavior problems have changed little with the application of E.M. and data augmentation. This likely stems from a combination of the fact that child behavior is probably a less contentious issue than partner violence (which means that the bias is less unidirectional) and has a lower rate of item non-response.

Table 2: Child Behavior Problems

Variable	n	% missing	List-wise Deletion		Data Augmentation	
Total	9910	15.61%	Mean	S.E.	Mean	S.E.
Internalizing Behavior	5726	16.88%	9.241	0.112447	9.314	0.125606
Externalizing Behavior	5726	16.88%	10.876	0.138218	10.660	0.146705
Total Behavior Problems	5726	16.88%	27.188	0.342099	26.627	0.372214

Table 3, shown below, provides valid counts and missing rates for other variables used in the algorithm. The table also compares means and standard errors for list-wise deletion and data augmentation. The variables here were selected from among hundreds in the P.H.D.C.N. data for their relevance in predicting both domestic violence and child behavior problems. The data show that about 1/3 of primary caregivers were not married and that education levels were low (educ=3 for high school graduates). Family sizes were substantially larger than national averages, possibly indicating the presence of extended family, and the average maximum household salary was between 20 and 30 thousand dollars per year (indicating that the sample is lower income than national samples). Most of the sample is employed, and the average caregiver is in her early 30's. Some parenting measures below seem more informative than others. The fact that 98% of caregivers claim that their child has a curfew makes it seem like answers to this question will have less variability and less use than others.

Table 3: Other Predictors

Variable	n	% missing	List-wise Deletion		Data Augmentation	
Total	9910	15.61%	Mean	S.E.	Mean	S.E.
Marital Status	8023	7.23%	0.334	0.006	0.339	0.0063
Education Level P.C.	7690	11.08%	2.924	0.02	2.914	0.0202
Age P.C.	9780	1.31%	34.74	0.069	34.76	0.079
Employment	6772	27.02%	1.533	0.010	1.50	0.009

Family Size	4809	2.95%	5.292	0.026	5.32	0.027
Salary	8152	12.14%	4.246	0.027	4.25	0.025
Neighborhood SES	8273	16.52%	1.896	0.012	1.892	0.011
Child's Age	9247	6.69%	10.747	0.023	10.88	0.021
WISC	5950	10.42%	25.55	0.16	25.84	0.149
Ever Smoked	5330	10.36%	0.302	0.007	0.310	0.0073
Ever Drank	5328	10.39%	0.353	0.007	0.362	0.0075
Ever Marijuana	4498	12.11%	0.171	0.006	0.185	0.0058
Truant	4008	14.43%	0.182	0.007	0.197	0.0068
Repeated a Grade	4846	14.43%	0.13	0.006	0.142	0.0059
Problems with School Work	5887	11.37%	1.350	0.009	1.369	0.009
# Non-sport school activity (dp1)	2942	44.85%	1.997	0.009	1.729	0.012
# obeyed rules (dp5)	4634	12.81%	2.179	0.0084	2.176	0.008
# in trouble (dp7)	4626	12.96%	1.953	0.009	1.948	0.009
# use tobacco (dp29)	4686	11.83%	1.454	0.010	1.460	0.009
# use alcohol (dp27)	5057	14.95%	1.626	0.011	1.655	0.009
# use marijuana (dp26)	4959	16.60%	1.482	0.006	1.508	0.006
How often asked go drinking (dp31)	5109	14.08%	1.564	0.013	1.557	0.012
How often offered pot (dp34)	5063	14.85%	1.391	0.012	1.384	0.009
crime (dp15,17,23)	4936	16.99%	4.050	0.019	4.075	0.020
P.C. participates organization, hg20	7760	10.27%	0.238	0.006	0.242	0.0056
Curfew (hg106)	5928	10.75%	0.981	0.001	0.975	0.001
Rules (hg113)	5922	10.84%	0.935	0.003	0.926	0.003
Health Emergency (hg120)	5925	10.79%	0.922	0.001	0.914	0.002
Discuss tv (hg55)	5784	13.23%	0.779	0.0063	0.770	0.0063
Discuss current events (hg54)	5774	13.38%	0.751	0.0055	0.740	0.0055
lost temper (hg129	5780	13.29%	0.660	0.0063	0.652	0.0063
discussed alcohol (hg123)	4342	25.78%	0.944	0.004	0.913	0.0063
denies alcohol (hg126)	4365	25.38%	0.666	0.006	0.707	0.011
Cohort	9910	0%	3.225	0.007	3.225	0.007
Wave #	9910	0%	1.5	0.00	1.5	0.00
Child's sex	9910	0%	0.500	0.007	0.500	0.007

Conclusion

This chapter used E.M. and data augmentation to examine under-reporting of domestic violence in the P.H.D.C.N. data. While no evidence was found to support Johnson's (1995) hypothesis that the missing cases in quantitative data contain a much higher proportion of patriarchal terrorism than common couple violence, the results do support the premise that serious under-reporting of domestic violence, particularly partner violence, occurs, resulting in under-estimates of the number of victims affected. My analyses, extrapolated to the city of Chicago, suggest that complete case analysis results in an undercount of victims of severe male violence on the order of 57,000 people. This situation is likely to result in shortages of services for victims, insufficient administrative support for police and the judicial system in handling the perpetrators and a continuation of the problem of 'hidden' domestic violence. The importance of using statistically sound techniques for the handling of missing domestic violence data cannot be overstated.

Chapter 6: Baseline Results of the Analysis

Descriptive Statistics

Descriptive statistics of variables in the analysis for the entire sample were presented in the last chapter. The prevalence of severe male violence in the sample (over both years) rises from 10% to 12% once the data are augmented. While the statistics presented in the previous chapter were important to present, breaking down the variables by wave, allowing for the depiction of trends over time, will be even more useful.[63]

[63] In addition, the descriptive statistics shown here derive from 9 multiply imputed data sets, rather than 6. Descriptive statistics and analyses here reflect the addition of 3 more multiply imputed data sets

Tables 1-5 below present means and standard errors of the variables from waves 1 and 2. Standard errors are given in parentheses below the means.

The table below presents family demographic descriptive statistics for waves 1 and 2 combining information from 9 multiply imputed data sets. Small increases seem to have occurred between the waves in both neighborhood socio-economic status, the primary caregiver's educational status and the primary caregiver's marriage/cohabitation status. Salary also increased substantially between waves. These changes are consistent with the booming economy of the 1990's and simple time trends. The increases were all statistically significant. Family size and the age of the primary caregiver were not measured in wave two.

Table 1: Descriptive Statistics for Waves 1 & 2; Family Demographics

Variable	Wave 1 (1994)	Wave 2 (1997)
Neighborhood SES	1.8794 (0.0108)	1.9055 (0.0109)
P.C.'s Education	2.8674 (0.0206)	2.9609 (0.0196)
P.C.'s Marital Status	0.3162 (0.0072)	0.3609 (0.0071)
P.C.'s Employment status	1.6903 (0.0126)	1.3167 (0.0070)
Highest Salary in House	3.8860 (0.0268)	4.6689 (0.0374)
Family Size	5.3220 (0.0273)	NA
Age of P.C.	35.5073 (0.1102)	NA

Table two provides descriptive statistics for changes in violence against partners and violence against children over time. Encouragingly, all forms of domestic violence show significant ($p<0.05$) decreases between waves 1 and 2. However, whether this is because families suffering from partner violence are likely to separate from the abuser, parents are less likely to use violence against their children as they get older (or as the

(augmented to 6000, 7000 and 8000 iterations). The additional sets were created primarily to decrease the variance resulting from uncertainty about missing cases. The averages changed very little.

parents become more experienced) or because those cases for which domestic violence persisted or began were more likely to fall out from attrition is unclear.

Table 2: Descriptive Statistics of Domestic Violence from Waves 1 & 2

Variable	Wave 1 (1994)	Wave 2 (1997)
Minor violence by female	0.0241 (0.0015)	0.0169 (0.0006)
severe violence by female	0.1964 (0.0053)	0.118 (0.0038)
minor violence by male	0.1541 (0.0051)	0.1225 (0.0040)
severe violence by male	0.1578 (0.0049)	0.0870 (0.0033)
minor violence to child	0.7109 (0.0074)	0.3610 (0.0068)
severe violence to child	0.3217 (0.0071)	0.1269 (0.0047)

On the other hand, the rates of violence in wave one are distressingly high. In this sample of Chicago households 19.6% of females perpetrated severe violence against their male partners, 15.8% of males perpetrated severe violence against female partners, and 32% of children were victimized by severe violence. These are substantially higher than the rates found by Straus & Gelles (1990) in their random sample study of the United States. This may be related to the fact that the income range is lower than the national average, to particular characteristics of Chicago or to differences in sampling.

The means and standard errors of the dependent variables are shown in table 3. The three child behavior variables from Achenbach's Child Behavior Checklist are shown first. Interestingly, internalizing is increasing while externalizing is decreasing

Table 3

Variable	Wave 1 (1994)	Wave 2 (1997)
Internalizing	8.7838 (0.1308)	9.8634 (0.1388)
Externalizing	12.3636 (0.1632)	8.9505 (0.1269)
Total CBCL score	30.8293 (0.4134)	22.4283 (0.3229)
Poor School Work	1.3087 (0.0111)	1.4288 (0.0107)

WISC score	23.1601 (0.1539)	28.5023 (0.1650)
Ever Smoked	0.2602 (0.0080)	0.3612 (0.0079)
Ever Drink	0.3143 (0.0082)	0.411 (0.008)
Ever Use Pot	0.1101 (0.0074)	0.2390 (0.0065)
Ever Truant	0.1656 (0.0083)	0.2290 (0.0081)
Ever Repeat a Grade	0.1078 (0.0062)	0.1910 (0.0075)

between the two waves. There is a large decrease in total behavior problems between waves. A large majority reports no problems with school work and consistent with an overall increase in age the score on the WISC increases substantially. The percentage of children over nine smoking increases between waves (as makes sense given the increases in age and exposure) but is disturbingly high in both waves. Twenty-six percent of children in the sample over 9 had tried smoking in the first wave. By the second wave the percentage of these was thirty-six percent. The consumption of alcohol and pot in this group is also high. Rates of truancy and grade repetition are also substantial. It would seem that if few effects of domestic violence are found it will not be for lack of children with problem behaviors.

Table 4 provides descriptive statistics of child characteristics and parent-child relationship indicators. Clearly, a large proportion of care-givers in both waves claim their child has a curfew, that she has rules for behavior with peers and that they have discussed health emergencies and alcohol with their children. Given the small amount of variation in these variables, they may not be able to explain much variation in anything else. The remaining variables may be more productive. Drops in primary care-giver participation in a child-centered organization and in the denial of alcohol in the home are perhaps both consistent with the aging of the child. The increase in anxiety/depression may reflect the difficulty children experience with adolescence, as a larger proportion of the sample enters its teens in wave 2.

Table 4: Child and Parent-Child Descriptive Statistics

Variable	Wave 1 (1994)	Wave 2 (1997)
Child has a curfew	0.9847 (0.0017)	0.9649 (0.0028)
PC has rules for child's behave w/ peers	0.9406 (0.0041)	0.9121 (0.0045)
PC participates in a child organization	0.2795 (0.0069)	0.2059 (0.0057)
PC discusses handling health emergency	0.9252 (0.0024)	0.9020 (0.0048)
PC discusses tv with child	0.7725 (0.0088)	0.767 (0.006)
PC discusses current events w/ child	0.8044 (0.0080)	0.7046 (0.0056)
PC has lost temper w/ child in last week (>2x?)	0.6994 (0.0094)	0.6247 (0.0069)
PC has discussed dangers of alcohol	0.9183 (0.0069)	0.9117 (0.0035)
PC denies child alcohol in home	0.7824 (0.0105)	0.6837 (0.0038)
Child's Age	9.8287 (0.0218)	11.9287 (0.0354)
Child's Anxiety/Depression Score	3.8858 (0.0717)	4.3796 (0.0688)

Finally, Table 5 provides means and standard errors for deviance of peers variables in waves one and two. These ask whether none, some or all of a child's peers engaged in the behavior described. The final category (crime) combines information about how many peers are committing vandalism, theft and assault. The range of this variable is from 3 (no peers committing any of these) to 9 (all peers committing all of these). On average, at least some peers are committing one of these types of crime.

Table 5: Deviance of Peers Descriptives

Variable	Wave 1 (1994)	Wave 2 (1997)
Number involved in non-sport school activity	2.0392 (0.0090)	1.3455 (0.0085)
Number obeyed rules	2.1842 (0.0101)	2.1645 (0.0105)
Number in trouble	1.9957 (0.0102)	1.8853 (0.0098)
Number use tobacco	1.4555	1.4676

	(0.0108)	(0.0117)
Number use marijuana	1.4311 (0.0110)	1.5847 (0.0107)
Number use alcohol	1.5887 (0.0115)	1.7235 (0.0112)
How often asked to go drinking	1.4626 (0.0125)	1.6536 (0.0127)
How often offered pot	1.3282 (0.0113)	1.4432 (0.0114)
How often Commit Crimes (vandalism, theft & assault)	4.0739 (0.0219)	4.0718 (0.0203)

Baseline Fixed Effects Models

In this section, I present the results of my fixed effects analyses. As discussed in chapter 4, fixed effects models simultaneously solve the problem of dependence in longitudinal data and eliminate bias from omitted variables which do not change over time (e.g. grandparent's education) as well as secular trends pertaining uniformly to the whole sample. The fact that these models only examine variation within children, rather than between them, renders the inclusion of controls for variables which remain constant (grandparent's education, where the child was born, etc) not only unnecessary but impossible. They present a tremendous advantage to a researcher because they control for selection effects. If one believes, for example, that both domestic violence and problematic child behavior are both caused by the social class into which one is born (e.g. being born into a poor family causes both, see Straus & Gelles, 1990, pg. 330) one must control for this relationship. The P.H.D.C.N. data have no information on this, making an explicit control impossible. However, the fixed effects model eliminates bias from this variable and many others. Fixed effects regression was used to model the child's score on the Wechsler's Intelligence Scale for Children vocabulary test and externalizing behavior, internalizing behavior and total behavior problems as measured by Achenbach's (1983) Child Behavior Checklist. Fixed effects logistic regression was used for ever drank alcohol, ever smoked, ever used marijuana, trouble with schoolwork, ever truant and ever repeated a grade.

A multiple inference problem exists because there are ten dependent variables and thus ten different models. Thus, biased inferences[64] result if model significance is checked using the ordinary p=0.05 standard of statistical significance. In theory it would be possible to solve this problem by writing computer code to do multivariate analysis of variance with fixed effects models. This would be the ideal solution because it avoids the conservative Bonferroni criterion, which places a very high burden of proof for the conclusion of statistical significance. However, in this case, despite the conservative nature of the Bonferroni correction, all of the models passed it[65] ($p<(0.05/10) = p<0.005$), making the additional work of running the MANOVA unnecessary. Because this research used multiple imputation to correct for missing data problems, each model was run on nine (strongly related but slightly different) data sets. Results of these analyses were combined using Rubin's (2004) guidelines. This is to say that effects were calculated by taking the average of the 9 individual effects. Variances of effects were calculated by calculating the average variance within and adding it to (1 + 1/9) times the estimated variance between (see Rubin, 21). Standard errors are then calculated in the ordinary fashion from the variances.

As evidenced by the partner violence joint significance F and Chi-square statistics in the tables that follow, the results find that partner violence is a significant predictor of externalizing behavior, internalizing behavior, total behavior problems and drinking.

---

[64] In this case, an increased probability of 'false positives', which is to say that one will conclude results are statistically significant when they are not.

[65] For continuous models using fixed effects regression, the statistic was an F test comparing the full model with the null, for the dichotomous fixed effects logistic regression this was a chi-square (likelihood ratio) test comparing the full model to the null model. These tests all had $p<0.005$, indicating that, using the Bonferroni correction, all models were statistically significant at the $p<0.05$ level.

Partner violence was not a significant predictor of any other variables, but these results will be shown nonetheless. The first four tables that follow are the results for which partner violence is a significant predictor.

Table 6 below shows the results from the fixed effects regression of externalizing child behavior on domestic violence and highest household salary. Since the F-statistic is 8.31 on four degrees of freedom, partner violence (minor and severe violence by the female and male partners) is a highly significant predictor of externalizing behavior. The statistical significance seems to be mostly driven by male violence. The model indicates that, controlling for other types of partner violence, if a family moves from having no severe male violence against the female partner to having severe male violence against her, this change is associated with a 1.35 point increase in externalizing behavior. The standard deviation of externalizing behavior is 13.3 ($0.1635 * 6642^{1/2}$), so this effect is noteworthy. Minor violence by the male partner is associated with a 0.87 unit increase in externalizing behavior. Interestingly, while the maximum likelihood estimate of severe violence by the female partner is in the expected direction, the estimate for female minor violence is negative. Compared to no change in partner violence, minor violence by the female partner is associated (not significantly) with less acting out. Although partner

Table 6: Effect of Partner Violence on Externalizing Behavior (Fixed Effects)

Externalizing	coef/F	std. err	t-test	p
Minor Violence (f)	-0.405	1.796	-0.226	0.821
Severe Viol. (f)	1.036	0.681	1.521	0.128
Minor Viol. (m)	0.871	0.491	1.772	0.076
Severe Viol. (m)	1.348	0.666	2.024	0.043
Minor Violence Against the Child	2.141	0.312	6.861	0.000
Severe Violence Against the Child	2.429	0.384	6.330	0.000
Highest Salary	-0.144	0.100	-1.445	0.149
Model Significance (F)	99.613			0.000

Joint Significance of Partner Violence (F)	8.310			0.000

violence is jointly significant for the child behavior checklist outcomes and for drinking, this is the only model for which an individual partner violence predictor (severe violence by the male) is significant. It is interesting to note that while men and women seem to perpetrate about the same degree of violence towards each other in this sample, violence by the male has a stronger and more important effect on the child's externalizing behavior. Particularly interesting here is that the measures of male violence are statistically significant predictors of externalizing, while measures of female violence are not. This means that while it seems reasonable to conclude that male to female violence increases externalizing, we cannot conclude from the data that female to male violence increases externalizing behavior. The development of violence directed by the care-giver and partner against the child are both strongly and significantly related to an increase in acting out by the child. However, this finding is subject to a chicken and egg problem familiar to most researchers of child abuse. While it seems very likely that an increase in parent violence against their children will result in more acting out, it is also possible that increases in problematic child behavior occasion increases in parental violence. Thus, these estimates may suffer from bi-directional causality bias. Finally, while not significant, the maximum likelihood estimate indicates that an increase in salary may be associated with a decrease in externalizing behavior.

Below the results from the fixed effects regression of internalizing child behavior on domestic violence and highest household salary are shown in Table 7. The F-statistic is 2.56 on four degrees of freedom, indicating that partner violence is a significant predictor of internalizing behavior. While the effects of partner violence are collectively significant, none of the individual effects achieves significance.[66] Worth noting, however, is the fact that among these the largest effect on internalizing behavior is severe violence by the *female* partner. The idea that male violence may cause externalizing behavior while female violence may cause internalizing behavior is an intriguing one. While violence by either partner probably results in emotional difficulty, it seems possible that the stereotypical female caretaking role may result in an attributional logic in which the child comes to believe blame him/herself for the violence. On the contrary, since the father or father-figure is perhaps less central to the caretaking role and hence child's sense of well-being, it may be less of a threat to the child's felt security for the child to blame the male partner for the violence he perpetrates. On the other hand, blaming the primary caregiver (who was always female in these data) may incite fear of alienating the central figure on whom the child depends, thus posing a greater threat to the child's sense of well being.

Table 7: Effect of Partner Violence on Internalizing Behavior

Internalizing	coef/F	std. err	t-test	p
Minor Violence (f)	0.245	1.550	0.158	0.874
Severe Viol. (f)	0.834	0.515	1.621	0.105
Minor Viol. (m)	0.284	0.441	0.643	0.520
Severe Viol. (m)	0.351	0.582	0.604	0.546
Minor Violence Against the Child	1.452	0.315	4.613	0.000
Severe Violence Against the Child	0.807	0.334	2.414	0.016
Highest Salary	-0.192	0.103	-1.859	0.063
Model Significance (F)	17.273			0.000
Joint Significance of Partner Violence (F)	2.562			0.037

[66] As described above, the formula for calculating variance with multiply imputed data sets is average variance within + (1+1/m)*variance between, where m is the number of imputed data sets. Thus, the variance depends on the number of imputed data sets. It is possible that, if more sets were imputed, some of the effects not significant here (in this case perhaps the effect for severe violence by the female partner) would become significant. In this context, the reader should particularly pay attention to effects when (in cases like this one) the joint significance of the partner violence variables is established.

The coefficients for minor and severe violence against the child are highly significant predictors of internalizing behavior. However, as one would expect if one thinks the bi-directional bias to be smaller for the internalizing case, these coefficients are substantially smaller than those for externalizing behavior. While the bi-directionality problem may be present for internalizing behavior, it is certainly a harder case to make that parents are more likely to abuse a child with depressive or other internalizing behaviors. It seems likely that the bi-directional causation problem is probably substantially smaller in this case. Thus, it seems reasonable (and perhaps, to some, obvious) to conclude that violence against child causes increases in internalizing behavior.[67]

Table 8 provides estimates of the effect of partner violence on total behavior problems as measured by Achenbach's (1983) Child Behavior Checklist. The F-statistic of 6.81 on (4, 3313) degrees of freedom indicates that intimate partner violence as a whole is a highly significant predictor of total behavior problems. Since this scale combines internalizing behavior (for which severe female violence has the largest effect), externalizing behavior (for which severe male violence has a strong effect), somaticization problems as well as many other types, it is unsurprising that the severe male violence and severe female violence are the strongest partner violence effects.

Table 8: Effect of Partner Violence on Total Behavior Problems (C.B.C.L.)

Total Behavior Problems	coef/F	std. err	t-test	p
Minor Violence (f)	-0.822	4.490	-0.183	0.855
Severe Viol. (f)	2.984	1.614	1.849	0.065
Minor Viol. (m)	1.820	1.134	1.604	0.109

[67] By association, it also seems reasonable to conclude that violence against the child also causes increases in externalizing behavior. This relies on two assumptions (1) no substantial bi-directional causation bias in the coefficients predicting internalizing behavior and (2) similar effects of violence against the child on both externalizing and internalizing behavior.

Severe Viol. (m)	2.499	1.620	1.542	0.123
Minor Violence Against the Child	5.071	0.835	6.077	0.000
Severe Violence Against the Child	5.031	0.924	5.448	0.000
Highest Salary	-0.390	0.272	-1.432	0.152
Model Significance (F)	87.059			0.000
Joint Significance of Partner Violence (F)	6.808			0.000

The estimated effects of minor and severe violence against the child are highly statistically significant and huge. The standard deviation of the Child Behavior Checklist is 33.67 ($0.4131* 6642^{1/2}$), so compared to no change in child abuse, moving from no child abuse to having severe violence against the child is associated with a 0.15 (5/33.7) standard deviation increase in behavior problems.

The final outcome for which partner violence was a significant predictor was alcohol consumption. Below Table 9 provides logistic regression results of ever drink regressed on partner violence. Comparing nested models in logistic regression involves alikelihood ratio test (the difference of log-likelihoods from the restricted and full models). When this difference is multiplied by negative two, it has a large sample chi-square distribution. The expected value of a Chi-square distribution is simply it's degrees of freedom. Since the statistic which tests the joint significance of the partner violence variables is 10.14 with 4 degrees of freedom, the reader can see that it is substantially larger than its expected value.[68] Thus, it is significant at the 95% confidence level and partner violence is a significant predictor of whether the child/teen ever drank. Since none of the individual effects of partner violence are significant but the F-test is, this seems to indicate that the standard errors when the partner violence variables broken down by violence type and sex of perpetrator are too large (perhaps because of smaller

[68] The expected value for a Chi-square distribution with 4 degrees of freedom is four.

n's associated with these divisions of the partner violence variable). Given the significance of partner violence as a whole, it would thus be erroneous to conclude that there are no effects of partner violence in this case.

Table 9: Effect of Partner Violence on Drinking

Drinking	coef/Chi Square	std. err	Odds Ratio	p
Minor Violence (f)	-4.382	2.798	0.013	0.117
Severe Viol. (f)	0.023	0.374	1.024	0.950
Minor Viol. (m)	0.656	0.421	1.927	0.119
Severe Viol. (m)	-0.317	0.403	0.729	0.432
Minor Violence Against the Child	0.421	0.226	1.523	0.062
Severe Violence Against the Child	0.049	0.245	1.051	0.840
Highest Salary	0.101	0.068	1.106	0.136
Model Significance (Chi)	175.010			0.000
Joint Significance of Partner Violence (Chi)	10.140			0.038

Coefficients in logistic regression indicate the change in log odds of drinking associated with a one unit increase in the predictor. Since it is difficult to think through consequences on the log-odds level, a convenient transformation in logistic regression is to exponentiate the coefficients, yielding odds ratios (shown in the 3rd column). The odds ratios have a multiplicative relationship with the odds of drinking. Thus, having minor male violence is associated with a 1.93 times increase in the odds of drinking. The odds increase by 1.93 times. The most striking effect here, however, is the *huge* decrease in odds of drinking associated with minor female violence. The presence of minor violence by the female partner decreases the odds of drinking by 0.013 times. It is unclear why this relationship exists, perhaps it indicates parentification? In any case, the large negative effects were seen in all 9 imputed data sets.[69] Interestingly, severe violence by the male also has a negative coefficient, and thus an odds ratio which is less than one.

[69] This is another case in which it seems possible that a larger number of imputed data sets might produce a statistically significant effect.

Minor violence against the child is associated with an increase in odds of drinking by 1.5 times. Severe violence directed against the child is associated with a more modest 5.1% increase in the odds of drinking. The effect is not significant, but it is still odd that the estimated effect of an increase in salary increases the odds of drinking.

Table 9 provides logistic regression estimates of the effects of domestic violence on the odds of poor school work. The partner violence variables are not jointly significant, and thus the results do not justify the conclusion that there is a relationship between partner violence and poor school work. However, minor violence against the child is associated with an increase in the probability of poor school work. Minor violence increases the odds of poor school work by 1.74 times. As with violence against the child and externalizing behavior, we can infer that there may be a bi-directional causation problem with this odds ratio. Nonetheless, since the direction of the relationship is opposite to that which some parents may hope for or expect, this is worth noting.

Table 10: Effect of Partner Violence on Poor School Work

Poor School Work	coef/Chi Square	std. err	Odds Ratio	p
Minor Violence (f)	0.554	0.903	1.740	0.540
Severe Viol. (f)	0.203	0.225	1.225	0.369
Minor Viol. (m)	0.144	0.235	1.154	0.542
Severe Viol. (m)	-0.049	0.220	0.952	0.824
Minor Violence Against the Child	0.554	0.138	1.741	0.000
Severe Violence Against the Child	-0.005	0.132	0.995	0.972
Highest Salary	0.051	0.036	1.052	0.157
Model Significance (Chi)	159.084			0.000
Joint Significance of Partner Violence (Chi)	4.862			0.302

Table 11 shows the fixed effects regression results of vocabulary test score regressed on domestic violence variables and salary. Controlling for violence against the child salary and fixed effects, the partner violence variables do not predict test scores.

Table 11: Effect of Partner Violence on W.I.S.C. Vocabulary Score

W.I.S.C. Vocabulary Test	coef/F	std. err	t-test	p
Minor Violence (f)	1.014	1.418	0.716	0.474
Severe Viol. (f)	0.110	0.415	0.265	0.791
Minor Viol. (m)	0.030	0.438	0.069	0.945
Severe Viol. (m)	-0.026	0.423	-0.061	0.952
Minor Violence Against the Child	0.392	0.233	1.677	0.094
Severe Violence Against the Child	-0.114	0.297	-0.383	0.702
Highest Salary	0.520	0.086	6.016	0.000
Model Significance (F)	277.531			0.000
Joint Significance of Partner Violence (F)	0.693			0.597

Interestingly, increases in salary are significantly associated with increases in test score. Since these analyses control for fixed effects, this suggests that household income has an effect on the child's intellectual performance above and beyond ascriptive class status characteristics.

Because, controlling for fixed effects, none of the independent or control variables had any effects on the remaining outcomes, these results are combined into one table. None of the partner violence variables were jointly significant or significant predictors at the individual level and neither were the violence against child variables or salary.[70] Since all of the remaining outcomes were dichotomous, Table 12 provides odds ratios, with coefficients and their standard errors beneath in parentheses. Double

Table 12* Effects of Partner Violence on Smoking, Marijuana use, Truancy and Flunking

[70] Not only were none of these significant at the 0.05 level, all of the p values were over 0.1. Thus, the existence of a relationship seems dubious here, at least in these data.

Not Significant	Truancy	Grade Repeat	Ever Smoke	Marijuana
Minor Violence (f)	2.136 (0.759 | 1.57)	2.521 (0.925 | 1.384)	0.423 (-0.86 | 1.967)	0.048 (-3.04 | 4.189)
Severe Viol. (f)	1.111 (0.105 | 0.327)	1.075 (0.072 | 0.369)	0.840 (-0.174 | 0.338)	1.306 (0.267 | 0.635)
Minor Viol. (m)	1.003 (0.003 | 0.298)	0.764 (-0.269 | 0.363)	1.219 (0.198 | 0.452)	1.536 (0.429 | 0.688)
Severe Viol. (m)	0.788 (-0.239 | 0.355)	0.868 (-0.142 | 0.389)	1.281 (0.248 | 0.369	0.694 (-0.365 | 0.761)
Minor Violence Against the Child	1.125 (0.118 | 0.185)	1.064 (0.062 | 0.217)	1.174 (0.16 | 0.214)	1.215 (0.195 | 0.299)
Severe Violence Against the Child	0.843 (-0.171 | 0.194)	1.128 (0.121 | 0.230)	1.271 (0.24 | 0.245)	0.807 (-0.214 | 0.359)
Highest Salary	0.996 (-0.004 | 0.048)	0.934 (-0.068 | 0.073)	1.089 (0.086 | 0.060)	1.067 (0.065 | 0.094)
Model Significance (Chi)	43.600**	39.984**	169.068**	136.559**
Joint Significance of Partner Violence (Chi)	3.246	2.793	2.459	5.664

*parentheses contain coefficients, followed by standard errors

asterixes are used to indicate that for model significance p<0.005. It is difficult to say much about this table, since the lack of precision does not allow me to draw conclusions. However, since minor violence by the female partner has some pretty large odds ratios, this may have some effect on truancy or grade repetition.

To sum up, intimate partner violence seems to have effects on externalizing, internalizing, total child behavior and drinking. Generally, the coefficients indicated that partner violence is associated with increases in behavior problems and drinking. In particular, severe male violence seems to have an important effect on externalizing behavior. Violence directed against the child by parents is also a strong predictor of these outcomes. These findings derive from rigorous tests using fixed effects controls, and are thus not subject to many types of omitted variable bias (e.g. from ascriptive characteristics). They are still, however, subject to bi-directional causation bias, as well as anything which varies within individuals over time, or which varies differently over time for different individuals. Thus, for example, if changes over time in neighborhood socio-economic status cause both externalizing behavior and intimate partner violence, this would bias the fixed effects coefficients, resulting in a potentially spurious relationship. The next chapter examines precisely this topic. Specifically, based upon a number of different theories about deviance, development and stress, the following chapter explores what might explain the relationships between partner violence and outcomes which were found in this chapter.

Chapter 7: Can Theory Explain the Baseline Results?

Introduction

This chapter examines whether any of the theories developed in chapter 3 seem to have explanatory power for the effects found in the previous chapter. I examine whether theories developed from the deviance, development and stress literatures seem to mediate the effects of intimate partner violence on externalizing, internalizing and total behavior problems, as well as alcohol consumption. The other outcomes, on which partner violence seemed to have no effect, are not examined in this chapter. If mediation is found to occur, this will provide some support for the theory driven hypothesis. The chapter is divided into five sections. The first section tests the hypothesis that the acute stress of exposure to intimate partner violence results in anxiety symptoms which produce the negative outcomes seen in the previous chapter. The second section looks broadly and narrowly at the effects of age and the Piagetian hypothesis. The third section tests the possibility that the parent-child relationship explains relationships between partner violence and outcomes. The fourth section examines the evidence for whether the relationship between partner violence and outcomes is mediated by deviant peers. The fifth and final section takes into account the possibility that changes in neighborhood socio-economic status are an omitted variable. I use Baron and Kenny's (1986) criteria for establishing a mediating relationship. That is, first, the partner violence-outcome relationship must be significant. Second, controlling for partner violence, the mediator-outcome relationship must be significant. Third, the effect of partner violence on the outcome, when the mediator is included in the controls, must be significantly smaller than before (or reduced so that its statistical significance is eliminated). Like chapter 7, this chapter uses fixed effects models. Coefficients shown in tables are regression coefficients. Logistic regression coefficients are shown for drinking.[71]

Except for externalizing, none of the outcomes have partner violence coefficients which are significant at the 95% confidence level. For this reason, it is necessary to rely on the joint significance statistics (F and Chi square). Since these ordinarily have no standard error, one could usually only use these to show the existence of full mediation (in the full model the joint significance statistic would not be significance). However, in

[71] These indicate the change in log odds of drinking per unit increase in the predictor. A positive coefficient indicates positive association, a negative coefficient negative association.

this case the existence of multiply imputed data sets means that the joint significance statistics do have a standard error. These will be used to determine partial mediation. That is, if the joint significance statistic is significantly smaller in the full model, this will be judged as evidence for partial mediation of the effect.

Anxiety

Looking across the first row, anxiety was a significant predictor of externalizing, internalizing and total behavior problems. However, its prediction of internalizing may be an artifact of sharing some of the same questions as the internalizing variable. For this reason, I will not pay much attention to (or further note) the fact that anxiety appears to mediate the effect of partner violence on internalizing.

With respect to externalizing behavior, controlling for anxiety seems to have a moderate effect on the partner violence coefficients (they are a little smaller). The change in F-statistic shown at the bottom of the chart indicates that this change is jointly significant. Since partner violence significantly predicts externalizing in the baseline model, anxiety significantly predicts externalizing in the full model, and since there is a significant collective decrease in the fixed effects regression partner violence coefficients, I conclude that anxiety does mediate the effect of partner violence on externalizing behavior, albeit not dramatically.

Table 1[72]: Baseline Models Compared to Models Including Anxiety

	External Baseline	External Full***	Internal Baseline	Internal Full***	Total Behavior	Total Behavior	Drink Baseline	Drink Full

[72] † p<0.10
* p<0.05
**p<0.01
***p<0.005
α p<0.05 for difference between baseline & full model statistics (partial mediation).
Asterixes and daggers in the first row next to the full models indicate whether the mediator was a (jointly) significant predictor of the outcome.

					Baseline	Full***		
Minor Violence (f)	-0.405 (1.796)	-0.423 (1.57)	0.245 (1.55)	0.214 (0.745)	-0.822 (4.490)	-0.889 (3.160)	-4.382 (2.798)	-4.401 (2.795)
Severe Viol. (f)	1.036 (0.681)	0.681 (0.525)	0.834 (0.515)	0.245 (0.217)	2.984† (1.614)	1.654† (0.942)	0.023 (0.374)	-0.012 (0.383)
Minor Viol. (m)	0.871† (0.491)	0.593 (0.439)	0.284 (0.441)	-0.177 (0.22)	1.820 (1.134)	0.780 (0.780)	0.656 (0.421)	0.654 (0.424)
Severe Viol. (m)	1.348* (0.666)	1.203* (0.577)	0.351 (0.582)	0.112 (0.272)	2.499 (1.62)	1.960† (1.077)	-0.317 (0.403)	-0.315 (0.407)
Minor Violence Against the Child	2.141*** (0.312)	1.436***$^{\alpha}$ (0.245)	1.452*** (0.315)	0.285* (0.127)	5.071*** (0.835)	2.44***$^{\alpha}$ (0.483)	0.421† (0.226)	0.406† (0.227)
Severe Violence Against the Child	2.429*** (0.384)	2.073*** (0.304)	0.807* (0.334)	0.218 (0.144)	5.031*** (0.924)	3.701*** (0.56)	0.049 (0.245)	0.031 (0.247)
Highest Salary	-0.144 (0.10)	-0.059 (0.077)	-0.192 (0.103)	-0.051 (0.034)	-0.390 (0.272)	-0.072 (0.148)	0.101 (0.068)	0.100 (0.068)
Anxiety		0.946*** (0.031)		1.569*** (0.017)		3.542*** (0.06)		0.031 (0.032)
Joint Significance of Partner Violence (F/Chi)	8.310*** 0.831	6.74*** $^{\alpha}$ (0.762)	2.562* (0.317)	1.5 $^{\alpha}$ (0.286)	6.808*** (0.708)	6.069*** (0.725)	10.140*	10.137* (1.509)
Standard error of difference in Joint Significance[73]		0.42		0.367		0.414		0.714

While both anxiety and partner violence are highly significant predictors of externalizing ($p<0.005$) for both, there is little change in the partner violence coefficients or the F statistic. Anxiety does not appear to mediate the effects of partner violence on total behavior problems. Anxiety is not predictive of drinking, and controlling for it produces almost no change in the chi square statistic.

Anxiety also seems to mediate substantially the relationship between minor violence directed against the child and externalizing, internalizing and total behavior problems. Controlling for anxiety in all cases shrank the coefficient by more than two standard errors. It is a curious fact that the reduction for the coefficients for severe violence was less dramatic. If one uses the larger standard error as a conservative

[73] Calculated using the pairwise formula for variance (var(x-y) = var(x)+var(y)-2cov(x,y))

estimate, in no case is the change significant at the 95% confidence level. It may be the case that there is more variation in anxiety among children who only suffer from minor violence. Anxiety may for these children mark the presence of some type of acute stress disorder which then causes externalizing behavior and other behavior problems. Children who suffer from severe violence may almost uniformly have behavior problems, resulting in a decline in the usefulness of anxiety as an explanation.

Age

While Table 2 below reveals large drops in F and Chi square statistics when age x partner violence interactions are included, as a group the age x partner violence variables were not significant for any of the outcomes, and thus a critical criterion for mediation is not present. A full interaction of all partner violence variables and cohort variables (cohort age 3, 6, 9, 12, and 15) was run, using cohort 3 as the reference group. However, since there are 15 of these coefficients, showing all of them is potentially tedious for the reader. Instead, only the coefficients relevant to the Piagetian hypthesis are shown. If this hypothesis is to be supported, the coefficients (since violence x cohort 3 is the reference group) should be positive and significant. Yet many of them are negative, and none of them are significant predictors of behavior problems or drinking. This does not support the hypothesis I derived from Piaget. Further, rather than reduce the size of the coefficients, the size of many of the coefficients for severe violence by the male partner have increased sizably (albeit not significantly). In addition, while the significance of the main effects of partner violence is significantly reduced by including the interaction terms, the interaction terms themselves are not jointly significant predictors of any outcomes. This is a blow not only to arguing that age modifies the effect of partner violence via the hypothesis derived from Piaget, it is a blow to developmental theory, which would argue that the effect of partner violence should vary by age. However, give the size of the standard errors for the age interaction terms, there may be a power problem with estimating so many additional coefficients. Additional research may examine the effect of age x partner violence variables, perhaps with just a linear and quadratic term. This would substantially reduce the number of coefficients estimating and, perhaps, the standard errors. Including the age x violence interactions also had almost no effect on the violence against the child coefficients. Broadly, cohort does not seem to have much effect on these relationships.

Table 2[74]: Baseline Models Compared to Models Including Age

	External Baseline	External Full	Internal Baseline	Internal Full	Total Behavior Baseline	Total Behavior Full	Drink Baseline	Drink Full
Minor Violence (f)	-0.405 (1.796)	-0.970 (3.81)	0.245 (1.55)	-1.473 (3.652)	-0.822 (4.490)	-1.936 (10.206)	-4.382 (2.798)	-3.661 (3.729)
Severe Viol. (f)	1.036 (0.681)	0.627 (0.776)	0.834 (0.515)	0.448 (0.74)	2.984† (1.614)	1.847 (1.945)	0.023 (0.374)	0.058 (0.864)
Minor Viol. (m)	0.871† (0.491)	0.658 (1.621)	0.284 (0.441)	0.055 (1.177)	1.820 (1.134)	1.277 (4.471)	0.656 (0.421)	0.382 (1.265)
Severe Viol. (m)	1.348* (0.666)	1.864 (1.297)	0.351 (0.582)	0.788 (1.789)	2.499 (1.62)	3.894 (4.746)	-0.317 (0.403)	-0.338 (0.848)
Minor Violence Against the Child	2.141*** (0.312)	2.119*** (0.315)	1.452*** (0.315)	1.427*** (0.321)	5.071*** (0.835)	5.000*** (0.844)	0.421† (0.226)	0.418† (0.231)
Severe Violence Against the Child	2.429*** (0.384)	2.439*** (0.380)	0.807* (0.334)	0.822* (0.334)	5.031*** (0.924)	5.071*** (0.917)	0.049 (0.245)	0.045 (0.255)
Highest Salary	-0.144 (0.10)	-0.145 (0.098)	-0.192 (0.103)	-0.191† (0.102)	-0.390 (0.272)	-0.389 (0.268)	0.101 (0.068)	0.099 (0.069)
Min. Viol (f)* cohort 6		1.711 (4.673)		2.463 (4.912)		2.486 (12.447)		-
Sev. Viol (f)* cohort 6		-		-		-		-

74 † p<0.10
* p<0.05
**p<0.01
***p<0.005
α p<0.05 for difference between baseline & full model statistics (partial mediation).

Min. Viol (m)* cohort 6		-0.192 (1.679)		-0.143 (1.318)		-0.274 (4.502)		-
Sev. Viol (m)* cohort 6		-0.079 (1.595)		-0.604 (1.931)		-0.215 (5.115)		-
Min. Viol (f)* cohort 9		4.044 (7.945)		2.703 (7.923)		9.028 (21.210)		-
Sev. Viol (f)* cohort 9		0.441 (1.240)		-0.001 (1.195)		0.907 (3.152)		0.532 (1.224)
Min. Viol (m)* cohort 9		0.574 (1.572)		0.741 (1.374)		1.393 (4.301)		-0.444 (1.367)
Sev. Viol (m)* cohort 9		-0.620 (1.325)		-0.249 (1.720)		-1.564 (4.179)		-5.457 (972)
Joint Significance of Partner Violence (F/Chi)	8.310*** 0.831	2.140† (0.354)	2.562* (0.317)	1.276 (0.15)	6.808*** (0.708)	2.228† (0.367)	10.140*	6.635 (1.251)
Standard error of difference in Joint Significance[75]		0.872		0.335		0.746		0.968

Relationship

I next examine whether or not parent-child relationship indicators mediate the relationship between partner violence and these outcomes. These were jointly significant predictors of externalizing in the full model, and had borderline significance (p<0.10) for drinking. Many of these variables are indicators for the existence of structure (rules), others are closer to the affective relationship (whether the parent has lost his/her temper with the child often). The most important indicators were whether the caregiver had discussed how to handle a health emergency, (although why this should be positively associated with behavior problems is perplexing), whether the caregiver often loses her/his temper with the child and, for drinking, whether or not the caregiver denies the child access to alcohol in the home. However, the effect of loss of temper on externalizing should not, perhaps be taken too seriously, since the externalizing behavior

[75] Calculated using the pairwise formula for variance (var(x-y) = var(x)+var(y)-2cov(x,y))

is as likely to occasion the loss of the p.c.'s temper as the loss of temper is to occasion externalizing behavior.

The relationship indicators do significantly mediate the effect of partner violence on externalizing behavior. The fact that only externalizing behavior is mediated, while the other outcomes are not, lends more support to Hirschi's theory of deviance than to attachment theory. If attachment was the mediator, theory would suggest an increase in behavior problems in general, not externalizing problems specifically. Counter-intuitively, the relationship indicators not only failed to reduce the size of the partner violence coefficients, but actually increased them. This was not significant a significant change, however. Similarly, including these indicators increased the size of the coefficients for effects of violence against the child on behavior problems.

Table 3[76]: Baseline Models Compared to Models Including Parent-Child Relationship

	External Baseline	External* Full	Internal Baseline	Internal Full	Total Behavior Baseline	Total Behavior Full	Drink Baseline	Drink Full†
Minor Violence (f)	-0.405 (1.796)	-2.344 (2.754)	0.245 (1.55)	-0.185 (2.657)	-0.822 (4.490)	-4.401 (6.914)	-4.382 (2.798)	-4.520 (3.006)
Severe Viol. (f)	1.036 (0.681)	1.288 (0.866)	0.834 (0.515)	1.449* (0.695)	2.984† (1.614)	4.182* (1.923)	0.023 (0.374)	0.068 (0.419)
Minor Viol. (m)	0.871† (0.491)	1.269† (0.734)	0.284 (0.441)	0.397 (0.719)	1.820 (1.134)	2.499 (1.827)	0.656 (0.421)	0.703 (0.429)
Severe Viol. (m)	1.348* (0.666)	1.309 (1.037)	0.351 (0.582)	0.370 (0.826)	2.499 (1.62)	2.219 (2.387)	-0.317 (0.403)	-0.443 (0.456)
Minor Violence Against the Child	2.141*** (0.312)	2.589*** (0.475)	1.452*** (0.315)	1.507*** (0.467)	5.071*** (0.835)	5.884*** (1.264)	0.421† (0.226)	0.359 (0.250)
Severe Violence Against the Child	2.429*** (0.384)	2.823*** (0.587)	0.807* (0.334)	1.033* (0.524)	5.031*** (0.924)	6.035*** (1.436)	0.049 (0.245)	0.015 (0.283)
Highest Salary	-0.144 (0.10)	-0.146 (0.168)	-0.192 (0.103)	-0.057 (0.162)	-0.390 (0.272)	-0.160 (0.434)	0.101 (0.068)	0.089 (0.079)

[76] † p<0.10
* p<0.05
**p<0.01
***p<0.005
α p<0.05 for difference between baseline & full model statistics (partial mediation).

hg106: child has a curfew		-0.437 (1.192)		-0.952 (1.106)		-3.039 (3.013)		0.652 (0.667)
hg113: pc has rules for child's behave w/ peers		0.143 (0.749)		-0.308 (0.737)		-0.604 (2.004)		-0.175 (0.394)
hg20: PC participates in a child organization		0.265 (0.525)		-0.449 (0.472)		-0.155 (1.29)		-0.057 (0.279)
hg120: PC has discussed handling health emergency		1.386† (0.802)		1.225† (0.742)		3.369 (2.089)		-0.642 (0.424)
hg55: PC discusses tv with child		0.237 (0.510)		0.210 (0.525)		0.080 (1.423)		-0.191 (0.253)
hg54: PC discusses current events w/ child		-0.086 (0.599)		0.336 (0.565)		0.505 (1.575)		-0.129 (0.308)
hg129: PC has not lost temper w/ child in last week (>2x?)		-1.147*** (0.394)		-0.743† (0.404)		-2.187* (1.020)		-0.085 (0.219)
hg123: PC has discussed dangers of alcohol		-0.134 (0.858)		-0.115 (0.816)		-0.255 (2.158)		0.324 (0.440)
hg126: PC denies child alcohol in home.		-0.607 (0.517)		-0.470 (0.491)		-1.462 (1.289)		-0.60* (0.301)
Joint Significance of Partner Violence (F/Chi)	8.310*** 0.831	4.910***$^{\alpha}$ 0.424	2.562* (0.317)	2.559* (0.212)	6.808*** (0.708)	4.3*** (0.326)	10.140*	10.836* (1.578)
Standard error of difference in Joint Significance[77]		0.606		0.356		0.584		0.893

One might contend that while the parent-child relationship does mediate the effects of partner violence on externalizing, a potential omitted variable is an aggressive parent personality, which could make losing one's temper, externalizing behavior and partner violence all more likely. However, this is a fixed effects model, and personality changes little, if at all, over time. In this case it has been eliminated as a potential source of bias.

Deviance of Peers

As shown in table 4, deviance of peers indicators significantly predicted externalizing, internalizing, total behavior problems and drinking in the full models.

[77] Calculated using the pairwise formula for variance (var(x-y) = var(x)+var(y)-2cov(x,y))

Deviance of peers does appear to be a very important predictor of all of these outcomes. Having peers who smoke significantly predicts externalizing behavior. In addition, the number of peers who drink and ask the youngster to go drinking not surprisingly predict drinking. However, while deviance of peers appears to be an important predictor of behavior problems, it does not mediate the effects of intimate partner violence involving the primary caregiver. Neither the partner violence coefficients nor the F and

Table 4[78]: Baseline Models Compared to Models Including Deviance of Peers

	External Baseline	External Full***	Internal Baseline	Internal Full*	Total Behavior Baseline	Total Behavior Full***	Drink Baseline	Drink Full***
Minor Violence (f)	-0.405 (1.796)	-1.085 (2.67)	0.245 (1.55)	-0.419 (2.05)	-0.822 (4.490)	-2.328 (5.71)	-4.382 (2.798)	-4.200 (3.275)
Severe Viol. (f)	1.036 (0.681)	1.176 (0.827)	0.834 (0.515)	1.033† (0.571)	2.984† (1.614)	3.551* (1.799)	0.023 (0.374)	0.094 (0.446)
Minor Viol. (m)	0.871† (0.491)	1.295* (0.607)	0.284 (0.441)	0.573 (0..532)	1.820 (1.134)	2.614† (1.405)	0.656 (0.421)	0.575 (0.510)
Severe Viol. (m)	1.348* (0.666)	1.313† (0.791)	0.351 (0.582)	0.343 (0.656)	2.499 (1.62)	2.096 (1.863)	-0.317 (0.403)	-0.611 (0.451)
Minor Violence Against the Child	2.141*** (0.312)	2.292*** (0.373)	1.452*** (0.315)	1.468*** (0.358)	5.071*** (0.835)	5.402*** (0.963)	0.421† (0.226)	0.441† (0.248)
Severe Violence Against the Child	2.429*** (0.384)	2.450*** (0.467)	0.807* (0.334)	0.720† (0.378)	5.031*** (0.924)	4.933*** (1.069)	0.049 (0.245)	0.073 (0.273)
Highest Salary	-0.144 (0.10)	-0.142 (0.11)	-0.192 (0.103)	-0.180 (0.112)	-0.390 (0.272)	-0.359 (0.286)	0.101 (0.068)	0.069 (0.071)
crime (vandalism theft, assault)		0.171 (0.173)		-0.039 (0.166)		0.343 (0.445)		0.007 (0.105)
dp1 # in non-sport school activity		0.049 (0.346)		-0.332 (0.296)		-0.546 (0.894)		-0.040 (0.232)
dp5: # obeyed rules		-0.208 (0.266)		-0.197 (0.255)		-0.252 (0.689)		0.031 (0.207)
dp7: # in trouble		0.502 (0.341)		0.115 (0.316)		0.793 (0.845)		-0.016 (0.234)
dp29: # use tobacco		0.695* (0.353)		0.498 (0.38)		1.558 (0.973)		0.088 (0.22)

[78] † p<0.10
* p<0.05
**p<0.01
***p<0.005
α p<0.05 for difference between baseline & full model statistics (partial mediation).

dp26# use marijuana		0.316 (0.4)		-0.241 (0.370)		0.197 (0.978)		0.465 (0.265)
dp27 # use alcohol		0.130 (0.352)		0.410 (0.345)		0.852 (0.898)		0.670** (0.251)
dp31 How often asked to go drinking		0.592† (0.308)		0.379 (0.285)		1.474† (0.783)		0.737*** (0.215)
dp34: How often offered pot.		0.076 (0.335)		0.108 (0.315)		0.191 (0.865)		0.193 (0.219)
Joint Significance of Partner Violence (F/Chi)	8.310*** 0.831	7.533*** (0.735)	2.562* (0.317)	2.764* (0.338)	6.808*** (0.708)	6.082*** (0.647)	10.140*	9.102† (1.578)
Standard error of difference in Joint Significance[79]		0.492		0.219		0.413		1.256

Chi square statistics changed very much at all. The violence against the child coefficients also remained quite strong and unchanged. This leads to the conclusion that while deviance of peers is important to consider, it may not be a route by which the effect of partner violence on children can be explained.

Neighborhood SES

The final deviance theory examined argued that the quality of the neighborhood would cause both partner violence and deviance. If this is the case, then once neighborhood is included in the model, the effects of partner violence, particularly on externalizing behavior, should go to zero. This is obviously not what happened. Changes in socio-economic status of the neighborhood did not significantly predict any of the outcomes, and the coefficients for partner violence remain basically unchanged. It does not seem that neighborhood S.E.S. is an omitted variable in this case. Other neighborhood characteristics may, perhaps, explain the relationship between externalizing and partner violence, but this broad measure of S.E.S. does not appear to do

[79] Calculated using the pairwise formula for variance (var(x-y) = var(x)+var(y)-2cov(x,y))

so. It might be interesting to investigate whether the effect of partner violence on externalizing behavior varies by neighborhood characteristics. Future research might fruitfully search for interaction effects, but main effects do not seem to be present.

Table 5[80]: Baseline Models Compared to Models Including Neighborhood SES

	External Baseline	External Full	Internal Baseline	Internal Full	Total Behavior Baseline	Total Behavior Full	Drink Baseline	Drink Full
Minor Violence (f)	-0.405 (1.796)	-0.420 (1.793)	0.245 (1.55)	0.239 (1.552)	-0.822 (4.490)	-0.846 (4.489)	-4.382 (2.798)	-4.480 (2.865)
Severe Viol. (f)	1.036 (0.681)	1.039 (0.680)	0.834 (0.515)	0.833 (0.516)	2.984† (1.614)	2.988† (1.613)	0.023 (0.374)	0.018 (0.373)
Minor Viol. (m)	0.871† (0.491)	0.863† (0.494)	0.284 (0.441)	0.285 (0.443)	1.820 (1.134)	1.806 (1.138)	0.656 (0.421)	0.656 (0.424)
Severe Viol. (m)	1.348* (0.666)	1.339* (0.669)	0.351 (0.582)	0.353 (0.587)	2.499 (1.62)	2.487 (1.629)	-0.317 (0.403)	-0.324 (0.406)
Minor Violence Against the Child	2.141*** (0.312)	2.139*** (0.311)	1.452*** (0.315)	1.454*** (0.314)	5.071*** (0.835)	5.071*** (0.834)	0.421† (0.226)	0.443† (0.228)
Severe Violence Against the Child	2.429*** (0.384)	2.431*** (0.386)	0.807* (0.334)	0.807* (0.333)	5.031*** (0.924)	5.034*** (0.923)	0.049 (0.245)	0.053 (0.249)
Highest Salary	-0.144 (0.10)	-0.149 (0.097)	-0.192 (0.103)	-0.190† (0.102)	-0.390 (0.272)	-0.394 (0.265)	0.101 (0.068)	0.105 (0.067)
Low SES Neighborhood		-0.111 (0.834)		0.076 (0.628)		-0.018 (2.002)		0.172 (0.429)
Middle SES Neighborhood		-0.344 (0.685)		0.072 (0.648)		-0.415 (1.761)		-0.191 (0.396)
Joint Significance of Partner Violence (F/Chi)	8.310*** 0.831	8.247*** (0.841)	2.562* (0.317)	2.561* (0.320)	6.808*** (0.708)	6.776***	10.140*	10.357* (1.581)
Standard error of difference in Joint Significance[81]		0.401		0.152		0.340		0.742

Discussion

[80] † p<0.10
* p<0.05
**p<0.01
***p<0.005
α p<0.05 for difference between baseline & full model statistics (partial mediation).
[81] Calculated using the pairwise formula for variance (var(x-y) = var(x)+var(y)-2cov(x,y))

Chapter three used several theories to make predictions about both the effect of partner violence on various outcomes and which outcomes were likely to be affected.[82] The basic assumption that the effects of partner violence should vary by age was not supported. The other basic assumptions (baseline effects of partner violence on outcomes, even after controlling for fixed effects and child abuse) were supported. Controlling for fixed effects and child abuse, effects of partner violence were found on externalizing behavior, internalizing behavior, total behavior problems and drinking. Given that the strongest effects were for externalizing behavior and similar behavior problems, one of the basic assumptions of deviance theories was met, while other theories which predicted broader effects were not.

With respect to the specific theories, anxiety and the parent-child relationship both partially mediated the effects of partner violence on externalizing behavior. Anxiety also mediated the effect of internalizing, but this is probably an artifact. No mediation was found for any other outcomes. In addition, none of the theories which predicted variation in the effect of partner violence by age were supported, neither was the theory that neighborhood s.e.s. is an omitted variable which explains the relationship between partner violence and child outcomes. In short, the theories predicting anxiety and the parent-child relationship as mediators were most supported. Because the parent-child relationship specifically mediated externalizing behavior, but not other behavior problems, more credence is lent to Hirschi's (1969) invocation of the parent-child relationship than Bowlby's (1969) attachment theory. The effect of parenting may have more to do with providing structure and the affective relationship between parent and

[82] The reader may wish to refer to the table at the end of chapter 3.

child than felt security per se. The final chapter discusses some of the implications of these findings.

Chapter 8: Conclusion

After using rigorous statistical techniques to control for potential selection effects, the research finds that intimate partner violence significantly predicts externalizing behavior (acting out), internalizing behavior (e.g. depression), total behavior problems and the use of alcohol among children in the household. I then examined which theories seemed to have traction in explaining these effects, as evidenced by mediating relationships predicted by the theories. Age, deviance of peers and neighborhood S.E.S. did not explain this relationship. Indicators for the parent-child relationship and anxiety both mediated the relationship between partner violence by the parents and externalizing (deviant) behavior of the child. These findings suggest that exposure to violence between parents will traumatize children in severe cases. It also suggests that the violence negatively impacts the relationship between parents and children, resulting in problem behaviors. It should be noted, however, that both cases were only of partial mediation. This leaves room for more theoretical work which tries to refine the explanation for the effect of partner violence on child behavior and drinking.

Implications

The impact of partner violence on externalizing child behavior is disturbing. An National Institute of Justice study found that the annual cost of intimate partner violence to victims alone was $67 billion (National Institute of Justice, 1996). This is costly, but my research suggests that some costs may be temporarily hidden, and not incurred until some future period. Specifically, if exposure to partner violence places the child on a trajectory which is likely to include more acting out, criminal and gang activity may be more likely later. The impact that anxiety has on externalizing behavior should be taken into consideration by policy makers and clinicians when dealing with the consequences of exposure to intimate partner violence. Much literature documents that exposure to partner violence traumatizes children. This research is in accord with that literature. The mediation of externalizing behaviors by anxiety suggests that individual treatment of children exposed to domestic violence may help to reduce the anxiety, and hence some of the problematic behaviors. In particular, clinical interventions should be competent to diagnose and treat acute stress disorder and post traumatic stress disorder, as these are the anxiety disorders most likely to be occasioned by exposure to partner violence. In addition, in these data, about 48% of the children exposed to severe partner were also severely abused themselves. While a common contention is that children are abused and injured when intimate partner violence occurs, this is only one of a number of possibilities. It is also possible that an abused spouse may be less likely to have much patience with the children and more likely to lash out and use harsh parenting. Clinical interventions must, therefore, be prepared to deal with the consequences of both exposure and child abuse. Future studies may be carried out on the cost effectiveness of treatment for anxiety produced by exposure to partner violence and child abuse. This would entail getting robust estimates for the predicted decrease in anxiety symptoms after treatment, then predicting the subsequent reduction in externalizing behavior. The cost of the behavior to society could then be totaled, along with the cost of treatment to determine which is cost effective.

A cost benefit analysis of this type of treatment might well be compared to a cost benefit analysis of interventions to improve the parent-child relationship. This was the other variable which seemed to mediate the relationship between partner violence and externalizing behavior. Some intervention attempting to strengthen both the affective bond between the parent and child and help her to create more structure (concrete , consistent and reasonable rules) in the life of her child may be helpful. A critical intervention for parents may be attempting to teach the parent skills which will obviate the high likelihood of child abuse in the context of intimate partner violence. Severe violence against the child will both traumatize the child and result in a poor parent-child relationship, substantially increasing the likelihood of externalizing behavior problems. It seems likely that the best approach will attempt to incorporate treatment for trauma, improvements for the parent-child relationship and child abuse prevention.

Almost as interesting as the relationships which were found are those which were not found. Controlling for child abuse, the income of the household bread-winner and fixed effects, no effect of partner violence was found on child W.I.S.C. vocabulary score, school performance as measured by reported trouble with school work, truancy, grade repetition, smoking or marijuana use. Stone and Fialk (1997) outline the positions for and against criminalization of child exposure to intimate partner violence. This debate concerns many battered women's advocates, because they are concerned that it may be used to justify separating a non-abusive mother involved in an abusive relationship from her children. There is basic consensus that removing a child from the home can be justified in the case of child abuse. Therefore, if the effects of exposure to partner violence were similar (as deleterious) to the effects of severe violence directed against the child, an argument might be made for the removal of children from homes with partner violence. However, my research finds that while there are effects, these are generally substantially smaller than the effects of direct violence against the child. I do not feel that my research provides justification for removal of children from homes in which partner violence persists. However, neither does it warrant complacency. Partner violence is associated with a higher probability of externalizing behavior, internalizing behavior, general behavior problems and drinking. These effects persist when fixed effects controls are implemented, and are only partially explained by anxiety and the parent-child relationship. Efforts to prevent exposure may also, thus be productive.

While I do not believe the effects I have found can justify the removal of the child from the home, they do justify the attempt to attenuate exposure. If one partner is found to perpetrate or initiate the violence, limiting the child's exposure to this partner may help to reduce anxiety and the unexplained effects of partner violence on externalizing. Given the complexity of social and psychological problems, it is often helpful to combine a cocktail of treatments shown to be effective. This is particularly true when there may be economies of scale. Supervised visitation might be one way in which the child's exposure to partner violence can be reduced. Such visitation might also take advantage of the presence of the parents to provide clinical support for the parent-child relationship in order to ameliorate some of the deleterious effects of exposure, or the presence of the children to offer treatment for acute stress and post traumatic stress disorder, or parenting classes.

The persistence of domestic violence and its affect on children is of concern not only to social workers and the criminal justice system, but to the whole society. A myriad of indirect effects of this problem influence the well being of the entire population. Educators must cope with children who are more inclined to act out because of the violence they witness at home. Children who have acting out problems often make the lives of other people, often strangers, difficult to say the least. Insofar as they may be more inclined to crime, there are concrete costs when we fail to address this problem. There is also an opportunity cost. Children with behavior problems are, presumably, not as able to take advantage of their youth to acquire social and work skills which will benefit them, and the economy in adulthood. In this way, we face more than a compelling moral obligation to intervene to help these children, and to try to continue to understand the problems they face. Beyond simple ethics, continued intervention efforts and research belong indisputably to our collective self interest.

Acknowledgements

This research was funded by a graduate research fellowship from the National Institute of Justice (Grant # 2005-WG-BX-0001). The support is much appreciated.

Appendix I: Summary and Structure of the Program.

16 steps summarized

1. Use cohort, child's sex and wave to augment neighborhood s.e.s. and child's age.
2. Re-augment the data using variables from (1) but adding salary, and excluding cases from cohort 18, wave 2. Attach values of neighborhood s.e.s. & age for the excluded cases using data produced by (1).

3. Re-augment the data from (2), adding p.c.'s education level, marital status, employment status, p.c.'s participation in a child organization, and all domestic violence and child abuse variables using the variables from (2).
4. Using the variables from (2), augment WISC vocabulary score, poor school work, internalizing, externalizing and total behavior problems, curfew, p.c. has rules and p.c. has talked with child about how to deal with a health emergency.
5. Augment # involved in non-sport activities, # obeyed school rules, # gotten into trouble in school & number used tobacco using data from (2).
6. Augment the same variables in (5), but using data from (3) for all cases excluding cohort 18 wave 2. Attach values for the variables for cohort 18 wave 2 using data produced by (5).
7. Augment ever smoked, ever drank, # used marijuana, # used alcohol, how how often asked you to go drinking, how often offered you marijuana and number of criminal acts by peers using data from (1).
8. Augment the same variables as in (7), but using data from (6) and excluding data from cohort 18. Attach values for cohort 18 using data from (7).
9. Augment family size using data from (1).
10. Augment family size using data from (3), but excluding cases from cohort 18. Attach values for family size for cohort 18 using values (augmented data produced) from (9).
11. Augment p.c.'s age using data from (produced by) (10).
12. Augment p.c. discussed t.v. programs, p.c. discussed current events and p.c. has not lost temper using data from (3).
13. Augment p.c. discussed dangers of alcohol & drugs with child and p.c. denies child access to alcohol in the home using data from (12).
14. Augment child was truant using data from (8).
15. Augment child repeated a grade using data from (13).
16. Augment ever used marijuana using data from (8).

The Program (for the 5000th iteration data):

```
#STEP 1
library(mix)
mis<-read.table("mis9_28.txt", h=T)
mis<-mis[order(mis$cohort, mis$wave, mis$subid),]
st1<-mis[,c(2:5, 39)]
st1<-as.matrix(st1)
for (i in 1:5) {
      st1[,i]<-as.numeric(st1[,i])
}

s<-prelim.mix(st1, 4)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st1imp<-imp.mix(s, newtheta)
st1imp<-cbind(mis$subid, st1imp)



#STEP 2

st1.5<-mis[c(1:9279),c(2, 4:5, 3, 38:39)]
st1.5<-as.matrix(st1.5)
for (i in 1:6) {
      st1.5[,i]<-as.numeric(st1.5[,i])
```

```
}

s<-prelim.mix(st1.5, 3)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st1.5imp<-imp.mix(s, newtheta)
st1.5imp<-st1.5imp[,c(1,4,2:3, 5:6)]
temp<-cbind(st1imp[9280:9910, 2:5], mis[9280:9910, 38],
st1imp[9280:9910, 6])
st1.5imp<-rbind(st1.5imp, temp)
st1.5imp<-cbind(mis$subid, st1.5imp)


#STEP 3   educ_pc, mstat_pc, employ, hg20, minorviolfem, sevviolfem,
minorviolman, sevviolman, minabuse, sevabuse

st2<-cbind(mis[1:8648,2:5], mis[1:8648, c(6, 7, 27, 31:37)],
mis[1:8648, 38:39])
st2<-as.matrix(st2)
for (i in 1:16) {
      st2[,i]<-as.numeric(st2[,i])
}

s<-prelim.mix(st2, 4)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st2imp<-imp.mix(s, newtheta)
temp<-cbind(st1.5imp[8649:9910,2:5], mis[8649:9910, c(6, 7, 27,
31:37)], st1.5imp[8649:9910, 6:7])
st2imp<-rbind(st2imp, temp)
st2imp<-cbind(mis$subid, st2imp)

#Note:  NA's which appear in st2imp$employ are not a problem, just
stuck in for cohort 18 wave 2 only.



#STEP 4:  wiscraw, cc61, intern2, extern2, tcbcl, hg106, hg113, hg120
(0 for cohorts 3 & 18)

st3<-cbind(mis[2007:8648,2:7], mis[2007:8648, c(8, 20:21)],
mis[2007:8648, c(27:28, 31:39, 41, 43:45)])
st3$cohort<-st3$cohort-1
st3<-as.matrix(st3)
for (i in 1:24) {
      st3[,i]<-as.numeric(st3[,i])
}

s<-prelim.mix(st3, 4)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st3imp<-imp.mix(s, newtheta)
st3imp[,1]<-st3imp[,1]+1
```

```
temp1<-as.matrix(cbind(st2imp[1:2006,2:7], mis[1:2006, c(8, 20:21)],
st2imp[1:2006, 8], mis[1:2006, 28], st2imp[1:2006, 9:17], mis[1:2006,
c(41, 43:45)]))
temp2<-as.matrix(cbind(st2imp[8649:9910,2:7], mis[8649:9910, c(8,
20:21)], st2imp[8649:9910, 8], mis[8649:9910, 28], st2imp[8649:9910,
9:17], mis[8649:9910, c(41, 43:45)]))
st3imp<-rbind(temp1, st3imp, temp2)
st3imp<-as.data.frame(st3imp)
st3<-as.data.frame(st3)
names(st3imp)<-names(st3)
st3imp<-cbind(mis$subid, st3imp)


#STEP 5  dp1, dp5, dp7 & dp29 using data from #2, 0 for wave 2 cohort
18, 0 for cohort<9

st3.25<-cbind(st1.5imp[3965:9279,c(2, 4:7, 3)], mis[3965:9279, c(12:14,
17)])
st3.25$cohort<-st3.25$cohort-2
st3.25<-as.matrix(st3.25)
for (i in 1:10) {
      st3.25[,i]<-as.numeric(st3.25[,i])
}

s<-prelim.mix(st3.25, 3)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st3.25imp<-imp.mix(s, newtheta)
st3.25imp[,1]<-st3.25imp[,1]+2
st3.25imp<-st3.25imp[,c(1,6, 2:5, 7:10)]
temp1<-as.matrix(cbind(st1.5imp[1:3964,2:7], mis[1:3964, c(12:14,
17)]))
temp2<-as.matrix(cbind(st1.5imp[9280:9910,2:7], mis[9280:9910, c(12:14,
17)]))
st3.25imp<-rbind(temp1, st3.25imp, temp2)
st3.25imp<-as.data.frame(st3.25imp)
names(st3.25imp)<-c("cohort", "wave", "sex", "ses_nc", "salary", "age",
"dp1", "dp5", "dp7", "dp29")
st3.25imp<-cbind(mis$subid, st3.25imp)


#STEP 6: dp1, dp5, dp7 dp29 using data from #3, for <18 wave 2, attach
values from #5 for 18 w2

st3.5<-cbind(st3imp[3965:8648,2:25], mis[3965:8648, c(12:14, 17)])
st3.5$cohort<-st3.5$cohort-2
st3.5<-as.matrix(st3.5)
for (i in 1:28) {
      st3.5[,i]<-as.numeric(st3.5[,i])
}

s<-prelim.mix(st3.5,4)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st3.5imp<-imp.mix(s, newtheta)
```

```
st3.5imp[,1]<-st3.5imp[,1]+2
temp1<-as.matrix(cbind(st3imp[1:3964,2:25], st3.25imp[1:3964, 8:11]))
temp2<-as.matrix(cbind(st3imp[8649:9910,2:25], st3.25imp[8649:9910,
8:11]))
st3.5imp<-rbind(temp1, st3.5imp, temp2)
st3.5imp<-as.data.frame(st3.5imp)
names(st3.5imp)<-c("cohort", "wave", "sex", "ses_nc", "educ_pc",
"mstat_pc", "cc61", "hg106", "hg113", "hg20", "hg120", "minorviolfem",
"sevviolfem", "minorviolman", "sevviolman", "minabuse", "sevabuse",
"employ", "salary", "age", "wiscraw", "intern2", "extern2", "tcbcl",
"dp1", "dp5", "dp7", "dp29")
st3.5imp<-cbind(mis$subid, st3.5imp)

final5000<-st3.5imp


#Step 7:  sv1a0, sv3a0, dp26, dp27, dp31, dp34, crime using data from
#1

st4<-cbind(st1imp[3965:9910,2:6], mis[3965:9910, c(9,10,15, 16, 18, 19,
46)])
st4$cohort<-st4$cohort-2
st4<-as.matrix(st4)
for (i in 1:12) {
      st4[,i]<-as.numeric(st4[,i])
}

s<-prelim.mix(st4,4)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st4imp<-imp.mix(s, newtheta)
st4imp[,1]<-st4imp[,1]+2
temp1<-as.matrix(cbind(st1imp[1:3964,2:6], mis[1:3964,
c(9,10,15,16,18,19,46)]))
st4imp<-rbind(temp1, st4imp)
st4imp<-as.data.frame(st4imp)
st4<-as.data.frame(st4)
names(st4imp)<-names(st4)
st4imp<-cbind(mis$subid, st4imp)


#Step 8:  sv1a0, sv3a0, dp26, dp27, dp31, dp34, *crime* for <18 using
data from #6, attach values for cohort=18 from #7

st4.5<-cbind(st3.5imp[3965:8648,2:29], mis[3965:8648, c(9,10,15, 16,
18, 19, 46)])
st4.5$cohort<-st4.5$cohort-2
st4.5<-as.matrix(st4.5)
for (i in 1:35) {
      st4.5[,i]<-as.numeric(st4.5[,i])
}

s<-prelim.mix(st4.5,4)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
```

```
st4.5imp<-imp.mix(s, newtheta)
st4.5imp[,1]<-st4.5imp[,1]+2
temp1<-as.matrix(cbind(st3.5imp[1:3964,2:29], st4imp[1:3964, 7:13]))
temp2<-as.matrix(cbind(st3.5imp[8649:9910,2:29], st4imp[8649:9910,
7:13]))
st4.5imp<-rbind(temp1, st4.5imp, temp2)
st4.5imp<-as.data.frame(st4.5imp)
st4.5<-as.data.frame(st4.5)
names(st4.5imp)<-names(st4.5)
st4.5imp<-cbind(mis$subid, st4.5imp)


final5000<-st4.5imp


#Step 9: augment famsize using data from #1

mis<-mis[order(mis$wave, mis$cohort, mis$subid),]
st1imp<-as.data.frame(st1imp)
st1imp<-st1imp[order(st1imp$wave, st1imp$cohort, st1imp[,1]),]
st7<-cbind(st1imp[1:4955,2:6], mis[1:4955, 40])
st7<-as.matrix(st7)
for (i in 1:6) {
      st7[,i]<-as.numeric(st7[,i])
}

s<-prelim.mix(st7,4)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st7imp<-imp.mix(s, newtheta)
temp1<-as.matrix(cbind(st1imp[4956:9910,2:6], mis[4956:9910, 40]))
st7imp<-rbind(st7imp, temp1)
st7imp<-as.data.frame(st7imp)
st7<-as.data.frame(st7)
names(st7imp)<-names(st7)
st7imp<-cbind(mis$subid, st7imp)
st7imp<-st7imp[order(st7imp$cohort, st7imp$wave, st7imp[,1]),]
mis<-mis[order(mis$cohort, mis$wave, mis$subid),]
st1imp<-st1imp[order(st1imp$cohort, st1imp$wave, st1imp[,1]),]


#Step 10: augment famsize using data from #2 for cohort<18, supplement
from #9 for cohort=18

mis<-mis[order(mis$wave, mis$cohort, mis$subid),]
st2imp<-as.data.frame(st2imp)
st2imp<-st2imp[order(st2imp$wave, st2imp$cohort, st2imp[,1]),]
st7imp<-st7imp[order(st7imp$wave, st7imp$cohort, st7imp[,1]),]
st7.5<-cbind(st2imp[1:4324,2:17], mis[1:4324, 40])
st7.5<-as.matrix(st7.5)
for (i in 1:17) {
      st7.5[,i]<-as.numeric(st7.5[,i])
}

s<-prelim.mix(st7.5,4)
thetahat<-em.mix(s)
```

```
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st7.5imp<-imp.mix(s, newtheta)
temp1<-as.matrix(cbind(st2imp[4325:9910,2:17], st7imp[4325:9910, 7]))
st7.5imp<-rbind(st7.5imp, temp1)
st7.5imp<-as.data.frame(st7.5imp)
st7.5<-as.data.frame(st7.5)
names(st7.5imp)<-names(st7.5)
n<-c(names(st7.5imp)[1:16], "famsize")
names(st7.5imp)<-n
st7.5imp<-cbind(mis$subid, st7.5imp)
st7.5imp<-st7.5imp[order(st7.5imp$cohort, st7.5imp$wave,
st7.5imp[,1]),]
st7imp<-st7imp[order(st7imp$cohort, st7imp$wave, st7imp[,1]),]
mis<-mis[order(mis$cohort, mis$wave, mis$subid),]
st2imp<-st2imp[order(st2imp$cohort, st2imp$wave, st2imp[,1]),]



final5000<-cbind(st4.5imp, st7.5imp$famsize)

#Step 11:  augment age1_pc using data from #10

mis<-mis[order(mis$wave, mis$cohort, mis$subid),]
st7.5imp<-st7.5imp[order(st7.5imp$wave, st7.5imp$cohort,
st7.5imp[,1]),]
st8<-cbind(st7.5imp[1:4324,2:18], mis[1:4324, 42])
st8<-as.matrix(st8)
for (i in 1:18) {
      st8[,i]<-as.numeric(st8[,i])
}

s<-prelim.mix(st8,4)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st8imp<-imp.mix(s, newtheta)
temp2<-as.matrix(cbind(st7.5imp[4325:9910,2:18], mis[4325:9910, 42]))
st8imp<-rbind(st8imp, temp2)
st8imp<-as.data.frame(st8imp)
st8<-as.data.frame(st8)
names(st8imp)<-names(st8)
n<-c(names(st8imp)[1:17], "age_pc")
names(st8imp)<-n
st8imp<-cbind(mis$subid, st8imp)
st8imp<-st8imp[order(st8imp$cohort, st8imp$wave, st8imp[,1]),]
st7.5imp<-st7.5imp[order(st7.5imp$cohort, st7.5imp$wave,
st7.5imp[,1]),]
mis<-mis[order(mis$cohort, mis$wave, mis$subid),]

final5000<-cbind(final5000, st8imp$age_pc)


#Step 12:  augment hg55, hg54, hg129 using data from #3  (0 for wave 1
& cohort<9 *or* cohort 18)
```

```
st9<-cbind(st2imp[c(1004:2006, 2986:8648), 2:17], mis[c(1004:2006,
2986:8648), c(22,23, 26)])
st9<-st9[,c(1,3:19, 2)]
st9<-as.matrix(st9)
for (i in 1:19) {
      st9[,i]<-as.numeric(st9[,i])
}

s<-prelim.mix(st9,3)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st9imp<-imp.mix(s, newtheta)
st9imp<-st9imp[,c(1,19, 2:18)]
st9<-st9[,c(1,19, 2:18)]
temp1<-as.matrix(cbind(st2imp[1:1003, 2:17], mis[1:1003, c(22,23,26)]))
temp2<-as.matrix(cbind(st2imp[2007:2985,2:17], mis[2007:2985,
c(22,23,26)]))
temp3<-as.matrix(cbind(st2imp[8649:9910,2:17], mis[8649:9910,
c(22,23,26)]))
z<-dim(st9imp)
st9imp<-rbind(temp1, st9imp[1:1003,], temp2, st9imp[1004:z[1],], temp3)
st9imp<-as.data.frame(st9imp)
st9<-as.data.frame(st9)
names(st9imp)<-names(st9)
st9imp<-cbind(mis$subid, st9imp)

final5000<-cbind(final5000, st9imp[,18:20])

#Step 13:  augment hg123, hg126 using data from #12: (0 for wave 1
cohorts 3:9, 0 for wave 18.

st10<-cbind(st9imp[c(1004:2006, 2986:3964, 4793:8648), 2:20],
mis[c(1004:2006, 2986:3964, 4793:8648), c(24,25)])
st10<-as.matrix(st10)
st10<-st10[, c(1, 3:21, 2)]
for (i in 1:21) {
      st10[,i]<-as.numeric(st10[,i])
}

s<-prelim.mix(st10,3)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st10imp<-imp.mix(s, newtheta)
st10imp<-st10imp[,c(1,21, 2:20)]
st10<-st10[,c(1,21, 2:20)]
temp1<-as.matrix(cbind(st9imp[1:1003, 2:20], mis[1:1003, c(24,25)]))
temp2<-as.matrix(cbind(st9imp[2007:2985,2:20], mis[2007:2985,
c(24,25)]))
temp3<-as.matrix(cbind(st9imp[3965:4792,2:20], mis[3965:4792,
c(24,25)]))
temp4<-as.matrix(cbind(st9imp[8649:9910,2:20], mis[8649:9910,
c(24,25)]))
st10imp<-rbind(temp1, st10imp[1:1003,], temp2, st10imp[1004:1982,],
temp3, st10imp[1983:5838,], temp4)
st10imp<-as.data.frame(st10imp)
```

```
st10imp<-cbind(mis$subid, st10imp)

final5000<-cbind(final5000, st10imp[,21:22])

#Step 14:  augment sr2a1 using data from #8 (0 for cohort<9, 0 for
cohort 18

st11<-cbind(st4.5imp[3965:8648, 2:36], mis[3965:8648,29])
st11[,1]<-st11[,1]-2
st11<-as.matrix(st11)
for (i in 1:36) {
      st11[,i]<-as.numeric(st11[,i])
}

s<-prelim.mix(st11,3)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st11imp<-imp.mix(s, newtheta)
st11imp[,1]<-st11imp[,1]+2
temp1<-as.matrix(cbind(st4.5imp[1:3964, 2:36], mis[1:3964, 29]))
temp2<-as.matrix(cbind(st4.5imp[8649:9910, 2:36], mis[8649:9910, 29]))
st11imp<-rbind(temp1, st11imp, temp2)
st11imp<-as.data.frame(st11imp)
names(st11imp)[36]<-"sr2a1"
st11imp<-cbind(mis$subid, st11imp)

final5000<-cbind(final5000, st11imp$sr2a1)


#Step 15:  augment sb23 using data from #13, (0 for cohort <6, 0 for
cohort 18, and 0 for cohort 6, wave 2

st12<-cbind(st10imp[c(2007:2985, 3965:8648), 2:22], mis[c(2007:2985,
3965:8648), c(30)])
st12<-as.matrix(st12)
st12[,1]<-st12[,1]-1
st12<-st12[, c(1, 3:22, 2)]
for (i in 1:22) {
      st12[,i]<-as.numeric(st12[,i])
}

s<-prelim.mix(st12,3)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st12imp<-imp.mix(s, newtheta)
st12imp<-st12imp[,c(1,22, 2:21)]
st12<-st12[,c(1,22, 2:21)]
st12imp[,1]<-st12imp[,1]+1
temp1<-as.matrix(cbind(st10imp[1:2006, 2:22], mis[1:2006, c(30)]))
temp2<-as.matrix(cbind(st10imp[2986:3964, 2:22], mis[2986:3964,
c(30)]))
temp3<-as.matrix(cbind(st10imp[8649:9910,2:22], mis[8649:9910, c(30)]))
st12imp<-rbind(temp1, st12imp[1:979,], temp2, st12imp[980:5663,],
temp3)
st12imp<-as.data.frame(st12imp)
```

```
names(st12imp)[22]<-"sb23"
st12imp<-cbind(mis$subid, st12imp)

final5000<-cbind(final5000, st12imp$sb23)




#Step 16:  augment sv7a0 using data from #8  (0 for cohort<9 & 0 for
wave 1, cohort 9)

st13<-cbind(st4imp[4793:9910, 2:13], mis[4793:9910, c(11)])
st13<-as.matrix(st13)
st13[,1]<-st13[,1]-2
st13<-st13[, c(1, 3:13, 2)]
for (i in 1:13) {
      st13[,i]<-as.numeric(st13[,i])
}

s<-prelim.mix(st13,3)
thetahat<-em.mix(s)
rngseed(1234567)
newtheta<-da.mix(s, thetahat, steps=5000, showits=TRUE)
st13imp<-imp.mix(s, newtheta)
st13imp<-st13imp[,c(1,13, 2:12)]
st13<-st13[,c(1,13, 2:12)]
st13imp[,1]<-st13imp[,1]+2
temp1<-as.matrix(cbind(st4imp[1:4792, 2:13], mis[1:4792, c(11)]))
st13imp<-rbind(temp1, st13imp)
st13imp<-as.data.frame(st13imp)
names(st13imp)[13]<-"sv7a0"
st13imp<-cbind(mis$subid, st13imp)

final5000<-cbind(final5000, st13imp$sv7a0)

write(names(final5000), file="final5000.txt", ncolumns=46)
write(t(as.data.frame(final5000)), file="final5000.txt", ncolumns=46,
append=T)
```

Appendix II: Tables with Simple Random Sample (i.e. uncorrected) Standard Errors

Table 1: Domestic Violence

Variable	n	% missing	List-wise Deletion	Data Augmentation

Total	9910	15.61%	Mean	S.E.	Mean	S.E.
Minor Violence Female	5491	36.51%	0.006	0.000	0.020	0.001
Severe Violence Female	6212	28.17%	0.136	0.005	0.158	0.004
Minor Violence Male	6192	28.40%	0.111	0.004	0.138	0.005
Severe Violence Male	6137	29.04%	0.102	0.004	0.123	0.004
Minor Abuse of Child	7809	9.70%	0.549	0.006	0.536	0.005
Severe Abuse of Child	7732	10.59%	0.224	0.005	0.224	0.005

Table 2: Child Behavior Problems

Variable	n	% missing	List-wise Deletion		Data Augmentation	
Total	9910	15.61%	Mean	S.E.	Mean	S.E.
Internalizing Behavior	5726	16.88%	9.241	0.094	9.314	0.105
Externalizing Behavior	5726	16.88%	10.876	0.114	10.660	0.121
Total Behavior Problems	5726	16.88%	27.188	0.284	26.627	0.309

Table 3: Other Predictors

Variable	n	% missing	List-wise Deletion		Data Augmentation	
Total	9910	15.61%	Mean	S.E.	Mean	S.E.
Marital Status	8023	7.23%	0.334	0.005	0.339	0.005
Education Level	7690	11.08%	2.924	0.015	2.914	0.015
Age P.C.	9780	1.31%	34.74	0.069	34.76	0.079
Employment	6772	27.02%	1.533	0.010	1.50	0.009
Family Size	4809	2.95%	5.292	0.026	5.32	0.027
Salary	8152	12.14%	4.246	0.021	4.25	0.020
Neighborhood SES	8273	16.52%	1.896	0.009	1.892	0.009
Child’s Age	9247	6.69%	10.747	0.016	10.88	0.015
WISC	5950	10.42%	25.55	0.12	25.84	0.111
Ever Smoked	5330	10.36%	0.302	0.006	0.310	0.006
Ever Drank	5328	10.39%	0.353	0.006	0.362	0.006
Ever Marijuana	4498	12.11%	0.171	0.005	0.185	0.005
Truant	4008	14.43%	0.182	0.006	0.197	0.006
Repeated a Grade	4846	14.43%	0.13	0.005	0.142	0.005
Problems with School Work	5887	11.37%	1.350	0.008	1.369	0.008
# Non-sport school activity (dp1)	2942	44.85%	1.997	0.009	1.729	0.012
# obeyed rules (dp5)	4634	12.81%	2.179	0.008	2.176	0.008
# in trouble (dp7)	4626	12.96%	1.953	0.008	1.948	0.008
# use tobacco (dp29)	4686	11.83%	1.454	0.009	1.460	0.008
# use alcohol (dp27)	5057	14.95%	1.626	0.009	1.655	0.009
# use marijuana (dp26)	4959	16.60%	1.482	0.009	1.508	0.008
How often asked go drinking (dp31)	5109	14.08%	1.564	0.011	1.557	0.010
How often offered pot (dp34)	5063	14.85%	1.391	0.010	1.384	0.008

crime (dp15,17,23)	4936	16.99%	4.050	0.017	4.075	0.017
P.C. participates organization, hg20	7760	10.27%	0.238	0.005	0.242	0.005
Curfew (hg106)	5928	10.75%	0.981	0.001	0.975	0.001
Rules (hg113)	5922	10.84%	0.935	0.003	0.926	0.003
Health Emergency (hg120)	5925	10.79%	0.922	0.001	0.914	0.002
Discuss tv (hg55)	5784	13.23%	0.779	0.006	0.770	0.006
Discuss current events (hg54)	5774	13.38%	0.751	0.005	0.740	0.005
lost temper (hg129	5780	13.29%	0.660	0.006	0.652	0.006
discussed alcohol (hg123)	4342	25.78%	0.944	0.004	0.913	0.006
denies alcohol (hg126)	4365	25.38%	0.666	0.006	0.707	0.011
Cohort	9910	0%	3.225	0.005	3.225	0.005
Wave #	9910	0%	1.5	0.00	1.5	0.00
Child's sex	9910	0%	0.500	0.005	0.500	0.005

Addendum on Statistical Power

The P.H.D.C.N. dataset offers a rare opportunity to study detailed questions about domestic violence with a large and representative dataset. Still, some of the methods I use, particularly fixed-effects modeling, use up a large number of degrees of freedom. There are 6,212 children in the data. From the first time period until the second, 1,976 of these children experienced a change in the amount of intimate partner violence in their household. Of these, 421 experienced an increase from no intimate partner violence in the household at time one to at least one act of violence at time two. Below I have constructed a table which gives effect sizes and standard deviations found by previous studies, along with the sample size needed to detect an effect of that size and spread with 80% and 90% probability (power), assuming a significance level of $p<0.05$.

Dependent Variable	Study	Effect Size (difference in group means)	Average[83] Standard Deviation of 2 groups	N required for 80% Power	N required for 90% Power
I.Q.	Koenen; Moffit; Caspi et al.	-4.78	22.03	338	450
C.B.C.L.	Dubowitz; Black; Kerr et al.	2.7	7.20	226	301
Grades (G.P.A)	Luster; Small & Lower	-0.15	0.84	987	1320
Academic	Kitzman;	-0.52	0.38	13	16

[83] The average is shown here to conserve space. The power analyses assumed independent samples with unequal variances.

Problems	Gaylord et al				
substance abuse	Luster; Small & Lower	0.82	2.06	200	266

Since the required numbers are the total sample sizes needed (both those exposed and not exposed to intimate partner violence), the numbers of those exposed and not exposed in the P.H.D.C.N. data seem quite large with respect to the minimum requirements in the table. All of the required minimum numbers are smaller than the 1,976 cases of change in the data set. While I am still in the process of organizing the data, I was able to conduct a rough empirical test. I did find a statistically significant bivariate relationship (in the expected direction) between total acts of intimate partner violence and the Child Behavior Checklist in the P.H.D.C.N. data. I thus feel well positioned to provide statistically meaningful (powerful) tests of my hypotheses, and do not feel that the number of cases in the data will limit my ability to draw conclusions.

Appendix III

Variables in the Models

Dependent Variables	Independent Variables	Potential Mediators
Child Intelligence/cognitive	Intimate Partner Violence	Child Age X Intimate

ability		Partner Violence
Grades (#61 poor school work - cbcl)	Child Abuse (times 1 & 2)	Attachment to Family
Behavior Problems	Controls (times 1 & 2): Income # children in the family	Stress/P.T.S.D
Grade Repetition		Neighborhood
Truancy		Deviance of Peers
Drug Use		

Table of Theoretical Constructs and the Scales Used to Measure them

Construct	Scale	Description
Intelligence	Wechsler Intelligence Scale for Children	A list of 32 vocabulary questions meant to capture the child's cognitive ability.
Child Behavior	Child Behavior Checklist	A list of 113 questions asked to the parent about the child's behavior. The questions are meant to elicit types of problem behaviors that are roughly comparable to D.S.M. IV categories.
Stress/Anxiety	Anxiety Subsection of the C.B.C.L.	This is a subsection of the scale above which is meant to roughly capture the anxiety disorders outlined in the D.S.M. IV. Since this subsection is used as an independent variable, it will be removed from the C.B.C.L. when Child Behavior is the dependent variable.
Attachment to Parents/Family	Subsection of the Provision of Social Relations Scale	Questions about how close the child feels to the family, and how reliable s/he feels them to be.
Subculture of Deviant Friends	Deviance of Peers Scale	A list of 36 questions about the activities of the child's friends. This includes behavior at home & school, criminal activity and peer pressure to participate in deviant activities.
Intimate Partner Violence	Conflict Tactics Scale	A list of 15 questions about

		the types of verbally and physically abusive acts perpetrated in the context of couple conflict.
Child Abuse	Child Conflict Tactics Scale	Like the above, but targeted at the relationship between the child and the primary caregiver.

Appendix IV: Bibliography for Empirical Literature Review.

* for articles which were deemed irrelevant & not in review
** for review articles which did not have an empirical study.

Anda, R., Felitti, V., Chapman, D., Croft., J., Williamson, D., Santelli, J., Dietz., P., and Marks, J. “Abused Boys, Battered Mothers, and Male Involvement in Teen Pregnancy” *Pediatrics*, February, 2001, 107(2): 1-8.

Anda, R., Whitfield, C., Felitti, V., Chapman, D., Edwards, V., Dube, S. and Williamson, D. “Adverse Childhood Experiences, Alcoholic Parents, and Later Risk of Alcoholism and Depression” *Psychiatric Services*, August, 2002, 53(8): 1001-1009.

**Anderson, S. and Cramer-Benjamin, D. “The Impact of Couple Violence on Parenting and Children: an Overview and Clinical Implications” *American Journal of Family Therapy*, 1999, 27:1-19.

**Appel, A. and Holden, G. “The Co-Occurrence of Spouse and Physical Child Abuse: a Review and Appraisal” *Journal of Family Psychology*, 1998, 12(4): 578-599.

Baldry, A. “Bullying in Schools and Exposure to Domestic Violence” *Child Abuse & Neglect*, 2003, 27: 713-732.

Baldry, A. and Winkel, F. “Direct and Vicarious Victimization at School and at Home as Risk factors for Suicidal Cognition Among Italian Adolescents” *Journal of Adolescence*, 2003, 26: 703-716.

Bevan, E. and Higgins, D. “Is Domestic Violence Learned? The Contribution of Five Forms of Child Maltreatment to Men’s Violence and Adjustment” *Journal of Family Violence*, September, 2002, 17(3): 223-245.

Bowen, K. “Child Abuse and Domestic Violence in Families of Children Seen for Suspected Sexual Abuse” *Clinical Pediatrics*, January, 2000, 39: 33-40.

Briere, J., Johnson, K., Bissada, A., Damon, L., Crouch, J., Gil, E., Hanson, R., and Ernst, V. “The Trauma Symptom Checklist for Young Children (TSCYC): Reliability and Association with Abuse Exposure in a Multi-Site Study” *Child Abuse & Neglect*, 2001, 25: 1001-1014.

Carr, J. and VanDeusen, K. “The Relationship Between Family of Origin Violence and Dating Violence in College Men” *Journal of Interpersonal Violence*, June, 2002, 17(6): 630-646.

*Christoffersen, M. “Growing Up with Unemployment, a Study of Parental Unemployment and Children’s Risk of Abuse and Neglect Based on National Longitudinal 1973 Birth Cohorts in Denmark” *Childhood*, 2000, 7(4): 421-438.

*Corvo, K. and Carpenter, E. “Effects of Parental Substance Abuse on Current Levels of Domestic Violence: a Possible Elaboration of Intergenerational Transmission Process”, *Journal of Family Violence*, 2000, 15(2): 123-135.

Cox, C., Kotch, J., and Everson, M. "A Longitudinal Study of Modifying Influences in the Relationship Between Domestic Violence and Child Maltreatment", *Journal of Family Violence*, February, 2003, 18(1): 5-17.

**Delsol, C. and Margolin, G. "The Role of Family-of-Origin Violence in Men's Marital Violence Perpetration" *Clinical Psychology Review*, 2004, 24: 99-122.

DeVoe, E. and Smith, E. "The Impact of Domestic Violence on Urban Preschool Children, Battered Mothers' Perspectives" *Journal of Interpersonal Violence*, October, 2002, 17(10): 1075-1101.

Dubowitz, H., Black, M., Kerr, M., Hussey, J., Morrel, T., Everson, M. and Starr, R. "Type and Timing of Mothers' Victimization: Effects on Mothers and Children" *Pediatrics*, April, 2001, 107(4): 728-735.

Dube, S., Anda, R., Felitti, V., Chapman, D., Williamson, D. and Giles, W. "Childhood Abuse, Household Dysfunction, and the Risk of Attempted Suicide Throughout the Life Span, Findings from the Adverse Childhood Experiences Study" *Journal of the American Medical Association*, December, 2001, 286(24): 3089-3095.

**Edleson, J. "Children's Witnessing of Adult Domestic Violence" *Journal of Interpersonal Violence*, August, 1999, 14(8): 839-870.

*Edleson, J., Mbilinyi, L., Beeman, S. and Hagemeister, A. "How Children are Involved in Adult Domestic Violence" *Journal of Interpersonal Violence*, January, 2003, 18(1): 18-32.

Ehrensaft, M., Cohen, P., Brown, J., Smailes, E., Chen, H. and Johnson, J. "Intergenerational Transmission of Partner Violence: a 20-Year Prospective Study" *Journal of Consulting and Clinical Psychology*, 2003, 71(4): 741-753.

Eitle, D. and Turner, R. "Exposure to Community Violence and Young Adult Crime: the Effects of Witnessing Violence, Traumatic Victimization, and Other Stressful Life Events" *Journal of Research in Crime and Delinquency*, May, 2002, 39(2): 214-237.

English, D., Marshall, D. and Steward, A. "Effects of Family Violence on Child Behavior and Health During Early Childhood" *Journal of Family Violence*, February, 2003, 18(1): 43-57.

**Guille, L. "Men Who Batter and Their Children: An Integrated Review" *Aggression and Violent Behavior*, 2004, 9: 129-163.

Fantuzzo, J., Boruch, R., Beriama, A., Atkins, M., and Marcus, S. "Domestic Violence and Children: Prevlance and Risk in Five Major U.S. Cities" *Journal of the American Academy of Child and Adolescent Psychiatry* January, 1997, 36(1):

116-122.

Feerick, M. and Haugaard, J. “Long-Term Effects of Witnessing Marital Violence for Women: the Contribution of Childhood Physical and Sexual Abuse” *Journal of Family Violence*, 1999, 14(4): 377-398.

**Feerick, M. and Prinz, R. “Introduction” *Clinical Child and Family Psychology Review* September, 2003, 6(3): 147-149.

Felitti, V., Anda, R., Nordenberg, D., Williamson, D., Spitz, A., Edwards, V., Koss, M., and Marks, J. “Relationship of Childhood Abuse and Household Dysfunction to Many of the Leading Causes of Death in Adults” *American Journal of Preventive Medicine,* 1998, 14(4): 245-257.

Friedrich, W., Davies, H., Feher, E. and Wright, J. “Sexual Behavior Problems in Preteen Children, Developmental, Ecological, and Behavioral Correlates” *Annual New York Academy of Sciences*, 2003, 989: 95-104.

Gjelsvik, A., Verhoek-Oftedahl, W. and Pearlman, D. “Domestic Violence Incidents with Children Witnesses: Findings from Rhode Island Surveillance Data” *Women’s Health Issues*, 2003, 13: 68-73.

Graham-Bermann, S. “Family Worries: Assessment of Interpersonal Anxiety in Children From Violent and Nonviolent Families” *Journal of Clinical Child Psychology*, 1996, 25(3): 280-287.

Herrera, V. and McCloskey, L. “Gender Differences in the Risk for Delinquency Among Youth Exposed to Family Violence”, *Child Abuse & Neglect*, 2001, 25: 1037-1051.

Hodgins, H. and Belch, C. “Interparental Violence and Nonverbal Abilities”, *Journal of Nonverbal Behavior,* Spring, 2000, 24(1): 3-23.

**Holden, G. “Children Exposed to Domestic Violence and Child Abuse: Terminology and Taxonomy” *Clinical Child and Family Psychology Review*, September, 2003, 6(3): 151-160.

Hillis, S., Anda, R., Dube, S., Felitti, V., Marchbanks, P. and Marks, J. “The Association Between Adverse Childhood Experiences and Adolescent Pregnancy, Long-Term Psychosocial Consequences and Fetal Death” *Pediatrics*, February, 2004, 113(2): 320-327.

Hillis, S., Anda, R., Felitti, V., Nordenberg, D, and Marchbanks, P. “Adverse Childhood Experiences and Sexually Transmitted Diseases in Men and Women: a Retrospective Study”, *Pediatrics*, July, 2000, 106(1): 1-6.

**Holtzworth-Munroe, A., Smutzler, N. and Sandin, E. "A Brief Review of the Research on Husband Violence, Part II: the Psychological Effects of Husband Violence on Battered Women and their Children" *Aggression and Violent Behavior*, 1997, 2(2): 179-213.

Hughes, H., Parkinson, D. and Vargo, M. "Witnessing Spouse Abuse and Experiencing Physical Abuse: A 'Double Whammy'?", *Journal of Family Violence,* 1989, 4(2): 197-209.

Huth-Bocks, A., Levendosky, A. and Semel, M. "The Direct and Indirect Effects of Domestic Violence on Young Children's Intellectual Functioning", *Journal of Family Violence,* 2001, 16(3): 269-289.

*Huth-Bocks, A., Levendosky, A., Theran, S. and Bogat, A. "The Impact of Domestic Violence on Mothers' Prenatal Representations of Their Infants" *Infant Mental Health Journal*, 2004, 25(2): 79-98.

**Jaffe, P., Crooks, C. and Wolfe, D. "Legal and Policy Responses to Children Exposed to Domestic Violence: the Need to Evaluate Intended and Unintended Consequences", *Clinical Child and Family Psychology Review*, September, 2003, 6(3): 205-213.

Jaffee, S., Moffitt, T., Caspi, A., Taylor, A. and Arseneault, L. "Influence of Adult Domestic Violence on Children's Internalizing and Externalizing Problems: An Environmentally Informative Twin Study" *Journal of the American Academy of Child and Adolescent Psychiatry*, September, 2002, 41(9): 1095-1103.

Jankowski, M., Leitenberg, H., Henning, K., and Coffey, P. "Intergenerational Transmission of Dating Aggression as a Function of Witnessing Only Same Sex Parents vs. Opposite Sex Parents vs. Both Parents as Perpetrators of Domestic Violence" *Journal of Family Violence*, 1999, 14(3): 267-279.

**Jonson-Reid, M. "Youth Violence and Exposure to Violence in Childhood: An Ecological Review", *Aggression and Violent Behavior* 1998, 3(2): 159-179.

Jouriles, E., Spiller, L., Stephens, N., McDonald, R. and Swank, P. "Variability in Adjustment of Children of Battered Women: the Role of Child Appraisals of Interparent Conflict" *Cognitive Therapy and Research*, 2000, 24(2): 233-249.

Kearney, M., Munro, B., Kelly, U. and Hawkins, J. "Health Behaviors as Mediators for the Effect of Partner Abuse on Infant Birth Weight" *Nursing Research*, January-February, 2004, 53(1): 36-45.

Kelly, J. "Children's Adjustment in Conflicted Marriage and Divorce: a Decade Review of Research" *Journal of the American Academy of Child and Adolescent Psychiatry*, August, 2000, 39(8): 963-973.

**Kent, L. “Comment, Addressing the Impact of Domestic Violence on Children: Alternatives to Laws Criminalizing the Commission of Domestic Violence in the Presence of a Child” *Wisconsin Law Review*, 2001, 1337-1369.

Kernic, M., Wolf, M., Holt, V., McKnight, B., Huebner, C. and Rivara, F. “Behavioral Problems Among Children Whose Mothers are Abused by an Intimate Partner” 2003, 27: 1231-1246.

Kesner, J. and McKenry, P. “The Role of Childhood Attachment Factors in Predicting Male Violence Toward Female Intimates”, *Journal of Family Violence*, 1998, 13(4): 417-432.

Kilpatrick, K. and Williams, L. “Potential Mediators of Post-Traumatic Stress Disorder in Child Witnesses to Domestic Violence” *Child Abuse & Neglect* 1998, 22(4): 319-330.

Kitzmann, K., Gaylord, N., Holt, A. and Kenny, E. “Child Witnesses to Domestic Violence: A Meta-Analytic Review” *Journal of Consulting and Clinical Psychology*, 2003, 71(2): 339-352.

Koenen, K., Moffitt, T., Caspi, A., Taylor, A. and Purcell, S. “Domestic Violence is Associated with Environmental Suppression of IQ in Young Children” *Development and Psychopathology*, 2003, 15: 297-311.

**Lehmann, P. “Posttraumatic Stress Disorder (PTSD) and Child Witnesses to Mother-Assault: A Summary and Review” *Children and Youth Service Review*, 2000, 22(3/4): 275-306.

Levendosky, A. and Graham-Bermann, S. “Parenting in Battered Women: the Effects of Domestic Violence on Women and Their Children” *Journal of Family Violence*, 2001, 16(2): 171-191.

Levendosky, A., Huth-Bocks, A. and Semel, M. “Adolescent Peer Relationships and Mental Health Functioning in Families with Domestic Violence”, 2002, 31(2): 206-218.

*Levendosky, A., Huth-Bocks, A., Semel, M. and Shapiro, D. “Trauma Symptoms in Preschool-Age Children Exposed to Domestic Violence”, *Journal of Interpersonal Violence*, February, 2002, 17(2): 150-164.

Levendosky, A., Huth-Bocks, A., Shapiro, D. and Semel, M. “The Impact of Domestic Violence on the Maternal-Child Relationship and Preschool-Age Children’s Functioning” *Journal of Family Psychology*, 2003, 17(3): 275-287.

*Lewendowski, L., McFarlane, J., Campbell, J., Gary, F. and Barenski, C. “’He Killed

My Mommy!' Murder or Attempted Murder of a Child's Mother" *Journal of Family Violence*, August, 2004, 19(4): 211-220.

Litrownik, A., Newton, R., Hunter, W., English, D. and Everson, M. "Exposure to Family Violence in Young At-Risk Children: a Longitudinal Look at the Effects of Victimization and Witnessed Physical and Psychological Aggression" *Journal of Family Violence*, February, 2003, 18(1): 59-73.

Litrownik, A., Newton, R., Mitchell, B. and Richardson, K. "Long-Term Follow-Up of Young Children Placed in Foster Care: Subsequent Placements and Exposure to Family Violence" *Journal of Family Violence*, February, 2003, 18(1): 19-28.

Luster, T., Small, S. and Lower, R. "The Correlates of Abuse and Witnessing Abuse Among Adolescents" *Journal of Interpersonal Violence*, December, 2002, 17(12): 1323-1340.

**Margolin, G. and Gordis, E. "The Effects of Family and Community Violence on Children" *Annual Review of Psychology*, 2000, 51:445-479.

McCloskey, L. and Lichter, E. "The Contribution of Marital Violence to Adolescent Aggression Across Different Relationships" *Journal of Interpersonal Violence*, April, 2003, 18(4): 390-412.

McFarlane, J., Groff, J., O'Brien, J. and Watson, K. "Behaviors of Children Who are Exposed and Not Exposed to Intimate Partner Violence: An Analysis of 330 Black, White, and Hispanic Children" *Pediatrics*, September, 2003, 112(3): 202-207.

McGuigan, W. and Pratt, C. "The Predictive Impact of Domestic Violence on Three Types of Child Maltreatment" *Child Abuse & Neglect*, 2001, 25: 869-883.

Mitchell, K. and Finkelhor, D. "Risk of Crime Victimization Among Youth Exposed to Domestic Violence", *Journal of Interpersonal Violence*, September, 2001, 16(9): 944-964.

Morrel, T., Dubowitz, H., Kerr, M. and Black, M. "The Effect of Maternal Victimization on Children: a Cross-Informant Study" *Journal of Family Violence*, February, 2003, 18(1): 29-41.

Muller, R., Goebel-Fabbri, A., Diamond, T. and Dinklage, D. "Social Support and the Relationship Between Family and Community Violence Exposure and Psychopathology Among High Risk Adolescents", *Child Abuse & Neglect*, 2000, 24(4): 449-464.

Neggers, Y., Goldenberg, R., Cliver, S. and Hauth, J. "Effects of Domestic Violence on Preterm Birth and Low Birth Weight" *Acta Obstetricia et Gynecologica*

Scandinavica, 2004, 83: 455-460.

Nelson, D., Grisso, J., Joffe, M., Brensinger, C., Ness, R., McMahon, K., Shaw, L. and Datner, E. "Violence Does Not Influence Early Pregnancy Loss" *Fertility and Sterility* November, 2003, 80(5): 1205-1211.

Onyskiw, J. and Hayduk, L. "Processes Underlying Children's Adjustment in Families Characterized by Physical Aggression", *Family Relations* 2001, 50: 376-385.

Orbach, Y., Lamb, M., Sternberg, K., Williams, J. and Dawud-Noursi, S. "The Effect of Being a Victim or Witness of Family Violence on the Retrieval of Autobiographical Memories", *Child Abuse & Neglect*, 2001, 25: 1427-1437.

**Osofsky, J. "Prevalence of Children's Exposure to Domestic Violence and Child Maltreatment: Implications for Prevention and Intervention" *Clinical Child and Family Psychology Review*, September, 2003, 6(3): 161-170.

**Peled, E. "Parenting by Men Who Abuse Women: Issues and Dilemmas" *British Journal of Social Work*, 2000, 30: 25-36.

**Prinz, R. and Feerick, M. "Next Steps in Research on Children Exposed to Domestic Violence" *Clinical Child and Family Psychology Review* September, 2003, 6(3): 215-219.

Ragin, D., Pilotti, M., Madry, L., Sage, R., Bingham, L. and Primm, B. "Intergenerational Substance Abuse and Domestic Violence as Familial Risk Factors for Lifetime Attempted Suicide Among Battered Women" *Journal of Interpersonal Violence*, October, 2002, 17(10): 1027-1045.

Raviv, A., Erel, O., Fox, N., Leavitt, L., Raviv, A., Dar, I., Shahinfar, A., and Greenbaum, C. "Individual Measurement of Exposure to Everyday Violence among Elementary Schoolchildren Across Various Settings", *Journal of Community Psychology*, 2001, 29(2): 117-140.

Reynolds, M., Wallace, J., Hill, T., Weist, M., Nabors., L. "The Relationship Between Gender, Depression, and Self-Esteem in Children Who Have Witnessed Domestic Violence", *Child Abuse and Neglect*, 2001, 25: 1201-1206.

**Rudo, Z., Powell, D. and Dunlap, G. "The Effects of Violence in the Home on Children's Emotional, Behavioral and Social Functioning" *Journal of Emotional and Behavioral Disorders*, Summer, 1998, 6(2): 94-114.

**Runyan, D. and Litrownik, A. "Introduction to Special Issue: LONGSCAN and Family Violence", *Journal of Family Violence*, February, 2003, 18(1): 1-4.

Silva, R., Alpert, M., Munoz., D., Singh, S., Matzner, F. and Dummit, S. "Stress and

Vulnerability to Posttraumatic Stress Disorder in Children and Adolescents" *American Journal of Psychiatry*, August, 2000, 157(8): 1229-1235

**Slep Smith, A. and O'Leary, S. "Examining Partner and Child Abuse: Are We Ready for a More Integrated Approach to Family Violence?" *Clinical Child and Family Psychology Review*, 2001, 4(2): 87-107.

Stephens, D. "Battered Women's Views of Their Children", *Journal of Interpersonal Violence*, July, 1999, 14(7): 731-745.

**Stiles, M. "Medicine and Society, Witnessing Domestic Violence: the Effect on Children" *American Family Physician*, December, 2002, 66(11): 2052-2066.

Street, A., King, L., King, D. and Riggs, D. "The Associations Among Male-Perpetrated Partner Violence, Wives' Psychological Distress and Children's Behavior Problems: a Structural Equation Modeling Analysis" *Journal of Comparative Family Studies*, 2003, 23-40.

Sullivan, C., Juras, J., Bybee, D., Nguyen, H. and Allen, N. "How Children's Adjustment is Affected by Their Relationships to Their Mother's Abusers" *Journal of Interpersonal Violence*, June, 2000, 15(6): 587-602.

**Vostanis, P. "The Impact, Psychological Sequelae and Management of Trauma Affecting Children" *Current Opinion in Psychiatry*, 2004, 17: 269-273.

Whitfield, C., Anda., R., Dube, S. and Felitti, V. "Violent Childhood Experiences and the Risk of Intimate Partner Violence in Adults" *Journal of Interpersonal Violence*, February, 2003, 18(2): 166-185.

Wolfe, D., Crooks, C., Lee, V., McIntyre-Smith, A. and Jaffe, P. "The Effects of Children's Exposure to Domestic Violence: a Meta-Analysis and Critique", *Clinical Child and Family Psychology Review*, September, 2003, 6(3): 171-187.

*Worley, K., Walsh, S. and Lewis, K. "An Examination of Parenting Experiences in Male Perpetrators of Domestic Violence: A Qualitative Study" *Psychology and Psychotherapy: Theory, Research and Practice*, 2004, 77:35-54.

Yates, T., Dodds, M., Sroufe, A. and Egeland, B. "Exposure to Partner Violence and Child Behavior Problems: A Prospective Study Controlling for Child Physical Abuse and Neglect, Child Cognitive Ability, Socioeconomic Status, and Life Stress" *Development and Psychopathology*, 2003, 15: 199-218.

References:

Achenbach, T. & Edelbrock, C. Manual for the Child Behavior Checklist and Revised Child Behavior Profile, Department of Psychiatry, University of Vermont, 1983.

Bandura, A. Aggression a Social Learning Analysis, Prentice-Hall, 1973.

Baron, R. & Kenny, D. "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic and Statistical Considerations" *Journal of Personality and Social Psychology* 6:1173-1182, 1986.

Becker, H. Outsiders, the Free Press, 1973.

Bowlby, J. Attachment and Loss, Volume I: Attachment, Basic Books, 1982

Briere, J., Johnson, K., Bissada, A., Damon, L., Crouch, J., Gil, E., Hanson, R., and Ernst, V. "The Trauma Symptom Checklist for Young Children (TSCYC): Reliability and Association with Abuse Exposure in a Multi-Site Study" *Child Abuse & Neglect*, 2001, 25: 1001-1014.

Browning, C. "The Span of Collective Efficacy: Extending Social Disorganization Theory to Partner Violence" *Journal of Marriage and the Family*, November, 2002, 64(11):833-850.

Bureau of Justice Statistics, Crime and Victims, Intimate Partner Violence, www.ojp.usdoj.gov/bjs.

Cappell, C. & Heiner, R.: "Intergenerational Transmission of Family Aggression" *Journal of Family Violence* 5(2) 1990.

Cassidy, J. & Shaver, P.: Handbook of Attachment: theory, research and clinical applications, Guilford Press, 1999.

Cloward, R., and Ohlin, L. Delinquency and Opportunity, the Free Press, 1960.

Cochran, W. Sampling Techniques, 3rd edition, John Wiley & Sons, 1977.

Diagnostic and Statistical Manual of Mental Disorders, fourth edition, Jaypee Brothers Medical Publishers, 1994.

Dobash, RE. and Dobash, R.P. Violence Against Wives, a Case Against Patriarchy, Free Press, 1979.

Dubowitz, H., Black, M., Kerr, M., Hussey, J., Morrel, T., Everson, M. and Starr, R. "Type and Timing of Mothers' Victimization: Effects on Mothers and Children" *Pediatrics*, April, 2001, 107(4): 728-735.

Edleson, J. "Children's Witnessing of Adult Domestic Violence", *Journal of Interpersonal Violence*, August, 1999, 14(8): 839-870.

Ehrensaft, M., Cohen, P., Brown, J., Smailes, E., Chen, H. and Johnson, J. "Intergenerational Transmission of Partner Violence: a 20-Year Prospective Study" *Journal of Consulting and Clinical Psychology*, 2003, 71(4): 741-753.

Elder, G.: "The Life Course and Human Development" in Handbook of Child Psychology, Volume 1: Theoretical Models of Human Development, Lerner & Damon eds., Wiley Press, 1998.

Erikson, E. Childhood and Society, W.W. Norton & Company, 1963.

Felitti, V., Anda, R., Nordenberg, D., Williamson, D., Spitz, A., Edwards, V., Koss, M., and Marks, J. "Relationship of Childhood Abuse and Household Dysfunction to Many of the Leading Causes of Death in Adults" *American Journal of Preventive Medicine*, 1998, 14(4): 245-257.

Fishbach, R., and Herbert, B. "Domestic Violence and Mental Health: Correlates and Conundrums Within and Across Cultures" *Social Science & Medicine*, October, 1997, 45(8): 1161-1176.

Freud, S. Three Essays on the Theory of Sexuality, Basic Books, 1975.

Galatzer-Levy, R. & Cohler, B. The Essential Other, Basic Books, 1993.

Gelles, R. "Estimating the Incidence and Prevalence of Violence Against Women" *Violence Against Women* July, 2000 6(7): 784-804.

Gelles, R. & Cornell, C. Intimate Violence in Families, 2nd edition, Sage Publications, 1990.

Gelles, R. and Straus, M. Intimate Violence: the Causes and Consequences of Abuse in the American Family, Simon & Schuster, 1989.

Giles-Sims, J. Wife Battering, a Systems Theory Approach, the Guilford Press, 1983.

Gould, M. Revolution in the Development of Capitalism, University of California Press, 1987.

Gottfredson, M. & Hirschi, T. "The True Value of Lambda Would Appear to be Zero" in Life-Course Criminology, Contemporary and Classic Readings, Piquero, A. & Mazerolle, P. (eds.), Wadsworth Series in Criminological Theory, 2001.

Graham-Bermann, S. "Family Worries: Assessment of Interpersonal Anxiety in Children From Violent and Nonviolent Families" *Journal of Clinical Child Psychology*, 1996, 25(3): 280-287.

Groves, B. "When Home Isn't Safe: Children and Domestic Violence" *Smith College Studies in Social Work*, March, 2001, 71(2): 183-207.

Hamel, Hendrik. Hamel's Journal and a Description of the Kingdom of Korea, 1653-

1666, Translation from the Dutch by Jean-Paul Buys of Taize, Royal Asiatic Society, Korea Branch, 1998.

Herman, J.: Trauma and Recovery, Basic Books, 1992.

Hirschi, T. Causes of Delinquency, Transaction Publishers, 2002.

Holden, G. "Children Exposed to Domestic Violence and Child Abuse: Terminology and Taxonomy" *Clinical Child and Family Psychology Review*, September, 2003, 6(3): 151-160.

Holden, G., Geffner, R. & Jouriles, E. Children Exposed to Marital Violence, Theory, Research and Applied Issues, American Psychological Association, 1998.

Holtzworth-Munroe, A. and Stuart, G. "Typologies of Male Batterers, Three Subtypes and the Differences Among Them" *Psychological Bulletin*, 1994, 116(3): 476-497.

Holtzworth-Munroe, A., Smutzler, N., and Sandin, E. "A Brief Review of the Research on Husband Violence. Part II The Psychological Effects of Husband Violence on Battered Women and Their Children" *Aggression and Violent Behavior*, 1997, 2(2): 179-213.

Hughes, H., Parkinson, D. and Vargo, M. "Witnessing Spouse Abuse and Experiencing Physical Abuse: A 'Double Whammy'?", *Journal of Family Violence*, 1989, 4(2): 197-209.

Johnson, M. "Patriarchal Terrorism and Common Couple Violence: Two Forms of Violence Against Women" *Journal of Marriage and the Family* 57:283-294, 1995.

Kalmuss, D.: "The Intergenerational Transmission of Marital Aggression" *Journal of Marriage and the Family* February, 1984.

Kernic, M., Wolf, M., Holt, V., McKnight, B., Huebner, C. and Rivara, F. "Behavioral Problems Among Children Whose Mothers are Abused by an Intimate Partner" 2003, 27: 1231-1246.

Kitzmann, K., Gaylord, N., Holt, A. and Kenny, E. "Child Witnesses to Domestic Violence: A Meta-Analytic Review" *Journal of Consulting and Clinical Psychology*, 2003, 71(2): 339-352.

Koenen, K., Moffitt, T., Caspi, A., Taylor, A. and Purcell, S. "Domestic Violence is Associated with Environmental Suppression of IQ in Young Children" *Development and Psychopathology*, 2003, 15: 297-311.

Knauft, B. "Foucault Meets South New Guinea: Knowledge, Power, Sexuality", *Ethos*, 1994, 22(4): 391-438.

Koryo-sa, Volume 84, Chapter 38, Criminal Law 1. Kong Ch'op Sangt'ongshik Dae-ak.

Laumakis M.; Margolin, G. & John, R.: "The Emotional, Cognitive and Coping Responses of Preadolescent Children to Different Dimensions of Marital Conflict", in Children Exposed to Marital Violence, Holden, G., Geffner, R., & Jouriles, E., eds., American Psychological Association,1998.

Lazarus, R.S. & Folkman, S.: Stress Appraisal & Coping, Springer Publishing, 1984.

Levendosky, A. and Graham-Bermann, S. "Parenting in Battered Women: the Effects of Domestic Violence on Women and Their Children" *Journal of Family Violence,* 2001, 16(2): 171-191.

Levendosky, A., Huth-Bocks, A. and Semel, M. "Adolescent Peer Relationships and Mental Health Functioning in Families with Domestic Violence", 2002, 31(2): 206-218.

Levendosky, A., Huth-Bocks, A., Shapiro, D. and Semel, M. "The Impact of Domestic Violence on the Maternal-Child Relationship and Preschool-Age Children's Functioning" *Journal of Family Psychology,* 2003, 17(3): 275-287.

Lewis, N. and Reinhold, M. Roman Civilization, Volume I the Republic, Columbia University Press, 1951.

Lewis, S. (M.S.W.). Private Conversation, January, 2004

Luhmann, N. "Generalized Media and the Problem of Contingency" in Loubser, Baum, Effrat and Lidz, (eds) Explorations in General Theory in the Social Sciences, volume 2, the Free Press, 1976.

Luhmann, N. Social Systems, Stanford University Press, 1995.

Luster, T., Small, S. and Lower, R. "The Correlates of Abuse and Witnessing Abuse Among Adolescents" *Journal of Interpersonal Violence*, December, 2002, 17(12): 1323-1340.

MacEwen, K.E.: "Refining the Intergenerational Transmission Hypothesis" *Journal of Interpersonal Violence* 9(3) 1994.

Marshall, G. Oxford Dictionary of Sociology, Oxford University Press, 1998.

Matza, D. Delinquency and Drift, Transaction Publishers, 1990.

McCullagh, P. Personal communication, July, 2005.

Mental Measurements Yearbook, Volume 12, Rutgers University Press, 1991.

Mental Measurements Yearbook, Volume 13, Rutgers University Press, 1992.

Merton, R. Social Theory and Social Structure, 1968 Enlarged Edition, the Free Press, 1968.

Muller, R., Goebel-Fabbri, A., Diamond, T. and Dinklage, D. "Social Support and the Relationship Between Family and Community Violence Exposure and Psychopathology Among High Risk Adolescents", *Child Abuse & Neglect*, 2000, 24(4): 449-464.

Murray Research Center, Harvard University. "Project on Human Development in Chicago Neighborhoods, Longitudinal Cohort Study, 1994-2001, Felton Earls", data archive, www.radcliffe.edu/murray/data, President and Fellows of Harvard College, 2005. .

National Institute of Justice. "Victim Costs and Consequences: A New Look" January, 1996. www.ojp.usdoj.gov/nij/pubs-sum/155282.htm.

Osofsky, J. Children, Youth and Violence: the Search for Solutions, Guilford Press, 1997.

Parsons, T. The Structure of Social Action, Volume I, the Free Press, 1968.

Piaget, J. The Moral Judgment of the Child, the Free Press, 1965.

The R Project, http://www.r-project.org/, 2005.

Reber, A. and Reber, E. The Penguin Dictionary of Psychology, third edition, Penguin Books, 2001.

Rossman, B. "Descartes's Error and Posttraumatic Stress Disorder: Cognition and Emotion in Children Who are Exposed to Parental Violence" in Children Exposed to Marital Violence, Holden, G., Geffner, R., & Jouriles, E., eds., American Psychological Association, 1998.

Rubin, D. Multiple Imputation for Nonresponse in Surveys, John Wiley & Sons, 1987.

Sameroff, A. & Marshall, M.: The Five to Seven Shift, University of Chicago Press, 1996.

Schafer, J.L. Analysis of Incomplete Multivariate Data, Chapman & Hall, 1997.

Schafer, J.L. "Software for Multiple Imputation" http://www.stat.psu.edu/~jls/misoftwa.html, 1999.

Schoua-Glusberg, A. "Project on Human Development in Chicago Neighborhoods Study Overview" unpublished paper, May, 2002.

Schoua-Glusberg, A. Private telephone conversation, Saturday January 29, 2005.

Silverman, A. & Gelles, R. "The Double Whammy Revisited: the Impact of Exposure to Domestic Violence and Being a Victim of Parent to Child Violence" *Indian Journal of Social Work* July, 2001, 62(3): 305-327.

Stephens, D. "Battered Women's Views of Their Children" *Journal of Interpersonal Violence*, July, 1999, 14(7): 731-746.

Stone, A. & Fialk, R. "Criminalizing the Exposure of Children to Family Violence: Breaking the Cycle of Abuse" *Harvard Women's Law Journal* 20:205-228, 1997.

Straus, M. & Gelles, R. Physical Violence in American Families, Risk Factors and Adaptations to Violence in 8,145 Families Transaction Publishers, 1990.

Street, A., King, L., King, D. and Riggs, D. "The Associations Among Male-Perpetrated Partner Violence, Wives' Psychological Distress and Children's Behavior Problems: a Structural Equation Modeling Analysis" *Journal of Comparative Family Studies*, 2003, 23-40.

Susi, P. "The Forgotten Victims of Domestic Violence", *Journal of the Missouri Bar*, September-October, 1998, 54(5).

Tanner, M.A. & Wong, W.H. "The Calculation of Posterior Distributions by Data Augmentation" *Journal of the American Statistical Association* 82(398):528-540, 1987.

Wakefield, J. "Psychotherapy, Distributive Justice and Social Work: Part 1: Distributive Justice as a Conceptual Framework for Social Work", *Social Service Review*, 1988, 62: 187-210.

Walker, L. The Battered Woman, Harper and Row, 1979.

Wechsler, D. Manual for the Wechsler Intelligence Scale for Children-Revised, the Psychological Corporation, 1974.

Whitfield, C., Anda., R., Dube, S. and Felitti, V. "Violent Childhood Experiences and the Risk of Intimate Partner Violence in Adults" *Journal of Interpersonal Violence*, February, 2003, 18(2): 166-185.

Widom, C. "Does Violence Beget Violence? A Critical Examination of the Literature" *Psychological Bulletin*, July, 1989, 106(1): 3-28.

Wolfe, D., Crooks, C., Lee, V., McIntyre-Smith, A. and Jaffe, P. "The Effects of Children's Exposure to Domestic Violence: a Meta-Analysis and Critique", *Clinical Child and Family Psychology Review*, September, 2003, 6(3): 171-187.

Zeanah, C.H. & Scheeringa, M.S.: "The Experience and Effects of Violence in Infancy" in Children in a Violent Society, Osofsky, J. ed., Guilford Press, 1997