How Does Violence Affect Exporters? Evidence from Political Strikes in Bangladesh*

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November, 2019

* We thank the editor, Peter Egger, and an anonymous referee for very helpful comments and suggestions. We also thank Emma Aisbett, Arpita Chatterjee, Shahe Emran, Rachel Heath, Raja Junankar, Fahad Khalil, Phil McCalman, Adam Osman, Laura Puzzello, Eik Swee, and various seminar and conference participants for their comments. Mahbuba Khatun and Amin Bin Hasib provided excellent research assistance. We gratefully acknowledge funding from the International Growth Centre for this project. The standard disclaimer applies.

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The primary data that support the findings of this study are available at:

https://www.theigc.org/project/political-strikes-and-its-impacts-on-trade-evidence-from-bangladeshi-transaction-level-export-data/

Upon publication, all data (including any supporting datasets) that support the findings of this study will be publicly available.

Abstract

Using novel daily data, we examine the impact of political violence on firm-level export activity. Our data cover the universe of political strikes and export transactions in Bangladesh during 2010 to 2013 and allow us to examine the effects of these strikes at a highly granular level. We first show that multi-day political strikes lower the likelihood that a firm will export by 6.30 percentage points. We then examine whether these disruptions result in adverse effects on export prices. Given that this violence creates greater risk of missed shipments, importers may respond by demanding lower prices as compensation. We provide the first evidence of such adverse price effects of political violence. Our results suggest that during July to December, 2013, when there was a multi-day political strike every five days, the prices of time-sensitive Bangladeshi products declined by 1.59 percent.

Keywords: Exports, Political Violence, Garments.

JEL Codes: F14, D74, O14

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Article type : Original Article

1. Introduction

Political violence is an endemic feature in many developing countries. According to Strauss & Taylor (2009), 58 percent of elections in Sub-Saharan Africa during 1990 to 2007 involved some form of violence.[1] Apart from the tragic human toll, such violence can have important disruptive effects on export activity. This is especially important for developing countries, where exports have played a crucial role in improving recent economic performance (WTO, 2003). In this paper, we examine the impact of political violence on exports by using novel daily data on political strikes in Bangladesh. These strikes are designed to disrupt the country's transportation network and are typically used by opposition parties to pressure the government to accept its demands. Our self-collected data include all 99 of these political strikes that occurred during 2010 to 2013.[2] We pair these data with the universe of firm-level, daily export transactions during the same period. These administrative data allow us to construct a daily panel of over 5,500 exporters and examine the adverse effects of political violence on exports at a highly granular level.[3]

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[1] Political violence can take many forms such as repression, civil war, and electoral violence (Besley & Persson, 2011). Given the context of our study, our focus in this paper will be on electoral violence. See Blattman & Miguel (2009) and Davenport (2007) for reviews on the literature on civil conflict and state repression respectively.

[2] Note that these strikes are entirely political in nature and do not involve any labor unrest or work stoppages. A related form of political protest is prevalent in India and Nepal today, where they are referred to as *bandhs*. Further, the disruptive effects of these strikes share some similarities with general strikes in Bolivia and elsewhere.

[3] Our decision to focus on exports rather than production is driven by the high-frequency nature of our political violence data. While daily export data are now available for several countries (see for example the data used in Eaton, Kortum, & Kramarz, 2011), this is not the case for production data. A notable exception

Our daily political violence data offers us two key advantages. First, it allows us to provide the first evidence of how political violence affects the prices received by exporters in a developing country. By disrupting export activity, such violence increases the risk associated with importing from a country. We show that this added risk leads to economically significant effects on the prices received by exporters. Second, the political strikes we study were exogenous to export activity. We show below that these strikes were independent of export shocks and were entirely motivated by political and electoral concerns. Further, we show that the timing of these strikes was uncorrelated with seasonal changes in export activity. Thus, these strikes provide exogenous shocks to an exporter's cost of transporting goods to the port.

We use our daily data to first conduct an event study where we examine the impact of a strike on the timing of a firm's decision to export, the value of its shipments, and its decision to use costlier, air transport. Our event study results suggest that political strikes that span multiple days are especially disruptive to export activity. These multi-day strikes represent 68 percent of all strikes in our sample. We find that over a six-day event window, multi-day political strikes result in a 6.30 percentage point reduction in the likelihood of making an export shipment. This is a large decrease from a baseline export probability of 26 percent over a typical six-day period. We also find that while these multi-day strikes did not affect the size (in monetary value) of export shipments, they did increase the likelihood of using air transport. The latter results in a much higher transport cost per shipment (Hummels & Schaur, 2013).

Given these disruptive effects, we next explore the broader implications of such political violence. In particular, if political violence does increase the risk of missed shipments, it will reduce the payoff from sourcing products from Bangladesh. If so, Western importers may require a reduction in the price to compensate them for the added risk caused by political violence. Such an effect should be especially acute for time-sensitive products. To explore these implications, we use our transaction-level export data to construct an HS8 product-level dataset of export prices. We then regress the natural logarithm of each product's daily price on the intensity of multi-day strikes in a month interacted with an indicator for whether the product is time sensitive.[4] Thus, this regression allows us to examine whether, all else equal, the relative

to this is the data used by Ashraf, Machiavello, Rabbani, & Woodruff (2015), although their data only cover 33 factories.

[4] We categorize a product as time sensitive if the fraction of its shipments made by air transport during the pre-sample period is above the sample median. We classify all other products as time insensitive. We use pre-sample data for this categorization to ensure that our categories are unrelated to political violence.

export price of time-sensitive Bangladeshi products decline during months in which political strikes are prevalent. Our econometric approach incorporates product and time fixed effects, which allow us to absorb any country-level institutional and political characteristics that may be correlated with both political strikes and exports.

Our results confirm that political violence has a negative effect on the export price of time-sensitive products. We find that during July to December, 2013, when there was a multi-day political strike every five days, the prices of time-sensitive Bangladeshi export products declined by 1.59 percent relative to time-insensitive ones. To put this effect in to context, Fan, Li, & Yeaple (2015) find that a 3.31 percentage point increase in Chinese intermediate input tariffs is associated with a similar decrease in export prices. We also find that the adverse price effects are especially acute for smaller and newer exporters and are not driven by compositional changes in the set of products that are exported from Bangladesh.

Our paper is related to a growing literature that documents the adverse, microeconomic effects of political violence on firms. A related paper in this literature is Ksoll, Machiavello, & Morjaria (2014), who use daily export data to examine the impact of election-related violence in 2008 on Kenya's floriculture industry. They find that this political violence lowered the weekly export values in affected regions.[5] While our results complement their findings, we extend their analysis by demonstrating the causal effect of political violence on the prices received by exporters. To our knowledge, this additional channel through which violence affects exporters has not been studied before.

Our paper is also related to a literature that examines the impact of political violence and instability on other aspects of firm performance using less granular data. For instance, Shonchoy & Tsubota (2015) use annual firm-level data to show that political strikes in Bangladesh are associated with higher costs of production. However, they do not examine the effect of these strikes on export prices or on the high-frequency adjustments made by exporters. Collier & Duponchel (2012) examine how the greater intensity of fighting in Sierra Leone affects firm output. Similarly, Guidolin & La Ferrara (2007) and Abadie & Gardeazabal (2003) examine how the sudden end of civil conflict in Angola and a truce announced in the Basque region of Spain respectively affected the stock-market returns of firms operating in these regions.

[5] In another related paper, Machiavello & Morjaria (2015) examine how election-related violence affects the relationship between Kenyan flower exporters and its foreign buyers.

Next, our paper is also related to an earlier literature that examines the effect of terrorism and conflict on aggregate, bilateral trade (Nitsch & Schumacher, 2004; Blomberg & Hess, 2006; Martin, Mayer, & Thoenig, 2008; Glick & Taylor, 2010) and to a literature that examines the impact of supply-chain uncertainty on trade (Clark, Kozlova, & Schaur, 2016). Finally, our paper is related to a literature that documents the trade-reducing effects of transportation delays (Djankov, Freund, & Pham, 2010; Hummels & Schaur, 2013) and to a literature that uses natural disasters to identify the causal effect of transport disruptions on trade (Volpe Martincus & Blyde, 2013; Besedes & Murshid, 2015). We contribute to this literature by showing that disruptions to export activity can have adverse effects on the prices received by exporters.

We structure the remainder of the paper as follows. In section 2, we provide further background on political strikes in Bangladesh as well as on its export-oriented garments industry. In section 3, we describe our political strikes data and discuss the evolving nature of these strikes during our sample period. We also discuss our export data in this section. In section 4, we discuss our event-study analysis. In section 5, we discuss the econometric strategy we use to identify the effect of political violence on export prices. In section 6, we describe our baseline price results, the underlying channels that are driving these results, and explore various heterogeneous effects and robustness checks. Finally, in section 7 we provide a conclusion.

2. Background

2.1 *Hartals* in Bangladesh

Political strikes, or *hartals* from hereon, are a form of political protest that has a long history in South Asia. *Hartals* were first used as early as 1919 by Mahatma Gandhi as a voluntary and largely non-violent method of civil disobedience against British colonial rule. In Bangladesh's pre-independence period (1947 to 1971), *hartals* were seen as a legitimate method of protest against misrule by West Pakistan. As a result, *hartals* during this period had relatively greater popular support. In the 1980s, *hartals* were used to protest the authoritarian, military ruler at the time and also enjoyed widespread support. This historical success and popular support lend contemporary *hartals* a degree of legitimacy in the eyes of Bangladeshi political parties (Suykens & Islam, 2013).

While Bangladesh has a tradition of using *hartals* to protest misrule, in recent years its use has become more widespread. This is because, despite being a parliamentary democracy since 1991, Bangladesh's democracy is characterized by a general intolerance for the views of the opposition. As a result, institutional mechanisms for addressing the grievances of opposition parties either do not exist or do not work well. In the Bangladeshi context, the main grievance is regarding the fairness of general elections. As in the case in other illiberal democracies, opposition parties in Bangladesh do not trust the incumbent to hold fair elections. As a result, *hartals* are viewed as the only viable way to force the incumbent to either enact electoral reforms or to resign and allow a neutral government to hold fair elections (Sobhan, 2004a).

Despite its history of popular support, *hartals* today are deeply unpopular among ordinary Bangladeshis. A 2013 poll conducted jointly by the Asia Foundation and a local newspaper found that 31 percent of all respondents considered *hartals* and political violence to be the country's leading problem (Daily Star, 2013) So why do political parties use them? There are three main reasons. First, a successful *hartal* sends a signal to the government that the opposition party is sufficiently powerful and organized and poses an electoral threat to the government. It is typically the case that other non-violent political activities such as processions, meetings, etc. are also scheduled to coincide with a *hartal*. As a result, a *hartal* is seen as a tool with which to regroup opposition political activists and to place pressure on the incumbent government to accept the opposition's demands.

Second, Bangladeshi politics is dominated by two main political parties: the Awami League and the Bangladesh Nationalist Party. This duopoly engenders a belief that the voter will not punish opposition parties that call *hartals* since their choice is between the opposition and a typically unpopular incumbent (Sobhan, 2004a).[6] Moreover, both political parties have built a sizable base of loyal supporters. This means that the probability of losing significant political support as a result of staging a violent *hartal* is low. Lastly, given the typical heavy-handed response by police, *hartals* are viewed by opposition parties as an effective method with which to garner greater voter support (Sobhan, 2004b). As described below, a common tactic adopted by opposition activists during a *hartal* is to goad the police into violent confrontations. The resulting response by police, which typically involves the use of excessive force, generates widespread sympathy for injured opposition activists.

[6] This is supported by the observation that in all four general elections held in Bangladesh in which both parties actively participated, the opposition used *hartals* extensively prior to the election and was still voted to office.

So what happens during a *hartal*? As described in greater detail in Ahmed & Mortaza (2005), *hartals* are enforced by activists that include armed mercenaries along with hired protestors. The latter are typically drawn from various urban slums. The main aim of these activists is to restrict vehicular movement in key urban areas. This is done in three ways. First, the armed activists goad the police into violent confrontation. Second, *hartal* activists set off homemade grenades and other improvised explosives at various urban areas (Human Rights Watch, 2014). Finally, a third tactic is to torch vehicles (private cars, buses, vans etc.) that ignore the *hartal* restrictions and are seen on city streets.[7] These activities typically start the night before the *hartal* itself and its aim is to create a sense of fear among everyday citizens and entrepreneurs and to discourage them from using motor vehicles.

An important feature of *hartals* is that, while they are costly to exporters, these costs are almost entirely due to transport disruptions. By making motor vehicle movement riskier, *hartals* lead to higher transport prices to compensate transport companies for the added risk they bear. They also lead to longer transit times as drivers avoid violence-prone areas in cities. Further, there is also a non-negligible probability of shipment loss if a shipment is damaged or destroyed by political activists. In contrast, *hartals* do not make it significantly costlier for garments workers to travel to their factory. The mainly female workforce in the garments industry tends to live very close to their place of work. This is supported by the results in Ashraf et al. (2015) who find that *hartals* do not affect worker absenteeism or productivity in garments factories. *Hartals* also do not adversely affect port operations for export shipments. While precise data regarding this are difficult to find, media reports suggest that any adverse effects on port operations are restricted to the import side (Haroon, 2012). On a typical day, an imported container is offloaded from a ship and then placed on a truck for transport to the relevant factory. During a *hartal*, these containers are placed in port storage as trucks are less able to transport them to the factories. In contrast, if a container intended for export is already in the port premises on the day of a *hartal*, they are loaded on to ships. The delay in export shipments occur due to the inability of some shipments to reach the port itself during a *hartal*.

[7] It is evident that to successfully stage a *hartal*, where success is measured by the amount of disruption caused, opposition parties need to have the organizational capacity to hire a sufficient number of armed activists and other individuals. This work is typically the responsibility of mid- and low-level party operatives. Demonstrating competence in organizing disruptive *hartals* is considered by these party operatives to be highly valuable as it often leads to patronage if the party is voted to government. As a result, *hartals* tend to be very popular among such operatives (Suykens & Islam, 2013).

2.2 The Ready-Made Garments Industry in Bangladesh

The disruptions caused by a *hartal* are particularly problematic for the export-oriented, ready-made garments industry (garments from here on) in Bangladesh. This industry has played a vital role in driving the country's recent economic growth. It emerged in the late 1970's through a partnership between a local firm, Desh Ltd., and a South Korean manufacturer, Daewoo Corporation. At the time, the low export of garments from Bangladesh meant that it was not subject to binding quotas in Western markets. Daewoo's objective was to use Bangladesh as an export platform to circumvent the quotas that applied to its exports from South Korea. According to Quddus & Rashid (2000), as part of this venture, Desh sent 130 of its employees to South Korea to participate in an eight-month training program. The vast majority of these employees then went on to start their own garments factories. From this humble beginning, the garments industry in Bangladesh has grown at a dramatic rate over the last four decades (Heath & Mobarak, 2015) and has emerged today as one of the leading garments exporters in the world. According to McKinsey (2011), Bangladesh's garments industry in 2011 employed around 3.60 million workers, most of whom were women.

During this period in which the garments industry in Bangladesh has expanded, the nature of garments sourcing has changed dramatically. Traditional garments sourcing methods resulted in orders being placed by Western retailers to overseas factories approximately six months before a season in the West (Birtwistle, Siddiqui, & Fiorito, 2013). The size of the orders was forecasted based on sales from previous years. Errors in these forecasts created a mismatch between the demand for an item and its available stock in retail outlets. To lower such inefficiency, an increasing number of Western garments retailers switched to quick-response (QR) methods of supply-chain management starting in the 1990's (Taplin, 2014). QR methods are designed to reduce the gap between when an order is placed to factories and the date at which the customer purchases the item. A lower gap allows retailers to better predict what the trendy items are likely to be in any given season. It also means that once it becomes evident that an item is popular, retailers can quickly order a new batch from its supplier. The use of QR methods meant that the typical order to an overseas supplier changed from having a predictable several-month lead time to a series of small and frequent orders with low lead times that better reflect real-time demand.[8] While QR methods lower costs for retailers and prices for consumers, it

[8] Lead time is defined in this context as the gap between an order date and the required delivery date.

places a greater strain on suppliers as they have to be flexible enough to respond to volatile changes in fashion trends. The use of QR methods also places a greater emphasis on timely delivery as any delays may cause popular items to be understocked in retail stores.

3. Data

3.1 *Hartal* Data

To examine the effects of *hartals* on export behavior, we compiled a database of all nation-wide *hartals* in Bangladesh during the period 2005 to 2013. We did so using two popular Bengali and English language newspapers: the Daily *Ittefaq* and The Daily Star respectively. We independently went through the archives of these newspapers for each day of our sample period to collect information on *hartals*. To avoid data collection errors, we then compared each set of entries and corrected any discrepancies. Apart from collecting the date on which the *hartal* occurred, we also collected the announcement date of the *hartal*, the length of the *hartal*, the political party/parties announcing the *hartal* and the official reason for announcing the *hartal*. Our data yield the following stylized facts about *hartals* in Bangladesh.

Hartals Are Mainly Timed Around Elections

Figure 1 illustrates the annual trend in *hartals* during the period 2005 to 2013. In the first half of this period (2005 to 2009), there were a total of 53 *hartals* in Bangladesh. The prevalence of *hartals* during this period reached its peak immediately before the general elections that were scheduled for 22nd January, 2007. In the face of increasingly violent unrest, the Bangladeshi military intervened on 11th January, 2007 and installed a military-backed caretaker government. This government remained in power until the general elections held on 29th December, 2008. In the second half of this period (2010 to 2013), there were 99 *hartals* in Bangladesh. As before, the prevalence of *hartals* again increased during the year preceding the general elections that were held on 5th January, 2014.[9]

[INSERT FIGURE 1 HERE]

Hartals Have Become Increasingly Disruptive

[9] Over the entire 2005 to 2013 period, there were approximately 17 *hartals* per year. This is almost the same as the number of public holidays per year (19).

Next, as Table 1 demonstrates, not only have *hartals* become more frequent during the second half of this period, they have also become more disruptive. When announcing a *hartal*, a political party can stipulate whether the *hartal* is going to be span a single day or whether they will span multiple days. Our data suggest that the percentage of single-day *hartals* decreased significantly during the second half of our sample period. For instance, during the period 2005 to 2009, 49 percent of *hartals* spanned a single day while 19 percent spanned two-days and 32 percent spanned more than two days. In contrast, during the period 2010 to 2013, 32 percent of *hartals* spanned a single day, 22 percent spanned two days, and 46 percent spanned more than two days. Parties that announce a *hartal* can also stipulate the number of hours during which the *hartal* will apply. Our data suggest that the average length of *hartals* increased from 14.60 hours during the first half of the sample period to 16.13 hours during the second half.

Further, the *hartals* in the second half of our sample period were also announced with less notice. For instance, during the period 2005 to 2009, *hartals* were announced 7.28 days before the *hartal* itself. However, during the period 2010 to 2013, *hartals* were announced 4.62 days before the *hartal* itself. In fact, the median gap between the announcement date and the *hartal* date was three days during the second half. Lastly, during the first half of our sample period, there were about 0.5 deaths per *hartal* whereas in the second half, there were about two deaths per *hartal*.[10] Thus, along all dimensions reported in Table 1, *hartals* have become more disruptive in Bangladesh in recent years.

[INSERT TABLE 1 HERE]

3.2 Transaction-Level Export Data

We combine our *hartal* database with transaction-level export data. These administrative data represent the universe of export transactions during our sample period and are collected by the National Board of Revenue (NBR). These data were digitized using the Automated System for Customs Data designed by the United Nations Conference on Trade and Development (UNCTAD). The NBR records the bill of entry details associated with each export shipment. These bills of entry provide the date of an export shipment, the exporter's unique identification number, the total value of export, the 8-digit HS code of the product that is exported, the port

[10] When the two newspapers we use to construct our *hartal* database provide conflicting estimates of deaths and injuries, we take an average of these two estimates. This is why some *hartals* in our sample have a reported number of deaths/injuries that are in fractions.

through which the product is exported, and the destination of the export shipment. These data allow us to construct a daily, exporter-level panel for the period 2005 to 2013.

To gauge the reliability of these data, we compare the aggregate exports calculated from our customs data with that reported by the World Bank. This comparison is demonstrated in Table 2. In both columns (1) and (2), we report the total annual exports from Bangladesh for the period 2005 to 2013. In column (1), we use the customs data while in column (2), we use the World Bank data. In column (3), we report the ratio of annual exports from the customs data to the annual exports from the World Bank data. Over the entire sample period, this ratio takes the value of 0.99. Thus, over this entire period, the customs data accurately capture almost all export transactions from Bangladesh. However, if we examine this ratio by year, certain anomalies stand out. In particular, the ratios in 2006 and especially 2007 are outliers and suggest that there was a decrease in exports in 2007, which is surprising given the widely reported uninterrupted rise of exports in Bangladesh during this period. Due to these concerns about data quality, we chose to restrict our working sample to the period 2010 to 2013.[11]

[INSERT TABLE 2 HERE]

To construct our working sample, we restrict our data to exporters in the ready-made garments industry. During our sample, ready-made garments exports accounted for 79.40 percent of all Bangladeshi exports and 76.31 percent of all Bangladeshi exporters. We also omit observations that do not include the date of export and drop exporters whose average number of shipments per year is less than or equal to the 3rd percentile and exporters whose average value of annual shipments is less than or equal to the 3rd percentile.[12] We then aggregate each firm's

[11] When we use the entire period (2005 to 2013), we still observe that a reduced probability of making an export shipment during a *hartal*, but the magnitude of the effect is considerably larger than what we report below. Further, with the entire period, we observe a large, negative cumulative effect over our event window. This result could reflect the fact that *hartals* were more costly in the past or it could be the result of measurement error in the earlier data. Unfortunately, it is not possible for us to distinguish between the two. As a result, we err on the side of caution and restrict our sample to the 2010 to 2013 period, where measurement error is not a first-order concern. Note that in doing so, we are presenting more conservative estimates.

[12] These omissions are motivated by the presence of exporters that send samples to Western buyers to demonstrate the quality of their work. These exporters are not responding to an actual purchase order from a buyer but are instead trying to establish a reputation for quality in the hopes of obtaining a future purchase order. We chose to omit these exporters as they engage in transactions that are fundamentally different from the remaining exporters in our data. These omitted exporters account for just 2.18 percent of total garments exports in Bangladesh over our entire sample period.

export by day. In some cases, firms have multiple consignments on the same day, often for the same product.[13] We aggregate these to ensure that there is only one observation per firm per day.

In Table 3, we report some descriptive statistics of the exporters in our working sample. Our sample consists of 5,551 garments firms that have exported during our sample period of 2010 to 2013.[14] On average, 598 firms export on any given day. The average exporter in our sample exports 5.46 products per year, where a product is defined at the HS6 level. Such a firm also exports to 5.48 destinations per year and makes 94.75 shipments per year. The average firm in our sample uses air transport for 22 percent of its shipments. Thus, our sample consists of high-frequency, multi-product, and multi-destination exporters.[15]

[INSERT TABLE 3 HERE]

Lastly, we also use our transaction-level export data to examine whether the prices paid for Bangladeshi garments decline during *hartal*-intensive periods. We calculate product-specific unit values to proxy product prices. Unit values are defined as the ratio of the value of a shipment divided by the shipment quantity and is a commonly used proxy for price in the trade literature (Schott, 2004; Hallak, 2006). However, as Hallak (2006) points out, differences in unit values could reflect heterogeneity in the type of goods that are exported under a product category. To account for such compositional differences, we calculate unit values at the HS8 level, which is the lowest level of aggregation possible in our data. Further, to account for outliers, we follow Hallak (2006) and omit observations with unit values that are greater than four times the HS8 product-specific mean unit value. We further omit unit values that are below

[13] We define a shipment as the value of goods that a firm exports on a given day while we define a consignment as the value of goods reported in each bill-of-entry. To make this clearer, suppose that an exporter is planning to export 1,000 units of a product on a given day. She decides to transport them to the port in four trucks consisting of 250 units per truck. In our analysis, each truck is considered a consignment while the total quantity exported on that day (1,000) is the shipment.

[14] Thus, for each of these firms we have 1,453 daily observations during the period 2010 to 2013. This excludes seven dates that are missing in our sample. These missing dates typically coincide with *Eid*, which is the main public holiday in Muslim-majority Bangladesh.

[15] The most common destination for these exports is the United States, which accounts for 29.93 percent of all Bangladeshi garments exports. This is followed by Germany, which accounts for 24.96 percent of all exports.

one fourth the HS8 product-specific mean unit value.[16] Summary statistics of the price data used in this paper are provided in Table 3.

4. An Event Study of *Hartals* and Export Shipments

4.1 Event Study Method

Since *hartals* provide a transportation shock to Bangladeshi exporters, we would expect there to be a reduction in export shipments on the day of the *hartal* itself. What is less well understood is the lag structure with which *hartals* will affect the decision to export. To explore this further, consider an exporter's operational phase. This operational phase consists of two segments: (a) a production segment where the goods intended for export are produced and (b) a transportation segment where the goods intended for export are transported to the port. As mentioned above, *hartals* are a unique form of political violence because they are targeted towards disrupting transportation and do not cause any direct disruption to production. Thus, if a *hartal* falls on an exporter's production segment, we should not observe a disruption to its production and therefore should not observe an effect on its probability of exporting or the value of its exports on the shipment day.

On the other hand, if a *hartal* falls on an exporter's transportation segment, an exporter's ability to transport its goods to the port in a timely manner will be adversely affected. It follows that the exports on a given day will only be affected by a *hartal* on that day itself or by *hartals* on days within a short window before the shipment date. With this is mind, we estimate the following specification:

$$\Pr[X_{it} > 0] = \alpha_1 + \sum_{s=N_L}^{N_H} \beta_s H_{t-s} + \theta_i + \theta_t^W + \theta_t^Y + \theta_y + \varepsilon_{it} \tag{1}$$

where X_{it} is the value of total exports for exporter i on day t. Our aim here is to capture whether an exporter responds to a *hartal* by choosing not to export at all on a *hartal* day. Thus, the regression in (1) estimates the effect of a *hartal* on the extensive margin. To identify the effect on the intensive margin, we also use as a dependent variable the natural logarithm of a firm's total

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[16] As we show below, our results are robust to keeping these outliers in our sample. Note that the quantity of goods in a shipment was not recorded between July, 2012 and June, 2013. As a result, we were not able to calculate unit values during this period. We omitted this period from our price regressions in section 6.

daily exports. Lastly, to explore other coping mechanisms, we also replace the dependent variable in (1) with an indicator for whether a firm uses air transport on day t.

When $s = 0$, H_t is an indicator variable for whether there was a *hartal* on that day. For all other values of s, H_{t-s} takes the value of one if there was a *hartal* $t - s$ days ago and there wasn't a *hartal* on day t. Thus, each coefficient β_s captures the impact of a *hartal* that occurred s days ago on today's exports. The use of lagged and lead *hartal* indicators allows us to capture the extent to which exporters reallocate their shipment away from *hartal* days and towards days immediately before and after a *hartal*. Thus, if such reallocation were absent, we would expect β_s to equal zero for all $s \neq 0$. Note that $N_L < 0$ and $N_H > 0$ determine the length of the event window over which we examine the effects of a *hartal*. As we show below, our key results are robust to alternate event window lengths.

Next, we include firm fixed effects, θ_i, in our baseline specification to allow an exporter's exposure to a *hartal* to be heterogeneous. For instance, an exporter that is located close to the port may have a lower exposure to a *hartal* compared to an exporter located further away. The firm fixed effects will control for such differential *hartal* exposure. Our specification above also extensively controls for any seasonal patterns in the data. We include day-of-week fixed effects, θ_t^W, which will capture any secular variation in exports during the week. We also include day-of-year fixed effects, θ_t^Y, to control for any seasonal factors that might be correlated with exports. Further, we include year fixed effects, θ_y, to capture macro-level factors that are correlated with *hartals* as well as a firm's export decision. This means that the β_s coefficients that we estimate in equation (1) tell us the likelihood that an average firm in our sample exports on the day of a *hartal* compared to a seasonally adjusted non- *hartal* day. Lastly, ε_{it} is a classical error term.

Note that our event-study specification does not account for spatial variation in *hartals*. This is due to the following reasons. First, our customs data do not report the location of each exporter's factory. However, even if we were to observe the location of each factory, the geographic concentration of Bangladesh's garments industry will limit any spatial variation for us to exploit. For instance, Fernandes (2008) shows that 67 percent of garments firms in her sample were in either the capital, Dhaka, or the Dhaka Export Processing Zone. Second, the *hartals* in our sample are held throughout the country, which further limits any potential spatial variation for us to exploit.

Finally, before presenting our event-study result, it's worth pointing that our choice of a short event window requires that firms in our sample export at a relatively high frequency. If the typical gap between shipments is sufficiently large, then our event window may not be long enough to observe the adjustment behavior of firms. Fortunately, we find that the average exporter in our sample exports 94.75 days per year. Further, the average gap between shipment days is 5.65 days. Both numbers suggest that the firms in our working sample export with relatively high frequency and therefore a relatively short event window is sufficient for us to observe the adjustment behavior of firms.

4.2 Event Study Results

We begin by estimating equation (1) for various event windows using a linear probability model. We begin in column (1) of Table 4 by estimating the contemporaneous effect of a *hartal*. The dependent variable is an indicator that takes the value of one if a firm exports on day t and is zero otherwise. The coefficient of the *hartal* indicator, H_t, is negative and statistically significant. It suggests that a *hartal* reduces the average firms' probability of exporting by 1.80 percentage points. This represents an 18.29 percent decline from the baseline probability of exporting. In column (2), we include the first lead of the *hartal* indicator, H_{t+1}, which takes the value of one if there is a *hartal* tomorrow but no *hartal* today. This indicator will capture the extent to which exporters bring forward their export shipment date to lower their exposure to a *hartal*. The results in this column suggest that while there is a 1.70 percentage point reduction in the probability of making an export shipment on the day of the *hartal* itself, there is a 1.10 percentage point increase in this probability the day before the *hartal*.[17]

[INSERT TABLE 4 HERE]

We can use our estimates in column (2) to introduce our method for calculating the cumulative effect of a *hartal*. Suppose there is a *hartal* on day t. From our estimates in Table 4, we know that this *hartal* will affect the probability of making a shipment on day t. We also know that this *hartal* will affect an exporter's probability of making a shipment on the day before.

[17] Any reallocation result we find can be biased by systematic errors in dating export shipments. For instance, to the extent that port activities were disrupted during a *hartal*, it may have led to the incorrect date being assigned to a shipment. While we have found no evidence to suggest that port activities were disrupted during *hartals*, any bias caused by this is likely to work against us. For instance, suppose a *hartal* today disrupts port activities. The likely result of this is that shipments that arrived at the port today will be processed and dated the day after. In turn, this will appear as a delayed shipment in our data. This bias will make it less likely for us to find that shipments were reallocated to the day before a *hartal*.

Further, this *hartal* may also affect an exporter's probability of making a shipment on the days immediately after. Thus, the sum of these three effects represents the cumulative effect of a *hartal*. More precisely, the cumulative effect is given by $\sum_{s=N_L}^{N_H} \beta_{t-s}$. This cumulative effect is reported at the bottom of column (2). For the two-day event window examined here, the cumulative effect is a 0.60 percentage point reduction in the probability of making an export shipment.

The results in column (2) suggest that we cannot reject the null hypothesis that the cumulative effect of a *hartal* over a two-day event window is zero. This indicates that for the average *hartal*, exporters adjust by moving their shipments to the day before.[18] While this is the case, it is worthwhile to verify that there is no other adjustment behavior in the days before and after a *hartal*. To do so, we add a second lead *hartal* indicator, H_{t+2}, in column (3) of Table 4. The coefficient of this new indicator is statistically insignificant. Next, in column (4) we add two lagged *hartal* indicators, H_{t-1} and H_{t-2}. Once again, these two new indicators are statistically insignificant. In fact, we have extended our event window to six days after the *hartal* itself. The resulting cumulative effect is illustrated in Figure 2. As is clear from this diagram, there is no evidence of adjustment behavior in the days following an average *hartal*. Taken together, our results suggest that *hartals* in Bangladesh are disruptive. For instance, the estimates in column (2) of Table 4 suggest that the probably of a firm exporting during a *hartal* is 17.35 percent lower than the baseline probability of exporting. However, our results also suggest that Bangladeshi garments exporters respond to this disruption by transferring their shipments to the day before a *hartal*.

[INSERT FIGURE 2 HERE]

4.2.1 The Effect of Multi-Day *Hartals*

Up to now, we have considered the effect of an average *hartal* on the export behavior of Bangladeshi garments manufacturers. However, recall from Table 1 that there is considerable heterogeneity in the duration of a *hartal*. In particular, 40 percent of the *hartals* during our sample period spanned multiple days. We now examine whether such multi-day *hartals* have a stronger effect on export activity. To implement this, we first isolate all *hartals* in our sample that spanned

[18] Note that our data only allow us to examine the impact of *hartals* on exports. It is likely the case that *hartals* also affect a firm's ability to acquire imported inputs from the port in a timely manner, which would amplify the adverse effects of *hartals* on exporters. Thus, our estimates of the cumulative effect of the average *hartal* is a lower bound on its true cost to exporters.

between two to four days. We then construct our *hartal* indicators as follows. Consider a sequence of *hartals* that span four days. We let H_t^M take the value of one on the first day of the *hartal* sequence, we let H_{t-1}^M take the value of one on the second day of the *hartal* sequence, we let H_{t-2}^M take the value of one on the third day of the *hartal* sequence, and we let H_{t-3}^M take the value of one on the fourth day of the *hartal* sequence. We define our *hartal* indicators in a similar manner in the case of two and three-day *hartals*.[19] We report the results from estimating the effect of multi-day *hartals* on export behavior in column (1) of Table 5. Before we describe the results, it is worth discussing a couple of features of this regression. First, to ensure that our counterfactual is the export shipment probability on a seasonally-adjusted non- *hartal* day, we omit from our sample in column (1) days in which there was a single-day *hartal*.[20] Second, since the *hartal* period now spans up to four days, we extend our baseline event window from three days to seven days. More precisely, we now define our *hartal* indicators, H_{t-s}^M, for $s = -2$ to $s = 4$.

[INSERT TABLE 5 HERE]

The results in column (1) suggest that, for the average exporter, the probability of making an export shipment drops significantly on the second and third days of a multi-day *hartal* sequence. Interestingly, unlike the baseline case, we do not observe any days in our event window where there is a significant increase in the probability of making a shipment. This suggests that these multi-day *hartals* are much more disruptive to exporters in the sense that it does not allow them to fully reallocate their shipments. This is also reflected in the cumulative effect shown at the bottom of column (1), which indicates that over a seven-day event window, a multi-day *hartal* leads to a statistically significant 6.30 percentage point reduction in the probability of making an export shipment.[21,22]

[19] As we show in Table 1, relatively few *hartals* span two, three, and four days respectively. Thus, if we were to consider two, three, and four-day *hartals* separately, we will be left with *hartal* indicators with very little variation. To avoid this problem, we group together two, three, and four-day *hartals*.

[20] In our baseline estimation, we compared the export shipment probability of firms in our sample on the day of a *hartal* with the shipment probability on a seasonally-adjusted non- *hartal* day. Thus, seasonally-adjusted non- *hartal* days were our counterfactual. In column (1) of Table 5, the unadjusted counterfactual includes both non- *hartal* days as well as *hartal* days that spanned a single day. To ensure that our counterfactual is appropriate, we exclude single-day *hartals* from our sample in column (1). This adjusted counterfactual now only includes non- *hartal* days, as was the case with the baseline results above.

[21] Note that the coefficient of H_t^M in column (1) of Table 5 is not directly comparable to the coefficients of H_t in Table 4. To see this, consider a three-day *hartal* sequence. In Table 4, H_t would have taken the value of one on all three of these *hartal* days. In contrast, in Table 5, H_t^M takes the value of one on the first *hartal* day but not on the remaining days.

Our analysis thus far has focused on the effect of *hartals* on an exporter's choice of shipment date. In other words, we have examined whether a *hartal* affects a firm's export decision at the extensive margin. In column (2) of Table 5, we examine whether multi-day *hartals* also affect a firm's export decision at the intensive margin. That is, we now ask whether, conditional on making a shipment, a *hartal* alters the value of the goods that a firm exports on any given day. In column (2) we restrict the sample to observations with positive exports and then estimate a version of equation (1) with the natural logarithm of a firm's daily exports as the dependent variable. The results suggest that exporters not only reduce the probability of making a shipment on the second day of a multi-day *hartal* sequence, they also reduce the size of the shipment. We further observe a statistically significant increase in the size of shipments on the day before the start of a multi-day *hartal* sequence. The cumulative effect at the bottom of column (2) indicates that while the size of shipments does fall over the event window, this reduction is not statistically significant.

Lastly, in column (3) of Table 5, we examine whether a multi-day *hartal* affects an exporter's likelihood of using air transport to make up for the disruption caused by a *hartal*. Given that air transport is significantly more expensive (Hummels & Schaur, 2013), greater use of air transport can have an adverse effect on the profit margin of garments exporters. To examine whether this is the case, we estimate a version of our baseline econometric specification where the dependent variable is now an indicator that takes the value of one if an exporter uses air transport on any given day and is zero otherwise. The results in column (3) suggest that the coefficient of the *hartal* indicator, H_t, is positive, statistically significant, and large in magnitude. This suggests that the average exporter in the sample does increasingly use air transport on the day of a *hartal*. We also see that exporters increase their use of air transport on the second day of a multi-day *hartal* sequence. While there is a reduction in the use of air transport the day before the start of this sequence, this adjustment activity does not fully account for the increased air transport use on the other days of the event window. This is reflected in the cumulative effect at the bottom of column (3), which is positive and statistically significant.

5. *Hartals* and Export Prices: Econometric Strategy

[22] The results in column (1) are robust to extending our event window. For instance, when we extend our window by a further three days, we find that all additional *hartal* indicators are statistically insignificant. In addition, we find that the cumulative effect continues to be negative and statistically significant with a magnitude that is similar to that reported at the bottom of column (1).

Our results thus far suggest that multi-day *hartals* lead to a reduction in the number of shipments made by Bangladeshi garments exporters. We now examine the broader implications of these disruptive effects. To fix ideas, suppose that a Western retailer agrees to source a product, k, from Bangladesh. At an initial period, the retailer and the Bangladeshi exporter negotiate the quantity to be produced, q_k, the sourcing price, P_k, as well as a shipment date. For simplicity, suppose that q_k is constant. Let the per-unit value of this product to the retailer be $(1-\varphi)P_k^r$, where $P_k^r > P_k$ is the retail price of k and φ is the probability that this product is not shipped from Bangladesh on time. It follows that from the retailer's perspective, the value of sourcing garments from Bangladesh will be inversely related to the likelihood of a missed shipment, φ. Thus, during *hartal*-intensive periods, the retailer will need to be compensated with a lower sourcing price if it is to agree to source garments from Bangladesh.

Before we introduce our econometric specification, recall that the median *hartal* in our sample was announced with three days' notice. Thus, it is unlikely that Western retailers will be able to anticipate specific *hartals* and adjust their prices accordingly. This means that a regression of daily prices on a daily *hartal* indicator is inappropriate. Instead, we examine whether the price of exported products depends on the intensity of *hartals* over a more extended period. Observing *hartals* over an extended period will better allow a retailer to form their expectations of φ and negotiate a more appropriate sourcing price. With this in mind, we estimate the following econometric specification:

$$\ln P_{kty} = \alpha_2 + \gamma HI_{my} \times A_k + \theta_m \times \theta_y + \theta_k + \theta_t^Y + \theta_t^W + \vartheta_{kty} \quad (2)$$

where P_{kty} is the average price of an HS8 product k on day t in year y.[23] Note that we estimate (2) using the same data as in section 4, but our unit of observation is now product-day rather than firm-day. HI_{my} is an indicator variable that captures the intensity of *hartal* activity in month m and year y. Our default measure is the fraction of days in a month that was part of a multi-day *hartal* sequence.

A regression of prices on HI_{my} alone may be contaminated by the presence of other month- and year-specific shocks. One way to address this is to interact HI_{my} with a treatment indicator, A_k, that distinguishes between products that are time sensitive with those that are not.

[23] The raw price data are at the firm-product-day level. We aggregated these data to the product-day level by calculating a simple average. We show below that our results are robust to using weighted average prices instead where the weights are each firm's share of daily exports for a given product.

To the extent that *hartals* affect export prices, this effect should be stronger for time-sensitive products. To measure time sensitivity, we first calculate the fraction of each product's exports that occur using air transport. We then define a product as time sensitive if its share of air transport use is above the sample median. All other products are classified as being time insensitive. To ensure that this measure is not a function of *hartals*, we calculate the share of air transport for each product using data from 2008 and 2009. Recall from Figure 1 that there were no *hartals* during these years. Our underlying assumption in using this categorization is that, conditional of product fixed effects, products that are more likely to be transported using airplanes are more time sensitive. If Western retailers do respond to *hartals* by negotiating a lower price, we would expect γ to be negative.

The advantage of estimating the interaction between *hartal* intensity and a product's time sensitivity is that it allows us to also include the interaction between a month fixed effect, θ_m, and a year fixed effect, θ_y. This interaction fixed effect controls for all other month- and year-specific shocks that may confound our results. Note that these fixed effects absorb the level effect of HI_{my}, which is why the latter is not included in equation (2). We also include product fixed effects, θ_k, to capture any time-invariant product characteristics that may explain variation in product prices. Next, to ensure that our identification of γ is not driven by spurious trends, we include in (2) a day-of-year fixed effect, θ_t^Y, and a day-of-week fixed effect, θ_t^W. Finally, we include a classical error term, ϑ_{kty}.

[INSERT FIGURE 3 HERE]

Our identification of (2) relies on two key assumptions. The first is that the decision to organize a *hartal* is independent of changes in export prices or more generally shocks to export activity. If this were to be the case, then our results may be picking up a spurious negative correlation between *hartals* and export prices. To examine whether this is the case, we explore the reasons for organizing a *hartal*. Recall that when we constructed our *hartal* database we recorded the official reason for announcing each *hartal*. We group these reasons into various categories and illustrate their frequencies in Figure 3. As this figure clearly demonstrates, the main reasons for announcing a *hartal* are political. The most common reason is a demand for election reforms. Since the beginning of electoral democracy in Bangladesh in 1991, elections there have been marred by distrust and violence. As a result, many pre-election *hartals* are motivated by the desire for electoral reforms to minimize any advantage for the incumbent party. Other common reasons for announcing *hartals* are to protest police violence against opposition activists and to protest a recent War Crimes trial. Importantly, of the 99 *hartals* during our sample period, only four were motivated by economic factors. In all four cases, the motivation for announcing the *hartal* was the rising price of essential goods and, therefore, was not directly related to exports.

[INSERT FIGURE 4 HERE]

While *hartals* may be organized due to political reasons, they may be timed around important economic periods. Thus, the second identifying assumption required for (2) is that the timing of *hartals* is not related to export activity. For instance, if particular months of the year represent peak exporting periods, opposition parties may refrain from organizing *hartals* then to minimize any adverse effect on exports. To examine whether this is the case, we plot the share of exports by month and the share of *hartals* by month in Figure 4. As this figure illustrates, garments exports in Bangladesh are evenly spread out throughout the calendar year. This is mainly a function of the fact that garments are in demand throughout the year. While the exact product to be exported will vary (e.g. summer vs. winter clothing), the export of garments overall is unlikely to be specific to any seasons.[24] In contrast, *hartals* are more prevalent at the end of the calendar year. This is because of two main reasons. First, elections in Bangladesh are typically held in January and February. Further, the dryer and cooler weather at the end of the year is more conducive to staging a *hartal*. For these reasons, *hartals* in Bangladesh peak around November and December. Thus, there is no evidence in Figure 4 of *hartals* being timed around peak export periods, mainly because the uniform nature of garments exports throughout the year in Bangladesh means that significant peak periods are non-existent.

6. Results

We report the results from estimating (2) in Table 6. We begin in column (1) by estimating a parsimonious version of (2) where we regress the natural logarithm of a product's daily price on HI_{my} alone. Our goal here is to examine whether there was a general change in prices during *hartal*-intensive months. Since HI_{my} varies by month and year, we do not include

[24] If monthly garments exports are a function of *hartals*, then the stability observed in Figure 4 will be spurious. To guard against this, we recreated Figure 4 after dropping exports in 2013. Recall that this is the year in which *hartals* were especially prevalent. The stability of garments exports throughout the year remained unchanged.

month and year interaction fixed effects. We leave all other aspects of equation (2) unchanged. The coefficient of interest in column (1) is statistically insignificant. It suggests that the average price of Bangladesh's garments exports did not decline during *hartal*-intensive months.

In column (2), we interact HI_{my} with an indicator for the time sensitivity of a product. Before describing these regression results, it is instructive to first examine whether the differential impact of *hartals* on time-sensitive and time-insensitive prices is evident in the raw data. To implement this, we first de-trend our price data and use it to calculate an average monthly price separately for time-sensitive products and time-insensitive products respectively.[25] Next, we plot monthly *hartal* intensity as well as average monthly prices for both time-sensitive and time-insensitive products respectively in Figure 5. To smooth out month-to-month volatility, we plot a three-month moving average for both category of products.

[INSERT FIGURE 5 HERE]

The trends in this figure suggest that the average monthly price of both time-sensitive and time-insensitive move in a cyclical manner with periods of price increases followed by periods of price decreases. Further, for the vast majority of the sample period, these two price series trend in an almost identical manner. However, these trends diverge during the *hartal*-intensive period of July to December, 2013. While the average monthly price of time-insensitive products continues to follow its typical cyclical pattern, the average monthly price of time-sensitive products breaks from its cyclical pattern and experiences a clear downward trend. Importantly, this downward trend coincides with the beginning of the *hartal* intensive period in 2013, which indicates any results described below are being driven by *hartals*. To verify that the effect of *hartals* evident in Figure 5 holds at the product-day level, we report the results from estimating a version of equation (2) where we include both HI_{my} as well as its interaction with a product's time sensitivity. We report these results in column (2) of Table 6. The coefficient of the interaction term is negative and statistically significant. It suggests that during *hartal*-intensive months, the export price of time-sensitive products decline relative to time-insensitive ones.

[INSERT TABLE 6 HERE]

[25] To de-trend the price data, we regress the natural logarithm of prices on a day-of-year fixed effect as well as on month, year, and day-of-week fixed effects. We also include product fixed effects to account for any time-invariant product-specific factors that may explain its price variation over time. We then collect the residuals from this regression, which is our de-trended price data.

A limitation of the results in column (2) is that it can be confounded by other month- and year-specific shocks. To account for this, we include month and year interaction fixed effects in column (3). These interaction fixed effects capture the level effect of HI_{my}, which is why it is excluded from this column. As the results demonstrate, the interaction coefficient of interest continues to be negative and statistically significant. To get a sense of how large the size of this effect is, consider the period of July to December, 2013. These are the months that immediately preceded the January, 2014 elections and was a time when *hartals* were especially prevalent in Bangladesh. In fact, during this period, a fifth of days were part of a multi-day *hartal* sequence. The results in column (3) suggest that having a multi-day *hartal* every five days resulted in a 1.59 percent decrease in the relative export price of time-sensitive Bangladeshi products.

The trends in Figure 5 suggest that the adverse effects of multi-day *hartals* happened during the last half of 2013. There were no visible effects for the small number of multi-day *hartals* during other months in our sample. To verify that this is also the case in the regression analysis, we isolate the multi-day *hartals* during the last six months of 2013.[26] More precisely, we define a pre-election indicator variable that is one during July to December, 2013 and is zero in all other months. We then estimate a version of equation (2) where we replace HI_{my} with this indicator variable. We report the results from this regression in column (4) of Table 6. The coefficient of the interaction term of interest is negative and statistically significant. This result confirms that the adverse effects of *hartals* that we have found so far is being driven by this pre-election period.

6.1 Channels

An advantage of replacing HI_{my} with a pre-election indicator is that it allows us to conduct a falsification test to further validate our core result. We know that the frequency of multi-day *hartals* increased during the last half of 2013. This is also a period in which winter products are being increasingly exported from Bangladesh. Thus, our results could be driven by winter-specific shocks to export prices. To verify whether this is the case, we conduct the following falsification exercise. First, we construct a false pre-election indicator that is one during

[26] Another argument for focusing on the pre-election period is as follows. To pre-emptively adjust prices based on *hartals*, Western retailers need to be able to anticipate the likelihood of a *hartal* occurring. It is unlikely that retailers will be able to do so for isolated periods of *hartals*. Instead, based on the historical trends evident in Figure 1, retailers are likely to anticipate that *hartals* will be more prevalent in pre-election months. If this is true, then the adverse price effects that we have shown thus far should be driven by the period that immediately preceded the January, 2014 elections.

July to December in all years other than 2013. We then interact this indicator with our measure of time sensitivity. If our results are indeed being driven by winter-specific shocks to prices, then this false interaction term should also be negative and statistically significant. The results in column (1) of Table 7 indicate that this is not the case. There are no differential effects on the price of time-sensitive products during the winter months of years other than 2013.

In our discussion in section 5, we hypothesized that greater prevalence of multi-day *hartals* will lead to Western retailers negotiating down the price that they pay to Bangladeshi exporters. In doing so, we assumed that the composition of products that are exported from Bangladesh does not change during *hartal*-intensive periods. That is, we assumed that the probability that a product is exported from Bangladesh is not affected by *hartals*. If such an extensive margin effect were to exist, then this compositional change may explain our results in Table 6. To examine whether this extensive margin effect exists, we estimate a version of equation (2) where we use an indicator for whether a product is exported on a given day as our dependent variable. We estimate this regression on a sample that includes days when a product is exported (as in Table 6) as well as days in which it is not. We leave all other aspects of equation (2) unchanged. We report the results from estimating this regression in column (2) of Table 7. The coefficient of HI_{my} interacted with time sensitivity is negative and statistically significant. This result confirms that the day-to-day composition of products that are exported from Bangladesh is affected by *hartals*.

[INSERT TABLE 7 HERE]

The composition changes highlighted in column (2) are especially problematic for us if Western retailers respond to multi-day *hartals* by reallocating their orders of higher-priced garments to other countries. If this is the case, then the average price of Bangladeshi garments exports during *hartal*-intensive periods will be downward biased. Such a compositional effect can also explain our results in Table 6. To explore this effect, we first categorize all products in our data in to high-priced and low-priced bins. To do so, we calculate each product's average price during 2008 and 2009. Recall that there were no *hartals* during these years, which ensures that our price categorization is independent of *hartals*. We then classify a product as high priced if its average 2008/2009 price is above the sample median. All other products are classified as being low priced. We then regress our product and day-level export indicator on the interaction between HI_{my} and the high-priced indicator. We report these results in column (3) of Table 7.

Here we find that our interaction coefficient of interest is both small in magnitude and statistically insignificant. Thus, there is no evidence of *hartals* leading to a disproportionate decrease in the probability of exporting high-priced products.

Next, we examine whether *hartals* lead to a disproportionate decrease in the export of high-priced, time-sensitive products relative to low-priced, time-sensitive products. We do so by regressing our export indicator on HI_{my} interacted with time sensitivity, HI_{my}interacted with the high-priced indicator, and a triple interaction between HI_{my}, time sensitivity, and the high-priced indicator. We report these results in column (4) of Table 7. The coefficient of the triple interaction term is statistically insignificant. It suggests that the reduced probability of a high-priced, time-sensitive product being exported during *hartal*-intensive periods is no different from that of a low-priced, time-sensitive product.

Finally, in column (5) we estimate a Heckman selection correction to account for the compositional changes in our sample. As these results demonstrate, our coefficient of interest is very similar to the baseline finding in column (3) of Table 6. Taken together, the results in columns (2) to (5) of Table 7 suggest that while there are compositional changes in the products exported from Bangladesh during *hartal*-intensive periods, these changes do not explain our results in Table 6.

6.2 Exporter Heterogeneity

Next, in Table 8 we explore whether the reduction in prices due to *hartals* vary by exporter characteristics. We begin in columns (1) and (2) by examining whether exporter size provides important sources of heterogeneity. Recall that our baseline dependent variable in Table 6 was the average daily price of an HS8 product. In column (1) of Table 8, our dependent variable is the average daily price of an HS8 product calculated using a subsample of small exporters. To identify small exporters, we first calculate each exporter's annual export value in the first year in which it joined the sample. We then classify an exporter as small if this annual export value is below the median initial year export value. All other exporters are classified as large. For the dependent variable in column (1), we restrict the sample to small exporters and then calculate the average daily price for an HS8 product. In contrast, in column (2), we restrict the sample to large exporters before calculating the average daily price. The results in these columns suggest that the price declines we've captured thus far are more acutely felt by smaller exporters.

[INSERT TABLE 8 HERE]

In columns (3) and (4), we examine another source of heterogeneity: a firm's export history. For the dependent variable in column (3), we restrict the sample to newer exporters and then calculate the average daily price for an HS8 product. In contrast, in column (4), we restrict the sample to older exporters before calculating the average daily price. We define a newer exporter as a firm that first exported after 2005. All other firms are defined as older exporters. The results in these columns suggest that newer exporters face much sharper decline in prices relative to older exporters during *hartal*-intensive period. The results in Table 8 are consistent with the idea that smaller and newer exporters have less bargaining power when it comes to negotiating prices with a Western retailer and therefore suffer much larger price declines.

6.3 Robustness Checks

In Table 9, we examine the sensitivity of our price results by using alternate measures of *hartal* intensity and alternate daily price averages. In column (1), we use the number of multi-day *hartals* (instead of the fraction) as our measure of *hartal* intensity. As the results demonstrate, the interaction between *hartal* intensity and time sensitivity remains negative and statistically significant. In column (2), we proxy *hartal* intensity by calculating the average length (in days) of *hartals* during a month. Thus, months in which there are more multi-day *hartals* will have a higher average length value. As in column (1), our coefficient of interest remains negative and statistically significant in column (2).

Next, in columns (3) and (4), we use alternate measures of daily, product-level prices. Recall that our baseline measure is the simple average of a product's price on any given day. In column (3), we use a weighted average instead where the weights are each firm's share of daily exports for a given product. The advantage of using this weighted average is that it places lower weights on export transactions involving small quantities of goods. This minimizes the risk that the daily average is being driven by potential outliers. As the results in column (3) demonstrate, the interaction between *hartal* intensity and time sensitivity remains negative and statistically significant. In fact, the magnitude of this coefficient is much larger than the baseline.

[INSERT TABLE 9 HERE]

Finally, in column (4) we examine whether our results are sensitive to the omission of price outliers. Recall from section 3.2 that we omitted observations with prices that were greater than four times the HS8 product-specific mean price. We further omitted prices that were below one fourth the HS8 product-specific mean price. These omissions were designed to ensure that our results were not being driven by outliers. However, in column (4) of Table 9, we examine whether our results hold if we include these omitted values. The dependent variable is the simple daily average of an HS8 product's price when all prices are included in the sample. As these results demonstrate, our coefficient of interest remains negative and statistically significant.

7. Conclusion

In this paper, we used novel, high-frequency data to examine the impact of political strikes on firm-level export activity. These data include daily information on all political strikes and firm-level exports in Bangladesh over a four-year period and allowed us to identify the impact of political violence and exporters' adjustment behavior at a highly granular level. We used these data to first conduct an event study where we examined the effect of political strikes on a firm's decision to export, the size of its shipment, and its decision to use air transport. We found that over a six-day event window, political strikes that spanned multiple days led to a 6.30 percentage point reduction in the likelihood that a firm will export. While we did not find any cumulative effect on the size of shipments, we did find that political strikes increased the likelihood of using air transport.

Having documented these disruptive effects, we then examined the broader implications of these political strikes for Bangladeshi exports. To the extent that political strikes increase the likelihood of missed or delayed shipments, it will lower the value that Western retailers obtain from sourcing products from Bangladesh. In turn, they may require a reduction in the price that they pay to compensate them for this added risk. If such a price effect does exist, it is likely to be more acute for time-sensitive products where delays are much more consequential. To explore this hypothesis, we regressed the natural logarithm of daily export prices for HS8 products on the intensity of multi-day political strikes in a given month interacted with an indicator for whether an HS8 product is time sensitive. A key advantage of our analysis is the exogeneity of these strikes to export activity. In particular, we showed that the decision to organize these political strikes were independent of export shocks and that its timing was uncorrelated with seasonal changes in export activity. Thus, these strikes provided us with exogenous shocks to an exporter's cost of transporting goods to the port.

Our results confirmed that political strikes led to a reduction in the export price of time-sensitive products. More precisely, we found that during July to December, 2013, when there was a multi-day political strike every five days, the prices of time-sensitive Bangladeshi export products declined by 1.59 percent relative to time-insensitive ones. To put this effect in to context, consider that Fan, Li, & Yeaple (2015) find that a 3.31 percentage point increase in Chinese import tariffs is associated with a similar decrease in export prices. We also found that these effects were especially acute for smaller and newer exporters and were not driven by compositional changes in the set of products that were exported from Bangladesh. While we have focused on the price effects of political strikes in this paper, an alternate implication of these strikes is that it may deter some Western retailers from sourcing products from Bangladesh. Using firm-level data to examine whether political violence has these extensive margin effects is a fruitful avenue for future research.

References

Abadie, A., & Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, 93(1), 113−132.

Ahmed, I., & Mortoza, G. (2005). The Anatomy of Hartal: How to Stage a Hartal. in *Beyond Hartal: Toward Democratic Dialogue in Bangladesh*. Dhaka: United Nations Development Programme.

Ashraf, A., Machiavello, R., Rabbani, A., & Woodruff, C. (2015). The Effect of Political and Labour Unrest on Productivity: Evidence from Bangladeshi Garments. Mimeograph.

Besedes, T., & Murshid, A. (2015). Experimenting with Ash: The Trade Effects of Airspace Closures in the Aftermath of Eyjafjallajkull. Mimeograph.

Birtwistle, G., Siddiqui, N., & Fiorito, S. (2013). Quick Response: Perceptions of UK Fashion Retailers. *International Journal of Retail & Distribution Management*, 31(2), 118−128.

Blattman, C., & Miguel, E. Civil War. (2010). *Journal of Economic Literature*, 48(1), 3−57.

Blomberg, S., & Hess, G. (2006). How Much Does Violence Tax Trade? *The Review of Economics and Statistics*, 88(4), 599−612.

Clark, D.P., Kozlova, V., & Schaur, G. (2016). Supply Chain Uncertainty in Ocean Transit as a Trade Barrier. Mimeograph.

Collier, P., & Duponchel, M. (2012). The Economic Legacy of Civil War: Firm-Level Evidence from Sierra Leone. *Journal of Conflict Resolution*, 57(1), 65−88.

Daily Star. (2013). National Public Perception Study: A Special Supplement. November 2.

Davenport, C. (2007). State Repression and Political Order. *Annual Review of Political Science*, 10(1), 1−23.

Djankov, S., Freund, C., & Pham, C. (2010). Trading on Time. *The Review of Economics and Statistics*, 92(1), 166−173.

Eaton, J., Kortum, S., & Kramarz, F. (2011). An Anatomy of International Trade: Evidence from French Firms. *Econometrica*, 79(5), 1453−1498.

Fan, H., Li, Y.A., & Yeaple, S.R. (2015). Trade Liberalization, Quality, and Export Prices. *The Review of Economics and Statistics*, 97(5), 1033−1051.

Fernandes, A. (2008). Firm-Level Productivity in Bangladesh Manufacturing Industries. *World Development*, 36(10), 1725−1744.

Glick, R., & Taylor, A. (2010). Collateral Damage: Trade Disruption and the Economic Impact of War. *The Review of Economics and Statistics*, 92(1), 102−127.

Guidolin, M., & La Ferrara, E. (2007). Diamonds Are Forever, Wars are Not: Is Conflict Bad for Private Firms? *American Economic Review*, 97(5), 1978−1993.

Hallak, J.C. (2006). Product Quality and the Direction of Trade. *Journal of International Economics*, 68(1), 238−265.

Haroon, J. (2012). Hartal Halts 4,000 Containers Daily at Ctg Port. *The Financial Express*, April 30.

Heath, R., & Mobarak, A.M. (2015). Manufacturing Growth and the Lives of Bangladeshi Women. *Journal of Development Economics*, 115, 1−15.

Human Rights Watch. (2014). *Democracy in the Crossfire*.

Hummels, D., & Schaur, G. (2013). Time as a Trade Barrier. *American Economic Review*, 103(7), 2935−2959.

Ksoll, C., Machiavello, R., & Morjaria, A. (2014). Guns and Roses: Flower Exports and Electoral Violence in Kenya. Mimeograph.

Machiavello, R., & Morjaria, A. (2015). The Value of Relationships: Evidence from a Supply Shock to Kenyan Rose Exports. *American Economic Review*, 105(9), 2911−2945.

Martin, P., Mayer, T., & Thoenig, M. (2008). Civil Wars and International Trade. *Journal of the European Economic Association*, 6(2-3), 541−550.

McKinsey. (2011). *Bangladesh's Ready-Made Garments Landscape: The Challenge of Growth*.

Nitsch, V., & Schumacher, D. (2004). Terrorism and International Trade: An Empirical Investigation. *European Journal of Political Economy*, 20(2), 423−433.

Quddus, M., & Rashid, S. (2000). *Entrepreneurs and Economic Development: The Remarkable Story of Garment Exports from Bangladesh*. Dhaka: University Press Limited.

Schott, P.K. (2004). Across-Product Versus Within-Product Specialization in International Trade. *Quarterly Journal of Economics*, 119(2), 647−678.

Shonchoy, A.S., & Tsubota, K. (2015). Economic Impact of Political Protests (Strikes) on Manufacturing Firms: Evidence from Bangladesh. IDE Discussion Paper No. 523.

Sobhan, R. (2004a). Structural Dimensions of Malgovernance in Bangladesh. *Economic and Political Weekly*, 39(36), 4101−4108.

Sobhan, Z. (2004b). The Mathematics of Hartals. *The Daily Star*, March 24.

Strauss, S., & Taylor, C. (2009). Democratization and Electoral Violence in Sub-Saharan Africa. Mimeograph.

Suykens, B., & Islam, A. (2013). *Hartal* as a Complex Political Performance: General Strikes and the Organisation of (Local) Power in Bangladesh. *Contributions to Indian Sociology*, 47(1), 61−83.

Taplin, I. (2014). Global Commodity Chains and Fast Fashion: How the Apparel Industry Continues to Re-Invent Itself. *Competition and Change*, 18(3), 246−264.

Volpe Marincus, C., & Blyde, J. (2013). Shaky Roads and Trembling Exports: Assessing the Trade Effects of Domestic Infrastructure Using a Natural Experiment. *Journal of International Economics*, 90(1), 148−161.

World Bank. (2016). *Doing Business in 2016: Measuring Regulatory Quality and Efficiency*. Washington, D.C.

WTO. (2003). *World Trade Report 2003: Trade and Development*. Geneva: WTO.

Table 1: *Hartals* in Bangladesh

	(1)	(2)	(3)
Years Included	2005-2013	2005-2009	2010-2013
Total *Hartals*	152	53	99
Fraction of *Hartals* that spanned:			
Single Day	0.38	0.49	0.32
Two Day	0.21	0.19	0.22
Greater than Two Days	0.41	0.32	0.46
Length of *Hartals* (in hours)	15.60	14.60	16.13
Notice Provided (in days)	5.55	7.28	4.62
Number of Deaths	1.49	0.52	2.01
Number of Injuries	112.68	132.92	101.84

Notes: the reported numbers are authors' calculations using data collected from two leading Bangladeshi newspapers: The Daily Star and the *Ittefaq*.

Table 2: Validation of the Customs Exports Data

	(1)	(2)	(3)
Year	Customs	World Bank	Customs / World Bank
2005	577,769	571,766	1.011
2006	914,655	792,638	1.154
2007	631,699	860,018	0.735
2008	1,050,898	1,054,508	0.997
2009	1,059,283	1,037,734	1.021
2010	1,340,978	1,327,932	1.010
2011	1,803,050	1,739,932	1.036
2012	2,168,282	1,988,230	1.091
2013	2,212,223	2,327,139	0.951
All Years	11,758,837	11,699,897	0.995

Notes: in column (1), we report the aggregate annual exports for Bangladesh calculated using our customs data. In column (2), we report the aggregate annual export data as reported by the World Bank. These are based on balance of payments calculations. The correlation coefficient between the two is 0.98. In column (3), we report the ratio of the customs aggregate to the World Bank aggregate. The monetary values are in millions of constant 2005 Bangladeshi *Takas*. One US dollar was approximately equivalent to 61.5 *Takas* in 2005.

Table 3: Descriptive Statistics of Exports Data

	(1)	(2)
	Mean	Median
Total Number of Exporters	5,551	-
Exporters per Day	598.37	601.00
	[142.79]	
Daily Firm Exports	4.64	2.37
	[7.36]	
Number of HS6 Products per Firm per Year	5.46	4.00
	[5.04]	
Number of Destinations per Firm per Year	5.48	4.00
	[6.23]	

Number of Firm Shipment Days per Year	94.75 [69.15]	75.00
Fraction of Shipments Made Using Air Transport	0.22 -	-
Ln (Export Price)	6.59 [0.48]	6.59

Notes: in column (1), we report the mean of each variable along with its standard deviation in brackets. In column (2), we report the median of each variable. All monetary values are in millions of constant 2005 Bangladeshi *Takas*. One US dollar was approximately equivalent to 61.5 *Takas* in 2005.

Table 4: The Impact of *Hartals* on The Probability of Exporting

	(1)	(2)	(3)	(4)
Dependent Variable	Indicator for Exporter			
H_t	-0.018***	-0.017***	-0.017***	-0.017***

	(0.003)	(0.003)	(0.003)	(0.003)
H_{t+1}		0.011***	0.011***	0.011***
		(0.003)	(0.003)	(0.003)
H_{t+2}			-0.001	-0.001
			(0.003)	(0.003)
H_{t-1}				0.003
				(0.003)
H_{t-2}				-0.000
				(0.003)
Cumulative effect ($\sum H_{t+s}$)	-	-0.006	-0.007	-0.004
P-value ($H_0: \sum H_{t+s} = 0$)	-	[0.155]	[0.210]	[0.564]
Observations	8,065,603	8,065,603	8,065,603	8,065,603
R-squared	0.186	0.186	0.186	0.186

Notes: the dependent variable in all columns is an indicator for whether a firm exports on a given day. All regressions include firm fixed effects, day-of-year fixed effects, day-of-week fixed effects, year fixed effects, and a constant that is not reported. Robust standard errors in parentheses are clustered at the day level in all columns. *** $p < 0.01$.

Table 5: Multi-Day *Hartals* and Exports

	(1)	(2)	(3)
Dependent Variable	Export Indicator	Ln(Export)	Air Transport Indicator
H^M_{t+2}	-0.007	-0.034	0.005
	(0.007)	(0.030)	(0.007)
H^M_{t+1}	0.010	0.081**	-0.023*
	(0.007)	(0.039)	(0.014)
H^M_{t}	-0.006	-0.019	0.022**
	(0.006)	(0.028)	(0.010)
H^M_{t-1}	-0.040***	-0.222***	0.097***
	(0.007)	(0.042)	(0.016)
H^M_{t-2}	-0.015**	0.012	-0.002
	(0.007)	(0.036)	(0.018)
H^M_{t-3}	-0.003	0.045	0.000
	(0.007)	(0.035)	(0.010)
H^M_{t-4}	0.000	0.030	-0.007
	(0.007)	(0.032)	(0.008)
Cumulative effect ($\sum H_{t+s}$)	-0.063	-0.108	0.093
P-value ($H_0: \sum H_{t+s} = 0$)	[0.000]	[0.267]	[0.006]
Observations	7,876,869	772,325	772,325
R-squared	0.186	0.221	0.186

Notes: the dependent variable in column (1) is an indicator for whether a firm exports on a given day. The dependent variable in column (2) is the natural logarithm of a firm's daily export value while the dependent variable in column (3) is an indicator for whether a firm used air transport on a given day. All regressions include firm fixed effects, day-of-year fixed effects, day-of-week fixed effects, year fixed effects, and a constant that is not reported. Robust standard errors in parentheses are clustered at the day level in all columns. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Multi-Day *Hartals*, Time Sensitivity, and Export Prices

	(1)	(2)	(3)	(4)
Dependent Variable		Ln(Export Price)		
Fraction of Multi-Day *Hartals*	0.026	0.055*		
	(0.028)	(0.033)		
Fraction of Multi-Day *Hartals* × Time-Sensitive		-0.074**	-0.074**	
		(0.033)	(0.032)	
Pre-Election Period × Time-Sensitive				-0.044***
				(0.010)
Constant	6.365***	6.372***	6.411***	6.415***
	(0.052)	(0.052)	(0.050)	(0.051)
Month Fixed Effects	Yes	Yes	-	-
Year Fixed Effects	Yes	Yes	-	-
Month × Year Fixed Effects	No	No	Yes	Yes
Observations	83,053	82,027	82,027	82,027
R-squared	0.413	0.416	0.419	0.419

Notes: the unit of observation is HS8 product by day. The dependent variable in all columns is the average daily unit value (in natural logarithm) of an HS8 product. Fraction of Multi-Day

Hartals represents the fraction of days in a month that is part of a multi-day *hartal* sequence. Time Sensitive is an indicator variable that is one for HS8 products that have a fraction of air shipments that is greater than the sample median. Pre-Election Period is an indicator that is one during July to December, 2013, which immediately preceded the January, 2014 general elections. All regressions include product fixed effects, day-of-year fixed effects, and day-of-week fixed effects. The standard errors in parenthesis are clustered at the month-year and product level in all columns. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Multi-Day *Hartals* and Export Prices − Channels

	(1)	(2)	(3)	(4)	(5)
Dependent Variable			Ln(Export Price)		
False Pre-Election Period × Time-Sensitive	0.006				
	(0.008)				
Fraction of Multi-Day *Hartals* × Time-Sensitive		-0.095***		-0.085**	
		(0.027)		(0.034)	
Fraction of Multi-Day *Hartals* × High			-0.014	-0.007	

Priced			(0.027)	(0.042)	
Fraction of Multi-Day *Hartals* × Time-Sensitive ×High Priced				-0.021	
				(0.053)	
Fraction of Multi-Day *Hartals* × Time-Sensitive					-0.074**
					(0.032)
Constant	6.407***	0.226***	0.224***	0.227***	6.410***
	(0.050)	(0.026)	(0.025)	(0.026)	(0.050)
Heckman Selection Correction	No	No	No	No	Yes
Observations	82,027	245,250	245,250	245,250	83,687
R-squared	0.419	0.530	0.530	0.530	-

Notes: the dependent variable in column (1) and column (5) is the average daily unit value (in natural logarithm) of an HS8 product. The dependent variable in all other columns is an indicator that is one if an HS8 product is exported on a given day. False Pre-Election period is an indicator that is one during July to December in all years other than 2013. Time Sensitive is an indicator variable that is one for HS8 products that have a fraction of air shipments that is greater than the sample median. Fraction of Multi-Day *Hartals* represents the fraction of days in a month that is part of a multi-day *hartal* sequence. High Priced is an indicator that is one for HS8 products that have an average price that is above the sample median. The regressions in columns (2) to (4) include both days when a product is exported as well as days when it is not. This is why the sample sizes in these columns are larger. The estimates in column (5) are from a Heckman selection correction regression. All regressions include product fixed effects, month and year interaction fixed effects, day-of-year fixed effects, and day-of-week fixed effects. The standard errors in parenthesis are clustered at the month-year and product level in all columns. *** $p < 0.01$, ** $p < 0.05$.

Table 8: Multi-Day *Hartals* and Export Prices − Exporter Heterogeneity

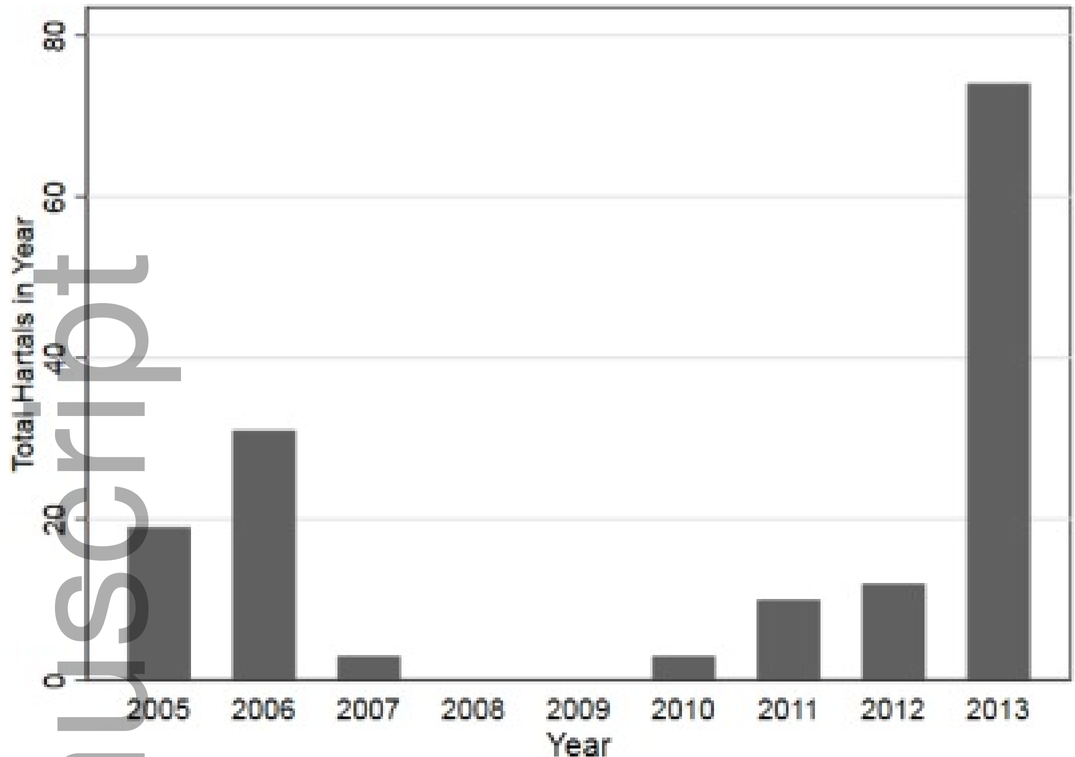
	(1)	(2)	(3)	(4)
Exporters Included	Small	Large	Newer	Older
Dependent Variable	Ln(Export Price)			
Fraction of Multi-Day *Hartals* × Time-	-0.095**	-0.048	-0.112***	-0.028
Sensitive	(0.048)	(0.036)	(0.043)	(0.050)
Constant	6.331***	6.456***	6.350***	6.379***
	(0.059)	(0.064)	(0.056)	(0.091)
Observations	58,579	62,358	54,977	63,339
R-squared	0.387	0.405	0.377	0.428

Notes: the dependent variable in column (1) is the average daily unit value (in natural logarithm) of an HS8 product constructed using the subsample of small firms. Small firms are those with total annual exports in their initial year in the sample that is below the sample median. All other firms are classified as large firms. The dependent variable in column (2) is the average daily unit value (in natural logarithm) of an HS8 product constructed using the subsample of large firms. The dependent variable in columns (3) and (4) is the average daily unit value (in natural logarithm) of an HS8 product constructed using the subsample of newer and older exporters respectively. Newer exporters are defined as those that first export after 2005. All other firms are classified as older exporters. Fraction of Multi-Day *Hartals* captures the fraction of days in a month that is part of a multi-day *hartal* sequence. Time Sensitive is an indicator variable that is one for HS8 products that have a fraction of air shipments that is greater than the sample median. All regressions include product fixed effects, month and year interaction fixed effects, day-of-year fixed effects, and day-of-week fixed effects. Robust standard errors in parenthesis are clustered at the month-year and product level in all columns. *** $p < 0.01$, ** $p < 0.05$.

Table 9: Multi-Day *Hartals* and Export Prices − Robustness Checks

	(1)	(2)	(3)	(4)
Dependent Variable	Ln(Export Price)		Ln(Weighted Export Price)	Ln(Raw Export Price)
Number of Multi-Day *Hartals* × Time-Sensitive	-0.002**			
	(0.001)			
Average *Hartal* Duration × Time-Sensitive		-0.009***		
		(0.003)		
Fraction of Multi-Day *Hartals* × Time-Sensitive			-0.141**	-0.074**
			(0.070)	(0.033)
Constant	6.411***	6.414***	6.009***	6.411***
	(0.050)	(0.050)	(0.119)	(0.051)
Observations	82,027	82,027	83,687	82,027
R-squared	0.419	0.419	0.126	0.416

Notes: the dependent variable in columns (1) and (2) is the average daily unit value (in natural logarithm) of an HS8 product. The dependent variable in column (3) is the weighted average daily unit value (in natural logarithm) of an HS8 product, where the weights are a firm's share of total daily exports for that product. The dependent variable in column (4) is the average daily unit value (in natural logarithm) of an HS8 product with all outliers included. Number of Multi-Day *Hartals* captures the number of days in a month that is part of a multi-day *hartal* sequence. Average *Hartal* Duration is the total average length of a *hartal* (in days) in a given month. Time Sensitive is an indicator variable that is one for HS8 products that have a fraction of air shipments that is greater than or equal to the sample median. All regressions include product fixed effects, month and year interaction fixed effect, day-of-year fixed effects, and day-of-week fixed effects. Robust standard errors in parenthesis are clustered at the month-year and product level in all columns. *** $p < 0.01$, ** $p < 0.05$.



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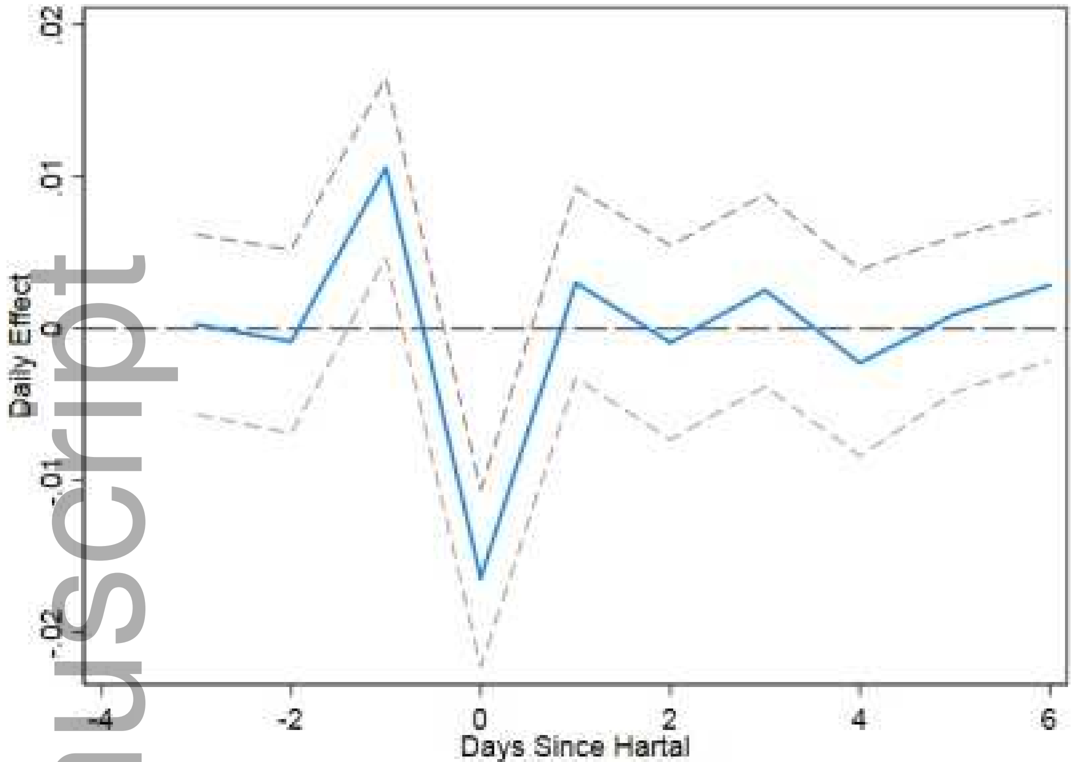

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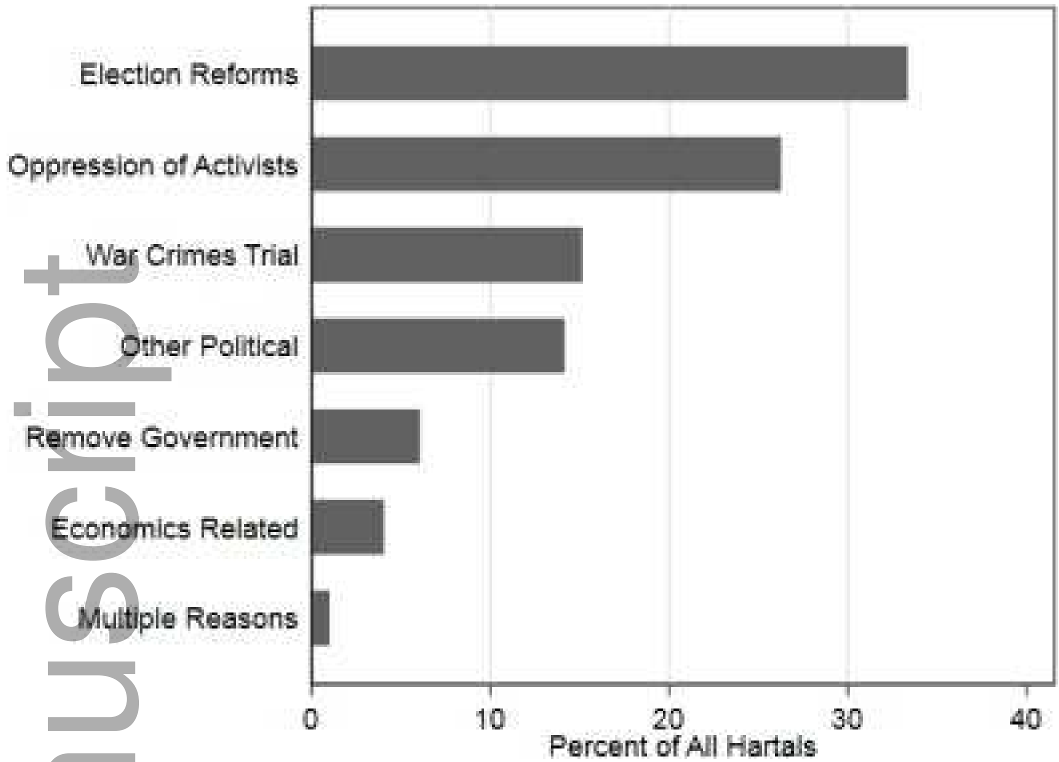

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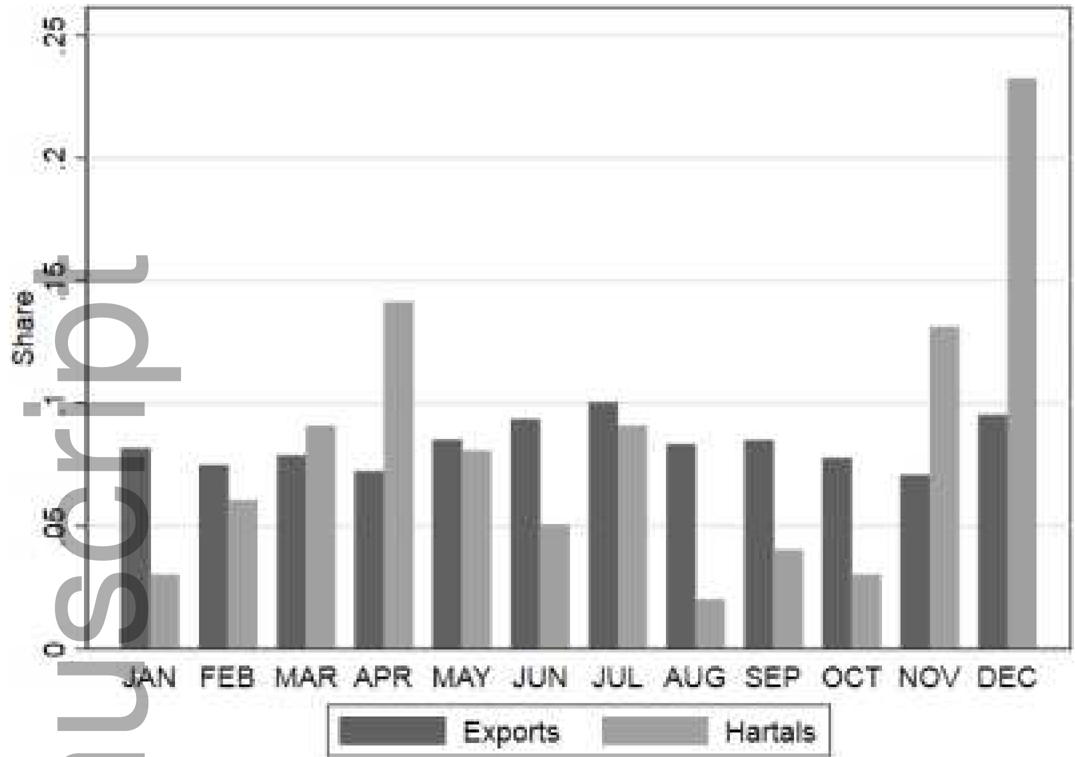

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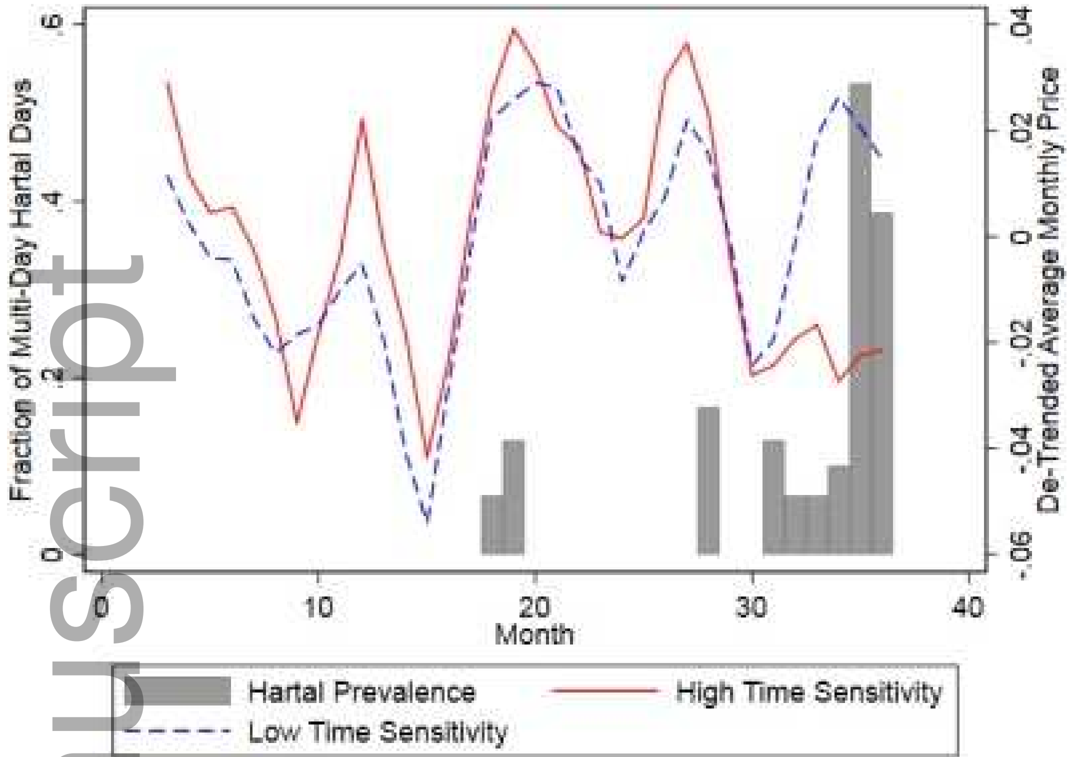

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