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Essays on Women Empowerment Focusing on Paid Family Leave and Domestic Violence

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ESSAYS ON WOMEN EMPOWERMENT FOCUSING ON PAID FAMILY LEAVE AND DOMESTIC VIOLENCE

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of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Zeinab Golmohammadian

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The Dissertation of
Zeinab Golmohammadian is approved:

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Contents

List of Figures

List of Tables

Abstract

ESSAYS ON WOMEN EMPOWERMENT FOCUSING ON PAID FAMILY LEAVE AND DOMESTIC VIOLENCE

Zeinab Golmohammadian

Empowerment of women is one of the main processes through which nations, communities, and organizations pursue economic development and improved human rights. Many laws, regulations, and social norms, as well as socioeconomic circumstances, affect women's empowerment, which in turn influences women's roles in the community and their contribution to the economy. In this research we study both empowering and disempowering factors for women, and the downstream effect on women's social and economic lives. In the first chapter we study paid family leave as an empowering factor for women. The results show that paid family leave does not affect overall labor supply of women, suggesting that paid time leave is likely compensated by increase in number of women participating in the labor force. The second and third chapters offer a new insight into domestic violence and factors contributing to it. One in three women across the world have reported experiencing some form of physical or sexual violence by their intimate partners. Domestic violence is not only a violation of women's human rights, but also the root cause for an array of long-term physical and psychological problems. The second chapter analyzes the effects of rainfall on domestic violence, arguing that rain affects income and income has a direct impact on human behavior including violence. We show that increase in rain (below catasrophic flood levels) decreases violence, suggesting that violence declines with household resources. We also show that extreme rainfall events increase violence. The third chapter examines the correlation between domestic violence and household characteristics such as age, education and the gap between husband and wife. We find that family history of violence makes girls more likely to experience and even accept and justify violence by their intimate partners. The results also show that poorer households, lower educated women, and younger women are more prone to experiencing domestic violence.

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I am thankful to my family who mean a lot to me. My parents and my sisters for all their love and encouragement. Thanks to my lovely sons, Hossein and Ehsan who are the hope and joy of my life. Hossein was so supportive, patient and understanding during my entire PhD. I also adore and appreciate my little cute Ehsan for accompanying me with flexibility and smile in his first year of life. Words cannot begin to describe how grateful I am for and to both of them.

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This dissertation is dedicated to my loving, supportive, and empowering husband; Mohsen.

Chapter 1

The Effects of Paid Family Leave on Labor Supply and Wages

Abstract

The United States is the only economically advanced country which does not have a federal paid family leave law [Rossin-Slater et al., 2013]. While the federal Family and Medical Leave Act (FMLA) entitles employees to unpaid leaves and job protection, California, New Jersey, and Rhode Island are the only states who have implemented a paid family leave law, in 2004, 2009, and 2012, respectively. In this research we have studied the effects of these policies on the labor supply and wages of men and women, in California. The data regarding labor force participation and wages was obtained from the March Supplement of the Current Population Survey (CPS), and used to synthesize a synthetic control group. The synthetic control method constructs a counterfactual control group which is similar to California before the PFL laws took effect, but simulates the California labor market without PFL for the years after. Using this method to derive weights, we run a regression and conduct a difference-in-difference

analysis. We compare labor supply and wages of men and women in working age (18 through 65) in California, before and after the enforcement of the PFL laws, to that of the synthetic control group. Results show that implementation of PFL in California did not have any significant impact on the labor supply or wages of women. Neither did PFL have any significant impact on the labor supply and wages of men in California, due to PFL, compared to the synthetic control group.

1.1 Introduction

This research studies the households' decision making framework following an exogenous income shock; the introduction of paid family leave (PFL) in California. The goal is to first find out if households follow a unitary or non-unitary framework, and what causes them to do so. Secondly, the study tries to identify how implementation of PFL could impact the labor supply of men and women, as well as their average wages.

We use the Synthetic Control Group method to demonstrate that following the implementation of PFL in California, women's labor supply and their wages did not change significantly compared to a synthesized control state. Also, we did not find any significant effect on the labor supply or wages of men in the study sample.

Section 1.2 presents the background of paid family leave and its history in the United States, as well as California. Section 1.3 reviews the literature on paid family leave and other family friendly policies. We elaborate on the empirical framework of the research and explain how the synthetic control group is built and how its methodology works in Section 1.4. Finally the results of the analysis is presented and discussed in Sections 1.5 results.

1.2 Background

Researchers have found strong association between policies that support working parents, women specifically, and the improvement in workforce participation of women [Rossin-Slater et al., 2013]. Policies such as paid family leave, subsidized child care, and support for part-time work have expanded widely in developed countries - except for the United States - in the past two decades. Such policies are designed to facilitate women's participation in the workforce, by making it possible for them to hold a job over the span of years, as their role in the family evolves.

The absence of substantial labor policies to support working parents and families in the workforce has lowered the rank of the United States with regards to women's workforce participation. Within twenty years, European countries not only increased women's workforce participation significantly, but most of them overtook the US who had one of the highest participation rates in 1990 [Blau and Kahn, 2013]. However, as a result, women in European countries are more likely to be in part-time jobs, and less likely to be in high ranking leadership positions. Blau and Kahn [2013]find that women are as likely as men to be managers in the US, while they are half as likely as men to be managers in Europe.

One of the most critical components of family-friendly policies is Paid Family Leave (PFL). PFL allows new mothers (and fathers) to take time off to care for a new child (or a sick family member) while guaranteeing that they would keep their job and most of their employer sponsored benefits (such as insurance), and also getting partially paid.

While most nations have some sort of a PFL program, the United States is the only advanced industrialized country without a federal law for PFL [Rossin-Slater et al., 2013] . To date, only three states - California, New Jersey, and

Rhode Island - have implemented some form of paid family leaves. The State of Washington passed the law in 2007, but following the financial crisis the implementation of it was indefinitely postponed.

PFL in California

California was the first state in the US to legally mandate a paid family leave, starting in 2005. California's law used an insurance mechanism to pay for six weeks of leave for workers to care for a new child or a seriously ill family member [Engeman, 2012].

Unlike the federal FMLA that has employer size and employee work history requirements, almost all private sector workers are eligible for California paid family leave. California PFL offers six weeks of partially paid leave to bond with a newborn or a recently placed foster or adopted child, or for other reason (such as to care for seriously ill relatives). The law pays 55% of the employee's wage, up to a ceiling based on the state's average weekly wage. Job protection is limited to what FMLA offers, and is conditional on being eligible and simultaneously using FMLA. California PFL has many elements in common with the Temporary Disability Insurance and the two programs are closely coordinated. PFL applies equally to mothers and fathers [Rossin-Slater et al., 2013].

1.3 Literature Review

In order to study household decision making framework, we focus on the introduction of Paid Family Leave (PFL) law as an exogenous income shock for the households. We study how PFL impacts labor supply and wages for men and women in California. The following section is a review of previous literature on this topic.

Ruhm [1996] studied the economic impact of paid family leave in nine European countries between the years of 1969 and 1993. He finds that the legislation guaranteeing a paid parental leave, with even short durations of absence - substantially increases the percentage of women employed.

Other researchers confirm the findings of Ruhm [1996] with regards to increased workforce participation of women, when provided with a paid family leave. Abe, Higuchi, & Waldfogel [1998] found similar results by analyzing employment decisions made by women with young children. The authors looked at panel data of women with a variety of family leave coverage across three countries; Japan, United States, and Britain. They show that maternity leave coverage has a significant effect on women going back to work with their employers after childbirth. Japan, among the three sample countries, shows the highest effect [1998]. Also Berger & Waldfogel [2004] show that maternity leave coverage is related to leave taking, as well as the length of time that a new mother stays home after a birth. They found that among mothers who were employed before giving birth, those with leave coverage were more likely to take a leave of up to 12 weeks, but return more quickly after 12 weeks. The faster return to work reinforces the theory that paid family leaves increases the labor supply of women.

The right to paid leave, as Ruhm[1996] puts it, increases employed female population by 3 to 4 percent, while having a greater impact on women of childbearing age. The author explains that about one-quarter of this increase is due to reclassification of women who are taking the leave in the “employed but absent from work” group. Finally Ruhm has shown that short guaranteed leaves have little or no effect on women’s earnings, but longer leaves are associated with 2 to 3 percent drop in relative wages for them.

Blau and Kahn [2013] offers an extensive analysis of the labor market dynamics under the influence of family-friendly policies. She explains that there may be a “tradeoff” between making work easier for women, and them becoming more successful in their jobs. While changes in workforce supply are primarily a function of the decisions made by employees, changes in demand are predominantly a function of what the employer desires to do. On the employee side family-friendly policies facilitate entry into the workforce or job retention for women who prefer to to reduce their workplace commitments. On the other hand, women who would have otherwise been more committed to their jobs, may take advantage of long, paid family leaves, part-time work, or lower level positions.

On the employer side, however, these policies could lead to statistical discrimination against women in terms of being offered competitive wages and equal growth opportunities as men. Women within childbearing ages might be considered to be more likely to take a leave. Hence employers may perceive women as less productive or more costly, depending on how they look at the issue. Consequently, women may not be considered for high-level positions as frequently as men, or be paid wages competitive with their male counterparts.

To summarize, long family leaves end up being costly for employers, especially for positions that require training and experience. Hence companies would consider the risk of an employee leaving for a year at a time in their hiring calculations.

Rossin-Slater, Ruhm & Waldfogel [2013] study the effects of paid family leave law in California on women’s labor force participation. They formed a treatment group consisting of mothers with young children or infants, and a control group consisting of mothers with older children, childless women, men with non-infant children or new mothers living in other states. The authors compared the leave taking behavior between the treatment and control groups and showed that overall maternity leave use increased more than 100% in California after the implementation of the PFL law.

Furthermore, they found that between 1 to 3 years after taking a paid maternity leave, employed mothers experienced an increase in working hours of 6% to 9%, with a similar growth in their wage. More broadly speaking, the authors did not find paid maternity leaves to have any negative effect on the labor market for employed mothers using the benefit. Finally, it is noteworthy that the growth of hours worked or wage was substantially higher among unmarried mothers, non-white ethnics, mothers with lower education attainment, or those with lower income levels.

1.4 Empirical Strategy

1.4.1 Data

The data used in this research is obtained from the March Supplement of the Current Population Survey (CPS), for years 2002 to 2013. The CPS is produced jointly by the U.S. Census Bureau and the U.S. Bureau of Labor Statistics (BLS), and is the primary source of information for labor statistics, employment, and earnings of different demographic groups. (United States Census Bureau, 2014)

While CPS is a monthly survey, Some CPS supplemental surveys are conducted annually to focus on specific topics. The March supplement is an annual inquiry specifically designed to focus on data concerning family and household characteristics. It contains such information as household composition, marital status, education, health insurance coverage, income level and income sources, etc. (United States Census Bureau, 2014)

Labor supply is defined as the total number of hours worked per week, on all jobs inclusive of part-time and full-time, temporary and permanent, by each individual. Those who work and don't work are included in the models, so we take into account the labor supply fluctuations of those who join or leave the workforce over the years. We have included all men and women in the working age (defined as ages of 18 through 65) in the data set.

Finally, wage is defined as total earnings from wages and salaries, but does not include other types of income such as unemployment compensation, social security, survivor benefits, disability benefits, pension or retirement income, etc.

1.4.2 Synthetic Control Group Methodology

In this research, I use a Synthetic Control Group approach. The Synthetic Control Group Method was first introduced by Abadie and Gardeazabal [2003] and Abadie, Diamond, & Hainmueller [2011]. This is a method for comparative case studies for when none of the available control groups are a good comparison to the treatment group individually, or if we don't know which control group may be. The technique in this method is to generate a linear combination of individual control groups to synthesize a new control group; i.e. the synthetic control group. The synthetic group would be comparable to the treatment group in terms of the observed outcome, before the intervention (the shock). The rationale is that the synthetic control group's outcome after the intervention will approximately track the counterfactual outcome of the treatment group in the absence of the intervention.

Abadie and Gardeazabal [2003] argue that the synthetic control group method follows a data-driven approach to construct a suitable control group, and offers a framework for evaluating the comparability of the treatment and control groups. The process of constructing the synthetic control group quantifies the weight for each individual control. It also quantifies the degree of similarity between the treatment group and the synthetic control group. To the contrary, in traditional case study methods the selection of the control group is at the discretion of the analyst. Hence, one could question the extent to which the control group can accurately track the counterfactual outcomes of the treated, in the absence of the treatment.

Furthermore, the synthetic control method is described as a generalized form of the fixed-effects model which is commonly applied to empirical studies. The difference would be that the synthetic control method allows for the effect of unobserved variables to vary over time.

Abadie et al. [2011] provide a comprehensive explanation of the theoretical details of the synthetic control method. They describe the econometrics model used to derive the synthetic control estimator and show how it generalizes the usual difference-in-differences models. Here we focus on how we have used the Synth method in the context of the problem and described key steps using Stata Synth package.

Building a Synthetic Control Group

To build a viable synthetic control group, we use a set of characteristics relevant to the outcome to make sure the resulting control group accurately tracks the outcome values of the treatment group prior to the treatment. Since the synthetic control group is a weighted average of individual control groups, the key is to building a good synthetic group is to find the best set of characteristics relevant to the outcome that would yield the closest pre-treatment outcome values to that of the treatment group. Only then the post-treatment outcomes for the synthetic control group can be used to estimate the counterfactual outcomes that would have been observed in the treatment group in the absence of the treatment.

The first step in this process would be to derive the weights for the weighted average. The weights can be chosen to be positive and add up to one (convex combination). We define a $(J \times 1)$ vector of weights $W = (\omega_2, ..., \omega_{J+1})$' such that:

$$\omega_j \geq 0 \quad for\ j = 2, ..., J+1\ and\ \omega_1 + ... + \omega_{(J+1)} = 1 \tag{1.1}$$

In this analysis $j = 1$ represents the treatment state; California. All other states (excluding New Jersey because it implemented PFL in 2010) would be $j = 2$ through 50. The weights are chosen so that the new synthetic "state" most closely resembles California before the implementation of PFL. The following is centered on California as the treatment state, and labor supply as the outcome.

In order to estimate the weights, we must first choose a set of characteristic relevant to the outcome; labor supply of women in California. We choose k variables and form a $(k \times 1)$ vector of pre-intervention characteristics for the treatment group (call it X_1) and a $(k \times J)$ matrix of the pre-intervention characteristics of the individual control groups (call this X_0). The weights must be chosen so that the distance $||X_1 - X_0W||$ is minimized. As a result the mean values of the relevant characteristics in the synthetic control group will be the closest possible to that of the treatment group.

The next step of the process is to find W^* which minimizes the distance $||X_1 - X_0W||$. Let V be a $(k \times k)$ diagonal positive matrix carrying the weights for the k variables we chose earlier. Essentially, V is introduced to allow for different weights to the variables used in synthesizing the outcome, depending on their predictive power on the outcome. The optimal choice of V minimizes the mean square error of the synthetic control estimator over the pre-treatment periods:

$$||X_1 - X_0W||V = \sqrt{((X_1 – X_0W)'V(X_1 - X_0W))} \tag{1.2}$$

The solution W^* will depend on V; which reflects our prior knowledge of the relative importance of each particular variable in predicting the outcome. When solving manually, V can be calculated by minimizing the difference between the most important predictor in the synthesized control group and the treatment group [Abadie and Gardeazabal, 2003]. We use the synth package in STATA to estimate the control group weights vector W, the variable weights matrix V, and the RSMPE (Root Mean Square Prediction Error). The RSMPE is essentially a quantitative measure for how close the characteristics of a particular synthetic control group are to that of the treatment group.

1.5 Results

The goal of this analysis is to evaluate the effect of paid family leave on the wages and labor supply in California. As explained in the methodology section, the first step is to choose a set of characteristics as the predictors of the outcome; labor supply or wage, in the pre-treatment time period. We list a broad set of predictors based on Oreffice study (2007) to begin with. These variables are primarily demographic and employment characteristics of households such as: age, education, household size, ethnicity, family total income, employment status (part-time or full-time, salaried or hourly), etc. This is not the final selection, but rather pool of relevant variables to choose from [Oreffice, 2007].

The selection of weights for constructing the synthetic control group is the next step. The best set of weights would produce a synthetic control group resembling California before the introduction of PFL, in terms of the output. Mathematically speaking, optimum weights are chosen to minimize the root mean square of predictor error (RSMPE) based on the distance between synthetic control group and treatment group within pre-treatment periods. To optimize the weights for each outcome - i.e. minimize the RSMPE - we drop a couple of the relevant variables listed before. We arrive at the lowest RSMPE by iteratively running the synth package in STATA with different subsets of the relevant variables. Once we finalize the list of relevant variables, the synth package produces the resulting weights for each state to construct the synthetic control group. Using this method, we synthesize a unique set of weights to create the control group, to be used in the analysis of labor supply and wages.

State	Weight	State	Weight
Maine	0	West Virginia	0
New Hampshire	0	North Carolina	0
Vermont	0	South Carolina	0
Massachusetts	0	Georgia	0
Rhode Island	0	Florida	0
Connecticut	0.134	Kentucky	0
New York	0.252	Tennessee	0
New Jersey	-	Alabama	0
Pennsylvania	0	Mississippi	0
Ohio	0	Arkansas	0
Indiana	0	Louisiana	0
Illinois	0	Oklahoma	0
Michigan	0	Texas	0.228
Wisconsin	0	Montana	0
Minnesota	0	Idaho	0
Lowe	0	Wyoming	0
Missouri	0	Colorado	0
North Dakota	0	New Mexico	0
South Dakota	0	Arizona	0.093
Nebraska	0	Utah	0.17
Kansas	0	Nevada	0
Delaware	0	Washington	0
Maryland	0	Oregon	0
District of Columbia	0.066	Alaska	0
Virginia	0	Hawaii	0.058

Table 1.1: State weights in the synthetic California

Table 1.1 shows the weights for individual control states in the synthetic control group. These weightes can be interpreted as: wages in California prior to introduction of PFL is best reproduced by a synthetic control group which is a combination of Connecticut, New York, District of Columbia, Texas, Arizona and Hawaii. Other states were assigned a weight of zero in construction of the synthetic control group. Table 1.2 shows the mean value for key variables, comparing California and the synthesized control group for the period before 2005.

	California	Synthetic Group	p-value
Age-Women	39.47	39.68	0.77
Age-Men	38.84	39.20	0.58
Education - Women	10.26	9.86	0.13
Education - Men	9.83	10.22	0.15
Number of Own Children Under 6	0.25	0.24	0.86
Number of Person in the Household	3.48	3.29	0.46
Family Total Income Amount	68,518	68,867	0.93
Full Time Labor Force - Women	0.51	0.54	0.42
Full Time Labor Force - Men	0.75	0.75	0.96
Hourly Labor Force - Women	0.58	0.58	0.97
Hourly Labor Force - Men	0.53	0.51	0.53
Hispanic	0.34	0.17	0.02**

Table 1.2: Mean values in California vs. synthetic control group

Model 1. Wage of Women in California

Using the weights derived above, we construct the wages in the synthetic California and compare it againts the wages in California. Figure 1.1 plots the average wage for all working age men and women in California and in the synthetic group, and Figure 1.2 plots the gap between the two. In order to identify any significant effect for PFL on wages, we use the following regression:

$$\begin{aligned} WeeklyWages &= \beta_0 + \beta_1 Female + \beta_2 After2005 + \beta_3 California \\ &\quad + \beta_4 Female * After2005 + \beta_5 Female * California \\ &\quad + \beta_6 California * After2005 \\ &\quad + \beta_7 Female * California * After2005 + \varepsilon_{it} \qquad (1.3) \end{aligned}$$

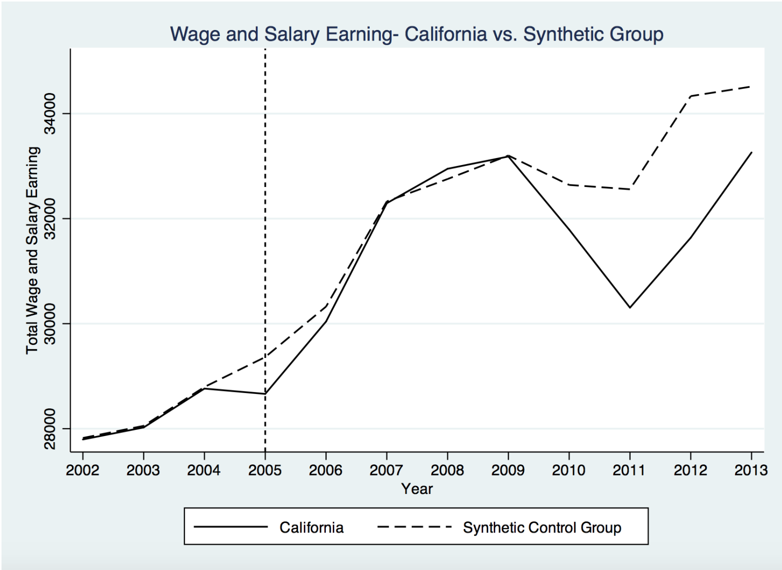

Figure 1.1: Gap in average hours worked per week between California and synthetic California

Figure 1.2: Gap in average hours worked per week between California and synthetic California

$Female$ is a dummy variable which equals 1 for female subjects and 0 for male. $After2005$ is dummy indicating all years after 2005 in which the PFL policy was in effect in California. $California$ is a dummy indicating the treatment group which is subjects residing in California. Other attributes are interaction terms constructed based on these three dummies. The dependent variable is average weekly wages reproted by the subjects.

To run this regression, we apply the weights derived from the synthetic control group (Table 1.1) to the model, while applying a weight equal to 1 to observations from California. As a result, the control group observations are the observations from states which built the sythetic control group with those weights. This model measures the effect of PFL on the average weekly salary of women relative to men in California, compared to the sythetic California, which simulates the absence of PFL. This effect is captured byβ_7, the coefficient for $Female * California * After2005$. When comparing women in California to women in the synthetic control group, the effect of PFL is captured by $\beta_6 + \beta_7$, the sum of coefficients for $California * After2005$ and $Female * California * After2005$.

The results of the regression are shown in Table 1.3. The first regression comes with no fixed effects, the second and third regressions include year fixed effects. The third regression also includes demographic and employement data points.

The results show that both β_6 and β_7 are insignificant. We also conduct an f-test on the significance of $\beta_6 + \beta_7$ and find that PFL had no impact on wages of women in California, compared to women in the synthetic control group. This finding confirms the conclusions of Ruhm [1996] that short guaranteed leaves have little or no effect on women's earnings.

Model 2. Labor Supply in California

Figure 1.3 plots women's labor supply in hours worked per week for California and the synthetic California. It appears that the labor supply of women in the synthetic control group closely follows the annual averages for California,

	Dependent Variable: Total Wage and Salary Earnings		
Female	**-15733.12*** **	**-15733.78*** **	**-9577.53*** **
	(417.52)	(417.56)	(376.50)
Years After 2005	**3921.15*** **	**6004.20*** **	**5105.43*** **
	(433.02)	(675.17)	(607.26)
Treatment Group (California)	403.26	403.11	**1002.07* **
	(572.80)	(572.81)	(515.11)
Female * After 2005	-697.34	-692.91	**-1286.31*** **
	(504.89)	(504.87)	(453.32)
Female * California	838.62	838.36	**1582.96*** **
	(680.21)	(680.27)	(608.74)
California * After 2005	-69.62	-63.52	437.72
	(685.33)	(685.30)	(616.05)
Females in California After 2005	-331.95	-334.79	-497.58
	(812.34)	(812.37)	(727.62)
Person's Characteristics			
Age			**378.18*** **
			(7.512)
Education			**4155.63*** **
			(40.829)
Number of Person in the Household			**407.61*** **
			(57.693)
Hispanic			**2954.55*** **
			(182.308)
Full Time Labor Force or Part Time			**31191.13*** **
			(168.393)
Constant Term	**35245.38*** **	**34953.31**	**-175104.3*** **
	(359.98)	(464.70)	(1815.11)
Year Fixed Effect	No	Yes	Yes
Number of Observation	411,207	411,207	411,207
*P value for CA * After 2005 + Females in CA After 2005 = 0*	0.36	0.36	0.88

*, **, and *** indicate significance at 10%, 5%, and 1%, respectively.
Data is weighted by the weights of the synthetic control group built for total wage and salary

Table 1.3: Mean Values in California vs. Synthetic Control Group - Total Wage and Salary Earning

prior to implementation of the PFL. In the years immediately following the introduction of PFL, women's labor supply in California diverges from that of the synthetic control group. Figure 1.4 (solid line) shows the difference of labor supply between the two lines in Figure 1.3. Immediately after the implementation of PFL, in 2005, women's labor supply in California shows a drop relative to labor supply in synthetic California. The gap remained big for several years, until 2011 when an upward trend appeared.

In order to determine any significant effect for PFL on labor supply, we use the following regression, applying the same weights from Model 1:

$$\begin{aligned} Hours\,Worked \;=\; & \beta_0 + \beta_1 Female + \beta_2 After2005 + \beta_3 California \\ & + \beta_4 Female * After2005 + \beta_5 Female * California \\ & + \beta_6 California * After2005 \\ & + \beta_7 Female * California * After2005 + \varepsilon_{it} \end{aligned} \tag{1.4}$$

The variable of interest, which is the coefficient for $Female * California * After2005$, is 0.11 in the first two regressions and 0.12 in the third regression. But none of these values are statistically significant. This means that PFL does not have a noticeable effect on labor supply of women in California relative to men. Furthermore, the coefficient for $California*After2005$ is not significant in any of the regressions either. Finally, to verify that the conclusions above are valid for women in California versus women in the control group, we conduct an f-test for the sum of two coefficients for $California*After2005$ and $Female*California*After2005$. The f-test shows that the sum of these two coefficients is not significant, hence verify that the effect of PFL does not have a significant impact on labor supply of women in California.

This could be a result of two contradicting effects. First an increase in labor force participation where more women are encouraged to take on a job. Second lowered average hours worked as a result of taking paid family leave under the new law. Hence our results confirm the ambiguity of the effects of PFL on labor supply explained by Blau and Kahn [2013].

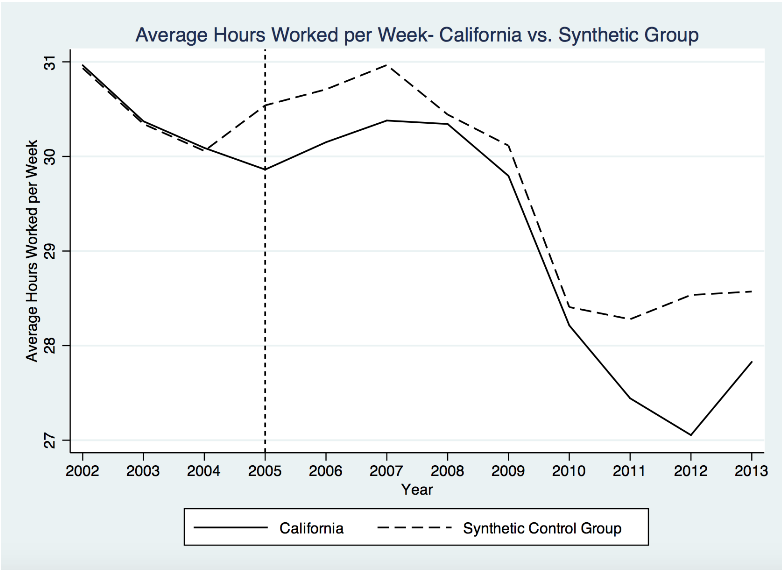

Figure 1.3: Gap in average hours worked per week between California and synthetic California

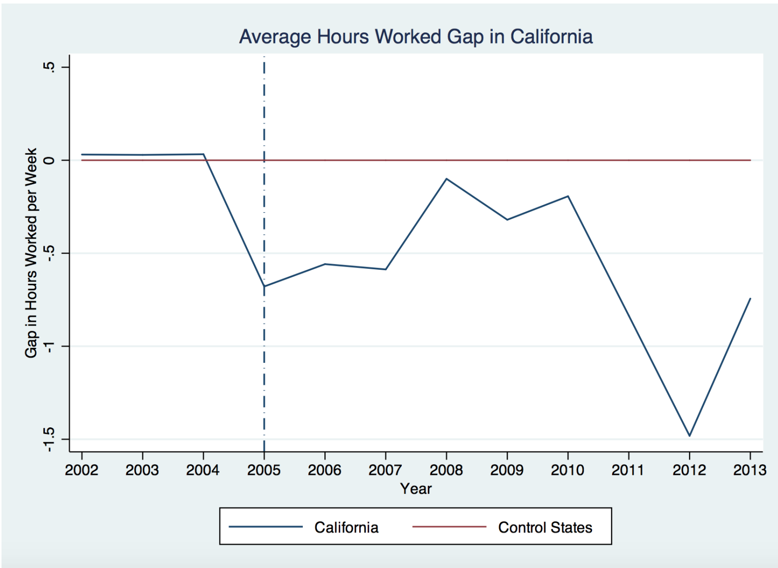

Figure 1.4: Gap in average hours worked per week between California and synthetic California

	Dependent Variable: Hours Worked per Week		
Female	**-9.21*** **	**-9.21*** **	**-3.41*** **
	(0.18)	(0.18)	(0.13)
Years After 2005	**-1.26*** **	**-1.71*** **	**-1.82*** **
	(0.15)	(0.24)	(0.18)
Treatment Group (California)	**-0.60*** **	**-0.60*** **	**-0.45*** **
	(0.21)	(0.21)	(0.16)
Female * After 2005	0.27	0.27	0.00
	(0.21)	(0.21)	(0.15)
Female * California	0.04	0.04	**0.55*** **
	(0.30)	(0.30)	(0.22)
California * After 2005	**-0.45***	**-0.47***	-0.18
	(0.24)	-(1.91)	(0.18)
Females in California After 2005	0.11	0.11	0.12
	(0.34)	(0.34)	(0.25)
Person's Characteristics			
Age			**0.01*** **
			(0.003)
Education			**0.63*** **
			(0.011)
Number of Person in the Household			**-0.24*** **
			(0.019)
Hispanic			-0.05
			(0.073)
Full Time Labor Force or Part Time			**27.02*** **
			(0.075)
Constant Term	**35.66*** **	**36.13*** **	**-8.57*** **
	(0.13)	(0.18)	(0.47)
Year Fixed Effect	No	Yes	Yes
Number of Observation	411,207	411,207	411,207
*P value for CA * After 2005 + Females in CA After 2005 = 0*	0.16	0.15	0.75

*, **, and *** indicate significance at 10%, 5%, and 1%, respectively.
Data is weighted by the weights of the synthetic control group built for hours worked per week

Table 1.4: Effect of paid family leave on average hours worked per week on working age men and women in California

1.6 Conclusion

We studied the effect of Paid Family Leave on labor supply (average hours worked per week) and wages (average earning per week) of men and women in California, where PFL was introduced in 2005. The dataset included men and women between the ages of 18 and 65 (working age) from the March Supplement of the Current Population Survey between the year of 2002 and 2013. We used the synthetic control group method to construct a counterfactual California labor market in the absence of PFL. Using the weights derived from the construction of the synthetic control group, we then ran a regression model to identify the effects of PFL on women's labor supply in California, relative to the synthetic California group. The same model is used to capture the causal effect of PFL on men in California, as well as the impact of PFL on women relative to men. We found that PFL had no significant effect on working age women's labor supply. We used the same methodology to run a similar model for wages. We found that California's Paid Family Leave did not have an impact on average earnings of working age women. This is potentially due to the cancelling effect of (a) increase in labor force participation by women (b) decrease in average hours worked by women as a result of taking leaves. It also confirms findings of previous researchers who showed that short guaranteed leaves have little or no effect on women's earnings.

Chapter 2

Does Rain Make Women Safer? The Impact of Rainfall on Domestic Violence

Abstract

One in three women across the world have reported experiencing some form of physical or sexual violence by their intimate partners. Domestic violence is not only a violation of women's human rights, but also the root cause for an array of long-term physical and psychological problems. In this research we study the effects of rainfall on the prevalence of domestic violence against women. We use data regarding domestic violence in 25 countries, and combine it with granular precipitation data for 30 years to establish a relationship between rain and violence. Rainfall and temperature data were obtained from the University of Delaware, and the domestic violence data from the Demographic and Health Survey (DHS). We ran regression models to estimate the effect of regular and extreme rainfall changes on prevalence of different forms of domestic violence.

We find that rain is mostly negatively correlated with domestic violence, but extremely high rainfall increases the rate of violence.

2.1 Introduction

Domestic violence is a serious social issue which is often overlooked due to traditional belief systems which treat it as a private and familial affair. Victims, predominantly women, are often subjected to public shaming, and suffer from a tendency to blame themselves for the brutality they have faced. While the physical, sexual and psychological consequences of domestic violence is evident, it also causes severe personal and social repercussions [Sahay and Venumadhava, 2016]. Long term domestic violence penetrates the entire family structure, making it dysfunctional [Saenger, 2000]. This in turn impacts children, and soon, communities and countries at large are affected. Such violence leads to increased socioeconomic costs, thus adversely affecting the economic development of the community. In addition, victims of domestic violence are often held back from participating and contributing to society. A better understanding of these consequences has prompted societies and governments to change their outlook on domestic violence, and slowly, authorities are realizing it is their duty to work towards eradicating this social evil.

Violence against women is a global issue that permeates all social, economic, and cultural strata. Studies have shown that more than one-third of all women (35%) experience either physical or sexual violence in some form, throughout their lifetime, where the perpetrators are predominantly their intimate sexual partners. Shockingly, intimate partners are responsible for 38% of murders of female victims [World Health Organization, 2013]. Nearly half of all homicides involving women were perpetrated by male family members or sexual partners in 2012, while the corresponding number for male victims was less than 6% [United Nations, 2013]. More than one in every ten girls (120 million) experience forced sexual acts by former or current sexual partners and, while in some countries, nearly a third of the female population report their first sexual experience as forceful [Unicef et al., 2015]. Between 45% and 55% of all women in the European union experience some form of sexual harassment since the age of 15.

In addition to having their human rights heinously violated, the victims of abuse also suffer from an array of physical and emotional problems. Abortion rates and reported cases of depression are double among women who experience domestic violence compared to others. Also underweight births are 16% more prevalent among women who reported such abusive experiences [World Health Organization, 2013].

The statistics discussed above highlight the importance of addressing this social issue. Studying various factors on which it depends is the first step towards this end. One such factor is the relationship between domestic violence and climate change.

There are numerous pathways linking human behavior to climatic conditions. Climatic changes such as droughts or floods are likely to cause a scarcity of necessary resources, resulting in conflicts over their allocation. With significant improvements in quality and availability of climatic data, it is possible to quantitatively analyze these links and identify climatic conditions that are conducive to violent behavior. In this research we specifically investigate the relationship between rainfall and domestic violence against women. This research studies the effect of precipitation on domestic violence. The underlying hypothesis is that rainfall has direct and indirect effects (e.g. via changes to income) on the prevalence of domestic violence. We analyzed 30 years of precipitation data for

37 countries to identify its relationship with the prevalence of domestic violence against women.

2.2 Literature Review

Hsiang et al. [2013] studied literature available to identify links between human behavior and climate shocks. They identified strong causal evidence linking climate change to incidents of human conflicts. This significant link was found to be a global phenomenon throughout history. The study shows that for each standard deviation change in climatic factors such as temperature, rainfall etc, the median interpersonal violence rises by 4%, and the median value of intergroup conflicts rises by as much as 14%. Due to global warming, many regions of the world are likely to experience climatic variations of two to four standard deviations by 2050. This level of climate change could significantly influence the patterns of human conflict across societies.

In their study, Hsiang et al. define conflict broadly to include both individual level aggression and larger societal instabilities such as riots, civil wars, political instabilities, institutional breakdown, etc. One hypothesis argues that during climate shocks, the local economic conditions and labor markets are adversely affected. This raises the value of taking part in conflict relative to the value of taking part in normal economic transactions. An alternate hypothesis argues that the control of government institutions weaken during climate shocks, limiting its ability to discourage criminal acts and rebellions. This in turn can lead to increase in crime.

In a similar study, Miguel [2005] uses data of rainfall in rural Tanzania to correlate income shocks triggered by precipitation changes with increased witch killing rates in these districts. In a largely agricultural society, precipitation shocks such as droughts or floods lead to poor harvest and acute food shortages. Such changes were accompanied by an increase (a nearly 100% increase) in the murder of elderly women in rural Tanzania. These women who were referred to as witches were often killed by their relatives. These results from 67 villages over a span of 11 years provide concrete and novel evidence linking climate induced income shock to faith based violence.

Ethnographic literature of the region suggests that witches are capable of controlling weather phenomenon (including precipitation) as well as disease epidemics. This should lead to elderly women (witches) being held accountable for both climate shocks and disease epidemics. In either case, the household may choose to eliminate the cause of their suffering by murdering the witch. However, it is seen that only changes that adversely affect the family income (precipitation shock) leads to higher violence against these women. Epidemics have no direct influence on income levels, and hence, these do not lead to increased crime rates. The study suggests methods such as providing formal insurance against climatic shocks to reduce the incidence of crimes against elderly women [Miguel, 2005].

Sekhri et al. [2012] link rainfall shocks to violence against women in India. This study uses data from 583 Indian districts over five years (2002-2007). The study found that one standard deviation decrease in mean rainfall increases reported cases of domestic violence by 4.4% and dowry deaths by 7.8%. It also provides evidence linking droughts to increased dowry payments. Droughts lead to a decrease in income, and dowry demands increase as a way of compensating for this loss in income. The decrease in income also dissuades families from reporting harassments, leading to lower reported sexual harassment rates during a dry shock. Wet shocks show no significant correlation to crime rates.

Another study on the relationship between crimes and rainfall shocks in the Indian context is by Blakeslee and Fishman [2013]. They use crime and rainfall data for the years 1971-2000 to find a relation between rainfall shock and crime rates. Defining rain in excess of one standard deviation above average as a “positive” rainfall shock, and rain less than one standard deviation below average as “negative” shock, they show that both positive and negative rainfall shocks lead to an increase in property crimes, in agricultural societies. But violent crime only increases if the change in precipitation leads to a negative income shock. During such times of scarcity, an individual has less to lose if caught in a violent act, leading to an increase in such crimes. They also show that a positive income shock often increases the cost and benefit of a criminal act. A person with higher non-criminal income has more to lose by engaging in a criminal act. At the same time, the rewards associated with a crime may also increase in property crimes.

Blakeslee and Fishman [2013] catalogued crimes and estimated their correlation with extreme rainfall events. They showed that property crimes respond positively to both dry and wet shocks, while there is no correlation between wet shocks and violent crime. An older study on property crimes was conducted by Mehlum et al. [2006]. This work studies the effect of rainfall on property crimes for 19th century Bavaria (Germany). The indicator considered is rye price as it was a major determinant of living standard. A standard deviation decrease in rye price increased property crimes by 8%. In this work correlates rye price to rainfall, thus linking precipitation shocks to property crimes. It is shown that rainfall is responsible for up to 28% variations in rye price. An increase in rainfall interferes with both the sowing and harvesting of rye, leading to higher rye prices. This reduces the real income available for urban population and farm laborers, while farmers themselves suffer due to partial destruction of crops. The study used a two stage least square approach to address the errors caused by the regression or due to omission of key variables. Mehlum et al. [2006] calculate an elasticity factor of 0.20 between property crimes and rainfall shock. The study found a sharp drop in violent crime with increase in rye price and attributes it to an increase in beer prices which brought down alcohol related crimes.

In addition to property crimes, ethnic violence has also been linked to precipitation shocks. Short term fluctuations in economic growth often explains the occurrences of communal riots during certain periods of time. Bohlken and Sergenti [2010] studied 15 Indian states for the period 1982-1995, and while not directly correlating ethnic violence to precipitation shocks, they showed that percentage change rainfall is an important factor influencing economic growth. It was shown that a 1% increase in economic growth increases the number of riots by 5%.

All the literature covered in this section clearly illustrate a relationship between climate shocks and various types of crimes. Also, women, elderly and ethnic minorities are more susceptible to violent crimes in the event of a precipitation shock.

2.3 Data and Model

2.3.1 Data Sources

The DHS Survey Data

The Demographic and Health Surveys (DHS) program, funded by the US Agency for International Development (USAID), supports more than 300 surveys in over 90 countries. These surveys offer a unique view into population demographics and health trends. An important data point in these surveys is the frequency, form, and severity of domestic violence, as well as the context in which violence occurs. What makes this data much more useful is that the DHS Household questionnaire collects additional data points on all household member such as: age, sex, education, relationship to the household head, assets, as well as access to infrastructure and sanitary facilities such as electricity, toilets, and clean water.

The other important DHS questionnaire which surveys women between the ages of 15 and 49 years on a variety of personal and relationship characteristics. This includes age, marital status, contraceptive use, education, employment, and empowerment status, as well as their husband's education, occupation, and alcohol consumption. Given the availability of information for both the wife and the husband, researchers can portray a picture of the relationship between the couple, describe the victim and the perpetrator as well as the context of violence, and finally identify risk factors in domestic violence.

The DHS database also collects the geographical location of the respondents in the course of some surveys. While making sure the exact location of households is kept confidential, DHS offers a mechanism to roughly locate the households within a certain boundaries. This information can be used to relate climatic data, as well as other location-based information. For surveys which do not include the exact longitude and latitude of the respondent, the name of the region, county, or state can be used as a proxy for geo-location.

Rainfall Data

The Earth Systems Research Lab at the University of Delaware collects and records monthly global data for air temperature and precipitation. The data is collected from gridded land stations and reported with the high resolution of 0.5 degrees of latitude and longitude. This data covers all points on land for the period of 1900 to 2010. Therefore the data is easily mapped to DHS data by simply choosing the closest coordinates of rainfall data to the coordinates of the center of the district, region, or exact location of the survey respondent, within the month and year of the survey.

2.3.2 Regression

The goal of the regression is to estimate the effect of extreme rainfall events on the prevalence of domestic violence. In this regression shocks are not dummy variables, but continuous ones. The shock is essentially rain squared which grows exponentially with rainfall deviating from the average. In addition, we include the normalized rainfall into the regression to account for regular changes in annual rain. We have chosen to use an OLS regression to estimate prevalence of violence based on household attributes. A simplified view of our regression regressions can be written as:

$$\begin{aligned} Rate\,of\,violence &= \beta_0 + \beta_1\,Normalized\,Rainfall_{it} \\ &\quad +\beta_2\,Normalized\,Rainfall\,Squared_{it} \\ &\quad +\beta_3\,\alpha_i + \beta_4\,\mu_t + \beta_5\,\rho_i + \epsilon_{it} \end{aligned} \tag{2.1}$$

In this regression locations are indexed by i, observational periods are indexed by t. α_i is a set of variables describing some of the characteristics of the subject (women) and their households. μ_t shows the time fixed effect, ρ_i is the regional fixed effects, and finally ε_{it} is the error term. The region fixed effects show differences in average prevalence of violence between different regions, which exist perhaps due to geographic, economic, political, or cultural differences. Similarly, year fixed effects will isolate macro trends over time that could be correlated with most time varying attributes such as macroeconomic conditions and long-term cyclical climate changes [Hsiang et al., 2013].

The parameter of interest would be β_2, showing the effect of extreme rainfall events on rate of violence. Also β_1 would capture the effect normal and small changes in rainfall.

2.3.3 Dependent Variables

The DHS program collects data on a variety of experiences when it comes to domestic violence. We categorized these experiences into three types and carry out the analysis on these types of violence separately, as well as collectively:

- Physical Violence: including both severe violence and less severe violence.
  - Severe violence: Ever been kicked or dragged, strangled or burnt , threatened with knife/gun or other weapon by husband/partner
  - Less severe violence: Ever been pushed, shook or had something thrown, punched with fist or hit by something harmful, arm twisted or hair pulled by husband/partner
- Sexual Violence
  - Ever been physically forced into unwanted sex, forced into other unwanted sexual acts by husband/partner or physically forced to perform sexual acts respondent didn't want
- Emotional Violence:
  - Ever been humiliated, threatened with harm, insulted or made to feel bad by husband/partner
  - Perpetrator had done things to scare or intimidate her on purpose, e.g. by the way he looked at her, by yelling or smashing things

– Perpetrator had threatened to hurt someone she cared about

For each of the categories above, we define a dummy variable which carries the value of 1 if the respondent had experienced at least one of the defined domestic violence experiences within 12 months prior to the survey. We also define "any violence" as 1 if the respondent reports any single one of the shapes of violence mentioned above. We treat the dummy as zero if all cases of violence are reported to be absent, or not reported at all (missing). However, if all violence data points are missing, then "any violence" will also be missing.

2.3.4 Independent Variables

Rainfall

The coefficients for rainfall and rainfall-squared are the variable of interest in this research. Rainfall data is obtained from the University of Delaware monthly global precipitation database. We normalize rainfall by subtracting the 30 year average annual rain and dividing the value by the 30 year standard deviation. The long-term average and standard deviation are obtained from the time period of 1980 through 2010. For each observation, normalized rainfall and normalized rainfall squared are calculated for two time periods:

- 1 year prior to the survey: 1 through 12 months before the interview date
- 2 years prior to the survey: 13 through 24 months before the interview date

As mentioned earlier, geo-location data is available for a subset of the survey responses. In order to take the best advantage of the available data, we created two sets of data for mapping rainfall data to survey data. The first one, called "regional mapping", which does not use the geo-location of respondents, instead maps rainfall data to the province or district of their residence. The second data set is called "individual mapping" which uses the individuals' geo-locations, if available, to map the rainfall data to the survey data.

Regional mapping means that all respondents in a given district, state or province are assigned to a single data point for rainfall and that is the rainfall at the geographical center of the region (GPS coordinates' centroid). In other words we are assuming that the entire region received the same rainfall in the given time periods as the center of the region. Individual mapping data uses the specific GPS coordinates of each respondent to find the closest set of coordinates in the precipitation data. As a result each respondent is assigned to the rainfall of a point which is at most 2 miles away from their location. This is much more accurate in terms of mapping rainfall data to DHS surveys, but the GPS coordinates are not available for all respondent. That is why we chose to have two regressions. Overall, we run the analysis twice; once for regional mapping and once for the individual mapping data set.

Household Characteristics

We control for available relevant household characteristic data by adding the following to the regression as independent variables:

- Age of wife
- Age difference between husband and wife
- Education of wife: highest year of education
- Education of husband: highest year of education
- Husband alcohol consumption: dummy if partner drinks alcohol

History of Violence

Having a background or history of violence, or being witness to such events in the family prior to marriage has a significant impact on how violence is perceived or even tolerated. The DHS questionnaire includes some questions about the history of violence and perception of violence which we include in the regression.

- History of violence: Dummy variable indicating if the respondent's father ever beat her mother or has ever physically hurt respondent
- Beating justified: Dummy variable indicating that the respondent believes husband is justified to beat his wife under any of these circumstances:
  - if wife goes out without telling husband,
  - if wife neglects the children,
  - if wife argues with husband,
  - if wife refuses to have sex with husband,
  - if wife burns the food

Time and Location Fixed Effects

Since the survey data is collected from 37 different countries (350 different regions), over a span of 10 years, we choose to include time and region (location) fixed effects. Time fixed effects are implemented in form of dummy variables for year of the survey and location fixed effects are dummy variables for each region of each country.

Section 5 shows the estimated effect of rainfall on the rate of domestic violence. Next chapter is dedicated to explaining other root causes of domestic violence, including household characteristics, in details.

Variables	Mean	Standard deviation	Minimum	Maximum	Observations
Sexual Violence	0.09	0.29	0	1	276,320
Physical Violence	0.29	0.45	0	1	285,348
Emotional Violence	0.21	0.40	0	1	223,889
Any Kind of Violence	0.36	0.48	0	1	285,392
Respondent's Characteristics:					
Age	29	10	13	49	368,772
Age Difference b/w Husband and Wife	6	6	-32	81	248,886
Years of Education	4	2	0	16	295,427
Husband's Years of Education	7	5	0	24	280,312
Husband Drinks Alcohol	0.44	0.50	0	1	226,024
History of Violence					
Father Beat Her/Her Mother	0.35	0.48	0	1	240,706
Justify Beating	0.35	0.48	0	1	323,266

Table 2.1: Summary statistics

2.3.5 Summary Statistics

Table 2.1 shows the mean values and standard deviation for the dependent and key independent values in the data set. These statistics show that more than one in three women reported experiencing some form of domestic violence in the 12 months prior to the survey. Physical violence is the most prevalent type of violence with 29% reporting. More than one in five - 21% - reported experiencing experiencing emotional violence, and 9% reported experiencing sexual violence. More than a third of the respondents report having seen some form of violence in their parents' families. Shockingly so, about the same percentage believe husband beating of wife is in some circumstances justified.

DHS's women's survey interviews female subjects between the age of 15 and 50. The average age of the respondents in this data set is 29 years and they are on average 6 years younger than their husbands or partners. Also women in this survey have on average 4 years of education while their husbands or partners have 7 years of education. Finally, 44% of the respondents reported that their husband drinks alcohol.

Table 2.2 shows the breakdown of domestic violence reports by country and year. Our data set includes 376,486 observations across 25 countries, and 37 country year combinations. The highest rate of violence was reported in Uganda in 2006 when two-thirds of women reported some form domestic violence. Close to half of the respondents had experienced physical violence, about half experienced emotional violence, and close to one-third had undergone sexual violence and abuse. Following closely, 57% of Rwandan women and 54% of Zambian women reported domestic violence in 2010 and 2007, respectively. On the opposite end of the spectrum, Azerbaijan and Honduras reported just below 15% domestic violence in 2006 and 2005, respectively.

Eligible women are defined in DHS surveys as women of reproductive age (15 to 49). In some countries, the eligibility criteria restrict the survey to ever married women. Columbia and India have the highest number of survey respondents, contributing 25% and 22% of total number of eligible women to the data set. The smallest countries in the data set are Sao Tome and Principe and Uganda with close to 2000 survey respondents.

2.4 Results

As explained earlier, we ran an OLS regression to estimate the causal effect of rainfall changes on the prevalence of domestic violence. We conduct eight distinct analyses, and present the coefficients thereof in Table 2.3. We estimated the effect of rainfall on three types of violence: physical violence, emotional violence, and sexual violence, as well as an estimation for any violence. We offer two versions for each regression. In the first version rainfall data is only included for the 12 months leading to the survey date and in the second version rainfall data is included for both the survey year and the preceding 12 months. The rainfall data is mapped onto domestic violence data at the regional level.

Country	Year	Experienced any kinds of violence	Experienced any physical violence	Experienced any sexual violence	Experienced any emotional violence	Number of Eligible Women
Azerbaijan	2006	0.146	0.128	0.026	0.068	5,617
Bangladesh	2007	0.487	0.487			8,934
Cambodia	2000	0.250	0.164	0.036	0.178	2,403
Cambodia	2005	0.223	0.128	0.027	0.185	2,901
Cameroon	2004	0.500	0.389	0.146	0.292	3,290
Colombia	2005	0.307	0.207	0.069	0.219	40,791
Colombia	2010	0.374	0.366	0.097		52,952
Congo	2007	0.714	0.570	0.354	0.430	3,436
Dominican Republic	2002	0.248	0.184	0.065	0.178	8,746
Dominican Republic	2007	0.298	0.162	0.052	0.262	10,140
Haiti	2002	0.294	0.174	0.171	0.132	10,159
Haiti	2005	0.247	0.134	0.108	0.171	3,568
Honduras	2005	0.147	0.137	0.044		19,948
India	2005	0.398	0.351	0.100	0.158	83,703
Jordan	2007	0.302	0.206	0.076	0.200	3,444
Kenya	2003	0.475	0.400	0.158	0.256	5,878
Kenya	2008	0.453	0.370	0.145	0.295	6,318
Liberia	2007	0.497	0.355	0.102	0.363	4,913
Malawi	2004	0.315	0.210	0.140	0.133	9,707
Malawi	2010	0.385	0.218	0.167	0.252	6,229
Mali	2006	0.250	0.202	0.045	0.116	9,849
Moldova	2005	0.317	0.241	0.041	0.230	5,695
Nigeria	2008	0.307	0.176	0.039	0.238	23,752
Rwanda	2005	0.386	0.346	0.139	0.130	4,066
Rwanda	2010	0.566	0.558	0.176		5,008
Sao Tome and Principe	2008	0.331	0.265	0.075	0.233	1,980
Tanzania	2010	0.490	0.392	0.148	0.363	7,047
Timor-Leste	2009	0.359	0.335	0.023	0.083	2,951
Uganda	2006	0.663	0.481	0.310	0.486	2,087
Ukraine	2007	0.246	0.128	0.029	0.227	2,903
Zambia	2007	0.541	0.467	0.168	0.257	5,236
Zimbabwe	2005	0.457	0.300	0.138	0.301	6,293
Zimbabwe	2010	0.434	0.288	0.155	0.265	6,542

Table 2.2: Percent of ever-married women age 15-49 who have experienced violence by a husband or partner in the 12 months Leading to the survey

All eight regressions account for year fixed effects and region fixed effects. Furthermore, the regressions are clustered at the region level. Finally, all regressions use the sample weights of the DHS survey data, as instructed by the report. The dependent variable for columns 1 and 2 is any violence, for columns 3 and 4 is sexual violence, for columns 5 and 6 is physical violence, and finally for columns 7 and 8 is emotional violence.

By definition of normalized rainfall, the coefficients are interpreted as the effect of one unit change in normalized rainfall on the violence, where the unit here would be one standard deviation of annual rainfall. Normalized rainfall squared

	Dependent Variables							
	Any Violence		Sexual Violence		Physical Violence		Emotional Violence	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Normalized Rain, Survey Year	**-0.086***** (0.016)	**-0.074***** (0.002)	**0.017***** (0.007)	**-0.014***** (0.001)	0.010 (0.012)	**-0.069***** (0.002)	**-0.091***** (0.014)	**-0.031***** (0.002)
Normalized Rain, Previous Year		**-0.039***** (0.011)		**-0.110***** (0.005)		**-0.110***** (0.009)		**0.055***** (0.009)
Normalized Rain Squared, Survey Year	**0.266***** (0.036)	**0.250***** (0.004)	**0.059***** (0.016)	**0.149***** (0.002)	-0.032 (0.028)	**0.163***** (0.003)	**0.292***** (0.033)	**0.152***** (0.004)
Normalized Rain Squared, Previous Year		**0.044***** (0.004)		**0.094***** (0.002)		**0.072***** (0.004)		**-0.027***** (0.003)
Respondent's Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
History of Violence	YES	YES	YES	YES	YES	YES	YES	YES
Region Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Mean of Rate of Violence	0.36	0.36	0.09	0.09	0.29	0.29	0.21	0.21
S.D of Rate of Violence	0.48	0.48	0.29	0.29	0.45	0.45	0.40	0.40
Number of Observation	180,612	180,612	174,890	174,890	180,594	180,594	135,039	135,039

*, **, and *** indicate significance at 10%, 5%, and 1%, respectively.
Data clustered by region
Rainfall data is recorded at the regional level for all samples.
Age and age difference are dividided by 100, and years of eduation is divided by 10 to bring coefficiens to a comparable range

Table 2.3: Effect of rainfall on prevalence of domestic violence, rainfall data matched to respondents at the regional level

is used to estimate the effect of extreme rainfall events, which is expected to have a different effect on income, and consequently on violence, than that of regular changes in rain. For example, while regular increase in rainfall is helpful to the agriculture industry, too much rain can ruin products or damage infrastructure, leading to a negative impact on income.

For all measures, higher rain is negatively correlated with the rate of domestic violence. This can be attributed directly to the effect of rain on household income. Furthermore, the coefficient for rainfall-squared is positive, meaning that too much rain (i.e. floods) increases domestic violence. The combination of the two coefficients for rainfall and rainfall squared determines a threshold above which increase in rain starts having an increasing effect on the estimated rate of violence. The threshold for any violence is 0.32 standard deviations above average rainfall. Therefore, for example, rainfall equal to one standard deviation above long-term average, is expected to increase the rate of violence by 0.18.

Overall, except for regressions 3 and 8, all other regressions show the same consistent signage for coefficients: negative for rainfall and positive for rainfall squared. Hence the overwhelming conclusion of these results is that increases in rain decrease violence, though extreme rain also increases violence.

We also tried mapping the precipitation data to domestic violence data at the individual respondents' level by finding the rainfall data recorded on the coordinates closest to the respondents GPS location. However, the regressions ran on this set of data did not yield any significant or consistent results. We believe this is due to the deliberate error introduced to maintain respondents' privacy in the DHS reports.

2.5 Conclusion

Domestic violence, including physical, sexual, and emotional violence, are shown to be the cause of many physical and psychological problems for the victims, as well as major public health issues for families, children, and communities at large. The issue of domestic violence is extremely widespread around the world, to the extent that the World Health Organization reported that around half of all women in the European Union experienced some form of sexual harassment since the age of 15. The literature shows that climatic events such as rain and temperature have a direct impact on the rate of violence and crime. This is believed to be to be due to the impact climate has on income and wealth.

We study over 375,000 surveys reporting domestic violence in various forms in 25 countries, reported by the Demographic and Health Survey (DHS). Furthermore, we obtain precipitation data from the University of Delaware and join it to the DHS data on a regional level. In order to estimate the effect of rainfall on various forms of domestic violence, we run a regression model with normalized rainfall and normalized rainfall squared as independent variables.

The results show that rain decreases violence. But when rainfall is extremely higher or lower than the long-term average, it results in increased domestic violence. For example rain in excess of one standard deviation above the long-term average increase the rate of violence by 0.18. This can be attributed to the argument that small changes in rain have a positive correlation with income (more rain results in higher agricultural income), while too much rain can ruin the crop or damage the infrastructure. The models also show that the natural threshold of rain at which it could be described as "excessive" - from the point of view of domestic violence - is lower than 1 standard deviation above the long-term average.

2.6 Appendix

	Dependent Variables:							
	Any Violence		Sexual Violence		Physical Violence		Emotional Violence	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Normalized Rain, Survey Year	**-0.007**	**-0.006**	**-0.003**	**-0.002**	-0.007	**-0.006**	**0.002**	**0.005**
	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.007)
Normalized Rain, Previous Year		**0.001**		**0.005**		**0.004**		**-0.002**
		(0.005)		(0.003)		(0.004)		(0.007)
Normalized Rain Squared, Survey Year	**-0.006**	**-0.006**	**-0.005**	**-0.005**	-0.006	**-0.006**	**-0.002**	**-0.002**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Normalized Rain Squared, Previous Year		**0.004**		**-0.003**		**-0.001**		**0.009**
		(0.004)		(0.002)		(0.004)		(0.005)
Respondent's Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
History of Violence	YES	YES	YES	YES	YES	YES	YES	YES
Region Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Mean of Rate of Violence	0.36	0.36	0.09	0.09	0.29	0.29	0.21	0.21
S.D of Rate of Violence	0.48	0.48	0.29	0.29	0.45	0.45	0.40	0.40
Number of Observation	145,313	145,313	136,275	136,275	145,282	145,282	99,015	99,015

*, **, and *** indicate significance at 10%, 5%, and 1%, respectively.
Data clustered by region
Rainfall data is recorded at the local (sub-region geo-location) level. This level of granual geo-location information is only available for a subset of the sample
Age and age difference are divided by 100, and years of eduation is divided by 10 to bring coefficiens to a comparable range

Table 2.4: Effect of rainfall on prevalence of domestic violence, rainfall data matched to respondents at individual level

	Dependent Variables							
	Any Violence		Sexual Violence		Physical Violence		Emotional Violence	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Shocks								
Wet Shock, Survey Year	**0.405***** (0.067)	**0.017***** (0.005)	**0.190***** (0.033)	**0.053***** (0.003)	**0.241***** (0.057)	**-0.041***** (0.004)	**0.288***** (0.035)	**0.048***** (0.003)
Dry Rainfall Shock, Survey Year	**0.156*** (0.090)	**0.156*** (0.090)	0.021 (0.042)	0.021 (0.042)	**0.156**** (0.077)	**0.156**** (0.077)	0.035 (0.053)	0.035 (0.053)
Wet Shock, Previous Year		**0.388***** (0.072)		**0.137***** (0.036)		**0.282***** (0.061)		**0.240***** (0.037)
Dry Shock, Previous Year		0.095 (0.090)		0.039 (0.042)		**0.128*** (0.077)		0.063 (0.053)
Respondent's Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
History of Violence	YES	YES	YES	YES	YES	YES	YES	YES
Region Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Mean of Rate of Violence	0.36	0.36	0.09	0.09	0.29	0.29	0.21	0.21
S.D of Rate of Violence	0.48	0.48	0.29	0.29	0.45	0.45	0.40	0.40
Number of Observation	178,852	178,852	173,131	173,131	178,834	178,834	135,039	135,039

*, **, and *** indicate significance at 10%, 5%, and 1%, respectively.
Data clustered by region
Rainfall data is recorded at the regional level for all samples.
Rainfall shock is calculated based on one standard deviation distance from long-term average rainfall for the region.
Age and age difference are divided by 100, and years of eduation is divided by 10 to bring coefficiens to a comparable range

Table 2.5: Effect of rainfall shock on prevalence of domestic violence; shock defined as one standard deviation variation from long term average rainfall

In Table 2.6 below, we try to replicate the works of past researchers - as explained in the literature review - by defining a rainfall shock to be 1 standard deviation variation from long-term average annual precipitation. “Wet shock” is defined as a dummy variable which takes the value of 1 when annual rainfall is one standard deviation above the long-run average rainfall for that specific district or region. “Dry shock” is defined as a dummy variable which takes the value of 1 when annual rainfall is one standard deviation below the long-run average rainfall for the specific district or region. Shocks are defined for two time periods and we run alternative models to estimate the impact of each

1. 1 year prior to the survey: 1 through 12 months before the interview date
2. 2 years prior to the survey: 13 through 24 months before the interview date

The results are consistent with our main analysis, as well as confirming the findings of previous literature: both wet shocks and dry shocks increase domestic violence, almost consistently across all types of violence experiences.

Chapter 3

The Demographics of Domestic Violence: A Multi-country Study

Abstract

Domestic violence is a globally widespread issue which has consequences beyond physical or psychological harm to victims. The root causes of occurrence and prevalence of domestic violence has been studied by many researchers across the world. In this paper we explore how demographic and household characteristics could increase or decrease intimate partner violence. We study a cross-sectional sample of ever married women between the ages of 15 and 49 from 25 countries, obtained from the Demographic and Health Survey (DHS). We find that family history of violence makes girls more likely to experience and even accept and justify violence by their intimate partners. Furthermore, the results show that poorer households, less educated women, and younger women are more prone to experiencing domestic violence. Being employed increases a woman's chance of experiencing abuse. The literature attributes this to the gap in social status of men and women. Last but not least, alcohol consumption by

male partners is strongly associated with domestic violence.

3.1 Introduction

Domestic violence is a complex social issue that has devastating consequences for the victims who experience it and traumatic effects on those who witness it, particularly children. It is a human rights issue which affects women, families, communities, and future generations to come. While it continues to be frighteningly common and accepted as "normal" within too many societies, more often than not, the perpetrators are surprisingly well known to their victims.

The United Nations defines domestic violence as: "any act of gender-based violence that results in, or is likely to result in, physical, sexual or psychological harm or suffering to women, including threats of such acts, coercion or arbitrary deprivations of liberty, whether occurring in public or private life". Other literature have defined domestic violence as rape, physical assault, and stalking perpetrated by current and former dates, spouse and cohabiting partners [Tjaden and Thoennes, 2000, Matthews, 2004].

It is theoretically plausible that women's economic empowerment through the process of development may be linked to intimate partner violence. On the one hand, women who earn an income and help themselves and their families, have means to get out of bad marriages or not to marry at all. When women have more options, this should decrease likelihood of their being in an abusive relationship [Rahman et al., 2011]. Or as Kabeer [1994] suggested, poor women are often the most vulnerable to violence. On the other hand, women's economic empowerment may promote male insecurity and feelings of economic inadequacy, leading to more violence in relationships. Hence, promoting women empowerment in the household without men's support may put women at more risk of intimate partner violence.

This study focuses on the demographics and socioeconomic characteristics of victims of domestic violence and their households, aiming to uncover how and to what extent individual and economic empowerment of women is related to domestic violence. We study a cross-sectional sample of more than 375,000 of ever married women between the ages of 15 and 49, in 25 countries over multiple years. This data was obtained from the Demographic and Health Survey (DHS).

Section 3.2 below offers a brief review of the literature which focused on the root causes of domestic violence. Section 3.3 presents the data, variables, and our regression models, and Section 3.4 discusses the results of these models.

3.2 Literature Review

The root causes of domestic violence within various economic, social, and cultural contexts have been the subject of interest for many economists and social scientists. Research has found that lower economic resources and poor standards of life increase the incidence of domestic violence [Yount and Carrera, 2006]. The literature further suggests that women who have more autonomy, mobility and economic independence are relatively safer from such violence [Jejeebhoy and Cook, 1997]. This is also seen to be true for households with a higher level of education. Disparity between husband and wife in terms of education and wages, pointing to a superior socioeconomic status for women would, however, lead to an increase in domestic violence [Thoits, 1992].

This literature review categorizes the root causes of domestic violence in the respective works of researchers.

3.2.1 Resources, Income and Status

Household Socioeconomic Status

Studies show that domestic abuse is correlated with socioeconomic status. Yount and Carrera [2006] studied the effect of resource availability and formative experiences on domestic violence using a sample of more than two thousand married Cambodian women. They found that a higher standard of living decreased the incidence of physical domestic violence. Another correlation study found a positive relationship between low socioeconomic status and higher incidence of domestic violence in India [Jejeebhoy and Cook, 1997]. The study further showed that households with fewer consumer durables had a higher frequency of domestic violence. They were able to show that in India, where wife beating is rather a common phenomenon; women with higher autonomy, mobility and economic independence fared better than others when measuring domestic violence. These women were noticed be better educated and married later than average. Moreover, a link between dowry and domestic violence was found; women who had higher dowries were shown to be relatively safer from domestic abuse. Many other papers, including Koenig et al. [2003] and Hoffman et al. [1994] linked higher education, better socioeconomic status and larger land holdings to lower incidence of domestic violence, at a global scale. Hoffman et al., in an effort to quantify this behavior, developed an index linking family income and husband's education and employment levels to the frequency of wife abuse.

Women's Income, Wealth, and Independence

Patriarchal households, in which male dominance is norm, are quite common in many traditional societies [Hoffman et al., 1994, Gelles, 1993]. Traditional male-dominant family dynamic puts a lot of pressure on husbands to be in power and in control. As a result of this pressure, husbands with less resources may often view themselves as inadequate. This could lead them to engage in violence against their family, in order to establish the perception of control and dominance. This tendency is further amplified when women in such households do not possess the economic and personal resources necessary to live outside their violent relationships [Gelles, 1993]. This incidence of violence does not necessarily ensue from the husband's feeling of inadequacy, but is reinforced by the lack of independence and wealth from the spouse. The study by Yount and Carrera [2006] offers a rationale for this violence: that higher stress levels linked to resource scarcity may induce domestic violence. It is important to note that these correlations are not necessarily indicative of a causal relationship leading to violence. But rather strong association, some of which may be causal.

Moreover, literature shows that women's asset ownership can significantly reduce the incidence of domestic violence. Bhattacharyya et al. [2011] and Panda and Agarwal [2005] found that ownership of property by women's strongly correlated with abuse. The argument follows that property ownership increases economic security and thus makes it less likely that a woman will stay in an abusive relationship. These studies suggest that since steady income generating opportunities and ownership over property reduces the chances of domestic violence, policies encouraging these opportunities for women can aid in making them less vulnerable to violence.

Similarly, Schuler et al. [1996] suggests that self help groups and similar credit schemes increase the financial independence of women, thereby reducing incidents of domestic violence. In addition to financial resources, such schemes make women more visible in the public arena, further reducing the threats and likelihood of abuse.

Mocan and Cannonier [2012] studied the effects of education on domestic violence in Sierra leone. Their study found that the recent educational programs in Sierra Leone has greatly benefited primary school children and had little effect on older students. They use this discrepancy to highlight the positive changes in women's attitude towards health and domestic violence brought about by education. The same program, however, failed to have any positive effect on the male students and their views on domestic violence.

Status Inconsistency in the Partnership

The research discussed above showed that financial independence and education are correlated with reduced domestic violence. However, a detailed study in this regard shows that women whose socioeconomic status exceeds that of their male partners are more prone to violence. This, as explained by Thoits [1992], is because the male partner might feel threatened by his spouse's higher status and may resort to violence as a means of control. In another study with similar findings, Hornung et al. [1981] found that in Kentucky, women with higher educational qualifications than their spouses were more likely to suffer severe violence. Violence was also prevalent between couples with equal educational qualifications where women had a higher income, according to Anderson [1997]. In essence, the likelihood of a woman suffering spousal abuse depends not only on her employment status, but on that of her partner's as well. Macmillan and Gartner [1999] claim that the difference in socioeconomic levels between spouses determines the effort men are likely to put into controlling their spouses.

This finding is not uniform across all countries and cultural backgrounds. Anderson [1997] found that this form of violence was not evident in Canada. In Thailand, the difference in spousal education and prestige, adjusted for socioeconomic status, had no effect on the likelihood of domestic violence [Hoffman et al., 1994]. Moreover, Yllö [1983] identified a U-shaped relationship between status of the female and domestic violence in the United States. A very low socioeconomic status reduces the options available to a woman, thereby making her more prone to violence. Similarly, a high socioeconomic status is likely to threaten the male ego, leading to more violence.

Other researchers have also identified patterns where the difference in the partner's status is a stronger predictor of domestic violence than the absolute status of men or women. Hornung et al. [1981] developed a theoretical understanding of the links between spousal abuse and socioeconomic status of the parties involved. They found that a difference in status between partners is the key parameter governing the likelihood of spousal abuse. As status discrepancy (and not absolute status) is the key parameter, it was noted that the housewives in Kentucky were often less likely to have experienced violent relationships than their employed counterparts. The wife's objective (economic) and subjective (perceived) dependence on the marriage and its relation to spousal abuse is also studied by Kalmuss and Straus [1982] using a sample of 2143 adult men and women from the United States. While psychological (subjective) dependence often resulted in incidents of minor violence, it is mostly objective dependence (or lack of financial freedom) that forces women to stay in severely violent relationships.

Aizer [2007] identified female-male wage gap as the major factor governing incidents of domestic violence. A smaller wage gap reduced spousal abuse. Using survey and administrative data, she linked the recently improved labor market conditions for women to a 10% reduction in incidents of domestic violence. Equal representation of women in high wage industries may reduce this wage gap, and consequently will reduce violence against women by another 16%. She also suggests that the decrease in domestic violence in lower wage gap families may also improve child health in these families.

Dugan et al. [1999] used data from 29 major US cities for the years 1976 to 1992, and postulated that employment of either partner reduces domestic violence as employment decreases the time available for domestic abuse. In support of the idea that economic empowerment can decrease intimate partner violence, Blumberg [1988] provides evidence that having their own income improves women's ability to have a say over fertility preferences, input into household decision-making, and self-esteem. Accordingly, when women feel empowered, they are better able to take action at the household level to improve their own and their children's well-being. In contrast to the inverse association between women's economic empowerment and domestic violence, he also points to evidence that women who gain more domestic power due to earned income, they may also face resistance and violence from their spouses.

Employment and Divorce

Researchers have also found a relationship between divorce and domestic abuse. Bowlus and Seitz [2006] studied the effect of domestic abuse on employment status and divorce rates. The results show that abusive relationships are more likely to end in divorce, and victims are more likely to be employed regardless of their marital status. In addition, the study found that children who grow up in abusive households have higher tendency to enter into abusive relationships themselves. Furthermore, they noticed marked differences between the average abusive couple when compared to their nonviolent counterparts. Abused women are less likely to have acquired higher education. The victims usually marry early, and are likely to have children at a younger age than women in nonviolent relationships. Furthermore, they are less likely to participate in workplace activities or take up full year employment.

Another recent research on Bangladesh [Heath, 2014] found similar results. The study found that the domestic violence was rather higher among employed women. However, the paper uses data only of women who were married at a young age and did not possess higher education. Using data from 60 villages around Dhaka; the author shows that women who do paid work were 4.7% more likely to suffer from domestic abuse than their nonworking counterparts. The risk of abuse among nonworking women goes up by 0.3% annually as the subject ages. The corresponding rise among working females is reported to be 1.4%. Heath explains that this rise in domestic violence is an attempt to negate the increase in women's bargaining power created by employment.

Contrary to the above, a study by Bhattacharyya et al. [2011] using data from an underdeveloped village, Kaushambi in India, found a negative relationship between domestic violence and female employment and property ownership.

Finally, Eswaran and Malhotra [2011] present a non-cooperative model for typical South Asian households. Their study shows that in this region, husbands use violence as a tool for controlling their wives; thereby having better control over domestic resources. In these societies, it is seen that employment may raise a woman's chances of getting abused. Among employed women, those who worked away from home are more likely to encounter greater domestic violence.

3.2.2 History of Violence

Studies show that exposure to violence at young age is correlated with a person's chances of being in an abusive relationship as an adult. Growing up amidst family violence leads to the belief that abuse is normal. Young boys from such households are more likely to become abusive husbands later. Girls with similar backgrounds have lower self esteem, and are more likely to stay in abusive relationships as adults [Jewkes et al., 2001, Kalmuss, 1984, Martin et al., 2002, Whitfield et al., 2003]. This could as well be a results of inter-generational poverty, or culture, being passed to the next generation, instead of a direct causal effect of violent upbringing on violent behavior in future.

While there is contrasting research [Ellsberg et al., 1999], a meta analysis with 52 samples from the US highlight the influence of violent childhood experiences, especially those in the wife's family, on domestic violence after marriage [Hotaling and Sugarman, 1986]. Data from US illustrates that boys who grew up watching their mothers getting abused are as adults, three times more likely to become abusive husbands [Strauss et al., 1980]. Yount and Carrera [2006] also showed that having surviving parents or siblings did not affect domestic violence or the attitude towards wife beating. However, children growing up in urban households with strict fathers were more likely to experience physical and psychological abuse. Similarly, domestic violence against mothers is highly correlated with the prevalence of children having violent relationships as adults.

3.3 Data and Model

3.3.1 Data Sources: DHS Survey Data

The data for this study is obtained from the Demographic and Health Surveys (DHS) program. The DHS program is described in Section 2.5.1 of the previous chapter. As mentioned there, the DHS questionnaire surveys women between the ages of 15 to 49 years, and includes data points such as age, marital status, contraceptive use, education, employment, and empowerment status, as well as their husband's education, occupation, and alcohol consumption.

3.3.2 Regression Models

In this study we run three regressions using different combinations of independent variables. The first regression shown in Equation 1 estimates the effect of key demographic factors on the rate of violence. Equation 2 shows the second regression which estimates the effect of household characteristics on the rate of violence. In the third regression we use a combination of these two sets of independent variable to build a more comprehensive model.

$$\begin{aligned} Rate\,of\,Violence &= \beta_0 + \beta_1\,Age_{it} + \beta_2\,Education_{it} + \beta_3\,Employment_{it} \\ &+\beta_4\,Wealth\,Index_{it} + \beta_5\,Age * Education_{it} \\ &+\beta_6\,Education * Employment_{it} \\ &+\beta_7 Age\,Difference\,Between\,Husband\,and\,Wife_{it} \\ &+\beta_8\,Husband's\,Education_{it} + \beta_9\,\mu_t + \beta_{10}\,\rho_i + \epsilon_{it} \end{aligned} \tag{3.1}$$

$$\begin{aligned} Rate\,of\,Violence &= \beta_0 + \beta_1 Children_{it} + \beta_2\,History\,of\,Violence_{it} \\ &+\beta_3\,Justify\,Beating_{it} + \beta_4\,Access\,to\,Media_{it} \\ &+\beta_5\,Husband\,Drinks\,Alcohol_{it} + \beta_6 Rural_{it} \\ &+\beta_9\,\mu_t + \beta_{10}\,\rho_i + \epsilon_{it} \end{aligned} \tag{3.2}$$

In these models locations are indexed by i and observational time periods are indexed by t. μ_t is the time fixed effect, ρ_i is the regional fixed effects, and finally ε_{it} is the error term.

3.3.3 Dependent Variables

We categorized experiences of domestic violence into three types and carry out the analysis on these types of violence separately, as well as collectively: physical, sexual, and emotional violence. A detailed description of each type of violence is offered in Chapter 2.

For each of the categories above, we define a dummy variable which carries the value of 1 if the respondent reported experiencing at least one of the defined domestic violence experiences within 12 months prior to the survey. We also define "any violence" as 1 if the respondent reported any one form of violence mentioned above. We treat the dummy as zero if all cases of violence are reported to be absent, or not reported at all (missing). However, if all violence data points are missing, then "any violence" will also be missing.

3.3.4 Independent Variables

We use following variables, where available, as independent variables in the regression models:

- Age of wife
- Age difference between husband and wife
- Education of wife and husband measured in highest year of education
- Wealth index: households are categorized into five groups: poorest, poorer, middle, richer, and richest
- Husband alcohol consumption: dummy if husband / partner drinks alcohol
- Number of living children in the household

- Access to media: if women report listening to radio, watching television, or reading the news on a newspaper or magazine
- Rural or urban lodging
- Employed: dummy variable showing if the female subject is employed
- History of violence
- Time and location fixed effects

A detailed description of history of violence and fixed effects are offered in Section 2.5.4 of the previous Chapter.

3.3.5 Summary Statistics

Table 3.1 shows the number of women interviewed and the number of eligible women by country and year of interview. Eligibility in DHS surveys is defined as women of reproductive age (15 to 49). In some countries, the eligibility criteria restrict the survey to ever married women. Columbia and India have the highest number of survey respondents, contributing 25% and 22% of total number of eligible women to the data set. The smallest countries in the data set are Sao Tome and Principe and Uganda with close to 2000 survey respondents each.

Table 3.2 presents the mean value and standard deviation of key demographic data points and household information, by different violence experiences, compared to the general population of survey respondents. In some variables there is a clear gap between the group of women who did not report experiencing any violence and those who were victims of violence. For example, proportion of women who believe husbands' beating of their wife is justified is almost double among victims compared to non-victims. Also, victims have twice the proportion of women with a history of violence in their parents' house, than non-victims. Another noticeable pattern is that the proportion of employed women is significantly higher among victims. Finally, the prevalence of alcohol consumption is much higher among husbands of the victims than non-victims, speaking to the role of alcohol in domestic violence.

Country	Dates of Fieldwork	Number of Women Interviewed	Number of Eligible Women
Azerbaijan	2006	8,444	5,617
Bangladesh	2007	21,992	8,934
Cambodia	2000	15,351	2,403
Cambodia	2005	16,823	2,901
Cameroon	2004	10,656	3,290
Colombia	2005	41,344	40,791
Colombia	2010	53,521	52,952
Congo	2007	9,995	3,436
Dominican Republic	2002	23,384	8,746
Dominican Republic	2007	27,195	10,140
Haiti	2002	10,159	10,159
Haiti	2005	10,757	3,568
Honduras	2005	19,948	19,948
India	2005	124,385	83,703
Jordan	2007	10,876	3,444
Kenya	2003	8,195	5,878
Kenya	2008	8,444	6,318
Liberia	2007	7,092	4,913
Malawi	2004	11,698	9,707
Malawi	2010	23,020	6,229
Mali	2006	14,583	9,849
Moldova	2005	7,440	5,695
Nigeria	2008	33,385	23,752
Rwanda	2005	11,321	4,066
Rwanda	2010	13,671	5,008
Sao Tome and Principe	2008	2,615	1,980
Tanzania	2010	10,139	7,047
Timor-Leste	2009	13,137	2,951
Uganda	2006	8,531	2,087
Ukraine	2007	6,841	2,903
Zambia	2007	7,146	5,236
Zimbabwe	2005	8,907	6,293
Zimbabwe	2010	9,171	6,542
Total		**610,166**	**376,486**

Table 3.1: Number of women interviewed, and number of eligible women defined as ever-married and between the ages of 15 and 49

	Women Who Experienced Violence			Reported No Violence	All Respondents
	Physical Violence	Sexual Violence	Emotional Violence		
Respondent's Characteristics:					
Age	32.33	31.99	32.27	32.32	29.15
	(8.66)	(8.70)	(8.64)	(8.96)	(9.91)
Years of Education	4.12	4.15	4.26	4.25	4.13
	(1.95)	(2.00)	(2.03)	(1.93)	(1.95)
Employed	0.65	0.68	0.68	0.56	0.55
	(0.48)	(0.47)	(0.47)	(0.50)	(0.50)
Living in Rural Area	0.59	0.61	0.61	0.54	0.52
	(0.49)	(0.49)	(0.49)	(0.50)	(0.50)
Number of Children Ever Born	3.32	3.37	3.41	2.90	2.30
	(2.28)	(2.35)	(2.40)	(2.27)	(2.37)
Justify Beating	0.44	0.45	0.51	0.32	0.35
	(0.50)	(0.50)	(0.50)	(0.47)	(0.48)
History of Violence in the Family	0.53	0.53	0.46	0.27	0.38
	(0.50)	(0.50)	(0.50)	(0.44)	(0.48)
Husband's Characteristics:					
Age	37.94	37.54	38.54	37.96	37.96
	(10.15)	(10.30)	(10.44)	(10.50)	(10.46)
Education	6.61	6.61	6.58	7.59	7.26
	(5.02)	(4.75)	(4.70)	(5.25)	(5.18)
Drink Alcohol	0.58	0.59	0.55	0.37	0.44
	(0.49)	(0.49)	(0.50)	(0.48)	(0.50)

The numbers in parentheses are standard deviations

Table 3.2: General characteristics of respondents, by type of violence experience

3.4 Results

Tables 3.3 shows the results of the regressions for domestic violence on various household demographic and behavioral characteristics.

The results show that higher educated women experience a lower rate of violence, a testimony to the role of education in empowering women against domestic violence. Moreover, the husbands' years of education is also a major contributing factor in reducing domestic violence. However, empowerment is not always a means of reducing domestic violence. For example women's employment has a positive and significant coefficient. This means that employment, after controlling for its effect on wealth, could increase the rate at which women fall victim to domestic violence. This is in line with findings of other researchers who showed that male partners of employed women see their partner's empowerment as a threat to their traditional dominance in the household, hence resort to violence to counteract their spouses' increased bargaining power [Blumberg, 1988, Heath, 2014].

Women who are taught that husbands' acts of violence could be justified in certain circumstances, are more frequently victims of such acts later in life. The results also confirm that younger women experience more violence, and it only grows if they have a family history of violence or their partners consume alcohol.

Wealth, as explained before, is a predictor of lower violence, since higher standards of life lowers the household stress levels and reduces scarcity of resources. On the other hand, having more children is highly correlated with the prevalence of violence, indicating that women may be more likely to stay in abusive relationships if they have children. Yet again, we can't definitively conclude causality from these results.

	Dependent Variables:			
	Any Violence	Sexual Violence	Physical Violence	Emotional Violence
Respondent's Characteristics:				
Age	**-0.26*** **	**-0.08*** **	**-0.27*** **	**-0.08*** **
	(0.03)	(0.02)	(0.04)	(0.04)
Years of Education	**-0.03*** **	**-0.02*** **	**-0.03*** **	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Respondent Is Employed	**0.05*** **	0.01	**0.05*** **	**0.04*** **
	(0.01)	(0.01)	(0.01)	(0.01)
Years of Education * Employed	0.00	**0.03*** **	-0.01	-0.01
	(0.02)	(0.01)	(0.02)	(0.02)
Wealth Index	**-0.02*** **	**-0.003*** **	**-0.01*** **	**-0.01*** **
	(0.00)	(0.00)	(0.00)	(0.00)
Number of Living Children	**0.02*** **	**0.01*** **	**0.02*** **	**0.01*** **
	(0.00)	(0.00)	(0.00)	(0.00)
Rural	**-0.04*** **	0.00	**-0.04*** **	**-0.02*** **
	(0.01)	(0.00)	(0.01)	(0.01)
Husband's Characteristics:				
Age Difference b/w Husband and Wife	**-0.12*** **	**-0.01*** **	**-0.16*** **	0.03
	(0.03)	(0.02)	(0.03)	(0.03)
Husband's Years of Education	**-0.06*** **	**-0.03*** **	**-0.05*** **	**-0.04*** **
	(0.01)	(0.00)	(0.01)	(0.01)
Husband Drinks Alcohol	**0.15*** **	**0.05*** **	**0.15*** **	**0.10*** **
	(0.01)	(0.00)	(0.01)	(0.01)
History of Violence in Family				
Father Beat her/Her Mother	**0.20*** **	**0.05*** **	**0.18*** **	**0.11*** **
	(0.01)	(0.01)	(0.01)	(0.01)
Women Justify Wife-Beating	**0.07*** **	**0.02*** **	**0.07*** **	**0.04*** **
	(0.01)	(0.00)	(0.01)	(0.01)
Year Fixed Effect	YES	YES	YES	YES
Country Fixed Effect	YES	YES	YES	YES
Sample Mean (any violence)	0.36	0.09	0.29	0.21
Sample St.Dev.	0.48	0.29	0.45	0.40
Number of Observation	127,450	121,730	127,432	108,837

Age and age difference are divided by 100, and years of eduation is divided by 10 to bring coefficiens to a comparable
*, **, and *** indicate significance at 10%, 5%, and 1%, respectively.
Data clustered by region

Table 3.3: Regression of prevalence of any type of violence on general characteristics of subjects, history of violence in family, justification of violence, prevenlance of alcohol use

3.5 Conclusion

Intimate partner violence is one of the most complex interpersonal dynamics of human behavior where victims suffer physical and psychological harm by the hands of their intimate partners. Many researchers have tried to identify the root causes of domestic violence in various socioeconomic, cultural, and demographic contexts. This paper uses data from over 375,000 surveys reporting on domestic violence in various forms in 25 countries, reported by the Demographic and Health Survey (DHS). We study the relationship between domestic violence and victims, individual and household demographics. The results show that girls who witness or experience violence by their fathers at home are more likely to suffer from it as an adult. Furthermore, younger women and those with less education are at a higher risk of violence. On the other hand, we show that wealthier households who have less concerns about resource scarcity, have lower rates of violence. Finally, while education is correlated with reduced rates of violence against women, being employed - controlling for its effect on wealth - is positively correlated with violence. This is believed to be due to the fact that male partners feel that their traditional dominance in the family is threatened when their wife gains higher social status.

3.6 Appendix

	Any Violence	Sexual Violence	Physical Violence	Emotional Violence
Educational Attainment				
No education	29.03	26.76	29.99	29.05
Incomplete primary	21.73	26.31	21.24	22.88
Complete primary	13.25	14.35	13.33	13.28
Incomplete secondary	21.78	21.27	21.53	22.01
Complete secondary	8.39	6.89	8.47	7.27
Higher	5.81	4.43	5.43	5.51
p-value	*0.00*	*0.00*	*0.00*	*0.00*
Employment Status				
All year	56.05	52.28	56.14	56.1
Seasonal	35.8	38.05	35.88	36.09
Occasional	8.01	9.45	7.84	7.67
p-value	*0.00*	*0.00*	*0.00*	*0.00*
Wealth Index				
Poorest	20.94	21.53	21.27	21.17
Poorer	22.29	22.3	22.54	22.47
Middle	21.7	22.21	21.8	21.07
Richer	19.85	19.65	19.83	19.57
Richest	15.21	14.31	14.56	15.72
p-value	*0.00*	*0.00*	*0.00*	*0.00*
Women Don't Access to				
News paper	73.2	73.83	75.03	69.75
Radio	42.08	39.48	44.03	38.5
Television	50.63	56.65	50.45	50.4
Residence				
Urban	40.83	38.71	41.02	39.35
Rural	59.17	61.29	58.98	60.65
p-value	*0.00*	*0.00*	*0.00*	*0.00*
Husband's Years of Education				
No education	20.05	17.59	20.64	20.06
Incomplete primary	21.82	25.24	22.06	20.65
Complete primary	11.55	12.92	11.36	12.44
Incomplete secondary	29.63	29.34	30.11	27.25
Complete secondary	7.89	7.12	7.45	10.07
Higher	7.42	5.87	6.88	7.43
p-value	*0.00*	*0.00*	*0.00*	*0.00*
Times partner gets drunk				
Never	14.73	13.26	14.09	10.62
Often	33.79	43.25	35.56	37.76
Sometimes	51.21	43.14	50.11	51.25
p-value	*0.00*	*0.00*	*0.00*	*0.00*
History of Violence in Family				
Father beat her	4.1	4.23	4.33	4.66
Mother beat her	5.57	5.9	5.71	6.58
Fathe beat her mother	37.63	41.77	39.78	37.11
p-value	*0.00*	*0.00*	*0.00*	*0.00*
Women Justify Wife-Beating If She				
goes out without telling her husband	29.26	30.18	29.13	34.71
neglects the children	32.41	33.41	32.35	37.98
argues with her husband	27.75	28.3	27.96	32.36
refuses to have sex with her husband	19.4	22.35	18.86	23.69
burns the food	16.88	17.5	17.31	18.93
p-value	*0.00*	*0.00*	*0.00*	*0.00*

Table 3.4: Women characteristics and rate of different forms of violence in the past 12 months among eligible women

References

Alberto Abadie and Javier Gardeazabal. The economic costs of conflict: A case study of the basque country. *The American Economic Review*, 93(1):113–132, 2003.

Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Synth: An r package for synthetic control methods in comparative case studies. *Journal of Statistical Software*, 42(13), 2011.

Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association*, 2012.

Anna Aizer. Wages, violence and health in the household. Technical report, National Bureau of Economic Research, 2007.

Richard Akresh. In) efficiency in intrahousehold allocations. 2008.

Kristin L Anderson. Gender, status, and domestic violence: An integration of feminist and family violence approaches. *Journal of Marriage and the Family*, pages 655–669, 1997.

Kajsa Åsling-Monemi, Rodolfo Peña, Mary Carroll Ellsberg, and Lars Åke Persson. Violence against women increases the risk of infant and child mortality: a case-referent study in nicaragua. *Bulletin of the World Health Organization*, 81(1):10–16, 2003.

Orazio Attanasio and Valerie Lechene. Tests of income pooling in household decisions. *Review of economic dynamics*, 5(4):720–748, 2002.

Lawrence M Berger and Jane Waldfogel. Maternity leave and the employment of new mothers in the united states. *Journal of Population Economics*, 17(2): 331–349, 2004.

Manasi Bhattacharyya, Arjun S Bedi, and Amrita Chhachhi. Marital violence and women's employment and property status: Evidence from north indian villages. *World Development*, 39(9):1676–1689, 2011.

David S Blakeslee and Ram Fishman. Rainfall shocks and property crimes in agrarian societies: Evidence from india. *Available at SSRN 2208292*, 2013.

Francine D Blau and Lawrence M Kahn. Female labor supply: Why is the us falling behind? Technical report, National Bureau of Economic Research, 2013.

Rae Lesser Blumberg. Income under female versus male control hypotheses from a theory of gender stratification and data from the third world. *Journal of Family Issues*, 9(1):51–84, 1988.

Richard Blundell, Pierre-Andre Chiappori, Thierry Magnac, and Costas Meghir. Collective labour supply: Heterogeneity and non-participation. *The Review of Economic Studies*, 74(2):417–445, 2007.

Gustavo J Bobonis. Is the allocation of resources within the household efficient? new evidence from a randomized experiment. *Journal of political Economy*, 117(3):453–503, 2009.

Anjali Thomas Bohlken and Ernest John Sergenti. Economic growth and ethnic violence: An empirical investigation of hindu-muslim riots in india. *Journal of Peace research*, 2010.

Audra J Bowlus and Shannon Seitz. Domestic violence, employment, and divorce. *International Economic Review*, 47(4):1113–1149, 2006.

Lucy Burns. World drug report 2013 by united nations office on drugs and crime new york: United nations, 2013isbn: 978-92-1-056168-6, 151 pp. grey literature. *Drug and Alcohol Review*, 33(2):216–216, 2014.

Pierre-André Chiappori. Rational household labor supply. *Econometrica: Journal of the Econometric Society*, pages 63–90, 1988.

Pierre-André Chiappori and Olivier Donni. Non-unitary models of household behavior: A survey of the literature. 2009.

Laura Dugan, Daniel S Nagin, and Richard Rosenfeld. Explaining the decline in intimate partner homicide the effects of changing domesticity, women's status, and domestic violence resources. *Homicide Studies*, 3(3):187–214, 1999.

Mary C Ellsberg, Rodolfo Pena, Andres Herrera, Jerker Liljestrand, and Anna Winkvist. Wife abuse among women of childbearing age in nicaragua. *American journal of public health*, 89(2):241–244, 1999.

Cassandra D Engeman. Ten years of the california paid family leave program. 2012.

Mukesh Eswaran and Nisha Malhotra. Domestic violence and women's autonomy in developing countries: theory and evidence. *Canadian Journal of Economics/Revue canadienne d'économique*, 44(4):1222–1263, 2011.

RichardJ Gelles. Through a sociological lens: Social structure and family violence. 1993.

Jeffrey S Gray. Divorce-law changes, household bargaining, and married women's labor supply. *The American Economic Review*, 88(3):628–642, 1998.

Rachel Heath. Women's access to labor market opportunities, control of household resources, and domestic violence: Evidence from bangladesh. *World Development*, 57:32–46, 2014.

Kristi L Hoffman, David H Demo, and John N Edwards. Physical wife abuse in a non-western society: an integrated theoretical approach. *Journal of Marriage and the Family*, pages 131–146, 1994.

Carlton A Hornung, B Claire McCullough, and Taichi Sugimoto. Status relationships in marriage: Risk factors in spouse abuse. *Journal of Marriage and the Family*, pages 675–692, 1981.

Gerald T Hotaling and David B Sugarman. An analysis of risk markers in husband to wife violence: The current state of knowledge. *Violence and victims*, 1(2):101–124, 1986.

Solomon M Hsiang, Marshall Burke, and Edward Miguel. Quantifying the influence of climate on human conflict. *Science*, 341(6151):1235367, 2013.

Shireen J Jejeebhoy and Rebecca J Cook. State accountability for wife-beating: the indian challenge. *The Lancet*, 349:S10–S12, 1997.

Rachel Jewkes, Loveday Penn-Kekana, Jonathan Levin, Matsie Ratsaka, and Margaret Schrieber. Prevalence of emotional, physical and sexual abuse of women in three south african provinces. *South African medical journal= Suid-Afrikaanse tydskrif vir geneeskunde*, 91(5):421–428, 2001.

Naila Kabeer. *Reversed realities: Gender hierarchies in development thought*. Verso, 1994.

Debra Kalmuss. The intergenerational transmission of marital aggression. *Journal of Marriage and the Family*, pages 11–19, 1984.

Debra S Kalmuss and Murray A Straus. Wife's marital dependency and wife abuse. *Journal of Marriage and the Family*, pages 277–286, 1982.

Sunita Kishor and Kiersten Johnson. Profiling domestic violence: a multi-country study. 2004.

Michael A Koenig, Saifuddin Ahmed, Mian Bazle Hossain, and ABM Khorshed Alam Mozumder. Women's status and domestic violence in rural bangladesh: individual-and community-level effects. *Demography*, 40(2): 269–288, 2003.

Shelly Lundberg. Labor supply of husbands and wives: A simultaneous equations approach. *The Review of Economics and Statistics*, pages 224–235, 1988.

Shelly Lundberg and Robert A Pollak. Noncooperative bargaining models of marriage. *The American Economic Review*, 84(2):132–137, 1994.

Shelly Lundberg and Robert A Pollak. Marriage market equilibrium and bargaining in marriage. *manuscript, University of Washington*, 2008.

Shelly J Lundberg, Robert A Pollak, and Terence J Wales. Do husbands and wives pool their resources? evidence from the united kingdom child benefit. *Journal of Human resources*, pages 463–480, 1997.

Ross Macmillan and Rosemary Gartner. When she brings home the bacon: Labor-force participation and the risk of spousal violence against women. *Journal of Marriage and the Family*, pages 947–958, 1999.

Sandra L Martin, Kathryn E Moracco, Julian Garro, Amy Ong Tsui, Lawrence L Kupper, Jennifer L Chase, and Jacquelyn C Campbell. Domestic violence across generations: findings from northern india. *International journal of epidemiology*, 31(3):560–572, 2002.

Dawn D Matthews. *Domestic Violence Sourcebook: Basic Consumer Health Information about the Causes and Consequences of Abusive Relationships, Including Physical Violence, Sexual Assault, Battery, Stalking, and Emotional Abuse... Along with a Glossary of Related Terms and Resources for Additional Help and Information*. Omnigraphics Incorporated, 2004.

Patrick C McKenry, Teresa W Julian, and Stephen M Gavazzi. Toward a biopsychosocial model of domestic violence. *Journal of Marriage and the Family*, pages 307–320, 1995.

Halvor Mehlum, Edward Miguel, and Ragnar Torvik. Poverty and crime in 19th century germany. *Journal of Urban Economics*, 59(3):370–388, 2006.

Edward Miguel. Poverty and witch killing. *The Review of Economic Studies*, 72(4):1153–1172, 2005.

Naci H Mocan and Colin Cannonier. Empowering women through education: Evidence from sierra leone. Technical report, National Bureau of Economic Research, 2012.

United Nations Office on Drugs and Crime. *Global study on homicide 2013: trends, contexts, data*. 2013.

Sonia Oreffice. Did the legalization of abortion increase women's household bargaining power? evidence from labor supply. *Review of Economics of the Household*, 5(2):181–207, 2007.

World Health Organization et al. Who multi-country study on women's health and domestic violence against women: summary report of initial results on prevalence, health outcomes and women's responses. 2005.

World Health Organization et al. Department of reproductive health and research, london school of hygiene and tropical medicine, south african medical research council. *Global and regional estimates of violence against women prevalence and health effects of intimate partner violence and non-partner sexual violence. Geneva, Switzerland: World Health Organization*, 2013.

Pradeep Panda and Bina Agarwal. Marital violence, human development and women's property status in india. *World Development*, 33(5):823–850, 2005.

Mosfequr Rahman, Md Aminul Hoque, and Satoru Makinoda. Intimate partner violence against women: Is women empowerment a reducing factor? a study from a national bangladeshi sample. *Journal of Family Violence*, 26(5):411–420, 2011.

Maya Rossin-Slater, Christopher J Ruhm, and Jane Waldfogel. The effects of california's paid family leave program on mothers' leave-taking and subsequent labor market outcomes. *Journal of Policy Analysis and Management*, 32(2):224–245, 2013.

Christopher J Ruhm. The economic consequences of parental leave mandates: Lessons from europe. Technical report, National bureau of economic research, 1996.

Sieglinde A Saenger. Family violence: A review of the dysfunctional behavior patterns. *Minnesota Center Against Violence and Abuse, MINCAVA electronic clearinghouse*, 2000.

Mayuri Sahay and G Venumadhava. Effects of domestic violence on women. *Global Journal For Research Analysis*, 5(2), 2016.

Paul A Samuelson. Social indifference curves. *The Quarterly Journal of Economics*, pages 1–22, 1956.

Sidney Ruth Schuler, Syed M Hashemi, Ann P Riley, and Shireen Akhter. Credit programs, patriarchy and men's violence against women in rural bangladesh. *Social science & medicine*, 43(12):1729–1742, 1996.

Sheetal Sekhri, Adam Storeygard, et al. Dowry deaths: Consumption smoothing in response to climate variability in india. *Unpublished manuscript*, 2012.

Michael D Smith. Sociodemographic risk factors in wife abuse: Results from a survey of toronto women. *Canadian Journal of Sociology/Cahiers canadiens de sociologie*, pages 39–58, 1990.

Murray Strauss, Richard Gelles, and Suzanne Steinmetz. Behind closed doors: Violence in the family. *Garden City, NY: Anchor/Doubleday*, 1980.

Peggy A Thoits. Identity structures and psychological well-being: Gender and marital status comparisons. *Social Psychology Quarterly*, pages 236–256, 1992.

Patricia Godeke Tjaden and Nancy Thoennes. *Extent, nature, and consequences of intimate partner violence: Findings from the National Violence Against Women Survey*, volume 181867. National Institute of Justice Washington, DC, 2000.

Christopher Udry. Gender, agricultural production, and the theory of the household. *Journal of political Economy*, pages 1010–1046, 1996.

Unicef et al. Hidden in plain sight: A statistical analysis of violence against children. Technical report, eSocialSciences, 2015.

Jane Waldfogel, Yoshio Higuchi, and Masahiro Abe. Maternity leave policies and women's employment after childbirth: evidence from the united states, britain and japan. 1998.

Charles L Whitfield, Robert F Anda, Shanta R Dube, and Vincent J Felitti. Violent childhood experiences and the risk of intimate partner violence in adults assessment in a large health maintenance organization. *Journal of interpersonal violence*, 18(2):166–185, 2003.

Kirk R Williams. Social sources of marital violence and deterrence: Testing an integrated theory of assaults between partners. *Journal of Marriage and the Family*, pages 620–629, 1992.

Kersti Yllö. Sexual equality and violence against wives in american states. *Journal of Comparative Family Studies*, pages 67–86, 1983.

Kathryn M Yount and Jennifer S Carrera. Domestic violence against married women in cambodia. *Social Forces*, 85(1):355–387, 2006.