Political Violence and Economic Activity in Bangladesh: A Robust Empirical Investigation

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Abstract

Using daily and monthly level night light products from National Aeronautics and Space Administration (NASA) Black Marble suite (NASA and Administration, 2199) and extrapolating hartal / strike related violence data with keyword search from geocoded Armed Conflict Location & Event Data Project (ACLED) database, we investigate the impact of such events on urban & economic activity in Bangladesh. We focus our investigation firstly at daily level, to discern the immediate impacts of such events on daily urban activity and secondly at monthly level, to extrapolate the economic impact stemming from hartal induced shocks to key infrastructural sectors, namely transport. For daily level analysis, we utilize Autoregressive Conditional Heteroskedasticity (ARCH) estimation to factor in the deeply autoregressive nature of daily night lights, to identify immediate (within-day) effects from hartals, individually for key subdistricts. At the monthly level, to factor in the emergent consequent spatial dependence as well as suspected endogeneity from hartals, we analyze country wide dynamics in a control function approach with bias corrected Quasi Maximum Likelihood approach as suggested by fei Lee and Yu (2010b) in the second stage. In first stage we use either lagged count of peaceful non-hartal events or 2008 election division level majority party parliamentary seat shares, interacted with subdistrict specific trends, as instruments. At daily level, over 2012-21, in the capital Dhaka, we find that daily hartals have an immediate statistically significant impact of -0.9 percent on daily night lights. However this effect does not hold uniformly across all subdistricts, and only does so for a select number of subdistricts. At the monthly level, we find evidence of statistically significant country wide effects of up to 6 percent.

Keywords: Regional Economics, Political Strikes, Spatial Analysis, Sub-national Economic Activity.

JEL Classification: C22, C23, C32, C33, F35, O11, O12, O20, O22, R12.

1 Introduction

Political violent protests in the form of strikes have long been prevalent throughout the history of Bangladesh. The intent behind staging these violent protests, also known as *hartals*, is primarily to cause large scale shutdown of economic activities and thereby destabilize and jeopardize the current sitting government. Measuring accurately the socio-economic impacts have long been a

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contentious issue among-st international funding agencies and government policy makers. To a great extent, this is the consequence of lack of accurate sub-national official statistics on economic activity, which has made accurate measurement of impact of political violence on economic activity difficult, as well as a perceived lack of methodological robustness in the empirical methods employed in studies of impact of political violence on economic activity. In this paper we look to investigate effect of political strikes, aka *hartals* on general economic activity, which is proxied by satellite derived night lights in Bangladesh. Like other developing nations, Bangladesh's history has long been intertwined with a culture of violent confrontational politics, with opposition political parties utilizing *hartals* in attempting to advance their political agenda. Such enforcement of hartals is considered successful when all shops and retail activity remain closed and motorized transport and long distance transportation is stymied, and public life comes to a standstill (Suykens and Islam, 2013). In particular, the breakdown of the transportation sector and associated supply chain disruptions, alongside uncertainty are noted to be key transmission channels through which hartal incidence registers its wider and staggered economic impact.

In this paper we look to firstly identify immediate instantaneous effects of hartals by leveraging daily night lights data derived from NASA's Black Marble suite of satellite data products, to act as proxy for economic activity, and conflict data from ACLED (Armed Conflict Location & Event Data Project). The usage of satellite derived nights as a viable proxy for economic activity at sub-national level has been well established in the literature for some time now, and in the absence of official data or presence of poor quality data, night lights work well as a proxy. Importantly it has proven to be an excellent proxy in tracking urban activity. Ahsan and Iqbal (2016) and Shonchoy and Tsubota (2015) previously investigated the effects of hartals onthe manufacturing and exporting sectors of Bangladesh's economy respectively. The latter utlized an instrumentation strategy to factor in the endogeneity of hartals by using election seat shares of majority party at division level interacted with time and division level dummies. While both found substantive impact of hartals, the scope and high frequency nature of the nights lights data, in conjunction with the geocoded conflict data from ACLED, enables us to look at the immediate effects of hartals on general economic activity, at sub-district level. In part due to its high frequency nature, the daily night lights product as used exhibits a deep autoregressive nature, the failure to account for which may to unreliable inference from empirical applications with the data. As such, conditional autoregressive heteroskedasticity estimation (ARCH) was used to model the daily effects of hartals on night lights. These daily level analyses were implemented individually on a select number of sub-districts, which was based on a threshold of minimum number of hartals in a given sub-district over the time-span of 2012-2021. We find that at daily level, relatively a small number of subdistricts exhibit immediate (same day) effects from hartals, while a few regions exhibit lagged responses. Prominent amongst these regions is the capital Dhaka, which exhibits a -0.9 percent immediate impact in night lights in response to hartal(s) on the same day. The nature of the impact of hartals may be attributed to the level of enforcement of said protests, and unsurprisingly these tend to be highest in intensity and count in the capital Dhaka, which is also the seat of the Government.

The consistent pattern of such events incurs a longer term impact on economic development. These may be manifested in terms of attritional disruptions to the transport sector and the accompanying uncertainty which injects an element of instability into the economy, and thus may result in a cascading effect whereby other sectors of the economy may take a hit. To capture these intermediate term impacts on the economy, we later utilize the monthly night lights product in a spatial dynamic panel approach, so as to address the endemic cross sectional dependence within economic activity borne out of spatial dependence. We address endogeneity concerns regarding hartals by using two months lagged counts of peaceful non-hartal events, which is based on our premise of being a predictor of current hartal count in a given sub-district, as well as fulfilling exclusion restriction by not having direct impact on current economic activity. Similar to Shonchoy and Tsubota (2015), we also use division level parliamentary voting shares, but interacted with sub-district specific time trends, as instruments so as to identify the exogenous variation within hartal spread. With this, we see that the effect of hartals is approximately 6 percent on economic activity.

The paper is thus structured as follows: Section 2 provides a brief background into the history of hartals in Bangladesh; Section 3 runs down data description; Section 4 introduced the respective econometric methodologies to be utilized; Section 5 presents the results and robustness checks; and finally Section 6 presents the conclusion

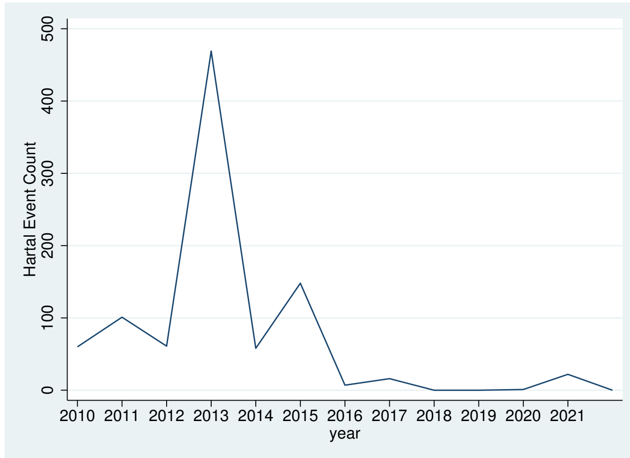

Figure 1: Hartal Count in Bangladesh 2010-2022

2 Background

2.1 Political Violence & Hartals

Violent conflict may be defined as the 'systematic breakdown of the social contract resulting from and/or leading to changes in social norms, which involves mass violence instigated through collective actionRegarding empirical coverage of impact and consequences of violent conflict, Collier (1999) has had the greatest impact, with the study focusing only on civil conflicts. Collier stated that civil conflict affects growth through (i) the destruction of resources; (ii) the disruption of infrastructure and social order; (iii) budgetary substitution; (iv) dissaving; and (v) portfolio substitution by foreign investors (Brück and Groot, 2013). This led him to conclude that the length of the conflict is going to influence the impact of the post-conflict period. In particular, he argues that long-running conflicts are more likely to be followed by an increase in growth, whereas short-lasting conflicts will suffer reduced growth rates over a longer period of time (known as a legacy effect).

Separately there are two main approaches in gauging outcomes from specific case studies concerning the occurrence and duration of conflict: the so-called accounting technique, which aims to calculate the total replacement value of goods destroyed as a result of conflict; and counterfactual analysis, which estimates a conflict-free outcome and considers the gap between such a counterfactual and the actual situation as the costs attributable to conflict (Brück and Groot, 2013; Groot et al., 2009) . For example, Abadie and Gardeazabal (2003), in a seminal study, found that after the outbreak of terrorism in the late 1960's, per capita GDP in the Basque Country declined about 10 percentage points relative to a synthetic control region without terrorism.

Conflict involves costs that are economically very important, ranging from the valuable resources diverted away from investment and consumption and instead allocated directly to arming and the resources destroyed in conflict to the reduction in trade and in the accumulation of productive capital (Garfinkel and Skaperdas, 2007). Violent conflict has also been found to have large macroeconomic shocks, with GDP per capita about 28 percent lower ten years after conflict onset. This is associated with dramatic declines in official trade and significant refugee outflows to neighboring non-advanced countries in the short run, and relatively small but very persistent refugee outflows to advanced countries over the long run (Novta and Pugacheva, 2020).

Humphreys (2003), summarizing earlier research, concluded that government policies as chosen play a significant role in determining the likelihood of conflict. Policies that induce conflict may result from deliberate decisions to weaken state institutions so that leaders can more easily enrich themselves. In countries like Bangladesh, whose history has been intertwined with political violence, such is the case. Van der Windt and Humphreys (2014) piloted a novel data-gathering system in the Democratic Republic of Congo in which villagers in a set of randomly selected communities report on events in real time via short message service (SMS). In our instance, we rely on Armed Conflict and Location & Event Data Management (ACLED) geocoded data. The data itself is collected from newspaper reports regarding political violence events in Bangladesh Ahsan and Iqbal (2016) and Shonchoy and Tsubota (2015) also scrape conflict event data from newspaper reports in order to find impact of political strikes on export oriented garments industry in Bangladesh, which is a key driver of Bangladesh's economic growth, and manufacturing firms. However those studies did not look at the aggregate economic impact of political strikes.

Originally a form of collective action devised during the anti-colonial struggle against the British, hartals have played an instrumental role during the struggle for independence from Pakistan and against the autocratic and military rulers of the country since 1971. However since 1991, hartals have become the preferred means of the opposition parties to voice their concerns with the ruling party. The winner-takes-all form of politics in Bangladesh is seen as the main reason why opposition parties take to the streets to voice their concerns, rather than going to the parliament (Suykens and Islam (2013)). Despite the documented utter lack of impact of hartals on the incumbent government's standing, and despite the resentment from the general populace, the usage of hartals have persisted amongst the opposition parties who have claimed that it is the only medium through which they can voice and channel their frustrations. Suykens and Islam (2013) in their study of hartals in Bangladesh and its causes argued that hartals play a crucial role in the political careers of local elites and party organizers, and thus may be described a useful stepping stone to the upper echelons of power within the political parties. The culture of hartals is further reinforced by the fact that during the electoral term of the government in power, the party in power effectively canvasses all powers to itself with little delegated to non party entities. This limited scope is often presented as a key excuse for the opposition parties to operate within a violent confrontational politics framework. Typically hartals thus tend to peak at around election times. Figure 1 gives a year wise breakdown of the number of hartal events year wise since 2010. Since 2015, with the government significantly clamping down on opposition party activities, there has also been a significant decline in number of hartals.

Table 1 reports the year wise distribtution of the key defined types of violence activity in Bangladesh in 2010-22. In ACLED data, we also uncovered data on general strikes, as enforced by factory and transport workers, as well as oppostion parties in enforcing transport shutdown or blockades, which we subsequently included in our hartal variable. These events do not have the keyword *hartal* in their event description and therefore would have not been included originally. Furthermore in construction of the non-hartal peaceful events, we disqualfied both hartals and strikes.

Table 1: Year wise distribution of hartals, non-hartal peaceful events and strikes

year	hartals	non-hartal peaceful event	strikes
2010	129	444	29
2011	214	451	22
2012	127	345	64
2013	761	239	27
2014	91	85	12
2015	196	238	18
2016	18	228	10
2017	30	212	13
2018	22	421	22
2019	23	869	23
2020	11	922	10
2021	39	1516	16
2022	2	386	2

Table 2: 2012-2021 Total Hartal related violent event counts

District	Sub-District	Total Hartal-related Event Count
Dhaka	Tejgaon	217
Chittagong	Kotwali	38
Naray Angonj	Narayanganj S.	35
Bogra	Bogra S.	33
Sylhet	Sylhet S.	30
Rajshahi	Boalia	28
Khulna	Kotwali	24
Comilla	Comilla S.	20
Lakshmipur	Lakshmipur S.	20
Natore	Natore S.	20
Shatkhira	Satkhira S.	17
Gazipur	Gazipur S.	16
Barisal	Barisal S.	13
Sirajgonj	Sirajganj S.	13
Nawabganj	Nawabganj S.	12
Feni	Feni S.	10

2.2 Night Lights

(a) Bangladesh January 2013

(b) Bangladesh December 2013

Figure 2: VNP46A3 Monthly Night Lights - Bangladesh

Night lights as sourced from satellite instruments is noted to be a strong proxy for economic activity (see Henderson et al. (2012), Sutton et al. (2007), Ghosh et al. (2009) and Doll et al. (2006)). This is partilcularly true in tracking sub-national economic activity in developing countries. Bluhm and McCord (2022) investigated the nonlinearities and measurement errors in the light production function within a country's economy abd found that for high statistical capacity countries nighttime lights are significantly less responsive to changes in GDP at higher baseline level of GDP, higher population densities, and for agricultural GDP. Much of the application in the social sciences has focused on the Defense Meteorological Satellite Program (DMSP) based Operational Linescan Sensor (OLS) sourced nighttime lights. The DSMP night lights are however flawed by lack of calibration, presence of top-coding, coarse resolution and blurring (Gibson et al., 2021, 2020; Elvidge et al., 2017). In 2011 the Joint Polar-orbiting Satellite System (JPSS) was launched, containing the onboard VIIRS (Visible Infrared Imaging Radiometer Suite) instrument. Since 2012, the Earth Observation Group (EOG, 2199) at the Colorado School of Mines have been producing these products at monthly and yearly level. Separately NASA and Administration (2199) has maintained the Black Marble suite of daily, monthly and yearly products from VIIRS, which has led to the availability of the more finely grained and calibrated night lights products. To date it not seen wide scale adoption in the applied empirical literature. The VIIRS sensors have in-built calibration to ensure that data are comparable over time and space, with the continuous signal quantized with 14-bit precision (n = 16,384 potential values) compared to the 6-bit Digital Number for DMSP. DSMP Night Lights also have limited dynamic range, as it covers less than two orders of magnitude so it cannot simultaneously capture light from brightly lit areas and from dimly lit areas (Gibson et al., 2021). Thus the usage of VIIRS derived data would imply more robust and accurate measurement of economic activity, especially in regions lacking sufficiently robust official statistical institutions.

VIIRS lights are a promising supplementary source for standard measures on population and economic output at a small scale, such as for low population and economic density areas in Africa (Chen and Nordhaus, 2015). Stokes and Roman (2021) examined VIIRS deteced changes to societal behavior patterns as a result of COVID-19 lockdown by detecting changes to daily time series data from Black Marble, in the Middle East during Ramadan. However the study did not employ robust empirical investigation techniques. Liu et al. (2020) looked into the effect of COVID-19 pandemic lockdown in mainland China by analysing changes to Night Time Lights (NTL) radiance and Air Quality Index and found monthly mean radiance to be lower during lockdown than before lockdown. Li et al. (2018) analyzed the night-time light dynamics in Iraq over the period 2012-2017 by using VIIRS NTL monthly composites and found that a rapid loss of NTL radiance follows an ISIS invasion of a region. Jiang et al. (2017) examined the effect of the Yemen conflict by looking at changes in VIIRS NTL monthly composites. Their analyses at national scales showed that there was a sharp decline in the study period from February 2015 to June 2015 and that the total nighttime lights of Yemen decreased by 71.60 percent in response to the decline period.

3 Data: Night Lights & Hartals

Data regarding night lights are sourced from NASA's Black Marble suite. These observations are derived from Day/Night Band (DNB) sensor of the Visible Infrared Imaging Radiometer Suite (VIIRS), on-board the Suomi-National Polar-orbiting Partnership (S-NPP) and Joint Polar Satellite System (JPSS) satellite platforms, since 2012. The primary advantages of VIIRS sourced night lights, in comparison to the more traditional DMSP OLS night lights used in the literature are its relatively finer resolution, absence of top coding (DMSP OLS night lights being 6 bit values topped out at a maximum value of 63) as well as in built calibration. These improvements facilitate more accurate monitoring of nighttime phenomena and anthropogenic sources of light emissions. Until 2018 the Earth Observation Group (currently at the Colorado School of Mines) was the sole authority in dispensing night light products based off the VIIRS satellite derived day night band observations. Since 2018, NASA's Black marble Group has also stepped in, offering a different suite of refined products, corrected for atmospheric, terrain, lunar BRDF, thermal, and straylight effects. For our purposes we utilize the gap filled VNP46A2 product (daily night lights product adjusted for moonlights) and monthly moonlight adjusted nighttime lights product (VNP46A3). The VIIRS satellite overpass takes place approximately at around 1:30 am for every day, over a particular area. This is in contrast to the DMSP-OLS overpass times of between 7 to 9 pm, before 2013/14. A key issue presented is that at daily level, with area recorded data being logged at 1:30 am, it may become difficult to capture the decline in economic activity (relative to day of no hartal), especially in more rural areas and smaller towns. Nevertheless in larger urban centers, (for instance the capital Dhaka), a dip in recorded lights on day of hartal (relative to a day of no hartal) may still be recorded, and thus be succuessfully attributed to hartal event. Thus this is one of the first works (to our knowledge) to have incorporated this data for our analysis.

Direct lights are usually not isotropic due to light characteristics. For example, street light lamps might be top-covered. Therefore the lamps could not be viewed from a nadir look but may be observed from off-nadir measurements (and in all cases produce reflected light off the surface). Building lights consist of indoor lights through windows, direct lights installed on building façade, and building reflected lights common over commercial buildings. As such for our analysis at the monthly level we utilize the VNP46A3 off-nadir night lights product.

During days of cloudy / unusual weather , the data retrieval algorithm resorts to a temporal 'gap' filling technique, to reduce persistent data gaps (which may count up to a third of the daily observations. This data retrieval technique is based off of the latest high quality date. This gap filling procedure may partially also contribute to persistent patterns of heteroskedasticity / heterogeneity present within the data and contributes to its deep autoregressive nature. The data also features non-uniform temporal coverage for certain regions. We address this by filling in these gaps by averaging from immediate past and future values. While conventional unit root tests would rule out the null of unit root within VNP46A2 gap filled daily product, we experimented with ARFIMA (Autoregressive Fractionally Integrated Moving Average) modelling, which is instrumental for time series with long memory, that is where deviations from the long term mean decay more slowly than an exponential decay. However with such estimation approaches as employed for the VNP46A2 modelling the d parameter for long term dependence would come up to be non significant. As such to accurately model the NTL radiance dynamics over time, and to factor in the heteroskedasticity of the daily night lights data process, we utilize the ARCH (Autoregressive Conditional Heteroskedasticity) methodology. This class of models are suited for processes where the volatility varies through time and future volatility is modeled as function of prior volatility.

4 Estimation Methodology:

Given the high frequency nature of the VNP46A2 night lights product, we have found that the night lights data feature a high degree of deep autocorellation. While conventional unit root tests would rule out the null of unit root within VNP46A2,we experimented with ARFIMA (Autoregressive Fractionally Integrated Moving Average) modelling, which is instrumental for time series with long memory, that is where deviations from the long term mean decay more slowly than an exponential decay. However with such estimation approaches as employed for the VNP46A2 modelling the d parameter for long term dependence would come up to be non significant.

Thus to model the effectiveness of hartals on VNP46A2 night lights product, we adopted the ARCH (Autoregressive Conditional heteroskedasticity) estimator. This class of models are suited for processes where the volatility varies through time and future volatility is modeled as function of prior volatility

The ARCH generalization is thus (for a given subdistrict):

$$y_t = ARMA(p,q) + L(1/7)X_t\beta + L(1/7)WX_t\alpha + \epsilon_t \tag{1}$$

$$Var(\epsilon_t) = C_0 + C_1\epsilon_{t-1}^2 \tag{2}$$

Where the variable of interest is β. Importantly, we select up to 10 Autoregressive lags and up to 5 Moving Average terms so as to properly factor in the dynamic nature of the daily night lights product.

To explore the intermediate effects of hartals on economic activity, we utilize the VNP46A3 monthly night lights product and implement a dynamic panel regression of the type below:

$$y_{i,t} = B_0 W y_{i,t} + \sum_{j=1}^{d} y_{i,t-j}A_j + x_{a,i,t}C + x_{b,i,t}\theta + \gamma_t + \lambda_i + \epsilon_{i,t} \tag{3}$$

Here $y_{i,t}$ is economic activity as proxied by monthly Black Marble night lights and $i = 1..N$ refers to the individual regions or cross sectional units while $t = 1..T$ refers to the time period identifier. $Wy_{i,t}$ is the spatially lagged dependence term, and its presence factors in the spatial dependence that we suspect is endemic to economic activity i.e. economic activity in region i is likely to be affected by economic activity from region j. We include up to d lags of the dependent variable, where $d > 1$. $x_{a,i,t}$ is our vector of *hartalls*. $x_{b,i,t}$ refers to exogenous regressor(s), in this instance precipication total as gathered from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data), while γ_t refers to the time period fixed effects, to control for changes in satellite year to year calibration and their sensor setting as well as country wide economic and other developments. The row normalized spatial weight matrix W_N conveys the connectivity mechanism for spatial dependence, and is defined by geographically defined boundaries of the individual regions. Finally λ corresponds to subdistrict wise fixed effects intercepts and ϵ is a vector of iid distrubance terms.

For estimation Equation (3) is presented in matrix form below:

$$\begin{aligned} y = {} & B_0[W_N \otimes I(T)]y + y_{-s}A_s + x_aC + x_b\theta + [i(N) \otimes I(T)]\gamma \\ & + [I(N) \otimes i(T)]\lambda + \epsilon \end{aligned} \tag{4}$$

Where the variables are stacked across time and regions; $\otimes$ refers to Kronecker product operator and $I(T)$ and $I(N)$ are identity matrices of dimensions T, the number of time periods and number of regions N respectively. $i(N)$ and $i(t)$ are N X 1 and T X 1 column vectors respectively. The row normalized spatial weight matrix W_N is an N X N matrix and conveys the transmission mechanism for spatial dependence, and is defined by geographically defined boundaries of the individual regions. y_{-s} is a NT X s matrix of lags of y, where $s = 1..S$ is the maximum number of lags to be included; x_a is NT X 1 vector of *hartals* variable. γ refers to the T X 1 vector of time effects coefficients while Tr, the time trend, is T X 1 vector with $1...T$ entries; and finally λ is N X 1 vector of fixed effects intercepts.

Furthermore, given that we are looking to investigate the intermediate term effects of hartals, we lag the hartal variable by up to a certain number of months. Such a placement is also borne from a hypothesis that economy wide impacts of hartals in such a dynamic panel setting may take a while to fully register their effect. This strategy of using lagged hartal count is also justified by the fact that in our exploration with the daily level data, we do not see country wide immediate effects, on the contrary we see evidence of lagged effects, which points to hartals having economy wide impacts via economic multiplier channels, namely to via disruptions to the transport sector. While such a strategy may sidestep the very pertinent issue of addressing endogeneity (arising out of simulteneity), there is the other pressing point of non vanishing bias for fixed T presented by the lagged dependent variables as well as the predetermined variable itself (lagged hartals) which in the context of our specification are defined to be variables which may be affected by only past income shocks.

Conventionally fixed effects and time dummy may be eliminated from Equation (3) by multiplying both sides of the equation by:

$$I(N) \otimes [I(T) - i(T)i(T)'] \tag{5}$$

$$[I(N) - i(N)i(N)'] \otimes I(T) \tag{6}$$

Multiplication by (5) is intended to eliminate unit fixed effects, while multiplication by (6) eliminates time dummies from Equation (3) as nuisance parameters. However, maximum likelihood estimation in such a manner leads to biased estimates of the spatial dependence parameter, as well as introducing a degree of serial correlation (fei Lee and Yu (2010a)). This may be averted by instead using transformation approaches based on eigenvalue decompositions of (5) and (6) respectively, and thereby leading to elimination of time and unit fixed effects without imposing penalty on estimation of parameters of interest (fei Lee and Yu (2010b))[1]. Equation 5 is then estimated with is then estimated with Spatial Maximum Likelihood, which circumvents the issue of dealing with endogenous spatial lagged dependent variable by bringing it to the left hand side of the equation and consequently it becomes a question of Quasi Maximum Likelihood estimation with inclusion of log of determinant of $[I(N) - B_0 W]$ in the main log likelihood function. The concentrated log-likelihood function to be estimated then is:

$$lnF = (T-2)\ ln|A| - \frac{(N-1)(T-1)}{2}\ ln(\sigma^2) \tag{7}$$

[1]The eigenvalues of $[I(N) - i(N)i(N)']$ are N-1 ones and a single zero. Then F_N is N-1 x 1 matrix of stacked column eigenvectors corresponding to the eigenvalues of 1. Similarly F_T is T-1 x 1 matrix of column eigenvectors corresponding to eigenvalues of 1 from $[I(T) - i(T)i(T)']$.

Where:

$$|A| = Determinant\ of\ \Big(I(N-1) - B_0\ F_N' W_N F_N\Big) \tag{8}$$

$$\sigma^2 = \frac{1}{(N-1)(T-2)}\Big([A \otimes I(T-2)]\ CDy\ -\ CDx\beta\Big) \tag{9}$$

$$\beta = \Big((CD\ x)'(CD\ x)\Big)^{-1}\Big((CDx)'([A \otimes I(T-2)]\ CDy)\Big) \tag{10}$$

$$C = [F_N' \otimes I(T-2)] \tag{11}$$

$$D = [I(N) \otimes F_T'] \tag{12}$$

Where x refers to the set of all the regressors present in the specification. C and D are the transformation matrices described earlier for purging away time fixed effects and region fixed effects, while F_N and F_T are described in Footnote 2. From the concentrated log likelihood function, we may derive the estimate for the spatial autoregressive paramter B_0, and consequently the rest of the parameters (β and σ_2) may be derived from the closed form formulas in (9) and (10). It must be mentioned that prior to estimation of B_0, given the lack of smooth concavity of (7) in B_0, we must undertake at first a search procedure via a grid search procedure to locate the region of maximized value of the log likelihood.

A key issue is factoring in endogeneity of hartals. For example, the same unobservable factors affect the geographical distribution of current hartals and economic growth. In the literature although lagged endogenous variables have ben used to sidestep this issue of identification, it becomes clear that in our instance it is difficult to motivate such a decision, since it is more likely that lagged monthly hartal counts may have a direct bearing on current economic activity, given the entrnehcned nature of impact of hartals. Instead, we use lagged *non*-hartal peaceful event counts from the in the last 2 years as instruments. Given Bangladesh's political climate, where protests are intertwined in the identity and nature in Bangladesh, this premise suggests that past *non*-hartal peaceful event counts will not have a direct bearing on current economic activity. We adopt a control function methodology where we model the relationship between the endogenous variable, hartals, on in the set of instruments and other exogenous variables. Subsequently the residuals from the first-stage regression are used as controls in second stage 'main' regression to control endogeneity.

$$x_{a,it} = \beta_1 x_{0,it-1} + \beta_2 x_{0,it-2} + \beta_3 x_{b,it} + \gamma_t + e_{it} \tag{13}$$

Where $x_{0,it}$ is peaceful non-hartal event count in region i at time t, while $x_{b,it}$ is the exogenous regressor in (4).

As mentioned earlier, however it is well known in panel data regression with fixed effects that inclusion of lagged dependent variable leads to the now well known Nickell bias (Nickell (1981)). This may be treated as a subset of the broader problem facing inclusion of predetermined or weakly exogenous regressors. By far dynamic panel GMM (Generalized Method of Moments) approaches have been popular to deal with this problem of weakly exogenous regressors. However a key drawback of dynamic panel GMM estimation lies in the number of instruments, whose count is nT, where n is the number of weakly exogenous regressors, while T is the maximum lag length of the instruments. With longer time periods, thus the growing number of moments also lead to estimator bias. Importantly in dynamic models featuring spatial dependence, this large number of moments conditions leads to significantly worsened bias for the spatial autoregressive parameter. Yu et al. (2008) developed a robust bias corrected Quasi Maximum Likelihood estimation framework for dynamic panel models featuring spatial dependence in the dependent variable and fei Lee and Yu (2010a) incorporated time effects in the estimation; however, in their framework it is assumed that the rest of the regressors are strictly exogenous. It becomes difficult to derive closed form formula for the estimator bias in the presence of other weakly exogenous variables (aside from lagged dependent variables), which normally would not exist had the regressors been completely exogenous. Specifically the presence of weakly exogenous regressors lead to the estimators having an $O(T^{-1})$ bias. In our estimation of (13), lagged non hartal peaceful counts may only be affected by hartal shocks in the future. As such, under standard fixed effects estimation of (11), the resulting estimates in (11) would be biased. We thus adapt the split panel jackknife bias correction methodology as studied by Chudik et al. (2018) and Dhaene and Jochmans (2015) to remove the first order or $O(T^{-1})$ bias stemming from inclusion of the weakly exogenous regressors. A key attractive feature is that there no need to formally place a structure on the bias present, as is mandated under other analytical bias correction approaches as well as those based on residual and wild bootstrap , which only corrects bias in lagged dependent variables. This non-parametric method works by

$$\hat{\hat{\theta}} = 2\hat{\theta} - 1/2(\hat{\theta}_A + \hat{\theta}_B) \tag{14}$$

Where $\hat{\theta}_A$ is the dynamic panel estimator estimated over the first half of T, the time series sample, while $\hat{\theta}_B$ dynamic panel estimator estimated over the second half of T. $\hat{\theta}$ refers to the original dynamic panel estimates. The rationale behind the elimination of first order bias may be seen from the fact that in estimation of samples from Part A and Part B, given that there is the same number of nuisance parameters involved, the first order biases from estimation of the full sample and the individual half samples are:

$$\left(\frac{B}{T}, \frac{B}{T/2}, \frac{B}{T/2}\right) \tag{15}$$

Thus in estimation of (6) the first order bias is eliminated in the following manner:

$$2 * \frac{B}{T} - \left(\frac{1}{2} * \left(\frac{B}{T/2}\right) + \frac{1}{2} * \left(\frac{B}{T/2}\right)\right) = 0 \tag{16}$$

The bias corrected first stage estimates are then used as endogeneity controls in (3). As mentioned earlier, we then follow fei Lee and Yu (2010b) to further adjust estimates in (3) from inclusion of the lagged dependent variable. Given the lack of such estimation tools on common software platforms, namely relating to Spatial dynamic panel Quasi maximum likelihood estimation, the panel data application portion of this paper was implemented on Mata, Stata's matrix language.

In addition, we also consider a second instrumental variable, which is based largely off of the same rationale as in Shonchoy and Tsubota (2015). We use division level parliamentary seat shares of the majority party from 2008, interacted with sub-district specific trends, as an instrumental variable. Given that the primary motivation behind hartals is to bring down a rival or hostile administration in power, thus we envisage this new instrument to be correllated to hartal incidence in subdistrict i at time t.

$$x_{a,it} = \beta_4 z_{it} + \beta_5 x_{b,it} + \gamma_t + e_{it} \tag{17}$$

where z_{it} is the new instrumental variable. It may be mentioned however while since 2008 there has been 2 more countrywide parliamentary elections, in 2014 and 2018, we do not incorporate data from these events in our instrumental variable construction, given that in 2014, the main opposition party, Bangladesh Nationalist Party (BNP) did not participate altogether and voter turnout was also at an all time low with allegations of irregularities. By contrast in 2008, the Awami League, the governing incumbents since then, were riding a wave of heightened popularity given the bad press the previous BNP government garnered between 2001 and 2006, when corruption soared to an all time high. During 2018 elections, while there were widespread allegations regarding voting irregularities, the BNP was again consigned to an insignificant minority in the parliament. As such, given that the share of parliamentary seats of the majority party has by and large remained the same since 2008, we use use seat share data from that year as instrumental variable.

Table 3: Parliamentary Seat Shares Party Wise at Divisional Level

2008: Division/Party wise Election Resutls Statistics							
Party	Rajshahi	Khulna	Barisal	Dhaka	Sylhet	Chittagong	Total
Bangladesh Awami League (14P)	48	30	16	87	17	32	230
Bangladesh Nationalist Party (4P)	8	2	2	0	0	18	30
Jatiya Party (14P)	14	2	2	5	2	2	27
Jamat-E-Islami Bangladesh (4P)	0	0	0	0	0	2	2
Independent	1	1	0	1	0	1	4
Other	1	1	1	1	0	3	7
Total	72	36	21	94	19	58	300

5 Findings

5.1 Daily level Night Lights

Given that one of the primary rationale behind *hartals* is to impart a crippling blow to the incumbent governtment economically and socially,it stands to reason that these events are enforced with greater degree of rigor in economically important and more densely populated areas. As such Table 3 affords us a look at the number of hartal related events counts from ACLED between 2012-2021. It is evident that the capital city, Dhaka not surprisingly has the highest number of such events, followed by other urban areas. In fact, amongst the list of sub-districts, virtually all of them are urban centers of their respective districts. Furthermore it is also evident that more densely populated areas possesses larger hartal counts. As such, we focus on the the 9 sub-districts / towns / cities which boasts of the highest population in Bangladesh, except for Gazipur, given its status as a major textile industry hub in Bangladesh [2]. As elaborated earlier in the methodology section, we look to assess effects up to 7 days away from day of hartal. Table 4 gives the results of the benchmark ARCH specifications for those 9 key cities / towns. As mentioned earlier, we incorporate autoregressive lags of up to 10 and moving average terms of up to order 5, in order to factor in the high frequency nature of the daily VNP46A2 night lights product shows the impact for Dhaka. Given that at daily level, with night lights being recorded by VIIRS satellite at 1:30 am in the morning, it may be argued that meaningful changes in human activity patterns may be properly exhibited in urban centers. It also means that the 'contemporaneous' impact of political violence can only be picked up by first lagged term as regressor. Thus for the capital Dhaka we see an immediate impact of 0.9 percent in the day of a hartal being called; however we see that there are no lagged effects whatsoever. This points to the notion that in the capital, the city populace reverts back to general daily affairs within a day of hartal.

The situation regarding the other urban centers of interest exhibit different results; Chittagong, the main port city in Bangladesh, seemingly registers a statistically significant decline only on the third day after a hartal has been enforced; this is indicative of indirect effects of hartals manifesting through direct impacts of key economic sectors, primarily the transport sector. Gazipur (Column 5) registers a sharp statistically significant contemporaneous impact of 5.5 percent decline, while Khulna (Column 3), which is the third largest city in Bangladesh as well as boasting of significant

[2] in focusing on the top 44 subdistricts with highest hartal counts, the ARCH specifications consistently show misdiagnosis symptoms for a couple of regions, namely first order serial autocorellation. Furthermore for many regions, the estimates of immediate impact are unstable, which points more to the noisy nature of daily nightlights of the region in concern. Thus we focus on the economically important and populous subdistricts

Table 4: ARCH Specifications for Dhaka; Chittagong; Khulna; Sylhet; Gazipur; Barisal; Narayanganj; Bogra; Rajshahi - 2012-2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Residuals									
L.(sum) a0	-0.009***	0.024	0.029	-0.028*	-0.055*	-0.035	0.002	-0.029*	0.026
	(0.003)	(0.017)	(0.023)	(0.015)	(0.031)	(0.041)	(0.015)	(0.018)	(0.028)
L2.(sum) a0	0.003	0.012	-0.065***	0.008	0.052	-0.037	0.010	0.010	0.003
	(0.004)	(0.017)	(0.018)	(0.030)	(0.033)	(0.038)	(0.017)	(0.026)	(0.023)
L3.(sum) a0	-0.002	-0.034**	-0.042	0.003	-0.012	0.017	0.012	0.021	-0.002
	(0.005)	(0.016)	(0.034)	(0.022)	(0.033)	(0.034)	(0.010)	(0.023)	(0.024)
L4.(sum) a0	-0.002	0.007	0.008	0.015	-0.032	0.016	-0.012	-0.020	-0.018
	(0.004)	(0.016)	(0.032)	(0.020)	(0.025)	(0.050)	(0.016)	(0.026)	(0.035)
L5.(sum) a0	0.003	0.008	0.012	-0.047***	-0.023	-0.025	0.005	-0.022	0.031
	(0.003)	(0.017)	(0.035)	(0.018)	(0.034)	(0.047)	(0.018)	(0.022)	(0.028)
L6.(sum) a0	-0.004	0.005	-0.009	0.000	0.042	-0.014	-0.000	-0.002	0.016
	(0.004)	(0.017)	(0.029)	(0.021)	(0.028)	(0.038)	(0.014)	(0.019)	(0.026)
L7.(sum) a0	0.004	0.012	-0.012	-0.013	0.034	-0.005	0.001	-0.034	0.012
	(0.004)	(0.017)	(0.036)	(0.019)	(0.048)	(0.045)	(0.014)	(0.025)	(0.029)
Constant	-0.002	-0.002	-0.025**	0.002	-0.003	0.003	0.001	0.002	-0.014**
	(0.014)	(0.011)	(0.011)	(0.009)	(0.013)	(0.012)	(0.013)	(0.008)	(0.007)
ARMA									
L.ar	0.417***	0.573***	0.885	0.202**	0.540***	0.631***	0.618***	0.624***	0.200
	(0.029)	(0.028)	(0.864)	(0.083)	(0.029)	(0.026)	(0.030)	(0.036)	(0.243)
L2.ar	-0.013	-0.298***	-0.170	0.617***	-0.340***	-0.335***	-0.420***	-0.360***	0.585**
	(0.024)	(0.024)	(0.753)	(0.084)	(0.022)	(0.023)	(0.032)	(0.023)	(0.230)
L3.ar	-0.018	0.285***	-0.719***	-0.839***	0.324***	0.400***	0.348***	0.404***	-0.922***
	(0.022)	(0.024)	(0.124)	(0.034)	(0.025)	(0.023)	(0.036)	(0.028)	(0.051)
L4.ar	-0.217***	-0.350***	0.980	0.490***	-0.440***	-0.457***	-0.423***	-0.442***	0.513***
	(0.021)	(0.023)	(0.625)	(0.056)	(0.023)	(0.021)	(0.034)	(0.023)	(0.183)
L5.ar	1.049***	1.087***	-0.122	0.739***	1.086***	1.099***	1.075***	1.086***	0.655**
	(0.021)	(0.025)	(0.838)	(0.087)	(0.026)	(0.026)	(0.032)	(0.031)	(0.257)
L6.ar	-0.233***	-0.263***	0.019	-0.194***	-0.221***	-0.300***	-0.288***	-0.302***	-0.160**
	(0.028)	(0.027)	(0.084)	(0.035)	(0.030)	(0.029)	(0.029)	(0.033)	(0.064)
L7.ar	-0.032	0.000	-0.056*	-0.026	0.009	-0.009	0.051**	0.003	-0.044
	(0.022)	(0.020)	(0.034)	(0.025)	(0.022)	(0.022)	(0.023)	(0.023)	(0.028)
L8.ar	-0.007	-0.025	0.077	-0.035*	-0.025	-0.073***	-0.015	-0.065***	-0.000
	(0.021)	(0.020)	(0.065)	(0.021)	(0.022)	(0.020)	(0.023)	(0.020)	(0.021)
L9.ar	0.023	-0.011	-0.021	0.019	0.028	0.005	0.003	-0.023	0.036**
	(0.018)	(0.020)	(0.064)	(0.019)	(0.020)	(0.019)	(0.021)	(0.019)	(0.016)
L10.ar	-0.027	-0.043***	0.021	-0.032	-0.026	-0.003	-0.009	-0.002	-0.019
	(0.017)	(0.017)	(0.021)	(0.019)	(0.018)	(0.017)	(0.017)	(0.018)	(0.021)
L.ma	-0.062***	-0.217***	-0.583	0.160**	-0.200***	-0.280***	-0.253***	-0.245***	0.178
	(0.021)	(0.019)	(0.862)	(0.081)	(0.021)	(0.017)	(0.025)	(0.028)	(0.241)
L2.ma	0.041**	0.188***	0.022	-0.569***	0.270***	0.246***	0.275***	0.261***	-0.527***
	(0.018)	(0.015)	(0.492)	(0.057)	(0.016)	(0.012)	(0.024)	(0.019)	(0.141)
L3.ma	0.045**	-0.200***	0.773***	0.660***	-0.233***	-0.258***	-0.208***	-0.258***	0.743***
	(0.018)	(0.016)	(0.021)	(0.018)	(0.020)	(0.014)	(0.026)	(0.025)	(0.017)
L4.ma	0.287***	0.351***	-0.777	-0.198***	0.407***	0.392***	0.365***	0.380***	-0.212
	(0.017)	(0.015)	(0.663)	(0.056)	(0.015)	(0.012)	(0.023)	(0.019)	(0.185)
L5.ma	-0.835***	-0.839***	0.032	-0.738***	-0.810***	-0.878***	-0.809***	-0.867***	-0.663***
	(0.020)	(0.018)	(0.662)	(0.065)	(0.020)	(0.017)	(0.022)	(0.029)	(0.187)
ARCH									
L.arch	0.146***	0.194***	0.361***	0.247***	0.146***	0.216***	0.171***	0.193***	0.301***
	(0.018)	(0.020)	(0.024)	(0.024)	(0.021)	(0.021)	(0.020)	(0.019)	(0.023)
L2.arch	-0.003	0.028***	0.017	0.008	-0.022**	0.004	-0.023***	0.018**	-0.015
	(0.006)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.009)	(0.007)	(0.009)
Constant	0.009***	0.011***	0.017***	0.010***	0.012***	0.017***	0.014***	0.015***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3735	3735	3735	3735	3735	3735	3735	3735	3735

Standard errors in parentheses
a0 refers to hartal count
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: ARCH Specifications for Dhaka; Chittagong; Khulna; Gazipur; Barisal; Narayanganj; Bogra; Rajshahi - 2012-2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Residuals								
L.(sum) a0	-0.010***	0.018	0.027	-0.054	-0.032	0.001	-0.035**	0.036
	(0.004)	(0.018)	(0.022)	(0.034)	(0.041)	(0.023)	(0.018)	(0.026)
L2.(sum) a0	0.004	0.017	-0.087***	0.054	-0.053	0.010	0.001	0.006
	(0.005)	(0.017)	(0.018)	(0.035)	(0.042)	(0.020)	(0.027)	(0.023)
L3.(sum) a0	0.001	-0.031**	-0.024	-0.017	0.021	0.018	0.023	-0.009
	(0.005)	(0.016)	(0.035)	(0.035)	(0.038)	(0.015)	(0.026)	(0.026)
L4.(sum) a0	-0.002	0.005	0.010	-0.033	0.041	-0.011	-0.019	-0.015
	(0.005)	(0.017)	(0.031)	(0.027)	(0.048)	(0.019)	(0.026)	(0.034)
L5.(sum) a0	0.001	0.012	0.013	-0.027	-0.030	0.005	-0.032	0.026
	(0.004)	(0.017)	(0.030)	(0.036)	(0.050)	(0.022)	(0.022)	(0.025)
L6.(sum) a0	-0.005	-0.000	-0.001	0.042	-0.020	0.000	-0.007	0.013
	(0.005)	(0.018)	(0.028)	(0.032)	(0.043)	(0.017)	(0.021)	(0.025)
L7.(sum) a0	0.002	0.009	-0.014	0.034	0.005	-0.000	-0.034	0.018
	(0.004)	(0.017)	(0.037)	(0.050)	(0.048)	(0.015)	(0.026)	(0.026)
Constant	0.001	-0.009	-0.055***	0.002	0.008	-0.000	0.005	-0.011
	(0.028)	(0.020)	(0.019)	(0.023)	(0.014)	(0.028)	(0.008)	(0.013)
ARMA								
L.ar	0.289***	0.650**	0.435***	0.006	0.585***	0.620***	-0.339	0.777*
	(0.045)	(0.285)	(0.067)	(0.053)	(0.041)	(0.042)	(0.408)	(0.459)
L2.ar	0.227***	0.182	-0.385***	0.789***	-0.304***	-0.416***	0.108	0.008
	(0.037)	(0.297)	(0.033)	(0.050)	(0.032)	(0.033)	(0.287)	(0.495)
L3.ar	-0.348***	-0.754***	0.216***	-0.940***	0.403***	0.346***	-0.663***	-0.630***
	(0.034)	(0.093)	(0.044)	(0.042)	(0.033)	(0.037)	(0.071)	(0.208)
L4.ar	-0.027	0.845***	-0.418***	0.363***	-0.457***	-0.467***	-0.157	0.749**
	(0.036)	(0.201)	(0.031)	(0.054)	(0.032)	(0.035)	(0.299)	(0.346)
L5.ar	1.046***	0.302	1.061***	0.973***	1.108***	1.136***	0.652***	0.236
	(0.032)	(0.331)	(0.049)	(0.054)	(0.040)	(0.039)	(0.166)	(0.497)
L6.ar	-0.248***	-0.082	-0.185***	-0.211***	-0.288***	-0.319***	0.025	-0.076
	(0.043)	(0.080)	(0.059)	(0.046)	(0.042)	(0.045)	(0.224)	(0.103)
L7.ar	-0.024	-0.068*	0.093***	-0.066	0.009	0.061*	0.130	-0.087**
	(0.035)	(0.037)	(0.031)	(0.042)	(0.031)	(0.033)	(0.087)	(0.042)
L8.ar	0.060*	-0.001	0.020	0.066*	-0.115***	-0.010	0.011	0.014
	(0.032)	(0.030)	(0.030)	(0.037)	(0.028)	(0.033)	(0.079)	(0.045)
L9.ar	0.013	0.005	0.039	0.008	0.025	0.035	0.047	0.035
	(0.030)	(0.033)	(0.027)	(0.030)	(0.027)	(0.031)	(0.045)	(0.040)
L10.ar	-0.037	-0.105***	-0.028	-0.049*	-0.016	-0.034	0.036	-0.070**
	(0.027)	(0.030)	(0.028)	(0.028)	(0.026)	(0.025)	(0.031)	(0.030)
L.ma	0.097***	-0.264	-0.101*	0.358***	-0.242***	-0.218***	0.772*	-0.405
	(0.034)	(0.284)	(0.057)	(0.044)	(0.029)	(0.032)	(0.413)	(0.463)
L2.ma	-0.170***	-0.315*	0.328***	-0.659***	0.214***	0.265***	0.174	-0.149
	(0.033)	(0.187)	(0.039)	(0.045)	(0.021)	(0.023)	(0.468)	(0.332)
L3.ma	0.269***	0.671***	-0.037	0.680***	-0.258***	-0.214***	0.771***	0.619***
	(0.028)	(0.050)	(0.050)	(0.029)	(0.024)	(0.028)	(0.248)	(0.136)
L4.ma	0.205***	-0.496**	0.443***	-0.066	0.367***	0.420***	0.575	-0.539
	(0.033)	(0.206)	(0.038)	(0.042)	(0.021)	(0.024)	(0.414)	(0.349)
L5.ma	-0.800***	-0.378*	-0.748***	-0.777***	-0.864***	-0.822***	-0.323	-0.324
	(0.034)	(0.228)	(0.056)	(0.038)	(0.028)	(0.030)	(0.383)	(0.387)
ARCH								
L.arch	0.155***	0.261***	0.524***	0.188***	0.208***	0.139***	0.281***	0.153***
	(0.033)	(0.032)	(0.041)	(0.037)	(0.035)	(0.029)	(0.032)	(0.026)
L2.arch	0.008	0.023	-0.001	-0.032**	0.009	-0.022	0.046***	-0.015
	(0.017)	(0.016)	(0.014)	(0.013)	(0.019)	(0.016)	(0.013)	(0.011)
Constant	0.010***	0.011***	0.015***	0.012***	0.017***	0.016***	0.014***	0.014***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	1789	1789	1789	1789	1789	1789	1789	1789

Standard errors in parentheses
a0 refers to hartal count
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Non Hartal Violent Events: ARCH Specifications for Dhaka; Chittagong; Khulna; Sylhet; Gazipur; Barisal; Narayanganj; Bogra; Rajshahi - 2012-2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Residuals									
L.(sum) a5	-0.001	0.001	0.001	-0.014***	-0.010	0.024*	-0.003	-0.018*	0.006
	(0.002)	(0.005)	(0.014)	(0.005)	(0.010)	(0.013)	(0.011)	(0.010)	(0.008)
L2.(sum) a5	0.001	-0.001	0.020	0.008	0.003	-0.012	-0.001	-0.012	0.016*
	(0.002)	(0.005)	(0.013)	(0.006)	(0.010)	(0.012)	(0.012)	(0.011)	(0.009)
L3.(sum) a5	-0.004*	0.002	0.008	-0.008	0.005	-0.010	-0.012	0.001	0.005
	(0.002)	(0.005)	(0.012)	(0.006)	(0.011)	(0.012)	(0.010)	(0.011)	(0.007)
L4.(sum) a5	0.001	-0.003	0.009	0.001	-0.003	-0.020*	0.012	0.017**	0.002
	(0.002)	(0.006)	(0.012)	(0.005)	(0.010)	(0.011)	(0.012)	(0.009)	(0.009)
L5.(sum) a5	0.002	-0.006	-0.001	-0.008	-0.002	-0.026**	0.014	0.003	-0.011
	(0.002)	(0.005)	(0.010)	(0.006)	(0.010)	(0.011)	(0.012)	(0.009)	(0.009)
L6.(sum) a5	0.000	-0.007	-0.053***	0.007	-0.014	-0.007	0.015	-0.002	-0.003
	(0.002)	(0.005)	(0.008)	(0.006)	(0.010)	(0.014)	(0.012)	(0.010)	(0.009)
L7.(sum) a5	-0.003	0.002	-0.027**	-0.006	-0.009	0.016	-0.009	-0.012	0.006
	(0.002)	(0.005)	(0.013)	(0.006)	(0.009)	(0.012)	(0.011)	(0.009)	(0.008)
Constant	0.000	-0.001	-0.027**	-0.001	-0.002	0.003	0.001	0.002	-0.014**
	(0.015)	(0.011)	(0.011)	(0.010)	(0.013)	(0.012)	(0.013)	(0.008)	(0.007)
ARMA									
L.ar	0.467***	0.572***	0.093**	1.119***	0.541***	0.631***	0.619***	0.622***	1.381***
	(0.029)	(0.028)	(0.039)	(0.335)	(0.028)	(0.026)	(0.031)	(0.036)	(0.038)
L2.ar	-0.111***	-0.298***	0.426***	-0.281	-0.333***	-0.330***	-0.419***	-0.360***	-1.989***
	(0.024)	(0.024)	(0.028)	(0.348)	(0.022)	(0.023)	(0.032)	(0.023)	(0.037)
L3.ar	0.090***	0.286***	-0.512***	-0.740***	0.318***	0.402***	0.346***	0.405***	2.089***
	(0.024)	(0.024)	(0.023)	(0.077)	(0.025)	(0.022)	(0.036)	(0.028)	(0.065)
L4.ar	-0.290***	-0.350***	0.070**	1.228***	-0.430***	-0.460***	-0.422***	-0.444***	-1.653***
	(0.020)	(0.023)	(0.032)	(0.251)	(0.023)	(0.022)	(0.034)	(0.023)	(0.061)
L5.ar	1.062***	1.086***	0.941***	-0.335	1.084***	1.096***	1.075***	1.085***	1.341***
	(0.022)	(0.024)	(0.027)	(0.391)	(0.026)	(0.026)	(0.032)	(0.031)	(0.065)
L6.ar	-0.233***	-0.263***	-0.119***	0.059	-0.218***	-0.299***	-0.289***	-0.301***	-0.363***
	(0.028)	(0.027)	(0.029)	(0.089)	(0.029)	(0.029)	(0.029)	(0.033)	(0.060)
L7.ar	-0.030	0.001	-0.045**	-0.056**	0.002	-0.012	0.051**	0.004	0.100**
	(0.023)	(0.021)	(0.020)	(0.026)	(0.022)	(0.022)	(0.023)	(0.022)	(0.048)
L8.ar	-0.011	-0.025	-0.015	0.008	-0.021	-0.076***	-0.015	-0.067***	-0.073*
	(0.021)	(0.020)	(0.018)	(0.020)	(0.021)	(0.019)	(0.023)	(0.020)	(0.040)
L9.ar	0.028	-0.012	0.054***	0.036	0.024	0.007	0.004	-0.022	0.049*
	(0.018)	(0.020)	(0.017)	(0.025)	(0.020)	(0.019)	(0.021)	(0.019)	(0.026)
L10.ar	-0.028*	-0.041**	-0.032*	-0.058***	-0.028	0.000	-0.010	-0.001	-0.009
	(0.016)	(0.017)	(0.016)	(0.020)	(0.018)	(0.017)	(0.017)	(0.018)	(0.018)
L.ma	-0.110***	-0.216***	0.213***	-0.754**	-0.201***	-0.283***	-0.252***	-0.243***	-1.004***
	(0.021)	(0.018)	(0.033)	(0.336)	(0.021)	(0.017)	(0.025)	(0.029)	(0.033)
L2.ma	0.122***	0.186***	-0.336***	-0.009	0.263***	0.243***	0.274***	0.262***	1.607***
	(0.017)	(0.015)	(0.033)	(0.226)	(0.016)	(0.012)	(0.024)	(0.020)	(0.010)
L3.ma	-0.036**	-0.200***	0.472***	0.772***	-0.231***	-0.259***	-0.206***	-0.257***	-1.458***
	(0.018)	(0.015)	(0.021)	(0.017)	(0.019)	(0.014)	(0.026)	(0.026)	(0.047)
L4.ma	0.331***	0.352***	0.084**	-0.927***	0.402***	0.393***	0.364***	0.381***	1.084***
	(0.016)	(0.015)	(0.034)	(0.257)	(0.015)	(0.012)	(0.023)	(0.020)	(0.011)
L5.ma	-0.836***	-0.839***	-0.794***	0.049	-0.812***	-0.877***	-0.809***	-0.865***	-0.810***
	(0.020)	(0.018)	(0.030)	(0.291)	(0.020)	(0.017)	(0.022)	(0.029)	(0.031)
ARCH									
L.arch	0.143***	0.195***	0.389***	0.289***	0.148***	0.233***	0.174***	0.200***	0.308***
	(0.019)	(0.020)	(0.025)	(0.026)	(0.022)	(0.022)	(0.020)	(0.020)	(0.024)
L2.arch	-0.003	0.025**	0.017	0.019*	-0.022**	0.007	-0.022**	0.016**	-0.015
	(0.006)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.009)	(0.007)	(0.009)
Constant	0.010***	0.011***	0.016***	0.010***	0.012***	0.016***	0.014***	0.015***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3735	3735	3735	3735	3735	3735	3735	3735	3735

Standard errors in parentheses
a3 refers to Non HartalViolent Event count
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: ARCH Specifications for Dhaka; Chittagong; Khulna; Sylhet; Gazipur; Barisal; Narayanganj; Bogra; - 2012-2021 - POssible Effects from Annoounced Hartal Dates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Residuals								
(sum) a0	-0.004	0.022*	0.014	-0.005	-0.005	0.079**	-0.007	-0.031
	(0.004)	(0.013)	(0.026)	(0.015)	(0.025)	(0.036)	(0.022)	(0.021)
F.(sum) a0	0.002	-0.031**	0.037	0.007	-0.051*	0.033	0.007	0.002
	(0.004)	(0.015)	(0.026)	(0.016)	(0.031)	(0.056)	(0.022)	(0.016)
F2.(sum) a0	-0.007*	0.004	0.021	0.034	-0.006	-0.040	-0.038***	-0.029
	(0.004)	(0.017)	(0.028)	(0.021)	(0.034)	(0.039)	(0.009)	(0.020)
F3.(sum) a0	0.006*	-0.010	0.064*	0.006	0.025	-0.029	-0.020**	-0.009
	(0.004)	(0.020)	(0.037)	(0.018)	(0.036)	(0.041)	(0.010)	(0.025)
F4.(sum) a0	0.005	-0.009	0.077**	-0.018	0.001	-0.068**	0.001	0.004
	(0.004)	(0.015)	(0.035)	(0.021)	(0.030)	(0.034)	(0.015)	(0.022)
F5.(sum) a0	0.006*	0.007	0.036	0.001	0.036	-0.015	-0.004	0.005
	(0.003)	(0.015)	(0.034)	(0.024)	(0.028)	(0.039)	(0.016)	(0.025)
F6.(sum) a0	0.007*	-0.004	-0.008	-0.015	0.003	-0.037	-0.002	0.037**
	(0.004)	(0.018)	(0.021)	(0.022)	(0.025)	(0.040)	(0.019)	(0.017)
Constant	-0.000	-0.003	-0.026**	0.001	-0.001	0.005	0.004	0.001
	(0.014)	(0.011)	(0.011)	(0.010)	(0.013)	(0.011)	(0.013)	(0.008)
ARMA								
L.ar	0.422***	0.571***	0.474***	1.097***	0.536***	0.632***	0.616***	0.621***
	(0.029)	(0.088)	(0.038)	(0.300)	(0.028)	(0.026)	(0.031)	(0.035)
L2.ar	-0.035	-0.156	-0.382***	-0.265	-0.334***	-0.335***	-0.421***	-0.358***
	(0.024)	(0.123)	(0.022)	(0.313)	(0.022)	(0.023)	(0.032)	(0.023)
L3.ar	0.007	0.002	0.294***	-0.730***	0.314***	0.397***	0.345***	0.401***
	(0.023)	(0.130)	(0.031)	(0.073)	(0.025)	(0.023)	(0.036)	(0.027)
L4.ar	-0.232***	-0.056	-0.460***	1.193***	-0.429***	-0.458***	-0.417***	-0.438***
	(0.020)	(0.122)	(0.022)	(0.221)	(0.023)	(0.021)	(0.034)	(0.023)
L5.ar	1.053***	0.894***	1.001***	-0.300	1.079***	1.099***	1.070***	1.083***
	(0.021)	(0.104)	(0.031)	(0.347)	(0.026)	(0.026)	(0.032)	(0.031)
L6.ar	-0.226***	-0.211***	-0.177***	0.056	-0.213***	-0.300***	-0.283***	-0.297***
	(0.028)	(0.037)	(0.033)	(0.080)	(0.029)	(0.029)	(0.029)	(0.033)
L7.ar	-0.032	-0.015	0.039**	-0.057**	0.003	-0.010	0.050**	0.001
	(0.022)	(0.022)	(0.020)	(0.026)	(0.022)	(0.022)	(0.023)	(0.023)
L8.ar	-0.005	-0.021	-0.015	0.002	-0.018	-0.070***	-0.011	-0.061***
	(0.021)	(0.021)	(0.021)	(0.020)	(0.022)	(0.020)	(0.023)	(0.020)
L9.ar	0.021	0.008	0.030*	0.045*	0.023	0.007	-0.000	-0.025
	(0.018)	(0.022)	(0.016)	(0.025)	(0.020)	(0.019)	(0.021)	(0.019)
L10.ar	-0.029*	-0.059***	0.024	-0.064***	-0.025	-0.003	-0.008	-0.001
	(0.016)	(0.018)	(0.016)	(0.019)	(0.018)	(0.017)	(0.017)	(0.018)
L.ma	-0.070***	-0.213**	-0.157***	-0.737**	-0.197***	-0.282***	-0.252***	-0.244***
	(0.021)	(0.088)	(0.034)	(0.301)	(0.021)	(0.017)	(0.025)	(0.028)
L2.ma	0.059***	0.044	0.353***	-0.015	0.265***	0.246***	0.277***	0.262***
	(0.017)	(0.098)	(0.024)	(0.205)	(0.016)	(0.012)	(0.024)	(0.018)
L3.ma	0.026	0.032	-0.132***	0.761***	-0.228***	-0.257***	-0.206***	-0.259***
	(0.018)	(0.097)	(0.032)	(0.014)	(0.019)	(0.015)	(0.026)	(0.024)
L4.ma	0.297***	0.141	0.440***	-0.903***	0.403***	0.393***	0.362***	0.379***
	(0.017)	(0.091)	(0.023)	(0.228)	(0.015)	(0.012)	(0.023)	(0.019)
L5.ma	-0.834***	-0.734***	-0.741***	0.027	-0.809***	-0.878***	-0.807***	-0.867***
	(0.021)	(0.068)	(0.033)	(0.260)	(0.020)	(0.017)	(0.022)	(0.028)
ARCH								
L.arch	0.146***	0.192***	0.361***	0.289***	0.142***	0.211***	0.182***	0.188***
	(0.018)	(0.020)	(0.024)	(0.027)	(0.021)	(0.021)	(0.020)	(0.020)
L2.arch	-0.003	0.027**	0.006	0.012	-0.023**	0.004	-0.025***	0.014*
	(0.007)	(0.010)	(0.009)	(0.010)	(0.009)	(0.011)	(0.008)	(0.008)
Constant	0.010***	0.011***	0.017***	0.010***	0.012***	0.017***	0.014***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3736	3736	3736	3736	3736	3736	3736	3736

Standard errors in parentheses
a0 refers to hartal count
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: ARCH Specifications for Dhaka; Chittagong; Khulna; Sylhet; Gazipur; Barisal; Narayanganj; Bogra; Rajshahi - 2012-2021 - Effects from Consecutive Hartal Dates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Residuals								
L.conhartal	-0.011***	0.001	-0.046	0.020	-0.070	-0.048	-0.145***	-0.004
	(0.003)	(0.074)	(0.056)	(0.038)	(0.048)	(0.057)	(0.049)	(0.080)
L2.conhartal	0.002	-0.011	-0.035	0.018	0.061	-0.026	0.056	-0.053
	(0.005)	(0.043)	(0.066)	(0.101)	(0.071)	(0.061)	(0.112)	(0.089)
Constant	0.004	-0.001	-0.024**	-0.000	0.001	0.004	0.002	-0.013*
	(0.013)	(0.010)	(0.011)	(0.010)	(0.012)	(0.013)	(0.008)	(0.007)
ARMA								
L.ar	0.414***	0.572***	0.471***	1.102***	0.535***	0.615***	0.623***	0.218
	(0.029)	(0.028)	(0.039)	(0.316)	(0.028)	(0.031)	(0.035)	(0.281)
L2.ar	-0.013	-0.298***	-0.383***	-0.271	-0.331***	-0.417***	-0.360***	0.566**
	(0.024)	(0.023)	(0.022)	(0.329)	(0.022)	(0.032)	(0.023)	(0.266)
L3.ar	-0.016	0.284***	0.291***	-0.727***	0.315***	0.342***	0.399***	-0.919***
	(0.022)	(0.023)	(0.031)	(0.076)	(0.025)	(0.036)	(0.027)	(0.057)
L4.ar	-0.217***	-0.352***	-0.460***	1.198***	-0.428***	-0.416***	-0.440***	0.526**
	(0.021)	(0.023)	(0.022)	(0.232)	(0.023)	(0.034)	(0.023)	(0.212)
L5.ar	1.050***	1.083***	0.999***	-0.310	1.081***	1.069***	1.084***	0.632**
	(0.021)	(0.024)	(0.031)	(0.365)	(0.026)	(0.032)	(0.031)	(0.300)
L6.ar	-0.230***	-0.263***	-0.174***	0.058	-0.212***	-0.283***	-0.300***	-0.156**
	(0.028)	(0.027)	(0.033)	(0.084)	(0.029)	(0.029)	(0.033)	(0.072)
L7.ar	-0.030	0.000	0.040**	-0.055**	0.001	0.049**	0.001	-0.045
	(0.022)	(0.020)	(0.020)	(0.026)	(0.022)	(0.023)	(0.022)	(0.028)
L8.ar	-0.009	-0.024	-0.013	0.000	-0.020	-0.011	-0.060***	0.001
	(0.021)	(0.019)	(0.020)	(0.020)	(0.021)	(0.023)	(0.020)	(0.022)
L9.ar	0.023	-0.011	0.031*	0.045*	0.023	0.001	-0.022	0.036**
	(0.018)	(0.020)	(0.017)	(0.024)	(0.020)	(0.021)	(0.019)	(0.016)
L10.ar	-0.028*	-0.037**	0.025	-0.061***	-0.027	-0.008	-0.002	-0.018
	(0.016)	(0.017)	(0.016)	(0.019)	(0.018)	(0.017)	(0.018)	(0.021)
L.ma	-0.062***	-0.216***	-0.153***	-0.738**	-0.198***	-0.250***	-0.246***	0.160
	(0.020)	(0.018)	(0.035)	(0.317)	(0.021)	(0.025)	(0.028)	(0.279)
L2.ma	0.041**	0.186***	0.356***	-0.013	0.264***	0.273***	0.262***	-0.513***
	(0.018)	(0.014)	(0.024)	(0.215)	(0.016)	(0.024)	(0.018)	(0.163)
L3.ma	0.044**	-0.199***	-0.127***	0.758***	-0.230***	-0.204***	-0.258***	0.746***
	(0.018)	(0.015)	(0.032)	(0.015)	(0.019)	(0.026)	(0.025)	(0.018)
L4.ma	0.286***	0.353***	0.443***	-0.905***	0.401***	0.362***	0.380***	-0.225
	(0.017)	(0.015)	(0.023)	(0.239)	(0.015)	(0.023)	(0.019)	(0.215)
L5.ma	-0.835***	-0.838***	-0.738***	0.031	-0.810***	-0.807***	-0.868***	-0.644***
	(0.020)	(0.017)	(0.034)	(0.273)	(0.020)	(0.022)	(0.028)	(0.218)
ARCH								
L.arch	0.140***	0.198***	0.352***	0.283***	0.144***	0.172***	0.188***	0.309***
	(0.018)	(0.020)	(0.024)	(0.025)	(0.021)	(0.020)	(0.019)	(0.023)
L2.arch	-0.003	0.026**	0.009	0.014	-0.023**	-0.023***	0.014*	-0.016*
	(0.006)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.008)	(0.009)
Constant	0.010***	0.011***	0.017***	0.010***	0.012***	0.014***	0.015***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3740	3740	3740	3740	3740	3740	3740	3740

Standard errors in parentheses
a0 refers to hartal count
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: ARCH Specifications for Dhaka; Chittagong; Khulna; Sylhet; Gazipur; Barisal; Narayanganj; Bogra; Rajshahi - 2012-2021 - Effects from Non-consecutive Hartal Dates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Residuals								
L.nonconhartal	0.000	0.030*	0.069**	-0.044**	-0.065*	0.005	-0.020	0.041
	(0.010)	(0.017)	(0.033)	(0.017)	(0.035)	(0.015)	(0.019)	(0.032)
L2.nonconhartal	0.012	0.025	-0.051***	-0.003	0.039	0.011	0.009	0.018
	(0.007)	(0.018)	(0.020)	(0.023)	(0.036)	(0.014)	(0.022)	(0.025)
Constant	0.002	-0.001	-0.026**	0.003	0.001	0.004	0.002	-0.013*
	(0.013)	(0.010)	(0.011)	(0.009)	(0.012)	(0.013)	(0.008)	(0.007)
ARMA								
L.ar	0.365***	0.571***	0.243***	0.222**	0.537***	0.615***	0.624***	0.210
	(0.029)	(0.028)	(0.036)	(0.100)	(0.028)	(0.031)	(0.035)	(0.255)
L2.ar	0.084***	-0.298***	0.077***	0.590***	-0.334***	-0.418***	-0.361***	0.577**
	(0.024)	(0.023)	(0.023)	(0.101)	(0.022)	(0.032)	(0.023)	(0.242)
L3.ar	-0.117***	0.283***	-0.140***	-0.824***	0.316***	0.344***	0.401***	-0.920***
	(0.022)	(0.023)	(0.021)	(0.038)	(0.025)	(0.036)	(0.027)	(0.053)
L4.ar	-0.156***	-0.351***	-0.200***	0.501***	-0.429***	-0.418***	-0.441***	0.521***
	(0.021)	(0.023)	(0.022)	(0.066)	(0.023)	(0.034)	(0.023)	(0.192)
L5.ar	1.041***	1.082***	0.997***	0.709***	1.084***	1.070***	1.086***	0.645**
	(0.020)	(0.024)	(0.025)	(0.104)	(0.026)	(0.032)	(0.031)	(0.272)
L6.ar	-0.230***	-0.261***	-0.143***	-0.181***	-0.216***	-0.283***	-0.301***	-0.159**
	(0.027)	(0.027)	(0.029)	(0.038)	(0.029)	(0.029)	(0.033)	(0.067)
L7.ar	-0.036	-0.000	-0.001	-0.028	0.004	0.049**	0.003	-0.045
	(0.022)	(0.020)	(0.019)	(0.025)	(0.022)	(0.023)	(0.022)	(0.028)
L8.ar	-0.002	-0.023	-0.035**	-0.040**	-0.020	-0.012	-0.061***	0.000
	(0.021)	(0.020)	(0.017)	(0.020)	(0.022)	(0.023)	(0.020)	(0.022)
L9.ar	0.017	-0.011	0.066***	0.022	0.024	0.001	-0.022	0.035**
	(0.018)	(0.019)	(0.016)	(0.020)	(0.020)	(0.021)	(0.019)	(0.016)
L10.ar	-0.023	-0.038**	-0.016	-0.031	-0.029	-0.008	-0.003	-0.019
	(0.016)	(0.017)	(0.017)	(0.020)	(0.018)	(0.017)	(0.018)	(0.021)
L.ma	-0.012	-0.216***	0.058*	0.140	-0.198***	-0.251***	-0.246***	0.168
	(0.020)	(0.018)	(0.033)	(0.098)	(0.021)	(0.025)	(0.027)	(0.253)
L2.ma	-0.036**	0.187***	-0.031	-0.550***	0.264***	0.275***	0.262***	-0.522***
	(0.018)	(0.015)	(0.029)	(0.067)	(0.016)	(0.024)	(0.018)	(0.148)
L3.ma	0.120***	-0.199***	0.193***	0.654***	-0.230***	-0.205***	-0.258***	0.744***
	(0.017)	(0.015)	(0.023)	(0.020)	(0.019)	(0.026)	(0.024)	(0.017)
L4.ma	0.248***	0.353***	0.267***	-0.212***	0.402***	0.363***	0.380***	-0.219
	(0.018)	(0.015)	(0.027)	(0.066)	(0.015)	(0.023)	(0.019)	(0.194)
L5.ma	-0.835***	-0.838***	-0.792***	-0.716***	-0.810***	-0.807***	-0.868***	-0.655***
	(0.020)	(0.017)	(0.031)	(0.077)	(0.020)	(0.022)	(0.028)	(0.197)
ARCH								
L.arch	0.143***	0.201***	0.378***	0.238***	0.144***	0.170***	0.187***	0.304***
	(0.018)	(0.020)	(0.025)	(0.023)	(0.021)	(0.020)	(0.019)	(0.023)
L2.arch	-0.003	0.026**	0.015	0.012	-0.022**	-0.023***	0.014*	-0.015
	(0.006)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)	(0.009)
Constant	0.010***	0.011***	0.016***	0.010***	0.012***	0.014***	0.015***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3740	3740	3740	3740	3740	3740	3740	3740

Standard errors in parentheses
a0 refers to hartal count
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

economic importance, registers a statistically significant second day effect of 6.5 percent. Overall, however, while the immediate effects from hartals are evident, they do not last beyond a day, and the transitory nature of the immediate local impacts from hartals in general thus also points to the manner in which society have by and large have adapted to this phenomenon. We also see similar results for the other large city Sylhet, which registers a first day 2.8 percent decline in economic activity.

Table 5 repeats the above exercise but for the time-span 2012-2016, when hartals were arguably at their greatest extent since 2010. The overall pattern of local impacts from hartals however do not seemingly change significantly from Table 4, where, apart from the capital, Dhaka, there is seemingly no evidence of local immediate impact.

In Table 6, we look at the immediate local effects from non hartal political violent events, and the impacts are mostly absent. This is a crucial dimension where effects from political violence differ from for example Africa, which also has been studied extensively with regards to impact from political violence on economic activity; for Bangladesh, it is predominantly hartals that yield the most tangible impacts, for the reasons explained earlier.

Finally we also test the hypothesis that hartal announcements may also have an impact on regional economic activity. As alluded to earlier, in anticipation of hartal induced closures of transport sector and other key infrastructures, factories for example may push up their output so as to compensate for possible losses in output to be incurred later. Alternatively hartal announcements may lead to off-city commuters not opting to show up. Given that the time of satellite recording of surface night lights is at 1:30 AM locally, thus in Table 5, we look for such effects for up to 7 days before onset of hartal(s). While the capital Dhaka do not show substantive evidence of such effects, curiously Chittagong, the largest port city in Bangladesh, and Gazipur, the textile industry hub shows evidence of statistically significant negative impact two days prior to hartal related violence onset. For Gazipur, on the same day of hartal, the coefficient is negative, albeit statistically insignificant.

Tables 8 and 9 look at the impacts of consecutive and non-consecutive hartal days on those regions. Curiously Dhaka does not look to be affected when there are non-consecutive hartals, which more points to the notion that enforced hartals in the capital coincide largely with consecutive hartal days. Both Khulna and Gazipur also feature significant impacts from non consecutive hartal days.

Table 10: Spatial Dynamic Regression with Parliamentary seat share at division level party wise interacted with diustrict specific time trends as instruments and lagged nonhartal peaceful events as instruments

	(1)	(2)
Main		
L.d_lnlight1	0.187***	0.187***
	(0.003)	(0.003)
d_a0	-0.060***	-0.037***
	(0.007)	(0.009)
d_clim	0.000***	0.000***
	(0.000)	(0.000)
Residuals	0.070***	0.039***
	(0.008)	(0.009)
Spatial		
rho	0.771***	0.772***
	(0.003)	(0.003)
Variance		
sigma2_e	0.037***	0.037***
	(0.000)	(0.000)
Observations	55097	54634

Standard errors in parentheses
a0 refers to hartal count
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Monthly level Night Lights

Table 10 reports the control function 2 step estimates of impact of hartals with the two different instrumentation strategies. The standard errors are adnjusted as suggested by Murphy and Tuppell (1985). We also check for inclusion for up to 2 lags of the dependent variable; however in that instance, , the space time stationarity conditions are violated, which states that the summation of the spatial autoregressive and time autoregressive lags must be less than 1. Thus far on a country wide basis, it may be seen that hartals have a statistically significant impact on economic activity. More importantly, to ensure validity of the dynamic panel estimates, care must be taken to ensure that there is no serial autocorellation (namely first order serial correllation), which would invalidate the results. Thus for both the reported specifications, the serial correllation checks clear out. Although not reported, the results in the second stage as reported rely on strong correllation of the endogenous variable with the instrumental variables.

It is also important to mention possible violations of exclusion restrictions in defining of the instrumental variables; for example, it may be the case that regions with non-ruling party representation in parliament may find it difficult to attract investment in their respective regions, and adversely affecting regional economic growth. However such characteristics should be arguably more centered on long term fixed unobservable regeion specific factors, which, in our analysis, and for the time-frame in question, may thus be considered time invariant. /footnoteAlthough we did not specifically search for avenues to explore this issue, this is an ongoing check. However it is more straightforward to ensure exclusion restrictions regarding lagged peaceful non-hartal peaceful event count. The one plausible way region wise lagged peaceful non-hartal event counts can affect current economic activity is if the unobservable factors which affect both economic activity and such protests feature autocorrellation, which we look for by ensuring no serial autocorrellation in the model residuals.

6 Conclusion

In this paper we seek to address the question as to how political strikes, aka *hartals* have an impact upon the overall economy in Bangladesh, by leveraging new NASA Black Marble sourced night lights and geocoded conflict data from ACLED. Through keyword search we isolated the hartal events and find a consistent impact on economic activity countrywide, with evidence pointing to some degree of persistence of impact from hartals on an intermediate time span, as can be gathered from the statistically significant coefficients for up to 2 months lagged *hartal* count. Furthermore at daily level, we also see evidence of instantaneous impact of hartals in certain regions of the country, namely the capital, Dhaka. As such the findings substantiate the notions of *hartals* having significant economy wide impact.

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