Social Media Activism's Impact on Global Retailers

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March 16, 2020

Abstract

This paper investigates the impact of social media movements on shareholders' wealth. The #WhoMadeMyClothes Twitter campaign is an annual social media movement that emerged after the collapse of the Rana Plaza, a building in Bangladesh that housed five garment factories, in April 2013. The global campaign serves as a remembrance day for the factory victims and gives social media users an outlet to address ethical concerns towards apparel retail companies that were buyers of the Rana Plaza factories. My research investigates how this Twitter campaign, in specifically April 2015, impacted the stock returns of the companies involved in the Rana Plaza collapse. My analysis is based on 180 publicly traded, global apparel and retail firms. I find an overall negative stock market reaction towards the US firms, regardless of their relationship to the factories, when aggregating over the all active campaign days. However, when pooling firms from all represented countries, I find that only firms involved in the collapse experienced significant negative returns. These firms are also more likely to experience negative returns after the campaign day, compared to the other firms that were not involved in the collapse. On a global perspective, shareholders may have punished firms that had significant ties to the collapse during and after the campaign day. Isolating US firms, a spillover effect might explain the negative returns for apparel and retail firms in general, regardless of their relation to the collapse.

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†This paper has benefited from the research advice and guidance from my faculty advisor, Professor Lint Barrage, and my thesis class professor, Professor Shelly Lundberg.

1 Introduction

On April 24, 2013, the Rana Plaza building in Dhaka, Bangladesh collapsed, killing 1,138 people and injuring more than 2,500 and making it the fourth largest industrial disaster in history (Fashion Revolution). This building housed five garment factories where many global retailers and apparel companies sourced their textiles and clothing. Following the collapse, companies signed the Accord on Fire and Building Safety and the Alliance for Bangladesh Worker Safety, which I will abbreviate as "AFBSB" and "ABWS", respectively, throughout the paper. Both contracts stated that companies would promise to work towards a safe and healthy garment and textile industry in Bangladesh (Bangladesh Accord). Since then, consumers publicly questioned whether or not these companies have made a significant change in their supply chain model and the way garment factory workers are treated.

A month later, a non-profit organization, known as Fashion Revolution, decided to create an annual remembrance day for those who lost their lives in the Rana Plaza accident. On April 24, 2014, Fashion Revolution implemented the social media hashtag #insideout and encouraged users to take a selfie with their clothes and tagging the companies it came from to ask who made them (Hepburn, 2013). On April 24, 2015, they officially rebranded the hashtag to #WhoMadeMyClothes for search engine optimization purposes. In that month, 64 million people used the hashtag on Twitter and Instagram, totaling up to 124 million impressions from the combined social media platforms. In addition, with attention from news and media, the campaign had an estimated online media reach of 16.5 billion (Fashion Revolution). Not only was the campaign used by just consumers, but brands and companies engaged with the hashtag by replying with suppliers holding up the sign that stated the hashtag #IMadeYourClothes. The hashtag campaign was a huge, global trend that drew attention towards Rana Plaza victims and the supply chain model of global apparel companies. In addition, Fashion Revolution uploaded a campaign video on YouTube, titled "The 2 Euro T-Shirt - A Social Experiment", that informs experiment participants and video audiences about the supply chain of global apparel companies. This video reached

6.5 million views, which further increased publicity. In a way, it replicates how the collapse event itself drew much attention towards the same issues.

Social media movements and hashtag activisms are not new initiatives in this generation. #BlackLivesMatter in July 2013 raised national awareness on systematic racism after the hearing of George Zimmerman, who shot and killed Trayvon Martin, an African American teenager. This hashtag was used in 41 million posts. #MeToo in October 2017 raised global awareness for those to speak up about sexual harassment experiences after the sexual assault accusations of American film producer, Harvey Weinstein (Chubb, 2018). In the context of a corporation's reputation on social media, social media activism can be seen as exogenous events towards companies because the freedom of speech on social media platforms limits the corporations' control over what their stakeholders share with the public (Qualman, 2010). In addition, social movement theory has been studied to prove that traditional activism has a significant impact on targeted firms and the stock market (King and Soule, 2007). It is likely that social movement theory can be applied in a digital context, especially when the ease of user reach through social media can create a globally impactful, social movement for everyone involved.

My research involves a stock market analysis on global apparel and retail firms from the impact of social media movements. I use an event study methodology for the #WhoMadeMyClothes Twitter campaign during April 21st to April 29th in 2015. I calculate abnormal returns and cumulative abnormal returns to understand how much the firms' stocks fluctuated from predicted returns. To better understand fluctuation patterns based on firm characteristics, I separated my samples into groups based on the firms' involvement with the collapse, industry, and country of exchange. In addition, I run difference-in-difference regressions to observe changes in stock returns before and after the day of the campaign, and whether this observation differs between firms involved in the collapse and those that were not.

2 Literature Review

My research was motivated by multiple academic journals that discussed related topics including corporate social responsibility (CSR), financial impacts from public boycotting, event study methodology for stock return calculations, and more specifically, stock return fluctuations from industrial accidents. I have narrowed my literature review to the five following papers.

2.1 Event Study Methodology on Stock Returns

For my research, I use event study methodology to calculate abnormal and cumulative abnormal returns. This method is popularly used to dissect stock return impacts from M&A announcements and other events that are not previously known to investors which includes social activism. Stephen Brown and Jerold Warner extensively discuss the event study methodology used to observe particularly stock market returns in their paper, "Measuring Security Price Performance". Starting with the basics, stock market returns illustrate the wealth of the firms' shareholders. Event studies provide a test on market efficiency, which states that all information is known and immediately reflected in a particular firm's stock price. Therefore, nonzero abnormal returns should not be observed. If consistent with market efficiency, abnormal performance can be used to measure the impact of a specific event unless investors had full certainty in predicting the event. Brown and Warner find that "simple methodology based on the market model is both well-specified and relatively powerful under a wide variety of conditions" and simpler methods that do not explicitly control for market-wide influences can still be a good measure of abnormal performance. Their methodology is used in past research that observed the returns for firms involved in the Rana Plaza collapse, which I mention in the next section.

2.2 Financial Consequences on Firms from Rana Plaza Disaster

The paper, "The Effect of the Rana Plaza Disaster on Shareholder Wealth of Retailers: Implications for sourcing strategies and supply chain governance" by Brian Jacobs and Vinod Singhal, was the most influential towards my research question and methodology. The authors analyze the stock market reaction to the Rana Plaza disaster of the 39 publicly traded global apparel retailers that had a significant sourcing relationship in Bangladesh. The authors looked at the day of the collapse and 11 trading days following the collapse to observe any significant fluctuations. They concluded that although the immediate reaction to the Rana Plaza news showed negative returns, the statistical significance and magnitude of the fluctuations slowly disappeared during the trading days following the event. The authors imply that this may be because investors do not hold retail and apparel companies accountable for the Rana Plaza incident.

I used a similar methodology regarding the period used to estimate abnormal returns and cumulative abnormal returns for the purpose of observing trends. I also presented similar formatting of results seen in this paper, including the daily abnormal returns within the event window and the cumulative abnormal returns over the whole window period. In addition, this paper helped me identify the list of firms that signed onto the AFBSB or ABWS contracts, as of 2013.

2.3 Differences in Financial Effects from Firm Characteristics

Similar to Jacob's and Singhal's paper, "The Impact of the Rana Plaza Collapse on Global Retailers" by Laura Boudreau, Ryo Makioka, and Mari Tanaka, also dissect impacts from the Rana Plaza collapse. They analyze two main impacts: (1) The media on firm stock returns and (2) the heterogeneity in the effect of the news on stock returns across firms along specific dimensions, such as whether they were a buyer from the Rana Plaza factories and/or if they signed onto the AFBSB or ABWS following the collapse. In addition, the authors measured differences of these effects on their financials, including quarterly revenue, cost of goods sold, and operating income. Similar to the previous paper, the authors used abnormal and cumulative abnormal stock returns to measure the stock return fluctuations.

In addition, they ran difference-in-difference regressions to measure the financial effect of being a buyer or being part of the AFBSB/ABWS groups. I used similar regressions to observe any differences in returns from the Twitter campaign based on firm-specific characteristics. From the regressions, the collapse had negative impacts on both the revenue and the costs of goods sold for firms in either the AFBSB or ABWS group in the quarter starting with the collapse. This paper also helped me identify the list of firms that signed onto the AFBSB or ABWS contracts, as of 2015.

2.4 Financial Effects on Firms From Public Boycotting

Contrary to the previous two papers that are specific to my paper's context, the event I studied was not an industrial accident but rather a response to the accident. Therefore, it was important to expand my understanding of financial effects from general social movements, such as boycotting. In the paper, "Assessing the Efficacy of Consumer Boycotts of U.S. Target Firms: A Shareholder Wealth Analysis" by Kasaundra M. Tomlin, Tomlin analyzed the effect of public boycotts towards corporations on shareholder's wealth. She observed 125 US boycotts over the range of 39 years, from 1978 to 2017, and were announced in prominent news outlets. Similar to the purpose of the #WhoMadeMyClothes campaign, these boycotts were intended to promote corporate social responsibility and altruism. From observing these targeted US firms' cumulative abnormal returns, she found negative and statistically significant impacts on shareholders' wealth, compared to the cumulative abnormal returns of the synthetic control firms that were not targeted. She concluded that these negative impacts are robust and could not have come from idiosyncratic shocks unrelated to the boycotts. These findings helped to understand if boycotts were an effective tool to express discontent towards corporate behavior. The more shareholders punish firms for having a negative reputation, the stronger the financial effect from the boycotts.

Though the Twitter campaign is not identical to boycotting, their intentions are merely the same: to bring attention to corporate irresponsibility and demand for change. This paper helped develop my predictions for my research and my interpretations of my findings. This paper also uses an event study methodology to observe cumulative abnormal returns, which I use for my research. In addition, this paper emphasizes using a group of synthetic control firms, where she creates a control group that carries similar pretreatment characteristics as the targeted firms, including the same industry and firm size in terms of total sales. I used similar criteria to create my group of control firms, later defined as the firms not involved in the collapse, to measure the differences in abnormal stock returns.

2.5 Social Media Activism on Stock Markets

Even more specific to the type of social movement my paper observes, "The Power of Stakeholders' Voice: The Effects of Social Media Activism on Stock Markets" by Pablo Gomez-Carrasco and Giovanna Michelon, analyzed how Twitter campaigns related to advocating policy changes within the Spanish banking sector affected the stock price and trading volume for Spanish banking institutions. To measure the intensity of tweets, the authors collected data on the total number of tweets about a bank and the number of tweets posted by civic and consumer platforms and by trade unions. To measure visibility, they observed the number of followers reached by these tweets. Using these statistics, they regressed abnormal stock returns and abnormal trading volume for each bank in their sample on whether any relevant facts related to the firm were posted by the from the Spanish Securities and Exchange Commission, the number of tweets containing stock price information, number of tweets about the firm, and number of followers of the tweets. The authors concluded that Twitter activism by critical stakeholders, such as the consumers and trade unions, had a statistically significant impact on investors' decisions. Specifically, twitter posts published by trade unions created a negative impact on stock price and trading volumes.

This paper was important in developing my hypothesis because it involves stock market fluctuations as a result of the social media movement observed on Twitter, rather than news and media outlets. I also use the three, social media activism validity requirements (collective, organized, public) mentioned in the article to understand the magnitude of the #WhoMadeMyClothes Twitter campaign.

3 Empirical Strategy

From the methodology and results of the above literature review, I formulate the following two hypotheses:

1. The Twitter campaign has no statistically significant impact on stock return fluctuations for the publicly traded, global apparel and retail companies involved in the Rana Plaza collapse.

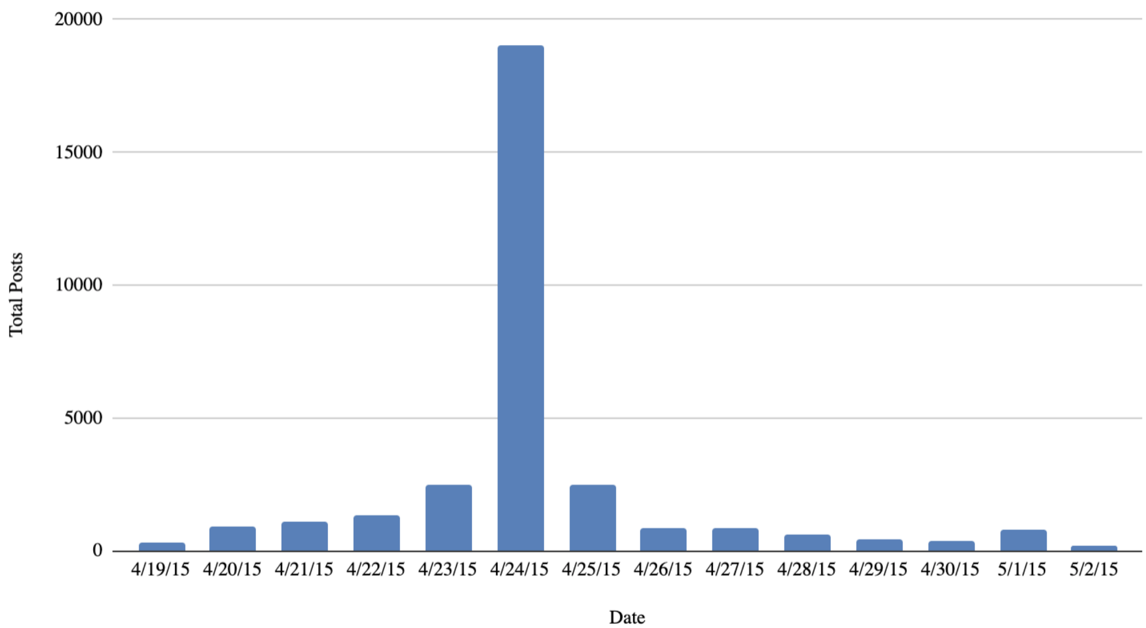
2. There is no statistically significant difference between the Rana Plaza firms' cumulative abnormal returns before & after the Twitter campaign date and the control firms' cumulative abnormal returns before & after the campaign date.

As mentioned before, I used an event study methodology to test my hypotheses. The specific event I focus on is the #WhoMadeMyClothes campaign, initiated on April 24, 2015, with campaign activity fluctuating before and after the date.

3.1 Abnormal and Cumulative Abnormal Stock Returns

As mentioned in Section 2.1, event study methodology to estimate abnormal stock returns and shareholder wealth has been studied to be empirically and theoretically powerful, using daily data. It is important that when studying the event associated with the firms, market-wide influences on stock prices are controlled to produce the most accurate results. To test my first hypothesis, I define the day of the campaign as t=0. I create a 6-day trading event window, 2 trading days before the event date (t=-2) and 3 days after the event date (t=3), to observe significant changes in the stock market for global apparel and retail companies. Due to the exclusion of the weekend in trading periods, it is important to note that my event window skips April 25th and April 26th, ending up with the following dates: April 21st, April 22nd, April 23rd, April 24th, April 27th, April 28th, and April 29th. This event window was determined by analyzing the volume of tweets that were published with the hashtag each day during the week of the Twitter campaign. Illustrated in Figure 1 below, the event window includes the dates when the campaign reached its highest level of activity; this is measured by the number of times a tweet with the hashtag #WhoMadeMyClothes or #FashionRevolution was published.

Figure 1: Volume of Tweets with Hashtag



The Fama French Model (1993), as used in the literature review, is used to calculate the abnormal stock return for each firm in my treatment and control sample. First, I use the recorded stock returns for each firm in the estimation window of 210 trading days before the event day, consistent with many event studies. It is important to note the estimation period mildly fluctuates around 210 trading days in the groups containing international firms and market indices, due to differences in government holidays and open trading days. These returns are used to predict the returns in the event window period, starting with the following regression specification:

$$R_{it} = \alpha_i + \beta_i R_{itm} + \epsilon_{it} \tag{1}$$

R_{it} is the daily stock return for i, α_i is the intercept of the relationship for stock i, β_i is the slope of the relationship for stock i with respect to the market return, and ϵ_{it} is the error term for stock i on day t, errors unexplained by market movements. I use ordinary least squares (OLS) estimators, $\hat{\alpha}$ and $\hat{\beta}_i$, derived from Equation 1 to predict the returns, in absence of the Twitter campaign, for the event window dates for each firm:

$$\hat{R}_{it} = \hat{\alpha}_i + \hat{\beta}_i R_{itm} \tag{2}$$

I subtract the predicted return from the actual return in the event window period to calculate the abnormal stock return, AR_{it}, for each firm i on day t:

$$AR_{it} = R_{it} - \hat{R}_{it} \tag{3}$$

Following the abnormal return calculations, the Carhart (1997) two-step generating process, augmented "momentum" factor model, is used to calculate the cumulative abnormal returns (CAR), as expressed in the following equation:

$$CAR_{t_1,\, t_2} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=t_1}^{t_2} AR_{it} \tag{4}$$

where N is the number of firms. The CAR is averaged over all firms for each event window, between the first day, t_1, in the event window (t=-2) and the last day, t_2, in the event window (t=3). Consistent with market efficiency, CAR, on average, should be close to zero, without the presence of the Twitter campaign. In theory, if we observe zero CAR's, it illustrates that shareholders feel neutral in response to the campaign. If we observe positive CAR's, shareholders respond positively to the campaign, and negative CAR's show that shareholders respond negatively.

3.2 Stock Returns in Regression Specification

While my first hypothesis tests daily stock return fluctuations and aggregated fluctuations in the entire window period, my second hypothesis tests for differences in returns before and after the Twitter campaign date (first difference) between treatment and control firms (second difference). To test my second hypothesis, I run the following difference-in-difference regression:

$$CAR_{it} = \beta_1 Postevent_{it} + \beta_2 (Treatment_i \times Postevent_{it}) + \alpha_i + \phi_t + \epsilon_{it} \tag{5}$$

My dependent variable is CAR_{it}, the cumulative abnormal returns for firm i on Day t. Postevent is a time-variant, dummy variable indicating if the observed data occurred before (0) or after (1) the event day (t=0) for each firm, $Treatment$ is a time-invariant, dummy variable for each firm to indicate whether or not the firm was involved in the Rana Plaza collapse, and $Treatment \times Postevent$ is the interaction between the two variables. α_i and ϕ_t are the firm and time fixed effects, respectively, and ϵ_{it} is the error term. For the firm and time fixed effects, I declared firms as the entity variable and trading day as the time variable, with a unit change of one day. Firm and time fixed effects help control for variables that vary across firms (but are constant over time) and variables that vary across time (but are constant across firms). The coefficient, β_2, on the interaction term can be expanded into the following:

$$\beta_2 = (\overline{CAR}_{T,After} - \overline{CAR}_{T,Before}) - (\overline{CAR}_{C,After} - \overline{CAR}_{C,Before}) \tag{6}$$

Equation 6 interprets the average difference in CAR fluctuations between treatment firms before and after the campaign date and CAR fluctuations between control firms before and after the campaign date. This term is important in testing my second hypothesis.

4 Data

4.1 Data Sources

The datasets involve the collection of tweets, hashtags, and stock market data. I used Crimson Hexagon, a digital consumer intelligence company that has an archive of over 1.2+ trillion social media posts dated back to 2008 (Brandwatch). This platform allowed me to collect, monitor, and analyze all tweets and activity in the year of 2015, associated with apparel and retail firms, the Rana Plaza collapse, and the #WhoMadeMyClothes campaign. This is how I built my event window, seen in Section 3.

Regarding stock market data, I used Thomson Reuter's Datastream, which provides historical time series data including equity, index, commodity, currency, bond, futures, options, and economic data (UCSB Library). I used this data platform to gather stock and market index returns to compute abnormal and cumulative abnormal stock market returns in Equations 3 and 4. I also used this platform to gather descriptive data such as the firm's headquarter location, country of exchange, Global Industry Classification Standard (GICS) sector/industry/sub-industry codes and their respective names, as well as financial statistics such as market valuation, total revenue, and net income after taxes.

The sample of firms involved in the Rana Plaza collapse is determined by the publicly traded firms that signed onto the AFBSB or ABWS, as of 2015. I label them as my treatment firms throughout the paper. This is a credible way of determining the firms that would be the most impacted by the collapse and, therefore, the Twitter campaign because "firms that signed either the AFBSB or the ABWS are probably the most impacted. Not only are these firms subject to possible supply disruptions but their public participation in an agreement conveys some level of responsibility and heightens the potential for reputational impact" (Jacobs and Singhal, 2013). Table 1 lists descriptive statistics of the combined sample of 33 firms. Firms exchanged in the US make up almost half (45.95%) of the sample, those exchanged in the UK make up 21.62% of the sample, and those exchanged in Canada make up 8.11% of my sample. In addition, those exchanged in European countries make up 43.24% of the sample. The three most commonly listed sub-industry groups are "Apparel Retail" (25504010), "Department Stores" (25503010), "Apparel, Accessories & Luxury Goods" (25203010), as these sub-industries made up a total of 64.87% of the sample. Table 2 further details the financial statistics of the combined sample. This table illustrates that our sampled firms are very large, as the mean (median) of their market valuation was $22.6 billion ($7.97 billion) at the start of 2015.

Table 1: Descriptive Statistics

Country	**Occurrences**	**GICS Sub-industry Group (Code)**	**Occurrences**
United States of America	17 (45.95%)	Apparel Retail (25504010)	10 (27.03%)
United Kingdom	8 (21.62%)	Department Stores (25503010)	10 (27.03%)
Canada	3 (8.11%)	Apparel, Accessories & Luxury Goods (25203010)	4 (10.81%)

Table 2: Financial Statistics

	Market Value (Million, $ USD)	**Total Revenue (Million, $ USD)**	**Net Income (Million, $ USD)**
Mean	22,597.22	34,959.50	1,088.42
Median	7,970.80	11,859.00	160.41
Standard deviation	48,121.02	80,361.61	2,817.79

It is important to address that this list of treatment firms is different from the list of firms in previous papers. This is due to the fact that new firms signed onto AFBSB or ABWS from the day of the collapse to the day of the social media campaign. Furthermore, some of the firms that were originally on the AFBSB or ABWS merged with different companies, acquired by bigger corporations, or were delisted from the public stock market to go private. Therefore, the sampled treatment firms for my research represents an updated list of firms as of 2015, the year of the campaign.

4.3 Sampled Control Firms

Contrary to the treatment firms, I created a list of firms that represent those that were not involved in the Rana Plaza collapse. This sampled "control" firms were firms that are located in the same countries, belong to the same market indices, identify with the same GICS codes, and fall into the same range of financial characteristics as the treatment firms. This methodology of matching firms with similar characteristics as the treatment firms is based on Boudreau et. al's paper, mentioned in Section 2.

The key difference between treatment and control firms is that the latter did not sign the AFBSB or ABWS by 2015, while the treated firms did. This methodology of selecting control firms is also stemmed from Jacobs and Singhal's paper. They clarify that "while it is possible that some firms buying garments from Bangladesh did not sign either agreement, they probably depend less on exports from Bangladesh, and hence, any impact from the Rana Plaza disaster is expected to be less than that of [signed] firms." As implied by the authors, if the firms that signed the AFBSB or ABWS are the most impacted, then it is fair to assume the firms that did not sign are subject to the least impact.

The control group helps me indicate if the treatment firms' had any unique characteristics in relation to the campaign, rather than a result of seasonal, industry patterns. For example, one may observe significant abnormal and cumulative abnormal returns for the treatment firms, but it is difficult to conclude if these effects were tied to the campaigns or seasonal trends for apparel, retail industries in the month of April. It may be the case that one observes similar, significant patterns in the control group, thus, the campaign may not have had a strict impact on solely the treatment firms.

4.4 Groups Divided by Industry and Country of Exchange

Furthermore, I was interested in observing if the Twitter campaign, whose campaign name had a direct target towards clothing firms, could have resulted in specifically the apparel industry to experience stronger fluctuations. Although the campaign addressed all firms involved in the collapse, it is fair to assume that the hashtag, #WhoMadeMyClothes, immediately targets fashion firms like H&M, Zara, and Aeropostale, compared to general, retail firms like Target or Walmart. To get more specific with my sampled groups, I was interested in observing the firms exchanged only in the US. American consumers have increasingly shown stronger opinions on ethical and sustainable issues. There has been an increasing number in sustainable product sales, illustrating a gradual shift towards firms that prioritize social impact efforts and away from firms with less explicit, sustainable business practices (Nielsen, 2018). This shift may create could result in long term financial consequences for US firms that were involved in the collapse if American consumers were more sensitive to these issues at the time of the campaign. Shareholders might react more negatively to this information and sell more shares that belong to US firms, thus, creating stronger fluctuations in their stock returns. In addition to testing this theory, this method helped me control for market forces that are unique to the country's market index.

Four main sampled groups have been created, with each group containing treatment and control firms indicated by a binary variable in the dataset. The following lists the four groups and their descriptions:

1. Narrow Selection, United States
   (a) These firms consist of a narrow selection of GICS sub-industries, which includes only "Apparel Retail", "Footwear", and "Apparel, Accessories & Luxury Goods".
   (b) The sampled firms are exchanged in the US, only.
2. Broad Selection, United States
   (a) These firms consist of a broad selection of GICS sub-industries, which includes "Department Stores", "Food Retail", "General Merchandise Stores", "Home Improvement Retail", "Hypermarkets & Super Centers", and "Internet & Direct Marketing Retail", in addition to the sub-industries found in the narrow selection.

(b) The sampled firms are exchanged in the US, only.

3. Narrow Selection, All Countries

   (a) These firms consist of a narrow selection of GICS sub-industries, identical to the ones found in the narrow group mentioned above.

   (b) The sampled firms are exchanged in all countries represented by the treatment group.

4. Broad Selection, All Countries

   (a) These firms consist of a broad selection of GICS sub-industries, identical to the ones found in the broad group mentioned above.

   (b) The sampled firms are exchanged in all countries represented by the treatment group.

5 Results

I divide up my results by the four groups I described in Section 4. For each group, I test my first hypothesis for both the treatment and control groups within the groups. I test if average abnormal returns for each day in the event window (Equation 3) and if the average cumulative abnormal returns across the entire window period (Equation 4) are significantly different from zero.

5.1 Results on Abnormal and Cumulative Abnormal Stock Returns

Tables 3 and 4 represent my findings from the group with the narrow selection of firms, exchanged in the US. As seen in Table 3, on the event date (t=0), the firms involved in the Rana Plaza collapse experienced a significant, negative abnormal return of -0.58%, while the control firms an insignificant, positive abnormal return of 0.23% on average. However, the control firms experienced negative and statistically significant abnormal returns on all three, consecutive days after the event date, while the treated firms experienced negative and statistically significant abnormal returns only two days after the event date. Table 4 states the average cumulative abnormal returns on the last event window date (t=3). On average, both the treatment and control groups experienced a negative and statistically significant cumulative abnormal return, by the end of the event window.

Table 3: Abnormal Returns for Firms in Narrow, US Group

	Treatment Group			**Control Group**		
Event Day	**N**	**Mean**	**t**	**N**	**Mean**	**t**
-2	8	-0.47%***	-3.44	35	-0.41%**	-2.05
-1	8	0.98%***	2.67	35	1.07%**	2.54
0	8	-0.58%***	-2.94	35	0.23%	0.62
1	8	-0.87%***	-2.64	35	-1.10%***	-4.05
2	8	-0.41%	-1.39	35	-1.10%***	-3.58
3	8	-0.39%	-0.38	35	-1.49%***	-5.23

Notes: All tests are two-tailed: ***p ≤ 0.01; **p ≤ 0.05 *p ≤ 0.10

Table 4: Cumulative Abnormal Returns for Firms in Narrow, US Group

	N	**Mean**	**t**	**Min**	**Max**
Treatment CAR	8	-1.75%*	-1.80	-6.18%	3.42%
Control CAR	35	-2.80%***	-3.02	-10.48%	19.71%

Notes: All tests are two-tailed: ***p ≤ 0.01; **p ≤ 0.05 *p ≤ 0.10. CAR are the cumulative abnormal returns within the 6-day event window.

Tables 5 and 6 represent my findings from the group with the broad selection of firms, exchanged in the US. Similar to my findings in Table 3, on average, the firms involved in the Rana Plaza collapse experienced significant negative abnormal returns of -0.58% on the event date as seen in Table 5, and the control firms experience insignificant positive abnormal returns of 0.14%. The control firms experienced significant negative abnormal returns on all three, consecutive days after the event date, while the treated firms experienced the same on only one day after the event date. Table 6 states that, on average, both the treatment and control groups experienced significant, negative cumulative abnormal returns, by the end of the event window, staying consistent with my findings in the cumulative abnormal returns of the previous group, observed in Table 4.

Table 5: Abnormal Returns for Firms in Broad, US Group

	Treatment Group			Control Group		
Event Day	**N**	**Mean**	**t**	**N**	**Mean**	**t**
-2	15	-0.31%**	-2.34	59	-0.47%***	-3.28
-1	15	0.57%**	2.30	59	0.82%***	3.03
0	15	-0.58%**	-2.47	59	0.14%	0.43
1	15	-1.05%***	-5.30	59	-1.05%***	-5.37
2	15	-0.11%	-0.40	59	-0.50%*	-1.64
3	15	-1.05%	-1.80	59	-1.85%***	-4.90

Notes: All tests are two-tailed: ***p ≤ 0.01; **p ≤ 0.05 *p ≤ 0.10.

Table 6: Cumulative Abnormal Returns for Firms in Broad, US Group

	N	**Mean**	**t**	**Min**	**Max**
Treatment CAR	15	-2.54%***	-4.31	-6.43%	3.17%
Control CAR	59	-2.91%***	-4.05	-20.57%	19.74%

Notes: All tests are two-tailed: ***p ≤ 0.01; **p ≤ 0.05 *p ≤ 0.10. CAR are the cumulative abnormal returns within the 6-day event window.

Tables 7 and 8 represent my findings from the group with the narrow selection of firms, exchanged in all represented countries. As seen in Table 7, on average, the firms involved in the Rana Plaza collapse experienced insignificant, negative abnormal returns on the event date of -0.33%, and the control firms experience insignificant, positive abnormal returns of 0.20%. On average, the control firms experienced significant, negative abnormal returns only on one day after the event date, while the treated firms experienced insignificant, negative abnormal returns observed on all three, consecutive days after the event date. Table 8 shows that, on average, both the treatment and control groups experienced a negative cumulative abnormal return, by the end of the event window, but only the treatment group's observation was statistically significant.

Table 7: Abnormal Returns for Firms in Narrow, All Countries Group

	Treatment Group			**Control Group**		
Event Day	**N**	**Mean**	**t**	**N**	**Mean**	**t**
-2	14	-0.09%	-0.21	81	-0.21%	-1.02
-1	14	0.56%**	1.96	81	0.61%	-1.02
0	14	-0.33%	-1.28	81	0.20%	0.53
1	14	-0.37%	-1.17	81	-0.03%	-0.10
2	14	-0.13%	-0.40	81	-0.47%**	-2.51
3	14	-0.61%	-0.97	81	-0.45%	-1.55

Notes: All tests are two-tailed: ***p ≤ 0.01; **p ≤ 0.05 *p ≤ 0.10

Table 8: Cumulative Abnormal Returns for Firms in Narrow, All Countries Group

	N	**Mean**	**t**	**Min**	**Max**
Treatment CAR	14	-0.98%*	-1.66	-5.98%	3.62%
Control CAR	81	-0.35%	-0.54	-16.85%	20.59%

Notes: All tests are two-tailed: ***p ≤ 0.01; **p ≤ 0.05 *p ≤ 0.10. CAR are the cumulative abnormal returns within the 6-day event window.

Tables 9 and 10 represent my findings from the group with the broad selection of firms, exchanged in all represented countries. As seen in Table 9, on average, the treatment firms experienced significant, negative abnormal returns leading up until a day after the event date. However, the control firms experience no consistent direction or significance of abnormal returns, similar to what I observed for the control group in Table 7. Table 10 shows that the treatment group experiences an average of -1.66% cumulative abnormal returns by the end of the event window, with statistical significance. On the other hand, the control group experiences a smaller magnitude of negative cumulative abnormal returns, with no statistical significance.

Table 9: Abnormal Returns for Firms in Broad, All Countries Group

	Treatment Group			Control Group		
Event Day	**N**	**Mean**	**t**	**N**	**Mean**	**t**
-2	33	-0.70%**	-2.19	147	-0.07%	-0.6
-1	33	0.36%**	2.09	147	0.01%	0.05
0	33	-0.26%*	-1.65	147	0.11%	0.51
1	33	-0.64%***	-3.55	147	0.08%	0.48
2	33	0.02%	0.13	147	-0.11%	-0.72
3	33	-0.43%	-0.99	147	-0.33%*	-1.69

Notes: All tests are two-tailed: ***p ≤ 0.01; **p ≤ 0.05 *p ≤ 0.10

Table 10: Cumulative Abnormal Returns for Firms in Broad, All Countries Group

	N	**Mean**	**t**	**Min**	**Max**
Treatment CAR	33	-1.66%***	-3.35	-6.13%	9.02%
Control CAR	147	-0.31%	-0.90	-24.34%	18.20%

Notes: All tests are two-tailed: ***p ≤ 0.01; **p ≤ 0.05 *p ≤ 0.10. CAR are the cumulative abnormal returns within the 6-day event window.

5.2 Results from Stock Returns in Regression Specification

After observing similar patterns when grouped by country of exchange, I decided to run difference-in-difference regressions on the two groups: (1) the broad selection of US firms and (2) the broad selection of firms from all represented countries. I focused my regressions on the broad selection of groups, rather than the narrow selection, because of the larger sample size, while still being able to isolate US firms.

For each regression table seen in Tables 11 and 12, I run five regressions. Model 1 is a standard, OLS regression of my dependent variable, CAR, on one explanatory variable *treatment*, a binary variable indicating if it is in the treatment or control group. Model 2 adds on another explanatory variable, *postevent*, a binary variable indicating if the CAR observation occurred before or after the Twitter campaign, $t < 0$ or $t \geq 0$ respectively. Model 3 adds on the interaction variable, *treatment_postevent*. Models 1-3 do not integrate time nor firm fixed effects. Model 4's regression includes a *postevent* variable with time and firm fixed effects. The time-invariant variable, treatment, drops from the regression. Model 5 adds on the interaction term to Model 4's regression, again dropping the time-invariant variable, *treatment*. Model 5 is the regression equation seen in Equation 5. I run these five models for two groups, the broad selection of US firms and the broad selection of firms from all represented countries, seen in Tables 11 and 12 respectively.

In Table 11, I observe no significant differences in stock market fluctuations before and after the campaign between treatment and control firms across US firms. However, on average, it seems to be more likely for US firms to experience negative CAR's of -0.95% after the campaign date, regardless of whether it belongs in the treatment or control group. This is consistent with my finding in Table 10 how both treatment and control firms in the US experienced on average negative CAR's at the end of the event window.

Table 11: Regression Table for Broad, US Group

Dependent Variable: Cumulative Abnormal Returns

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
treatment	-0.00268	-0.00268	0.000349		
	(0.00282)	(0.00273)	(0.00254)		
postevent		-0.0105***	-0.00954***	-0.0105***	-0.00954**
		(0.00292)	(0.00359)	(0.00344)	(0.00423)
treatment_postevent			-0.00454		-0.00454
			(0.00464)		(0.00529)
Constant	-0.00695***	2.77e-05	-0.000585	-0.000515	-0.000515
	(0.00214)	(0.00171)	(0.00187)	(0.00229)	(0.00229)
Observations	444	444	444	444	444
R-squared	0.001	0.019	0.019	0.047	0.048
Firm FE	No	No	No	Yes	Yes
Time FE	No	No	No	Yes	Yes
Number of Firms				74	74

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In Table 12, I observe no significant differences in CAR observations before and after the campaign across all US and foreign firms. However, on average, a treatment firm's CAR after the event date experiences a -0.684% in CAR's, compared to a control firm's CAR after the event date. This coefficient becomes more statistically significant after controlling for omitted variables that vary across firms and over time. Another observation to note is that the coefficient on the postevent turns positive after including the interaction term in both Models 3 and 5.

Table 12: Regression Table for Broad, All Countries Group

Dependent Variable: Cumulative Abnormal Returns

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
treatment	-0.00909***	-0.00909***	-0.00453*		
	(0.00187)	(0.00187)	(0.00263)		
postevent		-0.00105	0.000203	-0.00105	0.000203
		(0.00158)	(0.00181)	(0.00192)	(0.00228)
treatment_postevent			-0.00684*		-0.00684**
			(0.00360)		(0.00328)
Constant	-0.000550	0.000151	-0.000685	-0.00151	-0.00151
	(0.00103)	(0.00105)	(0.00109)	(0.00128)	(0.00128)
Observations	1,080	1,080	1,080	1,080	1,080
R-squared	0.014	0.015	0.017	0.001	0.005
Firm FE	No	No	No	Yes	Yes
Time FE	No	No	No	Yes	Yes
Number of Firms				180	180

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6 Conclusion

From this research, I observe no clear patterns of the signs on the abnormal stock returns nor their statistical significance that remains consistent across all four groups. However, there seem to be similar observations when firms are grouped by country.

The treatment firms in both the narrow and broad selection of US firms observed negative daily abnormal returns, with their statistical significance disappearing after the event date. In addition, both treatment and control firms experienced significant, negative cumulative abnormal returns by the end of the event window period. This makes it difficult to conclude if there was a spillover effect from the campaign to the firms that were not involved in the collapse or if this was a result of seasonal, industry-specific market forces.

On the other hand, for the firms exchanged in all the represented countries, I observe less significant, negative abnormal returns on the treatment firms. However, I observe only statistically significant and negative cumulative abnormal returns on the treatment firms, although the magnitude of cumulative abnormal returns is smaller than what I observed from the US firms. This hinted at the possible idea that firms from all the represented countries were more targeted as a result of the campaign. Yet, there needed to be a closer look into at which point in the event window countries started to experience more fluctuations.

The similarity in CAR results within firms in the same country of exchange, but differences across them, motivated me to run difference-in-difference regressions among my two, country-separated groups. This regression also allowed me to closely evaluate the impact at the start of the Twitter campaign, rather than aggregating the fluctuations across the whole event window period and observing differences in impact across treatment and control firms. After controlling for omitted variables that vary over time and across firms, both treatment and control US firms experience statistically significant declines in CAR's after the event date. However, when including foreign firms in our sample, only treatment firms experience statistically significant declines in CAR's after the event date. This is consistent with my findings from Table 10, which shows only the treatment firms in this sample, on average, experience a larger magnitude of negative CAR by the end of the event window period, with statistical significance.

There are parts of my methodology that can be altered to extend my research. This includes putting weight on my control firms. The selection of my control firms includes all publicly traded firm that represents the treatment firms' descriptive statistics such as similar industry, location, market index, and financial statistics. Although this selection makes my control group inclusive, it may cause possible bias depending on how much weight is put on each of the firm's characteristics. In addition, hypothesis testing and running regressions on multiple event window periods, such as narrowing the window period, would be helpful in identifying more specific fluctuations associated with the Twitter campaign. For example, extending my six-day window period is likely to incorporate more spillover information from the campaign, since the hashtag was used even before the initial start of my selected event window, as seen in Figure 1. However, this is a common challenge faced in event study methodology since extending the event window can result in capturing external market noise, resulting in a bias in our findings.

Overall, my paper aims to understand how shareholders react to social media movements that address a firm's corporate irresponsibility. With more modern consumers valuing a company's transparency of its labor and supply chain practices, these publicly addressed concerns could have a greater impact than just putting a firm in the spotlight. For publicly-traded firms, their shareholders' may play a role in affecting the company's stock performance as a response to the movement, as we observe from my findings. However, my findings are very specific to a narrow range of industries, thus, makes it is difficult to generalize the financial impacts of all social media movements. Nevertheless, with consideration of potential modifications to the methodology, my findings serve as a general observation of what we can take away from the effectiveness of social media campaigns on global retailers. Though from the US firms I observe no clear distinction between treatment and control firms, there seem to be differences in cumulative abnormal returns when including all foreign treatment firms and their respective control firms. This may suggest that the campaign had a bigger target towards foreign, treatment firms since there are no implications of spillover effects on foreign, control firms. The overall negative abnormal returns align with the results seen in previous papers that social movements can result in a negative impact on a firm's stock performance. With the continued use of Twitter as an outlet to voice opinions on topics similar to the campaign, the effectiveness of social media activism is likely to become more prominent in the future.

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