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The Impact of Criminal Justice Interventions and Social Policies on Family Violence: Theory and Evidence

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by

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Dedication

To my family, and my best friend Georgi

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Table of Contents

List of Tables

List of Figures

Abstract

In 2014, the Child Protective Services received 3.6 million referrals alleging child abuse and neglect, of which, 702,000 children were victims of abuse and neglect and an estimated 1,580 children died due to maltreatment. In addition to this appalling toll, the welfare effects of child victimization are substantial. Evidence suggests that compared to demographically similar adults who were non-victims, adults with documented histories of maltreatment are more likely to engage in criminal behavior; have adverse mental and physical health problems such as depression, addiction and post-traumatic stress disorder; and have lower levels of education and earnings. These essays contribute toward the understanding of the consequences of two very distinctive policies – mandatory arrest and medical marijuana laws – and their impact on child maltreatment.

An important and controversial question in criminal justice policy concerns whether aggressive sanctions, such as mandatory arrest policies, serve as effective deterrents to familial violence. **Chapter 1** provides a theoretical framework that models child abuse in which I allow for a strategic interaction between the child and his or her abuser. The comparative statics yield clear predictions of the impact of sanctions on child maltreatment – as the cost and probability of external interventions rise, the probability of violence falls. I follow this theoretical analysis with an empirical investigation of the impact of mandatory arrest policies on child victimization.

I find a statistically significant and positive relationship between states that have implemented mandatory arrest laws and reported child maltreatment rates. This may seem surprising; however there are two explanations for the results. The likely explanation is that reporting of maltreatment increased in states mandating arrest; alternatively, recidivism may have increased in these states. Evidence from the OLS estimates for the reporting of abuse and child fatality rates (a proxy for the true incidence of child abuse), demonstrates that the increase in maltreatment is not due to recidivism but, in fact, more people reporting abuse to the police and Child Protective Services. The most important result that emerges from the data, however, is that while reported abuse increases in states with mandatory arrest laws, the true incidence of maltreatment actually falls. The ultimate goal of this paper is to stimulate further theoretical and empirical research that focuses on child abuse and prevention, thus enhancing an understanding of how sanctions influence child victimization.

The next chapter looks at one potential risk factor for child maltreatment –marijuana use and liberalization –using evidence from medical marijuana laws (MMLs). **Chapter 2** begins by extending the current MML-crime literature by providing a comprehensive evaluation of the impact of MMLs implemented at the state level on reported child victimization rates. I show that specific modes of medical marijuana regulation differentially influence the magnitude of reported incidences of child abuse, a finding which sheds new light on the current literature. More specifically, using fixed effects analysis applied to data from the National Child Abuse and Neglect Database System (NCANDS) and the Uniform Crime Reports (UCR), I show that states that allow for home cultivation in addition to decriminalizing its use see a further increase in the magnitude of reported incidences of child maltreatment rates.

Since completing my dissertation, I have continued to investigate into issues that have implications for both theory and practice in my field. To that extent, I plan to analyze the slowly developing public sphere –a platform where culture and social change rely on both media and conversation.

Chapter 1: Interventions for Domestic Violence: Examining the Role of Mandatory Arrest Policies on Child Maltreatment

Child abuse or maltreatment constitutes all forms of physical and/or emotional ill-treatment, sexual abuse, neglect or negligent treatment or commercial or other exploitation, resulting in actual or potential harm to the child's health, survival, development or dignity in the context of a relationship of responsibility, trust or power.

WHO Consultation on Child Abuse and Prevention, 1999

1.1 Introduction and Motivation

Domestic violence in the United States accounts for an estimated 1,200 deaths and two million injuries to women each year (Black & Breiding, 2008). Early public attitude towards domestic violence was based on the belief that abuse was best handled within the family and, while injunctions were available to married women, criminal penalties against the spouse were negligible (Bourg & Stock, 1994). Recently, the feminist movement, various grassroots organizations and the research community have significantly shifted the way the criminal justice system treats and prosecutes perpetrators of domestic assaults. Several alternatives for appropriate enforcement in response to intimate partner violence have been researched, proposed and adopted as policy. These alternatives vary from doing nothing to more formal criminal sanctions such as arrests, restraining orders and coerced treatments (Fagan, 1996). For example, the Violence Against Women Act of 1994 (VAWA) was the first U.S. federal legislation to acknowledge domestic violence as a crime (NNEDV Safety Net Project and The Confidentiality

Institute, 2015). It created new legal remedies and penalties (e.g. pro arrest policies such as mandatory and preferred arrest); authorized extensive grants to states, NGOs and federal agencies for various anti-violence programs; and created a civil rights remedy (Silk & Hurwitz, p. 6).

Much of the research following the emergence of VAWA has focused on the effect of pro-arrest policies on recidivism rates (Hirschel et al., 2007). However, since not all pro-arrest policies are the same, policy effectiveness can be influenced by factors such as how the policy is written and implemented and the degree of support for and monitoring of such policies within the community (Browne & Williams, 1989). Many advocates view the actual arrest of batterers as the ultimate goal of mandatory arrest legislation (Fagan, 1996). Interestingly, to date, pro-arrest policy research has been slow to examine the net-widening effect of domestic violence arrest practices (Hirschel et al., 2007). Initially, domestic violence statutes only applied to violence between couples. The definition today encompasses a wide range of relationships– current/former spouse and cohabitant, child in common, dating relations and those related by marriage or blood (National Institute of Justice, 2008).

A great deal of research has focused on the deterrence of sanctions in the context of intimate partner violence, but few have examined the impact of sanctions on child abuse. Thus, the goal of this paper is to contribute to the understanding of this complex phenomenon by exploring the impact of a deterrent, such as mandatory arrest provision, on child maltreatment.

Child abuse is not a new phenomenon; however, it was not until “the battered child syndrome” was published in 1962 (Kempe, Silverman, Steele, Droegemueller & Silver) that researchers began to explore the etiology of child abuse. Studies have shown that children who are abused display signs of negative externalizing behavior, have an increased risk of aggressive behavior, experience anxiety and depression, and may perpetuate the cycle of violence by increasing the probability that the child grows up to be a perpetrator or victim of domestic violence (Summers, 2006; Kernic et al., 2003; Lichter &McClosky, 2004).

The magnitude of this problem is surprising. In 2008, the Child Protective Services received 3.3 million reports of children being neglected or abused, out of which 772,000 children were determined to be victims of abuse (Fang et al., 2012). According to the National Child Abuse and Neglect Database System, 1,640 children died from abuse and neglect in 2012. This translates to a rate of 2.20 children per 100,000 children in the general population and an average of four children dying every day from abuse or neglect. The average lifetime cost of nonfatal child maltreatment in 2008 was $210,012 and the average lifetime cost per death was $1,272,900 (Fang et al., 2012). Clearly, the impact of child maltreatment generates a significant economic burden for not only the victims but also, by extension, for society. Thus, child violence is a social issue of concern for individuals and policy makers alike.

The political potency of issues relating to child and other familial violence has garnered a certain urgency to the development of new laws and sanctions. Thus, this study seeks to answer the following research question: Do aggressive sanctions such as mandatory arrest and mandatory prosecution, serve as effective deterrents to child violence?

In this paper, I develop and present a simple model of violence between children and their abusers. This is a Stackelberg type model in which the abuser (parent/guardian) maximizes expected utility subject to the stochastic reaction function of the victim (child). The comparative statics yield clear predictions about the impact of sanctions and deterrents on child maltreatment. The predictions are intuitive. As the cost and probability of external intervention rise, the probability of violence falls.

I follow this model with an empirical estimation of the impact of aggressive sanctions, such as mandatory arrest, on child victimization. I find a statistically significant and negative effect of these laws on child fatality rates (controlling for state and year fixed effects). However, while examining the impact of these laws on child maltreatment (controlling for state trends), I find a significant but positive relationship. Although this positive relationship contradicts my model, it could be a consequence of an increase in the reporting of maltreatment and/or reprisal rate by abusers.

The contribution of my paper is two-fold. First, I provide a theoretical framework that models child violence, in which I allow for a strategic interaction between the child and his abuser. In recent years, researchers have developed game theoretic models with respect to marriage and intimate partner violence (Manser & Brown, 1980; Lundberg & Pollak, 1996; Bloch & Rao, 2002; Tauchen & Witte, 1991); little attention, however, has been paid to analyzing child violence. While no model can capture all the complex factors that affect child violence, my goal is to construct a model that generates testable hypotheses and stimulates further theoretical research, thus allowing for a better understanding of how sanctions influence child victimization.

My second contribution is that I attempt to bridge the gap between the intimate partner and child abuse literature by empirically testing the effect of domestic violence statutes on child maltreatment. Literature on the co-occurrence of child abuse and spousal abuse has been expanding as more researchers are evaluating the impact of spousal abuse on children. As previously stated, none have evaluated the impact of sanctions on child maltreatment. Policies and laws have an important role in the identification and cessation of child maltreatment. Thus, in order for academics to participate in this important debate, it is necessary to evaluate which policies are effective at exposing and reducing family violence.

The rest of this paper is organized as follows: **Section 1.2** maps the mandatory arrest and child maltreatment research that is relevant to my paper. **Section 1.3** presents a model of child violence and examines the theoretical effect of interventions on child violence. **Section 1.4** presents descriptive evidence. **Sections 1.5** and **1.6** present the empirical estimates of the impact of mandatory arrest policies on reported maltreatment rates and child fatality rates. **Section 1.7** concludes.

1.2 Literature Review

Until the 1970's, the criminal justice system tended to overlook domestic violence cases – domestic abuse was treated as a private affair and most police agencies discouraged their officers from arresting perpetrators of domestic violence (Bourg & Stock, 1994).

Mandatory arrest laws, according to Iyengar (2009), emerged largely in response to two events. First, a court decision in Connecticut found the local police accountable for failure to adequately respond to a domestic violence incident[1].

Second, the Minneapolis Domestic Violence Experiment was conducted. It randomly assigned a police response to domestic violence calls. Researchers found that arrest was the most effective method police used to reduce domestic violence. The other methods – counseling and

[1] Thurman v City of Torrington (1984) Police took twenty-five minutes to respond to Mrs. Thurman's call for help. After arriving at the scene, the officer watched the attack continue for another twenty minutes before arresting Mr. Thurman. A subsequent civil lawsuit was filed against the town and the police department in 1984. Mrs. Thurman was awarded $2.3 million. The Thurman lawsuit brought about sweeping national reform of domestic violence laws, including the "Thurman Law" (aka the Family Violence Prevention and Response Act) instituted in Connecticut in 1986, which made domestic violence an automatically arrestable offense, even if the victim did not wish to press charges.

separating the individuals – were considerably less effective at deterring future arrests (Sherman & Berk, 1984). This study was instrumental in spearheading research and policy evaluation for mandatory arrest laws. The results of this experiment were used by the US Department of Justice, academics, legislators, and criminal justice spokespersons to justify and support mandatory arrest policies (Mignon & Holmes, 1995). For example, the Violence Against Women Act was signed into law in 1994 as a federal response to violent crimes against women. Since then, according to the National Institute of Justice (NIJ), 15 states have adopted mandatory arrest policies within the past two decades[2].

After Sherman and Berk's 1984 study, several other regional experiments financed by NIJ (commonly known as the Spousal Assault Replication Program (SARP)) were conducted to test the deterrent effect of arrest policies on domestic violence. All the studies paint a complex picture of the effectiveness of arrest as a deterrent. In 1992, Sherman, Schmidt and others conducted another controlled experiment using data from the Milwaukee Police Department. Their study revealed that while arrest deters repeat domestic violence incidences in the short run, there was no evidence of an overall long term deterrent effect. Moreover, they found a decrease in violence with groups who were employed, married, or white, but violence increased with arrest groups who were unemployed, unmarried, high school drop-outs, or African American. Similarly, Berk et al. (1992) used data from Colorado Springs and found that arrest did have a deterrent effect on employed batterers but not on unemployed batterers. In contrast, Dunford's (1992) study on Omaha, and Hirschel & Hutchison's (1992) study on Charlotte found that arrest was no more effective an intervention than mediation or separation. And finally, Pate &

[2] Mandatory arrest policies completely remove police discretion and require arrest in all cases where officers have probable cause to believe that an act of domestic violence has occurred. No-drop policies require prosecution of a domestic violence perpetrator, regardless of the victim's wishes (Wriggins, 2001)

Hamilton (1992) using data from Metro-Dade found that arrest only marginally affected recidivism after six months.

The findings from these studies are merely snapshots and are limited in that they often include a single jurisdiction or small sample sizes. Overall, the studies failed to replicate the Minneapolis findings, and the authors reported inconsistencies in the direction and impact of arrest in domestic violence cases. Furthermore, when a finding of no effect is reported the readers have no formal way to assess whether the failure to find an effect was due to the absence of an effect or to the likelihood that the research design would not find an effect if it did exist (Garner et al., 1995).

It is argued that mandatory arrest laws can result in a more consistent and punitive response to domestic violence; it is one form of state intervention that reduces the incidence of abuse and sends the appropriate societal message to abusers (Forell, 2013). Furthermore, it is hypothesized that those households residing in states with aggressive legislation tend to have a lower probability of domestic violence (Dugan, 2003).

In sharp contrast to the hypothesis that mandatory arrest laws may reduce violence and recidivism rates, Iyengar's research found evidence to suggest that at the state level mandatory arrest laws increased the risk of intimate partner homicides[3].

Using the FBI's Supplementary Homicide Reports from 1976-2003, Iyengar (2009) tested to see if mandatory arrest laws affected the levels of domestic violence. A difference-in-difference analysis revealed that intimate partner homicides increased by about 60% in states with mandatory arrest laws, but familial homicides declined in response to mandatory arrests. In contrast, there were no significant effects of arrest laws on homicides. Furthermore, the author

[3] Maxwell et al., 2002; Sugarman & Boney, 2000; Pate & Hamilton, 1992; Berk et al., 1992

suggested that mandating arrest might not deter abusers from killing their victims if it decreased reporting by victims or increased reprisal by abusers.

Iyengar's study suggests that mandatory arrest laws may deter reporting, thereby nullifying the potential deterrence intended by the required arrest. In fact, given current penalties, the low probability of arrest and a high probability that prosecutors decline such cases, mandatory arrests laws may also have a negligible effect on future arrests and convictions (Sloan et al., 2013).

Most of the studies have been beset with methodological concerns that lead to strikingly different estimated effects of arrest laws on intimate partner abuse. Thus, researchers and policymakers who are unaware of the differences between studies may make generalizations about mandatory arrest laws that cannot actually be supported (Zeoli et al., 2011).

While the focus of interest in the domestic violence literature is understanding intimate partner abuse, more recent inquiry has sought to explore children's exposure to domestic violence. Previously children were thought of as being tangential and disconnected to the violence between their parents, and commonly labeled "silent witnesses" (McIntosh, 2003). More recent qualitative research, however, has disputed this opinion as researchers have established the interconnectedness between men's abuse of women and child abuse (Connolly et al., 2006; Cunningham & Baker, 2004; Edleson, 1999; Guille, 2004; Hester et al., 2000). McDonald and colleagues (2006) estimated domestic violence exposure at 15.5 million U.S. youth by calculating the number of children in two-parent homes where violence had occurred.

Children exposed to domestic violence may also be direct victims of maltreatment. A number of reviews have examined the co-occurrence of documented child maltreatment in families where adult domestic violence is also occurring (Hartley, 2002; Appel & Holden, 1998;

Edleson, 1999; McGuigan & Pratt, 2001; Bowker et al., 1988; Shipman et al., 1999; Stark & Flitcraft, 1988). Appel & Holden (1998) found that there exists a 41% median co-occurrence of child maltreatment and adult domestic violence in families studied, while a majority of the studies found a 30% to 60% overlap (Edleson, 1999; McGuigan & Pratt, 2001).

An obvious question confronting researchers and policymakers is: what types of policy initiatives would promote a child's wellbeing? In the early 1960s, with the support and encouragement of the federal government, U.S. states began enacting laws mandating the reporting of child abuse to government authorities. Some states mandated universal reporting while others targeted certain professionals (non-universal reporting). Palusci and Vandervort (2014) reviewed 213 counties in the 18 states that had universal reporting statutes. They found states with these statutes had higher confirmed report rates for neglect, but none for other maltreatment types. While universal reporting has been touted as increasing identification of children who suffer from child abuse and neglect, Palusci and Vandervort (2014) and Mathews and Bross (2008) suggest that additional reports made may not necessarily imply that more maltreated children would be found, especially for more serious cases such as physical and sexual abuse. Shpiegel and colleagues (2013) argue that the lack of sufficient evidence coupled with broad statutes, which may be ambiguous, can directly or indirectly affect the substantiation of reports. Thus, when state statutes do not provide comprehensive and understandable guidelines of what constitutes harm, substantiation decisions become increasingly problematic.

To date, there has been little detailed research conducted on the impact of policies on the actual maltreatment of children. Certainly, a contextual understanding of the importance of such provisions on child violence and an empirical analysis that distinguishes child maltreatment cases from other domestic violence cases is lacking. As such, examining the effect of statutes and policies that are meant to act as deterrents to child violence remains an issue to be further explored.

1.3 Theoretical Model

In a seminal contribution, Becker (1968) showed that the most efficient way to deter a crime is to impose the severest possible penalty (to maintain adequate deterrence) and economize on the cost of enforcement (Dhami & Nowaihi, 2011). If we applied that proposition to the domain of family violence, would harsher mandates and policies effectively reduce the probability of violence?

A more interesting question is do most abusers intend to abuse, or is it an irrational act? If the abuser has an impulse-control problem, why would a harsh deterrent such as mandatory arrest or no-drop policy work? One can argue that deterrence works even for those with control problems because it brings to light the wrongness of the act. Consequentially, systems of morality and social pressure act as a deterrent. Moral intolerance could also impact legislation. State legislators that declare the moral impropriety of child abuse may enact stricter sanctions, acting in concert with their constituents.

The following model is based on the assumption that there is a rational component to family violence. In this section, I present a simple model of child violence that draws on the previous work of Tauchen, Witte and Long (1985) who model intimate partner abuse. Like the authors, I view violence as an instrument for controlling the victim's behavior, z.

In a game theoretic context, I assume the dominant decision maker to be the parent, who maximizes his or her expected utility subject to the stochastic reaction function of the child. The parent imposes a behavior standard ($\bar{z}$) on the child and threatens a level of violence (v) if the rules are not obeyed. Randomness is an essential feature in which violence occurs for instrumental purposes (Tauchen et al., 1985). The random term (ε) reflects random changes in the child's behavior or the parent's perception of the child's behavior, or even the child's misinterpretation of $\bar{z}$. If not included, the parent would set behavior standard ($\bar{z}$) and the child would either obey or disobey with certainty.

In the remainder of this section I derive: 1) the child's choice problem; 2) the parent's choice problem; and 3) the resulting equilibrium.

1.3.1 The Child's Choice Problem

To keep this model simple, I assume the child's utility to be a function of behavior and violence, with *z* being the child's only choice variable. The child evaluates his utility function before knowing the state of the world in which he will be in.

Formally the child's utility function is:

$$U^c\,(z+\ \varepsilon, v) \tag{1}$$

$$U_v^c < 0$$

$$U_z^c < 0 \text{ beyond some z}$$

The parent sets the desired behavior, $\bar{z}$ and inflicts a level of violence (v) if the child fails to meet the standard. Note, this model only accounts for violence that is potentially criminal, v^l, where the CPS would deem as physical abuse or neglect. There are two types of parents that are not modeled here[4]. First, parents who choose to never be criminally violent or who would never resort to violence, $\bar{v} < v^l$. Second, I do not consider parents who are likely to threaten violence

[4] As stated before, I assume that there is a rational component to family violence. Therefore, by assumption, I am not modeling parents that are irrational or for whom violence is an emotional response. Since random behavior cannot be incentivized, any policy intervention would be ineffective.

before a policy intervention, but not after. The assumption being that these parents will have the same response as the parents for whom a threat is still being made after external sanctions or interventions.

Formally, the parent threatens to inflict violence that would be potentially criminal if:

$$v = \begin{cases} v^l, & z + \varepsilon < \bar{z} \\ 0, & z + \varepsilon \geq \bar{z} \end{cases} \tag{2}$$

I assume the child has a perceived probability density function, $g_c(\varepsilon)$, for the random variable that measures the child's misinterpretation of $\bar{z}$. I also assume the distribution function has the following properties: 1) ε has a zero mean; 2) it is unimodal: where its first derivative is positive for $\varepsilon < 0$ and negative for $\varepsilon > 0$; and 3) it is twice continuously differentiable.

Thus, the probability of violence (π) is:

$$\pi = pr(z + \varepsilon < \bar{z}) = \int_{-\infty}^{\bar{z}-z} g_c(\varepsilon) d\varepsilon \tag{3}$$

For interest, I assume the case for a problem child, wherein the child's behavior $(z + \varepsilon)$ may fall short of the required behavior $(\bar{z})$, $z + \varepsilon < \bar{z}$.

Then the expected utility of the child is:

$$\mathrm{E}U^c = \pi U^c(z + \varepsilon, v) + (1 - \pi) U^c(z + \varepsilon, 0) \tag{4}$$

Maximizing $\mathrm{EU^c}$ by the choice of z yields the following first order necessary condition for the child's optimum behavior

$$\frac{\mathrm{dE}U^c}{\mathrm{d}\hat{\mathrm{z}}} = -g_c(\varepsilon) U^c(\hat{z} + \varepsilon, v^p) + \pi \frac{\mathrm{d}U^c(\hat{z}, v^p)}{\mathrm{d}\hat{\mathrm{z}}} + g_c(\varepsilon) U^c(\hat{z} + \varepsilon, 0) + (1 - \pi) \frac{\mathrm{d}U^c(\hat{z}, 0)}{\mathrm{d}\hat{\mathrm{z}}} = 0 \tag{5}$$

The nature of the problem implies $\frac{\mathrm{d}U^c(\hat{z},v^p)}{\mathrm{d}\hat{z}} = \frac{\mathrm{d}U^c(\hat{z},0)}{\mathrm{d}\hat{z}}$. The child must choose a level of behavior before he realizes the state of the world, i.e. violence or no violence. Thus, the immediate disutility he gets from improving his behavior is not conditioned on whether there will be violence in the future.

$$g_c(\varepsilon)[U^c(\hat{z},v^p) - U^c(\hat{z},0)\,] - \frac{\mathrm{d}U^c}{\mathrm{d}\hat{z}} = 0 \tag{6}$$

The child weighs the cost of his behavior in terms of his reduced utility versus the benefit of his behavior which is the reduced probability of violence. For at-risk children $\frac{\mathrm{d}U^c}{\mathrm{d}\hat{z}} < 0$ so that equation (6) implies,

$$\frac{\mathrm{d}U^c}{\mathrm{d}\hat{z}} = g_c(\varepsilon)[U^c(\hat{z} + \varepsilon, v^p) - U^c(\hat{z} + \varepsilon, 0)] < 0 \tag{7}$$

Behavior that the child enjoys or that is not costly i.e. $U^c_z \geq 0$, never results in violence as the child obeys willingly or without cost. Thus, $U^c_{\hat{z}} < 0$ focuses on the at-risk children.

Totally differentiating equation (6) with respect to $\hat{z}$ and $\bar{z}$ yields

$$\frac{\mathrm{d}\left(\frac{\mathrm{dE}U^c}{\mathrm{d}\hat{z}}\right)}{\mathrm{d}\hat{z}}\,\mathrm{d}\hat{z} + \frac{\mathrm{d}\left(\frac{\mathrm{dE}U^c}{\mathrm{d}\bar{z}}\right)}{\mathrm{d}\bar{z}}\mathrm{d}\bar{z} = 0,$$

or

$$\left[\frac{d^2U^c}{d\hat{z}^2} - g_c(\varepsilon)\frac{\mathrm{d}U^c}{\mathrm{d}\hat{z}} + g_c(\varepsilon)\frac{\mathrm{d}U^c}{\mathrm{d}\hat{z}} + g_c'(\varepsilon)U^c(\hat{z} + \varepsilon, v^p) - g_c'(\varepsilon)U^c(\hat{z} + \varepsilon, 0)\right]\mathrm{d}\hat{z} + [g_c'(\varepsilon)U^c(\hat{z} + \varepsilon, 0) - g_c'(\varepsilon)U^c(\hat{z} + \varepsilon, v)]\mathrm{d}\bar{z} = 0 \tag{8}$$

This yields the comparative static result,

$$\frac{d\hat{z}}{d\bar{z}} = \left\{\frac{g_c'(\varepsilon)[U^c(\hat{z} + \varepsilon, v^p) - U^c(\hat{z} + \varepsilon, 0)]}{\frac{d^2U^c}{d\hat{z}^2} + g_c'(\varepsilon)[U^c(\hat{z} + \varepsilon, v^p) - U^c(\hat{z} + \varepsilon, 0)]}\right\} > 0 \tag{9}$$

As the parent raises the behavior standard, the child responds by increasing his optimal behavior.

The child has a perceived probability density function, $g_c(\varepsilon)$, for the random variable ε. Thus, if $\bar{\varepsilon} = 0$, and if $\varepsilon < 0$, then we can eliminate children who enjoy behaving or for when the cost of behaving is zero ($\frac{\mathrm{d}U^c}{\mathrm{d}\hat{z}} \geq 0$). For such children, the cost of obeying the standard set by the parent would always be less than the cost of violence incurred by disobeying. Such a child will never fall below the set standard, guaranteeing no violence. This is not a problem child[5].

Also, we can eliminate children who are always trying to please. If $\frac{d\hat{z}}{d\bar{z}} > 1$, then setting a higher $\bar{z}$ would increase the child's behavior by more than the set standard. This would result in the parent increasing the behavior standards, until the child was perfect. Children like this respond to the threat of violence and by exceeding any increase in $\bar{z}$, eliminating the probability of violence Thus, our child of interest is one for which $0 < \frac{d\hat{z}}{d\bar{z}} < 1$. Such a child naturally responds to an increase in the behavioral standard, but only partially.

Next, I model the parent's expectations concerning the child's reaction to the rules.

1.3.2 The Parent's Choice Problem

The parent's utility is a function of the behavior of the child and the cost of sanctions (fines, imprisonment) given outside intervention, C^P. The cost of outside intervention enters into the parent's utility function as it imposes costs such as legal fees, loss of potential income from being arrested, and disapproval and loss of support from the community

[5] Another corner solution is a child who is always disobedient, i.e. $\frac{d\hat{z}}{d\bar{z}} < 0$. For such children, the cost of behaving will always be greater than the cost of violence.

As with the child, I assume the parent has a perceived probability density function, $g_p(\varepsilon)$, for the random variable in the child's behavior. Let $\pi(\mathrm{v})$ be the probability of violence if the parent perceives that the child has fallen short of the behavior standard.

$$\pi(\mathrm{v}) = pr(\hat{z} + \varepsilon < \bar{z}) = \int_{-\infty}^{\bar{z}-\hat{z}} g_p(\varepsilon) d\varepsilon \tag{10}$$

Then, assuming external intervention occurs only when there is violence, the parent's utility function is[6]:

$$U^p = \begin{cases} U(\hat{z}(\bar{z}) + \varepsilon, 0) \; without\ intervention \\ U(\hat{z}(\bar{z}) + \varepsilon, C^P) \; with\ intervention \end{cases} \tag{11}$$

Let ρ be the probability of external intervention when there is violence. As noted previously, violence reflects abuse and neglect that would be legally penalized.

Formally, the parent's expected utility can be expressed as follows:

$$\begin{aligned} EU^P = {} & \rho\pi(v)U^p[\hat{z}(\bar{z}) + \varepsilon, C^P] + (1-\rho)\pi(v)U^p[\hat{z}(\bar{z}) + \varepsilon, 0] \\ & + \big(1-\pi(v)\big)U^p[\hat{z}(\bar{z}) + \varepsilon, 0] \end{aligned} \tag{12}$$

Maximizing EU^P by the choice of $\bar{z}$ yields the following first order necessary condition for the parent's choice problem:

$$\begin{aligned} \frac{\mathrm{d}EU^P}{\mathrm{d}\bar{\mathrm{z}}} = {} & \rho g_p(\varepsilon)U^p[\hat{z}(\bar{z}) + \varepsilon, C^P] + \rho\pi\frac{\mathrm{d}U^P(z,C)}{\mathrm{d}\hat{\mathrm{z}}}\frac{d\hat{z}}{d\bar{z}} + (1-\rho)g_p(\varepsilon)U^p[\hat{z}(\bar{z}) + \varepsilon, 0] \\ & + (1-\rho)\pi\frac{\mathrm{d}U^P(z,0)}{\mathrm{d}\hat{\mathrm{z}}}\frac{d\hat{z}}{d\bar{z}} - g_p(\varepsilon)U^P[\hat{z}(\bar{z}) + \varepsilon, 0] \\ & + (1-\pi)\frac{\mathrm{d}U^P(z,0)}{\mathrm{d}\hat{\mathrm{z}}}\frac{d\hat{z}}{d\bar{z}} = 0 \end{aligned} \tag{13}$$

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[6] The parent gets disutility from the cost of sanctions $\mathrm{U}_C^{\mathrm{p}} < 0$.

The nature of the problem implies $\frac{\mathrm{d}U^P(z,C)}{\mathrm{d}\hat{z}} = \frac{dU^P(z,0)}{d\hat{z}}$. The parent derives immediate utility from the child's behavior that is not conditional on external intervention.

Then,

$$\frac{\mathrm{d}U^P}{\mathrm{d}\hat{z}}\frac{d\hat{z}}{d\bar{z}} - \rho g_p(\varepsilon)\big[U^p[\hat{z}(\bar{z}) + \varepsilon, 0] - U^p[\hat{z}(\bar{z}) + \varepsilon, C^P]\big] = 0 \tag{14}$$

This implies,

$$\frac{\mathrm{d}U^P}{\mathrm{d}\hat{z}}\frac{d\hat{z}}{d\bar{z}} = \rho g_p(\varepsilon)\big[U^p[\hat{z}(\bar{z}) + \varepsilon, 0] - U^p[\hat{z}(\bar{z}) + \varepsilon, C^P]\big] > 0 \tag{15}$$

That is, the parent gets utility when the child responds positively to the behavior standard.

Totally differentiating with respect to C^P and $\bar{z}$ yields

$$\frac{d\left(\frac{\mathrm{d}EU^P}{\mathrm{d}\bar{z}}\right)}{dC^P}dC^P + \frac{d\left(\frac{\mathrm{d}EU^P}{\mathrm{d}\bar{z}}\right)}{d\bar{z}}\,d\bar{z} = 0,$$

$$\begin{aligned}&\left[\rho g_p(\varepsilon)\left(\frac{dU^p}{dC^P}\right)\right]dC^P \\ &\qquad + \left[\frac{\mathrm{d}^2U^P}{\mathrm{d}\hat{z}^2}\frac{d\hat{z}}{d\bar{z}} + \frac{\mathrm{d}U^P}{\mathrm{d}\hat{z}}\frac{d^2\hat{z}}{d\bar{z}^2}\right. \\ &\qquad \left. - \rho g_p'(\varepsilon)\big[U^p[\hat{z}(\bar{z}) + \varepsilon, 0] - U^p[\hat{z}(\bar{z}) + \varepsilon, C^P]\big]\right]d\bar{z} = 0\end{aligned} \tag{16}$$

Thus,

$$\frac{d\bar{z}}{dC^P} = \left\{\frac{-\rho g_p(\varepsilon)\left(\frac{dU^p}{dC^P}\right)}{\frac{\mathrm{d}^2U^P}{\mathrm{d}\hat{z}^2}\frac{d\hat{z}}{d\bar{z}} + \frac{\mathrm{d}U^P}{\mathrm{d}\hat{z}}\frac{d^2\hat{z}}{d\bar{z}^2} - \rho g_p'(\varepsilon)\big[U^p[\hat{z}(\bar{z}) + \varepsilon, 0] - U^p[\hat{z}(\bar{z}) + \varepsilon, C^P]\big]}\right\} < 0 \tag{17}$$

This leads to an important implication; the parent lowers the behavior standard (or raises the violence threshold) as the cost of sanctions increase[7].

Totally differentiating equation (13) with respect to ρ and $\bar{z}$:

$$\frac{d\left(\frac{\mathrm{d}EU^P}{\mathrm{d}\bar{z}}\right)}{d\rho}d\rho+\frac{d\left(\frac{\mathrm{d}EU^P}{\mathrm{d}\bar{z}}\right)}{d\bar{z}}\,d\bar{z}=0$$

$$-g_p(\varepsilon)[U^p(\hat{z}(\bar{z})+\ \varepsilon,0)-U^p(\hat{z}(\bar{z})+\ \varepsilon,\ C^P)]d\rho$$
$$+\left[\frac{\mathrm{d}^2U^P}{\mathrm{d}\hat{z}^2}\frac{d\hat{z}}{d\bar{z}}+\frac{\mathrm{d}U^P}{\mathrm{d}\hat{z}}\frac{d^2\hat{z}}{d\bar{z}^2}\right.$$
$$\left.-\rho g_p'(\varepsilon)\big[U^p[\hat{z}(\bar{z})+\ \varepsilon,0]-U^p[\hat{z}(\bar{z})+\ \varepsilon,\ C^P]\big]\right]d\bar{z}=0 \qquad (11)$$

This implies,

$$\frac{d\bar{z}}{d\rho}=\left\{\frac{g_p(\varepsilon)[U^p(\hat{z}(\bar{z})+\ \varepsilon,0)-U^p(\hat{z}(\bar{z})+\ \varepsilon,\ C^P)]}{\left(\left[\frac{\mathrm{d}^2U^P}{\mathrm{d}\hat{z}^2}\frac{d\hat{z}}{d\bar{z}}+\frac{\mathrm{d}U^P}{\mathrm{d}\hat{z}}\frac{d^2\hat{z}}{d\bar{z}^2}-\rho g_p'(\varepsilon)\big[U^p[\hat{z}(\bar{z})+\ \varepsilon,0]-U^p[\hat{z}(\bar{z})+\ \varepsilon,\ C^P]\big]\right]\right)}\right\}<0 \qquad (12)$$

Another important implication is that the parent lowers the behavior standard when the probability of detection or intervention increases. Thus, the parent takes the cost of sanctions and the probability of external intervention into consideration when setting the behavior standard for the child.

---

[7] As the cost of sanctions increase, the utility the parent receives from being violent falls: $\frac{dU^p}{dC^P}<0$
The denominator, $\frac{\mathrm{d}^2U^P}{\mathrm{d}\hat{z}^2}$ is negative by the concavity of U^p ; $\frac{\mathrm{d}U^P}{\mathrm{d}\hat{z}}<0$; $\frac{d\hat{z}}{d\bar{z}}>0$; $U^p[\hat{z}(\bar{z})+\ \varepsilon,0]>U^p[\hat{z}(\bar{z})+\ \varepsilon,\ C^P]$; $g_p'(\varepsilon)$ by assumption is greater than 0. Thus, $\frac{d\bar{z}}{dC^P}<0$; By the same logic, $\frac{d\bar{z}}{d\rho}<0$

1.3.3 Comparative Statics

$$\frac{d\pi}{dC^P} = \frac{d\pi}{d(\bar{z}-\hat{z})}\frac{d(\bar{z}-\hat{z})}{dC^P} = \frac{d\pi}{d(\bar{z}-\hat{z})}\left(\frac{d\bar{z}}{dC^P} - \frac{d\hat{z}}{d\bar{z}}\frac{d\bar{z}}{dC^P}\right) = \frac{d\pi}{d(\bar{z}-\hat{z})}\frac{d\bar{z}}{dC^P}\left(1-\frac{d\hat{z}}{d\bar{z}}\right) < 0 \quad (13)$$

And,

$$\frac{d\pi}{d\rho} = \frac{d\pi}{d(\bar{z}-\hat{z})}\frac{d(\bar{z}-\hat{z})}{d\rho} = \frac{d\pi}{d(\bar{z}-\hat{z})}\left(\frac{d\bar{z}}{d\rho} - \frac{d\hat{z}}{d\bar{z}}\frac{d\bar{z}}{d\rho}\right) = \frac{d\pi}{d(\bar{z}-\hat{z})}\frac{d\bar{z}}{d\rho}\left(1-\frac{d\hat{z}}{d\bar{z}}\right) < 0 \quad (14)$$

The two comparative static results, equations (20) and (21), are highly intuitive; the probability of external intervention and the costs imposed on the individual by sanctions, presumably could promote the reduction, or cessation of violent behavior. It would be less likely for the parent, or any abuser, to engage in violence if he or she perceived the cost of sanctions to be more certain or more severe. Correspondingly, the theory predicts that implementing sanctions, such as mandatory or pro-arrest policies – where arrest is certain given the reporting of abuse, should reduce the true incidence of child maltreatment.

This model can also be extended to allow for violence to be treated as a continuous variable and for variations in responses across victims. For example, as children get older, they may become more active and focused in trying to prevent or intervene in the abuse. Older children are more likely to strike back, leave or report an abusive parent. Thus, one would expect to see the probability of violence fall with children who are older and less dependent on the parent or the abuser. This would add another dimension and depth to the model – the abuser responds to the age of the victim, reducing violence as the child ages.

The relation between sanctions and behavior is complex, and hence it comes as no surprise that the literature on domestic violence documents mixed findings on the impact of sanctions and deterrence. The ultimate goal of this model is to stimulate further theoretical research that focuses on child abuse and prevention, thus enhancing an understanding of how sanctions influence child victimization.

A theoretical model alone, however, is not enough to determine the relative magnitude and deterrent effect of sanctions and provisions. Thus, testing the effectiveness and evaluating the legislative impact of policies that try to curb child violence remains an empirical question.

1.4 Data and Descriptive Evidence

Deterrence theory asserts that the perception of swift, severe, and certain legal sanctions contributes to an abstention from or reduction of illegal behavior (Heckert & Gondolf, 2000). The comparative static result of my theoretical model follows in line with this theory, in that, as the probability of external intervention and cost rise, violence should fall. A mandatory arrest provision is one such intervention – arrest is certain conditional on reporting. As previously discussed, a great deal of research has been conducted with regard to these legal sanctions on intimate partner abuse; however, none have examined the deterrent effects of these provisions on child abuse. Thus, the primary focus of this research is to test the effectiveness of such sanctions on child maltreatment rates.

State statistics about child maltreatment are derived from the data collected by the National Child Abuse and Neglect Data System (NCANDS). The Children's Bureau analyzes and publishes the data in an annual report that is available for download on its website. I use these reports in conjunction with the data provided through Cornell University – the National Data Archive on Child Abuse and Neglect (NDACAN) to construct a panel dataset from the years 1990 to 2010 for all 50 states (exclusive of District of Columbia).This is the first study to evaluate multi-state and multi-year comparisons of child maltreatment across the span of 20 years.

NCANDS was established in response to the Child Abuse Prevention and Treatment Act of 1988. As part of the act, it collects data aggregated at the state level through an annual survey. The survey asks each state to report the number of children who were the subjects of abuse or neglect; the number of child victims of maltreatment by age, sex and race; the number of reports and investigations of child abuse and neglect; the number of child fatalities; reporting of abuse to Child Protective Services (CPS); and other statistics (NDACAN). I calculate maltreatment and fatality rates using census estimates for state population with respect to age.

The Children's Bureau defines child fatality as children who have died due to abuse or neglect, and victims of maltreatment as children who have experienced or who were at risk of experiencing abuse or neglect. Perpetrator is defined as a parent or caretaker who has maltreated a child.

Police officers have three tiers of decision making power: full discretion (discretionary arrest laws); discretion with the state indicating a preference for arrest (preferred arrest laws); and little to no discretion (mandatory arrest laws). In determining the classification as to which states have these laws, I use the classification scheme from a study conducted by Zeoli et al. (2011). Table 1.1 lists the legislative date for each state that passed mandatory and recommended arrest policies.

I control for state-year factors that are potentially associated with the incidence of family violence which may in turn affect the child fatality and maltreatment rate. Economic measures such as median household income and unemployment rates were taken from the US Census Bureau. Additionally, income-inequality measures such as theil and gini, and human capital index measures such as high school and college attainment rate, were taken from a state-level panel data constructed by Frank, Mark (2009). I also control for state crime levels for violent and nonviolent crimes as reported by FBI's Uniform Crime Reports, and I account for social controls such as divorce rates (Wolfers, 2006; CDC).

Other controls include, unemployment rate for males, male-female employment ratio (US Census Statistical Abstracts); execution (Donohue and Wolfers, 2005); population density (US Census Statistical Abstracts); and share of prisoners to state population which may be indicative of police behavior and crime enforcement levels in a given state (US Census Statistical Abstracts). Table 1.2 gives a summary of the data sources I use in my analysis.

1.5 Empirical Strategy

1.5.1 Parallel Trends and Policy Exogeneity

Prior to the 1980s, the statutory structure for handling domestic violence cases could charitably be described as a benevolent neglect of a family problem (Buzawa & Buzawa, 1996). Since the late seventies, statutory changes have sought to mainly alter the official reaction and response to domestic violence. As noted earlier, there had been a recurrent exercise of discretion by the criminal justice system to avoid arresting and prosecuting domestic violence offenders. Current legislation mandating arrests have resulted from the interplay of pressure from feminist groups, concerned legislators, and professionals in the criminal justice system (Buzawa & Buzawa, 1996). However, according to the authors, this pressure was not due to the level of violence, but rather the perceived government treatment of offenders. They also argued that alternative reforms such as mediation were dismissed as inappropriate or sexist as American society became more conservative and punitive towards domestic violence offenders.

Stark (1993) posits that the most important reason for passing mandatory arrest laws was to control police behavior; reducing the level of violence was only of distant concern after the desire to avoid liability from inaction. For example, after the case of Thurman v City of Torrington, threats of future lawsuits served as a motivation for municipalities to protect themselves from liability, creating the desire to monitor and regulate police intervention in domestic violence incidents (Stark, 1993). This argument is further substantiated by Iyengar (2009), who suggests that the timing of arrest law passages is tied to the publication of the MDVE results, the promotion of these results by the Justice department in subsequent years, and finally federal funding of these policies after 1994. The preceding arguments collectively suggest that the motivation for most of the mandatory arrest laws does not appear to have been tied to the level of domestic or family violence.

Another underlying assumption here is that no other event, beside the implementation of the mandatory arrest policy alters the temporal path of either the treated or control groups. My data allows me to test and relax this identifying assumption as I look for graphical evidence of whether the two treatment groups diverged before the passage of the laws. In Figure 1.1, the dotted line represents the mean of the outcome variable for the two states (Utah and Rhode Island) that passed the mandatory arrest provision in 2000, with the solid line representing states with no such provision. As observed in the graph, the trends for child maltreatment prior to 2000 are very similar across the two groups, lending credibility to the empirical strategy in the next section.

1.5.2 Empirical Model

Using a difference in difference framework, I exploit the variation across states and time in the implementation of mandatory arrest policies. This allows me to identify the causal effect of these deterring policies under the assumptions of parallel trends and policy exogeneity.

My two main dependent variables are reported incidences of child maltreatment and child fatality rates. Since the nature of the database allows for some reporting effect, I expect the reporting of maltreatment to increase in states with mandatory arrest laws. However, following the prediction of my comparative static results in Section 1.3.3, I expect the true incidence of maltreatment to fall. I test this prediction by investigating the impact of mandatory arrest laws on child fatality rates. The underlying premise of this approach is that, with or without intervention, child fatality is always reported to the police; it is therefore immune to the reporting effect.

The explanatory variables of interest are states with mandatory arrest and recommended arrest laws. Since states with mandatory arrest statutes allow for little to no discretion by the police when making arrests, I predict a larger impact on child maltreatment than states with no such provisions.

My choice of controls is motivated by previous domestic violence research. I consider state and demographic controls that could affect familial violence and the decision to report. For example, schooling, employment, and income may alter the perpetrator’s risk of offending by increasing the opportunity cost of engaging in violence. As a result, I expect a negative correlation between these variables and child maltreatment. I also consider the judicial environment that may help capture the effects of deterrence caused by incarceration and additional policing. Finally, to allow for policies that are evolving over time, address time shocks and control for heterogeneity, I include state fixed effects, year fixed effects and state specific linear time trends.

Comparing child maltreatment rates before and after the passage of mandatory arrest laws, I estimate the impact of these laws on maltreatment rates per 1000 children. I use the following empirical specification:

$$y_{ST} = \beta_o + \beta_1 MandArr_{ST} + \beta_2 X_{ST} + \gamma_T + \theta_S + \varphi_{ST} + \epsilon_{ST} \quad (15)$$

For each state S in year T, y_{ST} is the maltreatment rate per 1000 children; *MandArr* is an indicator equal to 1 if a state has the mandatory arrest statute in effect at year T, and 0 otherwise; γ_T, θ_S and φ_{ST} are year fixed effects, state fixed effects and state-specific time trends respectively; X_{ST} is a vector of control variables. The coefficient of interest is β_1 which measures the effect of the mandatory arrest law provision on the child maltreatment rate. Column (2) of Table 1.4 reports the coefficients from this regression.

Using the same specification as (22), I also estimate the regression where the regressor of interest is the presence of recommended arrest policies. The recommended arrest effect variable is defined as 1 in states that have recommended arrest laws in effect at time T. Column (4) of Table 1.4 reports the coefficients from this regression.

1.6 Estimation Results

1.6.1 Main Results

Table 1.4 presents the estimates of the impact of mandatory arrest laws on reported child maltreatment rates based on the difference in difference framework. Each column represents a separate regression. I find a positive and highly statistically significant relationship between states that have implemented mandatory arrest laws and reported child maltreatment rates. The results suggest that mandatory arrest laws are responsible for an additional 3.33 children being reported as maltreated per 1000 children. The effect is relatively large in magnitude, suggesting that mandatory arrest policies result in an approximate 23.6% increase in reported child maltreatment rates[8]. This may seem surprising; however there are two explanations for the results. The likely explanation is that reporting of maltreatment increased in states with mandatory arrest laws; alternatively, recidivism may have increased in these states. Increased reporting lowers the probability of a child being abused. On the other hand, abusers may blame the victim for being arrested, thus penalizing the victims with repeat or escalating violence once the abuser is released.

To verify the reporting hypothesis, I use data from NDACAN to examine if states with mandatory arrest laws indeed see an increase in the reporting of child maltreatment to the CPS. Column (1) of Table 1.6 reports the results of these estimates. I find a positive and statistically significant relationship, suggesting that states with mandatory arrest provisions see an approximate 16.8% increase in the reporting of child maltreatment rates. In contrast, I find a

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[8] Note that reported child maltreatment coefficients are similar for the two pro-arrest policy states, as shown in Table 1.12. The only difference is that the estimates are larger, albeit not statistically so, for states with recommended arrest policies. When comparing the two extreme policy states, mandatory arrest vs discretionary arrest, estimates from the OLS regressions indicate that mandatory arrest policy states see a 24.2% increase in reported child maltreatment rates.

negative and statistically insignificant coefficient for states with recommended arrest laws. This supports the theory that in mandatory arrest policy states, the police and the CPS are recording more of the violence that citizens are reporting to them. Figures 1.3 and 1.4, show the trend in reporting rates to the CPS by law enforcement personnel.

Although child maltreatment is the most comprehensive measure of violence against children, it may often go unreported. Since maltreatment mostly occurs in the privacy of the home, it may be impossible to know what really happened as important facts can be either concealed or go undiscovered. Child fatality (death due to maltreatment) can serve as a useful proxy and reliable measure of violent crimes towards children. Since the death of a child is much harder to conceal, it is highly unlikely that fatalities would go unreported. Accordingly, I estimate the impact of mandatory arrest laws on child fatality rates.

Column (1) of Table 1.5 reports the results using only state and year fixed effects as controls. Estimates indicate that mandatory arrest law states see a decrease in child fatalities by 0.38 children per 100,000 children.[9] This corresponds to a 21% reduction in child fatality rates in states with mandatory arrest laws compared to states with no such policies. The results are statistically significant at the 5 percent level. However, as column (2) shows, the addition of a state-specific time trend to the model lessens the effect of these laws and makes the estimates indistinguishable from zero (from -0.38 and 5 percent significance to -0.051 and insignificant). It

[9] When comparing the two extreme policy states, mandatory arrest policies to discretionary arrest policies Table 1.13 (column 8)), I find that states with mandatory arrest laws see a 22% decrease in child fatality rates (controlling for state and year fixed effects). The results are statistically significant at the 5 percent level. I also find a negative and statistically significant relationship between pro-arrest policy states (i.e. states with either mandatory or recommended arrest) and child fatality rates, again controlling for year and state fixed effects.
On the other hand, when examining only recommended arrest policy states (Table 1.13, (Columns 3-4 & 7&8)) I consistently find that no statistically significant relationship to fatality rates exists. However, because of the magnitude of the coefficients, an economically significant relationship exists. This suggests that when some intervention is introduced, a reduction in the actual incidence of child maltreatment can be realized.

is important to note that the model specified in column (1) underscores the magnitude and economic significance of mandatory arrest statutes' impact on child fatality rates. Thus, using fatality as a proxy for child maltreatment yields valuable information about the true victimization rate of children.

My second hypothesis assumes that the increase in maltreatment rates may be due to an increase in the recurrence of child maltreatment. Figure 1.5 looks at the trend in recurrence within six months of offending from the years 2000 to 2010. One important characteristic can be seen. There seems to be a general reduction in the risk of recidivism over time. However, this may not be the result of any particular intervention. In fact, the high rate of offending observed immediately after the original event is a result of the high-risk people recidivating quickly, leaving the remaining sample in the risk set (medium and low risk individuals) to recidivate at different points in time (Kurlychek et al., 2012).

There is also a lack of consensus in the domestic violence literature as to the effectiveness of these laws on recidivism rates. In fact, most research indicates that arrest may have an effect in delaying or reducing intimate partner recidivism. Combining data from all five replication (SARP) studies, Maxwell and colleagues (2001) concluded that arrest only slightly reduced recidivism. Additionally, Hilton and colleagues (2007) find that by arresting higher-risk perpetrators a small beneficial effect of arrest, possibly in delaying recidivism, can be realized. In sum, to reduce recidivism, the best available evidence suggests that a police response, particularly one that results in an arrest, is the most effective offender-focused solution (Maxwell & Robinson, 2014).

Although it is likely that both the reporting of abuse and recidivism are operating, I find no strong evidence to suggest that states with mandatory arrest provisions see an increase in the risk of recurrence. Collectively, I view these findings as compelling evidence to support the hypothesis that states with mandatory arrest laws not only see an increase in the reporting of abuse but also a decrease in the true incidence of maltreatment.

Having established that mandatory arrest laws have a significant impact on overall child maltreatment, I now estimate the effect of these laws stratified by age of the victims. One extension of my theoretical model is that as children get older, they may become more active in trying to prevent or intervene in the abuse. Abused children entering school age also have a higher probability of being detected by concerned outsiders, thereby reducing the physical contact between the abuser and the child. When I stratify by age (Table 1.7), I find that the impact of mandatory arrest laws is considerably stronger for older victims.[10] The estimates however are insignificant, regardless of age. These findings are consistent with the hypothesis that as children get older, their abuse has a higher probability of being detected and reported.

1.6.2 Robustness Checks

Table (1.4) columns 7-9 estimate the sensitivity of the results to an alternate specification. Since the maltreatment rate data is intrinsically a count of child victims subjected to abuse within a discrete time period, I use the negative binomial likelihood function as a robustness check to estimate the original specification[11]. The corresponding regression estimates

[10] Estimates from the OLS regressions in Table 7 suggests mandatory arrest policy states see a 11% increase in maltreatment rates for victims between ages 0 and 3, and a 20.4% increase in reported maltreatment for older school-age victims, i.e. 4-11. As with the case of mandatory arrest policies, I find no statistically significant relationship exists between recommended arrest policy states and maltreatment rates stratified by age groups.

[11] The Poisson likelihood function assumes that the expected number of maltreatment rate is equal to its variance. If the variance is greater than the mean, then the resulting covariance matrix will be biased downward, and significance levels can be inflated (Liao 1994). The variance of the child maltreatment rate is nearly 10 times larger than the mean. I therefore rejected the Poisson model due to over-dispersion. The negative binomial distribution can be thought of as a Poisson distribution with unobserved heterogeneity which can be conceptualized as a mixture of two probability distributions, Poisson and Gamma (Schlattmann, 2009)

and patterns of statistical significance are similar across both models. Evidence from the negative binomial regression serves as a check on the linear results rather than an alternative to the difference in difference estimation.

I now conduct other robustness checks to analyze the plausibility of the identifying assumption. First, it may be that the adoption of mandatory arrest policies coincides with the adoption of other laws that address family violence, in which case my estimate could suffer from omitted variable bias. To address this, I run a negative binomial regression and I include controls for other state statutes such as 'hard' no-drop prosecution and universal reporting laws[12]. Table 1.9 reports the estimates of these coefficients. Of these additional controls, none have a statistically significant impact on child maltreatment. More importantly, the inclusion of these other policies does not reduce the statistical significance and positive effect of mandatory arrest laws on child maltreatment rates.

Second, there may be a concern that changes in maltreatment rates preceded the mandatory arrest policies. To address this, I create a placebo indicator which pretends that the treatment takes place one year earlier. Accordingly, I run a difference in difference and negative binomial regression. Table 1.10 reports the results from the estimation. All estimated coefficients are insignificant and close to zero. Thus, the placebo treatment does not influence changes in child maltreatment rates. This specification adds plausibility to the assumption that

[12] A hard no drop policy limits the prosecutor's discretion to drop a case solely because the victim is unwilling to cooperate. Hard no drop prosecution states are Utah, Wisconsin, Florida, and Minnesota.
Sixteen states specify not only certain professionals who must report suspected abuse but also require all persons to report suspected abuse or neglect, regardless of profession. Delaware, Florida, Idaho, Indiana, Kentucky, Maryland, Mississippi, Nebraska, New Hampshire, New Mexico, North Carolina, Oklahoma, Rhode Island, Tennessee, Texas, and Utah. (Source: National conference of state legislatures)

the maltreatment rates of states with and without mandatory arrest provisions follow a similar trend before the treatment.

Finally, there may be an interaction effect between arrest and certain demographic characteristics of the perpetrator such as the male and female unemployment rate, income, divorce and education. The estimates in Table 1.11 include these potential mechanisms, the policy change (states with mandatory arrest laws), and the interaction between the two terms. In the presence of unemployment, mandatory arrest seems to be a promising treatment and seems to deter all unemployed suspects. This result is of interest because unemployment by many is thought to increase spousal violence (Berk et al., 1992). Columns 5, 6 and 7 estimate the interactions of education, income and divorce. While all three estimates have negative signs, none are statistically significant at conventional levels.

1.7 Conclusion

Motivated by the cyclicality of abusive relationships in a domestic setting, this paper investigates the causal effect of policy interventions on children who are abused. The theory is premised on a simple hypothesis of deterrence, predicting that sanctions that are certain and severe contribute to the overall decline in observed child maltreatment. One example of such a sanction is a mandatory arrest provision, i.e. a policy that makes arrests certain conditional on reporting. Using data from the National Child Abuse and Neglect Data System from 1990 through 2010, I empirically test the impact of these laws on child maltreatment rates. I find that reported maltreatment rates increased in states with mandatory arrest laws. Evidence from the OLS estimates for child fatality rates demonstrates that the increase in reported maltreatment is not due to recidivism but, in fact, more people reporting child abuse to the CPS and law enforcement. The most important result that emerges from the data, however, is that while reported abuse increases in states with mandatory arrest laws, the true incidence of maltreatment actually falls.

It is also important to note that variations across counties in a state, along with their actual procedural implementation may differ and inadvertently bias my results. Additional studies of what happens within and among states over time will help determine the true impact of mandated arrest laws on child maltreatment. Also, once data with more heterogeneous groups of victims and longer follow-up periods become available, I suggest further investigation into the impact of interventions on the recurrence of child abuse.

This, and other future research, documenting the impact of various laws and their impact on abused children can help legislators design customized policies to meet the needs of victims. More importantly, continued cooperation between society and the criminal justice system to help identify and prosecute perpetrators is needed to address the pervasive problem of child victimization.

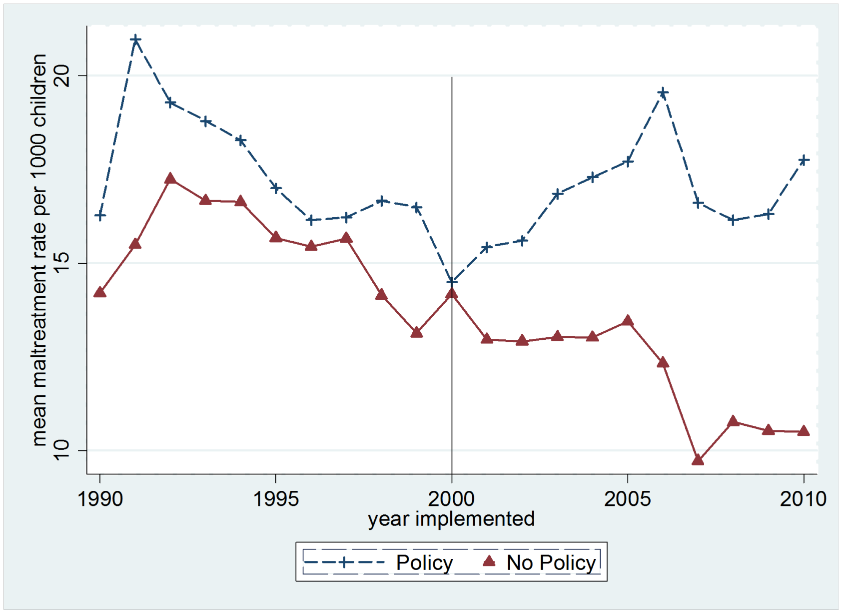

Figure 1.1 Parallel Trends

Notes: Figures plot group-specific yearly averages for maltreatment rate.
Passed Policy in 2000 states includes Utah and Rhode Island. "No Policy" states are states which had no mandatory arrest policies in place by 2010.

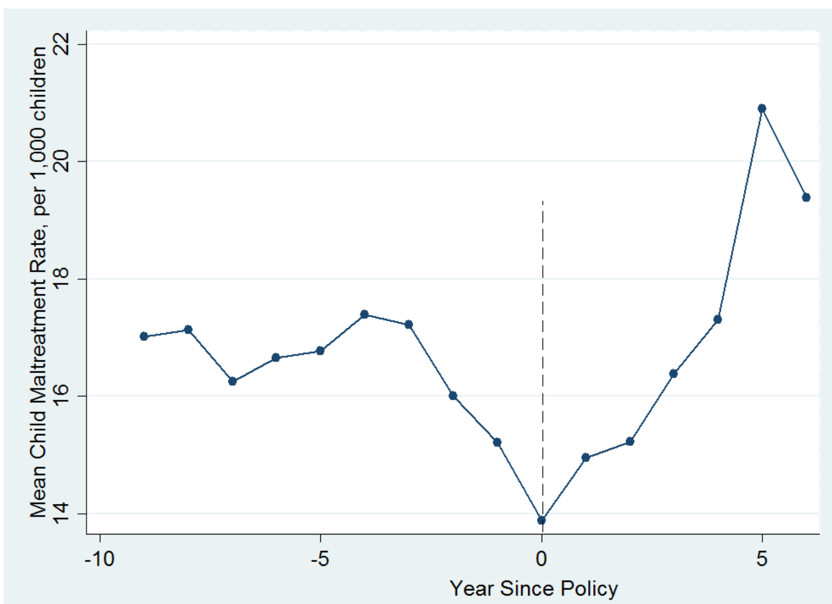

Figure 1.2 Trends in Child Maltreatment Rates, States with Mandatory Arrest Laws

Notes and Sources: Data is from the Child Maltreatment Reports and the National Data Archive for Child Abuse and Neglect (NDACAN). The Dashed line marks the timing of the mandatory arrest provision. As of 2010, 15 states have implemented mandatory arrest policies.

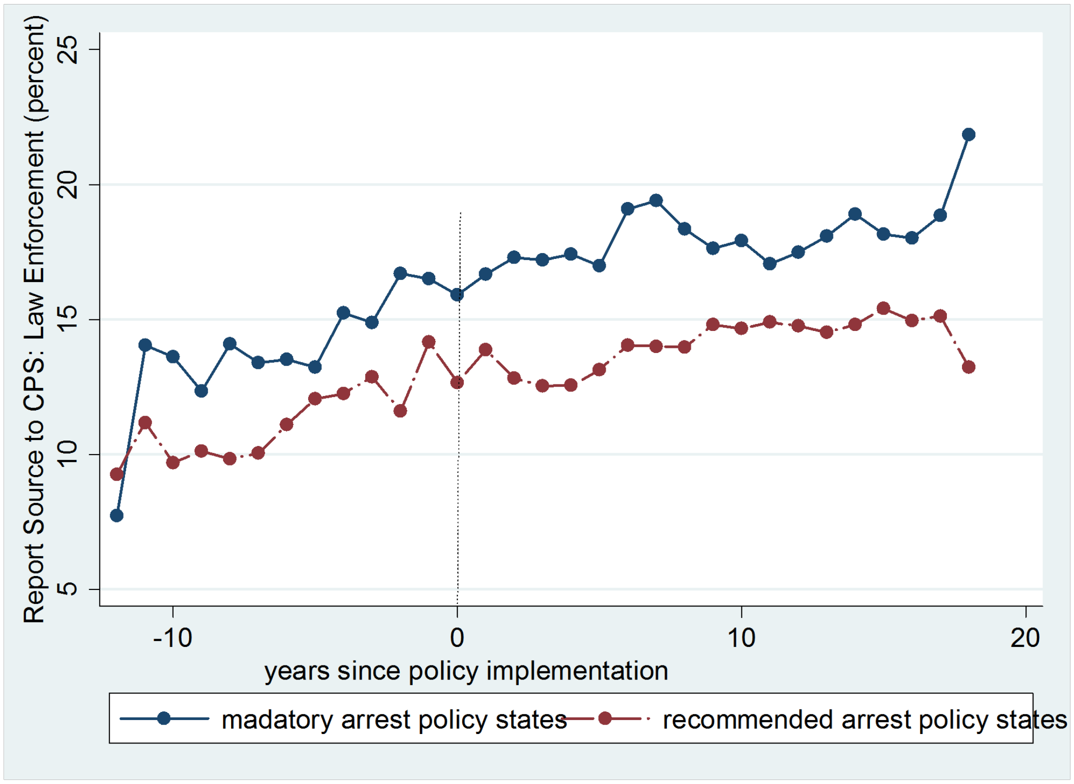

Figure 1.3 Report Source to CPS: Law Enforcement Personnel (percent)

For the solid line, the "zero" marker on the X-axis indicates the year in which the state passed the mandatory arrest policy. The non-solid lines, the "zero" marker on the X-axis indicates the year in which the state passed the recommended arrest policy. See Table 1.1 for state-specific legislative dates.

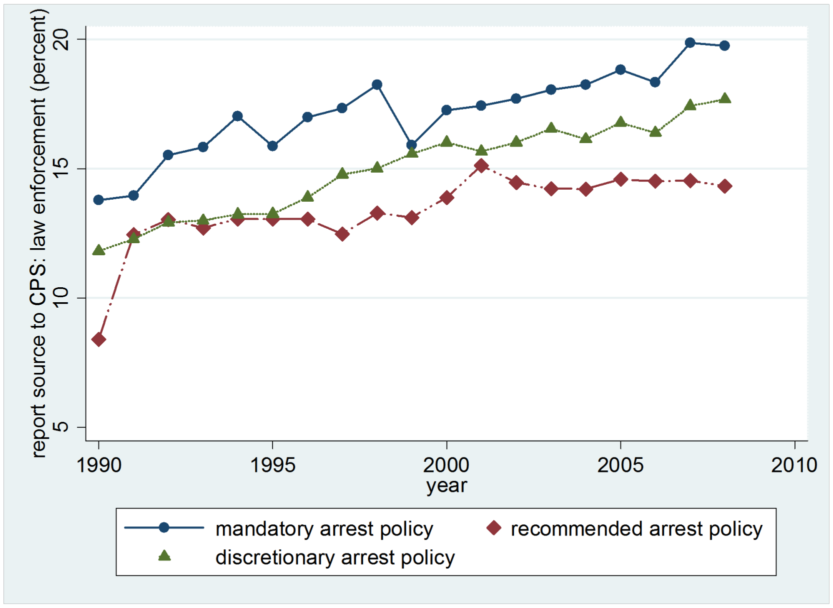

Figure 1.4 General Trend in the Reporting of Child Abuse by Law Enforcement

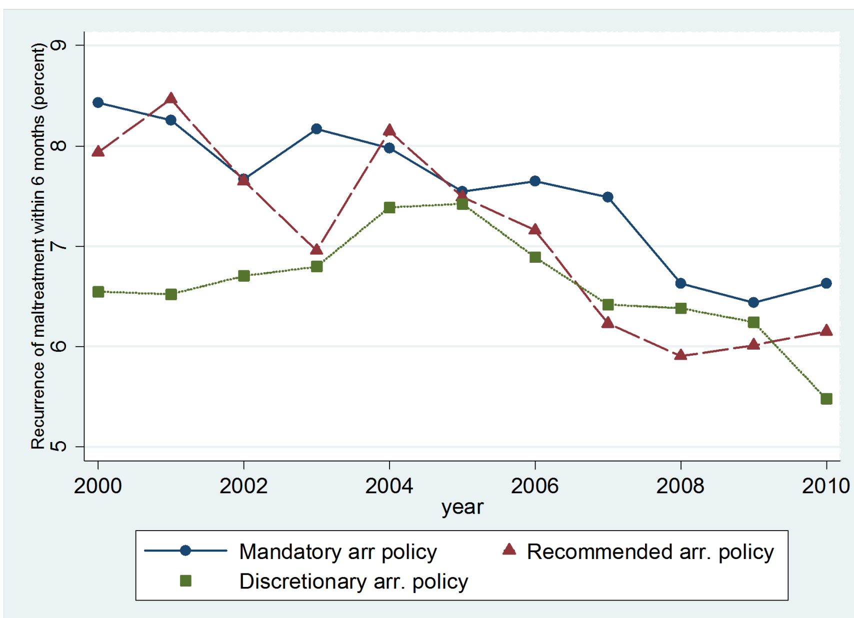

Figure 1.5 General Trend in Percent Recurrence of Abuse within 6 months (1999-2010)

Note: Figure 1.4 shows a general trend in the reporting of child abuse from 1990-2010. Figure 1.5 shows the general trend in the recurrence of abuse from 1999-2010. The solid line indicates states which have passed mandatory arrest laws. The non-solid lines represent reporting rates of states that have discretionary and recommended arrest policies. See Table 1.1 for state-specific legislative dates.

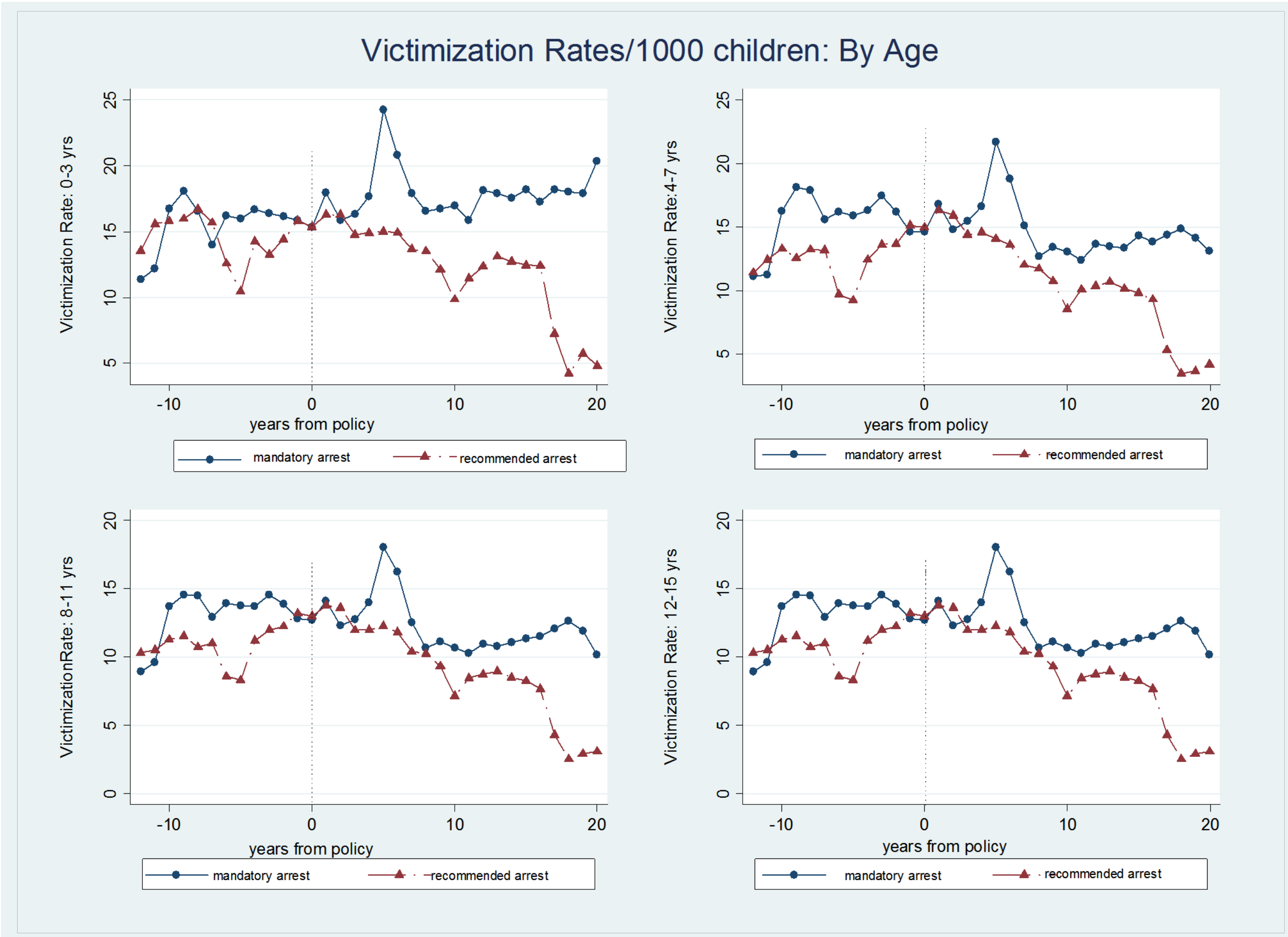

Figure 1.6 Victimization Rates per 1,000 Children, by Age Cohort

For the solid line, the “zero” marker on the X-axis indicates the year in which the state passed the mandatory arrest policy. The non-solid lines, the “zero” marker on the X-axis indicates the year in which the state passed the recommended arrest policy. See Table 1.1 for state-specific legislative dates.

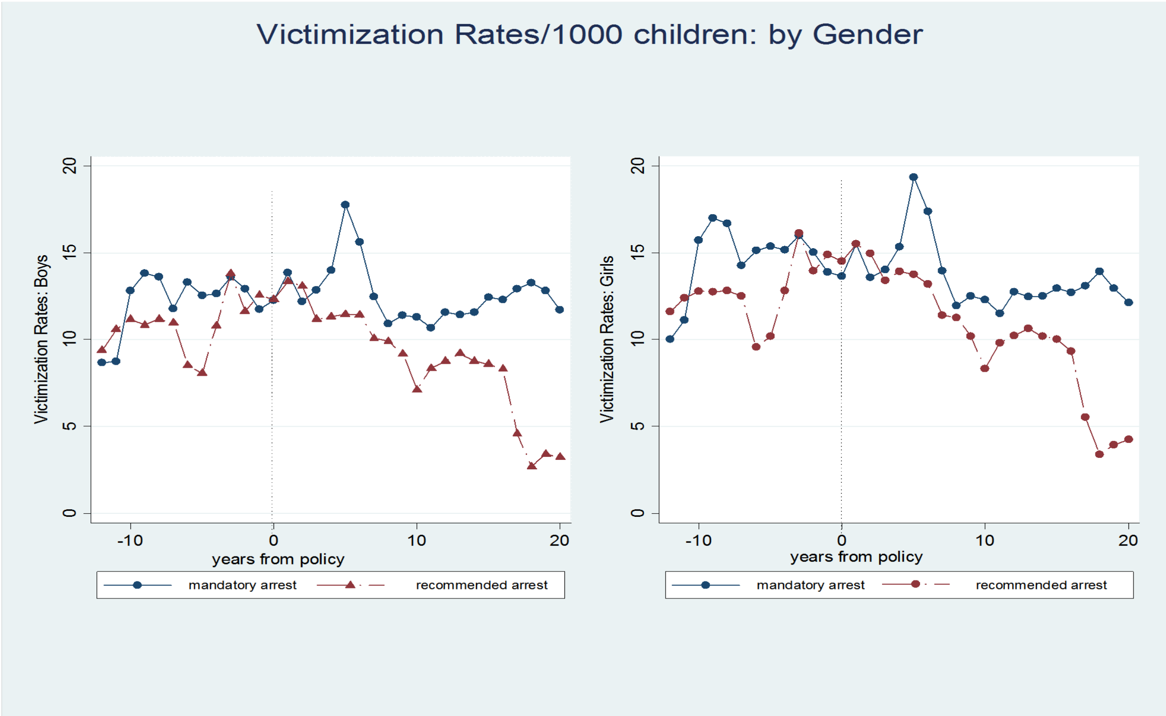

Figure 1.7 Victimization Rates per 1,000 Children, by Gender

For the solid line, the "zero" marker on the X-axis indicates the year in which the state passed the mandatory arrest policy. The non-solid lines, the "zero" marker on the X-axis indicates the year in which the state passed the recommended arrest policy. See Table 1.1 for state-specific legislative dates.

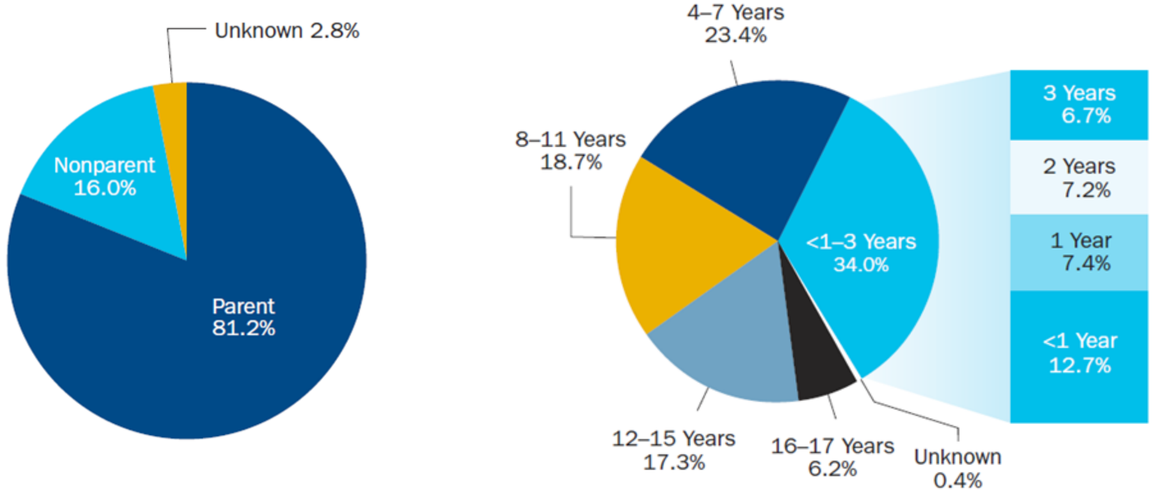

Figure 1.8 Perpetrators by Relationship to Victims (2010) & Victims by Age Cohort (2010)

Source: Child Maltreatment Report (2010)

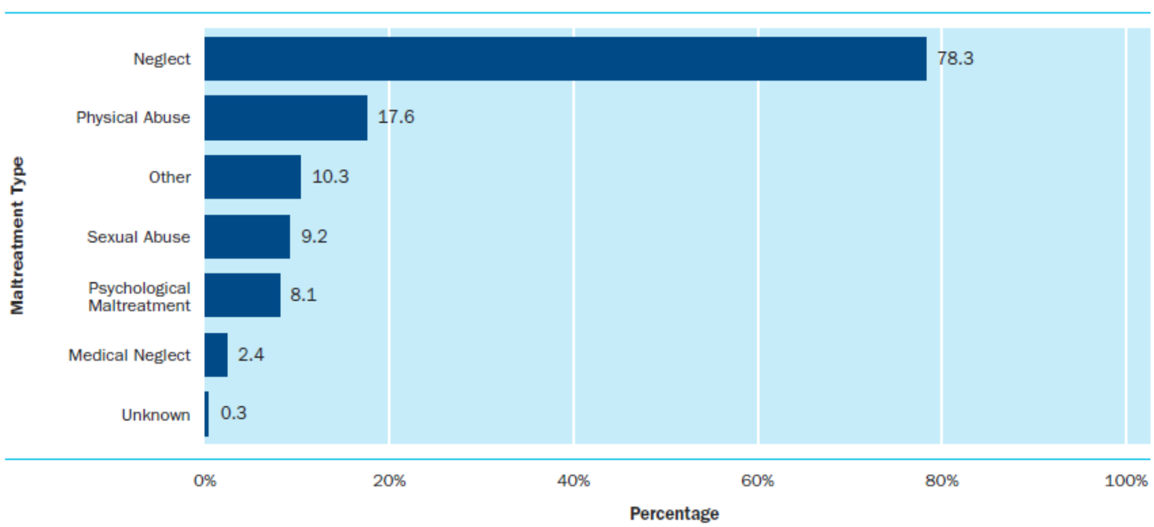

Figure 1.9 Reported Maltreatment by Type (2010)

Source: Child Maltreatment Report (2010)

Table 1.1 States with Mandatory Arrest, Recommended Arrest and Discretionary Arrest Policies

State	Policy	State	Policy
AL	Discretionary	**NE**	Discretionary
AK	Mandatory 1996	**NV**	Mandatory 1989
AZ	Recommended 1991	**NH**	Discretionary
AR	Discretionary	**NJ**	Mandatory 1991
CA	Recommended 1993	**NM**	Discretionary
CO	Mandatory 1994	**NY**	Recommended 1994
CT	Mandatory 1987	**NC**	Discretionary
DC	Mandatory 1991	**ND**	Discretionary
DE	Discretionary	**OH**	Recommended 1994
FL	Discretionary	**OK**	Discretionary
GA	Discretionary	**OR**	Mandatory 2001
HI	Discretionary	**PA**	Discretionary
ID	Discretionary	**RI**	Mandatory 2000
IL	Discretionary	**SC**	Recommended 2002
IN	Discretionary	**SD**	Mandatory 1998
IA	Mandatory 1990	**TN**	Discretionary
KS	Recommended 2000	**TX**	Discretionary
KY	Discretionary	**UT**	Mandatory 2000
LA	Discretionary	**VT**	Discretionary
ME	Mandatory 1995	**VA**	Mandatory 2002
MD	Discretionary	**WA**	Mandatory 1999
MA	Discretionary	**WV**	Discretionary
MI	Discretionary	**WI**	Mandatory 1996
MN	Discretionary	**WY**	Discretionary
MS	Recommended 1995		
MO	Recommended 1989		
MT	Discretionary		

Source: Zeoli et al. (2009)

Table 1.2 Summary of Data Sources

Variables	Definitions	Sources and years
Dependent Variables		
Child maltreatment	Children who have experienced or who were at risk of experiencing abuse or neglect.	NDACAN (1990-1999) Children's Bureau (2000-2010)
Child fatality rate	Children who have died due to abuse or neglect	
Reporting of maltreatment	A report source is defined as the category or role of the person who notified a CPS agency of the alleged child maltreatment	
Explanatory variables of Interest		
Classification of states with mandatory arrest and recommended arrest provisions	Mandatory arrest states are states which require an arrest conditional on a report of domestic violence. Recommended arrest states are states where officers are instructed but not required to make a warrantless arrest.	Zeoli et al. 2011 "Mandatory, Preferred, or Discretionary: How the classification of Domestic violence warrantless arrest laws impact their estimated effects on intimate partner homicide"
Family and State Environment		
Employment population ratio Male unemployment rate Unemployment rate Median Household income Poverty rate Population density per square mile (Proxy for urban rate)	(Total population/ Land area)	U.S. Census Bureau - Statistical Abstracts Series, Bureau of Labor Statistics
Divorce rate		Wolfers, Justin. 2006. Did Unilateral Divorce Raise Divorce Rates? A Reconciliation and New Results (1990 – 2000) CDC divorce rates (2000-2010)
Fraction of child population that is white Fraction of child population that is black	Information about the victim's race	U.S Census Bureau -Current Population Surveys
College attainment rate High school attainment rate Theil index	Human Capital Index Measures Income-Inequality Index	Frank, Mark. W. 2009 "Income Inequality, Human Capital, and Income Growth: Evidence from a State-Level VAR Analysis."
State Judicial Environment		
Death penalty & execution rate Incarceration rates	Prisoner to population ratio	Wolfers, Justin. 2006. Uses and Abuses of Empirical Evidence in the Death Penalty Debate U.S. Census Bureau - Statistical Abstracts Series
Crime rate	Crime to population ratio	FBI Uniform Crime Report (1990-2010)

Table 1.3 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Maltreatment rate per 1000 children	968	14.15387	8.22681	0.688966	82.62695
Victims ages 0-3	960	15.55099	8.962154	1.072743	113.9011
Victims ages 4-11	960	12.48899	7.530598	1.158864	95.88476
Victims ages 12-15	960	11.36321	6.924545	1.169128	88.93894
Reporting rate per 1,000 persons	953	6.92981	2.827277	1.777521	29.07375
Fatality rate per 100,000 children	963	1.770668	1.079786	0	7.863395
State-year controls:					
Divorce rate	865	4.384362	1.208081	2	10.8
Median household income (2012)	1050	52819.17	8417.866	32018	77506
High school attainment rate	1050	0.543162	0.04365	0.385799	0.637845
College attainment rate	1050	0.160779	0.040332	0.07519	0.342751
Employment population ratio	850	63.70447	4.400458	49.1	73.3
Unemployment rate, males	850	5.650471	2.125332	2	15.8
Execution rate	950	0.037048	0.096375	0	0.961847
Prisoner to population ratio	1050	0.003491	0.001509	0.000444	0.008856
Total crime to population ratio	1050	0.009219	0.004609	0.001307	0.024887
Population density per sq. mi.	1050	180.3238	245.2472	0.96	1186.41
Fraction of child pop. that is black	1023	0.128014	0.114996	0.003415	0.469574
Fraction of child pop. that is white	1023	0.699382	0.190164	0.127249	1.023237
Theil index	1050	0.756171	0.173633	0.443031	1.487246

Table 1.4 Effect of Mandatory and Recommended Arrest Laws on Child Maltreatment Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Child Maltreatment Rate per 1000 children								
Dependent variable mean	14.154								
Mandatory arrest law effect	1.558 (0.969)	3.334** (1.566)					0.1689** (0 .0755)		
Recommended arrest law effect			2.8043 (2.855)	5.0243 (4.483)				0.2049 (0.1797)	
Mand or Recom arrest law effect					2.019* (1.089)	3.961** (1.761)			0.217** (0.093)
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS	Neg. Bin.	Neg. Bin	Neg. Bin
Controls for other violent crimes	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-year economic & social controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
State demographic controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-specific time trend	N	Y	N	Y	N	Y	Y	Y	Y
Observations	588	588	549	549	547	547	588	549	547
R-squared	0.697	0.774	0.704	0.772	0.712	0.784	-	-	-

Notes:
The dependent variable for each column is the column title per 1000 children. Robust standard errors are reported in parentheses. Coefficients that are significant at the .01, .05 .1 percent levels are marked with ***, **, *.
Mandatory arrest states are states which require an arrest conditional on a report of domestic violence. Recommended arrest states are states where officers are instructed but not required to make a warrantless arrest when a domestic violence offense is reported.
Mand or Recom arr states are states with either mandatory arrest or recommended arrest statutes.
Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape.
State economic control variables include the variables: male unemployment rate, employment-population ratio, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, and the theil income inequality index (Frank, 2009), population density per square mile (U.S Statistical Abstracts).
State social policy controls are taken from Wolfers (2006) and include divorce rates, and indicators for the death penalty (number of state executions by year).
State demographic controls are based on the March Current Population Survey and include variables for the fraction of the child population that is black and white.

Table 1.5 Effect of Mandatory and Recommended Arrest Laws on Child Fatality Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Child fatality rate per 100,000 children								
Dependent mean	1.771								
Mandatory arrest	-0.380**	-0.0508					-0.216**		
	(0.180)	(0.236)					(0.0977)		
Recommended arr.			-0.183	-0.248				-0.114	
			(0.192)	(0.252)				(0.112)	
Mand or Recom arr.					-0.339**	-0.121			-0.196**
					(0.144)	(0.180)			(0.08)
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS	Neg. Bin.	Neg. Bin	Neg. Bin.
Controls for other violent crimes	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-year economic & social controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-specific time trend	N	Y	N	Y	N	Y	N	N	N
Observations	538	538	538	538	538	538	538	538	538
R-squared	0.451	0.575	0.447	0.576	0.451	0.576	-	-	-

Notes:

The dependent variable for each column is the child fatality rate per 100,000 children. Robust standard errors are reported in parentheses. Coefficients that are significant at the .01, .05 .1 percent levels are marked with ***, **, *.

Mandatory arrest states are states which require an arrest conditional on a report of domestic violence. Recommended arrest states are states where officers are instructed but not required to make a warrantless arrest when a domestic violence offense is reported.

Mand or Recom arr states are states with either mandatory arrest or recommended arrest statutes.

Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape.

State economic control variables include the variables: male unemployment rate, employment-population ratio, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, and the theil income inequality index (Frank, 2009), population density per square mile (U.S Statistical Abstracts).

State social policy controls are taken from Wolfers (2006) and include divorce rates, and indicators for the death penalty (number of state executions by year).

State demographic controls are based on the March Current Population Survey and include variables for the fraction of the child population that is black and white.

Table 1.6 Effect of Mandatory and Recommended Arrest Laws on the Reporting of Child Abuse

	(1)	(2)	(3)	(5)
	Reporting of child abuse per 1000 persons			
Dependent variable mean	6.93			
Mandatory arrest law effect	1.167**		0.151**	
	(0.586)		(0.0615)	
Recommended arrest law effect		-0.602		-0.116
		(0.546)		(0.0748)
Estimation method	OLS	OLS	Neg. Bin.	Neg. Bin.
All controls	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
State-specific time trend	Y	Y	Y	Y
Observations	527	527	527	527
R-squared	0.834	0.832	-	-

Notes:
Each column represents a separate regression. The dependent variable for each column is the Reporting of child abuse rate per 1000 persons. Robust standard errors are reported in parentheses. Coefficients that are significant at the .01, .05 .1 percent levels are marked with ***, **, *.
All regressions include State FE, Year FE, State economic and social policy controls, Crime controls, and a state-specific time trend.
All controls include:
Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape.
State economic control variables include the variables: male unemployment rate, employment-population ratio, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, and the theil income inequality index (Frank, 2009), population density per square mile (U.S Statistical Abstracts).
State social policy controls are taken from Wolfers (2006) and include divorce rates, and indicators for the death penalty (number of state executions by year).
State demographic controls are based on the March Current Population Survey and include variables for the fraction of the child population that is black and white.

Tables 1.7 Effect of Mandatory Arrest Laws on Child Maltreatment Rates (Stratified by Age)

	(1)	(2)	(3)	(4)	(6)	(8)
Maltreatment rate/1000 children by age	Ages 0-3	Ages4-11	Ages12-15	Ages 0-3	Ages4-11	Ages12-15
Dependent variable mean	15.55	12.48	11.36			
Mandatory arrest effect	1.710	2.549	2.288	0.0585	0.0952	0.0821
	(1.951)	(1.740)	(1.590)	(0.0889)	(0.0851)	(0.0837)
Estimation method	OLS	OLS	OLS	Neg. Bin	Neg. Bin	Neg. Bin
Observations	527	527	527	527	527	527
R-squared	0.807	0.786	0.778	-	-	-

Notes:
The dependent variable for each column is the column title per 1000 children. Robust standard errors are reported in parentheses. Coefficients that are significant at the .01, .05 .1 percent levels are marked with ***, **, *.
Mandatory arrest states are states which require an arrest conditional on a report of domestic violence.
Each column represents a separate regression. All regressions include state by year controls, state fixed effect, year fixed effect, and a state specific time trend
Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape.
State economic control variables include the variables: male unemployment rate, employment-population ratio, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, and the theil income inequality index (Frank, 2009), population density per square mile (U.S Statistical Abstracts).
State social policy controls are taken from Wolfers (2006) and include divorce rates, and indicators for the death penalty (number of state executions by year).
State demographic controls are based on the March Current Population Survey and include variables for the fraction of the child population that is black and white.

Table 1.8 Effect of Recommended Arrest Laws on Child Maltreatment Rates (Stratified by Age)

	(1)	(2)	(3)	(4)	(6)	(8)
Maltreatment rate/1000 children	Ages 0-3	Ages4-11	Ages12-15	Ages 0-3	Ages4-11	Ages12-15
Dependent variable mean	15.55	12.48	11.36			
Recommended arrest effect	0.194	1.083	0.966	0.0277	0.0823	0.0788
	(1.145)	(1.172)	(1.087)	(0.0701)	(0.0837)	(0.0868)
Estimation method	OLS	OLS	OLS	Neg. Bin	Neg. Bin.	Neg. Bin
Observations	527	527	527	527	527	527
R-squared	0.806	0.784	0.777	-	-	-

Coefficients that are significant at the .01, .05 .1 percent levels are marked with ***, **, *.

Recommended arrest states are states where officers are instructed but not required to make a warrantless arrest when a domestic violence offense is reported.
The dependent variable for each column is the column title per 1000 children. Robust standard errors are reported in parentheses.
Each column represents a separate regression. All regressions include state by year controls, state fixed effect, year fixed effect, and a state specific time trend
Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape.
State economic control variables include the variables: male unemployment rate, employment-population ratio, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, and the theil income inequality index (Frank, 2009), population density per square mile (U.S Statistical Abstracts).
State social policy controls are taken from Wolfers (2006) and include divorce rates, and indicators for the death penalty (number of state executions by year).
State demographic controls are based on the March Current Population Survey and include variables for the fraction of the child population that is black and white.

Table 1.9 Robustness Check: Effect of Mandatory Arrest, Hard No Drop Prosecution Policies, And Mandatory Reporting Of Child Abuse for All Persons on Child Maltreatment Rate

	Child Maltreatment Rate per 1000 children
Dependent variable mean	14.154
Mandatory arrest law	0 .1703 **
	(0 .076)
Hard no-drop prosecution policy	-0.0695
	(0 .071)
Mandatory reporting law	2.625
	(60.057)
Estimation method	Negative Binomial
All controls	Y
Observations	588
R-squared	-

Notes:
The dependent variable for each column is the Child maltreatment rate per 1000 children. Robust standard errors are reported in parentheses. Coefficients that are significant at the .01, .05 .1 percent levels are marked with ***, **, *.
Mandatory arrest states are states which require an arrest conditional on a report of domestic violence.
Hard no drop policy: is one in which the state will push forward a prosecution using all means available.
Mandatory reporting laws: any person who suspects child abuse or neglect is required to report.
In addition to hard no-drop policy and mandatory reporting by all persons laws.
Each column represents a separate regression. The regressions include all state by year controls in addition to, state fixed effect, year fixed effect, and a state specific time trend.

Table 1.10 Robustness Check: Effect of Mandatory Arrest Effect on Child Maltreatment Rate Using Placebo Indicator

	(1) Child maltreatment rate per1000 children
Placebo Mandatory arrest effect	.05617 (0 .0687)
Estimation method	Negative Binomial
Other state controls	Y
Observations	547

Notes:

Placebo Mandatory arrest: A Placebo indicator which pretends that the treatment (policy) is implemented one year earlier.
Each column represents a separate regression. The regressions include all state by year controls in addition to, state fixed effect, year fixed effect, and a state specific time trend.

Table 1.11 Robustness Check: Interaction Effects between Mandatory Arrest and Demographic Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Child maltreatment rate per 1000 children						
Dependent mean	14.154						
Mandatory arrest	0.16797**	0.459***	0.3642**	0.4086**	0.2166	0.2698	0.3197
	(0 .07547)	(0.1165)	(0.1526)	(0.164)	(0.2968)	(0.5457)	(0.2723)
MandXunemp		- 0.059***					
		(0.0211)					
mandXunempm			-0.0346				
			(0.0232)				
mandXunempf				-0.05146			
				(0.0356)			
mandXcollege					-.32376		
					(1.902)		
mandXHHincome						-1.70e-06	
						(9.70e-06)	
mandXdivorce							-0.03468
							(0.0605)
Observations	588	549	549	549	549	549	549

Notes:

Each column represents a separate regression using the negative binomial estimation method. Column (1) gives the estimates of the baseline regression.
The interaction terms include demographic characteristics of the perpetrator and mandatory arrest laws: unemployment rate (unemp), male and female unemployment rates (unempm & unempf), education (college), median household income (HHincome), and divorce.
All regressions include State FE, Year FE, State economic and social policy controls, Crime controls, and a state-specific time trend. See notes from table (1)
All controls include:
Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape.
State economic control variables include the variables: male unemployment rate, employment-population ratio, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, and the theil income inequality index (Frank, 2009), population density per square mile (U.S Statistical Abstracts).
State social policy controls are taken from Wolfers (2006) and include divorce rates, and indicators for the death penalty (number of state executions by year).
State demographic controls are based on the March Current Population Survey and include variables for the fraction of the child population that is black and white.

Table 1.12 Effect of Arrest Policies on Reported Child Maltreatment Rates per 1,000 children

	1	2	3	4	5	6	7	8	9	10
	Child maltreatment rate per 1,000 children									
Dependent mean	**14.154**									
Mandatory arr.[13]	1.558	3.334**								
	(0.969)	(1.566)								
Recommended arr.[14]			2.8043	5.0243						
			(2.855)	(4.483)						
Mand/Recom arr.[15]					2.019*	3.961**				
					(1.089)	(1.761)				
Recom vs Disc arr.[16]							4.172	5.112		
							(2.98)	(4.99)		
Mand vs Disc arr.[17]									1.206	3.431**
									(1.080)	(1.589)
All Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-specific time trend	N	Y	N	Y	N	Y	N	Y	N	Y
Observations	588	588	549	549	547	547	377	377	461	461
R-squared	0.697	0.77	0.70	0.77	0.71	0.78	0.70	0.79	0.74	0.81

[13] Mandatory arr.= 1 if a state implemented mandatory arrest laws, 0 otherwise (recommended or discretionary)
[14] Recommended arr. = 1 if a state implemented recommended arrest laws, 0 otherwise (mandatory or discretionary)
[15] Mand/Recom arr = 1 if a state implemented mandatory or recommended arrest law , 0 if discretionary
[16] Recom vs Disc arr = 1 if a state implemented recommended arrest laws, 0 if discretionary
[17] Mand vs Disc arr. = 1 if a state implemented mandatory arrest laws, 0 if discretionary

Table 1.13 Effect of Arrest Policies on Child Fatality Rates per 100,000 Children

	1	2	3	4	5	6	7	8	9	10
	Child fatality rate per 100,000 children									
Dependent mean	**1.771**									
Mandatory arr.[18]	-0.380**	-0.0508								
	(0.18)	(0.236)								
Recommended arr.[19]			-0.183	-0.248						
			(0.192)	(0.252)						
Mand/Recom arr.[20]					-0.339**	-0.121				
					(0.144)	(0.18)				
Recom vs Disc arr.[21]							-0.229	-0.255		
							(0.193)	(0 .262)		
Mand vs Disc arr.[22]									-0.392**	-0.094
									(0.185)	(0.248)
All Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-specific time trend	N	Y	N	Y	N	Y	N	Y	N	Y
Observations	538	538	538	538	538	538	376	376	451	451
R-squared	0.451	0.575	0.447	0.576	0.451	0.576	0.502	0.61	0.43	0.56

[18] Mandatory arr.= 1 if a state implemented mandatory arrest laws, 0 otherwise (recommended or discretionary)
[19] Recommended arr. = 1 if a state implemented recommended arrest laws, 0 otherwise (mandatory or discretionary)
[20] Mand/Recom arr = 1 if a state implemented mandatory or recommended arrest law , 0 if discretionary
[21] Recom vs Disc arr = 1 if a state implemented recommended arrest laws, 0 if discretionary
[22] Mand vs Disc arr. = 1 if a state implemented mandatory arrest laws, 0 if discretionary

Chapter 2: The Effect of Medical Marijuana Laws on Child Maltreatment: Evidence from State Panel Data, 1995-2014

2.1 Introduction and Motivation

It has been argued that marijuana use is part of a post-modern consumer culture which crosses class, gender, race, age and geographic boundaries (Simpson, 2003). Marijuana is also the most widely used illicit drug in the United States. In 2014, 27 million people aged 12 or older used an illicit drug in the past 30 days – these estimates are driven primarily by marijuana use with 22.2 million Americans reporting the use of marijuana in the past 30 days (SAMHSA, 2014). Public opinion on marijuana has shifted considerably in the last 40 years, with the majority of Americans (53%) now favoring legalization (PEW Research, 2015). Furthermore, a 2014 Gallup Poll found that 76 percent of Americans favored no jail time for those convicted of minor marijuana possession (PEW Research, 2014). This broader social acceptance of the drug has been reflected by policies being implemented at the state level that have allowed for the use of marijuana to be decriminalized, legalized, or approved for medicinal purposes in 23 states plus the District of Columbia.

How does the legalization of medical marijuana affect child maltreatment?

We might expect that children living with substance-abuse caregivers may experience a greater risk for maltreatment. In fact, the 2010 Fourth National Incidence Study found that illegal drug use was a factor in 9.5% of cases of physical abuse and about 12.5% of all neglect cases

(Sedlak et al., 2010). Parents who have substance use problems are more likely to contribute to severe family dysfunction, be physically abusive, and commit child neglect than those without diagnosed substance abuse problems (Ammerman et al., 1999; Appleyard et al., 2011). Caregiver substance misuse has also been documented as a predictor of severity in child maltreatment cases (Sprang, Clark & Bass, 2005; Staton-Tindall, Sprang & Straussner, 2016). Some studies suggest that cannabis may act as a gateway drug that encourages other forms of illicit drug use such as cocaine and heroin or alcohol use (see Jeffery DeSimone, 1998; Hall & Lynskey, 2009; Wen et al., 2015). While little attention has been paid to marijuana use and family violence, the link between illicit drug abuse, alcohol abuse and child maltreatment has been well documented. For example, Famularo and colleagues (1992) find specific associations between alcohol use and physical maltreatment, and cocaine abuse and sexual maltreatment. Considering the implications of a gateway effect, marijuana use could indirectly elevate the risk of child maltreatment. The gateway effect is one of the principal reasons cited in defense of laws prohibiting the use or possession of marijuana (Morral, McCaffrey & Paddock, 2002). Despite a number of scientific studies disputing this claim (*see* DeSimone, 1998, Tarter et al. 2016), the debate over the most appropriate policy has been generally polarized due to differing positions on the drug's harm.

Though clinical trials have demonstrated the benefits of cannabis in alleviating chronic and neuropathic pain, other scientific studies have indicated significant physical and psychotropic side-effects of the drug (Leung, 2011). Regular marijuana use has been linked to adverse health outcomes, including mental slowness, short-term memory loss, impaired reaction times, and accentuation of anxiety and depression (Crean, Crane & Mason, 2011; Cellucci, Jarchow & Hedt, 2004). Chronic use of marijuana in the long run increases the risk for a number of psychosocial outcomes including diminished relationship quality, lower satisfaction with life, and greater need for economic assistance (Dubowitz et al., 2015; Volkow et al., 2014). These effects can often lead to an unstable and chaotic environment for children, in which case basic needs such as nutrition, supervision and medical care may go unmet (Staton-Tindall et al., 2016). Similarly, parents with depression and anxiety disorders are less likely to prevent injury and harm to their children and more likely to exhibit stress or aggravation during parenting (Chung et.al., 2005).However, mental health problems cannot be causally connected to involvement in drug or marijuana use, even if it can be illustrated that its (ab)use may exacerbate pre-existing psychiatric disorders (Simpson, 2003; Crome, 1999).

So far, studies examining the link between marijuana use and psychosocial disorders have not addressed the nature of the following relationship: does marijuana use lead to such disorders or do issues such as anxiety and depression lead to the (over-) use of marijuana? In fact, one qualitative study found that parents who used marijuana reported that the drug improved their parenting by allowing them to relax and manage difficult emotions relating to parenting – thereby preventing them from yelling at or hitting their children (Thurstone et al., 2013). It must be noted that these results are preliminary in nature and must be interpreted with caution as they only include data from 11 parents in five focus groups. Additionally, conflicting results among most of the studies seem to be a result of differences in the degree of exposure, individual sensitivity, and drug potency (e.g., CBD/THC ratio[23]) (Niesink & Laar, 2013). Thus, research focused on the benefits and consequences of marijuana use merits further investigation.

[23] Tetrahydrocannabinol (THC) is the main psychoactive substance in cannabis. Cannabidiol (CBD) is a cannabinoid that appears in cannabis resin but rarely in herbal cannabis.

There is a growing body of empirical research examining the link between illegal drug consumption and intimate partner violence. However, due in part to differences in research design, the empirical support for this notion is rather mixed. While similar efforts exist with respect to marijuana use and child abuse (see Friesthler, Gruenewald & Wolf, 2014), no single analysis has assessed the overall impact of medical marijuana laws (MML) on child maltreatment rates across the United States.

Several studies have found that legalizing medical marijuana and decriminalizing its use leads to greater access and use of the drug (see Cerda et al., 2012; Anderson, Hansen & Rees, 2015; Freisthler et al., 2013). For example, at the state level, Pacula et al. (2013) conclude that states which allowed medical marijuana distribution through dispensaries or home cultivation had higher levels of past month marijuana use than states with no such laws. Additionally, legalization reduces the need for judicial and correctional spending on marijuana related offenses and facilitates the reallocation of police resources toward other violent crimes such as domestic violence. Thus this paper seeks to study the link between marijuana use and violence aimed at children, with the main purpose of examining the role that changes in marijuana legislation may play in the incidence of child abuse.

This paper begins by extending the current MML-crime literature by providing a comprehensive evaluation of the impact of MMLs implemented at the state level on reported child victimization rates. I show that specific dimensions of medical marijuana regulation differentially influence the magnitude of reported incidences of child abuse, a finding which sheds new light on the current literature. More specifically, using fixed effects analysis applied to data from the Child Maltreatment Reports (1995-2014) and the FBI's Uniform Crime Reports (UCR), I show that states that allow for home cultivation in addition to decriminalizing its use see an increase in the magnitude of reported incidences of child maltreatment rates This, of course, does not mean that marijuana legislation caused an increase in maltreatment rate. As noted in the first chapter, two factors influence reported incidences of abuse: actual maltreatment and the proportion of maltreated cases that are reported. Establishing a distinction between the two definitions can help understand the true impact of these laws.

There is an apparent gap between the enforcement of child safety laws and marijuana statutes. For example, there are no formal guidelines instructing child welfare professionals on how to handle cases where marijuana use has been recommended by a physician. Furthermore, reports of abuse and neglect that come to the attention of Child Protective Services (CPS) do not differentiate between specific substances used; thus very little is known about which specific drugs may be more likely to result in maladaptive parenting behaviors (Freisthler et al., 2015). Indeed, marijuana is still considered as an illicit drug by many professionals, and anecdotal evidence exists where CPS workers have removed children or denied custody because of the parents' legal use of marijuana[24]. This speculation of child endangerment due to marijuana use can lead to an increase in the reporting of child maltreatment cases.

To test the reporting hypothesis, I use an alternative proxy for maltreatment rates that is less likely to be biased by reporting: rates of child fatality from abuse and neglect. Child fatalities must always be reported, and using an extreme form of an incident is a common strategy among economists studying crime (*see* Iyengar, 2011; Levitt, 1998). I find that states that allow for home cultivation in addition to decriminalizing its use see a decrease in child fatality rates. This is obviously an imperfect proxy for overall maltreatment, but the fact that

[24] Jeanette Daggett v Dustin A. Sternick (2015): Sternick argues that the Maine Supreme Judicial court infringed on the protections afforded to him by the Maine Medical Use of Marijuana Act,22 M.R.S. § 2423-E(3) (2014), by reaching findings related to his marijuana use and that the court abused its discretion in awarding primary residence to Daggett based on Sternick's lawful marijuana use.

there is a consistent decline in fatality rates in states with marijuana regulation is evidence that states with MML do see a reduction in actual maltreatment.

Given that there is limited research on the relationship between marijuana consumption and child maltreatment, estimating the impact of various marijuana laws remains crucial. This paper improves on the existing literature in that it is the first to analyze the impact of drug regulatory variables on child victimization in a nationally representative, state-level panel dataset spanning 19 years.

The remainder of the paper is organized as follows. **Section 2.2** provides a brief historical background of MMLs in the U.S. **Section 2.3** summarizes the limited research examining the impact of MML on crime in general and, more specifically, family violence. **Sections 2.4** and **2.5** discuss data sources and methodology. I present the results from my analyses of the impact of these laws on child victimization rates in **Section 2.6**. Finally, **Section 2.7** concludes.

2.2 Background

2.2.1 Cannabis the Drug

Cannabis is largely derived from the female plant of cannabis sativa, with the two main active ingredients being delta-9-tetrahydrocannabinol (THC) and Cannabidiol (CBD).THC accounts for both the physical and psychotropic effects of cannabis, and hence is also the most widely studied. The mechanisms by which CBD exerts its effect are not precisely known, and by itself has almost no effect on normal physiological processes (Niesink & Laar, 2013). Not much is known of the safety and side effects of CBD either. Few studies have described the effects of CBD for therapeutic applications in clinical trials (Bergamaschi et al., 2011). While there is evidence from controlled trials that cannabinoids are effective in relieving nausea, alleviating severe pain, and improving appetite in people with HIV and cancer-related illnesses (Bergamaschi et al., 2011), chronic cannabis use is also associated with psychiatric toxicity and long-term psychiatric conditions (Reece, 2009). However, to date, there is no conclusive evidence to support the relationship between chronic cannabis use and the occurrence of psychosis. In fact, very few studies that have been published distinguish between the types of cannabis used, and none have given an indication of the THC/CBD ratio (Niesink & Laar, 2013).

2.2.2 A Brief History of Medical Marijuana Laws (MMLs) in the United States

America's connection with cannabis dates back to the early 1600s. The cultivation of cannabis (hemp) was the primary reason for America's colonization; it was produced initially by Jamestown settlers who were ordered by King James I in 1619 to grow 100 plants specifically for export (Deitch, 2003). Hemp cultivation remained a prominent industry until the mid-1800s, and throughout this period, the plant was commonly used by physicians to treat a broad spectrum of ailments (Anderson, Hansen & Daniel, 2013; Pacula et al., 2002). From 1850 to 1942, marijuana was listed in the United States Pharmacopeia and National Formulary; the official list of recognized medicinal drugs (Anderson, Hansen & Daniel, 2013). However, in 1937, the Marihuana Tax Act –which did not criminalize marijuana but did impose prohibitive taxes on its use – was passed after research indicated a link between marijuana use and crime (Deitch, 2003). Since then, several other laws were signed, including the Boggs Act (1952), the Narcotic Control Act (1956) and the Federal Controlled Substances Act (1970), which effectively discontinued the use of marijuana for medicinal purposes and ultimately criminalized it at the federal level (Blitz, 1992; Deitch, 2003).

The Controlled Substances Act classified marijuana as a Schedule I drug with high potential for abuse and no currently accepted medical uses in treatment. In 1973, Oregon became the first state to decriminalize cannabis – whereby possession of one ounce or less was treated as a misdemeanor with no jail time. By 1978, Nebraska became the eleventh state to pass the decriminalization legislation. During the Reagan administration, however, Congress passed several anti-drug legislation bills[25], which effectively ended the wave of states decriminalizing the possession of marijuana.

In 1996, California became the first state to legalize medical marijuana by passing the Compassionate Use Act (California Proposition 215). It removed criminal penalties for using, possessing and cultivating marijuana for medical purposes. The law provided immunity from criminal prosecution or sanction to physicians who recommended or prescribed marijuana to their patients. Despite federal restrictions, since 1996, 23 states have adopted medical marijuana laws, instituting their own specific restrictions for use, cultivation, possession limits, and allowance of dispensaries. While some states did allow doctors to prescribe marijuana before 1996, it had no practical effect since it was against federal law for pharmacies to distribute the drug (Anderson, Hansen & Daniel, 2013)[26].

2.3 Literature Review

2.3.1 Marijuana and Crime

While there is so far a dearth of literature reporting on the impact of medical marijuana laws on child maltreatment rates, considerable research has been conducted on the broader

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[25] Federal Bail Reform Act (1984); Anti-Drug Abuse Act of 1988

[26] Doctors in states where medical marijuana is legalized avoid violating federal law by recommending marijuana to their patients rather than prescribing the drug's use (Anderson, Hansen & Daniel, 2013)

subject of the impact of marijuana on negative life outcomes, criminal proclivity, and violent behavior.

As marijuana is a psychoactive substance, behavioral changes following its use are common and expected. The nature of some of these behavioral changes is subject to widespread academic debate, particularly when hostile or violent behavior is in focus. Some studies find that short-term use of marijuana may actually inhibit aggressive behavior, while long-term use can alter the nervous system in a way that augments violent proclivities (National Research Council, 1993). However, other studies have found socio-emotional deficits in marijuana users, including patterns of interpersonal withdrawal, hostility, and diminished interpersonal skills (Platt et al., 2010; Clopton et al., 1979; Roser et al., 2012). For example, Ansell et al. (2014) found hostile and impulsive behaviors as well as perceptions of hostility in others to be associated with marijuana use among subjects with no reported substance dependence. These findings were supported by Theunissen et al. (2012) who found that infrequent users of marijuana experience stronger effects on attention and inhibition following marijuana use relative to chronic users. However, further research is needed to examine whether these associations are causal since increases in interpersonal hostility could act an acute stressor that motivates the use of marijuana.

It is well documented that there is an association between illegal drugs and crime, but knowledge of this association alone may not be helpful in guiding policy designed to reduce violent crime (Markowitz, 2005). One might expect that marijuana use causes acceleration in criminal involvement; however, the empirical support for this notion is rather mixed. Bennet et al. (2008) conducted a systematic review of the literature and a meta-analysis of the strength of the relationship between types of drug used and criminal behavior. Results of the review of the ten studies found that marijuana users were 1.5 times more likely than non-marijuana users to commit a criminal offense. However, the authors found the relationship to be weaker than hard drugs such as heroin, crack, and cocaine.

To the extent that marijuana legalization may increase a broader acceptance and use of the drug, these policies could then help identify the potential causal relationships between marijuana access, use, and societal costs or benefits. Indeed, several studies have concluded that there is a positive association between MMLs, decriminalization, and consumption[27], and these policies could potentially shift its availability to adolescents. For example, Thurstone, Lieberman and Schmiege (2011) examined the prevalence of medical marijuana use among 80 adolescents in a substance treatment program in Denver, Colorado. Their study found that a large portion of the participants (48%) reported acquiring marijuana from someone with a medical marijuana ID card, concluding that persons with such ID cards may provide a source of supply for teenagers. Researchers have also tried to make use of the variation in MMLs to tease out the causal relationships between state policies and crime rates. Potentially, MMLs can lead to lower rates of crime and violence – prospective customers would prefer legal outlets because of reduced risk of arrest and the state regulatory systems could then design safeguards against potential criminal involvement (Shepard & Blackley, 2016).

While earlier studies may have suggested a positive link between decriminalization/MMLs and higher incidences of rape, robberies and assault,[28] there has been little evidence providing a systematic involvement of criminal behavior in states that have passed MMLs. In fact, evidence from recent studies show that MMLs may be associated with lower crime rates. For example, using an ecological cross-sectional design, Kepple and Friesthler (2012) studied the density of medical marijuana dispensaries and property/violent crime rates in

[27] See Chu, 2012; Cerda et al., 2012; Pacula et al., 2010; Harper et al., 2012; Freisthler et al., 2013
[28] See Salmelainen, 1995; Niveau & Dang, 2003; Pacula & Kilmer, 2003 Baker, 1998

Sacramento, California. Their study found no link between marijuana dispensaries and crime; concluding that the safety measures used by dispensaries (eg., doormen, and video cameras) may have had countervailing effects on criminal activity. Morris et al. (2014), generalized these results by using state level panel data from 1990-2006 to estimate the association between MML and property/crime rates. Findings from the research showed that the legislation preceded the decline in homicide and assault, suggesting a drop in violent crime. Morris et al. (2014) and Shepard & Blackley (2016) reached similar conclusions, concluding that the passage of medical marijuana laws did not precipitate an increase in criminal behavior, and furthermore possibly reduced it.

2.3.2 Marijuana and Interpersonal Violence

The majority of the studies that have examined the co-existence of substance abuse and interpersonal violence have focused on alcohol, without including other commonly used substances such as marijuana[29]. Of recent concern within the study of associations between substance use and violence is intimate partner violence, or IPV. So far research findings on the association between marijuana use and IPV have been inconsistent. Using data from 96 studies, Moore et al. (2008) conducted a meta-analytic review to quantitatively evaluate the relationship between specific drug use and intimate partner aggression. Their results suggest that the psychopharmacological effects of the drug produces increased aggression between intimate partners. Some studies have found that marijuana use is highly correlated with psychological abuse (Bennett et al. 2008), while others have linked more severe forms of IPV and IPV recurrence to marijuana use (Wofordt et al., 1994; Chermack et al. 2001). A major limitation of

[29] *See* Heyman, O'Leary & Jouriles, 1995; Leonard &Senchak, 1996; Schumacher et al., 2008)

the previous studies is that most of them have been cross-sectional. It is thus important to test whether marijuana use is predictive of subsequent IPV (Smith et al., 2014). Reingle, et.al. (2012) used longitudinal data from the National Longitudinal Study of Adolescent Health to examine the association between IPV and marijuana use. The authors found that consistent marijuana use, independent of alcohol use, was a strong predictor of intimate partner aggression for both victims and perpetrators.

Contrary to the previous literature some studies have suggested that marijuana use may be inversely associated with IPV. For example, a nine-year longitudinal study examining a community sample of newly married couples found that after controlling for important covariates (e.g., anti-social behavior, alcohol use), frequent use of marijuana generally predicted less frequent partner aggression over the first nine years of marriage (Smith et al., 2014). Additionally, Stuart et al. (2013) found that women were less likely to perpetrate physical aggression on days in which they had used marijuana relative to non-use days. There are also some studies suggesting a weak causal link between marijuana and IPV. The analyses of Fals-Stewart et al. (2003) indicated that the consumption of opiate-based drugs and cannabis were not associated with an increase in the likelihood of male-to-female partner aggression at any level of severity. Testa et al. (2003) reached similar conclusions; albeit being the most common drug used by the survey respondents. The authors reported that within ongoing relationships hard drug use (cocaine, heroin), but not marijuana use alone, predicted severe IPV and recurrence of IPV. In addition to the lack of association between marijuana use and partner aggression, the authors suggest that marijuana use may help suppress aggressive behavior.

The literature regarding the effects of marijuana use on child abuse and neglect have been limited. Using survey data from respondents living in 50 mid-size cities in California, Freisthler et al. (2015) used linear mixed effects multilevel modeling to assess the impact of marijuana use on abusive/neglectful parenting. They found a significant and positive association between the density of medical marijuana dispensaries and frequency of child physical abuse by parents. Their findings suggest that parents who are current users of marijuana engage in physical abuse more frequently, and may also have higher aggressive tendencies than their counterparts who do not use marijuana. However, the authors found little evidence to suggest that past year marijuana use related to supervisory neglect, and in fact found there was a negative relationship between marijuana use and physical neglect.

In summary, the current literature provides mixed and inconclusive evidence about the marijuana and domestic violence nexus, and is uncertain about the effects of MMLs on child victimization. Since the majority of the survey studies have been correlational or cross-sectional, the generalizability of the results may be limited due to over-reliance on self-reported measures, lack of information regarding severity and nature of the offenses, and response biases (e.g. social desirability bias) (Moore & Stuart, 2005). Freisthler et al. (2015) note that their reliance on data gathered through a list-assisted telephone sample of only landlines, likely underestimates the abuse and neglect rates among populations with no landlines. Thus the causal mechanisms of the relationship between marijuana use and child maltreatment remain unknown. Furthermore, due to social desirability bias, some parents may not disclose if they are abusive or neglectful parents, and may even report their abusive practices at lower rates than would be accurate. These inconsistent conclusions continue to fuel the debate about the marijuana-violence relationship. Indeed, a better understanding of how changes in marijuana legislation may affect child maltreatment at the population level is needed.

2.3.3 Extension of the Literature Review

The potential externality effect of marijuana legalization on crime and illegal drug consumption has been of primary concern in the current drug policy debate. Studies have shown that legalizing marijuana is associated with an increase in marijuana consumption among all ages. Consequently, the welfare implications will depend largely on whether marijuana use itself generates negative or positive externalities to children, and on the extent to which marijuana serves as a gateway to harder illicit drugs and to substance abuse.

A major societal concern about marijuana intoxication is the psychological and physical effects which may directly affect the well-being of children and other non-users of cannabis. For example, marijuana is known to impair motor skills, trigger psychiatric illnesses including mood disorder and latent schizophrenia, and cause short term memory loss and temporal distortions (Platt et al., 2010; Roser et al., 2012). These effects can increase the potential risk of parental neglect and abuse. On the other hand, preliminary clinical research supports the potential medicinal value of marijuana (see Walsh, Nelson & Mahmoud, 2003). Positive impacts on parenting are likely to result if parents used the drug under medical supervision to relieve chronic pain, anxiety, seizures, and other illnesses. Thus, depending on the degree to which these positive and negative effects are experienced across populations on average, marijuana legalization could either increase or decrease the risk of maladaptive parenting.

There is also a possibility of an indirect link to violence. A large body of research has established a positive causal connection between alcohol abuse, illicit drug use (e.g. cocaine and heroin) and domestic violence. A 1998 study by the National Center on Addiction and Substance Abuse found that children whose parents abused illicit drugs and alcohol were three to four times more likely to be severely maltreated than children of parents who were not substance abusers (Reid Macchetto & Foster, 1998).

There has also been substantial research on whether marijuana use is likely to precede the use of harder illicit drugs and other addictive substances such as alcohol. The findings thus far have varied. For instance, a longitudinal study found that among adults with no history of alcohol abuse, those who reported marijuana use during the first wave of the survey were more likely to develop an alcohol use disorder within three years relative to those who reported no marijuana use (Pacek, Martins & Crum, 2012). Wen et al. (2015) also found a positive association between MMLs and frequency of binge drinking for adults over 20 years of age. Additionally, a meta-analytic review by Merill et al. (1994) found that cocaine use was 17 times more likely in adults that used marijuana as children. Other studies have also found a significant correlation between marijuana use and illicit drug dependence (see Fergusson, Boden & Horwood, 2006).While these findings appear to support the gateway hypothesis, authors Morral, McCaffrey & Paddock (2002) suggest that factors such as familial relations, social environment, and genetic predisposition to illicit drugs may be more reliable predictors of future drug consumption. Further, using data from the 1993-2010 Behavioral Risk Factor Surveillance System, Anderson et al. (2013) found that MMLs may significantly reduce the probability of past month alcohol use and frequency of binge drinking. Clinical studies have also suggested that smoking marijuana may prevent the development of tolerance to opiates (see Cichewicz and Welch, 2003) and that MMLs are associated with a significant reduction in prescription opioid-related mortality (Bachhuber et al., 2014). The current debate provides little evidence to support or refute the suggestion that marijuana use and MMLs are causally linked to the subsequent abuse of alcohol and licit-illicit drugs.

Some studies suggest that marijuana may not only be a gateway to harder illicit drugs but also to crime and criminal behavior. According to the research conducted by Evans (2013), the probability of being arrested for a non-drug violent and income-producing crime is greater for marijuana users than for non-users. If so, parental marijuana use may increase child maltreatment. Indeed, some studies find that severe family dysfunction, such as parental criminality, elevates the risk of child maltreatment (Juby & Farrington, 2001). Additionally, Farrington (2010) suggests that poor parental supervision and parental criminality are the strongest predictors of juvenile delinquency and anti-social behavior. If, however, criminality is explained by marijuana's illegality, rather than from the drug itself, legalization can break marijuana's link to violence. Thus, depending on which pathways are the strongest, marijuana use and its medical availability can negatively or positively influence child welfare outcomes. This highlights the need for rigorous empirical research in this area.

2.4 Data and Descriptive Evidence

According to the literature, MMLs should increase both the supply and demand for marijuana, and thus increase the consumption of marijuana unambiguously (Anderson, Hansen & Rees, 2013). Since marijuana is a psychoactive substance, it may influence a perpetrators' perception of the expected costs or payoffs when supplying violence. If marijuana use does increase a caregivers' negligent or abusive behavior, I would expect legalization to lower the cost of engaging in violence. Reducing the cost of violence is expected to raise the amount of violence supplied**;** thus one possible outcome of legalization is a positive relationship between marijuana use and child victimization. It is also quite possible that a caregiver, under the influence of marijuana, may engage in certain types of maladaptive behavior, thus I separately examine the relationship between MMLs and the most common types of maltreatment (neglect and physical abuse).

To study the impact of medical marijuana laws and its different dimensions on child victimization, I employ the use of three major datasets: Child Maltreatment Reports, National Data Archive on Child Abuse and Neglect (NDACAN) and the FBI's Uniform Crime Reports (UCR). These data sources and variables have been described previously. Table 2.2 provides definitions for my outcome measures. Table 2.3 presents descriptive statistics.

Data taken from the maltreatment reports and NDACAN capture the severity of child victimization. The data assesses overall maltreatment rates, children who were victims of neglect and physical abuse, victims by age, and deaths attributed to child maltreatment (fatality rates). Additionally, publicly available data from the UCR provide information on crime and arrest rates (e.g., offenses against the family, drug offenses, alcohol offenses) and help reinforce the findings from the previous literatures' marijuana-crime link.

In 2014 the CPS received 3.6 million referrals alleging child abuse and neglect, of which more than 50 percent of the cases were investigated. 702,000 children were victims of abuse and neglect (9.4 victims per 1,000 children) and an estimated 1,580 children died due to maltreatment (2.3 per 100,000 children). According to the CPS there are two major risk factors that may increase the likelihood of victimization – caregiver alcohol abuse and caregiver drug abuse. While some states may have legalized marijuana, no formal guidelines exist on how welfare workers should handle a caregivers' recreational or even medicinal use of the drug.

In 2014, 27% of all child maltreatment cases were related to parental drug use (Child Maltreatment Report, 2014). Since marijuana is still classified as a schedule I substance, child welfare agents might not distinguish a parents' use of marijuana from other illegal substances such as heroin or cocaine even if it's used for medical purposes. This could potentially increase the number of at-risk victims being reported to the CPS – thereby increasing the reported incidences of child maltreatment rates.

I also investigate an alternative proxy for maltreatment that is less likely to be affected by the reporting bias: child fatality rates. Since institutions and authorities (law enforcement, state vital statistics departments, medical examiners, hospitals, etc.) must report any deaths due to maltreatment, and because such a report will be investigated by the CPS, this variable is unlikely to face reporting bias. One limitation, however, is that it is an extreme outcome, and as such could create noise in the proxy.

The primary independent variables of interest are states that have passed medical marijuana laws (MMLs). To determine when a MML was passed within each state, I used the research conducted by Pacula et al. (2015) and updated it with information from the official legislative website of each US state, NCLS[30] and NORML[31]. Specifically, dichotomous indicators are included for whether a state has the following: laws that allow for the medicinal use of marijuana (MML); legal protection for patients to grow their own plants for medicinal purposes (home cultivation laws); provisions for patients to use marijuana to mitigate chronic pain; and decriminalization statutes in conjunction with MMLs.

All state laws allow patients to possess and use small quantities of marijuana without being subjected to state criminal penalties. However there are variations within each state's MML –each have their own specific restrictions for possession limits, home cultivation and qualifying conditions. For example, while only two states – California and Washington – allow the use of marijuana to treat anorexia, the majority of states with MMLs include provisions for

[30] NCLS – National Conference of State Legislatures
[31] NORML – National Organization for the Reform of Marijuana Laws

conditions such as HIV-AIDS, cancer, cachexia, chronic pain, and other conditions approved by the state health department. Possession and cultivation limits can also vary from one ounce and six plants in Alaska to 2.5 ounces and 12 plants in Michigan (Hoffmann & Weber, 2010). Currently, only 15 states allow for home cultivation of medical marijuana by patients.

Users in the states which have decriminalized possession may face a lower expected penalty (Markowitz, 2005) and therefore a lower price of using marijuana. California's decriminalization statute (2010) provides an example of how the possession of small amounts (less than one ounce) of marijuana constitutes a simple misdemeanor:

Except as authorized by law, every person who possesses not more than 28.5 grams of marijuana, other than concentrated cannabis, is guilty of an infraction punishable by a fine of not more than one hundred dollars[32].

States that have home cultivation and decriminalization laws greatly liberalize access for patients and recreational users. It also provides a source of easily accessible marijuana for youth recreational use and broadens the social approval of marijuana use (Pacula et al., 2015). If as some research suggests, these laws lead to an increase in marijuana consumption and to an increase in IPV, then one would expect that in states that have the most lenient form of the law (i.e. home cultivation in conjunction with decriminalization) there would be an increased risk in the frequency and severity of child maltreatment. Table (2.1) gives a summary of the 23 states that have legalized marijuana for medical use and 17 states that have decriminalized its use.

Sociodemographic and economic characteristics may also play a role in determining a perpetrators' propensity toward supplying violence. These variables and their sources have been described in the previous chapter. To aid in controlling for a variety of time-varying and

[32] California Law: BILL NUMBER: SB 1449

potentially confounding factors I include each state's unemployment rate, male to female employment ratio, percent population living below the poverty level, college and high school attainment rate, median household income, population density, divorce rates, indicators of race, percent of the state population incarcerated, and violent crime rates. These variables serve as proxies for opportunities available to perpetrators. For example, higher unemployment and poverty rates may correspond to higher stress and depression due to fewer opportunities being available; parents then may be less likely to invest time and money in their children. In such cases basic needs can be neglected. Conversely, states with a higher proportion of educated people and higher income (real wages) have more well-paying employment opportunities, and have a higher cost of engaging in violence. As a result, a negative relationship is expected for education and household income.

Additional controls include the percent of the population between the ages of 15-24 and 25-45 (U.S. Census Statistical Abstracts); the number of police officers per 100,000 persons (Census Bureau, UCR); female share of officers per 100,000 persons (Census Bureau, UCR); arrest rates for types of offenses (UCR); and beer and alcohol consumption per capita (Beer Institute). These variables account for other state-level changes that could separately explain maltreatment rates. For example, arrest rates (enforcement) and the number of police officers measure the effectiveness of a state's efforts against crime in general. They are included in all models to measure the risk of punishment for committing a crime. I expect that higher police presence and higher arrest rates for family offenses would increase the cost of violence, thereby reducing maltreatment. Miller & Segal (2014) found lower domestic violence escalation rates as a result of an increase in reporting by female police officers. I expect a similar relationship with respect to female share of officers and reported child maltreatment rates. Additionally, a number of studies have found that alcohol is a significant contributory factor to child maltreatment, linking alcohol consumption to reduced self-control, mental health issues, antisocial personality characteristics, and thus a higher risk of physical abuse and neglect. Finally, to allow for variation in MMLs, to address time shocks and control for heterogeneity I include state fixed effects, year fixed effects and state specific linear time trends.

2.5 Empirical Strategy

2.5.1 Methodology

In light of the uncertainty of the effects of MMLs, this paper examines whether states that have implemented these laws see a change in child victimization rates. Specifically, to estimate these outcomes, I use the fixed effects model with Driscoll-Kraay standard errors to exploit the within-state variation introduced by the passage of MMLs in 23 states plus D.C. over the 19 year observation period.

One limitation of using the standard fixed effects model is that it does not account for cross-sectional dependence. This cross correlation of errors could be due to omitted common effects that may not be quantitatively measured, such as social norms or psychological behavior patterns (Chudik & Pesaran, 2013). In order to test whether the residuals in my fixed effects regression are spatially independent, I perform the Pesaran CD test, as recommended by Hoechle (2007). The null hypothesis of the CD test states that spatial dependence is indeed present. Since spatial dependence could lead to inconsistent coefficient estimates, I estimate the fixed effects model that is robust to heteroscedasticity, autocorrelation, and very general forms of cross-sectional and temporal dependence.

To carry out the fixed effects analysis I estimate equation (1) where each of the child offenses variable (i.e. child maltreatment rates, victims by age, fatality rates, arrest rates for family offenses), is the dependent variable. Formally, my empirical specification may be expressed as:

$$y_{ST} = \beta_o + \beta_1 MML_{ST} + \beta_2 X_{ST} + \gamma_T + \theta_S + \delta_{ST} + \epsilon_{ST} \quad (1)$$

where for each state *S*, in year *T*, y_{ST} is the child offense rate outcome variable; the main explanatory variable MML_{ST} is a dichotomous indicator equal to 1 if a state implemented a medical marijuana provision from year *T* forward, and 0 otherwise; γ_T and θ_S are year and state fixed effects; δ_{ST} is the state-specific time trend; and X_{ST} is a vector of control variables that include sociodemographic, economic, crime and public policy indicators. The coefficient of interest is β_1 which measures the effect of the MML on child victimization rate.

Using the same specification as (1) I estimate four separate regressions where the regressors of interest are states that have implemented home cultivation laws; provisions for pain; and decriminalization laws in conjunction with MMLs and home cultivation laws (HCL). *HCL* is an indicator set to 1 if the state provides legal protection for patients or caregivers to grow marijuana for medicinal purposes, 0 otherwise. *Decrim&HCL* is a dichotomous indicator equal to 1 if a state has implemented both home cultivation laws and decriminalization laws at year *T*, 0 otherwise. Finally, *MMLXDecrim* is an indicator equal to 1 if a state has implemented both MMLs and decriminalization laws at time *T*. As implied earlier, a state's implementation of MMLs is likely to either increase or decrease the likelihood of child victimization rates, thus the impact of MMLs on child abuse is tested in each model.

2.6 Estimation Results

2.6.1 Main Results

Deterrence theory asserts that reducing the perceived severity of legal sanctions associated with marijuana use will increase the demand for marijuana. However, the changes in legislation (i.e. an increase in demand) could result in significant and negative spillover effects to parents and their children, increasing the risk of child abuse and neglect.

Table 2.4 presents the impact of MMLs on reported maltreatment rates while controlling for other time-varying explanatory variables. Each column reports the estimated effect of state-level marijuana legalization from a unique regression. In the first column, I present a parsimonious specification that only includes state and year fixed effects. I find that the legalization of medical marijuana is associated with a 13.2% increase in reported child maltreatment rates. Adding state level controls in column (2) reduces the magnitude of the estimated relationship and the significance falls from the 1% to 5% level; more importantly, legalization is associated with a 11.4% increase in the reported incidences of child maltreatment.

I now extend the specification to include state-specific linear time trends to control for the influence of unobserved factors at the state level that trend smoothly over time (e.g., citizen and government sentiment toward marijuana use). Again, I find a statistically significant and positive effect of MMLs on child maltreatment rates. Specifically, the estimates suggest that after the passage of MMLs, states see an increase in reported incidences of child maltreatment by 1.30 per 1,000 children; this translates to a 9.8% increase in reported maltreatment rates.

Table 2.5 presents the estimates between MMLs and child maltreatment rates by age group. I expect victimization rates to be higher for younger children since they are more vulnerable to abuse and neglect than older children. Additionally, since marijuana is classified as a schedule I substance at the federal level, it is more likely for parents to get reported and be investigated for abuse and neglect if they use marijuana in the presence of younger children. I find the estimates of reported incidences of abuse for younger children (ages of 0 and 3 years) to be much larger in magnitude and are statistically significant compared to incidences of abuse for older children. More specifically, for younger children between the ages of 0 to 3 (Table 2.5, column 1), enforcement of MML is associated with a 16.5% increase in reported maltreatment, and for children between ages 12 to 15 (column 4), a (statistically insignificant) 13.73% increase in reported incidences of maltreatment.

Why does the implementation of MMLs increase child maltreatment?

If MMLs are associated with an overall increase in the incidence of reported maltreatment rates, what could explain such an effect? There are two likely mechanisms through which MML – legislation that aids patients with chronic health conditions – might affect child maltreatment estimates. First, MMLs caused an increase in actual maltreatment. Second, it may have increased the reporting rate of maltreatment. I employ two measures of child maltreatment to attempt to distinguish between the mechanisms and correct for any potential reporting bias: child fatality rates and arrest rates for family offenses.

First, I test whether reporting and arrest patterns for family offenses changed around the implementation of the policy. Arrest data are frequently used in the crime literature as a measure of crime and to account for changes in police reporting behavior. In column (2) of Table 2.6, I present estimates of the impact of MMLs on arrest rates for offenses against the family, including all the controls mentioned above. I find that states that adopt MMLs witness a (statistically insignificant) 6.1% increase in arrest rates for family violence relative to states with no such policies. However, as Dalbo & Aizer (2014) suggest, the estimated effect of arrest may not just reflect changes in reporting but also changes in arrests conditional on reporting. For example, police officers are more likely to arrest parents that use marijuana if the Department of Children and Family Services and courts consistently rule that parental usage of medical marijuana places the child at a substantial risk of harm. Indeed, until 2010, public opinion about legalizing marijuana rarely shifted, with a majority believing the drug should be made illegal and usage of the drug should be policed (PEW Research, 2014).

Next, I present regression estimates of the impact of MMLs on actual maltreatment. Albeit a noisy proxy for maltreatment due to its low-frequency, child fatality rates can serve as an appropriate proxy to measure an increase or decrease in actual maltreatment following the implementation of state-level MMLs. The underlying premise of this approach is that child fatalities will always be reported to the police and CPS, and as such it will be immune from any reporting effect (Levitt, 1998).

The main results are shown in Table 2.7, column (3). Baseline estimates in column (1) show that there is a negative and statistically significant relationship between MMLs and changes in fatality rates. However, these estimates become smaller and insignificant after controlling for socio-demographic factors and state-specific linear time trends (column 3). I find that MMLs have a negative (-0.174) impact on child fatality rates; more specifically, the results suggest that after the passage of the laws, states see a 9.45% reduction in child deaths due to maltreatment. The lack of significance could be explained, in some part, due to noise in the child fatality measure. While this finding does not provide evidence of a strong correlation between MMLs and fatality, it does not necessarily negate the possibility that an economically significant relationship exist. More importantly, the evidence suggests that there may indeed be a reporting effect going on, and not an increase in actual maltreatment.

Tables 2.8 and 2.9 (column 2) provide additional evidence that MMLs may be associated with an increase in the reporting of child maltreatment. Interestingly, the results show that there is no significant positive relationship between the adoption of MMLs and rates for physical abuse and neglect. Moreover, the estimates indicate there may be evidence of a drop in physical abuse in states with medical marijuana policies. Specifically, I find that states with MMLs are estimated to have 0.548 fewer children who are physically abused per thousand children relative to states without MMLs, a reduction of 21.4 % when assessed against the sample mean. On the other hand, I find a positive but statistically insignificant relationship between MMLs and neglect, showing a 10.7% increase in the reported incidences of neglect. The pattern of results so far is consistent with the reporting hypothesis: parents who use medical marijuana are more likely to be subject to a child neglect inquiry since social workers may determine that marijuana use would substantially impair a parent's judgement and ability to care for their children's basic needs.

Figure 2.2 presents graphical evidence of the effect of MMLs on reported maltreatment rates over time. The graph shows the means of yearly maltreatment rates before and after the implementation date of MMLs, with 1 on the X-axis denoting the first full year of the law being in effect. Prior to the implementation of MMLs, the maltreatment rates seem to be relatively stable; however, after the first full year of the law being in effect, there is a sharp increase in the reported incidences of maltreatment. After the fourth year, the treatment effect appears to be decreasing over time, suggesting an initial reporting effect.

In summary, the estimates from the NCANDs and UCR data indicate a 10–13% increase in reported child maltreatment rates after medical marijuana legalization. However, this positive effect largely comes from the increase in the reporting and investigation of cases of child neglect.

More importantly, evidence from the child fatality estimates show that the actual incidence of child maltreatment may be falling in states with MMLs.

2.6.2 Robustness Checks

Table 2.10 column (1) shows the estimates for pre-and post-legalization trends in child maltreatment rates. I add controls for four years of MML policy leads and three years of policy lags. In the years preceding the law, I find that reported maltreatment rates are negative and stable, but statistically insignificant; suggesting no policy endogeneity, thus lending credibility to the main estimates in Table 2.4. However, after the first full year of the law being in effect, MMLs are associated with a significant increase in reported maltreatment rates. The estimates for the reported maltreatment rates become even larger in magnitude, but are statistically insignificant, during the third year of post-legislation. However, after five or more years, while the estimates become negative, they continue to be statistically indistinguishable from zero.

It is somewhat surprising that the effect of MMLs does not grow over time; nevertheless this pattern of results is consistent with Figure 2.2, showing the reported incidences of maltreatment ramping up immediately after the legislation, and slowing down in the years after. One potential reason for this could be due to the nature of the data – since NCANDs aggregates the reports into a single yearly estimate, monthly growth over time may be missed. Additionally, this phenomenon is consistent with the reporting hypothesis; the behavioral response seems to follow immediately after the passage of the law. If, as anecdotal evidence suggests that opinions change, whereby there is a greater social acceptance of marijuana by law enforcement and social workers, especially for parents who use the drug for medicinal purposes, then I would not expect to see growth over time.

Next, Table 2.4, Column (4) estimates the sensitivity of my results to an alternate specification. Since maltreatment is intrinsically a count of victims within a discrete time period, I use the negative binomial model as a specification check for my primary analyses. Table 2.4 presents coefficients on the maltreatment rate variable from the OLS fixed effects and negative binomial specifications for completeness. The estimates confirm the results from my main estimation – states with MMLs see a significant increase in the reported incidences of child maltreatment, and a significant decline in fatality rates (Table 2.4, column 4). In addition, when I use the coding preferred by Pacula et al. (2015) to obtain the effective dates of the laws, I find a similar pattern of statistically significant results (Tables 2.15 & 2.16).

I now examine the impact of specific policy dimensions to capture the reporting effect and the true maltreatment effect: that is, provisions that allow for home cultivation and prescriptions for chronic pain. Since both provisions instrument for regulatory laxness, they are more likely to increase social availability and access to the drug. As such, these provisions are predicted to affect reporting behavior and consequently reported maltreatment rates through the changing perceived risk associated with the enforcement of parental marijuana use. I thus, expect parents and caregivers who grow marijuana, even if licensed, to be reported and investigated for (risk of) child endangerment.

Column (2) from Tables 2.11 and 2.12 show the estimates of home cultivation laws (HCLs) on child maltreatment and fatality rates. Overall, I find a positive and statistically significant legislative effect on reported child maltreatment rates. Specifically, the results suggest that states with HCLs are responsible for an additional 3.26 children being reported as maltreated per 1000 children, translating to a 24.6% increase in reported maltreatment rates. Note that these estimates are twice as large as the ones from MMLs. More importantly, when I estimate the effect of HCLs on child fatality rates in Table 2.12, I find the magnitude of the coefficients to be large and statistically significant, suggesting a 27% reduction in actual maltreatment rates. I find similar and statistically significant results (Column 3, Tables 2.11 & 2.12) when I test the impact of the provisions that allow the use of marijuana for chronic pain. Specifically, the implementation of provisions that allow for chronic pain is associated with a 14% increase in reported maltreatment rates, and a substantial 22.4% reduction in fatality rates.

I continue to explore the differential effects of state-specific medical marijuana regulations by interacting MMLs with states that have decriminalized the possession of marijuana. Tables 2.13 and 2.14 provide further evidence that the magnitudes of the interaction terms are much larger in states that impose relatively lax restrictions than those with no such policies. These findings are consistent with my previous estimates from Tables 2.11 and 2.12, and build on the work by Pacula et al. (2015) who recognized the heterogeneity in the implementation of state level marijuana regulations. Thus, the binary MML measure in Table 2.4 misses the heterogeneous effects and dynamics of these policies. Finally, these findings are consistent with the interpretation that MMLs not only influence the reported incidences of maltreatment, but they may also reduce the actual incidences of child maltreatment.

2.7 Conclusions

Recent research by Friestler and colleagues (2015) suggests that parental marijuana use is related to higher incidences of physical abuse and neglect. However, to my knowledge, no research has examined the relationship between state marijuana legislation and child victimization rates. The central findings gleaned from this paper provide indirect evidence that marijuana use, induced by increased access to medical marijuana, affects the reported incidences of child maltreatment positively. Specifically, estimates from the fixed effects regression suggest that after the passage of MMLs, states see a statistically significant (9.8%) increase in reported maltreatment rates. Using Driskoll-Kraay standard errors, these results are robust to heteroscedasticity, autocorrelation, and very general forms of cross-sectional dependence.

The findings from my main model raise an important follow-up question: does medical marijuana legalization increase child maltreatment or child maltreatment reporting? I examine one particular outcome of interest to proxy for the true incidence of maltreatment: child fatality rates. I find a negative but statistically insignificant relationship between MMLs and child fatality rates. However, as discussed by Pacula et al. (2015), MMLs vary greatly and can thus generate heterogeneous effects. Indeed, I find the largest estimates when I look at specific dimensions of MMLs, where the coefficients capture not only the reporting effect but also the true effect on maltreatment. For example, states with provisions that allow for home cultivation see a 24.6% increase in the reported incidences of maltreatment and, surprisingly, a statistically significant 27.6% reduction in the actual maltreatment rate. Further, these findings run contrary to the arguments suggesting a positive relationship between the legalization of medical marijuana and violence.

Data limitations do not allow me to explore all of the other channels through which MMLs may affect child outcomes – particularly pharmacological effects of the drug. However, identifying one specific mechanism through which MMLs may affect maltreatment, such as child fatality, does provide one piece of the puzzle. It is important to note that the negative relationship between MMLs and child fatality rates does not necessarily imply a strict causal connection that marijuana use reduces actual maltreatment. For instance, it is possible that marijuana regulation reduces child fatality rates through its positive reporting effect. Even if growing or consuming marijuana is legal, anecdotal evidence suggests that parental use of marijuana can be controversial. However, with the passage of time, I expect attitudes and behaviors toward parental medical marijuana use to be more tolerant and accepted. As such, it is unlikely that reported maltreatment rates will continue to increase. Indeed, trend analyses provide further evidence that child maltreatment may be decreasing over time. Clearly, distinguishing between child maltreatment and reporting is a subject that warrants further attention. In sum, as the narrative of medical and recreational marijuana legislation unfolds across the country, more substantive research is needed to determine how marijuana use impacts child outcomes and parenting.

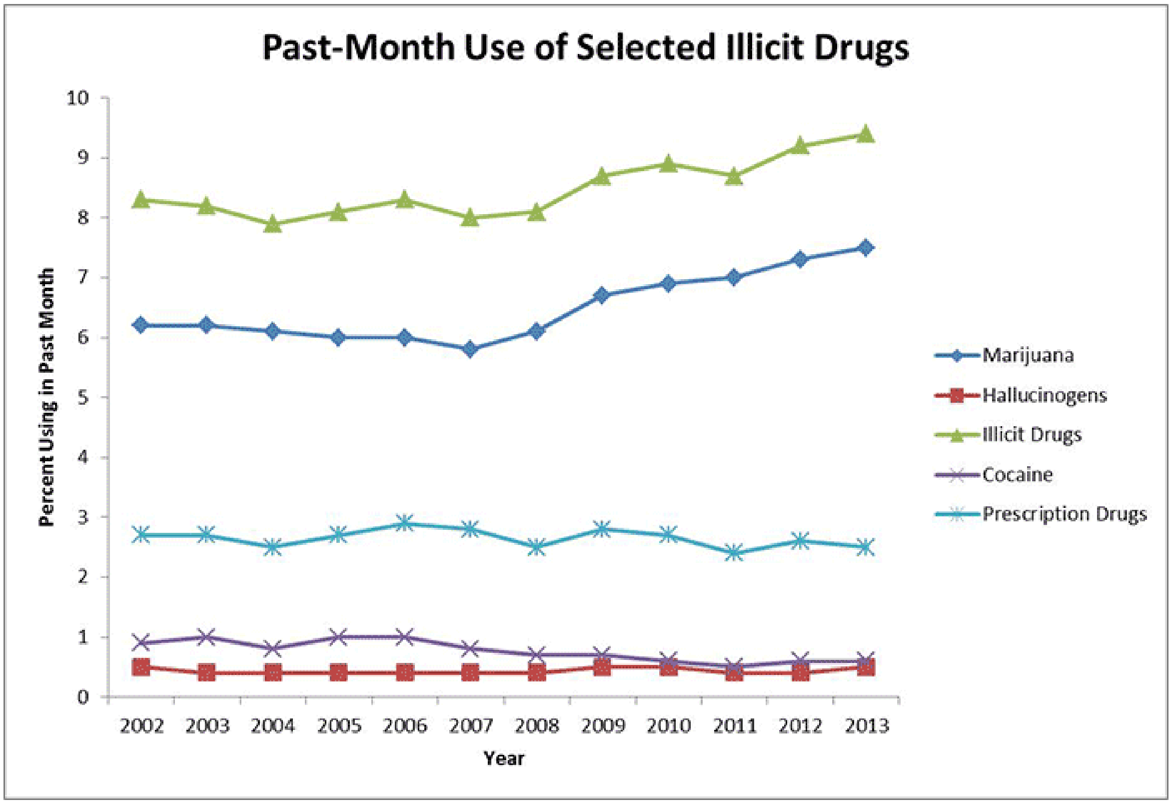

Figure 2.1 Past-Month Use of Selected Illicit Drugs

Source: National Institute on Drug Abuse (2013)

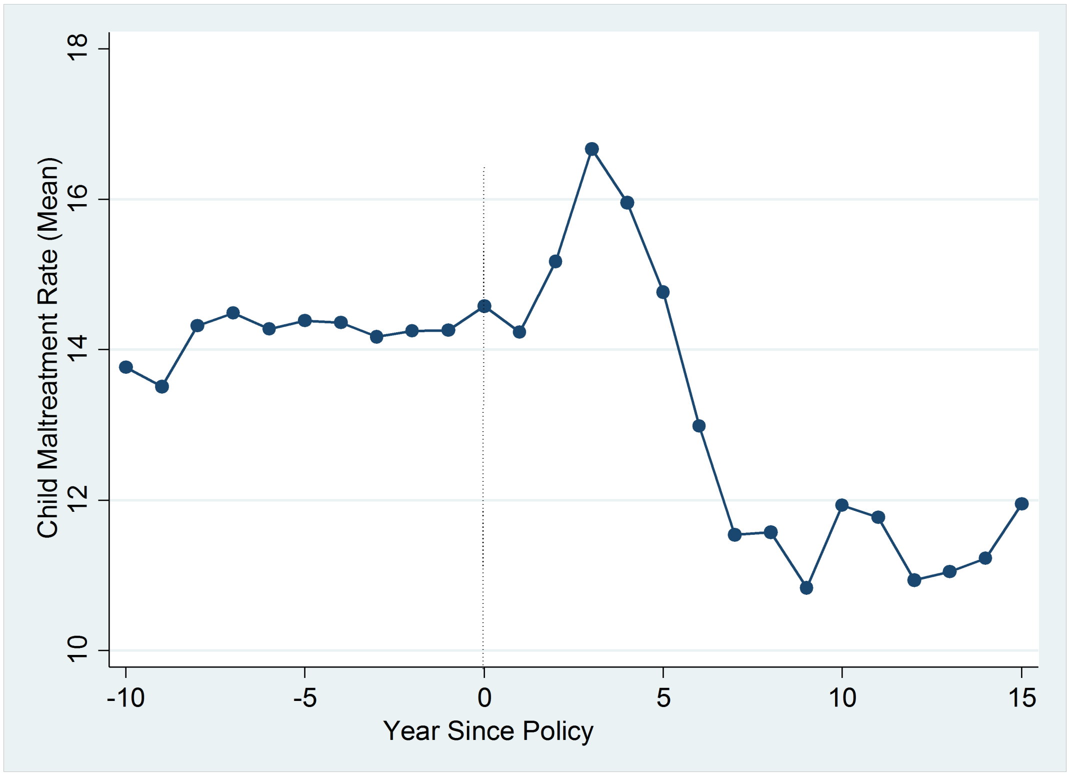

Figure 2.2 Trends in Child Maltreatment Rates, by State MMLs

Notes and Sources: Data is from the Child Maltreatment Reports and the National Data Archive for Child Abuse and Neglect (NDACAN), which provides prevalence of child maltreatment from 1995-2014. The Dashed line marks the timing of the medical marijuana law. As of 2014, 23 states plus D.C. have implemented MMLs; the law provides protection from criminal penalties for using marijuana for a medical purposes.

Table 2.1 MML Legislation Policies by State, 1996-2014

			Provisions			
State	Year Passed	Effective date	Pain	Home Cultivation	Marijuana Decriminalized	Possession Limit
Alaska	1998	1999	Yes	Yes	1975	1 oz/6 plants (3 mature, 3 immature)
Arizona	2010	2011	Yes	Yes	2011	2.5 oz/12 plants
California	1996	1996	Yes	Yes	1976	8 oz/ 6 mature or 12 immature
Colorado	2000	2001	Yes	Yes	2011	2 oz/ 6 plants (3 mature, 3 immature)
Connecticut	2012	2012				Not specified
District of Columbia	2010	2010			2014	2 oz/Not specified
Delaware	2011	2011	Yes			6 oz
Hawaii	2000	2000	Yes	Yes		3 oz/ 7 plants (3 mature, 4 immature)
Illinois	2013	2014				2.5 oz
Maine	1999	1999	Yes	Yes	1976	2.5 oz/6 plants
Maryland	2014	2014	Yes		2011	Not specified
Massachusetts	2012	2013		Yes	2009	Not specified
Michigan	2008	2008	Yes	Yes		2.5 oz/ 12 plants
Minnesotta	2014	2014			1976	Not specified
Montana	2004	2004	Yes	Yes		1 oz/ 4 plants (mature)
Nebraska					1977	
Nevada	2001	2001	Yes	Yes	2002	1 oz/ 7 plants (3 mature, 4 immature)
New Hampshire	2013	2013				2 oz
New Jersey	2009	2010	Yes			2 oz/ Not specified
New Mexico	2007	2007		Yes		6 oz/ 16 plants (4 mature, 12 immature)
New York	2014	2014			1977	Not specified
North Carolina					1977	
Ohio					1976	
Oregon	1998	1998	Yes	Yes	1973	24 oz/24 plants (6 mature, 18 immature)
Rhode Island	2006	2006	Yes	Yes	2013	2.5 oz/ 12 plants
Vermont	2004	2004	Yes	Yes		2 oz/ 9 plants (2 mature, 7 immature)
Washington	1998	1998	Yes	Yes	2012	24 oz/15 plants

Notes and Sources: Own data collection. Referred from the following sources: Procon.org; NORML; Pacula et al. 2013

Table 2.2 Summary of Data Sources

Variables	Definitions	Sources and years
Dependent Variables		
Child maltreatment	Children who have experienced or who were at risk of experiencing abuse or neglect.	NDACAN (1995-1999) Children's Bureau (2000-2014)
Child fatality rate	Children who have died due to abuse or neglect	
Offenses against the family arrest rate	Family violence includes all types of violent crime committed by an offender who is related to the victim either biologically or legally through marriage or adoption.	Bureau of Justice Statistics (1995-2014)
Explanatory variables of Interest		
Medical Marijuana Laws Decriminalization Laws	States that allow for the medical use of marijuana. Reduces penalties associated with the use or possession of small amounts of marijuana	NORML; State statutes; Pacula et al. (2013); ProCon.org
Family and State Environment		
Female labor force participation rate Unemployment rate Median Household income Poverty rate Population density per square mile (Proxy for urban rate)	(Total population/ Land area)	U.S. Census Bureau - Statistical Abstracts Series, Bureau of Labor Statistics (1995-2014)
Divorce rate Beer & Alcohol consumption per capita		Wolfers, Justin. 2006. (1995 – 2000) CDC divorce rates (2000-2014) Beer Institute (1195-2014)
Fraction of child population that is white Fraction of child population that is black Percent of the population between ages 15-24 Percent of the population between ages 25-44		U.S Census Bureau - Current Population Surveys (1995-2014)
College attainment rate High school attainment rate	Human Capital Index Measures	Frank, Mark. W. (2009) (1995-2014)
State Judicial Environment		
Law enforcement Female Officers Incarceration rates Drug abuse arrest rates	Law enforcement to population ratio Female officers to population ratio Prisoner to population ratio	Bureau of Justice Statistics U.S. Census Bureau - Statistical Abstracts Series (1995-2014)
Crime rate	Crime to population ratio	FBI Uniform Crime Report (1995-2014)

Table 2.3 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variables:					
Child Maltreatment Rate per 1,000 children	964	13.2315	8.42456	0.70364	82.627
Child Fatality Rate per 100,000 children	957	1.84094	1.26986	0	16.775
Maltreatment by age: 0-3	957	15.0515	8.7571	0.67	113.901
Maltreatment by age: 4-7	957	12.4261	6.65694	1	103.869
Maltreatment by age: 8-11	957	10.1774	6.65694	1.05	88.9389
Maltreatment by age: 12-15	957	9.98481	6.69793	1.16913	88.9389
Physical Maltreatment Rate per 1,000 children	966	2.56123	2.33376	0	21.7933
Neglect Rate per 1,000 children	967	6.94018	5.44813	0	48.3264
Arrest Rates for Offenses Against the Family, per 100,000 persons	956	39.094	35.4792	0.02083	230.472
Independent Variables:					
Percent of the population: 15-24	1020	14.239	1.13257	10.8858	20.2158
Percent of the population: 25-44	1020	28.0525	2.54601	22.882	36.8265
Beer consumption per Capita	1020	1.24542	0.20897	0.67	1.91
Alcohol Consumption per Capita	1020	2.3604	0.52117	1.2	4.7
Arrest Rates for Drug Abuse per 100,000 persons	986	390.072	177.734	4.5833	1105.24
Law Enforcement to Population Ratio	1018	0.00312	0.00096	0.00024	0.00933
Female Officers to Population Ratio	1018	0.00024	0.00022	1.6E-05	0.00177
Violent Crime to Population Ratio	1020	0.00438	0.00255	0.00067	0.02661
Prisoners to Population Ratio	1005	0.00413	0.00183	0.00085	0.01768
Poverty Rate	1020	13.1104	3.72273	4.5	26.4
Percent Black	985	13.8662	13.9825	0.44814	91.2646
Percent White	985	66.1245	20.1882	12.38	102.324
Population Density per sq. mile	1020	369.5	1319.51	1.06	10801.5
Labor force Participation Rate for Females	969	60.4909	4.44932	46.3	71.2
High School attainment Rate	1020	0.57703	0.05557	0.44878	0.74347
College Attainment Rate	1020	0.17783	0.045	0.08398	0.45932
Median Household Income	1020	53895.1	8260.62	35521	77506
Divorce Rate	919	3.98627	1.07179	1.5	10.4406
Unemployment Rate	1020	5.62978	1.96417	2.3	13.8

Table 2.4 Effects of MMLs on Child Maltreatment Rates

	(1)	(2)	(3)	(4)
	Child Maltreatment Rate per 1,000 Children			
Dependent variable mean	**13.23146**			
MML = 1	1.758***	1.505**	1.303*	0.104*
	(0.597)	(0.700)	(0.649)	(0.0583)
Estimation method	OLS	OLS	OLS	Neg. Bin
All Controls	N	Y	Y	Y
State fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
State-specific time trend	N	N	Y	Y
Observations	964	759	759	759
Within R-squared	.20	.25	.52	-
Number of groups	51	49	49	-

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variable for each column is the child maltreatment rate per1000 children. MML=1 if a state implemented a medical marijuana provision. This table provides the coefficient estimates from the regression model in (1) estimated by FE regression. Robust standard errors (in parentheses) are based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

All controls include:

Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape. Other crime controls include, family and drug abuse arrest rates per 100,000 persons; law enforcement to population ratio; female officers to population ratio; prisoner to population ratio

State economic control variables include the variables: unemployment rate, female labor force participation rate, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, (Frank, 2009)

State socio- demographic controls are based on the March Current Population Survey and the U.S Statistical Abstracts. They include variables for the percent of the child population that is black and white; divorce rates, percent of the population that's between the ages of 15-24 and 25-44; alcohol consumption per capita; beer consumption per capita; population density per sq. mile.

Table 2.5 Effects of MMLs on Child Maltreatment Rates, by Age Cohort

Child maltreatment rate per 1,000 children, by age groups	(1) 0-3	(2) 4-7	(3) 8-11	(4) 12-15
Dependent variable mean	**15.0515**	**12.426**	**10.177**	**9.985**
MML = 1	2.448* (1.395)	1.441 (1.200)	1.222 (0.965)	1.371 (0.973)
All Controls	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
State-specific time trend	Y	Y	Y	Y
Observations	742	742	742	742
Within R-squared	.422	.5062	.5146	.5408
Number of groups	48	48	48	48

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variable for each column is the child maltreatment rate per1000 children, by age cohort. MML=1 if a state implemented a medical marijuana provision. This table provides the coefficient estimates from the regression model in (1) estimated by FE regression. Robust standard errors (in parentheses) are based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

All controls include:

Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape. Other crime controls include, family offenses and drug abuse arrest rates per 100,000 persons; law enforcement to population ratio; female officers to population ratio; prisoner to population ratio

State economic control variables include the variables: unemployment rate, female labor force participation rate, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, (Frank, 2009), population density per square mile (U.S Statistical Abstracts).

State socio- demographic controls are based on the March Current Population Survey and the U.S Statistical Abstracts. They include variables for the percent of the child population that is black and white; divorce rates, percent of the population that's between the ages of 15-24 and 25-44; alcohol consumption per capita; beer consumption per capita; population density per sq. mile.

Table 2.6 The Effect of MMLs on Arrest Rates for Family Offenses

	(1)	(2)
Arrest rates for family offenses per 100,000 persons		
Dependent variable mean	**39.09395**	
MML=1	0.493	2.397
	(2.246)	(2.391)
All Controls	Y	Y
State fixed effects	Y	Y
Year fixed effects	Y	Y
State-specific time trend	N	Y
Observations	784	784
Within R-squared	.165	.6396
Number of groups	49	49

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variable for each column is the arrest rates for offenses against a family member, per 100,000 persons. MML=1 if a state implemented a medical marijuana provision. This table provides the coefficient estimates from the regression model in (1) estimated by FE regression. Robust standard errors (in parentheses) are based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

All regressions include state economic, socio-demographic policy and crime controls.

Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape. Other crime controls include, drug abuse arrest rates per 100,000 persons; law enforcement to population ratio; female officers to population ratio; prisoner to population ratio

State economic control variables include the variables: unemployment rate, female labor force participation rate, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, (Frank, 2009), population density per square mile (U.S Statistical Abstracts).

State socio- demographic controls are based on the March Current Population Survey and the U.S Statistical Abstracts. They include variables for the percent of the child population that is black and white; divorce rates, percent of the population that’s between the ages of 15-24 and 25-44; alcohol consumption per capita; beer consumption per capita; population density per sq. mile.

Table 2.7 The Effect of MMLs on Child Fatality Rates

	(1)	(2)	(3)	(4)
	Child fatality rate per 100,000 children			
Dependent variable mean	**1.841**			
MML = 1	-0.298*	-0.093	-0.174	-.1396
	(0.159)	(0.233)	(0.258)	(0.105)
Estimation method	OLS	OLS	OLS	Neg. Bin
All Controls	N	Y	Y	Y
State fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
State-specific time trend	N	N	Y	Y
Observations	957	794	794	794
within R-squared	.025	.147	.363	-
Number of groups	51	49	49	-

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variable for each column is the child fatality rate, per 100,000 children. MML=1 if a state implemented a medical marijuana provision. This table provides the coefficient estimates from the regression model in (1) estimated by FE regression. Robust standard errors (in parentheses) are based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.
All regressions include state economic, socio-demographic policy and crime controls.

Crime rate controls use FBI Uniform Crime reports for the number of violent crimes per 100,000 inhabitants. Indexed crimes included in the violent crime variable are murder, robbery, assault, and rape. Other crime controls include, law enforcement to population ratio; female officers to population ratio; prisoner to population ratio

State economic control variables include the variables: unemployment rate, female labor force participation rate, and state median household income (BLS and US Statistical Abstracts), college and high school attainment rate, (Frank, 2009), population density per square mile (U.S Statistical Abstracts).

State socio- demographic controls are based on the March Current Population Survey and the U.S Statistical Abstracts. They include variables for the percent of the child population that is black and white; divorce rates, percent of the population that's between the ages of 15-24 and 25-44; alcohol consumption per capita; beer consumption per capita; population density per sq. mile.

Table 2.8 The Effect of MMLs on Maltreatment Types: Physical Abuse

	(1)	(2)
Physical abuse rate per 1,000 children		
Dependent variable mean	**2.561**	
MML=1	-0.229	-0.548
	(0.309)	(0.532)
All Controls	Y	Y
State fixed effects	Y	Y
Year fixed effects	Y	Y
State-specific time trend	N	Y
Observations	761	761
within R-squared	.474	.581
Number of groups	49	49

Table 2.9 The Effect of MMLs on Maltreatment Types: Neglect

	(1)	(2)
Child neglect rate per 1,000 children		
Dependent variable mean	**6.94**	
MML =1	0.340	0.746
	(0.550)	(0.647)
All Controls	Y	Y
State fixed effects	Y	Y
Year fixed effects	Y	Y
State-specific time trend	N	Y
Observations	762	762
within R-squared	.232	.482
Number of groups	49	49

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variables are child physical abuse and neglect rate, per 1,000 children. MML=1 if a state implemented a medical marijuana provision. This table provides the coefficient estimates from the regression model in (1) estimated by FE regression. Robust standard errors (in parentheses) are based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors. **Crime rate controls** include the number of violent crimes per 100,000 inhabitants; family and drug abuse arrest rates per 100,000 persons; law enforcement to population ratio; female officers to population ratio; prisoner to population ratio. **State economic contro**l variables include unemployment rate, female labor force participation rate, and state median household income, college and high school attainment rate, population density per square mile. **State socio- demographic controls** include the percent of the child population that is black and white; divorce rates, percent of the population between the ages of 15-24 and 25-44; alcohol consumption per capita; beer consumption per capita; population density per sq. mile.

Table 2.10 Robustness of Estimates: The Effect of MMLs on Child Maltreatment Rates to Control for Policy Leads and Lags

VARIABLES	(1) All ages	(2) 0-3	(3) 4-7	(4) 8-11	(5) 12-15
3 Years Prior	-0.150	-0.893	-0.662	-0.905	-0.818
	(0.981)	(0.838)	(0.812)	(0.851)	(0.861)
2 Years Prior	-0.322	-0.404	-0.156	-0.213	-0.140
	(0.775)	(1.221)	(0.953)	(0.790)	(0.790)
1 Year Prior	-0.363	0.884	1.013	0.266	0.359
	(0.994)	(1.330)	(1.148)	(0.856)	(0.802)
Year Effective	0.461	1.086	0.809	0.358	0.518
	(0.684)	(1.109)	(0.910)	(0.765)	(0.731)
1 Year After	-0.00656	1.272	0.595	0.249	0.444
	(0.629)	(1.266)	(0.996)	(0.727)	(0.710)
2 Years After	1.170	2.635*	1.827	1.068	1.304
	(1.042)	(1.503)	(1.422)	(1.189)	(1.142)
3 Years After	3.102	6.360	5.070	3.924	4.290
	(2.798)	(4.930)	(4.406)	(3.680)	(3.622)
4 Years After	0.973	4.354*	2.629	1.888	2.119
	(1.339)	(2.279)	(2.068)	(1.675)	(1.693)
5+ Years After	-1.351	2.664	1.188	0.603	0.721
	(1.508)	(2.440)	(2.227)	(1.807)	(1.738)
Observations	759	742	742	742	742
Number of groups	49	48	48	48	48

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variable for each column is the arrest rates for offenses against a family member, per 100,000 persons. MML=1 if a state implemented a medical marijuana provision. This table provides the coefficient estimates from the regression model in (1) estimated by FE regression. Robust standard errors (in parentheses) are based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors. All regressions include state fixed effects, year fixed effects, state specific linear time trends. **Crime rate controls** include the number of violent crimes per 100,000 inhabitants; family and drug abuse arrest rates per 100,000 persons; law enforcement to population ratio; female officers to population ratio; prisoner to population ratio. **State economic contro**l variables include unemployment rate, female labor force participation rate, and state median household income, college and high school attainment rate, population density per square mile. **State socio- demographic controls** include the percent of the child population that is black and white; divorce rates, percent of the population between the ages of 15-24 and 25-44; alcohol consumption per capita; beer consumption per capita; population density per sq. mile.

Table 2.11 Heterogeneity in MMLs (HCL and MML-Pain): Child Maltreatment

	(1)	(2)	(3)
	Child maltreatment rate per 1,000 children		
Dependent variable mean	**13.231**		
MML=1	1.303*		
	(0.649)		
HCL = 1		3.260**	
		(1.432)	
MML-Pain = 1			1.854**
			(0.839)
Observations	759	759	759
Within R-squared	.52	.526	.521
Number of groups	49	49	49

Table 2.12 Heterogeneity in MMLs (HCL and MML-Pain): Child Fatalities

	(1)	(2)	(3)
	Child fatality rate per 100,000 children		
Dependent variable mean	**1.841**		
MML =1	-0.174		
	(0.258)		
HCL = 1		-0.508*	
		(0.293)	
MML-Pain =1			-0.412*
			(0.227)
Observations	794	794	794
Within R-squared	.363	.367	.365
Number of groups	49	49	49

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variables are child maltreatment rate per 1,000 children and child fatality rates per 100,000 children. MML=1 if a state implemented a medical marijuana provision. HCL =1 if a state allows for caregivers to grow marijuana for medicinal purposes. MML-Pain =1 if a state has provisions that allow marijuana to be used for chronic pain.

Table 2.13 Heterogeneity in MMLs: Child Maltreatment

	(1)	(2)	(3)
	Child maltreatment rate per 1,000 children		
Dependent variable mean	**13.231**		
MML =1	1.303*		
	(0.649)		
MML&Decrim =1		3.788**	
		(1.779)	
Decrim&HCL = 1			4.308**
			(2.000)
Observations	759	759	759
Within R-squared	.52	.527	.528
Number of groups	49	49	49

Table 2.14 Heterogeneity in MMLs: Child Fatalities

	(1)	(2)	(3)
	Child fatality rate per 100,000 children		
Dependent variable mean	**1.841**		
MML =1	-0.174		
	(0.258)		
MML&Decrim =1		-0.214	
		(0.429)	
Decrim&HCL = 1			-0.323
			(0.487)
Observations	794	794	794
Within R-squared	.363	.363	.363
Number of groups	49	49	49

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variables are child maltreatment rate per 1,000 children and child fatality rate per 100,000 children. MML=1 if a state has a medical marijuana provision. MML&Decrim =1 if a state has both MML and decriminalization laws. Decrim&HCL =1 if a state has both home cultivation and decriminalization laws.
All regressions include state fixed effects, year fixed effects, state specific linear time trends. **Crime rate controls** include the violent crime to population ratio; family and drug abuse arrest rates per 100,000 persons; law enforcement to population ratio; female officers to population ratio; prisoner to population ratio. **State economic contro**l variables include unemployment rate, female labor force participation rate, and state median household income, college and high school attainment rate, population density per square mile. **State socio- demographic controls** include the percent of the child population that is black and white; divorce rates, percent of the population between the ages of 15-24 and 25-44; alcohol consumption per capita; beer consumption per capita; population density per sq. mile. Robust standard errors (in parentheses) are based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

Table 2.15 Robustness of Estimates with the Use of MML Effective Dates, by Age Cohort

Child maltreatment rates per 1,000 children	(1) All ages	(2) 0-3	(3) 4-7	(4) 8-11	(5) 12-15
Dependent variable mean	**13.231**	**15.0515**	**12.426**	**10.177**	**9.985**
MMLeffective=1	1.429**	3.021**	1.948*	1.630*	1.801*
	(0.606)	(1.234)	(1.081)	(0.908)	(0.897)
Observations	759	742	742	742	742
Number of groups	49	48	48	48	48

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variables are child maltreatment rates, per 1,000 children and maltreatment by age groups. MMLeffective=1 if a state's medical marijuana provision became effective that year. This table provides the coefficient estimates from the regression model in (1) estimated by FE regression. Robust standard errors (in parentheses) are based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

All regressions include state fixed effects, year fixed effects, and state specific linear time trends **Crime rate controls** include the number of violent crimes per 100,000 inhabitants; family and drug abuse arrest rates per 100,000 persons; law enforcement to population ratio; female officers to population ratio; prisoner to population ratio. **State economic contro**l variables include unemployment rate, female labor force participation rate, and state median household income, college and high school attainment rate, population density per square mile. **State socio-demographic controls** include the percent of the child population that is black and white; divorce rates, percent of the population between the ages of 15-24 and 25-44; alcohol consumption per capita; beer consumption per capita; population density per sq. mile.

Table 2.16 Robustness of Estimates with the Use of MML Effective Dates, by Severity of Abuse

Severity of abuse	(1) Physical abuse rate/1,000 children	(2) Neglect rate/1,000 children	(3) Fatality rate/100,000 children
Dependent variable mean	**2.561**	**6.94**	**1.841**
MMLeffective = 1	-0.489	1.057**	-0.083
	(0.487)	(0.474)	(0.250)
Observations	761	762	794
Number of groups	49	49	49

*, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Notes: The dependent variables are types of maltreatment (physical abuse and neglect), per 1,000 children and child fatality rate per 100,000 children. MMLeffective=1 if a state's medical marijuana provision became effective at year *T*. This table provides the coefficient estimates from the regression model in (1) estimated by FE regression. Robust standard errors (in parentheses) are based on Driscoll-Kraay spatial-autocorrelation and cluster-robust standard errors.

All regressions include state fixed effects, year fixed effects, and state specific linear time trends **Crime rate controls** include the number of violent crimes per 100,000 inhabitants; family and drug abuse arrest rates per 100,000 persons; law enforcement to population ratio; female officers to population ratio; prisoner to population ratio. **State economic contro**l variables include unemployment rate, female labor force participation rate, and state median household income, college and high school attainment rate, population density per square mile. **State socio-demographic controls** include the percent of the child population that is black and white; divorce rates, percent of the population between the ages of 15-24 and 25-44; alcohol consumption per capita; beer consumption per capita; population density per sq. mile.

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