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 related violence data with keyword search from geocoded Armed Conflict Location & Event Data Project (ACLED) database, we investigate the impact of such events on economic activity in Bangladesh. We focus our investigation firstly at daily level and secondly at monthly level. At daily level, 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 sub-districts. At the monthly level, to factor in the emergent consequent spatial dependence we analyze country wide dynamics using a Split-Panel Jackknife bias corrected Maximum Likelihood estimations to see overall effects from lagged hartal event counts. 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 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 1.6 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 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

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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 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. While there were previous works that empirically investigated the effects of hartals (Ahsan and Iqbal (2016) and Shonchoy and Tsubota, 2015), these only looked at the manufacturing and exporting sectors of Bangladesh's economy respectively. As such 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. With regards to the night lights data, and in part due to its high frequency nature, it 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 may incur 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 more intermediate term impacts on the economy, we later utilize the monthly night lights product in a spatial dynamic panel approach. To address the endemic cross sectional dependence within night lights borne out of spatial dependence we factor that in our framework, while the consequent bias from inclusion of the lagged dependent and predetermined variables (lagged hartal) is corrected by a Split Panel Jackknife approach (Chudik,Pesaran & Yang, 2018). With this, we see that the effect from one month lagged hartals is approximately -1.7 percent, with the effect higher for the rest of the country sans Dhaka Division (at 4.4 percent).

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

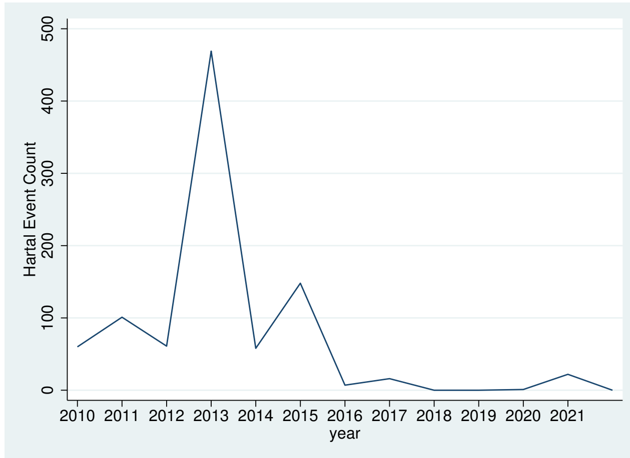

Figure 1: Conflict Events in Sub-Saharan Africa

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 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 consequent decline in number of hartals.

We use keyword search from the event descriptions of the aforementioned ACLED database to derive our hartal database.

2.2 Night Lights

(a) Bangladesh January 2013

(b) Bangladesh December 2013

Figure 2: VNP46A3 Monthly Night Lights - Bangladesh

Night lights data sourced from satellite sources 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)). However 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), Gibson et al. (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) instrumen. 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 to date not seen wide scale adoption in the applied empirical literature which has led to the availability of the more finely grained and calibrated night lights products. Bluhm and McCord (2022) investigated the nonlinearities and measurement errors in the light production function within a country's economy. It was 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. 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 , at the 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. This data retrieval technique is based off of the latest high quality date[1]. 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

[1]The existence of this temporal gap filling based on retrieval of the latest high quality date may imply some degree of upwards bias present in the final estimate of impact of hartals; however in our results, for key regions like the capital Dhaka with the effect being statistically significant at around 1 percent decline for night lights may imply that the actual values may be smaller

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.

The gap filled VNP46A2 product has been found to exhibit deep autoregressive nature. Furthermore, during days of cloudy / unusual weather , the data retrieval algorithm resorts to a temporal 'gap' filling technique, to reduce persistent data gaps. 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. 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. 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:

$$y_{i,t} = B_0 W y_{i,t} + \sum_{j=1}^{d} y_{i,t-j}A_j + \sum_{j=1}^{s} x_{a,i,t-j}C_j + x_{b,i,t}^2\theta + \gamma_t + \alpha_i Trend + \lambda_i + \epsilon_{i,t} \tag{3}$$

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 $d > 1$. Given that we are looking to explore the intermediate term impacts of $hartals$, we include up to s lags of hartal counts in a given region, where $x_{a,i,t-j}$ refers to time j lagged hartal count in region i. $x_{b,i,t}$ 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. $\alpha_i Trend$ denotes the subdistrict specific time trends. 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:

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

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; $x_{a,-j}$ is NT X j lags of $hartals$, where $j = 1..J$ is the maximum number of lags of hartals to be be included. 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, while α is an N X 1 vector of region specific time trend coefficients; 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))[2]. 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 $[I(N) - B_0W]$ in the main log likelihood function. The concentrated log-likelihood function to be estimated then is:

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

[2] 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.

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 model, lagged hartal counts may only be affected by economic activity shocks in the future. As such, under standard estimation of (7), the resulting estimates 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

$$\hat{\hat{\theta}} = 2\hat{\theta} - 1/2(\hat{\theta}_A + \hat{\theta}_B) \tag{13}$$

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:

$$\left(\frac{B}{T}, \frac{B}{T/2}, \frac{B}{T/2}\right) \tag{14}$$

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

$$2 * \frac{B}{T} - \left(\frac{1}{2} * \left(\frac{B}{T/2}\right) + \frac{1}{2} * \left(\frac{B}{T/2}\right) \right) = 0 \tag{15}$$

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.

Sample: 08feb2012 thru 30apr2022		Number of obs =	3735
		Wald chi2(29) =	52064.70
Log likelihood = 3198.368		Prob > chi2 =	0.0000

lnlight1desm	Coefficient	OIM std. err.	z	P>|z|	[95% conf.	interval]
lnlight1desm						
a0						
L1.	-.009814	.0041411	-2.37	0.018	-.0179305	-.0016976
L2.	.0009288	.0042243	0.22	0.826	-.0073506	.0092082
L3.	-.0019976	.0042702	-0.47	0.640	-.010367	.0063718
L4.	-.0015868	.0044229	-0.36	0.720	-.0102555	.007082
L5.	.0011618	.004216	0.28	0.783	-.0071013	.009425
L6.	-.0052481	.0043218	-1.21	0.225	-.0137187	.0032224
L7.	.0041955	.0041668	1.01	0.314	-.0039713	.0123623
wa0						
L1.	.0221803	.0509934	0.43	0.664	-.077765	.1221255
L2.	.0716882	.0543713	1.32	0.187	-.0348775	.1782539
L3.	.0609028	.0536546	1.14	0.256	-.0442584	.166064
L4.	-.0726122	.0538072	-1.35	0.177	-.1780723	.032848
L5.	.0211634	.0554301	0.38	0.703	-.0874777	.1298045
L6.	.0695047	.0536732	1.29	0.195	-.0356928	.1747023
L7.	.019863	.0563646	0.35	0.725	-.0906096	.1303356
_cons	-.0007728	.0137276	-0.06	0.955	-.0276783	.0261327

Figure 3: ARCH(p=10,q=5)Dhaka Specification,2012-2021

5 Findings

5.1 Daily level Night Lights

Given that there are 463 subdistricts total, we focus on the subdistricts with a minimum total of 8 hartal events throughout the 10 year sample period (2012-2021). We thus come to a list of 44 subdistricts. We look to assess lagged effects up to 7 days away from day of hartal, as well as effects from hartals in neighboring subdistricts. Figure 2 shows the impact for Dhaka. Given that at daily level, with night lights being recorded at 1:30 am in the morning, in effect in may be argued that the night lights being recoreded are actually of the day before. As such for 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 Dhaka, the city populace reverts back to usual business within a day of within a day of hartal. Comparing to a shorter timeframe 2012-2014 in Figure 3, when hartals were arguably at their greatest extent since 2010, we see that this immediate effect jumps to a statistically significant -1.5 percent in the capital (for parimony we did not include beyond 1st day lags of hartals given they yielded no significant results). One question that may be asked is what becomes in the scenario of consecutive hartal days ? Given that hartal enforcement are announced beforehand, the populace in general tend to know well the frequency and timings of the hartals. Thus when we look at the effect of consecutive hartal days in Dhaka, we find again no impact on the second day, pointing to the fact that on 2 day hartals, the second day may not be as rigorously imposed compared to the first day.

We analyze another sub-district, Gazipur, a key hub of the textile industry in Bangladesh. We find the immediate impact of hartals at -7.2 percent significant at 5 percent level. However there are no lagged effects.

Looking over at Chittagong, the main port city in Bangladesh, it could be seen that there is an immediate positive effect; this may be attributed to the fact that firms often have workers to come

ARCH family regression -- ARMA disturbances

Sample: 02feb2012 thru 31dec2014 | Number of obs = 1064 | Wald chi2(16) = 11299.71

Log likelihood = 853.0742 | Prob > chi2 = 0.0000

lnlight1desm	Coefficient	OPG std. err.	z	P>|z|	[95% conf. interval]	
lnlight1desm						
a0						
L1.	-.0152181	.0036575	-4.16	0.000	-.0223866	-.0080495
_cons	.0068154	.0342913	0.20	0.842	-.0603943	.0740252

Figure 4: ARCH(p=10,q=5 Dhaka Specification, 2012-2015

ARCH family regression -- ARMA disturbances

Sample: 03feb2012 thru 30apr2022 | Number of obs = 3740 | Wald chi2(17) = 52736.75

Log likelihood = 3193.516 | Prob > chi2 = 0.0000

lnlight1desm	Coefficient	OPG std. err.	z	P>|z|	[95% conf. interval]	
lnlight1desm						
conhartal						
L1.	-.0114287	.0029663	-3.85	0.000	-.0172425	-.0056149
L2.	.0004749	.0045984	0.10	0.918	-.0085377	.0094875
_cons	.0042343	.0130219	0.33	0.745	-.0212881	.0297567

Figure 5: ARCH(p=10,q=5) Dhaka Specification Consecutive Hartals,2012-2021

in factories early and stay well into the night at late hours, or even work extra hours on non-hartal days (Shonchoy and Tsubota, 2015).

```
ARCH family regression -- ARMA disturbances

Sample: 08feb2012 thru 30apr2022                Number of obs     =       3735
                                                Wald chi2(29)     =   2.46e+06
Log likelihood = 2897.719                       Prob > chi2       =     0.0000
```

lnlight1desm	Coefficient	OPG std. err.	z	P>|z|	[95% conf.	interval]
lnlight1desm						
a0						
L1.	-.0726167	.0334894	-2.17	0.030	-.1382547	-.0069787
L2.	.0602097	.0356136	1.69	0.091	-.0095917	.130011
L3.	-.0086977	.0298355	-0.29	0.771	-.0671742	.0497788
L4.	-.0494823	.0271476	-1.82	0.068	-.1026905	.003726
L5.	-.0118849	.0359853	-0.33	0.741	-.0824149	.0586451
L6.	.0684167	.032089	2.13	0.033	.0055234	.13131
L7.	.0450219	.0443237	1.02	0.310	-.0418509	.1318948
wa0						
L1.	-.0235576	.0226997	-1.04	0.299	-.0680483	.020933
L2.	.0513825	.0269429	1.91	0.057	-.0014245	.1041896
L3.	-.0180752	.0263478	-0.69	0.493	-.0697159	.0335655
L4.	-.0250254	.0326731	-0.77	0.444	-.0890635	.0390128
L5.	.0016346	.0225729	0.07	0.942	-.0426074	.0458767
L6.	-.0632793	.0282406	-2.24	0.025	-.1186299	-.0079286
L7.	-.0183615	.0310083	-0.59	0.554	-.0791365	.0424136
_cons	-.0004312	.0128538	-0.03	0.973	-.0256241	.0247617

Figure 6: ARCH(p=10,q=7)Gazipur Specification,2012-2021

5.2 Monthly level Night Lights

Table 1 reports both Standard 'uncorrected QML estimates and half panel jackknife bias corrected estimates. s. There is no need to recompute the analytical standard errors for bias corrected e estimators, given that the ones obtained for the uncorrected estimators remain valid for the bias corrections (Dhaene and Jochmans (2015). As such the standard uncorrected estimates may be seen to exhibit downward bias. We also check for inclusion for up to 2 lags of the dependent variable; however in that instance, as can be seen in Column 2, 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. Furthermore, we also see that including twice lagged hartals have a significant effect, greater than the previous month. This lends substance to the theory that intermediate term impacts of such political violence events takes a while to register fully upon countrywide

Table 1: Standard QML and Split Panel Jackknife Corrected QML

	1		2		3	
	FE	Half Panel Jackknife	FE	Half Panel Jackknife	FE	Half Panel Jackknife
Spatial Lag	0.76856 ***	0.76857 ***	0.76857 ***	0.75595 ***	0.76669 ***	0.75278 ***
	(0.00289)		(0.00289)		(0.00289)	
1st lag	0.17389 ***	0.21748 ***	0.17389 ***	0.21730 ***	0.15308 ***	0.18507 ***
	(0.00273)		(0.00273)		(0.00284)	
2nd Lag				0.21748 ***	0..07094 ***	0.10312 ***
					(0.00283)	
Hartal 1st Lag	-0.01125 ***	-0.01675 ***	-0.00692 *	-0.00976 **	-0.00636	-0.00879 **
	(0.00343)		(0.00396)		(0.00394)	
Hartal 2nd lag			-0.00864 **	-0.01865 ***	-0.00923**	-0.01921 ***
			(0.00396)		(0.00394)	
Cumby-Huizinga test p -value		0.4951		0.5034		0.0579
Region Specfic Trends	No		No		No	

lnlight1desm	Coefficient	std. err.	z	P>|z|	[95% conf.	interval]
lnlight1desm						
a0						
L1.	.0294878	.0143162	2.06	0.039	.0014286	.0575469
L2.	.0064709	.0151407	0.43	0.669	-.0232043	.0361462
L3.	-.0336713	.014623	-2.30	0.021	-.0623318	-.0050107
L4.	.0074206	.0165296	0.45	0.653	-.0249769	.0398181
L5.	.0071587	.0169888	0.42	0.673	-.0261387	.0404562
L6.	-.0014242	.0158328	-0.09	0.928	-.0324558	.0296075
L7.	.0054946	.0173714	0.32	0.752	-.0285527	.0395418
wa0						
L1.	.2199418	.1913162	1.15	0.250	-.155031	.5949145
L2.	-.3938201	.1523585	-2.58	0.010	-.6924372	-.095203
L3.	-.1598415	.2217248	-0.72	0.471	-.5944142	.2747312
L4.	-.61582	.1794926	-3.43	0.001	-.9676191	-.264021
L5.	.0967722	.3018321	0.32	0.749	-.4948078	.6883522
L6.	-.1373143	.1866856	-0.74	0.462	-.5032113	.2285828
L7.	-.2706954	.1206639	-2.24	0.025	-.5071923	-.0341984
_cons	.0770069	.0309408	2.49	0.013	.0163641	.1376498

Figure 7: ARCH(p=10,q=7)Chittagong Specification,2012-2021

economic activity, with its primary transmission mechanism being through disrupted transport sectors and other sectors which may end up registering a cascading effect on the economy. It might be worth mentioning that inclusion of third lag of *hartal* count leads to first order serial correllation issues, which invalidates the findings. Finally , although not shown here, we also experiment with other types of political violence data, based upon refining of our keyword search parameters. Not surprisingly amongst all designations of political violence, we find *hartals* to yield the greatest impact upon economic activity.

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 soourced 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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