Market Sensitivity to Product Quality, Personal Information, and Business Practice Scandals

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#### Abstract

The financial impacts of firm scandals have been widely studied in the literature. This paper exploits a unique setting that generates a large set of systematically reported scandals, allowing us to measure investors' responses across scandal types. The "3.15 Night" show is a Chinese TV program held annually on March  $15^{th}$ , which aims to protect consumers' rights. Since 1991, the program has exposed more than 250 firm violations. We document the recent 10-year scandals and use an event study approach to estimate the effects across product quality, personal information, and business practice scandals. We find that the effects are the largest for defective products, but there are also strong negative responses to personal information breaches. We find little stock response to the revelation of deceptive business practices. We also make comparisons across industry sectors and find that the consumer goods sector suffers the largest impacts, followed by the services sector, while the technology sector exhibits the smallest responses. These results shed light on how the market responds to various types of scandals and whether some industries are more vulnerable to negative effects.

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#### 1 Introduction

Contaminated food, faulty automobile engines, deceptive advertisements and personal information data breaches make the news on a regular basis. In 2017, 20 million pounds of food were recalled by the U.S. Department of Agriculture (USDA) and 30 million vehicles were affected by National Highway Traffic Safety Administration (NHTSA)'s recalls. In 2018, there was a breach of more than 50 million Facebook users' private information. These facts are not only harmful to consumers but can also be highly problematic for firms (Van Heerde et al., 2007). Existing literature has shown that firm scandals such as defective products, corporate fraud, and layoff announcements can impose costs on firms, pose a threat to firm reputations, and hurt stock prices (Marsh et al., 2004; Korkofingas and Ang, 2011; Crutchley et al., 2007; Farber and Hallock, 2009; Falkheimer and Heide, 2015). The paper contributes to the literature by examining if certain types of scandals generate larger shocks and if some industries are more exposed to negative effects.

A major challenge to answering these questions is that scandals are highly heterogeneous, receive different levels of media coverage, and may only be identified ex-post as scandals due to the level of attention they receive. Moreover, variation in the timing of a scandal being exposed further complicates comparisons due to changes in the market environment. A third challenge is that a variety of scandal types and industries are required. In practice, for example, the USDA announces only food safety issues and the NHTSA announces only automobile recalls, so most existing studies have only considered a single type of scandal for a single industry and therefore, does not make comparisons across different scandal classifications (Govindaraj et al., 2004; Korkofingas and Ang, 2011; Ni et al., 2016). By utilizing a unique event in China, this paper can systematically examine the effects of firm-level scandals under a uniform treatment. The "3.15 Night" is an annual television program held on China's consumer rights day. It is hosted by China's central government, the China Consumer Association and the predominant state television broadcaster, China Central Television (CCTV). The TV program first aired on March  $15^{th}$ , 1991 and has been broadcast annually for 28 years (1991-2018). As the show is hosted by the central government and airs on CCTV, a TV channel watching by 95.5% of the Chinese population, the program has high viewership. The two-hour program aims to expose a range of companies whose violations of laws affect Chinese consumers. More than 200 violations by 250 companies have been broadcast over the past 28 years. The scandal-hit companies vary from small local farms to Fortune Global 500 companies, and the violations range from bank employees selling personal information to fast food restaurants serving expired food. In the program, each scandal is revealed in a similar form as a 15-minute documentary. The documentary consists of both undercover investigations and interviews with victims, experts, and government agents. As the "3.15 Night" provides a platform that systematically exposes various scandals, we can consider both their average effects and differentiate effects on the extensive and intensive margins by scandal type and industry.

This paper examines the financial impacts of various scandal exposures on firms. Following the existing literature, we calculate the daily firm-level abnormal returns based on the market model (McWilliams and Siegel, 1997; Wang et al., 2014), and apply the standard event study approach to explore the changes in cumulative abnormal returns relative to the event day (Farber and Hallock, 2009; Nguyen and Nielsen, 2010). Using each episode of "3.15 Night" from 2007 to 2018, we document 178 scandal-hit Chinese and global firms. In order to conduct a heterogeneous analysis based on scandal types, we group the scandals into three categories: product quality, personal information breach, and deceptive business practices. Additionally, to make across sector comparisons, we divide all the firms into three sectors: consumer goods, consumer services, and technology. As our primary interest is studying stock price reactions, we evaluate publicly traded firms or firms whose parent companies are publicly traded.

The preliminary analysis reveals several interesting results. Existing studies estimating the average effects of negative firm-level shocks on stock market prices find effects range from -29% to nearly 0, and our estimate of the average effect is -4.1%, which is within this range. Regarding scandal types, we find that the market cares about the product quality scandal most, with a sharp drop of 9% right after the exposure and an average decline of 12%. However, this estimation is relatively larger than earlier studies focusing on those types of scandals. The larger magnitude may be attributed to three reasons. First, the severity of the scandal can affect the magnitude (Gokhale et al., 2014). As the scandals revealed in the show are all very significant and representative, the impacts could be larger. Secondly, the format of scandal revelations is different. Product hazard issues examined by prior studies, for example, are typically revealed by a recall announcement posted on the Wall Street Journal (Chen et al., 2009; Hsu and Lawrence, 2016; Ni et al., 2016), while in our settings, all scandals are exposed by undercover investigations and interviews broadcast on national televisions, and thus, may provide more direct evidence and be more salient to consumers. Thirdly, the scandal firms in our sample are made up of industry-leading companies. It is possible that an unexpected violation from those companies generates a larger market response (Rhee and Haunschild, 2006).

In today's digital world, businesses establish large databases with all kinds of personal information, from credit card numbers to the number of kids in a house, and therefore, breaches of privacy events are increasingly attracting researchers' attention. Recent studies by Malhotra and Kubowicz Malhotra (2011) and Martin et al. (2017) find such breaches have negative effects on firms' performances. Similarly, we also find breaches of personal information generate strong responses by the market. The scandal exposure causes an immediate value loss of 3.2% and an average value loss of 4.4%. Our results are in line with Campbell et al. (2003) that shows a 5.5% value loss due to breaches involving unauthorized access to customer personal data or proprietary firm data. However, we do not find any significant effects from deceptive business practices. Concerning different sectors, we find the consumer goods sector experiences average losses of 9% and appears to be the most vulnerable sector to scandals. The services sector is the second most impacted with an average loss of 6.5%. The market responds little to scandals in the technology sector. A possible explanation for this result could be problems that occur in this sector are less directly harmful, or markets tend to have a higher tolerance for this growth sector.

Our paper contributes to the literature in three ways. First, we utilize a unique event in which scandals are revealed in a systematic way. All firms are treated uniformly, enabling us to make comparisons across scandal types and sectors to uncover heterogeneity in market response. Although numerous empirical works have examined the consequences of adverse firm-level shocks, most of them only consider a single type of shock (Worrell et al., 1991; Farber and Hallock, 2009; Nguyen and Nielsen, 2010; Knittel and Stango, 2013) arising from a single industry (Thomsen and McKenzie, 2001; Govindaraj et al., 2004; Thirumalai and Sinha, 2011; Gokhale et al., 2014; Ni et al., 2016). Secondly, by using the unique event, we solve selection bias that occurs in the process of identifying scandals to consider. Media exposure of a scandal may increase the probability that an event is included in a study. However, we are able to consider all scandals reported by the show, so this type of selection is not an issue. Finally, under a uniform treatment allowing systematic scandal exposures for the same media coverage in similar timing via similar methods of reporting, the selection issue does not exist. Additionally, our study provides new empirical evidence on the effects of personal information breaches, which few studies have considered previously (Campbell et al., 2003; Acquisti et al., 2006).

The paper is organized as follows. Section 2 provides an overview of the "3.15 Night" show, its history, and the detail of its contents. Section 3 discusses the data sources and summarizes sample

characteristics. Section 4 introduces the empirical strategies used in this paper and section 5 presents empirical evidence on the effects of scandals. Section 6 concludes.

# 2 Background

In the early 1990s, China's market was flooded with fake and defective products. At that time, as the market system, mechanism and laws were underdeveloped, consumers played extremely weak roles, and their rights were frequently ignored and violated(Yin, 1998). In order to protect consumers' rights and suppress harmful business activities, on March 15<sup>th</sup>, 1991, a TV program called "3.15 Night" aired. The "3.15 Night" has been broadcast for 28 years(1991-2018) and is hosted by over 15 central government departments including the Supreme People's Court, the Supreme People's Procuratorate, the Ministry of Public Security, the Ministry of Justice, the Ministry of Commerce, the Ministry of Agriculture, the Ministry of Public Health, etc., together with the China Consumer's Association and the state television broadcaster, CCTV. During the past 28 years, the program successfully exposed business scandals from a variety of industries such as food, medical, automobile, finance, information technology, etc. More than 250 companies were accused of violating consumers' rights. These accusations include selling infant food with overdose additives, misleading consumers by fraudulent online transactions and reviews, producing poor quality tiers, and collecting personal information, etc.

The "3.15 Night" show airs annually on March 15<sup>th</sup> on the China's Consumer Rights Day. Every year, it has a unique theme and all scandal cases are organized around that theme. For example, the theme in 2012 was "Consumption in the Sun" and "Make Consumers More Dignified" in 2014. After deciding the theme, the core team starts to collect consumers' complaints and reports from various platforms and selects the most representative or promising leads to further investigate. Sometimes, the investigations could last as long as 6 months. All procedures are carried out under confidential agreements. Based on an interview from Huaxia Times, the security measures include 1) requiring all people to sign confidential agreements; 2) having closed-off management where staff from different cases are not allowed to communicate with each other; 3) building closed working environment that restricts personal activity; 4) prohibiting phone usage in-studio and 5) destroying all related drafts and manuscripts at least once a day.

During the show, a 15-minute documentary is played for each offensive behavior. The documentary typically consists of three parts 1) undercover investigations; 2) victim interviews, and 3) expert/government agent interviews.

Undercover Investigations Journalists from CCTV hide in targeted firms as employees, disguise themselves as business partners or pretend to be consumers to obtain trust and collect evidence. Secret cameras will record all the pictures and conversations used in the investigations. For example, in 2012, to collect evidence of McDonald's serving expired food, a journalist worked as an employee in McDonald's and recorded images of other employees using expired meat to cook burgers.

Victim Interviews In this part, victims voluntarily tell their own experiences with and stories of certain products. For instance, in 2014 Mr. Wan shared his story in the documentary about how Nikon kept refusing to replace his camera lens although it was still under warranty. In 2015, Mr. Liu shared a video of his Land Rover suddenly losing power when he was driving on an expressway.

**Experts/Government Agents Interviews** In the last part of the documentary, experts or government agents are invited to comment on the case. Typically, they point out what type of legislation those activities violated, how severe the violation is and how customers should protect themselves from such violations.

Hosted by the central governments and supported by authentic evidence, the "3.15 Night" generates huge impacts not only to Chinese firms but also to other global firms. For example, in 2013, the show criticized Apple of its discriminatory after-sales service in China. Early in 2012, the China Customer Association had warned Apple twice of its problematic service policy, but Apple did not give out any clear response. However, after the exposure on "3.15 Night", Apples CEO Tim Cook issued an apology letter to Chinese customers and made adjustments to the policy very quickly.

#### 3 Data

The data used in this study comes from a variety of sources. First, scandal-hit firms are obtained by watching each episode of "3.15 Night" from 2007 to 2018. Second, scandal-hit companies, as well as their parents companies, are linked to their daily closing prices and the corresponding market or industry sector indices. Finally, we collect business data such as total revenue, sector revenue, and

other important information for each exposed firm. This section describes detailed steps in dealing with all the data.

In order to get a complete list of scandal-hit firms, we watched each episode of "3.15 Night" from 2007 to 2018 and created a list that includes 178 investigated firms. Meanwhile, for each firm, we document its offenses, affected brands, product categories, or service, the legislation it violated, the length of each documentary, whether there was an undercover investigation, whether there was any interview, and whether there was any enforcement inspection, etc. As our primary interest is studying stock price reactions, we further narrow the sample to publicly traded firms or firms' parent companies are publicly traded. This gives us 44 different firms traded on seven global stock markets<sup>1</sup>. Table 1 displays all the publicly traded scandal firms in our sample. In some cases, firms are dual-listed across markets, and we use stock prices from their primary markets. It is also important to notice that firms such as the Agriculture Bank of China and Volkswagen AG are exposed more than once across years, and therefore, their stocks are counted more than once in our sample. We examine 52 affected stocks in total.

The daily closing stock prices of each firm are obtained from the Wind Financial Database. As our study includes firms from seven stock markets, we follow the existing literature on international stock markets and collect the most frequently used indices for each market. The indices we used in this paper are: 1) Shenwan Index for China mainland stock exchanges; 2) Heng Seng Index for the Hong Kong Stock Exchange; 3) S&P 500 Index for the United States; 4) Nikkei 500 for Japan; 5) KOSPI for South Korea; 6) DAX for Germany, and 7) CAC40 for France.

Finally, we gather business-related information from firms' financial statements and annual reports. As the scandal may or may not come from firms' primary sectors, we adjust the stock price responses into a comparable measure across scandals by collecting revenue shares of the scandal-hit sectors. Additionally, because the scandals arise from the Chinese market, the regional revenue also helps us measure the importance of the Chinese market and gets unbiased estimates. We also account for ownership shares of joint ventures in the relevant few cases. Other business information from the annual reports such as R&D spending, advertising spending, and political connections will also benefit our further analysis.

 $<sup>^{1}</sup>$ We exclude trading firms from China secondary stock markets or insufficient pre-event data were available to calculate abnormal returns

## 4 Methodology

#### 4.1 The Market Model

In an efficient market, stock prices can immediately reflect the financial impact of an unanticipated event (Malkiel and Fama, 1970). A rich literature has examined stock market reactions to understand the effects of firm-level scandals. For example, Ni et al. (2016) estimate firms' cumulative abnormal returns after recalls of tainted toys and Fisman and Wang (2015) study the negative stock returns after disclosures of workers' fatal accidents.

This paper examines changes in the cumulative abnormal returns of scandal-hit firms relative to the scandal exposure time. We follow MacKinlay (1997) and use an estimation window of the 250 prior trading days to estimate normal returns as shown in equation 1 and use the market model as McWilliams and Siegel (1997) to estimate the abnormal returns shown in equation 2. Prior literature has widely applied the market model to study firm-level scandals (i.e. Thirumalai and Sinha (2011); Wang et al. (2014); Ni et al. (2016)). The market model is defined in the following way,

$$R_{it} = \alpha_i + \beta_i R_{It} + \varepsilon_{i,t} \tag{1}$$

where  $R_{it}$  is firm i's daily return at day t and  $R_{It}$  is the market or industry index for that day. Next, the daily abnormal return is calculated as

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{It}) \tag{2}$$

and the cumulative abnormal return over an event window of  $[t_1,t_2]$  is defined as

$$CAR_{it}(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}$$
 (3)

The  $R_{It}$  plays the role of the control group in estimating the abnormal returns. Instead of using market indices as the control group, we compare scandal-hit stocks to their sector indices, because it helps to further isolate noises beyond the scandal impacts on the sector. A concern of using such indices is if most of the targeted firms come from the same sector or industry and make up significant parts of an index, then the sector index could be contaminated. However, in our settings, within a sector, only a tiny proportion of firms are investigated each year. Additionally, we do not observe any significant changes in the sector indices during the event windows.

## 4.2 Empirical Strategy

An event study framework has been traditionally used in understanding the financial impacts of events such as policy announcements or elections. It also has been widely employed in learning the effects of firm-level shocks such as product recalls (Govindaraj et al., 2004; Thirumalai and Sinha, 2011), layoff announcements (Farber and Hallock, 2009) and CEO deaths (Nguyen and Nielsen, 2010). Our baseline model follows the standard event study approach and assumes a single factor model. That is, for stock i at time t, we estimate the equation 4,

$$CAR_{it}^{adjusted} - CAR_{i0}^{adjusted} = \beta_0 + \beta_1 Post_t + stock_i + year_t + \varepsilon_{it}$$
(4)

where

$$CAR_{it}^{adjusted} = \frac{CAR_{it}}{ProductShare \times ChinaRevenueShare}$$
 (5)

 $CAR_{it}^{adjusted}$  is the adjusted cumulative abnormal returns. In reality, the magnitude of the stock responses will depend on whether the scandals arise from firms' major products and primary businesses. Additionally, as the scandals stem from China, the importance of the Chinese market should also be taken into account. For example, in 2017, NIKE, Inc. was accused of false advertising its basketball shoes in China. Therefore, in order to estimate the full scandal-hitting impacts on NIKE, we adjust the CAR by the share of revenues obtained from the footwear sector (0.61) and the Chinese market (0.12) in 2016. As a result, NIKE's CAR is scaled up by a multiplier of 13.7. The baseline day is set as March  $14^{th}$  (day 0), which is a day before the scandal announcement. As we are interested in changes of the CAR relative to the baseline day, we further subtract the  $CAR^{adjusted}$  at day 0 from day t to get the differences.  $Post_t$  is a dummy variable for scandal exposure on or after March 15 every year.  $stock_i$  is the fixed effects for scandal stocks and  $time_t$  is the year fixed effects. The coefficient of interests is  $\beta_1$  which represents the overall effects of scandal exposure.

We group scandals into three categories: product safety, personal information breach, and deceptive business practices. To get the magnitudes of different scandal types and make comparisons among them, we interact the  $Post_t$  dummy with the scandal categorical variable,

$$CAR_{it}^{adjusted} - CAR_{i0}^{adjusted} = \alpha_0 + \alpha_1 Post_t + \alpha_2 Post_t \times ScandalType_i$$

$$+ \alpha_3 ScandalType_i + stock_i + year_t + \varepsilon_{it}$$
(6)

where  $\alpha_2$  presents stock responses to various scandal types, and  $\alpha_1$  and  $\alpha_3$  will be absorbed by the fixed effects. Similarly, in order to find how firms from different sectors react distinctly to adverse shocks, we interact the  $Post_t$  dummy with the sector categorical variable, which includes consumer goods, consumer services, and technology. The coefficient in front of the interaction term reveals the vulnerability of those sectors to scandal.

### 5 Results

#### 5.1 Average Effects

Figure 1 displays the changes in daily cumulative abnormal returns relative to day 0 based on an event window of 20 trading days before and after the exposure. The regression results in Table 2 echo the pattern observed in Figure 1. As shown in panel A, the CAR between Day -20 and Day -1 are all insignificantly different from 0, which, to some extent, mitigates the concerns of information leakage. Panel B exhibits the daily effects after the exposures. It is clear that the descent increases gradually and becomes rather stable around day 7. Although existing literature has suggested that the event window should be set as short as possible (McWilliams and Siegel, 1997) and the efficiency market hypothesis implies the financial impact of an unanticipated event will be immediately reflected in stock prices (Malkiel and Fama, 1970), event windows selected by prior studies seem to vary. For example, Farber and Hallock (2009) use a two-day event window to study market reactions on layoff announcement while Fisman and Wang (2015) allow a 30-day event window after disclosures of workers' death. In this paper, we choose a relative longer event window for two reasons. First, as trading for some scandal-hit firms was immediately suspended following the exposure, it may put off the effects by one to two days. Secondly, as China is an offshore market for global companies, it may take time for information to spread. Thus, we use a 15-day event window [-7,7] as the baseline time length and conduct robustness tests on other time lengths.

Table 3 shows the average effects of the scandal exposures. In panel A, a 4.1% decline is detected, and the result is quite robust to the inclusion of various fixed effects. In panel B and C, we extend the analysis to the  $10^{th}$  and  $20^{th}$  trading day after the revelation, and find an average loss of 5.4% and 8.6% respectively. Existing studies estimating the average effects of negative firm-level shocks on the stock market various from -29% (Dowdell et al., 1992) to nearly zero, and our estimation is within this range.

### 5.2 Effects by Scandal Types

Figure 2 displays the distinct stock responses based on scandal types: product quality, personal information breaches, and deceptive business practices. Product quality includes violations such as selling expired food, defective household products, and problematic vehicles. Personal information breach refers to activities like collecting and selling private information without permission. Firms with false advertising, tricky warranties or that are charging hidden fees are accused of performing deceptive business practices. Table 1 provides details on the violations that each firm is accused of. From Figure 2, we can see that after the exposure, the product quality group drops sharply in the first three days, the privacy breach group gradually declines over time, and the deceptive businesses seem to be rather sticky.

Table 4 shows the daily effects by scandal types. Column 1 shows the daily impacts on the product quality group. Although during the pre-event period, the product quality group had three non-zero CAR, it should not be our primary concerns because the CAR for that group exhibited a first increasing and then decreasing trend shown in Figure 2. At day 1 and day 2, the market appeared to delay its reactions as we expect, but it generated immense responses afterward. At day 3, there was a sharp drop of 9.4%, and the declines continued to 20% in the subsequent days. Although the estimation is relatively larger than some previous studies, we are not the first one that captures such strong impacts. The larger magnitude may be attributed to three reasons. First, the severity of the scandal can affect the magnitude. For example, Gokhale et al. (2014) shows Toyota's floor mat recall generated zero effect to the stock price, the Saylor highway accident recall made Toyota's CAR reach a value of -7%, and the 2010 major recall caused its CAR to fall by 19.9%. As the scandals revealed in the show are all very significant and representative, the impacts could be larger. Second, the format of scandal revelations is different. Product hazard issues examined by prior studies, for example, are typically revealed by recall announcement posted on the Wall Street Journal (Chen et al., 2009; Hsu and Lawrence, 2016; Ni et al., 2016), while in our settings, all scandals are exposed by undercover investigations and interviews broadcast on national televisions, and thus, may provide more direct evidence and be more salient to the consumers. Third, the scandal firms in our sample are made up of the leading companies with higher reputation. Previous studies suggest that firms with strong reputation suffer severer market value losses than do firms with a weaker reputation (Rhee and Haunschild, 2006), so it is possible to have larger market responses than other studies due to the sample compositions. Column 3 presents the impacts of personal information breaches on the stock prices. Right after the announcement, the market responded strongly to the scandal with a drop of 3.2%. The magnitude is similar with Cavusoglu et al. (2004) that finds a loss of 2.1% of value over two days following the event, and the subsequent pattern is in line with Ko and Dorantes (2006) and Malhotra and Kubowicz Malhotra (2011) which imply firms' market value is negatively affected by a breach in both the short and long runs. Column 5 includes the effects of deceptive business practices and shows zero financial impacts.

Table 5 includes the results of the average effects by scandal types. Panel A presents the baseline findings, and the results are robust to the inclusion of various fixed effects. The product quality scandal generates the largest effects with an average drop of 12%. The market also shows strong responses to the breaches of privacy. Our work detects an overall loss of 3.6% of value over the 15-day event window, and the magnitude is within the range of earlier studies. However, it seems that the market does not react to deceptive business scandals. Additionally, our findings are robust to different event windows as shown in panel B and C. To sum up, investors believe that product quality scandals cause the largest drop in expected future profits, personal information breaches also generate significant value losses, while deceptive business practices seem to have minimal impacts.

#### 5.3 Effects by Sectors

We follow the Industry Classification Benchmark(ICB) launched by Dow Jones and FTSE in 2005 to classify all the firms into three sectors: consumer goods, consumer services, and technology. The consumer goods sector includes firms that produce food, vehicles and household products. Units such as banks, telecommunication companies, and restaurants are assigned to the services sector. Firms like Samsung and Apple are grouped into the technology sector. As most existing studies only consider scandals from a single industry, few of them has tried to compare the vulnerability to scandals across industries. Farber and Hallock (2009) is among the few existing papers that have addressed this. They find that between 1970-1999, job loss announcements generated more substantial impacts on firms in the manufacturing industry. Another related paper is Brounen and Derwall (2010) which shows that terrorist attacks have more substantial effects on firms in the services industry such as airlines and hotels. However, after adjusting that with systematic risk differences across industries, any divergence disappeared.

Figure 3 contains the market reactions of different sectors to the scandal exposures. It seems that both the goods and the services sectors experience significant drops after the revelations. Results in Tale 6 reflect these patterns. As we can see from column 1 and 3, both the goods and services

sector experienced a 7% loss at day 3, and the effects lasted more than 20 trading days, while in column 5, the technology sector showed zero effect. The average impacts on these three sectors are displayed in Table 7. The consumer goods sector suffered the largest hit with a decline of 7.6% during the 15-day window, and the services sector was the second most with a loss of 4.7%. It is not surprising that the consumer goods sector was the most impacted because violations from that sector can always lead serious and immediate issues. It seems that the technology sector survives in the scandal exposures, as problems that occur in this sector are less directly harmful, and since this sector is a growth sector, markets tend to have a higher tolerance for it.

#### 6 Conclusion

Financial impacts of firm-level scandals have been widely studied in the literature. An interesting question is which scandals the market is most sensitive to. Using a unique event that created systematic scandal exposure, this paper estimates the average effects of scandals and compares effects across scandal types and industry sectors. We find that scandal exposures cause an adverse effect on average. The effects are largest for firms revealed to have defective products. The market also exhibits a strong response to personal information breaches. However, we detect no impact on firms using deceptive business practices. When examining different industry sectors, the consumer goods sector suffers the largest effects, the services sector also experiencing losses. In contrast, the market exhibits higher tolerance to scandals within the technology sector. Our paper contributes to the literature in three ways. First, we are among the very first papers to make comparisons across scandal types and sectors. This is feasible due to the uniform nature of the treatment of each scandal. Secondly, the unique setting allows us to abstract from the issue of the selection bias in identifying scandals. Lastly, our study provides new empirical evidence on the effects of personal information breaches, which few studies have considered. The findings of this paper shed light on how the market responds to various types of scandals and whether some industries are more exposed to negative effects.

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# Figures and Tables

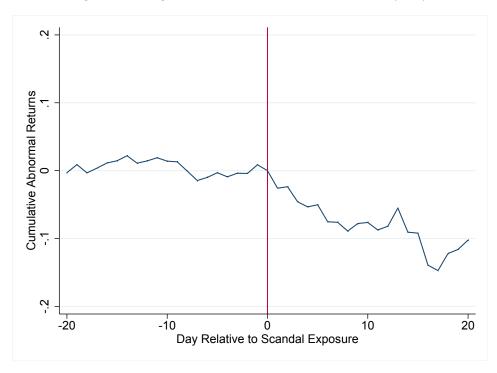
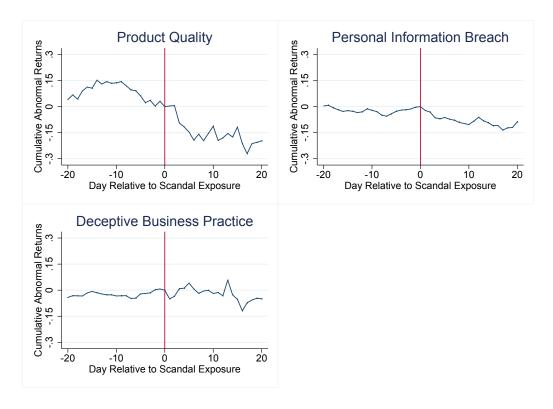


Figure 1: Changes in Cumulative Abnormal Returns, By Day

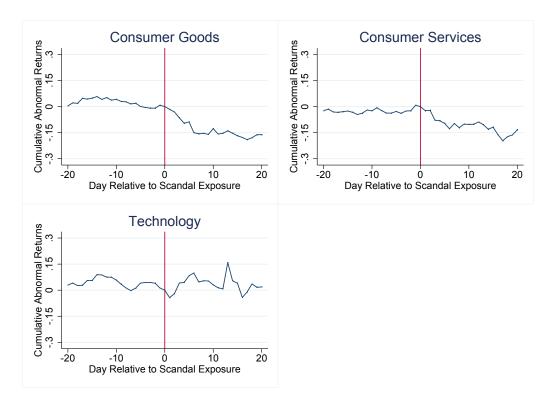
Notes: This figure plots the average CAR changes relative to the day before the scandal exposures (day 0) at an event window of [-20,20]. We line up all the daily CAR and winsorize them at the 5th and 95th percentiles. All the firms are equally weighted.

Figure 2: Changes in Cumulative Abnormal Returns, By Scandal Type



Notes: This figure plots the average CAR changes relative to the day before the scandal exposures (day 0) by scandal types at an event window of [-20,20]. We line up all the daily CAR and winsorize them at the 5th and 95th percentiles. All the firms are equally weighted.

Figure 3: Changes in Cumulative Abnormal Returns, By Sectors



Notes: This figure plots the average CAR changes relative to the day before the scandal exposures (day 0) by industry sectors at an event window of [-20,20]. We line up all the daily CAR and winsorize them at the 5th and 95th percentiles. All the firms are equally weighted.

Table 1: Scandal-Hit Publicly Traded Firms (2007-2018)

Firm	Scandal-Hit Year	Scandal Types
Aeon Co.,Ltd	2017	Deceptive Business Practices
Alibaba Group	2016	Deceptive Business Practices
Apple	2013	Deceptive Business Practices
Agriculture Bank of China*	2012&2015	Personal Information Breaches
Bank of China*	2015	Personal Information Breaches
BAIC Group	2015	Deceptive Business Practices
Carrefour S.A.	2012	Product Quality
China Merchants Bank*	2012	Personal Information Breaches
China Mobile*	2010&2015	Personal Information Breaches
China Telecommunications*	2012&2015	Personal Information Breaches
China Unicom	2014	Personal Information Breaches
Daimler AG	2015	Deceptive Business Practices
Dongfeng Motor Group	2017	Deceptive Business Practices
Dun & Bradstreet	2012	Personal Information Breaches
Focus Media Holding	2008	Personal Information Breaches
AutoNavi	2013	Personal Information Breaches
Gohigh Data Networks Technology Co,Ltd	2014	Personal Information Breaches
GOME Retail	2011	Deceptive Business Practices
HITACHI	2011	Deceptive Business Practices
Hewlett-Packard (HP)	2010	Deceptive Business Practices
Industrial and Commercial Bank of China*	2012&2015	Personal Information Breaches
Jianghuai Automobile	2013	Product Quality
Kumho Tier, Inc	2011	Product Quality
LG Corp.	2011	Deceptive Business Practices
Mcdonald's	2012	Product Qualities
NetEase,Inc	2013	Personal Information Breaches
Nike	2017	Deceptive Business Practices
Nikon	2014	Deceptive Business Practices
Nissan Motor Company Ltd	2015	Deceptive Business Practices
Nokia*	2007	Deceptive Business Practices
Panasonic	2011	Deceptive Business Practices
Koninklijke Philips N.V.*	2011	Deceptive Business Practices
RYOHIN KEIKAKU CO.,LTD	2017	Product Quality&Safety
SAIC Motor Corporation Limited	2013&2015	Product Quality&Safety
Samsung Electronics	2011	Deceptive Business Practices
Sharp Corp	2011	Deceptive Business Practices
SONY Corp*	2011	Deceptive Business Practices
Tata Motor	2015	Deceptive Business Practices
Toshiba Corp	2011	Deceptive Business Practices
Utstracom	2010	Deceptive Business Practices
VOLKSWAGEN AG	2013&2018	Product Quality
VOLKSWAGEN AG	2015	Deceptive Business Practices
Xiamen Kiongdomay Group Company	2017	Product Quality

Note: 1)We exclude trading firms from China secondary stock markets or with insufficient preevent data available to calculate abnormal returns. 2)Firms labeled with \* are dual-listed across markets, and we use the stock prices from their primary markets. Exceptions are applied to Chinese firms such as Agriculture Bank of China, Bank of China, China Merchants Bank, and Industrial and Commercial Bank of China. These firms are dual-listed in both the China mainland stock market and the Hong Kong stock market. As the Chinese mainland stock market does not open to foreign investors, the Hong Kong stock market can be regraded as a supplementary stock market. Thus, we weight them by the volumes traded on each market.

Table 2: Changes in Cumulative Abnormal Returns, by Day

Panel A: Days	before the	exposure			
Days Before	(1)	(2)	Days Before	(3)	(4)
Day -20	-0.003	(0.037)	Day -10	0.014	(0.033)
Day -19	0.009	(0.035)	Day -9	0.013	(0.030)
Day -18	-0.003	(0.035)	Day -8	-0.001	(0.027)
Day -17	0.004	(0.033)	Day -7	-0.015	(0.027)
Day -16	0.011	(0.032)	Day -6	-0.010	(0.028)
Day -15	0.015	(0.034)	Day -5	-0.003	(0.027)
Day -14	0.022	(0.033)	Day -4	-0.009	(0.026)
Day -13	0.011	(0.034)	Day -3	-0.004	(0.021)
Day -12	0.014	(0.034)	Day -2	-0.004	(0.016)
Day -11	0.019	(0.033)	Day -1	0.009	(0.011)

Panel B: Days	after the e	xposure			
Days After	(1)	(2)	Days After	(3)	(4)
Day 1	-0.026	(0.017)	Day 11	-0.087**	(0.033)
Day 2	-0.024	(0.020)	Day 12	-0.082**	(0.034)
Day 3	-0.046*	(0.025)	Day 13	-0.055*	(0.032)
Day 4	-0.053*	(0.027)	Day 14	-0.091**	(0.038)
Day 5	-0.050	(0.034)	Day 15	-0.092**	(0.039)
Day 6	-0.075**	(0.034)	Day 16	-0.139***	(0.038)
Day 7	-0.076**	(0.030)	Day 17	-0.139***	(0.038)
Day 8	-0.089**	(0.033)	Day 18	-0.147***	(0.043)
Day 9	-0.078**	(0.034)	Day 19	-0.147***	(0.043)
Day 10	-0.076**	(0.032)	Day 20	-0.102**	(0.039)
Observations	2,087		R-squared	0.071	

Notes: This table presents changes in the cumulative abnormal returns of scandal-hit stocks relative to baseline day (day 0). We winsorize the dependent variable at the 5th and 95th percentiles of the pooled distribution to reduce reliance on outliers. Standard errors are clustered at the stock level. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

Table 3: Average Effects of Scandal Exposures on Cumulative Abnormal Returns

Panel A: Event Windows [-7,7]							
	(1)	(2)	(3)	(4)			
Post	-0.039**	-0.041**	-0.040**	-0.041**			
	(0.019)	(0.019)	(0.019)	(0.019)			
Constant	-0.003						
	(0.013)						
Stock FE		X		X			
Time FE			X	X			
Mean Dep.	-0.021	-0.021	-0.021	-0.021			
Observations	758	758	758	758			
R-squared	0.024	0.435	0.133	0.435			

Panel B: Even	Panel B: Event Window [-10,10]								
	(1)	(2)	(3)	(4)					
post	-0.052**	-0.054**	-0.053**	-0.054**					
	(0.021)	(0.022)	(0.022)	(0.022)					
Constant	-0.000								
	(0.015)								
Stock FE		X		X					
Time FE			X	X					
Mean Dep.	-0.024	-0.024	-0.024	-0.024					
Observations	1,065	1,065	1,065	1,065					
R-squared	0.030	0.452	0.128	0.452					

Panel C: Even	Panel C: Event Window [-20,20]								
	(1)	(2)	(3)	(4)					
post	-0.086***	-0.086***	-0.087***	-0.086***					
	(0.030)	(0.030)	(0.030)	(0.030)					
Constant	0.004								
	(0.025)								
Stock FE		X		X					
Time FE			X	X					
Mean Dep.	-0.037	-0.037	-0.037	-0.037					
Observations	2,087	2,087	2,087	2,087					
R-squared	0.036	0.524	0.123	0.524					

This table presents the average changes in the cumulative abnormal returns of scandal-hit stocks relative to the baseline day (day 0). We winsorize the dependent variable at the 5th and 95th percentiles. Standard errors are clustered at the stock level. \* significant at 10%; \*\*\* significant at 5%; \*\*\*\* significant at 1%.

Table 4: Daily Cumulative Abnormal Returns, by Scandal Types

Day -20         0.041         (0.107)         0.003         (0.037)         -0.042         (0.02)           Day -19         0.067         (0.093)         0.008         (0.038)         -0.032         (0.02)           Day -18         0.043         (0.095)         -0.007         (0.036)         -0.033         (0.036)           Day -17         0.090         (0.086)         -0.018         (0.036)         -0.016         (0.036)           Day -16         0.113         (0.085)         -0.018         (0.036)         -0.016         (0.007)           Day -15         0.106         (0.092)         -0.023         (0.036)         -0.007         (0.007)           Day -14         0.152*         (0.081)         -0.027         (0.038)         -0.007         (0.007)           Day -13         0.130         (0.086)         -0.034         (0.038)         -0.022         (0.007)           Day -12         0.143         (0.084)         -0.030         (0.038)         -0.027         (0.007)           Day -11         0.137         (0.082)         -0.022         (0.034)         -0.026         (0.007)           Day -9         0.143**         (0.064)         -0.029         (0.032)         -0.	(6) (6) (066) (066) (067) (063) (.059 (060) (062) (064) (060)
Day -20         0.041         (0.107)         0.003         (0.037)         -0.042         (0.           Day -19         0.067         (0.093)         0.008         (0.038)         -0.032         (0.           Day -18         0.043         (0.095)         -0.007         (0.036)         -0.033         (0.           Day -17         0.090         (0.086)         -0.018         (0.036)         -0.016         (0.           Day -16         0.113         (0.085)         -0.018         (0.036)         -0.016         (0.           Day -15         0.106         (0.092)         -0.023         (0.036)         -0.007         (0.           Day -14         0.152*         (0.081)         -0.027         (0.038)         -0.007         (0.           Day -13         0.130         (0.086)         -0.034         (0.038)         -0.022         (0.           Day -12         0.143         (0.084)         -0.030         (0.038)         -0.027         (0.           Day -11         0.137         (0.082)         -0.022         (0.034)         -0.026         (0.           Day -9         0.143**         (0.064)         -0.029         (0.032)         -0.032         (0. <td>066) 066) 067) 063) .059 060) 060) 062)</td>	066) 066) 067) 063) .059 060) 060) 062)
Day -19         0.067         (0.093)         0.008         (0.038)         -0.032         (0.032)           Day -18         0.043         (0.095)         -0.007         (0.036)         -0.033         (0.           Day -17         0.090         (0.086)         -0.018         (0.036)         -0.033         (0.           Day -16         0.113         (0.085)         -0.018         (0.036)         -0.016         (0.           Day -15         0.106         (0.092)         -0.023         (0.036)         -0.007         (0.           Day -14         0.152*         (0.081)         -0.027         (0.038)         -0.007         (0.           Day -13         0.130         (0.086)         -0.034         (0.038)         -0.022         (0.           Day -12         0.143         (0.084)         -0.030         (0.038)         -0.027         (0.           Day -11         0.134         (0.085)         -0.013         (0.034)         -0.026         (0.           Day -10         0.137         (0.082)         -0.022         (0.034)         -0.033         (0.           Day -9         0.143**         (0.064)         -0.029         (0.032)         -0.032         (0.	066) 067) 063) .059 060) 060) 062)
Day -18         0.043         (0.095)         -0.007         (0.036)         -0.033         (0.02)           Day -17         0.090         (0.086)         -0.018         (0.036)         -0.033         (0.02)           Day -16         0.113         (0.085)         -0.018         (0.036)         -0.016         (0.02)           Day -15         0.106         (0.092)         -0.023         (0.036)         -0.007         (0.038)           Day -14         0.152*         (0.081)         -0.027         (0.038)         -0.007         (0.038)           Day -13         0.130         (0.086)         -0.034         (0.038)         -0.022         (0.032)           Day -12         0.143         (0.084)         -0.030         (0.038)         -0.027         (0.032)           Day -10         0.137         (0.082)         -0.013         (0.034)         -0.026         (0.000)           Day -9         0.143**         (0.064)         -0.029         (0.032)         -0.032         (0.032)           Day -8         0.121**         (0.053)         -0.049         (0.033)         -0.047         (0.000)           Day -7         0.096         (0.060)         -0.055         (0.033)         -0	067) 063) .059 060) 060) 062) 064)
Day -17         0.090         (0.086)         -0.018         (0.036)         -0.033         (0.           Day -16         0.113         (0.085)         -0.018         (0.036)         -0.016         (0.           Day -15         0.106         (0.092)         -0.023         (0.036)         -0.007         (0.           Day -14         0.152*         (0.081)         -0.027         (0.038)         -0.007         (0.           Day -13         0.130         (0.086)         -0.034         (0.038)         -0.022         (0.           Day -12         0.143         (0.084)         -0.030         (0.038)         -0.027         (0.           Day -10         0.137         (0.082)         -0.032         (0.034)         -0.026         (0.           Day -9         0.143**         (0.064)         -0.029         (0.032)         -0.032         (0.           Day -8         0.121**         (0.053)         -0.049         (0.033)         -0.031         (0.           Day -7         0.096         (0.060)         -0.055         (0.033)         -0.047         (0.           Day -5         0.061         (0.077)         -0.027         (0.024)         -0.021         (0. <td>063) .059 060) 060) 062) 064)</td>	063) .059 060) 060) 062) 064)
Day -16         0.113         (0.085)         -0.018         (0.036)         -0.016         (0.092)           Day -15         0.106         (0.092)         -0.023         (0.036)         -0.007         (0.           Day -14         0.152*         (0.081)         -0.027         (0.038)         -0.007         (0.           Day -13         0.130         (0.086)         -0.034         (0.038)         -0.022         (0.           Day -12         0.143         (0.084)         -0.030         (0.038)         -0.027         (0.           Day -11         0.134         (0.085)         -0.013         (0.034)         -0.026         (0.           Day -10         0.137         (0.082)         -0.022         (0.034)         -0.026         (0.           Day -9         0.143**         (0.064)         -0.029         (0.032)         -0.033         (0.           Day -9         0.143**         (0.064)         -0.029         (0.033)         -0.031         (0.           Day -8         0.121**         (0.053)         -0.049         (0.033)         -0.031         (0.           Day -7         0.096         (0.060)         -0.055         (0.033)         -0.047         (0.	.059 060) 060) 062) 064)
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Observations 527 834 726	,
R-squared 0.222 0.160 0.022	,

This table presents the daily changes in the cumulative abnormal returns of scandal-hit stocks relative to the baseline day (day 0). We winsorize the dependent variable at the 5th and 95th percentiles. Standard errors are clustered at the stock level. \* significant at 10%; \*\*\* significant at 1%.

Table 5: Average Effects of Scandal Exposures on Cumulative Abnormal Returns, by Scandal Types

Panel B: Event Window [-7,7]				
	(1)	(2)	(3)	(4)
Post×Product Quality	-0.126**	-0.129**	-0.127**	-0.129**
	(0.052)	(0.054)	(0.052)	(0.054)
Post×Personal Information Breach	-0.035	-0.036*	-0.035*	-0.036*
	(0.021)	(0.020)	(0.021)	(0.020)
Post×Deceptive Business Practices	0.017	0.017	0.017	0.017
	(0.020)	(0.021)	(0.021)	(0.021)
Stock FE		X		X
Time FE			X	X
Mean Dep.	-0.021	-0.021	-0.021	-0.021
Observations	771	771	771	771
R-squared	0.104	0.465	0.170	0.465

Panel B: Event Window [-10,10]				
	(1)	(2)	(3)	(4)
Post×Product Quality	-0.167***	-0.170***	-0.168***	-0.170***
	(0.059)	(0.061)	(0.059)	(0.061)
Post×Personal Information Breach	-0.043*	-0.044*	-0.043*	-0.044*
	(0.022)	(0.022)	(0.022)	(0.022)
Post×Deceptive Business Practices	0.018	0.019	0.018	0.019
	(0.023)	(0.023)	(0.023)	(0.023)
Stock FE		X		X
Time FE			X	X
Mean Dep.	-0.024	-0.024	-0.024	-0.024
Observations	1,065	1,065	1,065	1,065
R-squared	0.094	0.509	0.185	0.509

Panel C: Event Window [-20,20]				
	(1)	(2)	(3)	(4)
Post×Product Quality	-0.239***	-0.239***	-0.238***	-0.239***
	(0.085)	(0.087)	(0.086)	(0.087)
Post×Personal Information Breach	-0.064**	-0.065**	-0.066**	-0.065**
	(0.027)	(0.027)	(0.027)	(0.027)
Post×Deceptive Business Practices	-0.000	0.001	0.000	0.019
	(0.032)	(0.033)	(0.032)	(0.023)
Stock FE		X		X
Time FE			X	X
Mean Dep.	-0.037	-0.037	-0.037	-0.037
Observations	2,087	2,087	2,087	2,087
R-squared	0.081	0.566	0.168	0.566

Notes: This table presents the average changes of cumulative abnormal returns of scandal-hit stocks relative to the baseline day (day 0) by different scandal types. I winsorize the dependent variable at the 5th and 95th percentiles of the pooled distribution to reduce the reliance on outliers. Stander errors are clustered at stock level. \* significant at 10%; \*\*\* significant at 5%; \*\*\* significant at 1%.

Table 6: Daily Cumulative Abnormal Returns, by Industry Sectors

	Consume	r Goods	Consumer	Services	Techn	ology
	$\overline{}$ (1)	(2)	(3)	(4)	$\overline{}$ (5)	(6)
Day -20	0.004	(0.070)	-0.024	(0.050)	0.030	(0.092)
Day -19	0.021	(0.060)	-0.015	(0.049)	0.041	(0.088)
Day -18	0.018	(0.058)	-0.033	(0.047)	0.027	(0.091)
Day -17	0.047	(0.050)	-0.029	(0.047)	0.028	(0.088)
Day -16	0.043	(0.047)	-0.026	(0.047)	0.056	(0.085)
Day -15	0.048	(0.048)	-0.033	(0.048)	0.055	(0.091)
Day -14	0.057	(0.044)	-0.046	(0.049)	0.090	(0.086)
Day -13	0.041	(0.041)	-0.038	(0.048)	0.088	(0.090)
Day -12	0.052	(0.035)	-0.020	(0.046)	0.075	(0.097)
Day -11	0.037	(0.035)	-0.024	(0.046)	0.075	(0.094)
Day -10	0.042	(0.037)	-0.007	(0.039)	0.058	(0.095)
Day -9	0.037	(0.035)	-0.023	(0.039)	0.034	(0.090)
Day -8	0.027	(0.025)	-0.038	(0.041)	0.013	(0.076)
Day -7	0.015	(0.034)	-0.037	(0.044)	-0.002	(0.070)
Day -6	0.019	(0.028)	-0.028	(0.043)	0.012	(0.070)
Day -5	0.000	(0.027)	-0.028	(0.043)	0.044	(0.072)
Day -4	-0.005	(0.026)	-0.039	(0.038)	0.044	(0.071)
Day -3	-0.009	(0.025)	-0.026	(0.021)	0.040	(0.048)
Day -2	-0.009	(0.025)	-0.024	(0.018)	0.040	(0.048)
Day -1	0.008	(0.024)	0.007	(0.011)	0.013	(0.028)
Day 1	-0.016	(0.012)	-0.023	(0.015)	-0.043	(0.067)
Day 2	-0.031	(0.023)	-0.022	(0.024)	-0.020	(0.068)
Day 3	-0.065**	(0.029)	-0.078**	(0.035)	0.041	(0.070)
Day 4	-0.096**	(0.038)	-0.082**	(0.036)	0.045	(0.074)
Day 5	-0.088	(0.061)	-0.097**	(0.037)	0.084	(0.094)
Day 6	-0.150**	(0.057)	-0.128***	(0.039)	0.099	(0.078)
Day 7	-0.157**	(0.055)	-0.097***	(0.032)	0.048	(0.079)
Day 8	-0.154**	(0.059)	-0.121***	(0.041)	0.054	(0.086)
Day 9	-0.160**	(0.063)	-0.101**	(0.041)	0.053	(0.084)
Day 10	-0.127**	(0.048)	-0.103**	(0.039)	0.031	(0.089)
Day 11	-0.158**	(0.058)	-0.102**	(0.042)	0.014	(0.084)
Day 12	-0.154**	(0.058)	-0.089**	(0.038)	0.008	(0.095)
Day 13	-0.139**	(0.059)	-0.104**	(0.038)	0.159**	(0.057)
Day 14	-0.154**	(0.062)	-0.130***	(0.045)	0.054	(0.103)
Day 15	-0.168**	(0.064)	-0.118**	(0.049)	0.040	(0.101)
Day 16	-0.178**	(0.071)	-0.162***	(0.049)	-0.042	(0.106)
Day 17	-0.190**	(0.075)	-0.197***	(0.058)	-0.010	(0.102)
Day 18	-0.179**	(0.079)	-0.173***	(0.051)	0.036	(0.103)
Day 19	-0.162*	(0.080)	-0.163***	(0.050)	0.017	(0.099)
Day 20	-0.162*	(0.079)	-0.133***	(0.043)	0.019	(0.102)
Mean Dep.	-0.0	53	-0.00	66	-0.0	)23
Observations	57	0	997	997 520		20
R-squared	0.2	56	0.15	66	0.0	38
- squared	0.2	-	0.10	,,,	0.0	•••

This table presents the daily changes of cumulative abnormal returns of scandal-hit stocks relative to the baseline day (day 0) by sectors. I winsorize the dependent variable at the 5th and 95th percentiles of the pooled distribution to reduce the reliance on outliers. Stander errors are clustered at stock level. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

Table 7: Average Effects of Scandal Exposures on Cumulative Abnormal Returns, by Industry Sectors

Panel A: Event Windows [-7,7]							
	(1)	(2)	(3)	(4)			
Post×Consumer Goods	-0.076*	-0.076*	-0.076*	-0.076*			
	(0.038)	(0.039)	(0.038)	(0.039)			
Post×Consumer Services	-0.045	-0.047	-0.045	-0.047			
	(0.030)	(0.031)	(0.030)	(0.031)			
$Post \times Technology$	0.012	0.011	0.010	0.011			
	(0.016)	(0.015)	(0.016)	(0.015)			
Stock FE		X		X			
Time FE			X	X			
Mean Dep.	-0.021	-0.021	-0.021	-0.021			
Observations	758	758	758	758			
R-squared	0.100	0.451	0.164	0.451			

Panel B: Event Window [-10,10]						
	(1)	(2)	(3)	(4)		
Post×Consumer Goods	-0.104**	-0.105**	-0.104**	-0.105**		
	(0.045)	(0.046)	(0.045)	(0.046)		
Post×Consumer Services	-0.056	-0.058*	-0.056	-0.058*		
	(0.034)	(0.035)	(0.034)	(0.035)		
$Post \times Technology$	0.011	0.012	0.009	0.012		
	(0.017)	(0.016)	(0.017)	(0.016)		
Stock FE		X		X		
Time FE			X	X		
Mean Dep.	-0.024	-0.024	-0.024	-0.024		
Observations	1,065	1,065	1,065	1,065		
R-squared	0.101	0.471	0.159	0.471		

Panel C: Event Window [-20,20]						
	(1)	(2)	(3)	(4)		
Post×Consumer Goods	-0.158**	-0.159**	-0.158**	-0.159**		
	(0.062)	(0.063)	(0.062)	(0.063)		
Post×Consumer Services	-0.086*	-0.086*	-0.087*	-0.086*		
	(0.047)	(0.048)	(0.046)	(0.048)		
$Post \times Technology$	-0.007	-0.006	-0.008	-0.006		
	(0.022)	(0.023)	(0.023)	(0.023)		
Stock FE		X		X		
Time FE			X	X		
Mean Dep.	-0.037	-0.037	-0.037	-0.037		
Observations	2,087	2,087	2,087	2,087		
R-squared	0.087	0.538	0.147	0.538		

This table presents average changes in the cumulative abnormal returns of scandal-hit stocks for different sectors. We winsorize the dependent variable at the 5th and 95th percentiles. Standard errors are clustered at the stock level. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.