Chapter 1

Political Instability and Stock Market Returns: Evidence from Firm-level Panel data of Securities in Bangladesh

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Abstract

Conflict, political uncertainty and its impact on stock market has been a subject of interest in the literature. However, no study has yet explored the impact of political strikes on stock market outcomes. Political strike -- locally known as *Hartal* in Bangladesh -- is a different form of conflict than war or street protest, which is recurrent in nature. Using Dhaka Stock Exchange daily trading data of firms for the period 2005-2015 and controlling for a host of variables such as day, month, year, day-of-year trend and firm fixed effects, we find that political strike has a negative and statistically significant impact on stock market return. Our results show that, on the day of a political strike, stock market return drops about 0.14% which is economically sizable. This effect gets pronounced as the frequency of strike increases, based on week, month or year count of occurrences. Impact heterogeneity reveals that large firms are affected more from *hartals* compared to smaller firms.

JEL Classification: D24, D74, O14

1. INTRODUCTION

In this paper we study the impact of political instability on stock market return and its volatility in Bangladesh. We use political strike as an indicator of political instability which characterizes the confrontational political landscape in Bangladesh. Political strike, locally known as '*hartal*', is a political protest generally carried out by the opposition political parties to enforce their demand by disrupting vehicular movement on road and shutting down shops and businesses. At times, political strikes become very violent with huge toll on property and human lives.[1] This political strike offers a unique setup to study the impact of political violence and instability on economic outcomes such as firm productivity (Ashraf, *et al.* 2015), cost (Shonchoy and Tsubota, 2015) and export (Ahsan and Iqbal, 2017). Unlike the existing studies, we examine the effect of strike on financial side of the economy- the stock market return and volatility - using Dhaka Stock Exchange daily trading data of firms for the period 2005-2015.

The understanding of the impact of political violence and unrest on stock market outcomes is of particular interest largely because of three reasons. First, stock market captures the perception of the general investors about the growth of the firms as well as the economy. That is, stock return and volatility contain information on how general public as well market perceive the effect of political strike on the firms and economy. Second, political instability in a country generally dampens future economic outlook. Optimism about future is one of the key factors that drive stock prices up and leads people investing in the stock market. Political strikes which signal both current and future political and economic uncertainty have the potential to make a dent in the optimism of the investors. The impact of political strike on stock market outcomes thus can also capture the extent to which political strike affects the future outlook of the economy. Third, political uncertainty is argued to increase the riskiness of investment in stock market (Gulen and Ion, 2015; Beaulieu, Cosset, and Essaddam, 2005; Aggarwal, Inclan and Leal, 1999). Thus, political strike offers an interesting setting to study the impact of political uncertainty on the volatility of stock return, particularly due to its recurrent nature.

[1] http://archive.thedailystar.net/beta2/tag/hartal-violences/

In this study we matched daily security level stock market data with political strike data. We use political strike data collected by Ahsan and Iqbal (2017) which collects information from daily newspapers on the date of occurrence of political strike, announcement date, length of strike, political parties that announced the strike, stated reasons for strike, and number of death and injuries during strike. The daily stock market data is compiled from Dhaka Stock Exchange. We collect daily closing price, number of trade, volume of trade and market capitalization for each stock. This richness of this dataset also allows us to explore how impact varies with heterogeneity of firms as well as political strikes.

Understanding of the impact on firm heterogeneity is important because all firms may not be affected uniformly by political strike. The market fundamental of the firms may not be affected unvaryingly by political strikes. Manufacturing sector involving supply chain may be affected more than the firms involved in providing financial services such as banks and insurance companies. Even within the manufacturing and service sectors, some firms are more likely to be affected directly than other firms, depending on the product/service they produce as well as the location of the firms. Ahsan and Iqbal (2015) highlights the fact that the impact of strike on manufacturing firm such as RMG works largely through transportation phase. It indicates that the companies which are directly involved in transportation business are hard hit by strike such as firms involved in transport sector Further, there are firms for which transportation phase constitutes is a major part of their supply chain and these firms are highly vulnerable to strike. These types of firms include movers, courier service (private postal service), etc. For other firms which are not directly involved in transportation sector, strike may still increase the overall transportation cost and reduce the profit margin for all firms depending on their exposure to the strike. Therefore, the drop in firm’s profit and earning per share may vary substantially due to strike which may be reflected by the decline in stock prices.

In our benchmark regression specifications for stock return, we use daily, weekly, monthly and yearly returns as our dependent variables. While in case of daily return our variable of interest is whether there was a strike on that particular date, in case of stock returns in longer periods, we use the number of strikes in that period. We control for a host of time fixed effects and trends such as day-of-the-week, month and year fixed effect as well as day-of-year trend to capture all kinds of seasonality that might confound our results. We also run security level fixed effect to control for any unobserved heterogeneity of securities that might impact their return. Our results show that stock market return drops significantly on the day of *hartal*. With all time fixed effects and security fixed effect, this drop of daily return is about 0.14%. Note that average daily return of our sample is 0.02%. The strikes are also found have impact on stock return in longer horizon. As the number of strikes increases in a week, the weekly return decreases by 0.15%. Similarly, as the number of strikes in a month and in a year increases, the monthly and yearly returns drop by 0.11% and 0.25% respectively.

The benchmark specifications for volatility of stock return consider weekly, monthly and yearly volatility. Similar to stock return, we also control for all time and security fixed effects. The results show that, interestingly, as the number of strikes increases in a week, month and year, the volatility decreases by 0.09%, 0.036% and 0.025% respectively. This results are robust to inclusion of a host of time fixes effects and security fixed effects.

In order to explore the heterogeneous impact on firms/securities, we consider several cases. First, we group them into three sectors – finance, manufacturing and service. Second, to capture the differential effect of firm size, we divide the firms into two groups – above and below median of market capitalization and call them as large and small firms respectively. Stocks of some firms are traded more than others and it has consequences on return and volatility (Girard and Biswas, 2007; Lee and Rui, 2002). Hence, we define firms as high frequency firms which are above median and as low frequency firms which are below median. Similarly, we define high volume and low volume firms using the median of volume of trade per day. The regression results suggest that large firms are affected more from *hartal*s compared to smaller firms.

The rest of the paper is structured in the following way. The second section briefly review the relevant literature. Section three describes the sources of data and descriptive statistics. Section four dwells on regression models and estimation strategy. Section five describes regression results including basic specification and firm heterogeneity and section six draws conclusion.

2. LITERATURE REVIEW

The efficient market hypothesis states that any new innovation in the market will be undated in the firm's value and will be revealed in the firm's stock prices (Fama, 1970). Since firm stock prices reveal the discounted present values of all expected stream of payoffs, any factor that may affect the firms' future profitability, investor's perception on the future growth potential of the firm, and investor's discount value will affect the current stock price. Since firms are heterogeneous in terms of their exposure to political events, not all firms are expected to be affected in the same manner. Firms which are exposed or affected more by political conflicts are expected to exhibit more volatility in their stock return. The key assumption underlying the forward-looking and information-aggregating nature of the stock market is that agents are updating their beliefs in response to any innovations in an unbiased or rational manner (Zussman and Zussman, 2006). Based on the efficient market hypothesis, the relationship between political strikes and stock market is related to several streams of literature.

A number studies have looked into the link between political events, conflicts and violence and stock market outcome. However, to the best of our knowledge, only few studies established the causal impact of political conflicts on stock market outcome exploiting a micro-level framework. The closest to ours micro-empirical studies identify several factors that influence stock prices and volatility, including uncertainty arising from political instability, conflict related entry barriers, firms' rent-seeking activities, political connection of firms, private information etc. (Abadie and Gardeazabal, 2003; Acemoglu, Hasan and Tahoun, 2016; Beaulieu, Cosset and Essaddam, 2006; Bittlingmayer,1998; Dube, Kaplan and Naidu, 2011; Guidolin and La Ferrara, 2007; Peress, 2014; Wolfers, J., Zitzewitz, 2009; and Zussman and Zussman, 2006).

Investment under uncertainty induced by political conflicts and instability is generally low. Beaulieu, Cosset and Essaddam(2006) provided similar evidence in the case of 1995 Quebec referendum in Canada, where huge uncertainty surrounding the referendum outcome on separation of Quebec from rest of the country was created. Stock prices of firms with large share in Quebec fall while those of multinationals were less affected. The later groups are not affected or less affected because they are less susceptive to pessimistic scenarios including flight of capital, abandonment of the Canadian currency, institution of exchange controls to curb capital outflows, increase in income tax to finance the independent government's deficit, and an increase in the interest rate to offset the lender's risk related to debt sharing, and will be able to diversify political risk away to be less affected by a possible Quebec independence. Bittlingmayer (1998) exploit political events during the transition of imperial Germany to Weimar as a natural experiment to show that uncertainty arising from political instability lead to higher stock market volatility.

Investors incorporate how the political factors may influence the short-run or long-run profitability of the firms while optimizing their portfolio of investments. Exploiting the ceasefire to stop the political violence in Basque county in Spain in the nineties as a natural experiment, Abadie and Gardeazabal (2003) compared the stock value of firms located in Basque county to counterfactual firms located in other non-turbulent regions. They observed that the return from stocks of firms located in the Basque county increased at the beginning of the fourteen months long true but decreased at the end of the truce. Investors in the firm located in the Basque county perceived the truce as good news which is translated into higher prices for these firms' stocks. The end of a political conflict does not necessarily mean good news for the stock market. It rather depends on how investors assess the potential change in the value of their investment in response to the changed scenario. In an event study based on the sudden death of a rebel leader in Angola, Guidolin and La Ferrara (2007) showed that the stock prices of mining companies with concessions in Angola were negatively affected relative to those of counterfactual firms, as the end of conflict siphoned-off the benefits of the incumbent firms from conflict generated natural entry barriers and low bargaining power of the ruling government.

In addition, political conflict may extend the opportunities for exploiting political connections, which may directly affect investors expected profit. Beliefs about expected profitability are then reflected in future stock prices. Acemoglu, Hasan and Tahoun (2016) emphasized that stock values are also determined by the scope of rent-seeking activities of firms capitalizing their connection with the political government. Utilizing the variation in intensity of political protests in Tahrir square during the recent political turbulence in Egypt, they showed that strong protests against the ruling political party reduce investors' confidence in stocks of politically connected firms. Investors value the credible private information on the prospective gain of firms' value from change in political power, as has been evident in the high abnormal stock return of partially nationalized multinational companies in response to several US backed coup-authorization though such authorization is supposed to be classified as top-secret (Dube, Kaplan and Naidu, 2011).

Few studies attempted to capture the impact of probable war news in the media on the financial market variables including stock prices (Wolfers, J., Zitzewitz, 2009; Rigobon and Sack, 2005; Amihud and Wohl, 2004). The stock prices were more negatively affected with the intensity of war-risk related news, where intensity means how strong the likelihood of the war is. Exploiting the data on market trading in contracts tied to the ouster of Saddam Hussein that actually reveals market participants' perception about the probability of the Iraq war, Wolfers, J., Zitzewitz (2009) showed that a 10% increase in the probability of war was accompanied by a 1.5% decline in the S&P500 prices. While evaluating the effectiveness of Israel's counterterrorism policies, Zussman and Zussman (2006) showed that the assassination of Palestinian senior military leaders exerts a significant positive impact on both Tel Aviv stock prices but almost no impact in the case of assassination of a junior military leaders. The findings is explained by how the investors actually perceive the assassination events-the former type of assassination boosts investors' confidence in the success of the counterterrorism policy while the later does not.

Media, both electronic and print, has strong influence to propagate the innovation in political information into stock market behavior. While emphasizing the role of media in determining stock market outcome, Peress (2014) reported that newspaper strikes in several European countries did not affect the stock prices on the strike days but reduced trading volume and volatility of stock returns in a significant manner. The main reason of low trade volume is lower participation by traders as newspaper strikes deter dissemination of business related information. Note that their finding of reduced stock market volatility is in contrast to many other studies that showed heightened stock volatility in response to political events (Jianping and Guo, 2009; Bittlingmayer, 1998; Kim and Mei, 2001). They attribute the fall in volatility to reduced trading volume at extreme prices which is probably because of reduced participation of noise trader who are less prone to follow fundamentals of stock values.

Although our extensive literature search could not trace any study on the relationship between stock market and political strikes in Bangladesh, we identify three studies that empirically investigated how political conflicts affect manufacturing firms' productivity(Shonchoy and Tsubota, 2016; Ashraf et al., 2015) and exports(Iqbal and Ahsan, 2016). In fact, impact of political conflicts on stock market can be transmitted through production channel. Political conflict can affect production activity through several micro mechanisms including a distorted input supply for efficient functioning of the firms (Collier et al. 2003; Blattman and Miguel 2010, Shonchoy and Tsubota, 2016, Amodio and Maio, 2017). As a source of market imperfection, political violence can disrupt input supply for production process by limiting firms' access to labor supply due to increased workers absence, access to capital due to heightened level of insecurity in the lender-borrower relationship, access to foreign inputs due to uncertainty regarding the sustainability and scope of trading relationship (Macchiavello and Morjaria 2015). Another specific source of disruption for production system may come from distorted transportation system (Ahsan and Iqbal, 2016; Ashraf et al., 2015).

Note that all of these channels may shrink firm's profitability due to increased cost of production and will be revealed in stock market. Exploiting firm level export data from Bangladesh, Ahsan and Iqbal (2016) found that political strikes exert a negative impact on the probability of firm's export shipments on the day of strike but no cumulative impacts could be identified in a eight day window. However, their study found evidence that such political strikes can distort input supply and output delivery system by increasing transportation costs, for example, the cost of transporting goods to port increased by 69%. Similar qualitative findings on the input supply distortion in the readymade garments sector of Bangladesh during political strikes is reported by Ashraf e*t al (*2015).

Shonchoy and Tsubota (2016) also used firm-level manufacturing data from Bangladesh to estimate a flexible cost function, and reported that firms productivity decreases and cost of production increases due to political strikes as firms do not systematically re-optimize input choices to adapt to uncertainty generated by such political shocks. None of the above three studies in Bangladesh found evidence of heightened workers absenteeism during the political strikes and thus rule out the channel of labour shortage affecting production. Amodio and Maio (2017) reports that during the second Intifada in the occupied Palestinian territories, seventy percent of the fall in firm output can be attributed to inefficient substitution of locally produced materials for foreign materials due to distortion in accessibility to imported inputs, reduced bargaining power with input suppliers. In fact, political strikes is also related to the literature that showed empirically how external shocks could affect firms' productivity and efficient input use(Advaryu e*t al*. 2016, Alcott e*t al*. 2016). However, in contrast to the natural shocks, political strikes are recurrent and thus not surprising to the market players which suggest that impacts of political strikes on financial markets may be less intense. Because political strikes are pre-announced, firms and investors often get enough time to adapt and adjust their belief and update the information.

3. DATA

We compile daily stock market data for all listed securities from Dhaka Stock Exchange on the following variables: closing price of the day, number of trade, volume of trade and total number of shares issued by the firm for the period 2005-2015. Note that the closing price is the unadjusted price; that is, it does not consider stock split, cash and stock dividend. The political strike data is taken from Ahsan and Iqbal (2016). This dataset have information on the date the strike actually occurred, the date of announcement, the name of the political party/non-political organization calling the strike, stated reasons for calling strike and the number of people of killed and injured during strike. Since this dataset covers the period of 2005-2012, we update this dataset to include 2013-15 in our study. The richness of these both dataset allows us to pair them at the daily level to study the impact of strike on capital market variables.

We calculate continuously compounded return using log of the closing price. In case of daily return we take two consecutive days. Return on Sunday is calculated using closing price of Thursday and Sunday. Weekly return considers the difference between closing prices of two consecutive Thursday. In case of monthly and yearly return we consider the difference between the first days of months and first days of years respectively.

We report descriptive statistics for full sample as well as sub-samples in Table1. Since there was a bubble and a subsequent crash in 2009-10, we report the descriptive statistics separately for this period. We also split the sample into two periods – period before crash (2005-08) and after crash (2011-15). The daily return for the full sample is about 0.02%. During the period of bubble and crash, average daily return was about 0.04%. Interestingly, the market saw negative return (-0.04%) for the period 2005-08, right before the bubble was formed. However, right after the crash, the average daily return increased by about five folds from its pre-crash period to about 0.10%. Weekly and monthly returns follow the same patterns. Average yearly return for the full sample is about 8.27%. In the bubble-crash period, it shot up to about 16.27%. Yearly return was exorbitantly high for the period 2011-2015, which was about 36.13%.

The stock market was highly volatile in our sample period. The weekly volatility is about 9.77% whereas the average weekly return was only 0.15%. Similarly, volatility of yearly return is about 75.61%, against 8.27% of yearly return. Interestingly, the volatility during bubble-crash period was very similar to the full sample. It was about 74.29%. However, the volatility increased during the post-crash period of high return.

We plot incidence of *hartal* by year, month, week of a day and day of a month (Figure 1). Most of the *hartal*s occurred in 2013-2015. Of 144 *hartal*s in our sample, this period saw about 76% of them. 2015 alone had 61 days of *hartal*. Note that there was no *hartal* during the period 2007-2010. This was the period when the military backed caretaker government was in power.

We observe strong seasonal pattern. About 65% *hartal*s occurred in winter during November-February. Political activities in Bangladesh, such as rallies, demonstrations, blockades, *hartal*s, etc. take place in winter which offers favorable weather for such outdoor activities unlike in monsoon. Incidence of *hartal* is mostly spread out evenly across all week-days (Sunday-

Thursday), though there were a few on weekends (Friday and Saturday). However, we observe that Sunday and Thursday are slightly more likely to have *hartal* than other week days. Since Friday and Saturday are weekly holidays, in order to maximize the impact of *hartal*, political parties prefer to call *hartal* on Thursday or on Sunday, or on both days as it stretches the length of shutting down of businesses. Though there is no robust pattern of occurrence of *hartal* on a specific date of a month, the second half of the month is likely to see slightly fewer *hartal* than the first half.

Table 1: Descriptive Statistics

	Full sample 2005-2015	Full sample without 2009-2010 (stock market bubble and crash)	2005-2008	2011-2015
Average daily Return	0.02	0.04	-0.04	0.10
Average weekly return	0.15	0.28	-0.26	0.66
Average monthly return	0.61	1.11	-1.33	2.85
Average yearly return	8.27	16.23	-13.81	36.13
SD of weekly return	9.77	9.51	7.04	10.89
SD of monthly return	20.16	19.55	15.26	21.94
SD of yearly return	75.61	74.29	49.70	80.91
Average volume of trade per dealing day	968.35	958.99	197.33	1525.98
Average number of trade per dealing day	1.72	1.44	0.66	2.01
Market capitalization per security	35511625.27	36886265.21	NA	33480570.05
Average number of securities	203.60	202.24	179.93	222.82

We also want to check if there is any seasonal pattern in stock return. Figures 1a-1d also plot returns by years, months of a year, days of a month, and days of a week. There is a strong day-of-a-week effect of stock return. While average daily return for full sample is about .02%, it is about 0.4% on Sunday and about 0.15 on Monday (Figure 1c). For all other days, the average daily returns are negative. In case of day of a month, the first week of a month stands out. There is a sharp increase in return during 3rd to 5th day of the month (Figure 1d).

Figure 1: Frequency of strike in a period and stock return

Figure 1a: Number of *hartal* in a year and yearly return

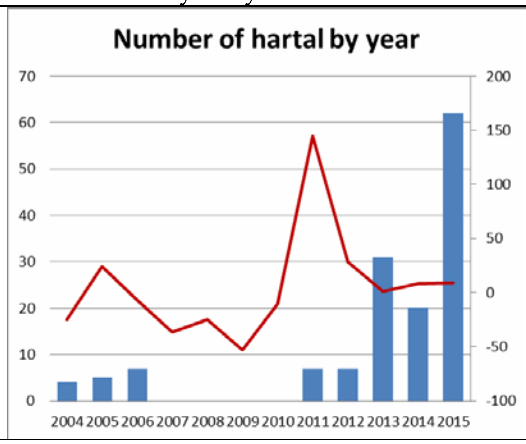


Figure 1b: Number of *hartal* in a month and monthly return

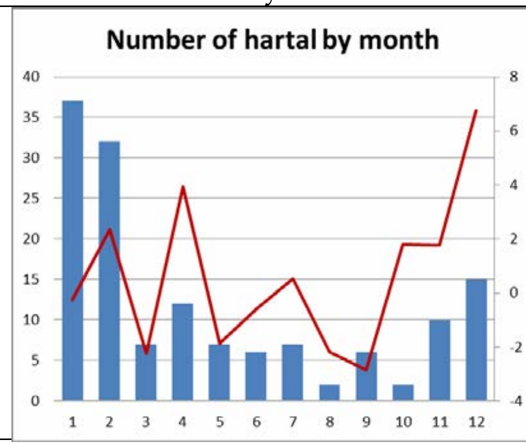


Figure 1c: Number of *hartal* on a day of week and weekly return

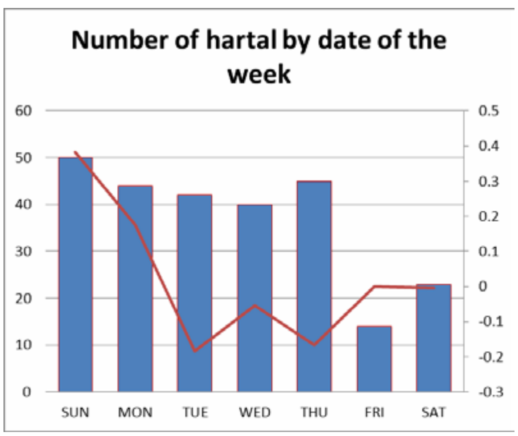
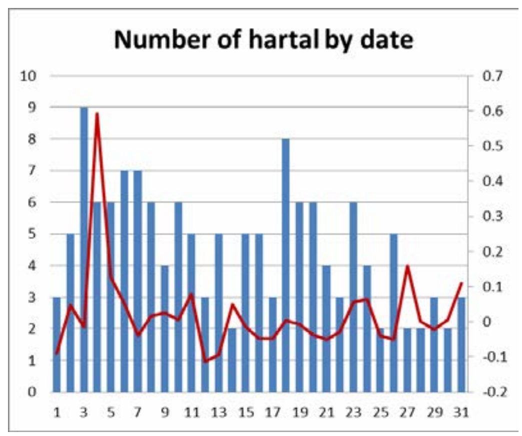


Figure 1d: Number of *hartal* on a day of a month and daily return



4. ESTIMATION STRATEGIES

4.1. Regression model

It is important to clarify at the outset of the study that the purpose of this study is not to model the behavior of stock return using market model, factor model or any simple constant mean return model[2]. The objective is to isolate the impact of political strike on capital market variables. The benchmark specifications are:

[2] See ?? for a survey paper on different types of models that explain the behavior of stock returns.

Impact on Stock Return

$$R^{d}_{it} = \alpha_1 + \beta H_t + \gamma \varphi^{y}_{d} + \theta_i + \theta^{w}_{d} + \theta_m + \theta_y + \epsilon_{it} \quad \text{[daily]} \ldots\ldots\ldots\ldots (1)$$

where R^{d}_{it} is the firm/security,[3] i's daily return. H_t is a binary variable which assumes one if there was a strike on day t and zero otherwise. Thus, β captures the contemporaneous effect of strike in this case. θ_i are security fixed-effects which capture the unobserved, time-invariant characteristics of firms/securities that are correlated with both stock return and strike. We also include a day-of-year trend (φ^{y}_{d}) in our regression model to capture any seasonal pattern of the stock returns. For instance, trading pattern of DSE might exhibit strong seasonal patterns. We also control for day-of-week fixed effects (θ^{w}_{d}) to capture any systematic variations of returns during a week. We further include month fixed effects (θ_m) and year fixed effect (θ_y) to further control for low frequency seasonal patterns. ϵ_{it} is the error term.

In case of weekly and monthly return H_t is defined as the number of political strikes in a week and in a month, respectively. However, the set of seasonal controls for weekly return will be different from the monthly one. Our weekly and monthly specifications are:

$$R^{w}_{it} = \alpha_1 + \beta H_t + \gamma \varphi^{y}_{w} + \theta_i + \theta_m + \theta_y + \epsilon_{it} \quad \text{[weekly]} \ldots\ldots\ldots\ldots (2)$$

$$R^{m}_{it} = \alpha_1 + \beta H_t + \gamma \varphi^{y}_{m} + \theta_i + \theta_y + \epsilon_{it} \quad \text{[monthly]} \ldots\ldots\ldots\ldots (3)$$

$$R^{y}_{it} = \alpha_1 + \beta H_t + \gamma \varphi^{y}_{m} + \theta_i + \epsilon_{it} \quad \text{[yearly]} \ldots\ldots\ldots\ldots (4)$$

where φ^{y}_{w} and φ^{y}_{m} are week-of-year and month-of-year trend.

Impact on volatility of return

$$\sigma^{w}_{it} = \alpha_1 + \beta H_t + \gamma \varphi^{y}_{w} + \theta_i + \theta_m + \theta_y + \epsilon_{it} \quad \text{[weekly]} \ldots\ldots\ldots\ldots (5)$$

$$\sigma^{m}_{it} = \alpha_1 + \beta H_t + \gamma \varphi^{y}_{m} + \theta_i + \theta_y + \epsilon_{it} \quad \text{[monthly]} \ldots\ldots\ldots\ldots (6)$$

$$\sigma^{y}_{it} = \alpha_1 + \beta H_t + \gamma \varphi^{y}_{m} + \theta_i + \epsilon_{it} \quad \text{[yearly]} \ldots\ldots\ldots\ldots (7)$$

[3] A number of financial products such as mutual funds are listed in Dhaka Stock Exchange. Since these are not firms, we use the term security in general. However, throughout the paper, we use security and firm interchangeably.

where $\sigma^{w}{}_{it}$, $\sigma^{m}{}_{it}$ and $\sigma^{y}{}_{it}$ are weekly, monthly and yearly volatility.

We use robust standard errors that are clustered at the firm level.

4.2. Econometric Issues

Our identification strategy involves ruling out three scenario. First, it could be the case that both the stock market and the decision to call a strike respond to a common factor such as an economic shock. While stock market tends to respond to economic shocks, the announcement of strike due to economic reasons is not common in Bangladesh. In fact, the political strike database of Ahsan and Iqbal (2016) has information on the official reasons for calling strike. We categorize these reasons into 7 groups in Figure A1 in the appendix. It shows that the electoral reform has been the most common reasons for calling political strike. Only about 4% of strikes were called for economic reasons. That is, out of 144 strikes in our sample, only 6 were related to economic causes. Therefore, we can safely rule out the case that a third factor is driving both announcement of strike and stock price movement.

Second, both the strike and greater stock price movement may have propensity to occur during the same period, though solely for different reasons. In order to draw causal inference, we have to make sure that we are not picking up this effect. To probe this, we plot monthly average of daily stock return and number of political strike by months. Figure 1b shows strong indication seasonality in political strike data, as discussed in section 3 – about 64 percentage of strike occurred during the winter in the months from November to February. The average stock return in a month tends to hover around 2% throughout the year with high degree of fluctuations, except for last two months – November and December. These last two months of the year saw steep increase in returns. The occurrence of greater number of strikes in winter can also be coincided with higher stock return, due to completely different reasons. Economic activitie4s tend to pick up in favorable weather in winter and the same congenial weather prompts political parties to call *hartal* during this time.

Literature also suggest that there is a day-of-week effect of stock price movement (Fama, 1965; French, 1980; Keim and Stambaugh, 1984; Jaff, Westerfield, and Ma, 1989, Kato, 1990). While there is no rigorous literature on this issue on Bangladesh, we examine this issue by plotting stock return and occurrence of strike on a day of a week (Figure 1c). The figure shows that while all week days (Sunday-Thursday) are more or less equally likely to see a strike, there is a subtle pattern. The average number of strikes decline gradually from 50 *hartal* on Sunday to 40 haral on Wednesday. The number again increased on Thursday. On the other hand, the stock returns exhibits strong day-of-week pattern. The first two days observe significantly higher stock returns than the other days of the week and returns also gradually decrease till Tuesday. Therefore, if we do not control for day-of-week effect, the coefficients in regressions may pick up spurious correlations. Therefore, in order to isolate the effect of seasonality, we use a host of fixed effects capturing the effect of month, day-of-week and year. We also include day-of-year trend in the regression model.

Third, some unobserved characteristics of the DSE-listed companies/securities may be correlated with the political strikes, particularly with the exposure to strike. That is, there might be exposure heterogeneity across listed companies. Companies in different locations may be exposed to different intensities of treatment (strike) and this may lead to identification problem in our case. In order to capture this heterogeneity we use firm-fixed effects, assuming that this treatment exposure heterogeneity does not change with time.

5. REGRESSION RESULTS

5.1. Regression Results: Benchmark Specification

The estimates of the specification for daily return, equation 1, are reported in table 2. The coefficient of *hartal* dummy, β in equation 1, turns out to be consistently negative and statistically significant, thus suggesting a negative association between *hartals* and daily return on stock. In the simplest specification where no controls for time variant factors are included, column 1, variation in daily return across trading days within a security reveal that average daily return is 0.08% lower on a *hartal* day compared to an otherwise normal day. Column 2 to 5 gradually includes additional controls for time variant factors. Column 5 controls for all sorts of time-variant confounding factors that may exhibit pattern by day-of-week, day-of-year, month-of-the-year, and years. Estimates from the most restricted specification suggest that, average daily return from stocks on a *hartal* day is 0.14% lower compared to a non-*hartal* day.

Table 2: Impact of hartal on daily stock return (Dependent variable: Daily stock return)

	1	**2**	**3**	**4**	**5**
Hartal dummy	-0.081***	-0.097***	-0.112***	-0.146***	-0.139***
	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)
Day-of-year trend		YES	YES	YES	YES
Day-of-week fixed effect			YES	YES	YES
Month of the year fixed effect				YES	YES
Year fixed effect					YES
Security fixed effect	YES	YES	YES	YES	YES
Constant	0.027***	-0.045***	-0.070***	-0.068***	-0.080***
	(0.001)	(0.004)	(0.006)	(0.009)	(0.012)
R-square	0.000	0.000	0.003	0.003	0.004
N	1407263	1407263	1407263	1407263	1407263

Note: *Hartal* is a dummy variable assuming 1 if the day was either a strike or blockade day or 0 otherwise. Standard errors, where relevant, are reported in the parentheses.

Table 3 reports the estimates for weekly, monthly and yearly stock return. In contrast to table 2, here impact of *hartal* is captured by including "number of *hartal* days" as the key explanatory variable in the model. For each of the return types, column 2 contains estimates from the most restricted specification with all sorts of controls for time-variant factors. We will interpret estimates from the restricted cases only. In all restricted specifications across return types, the estimates turn out to be consistently negative and statistically significant at less than one percent level. There is consistent evidence that *hartal* negatively affects the stock prices. The estimates for weekly return suggest that one additional day of *hartal* in the week shrinks average weekly return by 0.15%. One additional day of *hartal* in a month reduces the average monthly return by 0.11%. The impacts of *hartal* on monthly return is smaller in magnitude compared to impacts on weekly return estimates, which is probably because of the larger time horizon for stocks to rebound in the former case.

Table 3: Impact of Hartal on Weekly, Monthly and Yearly Stock Returns

Dependent Variable	Weekly Return		Monthly Return		Yearly Return	
	1	2	1	2	1	2
Number of *Hartal* in a week	-0.02	-0.15***				
	(0.011)	(0.015)				
Number of *Hartal* in a Month			0.002	-0.11***		
			(0.013)	(0.017)		
Number of *Hartal* in a Year					0.014	-0.25***
					(0.028)	(0.036)
Week of the year fixed effect	NO	YES	NO	NO	NO	NO
Month fixed effect	NO	YES	NO	YES	NO	NO
Year fixed effect	NO	YES	NO	YES	NO	NO
Security fixed effect	YES	YES	YES	YES	YES	YES
Year trend	NO	NO	NO	NO	NO	YES
Constant	0.16***	-0.15	0.61***	-2.31***	7.95***	-16.91***
	(0.005)	(0.101)	(0.024)	(0.302)	(0.661)	(1.779)
N	200753	200753	45933	45933	3698	3698
r2	0.000	0.028	0.000	0.060	0.000	0.026

Note: *Standard errors are clustered at the security level and are reported in the parentheses.*

The impact of *hartal*s on average stock return turns out to be larger in the case of yearly return- one additional day of *hartal* in the year reduces average yearly stock return by 0.25%. However, we are conservative while interpreting the yearly estimates. Note that the control for time-variant confounding factors is weakest in the cases of yearly return, which only contains a yearly linear trend. Since the key explanatory variable "number of *hartal*s in year" varies by year, the time fixed effects are excluded from the yearly stock return mode.

The benchmark specifications for volatility of stock return consider weekly, monthly and yearly volatility. Similar to stock return, we also control for all time and security fixed effects. There is consistent evidence that *hartal* is negatively associated with volatility of stock return. The results, as reported in Table 4, show that as the number of *hartal* days increases in a week, month, and year, the volatility of stock return decreases by 0.09%, 0.036% and 0.025% respectively. Similar to the case for average return on stocks, the magnitude of *hartal*s' impact on volatility is larger for weekly return compared to that of monthly return. Following the same argument as presented above, we are reluctant to interpret the volatility estimates obtained for yearly return.

Table 4: Impact of Hartal on Weekly, Monthly and Yearly volatility of stock returns

Dependent Variable	Weekly Volatility		Monthly Volatility		Yearly Volatility	
	1	2	1	2	1	2
Number of *Hartal* in a week	-0.119***	-0.090***				
	(0.005)	(0.005)				
Number of *Hartal* in a Month			-0.056***	-0.036***		
			(0.002)	(0.002)		
Number of *Hartal* in a Year					-0.024***	-0.025***
					(0.001)	(0.001)
Week of the year fixed effect	NO	YES	NO	NO	NO	NO
Month fixed effect	NO	YES	NO	YES	NO	NO
Year fixed effect	NO	YES	NO	YES	NO	NO
Security fixed effect	YES	YES	YES	YES	YES	YES
Year trend	NO	NO	NO	NO	NO	YES
Constant	1.807***	1.954***	2.157***	2.192***	3.137***	3.071***
	(0.002)	(0.067)	(0.004)	(0.086)	(0.023)	(0.089)
N	200753	200753	45933	45933	3698	3698
R square	0.002	0.041	0.006	0.058	0.058	0.058

***Note**: Standard errors are clustered at the security level and are reported in the parentheses.*

Our findings of drop in volatility of stock return in response to rising number of *hartals* is in contrast to literature that mostly suggests that stock market volatility increases during political uncertainty and instability (Bittlingmayer, 1998). However, it is consistent with the recent findings of Peress (2014). The explanation lies in the possibilities that on *hartal* days, stock prices move in synch, trading volume decreases significantly, and noise traders, who trade at extreme prices and increase market dispersion, participate less. The first two factors are testable in our settings. If *hartal* restricts the movements of traders by interrupted public transport system and vehicle movement, the trade frequency is more likely to drop on a *hartal* day, and so does the participation of noise traders.

5.2. Firm Heterogeneity and Political Strike

5.3. First, we categorize the firms according to their sector. We define three broad sectors – financial, manufacturing and service. Dhaka Stock Exchange classify all securities in 21 categories. We then group these 21 categories into the following three broad sectors. Before turning to regressions, we first document the descriptive statistics of these three sectoral groups (Table 6). Interestingly, average daily return of financial sector is much higher than

Table 5: Broad sectoral groups of securities

Financial	Manufacturing	Service
Bank	Tannery	Telecom
Life insurance	Ceramic	IT
General insurance	Pharmaceuticals	Service and real estate
NBFI	food	Paper and printing
Mutual Fund	Jute	Travel and leisure
Bond	Textile	
	Engineering	
	Cement	
	Miscellaneous	
	Fuel and Energy	

other two sectors. In fact, it is negative for the manufacturing sector. The daily returns are about 0.06%, -0.0001% and 0.003% for financial, manufacturing and service sectors respectively. It turns out that the average daily return for all securities in our sample period is largely driven by high returns of the financial sector. However, volatility of stock returns do not vary much across sectors. While the average weekly volatility for full sample is about 9.8%, it is 11.6% for financial sectors. The return turns out much higher compared to risk for the financial sector, when we compare the financial sector with other sectors or all securities.

We also group the firms by their size, frequency of trade and volume of trade. If the market capitalization is above the median, we call them large firms and small firms if it is below median.

Table 7 shows that average daily return is about three times higher for large firms than the small ones (0.03% vs. 0.01%). Again, note that the average daily return for the full sample is 0.02%. Similarly, weekly, monthly and yearly returns are also higher for large firms in more or less similar magnitude than the small firms. Yearly return is worth reiterating: average yearly return for large firms is about 13.23% whereas it is only 4.56% for small firms. Interestingly, there is hardly any differences in volatility between large and small firms. In case of weekly return, volatility for large firms is about 9.87% and 9.70% for small firms. The volatility for full sample is about 9.77%. It is puzzling that volatility is uniform across size of firms while the return is much higher for large firms.

Table 6: Descriptive statistics by sectors

	Financial	Manufacturing	Service
Average daily Return	0.0608687	-0.0001841	0.0034056
Average weekly return	0.4280044	-0.0020235	0.0223084
Average monthly return	1.748196	-0.0097263	0.0946105
Average yearly return	23.92712	-0.0536653	0.6924348
SD of weekly return	11.60335	8.801337	7.246658
SD of monthly return	23.75148	18.22427	15.50636
SD of yearly return	90.51221	66.14603	54.82944
Average volume of trade per day	1034.718826	911.8897428	983.3989601
Average number of trade per day	1.613940729	1.807461677	1.778085002
Market capitalization per security	27934493.38	33663326.59	121050526.6
Average number of securities	218.726	194.2767	187.525

Similar to size of firms, we divide the firms into high and low groups by their frequency of trade – 'high' if frequency of trade is above median and 'low' if it is below median. Firms whose securities are traded more frequently experience higher stock return. The return for high frequency firms is about 0.0475% and 0.0086% for low frequency firms. In case of yearly return, high and low frequency firms enjoy about 18% and 3.5% returns respectively. That is, high frequency firms enjoy about 8 times higher return than low frequency firms. Like market capitalization, weekly and monthly volatility is found to be similar for both high and low frequency firms, though yearly volatility is slightly higher for high frequency firms. Therefore, in this case also, higher return for high frequency firms is not coupled with high risk.

Volume of trade is defined as price times the number of shares traded. We define high and low firms using median as the cut-off points. In this case also, as expected, return is about 8 times higher for high firms than the low firms. Volatility has also been found to vary little across these two types. However, it is important to note that there is a high degree of correlation among these three groups. High frequency and high volume firms are more likely to be large firms (Table 7).

Table 7: Descriptive statistics by firm size, frequency and volume of trade

	Market capitalization		Frequency of trade		Volume of trade	
	Large	**Small**	**High**	**Low**	**High**	**Low**
Average daily Return	0.034	0.012	0.048	0.009	0.046	0.006
Average weekly return	0.236	0.084	0.331	0.059	0.322	0.042
Average monthly return	0.940	0.359	1.349	0.243	1.325	0.165
Average yearly return	13.235	4.565	18.054	3.517	17.646	2.622
SD of weekly return	9.868	9.699	10.524	9.378	10.208	9.491
SD of monthly return	20.388	19.988	21.832	19.278	21.309	19.409
SD of yearly return	75.95	75.16	80.15	72.85	76.40	74.58
Average volume of trade per day	126998.84	9145.51	334024.29	5044.71	274085.38	3240.21
Average number of trade per day	372.720	45.530	503.660	32.360	372.720	23.660
Market capitalization per security	5380000000	556000000	4220000000	600000000	3040000000	542000000
Average number of securities	200.240	186.690	214.130	178.110	213.940	172.730

Table 8 reports the estimates of impact of *hartals* on average return by heterogeneity of the firms. Overall, the results suggest that large firms are affected more from *hartal*s. The impact on weekly return does not vary by firm size, where firm size is defined by market capitalization per security: average weekly return is around 0.15% lower for an additional day of *hartal* in a week for both types of firms. However for average monthly return, the absolute magnitude of the impact of *hartal* is 3.8 percentage points larger for firms with higher market capitalization compared to those with lower market capitalization. Following the similar argument in the baseline specifications, we are not interpreting the yearly returns here.

In contrast to the case of market capitalization per security, firms exhibiting higher frequency of trade are affected more from an additional day of *hartal* relative to firms with lower frequency of trade. This turns out to be the case for both weekly and monthly stock return. The impact for high frequency trading firms is twice as large as that for the less frequently trading firms (0.11% vs. 0.22% for weekly return and 0.09% vs. 0.16% for monthly return). The findings are similar when we group the firms by volume of trade. Because of *hartal*, firms with high trading volume are twice more affected to those with low trading volume, though the magnitude of the impact is a bit smaller in the case of monthly return (0.10% vs. 0.21% for weekly return and 0.09% vs. 0.15% for monthly return).

Table 8: Impact of *hartal* on stock return by Size of firms

	Market capitalization		**Frequency of trade**		**Volume of trade**	
	Low	**High**	**Low**	**High**	**Low**	**High**
Weekly Return						
Number of *Hartal* in a Week	-0.148***	-0.147***	-0.111***	-0.216***	-0.102***	-0.210***
	(0.020)	(0.023)	(0.019)	(0.023)	(0.021)	(0.021)
Constant	0.091	-0.616***	-0.023	-0.801***	-0.101	-0.561***
	(0.137)	(0.142)	(0.120)	(0.161)	(0.124)	(0.154)
N	114796	85957	134548	66205	124140	76613
R square	0.034	0.025	0.028	0.033	0.031	0.029
Monthly Return						
Number of *Hartal* in a Month	-0.095***	-0.128***	-0.086***	-0.159***	-0.089***	-0.146***
	(0.020)	(0.028)	(0.023)	(0.023)	(0.025)	(0.021)
Constant	-1.702***	-3.655***	-2.359***	-3.653***	-2.528***	-3.194***
	(0.350)	(0.521)	(0.311)	(0.666)	(0.315)	(0.643)
N	26272	19661	30795	15138	28414	17519
R square	0.071	0.055	0.060	0.068	0.067	0.058
Yearly Return						
Number of *Hartal* in a Year	-0.098*	-0.453***	-0.131**	-0.506***	-0.133**	-0.441***
	(0.044)	(0.056)	(0.042)	(0.061)	(0.046)	(0.054)
Constant	-15.64***	-19.65***	-16.27***	-23.21***	-18.45***	-18.05***
	(1.922)	(3.210)	(1.969)	(3.267)	(2.021)	(3.152)
N	2118	1580	2489	1209	2308	1390
R square	0.016	0.048	0.018	0.053	0.021	0.042

Note: *Low means firms falling below median and high means firms in the above median. The weekly regression specifications include a bunch of fixed effects for week of the year, month of the year, year and securities. The monthly regression specifications include a bunch of fixed effects for month of the year, year and securities. The yearly regression specifications include fixed effects for securities and year trends. Standard errors are included in the parentheses.*

5.3 Strike Heterogeneity: Does Impact Vary With the Type of *Hartal*?

Hartal can be of various forms, strikes and blockade, and can vary by the intensity of violence and protests, and types of restriction imposed on regular economic activities. For illustration, blockades often put restriction on vehicle movements whereas strikes additionally interrupt other economic and business activity. Because of such differences, we split the estimates reported in Table 2 by the type of *hartal*. Table 9 presents estimates for the cases where *hartal* dummy assumes only general strikes while Table 10 presents those only for blockades. The estimates for strikes are in general consistent with those reported in Table 2, though larger in magnitude. In the most restricted specification with all possible sorts of control, as reported in column 5, average daily return on stocks are 0.19% larger on strike days compared to no-strike days. The impact is almost five percentage points larger compared to that reported in Table 2.

In contrast to the cases for strike, the impacts of blockades on stock return are less consistent across specifications and relatively smaller in magnitude. The coefficient of blockade dummy in the most restricted specification, as reported in column 5, suggests that average return on a strike day relative to an otherwise normal day is 0.034% lower. Comparison of estimates across *hartal* type suggests that impact of strikes is six times larger from those of blockades. Thus, the impact of *hartal* on average daily stock return is mainly driven by strikes. This is consistent given that strikes contains restriction of blockades, and the former imposes both a direct and indirect disruption on trading activities in the stock exchange and production activities of the firms.

Table 9: Impact of Strike on daily stock return (Dependent variable: Daily stock return)

	1	**2**	**3**	**4**	**5**
Hartal dummy	-0.140***	-0.147***	-0.166***	-0.178***	-0.191***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
Day-of-year trend		YES	YES	YES	YES
Day-of-week fixed effect			YES	YES	YES
Month fixed effect				YES	YES
Year fixed effect					YES
Security fixed effect	YES	YES	YES	YES	YES
Constant	0.027***	-0.042***	-0.068***	-0.076***	-0.089***
	(0.000)	(0.004)	(0.006)	(0.009)	(0.012)
R-square	0.000	0.000	0.003	0.003	0.004
N	1407263	1407263	1407263	1407263	1407263

Note: *Hartal is a dummy variable assuming 1 if the day was a strike day or 0 otherwise. Standard errors are clustered at the security level and are reported in the parentheses.*

Table 10: Impact of Blockade on daily stock return (Dependent variable: Daily stock return)

	1	2	3	4	5
Hartal dummy	0.014	-0.013	-0.020	-0.079***	-0.034**
	(0.010)	(0.010)	(0.011)	(0.013)	(0.012)
Day-of-year trend		YES	YES	YES	YES
Day-of-week fixed effect			YES	YES	YES
Month fixed effect				YES	YES
Year fixed effect					YES
Security fixed effect	YES	YES	YES	YES	YES
Constant	0.021***	-0.045***	-0.067***	-0.071***	-0.094***
	(0.000)	(0.004)	(0.006)	(0.009)	(0.012)
R-square	0.000	0.000	0.003	0.003	0.004
N	1407263	1407263	1407263	1407263	1407263

Note: *Hartal* is a dummy variable assuming 1 if the day was a blockade day or 0 otherwise. Standard errors are clustered at the security level and are reported in the parentheses.

6. CONCLUSION

Repeated and long-term political unrest and instability in the form of *hartal* could have lasting impact in the securities and exchange market. Employing high frequency stock exchange data-set of Bangladesh, this analysis sheds light on market movement and behavior due to political protests, how this is reflected in the daily index and price volatility**.** Using Dhaka Stock Exchange daily trading data of firms for the period 2005-2015 and controlling for a host of variables such as day, month, year, day-of-year trend and firm fixed effects, we find that political strike has a negative and statistically significant impact on stock market return. Our results show that, on the day of a political strike, stock market return drops about 0.14% which is economically sizable. This effect gets pronounced as the frequency of strike increases, based on week, month or year count of occurrences. Impact heterogeneity reveals that large firms are affected more from *hartals* compared to smaller firms.

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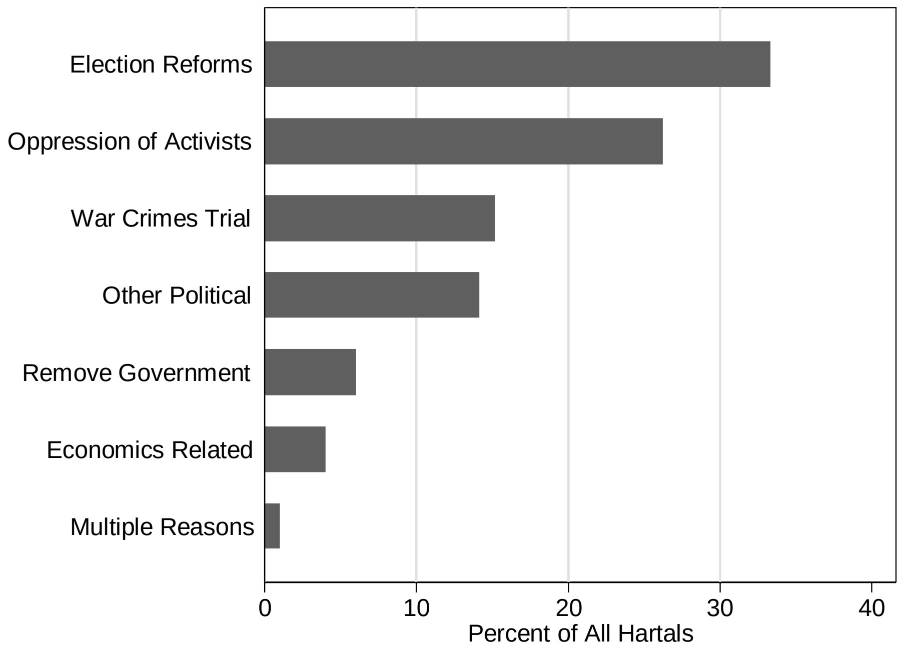
Appendix

Figure A1: Stated reasons for calling strike



Final page

別紙③
Attachment 3

調査研究報告書（Chosa Kenkyu Report）
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