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ABSTRACT

The Relationship between Female Labor Force Participation and Violent Conflicts in South Asia*

This paper explores the link between the prevalence of violent conflicts and extremely low female labor force participation rates (FLFPR) in South Asia. We merge Labor Force Surveys (LFSs) from Bangladesh, Sri-Lanka, India, and Pakistan to the Global Terrorism Database (GTD) to estimate the relationship between terrorist attacks and female labor supply. We exploit the availability of geographical level data on exposure to violence, comparing administrative units exposed to attacks with administrative units not exposed. We find that one additional attack reduces FLFP rates by about 0.008 percentage points, on average. Violence has less impact on male labor participation, thus widening the gender labor participation gap. Also, one extra wounded person or one extra killed person reduces FLFP rates by 0.0015 and 0.0048 percentage points on average, respectively. We test the added-worker effect theory - which posits that violence might increase FLFP as women try to make up for lost household income - and find mixed evidence: greater prevalence of attacks may encourage married women to exert more working hours, but when the environment gets more risky as number of dead and wounded people increase, all women work less hours. We also test the non- linearity of various violence effects, finding that violence decreases FLFP less where FLFP was already higher before the advent of violence, and that violence has a progressively greater impact on lowering FLFP where the number of attacks is higher.

JEL Classification: J21, F51, O53

Keywords: conflict, terrorism, female labor force participation, added-worker effect, South Asia

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1 Introduction

Countries in the South Asia region exhibit the lowest female labor force participation (FLFP) rates, and violent conflicts in the region have persisted for seventy years. This paper studies the relationship between conflict-related violence and women's decisions to work.

Determinants of FLFP have been extensively studied in developed countries, where it has been either high or increasing over the last 50 years (see Killingsworth and Heckman [1987] for a comprehensive literature review). FLFP rates in South Asia remain lower than in other countries with similar GDP per capita, and these countries have experienced limited progress during the last 16 years. As shown in Figure 1, Iran and Pakistan have the lowest FLFP rates in the region. In India and Sri Lanka FLFP rates keep falling. The literature cites several possible explanations, including:

i. Social and cultural norms and attitudes, since women hold prime responsibility for housework and childcare whereas men are expected to become the "breadwinners" (Field and Vyborny [2015])

ii. Information frictions, as women face longer search times and smaller networks (Schaner and Das [2016])

iii. Lack of appropriate human capital[1].

iv. Discrimination, as women earn between 50% and 70% of men for the same work (Pande et al. [2016])

v. Safety concerns and mobility barriers, since presence of women in public spaces is still rare in these countries (Sudarshan [2009]).

This paper focuses on how violent conflict affects FLFP. More specifically, we focus in the role that terrorism plays in shaping women's decisions about work[2]. Although there is no single universally accepted definition of terrorism, this paper we defines a "terrorist attack" as any threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or "intimidation".(START [2018]). As follows from this definition, terrorism aims to frighten the population and induce a change in behavior.

The directional impact of violence on FLFP, positive or negative, is not obvious, but Figure 2 suggests a negative relation between terrorist attacks incidence and FLFP rates across countries on the surface. There are at least two possible reasons for this negative relationship. On the one hand, Hudson and Leidl [2015] argue that societies that build and support institutions that inhibit FLFP tend to be more violent because reducing the rights of women is conducive to conflict.This argument suggests that long-run, systematic differences across countries increase the probability of violence in regions where women have fewer, or worse,

[1] Mitra and Singh [2006] describe the pathological situation that has taken place in India known as the "Kerala Puzzle" where womens' education has improved but its integration to the labor market has remained low.

[2] Conflicts started decades ago in South Asia have not came to a definite end. Instead, they have reached an equilibrium in which terrorism is used as tactic of war by radical groups but there are not two clear-cut sides in conflict.

labor market opportunities. On the other hand, violence increases the costs of working through the perceived risk of violence, and these costs may be especially salient for workers on the margin of the decision to work. Such a relationship would emerge in time-series data where regions with different exposure levels to violence would experience different FLFP rates accordingly. For example, Khan et al. [2017] find a short-lived negative effect of terrorism on labor market outcomes for Pakistani women that the authors attribute to fear.[3]

Using national-level panel data and novel instrumental variables, Berrebi and Ostwald [2016] find a negative impact of terrorism over female labor force participation. When their cross-country results are updated for the period 1990-2016, however, they prove to be sensitive to the inclusion of explanatory variables in the most parsimonious specifications. As Table 1 shows, the negative relation between violence (approximated by the three variables used throughout this paper) and FLFP looses significance after the inclusion of control variables which hints the existence of some other factors that drive both violence and FLFP. We argue that analyzing local labor markets as we do alleviates the confounding factors problem by exploiting within-country variations in FLFP and violence.

Focusing on the within-country variation in violence, however, may reveal a positive relationship between violence and FLFP. For instance, Gallegos [2012] finds that exposure to conflict between 1980 and 2000 increased the probability of women working in Peru as a mechanism to complement household's income. Menon and van der Meulen Rodgers [2015] show how civil war in Nepal affected women decisions about engaging in work outside the home. Kreibaum and Klasen [2015] estimate the effect of Vietnam's war on FLFP but they use a cohorts approach to find that the "added worker" effect is positive for people directly affected by the war and smaller for those individuals entering working age after the end of the conflict. Although these last two articles depart from our specific focus on terrorism, they are still relevant because they (i) clearly develop the argument of the "additional worker effect" that induces women to participate in the labor force as men are displaced from the household, dead or disabled; (ii) focus in countries with similar work morale, culture, and income level; (iii) focus at the sub-region level and have similar methodological concerns as we do.

This paper focuses on four countries with particularly low FLFP rates. Terrorist attacks have been persistent in these countries after the end of the crudest phase of civil conflicts experienced decades ago. Terrorist attacks in these countries are motivated mainly by political and religious reasons that, fortunately for our empirical approach, are not caused by FLFP per se. Indeed, our identification strategy rests on the fact that terrorist attacks are typically focused in specific places within countries and are not a function of an individual woman's decision to work. Due to data limitations, we are not able to provide a formal account of the motivations for each attack. However, we know that the main driver of the India-Bangladesh conflict

[3] Khan et al. [2017] use individual level data to capture characteristics of labor force but use district level data for violence measures. We argue this is flawed as delivers artificially significant estimates of the effect and deal with it explicitly in our estimation approach.

is rooted in India's 1947 geographic partition, which led to creation of an Islamic majority population in Bangladesh and Pakistan. This issue has remained unsolved, and borders have been disputed and subject to armed conflicts ever since. In the case of Sri Lanka, terrorist groups such as the Liberation Tigers of Tamil Eelam (LTTE) and Janatha Vimukthi Peramuna (JVP) have remained active after being defeated in the Sri Lankan Civil War (1983 to 2009), motivated by ethnic disputes between a Tamil minority and the Sinhalese majority. As a result, terrorism in SriLanka and India has concentrated in specific areas

This paper aimsto estimate the relationship between violence and women's decisions to work in four South Asian countries. In doing so, we aim to extend the literature in two directions. First, while other studies use national-level data, we look at within-country differences in violence using micro-data on employment and (i) number of attacks by administrative division; (ii) number of deaths, and (iii) number of wounded people as proxy measures for violence. Second, we pay particular attention to the distinction between the effect over the extensive and intensive margins; that is, whether women work or do notwork or to not work vis-Ã -vis the number of hours supplied, respectively. As such, our paper extends Menon and van der Meulen Rodgers [2015] and Kreibaum and Klasen [2015] by allowing for the possibility that the added worker hypothesis is at work in the context of terrorism in South Asian countries. In Section 2 we present two simple models that illustrate the relationship between violence and the extensive and intensive margins of female labor supply. Section 3 describes the data use in this paper. Section 4 explains the methods used to estimate the effect of our three violence measures on FLFP. Section 5 describes the results and their implications. Section 6 draws conclusions.

2 Theoretical Considerations

Labor supply decisions are distinguished between the extensive margin, the decision to work or not, and the intensive margin, the decision of how much to work. In this section, we describe the theoretic intuition for each concept in turn.

2.1 The extensive margin of labor supply

Women decide to work if the market wage, w, is above the sum of their reservation home value, h, and the costs of working (paid child care, transportation, and other factors) that we summarize in c. Therefore, the decision to work is represented by a simple equation:

$$\begin{gathered}\text{Work in market if } w-h-c\geq 0\\ \text{Work at home if } w-h-c<0\end{gathered}\tag{1}$$

While the presence of violent conflicts may increase the cost c of working in the market, we argue it is different from other costs because it introduces risk. As long as women do not like risk, we can decompose the cost of violent conflict into a level component that is included in c and the variance (as a component of risk) that we denote by σ^2. Thus, we can augment equation (1) by adding in the variance, or the uncertainty caused by conflicts. The new equation for the decision for a woman to work becomes:

$$\begin{aligned} &\text{Work in market if } w - h - c - \sigma^2 \geq 0 \\ &\text{Work at home if } w - h - c - \sigma^2 < 0 \end{aligned} \tag{2}$$

Importantly, the variance has a non-linear relationship with the probability of a terrorist attack. Specifically, it is very low for low and high probabilities of a terrorist attack, as specified by the solid line in Figure 5. Of course, a full specification of risk would consider the probability of attack times the impact of the event. Thus, the risk would be higher if deaths were involved, as represented by the dashed line. Note, however, that risk rises and then falls due to "banality"; or the psychological adjustment workers make when terrorist events become common and therefore affects behavior similarly to very low-probability terrorist events. In other words, people get used to the violence. In the middle of the range, there is much more uncertainty, which itself is a cost.

If we allow the variables in (1) to be randomized and then aggregated across individuals, simple comparative static predictions match those suggested in the literature. Specifically, the randomized and aggregated version of (1) predicts that, holding all else equal, higher wages (w) will be associated with higher FLFP. In addition, having a working partner (generally a male) will increase h and make FLFP less likely. When a working mate is lost, the reservation wage h falls, making FLFP more likely. This is the added worker effect described in the literature, which could be a result of terrorism (if a mate were a victim of terrorism, for example). Increases in c due to terrorism, such as rising transportation costs, will drive down FLFP linearly. And as discussed above, the nonlinear variance effect may introduce nonlinearity in the results. We evaluate all of these predictions using the data described above using the estimation methodology described in Section 4.

2.2 The intensive margin of labor supply

Instead of choosing whether to participate or to not participate in the labor market, women could choose the number of hours they work in a different way in the presence of violence. To formally allow for this possibility we follow Ashenfelter [1980] and Serneels [2002]. Consider a representative household that maximizes household utility subject to a shared budget constraint. After maximizing, an individual's labor supply (in number of hours) can be written as a function of her wage (w_i), a time constraint ($\overline{H}_i$), labor income from the other household members ($w_j H_j$), and a fixed cost of entering the labor force (f_i)[4].

$$H_i \quad = \quad f(w_i, \overline{H}_i, w_j H_j, f_i) \quad i = 1, .., n; i \neq j \tag{3}$$

We define the labor status of the family members by introducing a discrete variable as follows :

$$\begin{aligned} u_i = g(\overline{H}_i, w_i H_i) =& 1 \text{ if } H_i = 0 \\ =& 0 \text{ if } H_i \geq 0 \end{aligned} \tag{4}$$

Then, we can express the number of hours worked by household member i as a function of her own labor income, household income, labor status of the other members, and a fixed cost of working.

$$H_i \quad = \quad f(w_i, u_1, ..., u_n, f_i) \tag{5}$$

Note that this equation only holds whenever the wage income is high enough to cover the fixed cost of working. In other words, the number of hours is left-censored, so in the data we observe:

$$\begin{aligned} H_i = H_i^* & \text{ if } H_i > 0 \\ =0 \quad & \text{ if } H_i^* \leq 0 \end{aligned} \tag{6}$$

In this model, the heterogeneity summarized in f_i makes the less productive individuals move in and out of the labor force or supply more or less hours. In addition, when a shock as a terrorist attack hits a household, women face two choices: (i) Supply more hours of work to compensate for income lost by the main earner (because he eventually joins one of the bands in conflict or dies as a consequence of it, switching u_j), which is known as "the added worker effect" or (ii) Supply less hours of work, eventually leaving work for safety reasons (by changing f_i).

3 Data

We combine several sources of data, including the Global Terrorism Database and national labor force surveys. Each are described in turn in this section.

3.1 Terrorism in South Asia

The Global Terrorism Database (GTD, START [2018]) systematically records all attacks since 1972 around the world. For an incident to be included in the data-set three conditions are necessary:

[4]This cost may include the opportunity cost (e.g. reservation wage or value of foregone household work) and safety (terrorism risk)

i. It must be intentional;

ii. Must entail some level of violence or immediate threat of violence and

iii. Its perpetrators must be sub-national actors.

Additionally, at least two of the following three criteria must hold:

a. The act must be aimed at attaining a political, economic, religious, or social goal;

b. There must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims;

c. The action must be outside the context of legitimate warfare activities.

The dataset contains different variables that characterize each attack by type: assassination, bombing, kidnapping, and others; and by weapons used, target, perpetrator, and consequences. Critically for this paper, the availability of the number of killed and wounded people as a result of each attack allows measuring the level of violence and the exact coordinates of the incidents to match them to household location (Districts, States or Zilas, depending on availability for each country).

Between 1972 and 2016, Bangladesh suffered 1,605 terrorist attacks, India 10,978, and Sri Lanka 2,981 (GTD, 2016). Businesses have been the target in 10 percent of cases in India and 5 percent in both Sri Lanka and Bangladesh. Government institutions were targeted in 20 percent of cases in Bangladesh, 15 percent in India, and 12 percent in Sri Lanka. Citizens and their property - which includes public areas, markets, commercial streets, busy intersections and pedestrian malls - were targeted in 25 percent of cases in Bangladesh, 26 percent in India, and 19 percent in Sri Lanka. Transportation was targeted in approximately 8 percent of attacks in all three countries. The rest of the target types include tourists, utilities, and educational institutions, among others. Interestingly, religious sites are not particularly targeted, making up less than 4 percent of terrorist cases in all three countries. Lastly, military targets are important only in Sri Lanka (25 percent, versus 1 percent in Bangladesh and 7 percent in India).

As noted earlier, our identification strategy exploits the geographic variation in terrorist attacks. Simply put, when estimating the effect of the incidence of terrorism we compare the administrative units that are not attacked to those attacked after controlling for other relevant explanatory variables. Figure 3 shows the cumulative number of attacks since 1972 in each country by administrative divisions. In Sri Lanka, terrorist groups have targeted the Sinhalese-populated cities of Colombo and Batticaloa; while in India attacks have focused on the disputed west border with Pakistan, the east border with Bangladesh and densely populated cities Mumbai and New Delhi.

3.2 Labor Force Surveys

FLFP rates and distinct individuals' characteristics are measured using labor force surveys (LFS) that, due to our empirical strategy, we later collapse at different administrative divisions depending on the country. Importantly, labor force participation is not measured identically in the different country surveys and even within countries through years but we do our best to capture the notion of the willingness of the individual to work during the previous 7 days to the interview.

For Bangladesh we have data for 64 *zilas* for years 2005, 2010 and 2013; for India we have data of 31 states in years 1999, 2004, 2007, 2009 and 2011; for Sri Lanka we have 17 or 25 districts depending on the year between 1992 and 2015 (data for 2005, 2009 and 2010 is not available).

We merge the GTD to the LFS for each country using year and administrative division. Thus, we have individuals' characteristics for any given year along with the total number of attacks committed, and people killed and wounded for each District, Zilaor State. While individual-level data vary substantially, violence-related data do not since these are measured at the administrative division level. Therefore, we collapse the original data set at the administrative unit level to build a panel-like dataset with variables appropriately transformed to average age, share of males, and share of workers in the manufacturing sector of each administrative unit every year.

Our resulting dataset has two shortcomings: (i) there are many observations in earnings variables missing, which is an important weakness since market wages are a determinant of labor force participation[5] (ii) we lack data on the number of hours worked in India, so we drop this country from our estimations involving hours worked.

3.3 Summary Statistics

Table 2 contains the summary statistics. We obtain the figures presented here for individuals' (older than 15) characteristics by averaging the multiple geographical areas over time and by country separately. Violence variables also represent the average of the total number of attacks and deaths and wounded people in a given year and area (note that when we do not observe attacks, we impute a "zero" to all three variables). We observe a wide gender gap in labor force participation in all four countries, but the gap between male and females is especially large in Pakistan, where the female LFP rate is only 14 percent and male rate is 79 percent. As expected, we do not observe much variation in the share of males in each district. Bangladesh's economy is the most agriculturally oriented, with approximately 27 percent of employment in agriculture, as opposed to Pakistan where agriculture represents one fifth of employment. The manufacturing sector share of employment is similar throughout these countries, ranging between three and eight percent of total

[5] However, we are able to calculate average wages at the administrative unit level needed for some specifications.

employment. Regarding our violence measures,we observe that India is the country with the most attacks and wounded and killed people, and Bangladesh has the least. Figure 4 shows the that there is substantial variation in FLFP rates across administrative units in different countries over time which will be crucial for the empirical strategy described in the following section.

Figure 6 shows male and female labor force participation rates in selected administrative units of Sri Lanka, Pakistan, and India that suffered a given number of attacks in a year and had no attacks two periods before and two after the violence. In Hambantota, Sri Lanka, it appears that women left the workforce for safety reasons. Labor participation rates for both males and females increased in Bahawalpur, Pakistan and Galle, Sri Lanka, but these rates fell in Haryana, India.

4 Estimation Approaches

We face several challenges to meaningfully estimate the effect of violence over FLFP. First, there is a mismatch in the level of variation between our two key variables of interest: incidence of terrorist attacks and individual FLFP. Second, we want to test whether there is a non-linearity in the effect of violence and also if this effect is greater(smaller) in administrative units with higher(lower) FLFP rates for which we need special econometric specifications. Finally, we want to understand the effect on the intensive margin of labor supply (that is, hours worked). In this section we justify the use of each estimation strategy to answer different parts of the broader question on how violence affects FLFP.

4.1 Pseudo Panel Estimation

Our goal is to estimate the effect of violence at the district level over the extensive margin of labor supply at the individual level; that is, does more violence increase or decrease female labor participation. However, the difference in the level of variation in our two variables of interest would deliver artificially high standard errors of the regression coefficients, which is known as the "Moulton Problem". Hence, we solve it by collapsing the data-set at the district level so we get a panel-like dataset with administrative units in each country observed through time.

For our regression analysis, we use three alternative measures of violence as independent variables: number of attacks, number of killed people and number of wounded people in a given year and area. For the dependent variable we use the FLFP rates of each area for each year, expressed as a number between "zero" and "one". We add or remove year and areas fixed effects throughout the different specifications to shed light on how much each dimension plays in explaining changes in FLFP rates beyond their violence prevalence. Our interest lies in coefficient β of equation 7 which we interpret as the marginal change in FLFP rate in administrative unit a at year t caused by a marginal increase in number of attacks, wounded or killed people. Matrix $\mathbb{X}_{at}$ includes the share of workers in the manufacturing sector, the share of the male population and the average age of workers in each administrative unit over time.

$$\text{FLFP}_{at} \quad = \quad \alpha + \beta \text{Violence}_{at} + \delta \mathbb{X}_{at} + \varepsilon_{at} \tag{7}$$

In principle, our violence measures are exogenous to FLFPR as it is unlikely that labor labor force status of individual women influence the terrorist incidence. Additionally, observing areas over time allows us to rule out the presence of non-observable variables that might drive our results. We use least squares weighted by the number of women in each Area to deal with the "Moulton Problem" once the data are collapsed.

This empirical approach allows us to compare districts that are similar in observable characteristics with the only difference being the exposure to violence while dealing with non-observable variables with the use of panel data.

We run several models where the dependent variable is always FLFP rates expressed as a number between "zero" and "one". The variable of interest at the right hand side switches between different proxies of violence measured as flows at the district level for each year. In the Robustness section we provide alternative specifications with the aim of shedding light on the non-linearity of the relation by using (i) a single dummy variable equal to "one" if there was an attack in a year in a given area; (ii) a set of dummy variables for different ranges of attacks number; (iii) number of attacks lagged one time period.

4.2 Quantile Regressions

Violence may have different effects depending on the initial level of FLFP in each district. For instance, the occurrence of a terrorist attack could reduce participation relatively more in areas with higher initial participation or, alternatively, have more impact in areas with lower rates. Or there might be no difference in the effect along the distribution of rates. To formally test this possibility, we estimate a set of quantile regressions which basically look for estimates of parameters by minimizing the difference between the explanatory variables and a given quantile of the dependent variable (as opposed to OLS that minimize with respect to the mean). We run the estimations using five points of the FLFP rates distributions: quantiles 10, 25, 50, 75 and 90; and use our three measures of violence (attacks, wounded and killed people).

4.3 Tobit Estimation

An empirical approximation to equation 6 consists of estimating a Tobit model augmented by the exposure to violence in each district. Due to the widely missing data on wages for each worker, we use "education" as a proxy. However, we include for control the average district wage, calculated using available data in each country (relative to the mean) to proxy for the market value of working (or outside option of remaining in domestic work). Finally, we control for the number of kids under age seven in the household, as well as country, and time fixed effects.

$$H_{it} = \beta_0 + \beta_1 \cdot \overline{w}_{dt} + \beta_2 \cdot \text{N Kids<7}_{it} + \beta_3 \cdot \text{Violence}_{dt} + \beta_4 u^1_{it} + \beta_5 \text{Violence}_{dt} \cdot u^1_{it} + \varepsilon_{it} \tag{8}$$

Under this setting, the interaction term β_5 identifies the average difference in hours supplied between a woman whose spouse is employed compared to a woman whose spouse is unemployed when an attack occurs, measured as when one extra person dies or is wounded. We estimate equation (8) using only females who are not head of households, and we disregard presence or absence of other working household members. We remove India from this estimation, as mentioned, because we lack information on number of working hours, and we use the individual-level data (that is, we do not "collapse" the dataset.)[6]

5 Results

5.1 The extensive margin

Tables 3, 4 and 5 show the results of our benchmark specifications that use the level of FLFP rates as the dependent variable and our three measures of violence as explanatory variables: number of attacks, number of killed and number of wounded, respectively. Column (1) of Table 3 computes the simple correlation between our variables of interest: for each additional attack FLFP rate falls 0.1 percentage point on average. When including dummies by Area, however, this effect drops by three fourths and when including Year and Country fixed effects the point estimate is a negative 0.08 percentage point. In the last specification, we add control variables, but this does not significantly affect the results.

Using alternative measures of violence leads to similar results. For each additional wounded or killed individual FLFPR falls 0.02 and 0.07 percentage point, respectively. However, statistical significance disappears and point estimates fall, respectively, when fixed effects or controls are included in Tables 4 and 5.

All in all, point estimates fall by 80 percent between columns (1) and (2) and by 30 to 40 percent between columns (1) and (3) or (4). We argue that what remains after including control variables is the share of the negative relation observed in the data (i.e. columns (1)) that can be reasonably attributed to violence.

Therefore, on average, women tend to participate less in labor markets in the presence of violent conflicts. However, when we include variables that capture specific characteristics of the different regions, part of the

[6]Dealing with the Moulton Problem under this setting by collapsing the data would turn it more troublesome as we would eliminate all variation in the number of hours worked by women. Then, we opt to work with the individual-level data.

effect fades away as that variation explains FLFP. But since the effect of violence still persists, we claim that violence indeed has a causal effect on FLFP rate because, as shown in column (4) of Table 3, one extra attack reduces FLFP rate by 0.008 percentage point on average.

5.2 The intensive margin

In Figure 8 we show the predicted hours of work obtained after estimating equation 8. We find that that when no attacks occur - that is, when no one is killed nor wounded - predicted number of working hours is significantly higher for women whose spouses are unemployed, consistent with the predictions of Equation 6. However, for high levels of violence, the difference in hours is not significantly different. According to panel (a), hours of women with employed spouses increase with the number of attacks, while hours of women with unemployed spouses only slightly increase beyond 40 hours. This result suggests that women do complement spouse incomes in violent environments. According to panel (b), however, when using the number of wounded people, hours exerted by both women with unemployed spouses and women whose spouses are employed fall with the level of violence. This result indicates that violent environments significantly discourage women from working, to the extent that not even women whose spouses are unemployed work more. Finally, when using the number of killed people in panel (c), the same outcome holds, although hours exerted by women with employed spouses are more sensitive to the number of deaths compared to number of wounded people.

5.3 Non-Linearities

Table 6 switches the violence measure to a binary variable summarizing whether an area was hit or was not hit by a terrorist attack in a given year regardless of the number of attacks, killed or wounded people. The justification for performing this estimation is that risk perception is not caused by any particular number of attacks. Differently put, there is "non-linearity" related to whether an area is attacked only once or more times. We obtain high and significant point estimates in three specifications indicating that suffering an attack reduces FLFP rates between 5.1 and 5.6 percentage points. Significance disappears, however, and the point estimate drops to one fifth of the benchmark, when using area fixed effects but recovered with country and year fixed effects plus control variables. This difference in results in columns (2) and (4) is likely due to the fact that the "Dummy Attack" variable does not have enough variation beyond that of the area fixed effects.

Tables 7 through 9 show the results of the Quantile Regressions Estimations which we include to explore the possibility that violence may have different effects depending on the initial level of FLFP in each district. In other words, we test whether violence impacts differently at distinct points of the FLFP distribution. All specifications include country and year fixed effects. We find point estimates of the marginal effect at the different points of the FLFP distribution that are similar to those on the average. Moreover, the marginal effect of an attack is not statistically significant at the bottom of the distribution and reaches a peak at the median (-0.01 percentage point). In other words, the impact of an attack is higher in districts where women's work is more prevalent.

When measuring violence as the number of killed and wounded people, a similar pattern emerges. Point estimates are not significant for quantiles 10 and 25 of the FLFP distribution. However, the maximum effect is found at the right end of the distribution indicating that the higher number of killed and - in particular - wounded people, the higher the drop in FLFP rates. In the Appendix, we show the results of this same set of Quantile regressions but adding explanatory variables where point estimates slightly reduce and significance is gained also in the 25th Percentile.

To test whether a non-linear relationship exists between the number of attacks and FLFP rates we use a set of dummy variables splitting the range of attacks distribution (0, $(0, 5]$, $(5, 15]$ and $(15, +)$). The results depicted in Table 10 show that higher levels of violence have greater effect on FLFP rates. In particular, according to columns (1) through (4) the FLFP rate drops between 4 and 12 percentage points when 15 or more attacks take place a given year in a region relative to another where no attacks occur, on average. Note that significance remains robust when including explanatory variables and area, country and year fixed effects.

A complementary approach to test the non-linearity hypothesis is to use two different splines of the violence measures.[7] This approach delivers marginal effects that depend on the point at which we evaluate the violence (non-linearly in the second one), as shown in Figure 9. When using the square of violence measures, we find that for all of them the effect on FLFP rates decreases along with the level of violence. When using the cube of violence, we find a pattern not consistent with the hypothesis depicted in Figure 5 according to which the impact should be smaller for low and high levels of violence where the variance of attacks is smaller (see Figure 9 in the Appendix for the results of the same exercise but including control variables). Differently put, the marginal effect of one extra terrorist attack deters FLFP more when there are relatively few or relatively many attacks. We speculate that on one hand, an isolated event might be stranger and hence have a greater impact; on the other hand, when there is a extremely high level of violence women get particularly discouraged from participating in the labor market.

5.4 Robustness

Violence episodes also threaten the security of men, not only of women. Hence, it is plausible to expect violence to affect male labor participation even though we know that men are the main households earners in

[7] In concrete, we estimate two different regressions: (1)$\text{FLFPR}_{at} = \alpha + \beta_1 \text{Violence}_{at} + \beta_2 \text{Violence}^2_{at} + \delta \mathbb{X}_{at} + \varepsilon_{at}$ and (2) $\text{FLFPR}_{at} = \alpha + \beta_1 \text{Violence}_{at} + \beta_2 \text{Violence}^2_{at} + \beta_3 \text{Violence}^3_{at} + \delta \mathbb{X}_{at} + \varepsilon_{at}$

South Asia and we would expect their labor supply to be less elastic. Tables 11, 12 and 13 show the results of our benchmark estimations using the male labor force participation rate as dependent variable instead of FLFP. We find significant negative impact on men's labor participation, but it is between two and seven times lower than the negative impact for females. Therefore, a violent attack tends to widen the gender labor gap.

One last robustness check consists in running our main results using individual level data. The main reason to use the aggregated version was to deal with the Moulton problem since our violence measure varies only at the administrative unit level. Hence, we run slightly modified versions of our benchmark estimations clustering standard errors at the violence level variable to show the extent of the problem. While our collapsed version of the estimations control for the share of males, the share of workers in manufacturing and the average age of each district, the individual level data versions control only for the individual's age.

Most of our results are statistically significant (see Tables 14, 15 and 16). Moreover, in terms of the orders of magnitude, we get very similar point estimates to our benchmark estimates. When clustering standard errors and including years fixed effects, for each attack FLFP falls 0.147 percentage point; for each wounded person FLFP falls 0.0148 percentage point and for each killed person FLFP falls 0.047 percentage point.

6 Conclusions

This paper aims to estimate to what extent violence explains the extremely low female labor force participation (FLFP) rates in South Asia.

This is relevant for both academics and policy makers as FLFP is well-known to contribute to development. In addition to providing extra labor input and therefore increasing gross domestic product, women having earning power has been shown to increase investment in children, including education, which promotes future GDP growth (Duflo [2012]).

Direction of causality between violence and FLFP and its implications for identification represents a crucial challenge. One the one hand violence could increase FLFP through the added worker effect whereby women increasingly work outside the home to help support households during a crisis. On the other hand violence may increase the cost of working for women, either directly due to the risk of violence or indirectly by reducing economic opportunities. Therefore, economic theory does not offer a clear prediction about the relationship.

At first glance, evidence supports the latter rather than the former effect, because in a cross-section of countries or regions a negative correlation between violence and FLFP emerges; that is, FLFP is lower in areas where violence is higher. Thus, looking at aggregate data shows little evidence for the added worker effect.

We evaluate the validity of this argument using disaggregated data that tracks FLFP rates over repeated cross-sections. On the "extensive margin" of labor supply - that is, on women's decision whether to work or not work - we find that one extra-attack reduces FLFP by 0.008 percentage points. This results in a widening of the gender labor participation gap as the effect of violence men's labor participation is up to seven times smaller in our study. On the intensive margin - that is, on women's decision regarding how many total hours they work - the presence of violent attacks encourages married women to exert more working hours, but when the environment gets more risky, as the number of dead and wounded people increases, women reduce their working hours. We also find that violence has a greater impact on discouraging women from working in areas where female work is more prevalent before the advent of violence. Moreover, the effect of violence is non-linear as a greater number of attacks generates a greater impact on FLFPR.

Although we find a robust negative effect of terrorist attacks on FLFP using different estimation approaches, we recognize that the sizes of the effects found are not high enough to attribute the extremely low FLFP rates in the region solely to violence. Although we provide evidence that violence is indeed one of the determinants of low FLFP, further research and richer data is needed to establish how the presence of violence influences FLFP compared to drivers such as values, cultural norms, human capital differences, among other factors.

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7 Figures & Tables

Figure 1: Female Labor Force Participation Rates, Selected SA Countries

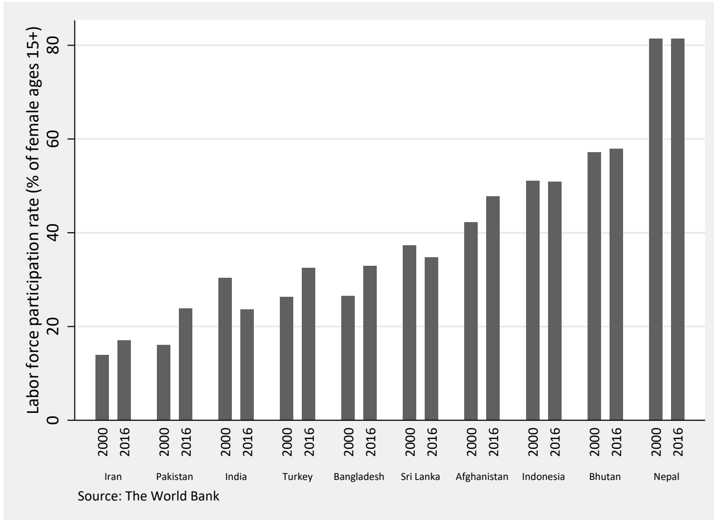


Figure 2: Number of Terrorists Attacks and FLFPR, worldwide

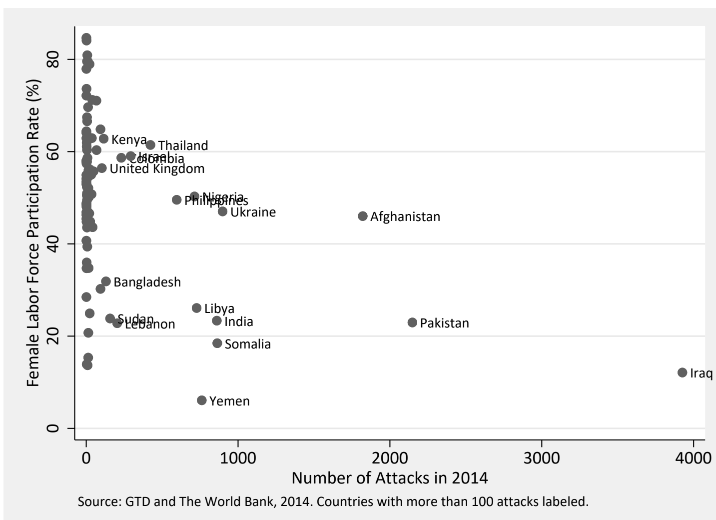
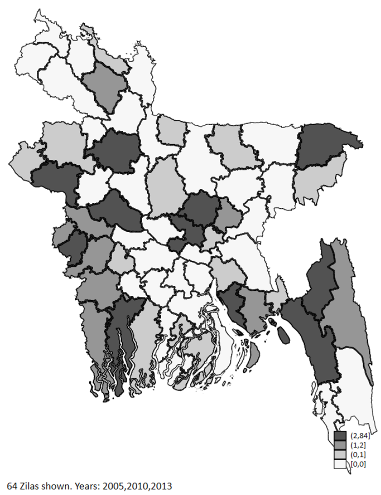
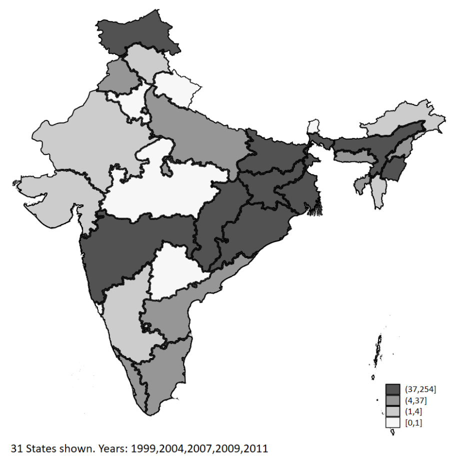


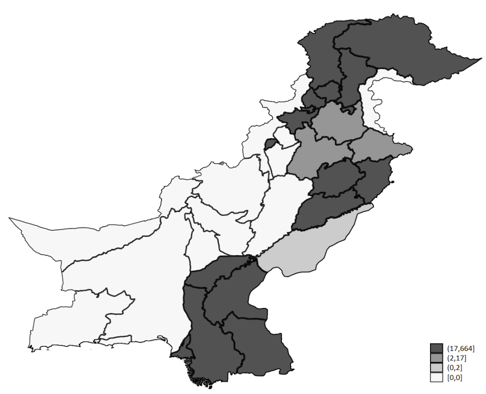
Figure 3: Cumulative number of attacks by Area



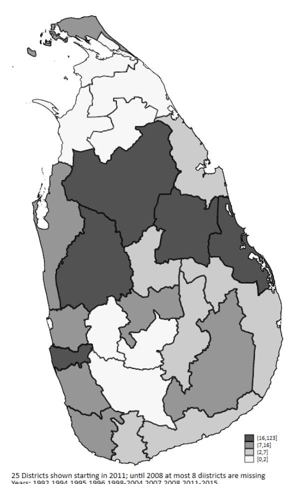
(a) Bangladesh



(b) India

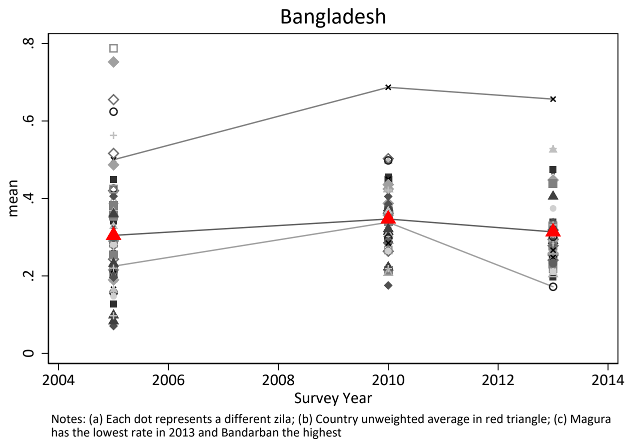


(c) Pakistan

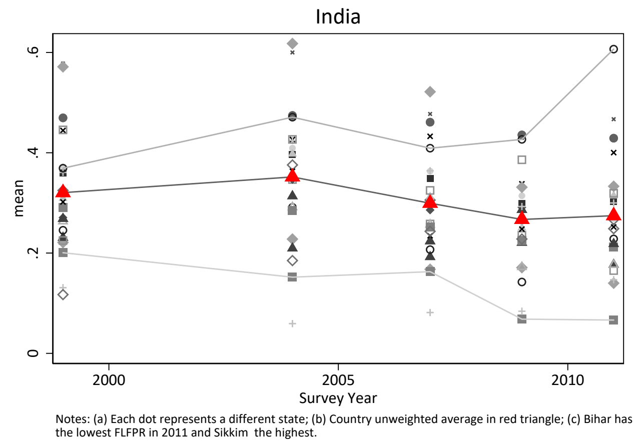


(d) Sri Lanka

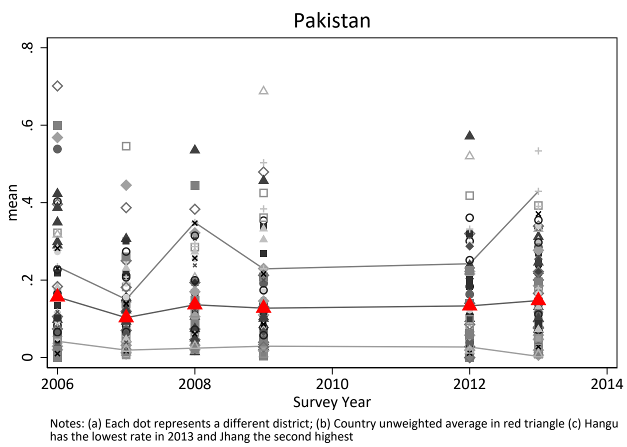
Figure 4: Female Labor Force Participation Rates by Administrative Division



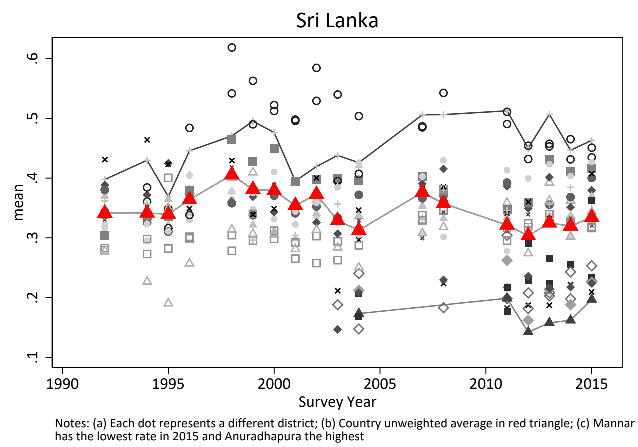
(a) Bangladesh



(b) India



(c) Pakistan



(d) Sri Lanka

Figure 5: Probability and Risk (Variance)

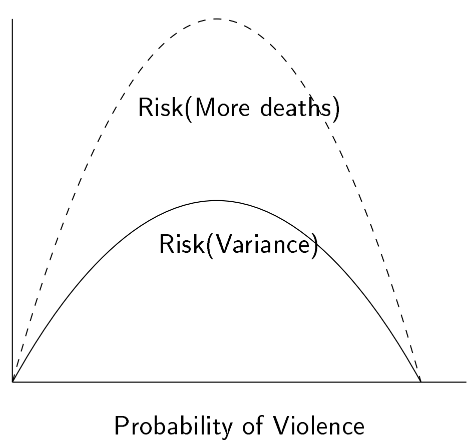


Figure 6: Attacks timing and Labor Force Participation

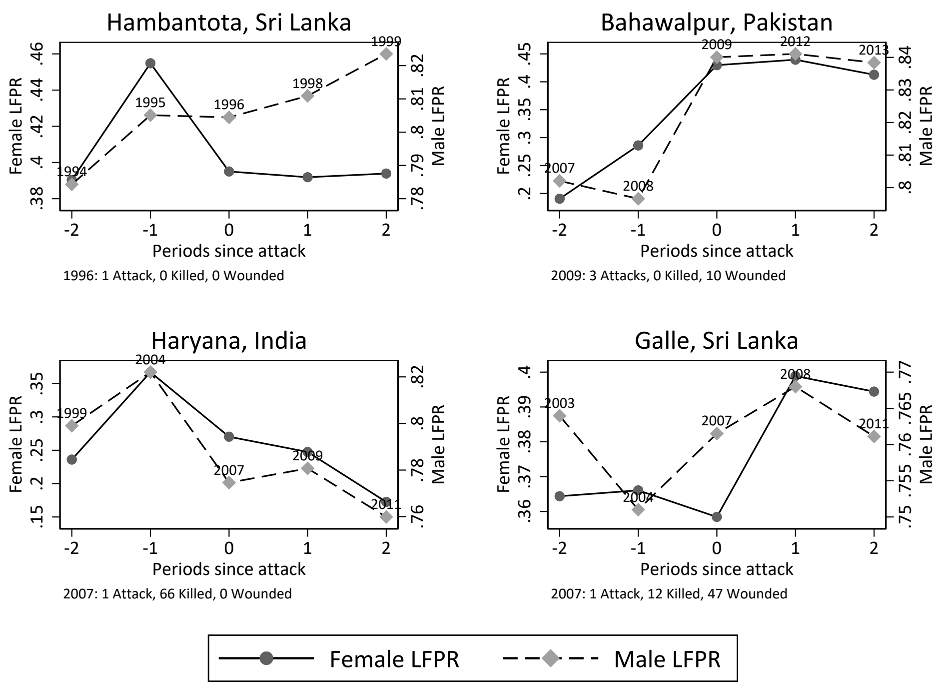
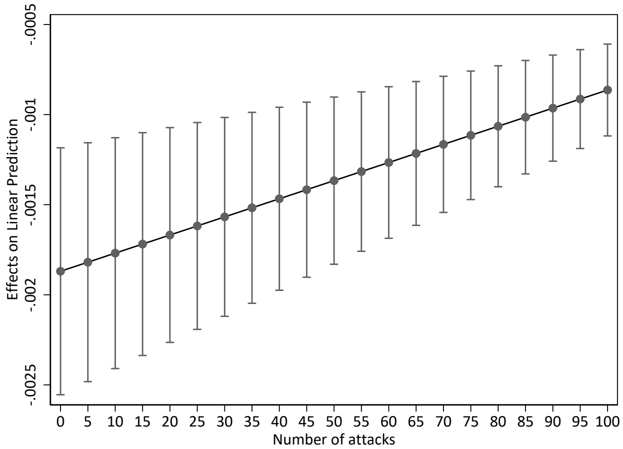
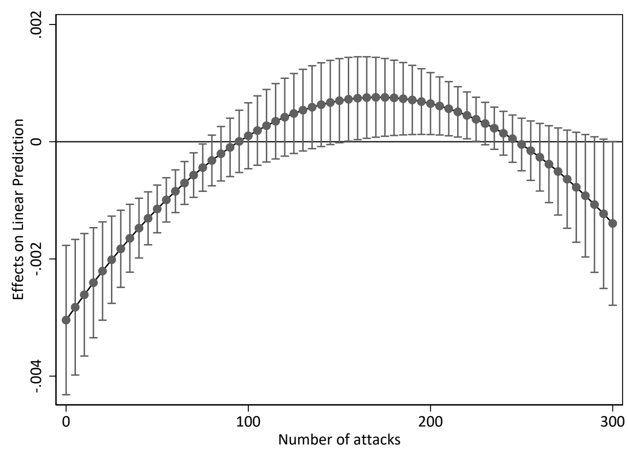


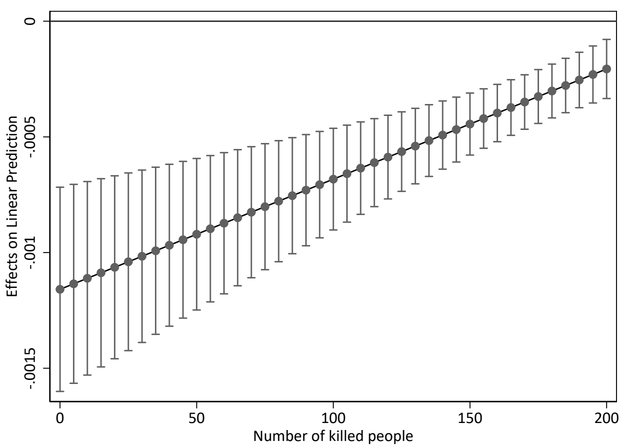
Figure 7: Conditional marginal effects of Violence



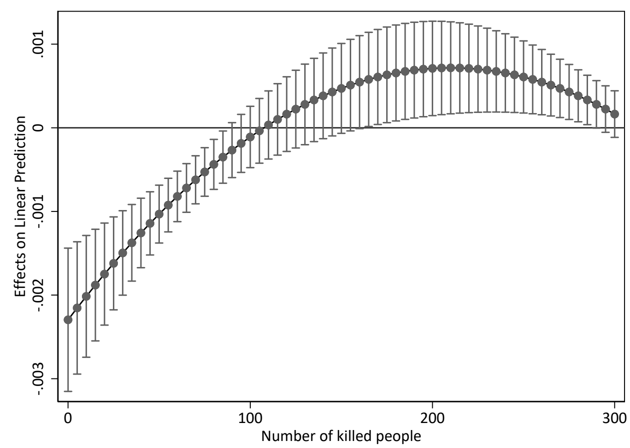
(a) Number of Attacks^2



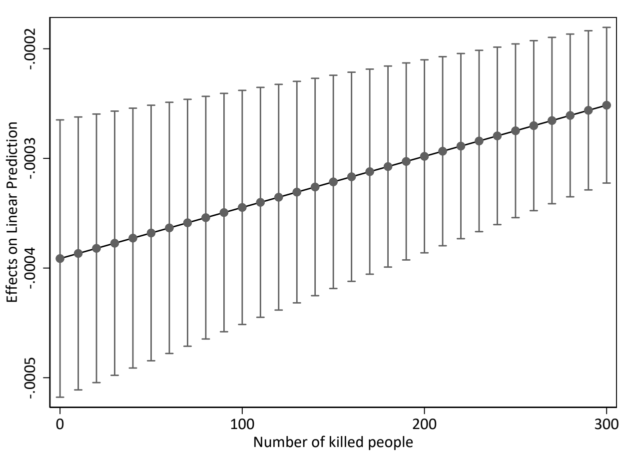
(b) Number of Attacks^3



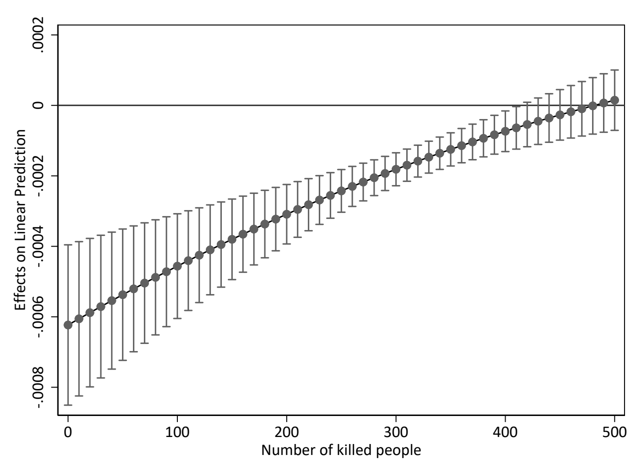
(c) Number of Attacks^2



(d) Number of Attacks^3



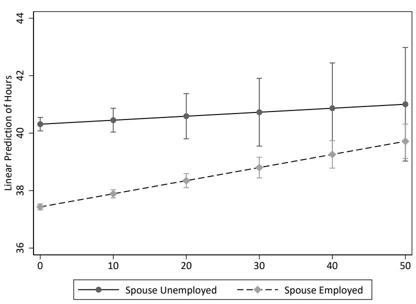
(e) Number of Attacks^2



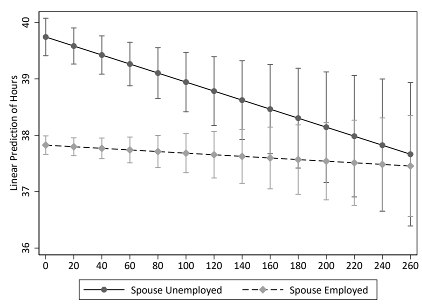
(f) Number of Attacks^3

Marginal effects from a model where FLFPR is at LHS and either the squared or the cube of Violence is at the RHS. All regressions at area level weighted by the number of women in each area. Year and country fixed effects included. Robust standard errors.

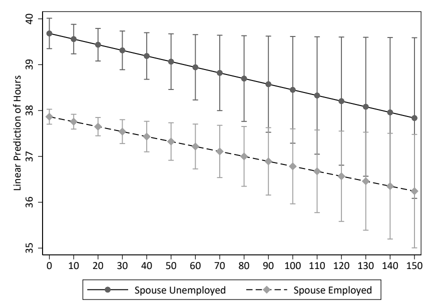
Figure 8: Linear Prediction from Tobit estimations of Hours Worked



(a) Number of Attacks



(b) Number of Wounded



(c) Number of Killed

Table 1: Effect of Violence on FLFP Rates, Cross-country estimates

	(1) FLFPR	(2) FLFPR	(3) FLFPR	(4) FLFPR	(5) FLFPR	(6) FLFPR
N Attacks	-0.0180***	0.00138				
	(-3.36)	(1.23)				
N Attacks(t-1)	-0.00261	-0.0000693				
	(-0.34)	(-0.05)				
N Attacks(t-2)	-0.00736	-0.00172				
	(-1.20)	(-1.42)				
N Wounded			-0.00236***	0.000161		
			(-3.76)	(1.20)		
N Wounded(t-1)			-0.00157*	0.000105		
			(-2.23)	(0.75)		
N Wounded(t-2)			-0.00140*	0.000134		
			(-2.08)	(1.00)		
N Killed					-0.00422***	0.000159
					(-3.44)	(0.63)
N Killed(t-1)					-0.00134	-0.0000186
					(-0.81)	(-0.06)
N Killed(t-2)					-0.00386**	-0.0000438
					(-2.67)	(-0.15)
Population Size/1M		-0.0374***		-0.0381***		-0.0376***
		(-9.35)		(-9.87)		(-9.72)
Urban Population(% of Total)		0.0563*		0.0605**		0.0571**
		(2.53)		(2.73)		(2.58)
Fertility (births per woman)		-0.0779		-0.0193		-0.0617
		(-0.35)		(-0.09)		(-0.28)
GDP per capita/1K		0.267***		0.266***		0.267***
		(10.58)		(10.53)		(10.56)
Gov Spending(% of GDP)		-0.0123		-0.0124		-0.0122
		(-0.89)		(-0.90)		(-0.88)
FDI(% of GDP)		0.000274		0.000266		0.000257
		(0.07)		(0.07)		(0.07)
Observations	3463	3463	3463	3463	3463	3463

Years 1990-2016; 142 countries. Country and Year fixed effects included when using controls. A categorical 7-categories variable for Civil Liberties index included in the estimations not shown. FLFPR $\in [0, 100]$.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Summary Statistics

	(1) Bangladesh mean/sd	(2) India mean/sd	(3) Pakistan mean/sd	(4) Sri Lanka mean/sd
Female LFPR	0.33	0.32	0.14	0.38
	0.12	0.13	0.13	0.10
Male LFPR	0.84	0.81	0.79	0.80
	0.05	0.04	0.08	0.03
Share of Males	0.50	0.51	0.51	0.48
	0.02	0.02	0.04	0.02
Share Agriculture	0.27	0.23	0.19	0.20
	0.09	0.11	0.13	0.11
Share Manufactures	0.06	0.06	0.03	0.08
	0.04	0.03	0.03	0.03
N of Attacks	0.86	10.70	6.57	1.02
	5.75	24.54	25.36	2.58
N of Wounded	1.91	26.61	23.55	14.09
	9.64	80.02	96.01	96.39
N of Killed	0.37	16.82	11.12	5.21
	1.56	38.02	42.75	18.82
Observations	192	155	575	360

Unit of observation: district/year. When no attacks ocurr in a given district/year a zero is inputed to N of Attacks, Wounded and Killed people.

Table 3: Effect of Attacks on FLFP Rates

	(1)	(2)	(3)	(4)
N of Attacks	-0.00119***	-0.000265*	-0.000811***	-0.000775***
	(-5.72)	(-2.23)	(-3.59)	(-4.05)
Area/Country/Year/Controls	No/No/No/No	Yes/No/No/No	No/Yes/Yes/No	No/Yes/Yes/Yes
Observations	1282	1280	1282	1282

Least Squares Weighted by the number of women in each Area/Year. FLFPR $\in [0, 1]$. Robust standard errors

Area, Country or Year fixed effects included as indicated. Controls include, by area, (1) The share of workers in Manufacturing; (2) Share of males and (3) Average age. t-statistics in parenthesis

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Effect of N Wounded on FLFP Rates

	(1)	(2)	(3)	(4)
N of Wounded	-0.000205**	-0.0000224	-0.000160***	-0.000148***
	(-2.65)	(-1.69)	(-4.31)	(-4.47)
Area/Country/Year/Controls	No/No/No/No	Yes/No/No/No	No/Yes/Yes/No	No/Yes/Yes/Yes
Observations	1282	1280	1282	1282

Least Squares Weighted by the number of women in each Area/Year. FLFPR $\in [0, 1]$. Robust standard errors
Area, Country or Year fixed effects included as indicated. Controls include, by area, (1) The share of workers in Manufacturing; (2) Share of males and (3) Average age. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Effect of N Killed on FLFP Rates

	(1)	(2)	(3)	(4)
N of Killed	-0.000753***	-0.000167**	-0.000513***	-0.000477***
	(-7.69)	(-2.92)	(-5.26)	(-5.45)
Area/Country/Year/Controls	No/No/No/No	Yes/No/No/No	No/Yes/Yes/No	No/Yes/Yes/Yes
Observations	1282	1280	1282	1282

Least Squares Weighted by the number of women in each Area/Year. FLFPR $\in [0, 1]$. Robust standard errors
Area, Country or Year fixed effects included as indicated. Controls include, by area, (1) The share of workers in Manufacturing; (2) Share of males and (3) Average age. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Effect of the presence of an attack on FLFP Rates

	(1)	(2)	(3)	(4)
Dummy Attack	-0.0560***	-0.0115	-0.0516***	-0.0512***
	(-5.24)	(-1.76)	(-5.45)	(-5.77)
Area/Country/Year/Controls	No/No/No/No	Yes/No/No/No	No/Yes/Yes/No	No/Yes/Yes/Yes
Observations	1282	1280	1282	1282

Least Squares Weighted by the number of women in each Area/Year. FLFPR $\in [0, 1]$. Robust standard errors
Area, Country or Year fixed effects included as indicated. Controls include, by area, (1) The share of workers in Manufacturing; (2) Share of males and (3) Average age. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Quantile Regression. Effect of Attacks on FLFP Rates

	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
N of Attacks	-0.000673	-0.000603	-0.00114***	-0.000709*	-0.000894***
	(-0.79)	(-1.86)	(-9.20)	(-2.01)	(-4.04)
Observations	1282	1282	1282	1282	1282

Quantile Regression weighted by the number of women in each Area/Year. FLFPR $\in [0, 1]$
Country and Year Dummies included. Robust standard errors. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Quantile Regression. Effect of N Killed on FLFP Rates

	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
N of Killed	-0.000184	-0.000337	-0.000661*	-0.000470***	-0.000688*
	(-0.91)	(-1.51)	(-2.54)	(-9.29)	(-2.56)
Observations	1282	1282	1282	1282	1282

Quantile Regression weighted by the number of women in each Area/Year. FLFPR $\in [0,1]$
Country and Year Dummies included. Robust standard errors. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Quantile Regression. Effect of N Wounded on FLFP Rates

	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
N of Wounded	-0.0000154	-0.000159	-0.000198***	-0.000165***	-0.000258***
	(-0.40)	(-0.92)	(-4.74)	(-3.90)	(-5.03)
Observations	1282	1282	1282	1282	1282

Quantile Regression weighted by the number of women in each Area/Year. FLFPR $\in [0,1]$
Country and Year Dummies included. Robust standard errors. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Effect of N Attacks on FLFP Rates

	(1)	(2)	(3)	(4)
N Attacks $\in (0,5]$	-0.0269*	-0.00837	-0.0372***	-0.0383***
	(-2.17)	(-1.22)	(-3.33)	(-3.66)
N Attacks $\in (5,15]$	-0.102***	-0.0321**	-0.0621***	-0.0606***
	(-4.52)	(-3.26)	(-3.57)	(-3.55)
N Attacks $\in (15,+)$	-0.128***	-0.0436***	-0.108***	-0.100***
	(-7.56)	(-3.68)	(-6.72)	(-6.51)
Area/Country/Year/Controls	No/No/No/No	Yes/No/No/No	No/Yes/Yes/No	No/Yes/Yes/Yes
Observations	1282	1280	1282	1282

Least Squares Weighted by the number of women in each Area/Year. FLFPR $\in [0,1]$. t-statistics in parenthesis.
Controls, Country, Area or Year Dummies included as indicated. Zero attacks is the base(excluded) category. Robust standard errors
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Effect of Attacks on Male LFP Rates

	(1)	(2)	(3)	(4)
N of Attacks	-0.000213***	-0.000150**	-0.000157**	-0.000267***
	(-3.46)	(-2.69)	(-2.79)	(-5.39)
Area/Country/Year/Controls	No/No/No/No	Yes/No/No/No	No/Yes/Yes/No	No/Yes/Yes/Yes
Observations	1282	1280	1282	1282

Least Squares Weighted by the number of men in each Area/Year. MLFPR $\in [0,1]$. Robust standard errors
Area, Country or Year fixed effects included as indicated. Controls include, by area, (1) The share of workers in Manufacturing; (2) Share of males and (3) Average age. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Effect of N Wounded on Male LFP Rates

	(1)	(2)	(3)	(4)
N of Wounded	-0.0000596***	-0.00000993	-0.0000493***	-0.0000681***
	(-4.20)	(-1.46)	(-4.43)	(-5.16)
Area/Country/Year/Controls	No/No/No/No	Yes/No/No/No	No/Yes/Yes/No	No/Yes/Yes/Yes
Observations	1282	1280	1282	1282

Least Squares Weighted by the number of men in each Area/Year. MLFPR $\in [0, 1]$. Robust standard errors
Area, Country or Year fixed effects included as indicated. Controls include, by area, (1) The share of workers in Manufacturing; (2) Share of males and (3) Average age. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Effect of N Killed on Male LFP Rates

	(1)	(2)	(3)	(4)
N of Killed	-0.000180***	-0.0000658*	-0.000148***	-0.000212***
	(-5.71)	(-2.08)	(-5.15)	(-9.07)
Area/Country/Year/Controls	No/No/No/No	Yes/No/No/No	No/Yes/Yes/No	No/Yes/Yes/Yes
Observations	1282	1280	1282	1282

Least Squares Weighted by the number of men in each Area/Year. MLFPR $\in [0, 1]$. Robust standard errors
Area, Country or Year fixed effects included as indicated. Controls include, by area, (1) The share of workers in Manufacturing; (2) Share of males and (3) Average age. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Effect of Attacks on FLFP Rates using individual-level data

	(1)	(2)	(3)
N of Attacks	-0.00186***	-0.00186***	-0.00147***
	(-93.18)	(-5.46)	(-3.45)
Cluster/Year FE	No/No	Yes/No	Yes/Yes
Observations	1437269	1437269	1437269

Ordinary Least Squares. FLFPR $\in [0, 1]$. Clustered S.E. at the district level and Year fixed effects as indicated.
All regressions control for individuals age. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Effect of N Wounded on FLFP Rates using individual-level data

	(1)	(2)	(3)
N of Wounded	-0.000164***	-0.000164	-0.000192*
	(-43.29)	(-1.52)	(-2.59)
Cluster/Year FE	No/No	Yes/No	Yes/Yes
Observations	1437269	1437269	1437269

Ordinary Least Squares. FLFPR $\in [0, 1]$. Clustered S.E. at the district level and Year fixed effects as indicated.
All regressions control for individuals age. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Effect of N Killed on FLFP Rates using individual-level data

	(1)	(2)	(3)
N of Killed	-0.000956***	-0.000956***	-0.000829**
	(-74.47)	(-3.45)	(-2.98)
Cluster/Year FE	No/No	Yes/No	Yes/Yes
Observations	1437269	1437269	1437269

Ordinary Least Squares. FLFPR $\in [0, 1]$. Clustered S.E. at the district level and Year fixed effects as indicated. All regressions control for individuals age. t-statistics in parenthesis

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8 Appendix

Table 17: Quantile Regression. Effect of Attacks on FLFP Rates

	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
N of Attacks	-0.000900	-0.000659***	-0.00109***	-0.000558**	-0.000794***
	(-1.44)	(-10.21)	(-4.61)	(-3.26)	(-5.22)
Observations	1282	1282	1282	1282	1282

Quantile Regression weighted by the number of women in each Area/Year. FLFPR $\in [0, 1]$
Controls, Country and Year Dummies included. Robust standard errors. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Quantile Regression. Effect of N Killed on FLFP Rates

	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
N of Killed	-0.000252	-0.000306**	-0.000579**	-0.000445***	-0.000502**
	(-1.28)	(-2.94)	(-3.04)	(-6.44)	(-2.85)
Observations	1282	1282	1282	1282	1282

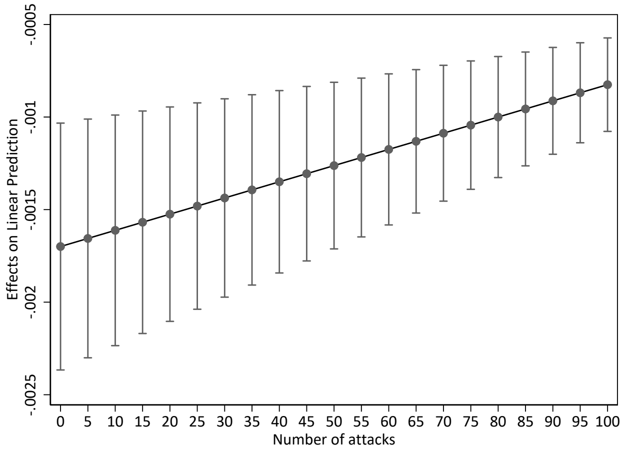
Quantile Regression weighted by the number of women in each Area/Year. FLFPR $\in [0, 1]$
Controls, Country and Year Dummies included. Robust standard errors. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Quantile Regression. Effect of N Wounded on FLFP Rates

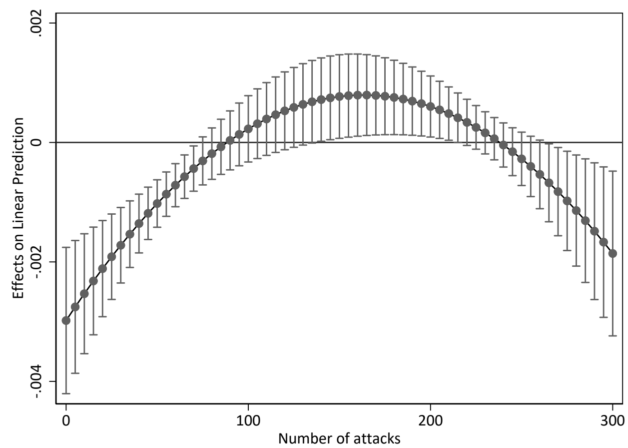
	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
N of Wounded	-0.0000365	-0.0000951***	-0.000189**	-0.000154*	-0.000201***
	(-0.28)	(-9.05)	(-2.74)	(-2.43)	(-3.62)
Observations	1282	1282	1282	1282	1282

Quantile Regression weighted by the number of women in each Area/Year. FLFPR $\in [0, 1]$
Controls, Country and Year Dummies included. Robust standard errors. t-statistics in parenthesis
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

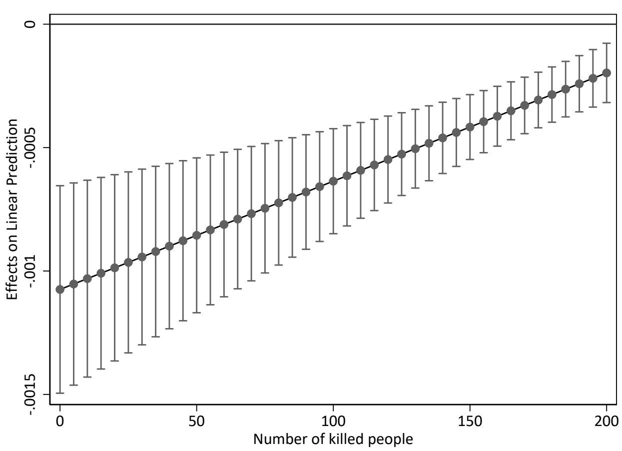
Figure 9: Conditional marginal effects of Violence



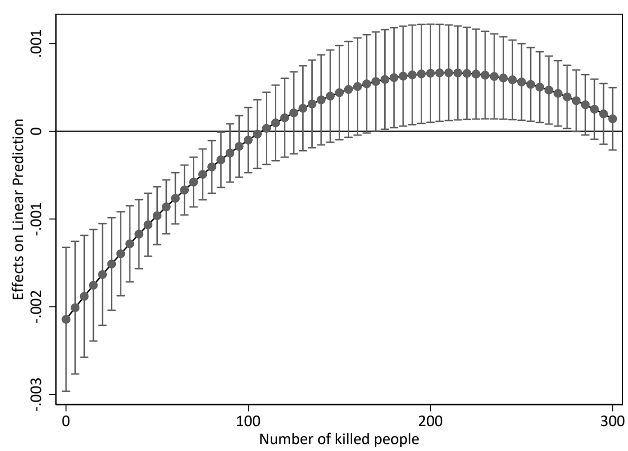
(a) Number of Attacks^2



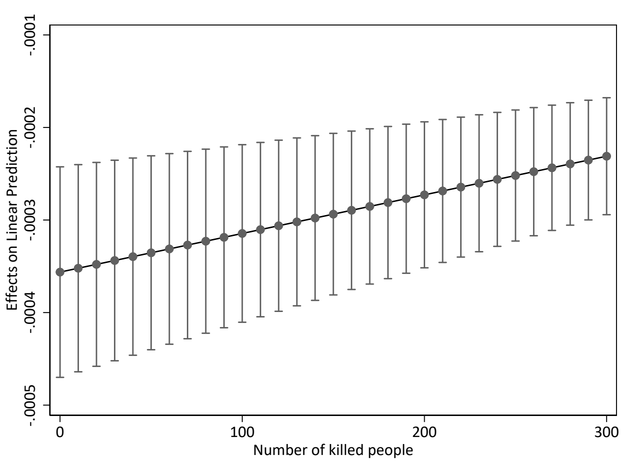
(b) Number of Attacks^3



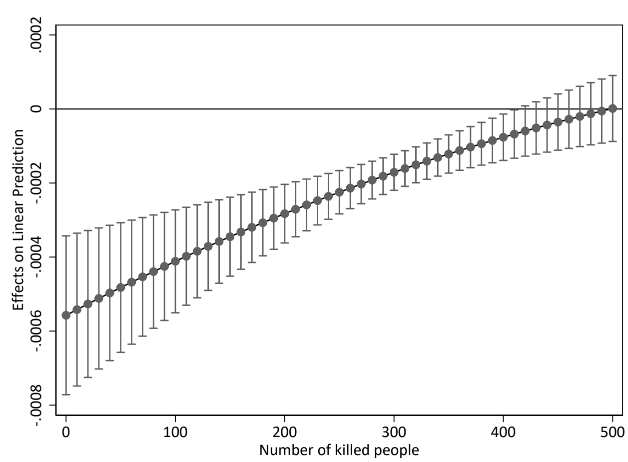
(c) Number of Attacks^2



(d) Number of Attacks^3



(e) Number of Attacks^2



(f) Number of Attacks^3

Marginal effects from a model where FLFPR is at LHS and either the squared or the cube of Violence is at the RHS. All regressions at area level weighted by the number of women in each area. Controls, Year and country fixed effects included. Robust standard errors.