Health care utilization amidst peaceful protests & political strikes

Adnan M. S. Fakir

PhD Candidate in Economics
University of Western Australia
Perth, WA 6009
adnan.fakir@uwa.edu.au

Tushar Bharati

Assistant Professor in Economics
University of Western Australia
Perth, WA 6009
tushar.bharati@uwa.edu.au

Work-in-Progress
Version: 01 Nov, 2019

Abstract

Political protests and strikes are one of the most common local disruptive events in the Indian sub-continent. Such events are generally meant to be non-violent but may have unintended consequences on health care utilization. To explore this possibility, we combine daily data from the Armed Conflict Location Event Data (ACLED) project with the 2011 & 2014 waves of the Demographic and Health Survey (DHS) of Bangladesh. Exploiting within-location variation in disruptive events over time, we find evidence of a negative effect of non-violent political protests and low-violence political strikes on health facility usage, hospital delivery and postnatal care. Examining specific impacts on sub-groups, we find evidence of son preference with lower utilization of health care facilities for female children reported sick compared to that of male children. Pregnant mothers are also found to be substituting away from delivering in hospitals to smaller local clinics during higher incidents of disruptions. The findings suggest that the cost of such arguably peaceful democratic protests might be higher than what it is believed to be with significant adverse impacts on early investments in human capital.

Keywords: health care utilization, protests, political strikes

1. Introduction

Exposure to violence, in-utero or during early years, is well established to affect child health outcomes in the academic literature (Brown, 2018; Shemyakina, 2015; Mansour & Rees, 2012; Akresh, Verwimp & Bundervoet, 2011; Chamarbagwala & Moran, 2011). Studies that have explored this nexus mostly focused on the role of civil, communal or religious conflict in driving the effect. Explorations undertaken ranged from the Mexican drug war (Brown 2018), political repression in Zimbabwe (Shemyakina, 2015), the Al-Aqsa Intifada armed conflict (Mansour & Rees, 2012) to the civil war in Rwanda (Akresh, Verwimp & Bundervoet, 2011) and in Guatemala (Chamarbagwala & Moran, 2011). However, alongside such established forms of conflict, local disruptions[1] can and often arise as part of a nation's democratic political process. Much of these politically motivated disruptive events are in the form of widespread protests or strikes, which are generally meant to be non-violent, but carry within the potential of violence[2]. Such events are most prominent in the Indian subcontinent, with Bangladesh alone facing 1,719 protests spread spatially in 852 days between 2000 and 2014 (ACLED, 2019). The effects imparted by such disruptive events, however, have received far less attention. Addressing this gap in the literature, this paper focuses on the impact of these politically motivated non-violent protests and strikes on health care utilization of mothers and children less than 60 months old in Bangladesh.

The mechanisms through which violence or disruptive events can affect health outcomes are also not well explored in the available literature. These mechanisms can arise from demand or supply side factors, often making it difficult to distinguish among them. Existing literature have emphasized on the following important mechanisms: maternal stress/fear/anxiety induced from exposure to violence hindering foetal development (Brown, 2018; Camacho, 2008; Mansour & Rees, 2012), reduced nutritional intake through income shocks, damage to local livelihood or health infrastructure and restricted access to local food or health markets. The unique nature of the political protests and strikes enable us to extricate the effect of at least one of the aforementioned mechanisms. In particular, individuals who live in communities with greater political strife translating to protests, peaceful or otherwise, carry a greater risk of encountering violence in daily activities. This

[1]We make a distinction in terminology between violence and disruption that is maintained throughout the paper. We term disruptive events as any man-made event (excluding natural disasters) that hampers the functioning of daily activities, which may or may not be violent in nature.

[2]Note that this is different from political repression which advocates violent persecution for political views (such as the 1966-76 Chinese Cultural Revolution, the 1976-83 Argentinian dirty war or the 2000-2005 Zimbabwean oppression of the MDC). See Davenport (2007) for a review on political repressions.

can be while going to a health facility for consultation or delivery, or while availing pre- or post-natal care. This fear induced stress can alter behaviour by increasing the cost of health care utilization to an individual's decision problem, reducing preventive and curative care, thereby imparting a negative impact on child health. The problem is further aggravated during political strikes which forces closure of most local markets along with the public transportation sector. This can prevent both individuals and doctors from reaching the health facility and community health workers from visiting households. These unique characteristics and relatively high frequency of political protests and strikes make studying their impact on health care utilization particularly important.

This paper contributes to three strands of the development economics literature. First, it adds to a large literature studying the impact of natural or man-made exogenous shocks to household behaviour, and in particular, to health outcomes. A sub-set of our findings further contribute to the literature on the prevalence of son-preference in developing countries. Second, it contributes to the literature on political economy and its relation to the welfare of citizens by taking a unique perspective towards the costs arising from democratic political processes in a developing country. Third, this study is one of the first to link and explore the impacts of political protests and strikes on health care utilization in a South Asian country.

Our identification strategy exploits within-location variation in daily disruptive events over time to estimate the impact of political protests and strikes on contemporaneous health facility utilization, prenatal care, place of delivery, postnatal care, and vaccination coverage. We use the exact date and location of disruption events from the Armed Conflict Location and Event Data (ACLED) between 2010 and 2014 to generate distance weighted disruption indices. We segregate the daily events into politically motivated peaceful protests, low- and high-violence political strikes, and other disruptions for comparative analysis. The disruption data is then combined by date of birth of child (or the interview date for contemporaneous health facility utilization) with household and health care data from the 2011 & 2014 waves of the Bangladesh Demographic and Health Survey (DHS) at the sub-district level. Similar analysis approach were used by Molina (2019), Shemyakina (2015), Minoiu & Shemyakina (2012) and Akresh & de Walque (2010).

The findings indicate a negative effect of peaceful political protests and low-violence political strikes on health facility usage, hospital delivery and postnatal care. Peaceful protests have a negative impact on the number of prenatal visits to a pregnant mother while we find no effect on vaccination coverage. Examining specific impacts on sub-groups, we find evidence of son preference with lower contemporaneous utilization of health care facilities for female children reported sick compared to that of male children. Pregnant mothers are also found to be substituting away from delivering in hospitals to smaller local clinics during higher incidents of disruptions. The results are robust to inclusion of multiple individual and household level controls as well as sub-district, district-year, month and day of the month fixed effects. The findings suggest that the cost of such arguably peaceful democratic protests might be higher than what it is believed to be.

2. Data and methods

2.1. Disruptions data

As aforementioned, we source our disruptions data, between 2010 and 2014, from the Armed Conflict Location and Event Data (ACLED) project. ACLED collates articles from 14 national and regional newspaper sources of Bangladesh on a daily basis to identify disruptive events and generate the dataset. This likely results in a downward bias for our estimates due to under-reporting of disruption events. ACLED has three main advantages over other available conflict data. It provides the exact date and geocoded location of the event at the admin 4 (union) level and includes an extract from the newspaper article of the recorded disruption event. The latter allows us to distinguish between low- and high-violence political strikes, while the date and location allows us to generate the distance weighted disruption indices.

ACLED comes with pre-identified variables for peaceful political protests defined as when "demonstrators are engaged in a protest while not engaging in violence or other forms of rioting behaviour and are not faced with any sort of force or engagement" (ACLED, 2019, p.13). We differentiate between low- and high-violence political strikes primarily based on human casualties and fatalities. Any political strike that resulted in a clash between two parties, or resulted in any human casualty/fatality from any party engaged[3], was identified as a high-violence political strike. Furthermore, any political strike that involved damage to any health infrastructure was also coded as a high-violence political strike. The rationale behind the latter is rooted in the fact that during normal political strikes, hospitals, clinics, and other health facilities are left unaffected. Only in the most severe of cases when the violence spirals out of control or the party involved wishes to exhibit a major show of power/media presence are these facilities targeted. All other political strikes were coded as low-violence. We compare the distinctions between the three measures and the possible mechanisms through which they can impact health outcomes in table 01.

[3]This can be a pro-strike party member, an anti-strike party member, a police or a civilian.

[Insert Table 01 here]

The resulting dataset contained 10,062 disruption events[4] spatially distributed in 1,758 days between 2010 and 2014. Out of these, there were 1,719 politically motivated peaceful protests and 1,241 political strikes spatially distributed in 852 and 214 days respectively. Among the political strike events, 636 (51.2 per cent) were identified as high-violence based on the aforementioned distinction criteria.

2.2. Health care utilization data

The health care utilization information is obtained from the 2011 and 2014 waves of the Bangladesh Demographic and Health Survey (DHS). In each wave, the DHS collects detailed data from a stratified random sample of households, representative at the national and divisional level, on maternal and child health. Women aged between 15 and 49 years old are deemed eligible for a detailed interview on fertility and birth history, which includes the exact date of birth for children below the age of 60 months. Each mother is asked questions on the place of delivery and child vaccination coverage about all children born in the last three years from the date of the interview. Mothers are also asked details about pre- and post-natal care received for the most recent pregnancy only. All of these questions are used as indicators of health care utilization and form the outcome variables for the study merged with the ACLED data on the date of birth of the child.

In addition, the present health status of all children in the past two weeks from the date of the interview is recorded. If a child is reported ill, the mother is inquired whether the child was taken to a health facility for consultation or treatment within the past two weeks from the date of the interview is recorded. This is used as the indicator of health facility utilization and is merged with the ACLED data on the date of interview. DHS also contains comprehensive individual and demographic information which we include as controls in our regression models.

2.3. Distance-weighted disruption indices

Disruptive events that take place nearer to a household will have a larger impact compared to events that take place further away. Conversely, individuals who needs to visit a health facility may still risk going there if the disruption event is further away from the

[4]Any personal disruption event, such as domestic violence, individual threats etc. that does not affect the local community was excluded.

household. It is important to generate measures that reflect this aspect. Figure 01 provides an example of how the distance-weighted disruption indices were created. Distance-weighted measures were created for each of the following categories of events: all disruptions, peaceful protests, all political strikes, low-violence political strikes and high-violence political strikes.

[Insert Figure 01 here]

We use the `geonear` command in Stata to generate the measures. DHS datasets provide the geocode of the centroid of each cluster of households[5] (green dot in figure 01). As these clusters are at a sub-district level, we create our indices also at the level of sub-districts. Each disruption event is first coded as 1, and 0 otherwise, for a daily dataset of each sub-district. We then identify all events (red dots in figure 01) within a 50 km radius from each household centroid for each day, calculating the distance between the household centroid and the geocode of the event. The inverse of the distance is used as the weight for each event such that events that take place further away from the household carry a smaller value. The daily index measure is created by summing all distance-weighted events within the 50 km radius for each household. This daily index measure is then finally summed over the relevant time period as required[6] and matched with the date of birth of the child (or the interview date for contemporaneous health facility utilization) for analysis.

2.4. Empirical model

The empirical analysis in this field is in generally limited to the sample of non-migrated surviving children leading to conservative estimates relative to the actual impact. For outcome h_{isdmy} of child i, living in sub-district s, who was born in day d, month m, and year y, we estimate the following empirical specification:

$$h_{isdmy} = \alpha + \beta_1 \underbrace{disindex_{sdmy}}_{spatial\ \times\ temp.} + \beta_2 X_i + \beta_3 D_i + \underbrace{\gamma_s + \tau_{zy} + \phi_m + \mu_d}_{FE} + \varepsilon_{isdmy} \tag{1}$$

where $disindex_{sdmy}$ is the relevant disruption index[7] of sub-district s, in day d, month m, and year y. The day, month and year represents the child date of birth when the outcome

[5]In the combined final dataset used for analysis, an average cluster contained 6.5 households.

[6]For example, in the case of analysing prenatal care, we sum the measures over a 9-months period before the date of birth of the child.

[7]In all combinations of disruption categories (for example, peaceful protests, low-violence political strikes, high-violence political strikes and other disruptions), we ensure that all disruption events are captured by the model to avoid omitted variable bias.

variable is any prenatal, delivery, postnatal or child vaccination measure. On the other hand, day, month and year represents the date of interview when the outcome variable is health facility utilization.

A key issue in identifying the impact of disruptive events is that such events, as in the case of violence, may not be exogenous. It should be noted, however, that given majority of our outcome indicators are related to the date of birth of the child, it is unlikely that pregnancy decisions were taken based on expectations regarding future disruptions. This assertion is further reiterated when we consider that households living in the same area for a long time may have acclimatized to local disruption events. Regardless, there may be other factors that impact health care utilization (h_{isdmy}) in an area that may also drive the disruptions ($disindex_{sdmy}$). We do two things in the base empirical specification to address this.

First, we include location fixed effects at the sub-district level (γ_s) to take advantage of within-location variation in disruptive events over time. This absorbs time invariant differences between sub-districts that might affect the outcome. Second, we further include district-year fixed effects (τ_{zy}) that exploits the variation in disruptive events within districts and within years. This absorbs time varying differences across districts that might affect the outcome. For example, hospital access can be affected by floods, with the southern districts of Bangladesh being more flood prone than others. In a year when none of the districts get flooded, the differences between the districts might be smaller than in a year when some of them are flooded. The district-year fixed effects will absorb such differences, allowing for different levels of differences across districts in each year. Similarly, this also absorbs time trends that are different across districts. In addition month fixed effects (ϕ_m) and day of month (μ_d) fixed effects further control for non-linear trends across the sample.

X_i is a vector of individual level controls containing child's gender, child's age in months (quadratic), mother's level of education (category fixed effects) and mother's age (quadratic). Similarly, D_i is a vector of demographic controls containing the household wealth score quintile (category fixed effects), whether the mother is a Muslim, whether the household head is female, age of the household head in years, household size, number of women aged between 15 and 49 years in the household, number of children aged under 60 months in the household and the number of living children of the mother. For all estimations, standard errors are clustered at the sub-district level with our sample covering 415 sub-districts of Bangladesh.

3. Results

3.1. Impact on health care utilization

We report the results of disruptive event indices on health facility utilization within the last two weeks conditional on a child being reported ill in table 2. Column (1) reports the impact of all disruption events which is then segregated into peaceful protests, all political strikes, and other disruptions in column (2). All political strikes in then further broken down into low-violence political strikes and high-violence political strikes in column (3).

[Insert Table 02 here]

Expectedly, a one unit increase in the all disruptions index lowers the expected probability of health facility utilization by 9.7%. What is more interesting are the results in column (2). Once segregated, politically motivated peaceful protests carry the largest magnitude in effect reducing the expected probability of health facility utilization by 31.6%. Stress induced from the fear of harm coupled with increased traffic congestion due to the protests do have a substantial negative impact as an unintended consequence. Political strikes also play a significant role reducing the expected probability of health facility utilization by 23.5%, which was expected given the additional lack of public transportation during strikes. Given the short two weeks' time frame of the analysis, health facility utilization is expected to be relatively elastic and it is possible that the households are substituting utilization across time, postponing their visit to when disruptive events are lower. When we further break down political strikes in column (3), the magnitudes still remain large although low-violence political strikes loses its significance.

In order to ensure that the estimated impacts are not driven by any serial correlation from past disruptive events we re-run the regression in column (3) by including monthly disruption measures. We include a 6-months window where t represents the month of interview and include 3 months before and after date of interview. The future months act as placebo checks since future disruption events should not affect health facility utilization in the present. We plot the coefficients from the results in figure 02, where the bars indicate 95% confidence interval.

[Insert Figure 02 here]

Even after including the other months as additional covariates, the coefficient on the month of birth t, retains its significant negative impact for peaceful protests and high-violence political strikes. None of the other coefficients indicate any significant effect with their confidence intervals overlapping the zero line.

In the following tables we report only the specification used for column (3) in table 02 containing the primary variables of interest. We next report the impacts on prenatal care received by the mother during her pregnancy in table 03 and on the place of delivery in table 04.

[Insert Table 03 here]

Neither political protests nor strikes have a significant impact on the binary indicator for prenatal visit in column (1). However, when looking into the number of prenatal visits, reported in column (2), only peaceful protests have a significant negative impact, reducing the expected probability of the number of prenatal visits by 7.4%. It is common in Bangladesh for community health workers to visit households to provide pre- and post-natal care to mothers in rural areas and small towns. It is possible the community health workers simply avoid providing the care during times of high protests, delaying the provision of preventive and curative services, expecting transportation hindrance during times of higher protests. We consider the channel to be operating through the health workers since we find a similar result for postnatal care (discussed below in table 05) while we do not find any substantial effect when considering prenatal visits to the hospital in column (3). Even though low-violence political strikes show a significant negative impact, the magnitude is very low with a reduction in expected probability of only 1.8%. Interesting, high-violence political strikes show no significant impact. We pick up this curious case further after table 04.

[Insert Table 04 here]

Impacts on place of delivery in table 04 reveal two interesting results. First, only low-violence political strikes seem to have a significant effect causing a substitution across place of delivery. We find a reduction in the expected probability of hospital delivery by 5.5% while an increase in the expected probability of smaller clinic delivery by 4.1%. Such a substitution should not be surprising since delivery carries an inelastic demand. Smaller clinics are higher in number and tend to be closer to households than hospitals, which are fewer and sparsely located. The shorter distance may be one reason why in the lack of transportation services individuals are substituting away from hospitals and towards smaller clinics. Another reason could be due to better attendance of doctors or midwives in smaller clinics compared to hospitals during strike days, again due to smaller clinics being higher in number and having a shorter work commute. Further empirical work needs to be done to identify which of the two channels are at work here.

The second interesting result in table 04 is one that echoes the curious case from table 03. High-violence political strikes show no significant impact on any place of delivery, where one would expect them to exhibit a larger magnitude than low-violence political strikes. It is possible that individuals are afraid to substitute across place of delivery during high-violence political strikes but then we should see a significant positive impact on home delivery. While we do see a larger magnitude for home delivery in the case of high violence political strikes, it remains insignificant which could be due to relatively large standard errors resulting from small sample size.

Interestingly, we find this difference arising in both the case of hospital delivery and prenatal visits to the hospital. If it is not the sample size issue, there can be three possibilities leading to this unexpected differential impact. First, human casualty/fatality is not a good enough criterion to segregate low-violence and high-violence political strikes. Instead the size or duration of clashes during political strikes may be a better indicator for segregation. However, data limitations hinder us from exploring this further. Second, consecutive days of low-violence political strikes may have a greater impact than temporally distant high-violence political strikes that disperses quickly or within a day. Third, it could be that high-violence political strikes are picking up effects from non-compliance with the strike. While this non-compliance would result in clashes and subsequently human casualty/fatality, this would also result in the transportation sector still being partially operational explaining the accompanying lower magnitude and insignificant coefficients. We would also get a similar result if the police comes and intervenes dispersing a strike induced conflict earlier in the day causing the transportation sector to become operational for the remaining time in the locale. As in the case of the hospital to smaller clinic substitution, further empirical work needs to be done to identify which of the channels are at work here.

We present the results of disruptive events on postnatal care in table 05. For both maternal and child postnatal care, only peaceful protests have a significant negative impact lowering the expect probability by 8.2% and 3.0% respectively. We find no significant impact of political strikes on prenatal care. The results are similar to that of column (2) in table 03 of prenatal care.

[Insert Table 05 here]

This lends further credence to the possibility that community health workers are avoiding providing care during times of increased protests. If this is indeed the case, the impact should remain for rural areas and towns but not for city corporations. We explore this possibility in table 06 where we do find negative impact in the case of towns and rural areas, significant only in the case of the latter.

[Insert Table 06 here]

While table 06 affirms a differential regional impact providing support for the community health workers channel, it does not extensively substantiate the claim. In order to assess that we have explore the differential impact by the number of community health workers in sub-districts over time. Furthermore, if this is the operating channel of the impact, it still remains a question as to why peaceful protests would hinder community health workers from being active but not the political strikes. Once again, there are a few possibilities that remain to be explored.

First, the community health workers village and town based treating only nearby households. They travel by bicycles and would thus not be affected by the lack of transportation services during strikes. Moreover, citizens know the community health workers active in their locality, often respecting their service to the community. Rioters may recognize them and simply let them pass to do their health work. Second, the people composition of peaceful protests are different from that of political strikes. While the former is mostly organized and participated by normal and active citizens, the latter are organized and participated by local political party members. It could be that during the protests, community health workers expect most household members to join the protests while pregnant mothers are left alone at home. If this is case, community health workers may choose to come at a later time when the protests calm down, expecting more members of the households to be present. They would do so since their job description involves provides providing basic health services to several members of the household and not only pregnant mothers. This is also likely since pre- and post-natal care have a relatively more elastic demand.

Finally, we present the results on child vaccination in table 07. We don't find much impact for any of the vaccination outcomes. The significant negative impacts of high-violence political strikes on DPT and polio are very low in magnitude at 1.6% each. This was expected given the high rate of child vaccination coverage in Bangladesh as seen from the mean of the dependant variable in the table.

[Insert Table 07 here]

3.2. Son preference in health facility utilization

If son preference still persists in the individual decision-making process, we would expect a differential impact by gender of the child. We test this for health facility utilization by interacting the gender of the child with each of the disruptive events indices. The results are presented in table 08.

[Insert Table 08 here]

We find evidence of son preference with lower utilization of health care facilities for female children reported sick compared to that of male children. A one unit increase in the index for peaceful protests lowers the expected probability of a female child who reported sick being taken to a health facility by 42.4% compared to a male child who reported sick. The magnitude of the expected probability reduction is even greater in the case of high-violence political strikes at 56.7%. This reiterates the son preference culture present in most developing countries, which further aggravates the cost in the presence of politically motivated disruptive events.

4. Conclusion

Exploiting within-location variation in disruptive events over time, this paper explored the role of politically motivated peaceful protests and strikes on health care utilization between 2010 and 2014 in Bangladesh. We find evidence of negative impacts of peaceful political protests and low-violence political strikes on health facility usage, hospital delivery and postnatal care. Several possible context-specific mechanisms were discussed with propositions for further empirical work to acutely identify the operating channels. Pregnant mothers are found to be substituting away from delivering in hospitals to smaller local clinics during higher incidents of disruptions. Furthermore, we find evidence of son preference with lower utilization of health care facilities for female children reported sick compared to that of male children. The findings suggest that the cost of such arguable democratic processes are indeed higher than what it is believed to be. Political protests or strikes should be organized in a manner that is mindful of their unintended consequences to minimize their negative impact on national health care utilization.

References

ACLED. 2019. Armed Conflict Location & Event Data Project (ACLED) Codebook, 2019.

Akresh, R. and D. de Walque. 2010. ”Armed Conflict and Schooling: Evidence from the 1994 Rwandan Genocide,” IZA Discussion Paper.

Akresh, Richard, Verwimp, Philip, and Bundervoet, Tom. 2011. “Civil War, Crop Failure, and Child Stunting in Rwanda.” Economic Development and Cultural Change 59(4): 777–810.

Brown, Ryan. 2018. “The Mexican Drug War and Early-Life Health : The Impact of Violent Crime on Birth Outcomes.” Demography

Camacho, A. 2008. ”Stress and Birth Weight: Evidence from Terrorist Attacks.” American Economic Review: Papers & Proceedings, 98(2), pp. 511–15.

Chamarbagwala, Rubiana and Morn, Hilcas E. 2011. “The human capital consequences of civil war: Evidence from Guatemala.” Journal of Development Economics 94(1): 41 – 61.

Mansour, Hani and Rees, Daniel I. 2012. “Armed conflict and birth weight: Evidence from the al-Aqsa Intifada.” Journal of Development Economics 99(1): 190–199.

Minoiu, C. and O. Shemyakina, 2012, ”Child Health and Conflict in Côte d’Ivoire,” American Economic Review Papers and Proceedings, Vol. 102, Issue 3, pp. 294-299.

Molina, T., 2019. Health-Seeking Amidst Violence: Evidence from the Philippines.

Shemyakina, Olga N. 2015. “Political Violence, Land Reform, and Child Health: results from Zimbabwe.”

Figures

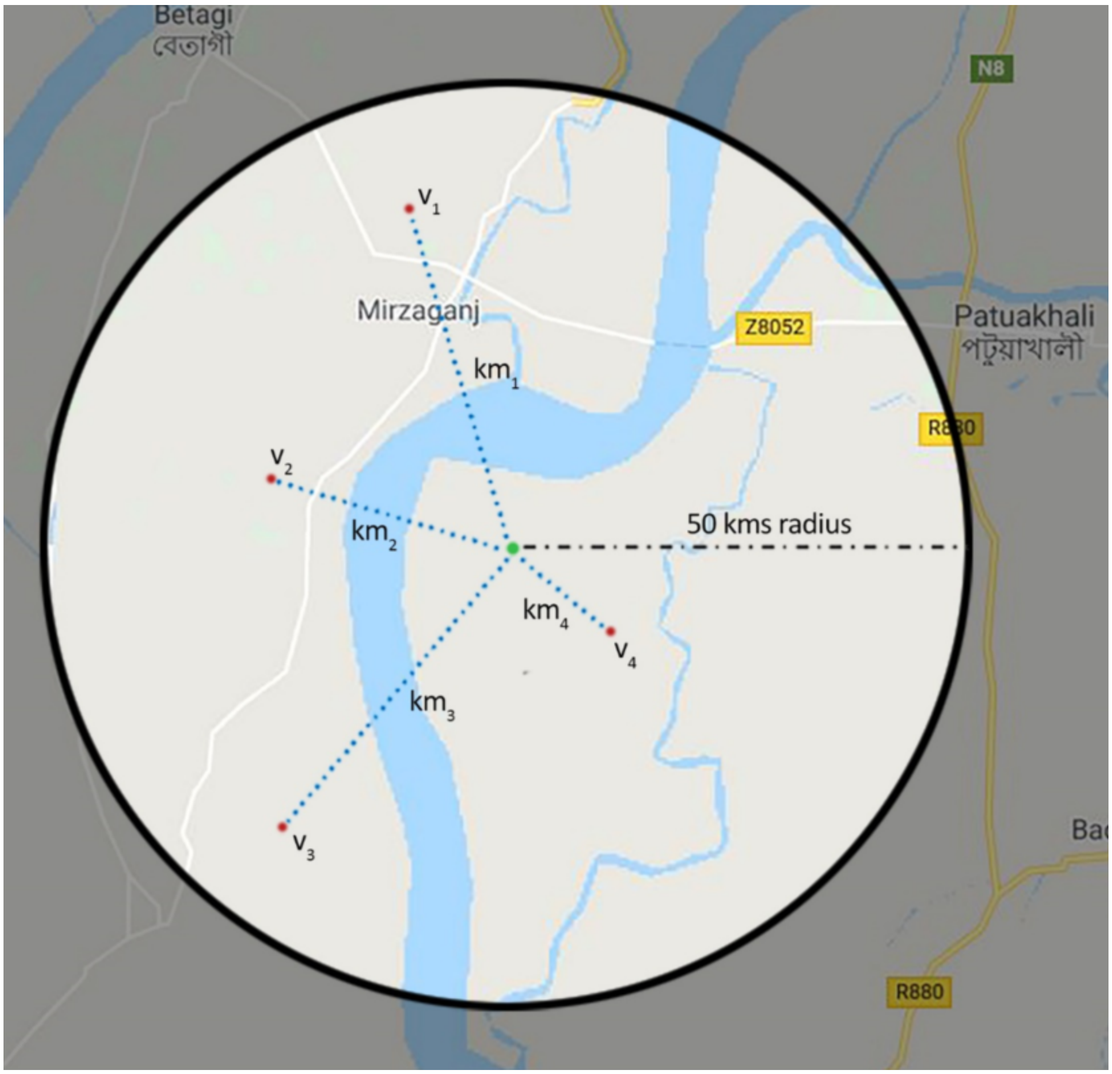

Figure 1: Generating distance-weighted disruption indices

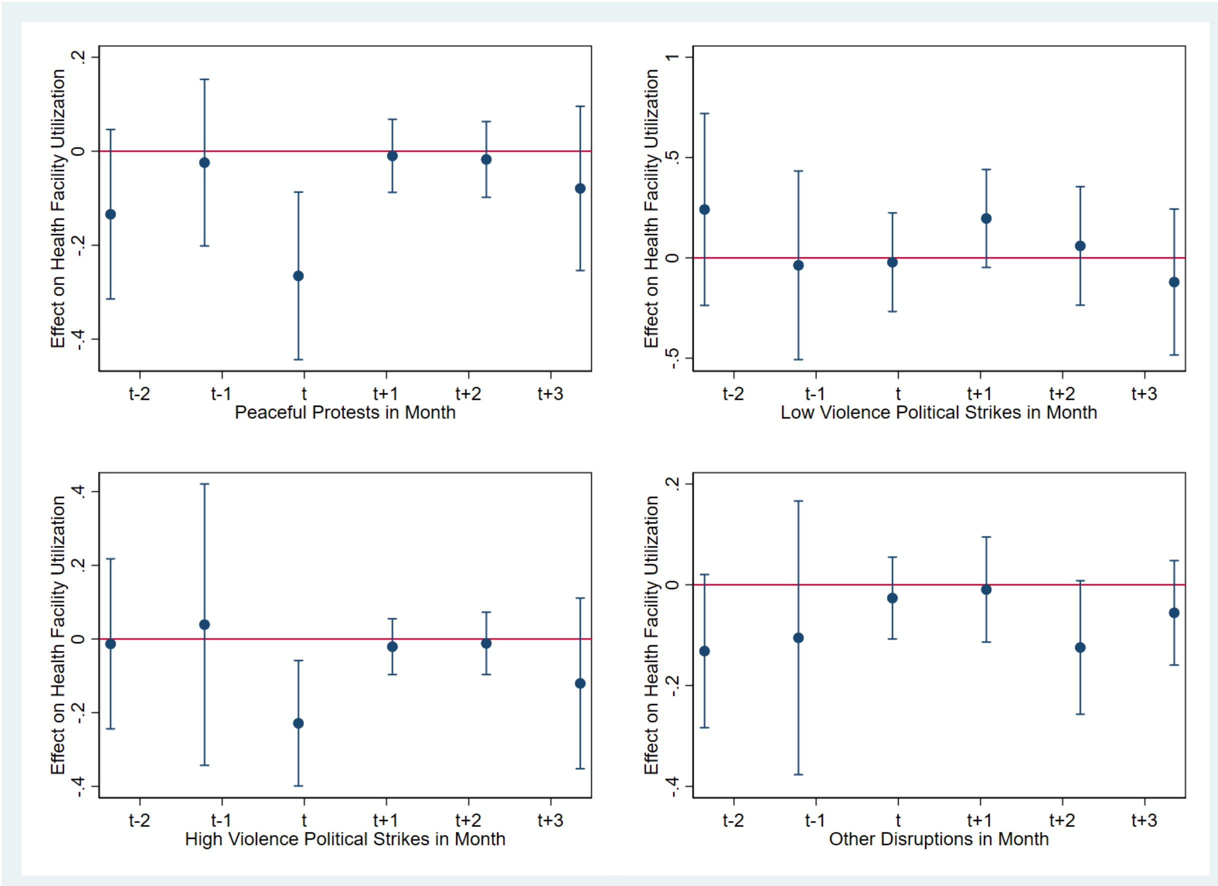

Figure 2: Impact on health facility utilization by month of disruptive events

Tables

Table 01: Distinctions between disruptive measures

Mechanism	Peaceful Protests	Low Violence Political Strikes	High Violence Political Strikes
Stress/fear/anxiety	✓	✓	✓
Limit access to markets	×	✓	✓
Shutdown of transportation services	×*	✓	✓
Damage to infrastructure (excluding health)	×	✓	✓
Damage to health infrastructure	×	×	✓
Human casualties/fatalities	×	×	✓

*creates extensive traffic congestion

Table 02: Disruptions on Health Facility Utilization

VARIABLES (2 weeks before survey)	(1) Visited Health Facility	(2) Visited Health Facility	(3) Visited Health Facility
	(in last 2 weeks before survey)		
All Disruptions	-0.097*		
	(0.057)		
Peaceful Protests		-0.316**	-0.356*
		(0.138)	(0.181)
All Political Strikes		-0.235*	
		(0.126)	
Low Violence Political Strikes			-0.184
			(0.149)
High Violence Political Strikes			-0.229**
			(0.103)
Other Disruptions		-0.029	-0.031
		(0.040)	(0.043)
Observations	3,224	3,224	3,224
Mean of DV	0.393	0.393	0.393
Individual Controls	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Fixed Effects	Sub-district, District-year, Month, Day of month		

- Robust standard errors clustered at the upazila level are reported in parentheses. (***p<0.01, **p<0.05, *p<0.10)
- Individual Controls include: child gender, child's age in months (quadratic), mother's education (category fixed effects) and mother's age (quadratic).
- Demographic Controls include: household wealth score quintile (category fixed effects), muslim mother, female household head, age of household head, household size, number of women aged 15-49 in the household, number of children aged under 5 in the household and number of living children of the mother.

Table 03: Disruptions on Prenatal Care

VARIABLES (9 Months before Birth)	(1) Any Prenatal Visit	(2) Number of Prenatal Visits	(3) Prenatal Visit to Hospital
Peaceful Protests	-0.004	-0.074**	-0.011
	(0.005)	(0.032)	(0.008)
Low Violence Political Strikes	0.003	-0.005	-0.018**
	(0.008)	(0.050)	(0.009)
High Violence Political Strikes	0.001	0.014	0.010
	(0.009)	(0.082)	(0.013)
Other Disruptions	-0.013***	-0.110**	-0.005
	(0.004)	(0.048)	(0.006)
Observations	4,605	4,605	3,629
Mean of DV	0.787	2.813	0.506
Individual Controls	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Fixed Effects	Sub-district, District-year, Month, Day of month		

- Robust standard errors clustered at the upazila level are reported in parentheses. (***p<0.01, **p<0.05, *p<0.10)
- Individual Controls include: child gender, child's age in months (quadratic), mother's education (category fixed effects) and mother's age (quadratic).
- Demographic Controls include: household wealth score quintile (category fixed effects), muslim mother, female household head, age of household head, household size, number of women aged 15-49 in the household, number of children aged under 5 in the household and number of living children of the mother.

Table 04: Disruptions on Place of Delivery

VARIABLES (1 Month before Birth)	(1) Hospital Delivery	(2) Home Delivery	(3) Smaller Clinic Delivery
Peaceful Protests	0.005	-0.004	-0.001
	(0.018)	(0.014)	(0.013)
Low Violence Political Strikes	-0.055**	0.014	0.041*
	(0.026)	(0.027)	(0.024)
High Violence Political Strikes	-0.021	0.032	-0.011
	(0.032)	(0.030)	(0.027)
Other Disruptions	-0.055*	-0.031	-0.024
	(0.030)	(0.034)	(0.024)
Observations	4,988	4,988	4,988
Mean of DV	0.289	0.605	0.106
Individual Controls	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Fixed Effects	Sub-district, District-year, Month, DOM		

- Robust standard errors clustered at the upazila level are reported in parentheses. (***p<0.01, **p<0.05, *p<0.10)
- Individual Controls include: child gender, child's age in months (quadratic), mother's education (category fixed effects) and mother's age (quadratic).
- Demographic Controls include: household wealth score quintile (category fixed effects), muslim mother, female household head, age of household head, household size, number of women aged 15-49 in the household, number of children aged under 5 in the household and number of living children of the mother.

Table 05: Disruptions on Postnatal Care

VARIABLES (relevant time period)	(1) Mother Checkup after Delivery within 1 Week	(2) Baby Checkup after Delivery within 2 Months
Peaceful Protests	-0.082*	-0.030**
	(0.043)	(0.014)
Low Violence Political Strikes	0.029	-0.002
	(0.070)	(0.015)
High Violence Political Strikes	0.016	0.004
	(0.054)	(0.021)
Other Disruptions	0.029	0.024
	(0.058)	(0.027)
Observations	4,840	4,836
Mean of DV	0.639	0.641
Individual Controls	Yes	Yes
Demographic Controls	Yes	Yes
Fixed Effects	Sub-district, District-year, Month, DOM	

- Robust standard errors clustered at the upazila level are reported in parentheses. (***p<0.01, **p<0.05, *p<0.10)
- Individual Controls include: child gender, child's age in months (quadratic), mother's education (category fixed effects) and mother's age (quadratic).
- Demographic Controls include: household wealth score quintile (category fixed effects), muslim mother, female household head, age of household head, household size, number of women aged 15-49 in the household, number of children aged under 5 in the household and number of living children of the mother.

Table 06: Disruptions on Postnatal Care by type of Region

VARIABLES	(1) Mother Checkup (City Corp.)	(2) Baby Checkup (City Corp.)	(3) Mother Checkup (Town)	(4) Baby Checkup (Town)	(5) Mother Checkup (Rural)	(6) Baby Checkup (Rural)
Peaceful Protests	0.027	0.018	-0.263	-0.058	-0.274***	-0.084*
	(0.042)	(0.016)	(0.170)	(0.065)	(0.095)	(0.050)
Low Violence Political Strikes	-0.088	0.007	0.177	0.014	0.063	-0.018
	(0.099)	(0.023)	(0.207)	(0.056)	(0.119)	(0.024)
High Violence Political Strikes	-0.048	-0.016	-0.153	-0.046	0.084	0.013
	(0.050)	(0.041)	(0.171)	(0.055)	(0.096)	(0.031)
Other Disruptions	0.040	-0.027	0.093	0.054	0.080	0.097
	(0.047)	(0.023)	(0.152)	(0.061)	(0.184)	(0.071)
Observations	543	543	1,075	1,074	3,222	3,219
Mean of DV	0.893	0.895	0.702	0.682	0.574	0.584
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sub-district, District-year, Month, Day of month					

- Robust standard errors clustered at the upazila level are reported in parentheses. (***p<0.01, **p<0.05, *p<0.10)
- Individual Controls include: child gender, child's age in months (quadratic), mother's education (category fixed effects) and mother's age (quadratic).
- Demographic Controls include: household wealth score quintile (category fixed effects), muslim mother, female household head, age of household head, household size, number of women aged 15-49 in the household, number of children aged under 5 in the household and number of living children of the mother.

Table 07: Disruptions on Child Vaccination Coverage within 12 Months

VARIABLES	(1) Full	(2) Measles	(3) BCG	(4) DPT	(5) Polio
Peaceful Protests	0.012	0.010	0.002	0.004	0.002
	(0.010)	(0.009)	(0.002)	(0.004)	(0.003)
Low Violence Political Strikes	0.004	0.002	-0.001	-0.002	-0.003
	(0.007)	(0.006)	(0.004)	(0.006)	(0.006)
High Violence Political Strikes	-0.009	-0.009	-0.009	-0.016*	-0.016*
	(0.010)	(0.009)	(0.007)	(0.009)	(0.009)
Other Disruptions	0.000	0.001	0.001	0.004	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	5,266	5,272	5,280	5,277	5,280
Mean of DV	0.866	0.886	0.976	0.931	0.934
Individual Controls	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sub-district, District-year, Month, Day of month				

- Robust standard errors clustered at the upazila level are reported in parentheses. (***p<0.01, **p<0.05, *p<0.10)
- Individual Controls include: child gender, child's age in months (quadratic), mother's education (category fixed effects) and mother's age (quadratic).
- Demographic Controls include: household wealth score quintile (category fixed effects), muslim mother, female household head, age of household head, household size, number of women aged 15-49 in the household, number of children aged under 5 in the household and number of living children of the mother.

Table 08: Son Preference in Health Facility Utilization

VARIABLES (2 weeks before birth)	(1) Visited Health Facility within last 2 weeks
Peaceful Protests	-0.163
	(0.197)
Female=1#Peaceful Protests	-0.424**
	(0.192)
Low Violence Political Strikes	-0.191
	(0.176)
Female=1#Low Violence Political Strikes	0.097
	(0.213)
High Violence Political Strikes	0.006
	(0.125)
Female=1#High Violence Political Strikes	-0.567***
	(0.216)
Other Disruptions	-0.092*
	(0.048)
Female=1#Other Disruptions	0.213
	(0.133)
Female=1	-0.033
	(0.022)
Observations	3,224
Mean of DV	0.393
Individual Controls	Yes
Demographic Controls	Yes
Fixed Effects	Sub-district, District-year, Month, Day of month

- Robust standard errors clustered at the upazila level are reported in parentheses. (***p<0.01, **p<0.05, *p<0.10)
- Individual Controls include: child gender, child's age in months (quadratic), mother's education (category fixed effects) and mother's age (quadratic).
- Demographic Controls include: household wealth score quintile (category fixed effects), muslim mother, female household head, age of household head, household size, number of women aged 15-49 in the household, number of children aged under 5 in the household and number of living children of the mother.