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The Friday Effect: Firm Lobbying, the Timing of Drug Safety Alerts, and Drug Side-Effects

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Safety alerts are announcements made by health regulators warning patients and doctors about new drug-related side-effects. However, not all safety alerts are equally effective. We provide evidence that the day of the week on which the safety alerts are announced explains differences in safety alert impact. Specifically, we show that safety alerts announced on Fridays are less broadly diffused – they are shared 34% less on social media, mentioned in 23-66% fewer news articles, and 12-51% less likely to receive any news coverage at all. As a consequence of this, we propose Friday alerts are less effective in reducing drug-related side-effects. We find that moving a Friday alert to any other weekday would reduce all drug-related side-effects by 9-12%, serious drug-related complications by 6-15%, and drug-related deaths by 22-36%. This problem is particularly important since Friday was the most frequent weekday for safety alert announcements from 1999 to 2016. We show this greater prevalence of Friday alerts might not be random: firms who lobbied the FDA in the past are 49-56% more likely to have safety alerts announced on Fridays.

In the United States, prescription drugs cause about two million hospitalizations and 100,000 deaths every year due to known side-effects (Lazarou et al. 1998, Light et al. 2013). For this reason, informing patients and the medical community about the potential dangers of pharmaceutical products is a significant challenge in public health (Dusetzina et al. 2012). In the United States this task is done by the U.S. Food and Drug Administration (FDA) which actively monitors drugs to provide the medical community with new information about potentially dangerous side-effects. When the FDA finds sufficient evidence of a new side-effect, it warns the public through a safety alert announcement. The goal of this announcement is to inform patients and doctors so they can adjust their prescription and consumption behavior to avoid these side-effects (Hurren et al. 2011). However, not all safety alerts are equally acted upon: some safety alerts trigger an immediate change in doctors' and patients' behavior leading to a reduction in drug-related problems, other safety alerts have very little or no impact at all (for review see Dusetzina et al. 2012). Therefore, a fundamental question is: why is there such variance in the impact of safety alerts?

The first goal of this study is to explain variance in how much safety alerts reduce avoidable side-effects. We propose that, in certain cases, doctors and patients are not effectively informed about new safety information. We draw from prior research suggesting that information is diffused differently depending on the weekday on which it is made public (DellaVigna and Pollet 2009). This research claims that the level of

attention of agents responsible for disseminating new information varies significantly over the week, with Fridays being the weekday on which their attention level is at the lowest. Consequently, new information released on Fridays is more likely to fall under the radar of these agents' attention and, therefore, is usually diffused less broadly. Recent studies in finance and accounting provide evidence of this effect by showing how announcements on Fridays take longer to be incorporated into stock prices (Hirshleifer et al. 2009, Louis and Sun 2010). We apply this same logic in our context to examine whether safety alerts announced on Fridays are less intensively diffused, reducing the probability that doctors and patients become informed, and thereby making Friday safety alerts less effective.

Our second goal is to explore whether firms may influence the weekday on which safety alerts are announced. Prior research suggests firms are aware that Friday news are diffused less broadly, and this is why they usually release bad news on Fridays to minimize their negative impact (Michaely et al. 2016). Therefore, to the extent that safety alerts are likely to negatively impact a firm's reputation and sales (Ahmed et al. 2002, Cheah et al. 2007, Dusetzina et al. 2012), it may be in the firm's interest to have safety alerts announced on Fridays. However, safety alerts are communicated by the FDA, not the firm. This suggests that only firms with some kind of political connection with the FDA would be able to influence the FDA's decision regarding when to announce safety alerts. Accordingly, we examine whether firms that undertake political activities targeting the FDA are more likely to have their alerts released on Fridays.

We explore our two research questions in a sample of 441 safety alerts on marketed drugs announced by the FDA in the 1999-2016 period. We provide evidence that safety alerts announced on Fridays are less broadly diffused – they are shared 34% less frequently on social media, 12 to 51% less likely to be covered in print media, and mentioned in 23 to 66% fewer news articles. Second, our findings suggest Friday alerts are less effective in reducing drug-related side-effects – we estimate moving a Friday alert to any other weekday would reduce all drug-related side-effects by 9 to 12%, serious drug-related complications by 6 to 15%, and drug-related deaths by 22 to 36%. Finally, we provide evidence that firms that have lobbied the FDA in the past are 49 to 56% more likely to have safety alerts announced on Fridays. Overall, our study highlights the presence of potential weaknesses in the process through which doctors and patients receive safety updates and suggests that firms' incentives may be worsening this problem by increasing the prevalence of alerts on the days in which these weaknesses are the greatest.

The structure of the paper is as follows. First, we examine how the diffusion of safety alerts depends on the weekday on which they are announced and how this affects the impact of safety alerts in reducing side-effects. Second, we explore how firms' political activities targeted at the FDA may influence the weekday in which the alert is announced. Finally, we outline our study's academic contributions and policy implications.

1. The Impact of Drug Safety Alerts: The Friday Effect

One of the roles of the FDA is to develop and disseminate information to the public regarding safety issues on marketed drugs (CDER 2007). The FDA relies on multiple sources of information such as post-marketing clinical trials, scientific publications, or patients' reports to identify the presence of side-effects in marketed drugs. Once the FDA obtains enough evidence suggesting that a drug causes a previously unknown side-effect, the Drug Safety Oversight Board, a specific branch of the FDA, is responsible for evaluating such evidence. Only when this board concludes that the evidence of a causal relationship between the drug and the side-effect is reliable enough, this safety information is made public. Safety information is communicated in the form of a safety alert, which provides a description of the newly found side-effect and a set of recommendations regarding how and when the drug should be prescribed/consumed based on the new evidence. Once doctors and patients become aware of the new safety information, they tend to adjust their prescription and consumption behavior accordingly (Dusetzina et al. 2012). This adjustment may come in the form of the removal of other drugs that may interacting with the drug in question, a reduction in the dose or strength of the actual drug, or the complete removal of the drug if a safer substitute is available. All these changes in prescription and consumption behavior should lead to a reduction in the number of problems related to that drug experienced by the patients taking that medication (Dusetzina et al. 2012).

The impact of safety alerts, therefore, depends on how quickly and broadly doctors and patients receive such safety information. Doctors can receive safety updates from the FDA and drug manufacturers, and more recently from alternative sources such as electronic prescribing systems. However, according to extant evidence, all these sources have important limitations. First, while the FDA is the primary source for safety information, there are important weaknesses in how FDA updates the medical community about safety-related issues. Since 1993, safety alerts are published in the FDA's MedWatch website and doctors can receive safety alert updates from the FDA's email subscription or, since 2011, from the FDA's MedWatch twitter account. Yet, many doctors acknowledge that they do not have enough time to continuously monitor and assess FDA updates (Advera 2013). Further, doctors receive updates not only on safety information, but on many other types of relevant knowledge (e.g., new approved drugs, new therapeutic properties of existing drugs). Therefore, they recognize that they are unable to keep track of all the safety (and non-safety) updates they receive every day (Advera 2013).[1]

[1] Doctors can be found liable for unintentional harm if a patient suffers damage due to a prescription error (Edersheim and Stern 2009). Liability is governed by tort law, and for doctors, the specific subset of tort law is known as professional negligence law. Doctors who do not stay current with the prescription recommendations on the medications in their field could be found guilty of negligence. In practice, however, doctors seem to face a low risk because (1) patients only have two years to bring a claim since the negligent behavior occurred and (2) around 90% of the claims are dismissed without payment due to the inability to prove malpractice (Peters 2009).

Second, doctors may receive safety updates from the drug manufacturer itself. Sales representatives, with whom doctors frequently interact, are an additional source of safety-related information. Yet, not all doctors have contact with sales representatives: around 35% of doctors do not see sales representatives at all (Alkhateeb et al. 2009). More importantly, recent studies show how doctors perceive that the amount of safety information they receive from sales representatives is insufficient (Mintzes et al. 2013).

Third, doctors' electronic prescribing systems (EPS), used to support their prescription decisions, can also inform doctors about safety updates. After their broad implementation in recent years, these systems provide a rather powerful way to prevent medication errors by providing doctors safety-related information in a quick manner (Porterfield et al. 2014). However, while EPS are now common practice, these systems are not standardized across hospitals. As one doctor we interviewed[2] for anecdotal evidence said: *"I only know what is in our system. If the patient has another condition treated at a different hospital that doesn't share our system, our database is not going to catch that the drug we prescribed might be problematic."* This lack of a unified database often means the most recent version of the medical records available to doctors is not up to date. As another doctor described: *"Our system will give a list of drugs that the patient is currently taking, however it is almost never right [...] half of them won't be up to date, and I'll have to change them or else I'll get an alert saying that the drug I'm prescribing could negatively interact with a medication that the patient is no longer taking."* Worse still, even when the system can highlight a problem, it is not as effective as expected because doctors override them in 49% to 96% percent of the cases when it comes to safety alerts information (Issac et al. 2009, Van de Sijs et al. 2006).[3]

In sum, it seems that these sources of safety-related information are not effective enough, in spite of all the improvements in recent years. Doctors acknowledge that this is the case and explain that, in practice, the way in which they end up receiving safety news many times is through their professional network: sharing best practices and information with their colleagues in the workplace or at conference meetings (Advera 2013). As one doctor we interviewed recognized, *"[...] often the way you hear about new safety information is by word of mouth when other doctors will say: have you heard about the problems with drug X or drug Y?"* Not only does this affect the knowledge of safety news but also the implementation. As another doctor we interviewed pointed out, not all safety alerts are viewed equally: *"[...] if I get an email about a safety alert but none of my colleagues seems to be concerned about it, I treat that differently to an email about a safety alert where everyone agrees we should change our prescription practices."* This suggests how effectively

[2] We conducted unstructured interviews with two doctors. One nephrologist and a general practitioner at two separate large university medical centers.

[3] A major limitation of these systems is the lack of alert specificity and overload of alerts, producing a phenomenon called alert fatigue: when presented with loads of alerts when each prescription is entered, doctors tend to stop reading the alerts and just quickly scroll through them, increasing the chance that a relevant alert is missed (Porterfield et al. 2014).

doctors become informed about safety alerts, and how they act upon that information, strongly depends on how broadly safety information is diffused by healthcare professionals within the medical community (Advera 2013).

As with doctors, patients are also not immediately updated about safety alert information. It is unlikely patients will be informed through the formal channels described above (e.g., the FDA, drug manufacturers, electronic prescribing systems). First, most patients rarely follow and monitor FDA safety communications. Second, doctors and drug manufacturers do not always contact patients to update them about safety news of previously prescribed medications. Third, pharmacists may provide updated safety-related information to patients when they purchase their medication since some pharmacies rely upon electronic systems to avoid medication errors. Yet, this source of information suffers from the same weaknesses reported above with respect to the electronic prescribing systems (Ojeleye et al. 2013). In the end, it is likely that many patients become informed about safety news from informal sources such as the mass media, an active disseminator of safety-related information for pharmaceutical products (Ahmed et al. 2002, Cheah et al. 2007).

Therefore, the extent to which doctors and patients become informed about safety news depends upon how intensively safety alerts are disseminated throughout healthcare and media networks. How intensely safety news is disseminated depends upon healthcare professionals that follow, assess and share safety information and media professionals that diffuse safety news through mass media outlets. Consequently, these agents play the role of information brokers that determine the extent to which the information eventually reaches doctors and patients (Deephouse and Heugens 2009, Madsen and Rodgers 2015). We argue that not all safety alerts will be diffused equally by these agents. The extent to which these agents will disseminate safety alerts depends on their level of attention when the alert is released (Deephouse and Heugens 2009, Hoffman and Ocasio 2001, Ocasio 1997, 2011). Alerts announced when information brokers? attention is low have a greater probability of being overlooked and, thus, diffused less broadly.

In our study, we propose that the attention of healthcare and media professionals will vary across the workweek. Specifically, we argue that healthcare and media professionals' attention is lowest on Fridays. Extant evidence is consistent with this claim. Research on employee motivation shows that motivation peaks on Mondays and Tuesdays, and is lowest on Fridays (Sotak et al. 2015). In a similar vein, surveys on employee productivity reveal that employees report being most productive on Tuesdays and least productive on Fridays (Accountemps 2013). Research looking at absenteeism reported higher levels of absenteeism on Fridays (Herrmann and Rockoff 2012, Johns and Al Hajj 2016, Miller et al. 2008), as well as a greater probability that employees take vacation days (paid absenteeism) on Fridays (Harrison and Hulin 1989). In addition, studies looking at the allocation of working hours throughout the week by professionals with time flexibility found that they worked the least amount of hours on Fridays (Beckers et al. 2008, Nader et al.

2012). Consistent with this, recent studies in finance and accounting show how stock analysts and investors are less likely to react to events taking place on Fridays (quarterly earnings (DellaVigna and Pollet 2009, Hirshleifer et al. 2009) and mergers and acquisitions (Louis and Sun 2010)). Overall these findings suggest that professionals are likely to pay less attention to events taking place on Fridays.

Taken together, this evidence suggests that healthcare and media professionals should diffuse safety alerts released on Fridays less intensively. Consequently, we expect safety alerts to reduce side-effects, but we expect such a reduction to be weaker for Friday alerts. In other words, we expect Friday safety alerts to have a lower impact compared to alerts released any other weekday.

Data

To identify drug safety alerts we looked into the FDA's MedWatch website (Carpenter et al. 2012, Cheah et al. 2007). This website provides information for all safety alerts reported since 1996. Specifically, it provides information about the date the alert was issued, the drug(s) involved in the alert, the nature of the safety problem(s), and the FDA's new prescription recommendations.

To test the *diffusion* of safety alerts through the healthcare community and mass media we rely on two different sources of data. First, to capture dissemination in the healthcare community we look at the extent to which healthcare professionals share safety alerts information. The FDA opened a twitter account in 2011 where it started announcing safety alerts (@medwatch). This twitter account reports safety-related information and is mainly followed by healthcare professionals with a special interest in drug safety. Therefore, by looking at the diffusion of safety alert tweets (i.e., retweets) we are able to capture the extent to which healthcare professionals with an interest in drug safety disseminate safety alerts. Second, to capture the diffusion of safety alerts through mass media we look into the Factiva database for articles covering safety alerts in the major U.S. newspapers (*New York Times, Washington Post, Wall Street Journal, Chicago Tribune, USA Today,* and *Los Angeles Times*). We build on the assumption that diffusion of safety alerts by these national media outlets captures how likely certain patients will be informed about safety news.

To estimate the *impact* of safety alerts we match the drugs that had safety alerts with data on patients' side-effects from the FDA's Adverse Event Reporting System (FAERS), a database that has been widely used in the medical literature (Hoffman et al. 2014, Sakaeda et al. 2013, Wittayanukorn et al. 2017). The adverse events included in the FAERS database are reported by doctors, pharmacists, nurses, manufacturers, and patients. The FDA uses the FAERS data as a critical component in monitoring whether drugs are having unintended consequences on patients. This data is available since 1998 and provides information on several important dimensions for this study, namely: (1) the day in which a given adverse event was experienced by the patient (the DEMOGRAPHIC files in the FAERS database), (2) the outcome of such adverse event for the patient (the OUTCOME files in the FAERS database), and (3) the drug that caused the adverse event

(the DRUG files in the FAERS database). The DRUG files list all the drugs that the patient was taking and thus could have caused the adverse event. There are four types of drugs associated with adverse events: (1) primary suspect drug, (2) secondary suspect drug, (3) concomitant drug, and (4) interaction drug. When assigning adverse events to the drug involved in a safety alert we considered only adverse events where the drug was listed as the primary suspect. This way we have greater confidence that those adverse events were indeed caused by the drug in question.[4]

It is important to acknowledge that the FAERS database has some limitations. Because the FAERS is self-reported, it systematically underestimates the total number of adverse events suffered by patients from a particular drug. At best, experts estimate the FAERS database only captures 1% to 10% of the actual adverse events in the country (Heinrich 2000). Therefore, the data cannot be used to calculate the absolute number of adverse events or medication errors in the U.S. population. Since we are looking at differences across alerts, this problem is ameliorated as long as the misreporting is homogenous across the alerts in our sample. This is why, when we compare Friday and non-Friday alerts, we always use relative rather than absolute amounts.

Matching the names of the drugs from the FDA's MedWatch database to the FAERS database is not straightforward. Drugs often have multiple trade names, for example Adderall is marketed as Adderall and Adderall XR. Yet, the FAERS database will just report Adderall as the drug causing the reported adverse event. Therefore, we match adverse events to drug safety alerts by looking at the first name of the drug only (e.g., Adderall). This means that we may be incorrectly assigning adverse events to certain drug safety alerts and omitting possible adverse events to safety alerts. We believe this is mainly adding noise, making our tests more conservative since this measurement error should mix the treatment and control groups, which would bias our estimates downwards and make it harder to find statistically significant effects.

Sample Construction

We take the following steps to create our final list of drug alerts. First, we look at safety alerts for the 1999 to 2016 period since the FAERS data has only been available since 1998. Second, we only look at alerts on drugs and exclude alerts on other products such as medical devices. Third, we restrict our sample to safety alerts on branded drugs (i.e., not generics), since we can reliably identify the drug's adverse events in the FAERS database and the company that owns the drug.[5] Fourth, we remove safety alerts on drugs owned by more than one company (5% of the alerts). In these cases, we cannot know which firm's characteristics are affecting our main outcomes, and therefore we exclude them. Fifth, in those few cases where a drug has

[4] We replicated our tests accounting for all adverse events in which a drug was listed (listed as primary suspect, secondary suspect, concomitant or interaction) and the results are substantively identical (available upon request).

[5] Alerts on branded drugs represent approximately 75% of all safety alerts in our studied period.

more than one alert on the same day, we ”collapse” both alerts into one single alert. After all these steps, we end up with a sample of 441 drug safety alerts.

Although all of our tests rely on these 441 alerts as the starting point, the nature and size of the sample used varies across tests. First, when we test the dissemination of safety alerts by looking at the diffusion of the FDA's safety alert tweets, we can only look at alerts after 2011 (139 safety alerts), since this was the year when the MedWatch twitter account was opened. Second, the number of alerts used when we look at the impact of safety alerts also varies. To test the impact of Friday alerts, we explore if the number of reported adverse events is reduced after a safety alert, and if this reduction depends on the weekday in which the safety alert is announced (Friday versus non-Friday). That is, we compare the number of drug adverse events reported in the days before and after the alert. It is unclear, however, how many days before and after the alert we need to look at to identify differences in the responses to Friday and non-Friday alerts. This depends on how long it takes for doctors and patients to react and incorporate safety news into their drug prescription and consumption behavior respectively. To be conservative we look at three different time windows: one, three, and six months before and after the safety alert announcement. However, because some drugs received more than one alert in our period of study, it is important to account for the possibility that reactions to a given drug alert are “contaminated” by the temporal proximity to another alert on the same drug. Therefore, when we have two alerts on the same drug whose time windows overlap, we remove those alerts from the sample. Therefore, as we increase the size of the time window we find more overlaps and, thus, end up with fewer alerts in our sample.

Measurements

Dependent Variables: To test the diffusion of safety alerts by healthcare professionals we look at the retweets done by healthcare experts to the FDA's MedWatch tweets informing about safety alerts. We assume that the intensity with which healthcare professionals share safety alert information through their social media accounts will capture the extent to which such safety alert is diffused within the healthcare community. Specifically, we look at the total *number of retweets* as our measure of diffusion of safety alerts through the healthcare community.

To capture mass media diffusion we look at the presence of articles in six major U.S. newspapers (*New York Times, Washington Post, Wall Street Journal, Chicago Tribune, USA Today,* and *Los Angeles Times*) mentioning a drug in the days after the FDA makes a safety alert announcement about it. Specifically, we searched Factiva for all the articles published in the first six days after the alert, where the name of the drug appeared in the article. We then read these drug-related articles and kept those where the article referred to the drug safety alert in question. We use two measures of *media coverage*: (1) a dummy variable that takes

a value of 1 when there was at least one article covering the safety alert and 0 otherwise (about 21% of the alerts in our sample received no coverage at all) and (2) the number of articles mentioning the safety alert.

To test the impact of safety alerts, we compare adverse events in the days before and after the alert. To identify the day in which a patient suffered an adverse event with a specific drug, we use the date in the FAERS dataset in which the patient reported experiencing the adverse event. This date may be different from the date in which this adverse event was reported to the FDA, a date that is also provided in the FAERS database. Although in the vast majority of the cases, the date in which the adverse event was reported to the FDA is very close to the date when the patient experienced the event, in some other cases these two dates are very far apart. Since we are interested in how safety alerts impact whether patients keep experiencing the same complications associated with the drug or not, we use the date the patients experienced the adverse event to create our main outcome in this test.

We look into three different types of adverse events: total adverse events, serious adverse events, and death adverse events. *Total Adverse Events* includes all adverse events reported in the FAERS database. This is the broadest measure and it does not differentiate between a headache and a death. We also look at *Serious Adverse Events*, which we measure by looking at adverse events that were recorded as death, hospitalization, disability, life-threatening, and/or congenital anomaly in the OUTCOME files of the FAERS database. Lastly, we look at *Death Adverse Events*, which only captures those adverse events that led to the death of the patient. The last two measures can only be used for safety alerts announced after 2004, the year in which the OUTCOME files became available. Often times, the reports of these adverse events spike in time, with no events being reported one day while other days have dozens of reports. For this reason, we take the natural logarithm of adverse events (adding one to avoid missing observations for those days with zero events) to account for its skewed distribution.[6]

Independent Variables: Our main explanatory variable is *Friday*, which takes the value of 1 if the alert was released on a Friday and 0 otherwise. In addition, we create the variable *After*, which is 1 for days after the safety alert was issued and 0 for days before the safety alert was issued.

Controls: We include several controls in our tests. At the firm level, we add the following measures. First, we control for the number of branded drugs the firm got approved in the last ten years as a proxy for firm size (*Firm # Drugs Prior*). We obtain this information from the FDA's Orange Book database, which lists all drug approvals for each firm. Second, we control for the number of safety alerts the firm has suffered in all of its drugs in the previous ten years, which is obtained from the Medwatch website described above (*# Safety Alerts Firm*). We expect that the presence of prior safety alerts on the same firm may affect how

[6] We also tried an unlogged measure, which produces similar results (available upon request).

broadly a new safety alert is covered and disseminated. Third, we control for whether the firm is publicly traded or not (*Public*), as a way to capture the firm's visibility. Fourth, we control for the natural logarithm of the amount of lobbying expenditures directed at the FDA (*FDA Lobbying*) and at agencies other than the FDA (*Other Lobbying*) in the two years before the safety alert. Since having political connections may affect the weekday in which the alert is released and the reactions to safety alerts, we include these controls to avoid a potential omitted variable bias.

At the drug level, we control for the following factors. First, we include a measure of the number of safety alerts the drug had in the previous five years, which we obtain from the MedWatch website (*# of Prior Alerts on Drug*). The presence of previous alerts on the same drug may affect how doctors and patients react to new alerts. Second, we control whether the drug required post-marketing tests after approval (*Post-Marketing*). In some cases, the manufacturer is required by the FDA to undertake post-marketing clinical trials to assess some safety aspects about the drug that could not be assessed during drug development, and this may affect how the healthcare community reacts to safety news. Third, we include a control for whether the drug enjoyed a priority review since this could affect the presence of unknown side-effects (*Priority Review*). Fourth, we include the logged number of days since the FDA approved the drug to capture for how long the drug has been in the market (*Days Since Approval*). Fifth, we include the number of adverse events related to the drug in the year before the alert, to control for the level of drug adverse events before the communication (*Prior Adverse Events*).[7]

Finally, we include the following controls at the alert level. First, we add a dummy variable that takes the value of 1 if there were other alerts communicated that same day and 0 otherwise (*Multiple Alerts on Same Day*) and another dummy that takes the value of 1 if the alert in question refers to more than one single drug in its communication and 0 otherwise (*Multiple Drugs in Safety Alert*). Second, we include a control for the severity of the alert (*Severity*). Looking at the description of the safety alert communication released by the FDA, we code the alert's severity in the following way: (1) a value of 1 if the most serious side-effect identified in the alert is fatal (i.e., may lead to death), (2) a value of 0.5 if the most serious side-effect is serious but does not lead to death and (3) 0 if the most serious side-effects has non-serious consequences for patients' health.

Analysis

For our tests on the effect of *Friday* on the number of retweets and the number of articles as a measure of *media coverage*, we rely on ordinary least squares (OLS) estimations. For the tests where we use the dummy

[7] In the regressions on total, serious, and death adverse events, this variable captures the average daily number of total, serious, and death adverse events in the timeframe before the alert respectively.

variable of *media coverage* we rely on a logistic estimation. In all these tests we include alert year fixed-effects to control for temporal dynamics in the reaction to drug safety alerts. Then, we estimate the number of retweets and number of articles on drug p, in year t, owned by firm f, using the following specifications:

$$\text{Diffusion}_{ptf} = \zeta_0 + \zeta_1 \textit{Friday}_{ptf} + \zeta \textit{Controls}_{ptf} + \varepsilon_{ptf}$$

We expect ζ_1 to be negative since we should see fewer retweets and less media coverage after Friday safety alerts.

To evaluate the impact of Friday safety alerts in reducing adverse events, we use a difference-in-difference design using OLS estimations. In these tests we compare the reduction of adverse events for safety alerts released on Fridays to the reduction of adverse events for safety alerts released on other weekdays. We run this difference-in-difference estimation using one, three, and six-month windows before and after the release of the alert to see how much the Friday effect lasts over time. We include alert year and day of the week fixed-effects to account for the possibility that the reporting of adverse events varies across the days of the week. Then, we estimate the number of adverse events on day d, before/after alert i, on drug p, in year t, owned by firm f, using the following specification:

$$\begin{aligned}\text{Log(Adverse Events+1)}_{ipdtf} = {} & \alpha_0 + \alpha_1 \textit{Friday}_{itf} + \alpha_2 \textit{After}_{ipdt} + \\ & \alpha_3(\textit{Friday}_{itf} \times \textit{After}_{ipdt}) + \alpha \textit{Controls}_{idptf} + \varepsilon_{ipdtf}\end{aligned}$$

We expect α_2 to be negative since we should see fewer adverse events reported after a safety alert. Yet, we expect this reduction to vary as a function of the weekday in which the alert is announced. Specifically, we expect that this reduction will be weaker for Fridays ($\alpha_3 > 0$).

Results

In Table 1 we report summary statistics for all the variables we use in our tests. Next, to get a sense of the raw data, we look at the number of retweets, media articles, and adverse events for both Friday and non-Friday alerts (see Tables 2 and 3). Table 2 shows that Friday alerts receive fewer retweets and are less likely to receive media coverage across all time windows. All these differences are statistically significant at the 5% level with the exception of two, which are significant at the 10% level. In addition, Table 3 shows the difference between the raw number of adverse events before and after the alert for all three types of adverse events described above and for all the time windows we use in our analysis. We find that safety alerts usually lead to a reduction in the number of adverse events for non-Friday alerts, but not for Friday alerts. The reduction of adverse events is significantly different from zero at the 5% level (see the t-test p-values) for

almost all types of adverse events across all time windows for non-Friday alerts, but not for Friday alerts.[8] Therefore, looking at just the raw data, we see that while non-Friday alerts seem to be effective in reducing adverse events, Friday alerts are not.

Tables 1, 2 & 3 about here

To account for unobserved heterogeneity we run the fully specified OLS and logistic regressions described above. In Table 4 we show the results of our estimations on *number of retweets* and *media coverage* adding our full list of controls. Overall, we find that Friday alerts receive fewer retweets and less media coverage. The coefficients in all models are always negative and statistically significant at the 5% level, with the exception of three cases where the significance is at the 10% level.

Table 4 about here

Next, we test the differences between Friday and non-Friday alerts in reducing adverse events running difference-in-difference estimations (reported in Table 5). We find strong evidence that safety alerts released on Fridays have less impact than safety alerts announced other weekdays. We find the main effect of *After* is always negative and significant across all time windows and types of adverse events (with the exception of serious adverse events in the one-month window), suggesting that safety alerts are, in general, effective in reducing patients' adverse events. We also find the interaction between *After* and *Friday* is always positive and statistically significant at the 5% level (with the exception of the six-month window for serious adverse events, which is significant at the 10% level). Overall, this evidence suggests Friday alerts are less effective in reducing the occurrence of patients' adverse events.[9]

Table 5 about here

[8] It is worth noting that, in some cases, we observe an increase in adverse events after a Friday alert, with one of them being 10% significant. The reason is that, in our sample, the number of adverse events before safety alerts is increasing over time. This is because new side effects are usually discovered in the first years of the drug in the market, which is when drug sales are increasing. Thus, as the number of patients taking the drug grows, the number of reported adverse events also grows. This means that, absent an alert, we should expect an increase in adverse events over time. Therefore, the fact that there is an increase in adverse events after several Friday alerts simply suggests that such alerts had no impact and the trend was very similar to the one we would see absent an alert.

[9] We replicate our main estimations with a dummy for each of the other weekdays (Monday, Tuesday, Wednesday and Thursday) instead of Friday. None of the other weekdays shows the same effect we find for Fridays. This shows that, not only do Friday alerts have less impact on average, but they that have the *lowest impact* (see Supplementary Appendix).

Magnitude of the Effects

To estimate the size of the effect of Friday alerts compared to non-Friday alerts we use post-estimation techniques derived by King et al. (2000) and introduced in the management literature by Zelner (2009). By taking the coefficients and the variance co-variance matrix estimated from our regression models we can use them as the basis of a multivariate normal distribution to simulate 100,000 random draws of our coefficients, which allows us to incorporate all of the uncertainty associated with our model. We are able to use these coefficient distributions to create statistical counterfactuals by changing the day of the alert, while holding all other variables at their means, and seeing the percent change on the dependent variable.

For our estimations on the *number of retweets* and *media coverage*, our findings suggest switching from a non-Friday alert to a Friday safety alert would result in 34% fewer retweets, 23 to 66% fewer articles, and a 12 to 51% reduction in receiving any news article at all. The size of these effects is provided for each model in Table 4. This is consistent with our proposition that healthcare and media professionals put less attention on Friday events and thus Friday alerts are disseminated less intensively.

We also estimate the size of the effect of Friday alerts compared to non-Friday alerts on the number of adverse events. Specifically, we find that changing Friday safety alerts to any other weekday would reduce total drug-related side-effects by 9 to 12%, serious drug-related side-effects by 6 to 15%, and drug-related deaths by 22 to 36%, depending upon the time interval.[10] The size of these effects is provided for each model in Table 5; interestingly, these effects become smaller the larger the window considered. This suggests alerts released on Fridays become similar to alerts released on other days the further away from the alert date. This is consistent with the idea that Friday alerts are disseminated more slowly, and thus it takes more time for doctors and patients to be informed.

Addressing Endogeneity Concerns

A potential source of concern is that maybe the weekday in which safety alerts are released is not random; meaning that certain drug, firm, or alert characteristics could increase the probability that a safety alert is released on a Friday. In fact, in the second section of our study we explore and show how firms who lobby the FDA are more likely to have safety alerts released on Fridays. Therefore, if any firm, drug, or alert characteristic affects the weekday when the alert is released *and* is also correlated with the amount of adverse events reported after a safety alert, then our tests in Table 5 may be subject to omitted variable bias. We deal with this potential bias in two ways.

[10] These figures are calculated as follows. First, we estimate the percentage change in adverse events after the alert for both Friday and non-Friday alerts separately. Second, we calculate the difference between these two percentage changes. For example, for the three-month window, the number of total adverse events after the alert is reduced by 11.6% for non-Friday alerts, but only reduced by 2.0% for Friday alerts. Thus, moving a Friday alert to any other weekday would have led to 9.6% fewer side-effects.

First, we replicate our main estimations including drug, alert, and firm fixed-effects. This rules out the possibility that our results are biased by the fact that patients and doctors report differently depending on the alert, the drug, or the firm that owns the drug. Some alerts might take place when drugs are experiencing many adverse events. Therefore, adding alert fixed-effects allows us to remove any differences in the amount of adverse events the drugs are experiencing (i.e., effectively demeaning all observations within the same alert). Moreover, doctors and patients may react to safety alerts differently depending on the nature of the drug in question (e.g., if it treats a chronic disease, when there are no alternative treatments). Therefore, adding drug fixed-effects allows us to remove this potential heterogeneity and look at existing variance within the same drug. Also, patients and doctors might react differently to safety alerts depending on the firm that owns the drug since certain firms may do a better job of informing doctors and patients about their drugs' safety updates. Including firm fixed-effects allows us to control for these potential firm-level differences. Adding these fixed-effects implies dropping all firm, alert, and drug-level control variables that do not change across observations, including the main effect of *Friday* since it does not change across alerts. We report our estimations in Table 6 and show very similar results. This evidence shows that even with this highly conservative model specification we find evidence of a Friday effect.

Table 6 about here

Second, we implement an additional test to address potential omitted variable bias. Specifically, we implement an entropy balancing procedure developed by Hainmueller (2012). This procedure is intuitively analogous to a matching procedure, with the advantage that it can assure the first and second moments of the observable variables for the treatment group are identical to those of the control group. While in classical matching procedures each treated observation is assigned a unique match, in the balanced procedure the goal is to create a weighted sample where the covariates of the control cases are equivalent to the sample of treated cases. Therefore, the balanced procedure is an optimal solution in those cases where there is a small number of treated and control observations and there is a need to match across multiple dimensions. In such cases, finding an observation from a small pool of control cases that matches the treated observation across many dimensions may not be possible. To show how the balancing procedure outperforms standard matching techniques in our setting, we provide Figure A2 in the supplementary appendix, which shows the differences across all dimensions between the treated sample (Friday) and the control sample (non-Friday), before and after the balancing procedure.

Therefore, we implement this balancing procedure using all control variables used in Table 5 as the key dimensions along with the levels and trend of pre-alert adverse events. To show how this works, in Figure

1a we report the number of adverse events, before and after the alert, for Friday and non-Friday alerts for the raw (un-balanced) sample; while in Figure 1b we do the same for the balanced sample. Note that in the balanced sample, both Friday and non-Friday alerts exhibit the same behavior before the alert, and after the alert the reduction in adverse events is smaller for Friday alerts. We also implement a regression using the balanced sample and show these results in Table 7. Overall, with this balancing procedure we find the same effects we report in our main estimations.

Table 7 and Figure 1a/1b about here

Evidence of the Mechanism

Our basic premise is that adverse events decrease after safety alerts mainly because doctors and patients reduce drug prescription and consumption after being informed of new safety issues with the drug. These newly discovered side-effects will trigger a reduction in drug consumption for certain patients since the benefits of the medication will no longer outweigh the risks, leading these patients to stop or reduce the use of the drug after the alert. This is what several studies in the medical literature have found (see Dusetzina et al. 2012, for a review).

In our study, we assume the reduction in drug consumption that follows a safety alert is weaker for Friday alerts, and this is why we see a smaller reduction in adverse events after the safety alert. To provide evidence of this assumption, we test how drug consumption changes after Friday and non-Friday safety alerts. To do this we collect information about the number of prescriptions dispensed for each drug from the State Drug Utilization database available on Medicaid.gov. Since the start of the Medicaid Drug Rebate Program, states report drug utilization for covered outpatient drugs paid for by state Medicaid agencies. This database provides information on the number of prescriptions reimbursed for each drug for a given quarter throughout the whole period in our sample (1999-2016).[11] We merged this data with our original database and created a new dependent variable, *drug prescriptions*, calculated as the natural logarithm of the number of prescriptions on the drug referred to in the safety alert.[12] With this new dependent variable, we replicate the difference-in-difference tests we report in Table 5, using the same independent (*After* and *Friday*) and control variables. It is important to note that, because information about prescriptions is provided on a quarterly basis, our whole sample is structured in quarters rather than days. This means that we can replicate

[11] This database includes only drugs covered by Medicaid, which represents 94.7% of our sample (233 drugs out of the 246 drugs in our original sample).

[12] This database provides two types of prescriptions: Fee-For-Service (FFS) and Managed Care Organization (MCO) prescriptions. Since the latter type is available only since 2010, we decided to use only the first type of prescription to have a homogenous measure across the whole time period.

the difference-in-difference tests for the three- and six-month windows, but not for the one-month window. In addition, the fact that the data is provided by quarters also has implications on how we measure our variable *After*: we give a value of 1 for those quarters after the safety alert was issued and 0 for those quarters before the safety was issued. With respect to the quarter when the safety alert was issued, we give *After* a value of 1 if the alert was issued in the first month of the quarter and 0 when the alert was issued in the second or third months of the quarter.[13] We replicate our main estimations with two specifications, (1) including alert year and quarter fixed-effects and (2) including alert year, quarter, and drug fixed-effects (see Table 8).

Table 8 about here

Consistent with prior studies in the medical literature (Dusetzina et al. 2012), we find that there is indeed a reduction in drug consumption after a safety alert: main effect of *After* is negative and significant across all four models. Moreover, we find that this reduction is weaker for Friday safety alerts: the interaction between *After* and *Friday* is positive and significant in three out of the four models. This suggests that while drug consumption drops after a safety alert, this drop is smaller for Friday alerts. If we look at the size of the effect over time, we can see that the coefficient of the interaction decreases as we move from the three-month to the six-month window. This is consistent with what we found with adverse events: the Friday effect seems to dissipate over time. Overall, this evidence suggests that the Friday effect we found in Table 5 is partly driven by differences in drug consumption.

2. Firm Lobbying and the Prevalence of Friday Safety Alerts

Our results so far suggest that Friday safety alerts have a lower impact than other safety alerts issued any other weekday. This means that, when announcements occur on Fridays, patients are more likely to continue suffering avoidable side-effects than if the alert was announced on Monday through Thursday. The natural question is: how big of a problem is this? Are Friday alerts rare? In Figure 2 we show the distribution of safety alerts announced by the FDA on branded drugs during the 1999-2016 period for each weekday. Surprisingly, rather than being rare, Fridays are the most common weekday for an alert (about 25% of all alerts). Using a Kolmogorov-Smirnov test we show the distribution of alerts is statistically different at the 0.1% level from the distribution of available days in that same period, suggesting the over-representation of Fridays is not random.

[13] We also tried giving *After* a value of 0 for the quarter when the alert was issued irrespective of the month in which the alert was announced and the results provide the similar support (available upon request).

Figure 2 about here

If the prevalence of Friday alerts is not random, why would the FDA be more likely to issue alerts on Fridays? According to the FDA, the timing of safety alert announcements is determined by the need to have people informed about potentially important safety information as early as possible and having that information thoroughly substantiated (CDER 2007). Based on this, there is no reason for one specific weekday to be overrepresented. We contacted the FDA who confirmed no specific weekday is favored, and the decision on when to announce a safety alert is made on a case by case basis. Next, we explore a potential explanation for why alerts might be more frequently announced on Fridays: that firms may influence the process.

Prior research has shown that safety alerts have several consequences for the firm commercializing the alerted drug (Chen et al. 2009, Hurren et al. 2011). First, these announcements are likely to negatively affect the firm's reputation in the marketplace, which can lower the firm's ability to attract consumers, business partners, and employees (Ahmed et al. 2002, Cheah et al. 2007, Dowdell et al. 1992). Second, firms experience a drop in sales after safety alerts due to a reduction in drug consumption as we showed above (Dusetzina et al. 2012, Hurren et al. 2011). Yet, while safety alerts are likely to threaten firm performance, we argue Friday safety alerts will have a weaker impact. First, as we showed with our results on prescriptions, Friday alerts lead to a smaller decrease in drug consumption, meaning that the impact of the alert on drug sales will be weaker. Second, as we showed with our results on media coverage, Friday safety alerts are less broadly disseminated. Therefore, Friday news is more likely to be overlooked by investors and key stakeholders, suggesting that Friday alerts will have a weaker negative impact on the firm's reputation in the marketplace. For these reasons firms will prefer their alerts to be announced on Fridays. This is consistent with the evidence reported in prior studies showing that firms are more likely to release bad corporate news on Fridays (Louis and Sun 2010, Michaely et al. 2016). In our context, however, firms do not choose which weekday safety alerts are announced, the FDA does. The question then becomes: can a firm influence the FDA's decision about when to release a safety alert? To answer this question, we first need to understand how much firms participate in this process.

The specific division responsible for evaluating safety information and making safety alert announcements is the Drug Safety Oversight Board, a branch of the FDA to which firms have little access. According to the FDA's statutes regarding the communication of safety information, the FDA has no obligation to inform the firm that it is evaluating the safety of one of its drugs. The FDA "intends to notify the relevant sponsor [...] at least 24 hours before the first instance in which emerging information about that drug is communicated" but it is not bound to do so (CDER 2007, p 13.). This makes influencing the Drug Safety

Oversight Board difficult without prior connections. Once the firm is aware that the Board evaluates one of its drugs, it might be too late.

We propose that lobbying may provide a bridge between the FDA's Drug Safety Oversight Board and the firm. Lobbying, as defined by the Lobbying Disclosure Act (2 U.S.C. §1601), is the provision of information to policy makers and agencies by individuals representing the firm interests. Therefore, previous lobbying activities to the FDA may open a communication channel with the agency.[14] This communication channel might allow firms to become aware of a potential safety alert for one of its drugs and allow them to provide information to the FDA with respect to the drug being evaluated. This should increase the firm's ability to influence the timing of the process, and thus when the safety communication will be announced. Accordingly, we explore whether firms with a history of lobbying the FDA are more likely to have their safety alerts issued on Fridays.

Data and Sample

We investigate the probability that an alert will be released on a Friday looking at the same 441 safety alerts during the 1999-2016 period used in our previous tests. To identify how much firms are lobbying the FDA we use data from the Center for Responsive Politics' OpenSecrets database.[15] This database tracks all lobbying activities disclosed by government-mandated reports from registered lobbyists. The database is available from 1998 to 2015 and includes the name of the client/employer, expenses for lobbying, and importantly for this study, which agency/agencies were lobbied.

Measurements

Dependent Variable: Our dependent variable is *Friday*, which takes the value of 1 if the alert was released on a Friday and 0 otherwise.

Independent Variables: We use two measures for *FDA Lobbying*: (1) a dummy variable that takes the value of 1 if the firm lobbied the FDA and 0 otherwise, and (2) the total amount of lobbying expenditures targeted at the FDA. We look into firms' lobbying activities in two different time intervals: one and two years before the safety alert announcement.

Controls: We include the same control variables we used in our previous tests.

[14] In some cases firms disclose keywords about the specific objectives of their lobbying activities as required by the Lobbying Disclosure Act (2 U.S.C. §1601). Consistent with our argument we find that firms indeed report that their lobbying efforts were related to issues such as "drug safety oversight", "prescription drug labelling", and related topics.

[15] See `www.opensecrets.org`.

Analysis

We test if firm lobbying influences whether the FDA announces safety alerts on Fridays. Given the binary nature of our dependent variable we use a logistic regression estimation. Thus, we estimate the probability that alert i, on drug p, in year t, owned by firm f, is announced on a Friday with the following specification:

$$\text{Friday}_{itpf} = \text{Bernoulli}(\text{logit}^{-1}(\delta_0 + \delta_1 \textit{FDA Lobbying}_{itpf} + \delta \textit{Controls}_{ipft}))$$

We expect that FDA Lobbying will increase the probability that a safety alert is announced on a Friday ($\delta_1 < 0$). In these regressions, we include alert year dummies to control for temporal dynamics in the reaction to drug safety alerts.

Results

We first look at simple descriptive statistics to explore whether Friday alerts are explained by firms' lobbying activities. Figure 3 shows the distribution of safety alerts along the days of the week, as in Figure 2, but with the sample split into two different groups: firms that lobbied the FDA in the two years before the safety alert and firms that did not. Two things are immediately evident in these figures. First, for alerts where firms did not lobby the FDA (77% of our sample) Thursdays were just as common as Fridays, with Tuesdays not far behind. Further, a Kolmogorov-Smirnov test does not reject the null hypothesis that this distribution is statistically different from a distribution of available days. This suggests the FDA is neutral in regard to the weekday it announces its alerts for firms with no political influence. Second, for alerts where firms lobbied the FDA (23% of our sample), Fridays are unequivocally the most likely weekday in which alerts were released: one third of all announcements fell on a Friday.

Figure 3 about here

To make sure these findings are not driven by drug, firm, or alert characteristics, we run our logistic estimations including the full list of controls and show the results on Table 9. In all models, *FDA Lobbying* is positively associated with the probability that the alert is announced on a Friday. It is important to note that all these regressions control for how much the firm lobbies agencies other than the FDA, allowing us to estimate the impact of lobbying the FDA specifically. The results of these logistic estimations show that all the coefficients are positive and significant at the 5% level (except for the dummy for *FDA Lobbying* two years prior, which is significant at the 10% level). Irrespective of the time window we consider and the nature of our measure (discrete versus continuous), these results suggest a clear story: lobbying the FDA increases the probability that a firm's safety alert is announced on a Friday.

Table 9 about here

Magnitude of the Effects

We use the post-estimation techniques described above to estimate the size of these effects (King et al. 2000). Specifically, we estimate the probability of receiving a Friday alert depending on whether the firm lobbied the FDA or not while holding all other variables at their means. The effect size is large: firms that lobby the FDA are anywhere from 49% to 56% more likely to receive a Friday alert than firms that have not previously engaged in lobbying (the size of these effects is reported in Table 9). These findings suggest that a set of firms are able to have their alerts on Fridays, while others have their releases on any random weekday.

Addressing Endogeneity Concerns

One important concern is that our regression results could provide biased estimates because of selection problems. For instance, it could be the case that alerts that affect multiple patients are more likely to be announced on Fridays because the FDA takes longer to debate the issues and this means that such alerts tend to be announced towards the end of the working week. Additionally, firms may be more likely to lobby for such alerts. If these two effects are in place, then the logistic regression will provide estimates of the effect of lobbying on the likelihood that the alert is announced on a Friday that are biased upwards.

To address this potential selection problem, we run an instrumental variable regression in which the instrumental variable is the amount of campaign donations made by the firm to the U.S. congress. If we assume that firms that engage more in political donations are more likely to use lobbying as well, then the presence of political donations will increase the likelihood of firm lobbying. This instrumental variable, therefore, meets the relevance condition. To make sure it meets the exogeneity condition, we look at donations made six years before the alert. We believe that it is highly unlikely that firm donations made six years before the safety alert would affect the weekday in which such alert is announced.

Using this instrumental variable, we run an IV Probit model in order to account for endogenous selection into lobbying. In the first stage, we regress *FDA Lobbying* on our control variables and the amount of campaign donations six years before as an instrument. Both of the first-stage F-tests are over 15, suggesting that our instrument is strong. In the second step, we re-estimate the probability of a *Friday* alert as a function of the instrumentalized measure of *FDA Lobbying* that comes from the estimations of the first stage. These results are provided in Table 10. Overall, we find support for our initial findings: we still find that *FDA Lobbying* increases the probability that a firm's safety alert is communicated on a Friday. The coefficient is still positive and statistically significant for both time intervals.

Table 10 about here

One plausible concern is that potential endogeneity associated with the firm's decision to lobby the FDA is driving the results we found above on adverse events. To alleviate this concern we replicate our main estimations by excluding any firm that has lobbied in both of the past two years on Table 11. In this subsample we still find support for the Friday effect.

Table 11 about here

3. Conclusions and Policy Implications

We provide evidence that Friday appears to be the least effective day of the week for the FDA release safety alerts in order to decrease avoidable drug-related side-effects. Our evidence suggests that Friday safety alerts have a lower impact because they are disseminated less broadly: Friday safety alerts receive 34% fewer retweets, 23 to 66% fewer articles, and are 12 to 51% less likely to receive any news article compared to alerts announced any other weekday. Further, we show changing Friday safety alerts to any other weekday would reduce all drug-related side-effects by 9 to 12%, serious drug-related complications by 6 to 15%, and drug-related deaths by 22 to 36%. It is important to highlight that alerts released on Fridays become similar to alerts released on other days as we get further away from the alert date. This is consistent with the idea that Friday alerts are disseminated more slowly, and thus it takes more time for doctors and patients to be informed. In addition, our evidence suggests that the lower reduction in adverse events for Friday alerts is driven by a lower reduction in drug consumption. We believe our finding is important since Friday was the most frequent weekday for safety alert announcements from 1999-2016. We suggest firm lobbying could be one explanation for why alerts have a greater probability of being announced on Fridays: lobbying the FDA leads to a 49% to 56% greater chance of firms getting their alerts issued on Fridays.

This has clear policy implications. The simplest and most straightforward conclusion is that, if Friday alerts are less effective, the FDA should shift these announcements to other weekdays. In addition, the fact that Friday alerts have a lower impact suggests another potential problem: doctors and patients might not be updated about safety news quickly enough. While there have been important advancements in the reporting of safety information in recent years, with the FDA implementing new and richer channels and the avoidance of prescribing errors with the implementation of electronic reporting systems, apparently these advancements have not been enough. Further improvements in this direction should involve the FDA, the medical community, as well as drug manufacturers.

While we believe we present robust evidence that Friday alerts have a lower impact, it is important to acknowledge our study's limitations. First, we propose two different mechanisms to explain the reasons

behind the Friday effect: doctors reducing prescriptions and patients reducing consumption. We are unable to distinguish which one is more important in driving our results. Future research should address this gap. Second, our findings about the reduction in avoidable adverse events after safety alerts refer only to adverse events generated by the drug. That is, we do not account for what happens to patients that stop taking the medication due to safety alerts. To assess the overall impact of safety alerts on patients' health we would need to compare the situation of patients that follow the safety alert recommendation and stop taking the medication with the situation of patients that do not follow those recommendations and still take the drug. However, if on average, safety alerts improve patients' health when patients and doctors follow their recommendations, then the FDA should reconsider releasing safety information on Fridays.

Finally, we think it is important to stress what our results can and cannot say with respect to the FDA and firms' motivations. Our findings do not imply that firms and the FDA are colluding to place drug alerts on days that will cause harm to patients. Nor do they imply that firms wish to harm people at the expense of profits, or that the FDA is willingly abdicating its responsibility towards consumer safety to benefit firms. It is to the FDA's advantage for firms to remain cooperative. Therefore, placing the alert on Fridays may seem like an innocuous concession in exchange for more cooperation with drug companies. The lack of evidence about the varying impact of safety alerts for different announcement days implies that the FDA may be unaware that Friday alerts might be disseminated less broadly and thus have a lower impact. Likewise, firms might also be unaware of the lower impact of Friday alerts in reducing drug sales and patients' side-effects, so maybe they are simply trying to have their alerts on Fridays to avoid the negative reputational crisis that follows safety scandals. Alternatively, if firms are aware of the Friday effect, their preference for Friday alerts may correspond to a shortsighted goal of minimizing immediate attention of problems with their drugs, overlooking the longer-term consequences with respect to patients' health and their reputation. We do not know the extent to which firms and the FDA are aware of the Friday effect and its consequences. Accordingly, why firms and the FDA behave like they do, and the ethical implications of their behavior, is something we do not and cannot answer in our study.

What our study does suggest is that Friday alerts are associated with a smaller reduction in drug side-effects. We hope our study will spur further research on this extremely relevant topic as a way to help improve the impact in the reporting of safety information.

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Tables

Table 1 Descriptive Statistics

		Number of Observations	Mean	Std Dev	Min	Max
Daily Measures	*Log Total Adverse Events*	322371	0.521	0.878	0	8.569
	Log Serious Adverse Events	257312	0.305	0.675	0	6.516
	Log Death Adverse Events	257312	0.090	0.326	0	5.541
Drug-Alert Measures	*Friday*	441	0.265	0.442	0	1
	Multiple Alerts on Same Day	441	0.265	0.442	0	1
	Multiple Drugs in Safety Alert	441	0.229	0.420	0	1
	# of Prior Alerts on Drug	441	0.936	1.407	0	8
	Severity	441	0.422	0.357	0	1
	Days Since Approval	441	7.372	0.963	0.693	8.897
	Post-Marketing	441	0.392	0.488	0	1
	Priority Review	441	0.251	0.434	0	1
Firm Measures	*Prior Adverse Events*	441	6.053	2.116	0	10.003
	# Safety Alerts Firm	441	6.176	7.599	0	35
	Firm # Drugs Prior	441	1.945	0.889	0	3.583
	Public	441	0.462	0.499	0	1
Lobbying Measures	*Lobbied Past Year*	441	0.287	0.453	0	1
	Lobbying Amount 1 Year Prior	441	3.256	5.215	0	14.821
	Other Lobbying 1 Year Prior	441	7.403	7.357	0	16.640
	Lobbied Past 2 Years	441	0.238	0.426	0	1
	Lobbying Amount 2 Years Prior	441	3.869	5.629	0	14.821
	Other Lobbying 2 Years Prior	441	8.061	7.591	0	17.349
News	*Retweets*	139	7.669	6.567	0	34
	Any News Article 1 Day After Alert	441	0.574	0.495	0	1
	Any News Article 2 Days After Alert	441	0.642	0.480	0	1
	Any News Article 3 Days After Alert	441	0.714	0.452	0	1
	Any News Article 4 Days After Alert	441	0.753	0.432	0	1
	Any News Article 5 Days After Alert	441	0.776	0.418	0	1
	Any News Article 6 Days After Alert	441	0.787	0.410	0	1

Table 2 Sample Average Differences: Friday v. Non-Friday

Variable	Mean Non-Friday	Mean Friday	Difference in Means t-test/χ^2-test p-value
Retweets	8.41	4.81	0.006
Any Article 1 Day After Alert	65%	37%	0.000
Any Article 2 Day After Alert	72%	42%	0.000
Any Article 3 Day After Alert	74%	61%	0.004
Any Article 4 Day After Alert	77%	69%	0.059
Any Article 5 Day After Alert	80%	71%	0.045
Any Article 6 Day After Alert	81%	73%	0.061

Table 3 Average Total Concerns per Alert: One, Three, & Six Months Before and After Alert

			Concerns	Serious Concerns	Deaths
1 Month	*Non-Friday*	1 Month Before Alert	78	36	6.5
		1 Month After Alert	70	31	5.1
		Change (Δ)	-8	-5	-1.4
		Δ Different from 0			
		t-test p-value	0.022	0.069	0.002
	Friday	1 Month Before Alert	62	21	3.9
		1 Month After Alert	65	23	5.1
		Change (Δ)	+3	+2	+1.2
		Δ Different from 0			
		t-test p-value	0.545	0.399	0.065
3 Month	*Non-Friday*	3 Months Before Alert	213	90	17
		3 Months After Alert	180	78	14
		Change (Δ)	-33	-12	-3
		Δ Different from 0			
		t-test p-value	0.023	0.001	0.003
	Friday	3 Months Before Alert	190	64	13.3
		3 Months After Alert	172	66	15.3
		Change (Δ)	-18	+2	+2
		Δ Different from 0			
		t-test p-value	0.248	0.789	0.165
6 Month	*Non-Friday*	6 Months Before Alert	403	146	28
		6 Months After Alert	298	127	24
		Change (Δ)	-105	-19	-4
		Δ Different from 0			
		t-test p-value	0.001	0.123	0.302
	Friday	6 Months Before Alert	332	114	20
		6 Months After Alert	285	111	23
		Change (Δ)	-47	-3	+3
		Δ Different from 0			
		t-test p-value	0.162	0.742	0.170

Table 4 Impact of Fridays on Retweets and Media Coverage - OLS and Logistic Regressions

	Dependent Variable:												
		Any News Article Written (Binary)						# of News Articles					
		# of Days After the Alert						# of Days After the Alert					
	# of Retweets	1 Day	2 Days	3 Days	4 Days	5 Days	6 Days	1 Day	2 Days	3 Days	4 Days	5 Days	6 Days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	OLS	Logit	Logit	Logit	Logit	Logit	Logit	OLS	OLS	OLS	OLS	OLS	OLS
Friday	-2.779*	-1.487**	-1.570**	-0.732**	-0.556+	-0.621*	-0.627*	-1.773**	-2.415**	-1.256*	-1.079+	-1.191+	-1.393*
	(1.183)	(0.264)	(0.270)	(0.268)	(0.284)	(0.299)	(0.303)	(0.320)	(0.433)	(0.542)	(0.578)	(0.634)	(0.660)
Multiple Alerts on Same Day	1.045	0.160	0.116	0.006	0.013	-0.096	-0.259	0.959*	1.561*	1.558*	1.861*	2.058*	2.265*
	(2.402)	(0.296)	(0.313)	(0.319)	(0.337)	(0.349)	(0.352)	(0.464)	(0.656)	(0.767)	(0.802)	(0.893)	(0.968)
Multiple Drugs in Safety Alert	1.135	0.502	0.455	0.350	0.371	0.200	0.067	0.685	0.776	0.676	0.741	0.670	0.724
	(1.348)	(0.323)	(0.340)	(0.366)	(0.386)	(0.392)	(0.394)	(0.483)	(0.620)	(0.680)	(0.710)	(0.757)	(0.806)
Severity	2.907+	-0.297	-0.162	-0.073	0.367	0.198	0.086	-0.212	-0.426	-0.275	0.118	0.119	-0.082
	(1.528)	(0.322)	(0.338)	(0.360)	(0.390)	(0.389)	(0.390)	(0.447)	(0.570)	(0.639)	(0.702)	(0.751)	(0.776)
# Safety Alerts Firm	0.123	0.029	0.031	0.026	0.016	0.015	0.013	0.004	0.036	0.036	0.042	0.031	0.030
	(0.313)	(0.024)	(0.026)	(0.025)	(0.025)	(0.026)	(0.025)	(0.039)	(0.054)	(0.064)	(0.069)	(0.076)	(0.081)
# of Prior Alerts on Drug	0.988	0.160	0.197+	0.311*	0.393**	0.395**	0.460**	0.097	0.036	0.127	0.294	0.302	0.403
	(0.717)	(0.103)	(0.110)	(0.124)	(0.121)	(0.125)	(0.137)	(0.160)	(0.210)	(0.252)	(0.263)	(0.291)	(0.308)
Firm # Drugs Prior	0.352	-0.268	-0.378*	-0.330+	-0.307	-0.134	-0.112	-0.076	-0.210	-0.165	-0.153	-0.161	-0.114
	(0.737)	(0.172)	(0.186)	(0.181)	(0.189)	(0.190)	(0.189)	(0.214)	(0.264)	(0.313)	(0.342)	(0.381)	(0.403)
Days Since Approval	1.522*	-0.305*	-0.195	-0.300*	-0.201	-0.126	-0.110	-0.200	-0.173	-0.183	-0.150	-0.133	-0.088
	(0.705)	(0.120)	(0.121)	(0.137)	(0.137)	(0.138)	(0.140)	(0.151)	(0.195)	(0.216)	(0.238)	(0.257)	(0.272)
Post-Marketing	1.333	-0.220	-0.077	-0.128	-0.290	-0.210	-0.091	-0.203	-0.373	-0.512	-0.810	-0.855	-0.900
	(1.534)	(0.264)	(0.286)	(0.285)	(0.296)	(0.306)	(0.312)	(0.336)	(0.441)	(0.533)	(0.576)	(0.615)	(0.645)
Priority Review	-1.366	-0.106	-0.190	0.016	0.116	0.006	0.037	-0.364	-0.614	-0.643	-0.919+	-0.906	-0.810
	(1.344)	(0.277)	(0.286)	(0.295)	(0.313)	(0.317)	(0.321)	(0.328)	(0.421)	(0.512)	(0.546)	(0.604)	(0.644)
Public	0.065	0.607*	0.656*	0.526+	0.489	0.438	0.381	0.396	0.461	0.342	0.252	0.029	-0.126
	(1.230)	(0.264)	(0.285)	(0.303)	(0.329)	(0.342)	(0.341)	(0.363)	(0.443)	(0.501)	(0.576)	(0.640)	(0.701)
FDA Lobbying	-0.001	-0.009	-0.020	-0.017	-0.022	-0.006	0.002	0.011	0.029	0.040	0.038	0.018	0.005
	(0.155)	(0.029)	(0.030)	(0.030)	(0.032)	(0.033)	(0.033)	(0.036)	(0.045)	(0.053)	(0.062)	(0.070)	(0.079)
Other Lobbying	-0.022	-0.007	0.000	-0.001	-0.008	-0.017	-0.012	0.008	0.015	0.021	0.034	0.048	0.050
	(0.104)	(0.023)	(0.024)	(0.025)	(0.027)	(0.028)	(0.028)	(0.031)	(0.040)	(0.047)	(0.054)	(0.063)	(0.071)
Prior Adverse Events	-0.174	0.193**	0.170**	0.197**	0.210**	0.152*	0.131+	0.377**	0.486**	0.559**	0.614**	0.731**	0.797**
	(0.355)	(0.062)	(0.066)	(0.066)	(0.065)	(0.066)	(0.068)	(0.076)	(0.098)	(0.114)	(0.121)	(0.139)	(0.149)
Constant	-3.256	1.821	1.817	2.779*	2.156+	1.577	1.488	0.873	1.009	1.121	0.874	0.710	0.506
	(6.397)	(1.108)	(1.140)	(1.290)	(1.235)	(1.254)	(1.262)	(1.416)	(1.838)	(2.043)	(2.261)	(2.466)	(2.600)
Non-Friday to Friday: % Decrease in Any/# Articles	-33.5%	-51.3%	-46.8%	-17.9%	-11.5%	-12.3%	-11.7%	-65.3%	-65.6%	-29.7%	-22.6%	-23.4%	-25.6%
Alert Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	139	441	441	441	441	441	441	441	441	441	441	441	441
R^2/Pseudo R^2	0.289	0.153	0.172	0.130	0.127	0.120	0.113	0.188	0.200	0.184	0.214	0.214	0.216

The row estimating the % Decrease in Any/# Articles is calculated by using post-estimation techniques from King et al. (2000). We use the coefficients and the variance-covariance matrix estimated in each regression model to simulate 100,000 draws of our coefficients. With these coefficients we create statistical counterfactuals by changing the day of the alert while keeping all other variables at a value equal to their means. The magnitude of the effect is computed as the percent change of the dependent variable.
Robust standard errors in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5 Impact of Friday Safety Alerts on Adverse Events - Difference in Difference Regressions

	Dependent Variable:								
	Log(# of Adverse Events)			Log(# of Serious Adverse Events)			Log(# of Deaths)		
	1 Month	3 Months	6 Months	1 Month	3 Months	6 Months	1 Month	3 Months	6 Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After	-0.034**	-0.049**	-0.057**	-0.013+	-0.025**	-0.023**	-0.014**	-0.010**	-0.006**
	(0.008)	(0.005)	(0.004)	(0.007)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)
Friday	-0.007	0.002	0.006	-0.007	-0.001	0.006	-0.001	-0.000	0.003
	(0.012)	(0.007)	(0.005)	(0.011)	(0.006)	(0.005)	(0.006)	(0.003)	(0.002)
Friday × *After*	0.054**	0.040**	0.034**	0.040**	0.035**	0.012+	0.032**	0.019**	0.014**
	(0.017)	(0.009)	(0.007)	(0.015)	(0.009)	(0.006)	(0.008)	(0.005)	(0.003)
Multiple Alerts on Same Day	0.003	-0.005	-0.021**	0.006	0.002	-0.009*	0.008	0.003	-0.005*
	(0.011)	(0.006)	(0.005)	(0.010)	(0.006)	(0.004)	(0.006)	(0.003)	(0.002)
Multiple Drugs in Safety Alert	-0.026*	-0.011+	0.006	-0.021*	-0.010+	0.011**	-0.008+	-0.004	0.000
	(0.011)	(0.006)	(0.004)	(0.009)	(0.005)	(0.004)	(0.005)	(0.003)	(0.002)
Post-Marketing	0.010	0.003	-0.007+	0.022**	0.012**	0.003	0.016**	0.005*	0.000
	(0.009)	(0.005)	(0.004)	(0.007)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)
Severity	-0.034**	-0.034**	-0.033**	-0.033**	-0.020**	-0.026**	-0.012*	-0.007*	-0.014**
	(0.011)	(0.006)	(0.005)	(0.010)	(0.005)	(0.004)	(0.005)	(0.003)	(0.002)
Public	-0.016+	-0.003	-0.008*	-0.013+	-0.002	0.001	-0.012**	-0.007**	-0.008**
	(0.008)	(0.005)	(0.004)	(0.008)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)
Priority Review	-0.005	0.003	-0.001	-0.011	-0.004	-0.001	-0.003	-0.002	0.001
	(0.009)	(0.005)	(0.004)	(0.009)	(0.005)	(0.003)	(0.005)	(0.003)	(0.002)
# Safety Alerts Firm	-0.000	0.001**	0.001+	-0.001	0.002*	0.000	-0.000	0.001	0.001*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
# of Prior Alerts on Drug	0.007+	0.011**	0.017**	-0.000	0.000	0.012**	-0.002	0.002	0.011**
	(0.004)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
Firm # Drugs Prior	0.011*	0.014**	0.014**	0.001	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)
Days Since Approval	-0.001	0.002	-0.004**	-0.002	-0.003+	-0.009**	-0.000	-0.001	-0.004**
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
FDA Lobbying	-0.001	-0.002**	-0.001	0.001	-0.000	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Other Lobbying	0.001	0.001**	0.000	0.001	0.001*	0.001**	0.000	0.001**	0.001**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prior Adverse Events	0.974**	0.930**	0.912**	0.997**	0.976**	0.959**	0.984**	0.973**	0.928**
	(0.007)	(0.004)	(0.004)	(0.010)	(0.006)	(0.006)	(0.021)	(0.014)	(0.014)
% Change in Adverse Events Moving from Friday to Non-Friday	-12.3%	-9.6%	-8.7%	-15.1%	-14.2%	-5.6%	-36.0%	-24.9%	-22.1%
Day of the Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Alert Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	23815	74210	131406	18920	58463	103818	18920	58463	103818
# of Safety Alerts	433	410	362	344	323	286	344	323	286
R^2	0.622	0.550	0.504	0.570	0.489	0.441	0.419	0.355	0.308

The row estimating the % Change in Adverse Events is calculated by using post-estimation techniques from King et al. (2000). We use the coefficients and the variance-covariance matrix estimated in each regression model to simulate 100,000 draws of our coefficients. With these coefficients we create statistical counterfactuals by changing the day of the alert while keeping all other variables at a value equal to their means. The magnitude of the effect is computed as the percent change of the dependent variable.
Robust standard errors in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6 Impact of Friday Safety Alerts on Adverse Events - Difference in Difference Regressions with Drug, Firm, and Safety Alert Fixed Effects

	Dependent Variable:								
	Log(# of Adverse Events)			Log(# of Serious Adverse Events)			Log(# of Deaths)		
	1 Month	3 Months	6 Months	1 Month	3 Months	6 Months	1 Month	3 Months	6 Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After	-0.034**	-0.049**	-0.057**	-0.013+	-0.025**	-0.023**	-0.014**	-0.010**	-0.006**
	(0.008)	(0.005)	(0.003)	(0.007)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)
Friday $\times$ *After*	0.054**	0.040**	0.034**	0.040**	0.035**	0.012+	0.032**	0.019**	0.014**
	(0.017)	(0.009)	(0.007)	(0.015)	(0.008)	(0.006)	(0.008)	(0.004)	(0.003)
# Safety Alerts Firm	0.064	0.021	-0.117	0.026	0.016	0.138*	0.001	0.004	0.009
	(0.055)	(0.078)	(0.076)	(0.057)	(0.055)	(0.056)	(0.015)	(0.012)	(0.008)
# of Prior Alerts on Drug	-0.019	-0.013	0.074	0.003	-0.005	-0.063*	0.007	0.001	-0.003
	(0.060)	(0.048)	(0.045)	(0.047)	(0.025)	(0.031)	(0.018)	(0.012)	(0.010)
Firm # Drugs Prior	-1.437	-0.524	-0.935	0.305	0.698	3.301*	0.195	-0.194	0.028
	(5.993)	(2.949)	(1.778)	(4.586)	(2.373)	(1.421)	(1.262)	(0.602)	(0.396)
Days Since Approval	-0.271	-0.102	-0.084	0.024	0.097	0.443*	0.027	-0.032	-0.002
	(0.961)	(0.460)	(0.265)	(0.726)	(0.363)	(0.206)	(0.201)	(0.098)	(0.066)
Prior Adverse Events	0.502	0.730	1.575**	0.546	0.597	-0.848	0.732	0.634*	0.473**
	(0.484)	(0.540)	(0.496)	(0.726)	(0.699)	(0.652)	(0.495)	(0.250)	(0.170)
Day of the Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Alert Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drug Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Safety Alert Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	23815	74210	131406	18920	58463	103818	18920	58463	103818
# of Safety Alerts	433	410	362	344	323	286	344	323	286
R^2	0.630	0.561	0.519	0.579	0.496	0.451	0.430	0.362	0.320

Robust standard errors in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 7 Impact of Friday Safety Alerts on Adverse Events - Difference in Difference Regressions with Entropy Balanced Sample

	Dependent Variable:								
	Log(# of Adverse Events)			Log(# of Serious Adverse Events)			Log(# of Deaths)		
	1 Month	3 Months	6 Months	1 Month	3 Months	6 Months	1 Month	3 Months	6 Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After	-0.028**	-0.047**	-0.062**	-0.007	-0.020**	-0.024**	-0.012**	-0.008**	-0.008**
	(0.010)	(0.006)	(0.004)	(0.009)	(0.005)	(0.004)	(0.005)	(0.002)	(0.002)
Friday	-0.008	0.001	0.003	-0.009	-0.002	0.002	0.000	-0.001	0.001
	(0.013)	(0.007)	(0.006)	(0.012)	(0.007)	(0.005)	(0.006)	(0.003)	(0.002)
Friday $\times$ *After*	0.049**	0.039**	0.039**	0.035*	0.030**	0.014*	0.030**	0.018**	0.015**
	(0.018)	(0.010)	(0.008)	(0.016)	(0.009)	(0.007)	(0.008)	(0.005)	(0.003)
Multiple Alerts on Same Day	0.006	0.001	-0.019**	0.016	0.014*	-0.001	0.006	0.007*	-0.001
	(0.012)	(0.007)	(0.005)	(0.011)	(0.006)	(0.005)	(0.006)	(0.003)	(0.002)
Multiple Drugs in Safety Alert	-0.042**	-0.021**	0.002	-0.041**	-0.021**	0.006	-0.015**	-0.008**	-0.002
	(0.013)	(0.007)	(0.006)	(0.011)	(0.006)	(0.005)	(0.005)	(0.003)	(0.002)
Post-Marketing	0.013	0.000	-0.004	0.022*	0.009+	0.008*	0.014**	0.003	0.002
	(0.011)	(0.006)	(0.004)	(0.009)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Severity	-0.036**	-0.035**	-0.035**	-0.030*	-0.017**	-0.022**	-0.015*	-0.008*	-0.013**
	(0.013)	(0.007)	(0.006)	(0.011)	(0.006)	(0.005)	(0.006)	(0.003)	(0.002)
Public	-0.011	-0.005	-0.005	-0.014	-0.004	0.002	-0.015**	-0.007*	-0.005**
	(0.010)	(0.006)	(0.004)	(0.009)	(0.005)	(0.004)	(0.005)	(0.003)	(0.002)
Priority Review	-0.012	-0.006	-0.025**	-0.013	-0.009+	-0.013**	0.001	-0.004	-0.004*
	(0.011)	(0.006)	(0.004)	(0.010)	(0.006)	(0.004)	(0.005)	(0.003)	(0.002)
# Safety Alerts Firm	-0.000	0.001+	0.001+	-0.001	0.001	-0.000	0.001	0.000	0.001*
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
# of Prior Alerts on Drug	0.005	0.011**	0.017**	-0.005	-0.001	0.009**	-0.003	-0.001	0.006**
	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
Firm # Drugs Prior	0.015*	0.013**	0.015**	0.002	-0.002	0.002	-0.002	-0.001	0.000
	(0.007)	(0.004)	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
Days Since Approval	0.004	0.005*	0.002	0.002	-0.001	-0.002	0.002	0.000	-0.000
	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
FDA Lobbying	-0.000	-0.001+	-0.000	0.001	0.001	0.001*	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Other Lobbying	0.000	0.001**	0.000	0.000	0.000	0.000	-0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prior Adverse Events	0.985**	0.934**	0.912**	1.010**	0.992**	0.951**	1.012**	1.020**	0.952**
	(0.009)	(0.006)	(0.005)	(0.013)	(0.008)	(0.007)	(0.026)	(0.017)	(0.014)
Day of the Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Alert Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	23815	74210	131406	18920	58463	103818	18920	58463	103818
# of Safety Alerts	433	410	362	344	323	286	344	323	286
R^2	0.565	0.501	0.452	0.471	0.396	0.370	0.351	0.312	0.263

Robust standard errors in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 8 Impact of Friday Safety Alerts on Medicaid Prescriptions - OLS Regressions

	Dependent Variable: Logged # of Prescriptions per Quarter			
	Timeframe			
	±1 Qtr	±1 Qtr	±2 Qtrs	±2 Qtrs
	(1)	(2)	(3)	(4)
After	-0.561**	-0.441**	-0.469**	-0.284**
	(0.168)	(0.0921)	(0.142)	(0.0734)
Friday	-0.317	-0.238	0.038	0.0816
	(0.245)	(0.184)	(0.216)	(0.147)
Friday × *After*	0.824**	0.576**	0.588*	0.222
	(0.314)	(0.194)	(0.268)	(0.160)
Multiple Drugs in Safety Alert	-0.059	-0.691**	-0.226	-0.480**
	(0.238)	(0.218)	(0.199)	(0.163)
Severity	-0.629**	-0.247	-0.505**	-0.435*
	(0.223)	(0.208)	(0.191)	(0.176)
# Safety Alerts Firm	0.007	0.004	0.033*	0.021
	(0.016)	(0.032)	(0.013)	(0.026)
# of Prior Alerts on Drug	0.381**	0.0948	0.389**	0.282**
	(0.049)	(0.082)	(0.045)	(0.076)
Firm # Drugs Prior	0.098	0.018	0.073	-0.118
	(0.112)	(0.256)	(0.095)	(0.182)
Days Since Approval	0.587**	0.551*	0.475**	0.682**
	(0.095)	(0.250)	(0.075)	(0.192)
FDA Lobbying	0.032+	0.033	0.047**	0.070**
	(0.019)	(0.024)	(0.016)	(0.019)
Other Lobbying	0.006	0.001	-0.009	-0.029
	(0.015)	(0.021)	(0.013)	(0.019)
Public Firm	0.0169		-0.137	
	(0.167)		(0.137)	
Priority Review	-1.121**		-1.173**	
	(0.161)		(0.131)	
Post-Marketing	0.791**		0.814**	
	(0.161)		(0.135)	
Multiple Alerts on Same Day	-0.373*		-0.367*	
	(0.184)		(0.165)	
Drug Fixed Effects		Yes		Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes
Alert Year Fixed Effects	Yes	Yes	Yes	Yes
# of Alerts	385	383	339	337
R^2	0.42	0.87	0.42	0.87

Robust standard errors in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 9 Impact of Lobbying on Likelihood of Friday Safety Alerts - Logistic Regressions

	Dependent Variable: Binary Variable for Friday Alert			
	(1)	(2)	(3)	(4)
FDA Lobbying				
Dummy 1 Year Prior	0.731*			
	(0.367)			
Amount 1 Year Prior		0.066*		
		(0.031)		
Dummy 2 Years Prior			0.672+	
			(0.375)	
Amount 2 Years Prior				0.072*
				(0.031)
Other Lobbying				
Amount 1 Year Prior	0.004	0.004		
	(0.025)	(0.025)		
Amount 2 Years Prior			0.016	-0.003
			(0.023)	(0.026)
Multiple Alerts on Same Day	1.028**	1.022**	1.042**	1.015**
	(0.322)	(0.319)	(0.319)	(0.319)
Multiple Drugs in Safety Alert	-0.775*	-0.799*	-0.738+	-0.792*
	(0.389)	(0.389)	(0.395)	(0.392)
Severity	-0.391	-0.397	-0.385	-0.359
	(0.385)	(0.385)	(0.388)	(0.389)
# Safety Alerts Firm	-0.045+	-0.047+	-0.042	-0.042
	(0.026)	(0.026)	(0.026)	(0.026)
# of Prior Alerts on Drug	-0.057	-0.056	-0.066	-0.071
	(0.107)	(0.106)	(0.108)	(0.108)
Prior Adverse Events	0.043	0.043	0.050	0.045
	(0.070)	(0.070)	(0.072)	(0.071)
Firm # Drugs Prior	-0.376*	-0.370*	-0.381*	-0.374*
	(0.180)	(0.180)	(0.183)	(0.185)
Days Since Approval	0.115	0.108	0.107	0.077
	(0.149)	(0.150)	(0.149)	(0.148)
Post-Marketing	0.326	0.310	0.360	0.328
	(0.281)	(0.282)	(0.283)	(0.282)
Priority Review	0.079	0.068	0.087	0.062
	(0.322)	(0.322)	(0.321)	(0.322)
Public	0.208	0.192	0.052	0.145
	(0.295)	(0.296)	(0.304)	(0.289)
Constant	-2.467+	-2.417+	-2.440+	-2.195
	(1.347)	(1.346)	(1.345)	(1.344)
No Lobby to Lobby - % Increase in Probability of Friday Alert	56%		49%	
Alert Year Fixed Effects	Yes	Yes	Yes	Yes
N	428	428	416	416
Pseudo R^2	0.128	0.129	0.122	0.126

The row estimating the % Increase in the Probability of Friday Alert is calculated by using post-estimation techniques from King et al. (2000). We use the coefficients and the variance-covariance matrix estimated in each regression model to simulate 100,000 draws of our coefficients. With these coefficients we create statistical counterfactuals by changing the day of the alert while keeping all other variables at a value equal to their means. The magnitude of the effect is computed as the percent change of the dependent variable.
Robust standard errors in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 10 Impact of Lobbying on Likelihood of Friday Safety Alerts - IV Probit Regressions

	First Stage	Second Stage	First Stage	Second Stage
	Total FDA Lobbying 1 Year Prior	Friday Alert	Total FDA Lobbying 2 Years Prior	Friday Alert
	(1)	(2)	(3)	(4)
FDA Lobbying				
Amount 1 Year Prior		0.186*		
		(0.081)		
Amount 2 Years Prior				0.290*
				(0.139)
Candidate Donations 6 Years Prior	0.232**		0.157**	
	(0.043)		(0.046)	
Other Lobbying				
Amount 1 Year Prior	0.341**	-0.058		
	(0.036)	(0.036)		
Amount 2 Years Prior			0.441**	-0.122+
			(0.037)	(0.070)
Multiple Alerts on Same Day	-0.233	0.622**	-0.188	0.628**
	(0.482)	(0.201)	(0.505)	(0.228)
Multiple Drugs in Safety Alert	0.400	-0.582*	0.851	-0.740*
	(0.549)	(0.249)	(0.586)	(0.309)
Severity	-0.229	-0.255	-0.171	-0.236
	(0.548)	(0.230)	(0.584)	(0.262)
# Safety Alerts Firm	0.163**	-0.055*	0.168**	-0.071*
	(0.041)	(0.023)	(0.045)	(0.032)
# of Prior Alerts on Drug	0.106	-0.045	0.124	-0.070
	(0.157)	(0.067)	(0.170)	(0.078)
Prior Adverse Events	-0.062	0.027	0.022	0.014
	(0.105)	(0.045)	(0.112)	(0.052)
Firm # Drugs Prior	-0.229	-0.210+	-0.396	-0.153
	(0.287)	(0.123)	(0.309)	(0.145)
Days Since Approval	0.295	0.016	0.454*	-0.072
	(0.216)	(0.097)	(0.228)	(0.125)
Post-Marketing	0.585	0.087	0.621	0.030
	(0.423)	(0.181)	(0.448)	(0.215)
Priority Review	-0.374	0.092	0.042	0.022
	(0.463)	(0.196)	(0.494)	(0.222)
Public	0.568	-0.019	0.394	-0.065
	(0.466)	(0.211)	(0.495)	(0.240)
Constant	-1.987	-1.020	-3.508	-0.290
	(2.039)	(0.941)	(2.151)	(1.171)
Alert Year Fixed Effects	Yes	Yes	Yes	Yes
N	428	428	416	416
χ^2		48.14		37.95
R^2	0.533		0.564	

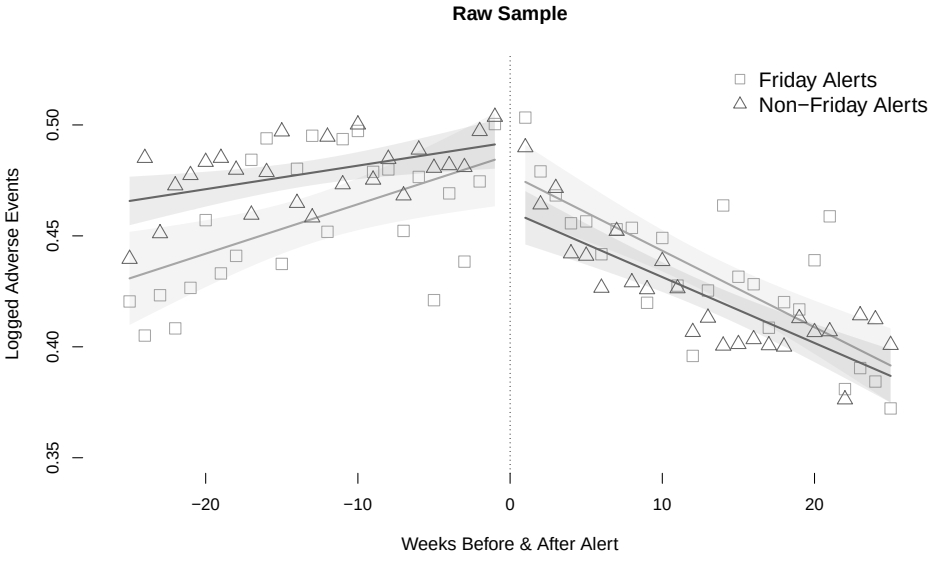
Robust standard errors in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 11 Impact of Friday Safety Alerts on Adverse Events - Difference in Difference Regressions with No Lobbying Sample

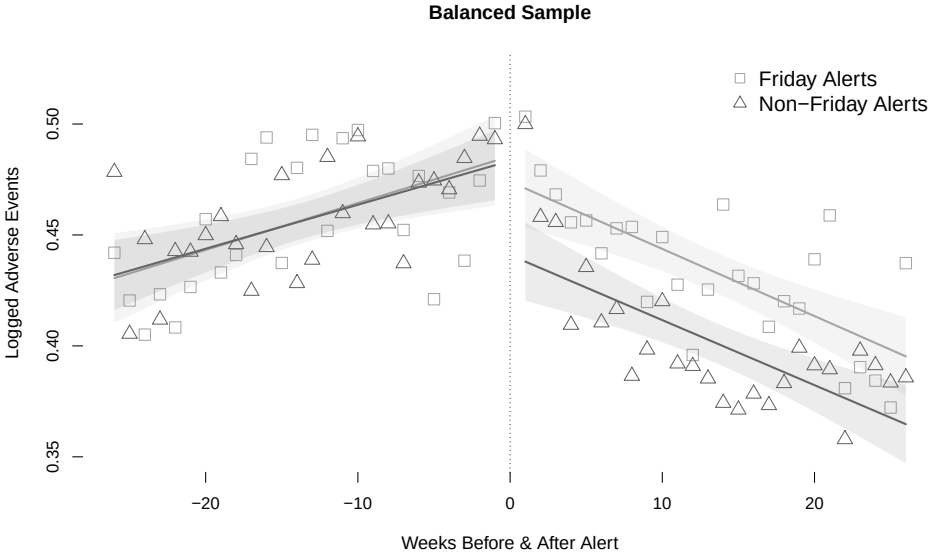
	Dependent Variable:								
	Log(# of Adverse Events)			Log(# of Serious Adverse Events)			Log(# of Deaths)		
	1 Month	3 Months	6 Months	1 Month	3 Months	6 Months	1 Month	3 Months	6 Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After	-0.037**	-0.048**	-0.055**	-0.012	-0.022**	-0.020**	-0.011*	-0.009**	-0.005**
	(0.009)	(0.005)	(0.004)	(0.008)	(0.005)	(0.003)	(0.005)	(0.002)	(0.002)
Friday	-0.009	0.000	0.003	-0.010	-0.001	0.004	-0.004	-0.001	0.003
	(0.013)	(0.008)	(0.006)	(0.012)	(0.007)	(0.005)	(0.006)	(0.004)	(0.003)
Friday × *After*	0.055**	0.024*	0.022**	0.031+	0.019+	-0.002	0.031**	0.018**	0.009*
	(0.018)	(0.011)	(0.008)	(0.017)	(0.010)	(0.007)	(0.009)	(0.005)	(0.004)
Multiple Alerts on Same Day	0.002	-0.010	-0.027**	0.003	-0.002	-0.008	0.008	0.001	-0.005*
	(0.012)	(0.007)	(0.005)	(0.011)	(0.006)	(0.005)	(0.006)	(0.004)	(0.003)
Multiple Drugs in Safety Alert	-0.034**	-0.031**	-0.009+	-0.022*	-0.011+	0.014**	-0.006	-0.004	0.001
	(0.012)	(0.007)	(0.005)	(0.010)	(0.006)	(0.004)	(0.005)	(0.003)	(0.002)
Post-Marketing	0.010	-0.001	-0.013**	0.028**	0.018**	0.004	0.016**	0.007**	0.000
	(0.010)	(0.006)	(0.004)	(0.008)	(0.005)	(0.003)	(0.005)	(0.003)	(0.002)
Severity	-0.031*	-0.019**	-0.022**	-0.036**	-0.011+	-0.021**	-0.012*	-0.003	-0.011**
	(0.012)	(0.007)	(0.005)	(0.011)	(0.006)	(0.005)	(0.006)	(0.003)	(0.002)
Public	-0.015+	0.001	-0.007+	-0.014+	0.000	-0.001	-0.009*	-0.006*	-0.008**
	(0.009)	(0.005)	(0.004)	(0.008)	(0.005)	(0.003)	(0.004)	(0.002)	(0.002)
Priority Review	0.003	0.005	0.008+	-0.001	0.004	0.010**	0.001	0.004	0.007**
	(0.010)	(0.006)	(0.004)	(0.009)	(0.005)	(0.004)	(0.005)	(0.003)	(0.002)
# Safety Alerts Firm	-0.000	0.002**	0.000	-0.000	0.003**	-0.000	-0.000	0.001+	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
# of Prior Alerts on Drug	0.009*	0.013**	0.021**	-0.001	0.003	0.018**	-0.002	0.005*	0.016**
	(0.004)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
# Drugs Firm	0.011+	0.012**	0.013**	-0.003	-0.006*	-0.004+	-0.001	-0.002	-0.001
	(0.006)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)
Days Since Approval	-0.003	-0.000	-0.005**	-0.001	-0.002	-0.008**	-0.000	-0.001	-0.004**
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
FDA Lobbying Past 2 Years	-0.000	-0.001+	-0.000	0.001	0.001	0.001*	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Other Lobbying Past 2 Years	0.001	0.000	0.000	0.001+	0.001**	0.001**	0.000	0.001**	0.001**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Previous Avg Adverse Events	0.975**	0.931**	0.916**	1.003**	0.970**	0.957**	0.987**	0.960**	0.909**
	(0.007)	(0.005)	(0.004)	(0.010)	(0.007)	(0.006)	(0.022)	(0.015)	(0.015)
Day of the Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Alert Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18150	56653	99825	14465	44888	79860	14465	44888	79860
# of Safety Alerts	330	313	275	263	248	220	263	248	220
R^2	0.669	0.607	0.556	0.625	0.541	0.481	0.488	0.399	0.336

This table replicates the same regressions as in Table 5 but only in the subsample of firms that did not lobby in the last two years.
Robust standard errors in parentheses: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Figures



(a) Raw Sample



(b) Balanced Sample

Figure 1 Raw & Balanced Sample's Adverse Events Before & After Safety Alert

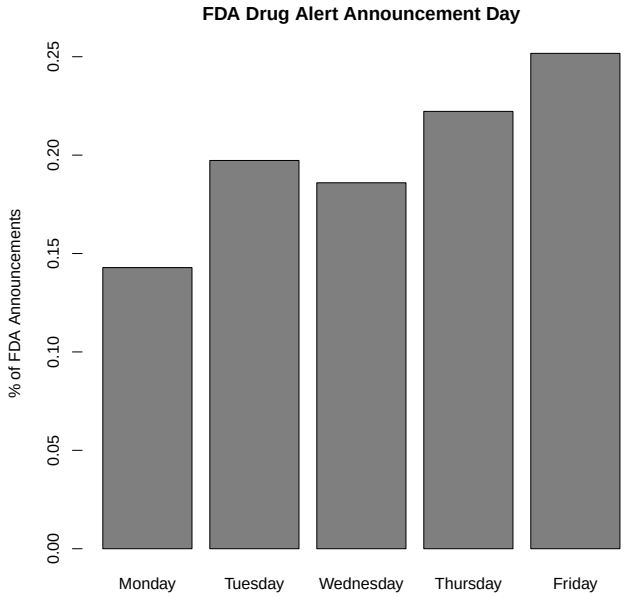


Figure 2 FDA Safety Alerts by Day - All Alerts

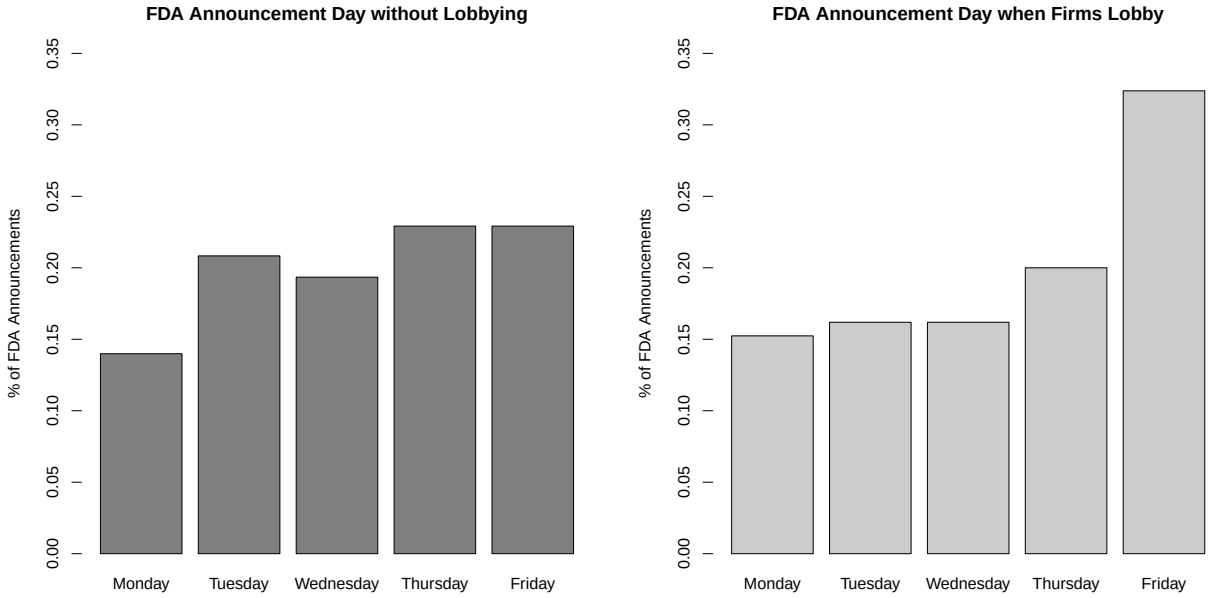


Figure 3 FDA Safety Alerts by Day & Lobbying